Alert the Inert! Switching Costs and Limited Awareness in Retail Electricity Markets*

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Abstract

We quantify how switching costs and limited awareness affect consumer inertia in liberalized retail electricity markets by developing and estimating a structural demand model using a novel data set on electricity contract choices in Belgium. Our data allow us to disentangle different sources of inertia by using a rich combination of macromoments and micromoments. Our estimates indicate that consumers perceive electricity contracts as differentiated and that both limited awareness and switching costs significantly hinder consumer engagement. Our counterfactual simulations reveal the potential for substantial welfare gains from retail choice compared to a market with a regulated monopolist.

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1 Introduction

More than 15 years ago, many countries implemented the liberalization of their electricity markets. The gains of these reforms have often remained muted, however. In particular, retail markets are still highly concentrated and incumbents continue to capture the largest share of the consumer base (CEER, 2017). Low consumer engagement may simply reflect consumer preferences, but it can also stem from different types of market frictions that prevent efficient contract choice and keep a large proportion of consumers on relatively expensive contracts.

These experiences have sparked a debate on whether the potential benefits of retail choice, in particular, access to a broader range of differentiated products and more intense competition among suppliers, justify the costs caused by market frictions, such as consumer search and switching costs. While policy makers in some regions have never pursued consumer choice in retail electricity markets,[1] others have opted for full retail choice and spend substantial resources on policies to increase consumer engagement.[2] In order to design these policies effectively, it is crucial to quantify the different channels of consumer inertia and understand the relative gains from reducing specific market frictions.

In this paper, we shed new light on the relative importance of different sources of consumer inertia in retail electricity markets by developing and estimating a structural demand model of the retail electricity market. Within a unified framework, our model encompasses the most important sources of inertia discussed in the literature, namely consumer preferences for differentiated contract attributes, switching costs and limited awareness about the available electricity contracts. Compared to existing studies that quantify market frictions in retail electricity markets, for example, Hortaçsu et al. (2017) and Giulietti et al. (2014), we exploit a richer data set that, in combination with our structural model, allows for more detailed insights into the specific channels of consumer inertia. Using our estimates, we conduct a series of counterfactual policy simulations that provide new insights on the most relevant margins for policy intervention, for example, in the form of facilitating the switching and search process. Moreover, our model allows for a comprehensive evaluation of the welfare gains from a liberalized electricity market compared to a regulated market that is operated by a monopolist. To the best of our knowledge, we are the first in the literature to quantify these welfare effects using a detailed structural model that allows for both differentiated electricity contracts and several types of market frictions.

We model consumer demand as a two-stage process in which consumers decide how much information about the market to acquire before choosing a contract. Limited awareness prevails in many markets in the sense that consumers are unlikely to consider all available options when making a choice. In retail electricity, the complex nature of the market with its quickly changing contract offers makes it difficult for consumers to be fully aware about the details of all available contracts, in particular, their prices.

[1]For example, in the United States, less than half of the states offer full retail choice in 2017 (NREL, 2017).

[2]For example, one pillar of the European Commission's "Clean Energy for all Europeans" package, published in November 2016, sets out new rules to overcome consumer inertia in retail electricity markets. In particular, it aims at increasing consumer awareness and encouraging supplier switching (COM(2016)864).

We focus on one specific aspect of consumer search for electricity contracts, namely the use of a price comparison website (PCW). The presence and usage of PCWs in many forms is growing.[3] On the one hand, PCWs enable consumers to become fully informed about the market in an easy and transparent way. On the other hand, using a PCW can be costly. For example, consumers need to become familiar with the website's interface or enter consumer-specific information. Therefore, only a consumer whose expected benefit exceeds the cost of using the PCW will use the website and become fully informed about all available contracts and their prices.[4]

In our application, the PCW is operated by the regulator and, therefore, differs considerably from for-profit PCWs, which are analyzed in Baye and Morgan (2001) and De Los Santos et al. (2017). In our context, the PCW does not involve fees for suppliers to advertise or for consumers to search. Instead, it is purely informative, i.e., it summarizes prices and other contract information, it is exhaustive and reliable and updated monthly. To the best of our knowledge, we are the first in this literature to identify and analyze the costs of search via a regulated PCW. In our model, consumers who do not use the PCW remain only partially informed and form their consideration sets stochastically as a function of supplier advertising similarly to Sovinsky Goeree (2008).

In the second stage, consumers evaluate the utility from each of the contracts in their consideration set when making a choice. We model electricity contracts as differentiated products based on the seminal framework by Berry et al. (1995) (henceforth, BLP) and allow for preference heterogeneity in several dimensions. Although electricity is a physically homogeneous product, consumers may perceive and value specific aspects in the generation and the supply of electricity differently. For example, suppliers may differ in the quality of their customer service and some consumers may prefer electricity that is produced from renewable sources or electricity that is provided by the incumbent because they believe that it offers more reliable service.

Switching costs can induce state dependence in product choices in markets where goods are purchased repeatedly (Klemperer, 1995), as is the case for electricity. Switching costs are not necessarily limited to monetary components, such as early contract termination fees. They may also stem from a consumer's hassle when switching suppliers. For example, a consumer who is aware of a better contract may decide to not switch, because the hassle of going through the switching process outweighs the utility gain associated with the alternative contract. Following the recent literature on the estimation of switching costs (Shcherbakov, 2016; Weiergraeber, 2018) we model switching costs as a one-time utility loss incurred when a consumer chooses a different supplier today than in the previous period.

We estimate the model using the generalized method of moments (GMM) and a combination of macromoments and micromoments, which match observed and predicted contract choices

[3]For example, the European Commission proposes a directive that would require EU member states to offer at least one certified and free-of-charge price comparison tool (Article 14, COM(2016)864).

[4]Consequently, our *PCW search cost* differs from most of the empirical search literature that estimates a distribution of costs for product-specific search, see, for example, Hong and Shum (2006) or Wildenbeest (2011). Our PCW search cost is best interpreted as a fixed "entry cost" for using the PCW.

at the consumer level, similar in spirit to Petrin (2002), Berry et al. (2004) and Sovinsky Goeree (2008).

We are able to separately identify the three potential sources of consumer inertia (preference heterogeneity, switching costs and limited awareness) by exploiting several novel data sets that contain rich variation on the aggregate and the individual consumer level that we combine in our structural demand model. In particular, our data contain a panel of contract-level market shares, which allows us to assess how product differentiation affects choices in much more detail than when using supplier-level data only. Furthermore, our data comprise a repeated cross section of an extensive survey of a large number of electricity consumers. Specifically, the survey responses link consumer demographics, the consumer's attitudes towards various aspects of electricity markets including her current contract, and most importantly, whether the consumer has used the PCW before making her choice. Finally, we obtained data on the usage statistics of the main PCW available in the market as well as a panel of the advertising expenditures of all relevant electricity suppliers.

There are two central identification challenges in our model. The first is to separate the effect of state dependence through switching cost from (potentially unobserved) preference heterogeneity. The second is to separate preferences from awareness, i.e., to determine whether a consumer does not search and switch to another contract because she is satisfied with her current contract or because the costs of becoming aware of alternative contracts are high. We address the first challenge following the arguments of Shcherbakov (2016) and Weiergraeber (2018). Since our data comprise a panel of aggregate market shares at the contract level, observing market shares today and their covariation with exogenous shifters in previous periods will identify the magnitude of the switching costs. Observing aggregate churn rates, i.e., the share of customers who switch suppliers in every period, allows us to construct additional moment conditions to pin down switching costs.

For the identification of the PCW search costs and the parameters determining the awareness process, we mainly rely on the consumer-level survey data, in which we observe variation in consumers' PCW usage and their contract choices conditional on their PCW usage behavior. Since we can construct PCW usage statistics for different demographic types, we are able to identify a demographic-specific PCW search cost. For example, we can allow the PCW to vary with a consumer's age.

Market shares conditional on consumers' PCW usage status will identify the remaining awareness parameters of the model. While contract choices of non-PCW users will be informative about the parameters of a consideration process through advertising, the conditional market share distribution among PCW users, will further help to pin down consumer preferences and the switching cost parameter. A crucial advantage of our application and our data is that we observe independent variation that arguably shifts either only the benefits or the costs of searching the PCW.

