Default Rules as a Soft Incentive in Promoting Renewable Energy Uptake

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I want to dedicate this dissertation to my husband.

Joscha, your love and support mean the world to me.

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Abstract

The application of default rules as a soft incentive to promote renewable energy uptake has proven successful in previous research. While the strength and longevity of the default effect is demonstrated to a large extent in current studies, analysis of its heterogeneity is still missing. This study aims to explore the heterogeneity of the default effect according to customer characteristics, such as the differentiation between household customers and business customers. Building on behavioural theories, it asks: Is the default setting of renewable energy more successful in influencing the choices of household customers than business customers? In this context, the household customers are the household customers and the business customers are the commercial customers of a Swiss utility company.

A customer dataset (*n*=237,333) received from the utility company gives insight into customers' contract choices over four years. The main focus of the quantitative analysis is the comparison of contract choices before and after the utility company introduced a renewable energy contract as its default product. The analysis of the dataset is led by recent and established theories coming from sociology, psychology, and economics.

An analysis of the data demonstrates that the default setting on renewable energy is more successful in influencing the contract choices of household customers than those of business customers.

The results indicate that heterogeneity can be found in the default effect with regards to customer characteristics. On this basis, it is advisable to adjust the implementation of a default rules intervention that promotes renewable energy uptake to different customer groups. Further research is needed when it comes to exploring the dependency of the default effect on the opt-out costs and the awareness of the customer concerning the behavioural intervention.

Kurzfassung

Die bisherige Forschung zeigt auf, dass die Anwendung von Default-Setzung ein sanfter Anreiz zur Verhaltenslenkung ist, der hervorragende Wirkung zeigt, wenn es darum geht, den Verkauf von erneuerbaren Energieprodukten zu steigern. Die verhaltenslenkende Wirkung der Default-Setzung wird in zahlreichen Studien als ein starker und langlebiger Effekt beschrieben. In der bisherigen Forschung fehlt jedoch bisher eine Untersuchung der Heterogenität in diesem Effekt. Die vorliegende Studie widmet sich spezifisch der Heterogenität im Default-Effekt hinsichtlich der Unterscheidung von Kundenmerkmalen, wie zum Beispiel, Haushalts- und Geschäftskunden. Aufbauend auf gängige Verhaltenstheorien wird gefragt: Hat die Default-Umstellung von einem konventionell gespeisten Energietarif auf einen erneuerbaren Energietarif eine stärkere verhaltensändernde Wirkung auf die Haushaltskunden als auf die Geschäftskunden?

Der vorliegende Kundendatensatz (*n*=237,333) zeigt die Tarifwahlen aller Kunden über den Zeitraum von vier Jahren. Der Hauptfokus der quantitativen Analyse, der Prinzipien der empirischen Sozialforschung folgt, liegt auf dem Vergleich der Tarifwahlen vor und nach der Default-Umstellung auf den erneuerbaren Energietarif. Die Datenaufbereitung und -analyse ist theoriegeleitet und bedient sich der neuesten Erkenntnisse aus Psychologie, Soziologie und Betriebswirtschaftslehre.

Die Analyse der Daten zeigt, dass die Default-Setzung auf den erneuerbaren Energietarif eine stärkere verhaltensändernde Wirkung auf die Haushaltskunden als auf die Geschäftskunden ausübt.

Die Ergebnisse zeigen auf, dass die Heterogenität, die im Default-Effekt vorhanden ist, mit Kundenmerkmalen korreliert. Daher ist es ratsam, bei der Planung einer Default-Umstellung auf einen erneuerbaren Energietarif die verschiedenen Kundengruppen mit zu bedenken. Aufbauend auf der vorliegenden Arbeit sollte sich die künftige Forschung einerseits dem Einfluss von der Höhe der Ausweichkosten und andererseits dem Einfluss von Probandenaufmerksamkeit auf den Default-Effekt widmen.

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1. Introduction

One goal of Switzerland's Energy Strategy 2050 is to reduce the country's energy-related environmental impact. The National Research Programme "Managing Energy Consumption" (NRP 71) was implemented in order to explore the behavioural aspects of energy efficiency. The study at hand is part of the NRP 71, and is dedicated to promoting renewable energy uptake among citizens through the use of soft incentives instead of hard regulations. The core obstacle in the promotion of renewable energy uptake in Switzerland is the regulated electricity market, in which existing customer pools in large majorities hold the cheapest form of electricity – that is, conventionally sourced. Motivating existing customer pools to switch to more expensive renewable energy without hard regulations marks the ultimate obstacle.

Previous research has demonstrated the successful application of default rules as a soft incentive in many areas, including the promotion of renewable energy uptake. Studies show that default rules interventions have strong and long-lasting effects on subjects' choices. While the strength and longevity of the default effect is demonstrated to a large extent in existing studies, analysis of heterogeneity in the default effect is still missing. The study at hand explores the default effect not only in its strength and longevity but also in its heterogeneity in influencing different subjects in different ways according to their characteristics. The main subject characteristics in the study at hand are whether the electricity customers are buying for a household or a business. In this context, the household customers are the household customers and the business customers are the commercial customers of a Swiss utility company. Other subject characteristics on the individual level are the amount of utility use, gender, and previous renewable energy uptake. On the municipality level, there potential influencing factors include the proximity to the nearest nuclear power plant, voting results for the nuclear power phase out initiative, and municipality structure. All these possible determinants are explored regarding their influence on either increasing or decreasing the renewable default product acceptance.

Heterogeneity in the default effect is analysed with the help of a quantitative analysis of a natural field experiment of one Swiss utility company changing its default product from a conventionally sourced electricity product to a renewably sourced one. The whole customer dataset (*n*=237,333) is made up of 229,658 household customers and 7,675 business customers. The dataset includes two different default rules treatments: the introduction of a renewable default product for 230,881 customers and the introduction of a renewable-plus default product for 6,452 customers. The dataset covers four years and includes a number of descriptive customer characteristics on the individual level. Customer characteristics on the municipality level have been added. The main focus of the quantitative analysis is the comparison of contract choice before and after the utility company introduced the renewable energy default products.

An analysis of the data shows that customer characteristics, both on the individual level as well as on the municipality level, influence default product acceptance. Therefore, there is proven heterogeneity in the default effect. The default product was accepted in larger quantities among household customers than business customers. On this basis, it is advisable to adjust the implementation of a default rules intervention that promotes renewable energy uptake to different customer groups. Further research is needed when it comes to exploring the dependency of the default effect on the opt-out costs and the awareness that the customer has of the behavioural intervention.

In this paper, Chapter 1 presents an introduction to the research problem. Chapter 2 addresses the relevant theoretical background. The theory chapter is divided in two sub-chapters (2.1 and 2.2). The first sub-chapter defines soft incentives and the four core characteristics of nudging (2.1) and explains nudging using the theory of behavioural change (2.1.1). The second sub-chapter defines default rules as a soft incentive intervention (2.2). It covers the application of default rules in a couple of different decision areas (2.2.1), the application of default rules in the area of renewable energy uptake (2.2.2), and the third sub chapter is dedicated to the unwanted side effects of the application of default rules interventions (2.2.3). The section describing the unwanted side effects is further divided into three sub-chapters (2.2.3.1, 2.2.3.2, and 2.2.3.3). The first section points out moral self-licensing as an unwanted side effect of default rules interventions (2.2.3.1). The second highlights ethical problems in form of manipulations as an unwanted side effect of default rules interventions (2.2.3.2). The third reveals other forms of possible unwanted side effects (2.2.3.3).

The theory chapter is followed by Chapter 3, which covers the study background and data. This chapter is divided into four sub-chapters (3.1, 3.2, 3.3, and 3.4). To set the scene, the first sub-chapter describes the renewably sourced electricity market in Switzerland (3.1). This general study background is followed up by a description of the experimental utility company (3.2). Next, there is a description of how the experimental utility company implemented the default product change (3.3). The fourth and last sub chapter concentrates purely on the data, covering data preparations (3.4), including data cleaning (3.4.1), and data re-coding (3.4.2).

Chapter 4 is dedicated to the results and is divided into three sub chapters: descriptive analyses (4.1), bivariate analyses (4.2), and multivariate analyses (4.3). The descriptive analyses show descriptive statistics for utility use (4.1.1), renewable energy contracts (4.1.2), and customers' contract choices (4.1.3). The bivariate analyses show a diverse range of analyses ranging from analysis of the main default effect (4.2.1), analyses of two sub-samples (moving customers (4.2.2) and renewable-plus default (4.2.5)), and analyses of municipality level characteristics, including the voting initiative for a nuclear power phase out (4.2.3) and the proximity to a nuclear power plant (4.2.4). The multivariate analyses are divided into three sub-chapters. The first examines the results of a logistic regression of the short-term default effect (4.3.1) and the second reports the results of a logistic regression of the long-term default effect (4.3.2). While the first two analyses are on the individual level, the third multivariate analysis adds variables on the municipality level (4.3.3).

The results chapter is followed by a summary of all the results (Chapter 5) and a discussion of results (Chapter 6) that is divided into two sub-chapters. The first sub-chapter of the discussion is concerned with the default effect and the unwanted side effects in the study at hand (6.1). The second sub-chapter explores the moral aspects of applying soft incentives and, more specifically, the application of nudges as a soft policy tool (6.2). Finally, Chapter 7 addresses potential future research questions.

2. Theory

This chapter will lay out the theoretical groundwork, building the foundation for the analysis and interpretation of the experiment. In Section 2.1, nudges will be explained, starting from the four core characteristics defining a nudge: (1) intentionally changing choice architecture, (2) not changing (economic) incentives, (3) leaving the freedom to choose, and (4) being transparent to the decision-maker. A psychological explanation of how nudges influence decision-making will be provided with the help of the theory of behavioural change. After establishing what defines a nudge and how a nudge operates, the application of nudges will be discussed as a paternalistic soft policy tool. Here it will become clear that the core characteristics of what defines a nudge are not only hard to objectively evaluate but also give rise to concerns when the nudge is applied.

In Section 2.2, default rules will be explored as they apply to nudges in this experiment. The different ways of framing a decision and different options on how to set a default will be explained. With the help of the dual process theory, how default rules influence decision-making will be laid out. Furthermore, several behavioural presuppositions will explain the efficiency of the default rule. After establishing what defines a default nudge and how a default nudge operates, the application of default rules, first in different decision-making areas and then more specifically in the area of renewable energy, will be documented.

At the end of the theory chapter, the unwanted side effects of nudges and specifically default rules will be laid out in Section 2.3. Tools of behavioural manipulation are deemed to be controversial, and this is the case with the default rule nudge. On the one hand, the manipulation of a choice through a nudge can have unforeseen side effects like rebound behaviour and moral licensing, where the nudge influences one target area positively but other areas in an unintended negative way. On the other hand, the influencing of choice has the potential to distort decision preferences and therefore comes with the ethical concerns surrounding manipulation.

Overall, the theory chapter will cover topics ranging from a broad perspective on nudges to the more specific case of default rules, and end with a discussion on possible side effects and ethical concerns of applying nudges and more specifically default rules.

This journey through theory will address the different characteristics of influencing choice through the application of a default rule, thus providing the documented experiment with a critical background from which the success of the default effect can be judged and considered in relation to its possible side effects.

2.1 Defining Nudging

Nudging is a popular term that receives frequent attention, but is not defined by a single agreed-upon definition (Gigerenzer, 2015; Michalek et al., 2016). With the publication 'Nudge: Improving Decisions about Health, Wealth and Happiness', Thaler and Sunstein demonstrated a number of examples of non-monetary incentives and systematically categorized them (Thaler & Sunstein, 2009). This book was a bestseller and gave the discussion about nudging its first real boost in attention, which was added to by subsequent publications and public discussions. Now riding the end of the public attention wave, nudging has become an over-simplified concept to the public. The public has seen it all, judged it all, and argued it all, resulting in a much-muddied idea of the term in the end. The definition of nudging given in this chapter weighs the different common definitions (Michalek et al., 2016) against each other with the aim to successfully distinguish nudging from other types of behavioural manipulations as monetary incentives or education campaigns. The two main defining features of nudging techniques are freedom of choice and transparency, which will be discussed in more detail. The dual process theory (Fazio, 1990; Kahneman, 2013) will be laid out as the behavioural theory explaining nudging techniques. In line with its name, the theory describes two ways of influencing behaviour through communicative interventions. One way is cognitive reflective, and is thus an active process of changing attitudes, intentions, and behavioural implementations. The other way is automatic, involving not reflective but intuitive processing to change attitudes, intentions, and behavioural interventions. Most researchers understand nudges to change behaviour through communicative interventions to fall into the second category (Ölander & Thøgersen, 2014; Sunstein, 2017; Thaler & Sunstein, 2009). The definitions about nudging as a behavioural influencing tool are as diverse as the classification schemes that try to sort nudging techniques in groups. One of the most common classifications will be discussed in this chapter, giving insight into the broad spectrum of nudging techniques.

Even though the term nudging is quite new in public discussion, the phenomenon of nudging is not. Multiple disciplines research and apply nudges, also called soft incentives, such as economics, sociology, psychology, and social marketing sciences. Nudging techniques have been researched for a long time in consumer research, psychologically oriented behavioural sciences, and environmental sciences, but without being called nudges. Tversky and Kahnemann for example, showed in their theory of loss aversion that framing the same question in terms of loss aversion rather than framing it in terms of the realisation of profits brought forth different degrees of risk-taking (Tversky & Kahneman, 1981). In a growing number of countries, nudging advisors give guidance on policy questions for governmental agencies and NGOs (for example, in the United States, Great Britain, and Denmark; for an overview, refer to Reisch & Sandrini, 2015). Consumer research has long known that nudges influence decision outcomes a great deal (Thaler & Sunstein, 2009). Nudging has received much attention as a promising new soft policy tool. The benefits of using nudging as such a policy tool along with the disadvantages will be discussed in this chapter. Examples will be used to illustrate both sides and develop some guidelines.

Nudging, therefore, does not have only one definition, but rather several interpretations. To bring clarity to this frequently debated term it will first be defined along with its core characteristics, and then sorted with the help of a system to categorize nudging. Subsequently, the way that nudges operate will be addressed with the help of the dual process theory. Finally, the application of nudges as a soft policy tool will be discussed.

The Four Core Characteristics of Nudging

While the term 'nudging' is heterogeneously defined (Gigerenzer, 2015; Michalek et al., 2016), most common definitions still seem to agree on the following four core characteristics: (1) intentionally changing choice architecture, (2) not changing (economic) incentives, (3) leaving the freedom to choose, and (4) being transparent to the decision-maker.

The first core characteristic of nudging is the intentionality with which the choice architecture is changed. For each choice, there is a choice architecture present. Nudging takes this choice architecture and changes it to make a certain choice outcome more likely to occur. Nudges can make one part of information about the choice more salient and with that, influence the intuitive decision-making that is described by the dual process theory as type 1 processing (automatic and intuitive processing). Information can be introduced or made more salient at the point of decision-making or beforehand. The nudging techniques 'framing' and 'default rules', for example, change the choice architecture at the time of the choice, and 'priming' changes the choice architecture before the choice (Michalek et al., 2016, pp. 8–9).

In the realm of libertarian paternalism, nudges change the decision-making architecture through ‘nudging’ in the sense of gently pushing the decision-maker to a specific outcome. Nudges, therefore, change the decision-making architecture with a specific outcome in mind (Reisch & Sandrini, 2015, p. 19). This specific outcome is seen as superior to the other outcomes. The superiority of an outcome can be argued on a number of grounds (Reisch & Sandrini, 2015, p. 19). The superior decision outcome can be the choice outcome that embodies social welfare improvement for the individual and/or for society. It could also be the outcome that is preferred by the majority, or just that it embodies the interest of the regulator who applies the nudge.

While a decision-making context is always present, it is the intentional influence on the decision-making context with a specific behavioural outcome in mind that defines nudging (Hansen & Jespersen, 2013). Therefore, if the decision-making context is not intentionally influenced, nudging has not occurred. This defining characteristic of nudging – the intentionality of changing the choice architecture – is commonly agreed upon (Hausman & Welch, 2010) and stands as the strongest argument against the assumption that there is no alternative to nudging. On the grounds of the intentionality characteristic, it becomes clear that there is an alternative to nudging, because nudging is not the omnipresent decision-making context but rather the intentional changing of the decision-making context (Hansen & Jespersen, 2013). It follows that an untouched decision-making context is not a nudge but a true alternative to a nudge.

The second core characteristic of a nudge is that it does not change the incentives of the choice alternatives, particularly the economic incentives. Thaler and Sunstein define nudging as intentionally changing choice architecture without changing economic incentives (Thaler & Sunstein, 2009, p. 6). Other definitions of nudging have an even broader understanding of not changing incentives, not only including economic incentives but also including all other things that could change the presumable cost of a choice alternative, such as time, and effort (Hausman & Welch, 2010).

The third core characteristic is that nudges allow freedom of choice. One important point in defining nudging is that the decision-making framework is changed in a way that leaves the decision-maker the option to opt-out and retain his or her individual freedom to go against the nudge (Reisch & Sandrini, 2015). If the freedom to choose is not preserved, the behavioural influencing strategy could not be termed a nudge, but would have to be described as mere prohibition. This simple characteristic of leaving the freedom to choose is debated when it comes to specifics. Section 2.2.3.2 (Ethical Problems of Manipulation) will discuss when and how a nudge leaves the freedom of choice intact. The freedom to choose cannot be directly translated as preserving the array of decision options or providing more than one choice alternative. The freedom to choose is only intact if the decision-maker can withstand the nudging influence so that his or her true freedom of choice is retained.

The fourth core characteristic is that nudges are transparent to the decision-maker. A nudging technique needs to be a transparent influence in the choice architecture, and an attentive decision-maker should be able to recognize the behavioural influencing strategy. Without this core feature, a nudge would not be able to be differentiated from a hidden manipulation (Reisch & Sandrini, 2015). Despite the defining characteristic that nudges are a transparent behavioural influence, some theorists have tried to divide nudges into transparent nudges and non-transparent nudges. This sub-categorization is vague at best and prone to subjectivity (see Hansen & Jespersen, 2013). Therefore, this work will assume that nudges have the defining characteristic of being transparent, and will not enter the diverse sub-discourse of which nudges are transparent and which are not. While it sounds obvious that nudges must be transparent in order to not be labelled as mere manipulations, the more specific terms of the transparency characteristic of nudging are also widely debated (Hansen & Jespersen, 2013). The main argument revolves around whether nudges that are defined by only influencing the automatic and intuitive processes of decision-making (see Section 2.1.1: Explaining Nudging Using the Theory of Behavioural Change) can ever be called transparent? How transparent can an intentional change to the choice architecture be if it is designed to only influence the automatic and intuitive response of the decision-maker (type 1 nudge)? A critical discussion on the arguments regarding transparency and the claims of manipulation regarding nudging techniques will be provided in Section 2.2.3.2 (Ethical Problems of Manipulation).

The four core characteristics of nudging techniques cannot be defined separately, but go hand in hand. The freedom to choose does not only mean that there are choices available, but also that the behavioural intervention needs to be transparent. A behavioural intervention that gives different decision options but has a lack of transparency can be described as a hidden manipulation, and is not fulfilling the terms of freedom of choice. Both freedom of choice and transparency need to be fulfilled to define a behavioural intervention as a nudging technique. Without those staple characteristics, nudging cannot be differentiated from hidden regulations or flat-out manipulation (Reisch & Sandrini, 2015, p. 20). In the same way, the presence of a choice architecture is not a nudge if it was not intentionally shaped with a specific outcome in mind.

Conclusion

In conclusion, nudges are behavioural interventions that clearly fulfil the four core characteristics: (1) intentionally changed choice architecture, (2) without changing (economic) incentives, (3) the freedom to choose, and (4) transparency to the decision-maker. Nudges purposefully change the choice architecture, thus influencing the occurrence of a choice outcome that is preferred by the regulator. Nudges are not to be confused with other behavioural interventions that lack these core qualities. Now that the definition of nudges is established, the next chapter will discuss how nudges influence choice outcomes.

2.1.1 Explaining Nudging Using the Theory of Behavioural Change

Building on the understanding of the four core characteristics of nudging techniques, the theory of behavioural change explores how nudging techniques affect decision outcomes. More specifically, the dual process theory will explain successful nudging as targeting one of two processes: type 1 processing, the automatic and intuitive processing. In line with the dual process theory, one of the common classification schemes for nudging techniques that divides nudges into type 1 nudges and type 2 nudges will be discussed. At the end of the chapter, cognitive biases will be discussed with respect to how they might be overcome by nudging techniques in the reality of policy making.

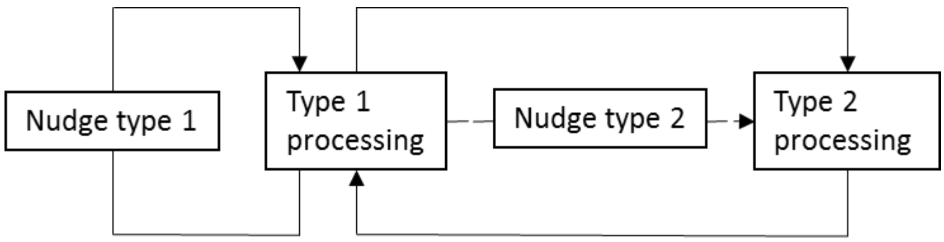
Dual Process Theory

Dual process theory has evolved over time but was initially developed in the 1970s, when it aimed to explain the connection between attitudes and behaviours (Wason & Evans, 1974). While different theories that mark the evolution of dual process theory (Epstein, Lipson, Holstein, & Huh, 1992; Evans & Stanovich, 2013; Fazio, 1990; Kahneman, 2013; Petty & Cacioppo, 1986) do not completely overlap, they have in common a distinction between two processes that govern behaviour. Type 1 processing is automatic, not reflective, but intuitive processing that changes attitudes, intentions, and behavioural implementation, and type 2 processing is cognitive reflective, and an active process in changing attitudes, intentions, and behavioural implementation (Michalek et al., 2016).

This work will follow the more recent dual process theory of Evans and Stanovich (2013), from which the terms type 1 processing and type 2 processing originated (Evans & Stanovich, 2013). According to the default-interventionist theory, type 1 processing happens automatically as the default processing in which type 2 processing can intervene

(Evans & Stanovich, 2013). Therefore, type 1 processing needs to be overridden by type 2 processing in order for type 2 processing to occur. As long as the individual is content with the outcome of his or her type 1 processing, he or she is less likely to engage in type 2 processing on the matter (Evans & Stanovich, 2013). Type 1 processing and type 2 processing interact with each other. Type 2 processing is always dependent on type 1 processing, but type 1 processing is not dependent on type 2 processing (Hansen & Jespersen, 2013). Type 2 processing is different from type 1 processing in the extended use of working memory resources needed for hypothetical thinking. Decision-making that considers all consequences, mental simulations, and cognitive decoupling is what marks type 2 processing (Evans & Stanovich, 2013). While type 2 processing's defining characteristic is the intense use of working memory resources, type 1 processing's defining characteristic its use of few working memory resources. The extent of working memory resource usage is what differentiates the two processes. Type 1 processing is the default method of processing and type 2 processing is only engaged when needed, which saves working memory resources (Evans & Stanovich, 2013). The use of few working memory resources in type 1 processing is the reason that it is also called autonomous processing, and makes it the quicker processing method of the two. Type 1 processing is also described as being more associative because the use of fewer working memory resources can also be described as requiring less controlled attention. Type 1 processing shows heterogeneity because automatic and intuitive processing can be applied to mundane task as well as complicated but familiar tasks (Evans & Stanovich, 2013). The behaviour resulting from type 1 processing, which can be described as reflexive, does not have to be a mundane, low involvement task; it can also be a complicated, mentally challenging behaviour that training has made into a reflex (Michalek et al., 2016). Even though the intense use of working memory resources is the defining characteristic of type 2 processing, there are other qualities that mark it this type as well. Type 2 processing is slower and more sequential than type 1 processing. Type 2 processing, along with working memory resources, is said to correlate with measures of general intelligence (Evans & Stanovich, 2013). Nudges aim for influencing type 1 processing (automatic and intuitive processes), and therefore are especially successful in directing behaviour to a specific outcome when the behaviour involved can be described as reflexive or time pressured, or calls for low personal involvement (Michalek et al., 2016).

Figure 1. Connections between Type 1 Processing/Type 2 Processing and Nudge Type 1/Nudge Type 2 (Michalek et al., 2016, p. 7)



Nudge Type 1 versus Nudge Type 2

Nudge type 1 is aimed at the outcome of type 1 processing (automatic and intuitive processing), and nudge type 2 is aimed at influencing the outcome of type 2 processing (reflective processing) by influencing type 1 processing as a priming agent (Michalek et al., 2016). Some argue that type 1 nudges are central to the definition of nudging techniques, saying that the pure definition of nudges comes down to their influence of the outcome of automatic and intuitive type 1 processing (Grüne-Yanoff & Hertwig, 2016). There are several behavioural influencing tools other than nudges that directly influence type 2 processing, for example, monetary incentives, prohibitions, and campaigns that try to educate or persuade. These behavioural influencing tools directly influence type 2 processing, which is why they are often confused with type 2 nudges. However, type 2 nudges only indirectly influence type 2 processing. Monetary incentives are not classified as nudges because they change the incentive structure of the choice alternatives. Prohibitions cannot be classified as nudges because they leave no freedom of choice and minimize the choice alternatives. Information campaigns that educate or persuade aim for influencing type 2 processing (reflective processing), and thus cannot be classified as type 1 or type 2 nudges (Michalek et al., 2016, p. 6).

The nudge type 1 is describes either biasing or re-biasing type 1 processing (automatic and intuitive processing). The re-biasing of type 1 processing can happen through a nudge type 1 that stresses information that leads to a re-consideration of the standard intuitive outcome of the type 1 processing. Biasing and re-biasing of type 1 processing can happen through type 1 nudges that trigger or block heuristics (Michalek et al., 2016). One example of a type 1 nudge is a change of default settings that aims for influencing automatic and intuitive processing (type 1 processing). This default setting change could be to place smaller plates and bowls in a more prominent location than bigger plates and bowls in a cafeteria setting.

This could result in less food intake by customers in that cafeteria, since the size of plates and bowls communicates the consumption norm. This nudge of changing the default setting influences automatic and intuitive processing, which leads most decision-makers to follow the new consumption norm automatically and consume less food (Wansink, 2004). In this example, it becomes clear that behaviour is influenced without reflective processing, which is the characteristic trademark of type 1 nudges (Hansen & Jespersen, 2013).

Informational nudges, on the other hand, are known as type 2 nudges. These motivate the individual to switch from type 1 processing to type 2 processing while priming the outcome of reflective type 2 processing using given information (Michalek et al., 2016).

One example of a type 2 nudge involves framing a choice that triggers an emotional response during automatic and intuitive processing (type 1 processing) that then influences reflective processing (type 2 processing) (Hansen & Jespersen, 2013). The engagement of reflective processing is the characteristic trademark of type 2 nudges (Hansen & Jespersen, 2013). Type 2 bias belongs to type 2 processing, and is harder to successfully address than the re-biasing of type 1 processing (Selinger & Whyte, 2011). Type 2 bias occurs when type 2 processing is used too much, leading to an overthinking-bias that creates enough cognitive noise to reduce preference consistency. In order to address this bias, one would have to find a way to let the individual switch back to type 1 processing, thus ending the overthinking bias through a switch to automatic and intuitive processing. Three ways to address type 2 bias have been described: reducing decision time, adding complexity to the decision, and activating heuristics (Michalek et al., 2016). Reducing decision time forces the individual to switch from reflective processing to automatic and intuitive processing, thus dissolving the overthinking bias. Adding complexity to the decision adds even more cognitive noise, which can lead the individual to switch back to automatic and intuitive processing, also dissolving the overthinking bias. Activating heuristics can simplify the decision for the individual in such a way that he or she would use automatic and intuitive processing instead of engaging type 2 processing and succumbing to the overthinking bias (Michalek et al., 2016).

It can be confusing that type 1 and type 2 nudging do not directly correspond to type 1 and type 2 processing. While type 1 nudges correspond directly to the outcome of type 1 processing, type 2 nudges correspond to the outcome of type 2 processing via influencing type 1 processing. It is important to understand that no type of nudge aims directly at changing type 2 processing (reflective processing), including type 2 nudges (Hansen & Jespersen, 2013). A nudge would not be called a nudge if it had the strength to directly change the outcome of type 2 processing. It would be called something more forceful than a nudge (in the literal sense) – maybe a ‘firm, unrelenting push’, because that is what it would take to influence as type 2 processing as effectively a nudge can influence type 1 processing. There are other forms of behavioural interventions that can be successful here: monetary incentives (positive and negative), information campaigns that educate or try to persuade, and flat-out prohibitions (Michalek et al., 2016).

The use of type 1 nudges is recommended if the aim is to influence type 1 processing in a non-lasting way under very specific circumstances. The use of type 2 nudges is recommended if the aim is to indirectly address the outcome of type 2 processing under longer-lasting and less restricted circumstances that ask for more reflective thinking. In the latter scenario, it would be necessary to administer the nudging stimuli over a longer time period (Michalek et al., 2016).

A clear understanding of what type 1 and type 2 nudges are and what their aims are can be very beneficial when planning a behavioural intervention. The type of nudge can be chosen depending on the outcome to be influenced. If an outcome of type 1 processing is to be influenced, a type 1 nudge can be planned. If an outcome of type 2 processing is to be influenced, a type 2 nudge can be planned. In some circumstances, however, it is not enough to plan on only influencing the outcome of type 1 processing or type 2 processing. Rather, both outcomes need to be addressed simultaneously. This can be due to suspected heterogeneity in responding to the decision using either automatic or reflective processing. This heterogeneity in processing methods can be found in the same individual reacting differently over time to a decision or among individuals being prone to react differently to a decision. A behavioural intervention that combines a type 1 nudge with a type 2 nudge is described as a 'fuzzy nudge' (Michalek et al., 2016). One real-life example of a fuzzy nudge is the Ambient Orb, a real-time feedback device measuring a household's energy use. It translates real-time energy feedback into colours, with red indicating high energy use. The colour red can be understood as priming with information (type 2 nudge), or it can be understood intuitively as something bad (type 1 nudge) (Selinger & Whyte, 2011). This fuzzy nudge can influence the outcome of type 1 processing when the red light is understood as something intuitively bad, resulting in an automatic response to minimize household energy use. However, it can also influence the outcome of type 2 processing by priming with the information that the red light indicates high household energy use, setting the framework for reflective processing. Not only can a fuzzy nudge address expected heterogeneity in processing a decision, it can also enhance the effect of nudging techniques. Many nudging techniques benefit from being combined with another type of nudge that is in the same category or in a different category. An example is the combination of a social descriptive norm nudge with salience. The added salience strengthens the effect that the social descriptive norm nudge has on the decision outcome (Michalek et al., 2016). Another example of a common combination of a type 1 nudge with a type 2 nudge is the combination of a social descriptive norm nudge with an injunctive norm nudge. This combination is known to balance out the boomerang effect that individuals who already fulfil the social descriptive norm (type 1 nudge), might adjust their behaviour in an undesirable way, as this is hindered by the injunctive norm (type 2 nudge) (Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007).

Cognitive Bias or Human Cognitive Presupposition?

Nudges influence decision outcomes by targeting type 1 processing. An additional concept that further explains how nudges influence decision outcomes is cognitive bias. The term 'cognitive bias' has a negative connotation. The word 'bias' in cognitive bias seems to describe a systematic mistake in human cognition, but if it is common and systematic, why should it be deemed a mistake? If having a cognitive bias is the norm, why not call it something more neutral, such as a cognitive presupposition? Hausman argues that cognitive biases are not factors that interfere with rational choice, but rather are rational determinants of choice (Hausman & Welch, 2010). The root of the negatively tainted word choice of cognitive bias can be found in its origin in economics. Economics as a field is driven by the assumption of homo economicus, the rational agent that always strives to maximize its utility, depicting the gold standard of human behaviour (Hansen & Jespersen, 2013). Any other form of behaviour that cannot be strictly translated as maximizing utility is, therefore from this perspective, considered biased behaviour. For sociologists, human behaviour is not necessarily measured and judged against the homo economicus. Cognitive bias can be translated and perceived as a human cognitive presupposition that is a defining marker of human processing, and not a sign of human insufficiency. A sociologist might want to add that our cognitive biases are indeed what make us human and differentiate the human species from mere machines. On the argument that human decision-making is systematically flawed by cognitive biases rests the justification for re-adjusting said flaws using paternalistically inspired behavioural interventions.[1] With nothing less than the individual liberty riding on either understanding – that human decision-making is either riddled with cognitive biases or just cognitive presuppositions – it is understandable that the discussion is diverse, given the high stakes.

Regarding successfully applying nudges as soft policy tools, Sunstein recognizes four main cognitive biases that strongly influence decision-making (Sunstein, 2011). Sunstein is an

[1] For a critical discussion on this argument, refer to Section 6.2 - Using Nudging as a Soft Policy Tool.

advocate of understanding human decision-making as systematically flawed, and thus promotes nudging as a way of either cancelling out or making use of these ‘cognitive biases’. The first is inertia and procrastination. Here, default rules can help to ease the negative consequences of inertia and procrastination through things like automatic enrolment and changing default settings from opt-in to opt-out. As complexity increases inertia and procrastination, simplification of information is another way to minimize the negative effects of inertia and procrastination. The cognitive bias of hyperbolically discounting the future is also classified as falling in the category of inertia and procrastination. While inertia and procrastination have short-term gains, they come with long-term costs that are hard to assess and are discounted in the present (Sunstein, 2011). The hyperbolic discounting of the future can also be described as a present bias. The focus on the present in decision-making concentrates on the short-term gains that are achieved through inertia and procrastination and takes attention away from possible long-term costs (Reisch & Sandrini, 2015). In the same way, hyperbolic discounting of the future hinders individuals in paying short-term costs that could lead to substantial gains in the future, for example, saving for retirement. Regarding policy-making, addressing inertia and procrastination successfully means setting default rules like automatic enrolment for important programs like retirement savings programs, thus minimizing the inconvenience of actively enrolling and the complexity of choosing the right retirement fund (Sunstein, 2011). An alternative perspective would be not to manipulate individuals into making the ‘right’ choice by enrolling them by default, but forcing an active choice instead. This active choice could be backed up with an educational campaign about the program.

The second cognitive bias that strongly influences decision-making is the framing and presentation of the decision. The salience of the information is connected to the attention a decision is given, and therefore can influence behaviour. Attention is a scarce resource, and only salient information can hope to influence behaviour. The cognitive bias of loss aversion is classified as falling in the category of framing and presentation. Loss aversion is the phenomenon that losses are disliked more than corresponding gains are preferred. A decision can easily be framed in terms of either gains or losses, but loss aversion concerning an individual’s status quo is less easy to manipulate. With the status quo being the reference point, the individual will judge the decision outcomes in terms of losses and gains, with a bias toward avoiding losses. This also leads to the status quo bias, which leads individuals to stick with the status quo for fear of losing something, namely the status quo. Even if the presumable gains associated with the change are sufficient, fear of losing the status quo is judged to have more weight in comparison. In regards to policy making, addressing framing and presentation of a decision requires being aware of loss aversion and framing decisions accordingly, as well as aiming to keep relevant information salient and clear (Sunstein, 2011). An alternative to manipulating the framing of a decision is stating clearly the resulting gains and losses (Gigerenzer, 2015). This gives the individual liberty to choose and weigh both gains and losses at the moment of decision-making.

The third cognitive bias that strongly influences decision-making is the social influence of what is perceived as the norm. The social descriptive norm nudge tries to take advantage of the fact that each individual is influenced by what they think the norm is. Individuals are motivated by a commitment to fairness and a fear of punishment for deviating from the norm. Regarding policy making, addressing social influence in a decision means communicating a new social norm or bringing attention to an established social norm in order to influence individual behaviour to align accordingly (Sunstein, 2011). The alternative to manipulating behaviour through social norm nudges is relying on individuals' own perceptions of common social norms and letting them choose accordingly.

The fourth cognitive bias that strongly influences decision-making is found in judging probabilities. As probabilities are abstract and complicated to assess, it is no wonder that this area shows many cognitive biases – or in other words, mental shortcuts to deal with this complexity that most likely do not do the complexity justice. The list of possible cognitive biases in this area is long, ranging from the above average effect to confirmation bias and availability bias. The above average effect is marked by unrealistic optimism when judging the probability of good fortune in comparison to the probability of bad fortune. A possible nudging techniques to minimize this behavioural presupposition would be to frame a decision in a way that heightens the salience of the probability of the negative event. Confirmation bias is in line with cognitive dissonance, giving more weight to information that confirms beliefs and less weight to information that contradicts beliefs. The availability bias refers to the positive connection a cognitively available event has with the probability given to that event (Sunstein, 2011). Both behavioural presuppositions can be addressed with nudging techniques that re-frame decision making and heighten salience to the information that is underestimated. The list of potential biases when judging probabilities show that decision-making according to one's own preferences based on probabilities is not an easy undertaking. In regards to policy making, addressing the challenge of judging probabilities correctly when decision-making means keeping the specific listed biases in mind and communicating the decision accordingly (Sunstein, 2011). An alternative to using a nudging technique to help judge conditional probabilities correctly is to reframe them in natural frequencies, which are easier to understand and judge (Gigerenzer, 2015).

Conclusion

Nudging techniques influence decision making through either targeting type 1 processing (automatic and intuitive processing) directly or type 2 processing (reflective processing) indirectly. Regulators using nudging techniques can either be motivated by an economic perspective, comparing human behaviour to that of the homo economicus, or by an alternative perspective that described cognitive biases as human cognitive presupposition. Finally, there are always alternatives to nudging techniques.

2.2 Defining Default Rules

Default rules are one of the most established nudging techniques due to their high efficiency in influencing decision-making on a diverse range of topics and situations. Default rules describe the default setting in a decision as one of the decision options. This decision option is pre-activated, and is realized if the decision-maker does not actively change the setting to another decision option. Default rules can be best described versus the neutral standard in decision-making, which is active choice.

Figure 2. Active Choice: No Presumed Consent and No Explicit Consent (own illustration)

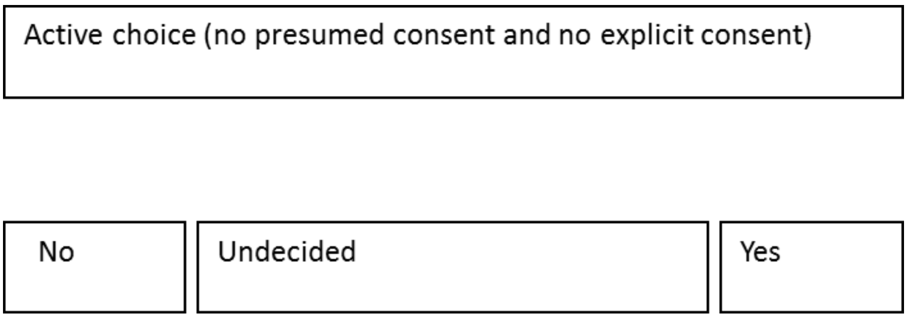


Figure 2 shows the active choice with no presumed consent and no explicit consent. In the most simplified way, the decision-maker has a choice between consenting, not consenting, or staying undecided. With an active choice, the decision-maker decides actively between those three possible options. If he or she does not actively consent, or chooses not to consent, the decision-maker stays in the category of ‘Undecided’. In this sense, the setting of a default choice is the direct opposite of an active choice. In an active choice setting, the decision-maker has to actively choose between the options, and no decision on the part of the decision-maker is translated into no choice on the matter. This stands directly opposite to the default setting. A default setting is the initial setting that is activated if the decision-maker does not actively change the initial setting to another setting (Pichert & Katsikopoulos, 2008). In many decision-making areas, an active choice is simply not feasible. For example, this is the case in the area of utility contract choices. Here, the decision-maker enters a contract with the utility company simply by switching on the light in a new apartment. Once the contract is entered, the utility company has to book the electricity consumed as one of the many products it offers. The utility company sends a letter to the new tenant letting him or her know the different products and asks them to make a choice. If the new renter does not answer with a product choice in one month, the utility company has to book the used electricity under some kind of product, which is naturally the default product. If there were no default product amongst the products the utility company offers, the utility company would have trouble booking all those new tenants that do not answer the utility company's letter in time. It would be unnecessarily complicated, and in most cases impossible, to first force the new renter to choose an electricity product and only then supply electricity to his or her new home. Here, a default setting on one of the electricity products is helpful for both parties.

Opt-in Versus Opt-out Default Settings

Default settings in their simplest form can be categorized as opt-in default settings or opt-out default settings. Of course, if the decision becomes more complicated, the default setting can be set on any of the choice options. But in the case where the decision-maker has only the choice to give consent, to withdraw consent, or to stay undecided, the default can only be set as an opt-in or an opt-out default setting.

Figure 3. Opt-out Default Setting: Presumed Consent (own illustration)

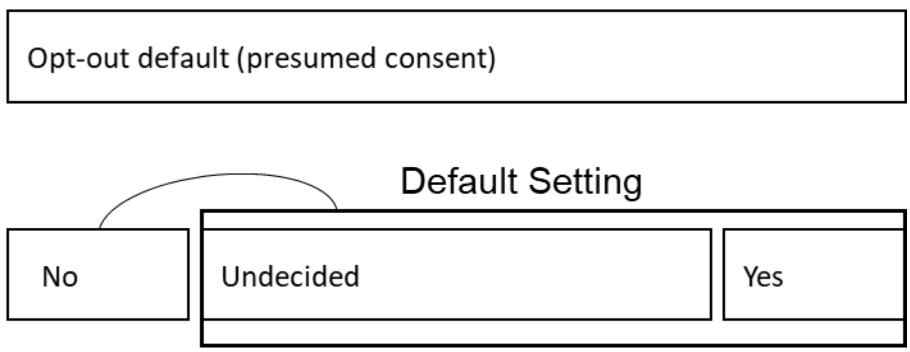


Figure 3 shows the opt-out default setting in which consent is presumed. The opt-out default setting can be translated as presumed consent by the decision-maker. In the case that the decision-maker does not actively choose to withdraw consent, it is assumed that he or she gives consent passively. This way, the group of decision-makers that neither choose to actively withdraw their consent nor actively give their consent – the undecided decision-makers – is counted towards those decision-makers who actively give their consent.

Figure 4. Opt-in Default Setting: Explicit Consent (own illustration)

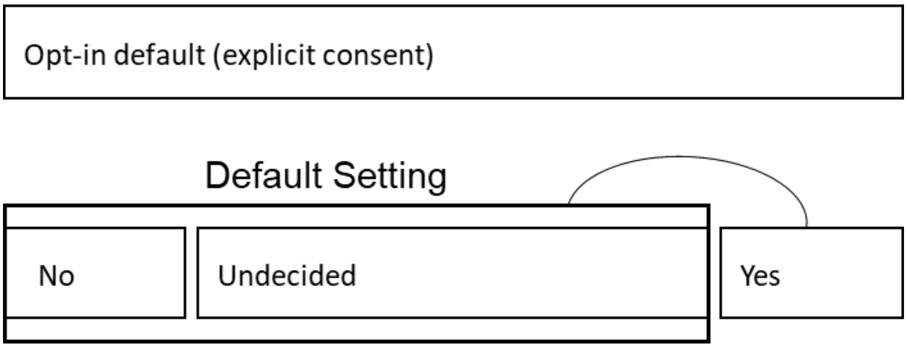
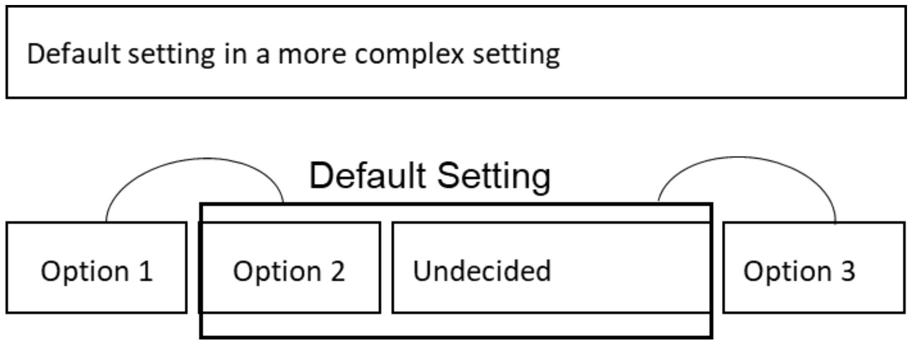


Figure 4 shows the opt-in default setting where explicit consent is needed. While with the active choice the decision-maker is left the option to be undecided about his or her consent, here the group of undecided decision-makers is counted towards the group that actively withdrew their consent. In this way, the opt-in default requires the explicit consent of the decision-maker, where only those decision-makers that actively give their consent are counted as consenting. A popular example that portrays the opt-out and the opt-in default setting use is the area of consent to becoming an organ donor. Here, different countries either presume consent (opt-out default setting) or require explicit consent (opt-in default setting). This example and many more are discussed in detail in Section 2.2.1, Applying Default Rules in Different Areas, and in Section 2.2.2, Using Default rules to Promote Renewable Energy Uptake.

Figure 5 shows a default setting in the more complex setting of three options. In a more complex decision setting, the default can be set on any of the choice options. Here in Figure 5, the default is set on Option 2. In this example, the group of undecided decision-makers is counted towards those who actively chose Option 2. In the sense of the former default settings, there is a presumed consent towards Option 2, and explicit consent is needed for options 1 and 3.

Figure 5. Default Setting in a More Complex Setting (own illustration)



Default settings can be communicated in different ways. For one, they can be in text form informing the decision-maker that, in the case that they do not choose otherwise, they will receive the default setting. For another, it can also be communicated by already pre-selecting the box of the default choice. In this case, the default option will be realized if the decision-maker does not actively select another option. While the text-based presentation is popular in written material, the pre-selection of the box indicating the default choice is popular in online formats.

Default Rules and Dual Process Theory

Default rules are well documented to work efficiently as a nudging technique. Numerous other studies in different decision-making areas testify to the strong effects of default rules (compare for example Ebeling & Lotz, 2015; Egebark & Ekström, 2013; Johnson & Goldstein, 2004; Pichert & Katsikopoulos, 2008). Several examples for default rules applied to different decision-making areas are given in Section 2.2.1, Applying Default Rules in Different Areas, and more specifically for renewable energy in Section 2.2.2, Using Default rules to Promote Renewable Energy Uptake. Default settings address, as with every other nudge, type 1 processing (automatic and intuitive processing), and do not address type 2 processing (reflective processing) directly. Therefore, they try to guide decision-making through influencing decision-makers' automatic and intuitive processing. With the help of behavioural theories, however, it will become clear that default settings can not only target type 1 processing (automatic and intuitive processing) directly, but they can also indirectly target type 2 (reflective processing) processing through priming the type 1 processing. While arguably most decision-makers will respond to the default setting with type 1 processing (automatic and intuitive processing), some decision-makers can also be primed by the default setting so that their type 2 processing (reflective processing) is influenced. In that sense, some decision-makers do not pay a lot of attention to the default setting but just accept it. Other decision-makers first process the default setting with type 1 processing (automatic and intuitive processing), and then engage type 2 processing (reflective processing) on the decision matter. Here, they can either reflectively think about the default as friendly guidance and accept the default or mistrust the default and choose an alternative option. Therefore, default rules hold the potential to influence the decision outcomes of decision-makers that process the default setting of the decision in an automatic and intuitive way as well as those who process it additionally in a reflective way.

Behavioural Presuppositions that Explain the Efficiency of Default Rules

There are different behavioural presuppositions that provide an explanation of the effectiveness of default rules in influencing decision outcomes. One behavioural construct is the costliness of gathering enough information to confidently make the decision without being led by the default. One reason is that default settings are often understood as 'the normal choice', 'the advised choice', or the choice that the majority would make. Default settings can relieve the decision-maker of making his or her own choice when decision-making is costly (Pichert & Katsikopoulos, 2008). The default effect is especially strong when the decision-maker is uncertain about the decision content and his or her preference. This uncertainty can happen for different reasons, such as a lack of information (Pichert & Katsikopoulos, 2008). Default settings are often seen as the norm that is accepted by society, which is then understood as the right choice (Pichert & Katsikopoulos, 2008). An active choice in comparison to the default setting is connected to costs such as gathering the information needed to make the choice and weighing the options presented according to one's own preferences. This behavioural construct of the costliness of choosing an alternative to the default choice is along the lines of default settings priming type 1 processing (automatic and intuitive processing) in order to influence type 2 processing (reflective processing). The decision-maker is primed by the default setting in automatic processing, engages his or her reflective processing on the matter, and comes concludes that the cost of gathering information in this case is too high. He or she finally chooses to be led by the default setting to avoid these costs.

Another behavioural construct that explains the effectiveness of default rules is called loss aversion. Loss aversion describes the phenomenon that people prefer safe gains and forgo risks, but are willing to take greater risks in order to compensate for losses (Sunstein, 2011, p. 1355). This great aversion to loss drives risk-seeking behaviour (Tversky & Kahneman, 1981). In a hypothetical decision-making experiment, people had the choice between two medical measures to fight a flu epidemic. One group saw a negative wording of the effects of the medical measurement ('probability of dying'). The other group saw a positive wording of the effects of the medical measurement ('probability of survival'). Holding all else constant, people choose differently in the two groups, and these choices were correlated to the positive and negative wording. The group that saw the treatment framed by the 'probability of dying' chose medical measurements with greater risks than the group that saw the treatment framed by the 'probability of survival' (Tversky & Kahneman, 1981). So far, studies have researched loss aversion as single nudges (not in terms of being part of default rules, etc.) only concerning individual commodities (Camerer, 2009; Kahneman, Knetsch, & Thaler, 1991). This means that gain and loss framing directly affects the individual decision-maker. The question remains if this would also work in terms of collective commodities that do not directly affect the individual decision-maker. When the context of decision-making is environmental sustainability, the commodity in question is of a collective kind, only indirectly affecting the loss and gain of the individual decision-maker. It is natural to assume that effects would be weaker for loss aversion concerning collective commodities in comparison to individual commodities. Loss aversion is a phenomenon mainly driven by type 1 processing (automatic and intuitive processing). The decision-maker is primed with the default option, and in automatic processing he or she experiences it as loss to change the default setting.

The effect that loss aversion has on the acceptance of default rules is mirrored in the behavioural presupposition of the status quo bias. The default setting can be experienced as the status quo of decision-making. In this way, the decision-maker would also experience a loss if he or she were to choose not to stay with the default choice. This tendency to accept the priming of the default setting as a kind of anchoring effect is also described as status quo bias. The decision-maker finds it in general easier to accept the default and be primed by it in later decision-making than to switch away from the default. The effect of the status quo bias becomes even higher with rise of decision complexity (Reisch & Sandrini, 2015).

Another cognitive presupposition is the simplification that a default setting potentially brings to any decision-making frame. Default rules simplify the decision-making process by offering a guiding choice. Active choice settings do not offer such a guiding choice. The more complicated the decision topic is, the more the decision-maker will be likely to accept this simplification by accepting the default choice. A decision can be experienced to be complex in many ways. It may be a decision topic that is emotionally complex (as in the decision to become an organ donor). The complexity can also stem from a great number of alternative choices. Even unclear preferences of the decision-maker can make it a complex task to align the possible choice alternatives to their preferences in such a fashion that a satisfying choice can be made in the end. The complexity of a decision can induce indifference, delay of action, and even confusion (Sunstein, 2011, p. 1402). Complexity cannot only make the acceptance of a default choice more likely, it can also lead to inaction. With a default setting, inaction or being undecided is directly translated into accepting the default choice. Thus, the complexity of a decision makes the acceptance of the default choice more likely (Sunstein, 2011, pp. 1352–1353). In order to analyse an application of a default rules intervention regarding the behavioural presuppositions that strengthen the default acceptance, it is also important to estimate the costs of opting out of the default. These opt-out costs are not only information costs but maybe, in some cases, be monetary costs or opportunity costs of facilitating the opt-out. Monetary costs can be estimated by, for example, comparing the price of the default choice with other choices. Opportunity costs can be estimated by analysing the opportunity costs of the opt-out options. Depending of the ease of the opt-out, not staying with the default option can be different costly. For example, contacting a company on the phone can be experienced as less costly as logging into an online interface of that same company.

Conclusion

Default rules are one of the most effective nudging techniques. As with any nudging technique, it targets type 1 processing (automatic and intuitive processing) and does not address type 2 processing (reflective processing) directly. Nevertheless, it holds potential to indirectly influence type 2 processing (reflective processing) through priming of the type 1 processing (automatic processing). This potential and several behaviour presuppositions lead to the high efficiency of the default setting. Default rules are documented to be an effective way to influence decision-making in many diverse decision-making areas, which will be documented in the next two chapters (2.2.1, Applying Default Rules in Different Areas, and 2.2.2, Using Default rules to Promote Renewable Energy Uptake).

2.2.1 Applying Default Rules in Different Areas

The nudging technique of default rules is widespread and has been successfully applied in many areas. It can be described as one of the more trusted nudges when it comes to steering a decision to a specific outcome. As formerly described, default rules show their strongest effects in decisions that decision-makers are reluctant to make. This reluctance or hesitation can occur for a multitude of reasons, ranging from avoiding a difficult topic, being faced with overly complicated choices, and decision consequences that seem to be too far in the future or not relevant, or even repressed at this point in time.

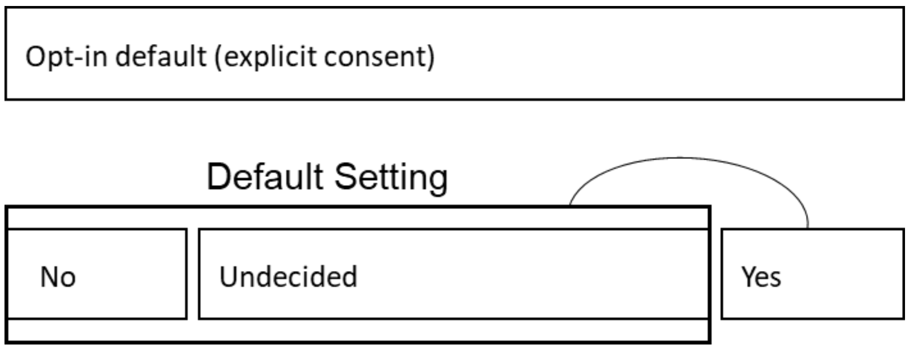
Default rules work well in simplifying the process of dealing with uncomfortable topics, which can be uncomfortable because of associated guilt, repressed fear, or other repressed feelings. Such decision topics include giving the consent to become an organ donor, which reminds decision-makers of their own mortality since they would only become organ donors after death. Another topic would be the choice of automobile insurance with different suing tariffs, from which one would only benefit if severely injured in an accident. Even the topic of choosing to engage or not to engage in energy saving behaviour can be experienced as uncomfortable, since personal comfort and injunctive morals of being a good person collide in this decision.

Default rules work well when the decision topic seems overly complicated and the decision-maker has not made up his or her mind before entering the decision time point. Rather, he or she looks for direction in the ad-hoc situation, which can be found in the default setting. Here, default rules are often understood as guidance to simplify the decision-making process, as they are interpreted as the choice that suits most people or as the choice that is recommended. Decisions regarding 401(k) retirement plans fall in this category. The options for choosing a 401(k) retirement plan are numerous and hard to compare. Default rules are also applied successfully when the topic of decision-making is connected with what seems to be far off future consequences, as in the area of 401(k) retirement plans. When young and just having started in the work force, the consequences of retirement and saving plans seem to be far off in the future. The consequences of not investing enough in pension savings are often underestimated, and it seems that old-age poverty is something that happens to everyone else but oneself. The same logic applies to insurance choices where options seem overly complicated and hard to compare. Default rules have also been applied successfully in the area of consumer research where the consumer has not only to make the decision to purchase a product or not, but also decide what features they want in that product and how much they are willing to pay for the end product. Here, defaults show strong effects due to complication of a multitude of choices and the complexity of comparing product features and their according prices. One's own preferences for product features must be compared with the willingness to pay for those product features. Internet privacy policies are also seen as an overly complicated affair, where the decision-maker is not prepared with already decided preferences but has to make a decision ad-hoc with what is often experienced as insufficient knowledge about the topic. Here, default settings are willingly accepted because they provide much needed guidance in what might be experienced as making a decision in a sea of excessive options.

In this chapter, the successful application of default rules will be explored in different decision areas and with different motivations behind the successful application of the default effect. The areas presented are: organ donations, 401(k) retirement plans, insurance choices, consumer research, Internet privacy policies, and energy reduction behaviour.

Default Rules in the Area of Organ Donations

Figure 6. Opt-in (Explicit Consent) for Organ Donations (own illustration)



The most popular example of the default effect is on the consent rate of organ donations. One reason that default rules work well in the area of organ donations is the common hesitation of people in making the decision of whether to become an organ donor. Thinking about organ donations makes most people uncomfortable, not only about possibly becoming an organ donor. Even the prospect of becoming ill enough to become an organ receiver can be frightening. An overview on countries and their policies for organ donations is in the paper 'Defaults and Donation Decisions' by Johnson and Goldstein, which was published in 2004. The paper contrasts two default conditions – opt-in (explicit consent) and opt-out (presumed consent) defaults – and their effects on organ donation consent rates in different countries (Johnson & Goldstein, 2004).

Figure 6 shows how the explicit consent of the opt-in default for organ donation counts the group of undecided decision-makers towards those who have decided to not become organ donors. Johnson and Goldstein compared consent rates for organ donations in different European countries. European countries with an opt-in (explicit consent) default show following consent rates by country: 4.25% for Denmark, 27.5% for the Netherlands, 17.17% for United Kingdom, and 12% for Germany (Johnson & Goldstein, 2004).

Figure 7. Opt-out (Presumed Consent) for Organ Donations (own illustration)

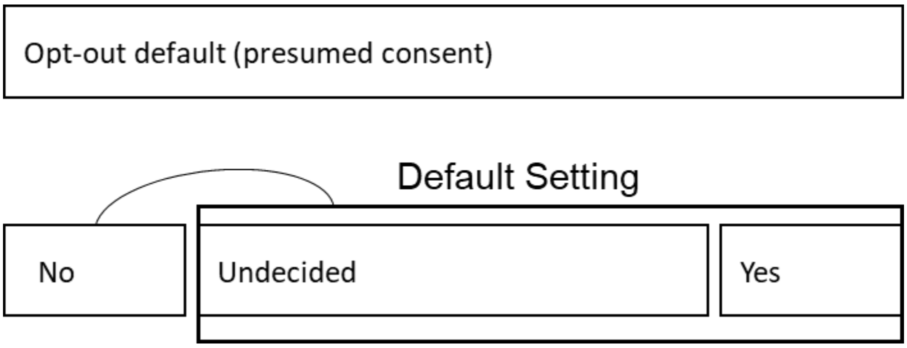


Figure 7 shows how presumed consent in the opt-out default setting counts the group of undecided decision-makers towards those who decided to become organ donors. European countries with an opt-out (presumed consent) default setting show the following consent rates by country: 99.98% for Austria, 98% for Belgium, 99.91% for France, 99.997% for Hungary, 99.5% for Poland, 99.64% for Portugal, and 85.9% for Sweden (Johnson & Goldstein, 2004). The choice of the opt-in versus the opt-out default setting has a strong effect on the consent rate. There is no overlap in the opt-in default and the opt-out default distribution, and both distributions are 58.4 percentage points apart. This goes to show how default settings can have a remarkable influence on decision outcomes. When comparing the percentages of organ donors in Austria (99.98%) to the percentages of organ donors in Germany (12%), the effect is drastic. In Austria, the default setting is that every citizen is a potential organ donor unless pro-actively indicated otherwise through a non-organ-donor-identification card. In Germany, the default setting is that every citizen is not a potential organ donor unless indicated otherwise through an organ-donor-identification-card. This difference in default setting results in a difference in organ donor rates of 87.98 percentage points (Johnson & Goldstein, 2004). The default setting of having every citizen be a potential organ donor can save many lives (Johnson & Goldstein, 2004).

In this example, it becomes clear that if a decision topic is mostly avoided due to discomfort, such as is the case with organ donation, most people do not form a strong opinion on the topic but rather stay undecided. When the topic is avoided, no opinion can be formed, and outside influences such as the country's default settings make the decision for those citizens who are undecided whether to become an organ donor or not. For the few citizens that braved facing this uncomfortable topic, the default setting might have a weaker effect. If they have a strong viewpoint on the topic that is in opposition to the default setting, they will choose to opt out of the default.

The question of choosing the default settings of explicit consent or presumed consent in organ donations is ultimately a choice between honouring the means of many or the means of the individual. The default setting of explicit consent in organ donation honours the means of the individual over the means of the many as it gives priority to the individual's right not to be pushed towards becoming an organ donor when they are undecided and do not clearly indicate that they want to become an organ donor. The default setting of presumed consent in organ donation gives priority to the means of the many over the means of the individual as it gives priority to the survival of many citizens as achieved through more available organ donations. Setting the default in organ donations is not only a practical choice but also a choice of ideology, and one that each country will have to decide for itself.

Default Rules in the Area of US Retirement Contribution Plans

Another topic in which default rules have a significant and relevant effect on citizen welfare is the participation in 401(k) retirement plans (Choi, Laibson, Madrian, & Metrick, 2001). The 401(k) plan is one of the main pension saving plans in the USA. In about 86% of companies, enrolment in the pension savings plan needs to be initiated by the employee (Choi et al., 2001). Due to the prevailing default of non-enrolment, companies fail to pass the IRS (Internal Revenue Service) non-discrimination rules in the 401(k) plan which aim for an equal share of highly compensated and lower-compensated members (Choi et al., 2001). The prevailing structural disparities on an individual level for participation rates are driven by the prevailing default of non-enrolment. The default of non-enrolment leads to more highly compensated employees signing up for and benefitting from pension plans. Most participants fit the demographic of mature age, higher income, and tenure, and tend to be male and Caucasian (Madrian & Shea, 2000). This failure to pass the IRS non-discrimination rules in the 401(k) plan motivates companies to change the default setting to enrolment.

One paper reporting on default setting effects on participation in 401(k) pension plans is ‘Defined contribution pensions: plan rules, participant decisions, and the path of least resistance’ by Choi et al., published 2001 (Choi et al., 2001). The natural field experiments and questionnaires conducted contrast the participation effects of default enrolment versus default non-enrolment in 401(k) pension saving plans. The paper has a sample size of almost 200,000 individuals in different firms in the USA with either default enrolment, default non-enrolment, or the introduction of default enrolment. This study collected covert data on participation rates through the natural experiment of comparing participation rates before and after the introduction of default enrolment and combines this with overt questionnaires on the preferences of employees concerning their pension savings behaviour. Default enrolment in in a 401(k) plan had a significant long-lasting positive effect on participation. So did the acceptance of a default contribution rate, which was not altered by an overwhelming majority of employees (Choi et al., 2001).

Another paper reporting on default effects on participation rates in the 401(k) retirement plans is ‘The power of suggestion: inertia in 401(k) participation and savings behavior’ by Madrian and Shea, published in 2000 (Madrian & Shea, 2000). The paper reports on a natural experiment that contrasts default enrolment with default non-enrolment on participation rates in 401(k) retirement plans. The covert study was conducted in the USA from June of 1997 through June of 1999, with the default setting change from non-enrolment to enrolment starting on April 1, 1998. The natural experiment compared 401(k) savings behaviour and participation rates of employees in a firm before and after the firm introduced the default change. Default enrolment in the 401(k) had a significant positive effect on participation rates compared to default non-enrolment. In the same line, defaults in contribution rates and investment allocations also had strong effects on saving behaviour. Many employees stuck with all three newly introduced defaults: the default ‘enrolment’, the default contribution rate, and the default fund. This stands in stark contrast to the savings behaviour choices that the same employees made before the change to default enrolment (Madrian & Shea, 2000).

Nonetheless, the prevailing default setting in the USA is still non-enrolment, which has difficulties passing the IRS non-discrimination rules in the 401(k) plan as it is prone to produce inequality, and might even reproduce wealth inequality through generations for a specific demographic. Having a default setting of enrolment not only increases participation rates overall, but especially for a specific demographic that would be more prone to old-age-poverty otherwise. It seems as if the default change to enrolment might be of help when it comes to breaking down wealth inequalities arranged by demographics. In a country where the topic of pension savings lays squarely on the shoulder of individuals and their immediate families, a default setting to a sensible pension plan can ease that load, especially for individuals who are already occupied with everyday financial trials. The default change to enrolment would hold the potential to foster equality as long as the default setting is truly in the interest of the decision-makers choosing a sensible contribution rate and fund.

Default Rules in the Area of Insurance Choices

Default settings do not only apply to the relevant and pressing topics of organ donations and pension funds. They also show significant effects when it comes to insurance choices. The paper 'Framing, Probability Distortions, and Insurance Decisions' by Johnson et al. was published in 1993 (Johnson, Hershey, Meszaros, & Kunreuther, 1993) and reports on default settings in automobile insurances in the USA and their effects on customer's insurance choices. It reports on a natural experiment contrasting two default rules that were facilitated in Pennsylvania and New Jersey concerning automobile insurance law. Both states introduced the option of a 'reduced right to sue' to lower insurance rates in the year 1992. The main difference was the interpretation of this change concerning insurance laws caused by introducing it in two different default settings.

Figure 8. New Jersey Default Low Insurance Rate and Reduced Right to Sue (own illustration)

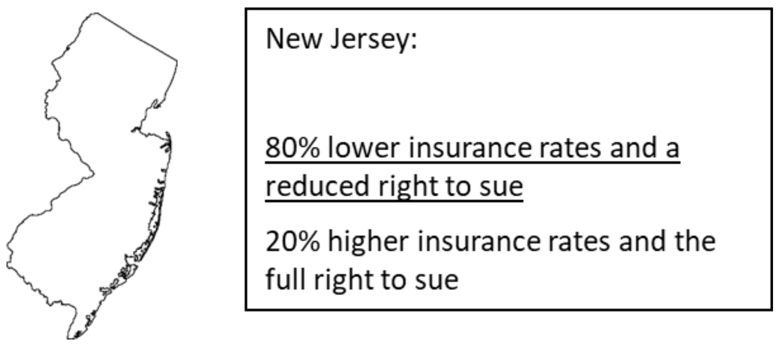
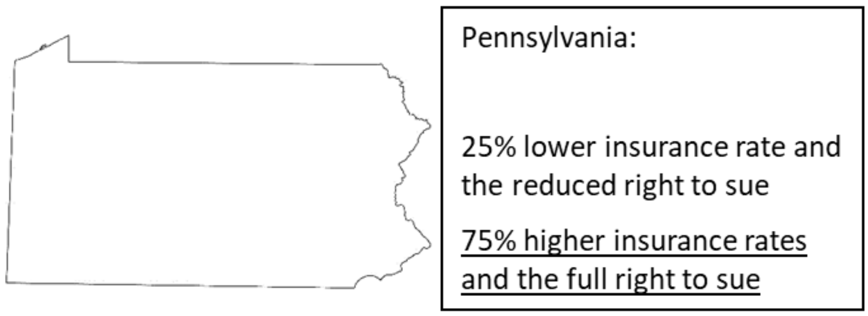


Figure 8 shows the New Jersey default setting, which is a lower insurance rate and a reduced right to sue. It also shows that 80% of customers in New Jersey picked the default setting. Only 20% opted out of the default setting and chose the higher insurance rate and the full right to sue.

Figure 9 shows the Pennsylvanian default setting, which is a higher insurance rate and a full right to sue. It also shows that, as a result, 75% of customers in Pennsylvania picked the default setting and only 25% choose the lower insurance rate and the reduced right to sue. In New Jersey, 80% stayed with the default of lower insurance rates and a reduced right to sue and only 20% bought the full right to sue at a premium. In Pennsylvania, 75% stayed with the default of higher insurance rates and the full right to sue and 25% opted for the lower insurance rate and the reduced right to sue. Therefore, the rate of citizens having the high insurance rate and full right to sue ranged from 20% (New Jersey) to 75% (Pennsylvania), and for the lower insurance rate and reduced right to sue, from 80% (New Jersey) to 25% (Pennsylvania). These rates depended on the state and their interpretations of the new insurance law through different default settings (Johnson et al., 1993).

Figure 9. Pennsylvania Default High Insurance Rate and Full Right to Sue (own illustration)



Insurance choices are a decision that often overwhelms decision-makers through (unnecessary) complication and confrontation with the uncomfortable notion of a disaster happening, against which the insurance is purchased. This combination is likely to make the decision-maker uneasy and uncertain of their preferences and therefore more willing to follow the guidance that the default setting is interpreted as offering. This is shown in the paper, which reports on immense default setting effects on the two different insurance options. Although the default setting is different in each state, it is understood as guidance in both cases. Most citizens accepted that guidance and stayed with the default (75% in Pennsylvania and 80% in New Jersey).

In particular, this paper illustrates that oftentimes, default rules are understood as guidance, reflecting what the majority wants and what is recommended to fit the majority. Therefore, the setting of the default should not be done hastily, but with the aim to actually reflect what would be of benefit to the majority of customers and not what would be of benefit to the insurance company. Insurance companies have a skewed playing field (in their favour) when it comes to the decision-making of their customers. This information advantage on the side of the insurance companies paired with the diffusion of responsibility found in larger entities can easily lead to decision frames and default rules that are not in the interest of the majority of customers but rather in the interest of the companies.

Default Rules in the Area of Consumer Research

Not only insurance companies take (unfair) advantage of default rules. This also happens in the area of consumer research. Consumer research is a field dedicated to encouraging individual consumption and spending.

The paper 'The Sceptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice' by Brown and Krishna was published in 2004 (Brown & Krishna, 2004), and reports on default effects on consumption and spending. The paper contrasts two interventions and their effects on consumer choices and the total price that the consumer pays for the final product. The two treatments were the default 'high product qualities with a high price' and the default 'low product qualities with a low price', which were tested in two overt questionnaire studies conducted in the USA. Both treatments used a small sample of undergraduate students (*n*=60 and *n*=96).

The study found that defaults carry meaning about the marketplace to the customer and change customers' perceptions of product value. Customers understand defaults in product design (low or high settings of product qualities set as the default product bundle) as intentional messages from the seller. In order to interpret the message hidden in the default setting, the customer goes back to their interpretation framework: the marketplace metacognition, which is argued to be the moderator for the default effect. If the customer experiences a default setting as incompatible with the marketplace metacognition, it will diminish the default effect or even result in a negative default effect.