Our data covers the retail electricity market in the Belgian region of Flanders between 2012 and 2016 and we find that all three sources of consumer inertia are present in our application. First, product differentiation affects consumer choice in this seemingly homogeneous product market. Seniors have a large willingness-to-pay (WTP) for the incumbent supplier. In our baseline model in which search costs are homogeneous across consumer types, seniors are willing to spend EUR 12 per month to be with the incumbent instead of an entrant. When we allow the PCW search cost to vary with age, this WTP is still significant but drops to EUR 5 per month. While on average Flemish consumers do not value electricity from renewable resources, the valuation varies substantially across consumers.

Second, we find that both switching costs and PCW search costs affect consumer choices substantially, and that both market frictions are of a similar magnitude, roughly equivalent to one half of the monthly electricity expenditure of an average household.[5] Consequently, our estimates indicate that even a fully informed consumer incurs significant hassle costs from switching suppliers. The cost for searching via the PCW generally vary only marginally over time, except for several months in 2012 when an information campaign run by the Flemish regulator lowered consumer search cost by 25% to 50% depending on our model specification.

Our estimates can provide guidance to policy makers who aim at reducing market frictions and enabling more efficient consumer choices. For example, making a regulated PCW available is a promising first step to distribute information about available contracts in the market, but our results show that it is crucial to ensure that these websites are easy to use and that consumers can translate this information into better choices. Therefore, policy measures that increase consumer awareness are likely to be most effective when combined with policies that facilitate the switching process, for example, by implementing a standardized switching procedure or regular information campaigns about different aspects of electricity markets.

In a series of counterfactual simulations, we analyze the effects of different policy interventions. First, we compare the effects of either reducing switching costs or reducing search costs in order to provide guidance on how a regulator may best spend its resources if its objective is to make consumer choice more efficient. For our application, we find that both switching compensations and search cost reductions result in large consumer welfare gains. Compensating consumers for 75% of their switching costs is welfare-equivalent to a policy that reduces the cost of searching the PCW by 70%. Both measures yield an average net gain in consumer surplus (per month and consumer) of roughly 20% of the average monthly electricity bill. Second, we evaluate the welfare gains of a specific information campaign that the Flemish regulator conducted in the fall of 2012 with the aim of increasing the use of the regulated PCW. We find that the information campaign generated a total consumer surplus gain of EUR 27 million for the whole region of Flanders and our sample period, which covers 53 months. These large welfare gains provide evidence that in many retail electricity markets fairly low-cost measures can already lead to significantly better contract choices by consumers.

[5] The total electricity bill of a Flemish household consists of several components: charges for the electricity delivered which is set by the specific supplier, a set of additional fees, such as network access charges and taxes. Since the additional fees enter linearly and are identical across suppliers, we do not include them in our model and the discussion of the results. Throughout the paper, the term *electricity bill* refers to the amount that an average consumer pays for electricity (including VAT), but it excludes fees and other charges. Fees and other charges made up 60% of the average bill for a Flemish consumer in June 2016. (Source: `http://www.creg.info/Tarifs/Boordtabel-Tableaudebord/Francais/tabbord201606.pdf`.)

Finally, we use our model to address the broader question of quantifying the welfare gains from deregulated retail electricity markets. Specifically, we compute consumer surplus when the market and its search and switching frictions are eliminated and all consumers are served by a regulated monopolist. Under the assumption that the monopolist charges the same prices as the incumbent observed in the data, we find that an average consumer would be worse off by EUR 10 per month compared to the actual market with retail choice and search and switching costs.

Related literature There are several studies that quantify market frictions in retail electricity markets.[6] However, previous research typically relies on more limited data and, therefore, focuses only on a subset of the different sources of inertia that we analyze. For example, Giulietti et al. (2014) estimate an equilibrium search model assuming homogeneous products and the absence of consumer switching costs. They analyze data on the UK electricity market and find that search costs must have been relatively high to explain the observed price dispersion and supplier markups.

The closest paper to ours is Hortaçsu et al. (2017) who study two potential sources of inertia in the Texas electricity market: inattention and consumer preferences towards the incumbent supplier. They find that both play a significant role during their sample period (2002 to 2006), in particular, within census tracks characterized by low average income and education levels and a high share of senior citizens. While our estimates and main welfare results are in line with theirs, there are several aspects that distinguish our study from theirs. First, we analyze a potentially very different market, both in terms of time period and geography. While Hortaçsu et al. (2017) investigate the market immediately after the deregulation in Texas, our data covers a time period more than ten years after the liberalization in a European country. Consequently, the market environment during our analysis is likely to be in a stable steady state, so that, for example, consumer learning is unlikely to be a relevant issue in our framework.

Second, our approaches differ in the identification and estimation strategy due to the use of different types of data. Hortaçsu et al. (2017) exploit large-scale electricity meter data that is not linked to the search behavior and the demographics of individual consumers. However, they observe the full matrix of conditional choice probabilities which enables them to identify awareness separately from preferences without observing consumers' consideration sets. Our analysis, relies on a broader range of data sets combining macro and micro data in which we partially observe the consideration sets of consumers, in particular, whether a consumer is fully informed or not. Furthermore, we are able to link consumer behavior with usage statistics of the market's main PCW which allows us to provide insights into the effects of PCWs for consumer search and switching behavior.

[6] Many studies explore potential reasons for inertia in energy markets with no attempt to quantify them (Giulietti et al., 2005; Wieringa and Verhoef, 2007; Giulietti et al., 2010; Sitzia et al., 2014; He and Reiner, 2017; Daglish, 2016; Six et al., 2016) or determine correlations between consumer characteristics and switching activity (Ek and Söderholm, 2008; Waddams Price and Zhu, 2016; Waddams Price et al., 2014; He and Reiner, 2017; Vesterberg, 2018; Gugler et al., 2018).

Finally, Hortaçsu et al. (2017) are agnostic about the specific drivers of inertia and model inattention in a reduced form in which consumers are either fully passive or search actively among all suppliers. This modeling approach does not allow them to distinguish different types of market frictions. Consequently, their inattention estimates are likely to capture a combination of both search and switching costs. Distinguishing the two, as we do in our analysis, can, however, be important for specific policy recommendations. For example, Wilson (2012) develops a general theory model that features both search and switching costs. He provides empirical evidence that, in many industries –including the UK electricity market– both frictions are likely to be present and that models that consider only one type of these costs can yield biased estimates. Therefore, a model that is able to disentangle the different channels is likely to provide more reliable guidance for economic policy.

Honka (2014) estimates a structural demand model incorporating both consumer search and switching behavior for the car insurance industry. Although similar in spirit to our approach, we analyze a different kind of search. While Honka (2014) models direct product-specific search, we focus on all-or-nothing search through a regulated PCW, that perfectly informs a consumer about all available options, and an exogenous awareness component created by supplier advertising as in Sovinsky Goeree (2008). Our approach is motivated by the typical process through which consumers acquire information in electricity markets, which differs from those in insurance markets, where consumer-specific quotes are important and PCW information is often not informative. Moreover, we base our analysis on a different type of data. While Honka (2014) observes a single cross section of individual-level survey data that contains information on both a consumer's consideration set and her previous choice, we rely on a combination of macro panel data and repeated cross sections of micro-level data to identify consumers' consideration sets and switching costs.

For modeling the consideration sets of consumers who are only partially informed, we build on and adapt previous work on limited information and advertising by Sovinsky Goeree (2008). Compared to her analysis, our data has the advantage that we partly observe consumer consideration sets, i.e., choices of fully and partially informed consumers depending on their PCW usage status, which allows us to estimate the advertising-awareness process directly without having to rely on media exposure as an instrument for awareness. A recent strand of literature deals with identification of preferences and consideration sets relying on choice data only. Abaluck and Adams (2017) show that incomplete consideration sets and preferences can be disentangled from the magnitude of the asymmetry between cross-price responses. Crawford et al. (2016) develop the concept of *sufficient sets* as a sufficient statistic for a consumer's unobserved true consideration set and show how it can be used to estimate preferences in various settings where only choice data are available. This literature analyzes how preferences can be identified using minimal data and structure, and can, in principle, be combined with our estimation strategy. We view our approach as complementary with a different focus; we exploit the availability of a combination of detailed data sets and reliable guidance on how consumers acquire information in electricity markets to quantify specific mechanisms of limited awareness and consumer inertia in our application.[7]

[7]Even though some of our model structure is specific to retail electricity markets, the data required to estimate the model, in particular, an aggregate panel of market shares and a repeated cross section of

Disentangling different reasons for consumer inertia is an important question in many other industries beyond retail electricity markets. For example, the presence of switching costs or inattention has been established in the market for cable TV (Shcherbakov, 2016), wireless services (Weiergraeber, 2018), pension plans (Luco, 2017), PCs (Sovinsky Goeree, 2008), hotels (Koulayev, 2014), retail banking (Honka et al., 2017) and most notably in health insurance markets (Gaynor et al., 2016; Heiss et al., 2016; Nosal, 2012).

The paper proceeds as follows. The next section summarizes the institutional background and important characteristics of the Flemish retail electricity market. Sections 3 and 4 describe our novel data set and provide reduced form evidence for limited awareness and state dependence to motivate our structural demand model that we develop in Section 5. Section 6 discusses the identification and estimation strategy. We present estimation results for the structural model and the counterfactual analyses in Section 7. Section 8 concludes.

2 Institutional Background

The Belgian electricity market is composed of three regional markets, Brussels-Capital, Flanders and Wallonia, and was fully liberalized in January 2007. The deregulation of the retail market consists of two main elements. First, consumers are now free to choose their electricity supplier. Second the *Intercommunales*[8], traditionally responsible for both distributing and selling electricity to consumers, are charged with the non-liberalized parts of the markets only, such as the management of the distribution network, technical installation and meters. The sale of electricity is now performed by commercial suppliers in a market open to competition.

Belgian regions have extensive legal competencies in energy policy. In particular, they are responsible for the regulation of the retail electricity market and the distribution and transmission of electricity (IEA, 2016). Flanders is the largest of the three Belgian regions in terms of population (57.5% in 2016, i.e., 6.5 million people), has the highest per capita income (6.7% above average in 2016) and forms one linguistic community.[9] The liberalization of the Flemish regional electricity market was implemented in July 2003. Brussels-Capital and Wallonia followed in 2007. This puts Flanders into the early waves of electricity market liberalization in Europe. Only six other European countries deregulated earlier (ACER, 2015).[10] As a consequence, it is plausible that our sample period (2012 to 2016) covers the

consumer surveys, are fairly standard and can be obtained for many other industries at low costs; therefore, our model can potentially be applied to other markets where similar market frictions may be prevalent.

[8]In 1999, the *intercommunales* supplied 61% of the Belgian market. 38% of the market was directly supplied by *Electrabel* and *SPE*, a producer in public hands that later becomes *Luminus*. Of the *intercommunales*, 20% were owned by a group of municipalities and the reminder by a public-private partnership (i.e., joint forces between municipalities and a private company, mainly the incumbent *Electrabel*). In 1995, 87% of all municipalities were tied to contracts from *Electrabel* who also had a dominant position in the generation segment of the electricity market (Verhoes and Sys, 2006).

[9]Data was collected from `www.statbel.fgov.be/`.

[10]The six countries are Austria, Germany, Finland, Norway, Sweden and the UK.

industry in a mature state since Flemish consumers had almost 10 years to become familiar with the market environment.

Following its liberalization, the Flemish market shows several indications of an increase in competition. First, since 2003 a large number of new suppliers entered the market. In 2016, residential consumers in Flanders can choose among more than 45 electricity suppliers although most firms have very small market shares of less than 0.3%. Second, by international comparison, Flemish consumers are very active in switching electricity suppliers. In 2014, 11.7% of consumers had switched suppliers, which makes Flanders score among the top six European countries in terms of supplier switching rates.[11] Despite these positive trends, market concentration remains high. In 2016, the incumbent supplier, *Electrabel*[12], still serves more than 40% of the market, although this share is amongst the lowest compared to other European countries.[13] Furthermore, many Flemish consumers remain with expensive electricity contracts and forgo savings that could be made by switching to cheaper contracts. For example, our data indicates that in July 2016 the electricity contract which was chosen most frequently has a 19.5% market share although it is twice as expensive for the average consumer as the cheapest offer in the market.

In 1999, the federal regulator, CREG (Belgian Federal Commission for Electricity and Gas Regulation), was created to ensure transparency and the competitiveness of the national electricity and gas markets and to protect consumer interests. Regional institutions are the *Vlaamse Regulator voor Elektriciteit en Gas* (VREG) in Flanders, the *Commission Wallonne pour l'Énergie* (CWaPE) in Wallonia, and the *Brugel* in Brussels-Capital. These regulators take an active role in enhancing switching and increasing awareness of electricity consumers in Belgium with the aim of increasing market competition. For example, in September 2012, they supported the Federal Ministry of Economic Affairs in the campaign *Dare to Compare* which aimed at informing electricity consumers about the market, in particular, by providing instructions on how to compare contracts and tariffs.[14] In a similar vein, since the liberalization, the Flemish regulator, VREG, conducts yearly surveys to evaluate the behavior and experiences of households in the energy market. Furthermore, the three regional regulators are in charge of running and promoting the main price comparison website (PCW) in each region.

The *V-test* (http://www.vtest.be) presents consumers with an exhaustive list of the various electricity products from all energy suppliers in Flanders. Figure A.2 in the Appendix displays an example from the V-test website for an average consumer. In a first step, a website user

[11] According to ACER (2015), supplier switching rates in 2014 were above 11.7% only in Ireland, the Netherlands, Norway, Portugal and Spain.

[12] In a small part of Flanders, *EDF* provided the incumbent service instead. For simplicity, we assume in our structural model that Electrabel is the incumbent supplier throughout all of Flanders.

[13] Incumbent market shares are lower only in the UK and Portugal (ACER, 2015).

[14] During the period of September 17-28, the Belgian Ministry, in collaboration with 493 of the 589 Belgian municipalities, mobilized more than 1,000 municipal employees and civil servants to organize at least 1,000 meetings to explain the specific characteristics of and differences across electricity tariffs and to instruct consumers on using the region-specific PCWs that are provided by the three regional regulators. Around 72,000 citizens are said to have been reached. At the same time, radio spots have been launched by the federal regulator, CREG, to call attention to the PCWs available.

needs to enter information about her own electricity consumption, location (i.e., zip code) and some details on the type of electricity meter. If electricity consumption is unknown, the website provides a simple estimate of an average consumption level based on household composition. Based on this consumer-specific information, the website displays electricity prices of all available contracts in form of the yearly electricity bill for the given consumption level in ascending order. It further displays information on other contract characteristics, including whether the energy source is renewable or not, as well as potential details of the pricing structure. The V-test PCW differs in several respects from traditional PCWs as, for example, described in Baye and Morgan (2001) and De Los Santos et al. (2017) because it neither builds upon an algorithm that searches the Internet for different price offers for the same product, nor does it involve fees to advertise a product or to search the website. Instead, the price comparison is based on information that electricity suppliers need to transmit to the regulator every month. Therefore, information on prices and other contract characteristics are reliable, up-to-date and the list is exhaustive. This provides us with an ideal setting to study the effects of limited awareness and switching costs in electricity markets.

Additionally, several legislative and regulatory changes have been implemented at the federal level to protect consumers and to make switching easier. For example, in September 2012 a change in the Belgian national legislation abolished contract termination fees imposed on electricity retail customers. As a consequence, consumers in Belgium can now switch their electricity contract free of charge at any time while respecting a cancellation period of one month. In order to switch suppliers, it is enough to provide all relevant information to the new supplier, who will then organize the switch for the consumer. The predominant contract structures in 2012 show that most suppliers anticipated this change and slashed contract termination fees long before the law became effective. In July 2012 only one supplier still applied such fees. The elimination of monetary switching costs provides us with an ideal setting to investigate the importance of a consumer's non-monetary costs of switching, which are typically much harder to quantify.