Brown and Krishna conclude that default settings should always be regarded in connection to what may be the main marketplace metacognition of the customer (Brown & Krishna, 2004). In other words, if the main marketplace metacognition that the customer holds is not in line with the presented default product bundle, the customer will notice and as a result will make a decision that is in opposition to the presented default. When the presented default product bundle is in line with the marketplace metacognition, the customer will be aware of that and be more likely to stick to the default.

In other words, the customer can become suspicious that the default product bundle is not really a guide that offers the best-matched product bundle to the preferences hold by the majority of customers. On the grounds of these suspicions, the default setting can be interpreted as a manipulation by the seller holding only the seller's interests in mind. Then the customer will not accept this default setting, but will be more likely to choose an alternative. This finding highlights the feature that the default setting in general is not mindlessly accepted by the majority due to inertia. The default setting has to be trustworthy, otherwise it can cause an opposite effect.

Another paper reporting on defaults in consumer research is 'Choosing what I want versus rejecting what I do not want: an application of decision framing to product option choice decisions' by Park, Jun, and MacInnis, published in 2000 (Park, Jun, & MacInnis, 2000). The paper is based on three studies that were all conducted in the USA. The first study cited was an overt survey study with 126 business students, the second was a randomized survey study with 302 business students, and the third cited study was a randomized survey study with 101 business students. All three studies tested either the default of a subtractive option-framing method or the default of an additive option-framing method on consumers' decisions regarding option choices. These two selection procedures of product qualities were contrasted for the same product.

Figure 10. Default Setting of Subtractive Option-Framing Method in Consumer Research (own illustration)

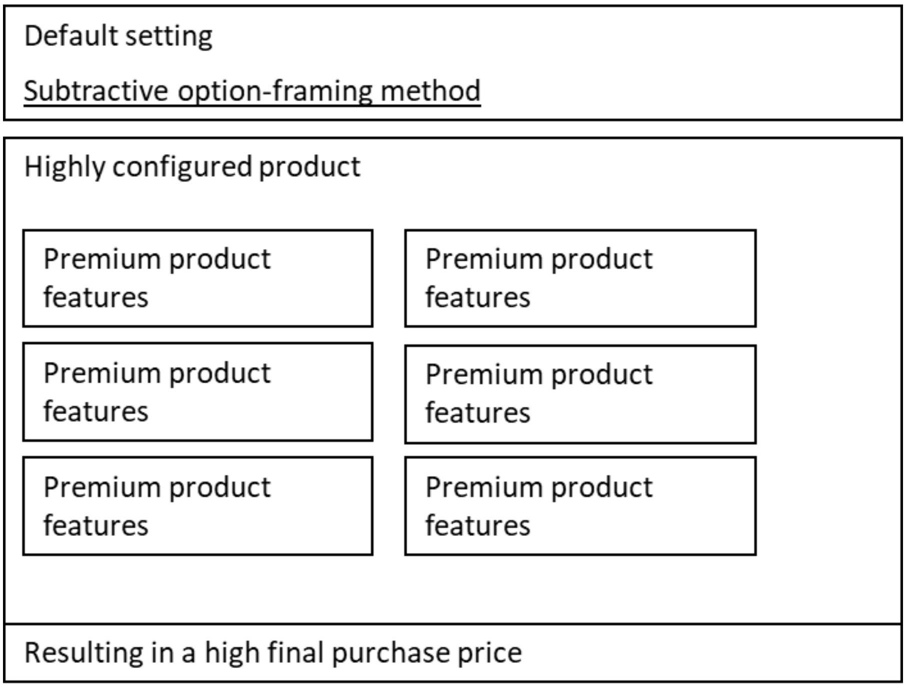


Figure 10 shows the default setting 'subtractive option framing method' in a highly configured product, which resulted in a high final purchase price in comparison to the additive option-framing method. In the default setting 'subtractive option-framing method', the consumer is confronted with a highly configured product and gets to subtract the configurations that he deems unnecessary before the final product purchase.

Figure 11. Default Setting of Additive Option-Framing Method in Consumer Research (own illustration)

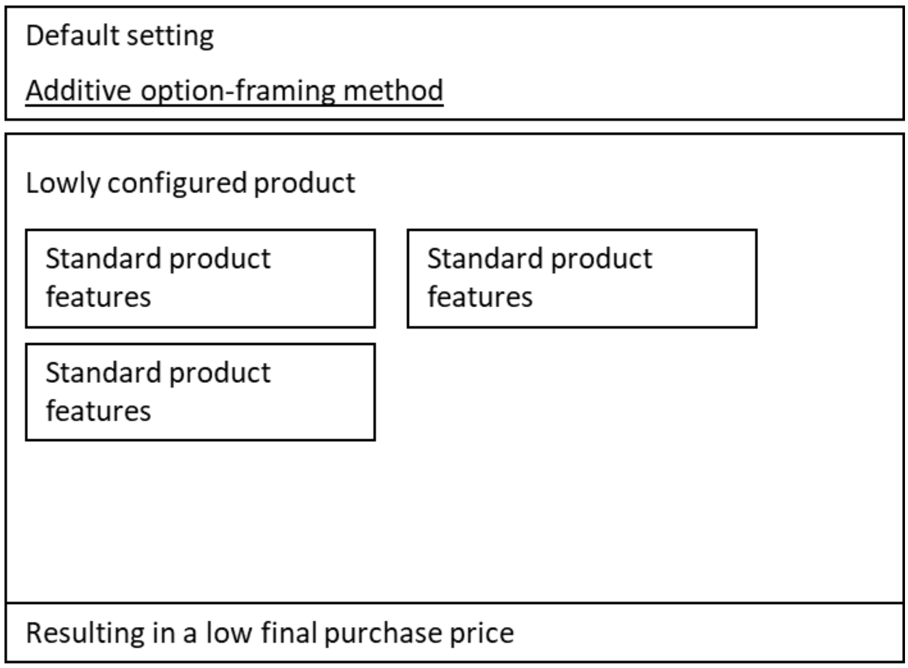


Figure 11 shows the default 'additive option-framing method' for a low-configured product, which resulted in a low final purchase price in comparison to the subtractive option-framing method. With the default setting 'additive option-framing method', the consumer is confronted with a low-configured product and has the option to add the configuration that he or she desires before the final product purchase. The studies show that consumers chose more additional product configurations with a higher total product price in the default 'subtractive option-framing method' in comparison to the default 'additive option-framing method' (Park et al., 2000).

The finding that consumers who start with a highly configured product, in which they get to subtract the configurations that they deem unnecessary before the final product purchase, receive a higher total product price highlights that defaults can be understood as guidelines or reflect the preferences of the majority. When faced with a complicated purchase choice and the balancing of feature preferences and willingness to pay, most customers are open to outside guidance, and a default setting can be understood as what the majority would want.

In order to deviate from what the majority prefers, one would need well-established personal preferences for product features and corresponding ideas of how much one is willing to pay for each feature. Therefore, most will accept the guidance of the default, only deviating on product features where they feel comfortable doing so and leaving all other product features for which they are uncertain on the default setting.

If the default setting is the highly configured product, all the uncertain features will remain on the highly configured type, resulting in an overall higher purchase price for the final product. Some other arguments why consumers end up with a higher final purchase price when starting with the highly figured product is loss aversion and anchoring. If the customer starts on a highly configured product, it makes him or her 'give up' high product features for low product features. It also anchors customers on a high price for the overall product to which every reduction of product features and according price is compared to in the process of shopping. Therefore, the customer will be more likely to end up with a highly featured and more expensive product than if they started with a lower priced and lower featured product.

Default Rules in the Area of Online Privacy Policies

As in insurance choices and consumer research, Internet privacy policies can also be counted towards those areas where default effects are mainly used not in the interest of the consumer, but as a tool to serve the interest of the company. The European Union Data Directive decreed in 1995 that the default for handling online privacy policies should be that the consumer needs to give their explicit consent to the program that collects their personal information. There are two contrasting ways of handling Internet privacy policy. One way is to make use of an opt-out default in which consumers have to explicitly opt-out of sharing their personal information with the online program. Another way is the use of an opt-in default, where consumers have to explicitly opt-in to sharing their personal information with the online program.

In the case of the United States, no default recommendation or restriction is given at this point in time. This results in a prevailing opt-out default on US websites in regard to Internet privacy policies. The consumers using any online program are assumed to agree with sharing their personal information with the online program. Only with an active request can a consumer opt-out of sharing their personal information with the website operators (Johnson et al., 2002). There are also no sufficient guidelines that the protocol for actively choosing not to share personal information should be easy for the consumer to follow. Therefore, online programs have no incentive to give consumers a fair chance to easily opt-out of the default rule that the website operators have skewed to their own advantage.

The effect of default rules on the sharing of personal information online is documented in the paper 'Defaults, framing and privacy: why opting in-opting out' by Johnson, Bellman and Lohse, published in 2002 (Johnson et al., 2002). The paper contrasts the different manifestations of the opt-in and opt-out responses that are an important element of online privacy and permission marketing. The opt-in and opt-out responses are all respondents' answers to the question of if the researchers would be allowed to contact respondents again for a health survey.

One study in the paper reported on the effects of positive and negative frames as well as defaults on participation rates. The randomized online survey experiment (*n*=277 from an US online panel) with four question formats asked the respondent to agree to be contacted for further studies (Johnson et al., 2002).

Figure 12. Formats of Participation Agreement Statements in Experiment 1 in 'Defaults, Framing and Privacy: Why Opting In-Opting Out' by Johnson, Bellman, & Lohse (2002)

Question	Percent Participating
(1) ☐ Notify me about more health surveys.	48.2
(1) ☐ Do NOT notify me about more health surveys.	96.3
(3) ☑ Notify me about more health surveys.	73.8
(4) ☑ Do NOT notify me about more health surveys.	69.2

Figure 12 shows the four different formats of participation agreement statements in the experiment by Johnson, Bellman, and Lohse (Johnson et al., 2002). The four conditions varied on whether the frame was positive or negative and whether the default was to participate or not participate. In the first condition (frame positive and default not participate), only 48.2% agreed to be contacted again. In the second condition (frame negative and default participate), 96.3% respondents agreed to be contacted again. Conditions three and four were the same as the first condition (frame positive and default not participate) and the second condition (frame negative and default participate), but with a pre-checking of the agreement.

This reversal of the defaults should have provided the opposite results of the first and second conditions. But instead of the opposite results, intermediate results of about 70% agreement can be found. A presumed reason is that the checkmark sign in front of the stated agreement is seen as a strong signal for a decision being made, and respondents had a heightened attention, resulting in the 69.2%, and 73.8% respectively, agreeing to be contacted again.

In conclusion, there is a major difference between first condition (48.2%) and the second condition (96.3%) that cannot solely be explained by low attention. When reversing the defaults by pre-checking the stated agreements, the reversed first condition (frame positive and default now participate) received a 73.8% participation rate. The reversed second condition (frame negative and default now not participate) received a 69.2% participation rate (Johnson et al., 2002).

Default Rules in the Area of Reducing Energy Behaviour

Default rules settings in the areas of insurance choices, consumer research, and Internet privacy policies show that default rules are often used at the disadvantage of the customer. But not all areas of decision-making that use default rules use default effect only in pursuit of their own interest. There are also some other areas where default rules are applied to serve the greater interest. One of these decision areas is reducing energy behaviour.

The paper 'Lights, building, action: Impact of default lighting settings on occupant behaviour' by Heydarian et al. was published in 2016 (Heydarian, Pantazis, Carneiro, Gerber, & Becerik-Gerber, 2016). The energy saving behaviour promoted was a lighting adjustment in a single occupancy virtual office space. The aim was to minimize the brightness of lighting and therefore the electricity usage of the participants. The overt experiment was conducted with a sample size of 160 subjects in the USA in a virtual environment. Respondents were put in a virtual environment that mimicked a single occupancy office space. The treatment was a default lighting of the office that varied in different artificial light and mimicked sunlight treatments. Defining the default lighting setting with simulated daylight had a significant positive effect on respondents keeping the default setting in comparison to the default lighting setting with no simulated daylight, where respondents were less likely to keep the default lighting setting and rather increased the amount of lighting. Therefore, choosing the right lighting setting as a default can promote energy saving behaviour (Heydarian et al., 2016).

Another paper reporting on the default effect on energy saving behaviour is ‘Motivating Energy-Efficient Behavior with Green IS: An Investigation of Goal Setting and the Role of Defaults’ by Loock, Staake, and Thiesse, published in 2013 (Loock, Staake, & Thiesse, 2013). The study uses default rules in goal setting in the form of a specific electricity usage goal to promote energy saving behaviour. The covert online experiment was conducted in Austria. It was facilitated with a web portal designed to motivate customers of a utility company to reduce their electricity consumption. A sample size of 1,791 customers of the utility company was divided into one of the three treatments, which were no goal-setting (control group) versus goal-setting with an active choice versus default goal-setting (Loock et al., 2013). The first treatment of no goal-setting was the control group, which was not asked to set a maximum electricity usage goal for a specific time. The second treatment of goal-setting was an active choice treatment, where the participants actively choose between different maximum electricity usage goals for a specific time. The third treatment was the default goal-setting, where customers received a default maximum electricity usage goal from which they could opt-out. The study ran from November 2010 to March 2011. The default goal led to statistically significant savings by affecting goal choice. The study also found that if default goals are set too low or too high with respect to a self-set goal, the defaults will detrimentally affect energy saving behaviour (Loock et al., 2013).

Conclusion

In conclusion, default rules show effects in versatile areas including organ donations, 401(k) retirement plans, insurance choices, consumer research, Internet privacy policies, and energy reduction behaviour. The versatile decision areas in which significant default effects are reported differ in many aspects. Some decisions are between two alternatives (to participate or not to participate), as in the area of organ donations or 401(k) retirement plans. Other decisions have a great variety of alternative choices, as in the area of consumer research. Regardless if the decision is between two alternatives or many, the default effect has proven significant among these varying decision formats. This highlights the core of a working default effect: as long as the decision content has an overwhelming feature, which might be due to the decision topic being uncomfortable or the alternatives being overwhelming, a default will deliver a highly accepted reference to guide behaviour towards the default setting.

Setting the default is not only a practical choice, but also a choice of ideology, as highlighted in the decision topic of organ donors. The choice between explicit consent and presumed consent in becoming an organ donor is a relevant to citizen welfare and balancing the means of many with the means of the individual. What might seem like lower stakes is the setting of defaults in Internet privacy policies. But here as well, citizen welfare is concerned. The right to privacy can be diminished by setting defaults in Internet privacy policies in such a way that websites gain and use private information to their own advantage, thus selling out citizens and their rights to privacy.

Consumer research also goes along these lines, taking advantage of default rules to gain a higher end price sale from the customer. It is remarkable to see that customers in this area judge defaults on the grounds of their former knowledge about the seller and will comply with the default only if it does not contradict with their knowledge about the seller. This illustrates that defaults that produce significant positive effects are mostly seen as trustworthy guidelines. If defaults are not willingly accepted by the majority, it might be a sign that the default setting is contradicting with some beliefs of the majority.

The act of default setting is a powerful tool with a relevant effect on the decision-making outcome of many. In most cases, the actors behind the default setting are not regulated to preserve the interest of citizens, but have an incentive to take advantage of their powerful position and serve their own interests instead. Without a doubt this is true in the case of consumer research, and can also be expected in the areas of Internet privacy settings and insurance choices.

2.2.2 Using Default Rules to Promote Renewable Energy Uptake[2]

Default rules are one of the nudging techniques that are often successfully applied to promoting renewable energy uptake and energy reduction. Default rules are often applied as a solo nudge treatment, and not in combination. One reason might be that it is one of the more potent nudging techniques, and is promising enough on its own in comparison to other nudging techniques that are mostly applied in combination due to their ambiguously documented effects.

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[2] The Section 2.2.2 Using Default rules to Promote Renewable Energy Uptake is also groundwork for the paper Liebe, Gewinner, and Diekmann (2018).

In this chapter, four papers will be presented that use default rules as a nudge to promote renewable energy uptake. All four papers are specifically selected to have used default rules as a solo nudge treatment, since a combination with other nudging techniques makes the interpretation and comparison of effects impossible. At the end of this section the main hypothesis is formulated and anchored in the research already done.

Studies using Default Rules to Promote Renewable Energy Uptake

The paper 'Domestic uptake of green energy promoted by opt-out tariffs' by Ebeling and Lotz was published 2015 and uses default rules to promote renewable energy uptake. The randomized experiment was conducted in Germany with a sample size of 3,512 households. The randomized experiment is covert and the experiment setup had a duration of 4.5 weeks. The two treatments, a conventional energy default and a renewable energy default, were randomly assigned. Respondents were prospective new customers of a specific utility company, and the experiment was conducted on the utility company's website. The website had two versions for the contract sign-up for new customers. The conventional energy default condition had an optional choice of 100% renewable energy, and respondents could activate this choice by ticking the corresponding box. The renewable energy default condition had an already activated choice of 100% renewable energy (the box of the optional renewable energy choice was already ticked) and respondents would have to actively tick the box again in order to return to the conventional energy contract (Ebeling & Lotz, 2015).

Figure 13. Basic Website Layout for Control (Left Side) and Treatment Groups (Right Side) (Ebeling & Lotz, 2015)

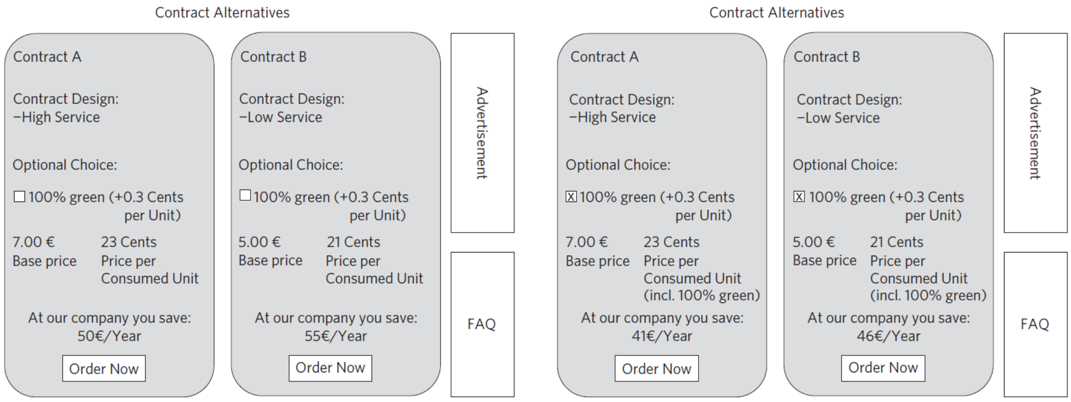


Figure 13 shows the basic website layout for the conventional energy default and the renewable energy default. In addition to the treatment of the renewable energy contract, two contracts were offered in both versions; one contract with high service and a higher base price and one contract with low service and a lower base price (Ebeling & Lotz, 2015).

Figure 13 further indicates that the 100% renewable energy contract in both cases was promoted as the 'optional choice'. This might lead respondents to think that the standard tariff choice is in reality the conventional energy contract. The renewable energy contract is promoted by the utility company as optional and can therefore be understood as not necessary. This choice of presentation could have a weakening effect on the renewable energy uptake in the renewable energy default condition.

In the control condition, 7.2% of purchased contracts were renewable energy, and in the treatment condition, 69.1% purchased contracts were renewable energy. The difference between control and treatment group was significant (χ^2 test, p<0.001). The study also reported on a small but significant negative effect of yearly energy consumption on the willingness to purchase the renewable energy contract (regression coefficient: -0.16; *z-value*: -1.95; p<0.10). The same goes for the unit price of energy: here they also report a small but significant negative effect on the willingness to purchase a renewable energy contract (regression coefficient: - 0.14; *z-value*: 2.39; p<0.10). When regional results from the last federal election were added, the researchers found a significant interaction between green party preference and the treatment. Green party preference on a regional level was associated with the renewable energy choice on the respondent level in the control treatment but not in the renewable energy treatment.

The study also did a small online follow up study (n=168) concerning the question of whether respondents consciously stayed with the renewable energy contract in the treatment condition. Of the respondents, 84.13% did recall making a conscious decision to stay with the renewable energy default in the treatment condition, and 100% of the respondents recalled it in the control condition (Ebeling & Lotz, 2015). As this result comes from an overt online study, it might be also the experimenter demand effect driving this high percentage on 'conscious decision-making'. It could be associated with negative emotions to own up to the truth that the respondent did not notice and might have also not cared about renewable energy versus conventional energy contract.

The paper 'From intention to action: can nudges help consumers to choose renewable energy?' by Momsen and Stoerk was published in 2014 and also experimented with default rules to promote renewable energy uptake (Momsen & Stoerk, 2014). This paper not only tested default rules against a control group, but also tested them in comparison with five other nudging techniques: priming, mental accounting, framing, decoys, and descriptive social norms.

The online survey was conducted in Germany with a sample of 475 mostly German students. The study was overt and had two treatments: an active choice condition and a renewable energy default condition. The active choice condition was a decision between a 100% conventional energy contract priced at 30 Euro a month and a 50% renewable energy/50% conventional energy contract priced at 45 Euro per month. The active choice condition (*n*=85) had no conventional default. The renewable energy default condition (*n*=33) was phrased as an active choice between the 100% conventional energy contract and the 50% renewable/50% conventional contract (same price difference), but here, respondents were informed that if they did not decide, they would keep the 50% renewable/50% conventional energy contract.

The renewable energy default was the only nudge in the study that had a significant positive effect in comparison to the active choice group. The renewable default product condition had an uptake of green energy of 69.7%, whereas the active choice condition had an uptake of 48.2% (Momsen & Stoerk, 2014). It might have been more realistic to have a conventional energy default condition instead of an active choice condition as the control group. At least in Switzerland (and other countries), the utility company has to have a default in place in the case that the customers do not make an active choice. When designing an experiment that aims to come close to the natural decision of a household choosing a contract, the control group should reflect the praxis of the conventional default. However, it is understandable that the authors chose the active choice condition as the control group because they wanted to not only compare the renewable energy default condition to that control group, but also four more nudges. Therefore, the active choice condition might have been moreover suitable to all nudges.

The paper 'Green defaults: Information presentation and pro-environmental behaviour' by Pichert and Katsikopoulos was published in 2008. This paper is the oldest in the selection to use default rules to promote green energy uptake (Pichert & Katsikopoulos, 2008). The paper reported on three relevant studies, all conducted in Germany: two natural experiments and one laboratory experiment.

The first study was a covert natural experiment with a sample size of 1,669 subjects, where the introduction of a renewable energy default was observed (Pichert & Katsikopoulos, 2008). The sample were the inhabitants of a little town in Germany that reacted to the Chernobyl disaster with a citizen initiative to no longer use nuclear power in the town. The citizen initiative bought the electricity grid from the former utility company one year before the German electricity market opened, meaning that for one year the citizens of that town were forced to take renewable energy contracts and afterwards had the ability to change to any electricity supplier and any electricity source. Therefore, from the time when the German electricity market was opened in 1998, the town's citizens had the choice between staying with their contract provided by the citizen initiative (mostly solar energy) or switching to any other electricity provider localized in Germany and downgrading to conventional energy. Eight years after the market opened and nine years after the renewable energy default was introduced in the town, 1,669 out of the 1,683 electricity meters remained with the renewable energy default (Pichert & Katsikopoulos, 2008). Hence, 99.17% of all electricity meters stayed with the renewable default in this natural experiment after the town's citizens had the choice to defer from the renewable energy default for eight years.

The second study was a covert natural experiment with a sample size of 150,000 respondents (Pichert & Katsikopoulos, 2008). A utility company in Southern Germany introduced a renewable energy default in 1999 to its 150,000 household and business customers. Customers had the choice between three energy contracts: a conventional energy contract (8% cheaper than default category), the renewable hydropower contract (default category), and a premium renewable contract (23% more expensive than the default category). Since this introduction of renewable energy tariffs and the introduction of a renewable energy default was one year after the German market was opened, customers also had the choice to switch to a different utility provider. Two months after this tariff change, 4.3% of the customers had changed to the conventional contract, less than 1% had changed to the premium renewable contract, 0.7% had changed to a different utility provider, and about 94% stayed with the newly introduced renewable energy default (Pichert & Katsikopoulos, 2008). The 94% of customers staying with the renewable energy default was a relevant amount, especially when customers had the opportunity to switch instead to the cheapest utility provider in Germany. Of course, this switch would have saved money, but it also would have cost time and effort looking for a different utility provider and comparing prices and services. Staying with the default did save the customer the time and effort of switching.

The third study was an overt laboratory experiment with a sample size of 225 respondents (Pichert & Katsikopoulos, 2008). The experiment randomized respondents on one of three treatments: an active choice condition, a conventional default condition, and a renewable default condition. For all three conditions, the starting point of the experiment was to let the respondents imagine that they had just moved to a new location and received offers of service letters from two different utility companies. One utility company offered renewable energy and the other utility company offered cheaper electricity from unnamed sources. The active choice condition was an active choice between the renewable energy utility provider and the conventional energy utility provider. The conventional default condition was described in a way that the respondent already had a contract with the conventional energy utility company and then received an offer of service from the renewable energy utility company. This led to the decision between staying with the conventional energy utility company and changing to the renewable energy utility company. The renewable default was constructed in the same fashion, but with the first letter and contract being the renewable energy utility company.

In the active choice condition (*n*=73), 67% chose the renewable energy utility provider. In the conventional default condition (*n*=75), 41% chose the renewable energy utility provider. In the renewable energy default condition (*n*=77), 68% of the respondents chose the renewable energy utility provider (Pichert & Katsikopoulos, 2008). Therefore, the renewable energy default got most respondents to choose renewable energy even though it came with a price increase of five Euro a month. The neutral condition was an active choice between conventional and renewable energy, which also led to a high enrolment in renewable energy. As this high percentage of renewable energy uptake (67%) was quite different from the number of people actually using renewable energy in Germany, it might hint at an experimenter demand effect or portray a decision framework that was not similar enough to one that could be found in reality. In reality, most households are already customers of a utility company holding a conventional energy contract due to the conventional energy contract being the prevailing one. This being the starting point, the customer would change to renewable energy only if their utility provider were to change the default product setting to renewable energy. When people are asked if they understand and agree with the importance of using more renewable energy, the overwhelming majority agrees. When people are asked if, hypothetically, they would prefer conventional or renewable energy, the overwhelming answer again is renewable energy (Farhar, 1999). But if they have to invest information and monetary costs in changing from the prevailing default product of conventional energy to a renewable energy contract, they are less likely to align their preference with actual product choice.

The paper 'Does Active Choosing Promote Green Energy Use? Experimental Evidence' by Hedlin and Sunstein was published in 2015 and used default rules to promote renewable energy uptake (Hedlin & Sunstein, 2015). The overt online experiment was conducted in the USA with a sample size of 1,037 recruited by Amazon Mechanical Turk. It had nine possible vignettes, resulting in a 3x3 design alternating study design between a renewable energy default, a conventional energy default, an active choice combined with an alternative of more expensive renewable energy, no cost or quality information provided, and information about identical cost and quality provided. Each respondent was only given one of the nine possible vignettes.

On average, across all nine vignettes, the active choice led to higher renewable energy uptake (82%) than the renewable energy default (76%) or the conventional energy default did (69%). The paper argues that active choosing caused respondents to feel guiltier about not enrolling in the renewable energy program relative to the renewable default and the conventional product default. They showed that the level of guilt reported by respondents was positively related to the probability of renewable energy uptake (Hedlin & Sunstein, 2015). The results of the renewable default were significantly different from the results of active choosing, however: active choosing had the most renewable energy uptake (Hedlin & Sunstein, 2015). This result again gives rise to the question of whether active choice is a feasible option in promoting renewable energy apart from experimenter demand effects and artificial decision-making setups.

Table 1 shows the descriptive details of the six studies in the four papers that used default rules to promote renewable energy uptake. All four publications are relatively recent, ranging from 2008 to 2015. It is remarkable that three of the four papers and the studies they reported on were conducted in Germany, even though the literature search concentrated on English-language papers only. The promotion of renewable energy seems to be a relevant topic among German researchers. The German electricity market was liberated in 1998, but so were most the markets of European countries. Therefore, the topic of introducing a renewable energy default product should be a relevant and timely topic of study in Europe. Half of the studies were covert and half of them were overt. As this can be described as the beginning phase of documenting default effects on the promotion of renewable energy, even overt studies (in this case online or laboratory experiments) can give important insights into what criteria make the default effect strong. The overt studies all report high percentages of renewable energy uptake for the active choice condition (ranging from 48.2% to 82%), which cannot be disentangled from the possibility of experimenter demand effects. The covert studies did not have the active choice condition, as it is not practical or legal for a utility company to have no default product in place. At least in Germany, the customer enters into a contract with the utility provider the moment he or she switches on the light bulb in his or her new home. It is in line with current law to have a contract in place for customers who do not decide whether they want a different contract. Even though when active choosing yields promising renewable energy uptake (minus the experimenter demand effect) it might not be a feasible solution in this specific case.

Table 1. Descriptive Statistics on a Sample of Four Papers and Six Studies of Default Rules with Dependent Variable Renewable Energy Uptake

Paper	Country	Sample size	Method	Covert or overt	Study design (% renewable energy contracts)
(Ebeling & Lotz, 2015)	Germany	3,512	Randomized experiment	Covert	Renewable default (69.1%) vs. conventional default (7.2%)
(Momsen & Stoerk, 2014)	Germany	475	Online survey	Overt	Renewable default (69.7%) vs. active choice (48.2%)
(Pichert & Katsikopoulos, 2008)	Germany	1,669	Natural experiment	Covert	Renewable default (99.17%) vs. no other condition
(Pichert & Katsikopoulos, 2008)	Germany	150,000	Natural experiment	Covert	Renewable default (94%) vs. no other condition
(Pichert & Katsikopoulos, 2008)	Germany	225	Laboratory experiment	Overt	Renewable default (68%) vs. conventional default (41%) vs. active choice (67%)
(Hedlin & Sunstein, 2015)	USA	1,037	Online experiment	Overt	Renewable default (76%) vs. conventional default (69%) vs. active choice (82%)

The literature shows different implementations of the default rules condition versus the control condition. Some studies have a conventional energy default product as their control condition (Ebeling & Lotz, 2015) and other studies have active choice as their control condition (Momsen & Stoerk, 2014). Still other studies compare the renewable energy default product to both an active choice and a conventional energy default product condition (Hedlin & Sunstein, 2015; Pichert & Katsikopoulos, 2008).

One paper reported on two natural experiments with no control conditions (Pichert & Katsikopoulos, 2008). When designing a control condition to a default rules condition, the question arises of what exactly the neutral condition in comparison to a default rules condition could be. Is the active choice condition the opposite of the default rules condition, or is it the conventional energy default product condition that can most commonly be found in real life? Besides understanding the point of the active choice condition as the control condition versus the renewable energy default product condition, it might be advisable to give preference to the conventional energy default product as the control condition. Having the active choice condition as a control condition gives answer, and contrast, to the question of what the real preference of people is. Having the conventional default product as a control condition answers the question of how people would change their contracts if a utility provider would change their default product setting from a conventional to a renewable default product setting. Both are important questions that should be differentiated from each other. In this light, one can see the question of active choice condition versus renewable energy default product condition in a different way. It is not the question of if active choice gets more people to choose renewable energy than a renewable energy default, but that they ask different things: the percentage of renewable energy uptake in the active choice condition (ranging from 48.2% to 82%) does not necessarily mean that customers would decide on their own to enrol in renewable energy if only they had an active choice. All German households have an active choice, and still only few energy customers choose a renewable energy contract. This documented high percentage of renewable energy uptake in the studies can be partly seen as the established injunctive norm to promote renewable energy, partly seen as the experimenter demand effect, and partly seen as the answer to: 'if you would hypothetically choose between a conventional and a renewable energy contract (with no monetary, no information cost, and no transaction cost) what would you choose?'.

Previous research on default rules interventions promoting renewable energy uptake have established the finding that their default effects show strength and longevity. While the default effect is sufficiently demonstrated in its strength and longevity, former research has yet to investigate the heterogeneity in default effects in the area of renewable energy uptake. The one study (Pichert & Katsikopoulos, 2008) that differentiated in its sample between business and household customers, did not report on heterogeneity in default effects for each customer type. The research gap of exploring possible heterogeneity in customer type (household versus business customers) is at the heart of this study. Ad-hoc, it is hypothesised that there is heterogeneity in default effect that correlates with the customer type household versus business. Household and business customers have one major distinctive customer characteristics that is hypothesized to respond differently to the renewable default product setting, which is the yearly amount of electricity usage. The yearly amount of electricity usage is significantly higher for the average business customer than for the average household customer. The new default product of renewable energy comes with an increase in price, in comparison to the conventional energy product. It follows, that business customers will experience that price increase, according to their higher yearly utility use, more severely than household customers will do, with their lower yearly utility use. Leading to the main hypothesis of the study at hand:

Hypothesis 1: Business customers will have a lower default product acceptance of the renewable default product than household customers.

This hypothesis will guide all following chapters and all analysis from descriptive to multivariate will explore the heterogeneity in default effect according to customer type household versus business.

2.2.3 Unwanted Side Effects of Default Rules

Even though default rules are popular because of their proven ability to steer individuals toward a specific decision outcome, they are not without potential unwanted side effects. This discussion concentrates mainly on the topics of moral licensing, ethical problems in the form of potential manipulation, the distortion of preferences, and rebound effects.

Moral self-licensing is described as a phenomenon in which moral behaviour increases the likelihood of immoral behaviour without the individual feeling like an immoral person. In the case of this field study, the default setting of a renewable energy contract could potentially be interpreted as moral behaviour that then is followed up by immoral behaviour, for example, higher electricity usage. Since the common social norm is to align individual behaviour with the collective goal of protecting the environment, the change from conventional to renewable energy can therefore be understood as moral behaviour. Coming from the same understanding, higher electricity usage is then understood as immoral behaviour. This very real side effect of moral self-licensing is described both in general and in specific regarding its application to the study at hand.

Nudging interventions are confronted with accusations of not only influencing target behaviour but also manipulating target behaviour. The manipulation accusation is discussed in regard to the deceptive and abusive potential that a nudging intervention may hold. The deceptive potential is anchored in the level of awareness that the individual being influenced will have of the behavioural intervention, and the abusive potential is dependent on the promoted end goal and whether it aligns with the individual’s interests that is receiving the intervention.

Other possible side effects include the distortion of preferences – when the individual becomes misaligned with his or her true preferences through the nudging intervention – and the rebound effect – when overuse nullifies the potential energy savings of a more energy efficient product. Both potential side effects are discussed as they apply to the study at hand.

In conclusion, the possible unwanted side effects that need to be considered when applying a renewable default option in the area of electricity contract choice are concerns of moral self-licensing (moral credits as well as moral credentials) and the general ethical problems of manipulation, the distortion of preferences, and the rebound effect.

2.2.3.1 Moral Self-licensing

Moral self-licensing is one of the main unwanted side effects of this specific default rules intervention. Moral self-licensing is described as a phenomenon in which moral behaviour increases the likelihood of immoral behaviour without the individual feeling him or herself to be an immoral person. When an individual's self-concept is assured enough through past moral behaviour, he or she can afford immoral actions in the present that do not negate the positive self-image that he or she holds and portrays to others (Merritt, Effron, & Monin, 2010).

Moral self-licensing is a consistency break with the stream of past behaviour that, under different circumstances, is not only experienced as an uncomfortable threat to self-identity but also gives ground to being judged as a hypocrite in the perspective of others (Barden, Rucker, & Petty, 2005). The threat to one's identity as well as the threat of being judged a hypocrite are both inhibiting psychological and social forces that keep an individual's present behaviour in line with his or her past behaviour, thus ensuring a strong pull towards consistency in behaviour (Barden et al., 2005; Lewin, 1947). Moral self-licensing occurs more often when both inhibiting forces – the social as well as the psychological – are overpowered, resulting in a consistency break between present and past behaviour. How and when the break in behavioural consistency – that is, moral self-licensing – occurs is described in this chapter. First rooting moral self-licensing in early social psychological theories and then returning to current findings, the spectrum of this phenomena is described more closely. The last part of this chapter will argue what the phenomena of moral self-licensing means for default rules interventions in general, and more specifically for default rules interventions in promoting renewable energy.

Behavioural Theories

Moral self-licensing is grounded in early social psychological theories describing behaviour as the outcome of exertion between forces that motivate actions and forces that inhibit actions (Lewin, 1947). Lewin describes the objective of social change as a process that occurs with a specific frequency in a certain timeframe. Wanting to alter a social process is wanting to alter the frequency with which it occurs in that timeframe. The frequency of a social process is described as the main tangible aspect of the ongoing social process. A state of ‘no social change’ is described as a quasi-stationary equilibrium in which the pull of forces that motivate and inhibit actions are somewhat stable. If one wanted to change this quasi-stationary equilibrium of ‘no social change’ toward ‘social change’, one would need to add to the motivating forces and/or diminish the inhibiting forces. Therefore, altering the forces can alter the quasi-stationary equilibrium toward social change (Lewin, 1947). Lewin describes the process of social change in three steps: unfreezing, moving, and freezing (Lewin, 1947). The quasi-stationary equilibrium of ‘no social change’ can be unfrozen and moved to ‘social change’ by altering the balance between the forces and freezing the social process at a new quasi-stationary equilibrium of ‘no social change’. The induced social change gives rise to a new force field of motivational and inhibiting forces that can reach a new quasi-stationary equilibrium and result in a new state of ‘no social change’ (Lewin, 1947). When explaining immoral behaviour, one needs to not only concentrate on the forces that motivate the immoral behaviour, but also on what inhibits the corresponding moral behaviour from occurring (Merritt et al., 2010). Moral self-licensing can be understood as one of the forces that acts as an inhibitor to moral behaviour, removing the social and psychological boundaries towards immoral behaviour and thus making it more likely to occur (Merritt et al., 2010). Moral self-licensing is not intuitive to understand. It describes inconsistent behaviour that is generally experienced as a threat to self-image, and it works against the pull that makes individuals behave in line with their former behaviour (Merritt et al., 2010). Moral self-licensing is the force that lets present/future behaviour deviate from the trends of past behaviour. The concept of consistency theory and accusations of hypocrisy are forces that consistently align behaviour with previous behaviour. But how can those opposite forces be mended, and how can individuals justify inconsistent behaviour as non-hypocritical and maybe even reinterpret it as consistent after all? This question leads to the two dominating theories that try to explain moral self-licencing: the theoretical framework of moral credits and the theoretical framework of moral credentials. In the following, both theories will be laid out and compared, focusing on their compatibility rather than their exclusiveness in explaining the phenomena of moral self-licensing.

Moral Credits

The framework of moral credits goes back to theories stating that in order to make a general judgement about a person’s character, one would need to average out both positive and negative attributes of that person's character (Effron & Monin, 2010). Following this logic, the sum of positive and negative character attributes would determine the character judgment and the sum of moral and immoral behaviour would determine the judgement of an individual's morality (Merritt et al., 2010). The framework of moral credits portrays moral self-licensing as a bank account in which moral behaviour represents credits and immoral behaviour represents debits (Effron & Monin, 2010). In this moral bank account, an individual can both invest and withdraw, and thus balance out his or her immoral behaviour with moral behaviour (Effron & Monin, 2010). In this argument, the presumable 'size' or weight of the moral or immoral behaviour is of great importance, influencing the end judgement of the total sum of morality in a person's character (Merritt et al., 2010). A positive moral bank account balance allows the individual to spend some moral credits on immoral behaviour. In the framework of moral credits, the immoral behaviour is still experienced as an immoral behaviour, and the individual understands the immoral behaviour to be a deviation from consistency and from his or her former moral behaviour. The judgement about morality is not altered, but the 'right' or entitlement to immoral behaviour is earned through a positive moral bank account balance. The individual calculates that even after spending some moral credits on an immoral behaviour, he or she will still have a positive moral bank account balance overall, and thus is in no danger of judging him/herself or being judged by others as immoral or of bad character. The accumulated moral credits secure the self-image of morality, and therefore, a leap can be taken without damage to the self-image as a consequence. Without damage to the self-image of morality, the individual can engage in immoral behaviour without experiencing his or her behaviour as inconsistent or being judged as hypocritical (Effron & Monin, 2010; Merritt et al., 2010). It seems as if the individual's positive moral bank account balance buys him or her room to deviate from his or her earlier behaviour, stretching out the array of behavioural possibilities from moral behaviour to immoral behaviour. This wider array of behavioural possibilities is calculated by the individual, who strictly weighs his or her accumulated moral credits to be able to afford some leeway without harming his or her self-perception and identity and without fearing judgement as a hypocrite.

The framework of moral credits builds on the logic of self-affirmation theory. Its core describes how moral behaviour strengthens an individual's perception of his or her morality and self-worth, and can be described as an act of self-affirmation (Merritt et al., 2010). The framework of moral credits also follows the arguments of theories that describe the trade-off of goals in an individual (Fishbach & Dhar, 2005). Moral credits allow the individual to change from one pursuit or goal (e.g. establishing morality through selfless behaviour) to the pursuit of a different goal (e.g. an immoral behaviour in pursuit of self-interest) (Fishbach & Dhar, 2005). In conclusion, regarding the moral credits framework, moral self-licensing is more likely to occur when a positive moral bank account balance allows for spending on some immoral behaviour without fear of a consequential threat to self-identity or judgement as a hypocrite.

Moral Credentials

In comparison to the framework of moral credits, moral credentials do not redeem immoral behaviour through moral behaviour as in a moral bank account. However, moral behaviour is used to establish moral credentials through which immoral behaviour is framed in a more favourable way (Effron & Monin, 2010). The established moral credentials build a lens through which the immoral behaviour is no longer seen as an immoral behaviour – thus, licensing it (Effron & Monin, 2010). The concept of moral credentials goes back to theories where prior information (the moral behaviour) shapes the interpretation of later information (the immoral behaviour) (Effron & Monin, 2010). In the sense of causal attribution, moral behaviour does not give entitlement to immoral behaviour, but it changes the reference frame that reinterprets immoral behaviour as acceptable behaviour (Merritt et al., 2010).

The concept of moral credentials can also be understood in the practice of tokenism, where (whatever little) evidence through a behaviour is used to establish moral credentials to shine a more favourable light on immoral behaviour (Monin & Miller, 2001). One example would be when companies flaunt their supposedly diverse workforce on an official picture by carefully over-selecting their small share of minority workers. This official picture is then proof enough for the company to not worry any longer about hiring practices that would foster a more diverse workforce (Monin & Miller, 2001). The official company picture establishes moral credentials as the company portrays itself as a non-racist workplace. The established moral credentials of non-racism let ongoing racist hiring practices seem less immoral to the company itself, and, they hope, to the judgement of others as well. In this regard, Monin and Miller write that: '…decision-makers seem disposed to treat what is at most a molehill's worth of goodwill as though it demonstrates a mountain's worth of virtue' (Monin & Miller, 2001). As can be inferred, moral credentials can even be successfully applied when moral and immoral behaviour seem off-balance, allowing the more and less prejudiced individuals in Monin and Miller's study to use the same moral credentials to voice prejudiced opinions (Monin & Miller, 2001). The motivations for being perceived as being without prejudice can range from internal motivations to external motivations to both or even none, and do not conflict with the ready use of moral credentials to voice prejudiced opinions (Monin & Miller, 2001). The opposing force to moral self-licensing and moral credentials is consistency theory, which states that an individual's actions commit him or her to acting similarly in the future and describes past behaviour as having a constraining power (Monin & Miller, 2001). Consistency theory is constraining, and the motivation is for present behaviour to be in line with past behaviour. Moral credentials are liberating, inhibiting the pull of consistency with past behaviour and opening up the possibility for deviating behaviour (Monin & Miller, 2001).

Even though consistency theory and moral credentials seem to be opposites, they do follow the same logic. Moral credentials show the defining power of past behaviour on the individual's self-image, but he or she uses that established image to deviate from past behaviour rather than to align present and past behaviour (Monin & Miller, 2001). Furthermore, moral credentials rely heavily on consistency theory, allowing the individual to feel and seem consistent with others while deviating in his or her behaviour – all possible through the establishment of moral credentials. Through the lens of moral credentials, immoral behaviour is perceived as moral and consistent with past behaviour (Monin & Miller, 2001). It is shown that moral credentials can be established not only through behaviour, but also through other methods – for example, group membership or by association with someone proving morality or otherwise taking into account what other people have done, providing a good excuse for immorality. All those scenarios strengthen moral credentials by providing a label of morality (Monin & Miller, 2001). Merrit et al. found signs in their study that moral self-licensing and, more specifically, moral credentials work not only in a passive ad-hoc way, but are actively calculated and pursued by the individual (Merritt et al., 2012). Moral credentials are described as a wilful bid by the individual to manage his or her moral track record in order to satisfy both his or her own judgement and the judgement of others. Individuals even actively pursue moral credentials if they expect future behaviour that is immoral (Merritt et al., 2012). Therefore, moral self-licensing, in the sense of moral credentials, is a way to carefully balance the judgement of one's moral track record and the judgement of others on one's moral track record by using moral behaviour as a lens through which immoral behaviour can be seen more favourably. Through establishing one's own moral credentials, one can license immoral behaviour by letting it seem less immoral and more ambiguous (Effron & Monin, 2010).

Moral Credits Versus Moral Credentials

At first glance, the frameworks of moral credits and moral credentials seem to describe two different ways of breaking with consistency and engaging in moral self-licensing behaviour. Moral credits give license to immoral behaviour by balancing it out through stored up moral behaviour. Moral credentials give license to immoral behaviour by reinterpreting it as moral behaviour through the lens of established morality. Both processes seem to describe moral licensing in different ways, but it has been theorized that neither one nor the other framework is closer to describing moral self-licensing – both merely describe the same phenomena under different circumstances (Effron & Monin, 2010). Those circumstances are the ones mediating the likelihood of moral self-licensing behaviour. One of the main moderators explaining the circumstances behind the pull of consistency versus moral self-licensing is the framing of moral behaviour as either proving commitment or proving adequate progress (Fishbach & Dhar, 2005). If the moral behaviour is proving commitment, the individual is more likely to stay in line with their past behaviour (Fishbach & Dhar, 2005). Goal commitment can be understood as a continuous variable that frames a behaviour as a core feature of one's self-concept. If a behaviour is framed by the individual within the realm of goal commitment, the individual is less likely to break out of that behaviour and follow other goals (Fishbach & Dhar, 2005). The opposite is true if the past behaviour is proving adequate progress towards a goal. Then, the individual is more likely to engage in a moral self-licensing behaviour and deviate from their past behaviour (Fishbach & Dhar, 2005). The individual feels entitled to actively pursue his or her other goals (that could be detrimental to the initial goal) when he or she frames behaviour as progress toward a goal. This subjective progress is not a continuous variable such as goal commitment, but is perceived as one step toward the actualization of the initial goal. Leaving the line of behaviour in order to follow another goal (that could be detrimental to the initial goal) is easier to justify since the judgement has been made that some subjective progress has been accomplished. This assessment of subjective progress towards the initial goal does not necessarily have to be proven by actual past behaviour. It is enough to merely anticipate the progress in order to engage in a switch to a different (even detrimental) goal and engage in moral self-licensing (Fishbach & Dhar, 2005). Therefore, moral self-licensing can be described as helping to balance multiple goals that consist of long-term commitments and short-term temptations (Fishbach & Dhar, 2005). In conclusion, framing a behaviour as a commitment does not provide an excuse for switching to the pursuit to another goal, but framing it as progress does give that excuse (Fishbach & Dhar, 2005).

Another moderator is the judgement of whether the licensed behaviour is a strong moral violation or only a suspected moral violation (Merritt et al., 2010). Concerning present immoral behaviour, moral self-licensing is more likely when the behaviour is only suspected of moral violation rather than being a strong moral violation. In scenarios where the present behaviour is ambivalently immoral, the behaviour reduces the pull to behave consistently and increases the likelihood of acting detrimentally since the bridged moral distance is understood to be less than when the behaviour is a strong moral violation (Merritt et al., 2010).

Most studies examine the likelihood of vague immoral transgressions instead of strong immoral transgressions as a sign of moral self-licensing (Merritt et al., 2010). But not only the likelihood of moral self-licensing is affected by the degree of the immoral transgression. The judgement of others also relies on it. In the same way that individuals feel pulled to act in line with former behaviour, they also judge others as hypocrites when they deviate from their former behaviour. In agreement with the moral credential framework, a strong immoral violation is not nullified by a former moral behaviour in the same arena, but only by an equally strong moral behaviour in a different arena. The strong immoral behaviour cannot be redeemed by a moral behaviour in the same arena because this brings up the judgement of hypocrisy. In agreement with the moral credit framework, a vague immoral transgression can be nullified by a moral behaviour in the same or a different arena (Merritt et al., 2010). This phenomena hints at another moderator that determines whether former behaviour is followed up consistently or is broken from: the similarity of the decision-making arena (Merritt et al., 2010).

Coming back to the two frameworks explaining moral self-licensing, the concept of moral credentials argues more on the side of moral self-licensing happening in the same decision area and the concept of moral credits argues that moral self-licensing happening among different decision arenas (Merritt et al., 2010). Moral credits are more likely under the condition of strongly immoral behaviour and when moral and the immoral behaviours are in different domains (Effron & Monin, 2010). Only moral credits can license strongly immoral behaviour because the moral ambiguity is missing and a reinterpretation of the immoral behaviour through moral credentials is less likely to be successful (Effron & Monin, 2010). The moral licensing of strongly immoral behaviour through moral behaviour in the same domain is altogether unlikely, no matter the process of moral credits or moral credentials, since the attribution of hypocrisy will be strong in such a case (Effron & Monin, 2010). Moral credits hold the potential to license behaviour among different domains since they do not rely on a re-interpretation of the immoral behaviour but rather a hard calculation of the immoral versus the moral behaviour (Effron & Monin, 2010). The process of moral credentials is likely to license behaviour when the immoral behaviour is more ambiguous and open to reinterpretation through established moral credentials, which should be pursued in the same domain in order to provide a believable basis for reinterpretation (Effron & Monin, 2010). The processes of moral credits and moral credentials are more likely under different circumstances, which shows how they work complementarily at different time points – or arguably, even at the same time point (Effron & Monin, 2010). It is presumable that when moral behaviour and ambiguous immoral behaviour happen in the same domain, moral credentials can skew the interpretation of the ambiguous immoral behaviour more favourably and moral credits can work to balance it out. This demonstrates the complementary nature of the two frameworks rather than their exclusiveness (Effron & Monin, 2010).

In order to engage in moral self-licensing behaviour, the individual does not necessarily need to behave morally. It is enough to anticipate the ideal behaviour that would redeem (moral credits) or change the interpretation (moral credentials) of an immoral behaviour (Tanner & Carlson, 2009). Moral self-licensing has two starting points: either moral behaviour in the past justifies immoral behaviour in the present, or moral behaviour in the present is carried out to justify immoral behaviour in the future (Merritt et al., 2010). As individual estimates about future behaviour are not simply more moral than their actual behaviour but tend to have a bias toward a perception of ideal behaviour, behavioural predictions tend to be far off, giving avenue to moral self-licensing behaviour (Tanner & Carlson, 2009). Another thing that opens up the possibility of moral self-licensing is merely imagining oneself engaging in moral behaviour. In one study, participants were asked to imagine being helpful to another student, which resulted in significantly lower donations than those of a control group in which participants did not have the task of imagining being helpful (Khan & Dhar, 2006).

Moral Self-licensing as an Unwanted Side Effect of Nudging Interventions

Now that the theoretical workings that make moral self-licensing possible are drawn up, the question remains: how do nudging techniques, and especially default rules, open up avenues for moral self-licensing as an unwanted side effect?

The study ‘For better or for worse? Empirical evidence of moral licensing in a behavior energy conservation campaign’ by Tiefenbeck et al. (2013) examined moral-licensing in energy-saving behaviour (Tiefenbeck, Staake, Roth, & Sachs, 2013). In their overtly controlled field experiment with a quasi-experimental design, a descriptive social norm nudge was used to reduce water consumption in households. After two weeks of baseline data, half of the 154 US households received weekly feedback on their own water consumption and the average water consumption of their communities along with water conservation tips for seven weeks (May to July 2011) (Tiefenbeck et al., 2013). The households' water consumptions were measured daily, and additionally, the households' electricity consumptions were measured on a weekly basis, even though electricity consumption was not addressed in the weekly feedback given to the households. The descriptive social norm intervention lowered water consumption on average by 6% in comparison to the control group. However, the intervention had the unwanted side effect of also increasing household electricity consumption by 5.6% in comparison to the control group (Tiefenbeck et al., 2013). On the one hand, as the dependent variable of the intervention was water consumption, the study could be considered to have successfully shown a significant effect of a descriptive social norm nudge on reducing water consumption. On the other hand, the intervention was successful in decreasing water consumption but came with the unwanted side effect of significantly increasing household electricity consumption. It is presumable that the true aim of the intervention was not only reducing household water consumption, but reducing household energy net consumption. With that aim in mind, a judgement of success for this study would have to calculate whether the reduction of 6% in water consumption was worth the increase of 5.6% in electricity consumption in the overall household energy sum. The unwanted side-effect of the increase of household electricity consumption can be ascribed to moral licencing behaviour. As the moral behaviour of saving water and the immoral behaviour of using more electricity both fall in the realm of energy-related behaviour, the process of moral self-licensing could be best described by the framework of moral credentials. The saving of water established moral credentials for the household members as being environmentally minded, through which lens the immoral behaviour of using more electricity can be judged more favourably. The additional focus on the connection between environmental-mindedness and water-saving behaviour through the intervention material gives more room for ambiguity in judging electricity-saving behaviour as less central to environmental-mindedness. With this ambiguity in mind, it is even more likely for household members to let their efforts in saving water license their increased usage of electricity through moral credentials. Since only water and electricity consumption were observed, one does not know whether the household members licensed even more immoral behaviour in the realm of energy usage through their established moral credentials. This behaviour could range in gravity from increasing the usage of cars to booking a cruise to Alaska. The moral act of water conservation could not only license behaviour in the same realm, but also in all other realms. Since only water and electricity consumption were measured, one does not know the numerous other ways that the household members may have engaged in moral self-licensing behaviour in other domains through moral credits. As described before, moral credits are transferable; they license behaviour among different domains, but are more bound to the same subjective level of moral behaviour than moral credentials. Depending on the subjective effort that the household members took to conserve water, they would be able to subsequently reinvest that effort in indulging in some immoral behaviours in some other domain. The conservation of water could give them an excuse to follow goals of self-interest that were previously latent, resulting in whatever behaviour is engaged in that self-interest. For example, the individual could buy an additional household appliance that he or she previously thought of as a luxury and not necessary. The moral credits gained might make this decision possible. While the overall aim for the intervention was to reduce the households' energy consumption, such a purchase could additionally nullify the conservation effect of decreased water consumption.

Only a few studies control for other kinds of energy consumption when testing an intervention meant to decrease one specific type of energy consumption. The electricity consumption of the households in this study shows that moral licensing behaviour should be accounted for as much as possible when judging the effect of a nudging intervention. It is not enough to only judge a nudging intervention in comparison to the control group in order to understand its potential to affect a target behaviour. A nudging intervention has to be also understood as an intervention in an entire system of choices and behaviours that are more complicated and less straightforward than most studies account for, and even could account for. In order to understand all the possible sides of the effects of a nudging intervention, one needs well-documented studies of interventions that investigate an array of behaviours for a long duration. The moral self-licensing effect of the increase in households' electricity consumption shows that nudging effects are less predictable and more multifaceted than they are portrayed. It is a caution for the logical link of actions and effects that is often praised in nudging interventions. Nudging interventions never affect only the target behaviour, but hold the potential to simultaneously affect a whole array of behaviour.

Another study reveals that environmentally-minded behaviour lets participants engage in moral self-licensing of immoral behaviour in other domains (Merritt et al., 2010). Studies show that even the purchase of environmentally friendly products can increase immoral behaviour such as lying and theft (Mazar & Zhong, 2010).

Moral Licensing as an Unwanted Side Effect of the Default Product Change Experiment

What holds true for nudging interventions in the area of promoting the purchase of environmentally friendly products or promoting environmentally minded behaviour in general also holds true in the more specific case of default rule interventions designed to promote renewable energy. Here as well, the probability of moral self-licensing behaviour should caution against too optimistic an evaluation of the default product change on the energy consumption of the households and the CO2 footprints of the household members. Accepting the default product of renewable energy can serve as an indication of the customer demonstrating to him- or herself, as well as to others, that he or she is indeed an environmentally conscious individual. The action of accepting a new renewable energy default can satisfy moral self-aspiration as well as support the image that an individual aims to portray to others so completely that in subsequent decisions, behaviour is no longer bound by those concerns. The individual is freed from the former necessity to prove to him- or herself and others that he or she is an ecologically minded person. This freedom of not having to prove ecologically mindedness through behaviour is loosely translated into engaging in behaviour that does not have to be in line with ecologically mindedness (Merritt et al., 2010). Agreeing to the default product change to renewable energy can be interpreted as a moral act holding the potential to license immoral behaviour in the domain of environmental mindedness through moral credentials or in an altogether different domain through moral credits. Staying in the same domain, the established moral credentials could be used to license increased electricity and/or other energy consumption as well as other non-environmentally-minded behaviour, for example, a stronger preference for traveling by plane instead of train. The default product change toward renewable energy could be understood by the customer as a blank check to engage in future behaviour that is not so ecologically minded. Therefore, the promotion of one environmentally friendly behaviour – through, for example, changing the electricity default product towards renewable energy – can be nullified when individuals fall into moral licensing and feel entitled to future non-environmentally-minded behaviour. As a result, a default effect that is thought to minimize the carbon footprint of an individual can in actuality heighten it. Even more, the moral behaviour of agreeing to a renewable energy default could also license behaviour in different domains through moral credits. In this way, the default product change to renewable energy could result in the licensing of an array of unforeseen immoral behaviours. This is especially hard to account for because the behaviour could emerge in all different domains. The credits gained in individuals' moral bank accounts through the acceptance of the change to renewable energy can be spent on any other similarly sized immoral endeavour without threating the individuals' self-images or causing them to be judged as hypocritical (Mazar & Zhong, 2010).

But what does the phenomena of moral self-licensing mean in light of the even more specific case of the default product change to renewable energy in this utility company? First of all, one is cautioned to judge the result of the default product change just as a significant increase in renewable energy uptake and not as an overall decrease of the carbon footprints of those households that agreed to the renewable energy uptake. As there are no possibilities to gather further information on the resulting behavioural changes of the customers, it is not possible to judge the extent of moral self-licensing behaviour and its effect on individuals' carbon footprints. Unwanted side effects in the shape of moral credentials are likely in the arena of environmental mindedness, ranging in severity and impact on total carbon footprints. One simple and direct thought would be that the default product change to renewable energy would increase households' electricity usage. This heightened electricity usage could stem from different behaviours, such as additional purchases of appliances or the changing of electricity saving habits toward spending more electricity now that one's moral credentials as an environmentally friendly individual are established. The utility consumption for the households in the years before and after the default product change was considered (referring to Section 4.1.1 Descriptive Analysis of Utility Use). Another presumable moral licensing avenue could be the increase in overall usage of water and/or gas, which could not be taken account of in this study. Decreases in other kinds of environmentally minded behaviour also could not be considered in this study. One factor that usually is a criticism of the default rule nudge can here be counted towards the benefits, possibly reigning in moral licencing: it is argued that the default effect is only so strong because participants paid little attention – or maybe did not pay attention at all – to the decision, since no active response was required to accept the default. If they are paying little or no attention, the individual will also be less likely to store an action as a moral decision, and as moral credits or moral credentials thus will be less likely be used to license future immoral behaviour. The passivity of the default product change on the side of the customers is in most cases argued to be manipulation. As can be understood here, it might not only be manipulation towards a specific decision outcome, but also manipulation towards decreasing moral self-licensing as an unwanted consequence when this decision outcome is realized.

Conclusion

Moral self-licensing is understood as one of the inhibitory forces making immoral behaviour more likely and removing the social and psychological boundaries against immoral behaviour (Merritt et al., 2010). However, it can also be understood in a more neutral way that enables individuals to make difficult trade-off decisions that would have been dilemmas marked by indecision otherwise (Merritt et al., 2010). When juggling the demands of moral socially desired behaviour with self-interest, moral self-licensing helps to resolve the dilemma and enables individuals to balance both interests (Merritt et al., 2010). For the specific case of promoting renewable energy through default rules, this means that the moral socially desired behaviour is realized through the default product change, but at what cost to their carbon footprint will the individual balance out his or her interests with a licensed behaviour of self-interest? The phenomenon of moral self-licensing shows that decisions cannot be analysed in a vacuum. Every decision and every decision manipulation needs to be understood as one in a sea of many. Each decision either hinders or promotes other decisions and their possible outcomes (Mazar & Zhong, 2010). Since there is no definitive answer on what kind of costs the default product change in this study will incur, there is only the thought of caution that remains. This includes caution in interpreting the uptake of renewable energy through the default product change as just that, and not jumping to conclusions of a substantial reduction of the carbon footprints for those households. This conclusion cannot be based on results, since information showing the frequency and gravity of moral self-licensing effects was not possible to collect.

2.2.3.2 Ethical Problems of Manipulation

Nudging techniques are being confronted with accusations of not only influencing behaviour, but actually manipulating behaviour. This section will confront ethical problems in the form of manipulation on a theoretical level. Chapter 6 – Discussion of Results confronts them on a more applied level, which is then discussed more critically.

Defining manipulation in the psychological sense of manipulation – intending ‘to change the perception, choices, or behaviour of others through underhanded, deceptive, or even abusive tactics’ (Hansen & Jespersen, 2013, p. 18) – gives a starting point from which to further develop the argument of ethical problems of manipulation regarding the use of nudging techniques. Nudging techniques have the aim of changing the perceptions, choices, and behaviour of individuals. In order to accomplish that, they use tactics that some describe as deceptive and, in some cases, even as abusive. While the description of deceptive tactics is defined by the awareness of the individual regarding the behavioural intervention, the description of abusive tactics is more defined by the promoted end goal of the behavioural intervention, and whether that end goal is in the interest of the targeted individual. This chapter will explore both avenues of the manipulation argument: first, if and when nudging techniques can be deceptive towards the decision-maker, and second, if and when nudging techniques promote end goals that are not in the direct interest of the decision-maker and therefore are considered abusive nudging interventions.

The deceptive and abusive potential that a nudging technique holds depends on the awareness of the individual that is being influenced through the nudging technique and whether the promoted end goal reflects the individual's interests. The ethical problems of manipulation when using nudging techniques will be discussed (1) regarding the way that nudging only directly influences type 1 processing (automatic and intuitive processing), (2) regarding the four core characteristics of nudging, and (3) in special regard to the nudging technique default setting.

The Manipulative Potential in Solely Aiming for Type 1 Processing

The argument of nudging techniques being deceptive has its firm roots in the way nudges are theorized to influence target behaviour. The dual process theory (Fazio, 1990; Kahneman, 2013) is a behavioural theory explaining how nudging techniques work.[3] In line with its name, the theory describes two ways of influencing behaviour through communicative interventions. One way is cognitive reflective, and is an active process of changing attitudes, intentions, and behavioural implementations (type 2 processing). The other way is automatic, involving not reflective but intuitive processing to change attitudes, intentions, and behavioural interventions (type 1 processing). Nudging techniques aim for the behavioural outcome of type 1 processing (automatic and intuitive processing) rather than the outcome of type 2 processing (reflective processing) (Gigerenzer, 2015; Ölander & Thøgersen, 2014; Sunstein, 2017; Thaler & Sunstein, 2009). There are a number of behaviour-influencing tools other than nudges that directly influence type 2 processing, for example, monetary incentives, prohibitions, and campaigns that try to educate or persuade (Michalek et al., 2016, p. 6). Bypassing reflective processing (type 2 processing) and aiming at automatic and intuitive processing (type 1 processing) likely results in a low awareness of the nudging technique in the targeted individual. This low awareness that the individual has of

[3] For a detailed understanding, refer to Section 2.1.1 – Explaining Nudging Using the Theory of Behavioural Change.

the behavioural intervention can cause the intervention to be labelled as deceptive or even manipulative. In conclusion, the core ethical problem of nudging techniques is that they target only automatic and intuitive processes. This core problem is the downside of what is praised in making nudging techniques so successful: nudges aim to influence type 1 processing (automatic and intuitive processes), and therefore are especially successful in directing behaviour to a specific outcome when the behaviour involved can be described as reflexive or time pressured or calls for low personal involvement (Michalek et al., 2016). The awareness of the subjects of a nudging intervention is not only dependant on targeting type 1 processing (automatic and intuitive processing). Subject awareness and the potential of manipulation in a nudging intervention also depend on whether the four core characteristics of nudging correctly apply.

The Manipulative Potential of the Four Core Characteristics of Nudging

Apart from the argument of nudging techniques being manipulative, in the sense of deception, for only targeting automatic and intuitive processing (type 1 processing), there are also the four core characteristics of nudging techniques to consider (for more details, refer to Section 2.1 – Defining Nudging).

The first core characteristic of a nudge is the intentionality with which the choice architecture is changed. One defining object that separates a nudging intervention from any other type of behavioural intervention is the intentional shaping of the choice architecture with a specific end goal in mind. The manipulative potential of a nudging intervention was brought up before in the accusation of an intervention being deceptive and/or abusive. The promotion of a specific end goal should be in the interest of the targeted individual or it could be accused of being abusive in nature. Therefore, when a regulator is intentionally changing choice architecture to promote end goals that are not in the interest of the targeted individual, the nudging intervention risks being labelled abusive and manipulative.

The second core characteristic of a nudge is that it does not change the incentives of the choice alternatives, particularly the economic incentives. Thaler and Sunstein define nudging as intentionally changing choice architecture without changing economic incentives (Thaler & Sunstein, 2009, p. 6). Other definitions of nudging have even a broader understanding of not changing incentives – not only including economic incentives but also all other things that could change the presumable cost of a choice alternative, such as time and effort (Hausman & Welch, 2010). When this defining characteristic is fulfilled, the grounds for the manipulation accusation are held to be minimal. A nudging intervention should avoid changing the (economic) incentives of the choice at hand. While the argument of not changing the economic incentives is clear in its definition, the argument of not changing other kinds of incentive structures (such as time and effort) is less clear. Judging the extent to which the whole incentive structure is held constant might be prone to subjectivity (for a critical discussion on this point, refer to Chapter 6 – Discussion of Results).

The third core characteristic of nudges is that they allow freedom of choice. One critical point in defining nudging is that the decision-making framework is changed in a way that leaves the decision-maker the option to opt-out and retain his or her individual freedom to go against the nudge (Reisch & Sandrini, 2015). If the freedom to choose is not preserved, the behavioural influencing strategy could not be termed a nudge and would have to be described as mere prohibition. This simple characteristic of leaving the freedom to choose is debated when it comes to specifics. Chapter 6 will critically discuss when and how a nudge leaves the freedom of choice intact.

The fourth core characteristic is that nudges should be transparent to the decision-maker. A nudging technique needs to be a transparent influence in the choice architecture, and an attentive decision-maker should be able to recognize the behavioural influencing strategy. Without this core feature of the nudge, a nudge would not be able to be differentiated from a hidden manipulation (Reisch & Sandrini, 2015). A transparent nudge is defined as 'a nudge provided in such a way that the intention behind it, as well as the means by which behavioural change is pursued, could reasonably be expected to be transparent to the agent being nudged as a result of the intervention' (Hansen & Jespersen, 2013, p. 17). The transparency of nudging interventions is the antidote that minimises the potential of the intervention to be labelled deceptive, and therefore, manipulative. Only a transparent nudging intervention can also allow the freedom of choice. Only an individual who is aware of the nudging intervention can have the freedom to choose to either be influenced or not in his or her decision making.

The Manipulative Potential of Default Rules

Finally, the more specific case of the manipulative potential of default rules need to be addressed. Default rules is a nudging technique that has been shown to be a powerful and reliable tool in shaping decision-making. As with all other nudging interventions, default rules address type 1 processing (automatic and intuitive processing) directly and have the potential to influence type 2 processing (reflective processing) indirectly. Targeted decision-makers respond to default rules with type 1 processing and then either follow the default setting automatically and intuitively or additionally bring in type 2 processing and reflect on the default setting before making a final decision. According to the four core characteristics that constitute a nudging technique, default rules should be set with intentionality, leave (economic) incentives intact, maintain the freedom to choose, and also be transparent to the decision-maker. In alignment with the previous argument, the promoted end goal of the default rules should be in the interest of the decision-maker in order to not be labelled as abusive. The (economic) incentives and the freedom to choose should also be untouched by the default rules intervention, otherwise it could again be labelled deceptive. Last but not least, the default setting has to be transparent to the decision-maker, or otherwise it could also be labelled deceptive. While in theory a default setting intervention can fulfil all the requirements of minimizing the potential of manipulation accusations, in practice there is still room for manipulation and the misuse of this nudging technique.[4]

Conclusion

In conclusion, a behavioural intervention can be defined as negatively manipulative if it is deceptive to the decision-maker and if its promoted end goals are abusive. The degree of deception that a nudging intervention can hold depends, on the characteristics of the intervention and on the awareness that the decision-maker has of the intervention. Both variables need to be looked at in tandem, since the characteristics of the intervention can heighten or lessen the awareness of the decision-maker. The promoted end goals should in general be in the interest of the decision-maker. Since in the wide field of nudging techniques the promoted end goals and the awareness of the decision-makers are all factors that are of a diverse nature and not easily generalized, the true potential of manipulation in a nudging intervention has to be addressed for each and every possible nudging intervention and target group separately in detail in order to achieve a full analysis.

2.2.3.3 Other Unwanted Side Effects

While there are highly likely scenarios of unwanted side effects when using default rules in the area of promoting renewable energy in electricity contract choice, there are also some scenarios that are less likely or can even be discarded altogether. Among those scenarios that need to be considered in general when using default rules but do not apply in this setting are the distortion of decision preferences and the rebound effect.

[4] For more information, refer to Section 6.2 – Using Nudging as a Soft Policy Tool.

The Distortion of Decision Preferences

While judging if the application of default rules can imply a distortion of decision preferences, two levels of argumentation must be addressed: the general case of the use of default rules and the more specific case of the use of default rules in the area of promoting renewable energy in electricity contract choice.