Despite the legislative change abolishing monetary switching costs and the efforts of the regulators to increase market transparency, consumer inertia remains an issue in the Flemish retail electricity market. For example, our survey data, that cover the period from 2012 to 2016, reveal the following. First, there is evidence for switching costs. On average 47% of the survey respondents who have not switched suppliers yet state that the high effort associated with switching is a reason for their inertia. Even consumers who visit a PCW and, therefore, most likely have full information about all potential savings, often decide not to switch due to the efforts involved. Second, limited awareness seems to influence contract choices too. The market share distributions differ significantly depending on the awareness status of a consumer. Those consumers who have used the PCW exhibit a more balanced supplier choice than consumers with limited awareness, who tend to choose the incumbent much more often.[15] Third, preference heterogeneity for green electricity and the reliability of the incumbent seem important as well. On average, 42% of the respondents that have

[15]This pattern is not necessarily indicative of awareness issues, since it could simply reflect an endogenous selection of consumers into PCW users and non-users. Therefore, we will model the decision of using the PCW explicitly in our structural model.

already switched suppliers based their choice on considerations for green electricity, and 44% of all survey respondents who have already switched suppliers have chosen their supplier on the basis of (perceived) service reliability.

3 Data

In our analysis, we combine data on the Flemish residential electricity market from different sources into a novel and unique data set that covers a period of 54 months (January 2012 to June 2016). It includes information on contract choices and contract attributes at the aggregate and the consumer level, on consumer characteristics including awareness status, and a panel on supplier advertisement expenditures.

3.1 Aggregate Data

Contract-level market shares Our first main data set consists of a monthly panel of aggregate market shares at the contract level. Observing market shares at the contract level, instead of just the supplier level, allows us to model product differentiation in greater detail than previous studies.[16]

Monthly market shares for all major residential electricity suppliers in Flanders are publicly available on the website of the Flemish regulator for electricity and gas (VREG). Market shares are measured in terms of access points as opposed to the amount of electricity supplied. We use additional confidential data provided by VREG to split the aggregate supplier shares in two contract categories: green and conventional contracts.[17] Green contracts are defined as contracts that offer electricity exclusively generated from renewable sources.[18] Our conventional category comprises all other contracts.

We merge the contract market shares to the corresponding monthly contract price, which we collected from the tariff information sheets that the Belgian regulator for electricity and gas (CREG) collects from every electricity supplier.

Our price data represent the component of a household's electricity bill that compensates the supplier for selling electricity to the household. It includes VAT but excludes other important bill components, such as charges for transporting and distributing electricity and other fees or taxes. These charges are location-specific, but they do not differ across electricity contracts. By construction, they cancel out in the choice probabilities prescribed by a discrete-choice

[16] In our main specification, we focus on the three arguably most important product dimensions: contract price, the origin of the electricity (green vs. conventional) and the supplier offering the contract.

[17] VREG provided us with the number of residential access points on each available contract per trimester, which allows us to calculate market shares at the contract level and to split supplier market shares by the origin of electricity. To perform the split, we assume that the division of supplier shares into contract categories is constant within one trimester.

[18] To classify contracts as *green*, we follow the indications given in the tariff information sheets or information about contracts found on the supplier websites. A 100% share of green electricity can either be attained by own production capacities or via buying green certificates.

model and, therefore, do not affect a consumer's contract choice. For the remainder of this analysis, the term *electricity bill* refers only to the price that the firm receives for supplying electricity and will exclude all other (linear) charges. The pure electricity component of the bill reflects the margin at which electricity suppliers can compete. Therefore, we relate our estimation results to this measure of a consumer's electricity expenditure. According to CREG, our price measure accounts for 20% to 40% of the final electricity bill of an average consumer in Flanders during our sample period.[19]

For simplicity, we abstract from consumption heterogeneity and follow the literature in assuming that all households consume an average amount of electricity.[20] We construct the monthly contract price as a twelfth of the yearly electricity expenditure of an average Belgian household who signs up for the specific contract in the given month.[21] Based on information from CREG, we assume an average yearly electricity consumption of 3,500 kWh per year. If a supplier offers more than one contract in each contract category (green or conventional), we use the average price over contracts within a category.

In our final sample, we include only suppliers with an aggregate market share above 1% on average over the 54 month considered in our analysis. The contracts of all other suppliers are pooled into an outside option. We drop access points that are with a social contract or the distribution network operator. According to VREG (2012), consumers are supplied by these contracts when no energy contract with a commercial supplier exists –mainly in case of payment defaults and due to problems encountered during moving. Because being supplied via these contracts does not represent a conscious choice we disregard consumers on such contracts.

This leaves us with ten contracts offered by 6 suppliers and one outside option. The commercial suppliers in our sample are: Electrabel Customer Solution (ECS), Electricité de France - Luminus (EDF), Eneco, Eni[22], Essent and Lampiris. All six suppliers offer green contracts, whereas only four also propose conventional contracts. We treat a contract-month combination as one observation, which yields a sample size of 594. Finally, we also observe the aggregate monthly churn rate measured as the proportion of electricity consumers that quit their supplier in a given month.

Table 1 displays the average market share by supplier in each year and the average monthly price per contract type throughout the sample period. The Flemish retail electricity market in 2016, i.e., 13 years after its full liberalization, is still relatively concentrated with ECS accounting for over 40% of the total market on average although its share experienced a continuous decline over the last five years. Average contract prices of ECS and EDF, the two traditional Belgian suppliers, exceed those of the newer entrants with the exception of the green contract offered by Eni. Excluding Essent, suppliers that offer both green

[19]Source: http://www.creg.be/fr/professionnels/fonctionnement-et-monitoring-du-marche/tableau-de-bord-marche-de-gros-et-de-detail

[20]Similar assumptions are used, for example, in Giulietti et al. (2014) and Hortaçsu et al. (2017).

[21]Throughout the analysis, we deflate all prices to 2012-EUR.

[22]Eni acquired Nuon Belgium in January 2012 and merged with Distrigas in November 2012 to become Eni gas & power.

and conventional contracts charge a higher price for contracts delivering green electricity compared to green-only suppliers.

Table 1: Market shares by supplier (yearly averages) and monthly average contract prices

	Market Shares					**Average Price (in EUR)**	
	2012	**2013**	**2014**	**2015**	**2016**	**conventional**	**green**
ECS	0.54	0.44	0.43	0.41	0.40	29.31	30.46
EDF	0.21	0.20	0.20	0.20	0.20	30.71	34.28
Eneco	0.02	0.05	0.05	0.04	0.04		26.63
Eni	0.10	0.11	0.12	0.12	0.14	26.53	31.39
Essent	0.05	0.08	0.08	0.09	0.07	28.15	27.92
Lampiris	0.03	0.06	0.05	0.06	0.06		27.94
Other	0.06	0.07	0.08	0.08	0.08	26.43	

Notes: Other includes all contracts offered by electricity suppliers with an average market share below 1% over the 5 years considered in the analysis. Market shares are recorded in terms of electricity access points. Prices are represented as a twelfth of the yearly expenditure for electricity paid by an average Belgian household consuming 3,500 kWh per year. Prices are averaged across contracts if a supplier offers more than one contract in a category.

Figure A.1 in Appendix A illustrates the evolution of prices over time. Over the years, there is a clear downward trend of conventional contract prices for all suppliers (left panel of Figure A.1). Prices of green contracts remain rather stable for Eneco and Lampiris, the small green suppliers. Green contract prices of ECS and suppliers that belong to an incumbent in another European market –EDF, ENI and Essent are owned by large energy companies from France, Italy and Germany respectively– decline substantially over time, which reduces the price spread across green contracts.

Advertising data The advertising data for Belgium come from the Nielsen Media Data Bank (MDB). Nielsen MDB contains the monthly advertising expenditures by announcer and media type and is established using information on media campaigns observed by Nielsen and declarations by media sellers. Advertising expenditures are measured as gross expenditures based on rate card tariffs. The following media types are covered: cinema, daily papers, Internet, monthly magazines, national and regional TV, out of home and radio. Unfortunately, the data does not cover directed advertising via home visits or telemarketing calls. Flores and Waddams Price (2018) find that these types of directed advertising seem to have no effect on search and switching behavior in electricity markets.

The advertising expenditures are reported monthly only by energy supplier and are not broken down into specific products, such as electricity or gas. As our analysis focuses on the electricity retail market exclusively, we control for advertising spending in the gas market by weighting each supplier's advertising expenditures by the supplier's market share in the retail electricity as opposed to the retail gas market. Finally, we account for differing advertising intensities across Belgian regions using data from the Belgian Union of Advertisers (UBA). The data indicates that in 2016 roughly 60% of media advertising in the energy sector is spend on Dutch speaking media and is therefore targeted at the Flemish market. Table A.1 in Appendix A summarizes yearly advertisement expenditures for the main electricity suppliers in our analysis.

Firm-level cost data Finally, we collected data on the cost structure of Belgian electricity suppliers. We use these data mainly to construct instrumental variables for contract prices in order to address potential price endogeneity concerns.

First, we use wholesale electricity prices from the spot market at the Belgian power exchange Belpex. The spot price is measured as a monthly average of the quarter-hourly electricity price. We introduce variation across suppliers by interacting wholesale prices with a proxy measuring each supplier's sensitivity to the wholesale markets. The supplier sensitivity is calculated as one plus the approximated share of electricity that a supplier needs to purchase, instead of producing itself, to satisfy its demand. More specifically, the share relates the observed electricity volumes that each supplier delivered in 2014 in Belgium to an estimate of the supplier's own production. The production estimate uses current production capacity data by supplier obtained from Belgium's electricity transmission system operator (Elia) and country-wide capacity factors by energy source based on data from the Federation of Belgian Enterprises for Electricity and Gas (FEBEG).[23] This approach captures that suppliers with a lot of own production capacity should be less sensitive to wholesale electricity price fluctuations.

Second, we use Hausman instruments. Based on our large price data set, that we collected from the CREG tariff information sheets and covers all three regions of Belgium, we construct average monthly prices for electricity and gas contracts offered by each supplier in the Belgian region of Wallonia, a market that is comparable but distinct and separated from Flanders.

3.2 Survey Data

The most novel component of our data is a pooled cross section of consumer-level choice data which complement our aggregate data and allow us to construct micromoments for our structural estimation. The consumer-level data come from an extensive survey that VREG conducts every year across a stratified random sample of 1,000 to 1,500 Flemish households. The survey covers a wide range of topics linked to a household's attitude towards energy markets. Households provide answers to about 100 questions, among others, about the perceived market environment in general, supplier and contract choices, previous switching

[23] Capacity factors describe the actual electricity output of a power plant to the maximum possible output over a given period of time. Therefore, multiplying installed production capacity per supplier by the country-wide capacity factor approximates the actual electricity production of a supplier.

behavior and future switching intentions, reasons for switching or non-switching, awareness and socio-demographic characteristics.

We exploit five years of the survey (2012-2016), and use it mainly to investigate the awareness process of consumers, since we can track which consumer has used the VREG PCW and how it affected her choices. On average, 20% to 33% of consumers use the PCW in a given year during our sample period. We interpret these consumers as being fully informed about the contract offers. Furthermore, we compute a monthly *information indicator* to represent the share of fully informed consumer per month by combining the yearly share of fully informed survey respondents with information on the number of clicks on the V-test website. More precisely, we weight the yearly share of fully informed consumers from the survey with the number of clicks on the PCW in a given month as a share of the total number of clicks in a given year. The number of clicks reported refers to those made in the last step of the price comparison and should therefore be informative about the number of users who finish the price comparison and become fully informed about all available contracts.[24] Finally, we keep track of several other survey replies to justify some of our modeling assumptions and to conduct reduced form regressions to guide the specification of our structural model.

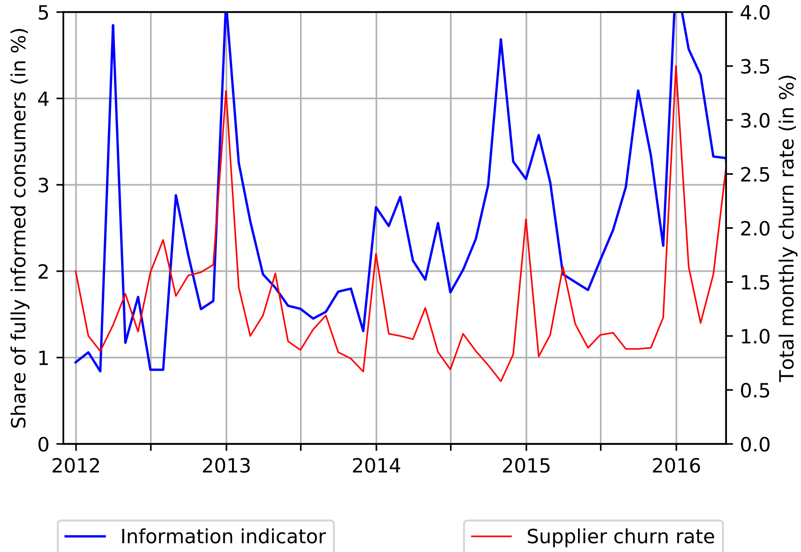
Figure 1 displays our monthly information indicator together with the aggregate supplier churn rate. Monthly churn rates range between 0.6% and 3.5% throughout our sample. During our sample period, there are several churn peaks with the most pronounced ones in January 2013 (3.3%) and January 2016 (3.5%). Comparing the monthly churn rate to our information indicator over our sample period reveals a positive correlation of 0.4, while the correlation during the last year of our sample (2016) is much higher (0.8).

First evidence for a link between the awareness status of consumers and their switching behavior comes from comparing supplier market shares from the survey data conditional on an individual's awareness status as measured by her PCW usage. Although we cannot display specific numbers for confidentiality reasons, contrasting the distribution of supplier market shares in the group of fully informed consumers (PCW users) to the distribution in the group of partially informed consumers (PCW non-users) indicates that supplier choice differs considerably with awareness status. Market shares are more evenly distributed across suppliers in the subsample of the fully informed consumers. In the subsample of partially informed consumers, market share distributions are skewed. For example, in 2016, within the group of fully informed consumers, the market share of the largest supplier is only 38% higher than the one of the second largest supplier. This difference amounts to 56% in the group of consumers that are only partially informed.

Note that in the aggregate, the market share distribution among all consumers interviewed in the survey strongly resembles the shares constructed from the aggregate data displayed in Table 1. Therefore, our survey data is plausibly representative for the whole market.

[24] Our weighting implicitly assumes that the proportion of individuals that perform the price comparison more than once in each month is constant within a year but may change across years. When constructing our information indicator based on the number of clicks and the number of Flemish households only, we obtain a very similar measure of aggregate PCW usage.

Figure 1: Information indicator and churn rates



Notes: The figure plots the evolution of the monthly share of fully informed consumers (defined as the share of PCW users in a given month) over time and the total monthly churn rate (aggregated over all suppliers).

Additional data on the empirical distribution of demographic characteristics, which we use for the simulation of consumers in our structural estimation, was collected from several publicly available sources. First, yearly data on the age distribution of the Flemish population comes from the Belgian Statistics Office.[25] Second, the yearly income distribution in Belgium is from Eurostat. Data on Internet penetration rates come from the OECD.

4 Reduced Form Evidence

As discussed in Section 2, despite major political and regulatory efforts to mobilize Flemish consumers to switch electricity suppliers, a look at our raw data reveals that substantial consumer inertia still prevails. In this section, we present reduced form evidence for the importance of informational frictions and state dependence in the Flemish electricity market that points towards switching costs and limited awareness as likely sources of the observed consumer inertia.

The potential for different reasons for consumer inertia and the complex structure of our data set, that contains several macro- and micro-level components, suggest the use of a structural model. A structural model enables us to combine different data sets and multiple sources of identification in order to much more credibly disentangle and quantify the different sources of consumer inertia. Consequently, the results presented in this section should not be

[25]Direction générale Statistique, `http://statbel.fgov.be/en/statistics/figures/`.

interpreted as causal effects but as simple correlations that we use to guide the development of our structural demand model in Section 5.

4.1 Evidence for Informational Frictions

This section presents evidence from our survey data showing that limited awareness is indeed an important factor in electricity contract choices of Flemish consumers. Table B.1 in Appendix B illustrates that there is significant heterogeneity in the probability of being fully informed about all available contracts across different consumer types. We regress a dummy (*Fully informed*) that is equal to 1 if the consumer has used the V-test PCW in the recent past on a series of demographic characteristics. Throughout the different specifications, seniors and women use the PCW much less. While less educated consumers are less likely to be informed, high-income and highly educated consumers use the PCW significantly more. Finally, we include a dummy that is equal to 1 if the consumers states that energy costs constitute an important part of the household's budget. The negative coefficient indicates that those consumers for which energy costs are important are less likely to be informed and might therefore leave money on the table; however, the coefficient is only weakly significant. In Column (2), we add a time trend (*Year*), whose positive coefficient indicates that PCW usage is increasing over time. Finally, we add a dummy describing whether the consumer is on a green contract. The positive and highly significant coefficient highlights that a preference for renewable energy is associated with the consumer being better informed.