At the general level, it can be argued that a distortion of decision preferences and the application of default rules that leave the decision architecture unchanged are incongruous. As long as all choices are still available to the decision-maker, he or she should be able to align his or her preference with his or her choices on a matter. However, while default rules do not change the decision architecture, they can manipulate the decision-maker into betraying his or her original choice preference. Directly targeting type 1 processing (automatic and intuitive processing) instead of type 2 processing (reflective processing), a default rules intervention can influence a decision-maker into staying with a default option, especially when he or she has only weak (or no) preference on the subject matter. In the case of respondents having clear and strong decision preferences, it is very unlikely that they would comply with a default option against that choice preference. They would be motivated to pay the transaction costs of changing the selection from the default option to their preferred option.

In the more specific case of using default rules in the area of electricity contract choice, it is possible to theorise that a default product change from conventional to renewable energy could go unnoticed for a share of the customer population at first. That said, it is less likely that this would be the case, after one year of quarterly bills that not only indicate the new energy tariff but also a cost increase for the household customer. While a default product change could hold the power to distort the decision preferences of the customers for a short while, with time, customers had the chance to correct any kind of decision preference distortion. The default product change was therefore applied in such a way that customers had enough time and freedom to align the contract choice with their true preference of electricity product. Apart from the argument that the change to renewable energy could bring on a distortion of decision preferences, if the default product change was unnoticed by the customers, there is also another point to consider: what are the decision preferences for the majority of the targeted customer group regarding the promoted product? Do customers have strong and readily available decision preferences when it comes to their energy contract and its price and sources? It turns out that customers in general seem to have neither a fixed preference for a specific electricity product nor the knowledge necessary to differentiate and compare products in quality and price (Truffer, Markard, & Wüstenhagen, 2001). With the upswing of renewable electricity, electricity as such has experienced a change in customer perception: before, electricity was not grasped as a commodity with different product features, but after the introduction of renewable electricity, it increasingly became a commodity in which customers need to learn how to distinguish different product features. Since this transformation is relatively new, customers commonly do not have fixed preferences about their electricity products (Truffer et al., 2001). If left to their own devices, customers in liberated electricity markets such as Germany show that differentiating electricity products by their qualities is challenging for the average consumer, which leads to most consumers differentiating only by price (Roe, Teisl, Rong, & Levy, 2001) or being willingly led by a default option (Pichert & Katsikopoulos, 2008). In surveys, one can see the public support for renewable energy (Farhar, 1999), but this is generally not directly translated by customers into renewable energy uptake. Only with a default product change towards renewable energy is the stated preference is translated into an actual choice (Pichert & Katsikopoulos, 2008). This too, speaks for the weak preference that most consumers hold when faced with electricity products. In surveys, respondents can state their preferences (arguably biased by the experimenter demand effect, which enforces the social norm of environmentally friendly behaviour) without paying a premium for electricity or paying the cost in convenience of contacting the electricity supplier and choosing a product. For the majority of customers, those preferences seem to be weak enough not to inspire them to action on their own, but if faced with a default product change to renewable energy, they willingly accept. The default product change to renewable energy bears the cost of contacting the electricity supplier and the information costs of finding the right product. Consumers now only have to pay a small premium, which they seem not to mind (Farhar, 1999). In conclusion, most customers hold no or weak preferences for the product features of electricity contracts. When asked hypothetically, most stated a preference for renewable energy (Farhar, 1999). A default product change from conventional to renewable energy does not only hold little potential to violate the none-to-weak preference spectrum of the consumers, but also aligns theoretically stated preferences with a matching default option, altogether giving few grounds for accusations of decision preference distortion in the case of applying a renewable default option in electricity contract choice. Nonetheless, Chapter 6 – Discussion of Results will critically discuss the potential for a distortion of decision preferences in the study at hand.

The Rebound Effect

The rebound effect describes the phenomenon when the surplus use of a product nullifies the reduction of energy use reached through the improved energy efficiency of that same product (Grubb, 1990). A common example illustrating the rebound effect can be found in the area of promoting more energy-efficient electrical appliances in order to reduce energy consumption in households. Here, the reduction of energy consumption through appliances that are more energy efficient is partly nullified by the overuse of these appliances. The effect of saving energy in households through, for example, using energy efficient washing machines or automobiles cannot be subtracted as is from the overall household energy consumption. With the knowledge of saving energy through a more energy-efficient appliance, individuals are likely to increase their use of that appliance. Depending on the energy savings of the appliance and the amount of additional use, the rebound effect is calculated. One main argument for additional use is that energy efficient appliances make usage cheaper, diminishing costs that would have restricted overuse before (Barker, Dagoumas, & Rubin, 2009). Therefore, the rebound effect is ascribed to the reduction of costs per use through heightened energy efficiency (Grubb, 1990). While other unwanted side effects of the default product change are likely to have occurred and should be considered in all their facets, the rebound effect does not strictly apply in the study at hand. With the default product change towards a renewable energy contract, the costs per kWh did increase, as did the costs for all the other contracts for that year. In the strict definition of the rebound effect, customers did not have the incentive to consume more electricity, since the costs per kWh increased instead of decreased.

Conclusion

In conclusion, in regard to the study at hand, the unwanted side effects of distortion of preferences and the rebound effect are considered less likely to occur. Nonetheless, following data analyses address both side effects, and conclusions will be addressed in Chapter 6 – Discussion of Results.

3. Study Background and Data

In this chapter, the general study background will be described, followed by more specific information regarding this specific dataset. In order to understand the study in its setting, it is necessary to first understand the development of the renewably sourced electricity market in Europe, and then more specifically, in Switzerland. This broad introduction to the topic of default product change in renewable energy will provide a background to the more specific information on the utility company from which the dataset comes and how the company decided to facilitate the default product change to renewable electricity. Once this necessary background information is established, the working process of preparing the data for analysis will be laid out, concentrating only on the most crucial variables. The specific characteristics of the dataset received from the utility company for the purpose of this research will be discussed and the handling of these obstacles will be documented.

3.1 The Renewably Sourced Electricity Market in Switzerland

During the past three decades, there have been significant changes to the internal electricity markets in EU countries and in Switzerland. The political goal of promoting renewable electricity that came into play two decades ago can be described as the starting point for these changes. From the decree to promote renewable electricity, the renewable electricity industry has evolved through the last two decades to the point where renewable electricity is holding a steadily growing market share.

Even though Switzerland is not an EU member country, it is influenced by the political climate of its neighbouring countries. Thus, to provide an understanding of the recent changes in the renewable electricity market in Switzerland, it will first be described how the European renewable electricity market has developed over the last two decades. The changing Swiss renewable electricity market will then be documented against the changes in the European markets. Similarities, influencing factors, and differences can be more fully understood in that framework. The main cornerstone of the renewable electricity market changes in the EU was the (full or partial) liberalisation of the internal markets and the obligation of eco-labelling for all renewable electricity products. After this framework of understanding is established, the changes in the Swiss renewable electricity market will be documented with special regard to Swiss partial liberalisation and eco-labelling initiatives. This historical account will be supplemented with the most recent descriptive statistics available showing the characteristics of the Swiss renewable electricity market in 2016. At the end of this chapter, the overwhelming public preference for renewable electricity will be discussed. This public preference for renewable electricity is in direct contrast to the still-low rates of uptake of renewable energy. This basic premise – that the public preference for renewable energy is strong while actual uptake of renewable energy is comparatively low – is a promising one for utility companies changing their default electricity products to renewable electricity.

Brief History of the European Union Renewable Electricity Market

Europe is at the forefront of renewable energy technologies ('European Commission's White Paper on Renewable Energy Sources,' 1997). The significant recent changes to the renewable electricity market can be dated back to 1997, when the European Commission published the White Paper 'Energy for the Future: Renewable Sources of Energy' and the Kyoto climate change conference was held. At the time when the White Paper was written, 1995, the share of renewable energy in the European Union members' overall gross inland energy consumption was 5.3% ('European Commission's White Paper on Renewable Energy Sources,' 1997). The White Paper was published just before the Kyoto climate change conference and made a proposal in line with the conference to reduce the greenhouse gas emissions of EU member countries by 15% by 2010 (the baseline being 1990) ('European Commission's White Paper on Renewable Energy Sources,' 1997). As one pivotal step to achieve this goal, the promotion of renewable energy was advocated, as it reduces carbon intensity and consequently CO_2 emissions ('European Commission's White Paper on Renewable Energy Sources,' 1997). Another benefit of promoting renewable energy was the possible reduction of EU energy imports, which had reached the 50% mark back in 1997 and was showing a strong upward trend ('European Commission's White Paper on Renewable Energy Sources,' 1997). It was argued that the promotion of renewable energy could reduce the need for energy imports and lessen the geopolitical risk of energy supply insecurities for the EU in the future ('European Commission's White Paper on Renewable Energy Sources,' 1997).

The benefits of strong promotion of renewable energy for the EU were not solely environmental. Renewable energy also promised new employment opportunities, fuel import reductions, increased energy supply security, export development, and local and regional development through new renewable power plants (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997). An increase from 1995’s 5.3% share of renewable energy to 12% of the overall gross inland energy consumption of EU member states by 2010 held the potential to save 402 million tonnes of CO_2 emissions per year (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997).

In 1997, most of the 5.3% share of renewable energy of the overall gross inland energy consumption of EU member states came from large-scale hydropower plants (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997). The rise of renewable energy uptake has not been translated as such into new renewable energy source developments. Rather, it has mostly come from existing renewable energy sources – in most cases, large hydropower projects (Bird, Wüstenhagen, & Aabakken, 2002). This lack of new renewable energy source development can be ascribed to the renewable electricity market being in its beginning stages. More renewable energy source development is expected to occur once the market is more established (Bird et al., 2002).

Since the potential for further large-scale hydropower infrastructure in the EU is mostly exhausted, further renewable electricity is expected to come from other renewable energy sources, such as small-scale hydropower plants, biomass combustion, wind energy farms, solar thermal collectors, photovoltaic devices, geothermal energy, and heat pumps (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997). Among EU member states, the share of renewable energy in the overall gross inland energy consumption in 1995 ranges from a low of 0.7% (United Kingdom) to a high of 25.4% (Sweden) with an average of 5.3% for the whole European Union (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997). In the proposal aiming to double the share of renewable energy in the European Union from 5.3% to 12%, the highest potential for increase was determined to exist in wind power, with an estimated increase potential of 37.5 GW by 2010, followed by hydropower, with an estimated increase potential of 13 GW by 2010 (‘European Commission’s White Paper on Renewable Energy Sources,’ 1997).

The White Paper ‘Communication from the Commission - ENERGY FOR THE FUTURE: RENEWABLE SOURCES OF ENERGY - COM(97)599 final (26/11/1997)’ was commissioned in 1997, and Directive 2001/77/EC on renewable energy was published in 2001. Both follow the same goal of promoting renewable electricity products effectively in the internal markets of EU member countries. Directive 2001/77/EC of the European parliament and council stated the need to promote electricity from renewable energy sources in internal electricity markets (DIRECTIVE 2001/77/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, 27.10.2001). It required the member states to set national targets for renewable energy consumption that are consistent with the member states' national commitments with the Kyoto protocol ('European Commission's White Paper on Renewable Energy Sources,' 1997). The White Paper formulates policies for the promotion of renewable energy which are needed, since the progress of renewable technology alone cannot overcome barriers in the energy market that are of a non-technical nature. Those policies aim to promote a stable framework for the renewable energy market that encourages investments in the development of renewable energy ('European Commission's White Paper on Renewable Energy Sources,' 1997).

The endeavour of promoting renewable electricity in the EU members' internal markets entails multiple policy changes and action steps, of which market liberalisation and eco-labelling are the most crucial in regard to this study. Market liberalisation gives consumers the freedom to choose their utility provider, and eco-labelling forces utility providers to indicate the composition of energy sources in their electricity products. Together, these policies allow consumers to make informed choices regarding electricity products that are clearly distinguishable as either renewable electricity products or non-renewable electricity products.

Liberalization of the European Union Electricity Market

By 2002, liberalization (either full or partial) of internal electricity markets had been introduced to most European countries (Bird et al., 2002). Some see liberalization of internal electricity markets as force that could push the increase of renewable electricity in the market (Truffer et al., 2001). Truffer et al. argue that liberalisation would increase competition between utility companies. As a result, consumers would have a broader range of electricity products to choose from, and utility providers may differentiate their products not only through prices, but also by other characteristics (Truffer et al., 2001). Two common strategies of companies attempting to dominate a larger share of the market are either to offer the cheapest product (cost leadership) or offer a product that is different from the others at a premium price (differentiation) (Truffer et al., 2001). Differentiation for an electricity product can be achieved through different means, such as technical features, product offerings for a special customer group, additional services, and also environmental characteristics (Truffer et al., 2001). Typically, an electricity product that can be clearly differentiated through environmental features, for example, can be sold competitively at a low-to-medium premium price (10-30%) in comparison to conventional electricity products (Truffer et al., 2001). Renewable electricity products not only enjoy strong public support in EU member states, but consumers also indicate their willingness to pay a premium for renewable energy when asked (Farhar, 1999).

With the assumption of a liberated electricity market, Roe et al. show that compulsory full disclosure of environmental information helps customers to correctly rank environmental attributes of different suppliers. However, once price information is added, it takes attention away from environmental information, and customers are less likely to correctly rank suppliers on environmental attributes. Thus, when renewable energy providers try to compete with less-expensive conventional energy providers, they should focus on strong, non-priced product differentiation. Another solution to stay competitive is for utility companies to offer both conventional electricity at a low price and renewable electricity at a premium price (Roe et al., 2001).

The liberalisation of internal electricity markets is seen as giving renewable electricity products the opportunity to increase their market shares, but also giving rise to a more cost-competitive electricity market in general. It is the aim of the White Papers' policies to see to it that renewable electricity is not at a disadvantage in newly liberalised electricity markets ('European Commission's White Paper on Renewable Energy Sources,' 1997).

Eco-labelling

Countries with a high share of hydropower (Switzerland, Norway, Sweden, and Austria) stand in stark contrast to countries with a high share of coal-based systems (Germany, UK, US) which is true in general for the characteristics of their internal electricity markets as well as for internal eco-labelling in specific. One of the first eco-labels for renewable electricity was introduced in Sweden in 1996 (Truffer et al., 2001). In a country with a high share of hydropower, renewable electricity and low CO_2 emissions are not unique selling points as characteristics of electricity products. However, in a country with a high share of coal-based systems, they are (Wüstenhagen et al., 2003). Therefore, it is no surprise that Sweden was one of the first countries with eco-labels, since their internal electricity market was already dominated by renewable electricity – namely, hydropower. This large share of hydropower might have been the driving element to motivate eco-labelling, resulting in clearer product differentiation and a more justified small premium on prices. Counterintuitively it seems that countries with a traditional high share of hydropower are profiting even more of eco-labelling than other countries. While coal-based energy countries can sell the novelty of renewable energy, hydropower countries had to re-invent the branding of their renewable energy products. For the re-branding and the justification of the premium prize eco-labelling was helpful – if not a necessity.

With the upswing in renewable electricity, electricity has experienced a change in customer perception. Before the upswing, electricity was not grasped as a commodity with different product features. However, after the introduction of renewable electricity, electricity increasingly became a commodity for which the customer has learned to distinguish between different product features. Since this transformation is relatively new, customers commonly do not have fixed preferences about their electricity products (Truffer et al., 2001). The dilemma of the choice between a conventional verses a renewable electricity product is that the individual would like to partake in the public good that is established through choosing renewable electricity, but at the same time is unwilling to bear the extra costs for it. While the benefits are at the group level, the costs are at the individual level. These extra costs include not only the premium that one has to pay for renewable electricity, but also the transaction costs, which are generally higher for environmentally friendly products since the customer has a harder time accurately evaluating the environmental characteristics of the product (Truffer et al., 2001). Successful third-party eco-labelling can minimize the transaction costs for the consumer and thus eliminate one hindrance standing between the motivation for choosing renewable electricity and the action of choosing renewable electricity (Truffer et al., 2001). A successful eco-label improves the customer's understanding of the product. It is marked by simplicity and accuracy in claims of criteria, and is widely recognized in the market (Truffer et al., 2001).

When utility companies embrace the possibility of labelling their various products for environmental attributes, the question arises whether it is ethically correct to differentiate between products when the electrons coming from these different products are not segregated throughout the delivery to the end consumer (Roe et al., 2001). Even if a household has purchased renewable electricity, it will get electricity from different electricity sources. Nonetheless, the choice strengthens demand and investment flow for renewable electricity (Pichert & Katsikopoulos, 2008).

The main focus of the decree to promote renewable electricity in Directive 2001/77/EC is the introduction of a compulsory guarantee of origin for all forms of renewably sourced electricity. This guarantee of origin for renewable electricity has been compulsory for EU member states since the 27th October 2003. Utilities have to name energy sources as well as the date and place of production. The compulsory guarantees of origin were introduced to help the producers of renewable electricity to prove that their renewable electricity is genuine (DIRECTIVE 2001/77/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, 27.10.2001).

Hence, eco-labelling builds on guarantees of origin and quality marks. It defines renewable energy sources as non-fossil renewable energy and applies to following energy sources: wind, solar, geothermal, wave, tidal, hydropower, biomass, landfill gas, sewage treatment plant gas, and biogas (DIRECTIVE 2001/77/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL, 27.10.2001). The credibility of an eco-label lies in that the claimed criteria will be guaranteed through quality control procedures that are objective and measurable (Truffer et al., 2001). Eco-labels in the area of renewable electricity have the aim to be quality marks for environmentally preferable electricity products. However, the claim of 'environmentally preferable electricity product' can be interpreted using quite different criteria. Some eco-labels follow the criterion of the argument that the energy source has to be renewable, translating 'environmentally preferable' as 'not using finite resources' (Truffer et al., 2001). Others have as the central criterion that the electricity has to be climate friendly and should have low CO_2 emissions in comparison to other energy sources (Truffer et al., 2001). Both criteria (renewable energy and climate friendliness) have in common that they strongly simplify their classification scheme to be more overt and simple to understand in comparison to the criteria of a life-cycle assessment[5] of an energy source (Truffer et al., 2001). Additionally, there is also the criterion considering location-specific characteristics of each power plant (Truffer et al., 2001). A final additional criterion, which is less concerned with the present and more with the future, is judging an electricity product for sustainable development concerning its social and economic impacts (Truffer et al., 2001).

A difficult line to walk is balancing the goal of broad market penetration with high credibility of an eco-label. Broad market penetration can be reached when the label's minimum environmental criteria are low enough to be applicable to a majority of the renewable electricity products in the market. However, high credibility of an eco-label requires a high minimal standard of environmental criteria. Striving for both broad market penetration and high credibility of an eco-label at the same time means aiming for competing goals that often exclude one another. One solution is to have a multilevel eco-label, such as the Swiss Naturemade eco-label (Truffer et al., 2001). The Swiss eco-label Naturemade has two levels: Naturemade Basic, applying to a general level of renewably sourced electricity, and Naturemade Star, applying to a narrower definition of renewably sourced electricity (Association for Environmentally Sound Energy). The benefits of a successfully established

[5] For an encompassing overview on the life cycle assessment, refer to Rebitzer et al. (2004).

and widely recognized eco-label include not only minimization of transaction costs for customers, but also that if customers show a higher willingness to pay for a premium good then providers can sell that premium good with minimal communication effort (Truffer et al., 2001).

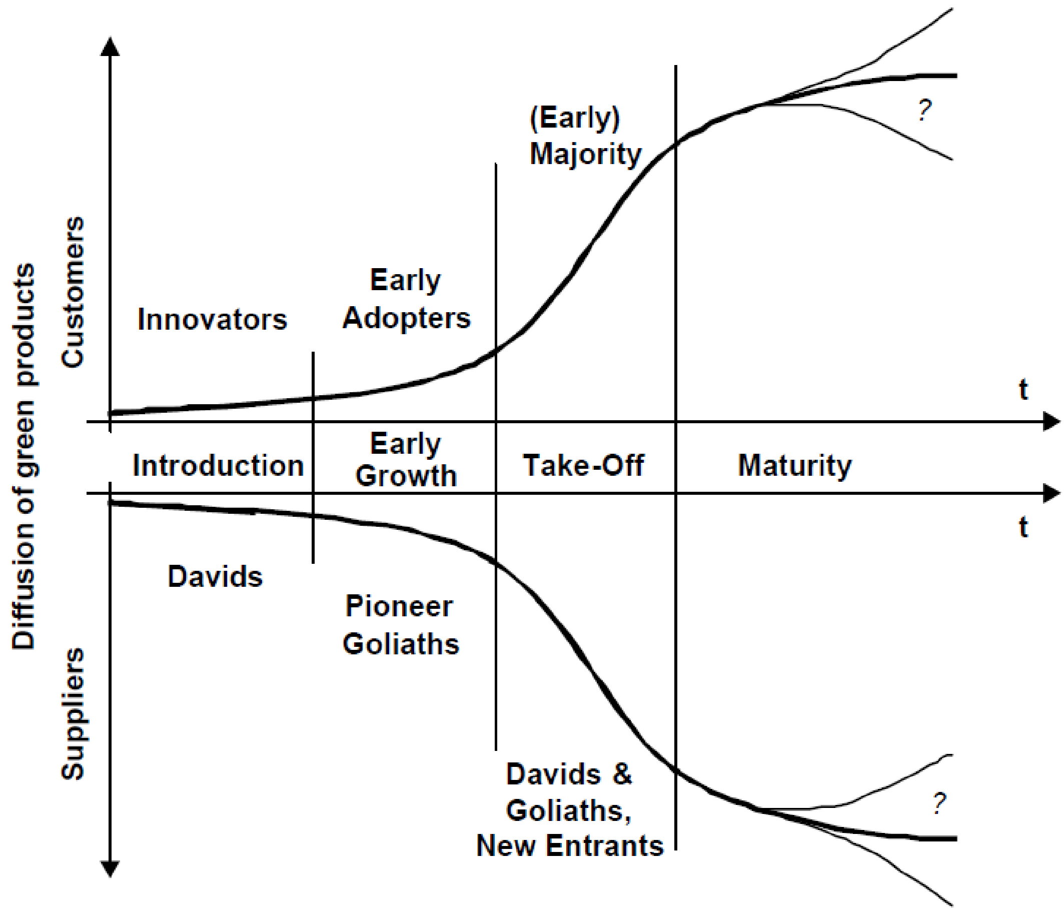
Short History of the Swiss Renewable Electricity Market

In comparison to EU countries, Switzerland's renewable electricity market activity was rated as moderate in the beginning of the second millennium (Bird et al., 2002). The first utility companies promoting renewable electricity started in the mid-1990s, offering first solar power and then wind power options. This first generation of renewable electricity products was sold in tranches, where customers could buy a specific amount of kWh per year of solar and/or wind power to substitute for conventional energy. The second and current generations of renewable electricity are full tariffs that rely heavily on hydropower combined with small shares of other renewably sourced energy (Bird et al., 2002). These low environmental impact hydropower combination tariffs have the benefit of being offered at a minimum premium.

In 2002, the Swiss renewable electricity market was expected to continue to grow, since customers indicated an above-average willingness to pay for renewable energy and Switzerland has access to certified low-impact hydropower that can be sold more cheaply than solar or wind power (Bird et al., 2002). The change in the Swiss renewable electricity market was indicated in the change from the first generation of renewable electricity products (solar and wind tranches) to the second generation (combination tariffs with a focus on hydropower) (Wüstenhagen et al., 2003). The Swiss electricity market is dominated by nuclear power and hydropower. It is similar to the markets in Norway, Sweden, and Austria in the sense that it holds a significant share of hydropower. However, in comparison to European countries, the Swiss electricity market is far behind in terms of the development of a liberated internal electricity market (Wüstenhagen et al., 2003). As of 2019, the Swiss electricity market has only been liberalized for commercial business consumers that consume more than 100,000 kWh per year.

Figure 14 shows the different stages of development for a green product in a market. The model of 'Diffusion of Green Products over time among Customers and Products' by Wüstenhagen et al. (2003) is an adaptation of the original model 'Diffusion of Innovation' which was coined by Everett Rogers (Rogers, 2003). Starting in the late 1980s and early 1990s, the Swiss market for renewable electricity had its introduction phase, in which its few custo-

Figure 14. Diffusion of Green Products Over Time Among Customers and Products (Wüstenhagen et al., 2003)



mers consisted of innovators. These innovators' environmental awareness and general interest in renewable energy motivated them to engage in the effort of purchasing renewable energy products (Wüstenhagen et al., 2003). While the customers at this market stage are called innovators, the suppliers are called 'Davids' – referring to smaller companies boldly introducing the new green products into the market (see Figure 14). The next market stage was the early growth stage in the late 1990s, with the market then engaging the wider population of environmentally-minded consumers and innovative business customers. In this market stage of early growth, the customers are labelled early adopters and the suppliers 'Pioneer Goliaths'. Pioneer Goliaths refer to bigger companies that are at this point comfortable with also getting into the market with new green products (see Figure 14). The take-off phase occurred in the early 2000s. It was marked by an increasing number of business customers and, more importantly, the introduction of competitive renewable electricity products sourced with mainly hydropower as well as the introduction of eco-labelling and certification schemes (Wüstenhagen et al., 2003). In the take-off market stage, the customers are called the early majority and the suppliers as Davids, Goliaths, and new entrants. At this market stage, small as well as bigger companies offer the new green product with the additional competition of new entrant companies. In this phase, the shift from the first generation of renewable electricity products to the second generation took place. This shift was not made without difficulty, since the former renewable electricity market, which had only entailed new renewable energy sources, now also included the existing hydropower that had historically made up a major share of the electricity market (Wüstenhagen et al., 2003). Even though hydropower is CO_2-free and highly energy-efficient, it has the downside of negatively affecting the aquatic ecosystem and surrounding landscape. Reinterpreting hydropower as a renewable electricity source was only accomplished through the introduction of the Swiss eco-labels Naturemade Basic and Naturemade Star (Wüstenhagen et al., 2003). The public image of hydropower was highly controversial. In 2003, 80% of the potential for hydropower had already been used in Switzerland. Citizens and environmentalists have a long history of opposing further exploitation, citing the downsides of hydropower plants (Wüstenhagen et al., 2003).

Eco-labelling in Switzerland

While only renewable electricity products can apply for eco-labels, all electricity products in Switzerland have to provide a proof of origin. Proofs of origin identify the electricity produced and fed into the electricity network through the institute of Swissgrid. Proof of origin has been obligatory since January 1st, 2013 in Switzerland for electricity production sites with a power output of more than 30 kVA (kilovolt-amperes). Proofs of origin are traded internationally as well as in Switzerland and are voided from the databank once they reach the end customer. Proofs of origin are not, in the strict sense, quality marks like eco-labels (Verein für umweltgerechte Energie VUE, Zürich, January 2018).

In contrast to proof of origin, eco-labels also have to provide information on the composition of energy sources for each product. Switzerland has the following eco-labels: Naturemade Basic, Naturemade Star, TÜV-EE01, and TÜV-EE02. Naturemade Basic and Naturemade Star will be introduced further below, since they mark the renewable electricity products in this study.

The Swiss Naturemade eco-label has two levels – Naturemade Basic and Naturemade Star – and uses as its environmental standard renewable energy sources and more narrowly qualified renewable energy sources respectively. Naturemade's assessment consists of a list of eligible sources based on life-cycle assessment for the Naturemade Basic label and additional local criteria for the Naturemade Star label. The Naturemade labels in principle allow for capacity enlargement and improvement for existing hydropower plants. It is supported by environmental groups, consumer organizations, renewable energy source support associations and utility companies alike (Truffer et al., 2001). Naturemade's first certification was made in the year 2000 (Truffer et al., 2001). In comparison to other eco-labels available in European countries, the Naturemade labels are well-assessed. They use the more encompassing criteria of life-cycle assessment and are supported by all stakeholder groups, leading to a broad acceptance of the label in all stakeholder groups (Truffer et al., 2001). Eco-labels are a voluntary system that aims to guarantee quality standards. The quality marks follow clearly measurable criteria for electricity products, are given out by an independent third party, and aim to differentiate renewable electricity products from conventional electricity products. The system of certification in Switzerland follows the guidelines of ISO 14001, calculating the ecological performance of an electricity product for its entire lifecycle and keeping an account of the amount of produced and sold electricity in order to avoid a surplus of demand. The quality marks try to create transparency, and with that, they increase the credibility of the marked electricity products for the customer (Verein für umweltgerechte Energie VUE, Zürich, January 2018). Not all electricity products carry quality marks in Switzerland. As time passes, the criteria for the quality marks for renewable electricity also change. In addition to considering the effects on the climate, it is now be becoming increasingly popular to take into account local effects, such as the protection of biodiversity in the countryside and in the water of hydropower plants, for example (Verein für umweltgerechte Energie VUE, Zürich, January 2018). The eco-label Naturemade Star (categorized in this study as 'renewable-plus') accounts for this new focus on local biodiversity by investing some percentage of its products' price in biodiversity funds.

Eco-labelling makes energy sources in electricity products transparent, and through that, enables the consumer to make more informed choices when choosing an electricity product. It minimizes the transaction costs of researching and comparing the environmental characteristics of different electricity products and strengthens the credibility of marked renewably sourced electricity products.

Descriptive Results of Swiss Renewable Electricity Market

A descriptive account of the renewably sourced electricity market in Switzerland can be given through the annual survey for Swiss utility companies by the governmental department of energy Bundesamt für Energie (BFE), which is conducted by the Association for Environmentally Sound Electricity (Verein für umweltgerechte Energie) (VUE) (Verein für umweltgerechte Energie VUE, Zürich, January 2018). The results presented below are the most fitting as they report from the year before and after the default product change. They describe the Swiss internal renewable electricity market in 2016 in comparison to 2015. This survey covers data on 299 Swiss utility companies offering renewable energy products. These companies account for 75% of the electricity sales in Switzerland. The results show the share of renewable electricity sales that are offered as either single-sourced products or combination-sourced products, and are restricted to companies that offer renewable as well as conventional electricity products. Customers were therefore not forced into a renewable electricity contract, but rather had a choice between different contracts, including those containing conventional electricity sources (Verein für umweltgerechte Energie VUE, Zürich, January 2018).

In 2003, Wüstenhagen et al. assumed that the mature renewable electricity market would occupy a share of 20-30% of the total electricity market when the renewable electricity market would reach maturity at an uncertain date. This could be accomplished if utility providers offer renewable electricity products at a low premium that have clear added environmental value (Wüstenhagen et al., 2003). According to the survey in 2016, 24% of the overall electricity usage in Switzerland is renewably sourced, with 14,183 GWh/a (gigawatt hours/year) of renewable electricity sold in 2016. This demonstrates an increase in renewable electricity consumption of 2,885 GWh/a in comparison to 2015 (Verein für umweltgerechte Energie VUE, Zürich, January 2018). About one third of all household customers of the utility companies in the survey choose (directly or indirectly) a renewable electricity tariff, which added up to 1,621,166 renewable contract choices in Switzerland. This is an increase of 293,239 contracts compared to the previous year (Verein für umweltgerechte Energie VUE, Zürich, January 2018). For business customers, 14-18% choose a renewable electricity tariff. This means that more than half of electricity consumption (53%) was renewably sourced (Verein für umweltgerechte Energie VUE, Zürich, January 2018).

Table 2 shows the renewable electricity products sold in Switzerland in 2016 by those utility providers that partook in the latest BFE survey, which was published in 2018. It differentiates between mono-sourced products (solar, wind, water, and biomass) and combination-sourced products (referred to as 'mixed'). For each mono-sourced product, the survey further differentiates between those products labelled with the eco-label Naturemade Star and those without the label.

Table 2. Renewable Electricity Products Sold in the Year 2016 in Switzerland (Verein für umweltgerechte Energie VUE, Zürich, January 2018)[a]

	Sold in 2016		**Product orders**	
	GWh/a	**Share in %**	**Number**	**Share in %**
Solar *Naturemade Star*	51		30,518	
Solar *other*	2		1,297	
Solar *total*	**53**	**0.4%**	**31,815**	**2.0%**
Wind: *Naturemade Star*	4		571	
Wind: *other*	<0.1		11	
Wind: *total*	**4**	**<0.1%**	**582**	**<0.1%**
Water: *Naturemade Star*	288		6,505	
Water: *other*	5,642		567,335	
Water: *total*	**5,930**	**41.8%**	**573,840**	**35.4%**
Biomass *Naturemade Star*	0		0	
Biomass *other*	5		52	
Biomass *total*	**5**	**<0.1%**	**52**	**<0.1%**
Mixed *Naturemade Star*	718		109,528	
Mixed *Naturemade Basic*	5,641		718,321	
Mixed *other*	1,831		187,028	
Mixed *total*	**8,191**	**57.7%**	**1,014,877**	**62.6%**
TOTAL	**14,183**	**100%**	**1,621,166**	**100%**

[a] *The data in the analysis is based on utility contracts and not on customer numbers. The customer numbers are always lower than the numbers of utility contracts because some households and business customers have multiple utility contracts. It is estimated that for each customer, the number of contracts is approximately 1.333. Naturemade Basic products are listed as mixed products only (Verein für umweltgerechte Energie VUE, Zürich, January 2018).*

For the combination-sourced products, it differentiates between products with the eco-labels Naturemade Basic and Naturemade Star and those without either label. To get an overview of the renewable electricity market one can look into the electricity amount supplied from renewable energies in kWh on the one hand and in contract choice on the other hand. The market share of solar energy was 53 GWh/a, which amounted to 0.4% of the overall renewable energy consumption in 2016. The market share of wind energy was 4 GWh/a, which corresponded to <0.1% of the overall renewable energy consumption in 2016. The market share of water energy was 5,930 GWh/a, which accounted for 41.8% of the overall renewable energy consumption in 2016. The market share of biomass energy was 5 GWh/a, which amounted to <0.1% of the overall renewable energy consumption in 2016. The market share of mixed energy was 8,191 GWh/a, which was 57.7% of the overall renewable energy consumption in 2016. Hydropower held the greatest market share among the single-sourced energy products, but came in second to the combination-sourced products. Solar, wind, and biomass energy played only minor roles in the renewable electricity market, with solar energy having the highest market share of the three.

Overall, according to the survey, 1,621,166 contract choices could be categorized as renewable electricity products in 2016. The market share of contract choices for solar energy was 31,815 GWh/a, which accounted for 2% of the overall renewable contract choices in 2016. The market share of contract choices for wind energy was 582 GWh/a, which amounted to <0.1% of the overall renewable contract choices in 2016. The market share of contract choices for water energy was 573,840 GWh/a, which accounted for 35.4% of the overall renewable contract choices in 2016. The market share of contract choices for biomasses energy was 52 GWh/a, which was <0.1% of the overall renewable contract choices in 2016. The market share of contract choices for mixed energy was 1,014,877 GWh/a, which was 62.6% of the overall renewable energy contract choices in 2016. The order of the energy sources according to their market shares was reflected in the number of choices made for each product.

The market share of Naturemade Basic-certified renewable electricity out of the overall renewable electricity consumption was 47.3% (6.7 TWh/a)[6], which was an increase compared to its share of 37.7% (4.3 TWh/a) in 2015 (Verein für umweltgerechte Energie VUE, Zürich, January 2018). It has been argued that the increase in the Naturemade Basic market share was due to more utility companies changing their default products to renewably sourced electricity products that were Naturemade Basic certified. The market share of Naturemade Star-certified renewable electricity out of the overall renewable electricity consumption was 7.5% (1061 GWh/a), which was a small decrease from its share of 8.8% (996 GWh/a) in 2015 (Verein für umweltgerechte Energie VUE, Zürich, January 2018). Nonetheless, if one were to calculate not only the solo tariffs with Naturemade Star certifications but also the amount of electricity in combination tariffs that are marked Naturemade Star, the total would be 1,459 GWh/a, which is an increase from 1,158 GWh/a in 2015 (Verein für umweltgerechte Energie VUE, Zürich, January 2018).

The dominant renewable electricity source in Switzerland was still hydropower. Single-sourced hydropower generated 5,930 GWh/a and the mixed products, which mostly rely on hydropower, generated 8,191 GWh/a. Across these products, hydropower accounted for 99.5% of renewable electricity sold in 2016. The overall trend of renewably sourced electricity products sold is rising from 2015 to 2016.

[6] TWh/a is the electrical unit terawatt hour per year.

The default electricity products of the 53 utility providers in Switzerland named in Wikipedia[7] show that the dominance of hydropower is also found in hydropower being the overwhelming default electricity product among those utility providers (see the table of utility providers and default settings in Appendix 1: Utility Companies in Switzerland and their Default Settings as of 12th July 2017).

Preferences and Motivations for Choosing Renewable Electricity

According to the most recently available descriptive data, the use of renewable electricity is on the rise in Switzerland. However, the uptake of renewable electricity is still remarkably lower than the stated preference for it. The question of what kind of internal and external variables influence the willingness to choose a premium renewable electricity tariff combines economic and psychological perspectives. The economic perspective looks at the external factors that could influence the participation uptake, such as consumers' incomes, prices for the tariffs, and the socio-economic characteristics of the consumers. The psychological perspective focuses on internal factors, which can be described as the consumers' values, beliefs, and attitudes (Clark, Kotchen, & Moore, 2003). While economists try to promote pro-environmental behaviour with rewards, punishments, and regulations, psychologists prefer using tools such as increasing awareness, education, guilt, and persuasion (Clark et al., 2003). Renewable energy can be understood as a public good that contains not only environmental benefits but also the possibilities of minimizing electricity costs in the long run through research and development and minimizing the possibility of fuel supply interruption (Clark et al., 2003). Results on who is most likely to take up a premium renewable electricity tariff show that smaller households, higher incomes, and pro-environmental and altruistic attitudes are correlated with renewable energy uptake (Clark et al., 2003). When looking into the motivations of customers choosing premium renewable electricity tariffs over cheaper conventional electricity tariffs, the strongest motivating factors are bio-centric motives, followed by altruistic and egoistic motives (Clark et al., 2003). For the household customer, the motivation to choose renewable electricity over conventional electricity comes mainly from a desire to improve his or her own environmental track record and engage in the impure altruism of the warm-glow effect[8] (Truffer et al., 2001). In the same way, for business customers, the motivation to choose renewable electricity comes mainly from a desire to improve their environmental image (Truffer et al., 2001). Pichert

[7] https://de.wikipedia.org/wiki/Kategorie:Elektrizit%C3%A4tsversorger_(Schweiz), last checked 10th July 2017.
[8] For the origin of the warm glow effect, refer to Andreoni (1989).

and Katsikopoulos show that consumers tend to use the kind of electricity product that is offered to them as the default product by their utility company (Pichert & Katsikopoulos, 2008). Therefore, changing the default from conventional energy to renewable energy can promote pro-environmental behaviour and translate public support of renewable energy (Farhar, 1999) into renewable energy uptake (Pichert & Katsikopoulos, 2008).

Over the past 10 years, most Swiss utility companies have changed their sales tactics toward offering consumers electricity products with different qualities from which they can choose actively. Now, an increasing number of the Swiss utility companies offer a renewable product as their default product. The first Swiss utility company introducing a renewable default product was Services Industriels de Genève (SIG) in 2003. According to the 2016 survey, at least 20 of the Swiss utility companies have decided on a default product change from conventional electricity to a fully renewably sourced electricity product (Verein für umweltgerechte Energie VUE, Zürich, January 2018).

In conclusion, motivations for renewable electricity uptake vary, and even though the stated preferences for renewable electricity are strong, there is only low renewable electricity uptake. The gap between the preference and actual choice of renewable electricity can be reduced by the introduction of renewably sourced default products (Pichert & Katsikopoulos, 2008).

Conclusion

The short history given for the past two decades of the European electricity market reveals significant changes that occurred when the promotion of renewable electricity was set into force. The liberalization of internal electricity markets as well as the eco-labelling of renewable electricity products all empowered consumers to make informed choices between renewably and conventionally sourced electricity products. That fact that the Swiss electricity market is still not fully liberalized can also be seen as an advantage in the sense that it shields utility providers from competitors and gives them the chance to experiment with new products such as renewably sourced products (Wüstenhagen et al., 2003). The high share of 24% renewably sourced electricity sold in Switzerland can be ascribed to the comparatively high willingness of customers to pay for renewable electricity and the significant share of hydropower in the electricity market, which opens up the possibility of offering low premium renewable energy products as well as high premium renewable energy products (Wüstenhagen et al., 2003). With a relatively large share of renewable electricity product sales that is still growing, it appears that renewable electricity products (at least those in the low premium sector) are competitive with cheaper conventionally sourced electricity products. The demand for renewable electricity is currently fulfilled mainly by hydropower offered at a low premium price, which seems well positioned and differentiated from other conventionally sourced products in the overall market. Further growth of the renewable electricity market share could come from more diversified renewable energy sources and the additional development of small-scale hydropower plants.

3.2 Description of the Utility Company

The data from the default experiment stems from a Swiss utility company and covers a timeframe of four years, ranging from 2013 to 2016. In this quasi-experimental natural field experiment, the utility company changed their default electricity product from a conventionally sourced electricity product to a renewably sourced electricity product. The utility company is a mono energy supplier based in Switzerland, which focuses on electricity solely. It supplies electricity to households, businesses, and the public sector. Since the utility company opted to remain anonymous, the details given to describe the utility company are minimized to the essentials.

Genesis and History of the Cooperation with the Utility Company

This project[9], along with a number of other projects, was submitted for funding at the Swiss National Science Foundation. The umbrella project under which funding was applied for was titled 'Reducing Energy Consumption and Promoting Green Electricity: The Role of Soft Incentives'. This research program contained, along with this project, one more project on the topic of defaults, two symbolic reward projects, and a national environmental survey. The Swiss National Science Foundation agreed to fund the entire research program under the national research program titled 'NRP71 Managing Energy Consumption'.[10]

After funding was cleared, the Swiss energy supplier agreed to share the anonymised data from its default product change. Data access was given through the data service company that processed all the data for the utility supplier. In cooperation with the utility company, research questions were formed. The research interests on both sides concentrated

[9] Contact with the Swiss energy supplier was made through Professor Ulf Liebe, who was at the time a professor of sustainable social development in the sociology department at the University of Berne. Mutual cooperation between the University of Berne and the Swiss utility provider was agreed upon and funding was applied for.

[10] For more information, refer to http://www.snf.ch/en/researchinFocus/nrp/nrp-71-managing-energy-consumption/Pages/default.aspx (last checked on 18.07.2018).

on the heterogeneity of the default effect among utility customers. The utility company was interested in finding out underlying similarities of customers who accepted the new default setting in comparison to customers who did not accept the new default setting. The topic of exploring the heterogeneity of the default effect was especially promising since the customer pool of the utility company contained not only household but also commercial business customers. As defined by the utility company, household customers are metering points with a household type utility contract. Most have a yearly utility usage of less than 20,000 kWh. Business or commercial customers are metering points with a commercial type utility contract. Most have a yearly utility usage of more than 8,000 kWh and less than 20,000 kWh.

The business customers brought more diversity to the range of utility use and geography of customers. The range of utility use was extended largely due to the fact that businesses in general have higher utility usages than household customers. The diversity of geographic locations occurred because customers that have a utility use higher than 100,000 kWh per year are not restricted to the regulated market but can freely choose their utility provider from anywhere in Switzerland. Therefore, many of the utility company's bigger business customers had geographic locations outside of the utility company's regulated trading area. This had the effect of bringing more geographic diversity to the dataset.

In cooperation with the data service company, key variables for answering the research question were identified. The data service company extracted the requested key variables from its three data sources for the timeframe in question and supplied the raw data. The first delivery of raw data was on June 28th 2017. At this time point, the variable utility usage for 2016 was only available as partly simulated data.[11] The tariff choices of the customers after the default product change were only available for the time point January 1st, 2016, which was the day of the default product change. Therefore, a second data delivery was planned for the real data on the utility use in 2016 of all metering points and the tariff choices, which was collected at a later point in 2016. The data service company extracted the necessary variables from the three different databases that the utility company used for their everyday business activities. With the feedback of the data service company, the data was prepared. There are specific conditions that apply to data from utility companies. One of these is that the databases from the utility company had as the dominator of all data the metering points and not the customer numbers. A metering point is fixed to each apartment/house and is a unique value, whereas a customer number could change houses (if the customer moved but stayed

[11] For clarification and details on the specifics of utility use data, refer to Section 4.1.1. - Descriptive Statistics for Utility Use.

in the supplier area) or apply to multiple apartments/houses (if the customer had more than one apartment/house). Having the metering point as the denominator is a typical occurrence when dealing with data in this research area.

During the process of cleaning and verifying the raw data from the first delivery, many lessons were learned and incorporated into processing the raw data from the second delivery, which arrived on April 30th, 2018. There was a major discrepancy in expectations of data quality between the utility company and the research team. While the utility company is used to working with forecasted and (partly) simulated data, in science, simulated data is often seen as inferior to real data. Another discrepancy was that the utility company, in its day-to-day business, did not need information on which customer held which differently sourced tariff choice before 2016. However, the research team needed that information in order to compare customer choices before and after the treatment. A different report was imported into the data that showed the tariff choices of customers in greater detail pre 2016.[12] The second raw dataset held all of the variables available that were related to answering the research questions in as much detail as possible. All analyses were re-calculated using the second dataset. The whole process of working on the first dataset led to improved data quality and ensured the data quality of the second dataset, which held all available important variables and was of the desired quality.

A Quasi-Experimental Natural Field Study

An ideal experiment involves measurements before and after an intervention and a random distribution of participants into intervention and control groups. While in this study there were measurements before and after the intervention, there was no random distribution of participants into intervention and control groups. Often, it is not possible to randomly distribute participants into intervention and control groups, and there might not even be a control group at all. In such cases, direct measurement before and after the intervention can help to minimise some of the hidden heterogeneity in the participants (Campbell & Stanley, 2011). The default setting was changed by the utility company for all of the customers in the regulated market and remained unchanged for all of the customers in the free market. Experimental designs without the randomisation of participants to treatment and control groups, but with precautionary measures to control distortion through heterogeneity in samples, are described as quasi-experimental designs (Diekmann, 2004,

[12] For more information on the re-coding of the tariff choices before 2016, refer to Section 3.4.2 – Re-coding.

p. 356). The current experiment has a quasi-experimental design, since customers of the utility company were not randomized to the treatments of the default product change and control group. Customers were not randomly part of either market type – regulated or free – but fulfilled certain criteria that sorted them into either market type. The distribution of customers receiving the default product change versus not receiving it was along the free versus regulated market structure that is the rule in Switzerland. The customers in the regulated market received the new default product, which was sourced renewably, and the customers in the free market kept their old contracts and stayed with the conventionally sourced energy default product. Only customers with a yearly utility usage of above 100,000 kWh and who had applied to be in the free market were in the free market group, which did not receive the default switch of the utility company. All other customers were in the regulated market. There was a minor subgroup of regulated market customers who received a renewable-plus default product which is a 100% renewable electricity product with premium qualities and price.[13]

Another crucial identification factor of field studies is that participants are not aware of the intervention or that a specific behaviour is being studied. The great advantage of the field experiment lies in its covertness in documenting real-life behaviour and decisions untainted by the common experimenter demand effect. When covert interventions on human subjects are administered, ethical concerns arise, which should be addressed appropriately (Diekmann, 2004, pp. 87–89). If the intervention is more of a natural kind, as it is in the case of this study, ethical concerns are held to be minimal. The utility company decided on the treatment and how the customers were assigned to the different treatment groups with no intervention from the outside. The study had a natural setting in which the researchers observe the quasi-experiment but do not intervene in the experimental setup. In this sense, this study offered behavioural-based data in a natural setting without the customers noticing that their choices were being studied.

Conclusion

In conclusion, the data received from the utility company could be categorized as a quasi-experimental natural field study. The benefits of the natural field study were the opportunity to study behaviour in a natural setting without fear of the behaviour being biased by the experimenter demand effect. The downside of this study design is that customers were

[13]For a description of this subgroup, refer to Section 3.3 – Implementation of the Default Product Change, and for an analysis of this subgroup, refer to Section 4.2.5 – Subsample Analysis: Renewable-plus Default.

not randomly assigned to treatment and control groups, but assigned according to customer characteristics. This missing randomization can be contained to some degree by the comparison of data before and after the treatment. All in all, the dataset received from the utility company offered great potential to explore the research question about heterogeneity in the default effect. It covered a diverse range of customers and their characteristics and thus held the potential to illustrate which customer traits responded best to the default product change.

3.3 Implementation of the Default Product Change

This chapter is dedicated to covering all relevant background information on the facilitation of this default product change. Starting with the chronological sequence of the default product change, the timeline is laid out over which customers were informed about the change and were able to choose to stay with the new default or opt out of the new default. The form letters that were used to inform customers about the default product change are the private propriety of the utility company and were not cleared to be printed in this work. Nonetheless, the original letters were accessed and are paraphrased and analysed in this chapter. Not only is the introduction of the default product change from conventional to renewable electricity of interest, but also the comparison of the same to the default product change from conventional to renewable-plus electricity. The differences in customer treatment while facilitating the default product change(s) will be explained with the help of a detailed description of which customer type was chosen to receive the renewable default and which to receive the renewable-plus default. At the end of this chapter, the choice architecture of the default product change will be shown in prices. For this overview, the prices of the most common energy product for each energy option will be shown and compared for time points before the renewable default introduction and after.

Chronological Sequence of the Default Product Change

In August 2015, the first communication of the default product change was sent out to all of the customers in the regulated market, as it is custom, to inform customers about price changes each August for the following year. The announcement of price changes, different product arrangements, and the default product change to renewable energy was done in writing. The households and business customers received letters with all the relevant information. The letter included a customer service phone number and a personalised code to access an online portal which was created for facilitating the default product change. There was no mail-in response card, and customers could either call the electricity company on a local phone number or use the personalised code to access the online portal where they then could change to a price upgrade (renewable-plus tariff, the premium renewable product) or downgrade (conventional tariff). Actually, most customers who logged into the portal chose the renewable tariff. It seems like those customers did not clearly understand that if they wanted to keep the default tariff (renewable tariff) they did not have to log into the portal. The online portal was open from the end of August to the end of November 2015. The default product change and switch to the new product arrangements and pricing went into effect on January 1st, 2016. From that date, the electricity company gave a grace period of six months during which customers were allowed to switch tariffs, affecting their utility bills back until January 1st, 2016.

Differences in Customer Treatment while Facilitating the Default Product Change

The utility company's customers in the regulated market – that is, the electricity market with customers using up to 100,000 kWh per year – received the renewable energy default on January 1st, 2016. The non-regulated/free market – that is, the electricity market with customers using more than 100,000 kWh per year – kept the old contracts from before.

For customers in the regulated market, there was an exception rule where customers received a renewable-plus energy default, the premium renewable product, instead of the renewable energy default. This affected customers who paid more than 2.5 Rappen/kWh on premium surcharges on average (not including the basic tariff). They would either have had to have chosen the tariffs Energy Nature or Energy Nature Star in the past or they would have had to pay 2.5 Rappen/kWh more than the basic tariff, which could only been archived through choosing eco-tranches of wind energy certified Naturemade Star and/or solar energy certified Naturemade Star in the past. At first glance, it seems like this special customer group only migrated from one premium renewable electricity product to another premium renewable electricity product. At closer look, they underwent the massive default product change from a decision-setting where conventional electricity was the default product to a new setting where the renewable-plus, the premium renewable electricity product, was their new default product.

The saturation of the conventional default setting on August 31st, 2015 was zero for business and household customers, as the database of this overview excludes the free market customers who stayed on the old default setting (see Table 3). The majority of the customers in the regulated market received the renewable default, and only a small minority received the renewable-plus default setting, the premium renewable electricity product. Altogether, this exception rule of the renewable-plus default affected 6,452 meter points, as can be seen in the descriptive statistics of the variable tariff choice from August 31st, 2015 that show the initial default setting for each metering point.

Table 3. Overview of the Saturation of the Default Setting on 31.08.2015

Default Setting	Whole Dataset (*n*= 237,333)	Household Dataset (*n*= 229,658)	Business Dataset (*n*= 7,675)
Conventional	0 (0%)	0 (0%)	0 (0%)
Renewable	230,881 (97.3%)	223,248 (97.2%)	7,633 (99.5%)
Renewable-plus	6,452 (2.7%)	6,410 (2.8%)	42 (0.5%)
TOTAL	237,333 (100%)	229,658 (100%)	7,675 (100%)

The customer letters announcing the default product change were sent out in August 2015. From that point, the customers were able to reject the new default setting until May 2016. The percent of metering points affected by the main default switch of conventional energy to renewable energy was 97.3% for the whole dataset, 97.2% for the household customer dataset, and 99.5% for the business customer dataset. The percent of metering points affected by the minor default switch from conventional energy to renewable-plus energy was 2.7% for the whole dataset, 2.8% for the household customer dataset, and 0.5% for the business customer dataset. This shows that the default switch to the renewable electricity product affected the overwhelming majority of the customers in the regulated market. The switch to the renewable-plus default occurred only in rare cases of customer characteristics which makes for a small and biased sample.[14]

Form Letters of Renewable and Renewable-plus Default for the Household Customers

The form letters for business customers and household customers in the regulated market were congruent. Here, the form letters for the majority of customers who identify as being household customers in the regulated market will be documented and analysed. Since the letters for the business and household customers were congruent, the letters for the

[14] For a description of this subgroup, refer to Section 3.3 – Facilitation of the Default product change, and for an analysis of this subgroup, refer to Section 4.2.5 – Subsample Analysis Renewable-plus Default.

household customers will represent the letters sent to both customer groups and the letters for the business customers will not be analysed separately. The form letters regarding the renewable default and the renewable-plus default were congruent in most parts, apart from the obvious difference that they announce either the change from a conventional default to a renewable default or from a conventional default to a renewable-plus default.

The letters announcing the default product change were send out to customers in the regulated market during August 2015. The letter head was titled 'New Energy Products and Prices from 2016 On'. The first paragraph gave an explanation of the reason for changing the structure of the energy products and the prices. Accordingly, the utility company wants to focus on renewable energy in the future and thus is introducing the renewable energy product as a default for all clients. This paragraph is the same in both letters. The letter for the renewable-plus default mentions not the renewable default but the renewable-plus default.

The second paragraph of the letter announced a 9% price increase overall and gave an explanation for the price increase. It stated that the overall price of electricity is made up of three components: the price for the energy, the price for network usage, and the price of government-ordered fees concerning the energy usage. The 9% price increase was due to the increased price of network usage. The letter stressed, both in text and in a figure, that this price increase was not due to changing the default product and that the price for energy was remaining the same. This paragraph was also congruent in both letters. At this point in the letter it would have been fitting to inform the customer of the option to combat the 9% price increase by downgrading to the conventionally sourced energy product. It seems like this information was purposefully not offered at that point in the letter and in general not offered prominently in the whole of the letter. Even though the overall 9% price increase was said to be not due to the utility company changing the default from the conventional to the renewable electricity product, staying with the old conventional default would have dampened the price increase.

The third paragraph introduced the newly restructured energy products: *Renewable-plus*, *Renewable,* and *Conventional*. The first part of the paragraph listed all three energy products and explained that *Renewable-plus* is made up of renewable energy that is sourced from solar and hydropower. *Renewable* was described as renewable energy mostly sourced from hydropower, and *Conventional* is sourced mostly from nuclear power. All of the energy products are produced mainly in Switzerland.

For the customers receiving the renewable-plus default, there was an additional paragraph at this point in the letter explaining to the customer why the renewable-plus product was chosen as the default product for this customer. It explained that since the customer had chosen renewable energy products in the past, it would be most suitable for them to migrate to the renewable-plus product at this point. It was stressed that this migration will not involve higher costs for the customer. But again, the information that a downgrade to the renewable or conventional products would save the customer some costs was not given.

The next paragraph was again the same for both default groups and explained the web portal where customers can log in with the help of a customer number and a code. In the web portal, customers could find a personalized calculation of their utility bill from January 1st, 2016 on. Customers are informed that they could change their energy product on this web portal. If customers did not change their choice before November 30th, 2015, they would receive the new default product (respectively, the renewable or renewable-plus products).

The last paragraph before the signatures of the utilities companies' chief of sale and chief of retail and marketing communication thanked customers for their trust in the utility company and welcomed customers into the 'renewable future'.

A postscript at the end of the letter added information on the monthly utility costs for an average four-room household with a yearly utility usage of 4,500 kWh for all three energy products. With the renewable-plus product, this household would pay approximately 105 CHF per month. With the renewable product, they would pay approximately 95 CHF per month, and with the conventional, approximately 91 CHF per month. Therefore, at the end of the letter, the information about price differences for the different products was revealed along with the information that the choice of the conventional product would save the customer money and possibly combat to a large extent the overall price increase. It seems intentional that this information was given in the postscript of the letter, where attention of the reader is supposedly the lowest. The choice to do so could be seen as a deceptive manoeuvre by the utility company, as judged from the customer's perspective. The form letters announced a price increase of 9% due to an increased price for network usage and increased government-ordered fees concerning energy usage. A logical way to combat that price increase would have been to keep the conventional default in place, but the utility company changed their default to the renewable electricity package, stressing that this default product change was not the reason for the price increase. As a customer, one might doubt that one can change from a conventional electricity product to a fully renewable electricity product without taking a price increase into account. Apart from this confusion, the utility company purposefully put the information that there is a cheaper electricity product than the default assigned in the postscript on the second page of the letter. Those two points – the statement that the price increase had nothing to do with the default product change and the semi-hidden information that there is a cheaper alternative to the default product – might have aroused some negative responses on the customer side. In the literature, the acceptance of nudges is quite high when respondents feel that they are for a good cause, like the protection of the environment (Reisch & Sunstein, 2016; Sunstein, 2015). Nonetheless, it is an open secret that utility companies are motivated to change their default product to a renewable product not only for environmental reasons, but also for monetary gain. The high acceptance of the default product change[15] may be an indicator that most customers were either unaware of the manipulative nature of the form letter or that their negative feelings were dampened by the promoted upfront cause of the default product change, which was environmental protection. This would mean that the customers were most likely unaware of the monetary gain in changing to a renewable default product for the utility company. Especially the argument given in the form letter that the default product change did not add to the price increase might have added to the illusion that both electricity products – the conventional as well as the renewable – bring the same return on investment for the utility company, even though sales margins are likely more profitable for the renewable product.

Choice Architecture of the Default Product Change in Prices

This price overview is a simplification of the tariff options in which the tariff option that had the most customers highlighted for each year (conventional/renewable/renewable-plus) and average prices are displayed for household customers or business customers in the regulated market (see Table 4). Tariff choices in 2016 relied on the simplified heuristic of the utility company that divided tariff choices into three categories: *Renewable-plus*, *Renewable,* and *Conventional*. *Renewable-plus* is made up of at least 50% solar energy and a maximum of 50% hydropower. The solar energy is mainly, but not solely, produced in Switzerland and the hydropower is only produced in Switzerland. Both energy sources in this tariff are certified as Naturemade Star. One Rappen per kWh of the hydropower is invested in an ecological fond that funds environmental projects.[16] *Renewable* is made up of 90% hydropower, certified as Naturemade Basic; 7.5% hydropower, certified Naturemade Star where 1 Rappen per kWh of the hydropower is invested in an ecological fund that funds environmental projects; and 2.5%

[15] For descriptive information on acceptance rates of the default products along the years, refer to Section 4.1.3 – Descriptive Statistics for Contract Choice: 2013-2016.
[16] For more information on eco-labelling in Switzerland, refer to Section 3.1 – The Renewably Sourced Electricity Market in Switzerland.

other renewable energy, certified Naturemade Star (solar energy, wind energy, and/or biomass). The energy is mainly produced in Switzerland. *Conventional* is made up of 75% nuclear energy, 20% hydropower, and 5% energy supported by the governmental Kostendeckende Einspeisevergütung (KEV) fee. This tariff is not certified and its energy sources are not solely in Switzerland.

Table 4. Choice Architecture of the Default Product Change in Prices: Comparing Electricity Prices 2015-2016

Package	Conventional Default Option (2015) Prices per kWh Day	Night	Renewable Default Option (2016) Prices per kWh Day	Night
Conventional	H: 0.26 CHF B: 0.12 CHF	H: 0.17 CHF B: 0.08 CHF	H: 0.28 CHF B: 0.11 CHF	H: 0.18 CHF B: 0.07 CHF
Renewable	H: 0.29 CHF B: 0.15 CHF	H: 0.20 CHF B: 0.11 CHF	H: 0.29 CHF B: 0.12 CHF	H: 0.19 CHF B: 0.08 CHF
Renewable-plus	H: 0.33 CHF B: 0.19 CHF	H: 0.24 CHF B: 0.15 CHF	H: 0.32 CHF B: 0.15 CHF	H: 0.21 CHF B: 0.11 CHF

Energy packages and average prices per kWh for 229,658 (96.77%) households (H) and 7,675 (3.23%) businesses (B) before (2015) and after the introduction of a renewable default option (2016). All descriptive details come from the dataset containing customers in the regulated markets, business and household customers, renewable and renewable-plus defaults.

The most commonly chosen tariffs for 2015 – when conventional electricity was the default – in the conventional categories were *Energy Basic* for household customers (*n*=138,679) and *Energy Basic Power* for business customers (*n*=6,762) in the customer group that later received the renewable or the renewable-plus defaults. *Energy Basic* is a double tariff for household customers with a higher utility usage during the night and a yearly utility usage of up to 20,000 kWh. A double tariff offers two different prices for utility usage depending on the time that the utility is used, differentiating a day tariff from a cheaper night tariff. *Energy Basic Power* is a double tariff for business customers who have a yearly utility usage ranging between 20,000 kWh and 100,000 kWh. The *Energy Basic* and *Energy Basic Power* tariffs are composed of mostly nuclear energy and energy from uncertified sources.

The most commonly chosen tariffs for 2015 in the renewable categories were *Energy Nature* for household customers (*n*=2,541) and *Energy Basic Nature* for business customers (*n*=9) in the customer group that later received the renewable or the renewable-plus defaults. *Energy Basic Nature* (not to be confused with the *Nature Basic* tariff) is a double tariff based on the *Energy Basic* tariff (household customers, higher utility usage during the night, yearly utility usage up to 20,000 kWh) but with a surcharge of 3 Rappen/kWh. *Energy Basic Power Nature* (not to be confused with *Nature Basic* tariff) is a double tariff based on the *Energy Basic Power* tariff (business customers, yearly utility usage ranging between 20,000 kWh and 100,000 kWh) but with a surcharge of 3 Rappen/kWh. The *Energy Basic Nature* and *Energy Basic Power Nature* tariffs have the following composition of energy sources, all certified with the Naturemade label: 85% hydropower, 5% solar energy, 5% wind energy, and 5% biomass energy.

The most commonly chosen tariffs for 2015 in the renewable-plus category were *Energy Basic Nature Star* for household customers (*n*=698) and *Energy Basic Power Nature Star* for business customers (*n*=3) in the customer group that later received the renewable or the renewable-plus defaults. *Energy Basic Nature Star* is a double tariff based on the *Energy Basic* tariff (household customers, higher utility usage during the night, yearly utility usage up to 20,000 kWh) but with a surcharge of 7 Rappen/kWh. *Energy Basic Power Nature Star* is a double tariff based on the *Energy Basic Power* tariff (business customers, yearly utility usage ranging between 20,000 kWh and 100,000 kWh) but with a surcharge of 7 Rappen/kWh. The *Energy Basic Nature Star* and *Energy Basic Power Nature Star* tariffs have the following composition of energy sources, all certified with the Naturemade Star label: 70% certified hydropower, 10% solar energy, 10% wind energy, and 10% biomass energy. 1 Rappen per kWh of the hydropower is invested in an ecological fund that funds environmental projects.

The most commonly chosen tariffs for 2016 (measured at the time point of January 1st, 2016) – when renewable and renewable-plus energy were the defaults –in the conventional category were *Energy Conventional Doppeltarif* for household customers (*n*=15,994) and *Energy Conventional Profistrom* for business customers (*n*=1,053). *Energy Conventional Doppeltarif* is a double tariff that is based on the *Energy Basic* tariff from 2015 (household customers, higher utility usage during the night, yearly utility usage up to 20,000 kWh). *Energy Conventional Profistrom* is a double tariff that is based on the *Energy Basic Power* tariff from 2015 (business customers, yearly utility usage ranging between 20,000 kWh and 100,000 kWh). The *Energy Conventional* tariff has following composition of energy sources: 75% nuclear energy, 22% hydropower, and 3% energy supported by governmental KEV fees.

The most commonly chosen tariffs on January 1st, 2016 in the renewable category were *Energy Renewable Doppeltarif* for household customers (*n*=120,605) and *Energy Renewable Profistrom* for business customers (*n*=5,703). *Energy Renewable Doppeltarif* is a double tariff based on the *Energy Basic* tariff (household customers, higher utility usage during the night, yearly utility usage up to 20,000 kWh) but with a surcharge of 1 Rappen/kWh. *Energy Renewable Profistrom* is a double tariff that is based on the *Energy Basic Power* tariff from 2015 (business customers, yearly utility usage ranging between 20,000 kWh and 100,000 kWh) but with a surcharge of 1 Rappen/kWh. The *Energy Renewable* tariff has following composition of energy sources: 90% hydropower certified Naturemade, 2.5% solar energy certified Naturemade Star, 4.5% hydropower certified Naturemade Star, and 3% energy supported by governmental KEV fees.

The most commonly chosen tariffs for 2016 (measured at the time point of January 1st, 2016) in the renewable-plus category were *Energy Renewable-plus Doppeltarif* for household customers (*n*=4,171) and *Energy Renewable-plus Profistrom* for business customers (*n*=34). *Energy Renewable-plus Doppeltarif* is a double tariff that is based on the *Energy Basic* tariff from 2015 (household customers, higher utility usage during the night, yearly utility usage up to 20,000 kWh) but with a surcharge of approximately 4 Rappen/kWh. *Energy Renewable-plus Profistrom* is a double tariff that is based on the *Energy Basic Power* tariff from 2015 (business customers, yearly utility usage ranging between 20,000 kWh and 100,000 kWh) but with a surcharge of 4 Rappen/kWh. The *Energy Renewable-plus* tariff has the following composition of energy sources: 50% solar energy and 50% hydropower, both certified Naturemade Star. Of the hydropower, 1 Rappen/kWh is invested in an ecological fund that funds environmental projects concerning nature conservation and the renaturation of waters and fish passes in the utility company’s service area.

Conclusion

In conclusion, the timeline of the default product change can be judged as sufficient for the customers to make their decisions to remain with or opt out of the new default product. The customers were informed in August 2015 and were able to opt out of the new default until May 2016 without being charged for the new default product. That means that even if a customer decided later than January 1st, 2016 that he or she did not want to receive the renewable default product, he or she could notify the company by May 2016 and the difference in bills would be corrected for the product chosen at this time point. Overall, customers were given three different defaults. The majority of customers in the regulated market received the renewable default and a small minority received the renewable-plus default. The customers in the free market kept the old conventional default and stayed on their former contracts. The form letters introducing the customers to the default product change could have been considered manipulative from the customers' perspective. Two critical reasons for this were the statement that the price increase had nothing to do with the default product change and the company hiding the information that there was a cheaper alternative to the default product on the second page of the letter in the postscript. The high acceptance rate of the default product hints to most customers being either unaware of the manipulative nature of the form letter or that their negative feelings were eased by the promoted upfront cause of the default product change: environmental protection. Regarding the majority of the customers, who received the renewable default and have the characteristics of being household customers in the regulated market, the price increase from one default setting to the next was 3 Rappen for the day tariff and 2 Rappen for the night tariff. Even if this customer group had chosen to stay with the conventional electricity product, they would have had to pay a price increase of 2 Rappen for the day tariff and 1 Rappen for the night tariff. For the second biggest group of customers, which could be identified as business customers in the regulated market who also received the renewable default, there was no price increase from one default product to the next. The prices for the business customers for either default (conventional or renewable) were the same for the day tariff as for the night tariff. If this customer group had chosen to stay with the conventional electricity product, they would have saved 1 Rappen for the day tariff and 1 Rappen for the night tariff. It seems like the price increase of 9% due to the costs of network usage and government-ordered fees on energy usage only affected the prices for household customers in the regulated market, and did not affect the business customers.

3.4 Data Preparations

As might be the case in any natural field experiment, data preparation is not only the process to prepare data for analysis but also a pivotal part of understanding and managing the data. The same holds true for this experiment on default setting. There are many unique attributes of data structure and quality in this field of study. As described earlier in this chapter, the utility company affiliated with this research works with a metering point-based data structure and not a customer-based data structure. For their day to day business, the utility company uses three different data management programs and often has to rely on forecasted simulated data. This especially applies to meter-read electricity data. The unique challenges that arise when working with meter-read electricity data are laid out in more detail in Section 4.1.1 – Descriptive Statistics for Utility Use. The data preparation process was done in close communication with both the utility company and its data service partner company. The data-cleaning process involved getting from a raw dataset from three data management programs to a clean dataset that only contained customers who received the treatment of the default product change on January 1st, 2016 and necessary information relevant to said default product change. This mainly meant removing all metering points that were in the free market and leaving only those in the regulated market as well as identifying all relevant variables that could offer intel on the default product change and incorporating them into the existing data structure. In addition, the utility company made major changes to their product range and customer treatment during the time span of 2013 to 2016. Standardizing the product ranges and making them comparable across years was a major but necessary endeavour. The struggle was in getting all the information on the energy quality and classification for each existing electricity product during the time span of 2013 to 2016. While from the researchers' perspective this information was crucial, for the utility company, it was not. The utility company concentrated on different attributes of the electricity products and had only just begun to document the energy quality and environmental classifications of their electricity products in preparation for the default product change. The work of re-coding the variables salutation and contract choices will be discussed in this chapter. Overall, the time invested in data preparation was necessary in order to prepare a database that could show a clear picture of the default effect on the customer's choice of contract.

3.4.1 Data Cleaning

The main goal of data cleaning was the identification of metering points that received the default switch and those that did not. As only the metering points in the regulated electricity market received the default switch, all metering points that were identified as belonging to the free market were excluded from the dataset. Another goal was to minimize unnecessary heterogeneity in the data, which translated to excluding the metering points for which a customer switch had happened during the years 2013 to 2016.