Table B.2 in Appendix B reveals that fully informed consumers tend to sign up for cheaper electricity contracts compared to consumers who do not use the PCW. We regress the monthly energy bill (*Average Price*) that a survey respondent would pay given her supplier and contract choice on the respondent's socio-demographic characteristics and her awareness status.[26] The dummy variable *Fully informed* takes the value 1 if the respondent has used the PCW and 0 otherwise. Socio-demographic characteristics include continuous variables, such as household size, family net income, a linear time trend and dummy variables indicating whether the respondent is a woman, a senior and whether the respondent stated that energy costs take an important part in the household's budget.

Not surprisingly, ceteris paribus, fully informed consumers tend to pay less for electricity. This is a first indication that full information about available contracts can lead to better choices saving the average consumer roughly EUR 7 per month, which represents approximately 24% of the monthly bill. Throughout the different specifications, seniors tend to pay more, although the coefficient is not statistically significant, and high income households pay significantly less. A striking observation is that households who report that energy costs are important pay significantly more for electricity. Specifically, they pay EUR 8 more per month than households who state that energy costs are not important to them. This coefficient can be interpreted as first evidence that deregulated electricity markets may have regressive distributional effects because low-income households seem to not take advantage

[26] *Average Price* is expressed as a monthly average based on our macro data. It is matched to the survey data based on a respondent's supplier and contract-type choice.

of the liberalized market environment. The last column adds the number of past supplier switches by the consumer as an additional regressor. The negative coefficient indicates that consumers who switch save significantly. Each additional switch is associated with an EUR 8 decrease in the consumer's monthly electricity bill.

Table B.3 in Appendix B provides evidence that the awareness status of a consumer is correlated with her switching behavior. The specifications in Columns (1) to (3) regress a dummy (*Past sw.*) indicating whether the survey respondent has already switched electricity suppliers in the past on the respondent's socio-demographic characteristics and her awareness status (*Fully informed*). Columns (4) to (6) report results from specifications in which the dependent variable is a dummy (*Intention*) indicating whether the respondent reports to consider switching electricity suppliers in the near future. Seniors are less likely to have switched in the past and are less inclined to intend to switch, while income has only a weak relationship with switching behavior and intentions. Throughout all specifications, PCW users are much more likely to have an intention to switch or have already switched in the past.

In summary, our reduced form results point towards informational frictions in the Flemish retail electricity market. These frictions have a large effect on consumers' switching behavior and the efficiency of their contract choices. Naturally, the reduced form results should be interpreted cautiously, as they may be biased due to endogeneity and selection issues. In order to address these concerns and to analyze the underlying channels of consumer inertia in more detail, we construct a structural model of electricity contract choices in the next section.

4.2 Evidence for State Dependence

Since our individual-level data is not a panel but only a repeated cross-section, we complement our reduced form regressions with an analysis of the panel of aggregate market shares to gain further insights into potential state dependence in consumer choices. Table B.4 in Appendix B presents the results from the associated OLS regressions. Following our arguments on identifying state dependence below, we regress contemporaneous contract-level market shares, s_{jt}, on contemporaneous contract attributes and other controls (including price), X_{jt}, and lagged market shares

$$s_{jt} = X_{jt}\beta + \alpha s_{jt-1} + \epsilon_{jt}.$$

Throughout, prices are instrumented using conventional Hausman instruments and the electricity price at the wholesale spot market as a cost shifter. Even though one should be careful in giving the estimates causal interpretations, we find strong initial evidence for state dependence.

For example, when we ignore lagged market shares in the estimation, we obtain implausible coefficients on almost all of the regressors, see Column (1). The price coefficient is positive and insignificant, the incumbent enjoys a huge brand advantage, advertising enters negatively, and green electricity has a negative significant coefficient. When including the lagged market shares, most of these revert to the expected signs, see Column (3). Price enters negatively, green electricity is valued positively, and advertising increases a firm's market share. In order to mitigate the likely endogeneity problem of the lagged market share, we first run the same regressions with firm-level fixed effects; see Column (2) for the results without lagged market shares and Column (4) for results with lagged market shares. The qualitative pattern remains the same but we generally get less significance. Finally, we instrument lagged market shares with lagged exogenous shifters as in Shcherbakov (2016). This IV approach accounts for the potential presence of serially uncorrelated unobservables. As displayed in Column (5), the results remain qualitatively similar and point to substantial state dependence in electricity contract choices.

5 Structural Model

In this section, we develop a structural demand model of the retail electricity market in order to disentangle the different channels of consumer inertia for which we found evidence in our raw data and the reduced form regressions.

First, we allow for rich patterns of consumer heterogeneity by employing a random coefficient utility function. Second, individuals face switching costs when choosing a contract offered by a supplier that is different from the individual's previous supplier. A model that does not account for such costs is likely to attribute too much importance to preference heterogeneity. Third, consumers may have different awareness sets depending on their information about the available electricity contracts.[27] A model that does not account for differences in awareness typically results in biased estimates of consumer preferences and switching costs.

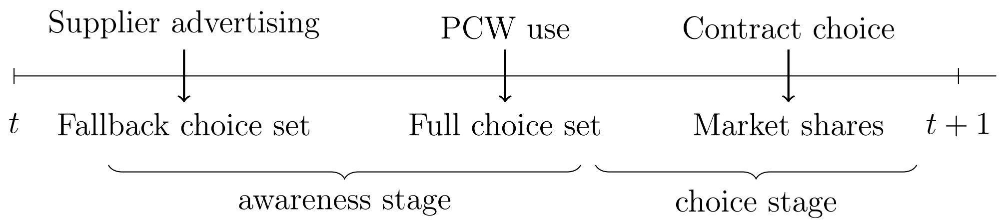
We incorporate switching costs into a BLP-style model similarly to Shcherbakov (2016) and Weiergraeber (2018). Our model of awareness combines elements from Sovinsky Goeree (2008) and Honka (2014). We model consumer choices as a multistage process. At the beginning of each period, consumers are exposed to supplier advertising and decide how much information about the market to acquire by deciding whether to use the PCW or not. In each period, a consumer uses the PCW if the expected benefit of doing so exceeds the PCW search cost. In this case, she becomes aware of all contracts that are available in this month. A consumer who does not use the PCW can become aware of contract offers through other channels, most notably supplier advertising. After consideration sets are determined each consumer chooses her utility maximizing contract. The model's timeline within a given period is illustrated in Figure 2.

(1) Awareness stage and consumers' consideration sets

We start by describing how consumers form their consideration sets and discuss the choice problem afterwards. The initial consideration set of a consumer in each period, the *fall-back choice set*, consists of her previous contract and of those contracts that the consumer successfully learns about through advertising.

[27] In our model, we do not distinguish between an awareness and a consideration stage, as analyzed, for example, by Honka et al. (2017). Therefore, we use the terms awareness set and consideration set interchangeably.

Figure 2: Timing in period t



Notes: The figure illustrates the timeline of our model within a given period t.

Whether a consumer becomes aware of a contract through advertising is modeled by an advertising-awareness Probit process similarly to Sovinsky Goeree (2008)

$$Pr(i \text{ is informed about firm } j \text{ in period } t) = \Phi(\alpha_0^A + W_{jt}\alpha_1^A + e_{it}^A), \tag{1}$$

where W_{jt} denotes the advertising expenditure of supplier j in period t, e^A is a normally distributed error shock, and α^A is a vector of parameters to be estimated. While, in principle, the above awareness process can be flexible and differ across contracts and consumer types, we assume that advertising is equally effective in raising awareness across products and consumers in order to keep the number of parameters reasonably low.

The advertising-awareness process in Equation (1) will also capture that some consumers may engage in direct firm-specific search, for example, by visiting supplier websites directly. Unfortunately, our data is not rich enough to incorporate this type of consumer search structurally into a model that also accounts for state dependence and product differentiation. The main reason for this is that we do not observe the consideration sets of consumers who do not use the PCW. Therefore, one should be careful in interpreting the coefficients in α^A structurally. However, we believe that advertising expenditure is a good proxy for how intensely a firm overall engages in directly informing and acquiring customers. Thus, supplier advertising should be informative about how easy it is for consumers to become informed about the contracts of a specific firm.