Regulated Versus Free Market

The dataset received contained all of the metering points of the utility company for the regulated as well as the free energy markets (n=338,574). In general, the regulated market contains customers in the utility company's service area that have a yearly utility usage lower than 100,000 kWh. The free market in general contains customers in the whole of Switzerland that have a yearly utility usage higher than 100,000 kWh a year. Since only customers in the regulated market received a default switch, data cleaning involved the differentiation of customers in the regulated market from customers in the free market. For this differentiation, not one but several variables had to be consulted for successful differentiation between metering points in the two market types.

One variable is the measuring point, which serves as an ID and builds the basic structure of the dataset. The measuring point is the natural subject level from the utility company's view. For billing purposes and other processes, the utility company concentrates on the measuring point and not on the customer number. The measuring point is a stable entity, as it marks the connection from the electricity network to the building where the electricity is used. The customer number is not a stable entity, because a customer can move and change measuring points. In the dataset received, there were measuring points without IDs, indicating that these are not using energy from the utility company but instead supplying energy back to the utility company. Since those back suppliers are not in the regulated market and also did neither receive electricity nor the default switch from the utility company, they have been excluded.

Another variable that provided some information on the differentiation between the two market types was the variable indicating the customer type, which sorted all customers into four different categories: *household customers*, *business customers*, *special,* and *VNB* (distribution network company). The customer type was coded on the basis of the contract type for each metering point. The contract type indicated if a metering point was billed as any one of the customer types. The customer types *special* and *VNB* are both in the free market and hence did not receive the default product switch. Therefore, over the course of data cleaning, the customer types *special* and *VNB* were excluded.

Another variable that contained information that indicated free market metering points was the variable of *contract choice* in the years 2013, 2014, 2015, and 2016. If a metering point had a dummy tariff in its contract choice in any of these years, it indicated that this metering point did not belong to the regulated market but to the free market. Therefore, all metering points with a dummy tariff were excluded over the course of data cleaning.

As mentioned before, the goal of data cleaning was to separate the regulated customer market from the free customer market. Omitting data without a measuring point and for the customer types marked *special* or *VNB* from the cleaned dataset sets in force the separation of the two markets. As can be seen in the cleaned dataset, the values for the variable of contract choice in 2016 indicate the successful separation of the regulated market from the free market. The tariffs *Renewable*, *Renewable-plus*, and *Conventional* all indicate customers in the regulated market, since only the regulated market received the package update to

Renewable, *Renewable-plus*, or *Conventional* and the renewable default/renewable-plus default. After data cleaning, only the tariffs *Renewable*, *Renewable-plus*, and *Conventional* remained. Other tariffs besides *Renewable*, *Renewable-plus*, and *Conventional* were additionally excluded. Before data cleaning, the tariffs besides *Renewable*, *Renewable-plus*, and *Conventional* marked the customers in the free market, since they had stayed with their old packages and did not receive the product update or the default product change to renewable energy. The IT service of the utility company is of the opinion that testing the distribution of the variable of contract choice in 2016 was a better indicator for testing a successful market separation than for testing the distribution of the variable utility usage in 2015, where logically, values under 100,000 kWh/year mark the regulated market and over 100,000 kWh/year mark the free market. Testing the distribution of the variable utility usage for 2015 was less clear, and had the disadvantage that customers at the threshold of 100,000 kWh/year could be miscategorised since their utility usage could fluctuate yearly. In addition, there was the possibility of miscategorising customers if their utility usage was higher than 100,000 kWh/year but they formally chose to stay in the regulated market.

Removing Metering Points with a Customer Switch

Another main goal for data cleaning besides isolating the regulated market from the free market was to make the measurements as homogenous as possible by excluding those metering points for which the customer had moved between 2013 and 2016. Apart from the physical makeup of a home, the behaviour of the individuals inhabiting that home is the biggest impact factor on electricity usage. In order to hold the heterogeneity of that impact factor to be as small as possible, all metering points on which the customer number switched were excluded. As the utility company did not have any information on household size and household makeup, there was no possibility of controlling for other changes in the household. Removing the metering points with a customer switch only identified the households where the billed individual had moved out. It cannot identify households where a person was added, like if child was born or a partner moved in, or subtracted, as in the death of a household member or a partner moving out.

Removing Empty Values in Initial Default Distribution and at the Point of the Default Product Change

Empty values in the variable initial default distribution (time point of measurement: August 2015) mostly correspond to the number of empty values in the variable that measured the contract choice at the point of the default switch realisation (time point of measurement: January 1st, 2016). In the original dataset, there were 34,163 empty values for the initial default distribution (August 2015), and 27,091 empty values were in the variable contract choice on January 1st, 2016 amongst other empty variables. Since all analysis focused on the default product change, cases with empty values in those two variables were excluded from the dataset. Having an empty value in the initial distribution of the default and at the point of the default switch does not only hinder the analysis of the default product change but also shows customers who have not received the default treatment and are thus likely to be in the free market.

Separating the Customers who Received the Renewable Default from Those Who Received the Renewable-plus Default

As written earlier, data cleaning involved the aim of keeping only customers who received the default product switch on the January 1st, 2016. Since there was not only one new default that was introduced but two parallel defaults, it was also necessary to identify which customers received which kind of default product change.

Figure 15. Number of Customers Receiving Renewable and Renewable-plus Defaults (own illustration)

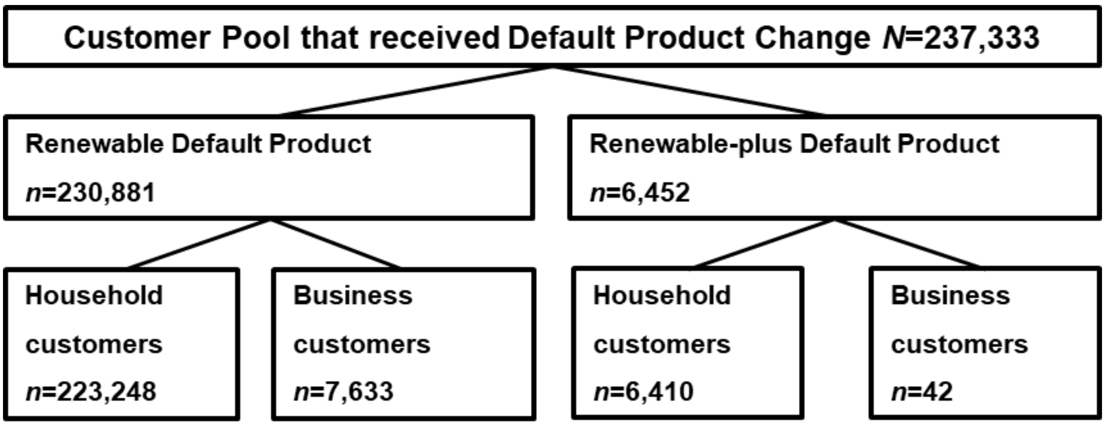


Figure 15 shows the number of customers on the renewable and on the renewable-plus default for the whole dataset and then separated for household customers and business customers. Identifying which customers received which default was imprecise and difficult with the first data transfer but simplified in the second data transfer through the new variable that showed the contract choice on August 2015. In August 2015, the customers first received the letters notifying of the default product change. After data cleaning, the whole dataset containing all household and business customers had *n*=237,333 data points, which is the sum of the whole dataset of the customers receiving the renewable default (*n*=230,881) and the renewable-plus default product (*n*=6,452). There were altogether 229,658 household customers, of which, 223,248 received the renewable default product and 6,410 received the renewable-plus default product. Of the 7,675 business customers, 7,633 received the renewable default product and 42 received the renewable-plus default product. As can be seen from the distribution of customers between the renewable and the renewable-plus defaults, the renewable default was applied to the vast majority of customers and only a few customers with special customer characteristics were treated to the renewable-plus default.[17] As a rule of thumb, the renewable default was the standard given to all the customers in the regulated market, with a few exceptions. In the following, the dataset including both default forms will be used for common statistic descriptive details, as can be found in the appendix. All main analysis will be based on the dataset only containing the renewable default, since this was the standard default treatment. The sub analysis regarding the renewable-plus default treatment will be based on the dataset only containing the renewable-plus default (see Section 4.2.5 – Subsample Analysis: Renewable-plus Default).

Conclusion

In order to prepare a clean dataset for analysis, the exclusion of free market metering points was pivotal. The aim was to only have metering points which received the default switch in the dataset in order to clearly analyse the effect of the default switch. The endeavour of cleaning the dataset of free market metering points was managed through the information given out in different variables. Another necessity in data cleaning was to hold everything as constant as possible by excluding customers who had moved metering points. Altogether, excluding free market metering points and metering points with customers who had moved prepared the data and established a common working ground for analyses.

3.4.2 Re-coding

While all of the variables received were re-labelled in their names, only the variables of salutation and contract choice had to also be re-coded in their structure and values. Salutation gives the salutation of the individual that is billed for the metering point. This

[17] For more on those special customer characteristics and on how it was determined who received the renewable-plus default, refer to Section 3.3 – Facilitation of the Default Product Change.

information, on individual level, is available for the years 2013 through 2016. Contract choice is the electricity contract for which the metering point is booked. This information is available for the years 2013, 2014, 2015, the beginning 2016, the end of 2016, as well as the initial default allocation for each metering point on August 2015. The re-coding of the salutation variables was very straightforward, concentrating on the indicated gender behind the salutation for each billed individual responsible for the metering point. The re-coding of the variables for contract choice took great research and care in order to establish a common heuristic among the contract names and energy source compositions that changed throughout the years.

Re-coding of Salutations, 2013-2016

The information given out in the salutations for the years 2013 through to 2016 provides valuable descriptions on the individual level. Since information such as household size and other social descriptive information are not available on an individual level in the utility company's data, salutation is the only variable that approaches the metering point on the individual level. Salutations connect each metering point with the individual who receives the bills for that metering point. In 2013 and 2014, there were 12 different kinds of salutations, and for 2015 and 2016, there were 13 different kinds of salutations. The 13 different forms of salutations and their distribution can be seen in the appendix. In the process of re-labelling the salutations, the 12 or 13 possible salutations were re-coded into four different kinds of salutations. The four salutations were 'female' (ranging in the years 2013 to 2016 from n=37,221 to n=39,336), 'male' (ranging from n=102,883 to n=103,086), 'mixed' (ranging from n=31,343 to n=32,790), and 'NA' (ranging from n=62,852 to n=65,886).[18] The re-coding of the salutations followed the heuristics of determining the gender of the billed individual on basis of the information given in the salutation. While 'female' and 'male' describe the salutations of billed individuals by clearly indicating the gender of the billed individual, the value 'mixed' was assigned when a clear gender indication could not be derived from the information given in the salutation. This was applicable when the salutation addressed a couple, a family, or some other term that did not reveal gender. The value 'NA' marks all missing entries for salutation.

The re-labelling of the salutations into the genders of the billed individuals is only that: the genders of the billed individual. It does not offer any grounds for further assumptions,

[18] For more information, refer to Appendix 2: Descriptive Statistics of Variables on the Metering Point Level.

such as household size, for example. A singular or plural form of salutation therefore is not an indication of a one-person or more-than-one-person household. In Switzerland, it is common practice that in the case of rented properties, the landlord will write to the utility company with the information of the tenant. If the tenant is a couple, the landlord can either send both names to the utility company or choose one of them. The landlord could be led in his or her decision by common prejudice and write the husbands name only, assuming that it is the husband's job to take care of the electricity bills. Or the landlord could be led in his or her decision by what names are on the lease agreement and send those to the utility company. In the case of owned property, the billed individual would be whoever feels responsible in the household to notify the utility company of the change of ownership. Only in the case of one-person households would the salutation give a clear indication that the decision-maker is either female or male, but since there is no information on household size, there is no clear indication of this.

Re-coding of Contract Choices, 2013-2016

For the year 2013, there is no clear information on renewable energy uptake and usage. As explained before, the utility company was not keeping records of energy quality and environmental classification for all of its electricity products before 2016. For 2015 and earlier, product descriptions did not entail information on the exact composition of energy sources and their environmental labels. In preparation for the introduction of the renewable electricity default, the utility company initiated a renewable energy report for the first time in 2014 and repeated it in 2015. This renewable energy report had the aim of filling in the missing information on energy sources and their composition and the environmental labelling of the electricity products. The report was initiated to show for the first time the share of renewable energy that customers ordered and used in a year. Starting in 2016, there was no need for a renewable energy report since for the first time ever, the tariff names clearly identified energy quality, source, and certifications. The renewable energy report was made at a different time point than the annual normal energy report. Thus, the variables in the renewable energy report may show a different utility use than the variables in the normal annual report. Before 2016, the utility company offered either the possibility of purchasing a fixed amount of yearly renewable electricity (a renewable electricity tranche) or a full renewable electricity tariff that covered all electricity usage during that year. The renewable electricity tranches (solar, wind, and hydropower) were separated by ordered amount of renewables tranche and used amount of renewables tranche. The ordered renewable tranche shows the amount of kWh that was ordered for a metering point for a given year. The used renewable tranche shows how much kWh had been used at a given point in time at a given metering point for that specific renewable energy tranche. The usage of kWh is subtracted from the ordered amounts of renewable energy tranches in the hierarchy of solar > wind > hydropower. This hierarchy is based on the pricing of the renewable tranches. Solar power is the highest priced form of renewable energy tranche, wind power is the second highest priced, and hydropower is the lowest priced form of renewable energy. If a metering point only has renewable energy tranches but not a full *Nature Basic* or *Nature Star* tariff, the metering point will fall back on conventional energy when its renewable energy tranches are used up. Metering points with a full *Nature Basic* or *Nature Star* tariff will fall back on this tariff when their renewable energy tranches are used up, resulting in a fully renewable energy supply for that year.

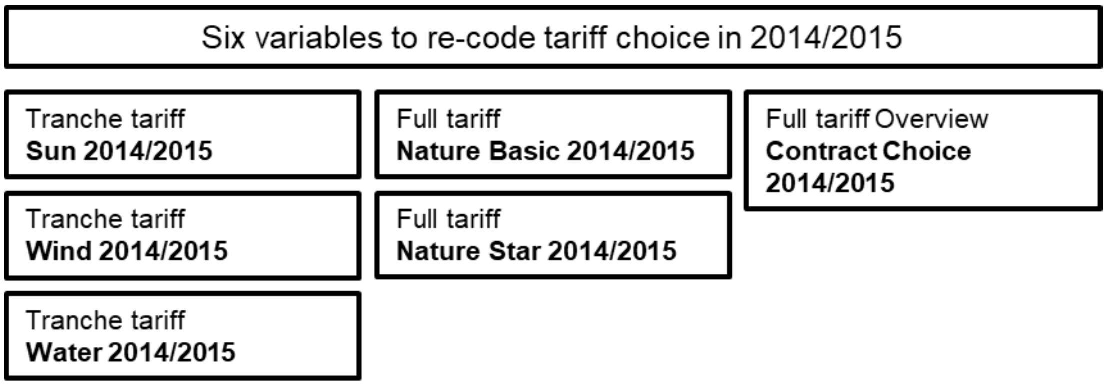
The product choices for 2014 and 2015 were re-categorized on the basis of the information of six variables. The surcharge for renewable electricity can be seen in tariff type and tranches from the renewable electricity reports for 2014 and 2015. Combining these six variables made sure that the heuristic behind tariff choices in 2014/2015 was the same as that behind tariff choices in 2016. Tariff choice in 2016 relied on the simplified heuristic of the utility company as it divided tariff choices for the first time ever into only three categories: *Renewable-plus,*[19] *Renewable,*[20] and *Conventional.*[21] For purpose of hiding the identity of the utility company the original product names were re-labelled respectively as *renewable-plus*, *renewable*, and *conventional*. The idea behind the re-labelling was to emphasis energy qualities and to stress that the new default product is in actuality a tariff of 100% renewable energy sources, thus labelling it 'renewable'. The default product change is in fact so drastic because it changed from a tariff that was mostly made up of nuclear energy to a tariff that holds 100% renewable energy sources. With the labels *renewable-plus*, *renewable*, and *conventional*, it is clearer that the major gap between energy qualities in the tariffs is between

[19] Renewable-plus Mix is made up by at least 50% solar energy and maximal 50% hydropower. The solar energy is mainly but not solely produced in Switzerland and the hydropower is only produced in Switzerland. Both energy sources in this tariff are certified as "naturemade star". One Rappen per kWh of the hydropower is invested in an ecological fond that funds environmental projects.
[20] Renewable Mix is made up by 90% hydropower which is certified "naturemade basic", 7.5% hydropower which is certified "naturemade star" where one Rappen per kWh of the hydropower is invested in an ecological fond that funds environmental projects and 2.5% renewable energy that is certified "naturemade star" (solar energy/wind energy/biomass). The energy is mainly produced in Switzerland but not limited to Switzerland.
[21] Conventional Mix is made up by 75% nuclear energy, 20% hydropower and 5% energy supported by the governmental KEV fee (KEV: "Kostendeckende Einspeisevergütung"). This tariff is not certified and its energy sources are not solely placed in Switzerland.

'*renewable*' and '*conventional*'. There is not a similar gap between *renewable* and *renewable-plus*. *Renewable-plus* is similar to *renewable* but with a little additional stipulation, thus the label name marking the premium renewable tariff. The original product naming of the utility company gave the false idea that the gaps between energy qualities for those three tariffs are fairly similar when they are not.

The heuristics for re-coding the tariff choices in 2014 and 2015 follow the logic of the tariff choices in 2016. Unfortunately, the necessary information on energy qualities could not be found conclusively in the variable of contract choice 2015 as they could for the year 2016, but had to be derived from additional variables from the renewable energy report in 2014 and 2015. The tariff choices of customers in 2014 and 2015 had to be re-coded based on information from six different variables.[22]

Figure 16. Overview of the Six Variables Used to Re-code the Tariff Choice of Customers in 2014/2015 (own illustration)



The six different variables are as follows:

(1) 'Tranche tariff Sun 2014/2015' is a variable from the renewable energy report for 2014/2015 showing the amount in kWh of solar energy that was pre-ordered by customers for the year 2014/2015. The energy quality is certified as Naturemade Star. This is a tranche product for which the customer chooses a specific annual amount and not a full tariff.

(2) 'Tranche tariff Wind 2014/2015' is a variable from the renewable energy report for 2014/2015 showing the amount in kWh of wind energy that was pre-ordered by customers for the year 2014/2015. The energy quality is certified as Naturemade Star. This is a tranche product for which the customer chooses a specific annual amount and not a full tariff.

[22] For more information on the descriptive details of the six variables, refer to Appendix 2: Descriptive Statistics of Variables on the Metering Point Level.

(3) 'Tranche tariff Water 2014/2015' is a variable from the renewable energy report for 2014/2015 showing the amount in kWh of certified water energy that was pre-ordered by customers for the year 2014/2015. The energy quality is certified as Naturemade Star. This is a tranche product for which the customer chooses a specific annual amount and not a full tariff. This water tranche is 'Nature Star Water' which is different from 'Nature Basic Water'. Both hydropower tranches/tariffs are made up off 100% certified hydropower made in Switzerland, but 'Nature Star Water' additionally invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations.

(4) 'Full tariff Nature Basic 2014/2015' is a variable from the renewable energy report for 2014/2015 showing the amount of actual used kWh for the year 2014/2015 that was booked on the *Nature Basic* tariff. This used amount is based on simulated data, meter-read data, and weighted data. The energy quality is certified as Naturemade Basic. This is a full tariff in which the customer chooses the tariff and not a specific amount as with a tranche product. Only the metering points with this *Nature Basic* tariff[23] fall back on hydropower after their renewable energy tranches are used up.

(5) 'Full tariff Nature Star 2014/2015' is a variable from the renewable energy report for 2014/2015 showing the amount of actual used kWh for the year 2014/2015 that was booked on the *Nature Star* tariff. This used amount is based on simulated data, meter-read data, and weighted data. The energy quality is certified as Naturemade Star. *Nature Star*[24] is a full tariff in which the customer chooses the tariff and not a specific amount as with a tranche product.

(6) 'Contract Choice 2014/2015' is a variable from the general energy report for 2016/2017 showing the tariff choice that the customer chose for the years 2014/2015 as recorded in December 2014 and 2015.

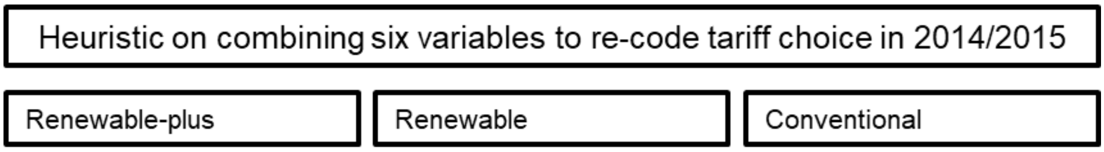
With the aim of categorising contract choices in 2014 and 2015 in line with the heuristics used in 2016, the desired end results for labels were again renewable-plus, renewable, and conventional. But not only do the labels needed to be the same as in 2016;

[23] Unfortunately not all metering points which have this tariff can be found out through this variable, some of them have "hidden" Nature Basic tariffs. The composition of the Nature Basic tariff is 95% Nature Basic Water, 2.5% Nature Star Water, 2.5% Nature Basic Sun, Wind, Bio. The difference between Nature Basic Water und Nature Star Water is that even though both are made up off 100% certified hydropower made in Switzerland but "Nature Star Water" additionally invest 1 Rappen for each kWh into ecological funds which invest locally in water renaturations.

[24] Nature Star composition: 70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, 10% biomass energy. The difference between Nature Basic Water und Nature Star Water is that even though both are made up off 100% certified hydropower made in Switzerland but "Nature Star Water" additionally invest 1 Rappen for each kWh into ecological funds which invest locally in water renaturations.

the qualities of the energy sources should also be in line with those for 2016. Combining information from the former six variables, the labels renewable-plus, renewable, and conventional were assigned with the hierarchy renewable-plus > renewable > conventional (see Figure 17).

Figure 17. Heuristic of Hierarchy of Energy Sources to Re-code Contract Choices in 2014/2015 (own illustration)

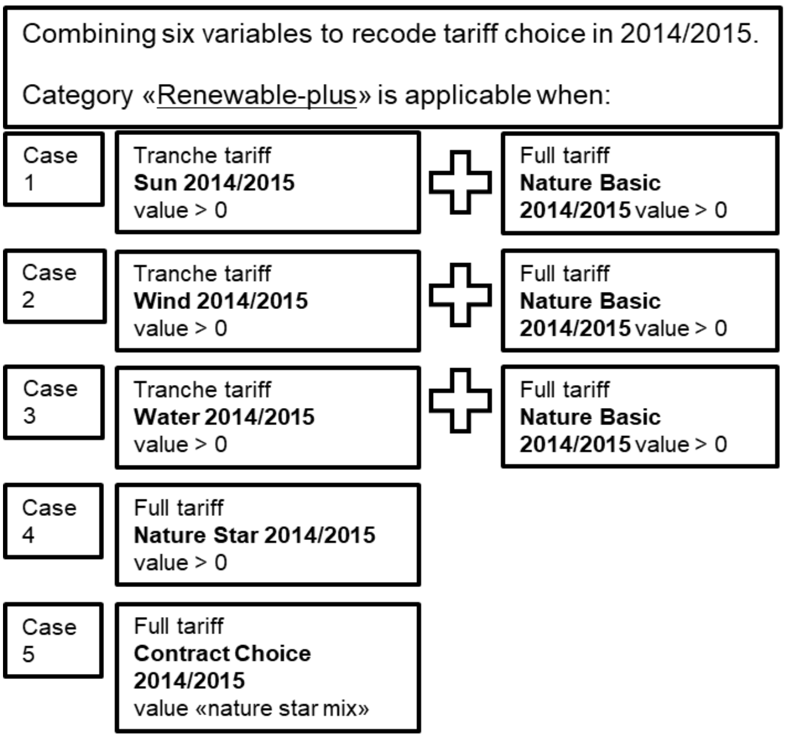


In that sense, the indicators for the categorization of renewable-plus were checked first, and if they were not applicable, indicators for the categorization of renewable were checked. If these were also not applicable, the conventional label was assigned.

In 2016, the renewable-plus label was given to the Renewable-plus Mix, which is made up of at least 50% solar energy and a maximum 50% hydropower. The solar energy is mainly, but not solely, produced in Switzerland and the hydropower is only produced in Switzerland. Both energy sources in this tariff are certified as Naturemade Star. Of the hydropower, 1 Rappen per kWh is invested in an ecological fund that funds environmental projects. The label 'renewable-plus' in 2014/2015 should be just as strict regarding energy sources, energy qualities, and certifications.

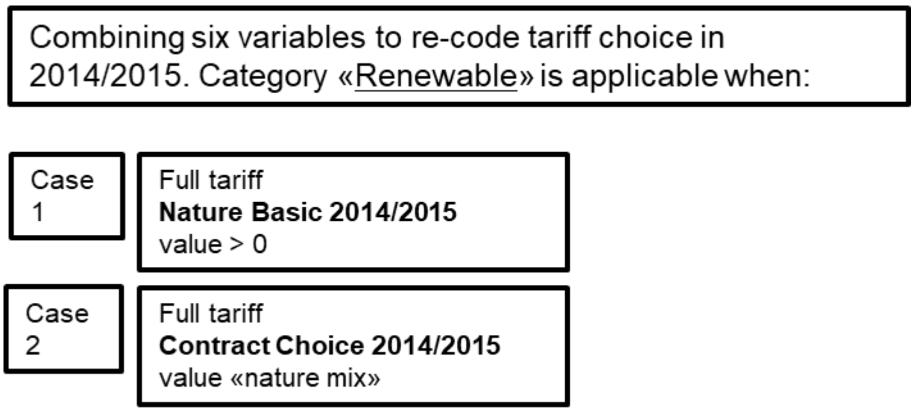
As can be seen in Figure 18, the renewable-plus label was given out in five different cases. The first case applied to metering points with a Naturemade Star certified solar energy tranche and a full Nature Basic tariff (95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Solar, Wind, and Biomass). This combination forms a 100% renewable energy-sourced contract that holds a significant share of Nature Star-certified energy sources. Only the metering points with this Nature Basic tariff fall back on hydropower after their renewable energy tranches are used up. All other metering points fall back on conventional energy, and thus only the combination of renewable energy tranches and a full Nature Basic tariff can be labelled renewable-plus. The second case applies to metering points with a Naturemade Star-certified wind energy tranche and a full Nature Basic tariff (95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Solar, Wind, and Biomass). This combination forms a 100% renewable energy-sourced contract that holds a significant share of Nature Star-certified energy sources. The third case applies to metering points with a Naturemade Star-certified hydropower energy tranche and a full Nature Basic tariff (95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Solar, Wind, and Biomass). This combination forms a 100% renewable energy-sourced contract that holds a significant share of Nature Star-certified energy sources.

Figure 18. Heuristics of the Category 'Renewable-plus' used to Re-code Contract Choice in 2014/2015 (own illustration)



The fourth case applies to metering points with a full tariff of Nature Star (70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, and 10% biomass energy), indicated in the variable Full tariff Nature Star 2014/2015. This is a 100% renewable energy-sourced contract that holds only Nature Star-certified energy sources. Even though this tariff holds 100% pure Nature Star-certified energy sources, it does concentrate on the lowest priced energy sources among them. In this case, the metering points from case 1 and 2 (see Figure 18) could pay much more for their kWh depending on the amount of renewable solar or wind energy tranches they hold, as those are the highest-priced energy sources of those certified as Nature Star. The full tariff of Nature Star cannot be deemed superior to the case descriptions 1 and 2 but in some cases to case 3. The fifth case applies to metering points that have a full tariff of Nature Star mix (70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, and 10% biomass energy) as indicated in the variable Contract Choice 2014/2015. The fourth and fifth cases describe the same full tariff, but the variables Full tariff Nature Star 2014/2015 and Contract Choice 2014/2015 do not mark all of the same metering points, and therefore both need to be listed, though the descriptions and reasoning for the full Nature Star tariff are the same.

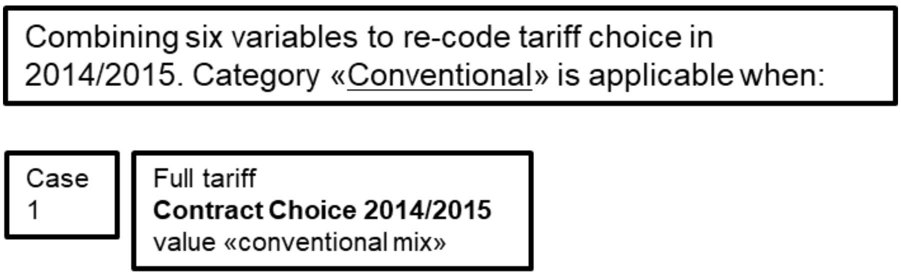
Figure 19. Heuristics of the Category 'Renewable' to Re-code Contract Choices in 2014/2015 (own illustration)



As can be seen in Figure 19, the renewable label was given out in two different cases (and only if the metering point had not received the label renewable-plus, which trumps the label renewable). The first case applies to metering points with a full *Nature Basic* tariff (95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio) indicated in the variable Full tariff Nature Star 2014/2015. The energy quality is certified as Naturemade Basic. The difference between Nature Basic Water and Nature Star Water is the following: both are made up off 100% certified hydropower made in Switzerland, but Nature Star Water additionally invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations. The full *Nature Basic* tariff is labelled renewable because it consists of only renewable energy sources with a concentration on locally produced hydropower, just like the tariff choice *Renewable* in 2016, which was also re-labelled as renewable. The second case also applies to metering points with a full *Nature Basic* tariff (95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio) as indicated in the variable Contract Choice 2014/2015. The first and second cases describe the same full tariff, but the variables Full tariff Nature Star 2014/2015 and Contract Choice 2014/2015 do not mark all of the same metering points and therefore are both listed, though the description and reasoning for the full *Nature* tariff is the same.

As can be seen in Figure 20, the label conventional was given out when the metering point did not yet receive the labels renewable-plus or renewable, both of which trump the conventional label. This group of metering points can also be identified as having a conventional mix in the variable Contract Choice 2014/2015, but not all metering points holding a conventional mix in this variable can be deemed automatically as conventional. The variable Contract Choice 2014/2015 does not indicate if the metering point also holds a renewable energy tranche and only in few cases indicates if the metering point holds a *Nature Basic* full tariff or a *Nature Star* full tariff. The hierarchy of giving out the labels from renewable-plus to renewable to conventional was set up to identify all information that is missing in the variable Contract Choice 2014/2015 with the help of other variables coming from the renewable energy report made for 2014/2015.

Figure 20. Heuristics of the Category 'Conventional' to Re-code Contract Choices in 2014/2015 (own illustration)



Conclusion

The steps of re-coding the pivotal variables salutation and contract choice ensured the establishment of a common heuristic of information in these variables, even though they differed greatly before. While the re-coding of the salutation variables was very straightforward, concentrating on the indicated gender behind the salutation for each billed individual responsible for a metering point, the re-coding of the contract choice variable took great research and care to establish a common heuristic among the contract names and energy source compositions as they changed over the years. Establishing a high comparability of information in these variables was the necessary groundwork for all of the following analyses.

4. Results

4.1 Descriptive Analyses

In this chapter, descriptive statistics of the main pivotal variables will be presented and discussed. The pivotal variables in the dataset are utility use and information on the renewable contract options before the default switch, which can be found for 2014 and 2015 in the renewable energy report of the utility company. The descriptive statistics of variables not discussed in this chapter can be found in detail in the appendix. These variables are the measurement of utility use and contract choice over the years 2013 to 2016. Given that the research is working with data provided by a utility company, there are some specifics in the measurement of these two variables that will be addressed in the necessary detail in this chapter.

Section 4.1.1 (Descriptive Statistics for Utility Use) explains the measurement of utility use, which is a yearly measurement that is not done for all customers at the same point in time. Customers are sorted into four equally sized groups. These four groups are structured after the four seasons in which each group is repeatedly measured. For example, the spring group's meters are read annually in spring.

Section 4.1.2 (Descriptive Statistics for Renewable Energy Contracts: 2014 and 2015) shows the proportion of renewably sourced tariffs and tranches in the two years before the default product change. In this section, the number of customers using those renewable electricity products as well as the utility booked on those products will be analysed. The information on renewably sourced electricity products comes from a renewable energy report that was specifically done for the years 2014 and 2015, but unfortunately not done for 2013.

Section 4.1.3 (Descriptive Statistics for Contract Choice: 2013-2016) shows the re-coded distribution of contract choices over the years. While in section 4.1.2 the descriptive details concentrate on the different renewable products and showing those in more detail, section 4.1.3 shows the broader picture for the distribution of contract choices grouped into the categories ‘renewable’, ‘renewable-plus’, and ‘conventional’.

4.1.1 Descriptive Statistics for Utility Use

The data for utility usage is relevant and at the heart of nearly every analysis in this dissertation. The utility provider allowed access to the data for utility usage for all its customers from the year 2013 through the year 2016, resulting in four years of measurements altogether. The data shows real measurements of the utility usage for each measuring point and includes no simulated data. The utility usage is read once a year in person by the staff of the utility provider. All customers are divided into four meter reading groups spread out over the four seasons. The spring group has their meters read every spring, the summer group has their meters read every summer, and so forth. For billing purposes, the utility company uses simulated data estimating the customer’s electricity usage based on their previous usage.

Figure 21. Meter Reading Cycles Explained for Utility Use: 2014 (own illustration)

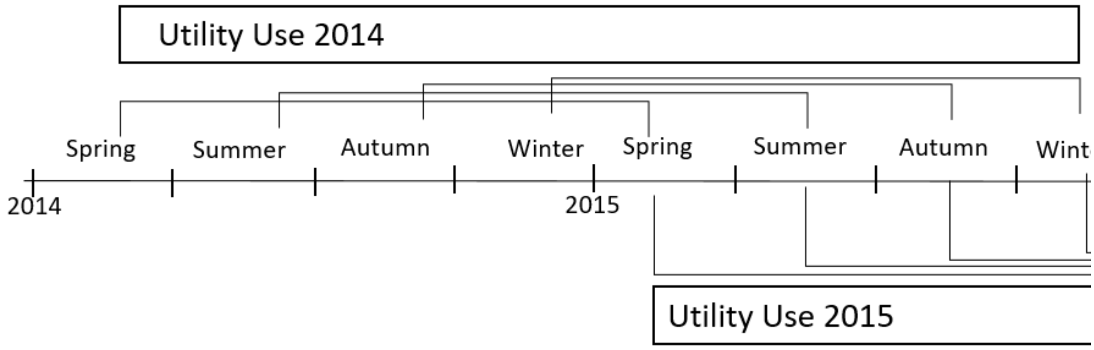
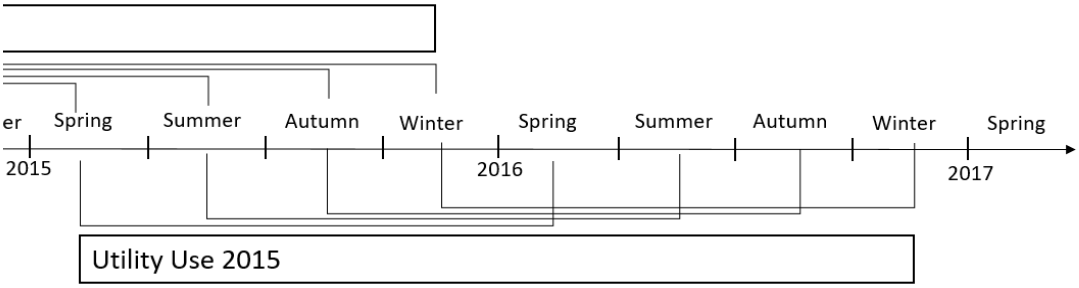


Figure 21 shows the four different meter reading groups and that the utility use for the year 2014 contains the utility usage from spring 2014 to spring 2015 for the spring group. Furthermore, it contains the utility usage from summer 2014 to summer 2015 for the summer group, the utility usage from autumn 2014 to autumn 2015 for the autumn group, and the utility usage from winter 2014 to winter 2015 for the winter group.

Figure 22 shows the four different meter reading groups and shows that the utility use for the year 2015 contains the utility usage from spring 2015 to spring 2016 for the spring group. Furthermore, it contains the utility usage from summer 2015 to summer 2016 for the summer group, the utility usage from autumn 2015 to autumn 2016 for the autumn group, and the utility usage from winter 2015 to winter 2016 for the winter group. Figures 21 and

22 together show how the annual utility use is made up of the corresponding meter reading groups and demonstrates the timeframe of the meter reading groups for that year.

Figure 22. Meter Reading Cycles Explained for Utility Use: 2015 (own illustration)



Once a year, when real utility usage data is available for the customer, the billing is adapted again. If the real utility data are higher than the simulated data, the customer gets a bill to pay for the surplus. If the real utility data are lower than the simulated data, the customer gets the overpaid amount credited to his or her next bill. Since the meters are read only once a year in the different quarters of that year, the full cycle of read meters for one year is finished exactly one year after. The real utility usage for the year 2016 was received in the end of 2017. The winter group, which got its meters read every winter, was the last one getting its meters read in winter 2017. The winter group's utility usage for 2016 shows their utility usage from winter 2016 to winter 2017. Since it was not possible to get an indicator of which measuring point belongs to which reading cycle, all metering points are treated as having the same timeframe. The stable allocation of measuring points to the four reading cycles and the nearly random distribution to the four reading cycles diminish the concerns that would otherwise arise for this key variable.

Table 5 shows the descriptive statistics for the yearly real utility usage of all customers (n=230,881) in the cleaned dataset from 2013 to 2016. This table holds the customers who received the renewable default in 2016 but excludes those customers who received the premium renewable-plus tariff instead. Through the act of data cleaning, the free market customers were divided from the regulated market customers, leaving only the later in the dataset. The distribution of the annual utility usage follows the same pattern throughout the years, speaking for the quality of measurement of the data. Due to a change in data treatment in the years 2014 and 2015, there are zero non-available measurements but a higher number of zero-measurements in comparison to the years 2013 and 2016. The important indicators

Table 5. Descriptive Statistics of Utility Usage: 2013 – 2016 (n=230,881)

	Utility Use 2013	**Utility Use 2014**	**Utility Use 2015**	**Utility Use 2016**
Number of values	224,821	230,881	230,881	229,830
Number of null values	30	2,822	1,550	34
Number of missing values	6,060	0	0	1,051
Minimal value	0.0	0.0	0.0	0.0
Maximal value	3,942,782	3,807,496	3,790,160	3,015,695
Range	3,942,782	3,807,496	3,790,160	3,015,695
Sum of all non-missing values	1,510,907,038	1,383,018,122.7	1,435,382,539.1	1,445,487,960
Median	3,875.5	3,421.0	3,567.0	3,558.0
Mean	6,720.5	5,990.2	6,217.0	6,289.0
Standard error on the mean	40.3	41.2	41.8	40.0
Confidence interval of the mean at the p level .95	79.0	80.8	82.0	78.0
Variance	364,931,654.2	392,235,314.3	404,000,344.7	366,709,301.0
Standard deviation	19,103.2	19,804.9	20,099.8	19,150.0
Variation coefficient defined as the standard deviation divided by the mean norm	2.8	3.3	3.2	3.0

All descriptive details come from the dataset containing only the regulated market of business and household customers with renewable defaults (n=230,881).

vary only slightly over the years, such as the median measurement ranging from 3,421.0 to 3,875.5. The mean measurement also deviates only a little over the years, ranging from 5,990.2 to 6,720.5. The sum of all non-missing values ranges from 1,383,018,122.7 kWh to 1,510,907,038 kWh and shows no indicative pattern over the years.

Conclusion

In conclusion, even though this measurement of utility usage presents common issues such as the once-a-year-measurement, the distribution of the variables shows that this measurement can be trusted as a stable basis for the analyses that follow.

4.1.2 Descriptive Statistics for Renewable Energy Contracts: 2014 and 2015

In order to fully understand the effect that the default switch had on customer choices, it is necessary to analyse the situation before the default product change happened. Only in comparison to the situation before the default product change can the default effect be accurately judged. Before the default product change in 2016, the utility company had conventionally sourced electricity contracts as the default for household and business customers alike. Only a minority of customers held renewably sourced electricity contracts in the years before the default product change. In preparation for the default product change, the utility company ordered a renewable energy report in the years 2014 and 2015. For the year 2013 and before, there is no clear information on renewable energy acquisition from customers and no identification of which customers bought how many renewable energy tranches. The report on renewable energy consumption was made for 2014 and 2015 in the following spring. From 2016 on, with the product change and default product change, there is a clear differentiation between the renewable tariff, the renewable-plus tariff, and the conventional tariff.

Heuristic Behind Renewable Energy Tranches and Tariffs in 2014 and 2015

Since the customer number for renewable energy contracts and tranches is relatively stable, only the most recent descriptive statistics, from 2015, will be documented in this chapter. Concerning the information on renewable energy tranches, the report on renewable energy acquisition differentiates between the ordered electricity amount and the actual used electricity amount. The ordered electricity amount of renewable energy tranche shows the amount of electricity in kWh for sun/water/wind tranches that has been ordered annually by the customers. The used electricity amount of renewable energy tranche shows the amount of electricity in kWh for sun/water/wind tranches that has been used in that year by the customers. The renewable energy tranches ordered are used up by the customer's energy demand in a specific hierarchical order that is built through the price hierarchy of the different energy tariffs and renewable energy tranches. The hierarchy order starts at the sun tranche, then goes to the wind tranche, then the water tranche, then the Nature Basic tariff, and finally the Energy Basic tariff. Below is an example of how renewable energy tranches are used up by the yearly energy demand of the customer.

Example 1:

Customer A ordered the following renewable energy tranches for 2014: 500 kWh sun energy, 400 kWh wind energy, and 300 kWh water energy. He ordered the Energy Basic tariff that was the default in 2014. In 2014, he has used 2,500 kWh. The energy demand was met using 500 kWh sun energy, 400 kWh wind energy, and 300 kWh water energy, and the final 1,300 kWh will was fulfilled by the Energy Basic tariff (mostly nuclear energy).

Example 2:

Customer B ordered the following renewable energy tranches for 2014: 1,500 kWh sun energy, 500 kWh wind energy, and 500 kWh water energy. She has ordered the Nature Basic tariff. In 2014, she used 4,500 kWh. The annual energy demand was filled by 1,500 kWh sun energy, 500 kWh wind energy, and 500 kWh water energy, leaving a remainder of 2,000 kWh that was filled through the Nature Basic tariff (hydropower).

Example 3:

Customer C ordered the following renewable energy tranches for 2014: 1,500 kWh sun energy, 0 kWh wind energy, and 500 kWh water energy. He has ordered the Energy Basic tariff. In 2014, he used 3,500 kWh. The annual energy demand was filled by 1,500 kWh sun energy, 0 kWh wind energy, and 500 kWh water energy, leaving a total of 1,500 kWh, which was filled with the Energy Basic tariff (mostly nuclear energy).

Depending on the tariff choice, it is possible that a customer could use renewable energy tranches such as solar power in combination with nuclear power because they hold the default tariff, which was nuclear power in the years before the default product changed. Customers who had the Nature Basic tariff (hydropower) fell back on hydropower instead of nuclear energy. Unfortunately, this differentiation between the Nature Basic tariff (hydropower) and the Energy Basic tariff (nuclear energy) in 2014 and 2015 cannot be seen in the data. The data shows only the customers who solely had the Nature Basic tariff without renewable energy tranches.

Table 6. Prices and Numbers of Customers Using Renewable Energy Tranches before Default Product Change (2015)

Renewable Energy Tranche	Price Surcharge	*n* Household Customers	*n* Business Customers
Solar Tranche 2015	+34.56 Rp./kWh	434	39
Wind Tranche 2015	+19.44 Rp./kWh	363	42
Certified Water Tranche 2015	+3.78 Rp./kWh	1,470	123
TOTAL		2,267	204

All descriptive details come from the dataset containing only the regulated market of business and household customers with renewable defaults.

The number of customers on renewable energy tranches in 2015 was very small and made up mostly of household customers (see Table 6). In the following, the descriptive statistics for customers on renewable energy tranches will be explored in detail, first for household customers and then for business customers. Household customers typically have much lower yearly utility usage than business customers. As a result, the two customer types also vary in their purchase amounts of kWh of renewable energy tranches in 2015 and should be looked at separately. The descriptive statistics given in this chapter are based on the variables given in the renewable energy report for 2015. For analysis purposes, the information given in the renewable energy reports for 2014 and 2015 were re-coded and re-structured in order to align with the logic of contract choices in 2016.[25]

Descriptive Statistics for Household Customers on Renewable Tranches before Default Product Change (2015)

Table 7 shows the descriptive statistic for the sun, wind, and certified water tranches in 2015. The data shown in the table are from the dataset (*n*=223,248) that contains household customers who received the renewable default a year later and excludes those who received no default product change or received the renewable-plus default. For this descriptive statistic, the 0-values are transformed into non-available values (NAs) to show the distribution of the variables more accurately. For this variables, the NA values do not mean that there are no available values for those measuring points, but rather indicate the custo-

[25] For a detailed report on how the re-coding was handled, refer to Section 3.4.2 - Re-Coding. For a descriptive overview of this simplified contract choice classification, refer to Section 4.1.3 - Descriptive Statistics for Contract Choice: 2013-2016.

Table 7. Descriptive Statistics for Solar, Wind, and Certified Water Tranches before Default Product Change (2015) (n=223,248)

	Sun: ordered amount 2015 in kWh (*n*=434)	**Wind: ordered amount 2015 in kWh (*n*=363)**	**Water: ordered amount 2015 in kWh (*n*=1,470)**
Number of values	434	363	1,470
Number of null values	0	0	0
Number of missing values	222,814	222,885	221,778
Minimal value	50	100	9.5
Maximal value	12,600	10,000	74,143
Range	12,550	9,900	74,133.5
Sum of all non-missing values	90,200	273,237.6	3,014,917
Median	100	250	2,000.0
Mean	207.8	752.7	2,051
Standard error on the mean	31.9	67.4	73.1
Confidence interval of the mean at the p level .95	62.7	132.5	143.3
Variance	442,005.5	1,646,773.6	7,849,776.3
Standard deviation	664.8	1,283.3	2,801.7
Variation coefficient defined as the standard deviation divided by the mean norm	3.2	1.7	1.4

All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults.

mers who did not book the tariff. In the process of data cleaning, the free market customers were separated from the regulated market customers, leaving only the latter in the dataset. The three tranches (plus the three tariffs below) show the whole range of electricity products that can be categorized as renewably sourced in 2015. There are 434 household customers who ordered the solar energy tranche in 2015. The tranche amounts ordered range from as little as 50 kWh to as high as 12,600 kWh, adding up to a total of 90,200 kWh (*Mdn*: 100 kWh; *M*: 207.8 kWh). The wind tranche was ordered by 363 household customers in 2015. The tranche amounts ordered range from as 100 kWh to 10,000 kWh, adding to a total of 273,237.6 kWh (*Mdn*: 250 kWh; *M*: 752.7 kWh). The certified water tranche was ordered by

1,470 household customers in 2015. The tranche amounts ordered range from as little as 9.5 kWh to 74,143 kWh, totalling 3,014,917 kWh (*Mdn*: 2,000 kWh; *M*: 2,051 kWh). One may notice that the number of household customers ordering the sun and wind tranches were less than those ordering the water tranche. This is due to the fact that the database includes the household customers who received only the renewable default. Customers with high amounts of sun and wind tranches would have received the renewable-plus default. However, as the main default switch was the switch to renewable energy, this small and unique group of customers are excluded in this specific overview that aims to demonstrate the renewable energy uptake for the main default before the switch happened.

Descriptive Statistics for Household Customers on Renewable Tariffs before Default Product Change (2015)

Table 8 shows the descriptive statistic for the Nature Basic, Nature Star, and Nature tariffs in 2015.[26] Only the metering points with the Nature Basic tariff fall back on hydropower after their renewable energy tranches are used up. Unfortunately, not all metering points that have this tariff can be found through this variable; some of them have 'hidden' Nature Basic tariffs which also fall back on hydropower after their renewable energy tranches are used up but this cannot be seen in this variable.

The data shown in the table are from the dataset (n=223,248) that contains household customers and contains only those customers who received the renewable default in 2016, and not those who received the premium renewable-plus tariff as a default. For this descriptive statistic, the 0-values are transformed into NAs to show the distribution of the variables more accurately.

The NA values in these variables do not mean that there are no available values for those measuring points, but rather indicate the customers that did not book the tariff. In the process of data cleaning, the free market customers were separated from the regulated market customers, leaving only the latter in the dataset. The three tariffs (plus the three tranches from above) show the whole range of electricity products that can be categorized as renewably sourced in 2015. There were 2,598 household customers who ordered the Na-

[26] Nature Basic composition: 95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio. Nature Star composition: 70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, and 10% biomass energy. Nature Star Water additionally invests 1 Rappen for each kWh into ecological funds that invest in local water renaturations. Nature composition: 85% Nature Basic Water, 5% Nature Basic Wind, 5% Nature Basic Sun, and 5% biomass energy. All three tariffs are full tariffs where the customer chooses the tariff, and not a specific amount as with a tranche product.

Table 8. Descriptive Statistics for Nature Basic, Nature Star, and Nature Tariffs before Default Product Change (2015) (n=223,248)

	Nature Basic 2015 in kWh (*n*=2,598)	**Nature Star 2015 in kWh (*n*=5)**	**Nature 2015 in kWh (*n*=10)**
Number of values	2,598	5	10
Number of null values	0	0	0
Number of missing values	220,650	223,243	223,238
Minimal value	0.00048	259.3	3.3
Maximal value	117,647.4	7,266.3	46,578.0
Range	117,647.4	7,006.9	46,574.7
Sum of all non-missing values	10,210,451.1	21,278.7	106,810.6
Median	3,284.8	4,484.6	7,515.6
Mean	3,930.1	4,255.7	10,681.1
Standard error on the mean	72.3	1,277.7	4,335.4
Confidence interval of the mean at the p level .95	141.8	3,547.5	9,807.4
Variance	13,585,912.3	8,162,591.2	187,959,494.4
Standard deviation	3,685.9	2,857.0	13,709.8
Variation coefficient defined as the standard deviation divided by the mean norm	0.9	0.7	1.3

All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults.

ture Basic tariff in 2015 (that are visible in the data). The utility booked through this tariff ranges from as little as 0.00048 kWh to as high as 117,647.5 kWh, with the total adding up to 10,210,451.1 kWh (*Mdn*: 3,284.8 kWh; *M*: 3,930.1 kWh). The Nature Star tariff was used by five household customers in 2015. The utility booked in this tariff ranges from as 259.3 kWh to 7,266.3 kWh, adding up to a total of 21,278.7 kWh (*Mdn*: 4,484.6 kWh; *M*: 4,255.7 kWh). The Nature tariff was used by 10 household customers in 2015. The utility booked through this tariff ranges from as little as 3.3 kWh to 46,578.0 kWh, ultimately totalling 106,810.6 kWh (*Mdn*: 7,515.6 kWh; *M*: 10,681.1 kWh). The high number of customers on the Nature Basic tariff in comparison to the small numbers of customers on the Nature Star and Nature tariffs is due to the profiles of the customers who received the renewable default. While most Nature Basic tariff holders were migrated to the renewable default treatment, most of the customers on the more expensive Nature Star and Nature tariffs were given the renewable-plus default. As Table 8 aims to demonstrate the situation of renewable energy uptake in 2015 for the main default switch, the customers receiving the renewable-plus default were excluded from this table.

Descriptive Statistics for Business Customers on Renewable Tranches before Default Product Change (2015)

Table 9 shows the descriptive statistic for the sun, wind, and certified water tranches in 2015. The data shown in the table are from the dataset (*n*=7,633) that contains business customers who received the renewable default in 2016. For these descriptive statistics, the 0-values were transformed into NAs to show the distribution of the variables more accurately. The NA values in these variables do not mean that there are no available values for those measuring points but indicate the customers that did not book the tariff. In the process of data cleaning, the free market customers were separated from the regulated market customers, leaving only the latter in the dataset. The three tranches (plus the three tariffs below) show the whole range of electricity products that can be categorized as renewably sourced in 2015. There are 39 business customers who ordered the solar energy tranche in 2015. The solar tranche amounts ordered range from as little as 50 kWh to as much as 11,300 kWh, adding up to 53,350 kWh (*Mdn*: 1,000 kWh; *M*: 1,367.9 kWh) total. Wind tranches were ordered by 42 business customers in 2015. The tranches ordered range from as 500 kWh to 20,000 kWh, adding up to a total of 150,500 kWh (*Mdn*: 2,000 kWh; *M*: 3,583.3 kWh). Certified water tranches were ordered by 123 business customers in 2015. The tranches ordered range from 1,000 kWh to 923,094 kWh – a total of 4,782,805.8 kWh (*Mdn*: 14,000 kWh; *M*: 38,884.6 kWh). One may notice that the numbers of business customers using the solar and wind tranches are smaller than the number using the water tranche. This is due to the fact that the database includes only business customers who received the renewable default.

Customers with high sun and wind tranche amounts would have received the renewable-plus default. As the main default switch is to renewable energy, this small and unique group of customers is excluded in this specific overview, which aims to demonstrate the situation of renewable energy uptake in 2015 for the main default switch.

Table 9. Descriptive Statistics for Solar, Wind, and Certified Water Tranches before Default Product Change (2015) (n=7,633)

	Sun: ordered amount 2015 in kWh (*n*=39)	**Wind: ordered amount 2015 in kWh (*n*=42)**	**Water: ordered amount 2015 in kWh(*n*=123)**
Number of values	39	42	123
Number of null values	0	0	0
Number of missing values	7,594	7,591	7,510
Minimal value	50	500	1,000
Maximal value	11,300	20,000	923,094
Range	11,250	19,500	922,094
Sum of all non-missing values	53,350.0	150,500.0	4,782,805.8
Median	1,000	2,000	14,000
Mean	1,367.9	3,583.3	38,884.6
Standard error on the mean	316.3	777.9	10,186.0
Confidence interval of the mean at the p level .95	640.4	1,570.9	20,164.2
Variance	3,902,827.3	25,413,617.9	12,761,850,308.7
Standard deviation	1,975.6	5,041.2	112,968.4
Variation coefficient defined as the standard deviation divided by the mean norm	1.4	1.4	2.9

All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults.

Descriptive Statistics for Business Customers on Renewable Tariffs before Default Product Change (2015)

Table 10 shows the descriptive statistics for Nature Basic in 2015.[27] There are no business customers in the group of customers who received the renewable default on the

[27] Nature Basic composition: 95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio. Nature Star composition: 70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, and 10% biomass energy. Nature Star Water additionally invests 1 Rappen for each kWh into ecological funds that invest in local water renaturations. Nature composition: 85% Nature Basic Water, 5% Nature Basic Wind, 5% Nature Basic Sun, and 5% biomass energy. All three

Table 10. Descriptive Statistics for Nature Basic before Default Product Change (2015) for Business Customers (n=7,633)

	Nature Basic 2015 in kWh (*n*=50)
Number of values	50
Number of null values	0
Number of missing values	7,583
Minimal value	1,250.9
Maximal value	364,875
Range	363,624.1
Sum of all non-missing values	1,552,582.9
Median	19,972.6
Mean	31,051.7
Standard error on the mean	7,475.4
Confidence interval of the mean at the p level .95	15,022.4
Variance	2,794,072,783.9
Standard deviation	52,859
Variation coefficient defined as the standard deviation divided by the mean norm	1.7

All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults.

tariffs Nature Star and Nature. The few business customers on those two tariffs were migrated to the renewable-plus default, and thus are excluded in this overview. As stated before, only the metering points with the Nature Basic tariff fall back on hydropower after their renewable energy tranches are used up. Unfortunately, not all metering points that have this tariff can be found through this variable, as some of them have 'hidden' Nature Basic tariffs. The data shown in the table are from the dataset that contains business customers who received the renewable default in 2016 (*n*=7,633). For this descriptive statistic, the 0-values were transformed into NAs to show the distribution of the variables more accurately. The NA values

tariffs are full tariffs where the customer chooses the tariff, and not a specific amount as with a tranche product.

in this variable do not mean that there are no available values for those measuring points, but rather indicate the customers who did not book the tariff. In the process of data cleaning, the free market customers were separated from the regulated market customers, leaving only the latter in the dataset. This tariff (plus the three tranches from above) includes the whole range of electricity products that can be categorized as renewably sourced in 2015. There were 50 business customers who ordered the Nature Basic tariff in 2015 (that are visible in the data). The utility booked in this tariff ranges from as little as 1,250.9 kWh to as much as 364,875 kWh – a total of 1,552,582.9 kWh (*Mdn*: 19,972.6 kWh; *M*: 31,051.7 kWh).

Conclusion

In conclusion, the descriptive statistics for the tariffs that can be categorized as being sourced from renewable energy sources for 2015 show the starting position for the default product change towards renewable energy in 2016. It is remarkable to see the small number of household customers and the even smaller number of business customers who booked a renewable tariff or tranche in 2015. The utility provider made efforts to market the renewable tranches and tariffs in 2014 and 2015, but it seems that the vast majority of customers were not interested and stayed with conventional tariffs. This documented lack of interest in and lack of initiative to actively choose renewable electricity products is the starting position for the default product change in 2016, and shows a background that makes the default effect even more pronounced.

4.1.3 Descriptive Statistics for Contract Choice: 2013-2016

The descriptive statistics on contract choice for the years 2013, 2014, 2015 and for the two time points in 2016 will document the default product change over the studied timespan. The contract choices were re-coded into three labels: conventional, renewable, and renewable-plus.[28] First, the descriptive statistics will be shown for those three contract categories for the household customers, and then for the business customers. A more in-depth analysis will wrap up the chapter with a concentration on the renewable contract category and how it developed over the years, separated for household and business customers.

[28] For more information on the re-coding process, refer to Section 4.1.2 - Re-coding.

Descriptive Statistics for Contract Choice 2013-2016: Household Customers

Table 11. Descriptive Statistics for Contract Choice 2013-2016: Household Customers (n=223,248)

Time Point	***n*** **Conventional Contracts**	***n*** **Renewable Contracts**	***n*** **Renewable-plus Contracts**	***n*** ***NA***
Contract Choice 2013	219,564	0	0	3,684
Contract Choice 2014	220,654	2,009	585	0
Contract Choice 2015	220,633	2,030	585	0
Default Product Changed From Conventional to Renewable Contract				
Contract Choice 01.01.2016	24,527	197,892	829	0
Contract Choice 24.12.2016	25,977	196,376	895	0

All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults.

In Table 11 the descriptive statistics for the household customer's contract choice from 2013 to 2016 can be seen. Since 2013 was before the utility company first had its renewable energy report (2014 and 2015), there is no sufficient information on renewable and renewable-plus contract holders for that year, and a small number of additional metering points have no description at all. This explains the unavailable number of contract holders for renewable and renewable-plus contracts in 2013. As a result, the 2013 data shows 219,564 (98.3%) household customers in the conventional contract category. With the improved data information on renewable and renewable-plus contracts in 2014, a small number of households in the renewable category (2,009 (0.9%)) and an even smaller number in the renewable-plus category (585 (0.3%)) become visible. The overwhelming majority of household customers hold contracts that are categorized as conventional (220,654 (98.8%)). For 2015, the distribution among the three categories remains stable, hinting at the possibility that if there had been information on customers with renewable and renewable-plus contracts in 2013, it would have been similar to the distributions found in 2014 and 2015. In 2015, the majority of household customers still held conventional contracts (220,633 (98.8%)), while a small number of household customers held renewable (2,030 (0.9%)) and renewable-plus (585 (0.3%)) contracts. The vast majority of customers holding conventional contracts in the years 2013, 2014, and 2015 also demonstrates the power of the default effect. In those years, the default contract was conventionally sourced and the majority of household customers accepted this default without deviating from it. In 2016, a new default setting was introduced: the renewably sourced contract. The distribution of household customers over the three contract categories on the 1st of January 2016 shows the time point of the default product change. The customers received a letter announcing the default product change to the renewably sourced contract in August 2015 and had until the 1st of January 2016 to change their contract settings. The time point 1st January 2016 marks the initial default product change realization but not the initial default distribution, since customers had four months to opt out of the new default. On the 1st January 2016, the majority of household customers now held renewable contracts (197,892 (88.6%)). There was a small share of household customers on conventional contracts (24,527 (11.0%)) and an even smaller share of household customers on renewable-plus contracts (892 (0.4%)). The small number of customers holding a renewable or even a renewable-plus tariff in this overview were treated the same as those holding a conventional tariff in 2015. While the 220,633 household customers on the conventional tariff in 2015 upgraded their energy source to renewable, the 2,030 household customers on the renewable tariff in 2015 did not change their energy sources, and the 585 household customers on the renewable-plus tariff downgraded to only renewable energy. Only the 6,452 household customers with special customer profiles were migrated to the renewable-plus default.[29] The distribution of the household customers over the three contract categories on the time point 24th December 2016 shows that the initial default product change effect is stable for that time period. There are 196,376 (88.0%) household customers on renewable contracts, 25,977 (11.6%) on conventional contracts, and 865 (0.4%) on renewable-plus contracts.

Descriptive Statistics for Contract Choice 2013-2016: Business Customers

Since 2013 was before the utility company had its first renewable energy report (2014 and 2015), there is not sufficient information on renewable and renewable-plus contract holders for that year, and a small number of additional metering points have no description at all. This explains the unavailable number of business contract holders of renewable and renewable-plus contracts in 2013. As a result, 2013 has 7,346 (96.2%) business customers in the conventional contract category. With the improved information on renewable and renewable-plus contracts in 2014, a small number of business customers in the renewable category (29 (0.4%)) and an even smaller number in the renewable-plus category (21 (0.3%))

[29] For more information on this customer group, refer to Section 4.3.5 – Subsample Analysis: Renewable-plus Default.

Table 12. Descriptive Statistics for Contract Choice 2013-2016: Business Customers (n=7,633)

Time Point	***n*** **Conventional Contracts**	***n*** **Renewable Contracts**	***n*** **Renewable-plus Contracts**	***n*** ***NA***
Contract Choice 2013	7,346	NA	NA	287
Contract Choice 2014	7,583	29	21	0
Contract Choice 2015	7,583	29	21	0
Contract Choice 01.01.2016	1,166	6,447	20	0
Contract Choice 24.12.2016	1,283	6,309	41	0

All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults.

become visible. However, the overwhelming majority of business customers hold contracts that are categorized as conventional (7,583 (99.3%)). For 2015, the distribution among the three categories remains stable hinting at the possibility that if there had been information on business customers with renewable and renewable-plus contracts in 2013, it would have been similar to the distributions found in 2014 and 2015. In 2015, the majority of business customers still held conventional contracts (7,583 (99.3%)), while a small number of business customers held renewable (29 (0.4%)) and renewable-plus (21 (0.3%)) contracts. The vast majority of business customers holding conventional contracts in the years 2013, 2014, and 2015 demonstrates the power of the default effect. In those years, the default contract was conventionally sourced, and the majority of business customers accepted this default without deviating from it. In 2016, a new default setting was introduced: the renewably sourced contract. The distribution of business customers across the three contract categories on the 1st of January 2016 shows the time point of the default product change realization. The customers received a letter announcing the default product change to renewably sourced contracts in August 2015 and had until the 1st of January 2016 time to change their default settings. Therefore, the time point 1st January 2016 marks the initial default product change realization but not the initial default distribution, since customers had four months to opt out. On the 1st January 2016, the majority of business customers held renewable contracts for the first time (6,447 (84.5%)). There was a small share of business customers on conventional contracts (1,166 (15.3%)) and an even smaller share of business customers on renewable-plus contracts (20 (0.3%)). The small number of customers holding renewable or even renewable-plus tariffs in this overview were treated the same as those holding conventional tariffs in 2015. While the 7,583 business customers on conventional tariffs in 2015 upgraded their energy sources to renewable, the 29 business customers on renewable tariffs in 2015 did not change their energy sources, and the 21 business customers on renewable-plus tariffs in 2015 even downgraded to only renewable energy. Only the 42 business customers with special customer profiles were migrated to the renewable-plus default.[30] The distribution of the business customers across the three contract categories on the time point 24th December 2016 shows that the initial default product change effect is stable for that time period. There are 6,309 (82.7%) business customers on renewable contracts, 1,283 (16.8%) on conventional contracts, and 41 (0.5%) on renewable-plus contracts.

In comparison to household customers, the distribution of the business customers indicates a stronger preference of business customers for conventional contracts even after the default product change in 2016 which supports the main hypothesis of business customers having lower acceptance rates of the renewable default product in comparison to household customers.[31]

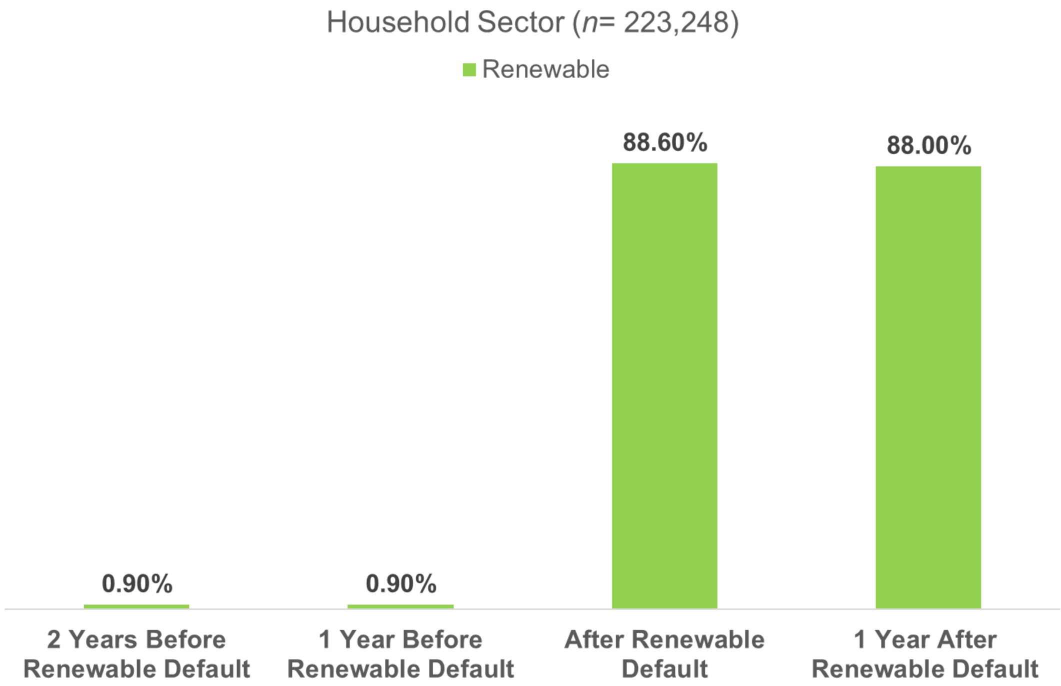
Number of Household Customers on Renewable Contracts: 2014 – 2016

Looking at the change in household customers on renewably sourced contracts over time, the default product change effect becomes even more obvious (see Figure 23). The number of household customers in the renewable contract category before the default product change is quite stable in 2014 (2,009 (0.9%)) and 2015 (2,030 (0.9%)). It can be inferred from this stability that similar numbers would have been seen for 2013 if the information had been accessible. After the default product change to the renewable contract default, the share of household customers with renewable contracts rose substantially to 88.6% (n=197,892). One year after the default product change, 88.0% (n=196,376) of household customers had renewable contracts. Thus, after the default product change, the number of household customers on renewable contracts remained quite stable. This points to the longevity of the dramatic default product change effect.

[30] For more information on this customer group, refer to Section 4.3.5 – Subsample Analysis: Renewable-plus Default.

[31] For more information, refer to Section 2.2.2 - Using Default rules to Promote Renewable Energy Uptake.

Figure 23. Number of Household Customers on Renewable Contracts: 2014 - 2016 (n=223,248) (own illustration)

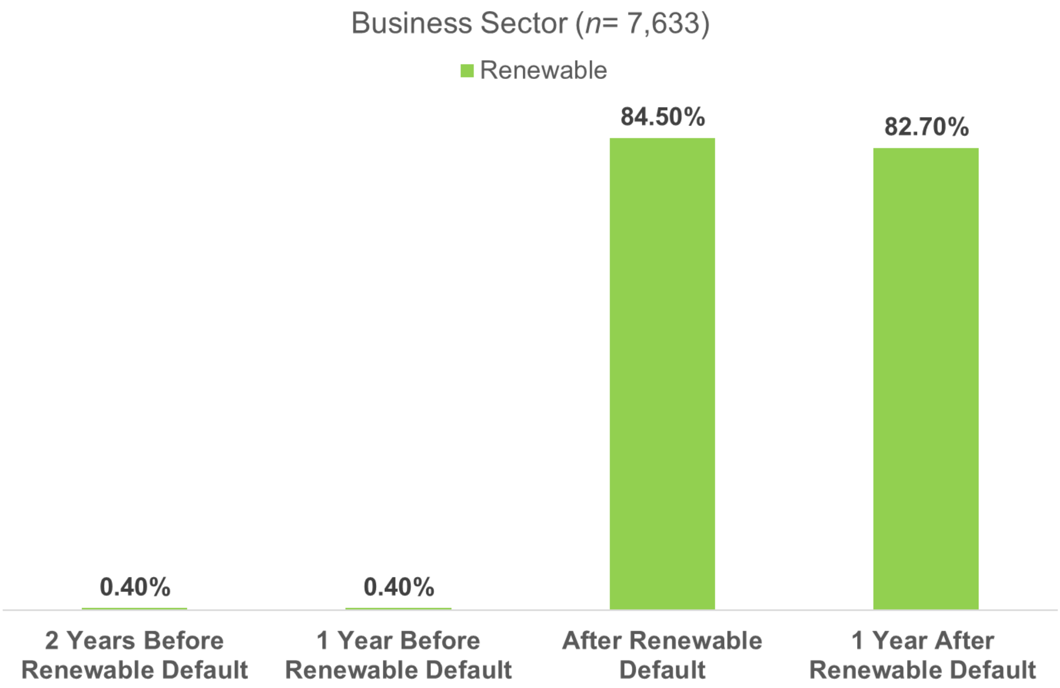


All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults. The year 2013 is left out in this graph because there was no information available on renewable contracts for that year.