After consumers have been exposed to supplier advertising, they decide whether or not to use the PCW. If the consumer uses the PCW, she incurs a fixed search cost κ and becomes aware of all the prices in the market. κ comprises the costs of finding the website and entering consumer-specific information that is required to establish a price quote. Consumer i chooses to use the PCW in period t, if and only if the expected utility from searching the PCW net of the search costs exceeds the utility from not searching, i.e., if and only if

$$E\left[u_{it}\right]^{search} - \kappa_{it} > E\left[u_{it}\right]^{nosearch}. \tag{2}$$

After having searched the PCW, the consumer is aware of all contracts and their prices in the market and makes a fully informed choice under state dependence. A consumer who does not use the PCW does not pay the search cost κ but is forced to either stick with her old contract or choose from her fallback choice set.

Our search process differs from the one modeled in, for example, Honka (2014) and Honka et al. (2017), in that our search is only binary: a consumer either searches the PCW and becomes fully informed about all contracts or does not search at all.[28] Our modeling approach can be justified by the nature of the PCW in our application. After having completed the PCW questionnaire, the consumer obtains a comprehensive overview of all relevant information about the available contracts.[29] These search results are very different from the ones, for example, in the car insurance industry which is analyzed in Honka (2014), where a consumer has to complete a firm-specific form in order to receive an individualized price quote.

In our model, the uncertainty which leads some consumers to consider only a subset of the available contracts comes only from price. Since electricity contract prices can fluctuate substantially from month to month, figuring out which contracts are currently the cheapest is likely to be the main information problem for consumers. Consequently, we assume that consumers know about the existence of all contracts in the market, about the contract characteristics and their preferences for each contract. We judge this information structure to be reasonable, as we model choices at the firm-contract type level and focus on the six main electricity suppliers and two contract types, so that there are only 11 products in a consumer's full consideration set.

The decision of whether to engage in PCW search or not depends on the consumer's belief about the price distribution in the market. We follow Honka (2014) in assuming that the consumer's belief about the price distribution in the market follows a Type-1-EV distribution, i.e., $p_{jt}^{B} \sim EV(\eta_{jt}, \mu)$.[30] We estimate the shape and scale parameters of the price belief distribution in an auxiliary regression to match the mean and variance of the observed empirical price distribution.

(2) Consumers' choice problem

After awareness sets are determined, each consumer chooses the utility maximizing contract from her consideration set. Consider $t = 1, \ldots, T$ periods and a continuum of consumers indexed by i. In each period t, individual i can choose among K electricity contracts that are offered by J suppliers. In our application, we analyze monthly contract choices over a period of 53 months. Our preferred decision frequency is monthly because consumers receive electricity bills every month, which may prompt them to reconsider their supplier choice. The inside goods in our model comprise 10 electricity contracts, that are offered by six different suppliers, and one outside good.[31] The utility of individual i from choosing contract k in month t can be decomposed into a mean utility δ_{kt}, that is common to all consumers, and a consumer specific utility μ_{ikt}, that is a function of observed demographic characteristics and

[28]Because of the all-or-nothing nature of our search process, the PCW search cost κ is conceptually very similar to an entry cost that a consumer has to pay to join the fully informed consumer segment.

[29]See Figure A.2 in Appendix A for an example screenshot of the results from using the PCW.

[30]Differently from Honka (2014), we use a simulation approach to compute the expected benefits from PCW search, so that we are not restricted to an extreme value distribution but could sample from any other distribution, such as a normal or the empirical price distribution observed in the data.

[31]We summarize all suppliers that have less than 1% market share on average throughout our sample in the outside good. Consequently, consumers do not have the option of not having any electricity at all.

unobserved taste shocks, denoted by D_{it}, which results in the following utility function

$$\begin{aligned} u_{ikt} &= \delta_{kt}(\theta_1) + \mu_{ikt}(\theta_2) + e_{ikt} \\ &= X_{kt}\bar{\beta} + \xi_{kt} + \alpha_i p_{kt} + X_{kt}D_{it}\beta_i + e_{ikt}. \end{aligned} \tag{3}$$

X_{kt} is a vector of observed contract attributes, such as a dummy variable indicating whether the contract delivers green electricity or whether the contract is offered by the incumbent supplier. The mean marginal utility associated with these contract attributes is captured by the parameter vector $\bar{\beta}$. Many contract features are unobservable to the econometrician but observed by consumers, for example, the quality of customer services provided by a supplier. As in the classical BLP model, this unobserved quality is captured by the scalar ξ_{kt}, which is assumed to be valued equally by all consumers. The monthly electricity expenditure of the average consumer if she subscribed to contract k in month t is denoted by p_{kt}.[32] Similarly to Hortaçsu et al. (2017) we abstract from consumption heterogeneity and assume that each consumer uses the average amount of electricity (3,500 kwh per year).[33] e_{ikt} is an *i.i.d.* error term that follows a Type-1 extreme value distribution.

Logit models that do not account for preference heterogeneity are likely to be misspecified and typically result in implausible substitution patterns. In our main specification, we therefore model preference heterogeneity in the three arguably most important dimensions.

First, individual i's marginal disutility from price depends on the deviation of an individual's income y_{it} from mean income $\bar{y}$, such that $\alpha_i = \bar{\alpha} + \alpha_y ln(\frac{y_{it}}{\bar{y}})$. Second, we allow for an interaction between an incumbent fixed effect and age which captures that, for example, seniors may attribute a larger brand advantage to the incumbent than younger consumers. Third, we allow for a normally distributed random coefficient on green electricity which captures that some individuals may have a much higher WTP for electricity from renewable sources than others. The parameters associated with the consumer-specific coefficient part are denoted by β_i.

Finally, we incorporate switching costs into the consumer's choice problem. Switching costs add a dynamic component to our model. We assume, however, that individuals are myopic and do not form beliefs about how the electricity market evolves in the future. While it is, in principle, possible to model forward-looking consumers, as in Gowrisankaran and Rysman (2012) and the subsequent literature, the computational burden would increase massively.

We opt for a model with myopic consumers for two reasons. First, in retail electricity markets, the future is generally very hard for consumers to predict so that a myopic model may well be a good description of consumer behavior. Anderson et al. (2013) and Hortaçsu et al. (2017) provide evidence that consumers do not behave in a forward-looking way in the gasoline

[32] This implies that our model abstracts from the issue of sticky prices, i.e., the fact that a consumer's contract price may only be determined by the prevailing price in the initial subscription period. Instead we assume that the consumer always pays the current contract price. At additional computational costs, our model can accommodate sticky prices. This would not involve the estimation of additional parameters but requires us to keep track not only of a consumer's contract choice but also the time period in which she subscribed to that contract.

[33] Consumption heterogeneity can be incorporated into our model, for example, by treating an individual's quantity as an additional (exogenous) demographic characteristic in D_{it}.

and electricity market, respectively. Second, a model with forward-looking consumers would require us to compromise heavily in other dimensions of the model, such as the awareness stage or consumers' preference heterogeneity, which is a focus of our analysis. In addition, a myopic model can be interpreted as a reduced form approximation to a fully dynamic process. In many cases, a myopic model can already lead to important insights, such as quantifying the relative importance of search and switching costs or measuring the extent of product differentiation.[34]

The switching component adds an additional parameter ψ to the utility function in Equation (3). We treat this parameter as constant across individuals and time.[35] Note that ψ captures all the costs associated with choosing a different supplier today than in the last period. Therefore, it captures not only all hassle costs associated with the switching process but also any potential poaching payment, for example, in the form of a *welcome bonus* that a supplier might offer to new customers. These bonus payments will effectively decrease the switching costs, so that our ψ-parameter should be interpreted as a net switching cost that could in principle be positive or negative.[36]

The utility function under state dependence becomes

$$u_{ikt} = \delta_{kt}(\theta_1) + \mu_{ikt}(\theta_2) - \psi \mathbb{1}_{a_{it} \neq a_{it-1}} + e_{ikt}, \tag{4}$$

where $\mathbb{1}$ denotes an indicator which takes the value 0 if individual i chooses the same supplier as in the previous month, and 1 if the individual switches suppliers and $a_{it} = 0, \ldots, J$ captures individual i's choice of supplier in month t.