Number of Business Customers on Renewable Contracts: 2014 – 2016

The default product change effect can be seen in the share of business customers with renewably sourced contracts along the years (see Figure 24). The number of business customers with renewable contracts before the default product change was quite stable in 2014 (29 (0.4%)) and 2015 (29 (0.4%)). It can be inferred from this stability that the same would likely have applied to 2013 if the data were available. After the default product change to the renewable contract default, the share of business customers with renewable contracts rose substantially to 84.5% (*n*=6,447). One year after the default product change, 82.7% (*n*=6,309) of business customers held renewable contracts. Therefore, even after the default product change, the number of business customers on renewable contracts remained quite stable. This further suggests the longevity of the dramatic default product change effect. In comparison to household customers, the business customers show a stronger preference for conventional contracts which supports the main hypothesis of heterogeneity in the default effect according to customer type.[32] This is manifested in an overall smaller default effect.

Figure 24. Number of Business Customers on Renewable Contracts: 2014 – 2016 (n=7,633) (own illustration)



All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults. The year 2013 is left out in this figure because there was no information available on renewable contracts for that year.

Conclusion

The distribution of household and business customers across the three different contract categories shows the power of the default effect. Before 2016, with a conventional default, the overwhelming majority of both customers held conventional contracts. After 2016, one can see the power of the default effect manifested in the overwhelming majority of both customer types on renewable contracts.

[32] For more information, refer to Section 2.2.2 - Using Default rules to Promote Renewable Energy Uptake.

4.2 Bivariate Analyses

After the descriptive analyses of the main variables of interest – the measurement of utility use and contract choices over the years – bivariate analyses will further explore the variable of contract choice's dependency on other factors on the municipality level.

Section 4.2.1 (The Default Effect) shows the short-term and long-term default effects separately for the household customers and for the business customers. A connection between short-term and long-term default effects depending on utility use will be made. As utility use is typically very different for household customers than for business customers, these analyses are performed separately for the two customer groups. Overall, it will become clear that the default effect in this study shows surprising stability among the different customer groups and quartiles of utility use.

Section 4.2.2 (Analysis of Moving Customers) shows a sub-analysis of customers who moved their business or living locations in the year of the default product change (2016). This subsample of customers was excluded from all main analyses in this study in order to keep the homogeneity of measurement as high as possible. After building factors, as for example the building's isolation, the inhabitants of the building space are the second biggest influence on electricity usage. Excluding moving customers meant cutting down on unobserved heterogeneity in the measurement of utility usage. It is hypothesised that customers who moved in the year of the default product change would read the letter announcing the default product change more carefully than would non-moving customers. This higher attention could manifest in a lower acceptance rate for the renewable default and a higher take up on conventional electricity contracts. However, there were no noticeable differences found in the variable of contract choice between the groups of movers and non-movers in 2016.

Section 4.2.3 (The Voting Initiative 'Nuclear Power Phase-Out' and Renewable Default Acceptance at the Municipality Level) connects the variable contract choice in 2016 with the voting results on the Nuclear Power Phase-Out initiative at the municipality level. The initiative came to a vote in the year just after the default product change, and thus relates to this study in both timely and topical manners. The direct democratic vote was either for or against a quick nuclear phase-out by 2029. It is hypothesised that municipalities with at least 50% of votes in favour of the quick nuclear phase-out would have a higher acceptance of the renewable default than other municipalities. This was verified, but the effect found was only small.

Section 4.2.4 (Proximity to Nuclear Power Plant and Renewable Default Acceptance) analyses the variable contract choice in 2015 and 2016 on the municipality level depending on proximity to a nuclear power plant. In the service area of the utility company is one municipality that has a nuclear power plant situated within. It is hypothesised that the closer municipalities are to a nuclear power plant, the higher their share of conventional electricity contracts and the lower their acceptance of the renewable default in 2016 would be. For contract choice in 2015, no difference could be found, but for 2016, the proximity to a nuclear power plant showed an influence on the acceptance of the renewable default.

In conclusion, bivariate analysis explores interesting potential influences on default acceptance. On the individual level, it connects the type of customer (household or business) as well as the moving status of customers to contract choice. On the municipality level, it connects results from the Nuclear Power Phase-Out initiative and proximity to one of the five Swiss nuclear power plants to contract choice.

4.2.1 The Default Effect

The impressive overall default effect can be documented over the short term as well as over the long term. The short-term default effect describes the time span between the announcement of the default product change in the end of August 2015 and the realisation of the default product change on 01.01.2016. During that time, customers – household and business – had four month to opt out of the new default into either the cost-efficient conventional electricity tariff or the premium-priced renewable electricity tariff. As documented, they were able to either opt out via personal login to an online portal or by calling a local phone number. The online portal held additional information relevant to the choice, such as a mock-up calculation of the customer's yearly utility usage and the cost for that usage under each tariff option.

The long-term default effect can be seen one year later after the realisation of the default product change (exact time point of measurement: 24.12.2016). At that time point, customers had received their four quartile electricity bills of 2016. Household customers would have had the chance to realise the (slight) additional costs in their four bills and business customers might have realised the opportunity to save money by downgrading to the cost-efficient conventional electricity tariff.

Table 13 shows the descriptive statistics for utility use in 2016 separated for business customers and household customers. Comparing the mean of utility use of business customers (45,856 kWh) with that of household customers (4,932.2 kWh) demonstrates the unique patterns of utility use for each customer group. As the tariff prices and typical electricity usage patterns vary for household and business customers, the default effect will be analysed separately for the two customer groups.

Table 13. Descriptive Statistics for Utility Usage 2016 for Customers with Renewable Default

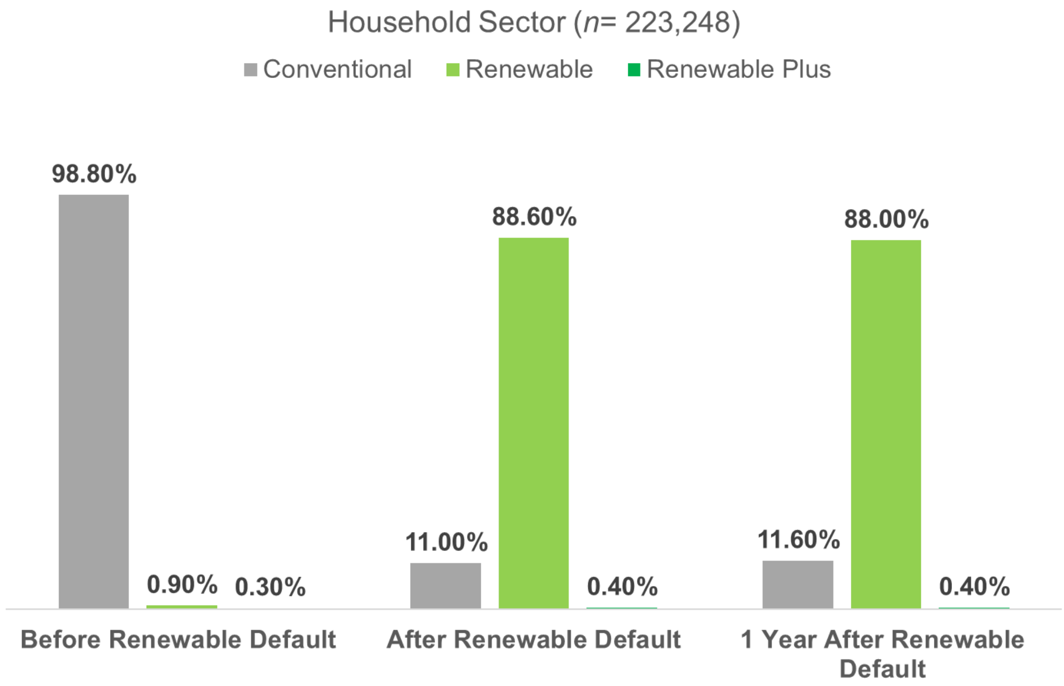
	Utility Usage 2016 Business in kWh (*n*=7,633)	**Utility Usage 2016 Household in kWh (*n*=223,248)**
Number of values	7,622	222,208
Number of null values	0	34
Number of missing values	11	1,040
Minimal value	1	0
Maximal value	3,015,695	541,692
Range	3,015,694	541,692
Sum of all non-missing values	349,517,067	1,095,970,893
Median	29,868	3,427.3
Mean	45,856	4,932.2
Standard error on the mean	1,051	12.6
Confidence interval of the mean at the p level .95	2,059	24.7
Variance	8,412,226,564	35,232,772.3
Standard deviation	91,718	5,935.7
Variation coefficient defined as the standard deviation divided by the mean norm	2	1.2

All descriptive details come from the whole dataset, regulated market, household and business customers, renewable default (n=230,881).

Default Effect for Household Customers

In Figure 25, the column 'Before Renewable Default' shows household customers' tariff choices in 2015, dominated by the conventional tariff and showing a miniscule number of renewable and renewable-plus tariffs. The column 'After Renewable Default' shows the household customers' tariff choices on 01.01.2016: the realisation of the default product change. Here, one can see that the renewable tariff is the dominant one, with 88.6% of household customers staying with the newly introduced default. The number of customers

Figure 25. Tariff Choices of Household Customers (n=223,248) at the End of 2015, the Beginning of 2016, and the End of 2016 (own illustration)

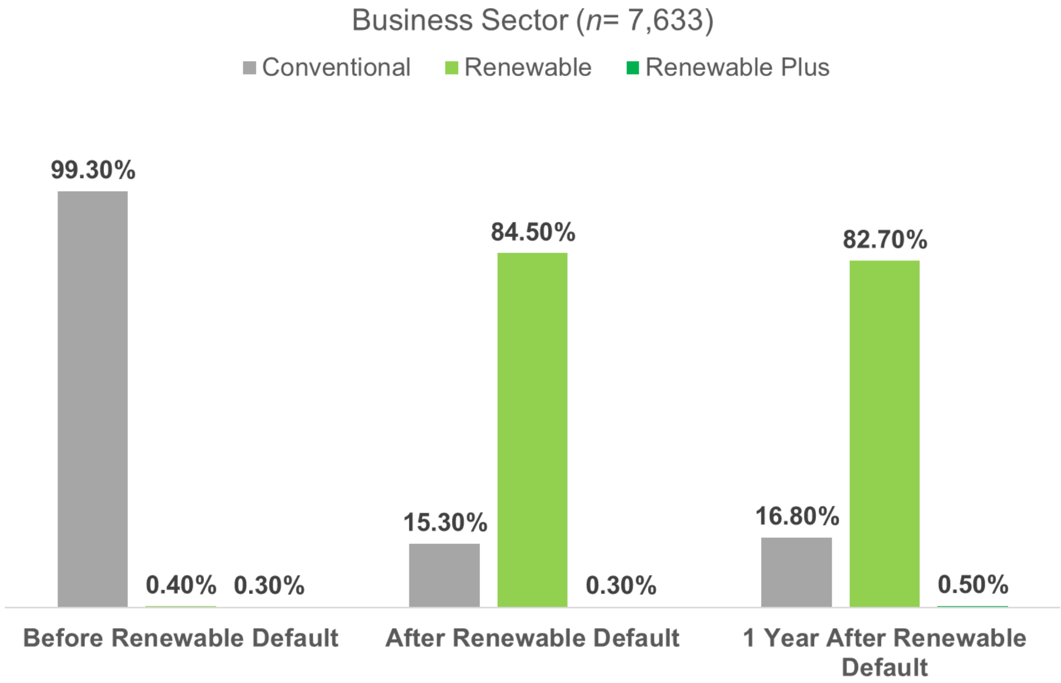


All descriptive details come from the dataset containing the regulated market of household customers with renewable defaults.

opting out of the default is relatively small – around 11.4%, with 11.0% downgrading to the conventional tariff and 0.4% upgrading to the premium renewable-plus tariff. The column '1 Year After Renewable Default' shows the household customers' tariff choices on 24.12.2016. Here, tariff choice is still dominated by the renewable default tariff (88.0%), with a small but stable number of customers choosing the conventional tariff (11.6%) or the premium renewable-plus tariff (0.4%). Calculating the default effect in the short term would mean subtracting the customers who choose the renewable tariff in 2015 from the number of customers who choose it in the beginning of 2016. This yields a short-term default effect of 87.7% (88.6% – 0.9%) for the household customers. Calculating the long-term default effect can be done by subtracting the percentage of customers already on the renewable tariff in 2015 from the percentage of customers staying with the renewable electricity default at the end of 2016. This yields a long-term default effect of 87.1% (88.00% – 0.9%) for the household customers. The default effect is substantial in the short-term measurement and remains stable in the long-term measurement.

Default Effect for Business Customers

Figure 26. Tariff Choices of Business Customers (n=7,633) at the End of 2015, the Beginning 2016, and the End of 2016 (own illustration)



All descriptive details come from the dataset containing the regulated market of business customers with renewable defaults.

In Figure 26, the column ‘Before Renewable Default’ shows the business customers’ tariff choices in 2015. These were strictly dominated by the conventional tariff, with a very small number choosing renewable or renewable-plus tariffs. The column ‘After Renewable Default’ shows the business customers’ tariff choices on 01.01.2016: the realisation of the default product change. Here, one can see that the renewable tariff is the dominant one, with 84.5% of business customers staying with the newly introduced default. The number of customers opting out of the default is relatively small. The total percent of business customers opting out is 15.6%, of which 15.3% downgraded to the conventional tariff and 0.3% upgraded to the premium renewable-plus tariff. The column ‘1 Year After Renewable Default’ shows the business customers’ tariff choices on 24.12.2016. Here, tariff choice is still dominated by the renewable tariff (82.7%), with small but stable number of customers choosing the conventional tariff (16.8%) or the premium renewable-plus tariff (0.5%). Calculating the default effect over the short term involves subtracting the percentage of customers who choose the renewable tariff in 2015 from the percentage of customers who choose the renewable tariff in the beginning of 2016. This yields a short-term default effect of 84.1% (84.5% – 0.4%) for the business customers. Calculating the long-term default effect can be done by subtracting the percentage of customers already on the renewable tariff in 2015 from the percentage of customers staying with the renewable electricity default at the end of 2016. This yields a long-term default effect of 82.3% (82.7% – 0.4%) for the business customers. The default effect for the business customers is not only substantial over the short term, but remains stable over the long term.

There is a similar pattern in both customer groups: households and businesses. The acceptance and longevity of the default effect seems lower for business customers than for household customers. It is hypothesised that this would be the case due to business customers being more price sensitive than household customers. This price sensitivity is grounded in the nature of businesses having to calculate costs more efficiently. The higher electricity usage that further differentiates business customers from household customers makes the price difference between electricity tariffs even more pronounced. To test this hypothesis, one can look into the default effect split up in quartiles of electricity usage, analysed separately for household customers and business customers. The relationship between the short-term/long-term default effects and the utility use in 2016 can be explored by looking at the pure default effect calculated for the quartiles of utility use. The short-term default effect is calculated with the contract choice in the beginning of 2016, and the long-term default effect is calculated with the contract choice in the end of 2016. The hypothesis formulated earlier breaks down into four separately distinguishable hypotheses as follows:

Hypothesis 1: The higher the utility use in 2016 for household customers, the lower their short-term default effect in the beginning of 2016.

Hypothesis 2: The higher the utility use in 2016 for household customers, the lower their long-term default effect in the end of 2016.

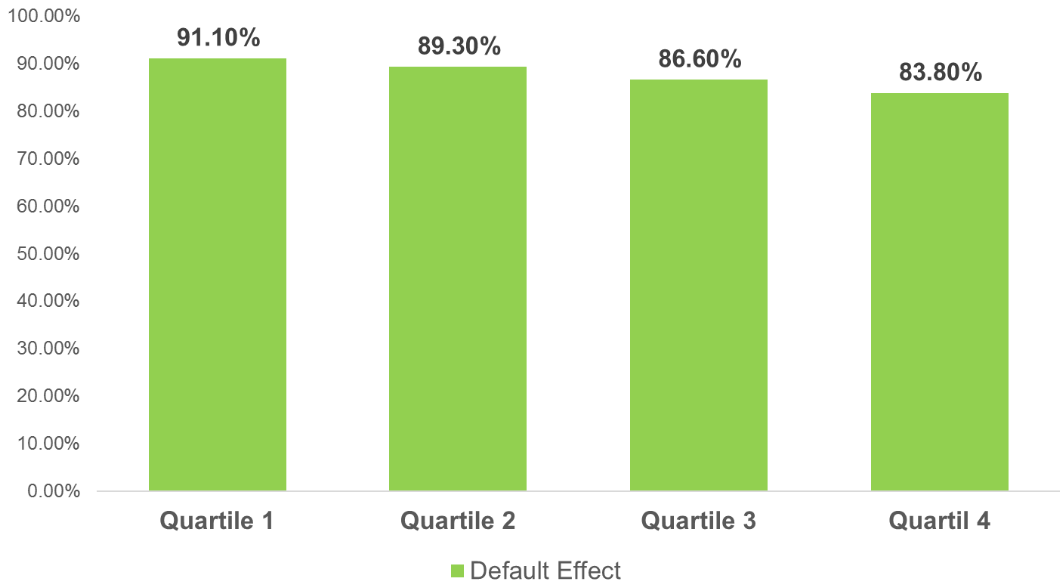
Hypothesis 3: The higher the utility use in 2016 for business customers, the lower their short-term default effect in the beginning of 2016.

Hypothesis 4: The higher the utility use in 2016 for business customers, the lower their long-term default effect in the end of 2016.

In order to analyse the relationship between utility use in 2016 and contract choice, one can calculate the quartiles of utility use in 2016 for households and then calculate the default effect for each quartile. The default effect is the number of customers with renewable energy tariffs in 2016 minus the number of customers with renewable energy tariffs in 2015. This number is then calculated into a percentage to find the pure default effect (the percentage of customers who only held a renewable energy tariff in 2016 because of the default product change). Both short-term and long-term default effects are calculated against the percentage of customers having renewable contracts in 2015.

Short-term Default Effect for Household Customers by Utility Use, 2016

Figure 27. Short-term Default Effect (01.01.2016) by Utility Use 2016 in the Household Sector (n=223,248) (own illustration)



All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults.

The short-term default effect by utility use in 2016 was calculated using the dataset containing only the regulated market and household customers with renewable defaults (*n*=223,248) (see Figure 27).

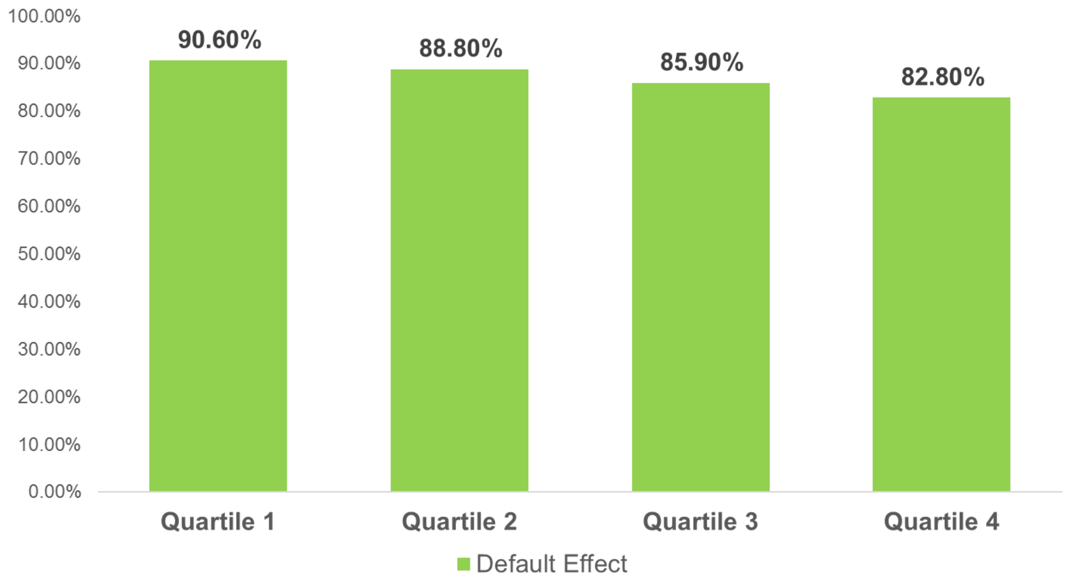
Quartiles of utility use for the household sector were calculated as follows: the first quartile ranges from 0 to 1,796.345 kWh of utility use in 2016, the second quartile ranges from 1,796.345 to 3,427.31 kWh, the third quartile ranges from 3,427.31 to 6,077.35 kWh, and the fourth quartile ranges from 6,077.35 to 541,692.00 kWh. Each quartile of utility use in 2016 has 55,552 customers.

For the first quartile (*n*=55,552), there were 51,076 households on the renewable tariff in the beginning of 2016 and 430 customers on the renewable tariff in 2015. This gives a short-term default effect of 50,646 customers (91.1%). For the second quartile (*n*=55,552), there were 50,189 households on the renewable tariff in the beginning of 2016 and 561 customers on the renewable tariff in 2015. This gives a short-term default effect of 49,628 customers (89.3%). For the third quartile (*n*=55,552), there were 48,747 households on the renewable tariff in the beginning of 2016 and 657 customers on the renewable tariff in 2015. This gives a short-term default effect of 48,090 customers (86.6%). For the fourth quartile (*n*=55,552), there were 46,916 households on the renewable tariff in the beginning of 2016 and 382 customers on the renewable tariff in 2015. This gives a short-term default effect of 46,534 customers (83.8%).

The first quartile has the highest short-term default effect percentage (91.1%), which steadily decreases in the second quartile (89.3%), the third quartile (86.6%), and the fourth quartile (83.8%). Based on the decrease on default effect with the increase of utility usage in 2016, hypothesis 1 holds true: the higher the utility use in 2016 for household customers, the lower their short-term default effect in the beginning of 2016.

Long-term Default Effect for Household Customers by Utility Use, 2016

Figure 28. Long-term Default Effect (24.12.2016) by Utility Use 2016 in Household Sector (n=223,248) (own illustration)



All descriptive details come from the dataset containing only the regulated market of household customers with renewable defaults.

The long-term default effect by utility use in 2016 was calculated using the dataset containing only the regulated market and household customers with renewable defaults (*n*=223,248) (see Figure 28).

Quartiles for the household sector were calculated as follows: the first quartile ranges from 0 to 1,796.345 kWh of utility use in 2016, the second quartile ranges from 1,796.345 to 3,427.31 kWh, the third quartile ranges from 3,427.31 to 6,077.35 kWh, and the fourth quartile ranges from 6,077.35 to 541,692.00 kWh. Each quartile of utility use 2016 has 55,552 customers.

For the first quartile (*n*=55,552), there were 50,791 households on the renewable tariff in the end of 2016 and 430 customers on the renewable tariff in 2015. This gives a long-term default effect of 50,361 customers (90.6%). For the second quartile (*n*=55,552), there were 49,894 households on the renewable tariff in the end of 2016 and 561 customers on the renewable tariff in 2015. This gives a long-term default effect of 49,333 customers (88.8%). For the third quartile (*n*=55,552), there were 48,365 households on the renewable tariff in the end of 2016 and 657 customers on the renewable tariff in 2015. This gives a long-term default effect of 47,708 customers (85.9%). For the fourth quartile (*n*=55,552), there were 46,370 households on the renewable tariff in the end of 2016 and 382 customers on the renewable tariff in 2015. This gives a long-term default effect of 45,988 customers (82.8%).

The first quartile has the highest long-term default effect percentage (90.6%), which steadily decreases in the second quartile (88.8%), the third quartile (85.9%), and the fourth quartile (82.8%). Based on the decrease in default effect with the increase of utility usage in 2016, hypothesis 2 holds true: the higher the utility use in 2016 for household customers, the lower their long-term default effect in the end of 2016.

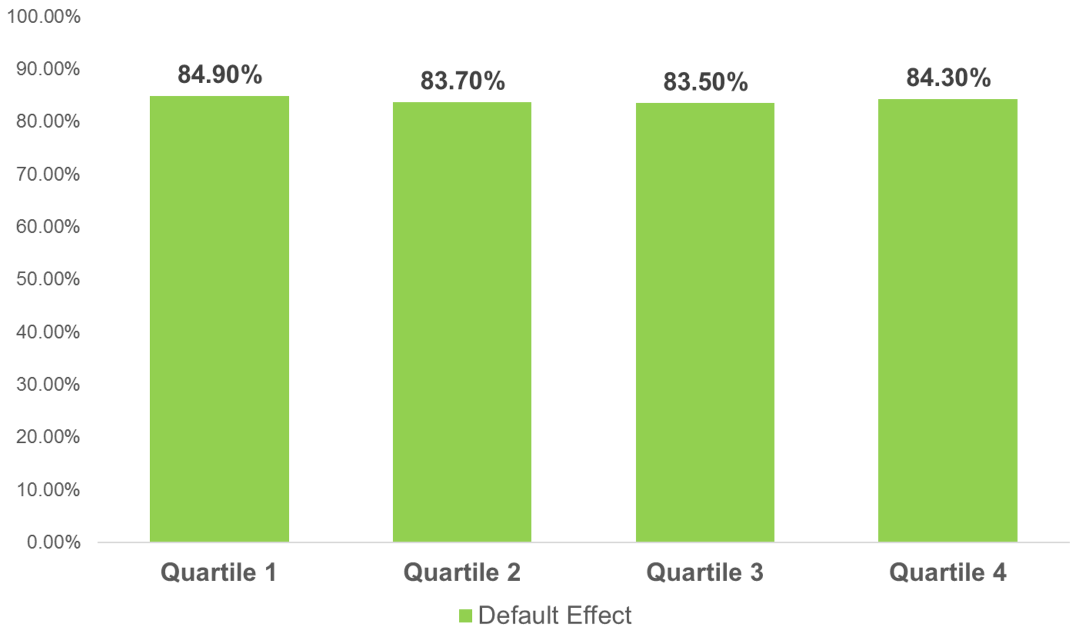
Short-term Default Effect for Business Customers by Utility Use, 2016

The short-term default effect by utility use in 2016 was calculated using the dataset containing only the regulated market and business customers with renewable defaults (*n*=7,633) (see Figure 29).

Quartiles for the business sector were calculated as follows: the first quartile ranges from 0 to 21,628.50 kWh of utility use in 2016, the second quartile ranges from 21,628.50 to 29,867.50 kWh, the third quartile ranges from 29,867.50 to 48,112.25 kWh, and the fourth quartile ranges from 48,112.25 to 3,015,695 kWh. Each quartile of utility use in 2016 had 1,905 or 1,906 customers.

For the first quartile (*n*=1,906), there were 1,631 businesses on the renewable tariff in the beginning of 2016 and 14 businesses on the renewable tariff in 2015. This gives a short-term default effect of 1,617 customers (84.9%). For the second quartile (*n*=1,905), there were 1,596 businesses on the renewable tariff in the beginning of 2016 and two businesses on the renewable tariff in 2015. This gives a short-term default effect of 1,594 customers (83.7%). For the third quartile (*n*=1,905), there were 1,600 businesses on the renewable tariff in the beginning of 2016 and nine businesses on the renewable tariff in 2015. This gives a short-

Figure 29. Short-term Default Effect (01.01.2016) by Utility Use 2016 in Business Sector (n=7,633) (own illustration)



All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults.

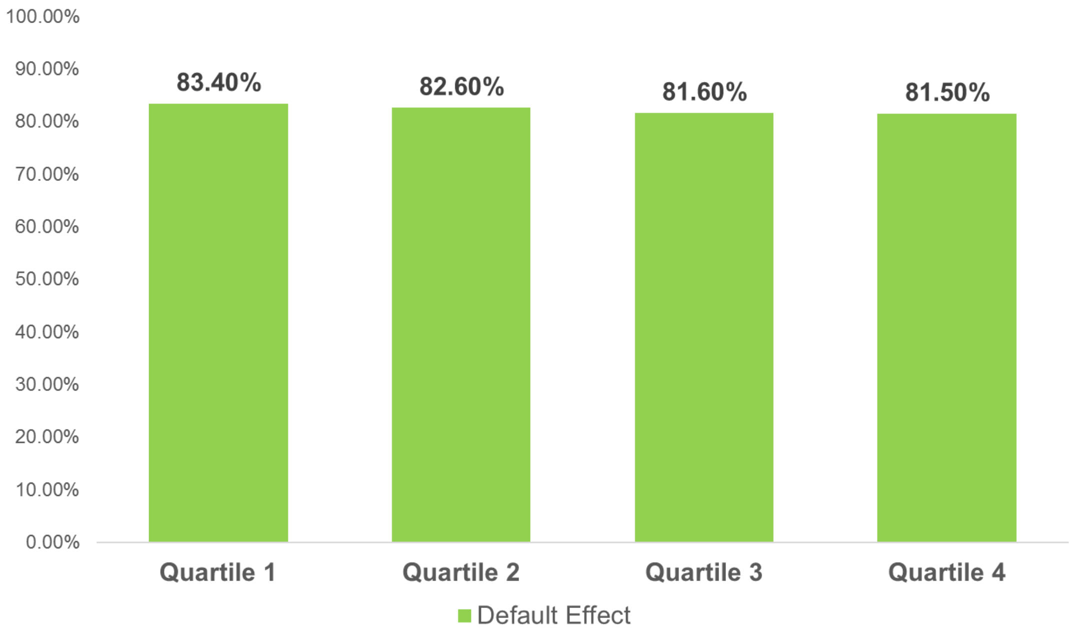
term default effect of 1,591 customers (83.5%). For the fourth quartile (*n*=1,906), there were 1,611 businesses on the renewable tariff in the beginning of 2016 and four businesses on the renewable tariff in 2015. This gives a short-term default effect of 1,607 customers (84.3%).

There is no significant variance in the default effects calculated for the quartiles of utility use in 2016 for the business customers. The default effects range from 83.5% to 84.9%. Aside from the small range of default effects, there is no pattern of a decrease in default effect with higher utility use. Based on the lack of decrease in short-term default effect given the increase in utility usage in 2016, hypothesis 3 is contradicted: the amount of utility use in 2016 does not influence the short-term default effect for business customers.

Long-term Default Effect for Business Customers by Utility Use, 2016

The long-term default effect by utility use 2016 was calculated using the dataset containing only the regulated market and business customers with renewable defaults (*n*=7,633) (see Figure 30).

Figure 30. Long-term Default Effect (24.12.2016) by Utility Use 2016 in Business Sector (n=7,633) (own illustration)



All descriptive details come from the dataset containing only the regulated market of business customers with renewable defaults.

Quartiles for the business sector were calculated as follows: the first quartile ranges from 0 to 21,628.50 kWh of utility use in 2016, the second quartile ranges from 21,628.50 to 29,867.50 kWh, the third quartile ranges from 29,867.50 to 48,112.25 kWh, and the fourth quartile ranges from 48,112.25 to 3,015,695 kWh. Each quartile of utility use in 2016 contains either 1,905 or 1,906 customers.

For the first quartile (*n*=1,906), there were 1,603 businesses on the renewable tariff in the end of 2016 and 14 businesses on the renewable tariff in 2015. This gives a long-term default effect of 1,589 customers (83.4%). For the second quartile (*n*=1,905), there were 1,576 businesses on the renewable tariff in the end of 2016 and two businesses on the renewable tariff in 2015. This gives a long-term default effect of 1,574 customers (82.6%). For the third quartile (*n*=1,905), there were 1,564 businesses on the renewable tariff in the end of 2016 and nine businesses on the renewable tariff in 2015. This gives a long-term default effect of 1,555 customers (81.6%). For the fourth quartile (*n*=1,906), there were 1,558 businesses on the renewable tariff in the end of 2016 and four businesses on the renewable tariff in 2015. This gives a long-term default effect of 1,554 customers (81.5%).

All four quartiles of utility use in 2016 have steady default effect percentages, ranging from 81.5% (the fourth quartile) to 83.4% (the first quartile). There is a small decrease in the long-term default effect with the increase of utility use in 2016, as can be seen in the decreasing default effects for the different quartiles of business customers. Based on the robustness of the default effect through the different quartiles of utility usage in 2016 for the business sector, hypothesis 4 is not supported. The relationship between utility use in 2016 and the long-term default effect in 2016 for business customers is weak at best.

Conclusion

The price sensitivity that was assumed to be more pronounced for the business customers than the household customers cannot be verified. For household customers, the pattern of a decreasing default effect with increasing utility usage is slight but stable for the short-term and long-term default effects. This pattern is more pronounced in the long-term default effect than in the short-term default effect, indicating that household customers can be described as relatively price sensitive. The picture for business customers is different. When looking at the short-term default effect, one can see that the default effect remains stable and only ranges from 83.5% (third quartile) to 84.9% (first quartile). In the long-term, the default effect for business customers is also remarkably stable along the different quartiles of utility usage in 2016, pointing to a lack of relationship between utility usage and the long-term default effect for the business customers. In conclusion, the hypothesis that with higher utility usage the short and long-term default effects will decrease holds true for the household customers, but not for the business customers.

4.2.2 Analysis of Moving Customers in 2016

It was theorized that customers who moved within the year of the default product change (2016) would pay more attention to the default product change.[33] Information on moving customers was extracted from changes in customer numbers on metering points in the time frame of 31.12.2015 – 31.12.2016. Those moving customers could be more inclined to actually read the utility company’s letter of the default product change since they are in a new house and have a first time contract with a new utility company. Existing customers might not be as likely to read every letter that their utility company sends, and thus might have missed reading the letter pronouncing the default product change. Another important reason for a separate analysis of moving customers in 2016 is that the utility provider provided information us that those who moved in 2016 received additional information on the different tariffs and the default product change. In contrast to the standard letter that

[33] The idea for a special analysis of the customers who moved in 2016 came from researcher Prof. Dr. Lorenz Götte of the Institute for Applied Microeconomics at the University Bonn.

was sent out to all regular customers and included only minimal information, the pamphlet sent out to moving customers included more detailed information on the different tariff choices. This additional detailed information could have led to more moving customers opting out of the default since they were more aware of their other choices than the regular customers.

For this analysis, the original raw dataset was used. It had to be prepared specially for this analysis since the cleaned dataset did not contain the movers (they were deleted as part of cleaning the dataset). The utility company treated customers and moving customers differently in 2016. Each metering point has a corresponding customer number that marks the individual who is responsible for paying the bill for that metering point. If one individual is responsible for the expenses of more than one metering point, the different metering points will all show the same individual's customer number. When a customer moves houses and stays geographically in the service area of the electricity company, he or she does not need to choose is or her tariff again. The tariff choice is saved under his or her customer number and implemented at the new metering point. Customer numbers are never recycled, as they are sequenced numbers. In the case of a customer moving outside of the service area and not qualifying as a free market customer, their customer number will not be re-used for a new customer. The new customer would get a new sequenced number.

The main differentiation between 'old customers' and 'new customers' that is of interest in this analysis is, as already stated, that the new customers received an additional pamphlet showing a clear overview of the prices and sources of all three possible electricity products, whereas old customers received the letter announcing the default product change. The letter announcing the default product change was less clear in communicating the possibility that the customer could also choose the cheaper conventional electricity product.

Apart from these customer groups receiving different extents of information on the three product choices, it became clear in the preparation of the data for this analysis that it would not be possible to draw a clear line between the old and the new customers in the moving customer group. In the year 2016, the utility company in this study bought two regional electricity companies. The two electricity companies together had about 13,000 customers, who were integrated into the study utility company's customer pool. The customers from this integration appear in 2016 as 'new customers', and cannot be differentiated clearly from other customers who actually moved to the utility company's supply area (indicated by a new sequenced customer number) or who moved inside the utility company's supply area (indicated by a change of consumer number for one connection object/metering point). This means that 13,000 moves of the total 29,493 moves in 2016 came from this integration (which comprises about 44% of the ‘mover 2016’ sample).

Altogether, this sample (*n*=29,493) contains all metering points where the customer number changed on the metering point (that is, on the connection object). As explained before, this change could indicate several different situations, each resulting in different customer treatments by the utility company. The three possible situations are described as follows.

Possibility A: An established customer moves inside the utility company’s supply area. As an established customer, she keeps the old chosen tariff that is saved under her customer number and is not asked again to choose between products.

Possibility B: A new customer moves inside the utility company’s supply area. As a new customer, he receives the default product change letter plus the pamphlet with a clear overview of the three products and chooses his preferred tariff (or passively receives the default tariff).

Possibility C: A new customer who previously held a contract with one of the two newly purchased electricity companies is integrated into the study utility company’s area. As a new customer, she receives the default letter plus the pamphlet with a clear overview of the three products and chooses her preferred tariff (or passively receives the default tariff).

As these three possible groups received different treatments from the utility company but cannot be differentiated from each other, it can be only estimated that the majority of the sample are new customers (possibilities B or C). It is expected that moving customers would treat the contract choice with more attention than non-moving customers and are therefore more likely to opt out of the renewable default. This is hypothesised as follows.

Hypothesis 1: Compared to established customers, moving customers have a higher rate of opting-out of the renewable default in 2016.

The *N* Total Mover (*n*=29,493) is the sum of *N* Business Mover 2016 (*n*=492) and *N* Households Mover 2016 (*n*=29,001) (see Table 14). The samples ‘Mover 2016’ and ‘Non-mover 2016’ are exclusive and do not overlap, since all customers in the Mover 2016 dataset were excluded in the normal sample (here, called ‘Non-mover 2016’).

Mover 2016 is comprised of 29,493 customers and Non-mover 2016 is comprised of 230,881 customers. The percentages of households versus businesses is slightly different in the two samples: while the Non-mover 2016 sample has 3.3% business customers (*n*=7,663), the Mover 2016 sample has 1.7% business customers (*n*=492). This difference of 1.6 percentage points might be due to the lower likelihood of business customers moving in comparison to household customers. Originally, It is hypothesised that moving customers

Table 14. Contract Choice on 24.12.2016 for Movers (n=29,493) and Non-movers (n=230,881): Total, Business, and Household Customers

	Mover 2016 (*n*=29,493)		**Non-mover 2016 (*n*=230,881)**	
Contract Choice	***n* Business (in %)**	***n* Households (in %)**	***n* Business (in %)**	***n* Households (in %)**
Conventional	60 (12.2%)	3,706 (12.8%)	1,283 (16.8%)	25,977 (11.6%)
Renewable	430 (87.4%)	25,192 (86.9%)	6,309 (82.7%)	196,376 (88.0%)
Renewable-plus	2 (0.4%)	103 (0.4%)	41 (0.5%)	895 (0.4%)
TOTAL	492 (100%)	29,001 (100%)	7,633 (100%)	223,248 (100%)

All descriptive details for the category 'Mover 2016' come from a sub-dataset representing moving customers in 2016, which was excluded from the other datasets during data cleaning (n=29,493). The Mover 2016 dataset contains only the regulated market, including household and business customers with renewable defaults. All descriptive details for non-movers in 2016 come from the whole dataset, containing the regulated market of household and business customers with renewable defaults (n=230,881).

would pay more attention to the letter about the default product change and thus opt out of the renewable default more frequently. However, as the table shows, there is only a slight difference in contract choice for 2016. Comparing the household samples shows that movers accepted the default at a rate of 86.9% and non-movers at a rate of 88.0%. Comparing the business samples shows that movers overall accepted the default at a rate of 87.4% and non-movers at a rate of 82.7%. A Welch's unequal variances t-test shows that the mean of moving customers choosing the renewable contract is significant different to the mean of non-moving customers choosing the renewable contract.[34] Therefore, the difference in accepting the default is more pronounced for business customers than for household customers. This larger difference for the group of business customers could also be an artefact of the smaller sample size for moving business customers (*n*=430).

[34] Results Welch's unequal variances t-test: t=8.867944; df=10,976.51; p-value=8.602589e-19.

Conclusion

In conclusion, coming back to the hypothesis formulated in the beginning, our data rejects that moving customers in comparison to established customers had a higher rate of opting out of the renewable default in 2016. This is especially true given that the difference between the two groups is small in general and points in different directions when split up for business and for household customers.

4.2.3 The Voting Initiative 'Nuclear Power Phase-Out' and Renewable Default Acceptance at the Municipality Level

Switzerland is unique in that it practices a direct democratic system. One of the ways that direct democracy is carried out is through voting initiatives that come to the public vote when an initiative request receives 100,000 signatures from the Swiss people in a timeframe of 18 months. The Nuclear Power Phase-Out initiative came to a public vote in the first year after the default product change in 2016. It was therefore only common sense to connect the data from the default product change experiment with the voting data found on the Swiss federal bureau of statistics to add an interesting descriptive variable at the municipality level. The vote on the Nuclear Power Phase-Out initiative was on the 27th of November 2016, which is in the first year after the default product change.[35,36]

The demand for the Nuclear Power Phase-Out initiative started to become more pronounced with the nuclear catastrophe in Fukushima on the 11th of March 2011. In the aftershock of this event, the Swiss Federal Council decided on a medium-term nuclear phase-out for Switzerland.[37] This decision can be seen as a direct consequence of action that was inspired by the nuclear catastrophe in Fukushima. This decision was confirmed by the Swiss parliament, whose implementation proposal stated that the building of new nuclear power plants is forbidden in Switzerland and already-existing nuclear power plants can be operated

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[35] Official website on the Nuclear Power Phase-Out initiative: Eidenössische Volksinitiative "Für den geordneten Ausstieg aus der Atomenergie (Atomausstiegsinitiative)", Website Schweizerische Eidgenossenschaft, Bundeskanzlei BK, Chronologie Volksinitiativen, https://www.bk.admin.ch/ch/d/pore/vi/vis407.html, last checked 18.12.2017.

[36] Official information pamphlet on the Nuclear Power Phase-Out initiative depicting the pro and con arguments of the political parties involved: Abstimmungsbüchlein zur Atomausstiegsinitiative, https://www.admin.ch/dam/gov/de/Dokumentation/Abstimmungen/Novembre2016/27-11-2016_DE_screen.pdf.download.pdf/27-11-2016_DE_screen.pdf , download 18.12.2017.

[37] "Historisch: Bundesrat beschliesst Atomausstieg", Tages Anzeiger, 25th May 2011, https://www.tagesanzeiger.ch/schweiz/standard/Historisch-Bundesrat-beschliesst-Atomausstieg/story/21114683#overlay , last checked on 18.12.2017.

for as long as the federal inspecting authority acknowledges their safety.[38] With this medium-term nuclear power phase-out comes a loss of energy supply in the future. To plan for sufficient energy supply in the future, a campaign has been founded that runs under the title '*Energiestrategie* 2050' (Energy Strategy 2050). The Strategy aims to, on the one hand, increase energy efficiency, and on the other hand, increase renewable energy sources. The prospect of the Energy Strategy 2050 is that increasing energy efficiency will slow the ever-rising demand for energy, and the extension of renewable energy sources will compensate for much of the energy demand that is now met by nuclear energy sources. The NFP71 research project[39], which financed the research on this default product change experiment, is based on the Energy Strategy 2050, and so is the NFP70 research project[40]. Even though the Energy Strategy 2050 has the year 2050 in its title, this does not necessarily mean that the nuclear power phase-out will be effectively realized by that year. There is no deadline for the realisation of the nuclear power phase-out set out. Which was the main reason why the GPS (*Grünen Partei der Schweiz*/Green Party of Switzerland) set off the federal petition for referendum '*Für den geordneten Ausstieg aus der Atomenergie (Atomausstiegsinitiative*)' (For the ordered nuclear power phase-out (Nuclear Power Phase-Out initiative)). The Green Party of Switzerland (GPS) demanded a nuclear power phase-out for Switzerland by the year 2029. The Swiss Federal Council and the parliament declined the initiative. In a vote on the 27th November 2016, the people of Switzerland declined the initiative as well.

The Nuclear Power Phase-Out initiative was started by the GPS on the 16th of November 2012 as a reaction to the nuclear catastrophe in Fukushima. On the 15th of January 2013, the initiative was ready for a vote with 107,533 signatures. Before 2013, there were several tries to get enough signatures to pass a vote for the Nuclear Power Phase-Out, but none of them got the necessary number of signatures (>100,000).[41]

Since 1969, Switzerland has generated energy using nuclear power plants. By 1984, Switzerland had built and connected a total of five nuclear power plants to the electricity

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[38] "Keine neuen AKW in der Schweiz", Tages Anzeiger, 19th September 2016, https://www.tagesanzeiger.ch/news/standard/national-und-staenderat-einigen-sich-auf-energiestrategie/story/18980254#overlay, last checked on 18.12.2018.

[39] The National Research Programme «Managing Energy Consumption» 71 is a SNF Project that focuses on the human factor of energy consumption. http://www.nfp71.ch/en/Pages/Home.aspx, last checked on 01.07.2019.

[40] The National Research Programme «Energy Turnaround» 70 is a SNF Project that focuses on the technological side of energy consumption. http://www.nfp70.ch/en/Pages/Home.aspx, last checked on 01.07.2019.

[41] NZZ Article "Atomausstiegsinitiative ist zustande gekommen" 17.01.2013, 15:43 Uhr. https://www.nzz.ch/schweiz/atomausstiegsinitiative-ist-zustande-gekommen-1.17945006 , last checked on the 18.12.2017.

network. In 2016, 34% of the electricity demand of Switzerland was met through its nuclear energy plants.[42]

The Nuclear Power Phase-Out initiative had the aim of forbidding the building of new nuclear power plants in Switzerland and limiting the run-time of the existing five nuclear power plants to a maximum of 45 years (with earlier closing due to safety concerns still possible). According to their years of installation, the initiative had the aim to close down the nuclear power plants Beznau 1, Beznau 2, and Mühleberg in 2017; Gösgen in 2024; and Leibstadt in 2029. This would have resulted in a complete nuclear power phase-out by 2029. Under prevailing legal norms, nuclear power plants are allowed to stay active as long as they are regarded by the federal inspection agency as safe to do so. As can be seen, the proposed timeline of the initiative was quite strict, with three out of five nuclear power plants being closed down only one year after the initiative came to a vote. This strict approach to a nuclear power phase-out is understandable in light of the Fukushima catastrophe and the old age of three of the five nuclear power plants. Nonetheless, this strict timeline might have been the deciding reason why the initiative was unsuccessful in the end.

Arguments for the Nuclear Power Phase-Out Initiative

Figure 31. Official Advertising Poster For the Nuclear Power Phase-Out Initiative

[42] For more information on nuclear power plants in Switzerland, refer to https://www.kernenergie.ch/de/home.html, last checked on 18.12.2017.

Figure 31 shows the official advertising poster of the political parties that supported the initiative. The poster for the Nuclear Power Phase-Out initiative states: '*ja. am 27. November zum geordneten Atomausstieg bis 2029*' (Yes. On the 27th of November for a controlled nuclear power phase-out by 2029). The three main arguments for the Nuclear Power Phase-Out initiative were the following: [43,44]

1. Nuclear power plants in Switzerland are too old to be safe.
   The nuclear power plant Beznau 1 is the oldest worldwide, and also the nuclear power plant that has been active the longest worldwide (47 years). Central elements of a nuclear power plant are not built to be replaced or restored (for example, the reactor). Mühleberg and Beznau 2 also are some of the oldest nuclear power plants worldwide.
2. The year 2029 is a clear date to finish the nuclear power phase-out.
   The Energy Strategy 2050 does not contain clear dates for the phase-out of the five nuclear power plants.
3. The controlled nuclear power phase-out is feasible.
   Renewable energy sources are being trialled and tested and can be expanded over the next 13 years until the nuclear power phase-out is completed in 2029.

The arguments for the initiative have as a main issue the fact that the Swiss nuclear power plants are some of the oldest worldwide, and therefore should be deemed unsafe. There is no precedent for running a nuclear power plant longer than those situated in Switzerland, and it is therefore uncharted territory. As no one can know from experience, no one can guarantee the safety of those nuclear power plants. Another argument is that the Energy Strategy 2050 has no deadline for the nuclear power phase-out, which makes the initiative necessary. In summary, the 'pro' side of the initiative is for a quick nuclear phase-out by 2029 and feels that it would be feasible.

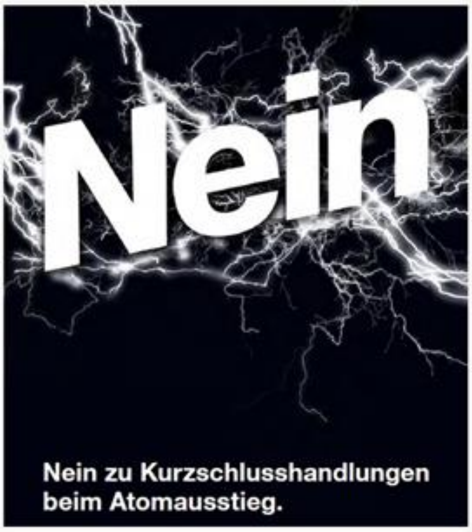
Arguments Against the Nuclear Power Phase-Out Initiative

Figure 32 shows the official advertising poster of the political parties against the Nuclear Power Phase-Out initiative. The poster against the initiative states: '*Nein. Nein zu Kurzschlusshandlungen beim Atomausstieg*' (No. No short-sighted panic reaction concerning

[43] Official information pamphlet on the Nuclear Power Phase-Out initiative depicting the pro and con arguments of the political parties involved: Abstimmungsbüchlein zur Atomausstiegsinitiative, https://www.admin.ch/dam/gov/de/Dokumentation/Abstimmungen/Novembre2016/27-11-2016_DE_screen.pdf.download.pdf/27-11-2016_DE_screen.pdf , download 18.12.2017.

[44] Website for the Nuclear Power Phase-Out initiative: http://www.geordneter-atomausstieg-ja.ch/de/, last checked on 18.12.2017.

Figure 32. Official Advertising Poster Against the Nuclear Power Phase-Out Initiative



the nuclear power phase-out). The three main arguments of the side against the Nuclear Power Phase-Out initiative are the following.[45]

1. More electricity would need to be imported from foreign countries.
   Through the initiative's aim to close three of the five Swiss nuclear power plants in 2017, Switzerland would produce 1/3 less electricity. This portion could not be balanced out quickly enough by renewable energy sources, and therefore electricity imports would rise. This electricity would mainly be imported from France and Germany, and could very well be coming from their nuclear power plants and/or coal-burning power plants.
2. Network infrastructure needs to be changed.
   The existing network infrastructure is not able to cope with the expected heightened electricity import from foreign countries.
3. Compensation money for the nuclear power plant operators would be expensive.
   If the initiative is accepted, it is to be expected that the operators of the five nuclear power plants would demand compensation money from the federal government.

In conclusion, the 'con' side of the Nuclear Power Phase-Out initiative stresses that the proposed timeline in the initiative is not feasible and brings with it risks in the form of energy

[45] Official information pamphlet on the Nuclear Power Phase-Out initiative depicting the pro and con arguments of the political parties involved: Abstimmungsbüchlein zur Atomausstiegsinitiative, https://www.admin.ch/dam/gov/de/Dokumentation/Abstimmungen/Novembre2016/27-11-2016_DE_screen.pdf.download.pdf/27-11-2016_DE_screen.pdf, downloaded 18.12.2017.

dependency on other countries and costs in the form of compensation money for the nuclear power plant operators.

Results of the Nuclear Power Phase-Out Vote

The results of the vote for the Nuclear Power Phase-Out initiative were 1,098,464 ‘yes’ votes and 1,301,520 ‘no’ votes from the Swiss public, and five ‘yes’ votes and 18 ‘no’ votes from the government.

Figure 33. Map Showing the Voting Results in Percentage of ‘Yes’ Votes at the Canton Level [46]

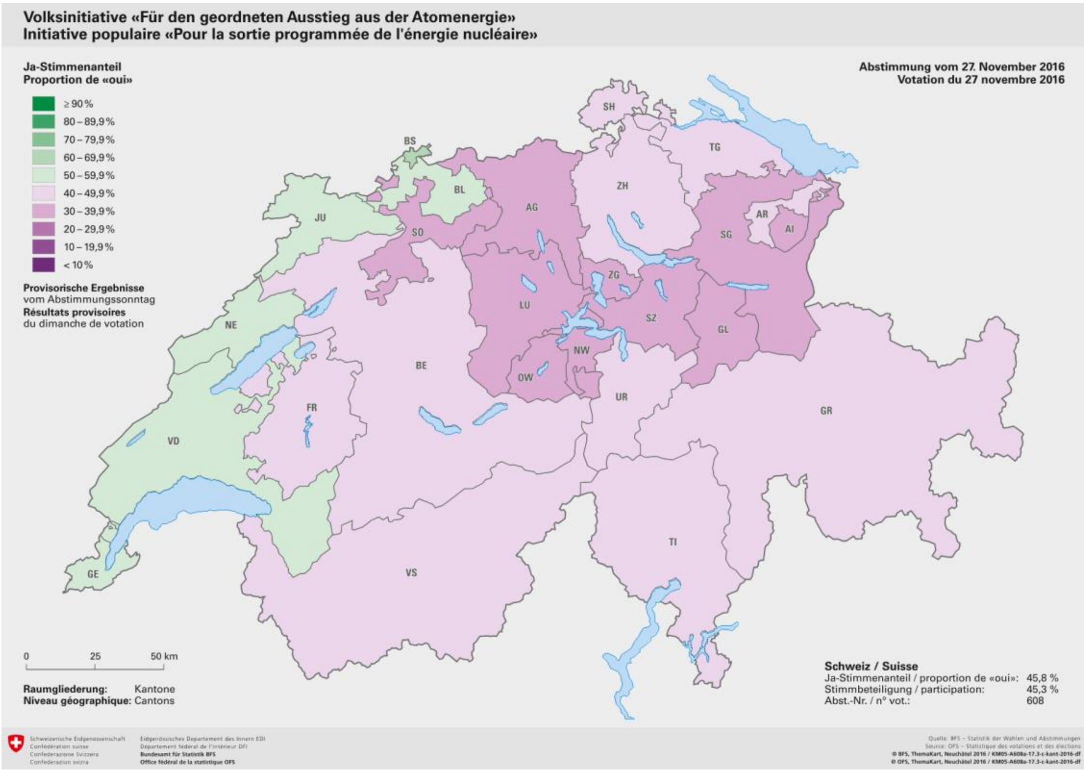


Figure 33 shows the ‘yes’ votes for the Nuclear Power Phase-Out initiative for each canton in Switzerland. ‘*Prozent Ja-Stimmen*’ (% ‘yes’ votes) are separated in 10 classes using the two colours purple (<50%) and green (>50%). Our sample is mainly located in the canton

[46] Source: https://www.bfs.admin.ch/bfs/de/home/statistiken/kataloge-datenbanken/karten.assetdetail.1503556.html , published on 27.11.2016 by the Swiss federal agency for statistics, grouping voting results based on cantons, BFS-Nummer: KM05-A608a-17.3-c-kant-2016-df, Copyright: BFS/OFS/UST/FSO

marked with a purple shade, which corresponds to 40 – 49.9% ‘yes’ votes. The surrounding cantons show different results, ranging from 20 – 59.9% ‘yes’ votes.
The voting results at the municipality level can be seen and downloaded from the homepage of the Swiss federal office for statistics.[47]

Connecting Voting Results of the Initiative with Contract Choice 2015/2016

Since this vote was in the first year of the default product change, the idea came up to connect the voting decision at a municipality level with the dataset received from the utility company. It is hypothesised that municipalities with a high ‘yes’ vote percentage for the Nuclear Power Phase-Out initiative would have low rates of changing from the renewable default to conventional electricity (mostly nuclear energy) in 2016. It is hypothesised that municipalities that had a majority agreeing with the plan of a quick nuclear phase-out would also be more accepting of the renewable electricity default. Hypotheses were formulated as follows.
Hypothesis 1: Municipalities with ‘yes’ vote rates of 50% and above have higher numbers of customers choosing to stay with the renewable energy default in 2016 compared to municipalities with ‘yes’ vote rates of less than 50%.
Hypothesis 2: Municipalities with ‘yes’ vote rates of 50% and above have higher numbers of customers choosing to upgrade to renewable-plus tariffs compared to municipalities with ‘yes’ vote rates of less than 50%.

In order to add the voting results at the municipality level to the dataset received from the utility company, the municipalities had to be matched with the voting data from the Swiss federal institute of statistics. All municipality names in the original dataset were listed and matched with those of the voting results. There are over 300 different municipality names in the dataset that received the renewable default, and these were each matched to a voting result.[48] The voting behaviour regarding the Nuclear Power Phase-Out initiative was added as the variable Nuclear Phase-out Voting 2016.[49]

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[47] Refer to https://www.bfs.admin.ch/bfs/de/home/statistiken/politik/abstimmungen/jahr-2016/2016-11-27/initiative-atomausstieg.assetdetail.1363831.html, downloaded on 21.09.2017.
[48] Exact number of municipalities cannot be given due to keeping the identity of the utility company hidden.
[49] For an overview on the descriptive statistics of the voting results at municipality level, refer to the Appendix 3: Descriptive Statistics of Variables on Municipality Level.

Table 15. Contract Choices Before and After the Renewable Default for Municipalities For (n=48,321) and Against the Initiative (n=169,970)

Contract Choice	Tariff choice **BEFORE** renewable default product change (2015)			Tariff choice **AFTER** renewable default product change (01.01.2016)		
	n Total (in %)	*n* For Initiative (in %)	*n* Against Initiative (in %)	*n* Total (in %)	*n* For Initiative (in %)	*n* Against Initiative (in %)
Conventional	228,216 (98.8%)	47,679 (98.7%)	168,071 (98.9%)	25,693 (11.1%)	4,334 (9.0%)	19,762 (11.6%)
Renewable	2,059 (0.9%)	488 (1.0%)	1,475 (0.9%)	204,339 (88.5%)	43,805 (90.7%)	149,597 (88.0%)
Renewable-plus	606 (0.3%)	154 (0.3%)	424 (0.2%)	849 (0.4%)	182 (0.4%)	611 (0.4%)
TOTAL	230,881 (100%)	48,321 (100%)	169,970 (100%)	230,881 (100%)	48,321 (100%)	169,970 (100%)

All descriptive details come from the dataset containing only the regulated market of household and business customers with renewable defaults.

Some metering points are excluded in this analysis because their municipalities do not have corresponding voting results at the municipality level (*n*=12,590). This sample comes from the dataset containing only the regulated market of business and household customers that received only the renewable default. In accordance with the general results of the voting, the majority of the municipalities in our sample were against the initiative (78%). *N* Total shows the contract choice in 2016 of the whole sample. The columns ‘For Initiative’ show the contract choice for municipalities with at least 50% ‘yes’ votes (metering points *n*=48,321). The columns ‘Against Initiative’ show the contract choice for the municipalities that had less than 50% ‘yes’ votes (metering points *n*=169,970) (see Table 15).

Table 15 shows the tariff choice with the conventional electricity contract as the default (2015) and with the renewable electricity contract as the default (01.01.2016). In the year 2015, there were no differences in the two samples concerning contract choice. With the introduction of the renewable energy default in 2016, a small difference in contract choice appeared. It is hypothesised that municipalities with the majority voting for the nuclear power phase-out would in larger numbers stick with the renewable default. This is supported, as ‘For Initiative’ has +2.7 percentage points of customers who stuck with the renewable default than ‘Against Initiative’. While the difference is small indeed, the results of the Welch's unequal variances t-test show that the mean of customers in the group that is for the initiative is significantly different from the mean of the customers in the group against the initiative.[50]

The second hypothesis was that municipalities with the majority voting for the Nuclear Power Phase-Out would also upgrade in larger numbers to the renewable-plus tariff. This was rejected, since the percentages of customers choosing the renewable-plus tariff were overall the same and did not vary between municipalities that voted for or against the initiative. The difference between the two samples is concentrated in the choice to accept the default or actively choose to downgrade to conventional energy. The main idea behind looking at voting behaviour on the initiative was to make a connection between the proclaimed strong dislike for nuclear energy that can be observed in voting for the Nuclear Power Phase-Out initiative. A preference for renewable energy could be a driver for customers accepting the default product change. It can be theorized that a 'yes' vote for the initiative and its strict time plan of action for a full nuclear phase-out is a good indicator of a stronger dislike of nuclear energy. At first glance, the high acceptance rate of the renewable electricity default (88.5%) stands in stark contrast with the vast majority of the municipalities in our sample voting against the Nuclear Power Phase-Out initiative (78%). How can this proclaimed preference for renewable electricity be reconciled with the overwhelming support of nuclear electricity? For one thing, the group of customers in each municipality is not congruent to the group of people voting on the initiative in the municipality. Even when abstracting to the municipality level, there are unobservable differences between those two groups. For another thing, there are many reasons to vote for or against the Nuclear Power Phase-Out initiative, and a preference for renewable energy does not have to go hand in hand with a 'yes' vote on the initiative. It is arguable that a person could be of the opinion that the renewable electricity that is already available should be preferred to non-renewable electricity, but that the initiative has too strict a timeline and thus vote against the initiative. The nuclear power phase-out is already a decided matter in Switzerland; only the timeline is not decided. The Nuclear Power Phase-Out initiative had a strict timeline that the majority of Swiss people seemed to have felt uncomfortable with, maybe mostly fearing energy dependency on neighbouring countries.

Conclusion

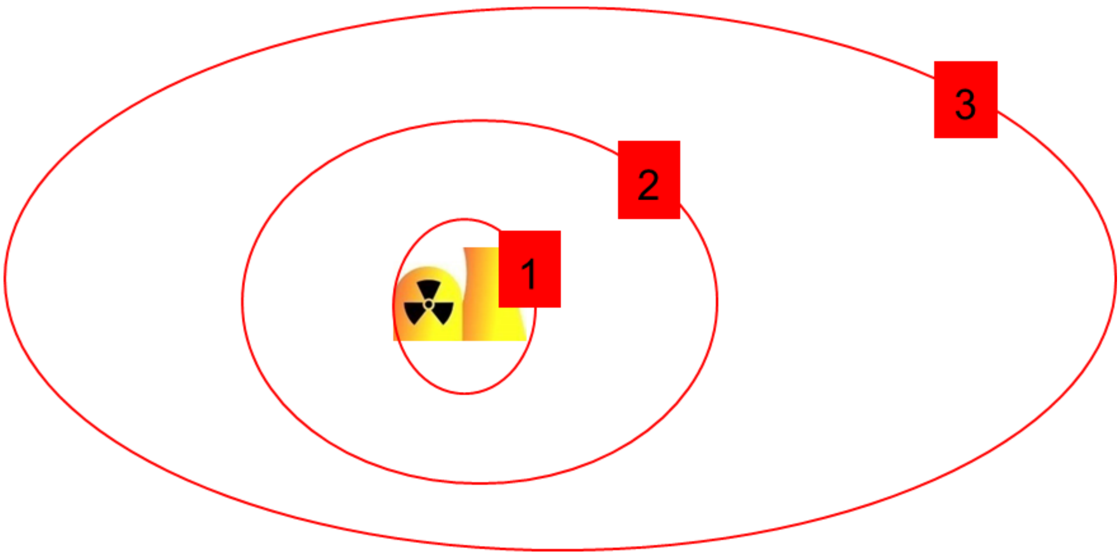
Interestingly, when splitting the municipalities in two groups – one group being those who voted at least 50% for the initiative and another group being those who voted less than 50% for the initiative – there is no difference between the groups' contract choices in 2015.

[50] Results Welch's unequal variances t-test: t= -17.13655; df= 85536.8; p-value= 1.020395e-65

Only with the introduction of the renewable energy default in 2016 does a small difference in contract choice between the municipalities that voted at least 50% for and the municipalities that voted less than 50% for the Nuclear Power Phase-Out appear. It is hypothesised that municipalities voting with the majority for the quick nuclear power phase-out would in larger numbers stick with the renewable default. This is supported, as 'For Initiative' has +2.7 percentage points more customers who stuck with the renewable default than 'Against Initiative'. In conclusion, connecting the data from the default product change experiment with municipality data in the form of voting behaviour regarding the Nuclear Power Phase-Out initiative added an insightful characteristic to the data at the municipality level. This connection will be further explored in the Section 4.3.3 (Multilevel Logistic Regression) of the multivariate analyses. The short timeframe between the realisation of the default product change experiment and the public vote was a fortunate coincidence.

4.2.4 Proximity to a Nuclear Power Plant and Renewable Default Acceptance at the Municipality Level

Figure 34. Overview of the Municipality with a Nuclear Power Plant and Surrounding Municipalities (own illustration)



In this chapter, the contrast between nuclear electricity and renewable electricity is a topic of study. In the previous section 4.2.3 (The Voting Initiative 'Nuclear Power Phase-Out' and Renewable Default Acceptance at the Municipality Level), the two electricity sources were contrasted through comparing voting results and renewable default acceptance at the municipality level. In this section, municipality location in regard to proximity to one of the five nuclear power plants in Switzerland is studied and connected to the renewable default acceptance. In Figure 34, one can see a schematic of the municipality holding the nuclear power plant and its direct neighbouring municipalities. Living in direct proximity to a nuclear power plant seems to underlie some mechanisms of self-selection. People with a strong dislike of nuclear power would self-select themselves to move away from the direct neighbourhood of the nuclear power plant. The nuclear power plant that is situated in one of the municipalities in the dataset was put into operation in 1970’s. Since then, people with a negative attitude towards nuclear energy have had enough time to move out of the neighbourhood as a response to the installation of the nuclear power plant. Or in case, that people were unable to move out of the neighbourhood, they would have time to develop a positive attitude towards nuclear energy for the sake of avoiding cognitive dissonance. The people that remained in the municipality were likely to have a positive attitude towards nuclear energy. This should result in an above-average positive attitude towards nuclear energy in the municipality with the nuclear power plant. The self-selection of people with a positive attitude towards nuclear energy should be visible when comparing the renewable default acceptance of the municipality holding the nuclear power plant with that of other municipalities in the dataset where such self-selection did not take place.

Connecting the dataset of the default product change with the municipality characteristics made it clear that one of the five Swiss nuclear energy plants is situated in one of the municipalities in the network area of the energy supplier.[51]

It is hypothesised that the nuclear power plant (NPP) municipality (the municipality with the nuclear power plant) would have a lower acceptance rate of the renewable default and a higher switch rate to conventional electricity in comparison to other municipalities in the dataset. The presumed higher switch rate to conventional electricity, when faced with the introduction of the renewable electricity default, could be seen as a sign of the above-average pro-nuclear-energy attitude in this municipality. It is imaginable that citizens who are strictly against nuclear energy would have pre-selected themselves by moving away. It also might be that citizens living in direct proximity to a nuclear power plant have built up their trust in nuclear energy and/or might even be employed at the nuclear power plant, and therefore identify themselves as being pro nuclear energy.

[51]For an overview on the five Swiss nuclear power plants, check the website of the Swiss news corporation: https://www.srf.ch/news/schweiz/die-schweizer-atomkraftwerke-im-ueberblick, last checked on 28.09.2017.

Hypothesis 1: The NPP municipality will have a lower share of renewable electricity contracts and a higher share of conventional electricity contracts in 2016 compared to the other municipalities.

It was also hypothesised that since the NPP municipality is only 26.3 km^2 large, the same effect, but weaker, might be detectable for the nine municipalities that share a boarder with the NPP municipality.

Hypothesis 2a: The municipalities in direct proximity to the municipality holding the nuclear energy plant will have lower shares of renewable electricity contracts in 2016 compared to the other municipalities and higher shares of renewable electricity contracts in 2016 compared to the municipality holding the nuclear power plant.

Hypothesis 2b: The municipalities in direct proximity to the NPP municipality will have higher shares of conventional electricity contracts in 2016 compared to the other municipalities and lower shares of conventional electricity contracts in 2016 compared to the NPP municipality.

Descriptive Statistics on the NPP Municipality and its Surrounding Municipalities

Table 16. Number of Metering Points and Population Size for Municipalities in Zone 1 and Zone 2

Municipality	**Metering points in dataset**	**Population Total**	**Voting Results NPP Phase-out Initiative in Yes-Votes %**
Zone 1	1,418	2,843	27.4%
Zone 2	9,523	155,213	40.7%

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults.

Table 16 shows the descriptive statistics for the NPP municipality (zone 1) and its surrounding municipalities (zone 2). The comparison of metering points and population for each municipality shows sufficient coverage for all but two municipalities.[52] Metering points describe the connection points between the electricity network and buildings. It is therefore to be expected that even a full coverage of metering points for a municipality will be in numbers way below the population size. Depending on household size, one metering point can be used by a number of citizens. For most municipalities, the number of metering points

[52] The detailed information of each municipality in zone 2 could not be listed due to data regulations.

in comparison to the population is roughly half. Only two municipalities stand out from this rule and have only eight or nine metering points. The municipalities directly neighbouring the municipality holding the NPP are quite diverse in population size, ranging from about 300 to 130,000 residents, adding up to altogether 155,213 inhabitants (see Table 16). The yes-votes that are for the initiative of the nuclear power phase out are 27.4% for zone 1 and a mean of 40.7% for the municipalities in zone 2. This is in stark contrast with the vast majority of the municipalities in our sample voting against the Nuclear Power Phase-Out initiative (72.83%).

Proximity to NPP and Contract Choices in 2015 and 2016

Table 17. Contract Choices Before and After the Renewable Default for Municipalities, Grouped in Zones Depending on Closeness to NPP

Contract Choice	Tariff choice **BEFORE** renewable default product change (2015)			Tariff choice **AFTER** renewable default product change (01.01.2016)		
	n Zone 1	*n* Zone 2	*n* Zone 3	*n* Zone 1	*n* Zone 2	*n* Zone 3
Conventional	1,403 (98.9%)	9,381 (98.5%)	217,432 (98.9%)	384 (27.1%)	1,275 (13.4%)	24,034 (10.9%)
Renewable	11 (0.8%)	98 (1.0%)	1,950 (0.9%)	1,032 (72.8%)	8,199 (86.1%)	195,108 (88.7%)
Renewable-plus	4 (0.3%)	44 (0.5%)	558 (0.3%)	2 (0.1%)	49 (0.5%)	798 (0.4%)
TOTAL	1,418 (100%)	9,523 (100%)	219,940 (100%)	1,418 (100%)	9,523 (100%)	219,940 (100%)

Zone 1 contains the NPP (n=1,418), Zone 2 directly neighbours zone 1 (n=9,532), and Zone 3 does not directly neighbour zone 1 (n=219,940). All descriptive details come from the dataset containing only the regulated market of household and business customers with renewable defaults.

Table 17 shows the contract choices in 2015 and 2016 for zones 1, 2, and 3. Since there is only one municipality with a nuclear power plant, the samples compared are not evenly divided but rather strongly skewed. There are 1,418 metering points in the dataset that can be located in the NPP municipality, which makes up 0.60% of the utility company's dataset. The nine municipalities directly neighbouring the NPP municipality correspond to a total of 9,523 metering points (4.02% of the utility company's dataset). These two samples are compared to the majority of the metering points, which identify as municipalities neither having a NPP nor neighbouring to a municipality with a NPP (*n*=219,940; 92.67% of the utility company's dataset). For easy identification, the NPP municipality is described as zone 1 and all directly neighbouring municipalities are described as zone 2. All other municipalities that do not house a nuclear power plant and do not neighbour a municipality that does are described as zone 3.

The table shows the tariff choices with the conventional electricity contract as the default (2015) and with the renewable electricity contract as the default (2016). In the year 2015, there are no remarkable differences in the three zones concerning contract choice. They all behaved very similarly concerning their contract choices. With the introduction of the renewable energy default in 2016, differences in contract choice appear. It is hypothesised that the NPP municipality would have a higher share of customers choosing the conventional contract, and thus actively opting out of the renewable default. This is supported by the data, as zone 1 had more customers who actively chose the conventional electricity contract compared to zone 3 (+16.2%). The second hypothesis was that municipalities directly neighbouring the municipality with the nuclear power plant would show a similar effect, and would actively choose the conventional electricity contract more often when faced with the renewable energy default. This is supported by the data as well, as zone 2 had more customers who actively choose the conventional energy contract compared to zone 3 (+2.5%). While zone 1 shows a strong preference for conventional energy even when faced with the renewable electricity default, zone 2 shows only a weak preference. Even though the difference of default acceptance between zone 2 and zone 3 is about 2.6%, a Welch's unequal variances t-test shows that the mean of customers in zone 2 choosing the renewable contract is significantly different from those in zone 3 choosing the renewable contract.[53]

Conclusion

In conclusion, the self-selection of people with pro-nuclear-energy attitude in a municipality harbouring a nuclear power plant seems to hold true for the municipality in this dataset. The metering points located in the municipality with the nuclear power plant have a higher than average rate of opting out of the renewable electricity default and downgrading their contracts to conventional electricity, which is sourced mostly through nuclear energy. This effect can be also seen for the municipalities directly surrounding the municipality with

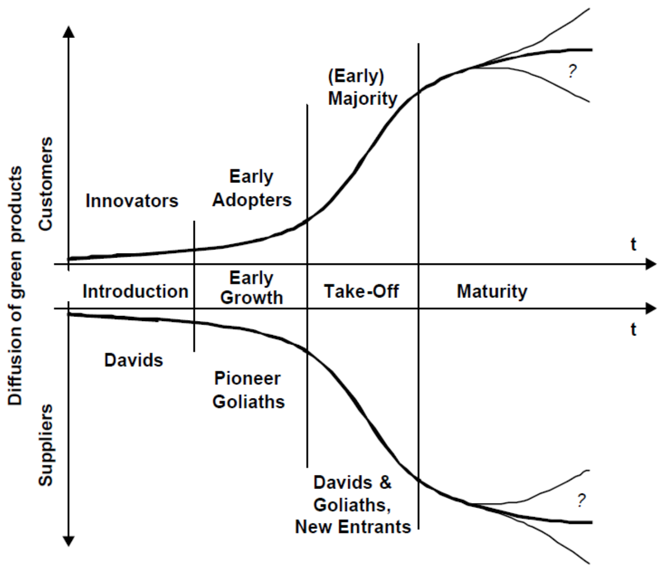
[53] Welch's unequal variances t-test statistics: t=-7.239318; df=10,223.77; p-value=4.833881e-13.

the nuclear power plant. The effect of the surrounding municipalities is visible but weaker in comparison to the municipality containing the nuclear power plant.

4.2.5 Subsample Analysis: Renewable-plus Default

In addition to the major default product change from conventional to renewable energy, this field experiment also offers insight into a small but specific customer group that switched from actively choosing renewable/renewable-plus electricity products in a conventional default product setting to a renewable-plus electricity product setting. It is natural to assume that this small customer group showed strong effort and motivation in choosing a renewable/renewable-plus product when the conventional product was the default product. They did not only pay surcharges on electricity for their renewable product choice, but also made the effort of getting product information from the electricity company and doing the paperwork for choosing a product that is not the default product.

Figure 35. Diffusion of Green Products Over Time Among Customers and Products (Wüstenhagen et al., 2003).



Coming back to the diffusion of green products over time among customers and products, this would indicate that this subgroup can be considered early adapters and that the diffusion stage can be described as early growth (see Figure 35) (Wüstenhagen et al., 2003). In the early growth stage, the market engaged a population of environmentally-minded consumers and innovative business customers. In the market stage, the customers are labelled early adopters and the suppliers 'Pioneer Goliaths'. Pioneer Goliaths refer to bigger companies that are at this point comfortable with getting into the market with new green products. Even though the Swiss renewable electricity market can be considered mature at the time point in question (just before the electricity supplier in question changed to the renewable default product), the small share of customers actively opting out of the conventional default product and choosing a renewable product indicates that the diffusion of the renewable product has only reached the early growth stage in this customer population. With the switch to the renewable/renewable-plus default product, the critical mass of customers using the green product was reached, so the diffusion stage can be described as take-off or even maturity (see Figure 35).

Short Summary of the Renewable-plus Default Facilitation

For customers in the regulated market, there was an exception rule where a small minority of customers received a renewable-plus energy default instead of the renewable energy default. This included customers who paid more than 2.5 Rappen/kWh on premium surcharges on average (not regarding the Energy Basic tariff). To fall into this category, the customer would have to have chosen the tariffs Energy Nature or Energy Nature Star, and/or eco-tranches of wind energy certified Naturemade Star, and/or solar energy certified Naturemade Star in the past year. This would identify the customer as having actively chosen a renewable or a renewable-plus product when the default product setting was a conventional product.

Table 18. Overview of the Saturation of the Default Setting on 31.08.2015

	Whole Dataset	**Household Dataset**	**Business Dataset**
Conventional	0 (0%)	0 (0%)	0 (0%)
Renewable	230,881 (97.3%)	223,248 (97.21%)	7,633 (99.45%)
Renewable-plus	6,452 (2.7%)	6,410 (2.79%)	42 (0.55%)
TOTAL	237,333 (100%)	229,658 (100%)	7,675 (100%)

Table 18 shows that the majority of customers in the regulated market received the renewable default (n=230,881) and only a small minority received the renewable-plus default setting (n=6,452). In total, this exception rule of the renewable-plus default concerns 2.7% of meter points. This can be seen in the descriptive statistics of the variable 'tariff choice' on 31.08.2015, which shows the initial default setting for each household before the default product change was realized. The customer letters announcing the default product change were sent out in August 2015. From then on, the customers were able to reject the new default setting until May 2016. The saturation of the minor default switch – from conventional energy to renewable-plus energy – is 2.7% for the whole dataset, 2.8% for the household customer dataset, and 0.6% for the business customer dataset. The switch to the renewable-plus default was realized only in rare cases of customer descriptions. As stated before, these customer descriptions entailed the necessary 2.5 Rappen/kWh premium surcharge on average (compared to the Energy Basic tariff). This was only possible when choosing the tariffs Energy Nature or Energy Nature Star and/or wind and solar tranches.

Table 19 shows the descriptive statistics of the utility use in 2016 separated for business and household customers which received the renewable-plus default treatment (*n*=6,452). The mean values of utility use 2016 for business and household customers with the renewable-plus default are lower than for those with a standard renewable default (Business customers: 24,703.24 vs. 45,856; Household customers: 3,214.4 vs. 4,932.2).[54] The difference in utility use patterns is more pronounced for the business customers. Nonetheless, this could be an artefact due to the small sample size of business customers with renewable-plus default.

At the end of August 2015, the renewable-plus default introduction was announced via a form letter. The form letters for the renewable default and the renewable-plus default were mostly identical, apart from the obvious difference that they announced either the change from a conventional default to a renewable default or the change from a conventional default to a renewable-plus default. For the customers receiving the renewable-plus default, there is an additional paragraph in the letter explaining to the customer why the renewable-plus product was chosen as the default for this customer. It explains that since the customer has chosen renewable energy products in the past, it would be most suitable to migrate to the renewable-plus product at this point. It is stressed that this migration will not involve higher costs for the customer. But again, the information that a downgrade to the renewable or conventional product would save the customer some money is not given. It is also explained that customers can change their energy product on the web portal. If customers do not

[54] For full information on utility use 2016 for business and household customers with the renewable default, refer to Section 4.2.1 - The Default Effect.

change their choice by the 30th of November 2015, they will receive the renewable-plus energy product from 01.01.2016 on.

Table 19. Descriptive Statistics for Utility Usage 2016 for Customers with Renewable-Plus Default

	Utility Usage 2016 Business in kWh (*n*=42)	**Utility Usage 2016 Household in kWh (*n*=6,410)**
Number of values	42	6,406
Number of null values	0	0
Number of missing values	0	4
Minimal value	1,901	0.5
Maximal value	108,910	96,694.0
Range	107,009	96,693.5
Sum of all non-missing values	1,037,536	20,591,624.2
Median	18,859.50	2,487.2
Mean	24,703.24	3,214.4
Standard error on the mean	3,617.75	36.3
Confidence interval of the mean at the p level .95	7,306.19	71.1
Variance	549,700,858.77	8,436,258.1
Standard deviation	23,445.70	2,904.5
Variation coefficient defined as the standard deviation divided by the mean norm	0.95	0.9

All descriptive details come from the whole dataset, regulated market, household and business customers, renewable-plus default (n=6,452).

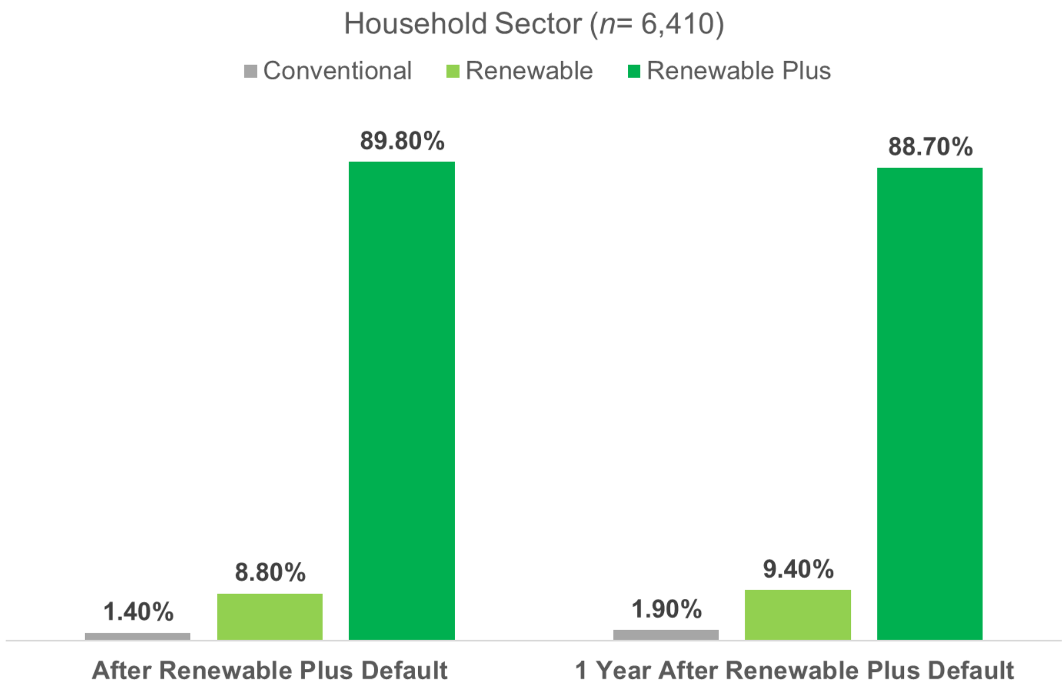
The Analysis of the Renewable-plus Default Effect

The renewable-plus default effect can be documented short-term as well as long-term. The short-term default effect describes the time span between the announcement of the default product change in the end of August 2015 and the realisation of the default product change on 01.01.2016. During that time, customers (household and business) had four months to opt out of the new default into either the conventional or the renewable electricity tariffs. As documented, they were able to either opt out via personal login into an online portal or by calling a local phone number. The online portal held additional information relevant to the choice, such as a mock-up calculation of the individual customer's yearly utility usage and the cost for that usage given each of the three new tariff options.

The long-term default effect can be seen one year after the realisation of the default product change (exact time point of measurement: 24.12.2016). At that time point, customers would have received their four quartile electricity bills of 2016. Customers would have had the chance to seize the opportunity to cut costs by downgrading to the conventional or renewable electricity tariffs.

As the tariff prices and typical electricity usage patterns vary for household and business customers, the default effect will be analysed separately for the two customer groups.

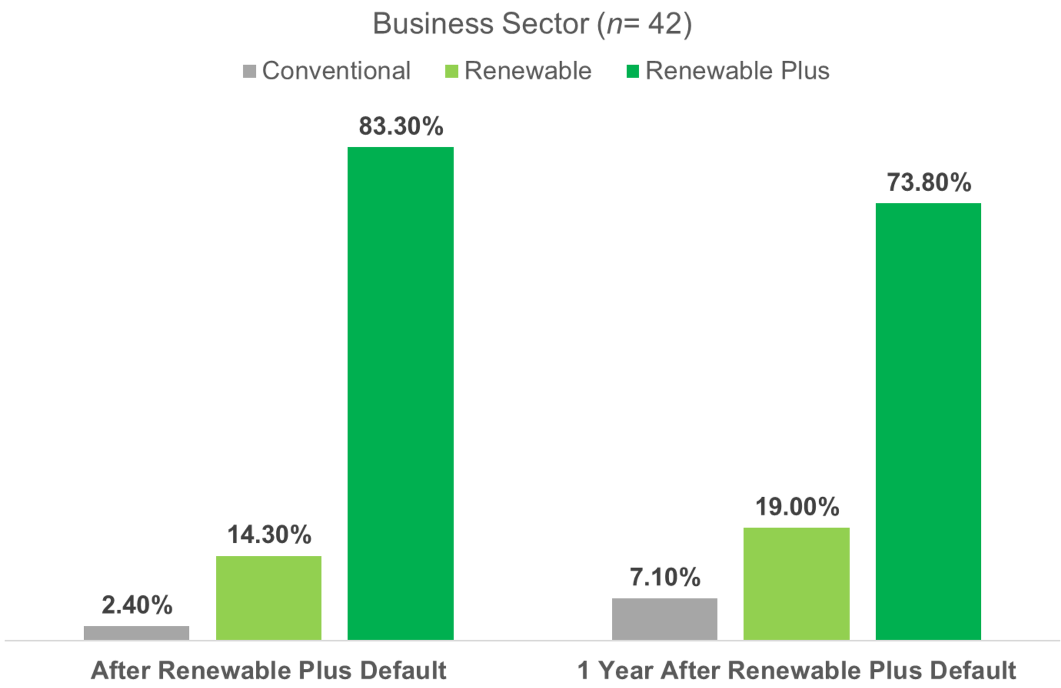
Figure 36. Tariff Choices of Household Customers (n=6,410) at the Beginning and End of 2016 (own illustration)



All descriptive details come from the dataset containing the regulated market of household customers with renewable-plus defaults (n=6,410).

Figure 36 illustrates the tariff choices of household customers who received the renewable-plus default treatment in August 2015 (*n*=6,410). The column 'After Renewable-plus Default' shows the household customers' tariff choices on 01.01.2016, the realisation of the default product change. Here, one can see that the renewable-plus tariff is the dominant one, with 89.8% of household customers staying with the newly introduced default (which was of similar price and quality to their former electricity products). The number of customers opting out of the default is relatively small – about 10.2%, with 1.4% downgrading to the conventional tariff and 8.8% downgrading to the renewable tariff. The column '1 Year After Renewable-plus Default' shows the household customers' tariff choices on 24.12.2016. Here, tariff choice is still dominated by the renewable-plus default tariff (88.70%), with a small but stable number of customers choosing the conventional tariff (1.90%) or the renewable tariff (9.4%).

Figure 37. Tariff Choices of Business Customers (n=42) at the Beginning and End of 2016 (own illustration)



All descriptive details come from the dataset containing the regulated market of business customers with renewable-plus defaults (n=42).

Figure 37 illustrates the tariff choices of business customers which received the renewable-plus default treatment in August 2015 (*n*=42). The column 'After Renewable-plus Default' shows the business customers' tariff choices on 01.01.2016, the realisation of the default product change. Here, one can see that the renewable tariff is the dominant one, as 83.3% of business customers stayed with the newly introduced default (which was of similar price and quality to their former electricity products). The number of customers opting out of the default is around 16.7%, of which 2.4% downgraded to the conventional tariff and 14.3% downgraded to the renewable tariff. The column '1 Year After Renewable-plus Default' shows the business customers' tariff choices on 24.12.2016. Here, tariff choice is still dominated by the renewable-plus tariff (73.8%). A small but increasing number of customers chose the conventional tariff (7.1%) or the renewable tariff (19.0%). Even though the default acceptance goes down from 83.3% in the short term to 73.8% in the long term, overall it can be said that the default effect remains stable in the long-term measurement for the business customers.

There are similar patterns working in both customer groups: households and businesses. The acceptance and longevity of the default effect seems lower for business customers than for household customers. It is hypothesised beforehand that this would be the case due to business customers being more price sensitive than household customers. This price sensitivity is grounded in the nature of businesses having the custom of calculating costs more efficiently. In addition, the higher electricity usage that further differentiates business customers from household customers makes the price differences between electricity tariffs even more pronounced.

Conclusion

In conclusion, business customers opted out of the renewable-plus default in larger numbers (16.7%) than household customers (10.2%) did in the short-term measurement. This was even more the case in the long-term measurement, where 26.1% of business customers opted out of the renewable-plus default and only 11.30% of household customers did. Comparing the short and long-term distributions of contract choices for business customers receiving the renewable-plus default, there is an increased rate of opting out of the default of 9.4% during the first year. For household customers, the increase is only 1.1%. This difference could possibly speak to the price sensitivity that is more pronounced in business customers, but could also possibly be due to the different sample sizes of household customers (n=6,410) and business customers (n=42) receiving the renewable-plus default.

Comparing the major default acceptance rates (the switch from conventional to renewable energy) to the minor default acceptance rates shows that default acceptance rates for the household sector are strikingly similar. Acceptance rates for the major default range from 88% (long-term) to 88.60% (short-term), and acceptance rates for the minor default range from 88.70% (long-term) to 89.80% (short-term). The same holds true for the percentage share of customers choosing to downgrade to cheaper tariffs. In the major default product change scenario, customers were able to choose the cheaper conventional tariff, which they did at rates of 11% (short-term) and 11.60% (long-term). In the minor default product change scenario, customers were able to downgrade to either the conventional or the renewable tariff, which they did at rates of 10.20% (short-term) and 11.30% (long-term). In both default product change scenarios, both default acceptance rates and downgrade rates held stable over the timespan of a year.

Comparing the major default acceptance rates to the minor default acceptance rates shows that default acceptance rates for the business sector are similar in the short-term measurement, but not in the long-term measurement. Acceptance rates for the major default range from 82.70% (long-term) to 84.50% (short-term), and acceptance rates for the minor default range from 73.80% (long-term) to 83.30% (short-term). While the acceptance rate for the major default was quite stable over the timespan of a year, the same does not hold true for the minor default acceptance rates. The acceptance rates for the minor default drops from 83.30% (short-term) to 73.80% (long-term), a drop of nearly 10%. This deviation in acceptance rate patterns should be judged keeping the numbers of business customers who are compared here in mind. The major default product change concerned 7,633 business customers and the minor default product change concerned only 42 business customers. This deviation therefore could be a mere product of the low number of business customers receiving the minor default product change. The same pattern holds true for the percentage share of customers choosing to downgrade to a cheaper tariff. In the major default product change scenario, customers were able to choose the cheaper conventional tariff, which they did at rates of 15.30% (short-term) and 16.80% (long-term). In the minor default product change scenario, customers were able to downgrade to either the conventional or the renewable tariffs, which they did at rates of 16.70% (short-term) and 26.10% (long-term). While, again, the measurement of the downgrade share of customers is stable over the course of a year in the major default product change scenario, it is not in the minor default product change scenario. In line with the 10% drop in acceptance rate, the downgrade rate saw an increase of about 10%. While the difference is obvious, it should not be read too much into. This difference in acceptance rate and downgrade share could be due to the small number of business customers who received the minor default switch.

4.3 Multivariate Analyses

The descriptive and bivariate analyses demonstrate the massive default effect standing on its own, as well as in dependence to other descriptive variables. The multivariate analyses will build on these former results, exploring the heterogeneity of the default effect in more detail. Here, available customer characteristics will be explored regarding their effects on short-term and long-term default acceptance in their accumulation and interdependency.

Section 4.3.1 (Logistic Regression with Short-Term Default Effect) shows a logistic regression with short-term default acceptance being the dependent variable. Models are estimated for the whole dataset as well as separately for the household customers and the business customers. The influences of utility use, previous renewable energy uptake, and customer salutation is explored.

Section 4.3.2 (Logistic Regression with Long-Term Default Effect) shows a logistic regression with long-term default acceptance being modelled as the dependent variable. Models are estimated for the whole dataset as well as separately for the household customers and the business customers. The influences of utility use and customer salutation is explored.

Section 4.3.3 (Multilevel Logistic Regression) shows a multilevel logistic regression with long-term default acceptance being the dependent variable. Models are estimated separately for the household customers and for the business customers. The independent variables on the individual level are customer salutation and utility use. On the municipality level, social descriptive details like population density, age structure, and voting results of the initiative of the nuclear power phase out were added. Furthermore, the closeness of municipalities to the only nuclear power plant in the geographical region of the sample was added. The results show how variables on the individual level affect the odds of customers accepting the default product and how variables on the municipality level affect the odds of customers grouped in municipalities accepting the default product.

In conclusion, the multivariate analysis explores interesting potential influences causing the heterogeneity of long-term default acceptance. On the individual level, it connects the type of customer (household or business), utility use, previous renewable energy uptake, and salutation with short-term and long-term default product acceptance. On the municipality level, it connects social descriptive information, voting behaviour, and geographic proximity to the NPP to the long-term default product acceptance.

4.3.1 Logistic Regression with Short-Term Default Effect

In order to explore possible heterogeneity in the default effect, the question that needs to be addressed is which customer characteristics boost default acceptance and which seem to be hindrances to default acceptance. It follows that default acceptance is the dependent variable and the available customer characteristics are independent variables. Even though the dataset received from the utility company covers a large pool of customers, it offers little information on the customers themselves. The default acceptance will be analysed in its short-term effect in this chapter and in its long-term effect in the following chapter (Section 4.3.2).

A Word on the Dependent Variable

Table 20. Contingency Table of Contract Choices on 01.01.2015 and 01.01.2016 (n=230,881)

	Conventional 01.01.2016 *n=25,693*	**Renewable 01.01.2016 *n=204,339***	**Renewable-plus 01.01.2016 *n=849***
Conventional 01.01.2015 *n=228,216*	25,641 (11.24%)	201,837 (88.44%)	738 (0.32%)
Renewable 01.01.2015 *n=2,059*	42 (2.04%)	1,950 (94.71%)	67 (3.25%)
Renewable-plus 01.01.2015 *n=606*	10 (1.65%)	552 (91.09%)	44 (7.26%)

A generalized linear model was estimated in which the dependent variable is the logarithm of the odds of accepting the default product. The dependent variable is the contract choice of the customers on 01.01.2016. The former three values (conventional/renewable/renewable-plus) of contract choice 01.01.2016 were recoded as the default product acceptance (1=yes/0=no) on 01.01.2016. The short-term default effect refers to the timeframe from August 2015, when the default product change was announced, to 01.01.2016, when the default product change was initiated.

Table 20 shows the contingency table for contract choices on 01.01.2015 and contract choices on 01.01.2016 (*n*=230,881). This contingency table shows how many customers changed their product choices over the course of the year 2015, which is the year during which the default product was changed from a conventional electricity product to a renewable electricity product. On the left side of the table, one can see the contract choices made on 01.01.2015, and on the right side of the table are the contract choices made on 01.01.2016.

The majority of the customer population held the conventional electricity product on 01.01.2015 (*n*=228,216) and the renewable electricity product on 01.01.2016 (*n*=201,837), showing the massive default effect on product choice. Of those customers who held the conventional standard product on 01.01.2015, 88.44% (*n*=201,837) accepted the new default product, 11.24% (*n*=25,641) downgraded to the conventional product, and 0.32% (*n*=738) upgraded to renewable-plus. Of the small customer population that held a renewable electricity product on 01.01.2015, 94.71% (*n*=1,950) accepted the renewable default product, 2.04% (*n*=42) downgraded to conventional, and 3.25% (*n*=67) upgraded to renewable-plus electricity. Of the even smaller number of customers who held a renewable-plus contract on 01.01.2015, 91.09% (*n*=552) accepted the renewable default, 7.26% (*n*=44) upgraded to the renewable-plus product, and 1.65% (*n*=10) downgraded to the conventional product. This contingency table of contract choices just before and after the default product change helps to show the distribution of the dependent variable in the model. With the overwhelming majority of customers moving from the old default product to the new default product, it becomes clear that the rate for the default acceptance is not an even distribution. In actuality, 88.50% of the customer population accepted the new default product. Another interesting point is the persistence of customers holding a renewable contract when the default product was still conventionally sourced energy. Of customers who had a renewable contract on 01.01.2015, 94.71% accepted the renewable default product on 01.01.2016. As this acceptance rate is higher than the average default acceptance rate (88.44%), it was modelled as one of the independent variables (see Contract Choice 2015 Renewable in Table 20).

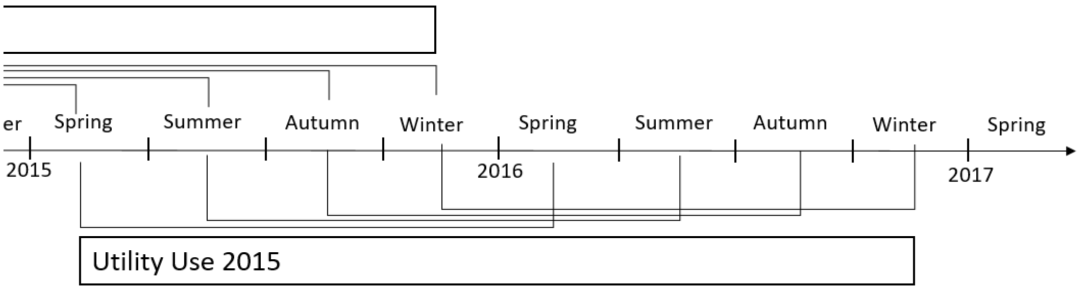
The Independent Variables

The other independent variables are Customer Type Household, Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male.

The independent variable Customer Type Household is a dummy variable based on the variable Customer Type (1=Household and 0=Business). The variable identifies customer types on the basis of tariff choice. Based on the main hypothesis[55] and the results of former bivariate analyses, it is hypothesised that the variable Customer Type Household would increase the log odds of the default acceptance significantly in comparison to the reference group Business.

The independent variables Utility Use 2015 and Utility Use 2015 Squared show the yearly utility usage for customers in the time range beginning in 2015 and continuing until the end of 2016.

Figure 38. Meter Reading Cycles Explained for Utility Use 2015 (own illustration)



As a recap, Figure 38 shows the four different meter reading groups. It shows that the utility use for the year 2015 contains the utility usage from spring 2015 to spring 2016 for the spring group. Furthermore, it contains the utility usage from summer 2015 to summer 2016 for the summer group, the utility usage from autumn 2015 to autumn 2016 for the autumn group, and the utility usage from winter 2015 to winter 2016 for the winter group. Chapter 4.1.1 shows in detail how the annual utility use is made up of the corresponding meter reading groups and demonstrates the timeframe of the meter reading groups for that year. Since the variable Utility Usage 2015 covers the utility usage before and after the default product change, it was chosen over the variable Utility Usage 2016. Based on the theory of price sensitivity, it is hypothesised that the variable Utility Usage 2015 would significantly decrease the log odds of default acceptance. The relationship between Utility Use 2015 and default product acceptance was hypothesised as non-linear based on former bivariate analysis, and therefore the independent variable Utility Usage 2015 Squared was hypothesised to be significant.

[55] For more information, refer to Section 2.2.2 - Using Default rules to Promote Renewable Energy Uptake.

The independent variable Contract Choice 2015 Renewable is a dummy variable based on the variable Contract Choice 2015. Based on the theory of market penetration of green products, It is hypothesised that customers already holding renewable electricity contracts before the default product change would have higher log odds of accepting the new renewable default product than customers who held conventional electricity products.

The independent variables Salutation 2016 Female and Salutation 2016 Male are both dummy variables based on the variable Salutation 2016. Since information such as household size and other social descriptive information is not available on an individual level in the utility company's data, salutation is the only variable that describes metering points on the individual level. The salutation used for billing connects each metering point with the individual who receives the bills for that metering point. The re-coding of the salutations followed the heuristics of determining the gender of the billed individuals on basis of the information given in the salutation. While 'female' and 'male' describe the salutations of billed individuals whose genders were clearly indicated, the value 'mixed' was assigned when a clear gender indication could not be derived from the information given in the salutation. This was applicable when the salutation addressed a couple, a family, or some other term that did not reveal gender. The value 'NA' marks all missing entries for salutation. For this analysis, the values 'mixed' and 'NA' were re-categorized as the reference category 'undefined'. Even though Salutation 2016 makes assumptions regarding the gender of the decision-maker, it is not conclusive. Salutation 2016 indicates the gender of the billed individual but not the gender (or number – singular/plural) of the decision-maker per se.[56] Due to the distribution of the variable Salutation 2016, in which the overwhelming number of salutations had undefined genders, as well as measurement problems with the variable, no hypotheses was formulated.

Table 21 shows the descriptive findings on the independent variables in the logistic regression short-term default acceptance model for all customers (*n*=230,881).

[56] For more information on the variable Salutation 2016, refer to Section 3.4.2 - Re-coding.

Table 21. Descriptive Findings on the Independent Variables in the Logistic Regression for Short-term Default Acceptance (n=230,881)

Variable	M	SD	Min	Max	Description
Customer Type Household	0.97	-	0	1	1=Household (*n=223,248*) 0=Business (*n=7,633*)
Utility Use 2015	6,217.0	20,099.8	0.0	3,790,160	Yearly utility use of the customers in the timespan 2015-2016 (depending on reading cycle)
Contract Choice 2015 Renewable	0.01	-	*0*	*1*	1=Renewable (*n=2,665*) 0=Conventional (*n=228,216*)
Salutation 2016 Female	0.16	-	0	1	1=Female (*n*=37,571) 0=Undefined (*n=193,310*)
Salutation 2016 Male	0.43	-	0	1	1=Male (*n*=98,956) 0=Undefined (*n=131,925*)

Results of Logistic Regression for Short-Term Default Acceptance for All Customers (*n=230,881*)

Table 22 shows the results of the logistic regression for the short-term default acceptance with Contract Choice 01.01.2016 being the dependent variable and Customer Type Household, Utility Use 2015, Utility Use 2015 Squared, Contract Choice 2015 Renewable, Salutation 2016 Female, and Salutation 2016 Male being the independent variables.

In interpreting the percentage change for the estimates, one has to take the odds ratio of the estimate, subtract 1, and multiply by 100 (Long, 2003, pp. 64–84). The result will give the percentage change that the binary outcome variable will be 1, which is in this case that the customer accepts the default product in the short-term. The variable Customer Type Household is an independent dummy variable where the reference category is business. The coefficient is 0.09 and the exponent of the coefficient is 1.094. The effect is significant (p=0.023) and supports the main hypothesis of business customers having lower renewable default acceptance than household customers. Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility Use 2015 (and also Utility Use 2015 Squared) does make Customer Type Household non-significant. It seems as if the distinction between household and business customers is mainly due to their different utility use profiles. When the highest 5% of utility use is excluded (which can directly be translated as

Table 22. Results of Logistic Regression for Short-Term Default Acceptance for All Customers (n=230,881)

Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|) [57]
Intercept	2.046	7.739	0.041	50.116	0.000
Customer Type *Household*	0.09	1.094	0.039	2.277	0.023
Utility Use 2015	-0.006	0.99	0.001	-11.521	0.000
Utility Use 2015 Squared	0	1.000	0.000	6.778	0.000
Contract Choice 2015 Renewable	0.687	1.988	0.081	8.455	0.000
Salutation 2016 Female	0.417	1.517	0.022	18.542	0.000
Salutation 2016 Male	-0.247	0.781	0.014	-17.601	0.000
Null Deviance=164,739 points on 230,880 degrees of freedom Residual Deviance=163,281 points on 230,874 degrees of freedom					

excluding the highest 5% of the utility use of the business customers) the significant distinction of how the customer type affects the log odds of short-term default acceptance gets lost. Therefore, the effect of the independent variable Customer Type Household is mostly driven by the underlying utility use profiles, and more specifically the extreme high utility users of the top 5% in the business sample.

The coefficients of the variables Utility Use 2015 and Utility Use 2015 Squared have to be interpreted together. Both variables have a significant effect on the odds of customers accepting the default product in the short term. Since the direction of Utility Use 2015 is negative, one can infer that Utility Use 2015 has a negative effect on the odds of accepting the default product in the short term. The direction of Utility Use 2015 Squared is positive, which indicates a curvilinear relationship between Utility Use 2015 and short-term default acceptance. Therefore, there is no basic linear relationship between Utility Usage 2015 and short-term default acceptance, but rather a significant curvilinear relationship. The odds for very low and very high utility use are significantly higher than the odds for medium utility use, supporting the hypothesised non-linear relationship between Utility Use 2015 and short-term default acceptance in the beginning. The coefficient of Utility Use 2015 is -0.006, and the exponent of the coefficient is 0.99. Therefore, holding all other variables constant, the

[57] A significance level of 5% is considered if not stated otherwise.

odds of short-term default acceptance were decreased for customers by 1% with an increase of 1,000 kWh utility use. With a *p*-value of 0, this effect is significant. The former hypothesis that Utility Use 2015 would significantly decrease the odds of short-term default acceptance for customers is supported by the data. Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility Use 2015 (and also Utility Use 2015 Squared) does not change the directions or significance levels of those two independent variables. Therefore, the curvilinear relationship of Utility Use 2015 and short-term default acceptance is valid and not due to uncleaned data containing influential data points.

Contract Choice Renewable 2015 is an independent dummy variable marking those customers that held a renewable contract on the 01.01.2015 when the conventional default product was still in place. The coefficient is 0.687, and the exponent of that is 1.988.
Therefore, holding all other variables constant, the odds of short-term default acceptance were increased by 99% for customers with renewable (or renewable-plus) contracts in comparison to customers with conventional contracts as measured on the first day of January 2015. This effect is significant, supporting the hypothesised positive influence of Contract Choice 2015 Renewable on short-term default acceptance and repeating the results of the former bivariate analysis (see Table 20. Contingency Table of Contract Choice 01.01.2015 and 01.01.2016 (n=230,881)).

The variable Salutation 2016 Female is an independent dummy variable marking the female salutations used for billing in 2016. The coefficient of Salutation 2016 Female is 0.417 and the exponent is 1.517. Therefore, holding all other variables constant, the odds of short-term default acceptance were increased by 52% for customers with a female salutation in comparison to customers with an undefined salutation. This effect is also significant (p=0.000). The variable Salutation 2016 Male is an independent dummy variable marking the male salutations used for billing in 2016. The coefficient of Salutation 2016 Male is -0.247 and the exponent is 0.781. Therefore, holding all other variables constant, the odds of short-term default acceptance were decreased by 22% for customers with a male salutation in comparison to customers with an undefined salutation. This effect is also significant (p=0.000). While both salutation variables show an unpredicted significant effect on the log odds of accepting the default product, this effect should be interpreted with care due to the measurement issues with the variable Salutation 2016.

Model Goodness of Fit

The analysis of deviance table shows the significance level of the independent variables, which were added sequentially (first to last) to the model. The table shows that all independent variables are significant. The ANOVA calculation comparing a model containing only the intercept and dependent variable with the model including all independent variables is also significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 164,739 on 230,880 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 163,281 points on 230,874 degrees of freedom, which is a reduction in deviance that is deemed significant. The residual deviance is reduced by 1,458 points with a loss of six degrees of freedom. Keeping in mind the large sample size and according number of degrees of freedom shows that the inclusion of the independent variables does not improve this model by much. Even though the inclusion of the independent variables is significant, its reduction of deviance might only be judged significant according to the high number of degrees of freedom. While the default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong.

Results of Logistic Regression for Short-Term Default Acceptance for Business Customers (*n*=7,633)

Table 23. Descriptive Findings on the Independent Variables in the Logistic Regression for Short-term Default Acceptance (n=7,633)

Variable	M	SD	Min	Max	Description
Utility Use 2015	46,123.68	97,896.43	0.0	3,790,160	Yearly utility use of the customers in the timespan 2015-2016 (depending on reading cycle)
Contract Choice 2015 Renewable	0.004	-	0	1	1=Renewable (*n=29*) 0=Conventional (*n=7,604*)
Salutation 2016 Female	0.027	-	0	1	1=Female (*n=207*) 0=Undefined (*n=7,426*)
Salutation 2016 Male	0.337	-	0	1	1=Male (*n=2,575*) 0=Undefined (*n=5,058*)

With the independent variable Customer Type Household having a significant influence on the odds of accepting the default product in the short-term in the former model with all customers, it is worth exploring this further by calculating a model separated for the business and household customers.

In the following, the logistic regression model will be calculated for only the business customers. The dependent variable is again the contract choice of the business customers on 01.01.2016, which is recoded as a dummy into the acceptance of the default product on 01.01.2016. The independent variables are Utility Use 2015, Utility Use 2015 Squared, Contract Choice 2015 Renewable, Salutation 2016 Female, and Salutation 2016 Male.

Table 23 shows the descriptive findings for the independent variables in the logistic regression model for short-term default acceptance in the business customer sample (*n*=7,633).

Table 24. Results of Logistic Regression for Short-Term Default Acceptance for Business Customers (n=7,633)

Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)
Intercept	1.819	6.164	0.053	34.521	0.000
Utility Use 2015	0.0002	1.000	0.001	0.378	0.705
Utility Use 2015 Squared	-0.0000004	1.000	0.000	-1.306	0.191
Contract Choice 2015 Renewable	0.494	1.639	0.473	1.044	0.297
Salutation 2016 Female	0.204	1.226	0.221	0.921	0.357
Salutation 2016 Male	-0.380	0.684	0.067	-5.71	0.000
Null Deviance=6,593.8 points on 7,632 degrees of freedom Residual Deviance=6,550.3 points on 7,627 degrees of freedom					

Table 24 shows the results of the logistic regression for short-term default acceptance for the business customer sample (*n*=7,633), with Contract Choice 01.01.2016 being the dependent variable and Utility Use 2015, Utility Use 2015 Squared, Contract Choice 2015 Renewable, Salutation 2016 Female, and Salutation 2016 Male being the independent variables.

The coefficients of the variables Utility Use 2015 (0.0002, *p*=0.705) and Utility Use 2015 Squared (-0.0000004, *p*=0.191) have no significant influence on the odds of customers accepting the default product. This finding contradicts the hypothesis that Utility Use 2015 would have a significant negative effect on the odds of customers accepting the default product. This effect was thought to be even more pronounced in the business sample since here the utility use is significantly higher than in the household sample, possibly increasing the theorised price sensitivity.[58]

The coefficient for Contract Choice Renewable 2015 is also not significant (0.494, p=0.297). This might be due to the unequal grouping of this variable that specifically can be found in the business sample and not in the household sample. Comparing the descriptive findings of the independent variable Contract Choice Renewable 2015 shows that only 29 business customers held a prior renewable contract choice. For the household customers, 2,030 customers held a prior renewable contract choice (see Table 21 and Table 23).

The coefficient of Salutation 2016 Female is not significant either (0.204, p=0.357). This also might be due to the unequal grouping of this variable that specifically can be found in the business sample and not in the household sample. Comparing the descriptive findings of the independent variable Salutation 2016 Female shows that only 207 business customers were marked with a female salutation, but for the household customers there were 37,364 customers.

Finally, the coefficient of Salutation 2016 Male is significant (-0.380, p=0.000). The exponent of the coefficient of Salutation 2016 Male is 0.684. Therefore, holding all other variables constant, the odds of short-term default acceptance were decreased by 32% for customers with a male salutation in comparison to customers with undefined salutations.

Model Goodness of Fit

The analysis of deviance table shows the significance level of the independent variables, which were added sequentially (first to last) to the model. It shows that only Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male are significant. The ANOVA calculation comparing a model containing only the intercept and dependent variable with the model including all independent variables is significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 6,593.8 on 7,632 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 6,550.3 points on 7,627 degrees of freedom. The residual deviance is reduced by 43.5 points with a loss of five degrees of freedom, which is a significant reduction in deviance. Even though the inclusion of the independent variables is partly

[58] For the sake of comparability to the other models, the curvilinear term of Utility Use 2015 was included in this model even though it is non-significant. Estimating the model with a linear term of Utility Use 2015 shows that the effect is still insignificant.

significant, its reduction of deviance can be considered small. While the default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong.

Results of Logistic Regression for Short-Term Default Acceptance for Household Customers (*n*=223,248)

Due to the binary outcome variable that is the acceptance of the default product on 01.01.2016, a generalized linear model in which the dependent variable is the logarithm of the odds of accepting the default product was created. The dependent variable is again the tariff choice of the customers on 01.01.2016, which was recoded as a dummy into the acceptance of the default on 01.01.2016. The independent variables are Utility Use 2015, Utility Use 2015 Squared, Contract Choice 2015 Renewable, Salutation 2016 Female, and Salutation 2016 Male.

Table 25. Descriptive Findings on the Independent Variables in the Logistic Regression for the Short-term Default Acceptance (n=223,248)

Variable	M	SD	Min	Max	Description
Utility Use 2015	4,852.543	5,819.726	*0.0*	766,533	Yearly utility use in 1,000 kWh of the customers in the timespan 2015-2016 (depending on reading cycle)
Contract Choice 2015 Renewable	0.009	-	*0*	*1*	1=Renewable (*n=2,030*) 0=Conventional (*n=221,218*)
Salutation 2016 Female	0.167	-	0	1	1=Female (*n=37,364*) 0=Undefined (*n=185,884*)
Salutation 2016 Male	0.432	-	0	1	1=Male (*n=96,381*) 0=Undefined (*n=126,867*)

Table 25 shows the descriptive findings on the independent variables and Table 26 gives the results of the logistic regression for short-term default acceptance for the household customers (*n*=223,248).

Table 26. Results of Logistic Regression for Short-Term Default Acceptance for Household Customers (n=223,248)

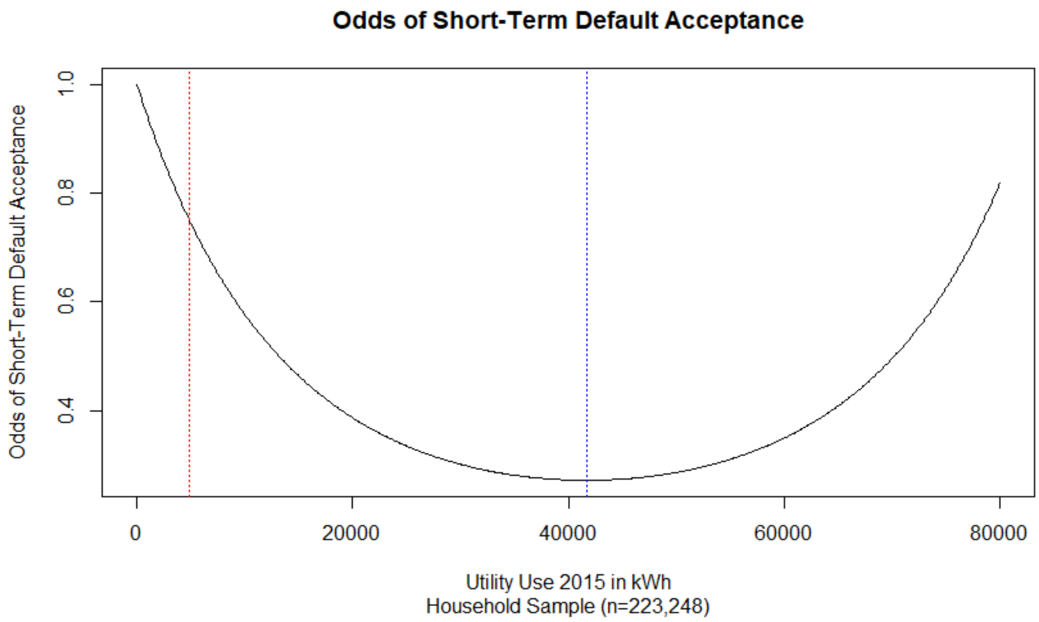
Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)
Intercept	2.394	10.955	0.014	168.933	0.000
Utility Use 2015	-0.062	0.94	0.002	-30.333	0.000
Utility Use 2015 Squared	0.0007	1.000	0.000	13.976	0.000
Contract Choice 2015 Renewable	0.672	1.958	0.083	8.136	0.000
Salutation 2016 Female	0.354	1.424	0.023	15.524	0.000
Salutation 2016 Male	-0.234	0.792	0.014	-16.251	0.000
Null Deviance=158,029 points on 223,247 degrees of freedom Residual Deviance=155,577 points on 223,242 degrees of freedom					

In Table 26 the results of the logistic regression for short-term default acceptance can be found for the household customer sample (*n*=223,248), with Contract Choice 01.01.2016 being the dependent variable and Utility Use 2015, Utility Use 2015 Squared, Contract Choice 2015 Renewable, Salutation 2016 Female, and Salutation 2016 Male being the independent variables.

The coefficients of the variables Utility Use 2015 (-0.062, *p*=0.000) and Utility Use 2015 Squared (0.0007, *p*=0.000) had a significant influence on the odds of household customers accepting the default product. This supports the hypothesis that utility use would have a negative effect on short-term default product acceptance and that this effect would be non-linear. Therefore, with very low and very high utility consumption, the odds of accepting the default product short-term significantly increased in comparison with moderate utility consumption. The coefficient of Utility Use 2015 is -0.062 and the exponent of the coefficient is 0.94. Therefore, holding all other variables constant, the odds of short-term default acceptance were decreased for customers by 6% for an increase in yearly utility use of 1,000 kWh. With a *p*-value of 0, this effect is significant. The former hypothesis that Utility Use 2015 would significantly decrease the odds of short-term default acceptance for customers is supported by the data. Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility Use 2015 (and also Utility Use 2015 Squared) does not change the direction or the significance levels of those two variables. Therefore, the curvilinear relationship of Utility Use 2015 and short-term default acceptance is valid and not due to uncleaned data containing influential data points.

Figure 39 shows the odds of short-term default acceptance for the utility use in 2015 in the household sample (*n*=223,248), holding all other independent variables constant. The lowest odds (0.27) occurred at a yearly utility use of 41,672 kWh (see Figure 39; point marked with a blue dotted line). For a better visual on the curvilinear relationship between Utility Use 2015 and the odds of accepting the default in the short-term, the x-axis ranges from 0 to 80,000, thus not including the very extreme cases of utility use in the household sample. As an orientation on the distribution of the variable, the mean of Utility Use 2015 for the household sample is marked with a red dotted line in Figure 39 (the mean of yearly utility use is 4,853 kWh in the household sample). The median of Utility Use 2015 for the household sample is 3,436 kWh.

Figure 39. Odds of Short-Term Default Acceptance for Utility Use 2015 (own illustration; n=223,248)



The coefficient for Contract Choice Renewable 2015 is 0.672 (*p*=0.000) and the exponent is 1.958. Therefore, holding all other variables constant, the odds of short-term default acceptance were increased by 96% for customers with renewable (or renewable-plus) contracts in comparison to customers with conventional contracts as measured on the first day of January in 2015. This supports the hypothesis that former renewable contract holders would more eagerly accept the new renewable default product. This is a result that is also seen in the bivariate analysis of the contingency table of Contract Choice 01.01.2015 and 01.01.2016 (see Table 20).

The coefficient for Salutation 2016 Female is 0.354 (*p*=0.000) and the exponent is 1.424. Therefore, holding all other variables constant, the odds of short-term default acceptance were increased by 42.4% for customers with female salutations in comparison to customers with undefined salutations.

The coefficient for Salutation 2016 Male is -0.234 (*p*=0.000) and the exponent is 0.792. Therefore, holding all other variables constant, the odds of short-term default acceptance were decreased by 21% for customers with male salutations in comparison to customers with undefined salutations.

Model Goodness of Fit

The analysis of deviance table that shows the significance levels of the independent variables added sequentially (first to last) to the model shows that all independent variables are significant. The ANOVA calculation, comparing a model containing only the intercept and dependent variable with the model including all independent variables, is also significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 158,029 on 223,247 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 155,577 points on 223,242 degrees of freedom, which is a significant reduction in deviance. The residual deviance has been reduced by 2,452 points with a loss of five degrees of freedom. Keeping in mind the large sample size and according numbers of degrees of freedom, the inclusion of the independent variables does not improve this model by much. Even though the inclusion of the independent variables is significant, the reduction of deviance can be considered small. While the default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong.

Conclusion

Table 27. Overview of Percentage Changes in Logistic Regression for Short-Term Default Acceptance

Variable	Percentage Change: Whole Dataset (*n*=230,881)	Percentage Change: Business Sample (*n*=7,633)	Percentage Change: Household Sample (*n*=223,248)
Customer Type *Household*	9.4%*		
Utility Use 2015	-1%***	0%	-6%***
Utility Use 2015 Squared	0%***	0%	0%***
Contract Choice 2015 Renewable	98.8%***	63.9%	95.8%***
Salutation 2016 Female	51.7%***	22.6%	42.4%***
Salutation 2016 Male	-21.9%***	-31.7%***	-20.9%***

*+p<0.10 *p<0.05 **p<0.01 ***p<0.001*

Table 27 gives an overview of the calculated percentage changes from the logistic regressions for short-term default acceptance in this chapter. From the results of these three models, it becomes clear that the whole dataset and the household sample show very similar directions and significance levels for the independent variables. This is mainly due to the fact that the overall sample is primarily made up of household samples. The business sample has more deviation in directions and significance levels for the independent variables. Only one independent variable is stable in its direction and significance level among all three models, and that is Salutation 2016 Male. Holding all other variables constant, the odds of short-term default acceptance are decreased by a range of 20.9% (business sample) to 31.7% (household sample) for customers with male salutations in comparison to customers with undefined salutations.

While the former descriptive and bivariate analyses showcase the strength of the default effect in the data, the multivariate analysis points out the shortcomings and lack of powerful explanatory variables in the data. Even though the dataset received from the utility company covers a large pool of customers, it offers only little information on the customers themselves. There is an imbalance of powerful default effect and weak explanatory variables. Drawing from theory, there are variables one can think of that are missing in this dataset and hold the potential to explain more in-depth what underlies the power of the default effect.

Most of those theorized variables are on the individual level, fleshing out the economic situation and the social descriptive characteristics of the decision-makers. Possible customer characteristics that are not captured in this dataset but could potentially hold explanatory power for the heterogeneity of the default effect are explored in the discussion of the results (Chapter 6).

4.3.2 Logistic Regression with Long-Term Default Effect

While the previous chapter analyses what influences the default product acceptance in the short-term, this chapter concentrates on the long-term default acceptance. In order to explore the possible heterogeneity in the long-term default effect acceptance, it needs to be asked which customer characteristics boost the default acceptance and which seem to be hindrances to the default acceptance. The default acceptance is the dependent variable, and the available customer characteristics are independent variables. The long-term default effect refers to the timeframe starting with the first day of January 2016, when the default product change was introduced, and ending on the 24th of December 2016. This time range covers nearly a full year, and with that, four utility bills to the customers.

A Word on the Dependent Variable

Due to the binary outcome variable – that is, the acceptance of the default product long-term – a generalized linear model in which the dependent variable is the logarithm of the odds of accepting the default product in which the predicted probability of the binary logistic regression is chosen. The dependent variable is calculated as the persistent acceptance of the default product throughout 2016. It combines information of the tariff choices of the customers on 01.01.2016 and on 24.12.2016. The former three values (conventional/renewable/renewable-plus) of the tariff choice on 01.01.2016 and 24.12.2016 were recoded into long-term default acceptance (1=default acceptance on both time points/0=default acceptance on only one of the time points or none of the time points).[59]

[59] Calculating a model where the persistence of default acceptance is modeled via an independent variable showed several problems. The persistence of default acceptance is very strong in the data while other independent variables only have none or weak explanatory power. The overwhelming strength of the coefficient is due to the fact that 99.17% (n=202,652) of the customers stayed with the renewable default contract from 01.01.2016 to 24.12.2016. Calculating a model where the persistence of default acceptance is modeled as an independent variable and comparing the same model without that independent variable shows the major explanatory power in the AIC value. Without the persistence of default acceptance variable the AIC value is 169,895 and with the variable it is 19,888. The unbalance of explanatory power between the independent variables shows itself through strong autocorrelation between the independent variable modeling the persistence of

Table 28. Contingency Table of Contract Choices 01.01.2016 and 24.12.2016 (n=230,881)

	Conventional 24.12.2016 *n=27,260*	**Renewable 24.12.2016 *n=202,685***	**Renewable-plus 24.12.2016 *n=936***
Conventional 01.01.2016 *n=25,663*	25,663 (99.88%)	28 (0.11%)	2 (0.01%)
Renewable 01.01.2016 *n=204,339*	1,594 (0.78%)	202,652 (99.17%)	93 (0.05%)
Renewable-plus 01.01.2016 *n=849*	3 (0.35%)	5 (0.59%)	841 (99.06%)

Table 28 shows the contingency table of the two variables contract choice 01.01.2016 and contract choice 24.12.2016 (*n*=230,881). This contingency table shows how many customers changed their products over the course of the year after the default product change initiation. On the left side of the table, one can see the contract choices made on 01.01.2016, and on the right side of the table are the contract choices made on 24.12.2016. Customers who choose to opt out of the renewable default product between August 2015 and the first of January 2016 and those who chose conventional electricity were 25,693, of which 25,663 (99.88%) stayed with their product choice over the course of the year. Only 28 (0.11%) switched back to renewable products and two (0.01%) opted to switch to the renewable premium product (renewable-plus). The number of customers who chose to stay with the renewable default product between August 2015 and the first of January 2016 was 204,339, of which 202,652 stayed with their product choice over the course of the year, 1,594 (0.78%) switched to conventional products, and 93 (0.05%) opted to switch to the renewable premium product (renewable-plus). The number of customers who chose to opt out of the renewable default product between August 2015 and the first of January 2016 and buy renewable-plus electricity was 849, of which 841 (99.06%) stayed with their product choice over the course of the year. Only three (0.35%) switched to conventional products and five

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default effect and the other independent variables. Summarizing, modeling the persistence of default effect as an independent variable leads to a fake deflation of the AIC value and showed strong autocorrelation with other independent variables. The presented model, where persistence of default effect is modelled as the dependent variable, has a much higher AIC value but is true to the data.

(0.59%) opted to switch to the renewable product. All in all, this shows that the choice persistence was high over the timespan of one year, irrespective of the product chosen. The percentage range of customers staying with the product they had chosen on 01.01.2016 over the course of 2016 ranged from 99.06% (renewable-plus) to 99.88% (conventional).

From Table 20 and Table 28, one can infer that most product migration was driven by the change of the default product. It also becomes clear that the response to the default product change had an imminent effect from August 2015 to the first of January 2016. The number of customers choosing conventional electricity on 01.01.2015 as well as on 01.01.2016 (*n*=25,641) also remained surprisingly stable through 24.12.2016 (*n*=25,663).[60]

The Independent Variables

The independent variables are Customer Type Household, Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male.

The independent variable Customer Type Household is a dummy variable based on the variable Customer Type (1=Household and 0=Business). The variable identifies customer types on the basis of tariff choice. Based on the main hypothesis, it was expected that the variable Customer Type Household would increase the odds of long-term default acceptance significantly in comparison to its reference group of business customers.[61]

The independent variables Utility Use 2015 and Utility Use 2015 Squared show the yearly utility use for the customers in the time range beginning in 2015 and continuing until the end of 2016. Chapter 4.1.1 shows in detail how the measurement of the annual utility use is made up of the corresponding meter reading groups and demonstrates the timeframe of the meter reading groups for that year. Since the variable Utility Use 2015 covers the utility usage before and after the default product change, it was chosen in preference to the variable Utility Use 2016. Based on the theory of price sensitivity, It is hypothesised that the variable Utility Use 2015 would decrease the odds of long-term default acceptance significantly. The relationship between Utility Use 2015 and default product acceptance was hypothesised as

[60] Comparing the acceptance rate of the default option in the beginning of 2016 (88.60% of *n*=223,248 household customers) and in the end of 2016 (88.00% of *n*=223,248 household customers) shows to tell that 0.60% of customers adjusted from the default option to their true preference. All of those household customers who opted out during the year of the default introduction chose the energy contract their originally held before: conventional energy. Therefore one could conclude that the 0.60% of household customers had an original preference for conventional energy, did not seem to notice the default product change at first but during the course of the first year and opted out during that time, realigning their preference with their actual contract choice.

[61] For more information, refer to Section 2.2.2 - Using Default rules to Promote Renewable Energy Uptake.

non-linear, and therefore the independent variable Utility Use 2015 Squared was hypothesised as significant.

The independent variables Salutation 2016 Female and Salutation 2016 Male are both dummy variables based on the variable Salutation 2016. Since information such as household size and other social descriptive information was not available on an individual level in the utility company's data, salutation is the only variable that describes the metering points on the individual level. Salutation 2016 connects each metering point with the individual who receives the bills for that metering point. The re-coding of the salutations followed the heuristics of determining the gender of the billed individual on the basis of the information given in the salutation. While 'female' and 'male' describe the salutations of billed individuals clearly indicating the gender of the billed individual, the value 'mixed' was assigned when a clear gender indicator could not be derived from the information given in the salutation. This was applicable when the salutation addressed a couple, a family, or some other term that did not clearly reveal gender. The value 'NA' marks all missing entries for salutation. For this analysis, the values 'mixed' and 'NA' were re-categorized as the reference category 'undefined'. Even though Salutation 2016 makes assumptions regarding the genders of the decision-makers, it is not conclusive. Salutation 2016 indicates the gender of the billed individual, but not the gender (or number – singular/plural) of the decision-makers per se.[62]

Table 29. Descriptive Findings on the Independent Variables in the Logistic Regression for Long-term Default Acceptance

Variable	M	SD	Min	Max	Description
Customer Type Household	0.967	-	0	1	1=Household (*n=223,248*) 0=Business (*n=7,633*)
Utility Use 2015	*6,217.0*	*20,099.8*	*0.0*	*3,790,160*	Yearly utility use in 1,000 kWh of the customers in the timespan 2015-2016 (depending on reading cycle)
Salutation 2016 Female	0.162	-	0	1	1=Female (*n=37,571*) 0=Undefined (*n=193,310*)
Salutation 2016 Male	0.429	-	0	1	1=Male (*n=98,956*) 0=Undefined (*n=131,925*)

[62] For more information on the variable Salutation 2016, refer to Section 3.4.2 - Re-coding.

Table 29 gives the descriptive findings on the independent variables and Table 30 shows the results of the logistic regression for long-term default acceptance for the all customers (*n*=230,881).

Results of Logistic Regression for Long-Term Default Acceptance for All Customers (*n=230,881*)

Table 30. Results of Logistic Regression for Long-Term Default Acceptance for All Customers (n=230,881)

Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)[63]
Intercept	1.970	7.173	0.040	49.129	0.000
Customer Type *Household*	0.100	1.106	0.038	2.610	0.009
Utility Use 2015	-0.007	0.992	0.001	-13.701	0.000
Utility Use 2015 Squared	2.735e-06	1.000	0.000	8.004	0.000
Salutation 2016 Female	0.421	1.524	0.022	19.322	0.000
Salutation 2016 Male	-0.226	0.798	0.014	-16.567	0.000
Null Deviance=171,506 points on 230,880 degrees of freedom Residual Deviance=170,012 points on 230,875 degrees of freedom					

In Table 30 the results of the logistic regression for long-term default acceptance can be found. The persistence of default acceptance throughout 2016 is the dependent variable and Customer Type Household, Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male are the independent variables.

The variable Customer Type Household has a coefficient of 0.1, and the exponent of the coefficient is 1.106. Therefore, holding all other variables constant, the odds of long-term default acceptance were increased by 10.6% for household customers in comparison to business customers. The effect is significant (*p*=0.009) and supports the hypothesis that business customers had a lower default acceptance than household customers.[64] Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility

[63] A significance level of 5% is considered if not stated otherwise.
[64] For more information, refer to Section 2.2.2 - Using Default rules to Promote Renewable Energy Uptake.

Use 2015 (and also Utility Use 2015 Squared) does make the effect of Customer Type Household non-significant. It seems that the distinction between household and business customers is connected to their different utility use profiles. When the highest 5% of utility users are excluded (which can directly be translated as excluding the highest 5% of utility use of business customers) the significant distinction of how the customer type affects the odds of long-term default acceptance is lost. Therefore, the effect of the independent variable Customer Type Household is to some extent driven by the underlying utility use profiles, and more specifically, the extremely high utility use of the top 5% of the business sample.

The coefficient of the variables Utility Use 2015 and Utility Use 2015 Squared have to be interpreted together. Both variables have a significant effect on the log odds of customers accepting the default product. Since the direction of Utility Use 2015 is negative, one can infer that Utility Use 2015 had a negative effect on the odds of accepting the default product long-term. The direction of Utility Use 2015 Squared is positive, which indicates a curvilinear relationship between Utility Use 2015 and long-term default acceptance. Therefore, there is no basic linear relationship between Utility Usage 2015 and long-term default acceptance, but there is a significant curvilinear relationship. The odds for very low and very high utility use are significantly higher than the odds for moderate utility use, supporting the hypothesised relationship between Utility Use 2015 and long-term default acceptance. The coefficient of Utility Use 2015 is -0.007, and the exponent of the coefficient is 0.992. Therefore, holding all other variables constant, the odds of long-term default acceptance were decreased for customers by 0.8% for each 1,000 kWh increase in Utility Use 2015. An increase of 1,000 kWh in yearly utility use would be approximately a change of a three person household becoming a four person household. With a *p*-value of 0, this effect is significant. The hypothesis that Utility Use 2015 would significantly decrease the odds of short-term default acceptance for customers is supported. Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility Use 2015 (and also Utility Use 2015 Squared) does not change the directions or the significance levels of those two independent variables. Therefore, the curvilinear relationship of Utility Use 2015 and long-term default acceptance is valid and not due to uncleaned data containing influential data points.

The variable Salutation 2016 Female is a dummy variable marking the female salutations used in 2016. The coefficient of Salutation 2016 Female is 0.421 and the exponent is 1.524. Therefore, holding all other variables constant, the odds of long-term default acceptance were increased by 52.4% for customers with female salutations in comparison to customers with undefined salutations. This effect is also significant.

The variable Salutation 2016 Male is a dummy variable marking the male salutations used in 2016. The coefficient of Salutation 2016 Male is -0.226 and the exponent is 0.798. Therefore, holding all other variables constant, the odds of long-term default acceptance were decreased by 20.2% for customers with male salutations in comparison to customers with undefined salutations. This effect is also significant. While both salutation variables show an unexpected significant effect on the odds of accepting the default product long-term, this effect should be interpreted with care due to the measurement issues with the variable Salutation 2016.

Model Goodness of Fit

The analysis of deviance table shows the significance levels of the independent variables, which were added sequentially (first to last) to the model. It shows that all the independent variables are significant. The ANOVA calculation comparing the model containing only the intercept and dependent variable with the model including the independent variables is also significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 171,506 on 230,880 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 170,012 points on 230,875 degrees of freedom. The residual deviance is reduced by 1,494 points with a loss of five degrees of freedom. Keeping in mind the large sample size and accordant number of degrees of freedom, the inclusion of the independent variables does not improve this model by much. Even though the inclusion of the independent variables is significant, the reduction of deviance might only be judged significant given the high number of degrees of freedom. While the long-term default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong.

Results of Logistic Regression for Long-Term Default Acceptance for Business Customers (*n*=7,633)

Since the independent variable Customer Type Household is significant in the main model including all customers, two separate models for each customer type were calculated. The model described next is the logistic regression model for the long-term default acceptance in the business sample. The dependent variable was calculated as the persistent acceptance of the default product throughout 2016. The independent variables are Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male.

Table 31. Descriptive Findings on the Independent Variables in the Logistic Regression for Long-term Default Acceptance (n=7,633)

Variable	M	SD	Min	Max	Description
Utility Use 2015	46,123.68	97,896.43	0.0	3,790,160	Yearly utility use of the customers in the timespan 2015-2016 (depending on reading cycle)
Salutation 2016 Female	0.027	-	0	1	1=Female (*n=207*) 0=Undefined (*n=7,426*)
Salutation 2016 Male	0.337	-	0	1	1=Male (*n=2,575*) 0=Undefined (*n=5,058*)

Table 31 shows the descriptive findings on the independent variables in the logistic regression for long-term default acceptance in the business customer sample (*n*=7,633).

Table 32. Results of Logistic Regression for Long-Term Default Acceptance for Business Customers (n=7,633)

Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)
Intercept	1.718	5.571	0.049	35.231	0.000
Utility Use 2015	-0.001	0.999	0.001	-1.395	0.163
Utility Use 2015 Squared	1.109e-08	1.000	0.000	0.050	0.960
Salutation 2016 Female	0.202	1.224	0.211	0.959	0.337
Salutation 2016 Male	-0.347	0.707	0.064	-5.425	0.000
Null Deviance=7,045.7 points on 7,632 degrees of freedom Residual Deviance=7,008.2 points on 7,628 degrees of freedom					

Table 32 shows the results of the logistic regression for long-term default acceptance for the business customer sample (*n*=7,633), with the persistence of default acceptance throughout 2016 being the dependent variable and Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male being the independent variables.

The coefficients of the variables Utility Use 2015 (-0.001, *p*=0.163) and Utility Use 2015 Squared (1.109e-08, *p*=0.960) had no significant influence on the log odds of customers accepting the default product. This is a surprising finding, since It is hypothesised that utility use would have a significant negative effect on the odds of customers accepting the default product long-term. It was expected that this would be even truer for the business sample, since the utility use was significantly higher than that of the household sample, which would possibly increase the hypothesised effect.[65]

The coefficient of Salutation 2016 Female is not significant (0.202, *p*=0.337). This might be due to the unequal grouping of this variable, which is even more pronounced in the business sample than in the household sample (or the main sample). Finally, the coefficient of Salutation 2016 Male is significant (-0.347, *p*=0.000). The exponent of the coefficient of Salutation 2016 Male is 0.707. Therefore, holding all other variables constant, the odds of long-term default acceptance were decreased by 29.3% for customers with male salutations in comparison to customers with salutations indicating undefined genders.

Model Goodness of Fit

The analysis of deviance table shows the significance levels of the independent variables, which were added sequentially (first to last) to the model. It shows that only Utility Use 2015, Salutation 2016 Female, and Salutation 2016 Male are significant. The ANOVA calculation comparing a model containing only the intercept and dependent variable with the model including all independent variables is significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 7,045.7 on 7,632 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 7,008.2 points on 7,628 degrees of freedom. The residual deviance is reduced by 37.53 points with a loss of four degrees of freedom, which is a reduction in deviance that is still deemed significant. Even though the inclusion of the independent variables is partly significant, the reduction of deviance can be considered small. While the persistence of the default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong. It seems that there is information missing on customer characteristics that would be able to explain the true heterogeneity in acceptance of the default product.

[65] For the sake of comparability to the other models, the curvilinear term of Utility Use 2015 was included in this model even though it is non-significant. Estimating the model with a linear term of Utility Use 2015 shows that the effect is still non-significant.

Table 33. Descriptive Findings on the Independent Variables in the Logistic Regression for Long-term Default Acceptance (n=223,248)

Variable	M	SD	Min	Max	Description
Utility Use 2015	4,852.543	5,819.726	0.0	766,533	Yearly utility use of the customers in the timespan 2015-2016 (depending on reading cycle)
Salutation 2016 Female	0.167	-	0	1	1=Female (*n=37,364*) 0=Undefined (*n=185,884*)
Salutation 2016 Male	0.432	-	0	1	1=Male (*n=96,381*) 0=Undefined (*n=126,867*)

Results of Logistic Regression for Long-Term Default Acceptance for Household Customers (*n*=223,248)

Due to the binary outcome variable that is the persistent acceptance of the default product throughout 2016, a generalized linear model in which the dependent variable is the logarithm of the odds of accepting the default product in which the predicted probability of the binary logistic regression was chosen. The independent variables are Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male.

Table 33 shows the descriptive findings on the independent variables in the logistic regression for long-term default acceptance in the household customer sample (*n*=223,248).

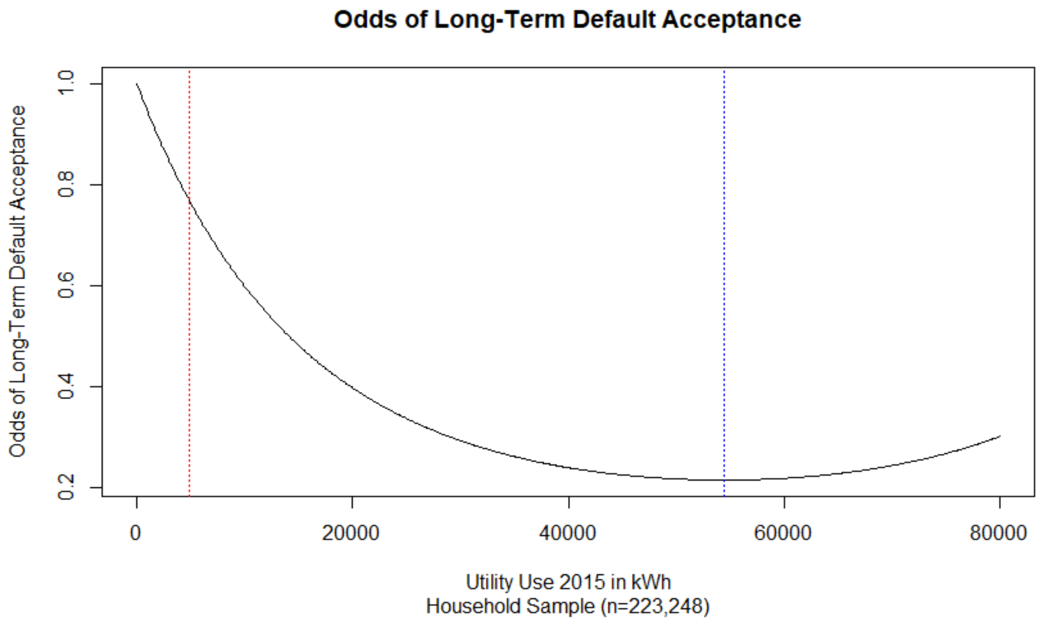
Table 34. Results of Logistic Regression for Long-Term Default Acceptance for Household Customers (n=223,248)

Variable	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)
Intercept	2.304	10.013	0.013	171.326	0.000
Utility Use 2015	-0.057	0.945	0.002	-31.471	0.000
Utility Use 2015 Squared	5.206e-04	1.000	0.000	13.272	0.000
Salutation 2016 Female	0.362	1.437	0.022	16.41	0.000
Salutation 2016 Male	-0.215	0.807	0.014	-15.35	0.000
Null Deviance=164,285 points on 223,247 degrees of freedom Residual Deviance=161,865 points on 223,243 degrees of freedom					

Table 34 shows the results of the logistic regression for long-term default acceptance in the household customer sample (*n*=223,248) with persistence of default acceptance in 2016 being the dependent variable and Utility Use 2015, Utility Use 2015 Squared, Salutation 2016 Female, and Salutation 2016 Male being the independent variables.
The coefficients of the variables Utility Use 2015 (-0.057, *p*=0.000) and Utility Use 2015 Squared (5.206e-04, *p*=0.000) had a significant influence on the odds of customers' long-term acceptance of the default product. This supports the hypothesis that utility use would have a negative effect on long-term default product acceptance and that this effect would be non-linear. Therefore, with very low and very high utility consumption, the odds of accepting the default product in the long term significantly increased in comparison to those with moderate utility consumption. The coefficient of Utility Use 2015 is -0.057, and the exponent of the coefficient is 0.945. Therefore, holding all other variables constant, the odds of short-term default acceptance decreased by 5.54% for each 1,000 kWh increase in Utility Use 2015. An increase of 1,000 kWh increase in yearly utility use would approximately equal a three person household becoming a four person household. With a *p*-value of 0, this effect is significant. The hypothesis that Utility Use 2015 would significantly decrease the odds of short-term default acceptance for customers is supported by the data. Calculating the same model and excluding the highest and lowest 5% of utility use in the variable Utility Use 2015 and Utility Use 2015 Squared does not change the directions or the significance levels of those two independent variables. Therefore, the curvilinear relationship of Utility Use 2015 and short-term default acceptance is valid and not due to uncleaned data containing influential data points.

Figure 40 shows the odds of the long-term default acceptance for Utility Use 2015 in the household sample (*n*=223,248), holding all other independent variables constant. The lowest odds (0.21) can be found at a yearly utility use of 54,418 kWh (see Figure 40; point marked with a blue dotted line). For a better visual on the curvilinear relationship between Utility Use 2015 and the odds of long-term default acceptance, the x-axis ranges from 0 to 80,000 kWh, not covering extreme cases of utility use in the household sample. For a better orientation of the distribution of the variable Utility Use 2015, the mean of Utility Use 2015 for the household sample (4,853 kWh) is marked with a red dotted line in Figure 40. The median of Utility Use 2015 for the household sample is 3,436 kWh.

Figure 40. Odds of Long-Term Default Acceptance for Utility Use 2015 (own illustration; n=223,248)



The coefficient for Salutation 2016 Female is 0.362 (p=0.000) and the exponent is 1.437. Therefore, holding all other variables constant, the odds of long-term default acceptance were increased by 43.7% for customers with female salutations in comparison to customers with salutations of undefined gender. This effect is significant.

The coefficient for Salutation 2016 Male is -0.215 (p=0.000) and the exponent is 0.807. Therefore, holding all other variables constant, the odds of long-term default acceptance decreased by 19.3% for customers with male salutations in comparison to customers with salutations of undefined gender. This effect is also significant.

Model Goodness of Fit

The analysis of deviance table that shows the significance levels of the independent variables, which were added sequentially (first to last) to the model, show that all independent variables are significant. The ANOVA calculation comparing a model containing only the intercept and dependent variable with the model including all independent variables is also significant. Concerning the goodness of fit of this generalized linear model, the null deviance indicates a value of 164,285 on 223,247 degrees of freedom. Including the independent variables (weight and displacement) decreases the deviance to 161,865 points on 223,243 degrees of freedom, which is a significant reduction in deviance. The residual deviance has decreased by 2,420 points with a loss of four degrees of freedom. Keeping in mind the large sample size and accordant number of degrees of freedom, the inclusion of the independent variables does not improve this model by much. Even though the inclusions of the independent variables are all significant, the reduction of deviance can be considered small. While the long-term default acceptance effect is very strong in the sample, the independent variables seem to not hold a lot of explanatory power of why this effect is so strong.

Conclusion

Table 35. Overview of Percentage Changes in Logistic Regression for Short-Term and Long-Term Default Acceptance

Variable	**Percentage Change: Whole Dataset (*n*=230,881)**	**Percentage Change: Business Sample (*n*=7,633)**	**Percentage Change: Household Sample (*n*=223,248)**
Customer Type Household	l-t: 10.6%** s-t: 9.4%*		
Utility Use 2015	l-t: -0.8%*** s-t: -1%***	l-t: -0.1% s-t: 0%	l-t: -5.54%*** s-t: -6%***
Utility Use 2015 Squared	l-t: 0%*** s-t: 0%***	l-t: 0% s-t: 0%	l-t: 0%*** s-t: 0%***
Contract Choice 2015 Renewable	l-t: - s-t: 98.8%***	l-t: - s-t: 63.9%	l-t: - s-t: 95.8%***
Salutation 2016 Female	l-t: 52.4%*** s-t: 51.7%***	l-t: 22.4% s-t: 22.6%	l-t: 43.7%*** s-t: 42.4%***
Salutation 2016 Male	l-t: -20.2%*** s-t: -21.9%***	l-t: -29.3%*** s-t: -31.7%***	l-t: -19.3%*** s-t: -20.9%***

*+p<0.10 *p<0.05 **p<0.01 ***p<0.001, s-t: short-term default acceptance which is calculated from August 2015 to 01.01.2016; l-t: long-term default acceptance which is calculated from 01.01.2016 to 24.12.2016.*

Table 35 gives an overview on the calculated percentage changes from the logistic regressions for the short-term and the long-term default acceptance in this chapter. From the results of these six models, it becomes clear that both the whole dataset and the household sample show very similar direction and significance levels for the independent variables. This is due to the fact that the whole sample is mainly composed of the household sample. The business sample has more deviation of directions and significance levels for the independent variables compared to the whole sample and the household sample. Only one independent variable seems to be stable in its direction and significance level among all three samples and all six models, and that is Salutation 2016 Male. Therefore, holding all other variables constant, the odds of default acceptance were significantly decreased by a range from 19.3% (long-term, household-only sample) to 31.7% (short-term, business-only sample) for customers with a male salutation in comparison to those with an undefined salutation. While the percentage changes are not directly comparable across samples and models, the direction and significance levels of Salutation 2016 Male are comparable and show stability.

Concentrating and comparing the direction of the effects and significance levels across the short-term and long-term default acceptance models, Customer Type Household had a significant positive effect on the odds of short-term/long-term default acceptance. Utility Use 2015 has a significant curvilinear relationship to the short-term/long-term default acceptance for the household sample (and the main sample) but not for the business sample. Furthermore, Utility Use 2015 had a significant negative effect on the odds of short-term/long-term default acceptance for the household sample (and the main sample) but not for the business sample. Salutation 2016 Female had a significant positive effect on the odds of short-term/long-term default acceptance in the household sample (and the main sample) but not the business sample. As pointed out before, Salutation 2016 Male had a significant negative effect on the odds of short-term/long-term default acceptance in all samples and all models.

While the previous descriptive and bivariate analyses showcase the impressive default effect in the data, the multivariate analysis points out the shortcomings and lack of powerful explanatory variables in the data. There is an imbalance of powerful default effects and weak explanatory variables. Drawing from theory, there are variables missing in this dataset that could hold the potential to explain more deeply what underlies the power of the default effect. Most of these variables are on the individual level, fleshing out the economic situations and the social descriptive characteristics of the decision-makers. Possible customer characteristics that are not captured in this dataset but would potentially hold explanatory power for the heterogeneity of the default effect are explored in the discussion of results (Chapter 6).

4.3.3 Multilevel Logistic Regression

As the experimental data of the customers of the utility company is nested in municipalities, a multilevel logistic regression was calculated to control for variance among municipalities. Additionally, municipality data was added in the form of social descriptive details such as population density, and age structure, as well as political voting data as in the voting results of the initiative of the nuclear power phase-out. The data on municipality characteristics was published by the Swiss Federal Department for Statistics. Based on the customers' geographic locations, the municipalities in the data set were matched with the information from the Federal Department for Statistics. Additionally, the proximity to the only nuclear power plant in the geographical realm of the sample was added. In two sections of the bivariate analyses, the influences of the voting results of the 'nuclear power phase-out'[66] initiative and the proximity to the nuclear power plant[67] as descriptive variables on the municipality level were analysed regarding their influence on the default acceptance. In the bivariate analysis, it was hypothesised that municipalities with the majority voting for a quick nuclear power phase-out would in larger numbers stick with the renewable default. This was verified, as municipalities voting 'For Initiative' had 2.7 percentage points more customers who stuck with the renewable default than those voting 'Against Initiative'. On the grounds of this finding, the voting results of the initiative 'nuclear power phase-out' will be further explored in the multilevel logistic regression in this chapter. In addition, the other bivariate analysis on the municipality level, which analysed the proximity to the nuclear power plant, showed valuable insights. The municipality with the nuclear power plant had a higher-than-average rate of opting out of the renewable electricity default product. This effect was also seen for the municipalities directly surrounding the municipality with the nuclear power plant. On the basis of this finding, information on the proximity to the nuclear power plant will be further explored in the multilevel logistic regression in this chapter.

The multilevel logistic regression models show not only the variance among municipalities but offer also insight into the degree to which this variance can be explained by the independent variables on the individual as well as on the municipality level (Gelman & Hill, 2006; Snijders & Bosker, 2012). This chapter entails a separate multilevel logistic regression model, first for the business customers and then for the household customers. At

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[66] For more information, refer to Section 4.2.3 - The Voting Initiative 'Nuclear Power Phase Out' and Renewable Default Acceptance on the Municipality Level.

[67] For more information, refer to Section 4.2.4 - Proximity to a Nuclear Power Plant and Renewable Default Acceptance on the Municipality Level

the end of the chapter, a summary will contrast the findings in both models and conclude with comparisons to the logistic regression models regarding long-term default acceptance in the previous chapter, 4.3.2.

A Word on the Dependent Variable

Due to the binary outcome variable – that is, the acceptance of the default product long-term – a generalized linear model in which the dependent variable is the logarithm of the odds of accepting the default product in which the predicted probability of the binary logistic regression was chosen. The dependent variable was calculated as the persistent acceptance of the default product throughout 2016. This combines information on the tariff choices of the customers on 01.01.2016 and on 24.12.2016. The three values (conventional/renewable/renewable-plus) of the tariff choices on 01.01.2016 and 24.12.2016 were recoded into the long-term default acceptance (1=default acceptance on both time points/0=default acceptance on one of the time points or none of the time points).[68]

The Independent Variables on the Individual Level

The independent variables on the individual level are Salutation 2016 Female, Salutation 2016 Male, and Utility Use 2015. Table 36 shows the descriptive findings for the independent variables on individual level in the multilevel logistic regression model for the household and business sample (*n*=230,881).

[68] Calculating a model where the persistence of default acceptance is modeled via an independent variable showed several problems in the logistic regression with long-term effect. The persistence of default acceptance is very strong in the data while other independent variables only have none or weak explanatory power. The overwhelming strength of the coefficient is due to the fact that 99.17% (*n*=202,652) of the customers stayed with the renewable default contract from 01.01.2016 to 24.12.2016. Judging on basis of the logistic regression with long-term effect, calculating a model where the persistence of default acceptance is modeled as an independent variable and comparing the same model without that independent variable shows the major explanatory power in the AIC value. Without the persistence of default acceptance variable the AIC value is 169,895 and with the variable it is 19,888. The unbalance of explanatory power between the independent variables shows itself through strong autocorrelation between the independent variable modeling the persistence of default effect and the other independent variables. Summarizing, modeling the persistence of default effect as an independent variable leads to a fake deflation of the AIC value and showed strong autocorrelation with other independent variables. The presented model in Section 4.3.2, where persistence of default effect is modelled as the dependent variable, has a much higher AIC value but is true to the data. Therefore, also for the multilevel logistic regression the dependent variable will be operated as the long-term default acceptance.

Table 36. Descriptive Findings for Independent Variables on the Individual Level in the Multilevel Logistic Regression

Variable	M	SD	Min	Max	Description
Salutation 2016 Female	0.163	-	0	1	1=Female (*n=37,571*) 0=Undefined (*n=193,310*)
Salutation 2016 Male	0.429	-	0	1	1=Male (*n=98,956*) 0=Undefined (*n=131,925*)
Utility Use 2015	6,217.0	20,099.8	0.0	3,790,160	Yearly utility use of the customers in the timespan 2015-2016 (depending on reading cycle)

The independent variables Salutation 2016 Female and Salutation 2016 Male are both dummy variables based on the variable Salutation 2016. Since information such as household size and other social descriptive information was not available on an individual level in the utility company's data, Salutation 2016 is the only variable that describes the metering points on the individual level as social descriptive information. Salutation 2016 connects each metering point with the individual who receives the bills for that metering point. The re-coding of the salutations followed the heuristics of determining the gender of the billed individual on basis of the information given in the salutation. While 'female' and 'male' describe the salutations of billed individuals by clearly indicating the gender of the billed individual, the value 'mixed' was assigned when a clear gender indication could not be derived from the information given in the salutation. This was applicable when the salutation addressed a couple or family or used some other term that did not clearly reveal gender. The value 'NA' marks all missing entries for salutation. For this analysis, the values 'mixed' and 'NA' were re-categorized as the reference category 'undefined'. Even though Salutation 2016 makes assumptions regarding the genders of the decision-makers, it is not conclusive. Salutation 2016 indicates the gender of the billed individual, but not the gender (or number – singular/plural) of the decision-maker per se.[69]

The independent variable Utility Use 2015 shows the yearly utility use for the customers in the time range beginning in 2015 and continuing until the end of 2016. Chapter 4.1.1 shows in detail how the measurement of the annual utility use is made up of the corresponding meter reading groups and demonstrates the timeframe of the meter reading groups for that year. Since the variable Utility Use 2015 covers utility usage before and after the default product change, it was chosen in preference to the variable Utility Use 2016.

[69] For more information on the variable Salutation 2016, refer to Section 3.4.2 - Re-coding.

Based on the theory of price sensitivity, it was hypothesised that the variable Utility Use 2015 would significantly decrease the odds of long-term default acceptance for customers.

The Independent Variables on the Municipality Level

On the municipality level, the following variables were added to the model: Nuclear Phase-out Voting 2016, Direct Proximity NPP, Indirect Proximity NPP, Population Density 2015, and Age Distribution: 0-19.

Table 37. Descriptive Findings for Independent Variables on the Municipality Level in the Multilevel Logistic Regression

Variable	M	SD	Min	Max	Description
Nuclear Phase-out Voting 2016	0.21	-	0	1	1=Yes-votes for the initiative 'Nuclear Power Phase Out' >50% (*n=48,321*) 0= Yes-votes for the initiative 'Nuclear Power Phase Out' <50% (*n=169,970*)
Direct Proximity NPP	0.0061	-	0	1	1=Municipality with NPP and neighbouring Municipalities (*n=1,418*) 0=All other Municipalities (*n=229,463*)
Indirect Proximity NPP	0.041	-	0	1	1=Municipality with NPP and neighbouring Municipalities (*n=9,523*) 0=All other Municipalities (*n=221,358*)
Population Density 2015	546.1	727.5	1	4,576	Density for people in km^2
Age Distribution: 0-19	19.8	2.2	7.7	30.2	The percentage of people who are 0 - 19 years old

Table 37 shows the descriptive findings for the independent variables on the municipality level in the multilevel logistic regression model for the household and business sample (*n*=230,881). The independent variable Nuclear Phase-out Voting 2016 shows the yes-votes in percentages concerning the public vote on the initiative 'Nuclear Power Phase-Out' on 27.11.2017. Section 4.3.2 (The Voting Initiative 'Nuclear Power Phase Out' and Renewable Default Acceptance at the Municipality Level) shows the bivariate analysis and further information on the public voting initiative. In the bivariate analysis, the group for the initiative has +2.7 percentage points of customers who stuck with the renewable default in comparison to the group against the Initiative. While the difference is small, the results of a Welch's unequal variances t-test show that the mean of customers in the group that was for the initiative is significantly different from the mean of the customers in the group against the initiative.[70] Based on this bivariate analysis, it was hypothesised that the variable Nuclear Phase-out Voting 2016 would significantly increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression models.

Population Density 2015 indicates the population density of the municipalities in population per km^2. For the multilevel logistic regression models, the variable Population Density 2015 was rescaled and measured in thousands of inhabitants per km^2.[71] It was hypothesised that the variable population density 2015 would increase the odds of long-term default acceptance significantly for the municipalities in the multilevel logistic regression models.

Direct Proximity NPP and Indirect Proximity NPP show the proximity of each municipality to the one nuclear power plant in the geographical area that is serviced by the utility company. The municipalities in the utility company's dataset are coded into three zones. The first zone identifies the municipality that contains the nuclear power plant (*n*=1,418). The second zone identifies the municipalities that are direct neighbours to the municipality with a nuclear power plant (*n*=9,523). The third zone identifies all municipalities that neither have a nuclear power plant nor neighbour the municipality with a nuclear power plant (*n*=219,940). Section 4.2.4 (Proximity to a Nuclear Power Plant and Renewable Default Acceptance at the Municipality Level) shows the matching bivariate analysis. The bivariate analysis shows that the metering points located in the municipality with the nuclear power plant had a higher-than-average rate of opting out of the renewable electricity default and downgrading their contracts to conventional electricity, which is sourced mostly through nuclear energy. This effect can also be seen for the municipalities directly surrounding the municipality with the nuclear power plant. The effect on the surrounding municipalities is visible but weaker in comparison to the municipality containing the nuclear power plant. The variable Direct Proximity NPP is a dummy variable where '1' marks the municipality that contains the NPP (zone 1) and '0' marks all the other municipalities. The variable Indirect Proximity NPP is a dummy variable where '1' marks the municipalities that directly neighbour on the municipality that contains the NPP (zone 2) and '0' marks all the other municipalities. Based on the results from the bivariate analysis, it was hypothesised that the variable Direct Proximity NPP, as well as the variable Indirect Proximity NPP, would decrease the odds of long-

[70] Results Welch's unequal variances t-test: t= -17.13655; df= 85536.8; p-value= 1.020395e-65.

[71] For more information on Population Density 2015, refer to Appendix 3: Descriptive Statistics of Variables on the Municipality Level.

term default acceptance significantly for the municipalities in the multilevel logistic regression models.

The variable Age Distribution: 0-19 shows the number of citizens in each municipality below 20 years of age.[72] For the multilevel logistic regression models, the variable Age Distribution: 0-19 was rescaled to express the proportion of people with a scale ranging from 0-1 instead of using the 0-100 scale. As families are shown to behave in a manner that is more environmentally friendly than, for example, single households, it was hypothesised that the variable Age Distribution: 0-19 would increase the odds of long-term default acceptance significantly for the municipalities in the multilevel logistic regression model.

Results of Multilevel Logistic Regression for Business Customers

Table 38 shows the results of a multilevel logistic regression model, which has 7,104 observations (the business customers) nested in 277 groups (the municipalities they are located in). The variance of the random intercepts is 0.05764 and therefore positive. As a result, the hypothesis holds true that the default acceptance of the business customers does vary across municipalities and the variation is worth further exploring through a multilevel logistic regression model.

In interpreting the percentage change for the estimates, one has to take the odds ratio of the estimate, subtract 1, and multiply by 100 (Long, 2003, pp. 64–84). This will give the percentage change that the binary outcome variable will take on 1, which in this case means that the customer accepts the default product long-term. For the variable Salutation 2016 Female, the coefficient is 0.227 and the exponent of the coefficient is 1.255. Therefore, holding all other variables constant, the odds of long-term default acceptance are increased by 25.48% for customers with a female salutation in comparison to customers with an undefined salutation. However, with a *p*-value of 0.288, this effect is not significant

For the variable Salutation 2016 Male, the coefficient is -0.207 and the exponent of the coefficient is 0.813. Therefore, holding all other variables constant, the odds of long-term default acceptance were decreased by 18.7% for customers with male salutations in comparison to customers with undefined salutations. With a *p*-value of 0.004, this effect is significant.

[72] For more information on Age Distribution: 0-19, refer to Appendix 3: Descriptive Statistics of Variables on the Municipality Level.

Table 38. Results of Multilevel Logistic Regression for Long-Term Default Acceptance for Business Customers (n observations=7,104; n groups=277) [73]

Fixed effect	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)[74]
Intercept	2.189	8.926	0.541	4.044	0
Salutation 2016 Female	0.227	1.255	0.214	1.062	0.288
Salutation 2016 Male	-0.207	0.813	0.072	-2.865	0.004
Log Utility Use 2015	-0.071	0.931	0.038	-1.895	0.058
Nuclear Phase-out Voting 2016	0.36	1.433	0.114	3.164	0.002
Population Density 2015	0.09	1.094	0.073	1.236	0.216
Direct Proximity NPP	-0.45	0.638	0.358	-1.258	0.208
Indirect Proximity NPP	0.14	1.15	0.195	0.717	0.474
Age Distribution: 0-19	0.554	1.74	1.781	0.311	0.756
N	***n* observations** 7,104 ***n* groups** 277				
Log Likelihood	-3213.2				
AIC	6446.4				
Random Part	**Variance Component**			**Std. Dev.**	
Level two variance	0.05764			0.2401	

For the variable Log Utility Use 2015,[75] the coefficient is -0.071 and the exponent of the coefficient is 0.931. Therefore, holding all other variables constant, the odds of long-term

[73] About the model convergence: It was difficult to get the multilevel logistic regression model to convergence. The convergence tolerance level of the algorithms was relaxed from the original 0.001 to 0.05. The algorithm was run several times, without a significant difference in the estimates, therefore results are stable even with the relaxed convergence tolerance level of 0.05.
[74] A significance level of 5% is considered if not stated otherwise.
[75] For utility use 2015 a logarithm function is used to rescale the values of the variable in a way that the range of this variable and the corresponding parameter size is of a similar magnitude of those of the other variables even though the interest lies in significance and not in marginal effects

default acceptance decreased for customers by 6.85% for each one-unit increase in the logarithm of Utility Use 2015. With a *p*-value of 0.058, this effect is not significant at the 5% level. It follows that the data contradicts the hypothesis that Utility Use 2015 would significantly decrease the odds of long-term default acceptance for customers.

For the variable Nuclear Phase-out Voting 2016, the coefficient is 0.36 and the exponent of the coefficient is 1.433. Therefore, holding all other variables constant, the odds of long-term default acceptance increased for municipalities who voted at least 50% for the nuclear phase out initiative by 43.33% in comparison to the municipalities that voted less than 50% for the nuclear phase out initiative. With a *p*-value of 0.002, this effect is significant. Hence, the data supports the hypothesis that Nuclear Phase-out Voting 2016 increased the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Population Density 2015, the coefficient is 0.09 and the exponent of the coefficient is 1.094. Therefore, holding all other variables constant, the odds of long-term default acceptance increased for municipalities by 9.42% for each thousand-inhabitant increase per squared kilometre. However, with a *p*-value of 0.216, this effect is not significant. This contradicts the hypothesis that Population Density 2015 would increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Direct Proximity NPP, the coefficient is -0.45 and the exponent of the coefficient is 0.638. Therefore, holding all other variables constant, the odds of long-term default acceptance decreased by 36.24% for the municipalities having a nuclear power plant in comparison to other municipalities. However, with a *p*-value of 0.208, this effect is not significant. This contradicts the hypothesis that Direct Proximity NPP would significantly decrease the odds of long-term default acceptance for municipalities in the multilevel logistic regression model.

For the variable Indirect Proximity NPP, the coefficient is 0.14 and the exponent of the coefficient is 1.15. Therefore, holding all other variables constant, the odds of long-term default acceptance increased by 15.03% for the municipalities directly neighbouring to a

comparison. In the former chapter utility use 2015 was used without the logarithm function and in addition utility use 2015 squared was inserted into the logistic regression model. In the multilevel model we had unfortunately problem of convergence when including the squared term and therefore we left it out. As a check for robustness of estimates, the multilevel logistic regression model is also calculated with utility use 2015 instead of the transformed, log utility use 2015, and all estimates showed no variation in significance level and direction, and non significant variation in size of the covariates. Since effect sizes are not comparable between the logistic regression model and the multilevel logistic regression model, the interest lies into the comparison of significance levels which is irrelevant of the operationalization of the variable.

municipality having a nuclear power plant in comparison to other municipalities. However, with a *p*-value of 0.474, this effect is not significant. This contradicts the hypothesis that Indirect Proximity NPP would significantly decrease the odds of long-term default acceptance for municipalities in the multilevel logistic regression model.

For the variable Age Distribution: 0-19, the coefficient is 0.554 and the exponent of the coefficient is 1.74. Therefore, holding all other variables constant, the odds of long-term default acceptance increased for municipalities by 74.02% for each one-percentage increase in Age Distribution: 0-19. With a *p*-value of 0.756, however, this effect is not significant. This contradicts the hypothesis that Age Distribution: 0-19 would significantly increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

Results of Multilevel Logistic Regression for Household Customers

Table 39 shows the results of a multilevel logistic regression model that has 210,849 observations, which are the household customers nested in 286 groups representing the municipalities in which they are located. The variance of the random intercepts is 0.09063 and therefore positive. Thus, the hypothesis holds true that the default acceptance of the household customers does vary by municipality, and the variation is worth further exploring through a multilevel logistic regression model.

For the variable Salutation 2016 Female, the coefficient is 0.544 and the exponent of the coefficient is 1.723. Therefore, holding all other variables constant, the odds of long-term default acceptance increased by 72.29% for customers with female salutations in comparison to customers with undefined salutations. With a *p*-value of 0, this effect is significant.

For the variable Salutation 2016 Male, the coefficient is -0.041 and the exponent of the coefficient is 0.96. Therefore, holding all other variables constant, the odds of long-term default acceptance decreased by 4.02% for customers with male salutations in comparison to customers with undefined salutations. With a *p*-value of 0.011, this effect is significant.

For the variable Log Utility Use 2015,[76] the coefficient is -0.187 and the exponent of the coefficient is 0.829. Therefore, holding all other variables constant, the odds of long-term

[76] For utility use 2015 a logarithm function is used to rescale the values of the variable in a way that the range of this variable and the corresponding parameter size is of a similar magnitude of those of the other variables even though the interest lies in significance and not in marginal effects comparison. In the former chapter utility use 2015 was used without the logarithm function and in addition utility use 2015 squared was inserted into the logistic regression model. In the multilevel model we had unfortunately problem of convergence when including the squared term and therefore we left it out. As a check for robustness of estimates, the multilevel logistic regression

Table 39. Results of Multilevel Logistic Regression for Long-Term Default Acceptance for Household Customers (n observations=210,849; n groups=286)[77]

Fixed Effects	Estimate	Odds Ratio	Std. Error	z value	Pr(>|z|)
Intercept	3.359	28.760	0.17	19.791	0
Salutation 2016 Female	0.544	1.723	0.024	22.866	0
Salutation 2016 Male	-0.041	0.956	0.016	-2.555	0.011
Log Utility Use 2015	-0.187	0.829	0.007	-28.665	0
Nuclear Phase-out Voting 2016	0.315	1.370	0.058	5.426	0
Population Density 2015	-0.11	0.896	0.049	-2.245	0.025
Direct Proximity NPP	-1.064	0.345	0.309	-3.437	0.001
Indirect Proximity NPP	-0.423	0.655	0.124	-3.401	0.001
Age Distribution: 0-19	0.73	2.075	0.769	0.949	0.343
N	***n* observations** 210,849 ***n* groups** 286				
Log Likelihood	-75434.4				
AIC	150888.8				
Random Part	**Variance Component**			**Std. Dev.**	
Level two variance	0.09063			0.301	

default acceptance decreased for customers by 17.06% for each one-unit increase in the logarithm of Utility Use 2015. With a *p*-value of 0, this effect is significant. The hypothesis that

model is also calculated with utility use 2015 instead of the transformed, log utility use 2015, and all estimates showed no variation in significance level and direction, and non significant variation in size of the covariates. Since effect sizes are not comparable between the logistic regression model and the multilevel logistic regression model, the interest lies into the comparison of significance levels which is irrelevant of the operationalization of the variable.

[77] About the model convergence: It was difficult to get the multilevel logistic regression model to convergence. The convergence tolerance level of the algorithms was relaxed from the original 0.001

Utility Use 2015 would significantly decrease the odds of long-term default acceptance for customers is supported by the data.

For the variable Nuclear Phase-out Voting 2016, the coefficient is 0.315 and the exponent of the coefficient is 1.37. Therefore, holding all other variables constant, the odds of long-term default acceptance increased for municipalities who voted at least 50% for the nuclear phase out initiative by 37.03% in comparison to the municipalities that voted less than 50% for the nuclear phase out initiative. With a *p*-value of 0, this effect is significant. This supports the hypothesis that Nuclear Phase-out Voting 2016 would increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Population Density 2015, the coefficient is -0.11 and the exponent of the coefficient is 0.896. Therefore, holding all other variables constant, the odds of long-term default acceptance decreased for municipalities by 10.42% for each thousand-inhabitant increase per km^2. With a *p*-value of 0.025, this effect is significant. This contradicts the hypothesis that Population Density 2015 would increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Direct Proximity NPP, the coefficient is -1.064 and the exponent of the coefficient is 0.345. Therefore, holding all other variables constant, the odds of long-term default acceptance for municipalities decreased by 65.49% for the municipality with a nuclear power plant in comparison to other municipalities. With a *p*-value of 0.001, this effect is significant. This supports the hypothesis that Direct Proximity NPP would significantly decrease the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Indirect Proximity NPP, the coefficient is -0.423 and the exponent of the coefficient is 0.655. Therefore, holding all other variables constant, the odds of long-term default acceptance for municipalities decreased by 34.49% for municipalities neighbouring directly to the municipality with a nuclear power plant in comparison to other municipalities. With a *p*-value of 0.001, this effect is significant. This supports the hypothesis that Indirect Proximity NPP would significantly decrease the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

For the variable Age Distribution: 0-19, the coefficient is 0.73 and the exponent of the coefficient is 2.075. Therefore, holding all other variables constant, the odds of long-term

to 0.05. The algorithm was run several times, without a significant difference in the estimates, therefore results are stable even with the relaxed convergence tolerance level of 0.05.

default acceptance increased for municipalities by 107.51% for each one-percentage increase in Age Distribution: 0-19. With a *p*-value of 0.343, however, this effect is not significant. This contradicts the hypothesis that Age Distribution: 0-19 would significantly increase the odds of long-term default acceptance for the municipalities in the multilevel logistic regression model.

Conclusion

Table 40. Overview of Percentage Changes from Multilevel Logistic Regression of Long-Term Default Acceptance

Variable	Percentage Change: Business Sample (*n* observations=7,104; *n* groups=277)	Percentage Change: Household Sample (*n* observations=210,849; *n* groups=286)
Salutation 2016 Female	25.48%	72.29%***
Salutation 2016 Male	-18.7%**	-4.02%*
Log Utility Use 2015	-6.85%+	-17.06%***
Nuclear Phase-out Voting 2016	43.33%**	37.03%***
Population Density 2015	9.42%	-10.42%*
Direct Proximity NPP	-36.24%	-65.49%***
Indirect Proximity NPP	15.03%	-34.49%***
Age Distribution: 0-19	74.02%	107.51%

*+p<0.10 *p<0.05 **p<0.01 ***p<0.001*

Table 40 gives an overview of the calculated percentage changes from the multilevel logistic regressions for the long-term default acceptance for the business sample and the household sample in this chapter. From the results of these two models, it becomes clear that the business sample and the household sample show apparent differences in the direction as well as significance levels for the independent variables. This was to be expected, based on the results of the logistic regression models in the previous two chapters.[78]

The main purpose of the multilevel logistic regression models was to detect possible variations in default acceptance among the municipalities. Independent variables on the municipality level were added to help to explain some of that variance. While the percentage changes of the independent variables are not directly comparable along the household and business samples and models, the direction and significance levels can be compared and are an indication of the stability of the effects. When comparing the significance levels of the effects among the household and business models, the different sample sizes should be kept in mind. Concentrating and comparing the direction of the effects and significance levels across the business and household multilevel logistic regression long-term default acceptance models, Salutation 2016 Female had a significant positive effect on the odds of long-term default acceptance in the household sample (72.29%***) but a non-significant positive effect in the business sample (25.48%). This finding replicates the findings of the logistic regressions in the prior chapter regarding the direction of the effects and the significance levels. Salutation 2016 Male had a significant negative effect on the odds of long-term default acceptance in the household sample (-4.02%*) as well as in the business sample (-18.7%**). This result replicates the findings of the logistic regressions in the prior chapter regarding the direction of the effects and the significant levels. Log Utility Use 2015 had a significant negative effect on the odds of long-term default acceptance in the household sample (-17.06%***), but a non-significant negative effect in the business sample (-6.85%$^{+}$). This result also replicates the findings of the logistic regressions in the prior chapter regarding the direction of the effects and the significance levels. While the independent variables on the individual level are similar in direction and significance level compared to the previous logistic regression models in terms of long-term default acceptance, the independent variables on the municipality level offer some new insights.

Nuclear Phase-out Voting 2016 had a significant positive effect on the odds of long-term default acceptance of municipalities in the household sample (37.03%***) as well as a significant positive effect of municipalities in the business sample (43.33%**). Population Density 2015 had a significant negative effect on the odds of long-term default acceptance of municipalities in the household sample (-10.42%*) but a non-significant positive effect of municipalities in the business sample (9.42%). Direct Proximity NPP had a significant negative

[78] For more information, refer to 4.3.1 Logistic Regression with Short-Term Default Effect and 4.3.2 Logistic Regression with Long-Term Default Effect.

effect on the odds of long-term default acceptance of municipalities in the household sample (-65.49%***) as well as a non-significant positive effect of municipalities in the business sample (-36.24%). Indirect Proximity NPP had a significant negative effect on the odds of long-term default acceptance of municipalities in the household sample (-34.49%***) as well as a non-significant positive effect of municipalities in the business sample (15.03%). Age Distribution: 0-19 had a non-significant positive effect on the odds of long-term default acceptance of municipalities in the household sample (107.51%) as well as a non-significant positive effect of municipalities in the business sample (74.02%).

Comparing the direction of the effects and significance levels of the independent variables on the individual level across the logistic regression models with long-term default acceptance with the multilevel logistic regression models proves the stability of the models. Among all four models ((1) Logistic Regression with Long-Term Default Acceptance in the Business Sample, (2) Logistic Regression with Long-Term Default Acceptance in the Household Sample, (3) Multilevel Logistic Regression with Long-Term Default Acceptance in the Business Sample, and (4) Multilevel Logistic Regression with Long-Term Default Acceptance in the Business Sample), the direction and significance levels of the independent variables Salutation 2016 Female, Salutation 2016 Male and Utility Use 2015 are similar. Salutation 2016 Female had a significant positive effect on the odds of long-term default acceptance in the household sample but not the business sample. As pointed out before, Salutation 2016 Male had a significant negative effect on the odds of long-term default acceptance in all samples and all models. Furthermore, Utility Use 2015 had a significant negative effect on the odds of long-term default acceptance for the household sample but not for the business sample.

While the independent variables on municipality level show new insights, compared to the other multivariate analyses, two of them replicate findings already established in the bivariate analyses. Those two variables are Nuclear Phase-out Voting 2016 and Direct Proximity NPP/Indirect Proximity NPP. On the grounds of the findings of the bivariate analyses, Nuclear Phase-out Voting 2016 was hypothesised to significantly increase and Direct Proximity NPP/Indirect Proximity NPP to significantly decrease the odds of municipalities accepting the default long-term. In both multilevel logistic models, Nuclear Phase-out Voting 2016 significantly increased the odds of municipalities accepting the default long-term. Therefore, the results of the former bivariate analyses were able to be replicated by the multilevel logistic models. For Direct Proximity NPP/Indirect Proximity NPP, only the multilevel logistic model in the household sample had a significant negative effect on the odds of municipalities accepting the default long-term. The finding of the previous bivariate analysis could not be replicated by the multilevel logistic regression model in the business sample.

5. Summary of Results

The summary of results recapitulates all statistical analyses ranging from bivariate analyses to the multivariate analyses.

The bivariate analyses explore the potential influences one by one on the default acceptance. On the individual level, the type of customer (household versus business), yearly utility use, previous renewable electricity use, and customer salutation are investigated for their influences on the default acceptance rates. On the municipality level, the voting results from the Nuclear Power Phase Out initiative and the proximity to one of the five Swiss nuclear power plants are investigated for their influences on the default acceptance rates. Apart from these investigations, two subsamples are analysed that are excluded in all the other analyses: the group of customers who moved in the first year of the default product change and the group of premium-paying customers who received the renewable-plus default product (the premium renewable product) instead of the renewable default product.

The multivariate analyses explore the potential influence in their interdependence on the default acceptance. Previous factors, that are also considered in the bivariate analyses are further explored with the more accurate tools of multivariate statistics. There are six logistic regression models and two multilevel logistic regressions models that investigate what causes heterogeneity in the default product acceptance both short-term and long-term. The independent variables, on individual level, range from type of customer (household versus business), yearly utility use, previous renewable electricity use, and customer salutation. On the municipality level, social descriptive details like population density, age structure, closeness of municipalities to the only nuclear power plant, as well as political voting data, as in voting results of the initiative of the nuclear power phase out are added. The logistic regression models lay out what affects the odds of customers accepting the default product short-term and long-term. The multilevel logistic regression model additionally models the municipalities and what affects the odds of municipalities accepting the default product long-term.

Heterogeneity in the Short-Term Default Effect

In order to fully understand the effect that the default switch had on customer choices, it is necessary to analyse the situation before the default product change took place (for all details, see Section 4.1.2, Descriptive Statistics for Renewable Energy Contracts 2014 and 2015). Only in comparison to the situation before the default product change can the default effect be accurately judged. Before the default product changed in 2016, the utility company had conventionally sourced electricity contracts as their default products for household and business customers alike. Only a small minority of customers (0.89%) held renewable electricity contracts in the years 2014 and 2015 – the years before the default product changed.[79] The new default product, a 100% renewably sourced electricity contract, was introduced to the customer population in August 2015 and implemented on the first of January 2016. The imminent strength of the default effect can be accurately judged by contrasting the percentage of customers who held renewable electricity contracts in the beginning of 2015 (0.89%) with the percentage of customers who held renewable electricity contracts in the beginning of 2016 (88.50%). This resulted in a short-term default effect[80] of 87.61% for all customers. Splitting up the customer pool into household customers and business customers shows the heterogeneity in the imminent response to the default product change. Only 0.91% of household customers held renewable electricity contracts in the beginning of 2015, and 88.64% of household customers held renewable electricity contracts in the beginning of 2016. This was a short-term default effect of 87.73% for household customers alone. Of business customers, 0.38% held renewable electricity contracts in the beginning of 2015 and 84.46% held renewable electricity contracts in the beginning of 2016. This was a short-term default effect of 84.08% for business customers alone. The household customer sample had a greater short-term default product acceptance rate than the business customer sample . In addition, the short-term default effect was greater for the household customers than for the business customers.

[79] In preparation of the default product change the utility company ordered a renewable energy report in the years 2014 and 2015. For the year 2013 and before there are no clear information on renewable energy acquisition from customers and no identification which customers bought how much renewable energy tranches. From 2016 on with the product change and default product change there is a clear differentiation in «Renewable-plus-tariff», «Renewable-tariff» and "Conventional-tariff".

[80] The default effect is the number of customers with a renewable energy tariff in 2016 minus the number of customers with a renewable energy tariff in 2015. This number is then calculated into percentage given out the pure default effect (the percentage of customers who only because of the default product change now hold a renewable energy tariff in 2016). Both short-term and long-term default effects are calculated against the percentage of customers having a renewable contract in 2015.

Heterogeneity in the Long-Term Default Effect

While the strength of the default effect is prominent, the question of the stability of this strong effect naturally arises. The acceptance of the new default product was not only measured on the 1st of January 2016 but also on the 24th of December 2016. Over this year, customers received four utility bills. Household customers would been able to recognize a slight increase in their utility bills due to the new default product, if they had not already opted for a different product (+0.03 CHF/kWh for the day tariff and +0.02 CHF/kWh for the night tariff). The bills for the business customers did not show any increases in price, but they did show information on the possibility of saving money by downgrading back to the conventional electricity product (possible savings -0.01 CHF/kWh for the day tariff and for the night tariff). Customers – both household and business – had the opportunity to opt out of the new default product at any time during that year simply by calling the utility company. Regardless of the increase in utility bills for the household customers and the opportunity to save costs for the business customers (who were considered more price-sensitive), the default effect showed surprising stability in its strength throughout the first year. As previously pointed out, only 0.91% of household customers held renewable electricity contracts in the beginning of 2015, and 87.96% of household customers held renewable electricity contracts at the end of 2016. This was a long-term default effect of 87.05% for household customers. Of the business customers, 0.38% held renewable electricity contracts in the beginning of 2015 and 82.65% held renewable electricity contracts at the end of 2016. This was a long-term default effect of 82.27% for business customers. The household customer sample had a greater long-term default effect on product acceptance than the business customer sample did (87.96% for the household sample vs. 82.65% for the business sample). In addition, the long-term default effect was greater for household customer (87.05%) than for business customers (82.27%).

Comparing the short-term and long-term default effects shows that the effect dropped from 87.73% to 87.05% for the household sample and from 84.04% to 82.27% for the business sample. In conclusion, the default effect was stable in both samples, with a slightly more pronounced decrease for the business sample.[81]

[81] For more information, refer to Section 4.2.1 - The Default Effect.

Default Effects Depending on Utility Use

The slight difference in responses to the new default product found for household and business customer types paved the way for further questions. On the grounds of the theory of price sensitivity, it can be presumed that business customers are more aware of utility costs than household customers and therefore more sensitive to the possibility of saving on their utility bills. Not only is the heuristic of business customers more aware of opportunities to decrease costs, but also their utility consumption is typically significantly higher than that of household customers. This higher utility use makes business customers even more likely to have a higher awareness of the opportunity to save costs on utility bills, because their possibility for monetary savings is much higher. Calculating the default effects for quartiles of yearly utility consumption separated by customer type gives a first indication of whether the default effect is stable among the different quartiles of utility use. According to the theory of price sensitivity, the higher the utility use the weaker the default effect should be. This pattern should be more pronounced in the business sample than in the household sample.

For the household sample, it was found that with increases in utility use the short-term default effect decreases. The first quartile of utility use had the highest percentage of short-term default effects (91.1%), which steadily decreased into the second quartile (89.3%), the third quartile (86.6%), and the fourth quartile (83.8%). The same pattern can be detected when it comes to the long-term default effect in the household sample. The first quartile of utility use had the highest percentage of long-term default effects (90.6%), which steadily decreased into the second quartile (88.8%), the third quartile (85.9%), and the fourth quartile (82.8%). This leads to the conclusion that with increasing utility consumption, the default effect decreases in the household sample in both the short-term and long-term.

Looking into the short-term default effects for each quartile of utility consumption shows different pictures for the business and household samples. There is not a significant variance for the business samples in the short-term default effects (ranging from 83.5% to 84.9%). Aside from this small range, there is also no pattern of a decrease in short-term default effects with higher utility use. The long-term default effects by utility quartile proves to be steady as well, but with a slight decrease. The percentages of long-term default effects in the business sample ranged from 81.5% (the fourth quartile) to 83.4% (the first quartile). There was a slight decrease in long-term default effects given increases in utility use, as can be seen in the decreasing default effects of the different quartiles for the business customers. It would be natural to conclude that the amount of utility use has no evident influences on the short-term default effect and only slight influences on the long-term default effect, but the small size of the business sample as well as the high range of utility use prohibits drawing a definite conclusion. The price sensitivity that is assumed to be more pronounced in the business than in the household sample is not supported by the data.[82]

Subsample Analysis of Moving Customers

Apart from connecting the default product acceptance to the type of the customer and the utility use profile of the customer, the awareness that the customer has for the default product change is another avenue worth exploring. Customers moving in the year of the default product change are different from the established customer pool in their awareness of the default product change. While customers in the established customer pool received a letter only, new customers also received a pamphlet explaining the three possible electricity products. Apart from this additional informational treatment, moving customers are also deemed to pay more attention to amenities when moving houses than already established customers. The sample of moving customers in 2016 is excluded in all other analyses. Apart from the building, the inhabitants are the second biggest influence on electricity usage. Excluding the moving customers meant reducing unobserved heterogeneity in the measurement of utility usage. It is hypothesised that customers who moved in the year of the default product change would read the letter (and pamphlet) announcing the default product change more carefully than non-moving customers. This greater attention should be noticeable in lower acceptance rates for the renewable default and higher uptake on conventional electricity contracts. It turns out that this was not the case. Moving customers, in comparison to established customers, did not have significantly higher renewable default opt-out numbers (13.2% for movers versus 12.2% for non-movers). This is especially true since the difference between the two groups is small in general and points in a different direction when split up into business (12.6% for movers versus 17.3% for non-movers) and household customers (13.3% for movers versus 12.0% for non-movers).

Default Effects in Dependency on the Nuclear Power Phase-Out Voting Initiative

While previous analyses concentrated on individual characteristics of the decision-maker and their influences on the default acceptance, the following analysis adds a customer characteristic on the group level. The Nuclear Power Phase-Out voting initiative, a direct democratic vote either for or against a rapid nuclear phase-out by 2029, came to a vote just

[82] For more information, refer to Section 4.2.1 - The Default Effect.

in the first year of the default product change. It was hypothesised that municipalities with at least 50% of votes for the realisation of the rapid nuclear phase-out would have higher rates of acceptance of the renewable default product than other municipalities. For this analysis, customers were grouped in their municipalities and the voting results for each municipality were added. Contrasting the short-term default acceptance of municipalities who voted with at least 50% in favour of the initiative with those who voted with less than 50% in favour of the initiative shows only a very small effect. The municipalities that voted with at least 50% for the initiative had a 1.9% higher short-term default acceptance.[83]

Default Effects Depending on Proximity to Nuclear Power Plant

Another interesting customer characteristic analysed on the municipality level was that of geographical proximity to the nuclear power plant situated in the service area of the utility company. It was hypothesised that municipalities closer to the nuclear power plant would have a self-selection bias demonstrated in a pro-nuclear attitude, and thus would have a lower short-term default acceptance of the renewable electricity product. The metering points localized in the municipality with the nuclear power plant had higher-than-average rates of opting out of the renewable electricity default and downgrading their contracts to conventional electricity (27.1% versus 10.9%). This effect can also be seen for the neighbouring municipalities directly surrounding the municipality with the nuclear power plant (13.4% versus 10.9%). Therefore, the added information of the proximity to the nuclear power plant on the municipality level adds some explanatory variable to investigate the heterogeneity in the default effect.[84]

Subsample Analysis of the Renewable-Plus Default

The subsample analysis of the renewable-plus default parallels the main default switch from conventional to renewable electricity for a small and specific subsample. This subsample was excluded in all other analyses, since the customers in it did not receive the main default treatment of the renewable electricity product. Comparing the acceptance rates from the major default treatment (conventional to renewable) to the acceptance rates of the minor default treatment (conventional to renewable-plus for the subsample of premium-paying customers) shows that default acceptance rates for the household samples are strikingly

[83] For more information, refer to Section 4.2.3 – The Voting Initiative 'Nuclear Power Phase-out' and Renewable Default Acceptance at the Municipality Level.
[84] For more information, refer to Section 4.2.4 – Proximity to Nuclear Power Plant and Renewable Default Acceptance at the Municipality Level.

similar, but this is not true for the business samples. The household sample accepted the major default at rates of 88.60% (short-term) and 88% (long-term) and the minor default at rates of 89.80% (short-term) and 88.70% (long-term). The business sample accepted the major default at rates of 84.50% (short-term) and 82.70% (long-term) and the minor default at rates of 83.30% (short-term) and 73.80% (long-term). The deviation in long-term acceptance rates for the business sample should be judged keeping in mind the numbers of business customers that are compared here (major default treatment *n*=7,633 vs. minor default treatment *n*=42).[85]

Logistic Regression Short-Term and Long-Term

A logistic regression model gives insight into what customer traits influence the short-term and long-term default product acceptance rates. The short-term logistic regression model investigates the effects of customer type, utility use, previous renewable energy consumption, and customer salutation on short-term default acceptance. The long-term term logistic regression model investigates the effects of customer type, utility use, and customer salutation on the long-term default acceptance. Two models (short-term and long-term) were separately estimated for all customers, only the business customers, and only the household customers. From the results of these six models, it becomes clear that the whole dataset and the household sample show very similar direction and significance levels for the independent variables. This is mainly due to the fact that the whole sample is primarily made up of the household customers. The business sample had more deviation of direction and significance levels for the independent variables compared to the whole sample and the household sample. Only one independent variable was stable in its direction and significance level among all three samples, and that was the male customer salutation. The male customer salutation significantly decreased the odds of default acceptance in the short-term and long-term by a range of 19.3% (long-term, household sample) to 31.7% (short-term, business sample).

Concentrating on the direction of the effects and significance levels across the short-term and long-term default acceptance models, Customer Type: Household had a significant positive effect on short-term/long-term default acceptance. Utility use had a significant curvilinear relationship to the short-term/long-term default acceptance for the household-only sample (and the main sample) but not for the business sample. Therefore, household customers with either very low or very high utility use has higher odds of accepting the

[85] For more information, refer to Section 4.2.5 – Subsample Analysis: Renewable-plus Default.

default product short-term/long-term than with an average utility use. A female salutation shows a significant positive effect on short-term/long-term default acceptance in the household sample (and the main sample) but not in the business sample. As pointed out before, a male salutation had a significant negative effect on short-term/long-term default acceptance in all samples.

While the previously described descriptive and bivariate analysis highlighted the impressive default effect in the data, the logistic regression models point out the shortcomings and lack of powerful, explanatory variables. There is an imbalance of a powerful default effect on the one side, and weak explanatory variables on the other side. Drawing from theory, there are variables one can think of that are missing in this dataset and hold the potential to explain more deeply what underlies the power of the default effect. Most of those variables are on the individual level, fleshing out the economic situation and the social descriptive characteristics of the decision-maker. Customer characteristics that are not captured in this dataset but could potentially hold explanatory power for the heterogeneity of the default effect are covered in the discussion of the results (Chapter 6).

Multilevel Logistic Regression

As the experimental data of the customers of the utility company is nested in municipalities, a multilevel logistic regression is calculated to control for variance among municipalities. Models are estimated separately for the household customers and for the business customers and show insight into what affects the odds of long-term default acceptance on the customer level, as well as on the municipality level. The independent variables, on individual level, are customer salutation and utility use. On the municipality level, social descriptive details like population density, age structure, closeness of municipalities to the only nuclear power plant, as well as political voting data, like the voting results of the initiative of the nuclear power phase out are added.

Results show how variables on the individual level affect the odds of customers accepting the default product and how variables on the municipality level affect the odds of customers grouped in municipalities accepting the default product. A female salutation has a significant positive effect on the odds of long-term default acceptance in the household sample but not the business sample. And, an male salutation has a significant negative effect on the odds of long-term default acceptance in both models. Furthermore, utility use has a significant negative effect on the odds of long-term default acceptance for the household sample and the business sample.[86]

While the independent variables on municipality level show new insights, compared to the other multivariate analyses, two of them replicate findings already established in the bivariate analyses. Those two variables are the voting results of the nuclear phase-out initiative in 2016 and the geographical proximity to a nuclear power plant. On the grounds of the findings of the bivariate analyses, the voting results of the nuclear phase-out initiative is hypothesised to significantly increase and proximity to the NPP to significantly decrease the odds of municipalities accepting the default product long-term. In both multilevel logistic models, the voting results of the nuclear phase-out initiative significantly increased the odds of municipalities accepting the default long-term. Therefore, the results of the former bivariate analyses are able to be replicated by the multilevel logistic models. Concerning proximity to the NPP, only the multilevel logistic model in the household sample had a significant negative effect on the odds of municipalities accepting the default long-term. Also the effect size of proximity to the NPP replicate the results found in the bivariate analysis. Unfortunately, the former bivariate analysis' finding could not be replicated by the multilevel logistic regression model in the business sample.

Additional variables on municipality level that can uniquely be found only in the multilevel logistic regression model are population density, and age distribution: 0-19. Population density has a significant negative effect on the odds of long-term default acceptance of municipalities in the household sample, but a non-significant positive effect of municipalities in the business sample. Age distribution: 0-19 has a non-significant positive effect on the odds of long-term default acceptance of municipalities in the household sample, as well as in the business sample.

Conclusion

In conclusion, the summary of results show the potential influences that affect the heterogeneity of short-term and long-term default product acceptance. On the individual level, it draws on the type of customer (household or business), utility use, previous renewable energy uptake, and salutation for further explanation. On the municipality level, it connects social descriptive information, voting behaviour and geographic proximity to the NPP to default product acceptance.

[86] The effect of utility use in the business sample is not significant at the 5% level, but at the 10% level.

6. Discussion of Results

The discussion of results starts with the strength and longevity of the default effect in the household sample as well as in the business sample. This will be followed up by exploring the heterogeneity of customers responding to the default product change. There are three different choices of electricity contracts (conventional, renewable, and renewable-plus) and three different time points where these contract choices were measured (beginning of 2015, beginning of 2016, and end of 2016) that are relevant for this analysis. While heterogeneity in response can be observed in the different contract choices at different time points, it are the customer characteristics behind it that are motivating and inhibiting forces on the choice. The heterogeneity in response can be partially explained by the customer characteristics. The available customer characteristics that were found to influence the response towards the default product change will be discussed in their significance and strength. On the individual level, these are customer type, utility use, previous renewable energy uptake, and salutation. On the municipality level, these are, for example, the closeness to a nuclear power plant. Furthermore, potential missing information on customer characteristics that is not available in the dataset from the utility company will be listed. Finally, a discussion of possible unwanted side effects that might have accompanied the default product change are presented at the end of the chapter and a more general, political discussion of using nudging techniques as soft policy tools follows suit (see Section 6.2 – Using Nudging Techniques as Soft Policy Tools). This ethical discussion of nudging is aimed at using nudging as policy tools, but it should also be carefully regarded by those who want to use nudging in commercial settings. Nudging interventions should not be applied to customers or citizens before considering the ethical discourse of protecting individual liberties. Responsible nudging would weigh costs and benefits of the application.

6.1 The Strong and Lasting Default Effect in this Sample

The default rules intervention in the study at hand highlights a strong and lasting default effect on the contract choice of the utility company's customers. Before 2016, when the conventional electricity default product was in place, the overwhelming majority of household and business customers held conventional contracts. After 2016, one can see the power of the default effect manifested in the overwhelming majority of both customer types holding renewable contracts. Looking at the change in only household customers with renewably sourced contracts over time, the effect of changing the default product to renewable electricity becomes evident. As previously pointed out, only 0.91% of household customers held renewable electricity contracts in the beginning of 2015, and 87.96% of household customers held renewable electricity contracts at the end of 2016, resulting in a long-term default effect[87] of 87.05% for household customers alone. For the business customers, 0.38% held renewable electricity contracts in the beginning of 2015, and 82.65% of business customers held renewable electricity contracts at the end of 2016, resulting in a long-term default effect of 82.27% for business customers alone. One customer characteristic that saw a difference in responses accepting the default product change is the differentiation between household and business customers. Household customers have a long-term default effect of 87.05%, while business customers have a lower long-term default effect of 82.27%.[88] In the logistic regression models for the short-term and long-term, the household customer type had a significant positive effect on short-term/long-term default acceptance verses the business customer type.[89] From the available information in the data set that further describes these two types of customers, the biggest difference is in the yearly amount of utility use. With increasing utility consumption, the default effect decreases in the household sample over both the short-term and the long-term. Also for the business customers the default effect slightly decreases in the long-term measurement.[90] Regarding the logistic

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[87] The default effect is the number of customers with a renewable energy tariff in 2016 minus the number of customers with a renewable energy tariff in 2015. This number was then calculated into percentage to determine the pure default effect (the percentage of customers who hold a renewable energy tariff in 2016 only because of the default product change). Both short-term as well as long-term default effects are calculated against the percentage of customers having a renewable contract in 2015.

[88] For more information, refer to Section 4.1.3 - Descriptive Statistics for Contract Choice: 2013 – 2016.

[89] For more information, refer to Section 4.3.1 - Logistic Regression with Short-Term Default Effect, and 4.3.2 Logistic Regression with Long-Term Default Effect.

[90] For more information, refer to Section 4.2.1 - The Default Effect.

regression models, utility use had a significant curvilinear relationship to short-term/long-term default acceptance for the household sample, but not for the business sample.[91] In the multilevel logistic regression model, utility use has a significant negative effect on the odds of accepting the renewable default product for business and household customers alike.[92] These findings repeat what can be found in the bivariate analysis, which shows that with increases in utility use, default acceptance decreases in the household sample.[93] Apart from the customer type (household versus business) and utility use, the former uptake of renewable energy is also valuable information for predicting the default acceptance of a customer. The number of customers choosing a renewable electricity contract in the year before the default product changed towards renewable energy had a significant positive influence on default acceptance for the household sample, but was not significant for the business sample. Furthermore, the salutation of the customer is also shown also to be relevant information as a customer characteristic that either can have a positive or negative influence on the acceptance of the default product. A female salutation had a significantly positive effect on short-term/long-term default acceptance in the household sample but not the business sample, regarding the logistic regression models. This effect was replicated in the multilevel logistic regression model for the household sample. Male salutations had a significant negative effect on short-term/long-term default acceptance in the household and business samples in all multivariate models. In conclusion, on the individual level, the customer type (household versus business) held the highest explanatory power for default product acceptance. Regarding the results for each sample alone, in the household sample, utility use shows a curvilinear relationship between default acceptance and former renewable energy uptake, and female salutations show a positive influence while male salutations show a negative influence on default product acceptance. The business sample is smaller and less well-balanced in its customer characteristics, and shows only male salutations to have a significantly negative influence on default product acceptance.

At the municipality level, there is the customer characteristic of living in a municipality where a nuclear power plant is located in or living somewhere neighbouring a municipality where a nuclear power plant is located in. The customers localized in the municipality with the nuclear power plant had a higher than average likelihood of opting out of the renewable electricity default and downgrading their contract to conventional electricity. This effect can

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[91] For more information, refer to Section 4.3.1 - Logistic Regression with Short-Term Default Effect, and 4.3.2 - Logistic Regression with Long-Term Default Effect.

[92] The effect of utility use in the business sample is not significant at the 5% level, but at the 10% level.

[93] For more information, refer to Section 4.2.1 - The Default Effect.

also be seen for the direct neighbouring municipalities surrounding the municipality with the nuclear power plant. Both effects are seen in comparison to municipalities neither neighbouring nor having a nuclear power plant.[94] This effect is visible in the bivariate analysis, as well as in the multilevel logistic regression model for the household sample. Another effect that is clearly visible in the bivariate analysis, as well as in the multilevel logistic regression models, is the significant positive effect that the voting initiative 'Nuclear Power Phase-Out' has on the default acceptance. Municipalities with at least 50% Yes votes regarding the initiative having significantly higher odds of accepting the default product than municipalities with less than 50% Yes votes. In the multilevel logistic regression models population density and the age distribution of children (0-19 Years) were added to further describe municipalities and the hypothesised variation among them. The population density has a significant negative effect on the odds of municipalities accepting the default in the household sample. The age distribution: 0-19 has a non-significant positive effect on the odds of default acceptance of municipalities in the household sample as well as in the business sample.

In general, there seems to be an imbalance, with a powerful default effect on the one side and rather weak explanatory variables on the other side. As previously stated, customer characteristics are drawn from theory, and information is missing in this dataset that holds the potential to explain what underlies the power of the default effect in more detail. On the individual level, those theorized customer characteristics would flesh out the economic situation and the social descriptive characteristics of the customers. The decision to accept the default product in the form of a renewable electricity contract can be described as a difficult trade-off between demands of morally and socially desired behaviour and self-interest (Merritt et al., 2010). The morally and socially desired behaviour is the collective goal of protecting the environment by agreeing to the default product of renewable energy. The self-interest is the individual goal of opting out of the default product and choosing the cheaper conventional product in order to save one's own monetary resources. The individual goal to save money on utility bills contrasts with the collective goal of choosing the more environmentally friendly action. This dilemma of contrasting goals is what surrounds the decision of accepting or not accepting the default product. The underlying motivations for accepting or not accepting the default product needs to be considered regarding what is pushing for and what is pushing against acceptance. Finally, a measurement of the strength

[94] For more information, refer to Section 4.2.4 - Proximity to Nuclear Power Plant and Renewable Default Acceptance.

of individual goals (as in price sensitivity, spendable income, and willingness to pay) as well as the strength of collective goals (as in importance of adhering to social norms to protect the environment and attitudes towards the goal of replacing all energy with renewably sourced energy) as they are balanced in the individual would be especially insightful.

Even though there is missing information that would describe in more detail why some customers accepted while others did not accept the default product in the study at hand, the acceptance rate overall is still an overwhelming number. A view back at the theories that seek to explain the influence that default rules can have on decision-making gives answers as to why the overwhelming majority of customers choose to stick with the new default product in this study. The different behavioural presuppositions that are said to underlie the effectiveness of default rules are that default rules minimize information costs and simplify decision-making, and the status quo bias strengthens the influence of the default setting.

The theory of default rules minimizing information costs would argue that the majority of the customers of the utility company stayed with the default product because it allowed them to avoid the costs of gathering enough information to confidently make decisions on their own. An active choice in comparison to the default setting is connected to costs such as gathering the information needed to make a confident choice and weighing the options presented according to one's own preferences. This behavioural construct of the costliness of choosing an alternative to the default choice is along the lines of default settings priming type 1 processing (automatic and intuitive processing) in order to influence type 2 processing (reflective processing). The customer is primed by the default setting in automatic processing, engages his or her reflective processing on the matter, and concludes that the cost of gathering information in this case is too high. He or she finally chooses to stay with the default product of renewable energy to avoid these costs. Pichert states that the default effect is especially strong when the decision-maker is uncertain about the decision content and his or her preferences. This uncertainty can happen for various reasons, such as a lack of information (Pichert & Katsikopoulos, 2008). This can be also true for the study at hand. The differentiation of electricity product characteristics is still rather new, and most customers have unclear preferences for product features and an unclear willingness to pay for those product features, which altogether increases information costs on the customer side that would apply to changing the electricity product manually without the help of the default product change.[95] Therefore, the default product change minimized the search and

[95] For more information, refer to Section 3.1 - Description of the Renewably Sourced Electricity Market in Switzerland.

information costs on the customer side that would have to be paid in changing from conventional electricity to the renewable contract.

Another factor that makes the default effect strong in this sample can be argued based on the theory stating that default rules simplify decision-making by offering a guiding choice. Active choice settings do not offer such a guiding choice. The more complicated the decision topic is, the more likely it is that the customer will accept this simplification by accepting the default product. As stated before, the product differentiation of electricity products is fairly new, and most customers have difficulties formulating preferences for different product features and connecting these preferences with their willingness to pay. Apart from that, most customers are not familiar enough with common certificates and do not feel informed enough to successfully evaluate electricity products in regard to their preferences for product features. When most customers do not feel informed enough to make a satisfying choice on their own, they tend to be led by the default settings in place. Complexity can lead decision-makers to inaction, and this inaction is then translated by the default rules intervention into the acceptance of the default product (Sunstein, 2011, pp. 1352–1353). Before 2016, that was the conventional electricity contract, and after 2016, it was the renewable electricity contract. The strong and lasting default effect, found in the study at hand, is therefore also a testimony to the subjectively experienced complexity that customers experienced when faced with choosing a type of electricity contract.

The default effect is strong in this sample and this decision topic because the default helped customers to avoid information costs and simplified decision-making. Apart from that, there are also other behavioural presuppositions that can strengthen the influence of the default rule, including the status quo bias. The status quo bias is a phenomenon mainly driven by type 1 processing (automatic and intuitive processing). The decision-maker is primed with the default option, and in automatic processing experiences it as loss to change the default setting and choose a different option instead. The default setting can be experienced as the status quo of decision-making. In this way, the decision-maker would also experience a loss if he or she were to choose not to stay with the default choice. This tendency to accept the priming of the default setting as a kind of anchoring effect is also described as status quo bias. The customer generally finds it easier to accept the default product and be primed by it in later decision-making than to switch away from the default product. The effect of the status quo bias becomes even stronger with rising decision complexity (Reisch & Sandrini, 2015). As already stated, the subjectively experienced complexity of choosing an electricity contract is high, which can underlie the power of the default effect in this sample.[96]

In summary, the strength and longevity of the default effect in this study could be due to minimizing information costs and simplifying the decision-making process as well as to status quo bias. The subjectively experienced complexity of choosing a type of electricity contract is high, and therefore the relief that the default rule intervention brings to this topic of decision-making seems to be more eagerly accepted, which could contribute to the size of the default effect.

The Default Effect and Unwanted Side Effects

Apart from discussing the long-lasting and strong default effect in the study at hand, it is also necessary to revisit the list of possible unwanted side effects that might accompany this default effect. As documented in Section 2.2.3 (Unwanted Side Effects of Default Rules), the unwanted side effects that are most prominent for this study are moral self-licensing and ethical problems in the form of manipulation. Of minor concern is the distortion of preferences, and the rebound effect is not applicable. In this section, first moral self-licensing and then the distortion of decision preferences will be discussed. Finally, a discussion on the ethical problems of manipulation will follow, which prepares for a more general discussion on using nudging techniques as a soft policy tool (see Section 6.2 – Using Nudging Techniques as a Soft Policy Tool).

Moral self-licensing is an unwanted side effect that is theorised to occur either in the form of moral credentials or moral credits. Both forms of moral self-licensing enable customers to balance out immoral behaviour with moral behaviour without feeling consequently immoral themselves (Merritt et al., 2010). In regard to the study at hand, the acceptance of the new default product setting on renewable electricity could be interpreted by customers as moral credentials or moral credits. Accepting the renewable default product is the moral and socially desired behaviour through which the consumer can earn moral credential or moral credits. When the moral and socially desired behaviour is realized through the default product change, the question remains of how the customer will now balance out his or her interests with licensed behaviour towards self-interest. The uptake of renewable electricity will most likely be framed as progress toward the goal of becoming an environmentally minded individual/household and not as a goal commitment to being an environmentally minded individual/household. Framing the moral behaviour as progress

[96] For more information, refer to Section 2.2 - Defining Default Rules.

instead of commitment to a goal makes moral self-licensing more likely to occur (Fishbach & Dhar, 2005). If the agreement with the new default product of renewable electricity was interpreted as a moral credential, moral self-licensing behaviour could occur in the same decision arena, with behaviour that is linked to the topic of protecting (or not protecting) the environment. The acceptance of the renewable electricity contract establishes moral credentials, and through this lens, some subsequent immoral behaviour is seen as acceptable, thus giving a nod to moral self-licensing behaviour (Effron & Monin, 2010). Therefore, it is plausible that agreement to the renewable electricity contract could have caused customers to license environmentally harmful behaviour as a consequence. Customers would feel their moral credentials as environmentally minded individuals had been established enough to license some minor behaviour that is not environmentally friendly. The magnitude of the licensed behaviour is not rationally but subjectively assessed. The yearly utility use in the years before and after the default product was changed did not indicate a significant increase in electricity consumption.[97] Apart from the possibly licensed behaviour of increasing electricity consumption, there are endless other possible behavioural outlets that could have been licensed once the moral credentials of environmental mindedness had been established. The licensed behaviour could range in magnitude of environmental impact from increasing water usage in the household to booking a cruise to Alaska for the whole family. Furthermore, the moral act of accepting the renewable electricity default product could not only license behaviour in the same realm (environmentalism), but also in other realms. Customers could engage in moral self-licensing behaviour in other domains through moral credits. Interpreting the agreement with the new default product as moral credits, moral self-licensing behaviour could occur in the same or any other decision arena. Since moral credits interpret moral behaviour as credits and immoral behaviour as debits, the earned credits of agreeing to the renewable electricity contract could be spend as debits on any kind of immoral behaviour considered by the individual to be of the same weight (Effron & Monin, 2010). Again, the weight of spendable moral credits is subjectively and self-determined by each customer. Depending on the subjective effort that customers took on themselves to accept the default product, they will be able to subsequently reinvest that effort in indulging in some immoral behaviour in some other domain. The acceptance of the renewable default product could give some an excuse to follow goals of self-interest that were previously latent, resulting in whatever behaviour is engaged in that self-interest. This could, for example, mean

[97] For more information, see Section 4.1.1 - Descriptive Statistics for Utility Use.

that the individual could buy an additional household appliance that he or she thought of as a luxury beforehand.

The unwanted side effects of moral self-licensing show that decisions cannot be analysed in a vacuum. Every decision and every decision manipulation needs to be understood as one in a sea of many. Each decision either hinders or promotes other decisions and their possible outcomes (Mazar & Zhong, 2010). This conclusion cannot be based on the results of this study, since information showing the frequency and gravity of moral self-licensing effects was not possible to collect. Since the study at hand had the aim of promoting renewable electricity uptake and not the aim of promoting environmentally friendly behaviour or even decreasing CO_2 output, it was not necessary, from the perspective of the utility company, to control for different kinds of moral self-licensing behaviour in order to be able to judge the goal of the invention as successful or not. In sum, moral self-licensing could be an unwanted side effect of the default product change that is neither possible to control for nor possible to conclusively evaluate in this study.

The distortion of decision preferences is a misalignment of what the customer prefers and what the customer finally chooses due to the influence of the nudging intervention.[98] As laid out in Section 4.3.2 (Logistic Regression with Long-Term Default Effect), the number of customers changing their contracts in the first year after the default product changed was miniscule. With the upswing of renewable electricity, electricity as such has experienced a change in customers' perceptions: before, electricity was not grasped as a commodity with different product features, but after the introduction of renewable electricity products, it increasingly became a commodity in which the customer needed to learn how to distinguish different product features. Since this transformation is rather new, customers commonly do not have fixed preferences about their electricity products (Truffer et al., 2001).[99] This can also be seen in the strong default effect before and after the default product change. If the household and business customers had strong preferences for the source or price of either electricity product, this would have become visible through lower acceptance rates and a higher number of customers switching back to their true preferences during the first year of the default setting change. The high acceptance rates of both default setting (conventional energy before 2016 and renewable electricity after 2016) testify to the customer population having weak and unclear preferences on their preferred types of electricity contract. Furthermore, the miniscule number of customers changing their electricity contracts in the

[98] For more information, refer to Section 2.2.3.3. - Other Forms of Unwanted Side Effects.

[99] For more information, refer to Section 3.1 - Description of the Renewably Sourced Electricity Market in Switzerland

year after the default product changed testifies to the default rule intervention not causing a considerable amount of distortion of preferences. This being said, with the social norm of environmental mindedness becoming stronger, it is presumable that customers held at least weak preferences for renewable electricity. Judging from the lack of motivation to switch to renewable electricity before the default product changed, these preferences seemed mostly latent. It is also presumable that the strength of the default effect is due to the social norm of environmental mindedness becoming stronger. Nevertheless, latent or weak preferences do not mean that the change in default setting is easily reversible with the same effect. A change back to a conventional default setting would go against the established social norm of environmental mindedness, as well as the latent preferences for renewable electricity that are now aligned with behaviour.

Apart from concerns of this nudging intervention causing moral self-licensing and a distortion of preferences, there are also accusations of manipulation to consider. In Section 2.2.3.2 (Ethical Problems of Manipulation) the theoretical applications of manipulation accusations in regard to nudging techniques are discussed. These theoretical applications are now boiled down to their specifics as they concern the application of default rules in promoting renewable electricity uptake, and more specifically the study at hand. In Section 2.2.3.2, the argument of manipulation accusations is broken down for nudging techniques only directly aiming at type 1 processing (automatic and intuitive processing) and the correct fulfilment of the four core characteristics of nudging. Manipulation is further defined as being deceptive and/or abusive. The deception criterion depends on the transparency of the nudging techniques and on the awareness that the targeted individual has of the nudging intervention. The criterion of a nudging intervention being abusive is defined in regard to the promoted end goal and whether that is in alignment with the targeted individual.

One of the main foundations for manipulation accusations can be found in the way default rules, as a nudging technique, influence behaviour. Default rules directly aim for the behavioural outcome of type 1 processing (automatic and intuitive processing) and not for understanding, which would be directly targeting the outcome of type 2 processing (reflective processing) (Gigerenzer, 2015). The default product change towards the renewable electricity contract also directly aimed for type 1 processing and only indirectly had the potential to influence type 2 processing. Therefore, there was a chance that customers might have low levels of awareness, or maybe even no awareness, of their behaviour being targeted by a behavioural intervention that promotes renewable electricity uptake. As theorized in Section 2.2.3.2, low or no awareness of a nudging intervention opens itself up to accusations of being deceptive and manipulative. However, while the default product change to the renewable electricity contract in the first notification could be missed due to customers ignoring the letter from the utility company, the following reminders of the product change, as well as the opportunity to change contracts any day of the year, minimized the potential customer deception. The regular quarterly utility letters have the function of reminding customers of their new electricity contracts. Customers have the possibility of opting out of the default electricity contract at any time by calling the local number of the utility company. The ease of the possible opt-out holds the cost of going against the default rules intervention to a minimum. Furthermore, the potential of deception in a nudging intervention also depends on its fulfilment of the four core characteristics of nudging. In the study at hand, all four core characteristics are fulfilled: the application of the default rules on the promotion of renewable electricity uptake intentionally changed the choice architecture while maintaining the (economic) incentive structure. It also maintained the freedom of choice and was transparent to the decision-maker.[100]

Apart from the argument of deception, there is also the argument of default rule interventions that promote end goals that are not aligned with the decision preferences of the targeted individuals. As stated in the paragraph before, on the topic of electricity contracts, most individuals hold no clear or strong preferences. When asked in theory, individuals show a preference for renewable electricity.[101] The switch towards renewable electricity can therefore be understood as promoting end goals that are in the interests of the customer population. This default rules intervention, which promotes the renewable electricity uptake, hence has few grounds for being labelled as an abusive tactic. In summary, the default rules intervention as applied in the study at hand can neither be called strongly deceptive nor abusive, which minimizes the potential unwanted side effects in the form of manipulation that can accompany a default rules intervention.

Concluding this section of the discussion of results, the default effect in this study is strong and shows longevity. The customer characteristics that show the most explanatory power are the customer type, with the household type having a positive influence on default acceptance in comparison to the business type. The default effect is strong in this nudging intervention, arguably due to most customers experiencing a choice between different electricity contracts to be complex decision-making. This subjectively experienced complexity is minimized by the customer simply accepting the new default product. Potential unwanted side effects including the distortion of decision preferences and accusations of manipulation

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[100] For more information, refer to Section 2.1 - Defining Nudging.
[101] For more information, refer to Section 3.1 - Description of the Renewably Sourced Electricity Market in Switzerland.

were kept minimal for this study. Moral self-licensing was neither possible to control for nor possible to fully evaluate here.

6.2 Using Nudging as a Soft Policy Tool

For a complete discussion of the results, it is also necessary to upscale the perspective on the default rules experiment and include a general political discussion of using nudging techniques as a soft policy tool. While in this study, nudging techniques were applied without a political agenda, nudging techniques are becoming a commonly used soft policy tool. When nudging techniques are used as soft policy tools, regulators should be aware of their positive and negative characteristics and the consequences of their use. The positives include cost-efficiency and the ability to directly affect target behaviour. The negatives include the short-term effects on target behaviour and the lack of effects on attitudes and cognitive reasoning. When discussing nudging as a policy tool, it is not enough to only consider its characteristics as a policy tool. It is also of great importance to consider the moral aspects of using nudging as a policy tool. When choosing a nudging technique as a policy tool, there is an unavoidable ethical discourse on manipulation and questioning the compatibility of nudging with democratic consent (Selinger & Whyte, 2011). Justifying the use of nudging techniques as policy tools goes back to the discrepancy between human behaviour and rational behaviour in the standard economics model. Thus, declaring human behaviour not to be aligned with the regulators' preferences gives ground to the paternalistic aspects of libertarian paternalism, which is translated into nudges that aim to align so-called irrational human behaviour with citizens' so-called true preferences (Hansen & Jespersen, 2013). Apart from this detailed discussion, this section will focus on the framework of libertarian paternalism that claims nudging as a libertarian policy tool. These claims of nudging being of libertarian nature will be contrasted with opposing opinions that consider nudging to be a paternalistic soft policy tool.

Nudging as a Soft Policy Tool

The definition of a soft policy tool is a tool that guides but does not restrict behaviour. As with nudging, soft policy tools can nudge an individual's behaviour to a decision outcome that is preferred but still leaves the individual the freedom to choose. Apart from nudging techniques, other forms of soft policy tools include positive or negative monetary incentives and providing information in order to educate or persuade individuals (Michalek et al., 2016).

Nudging techniques have as their unique selling point, among other soft policy tools, that they influence type 1 processing (automatic and intuitive processing). Other soft policy tools aim for influencing type 2 processing (reflective processing) (Michalek et al., 2016, p. 11). The combination of nudging techniques and other soft policy instruments is especially promising, since this combines the behavioural influence of type 1 processing with the behavioural influence of type 2 processing. Influencing both types of processing in the same intervention can help with heterogeneity among decision-makers who may make decisions using either or both processing types (Michalek et al., 2016, pp. 26–27).

There are four nudging techniques that are well-established soft policy tools: disclosure, default rules, salience, and the promotion of social norms. The disclosure of information can be described as a policy tool that makes information processing easier by shaping that information to be more in line with how people process information. Default rules as a policy tool also minimize the complexity of a decision by providing a default choice. Making some information related to the decision more salient is also a policy tool that minimizes complexity. Promoting public norms in line with public goals can also be an efficient public policy tool for aligning individual behaviour with public goals (Sunstein, 2011). In order to judge nudging techniques for their feasibility as soft policy tools, they need to be compared to other, more established soft policy tools regarding effectiveness, cost efficiency, and acceptance in society (Michalek et al., 2016, p. 12). Nudges are known for their cost-efficiency (Allcott & Mullainathan, 2010) and for maintaining individuals' freedom of choice, which increases their acceptance in society compared to more restrictive soft policy tools (Michalek et al., 2016, p. 12). Reisch and Sandrini state that the retained freedom of choice is the greatest benefit of using nudging as a soft policy tool (Reisch & Sandrini, 2015, p. 19). The discussion of whether nudging indeed maintains freedom of choice successfully leads to a discussion about the framework of liberal paternalism.

Nudges in the Framework of Liberal Paternalism

Thaler and Sunstein introduced the term 'libertarian paternalism' (Sunstein & Thaler, 2003). The idea of libertarian paternalism is to give nudging guidelines. For example, there is a stipulation that nudging should be done with the aim to increase citizen welfare (Thaler & Sunstein, 2009, p. 2). The regulator – in this case the public policy maker – is seen as the choice architect in charge of shaping the decision-making context in question (Thaler & Sunstein, 2009, p. 3). The decision-maker can be a citizen, an institution, or a company, and the object of the decision can be a product, a service, a bundle of products and services, or even a behavioural option (Reisch & Sandrini, 2015). According to the idea of liberal paternalism, nudges are used to change the decision-making framework in a way that is physical, social, or psychological, and thus change the decision-making architecture with a specific goal in mind (Reisch & Sandrini, 2015). The goal is to make one decision outcome, which is considered to be superior to the other outcomes, more likely. The promoted decision outcome may be found to be superior on the grounds of arguments such as the promotion of health, well-being, environmental sustainability, ecological benefits, or economic benefits. In short, the desired outcome is thought of as being in line with strengthening social welfare (Reisch & Sandrini, 2015).

Nudging techniques, used under the umbrella of libertarian paternalism, are defined by a regulator. The regulator defines the objective and engineers a nudging technique that brings forth the objective, justifying the choice of a soft policy tool through psychological research. The choice architecture is re-engineered with a specific objective in mind. Re-engineering through the application of a nudge is said to maintain citizens' freedom of choice. However, the choice of choosing a nudge to influence behaviour is also a choice against more lasting means of educating citizens to become self-governed decision-makers (Gigerenzer, 2015). The grounds on which Thaler and Sunstein judge a nudging intervention as being in the frame of libertarian paternalism is that the promoted decision outcome increases social welfare and is in line with what the individual would prefer if he or she were to act like homo economicus. Nonetheless, the judgement as to whether the promoted behaviour is in the interest of the decision-maker is not the defining characteristic of a paternalistic policy. Rather, the means and ends of a policy are what classify it as paternalistic (Hausman & Welch, 2010).

Libertarian Paternalism is Paternalism

Libertarian paternalism is an oxymoron, since a policy tool cannot be libertarian and paternalistic at the same time (Hausman & Welch, 2010). The contradiction of nudging is that it is neither fully in accord with libertarianism nor fully in accord with paternalism. The question is whether the opposed ideas of libertarianism and paternalism can find a compromise in nudging, or whether the paternalism overweighs the libertarianism (Reisch & Sandrini, 2015). It has been argued that libertarian paternalism is a 'distinctive variety of paternalism whose libertarian credentials are dubious' (Hausman & Welch, 2010, p. 124), and that the paternalistic motive is what drives libertarian paternalism (Hausman & Welch, 2010). The core of the paternalistic motive can be found in the use of the only soft policy instrument that aims at automatic and intuitive processing (type 1 processing), which renders its interventions nearly undetectable by those that it tries to influence. There are behavioural interventions and other policy tools that aim to address reflective processing that are better at respecting individuals' autonomy and making sure that the individual is free to control his or her choices. This is in direct opposite to nudging aimed at influencing type 1 processing, which can be a threat to an individual's control of their choices without the individual even noticing (Hausman & Welch, 2010). In this way, nudging as a policy tool can be a bigger threat to individuals' liberty and control over their choices than overt coercion (Hausman & Welch, 2010). In overt coercion, the decision-maker at least is aware that his or her liberty to choose is being taken away and can fight for his or her right to choose. With nudging, he or she might not even be aware that the liberty to choose is diminished, and thus cannot take action against it.

While Thaler and Sunstein state that libertarian paternalism is non-intrusive in its paternalism, it can also be seen as the most intrusive tool available to paternalism. With a prohibition, the decision-maker is at least able to independently choose whether to comply with the prohibition or not. The individual can make a decision with their autonomy unscathed and their control over the choice intact (Hausman & Welch, 2010). Nudges can be deceptive in that they minimize the set of choice alternatives in the perception of the decision-maker, even though the full set is still technically available. Maybe the right question to find out whether nudges maintain the freedom of choice would not be whether the number of choice alternatives and incentive structure is still intact, but whether they are perceived to be intact by the decision-maker (Hausman & Welch, 2010). Individual liberty cannot be boiled down to keeping choice alternatives constant or not changing the incentive structure behind the choice alternatives. Individual liberty should be defined more widely as retaining the individual's autonomy, or retaining 'the control an individual has over his or her own evaluations and choices' (Hausman & Welch, 2010, p. 128). There is a difference between the un-nudged outcome of a choice that is the individual's free action and the nudged outcome of a choice (Hausman & Welch, 2010).

The argument for labelling nudges as partly a libertarian policy tool springs from the controversial assumption that there is no alternative to nudging. Thaler and Sunstein promote the idea that there is no alternative to nudging and do not agree with the notion of a neutral decision-making design. Speaking in their terms, a choice architect is compared to a real architect. It is unavoidable that a building will be built, or likewise, that the context of a choice will be designed by the choice architect (Thaler & Sunstein, 2009, pp. 3–11). It is argued that wherever there is a choice, there is a choice architecture, and with that, there is a nudge. The contradicting argument to this can be found in the defining criteria of nudges – that is, intentionality. Even though the context of a choice is always present, if the context is not intentionally modified to promote a certain end, it cannot be defined as a nudge (Hansen & Jespersen, 2013).

Another justification is based on human decision-making being unlike the decision-making of rational agents in models of standard economics. Other policy tools, such as information provision and (in-) direct regulations, hold on to the assumption that citizens are capable of acting in line with their preferences as long as they are guided by information, incentives, and rules. Nudges often find their justification in the argument that citizens are unable to decide in line with their preferences, and thus need some paternalistic help to act rationally according to that argument (Hansen & Jespersen, 2013). However, the argument that humans behave in a way that from an economist view is called systematic irrationally cannot be directly translated into the need for paternalistic behavioural interventions that address this so-called systematic irrationality (Gigerenzer, 2015).

Nudges shape choices using the cognitive biases available to promote a specific end that is preferred by the regulator (Hausman & Welch, 2010). There are also differences in nudges concerning the argument of cognitive biases. There are nudges that empower individuals to choose according to their preferences by counteracting common cognitive biases. But there are also nudges that use cognitive biases to promote a certain decision outcome (Hausman & Welch, 2010). Regardless, the difference in nudges that act with or counteract cognitive biases is that the latter show the paternalistic motives behind the intervention, which are to steer assumedly incorrect behaviour towards what the regulator defines as correct behaviour. The argument that individuals are not able to decide according to their preferences is not an argument to use nudging liberally, but rather a paternalistic argument that leaves any claim of libertarianism even more dubious.

Nudging is More Paternalistic than Libertarian

At the core of the definition of a paternalistic policy stands the attempt to exchange the individuals' preferences for the regulators' preferences. The heuristic behind this is that the regulator knows what is good for the individual better than the individual himself does (Hausman & Welch, 2010). The definition of a paternalistic policy is as follows: 'a policy is paternalistic if and only if it aims to advance the interest of some person P either (a) via influencing P's choices by shaping how P chooses or limiting what P can choose or (b) by some means that will take effect regardless of what P does and against P's will' (Hausman & Welch, 2010, p. 129). Nudging is known to influence choice by shaping how an individual chooses, and therefore fulfils the definition of a paternalistic policy. It can even be argued that some nudges go one step further, drawing deceptive limits to the choices available while leaving the number of choice alternatives on paper intact.

Paternalistic tools justify their purpose depending on their means and ends (Hausman & Welch, 2010). Even though paternalism is morally problematic due to its interference with individual liberty, for the right reasons, it can make sense to use nudging techniques as paternalistic soft policy tools (Hausman & Welch, 2010). The justification for nudging, as for any other policy tool, is determined by the cost-benefit analysis of each specific case. This cost-benefit analysis should not only take into account the monetary cost efficiency of using a nudge in comparison to other policy instruments, but also the ethical cost of possibly hurting individual liberty. Nudges are not costless, but have the power to minimize individuals' control of their choices, and with that, their autonomy (Hausman & Welch, 2010). Nudges are paternalistic in nature, and therefore, default rules, as nudging techniques, are paternalistic in nature. Default rules address – as with every other nudge – type 1 processing (automatic processing) and do not address type 2 processing (reflective processing) through rational persuasion. In this way, default rules minimize the autonomy of the individual, and with that, the individual's control over evaluating choice alternatives and choosing one choice alternative independently. In the end, the individual's choice will reflect the regulator's preference more than his or her own independent decision-making (Hausman & Welch, 2010). The intentionality – one of the defining characteristics of nudging techniques – with which the choice architecture is changed to promote a certain outcome can be directly translated into imposing the regulator's will on the decision-maker (Hausman & Welch, 2010). The choice made is no longer a pure reflection of the decision-maker's choice, but of the regulator's preferences (Hausman & Welch, 2010). A government that respects its citizens as autonomous decision-makers should be careful when using behavioural interventions that aim for type 1 processing (automatic and intuitive processing), and should instead rely on policy tools that aim for type 2 processing (reflective processing) (Hausman & Welch, 2010). Behavioural interventions that address type 2 processing are more respectful of individuals' decision-making sovereignty, and allow individuals to retain their autonomy because the individuals are actually aware of the intervention (Hausman & Welch, 2010).

It seems like the libertarian claim of libertarian paternalism makes nudging more morally dubious than flat-out paternalistic policy tools (Hausman & Welch, 2010). The libertarian part of libertarian paternalism can only be understood as libertarian if the freedom to choose is defined by an untouched number and incentive structure of choice alternatives, and not defined by the actual untouched control of choice that defines an autonomous decision-maker (Hausman & Welch, 2010). The fact that nudges aim at influencing only type 1 processing (automatic and intuitive processing), and with that, minimizing individuals' control over their choices, makes nudging as a policy tool more morally questionable than openly constraining choices (Hausman & Welch, 2010). The problem with a policy tool that is only processed through automatic and intuitive processing is that it is open to abuse, since it is difficult for the decision-maker to monitor what is going on (Hausman & Welch, 2010).

A Warning About Nudges as Policy Tools: Unpredictable Behavioural Results

Apart from the argument that nudges are paternalistically motivated soft policy tools with questionable claims to libertarianism, nudges are also policy tools for which the behavioural results are hard to predict. The reason for these unpredictable behavioural results lies in the very nature of a policy tool that only affects automatic and intuitive processing and makes use of cognitive biases. Neither influencing automatic and intuitive processing nor taming cognitive biases is a straightforward process for which the effects can be predicted with certainty.

Cognitive biases or presuppositions can be numerous and heterogeneous among decision-makers, and nudges can only attempt to answer a small number of them. In the same way, the available heuristics differ from one decision-maker to the next. This can also be seen in how household and business customers react differently to the introduction of the renewable default product in this study. The diverse forces that surround decision-making can point in different directions, and thus influence the effect that nudging techniques have on the occurrence of the promoted outcome (Sunstein, 2011, pp. 1361–1362). One example of the unforeseen consequences of a social norm nudge that promoted energy saving was that households whose energy consumption was less than the average increased rather than decreased their energy consumption (Schultz et al., 2007). The social norm nudge, therefore, had different effects on different households, with the original household energy consumption being the characteristic that decided whether a household would decrease or increase its energy use. Deviation from the norm can refer to deviation above or below the norm. The social norm nudge motivated households to align with the stated norm of household energy consumption. Therefore, households above the norm decreased their energy consumption, and households below the norm increased their energy consumption (Schultz et al., 2007). As Lewin so pointedly states, 'in social management as in medicine, there are no patent medicines and each case demands careful diagnosis' (Lewin, 1947).

However, even careful diagnosis cannot foresee the multiple forces that surround decision-making.

Conclusion

When considering using nudges as a paternalistic policy tool, it is important not to let the positive traits of this tool alone guide a decision, but also to account for the negative traits. The decision should not be made lightly, driven by cost efficiency and the appeal of a quick way to affect target behaviour. The decision should be made by considering other options for policy tools that are better at retaining individuals' liberty to choose, and should not hinder citizens in becoming self-governed decision-makers. Only autonomous decision-makers can do their part in a democratic country, which is to scrutinize policies according to their means and ends. Not only does nudging contribute nothing to helping citizens become self-governed decision-makers, it can also be deceptive to the citizens in its means and ends, making their job to supervise that much harder.

Educating citizens is a long-term endeavour that cannot be replaced by just nudging citizens into the right behaviour. Governmental regulations are necessary to protect citizens and should not be replaced by nudging the worst consequences out of the way. Nudging, with its immediate effects on target behaviour, is a quick fix, and cannot compete with more permanent solutions achieved through other policy tools. Therefore, nudges as paternalistic soft policy tools should be administered only after careful cost-benefit analyses.

7. Outlook

The application of the default rules intervention by the utility company in this study was undeniably successful in the promotion of renewable electricity uptake among its customers. As theory and data show, default rules are a reliable nudging tool especially when decision-makers have low preferences and decision-making is experienced as complicated enough to induce inertia. Inertia then is translated successfully into an acceptance of the default setting. Low preferences are helpful in boosting the acceptance rate of the default setting overall.

Further research is needed that starts with the replication of the findings of the study at hand. One study alone cannot fill the research gap of heterogeneity in default effects in general, or more specifically, the heterogeneity of customers accepting a default product in the form of a renewable electricity contract. The explored heterogeneity found in customer characteristics, as summarized in Chapter 5, needs to be solidified through replication of the same effects in studies that are comparable to the study at hand.

Apart from the need to replicate the heterogeneity in default acceptance rates among the business and household customers, there is still more heterogeneity to explore in regard to customer characteristics and which information was missing in this dataset but is theorized to motivate or hinder default acceptance. More research is needed to gain further insights on default effect heterogeneity in customer populations.

In regard to other avenues worth further exploration, the costs of not accepting a default setting, as well as the height of awareness of default rules interventions come to mind. There is not enough research available exploring the effectiveness of default rules depending on opt-out costs. Opt-out costs can be marked by relative costs, as in the costs of contacting the company for the opt-out solution. Calling a company or logging into an online interface can be experienced as different costs by different demographics. To be even more specific, the duration of wait time when calling a utility company's customer service number is experienced as a cost by the customer. The length of the telephone service number or the complexity of the log-in instructions for the online service tool are also of relevance to the experienced costliness of the opt-out. Another factor would be the monetary cost of accepting the default product in comparison to other offered products. Finally, there are the information costs that the decision-maker has to invest in to confidently opt out of the default product setting.

Apart from further exploring the strength of a default effect depending on the opt-out costs, there is also further research to be done exploring the height of awareness of nudged individuals when faced with a default rules intervention. How large is the share of customers who do not understand that they are making a decision by simply not responding? And do they understand all the implications of the decision that they are making by simply not doing anything?

Last but not least, unwanted side effects of default rules interventions, as well as, nudging interventions need to be thoroughly addressed by future research. In order to get a more complete picture regrading unwanted side effects not only the extent to other decision making arenas has to be considered but also the length of time they occur in. An unwanted side effect can be regarded as less grave when the behaviour is only short lived.

In conclusion, building on the work at hand, future research is first advised to replicate the findings of this study, and then second to explore the influence of opt-out costs, intervention awareness on the default effect, and unwanted side effects.

8. References

Allcott, H., & Mullainathan, S. (2010). Energy. Behavior and Energy Policy. *Science (New York, N.Y.)*, *327*(5970), 1204–1205. https://doi.org/10.1126/science.1180775

Andreoni, J. (1989). Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy*, *97*(6), 1447–1458. https://doi.org/10.1086/261662

Association for Environmentally Sound Energy (VUE). Naturemade. Retrieved from https://www.naturemade.ch/en/startseite.html

Barden, J., Rucker, D. D., & Petty, R. E. (2005). "Saying one thing and doing another": examining the impact of event order on hypocrisy judgments of others. *Personality & Social Psychology Bulletin*, *31*(11), 1463–1474. https://doi.org/10.1177/0146167205276430

Barker, T., Dagoumas, A., & Rubin, J. (2009). The macroeconomic rebound effect and the world economy. *Energy Efficiency*, *2*(4), 411–427. https://doi.org/10.1007/s12053-009-9053-y

Bird, L., Wüstenhagen, R., & Aabakken, J. (2002). A review of international green power markets: Recent experience, trends, and market drivers. *Renewable and Sustainable Energy Reviews*, *6*(6), 513–536. https://doi.org/10.1016/S1364-0321(02)00033-3

Brown, C. L., & Krishna, A. (2004). The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice. *Journal of Consumer Research*, *31*(3), 529–539. https://doi.org/10.1086/425087

Camerer, C. F. (2009). Prospect theory in the wild: Evidence from the field. In D. Kahneman & A. Tversky (Eds.), *Choices, values, and frames* (pp. 288–300). New York, Cambridge: Russell Sage Foundation; Cambridge University Press.

Campbell, D. T., & Stanley, J. C. (2011). *Experimental and quasi-experimental designs for research* (Repr). Belomt: Wadsworth.

Choi, J., Laibson, D., Madrian, B., & Metrick, A. (2001). Defined Contribution Pensions: Plan Rules, Participant Decisions, and the Path of Least Resistance. Advance online publication. https://doi.org/10.3386/w8655

Clark, C. F., Kotchen, M. J., & Moore, M. R. (2003). Internal and external influences on pro-environmental behavior: Participation in a green electricity program. *Journal of Environmental Psychology*, *23*(3), 237–246. https://doi.org/10.1016/S0272-4944(02)00105-6

Diekmann, A. (2004). *Empirische Sozialforschung: Grundlagen, Methoden, Anwendungen* (11. Aufl., Orig.-Ausg). *Rororo Rowohlts Enzyklopädie: Vol. 55551*. Reinbek bei Hamburg: Rowohlt-Taschenbuch-Verl.

DIRECTIVE 2001/77/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL. (2001). *DIRECTIVE 2001/77/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL: on the promotion of electricity produced from renewable energy sources in the internal* *electricity market*. Official Journal of the European Communities. Retrieved from http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32001L0077

Ebeling, F., & Lotz, S. (2015). Domestic uptake of green energy promoted by opt-out tariffs. *Nature Climate Change.* Advance online publication. https://doi.org/10.1038/nclimate2681

Effron, D. A., & Monin, B. (2010). Letting people off the hook: when do good deeds excuse transgressions? *Personality & Social Psychology Bulletin*, *36*(12), 1618–1634. https://doi.org/10.1177/0146167210385922

Egebark, J., & Ekström, M. (2013). *Can Indifference Make the World Greener?*

Epstein, S., Lipson, A., Holstein, C., & Huh, E. (1992). Irrational reactions to negative outcomes: Evidence for two conceptual systems. *Journal of personality and social psychology*, *62*(2), 328–339. https://doi.org/10.1037/0022-3514.62.2.328

(1997). *European Commission's White Paper on Renewable Energy Sources* (No. COM(97)599 final). Retrieved from http://europa.eu/documents/comm/white_papers/pdf/com97_599_en.pdf

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-Process Theories of Higher Cognition: Advancing the Debate. *Perspectives on Psychological Science : a Journal of the Association for Psychological Science*, *8*(3), 223–241. https://doi.org/10.1177/1745691612460685

Farhar, B. C. (1999). *Willingness to Pay for Electricity from Renewable Resources: A Review of Utility Market Research* (No. NREL/TP.550.26148).

Fazio, R. H. (1990). *Multiple Processes by which Attitudes Guide Behavior: The Mode Model as an Integrative Framework* (Vol. 23).

Fishbach, A., & Dhar, R. (2005). Goals as Excuses or Guides: The Liberating Effect of Perceived Goal Progress on Choice. *Journal of Consumer Research*, *32*(3), 370–377. https://doi.org/10.1086/497548

Gelman, A., & Hill, J. (2006). *Applied regression and multilevel/hierarchical models*. *Analytical methods for social research*. Cambridge, New York: Cambridge University Press.

Gigerenzer, G. (2015). On the Supposed Evidence for Libertarian Paternalism. *Review of Philosophy and Psychology*, *6*(3), 361–383. https://doi.org/10.1007/s13164-015-0248-1

Grubb, M. J. (1990). Communication Energy efficiency and economic fallacies. *Energy Policy*, *18*(8), 783–785. https://doi.org/10.1016/0301-4215(90)90031-X

Grüne-Yanoff, T., & Hertwig, R. (2016). Nudge Versus Boost: How Coherent are Policy and Theory? *Minds and Machines*, *26*(1-2), 149–183. https://doi.org/10.1007/s11023-015-9367-9

Hansen, P. G., & Jespersen, A. M. (2013). Nudge and the Manipulation of Choice. *European Journal of Risk Regulation*, *4*(01), 3–28. https://doi.org/10.1017/S1867299X00002762

Hausman, D. M., & Welch, B. (2010). Debate: To Nudge or Not to Nudge *Journal of Political Philosophy*, *18*(1), 123–136. https://doi.org/10.1111/j.1467-9760.2009.00351.x

Hedlin, S., & Sunstein, C. R. (2015). Does Active Choosing Promote Green Energy Use? Experimental Evidence. Advance online publication. https://doi.org/10.15779/Z387G30

Heydarian, A., Pantazis, E., Carneiro, J. P., Gerber, D., & Becerik-Gerber, B. (2016). Lights, building, action: Impact of default lighting settings on occupant behaviour. *Journal of Environmental Psychology*, *48*, 212–223. https://doi.org/10.1016/j.jenvp.2016.11.001

Johnson, E. J., Bellman, S., & Lohse, G. L. (2002). Defaults, Framing and Privacy: Why Opting In-Opting Out. *Marketing Letters*, *13*(1), 5–15. https://doi.org/10.1023/A:1015044207315

Johnson, E. J., & Goldstein, D. G. (2004). Defaults and Donation Decisions. *Transplantation*, *78*(12), 1713–1716. https://doi.org/10.1097/01.TP.0000149788.10382.B2

Johnson, E. J., Hershey, J., Meszaros, J., & Kunreuther, H. (1993). Framing, probability distortions, and insurance decisions. *Journal of Risk and Uncertainty*, *7*(1), 35–51. https://doi.org/10.1007/BF01065313

Kahneman, D. (2013). *Thinking, fast and slow*. London: Penguin.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives*, *5*(1), 193–206. https://doi.org/10.1257/jep.5.1.193

Khan, U., & Dhar, R. (2006). Licensing Effect in Consumer Choice. *Journal of Marketing Research*, *43*(2), 259–266. https://doi.org/10.1509/jmkr.43.2.259

Lewin, K. (1947). Group decision and social change. In *Readings in Social Psychology* (pp. 197–211).

Liebe, U., Gewinner, J., & Diekmann, A. (2018). *What is missing in research on non-monetary incentives in the household energy sector?* Energy Policy, 123, 180–183. https://doi.org/10.1016/j.enpol.2018.08.036

Long, J. S. (2003). *Regression models for categorical and limited dependent variables* (8. printing). *Advanced quantitative techniques in the social sciences: Vol. 7*. Thousand Oaks: Sage Publications.

Loock, C.-M., Staake, T., & Thiesse, F. (2013). Motivating Energy-Efficient Behavior with Green IS: An Investigation of Goal Setting and the Role of Defaults. *MIS Quarterly*, *37*(4), 1313–1332. https://doi.org/10.25300/MISQ/2013/37.4.15

Madrian, B., & Shea, D. (2000). The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior. Advance online publication. https://doi.org/10.3386/w7682

Mazar, N., & Zhong, C.-B. (2010). Do green products make us better people? *Psychological Science*, *21*(4), 494–498. https://doi.org/10.1177/0956797610363538

Merritt, A. C., Effron, D. A., Fein, S., Savitsky, K. K., Tuller, D. M., & Monin, B. (2012). The strategic pursuit of moral credentials. *Journal of Experimental Social Psychology*, *48*(3), 774–777. https://doi.org/10.1016/j.jesp.2011.12.017

Merritt, A. C., Effron, D. A., & Monin, B. (2010). Moral Self-Licensing: When Being Good Frees Us to Be Bad. *Social and Personality Psychology Compass*, *4*(5), 344–357. https://doi.org/10.1111/j.1751-9004.2010.00263.x

Michalek, G., Meran, G., Schwarze, R., & Yildiz, Ö. (2016). Nudging as a new soft tool in environmental policy - An analysis based on insights from cognitive and social psychology. *ZfU*, *2016*.

Momsen, K., & Stoerk, T. (2014). From intention to action: Can nudges help consumers to choose renewable energy? *Energy Policy*, *74*, 376–382. https://doi.org/10.1016/j.enpol.2014.07.008

Monin, B., & Miller, D. T. (2001). Moral credentials and the expression of prejudice. *Journal of personality and social psychology*, *81*(1), 33–43. https://doi.org/10.1037/0022-3514.81.1.33

Ölander, F., & Thøgersen, J. (2014). Informing Versus Nudging in Environmental Policy.

Park, C. W., Jun, S. Y., & MacInnis, D. J. (2000). Choosing What I Want Versus Rejecting What I Do Not Want: An Application of Decision Framing to Product Option Choice Decisions. *Journal of Marketing Research*, *37*(2), 187–202. https://doi.org/10.1509/jmkr.37.2.187.18731

Petty, R. E., & Cacioppo, J. T. (1986). *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*. *Springer Series in Social Psychology*. New York, NY: Springer New York.

Pichert, D., & Katsikopoulos, K. V. (2008). Green defaults: Information presentation and pro-environmental behaviour. *Journal of Environmental Psychology*, *28*(1), 63–73. https://doi.org/10.1016/j.jenvp.2007.09.004

Rebitzer, G., Ekvall, T., Frischknecht, R., Hunkeler, D., Norris, G., Rydberg, T., Pennington, D. W. (2004). Life cycle assessment part 1: framework, goal and scope definition, inventory analysis, and applications. *Environment International*, *30*(5), 701–720. https://doi.org/10.1016/j.envint.2003.11.005

Reisch, L. A., & Sandrini, J. (2015). *Nudging in der Verbraucherpolitik: Ansätze verhaltensbasierter Regulierung* (1. Aufl.). *Schriftenreihe des Instituts für europäisches Wirtschafts- und Verbraucherrecht: Vol. 36*. Baden-Baden: Nomos.

Reisch, L. A., & Sunstein, C. R. (2016). Do Europeans Like Nudges? *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.2739118

Roe, B., Teisl, M. F., Rong, H., & Levy, A. S. (2001). Characteristics of Consumer-Preferred Labeling Policies: Experimental Evidence from Price and Environmental Disclosure for Deregulated Electricity Services. *Journal of Consumer Affairs*, *35*(1), 1–26. https://doi.org/10.1111/j.1745-6606.2001.tb00100.x

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Riverside: Free Press.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological Science*, *18*(5), 429–434. https://doi.org/10.1111/j.1467-9280.2007.01917.x

Selinger, E., & Whyte, K. (2011). Is There a Right Way to Nudge? The Practice and Ethics of Choice Architecture. *Sociology Compass*, *5*(10), 923–935. https://doi.org/10.1111/j.1751-9020.2011.00413.x

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd edition). Los Angeles: SAGE.

Sunstein, C. R. (2011). Empirically Informed Regulation. *The University of Chicago Law Review*, *4*, 1349–1429. Retrieved from http://www.jstor.org/stable/41552884

Sunstein, C. R. (2015). Which Nudges Do People Like? A National Survey. *SSRN Electronic Journal.* Advance online publication. https://doi.org/10.2139/ssrn.2619899

Sunstein, C. R. (2017). Behavioural economics, consumption and environmental protection. In L. A. Reisch & J. Thøgersen (Eds.), *Handbook of research on sustainable consumption* (pp. 313–327). Cheltenham, UK: Edward Elgar Publishing.

Sunstein, C. R., & Thaler, R. H. (2003). Libertarian Paternalism Is Not an Oxymoron. *The University of Chicago Law Review*, *70*(4), 1159. https://doi.org/10.2307/1600573

Tanner, R. J., & Carlson, K. A. (2009). Unrealistically Optimistic Consumers: A Selective Hypothesis Testing Account for Optimism in Predictions of Future Behavior. *Journal of Consumer Research*, *35*(5), 810–822. https://doi.org/10.1086/593690

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth and happiness*. London: Penguin Books Ltd; [distributor] Penguin Books Ltd.

Tiefenbeck, V., Staake, T., Roth, K., & Sachs, O. (2013). For better or for worse? Empirical evidence of moral licensing in a behavioral energy conservation campaign. *Energy Policy*, *57*, 160–171. https://doi.org/10.1016/j.enpol.2013.01.021

Truffer, B., Markard, J., & Wüstenhagen, R. (2001). Eco-labeling of electricity—strategies and tradeoffs in the definition of environmental standards. *Energy Policy*, *29*(11), 885–897. https://doi.org/10.1016/S0301-4215(01)00020-9

Tversky, A., & Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. *Science*, *211*(4481), 453–458.

Verein für umweltgerechte Energie VUE, Zürich. (2018). *Strom- und Biogasprodukte: Der Markt für erneuerbare Energieprodukte 2016*. Eine Umfrage bei Schweizer Energieversorgungsunternehmen.

Wansink, B. (2004). Environmental factors that increase the food intake and consumption volume of unknowing consumers. *Annual Review of Nutrition*, *24*, 455–479. https://doi.org/10.1146/annurev.nutr.24.012003.132140

Wason, P. C., & Evans, J. (1974). Dual processes in reasoning? *Cognition*, *3*(2), 141–154. https://doi.org/10.1016/0010-0277(74)90017-1

Wüstenhagen, R., Markard, J., & Truffer, B. (2003). Diffusion of green power products in Switzerland. *Energy Policy*, *31*(7), 621–632. https://doi.org/10.1016/S0301-4215(02)00147-7

Appendices

Appendix 1: Utility Companies in Switzerland and their Default Setting as of 12th July 2017

Utility Company/Power Plant	Product Name	Electricity Source	Note
AEK Energie	Standard Strom zu 100% erneuerbar	Undifferentiated renewable energy 100%	Solar etc.
AEW Energie	AEW classic naturstrom	Hydropower 90%, Solar 8%, Biomass 2%	
Albula-Landwasser Kraftwerke			Part of Axpo (see Axpo AG)
Alpiq Holding			No default product, does not deliver to households directly
Arosa Energie	Arosaenergie	Hydropower 100%	100% of local power plants
Atel Holding			Part of Alpiq holding (see Alpiq Holding)
Axpo AG			Only sells products to businesses, not to households
Axpo Holding			Only sells products to businesses, not to households
Axpo Trading			Only sells products to businesses, not to households
Kraftwerk Birsfelden			No products for households (only for shareholders, energy trading)
BKW Energie	Energy blue	Hydropower 97.5%, Undifferentiated renewable energy 2.5%	
Blenio Kraftwerke			No website, but assumed to deliver to other power plants instead of households
Bündner Kraftwerke			New 'Repower AG' (see Repower AG)
Centralscheizerische Kraftwerke	CKW Wasserkraft	Hydropower 100%	
EBL (Genossenschaft Elektra Baselland)	EBL Standard	Hydropower 95%, Undifferentiated renewable energy 5%	

Elektrizitätswerk des Kantons Schaffhausen	Normal Strom	Hydropower 96%, Undifferentiated renewable energy 4%	
Elektrizitätswerk Schwyz	EWS Wasserkraft - Der Klassiker	Hydropower 95%, Undifferentiated renewable energy 5%	
Elektrowatt			Does not exist anymore
Energie Wasser Bern	Ewb.NATUR.st rom	Hydropower 91.9%, Solar 4%, Biomass 4.1%	
Energiedienst Holding		Hydropower 100%	33% renewable energy according to EEG, 67% other renewable energy
Engadiner Kraftwerke			No products for households
EOS Holding			No products for households, energy trading
Etzelwerk			No products for households, supplies railway system
EWL Energie Wasser Luzern Holding	Ewl Naturstrom	Hydropower 97.5%, Undifferentiated renewable energy 2.5%	
Groupe E	Plus	Undifferentiated renewable energy 100%	No information on percentages, phone service did not want to provide this information
Industrielle Betriebe Interlaken	Bödeli Blaustrom	Hydropower 100%	90% from Swiss power plants, 10% from Saxetal
IWB	IWB Strom	Hydropower 94.95%, Wind 0.17%, Solar 0.28%, Undifferentiated renewable energy 4.6%	All from Swiss inhouse production
Kraftwerk Wägital	Ewz.basis	Undifferentiated renewable energy 100%	
Kraftwerke Hinterrhein			No products for households
Kraftwerke Linth-Limmern			Part of Axpo (no extra website, see Axpo AG)
Kraftwerke			Part of Axpo (no extra website, see Axpo

Sarganserland			AG)
Kraftwerke Vorderrhein			Part of Axpo (no extra website, see Axpo AG)
Elektrizitätsgesells chaft Laufenburg			Part of Axpo (no extra website, see Axpo AG)
EWL Genossenschaf	Schweizer Wasserkraft	Undifferentiated renewable energy 100%	Mostly hydro power
Maggia Kraftwerke			No products for households
NaturEnergie	Natuenergie	Hydropower 100%	Only has 1 product (default) 100% regional
Kraftwerke Oberhasli			No products for household customers
Elektrizitätswerk Obwalden	EWO NaturStrom	Undifferentiated renewable energy 100%	Mostly hydro and solar power
Regio Energie Solothurn	So regional		
Repower AG	Aqua Power	Hydropower 100%	
Romande Energie Holding	Terre Suisse	Hydropower 60%, Nuclear 40%	
Services Industriels de Genève		Hydropower 100%	
Società Elettrica Sopracenerina	Tiacqua	Hydropower 97.5%, Undifferentiated renewable energy 2.5%	100% Swiss production
St Gallisch-Appenzellische Kraftwerke	Naturstrom basic	Hydropower 95%, Photovoltaik 5%	
Steiner Energie	SEM Wasserkraft	Hydropower 95%, Solar 2%, Undifferentiated renewable energy 3%	Mostly from Swiss production
Swissgrid			No information online or on phone
Swisspower			Delivers to multiple city power plants, hence only delivers to household customers indirectly, e.g. through Stadtwerk Winterthur, IBAarau
EKT Holding			Consists of many different power plants, with different products and defaults

Wasserwerke Zug	100 Prozent Schweizer Wasserkraft	Hydropower 100%	
Elektrizitäts- und Wasserwerk Wettingen	Standard Strommix	Hydropower 96.2%, Undifferentiated renewable energy 3.8%	100% renewable energy from Swiss production
Stadtwerk Winterthur	E-Strom.Bronze (naturmade basic)	Hydropower 95%, Undifferentiated renewable energy min 5%	**All the same
Elektrizitätswerke des Kantons Zürich	Ewz-Basis	Hydropower 95%, Undifferentiated renewable energy min 5%	
IBAarau	STANDARD POWER	Undifferentiated renewable energy min 5%	**All the same
Elektrizitätswerk der Stadt Zürich	Ewz-Basis	Hydropower 95%, Undifferentiated renewable energy min 5%	**all the same

Appendix 2: Descriptive Statistics of Variables on the Metering Point Level

Variable: 'Metering Point'

The dataset is organized by metering points and not by customer numbers. The logic behind this is that one customer number could have a number of associated metering points, but each metering point has only one corresponding customer number. The original dataset entails all metering points with a supply tariff and a tariff for the electrical network (*n*=338,574). The variable metering point had NA entries (*n*=542) that were taken out in the process of data cleaning. Only a valid entry in the metering point ensured the possibility of actually measuring the electricity usage. The NA entries marked customers that did not have supply tariffs but only electrical network tariffs – in most cases, supplying electricity back into the utility company's electrical network.

Variable: 'Customer Number'

A 'customer number' was assigned to each customer by the utility company. One customer number can be tied to multiple metering points, as one customer can have multiple flats or houses (and thus multiple metering points) in his or her customer account.

Variable: 'Data Import Year'

The year when the dataset was scheduled to be delivered. Since there were two data shipments scheduled, the first data import is marked with the value '2016' and the second with '2017'. The first data import – 2016 – entails electricity readings for the whole year of 2015 and simulated electricity readings for 2016. The second import – 2017 – consists of electricity readings for the whole year of 2016 and simulated electricity readings for 2017. Each metering point was read only on a yearly basis but billed every three months. The meter readings were organized by dividing the meter points into four seasonal groups, for which one group was read each spring, summer, autumn, and winter. Electricity billing always relies on simulated data based on former electricity usage and some other constants (for example, approximated 'heating days'). After each yearly meter reading, the billing is adjusted for the next four quarters until the next annual reading. This billing and reading custom, which is typical for utility companies, controls the schedule of the data import.

Variable: 'Number of Connection Objects'

The connection object is the object in which the metering points are found, for example, a building that is a house or a flat. One connection object can have multiple metering points. For example, a connection object that is a one-family house can have one metering point for the main electricity usage and another metering point for the boiler in the house. In this case, the connection object would have two metering points in the dataset. Another example could be a connection object that is a high rise apartment building, with a metering point for each flat within it. In this case, the described connection object would have a multitude of metering points in the dataset.

Variable: 'Connection Object Postal Code'

Each connection object has one assigned postal code extracted from the billing information from the corresponding customer number. This is a geographical categorization.

Variable: 'Connection Object Place'

Each connection object has one assigned geographical location. This is also a geographical categorization.

Variable: 'Municipality Code'

Each connection object is assigned a political geographical location in the form of a municipality code.

Variable: 'Municipality Name'

Each connection object is assigned a political geographical location in the form of a municipality name.

Variable: 'Customer Type'

This variable identifies customer types on the basis of tariff choice and has five values: 'NA' (n=3,082), 'Business' (n=11,619), 'Household' (n=318,487), 'Special' (n=5,368), and 'Distribution Network Companies' (n=18) in the raw dataset (n=338,574). 'Special' describes tariff types that cannot be categorized as household customers, business customers, or distribution network companies. This could be, for example, the meter reading of electricity production of a facility that creates solar energy and needs meter readings for evidence of origin certificates. The groups 'Special' and 'Distribution Network Company' both were taken out during data cleaning because they do not entail normal utility readings or have normal electricity contracts.

Variable: 'Number of Metering Points in Connection Object'

This variable identifies the number of metering points for the connection object that the meters are planted in. The values have a range of 1-90. For example, a connection object that has 90 metering points is a high-rise apartment complex.

Variable: 'Type of Housing'

This variable identifies the type of housing (the kind of connection object) on the grounds of the information given out in the variable 'Number of Metering Points in Connection Object'. It has two values: 'House' (*n*=149,233) and 'Apartment' (*n*=189,340). 'House' describes all the connection objects with less than three metering points. 'Apartment' describes all the connection objects that have three or more metering points. This variable derives information from metering points on connection objects and is therefore not exact in the identification of connection objects as either houses or apartments.

Variable: 'Utility Usage 2013'

This variable is the 2013 annual meter reads for each metering point, including day and night utility usage for metering points that have double tariffs and 24-hour usage for metering points that have Basic tariffs. A value of 'NA' means that for 2013, no meter reading happened for this metering point. A value of '0.00' means that for 2013, a meter reading happened for this metering point but the utility usage was 0.00.

Table 41. Descriptive Statistic for Utility Usage 2013

	Utility Usage 2013 in kWh
Number of values	231,234
Number of null values	30
Number of missing values	6,099
Minimal value	0.0
Maximal value	3,942,782
Range	3,942,782
Sum of all non-missing values	1,534,395,422.6
Median	3,830.0
Mean	6,635.7
Standard error on the mean	39.2
Confidence interval of the mean at the p level .95	76.8
Variance	355,495,201.2
Standard deviation	18,854.6
Variation coefficient defined as the standard deviation divided by the mean norm	2.8

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable and renewable-plus defaults (n=237,333).

Variable: 'Utility Usage 2014'

This variable is the 2014 annual meter reads for each metering point, summing up day and night usage for metering points that have double tariffs and 24-hour usage for metering points that have Basic tariffs. A value of 'NA' means that for 2014, no meter readings happened for this metering point. A value of '0.00' means that for 2014, a meter reading had happened for this metering point but the utility usage was 0.00.

Table 42. Descriptive Statistics for Utility Usage 2014

	Utility Usage 2014 in kWh
Number of values	237,333
Number of null values	2,831
Number of missing values	0
Minimal value	0.0
Maximal value	3,807,496
Range	3,807,496
Sum of all non-missing values	1,404,117,263.7
Median	3,384
Mean	5,916.2
Standard error on the mean	40.1
Confidence interval of the mean at the p level .95	78.6
Variance	382,145,188.5
Standard deviation	19,548.5
Variation coefficient defined as the standard deviation divided by the mean norm	3.3

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable and renewable-plus defaults (n=237,333).

Variable: 'Utility Usage 2015'

This variable is the 2015 annual meter reads for each metering point, summing up day and night usage for metering points that have double tariffs and 24-hour usage for metering points that have Basic tariffs. A value of 'NA' means that for 2015, no meter reading happened for this metering point. A value of '0.00' means that for 2015, a meter reading happened for this metering point but the utility usage was 0.00.

Table 43. Descriptive Statistics for Utility Usage 2015

	Utility Usage 2015 in kWh
Number of values	237,333
Number of null values	1,554
Number of missing values	0
Minimal value	0.0
Maximal value	3,790,160
Range	3,790,160
Sum of all non-missing values	1,457,060,517.1
Median	3,528
Mean	6,139.3
Standard error on the mean	40.7
Confidence interval of the mean at the p level .95	79.8
Variance	393,625,618.3
Standard deviation	19,840
Variation coefficient defined as the standard deviation divided by the mean norm	3.2

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable and renewable-plus defaults (n=237,333).

Variable: 'Utility Usage 2016'

This variable is the 2016 annual meter reads for each metering point, summing up day and night usage for metering points that have double tariffs and 24-hour usage for metering points that have Basic tariffs. A value of 'NA' means that for 2016, no meter reading happened for this metering point. A value of '0.00' means that for 2016, a meter reading happened for this metering point but the utility usage was 0.00.

Table 44. Descriptive Statistics for Utility Usage 2016

	Utility Usage 2016 in kWh
Number of values	237,333
Number of null values	34
Number of missing values	1,055
Minimal value	0.0
Maximal value	3,015,695
Range	3,015,695
Sum of all non-missing values	1,467,117,120
Median	3,519
Mean	6,209
Standard error on the mean	39
Confidence interval of the mean at the p level .95	76
Variance	357,336,093
Standard deviation	18,903
Variation coefficient defined as the standard deviation divided by the mean norm	3

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable and renewable-plus defaults (n=237,333).

Variable: 'Contract Choice 2013'

This variable had 38 values in the beginning. These were recoded into two values: conventional energy (*n*=233,338) and 'NA' (*n*=3,995), which marks all the metering points for which contract information is missing.

Variable: 'Contract Choice 2014'

This variable had 45 values in the raw dataset and nine values in the cleaned dataset. A surcharge for renewable electricity as can be seen in the tariff type and tranches from the renewable electricity report. In the process of data preparation, additional variables from the renewable energy report 2014 were combined to mark which metering points held renewable and renewable-plus energy. The original variable contract choice for 2014 gave no indication as to which customers held renewable or renewable-plus energy contracts.

Table 45. Descriptive Statistics for Re-coded Contract Choice 2014

Time Point	***n*** **Conventional Contracts**	***n*** **Renewable Contracts**	***n*** **Renewable-plus Contracts**	***n*** ***NA***
Contract Choice 2014	234,167	2,138	1,028	0

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable and renewable-plus defaults (n=237,333).

Variable: 'Solar Tranche: Ordered Amount 2014'

This variable had entries for 6,976 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Solar Tranche: Ordered Amount 2014' shows the ordered amount of solar tranche in kWh that customers ordered in 2014. This ordered amount is not reflective of the actual used amount.

Variable: 'Wind Tranche: Ordered Amount 2014'

This variable had entries for 6,976 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Wind Tranche: Ordered Amount 2014' shows the ordered amount of wind tranche in kWh that customers ordered in 2014. This ordered amount is indifferent to the actual used amount.

Variable: 'Water Tranche: Ordered Amount 2014'

This variable had entries for 6,976 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Water Tranche: Ordered Amount 2014' shows the ordered amount of water tranche in kWh that customers ordered in 2014. This ordered amount is not reflective of the actual used amount. This water tranche is Nature Star Water, which is different from Nature Basic Water. Both hydropower tranches/tariffs are made up off 100% certified hydropower made in Switzerland, but Nature Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations.

Variable: 'Full Tariff Nature Basic 2014'

This variable had entries for 3,166 metering points. This is a full tariff (the customer chooses the tariff not a specific amount like a tranche product). Only the metering points with this Nature Basic tariff fall back on hydropower after their renewable energy tranches are used up. Unfortunately, not all metering points that have this tariff can be found through this variable – some of them have 'hidden' Nature Basic tariffs which can only be found out through additional information found in other variables. Nature Basic's composition is 95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio. (The difference between Nature Basic Water und Nature Star Water is that both hydropower tranches/tariffs are made up off 100% certified hydropower made in Switzerland, but Nature Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations). This used amount is based on simulated data, meter-read data, and weighted data.

Variable: 'Contract Choice 2015'

This variable had 45 values in the raw dataset and 16 in the cleaned dataset, which were recoded into the three values 'conventional' (*n*=231,105), 'renewable' (*n*=4,597), 'renewable-plus' (*n*=1,631). For the process of re-coding, additional variables from the renewable energy report 2015 were consulted. The surcharge for renewable electricity can be seen in the tariff type and tranches from the renewable electricity report.

Variable: 'Sun Tranche: Ordered Amount 2015'

This variable had entries for 9,355 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Sun Tranche: Ordered Amount 2015' shows the ordered amount of solar tranche in kWh that customers ordered in 2015. This ordered amount is not the actual used amount.

Table 46. Descriptive Statistics for Sun Tranche: Ordered Amount 2015

	Sun: Ordered Amount 2015 Household in kWh (*n*=434)	**Sun: Ordered Amount 2015 Business in kWh (*n*=39)**
Number of values	434	39
Number of null values	0	0
Number of missing values	222,814	7,594
Minimal value	50	50
Maximal value	12,600	11,300
Range	12,550	11,250
Sum of all non-missing values	90,200	53,350.0
Median	100	1,000
Mean	207.8	1,367.9
Standard error on the mean	31.9	316.3
Confidence interval of the mean at the p level .95	62.7	640.4
Variance	442,005.5	3,902,827.3
Standard deviation	664.8	1,975.6
Variation coefficient defined as the standard deviation divided by the mean norm	3.2	1.4

All descriptive details come from the whole dataset of the regulated market with renewable defaults (household dataset n=223,248; business dataset n=7,633).

Variable: 'Wind Tranche: Ordered Amount 2015'

This variable had entries for 9,355 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Wind Tranche: Ordered Amount 2015' shows the ordered amount of wind tranche in kWh that customers ordered in 2015. This ordered amount is not the actual used amount.

Table 47. Descriptive Statistics for Wind Tranche: Ordered Amount 2015

	Wind: Ordered Amount 2015 Households in kWh (*n*=363)	**Wind: Ordered Amount 2015 Business in kWh (*n*=42)**
Number of values	363	42
Number of null values	0	0
Number of missing values	222,885	7,591
Minimal value	100	500
Maximal value	10,000	20,000
Range	9,900	19,500
Sum of all non-missing values	273,237.6	150,500.0
Median	250	2,000
Mean	752.7	3,583.3
Standard error on the mean	67.4	777.9
Confidence interval of the mean at the p level .95	132.5	1,570.9
Variance	1,646,773.6	25,413,617.9
Standard deviation	1,283.3	5,041.2
Variation coefficient defined as the standard deviation divided by the mean norm	1.7	1.4

All descriptive details come from the whole dataset of the regulated market with renewable defaults (household dataset n=223,248; business dataset n=7,633).

Variable: 'Water Tranche: Ordered Amount 2015'

This variable had entries for 9,355 metering points. This is a tranche product (the customer chooses a specific annual amount) and not a full tariff. The variable 'Water Tranche: Ordered Amount 2015' shows the ordered amount of water tranche in kWh that customers ordered in 2015. This ordered amount is not the actual amount used. This water tranche is Nature Star Water, which is different from Nature Basic Water. Both hydropower tranches/tariffs are made up of 100% certified hydropower made in Switzerland, but Nature

Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations.

Table 48. Descriptive Statistics for Water Tranche: Ordered Amount 2015

	Water: Ordered Amount 2015 Households in kWh (*n*=1,470)	**Water: Ordered Amount 2015 Business in kWh (*n*=123)**
Number of values	1,470	123
Number of null values	0	0
Number of missing values	221,778	7,510
Minimal value	9.5	1,000
Maximal value	74,143	923,094
Range	74,133.5	922,094
Sum of all non-missing values	3,014,917	4,782,805.8
Median	2,000.0	14,000
Mean	2,051	38,884.6
Standard error on the mean	73.1	10,186.0
Confidence interval of the mean at the p level .95	143.3	20,164.2
Variance	7,849,776.3	12,761,850,308.7
Standard deviation	2,801.7	112,968.4
Variation coefficient defined as the standard deviation divided by the mean norm	1.4	2.9

All descriptive details come from the whole dataset of the regulated market with renewable defaults (household dataset n=223,248; business dataset n=7,633).

Variable: 'Full Tariff Nature Basic 2015'

This variable had entries for 9,355 metering points. This is a full tariff (the customer chooses the tariff, not a specific amount like for a tranche product). The metering points with this Nature Basic tariff fall back on hydropower after their renewable energy tranches are used up. Unfortunately, not all metering points that have this tariff can be identified through this variable. Some of them have 'hidden' Nature Basic tariffs. The composition of Nature Basic is 95% Nature Basic Water, 2.5% Nature Star Water, and 2.5% Nature Basic Sun, Wind, and Bio. (The difference between Nature Basic Water and Nature Star Water is that both hydropower tranches/tariffs are made up off 100% certified hydropower made in Switzerland, but Nature Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations). This used amount is based on simulated data, meter-read data, and weighted data.

Table 49. Descriptive Statistics for Full Tariff Nature Basic 2015

	Nature Basic 2015 Household in kWh (*n*=2,598)	**Nature Basic 2015 Business in kWh (*n*=50)**
Number of values	2,598	50
Number of null values	0	0
Number of missing values	220,650	7,583
Minimal value	0.00048	1,250.9
Maximal value	117,647.4	364,875
Range	117,647.4	363,624.1
Sum of all non-missing values	10,210,451.1	1,552,582.9
Median	3,284.8	19,972.6
Mean	3,930.1	31,051.7
Standard error on the mean	72.3	7,475.4
Confidence interval of the mean at the p level .95	141.8	15,022.4
Variance	13,585,912.3	2,794,072,783.9
Standard deviation	3,685.9	52,859
Variation coefficient defined as the standard deviation divided by the mean norm	0.9	1.7

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (household dataset n=223,248; business dataset n=7,633).

Variable: 'Full Tariff Nature 2015'

This variable had entries for 9,355 metering points. This is a full tariff (the customer chooses the tariff not a specific amount like a tranche product). The composition of this tariff is 85% Nature Basic Water, 5% Nature Basic Wind, 5% Nature Basic Sun, and 5% biomass energy. (The difference between Nature Basic Water and Nature Star Water is that both hydropower tranches/tariffs are made up off 100% certified hydropower made in Switzerland, but Nature Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations). This used amount is based on simulated data, meter-read data, and weighted data. For the customers who received only the renewable default, there were only household customers on the nature tariff in 2015, and no business customers.

Table 50. Descriptive Statistics for Full Tariff Nature 2015

	Nature 2015 Households in kWh (*n*=10)
Number of values	10
Number of null values	0
Number of missing values	223,238
Minimal value	3.3
Maximal value	46,578.0
Range	46,574.7
Sum of all non-missing values	106,810.6
Median	7,515.6
Mean	10,681.1
Standard error on the mean	4,335.4
Confidence interval of the mean at the p level .95	9,807.4
Variance	187,959,494.4
Standard deviation	13,709.8
Variation coefficient defined as the standard deviation divided by the mean norm	1.3

All descriptive details come from the whole dataset of the regulated market of household customers with renewable defaults (n=223,248).

Variable: 'Full Tariff Nature Star 2015'

This variable had entries for 9,355 metering points. This is a full tariff (the customer chooses the tariff, not a specific amount like a tranche product). The composition of Full Tariff Nature Star is 70% Nature Star Water, 10% Nature Star Wind, 10% Nature Star Sun, and 10% biomass energy. (The difference between Nature Basic Water and Nature Star Water is that both hydropower tranches/tariffs are made up of 100% certified hydropower made in Switzerland, but Nature Star Water invests 1 Rappen for each kWh into ecological funds that invest locally in water renaturations). This used amount is based on simulated data, meter-read data, and weighted data. Of the customers who received only the renewable default, there were only household customers on the Nature Star tariff in 2015, and no business customers.

Table 51. Descriptive Statistics for Full Tariff Nature Star 2015

	Nature Star 2015 Household in kWh (*n*=5)
Number of values	5
Number of null values	0
Number of missing values	223,243
Minimal value	259.3
Maximal value	7,266.3
Range	7006.9
Sum of all non-missing values	21,278.7
Median	4,484.6
Mean	4,255.7
Standard error on the mean	1,277.7
Confidence interval of the mean at the p level .95	3,547.5
Variance	8,162,591.2
Standard deviation	2,857.0
Variation coefficient defined as the standard deviation divided by the mean norm	0.7

All descriptive details come from the whole dataset of the regulated market of household customers with renewable defaults (n=223,248).

Variable: 'Initial Default Allocation'

The variable 'Initial Default Allocation' shows the initial default for each metering point at the end of August 2015. The default allocation was communicated via mail to each customer. There were three possible default allocations. Some customers did not receive a new default, but rather kept their old contracts (conventional default). The main group of customers received the new 'renewable' default and a small number of customers received the 'renewable-plus' default. The default allocation became active on 01.01.2016.

Variable: 'Contract Choice 01.01.2016'

The variable 'Contract Choice 01.01.2016' had 20 values initially. These were recoded into the three values 'conventional' (*n*=25,693), 'renewable' (*n*=204,339), and 'renewable-plus' (*n*=849).

Table 52. Descriptive Statistics for Contract Choice 01.01.2016

Time Point	***n*** **Conventional Contracts**	***n*** **Renewable Contracts**	***n*** **Renewable-plus Contracts**	***n*** ***NA***
Contract Choice 01.01.2016	25,693	204,339	849	0

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (n=230,881).

Variable: 'Contract Choice 24.12.2016'

The variable 'Contract Choice 24.12.2016' had 21 values initially. These were recoded into the three values 'conventional' (*n*=27,260), 'renewable' (*n*=202,685), and 'renewable-plus' (*n*=936).

Table 53. Descriptive Statistics for Contract Choice 24.12.2016

Time Point	***n*** **Conventional Contracts**	***n*** **Renewable Contracts**	***n*** **Renewable-plus Contracts**	***n*** ***NA***
Contract Choice 24.12.2016	27,260	202,685	936	0

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (n=230,881).

Variable: 'Salutation 2013'

This information was extracted from the salutation part of the address of the customer. This variable had 12 values that were recoded into four values: 'female' (*n*=37,221), 'male' (*n*=102,883), 'mixed' (*n*=31,343), and 'NA' (*n*=65,886).

Variable: 'Salutation 2014'

This information was extracted from the salutation part of the address of the customer. This variable had 12 values that were recoded into four values: 'female' (*n*=38,066), 'male' (*n*=102,970), 'mixed' (*n*=32,014), and 'NA' (*n*=64,283).

Variable: 'Salutation 2015'

This information was extracted from the salutation part of the address of the customer. This variable had 13 values that were recoded into four values: 'female' (*n*=38,760), 'male' (*n*=103,086), 'mixed' (*n*=32,635), and 'NA' (*n*=62,852).

Variable: 'Salutation 2016'

This information was extracted from the salutation part of the address of the customer. This variable had 13 values that were recoded into four values: 'female' (*n*=39,336), 'male' (*n*=102,130), 'mixed' (*n*=32,790), and 'NA' (*n*=63,077).

Variable: 'Mover 2014'

This information was extracted from changes in the customer numbers on metering points in the time frame of 31.12.2013 to 31.12.2014. This is a dummy variable marking the movers with an 'X', and therefore has two values: 'X' (*n*=26,552) and 'NA' (*n*=312,022). In line with data cleaning, all movers in 2014 were deleted. All descriptive details come from the clean dataset: the free and regulated market of business and household customers with renewable and renewable-plus contracts and no defaults.

Variable: 'Mover 2015'

This information was extracted from changes in the customer numbers on metering points in the time frame of 31.12.2014 to 31.12.2015. This is a dummy variable marking the movers with an 'X', and therefore has two values: 'X' (*n*=19,468) and 'NA' (*n*=319,106). In line with the data cleaning, all movers in 2015 were deleted. All descriptive details come from the clean dataset: the free and regulated market of business and household customers with renewable and renewable-plus contracts and no defaults.

Variable: ‘Mover 2016’

This information was extracted from changes in the customer numbers on metering points in the time frame of 31.12.2015 to 31.12.2016. This is a dummy variable marking the movers with an ‘X’, and therefore has two values: ‘X’ (*n*=32,505) and ‘NA’ (*n*=306,069). In line with data cleaning, all movers in 2016 were deleted. All descriptive details come from the clean dataset: the free and regulated market of business and household customers with renewable and renewable-plus contracts and no defaults.

Appendix 3: Descriptive Statistics of Variables on the Municipality Level

Variable: 'Nuclear Phase-out Voting 2016'

Yes-votes as a percentage on the municipality level were matched with the utility company's municipalities in their dataset. This variable concerns the public vote on the Nuclear Power Phase-Out initiative on 27.11.2017.

The voting data comes from the website of the Federal Department for Statistics (https://www.bfs.admin.ch/bfs/de/home/statistiken/politik/abstimmungen/jahr-2016/2016-11-27/initiative-atomausstieg.assetdetail.1363831.html, downloaded on 21.09.2017). The voting data was published by the Swiss Federal Agency for Statistics on 27.11.2016 on its website. The BFS-Number is je-d-17.03.03.bx.608.c.

Table 54. Descriptive Statistics for Nuclear Phase-out Voting 2016

	Nuclear Phase-out Voting
Number of values	218,291
Number of null values	0
Number of missing values	12,590
Minimal value	5.7
Maximal value	69.6
Range	63.9
Sum of all non-missing values	9,158,487.3
Median	42.6
Mean	42.0
Standard error on the mean	0.02
Confidence interval of the mean at the p level .95	0.04
Variance	83.2
Standard deviation	9.1
Variation coefficient defined as the standard deviation divided by the mean norm	0.2

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (n=230,881).

Variable: 'Proximity NPP'

Municipalities in the utility company's dataset were coded into three zones. The first zone identifies the municipality that contains a nuclear power plant (here, *n* is the number of metering points in that municipality; *n*=1,418). The second zone identifies the municipalities that are direct neighbours to the municipality with a nuclear power plant (*n*=9,523). The third zone identifies all the municipalities that neither have a nuclear power plant nor neighbour a municipality with a nuclear power plant (*n*=219,940). All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (*n*=230,881).

Variable: 'Population Density 2015'

One of the municipality characteristics, population density from the year 2015 (newest available data), was matched to the municipalities in the utility company's dataset. The data comes from the website of the Federal Department for Statistics (https://www.bfs.admin.ch/bfs/de/home/statistiken/regionalstatistik/regionale-portraets-kennzahlen/gemeinden.assetdetail.2422865.html, downloaded on 21.09.2017). The data on municipality characteristics was published by the Swiss Federal Department for Statistics on 18.05.2017. The data represents the time frame from 2014 until 2016. The BFS-Number is je-d-21.03.01.

Table 55. Descriptive Statistics for Population Density 2015

	Population Density 2015
Number of values	219,021
Number of null values	0
Number of missing values	11,860
Minimal value	1
Maximal value	4,576
Range	4,575
Median	214
Mean	546.1
Standard error on the mean	1.6
Confidence interval of the mean at the p level .95	3.0
Variance	529,278.9
Standard deviation	727.5
Variation coefficient defined as the standard deviation divided by the mean norm	1.3

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (n=230,881).

Variable: 'Age Distribution: 0-19'

The municipality characteristic of age distribution from the year 2015 (the newest available data) was matched to the municipalities in the utility company's dataset. 'Age Distribution: 0-19' describes the number of citizens in each municipality that are between 0 and 19 years old as a percentage.

The data comes from the website of the Swiss Federal Department for Statistics (https://www.bfs.admin.ch/bfs/de/home/statistiken/regionalstatistik/regionale-portraets-kennzahlen/gemeinden.assetdetail.2422865.html, downloaded on 21.09.2017). The data on municipality characteristics was published by the Federal Department for Statistics on 18.05.2017. The data represents the time frame from 2014 until 2016. The BFS-Number is je-d-21.03.01.

Table 56. Descriptive Statistics for Age Distribution: 0-19

	Age Distribution: 0-19
Number of values	219,021
Number of null values	0
Number of missing values	11,860
Minimal value	7.7
Maximal value	30.2
Range	22.5
Median	19.1
Mean	19.8
Standard error on the mean	0.005
Confidence interval of the mean at the p level .95	0.009
Variance	4.7
Standard deviation	2.2
Variation coefficient defined as the standard deviation divided by the mean norm	0.1

All descriptive details come from the whole dataset of the regulated market of household and business customers with renewable defaults (n=230,881).

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