The preference parameters to be estimated can be summarized by a vector of linear parameters $\theta_1 = (\bar{\beta}, \bar{\alpha})$ and a vector of non-linear parameters $\theta_2 = (\beta_i, \alpha_y, \psi)$.

Under the assumption that each consumer chooses her utility maximizing contract, the conditional probability that individual i chooses contract k in month t, if the individual has chosen contract l in the previous month is given by

$$P_{ikt}(k|l) = \frac{\exp(\delta_{kt} + \mu_{ikt} - \mathbb{1}_{k \neq l}\psi)}{\sum_{m=0}^{J} \exp(\delta_{mt} + \mu_{imt} - \mathbb{1}_{m \neq l}\psi)}, \tag{5}$$

where m is the summation index over all contracts in consumer i's awareness set in period t. In our main specification, we assume that switching costs occur only when switching suppliers but not when changing contracts with the same supplier. We judge this to be a reasonable assumption, since it is much more involved to transfer a contract between firms than to switch among contracts with the same firm. Individual-specific market shares can

[34]For the interpretation of our counterfactual simulations, however, we will typically have to take a stand on whether on whether the true data generating process is myopic or dynamic.

[35]Conceptually, it is straightforward to allow the switching cost to depend on the consumer type or the previously chosen contract, albeit at the expense of having to estimate additional parameters. In practice, we found it difficult to obtain robust estimates when modeling the switching cost in a very flexible way.

[36]Unfortunately, our data do not have detailed information on time- and contract specific welcome discounts so that we cannot incorporate this aspect in more detail.

then be computed recursively as

$$s_{ikt} = \sum_{l=0}^{J} P_{ikt}(k|l) s_{ilt-1}.$$

The predicted distribution of the aggregate contract market shares in month t is then obtained by integrating the individual choice probabilities over D_{it}, the distribution of demographics and taste shocks in the population,

$$s_{kt} = \int_i s_{ikt} dD_{it}. \tag{6}$$

These market share predictions form the basis for constructing the moment conditions for our estimation.

6 Identification and Estimation

In this section, we discuss our estimation strategy and which variation in the data identifies the different parameters of our model. We start by presenting the general identification arguments in subsection 6.1 and discuss our specific moment conditions and the choice of instruments in subsection 6.2.

6.1 Identification

The key challenge in assessing consumer inertia is to disentangle the effects of preference heterogeneity, of switching costs and of limited awareness. Observing that a consumer chooses a specific contract repeatedly can be evidence for switching costs but it might also reflect the fact that the consumer is not aware of other contacts or that the consumer simply has a, potentially unobserved, preference for the chosen contract. Our identification argument consists of three parts.

First, the identification of consumer preferences from aggregate market share data is well established following the seminal paper by BLP and the large subsequent literature. Identification of the mean preferences comes from observed variation in market shares when the characteristics of the available contracts vary. For example, observing how the market share of a contract adjusts when its price increases will be informative about the price coefficient.

Identification of preference heterogeneity, i.e., the distribution of the demographic-specific and random coefficients, comes from observed aggregate substitution patterns. For example, consider a setting in which the price of a green contract increases. Observing that consumers mostly substitute from this contract to another green contract points to preference heterogeneity with regard to green electricity. If, however, consumers substitute equally to all other contracts, the data provides evidence for only little preference heterogeneity regarding green electricity.

In line with these arguments, the main data to identify consumer preferences is our panel of monthly contract-level market shares and their prices and other attributes. In addition, we exploit observed individual-level contract choices conditional on consumer characteristics from our survey. Following the arguments of Petrin (2002) and Berry et al. (2004), the survey data enable us to construct additional micromoments in order to more precisely identify heterogeneous preferences for contract attributes. In particular, observing different demographic types choosing different contracts is informative about preferences linked to demographic characteristics, in our case, the interaction coefficients between price and income and age and incumbent preference.

Second, for separating preference heterogeneity and switching costs, we combine the arguments of Shcherbakov (2016) and Weiergraeber (2018). Identification of the switching cost is mainly based on variation of exogenous shifters over time and the idea that any correlation between contemporaneous contract market shares and lagged exogenous shifters, conditional on contemporaneous shifters, can only be explained by state dependence through switching costs.

As an illustration, consider a scenario in which the contracts A and B have the same attributes in period t but a different history, for example, different prices in period $t-1$ as a result of an exogenous cost shock specific to firm A. The lower price for contract A will attract consumers in period $t-1$ so that the share of A increases relative to that of B. If the market share of A is still relatively higher in period t, when all attributes of the two contracts are the same, the data provides evidence for switching costs. In the absence of switching costs a consumer should be indifferent between A and B in period t. Therefore, our panel of aggregate contract-level market shares, along with information on lagged exogenous demand or cost shocks over time, enables us to identify switching costs separately from preference heterogeneity.[37]

This identification argument crucially relies on the assumption that preferences with respect to observables, such as prices, green electricity and supplier identities, are time-invariant.[38] This assumption can be justified in our application, because we are analyzing the market in a mature state more than 10 years after the liberalization.

Identifying switching costs is facilitated by the fact that we also observe monthly churn rates. Conceptually, churn rates capture a subset of the conditional choice probabilities, namely the probability of choosing a different supplier today than in the previous period. Intuitively, this allows us to compare a function of the choice probabilities conditional on previous choices to the unconditional choice probabilities contained in the market share data. As initially proposed by Yang (2010) and applied by Weiergraeber (2018) and Cullen and Shcherbakov

[37]An alternative identification strategy for state dependence is employed, for example, by Luco (2017), Nosal (2012) and Handel (2013). They exploit consumers who are forced to make a choice. In electricity markets, one could consider movers to generate the necessary variation in the data. However, since the share of movers is typically low and we do not have a clean way of identifying movers in our survey data, this strategy seems less promising in our application.

[38]Most notably, this assumption rules out consumer learning, as, for example, analyzed in Dubé et al. (2010).

(2017), this logic can be used to construct additional moment conditions, similar in spirit to micromoments, that aid in identifying switching costs.

Third, for identifying the PCW search cost (κ) and the advertising-awareness parameters (α^A), we mainly rely on the individual-level data from the survey. Furthermore, we observe variation in advertising expenditure across time and firms. While our survey does not explicitly record which firms a consumer is aware of, we can distinguish consumers that have used the PCW, i.e., they are fully informed, from those that have not used the PCW, i.e., they are only partially informed. These data can be interpreted as partially observing consumers' consideration sets.[39]

This feature is a key advantage of our micro data. Intuitively, it allows us to compare how the joint distribution of consumers' PCW usage, the conditional market share distribution among PCW users and the conditional market share distribution of PCW non-users changes over time in response to different shocks to the market environment.

The conditional market share distribution among PCW users will by construction not be affected by advertising expenditures. This allows us to identify consumer preferences including the unobserved demand shocks ξ, which are by assumption identical across consumers. After having controlled for consumer selection into PCW usage, variation in the conditional market share distribution of the (partially informed) PCW non-users, whose behavior is affected by supplier advertising, will identify the parameters (α^A) of the advertising-awareness process in Equation (1). One key assumption for the identification for α^A is that advertising only affects awareness but not consumer preferences. Given that most of the advertising of electricity suppliers is purely informational and takes place in a mature market, this assumption seems reasonable in our application.[40]

Observing how the PCW usage of consumers evolves over time will be informative about the PCW search cost κ. In order to identify the PCW search cost separately from preferences it is helpful to observe variation that shifts the search cost independently of the expected benefits from search, which are a function of consumer preferences.[41]

On the one hand, our data contains variables that shift the PCW search cost but are unlikely to affect the expected benefits of search, namely Internet penetration rates and data on an information campaign by the Flemish regulator. The campaign explicitly aimed at increasing consumers' awareness about the opportunity to compare prices online and at facilitating the

[39] Abaluck and Adams (2017) show that, under relatively mild conditions, consumer preferences and consideration sets can be separately identified from data on choices alone. We regard their approach, which is based on "minimal data", as complementary to ours, that exploits the availability of detailed micro-level data for separating consumer preferences and awareness. In principle, their approach can be adopted and combined with our data structure and our identification strategy.

[40] Several papers find evidence that in a broad range of industries advertising plays mostly an informative role; see, for example, Ackerberg (2001) and Ackerberg (2003) for nondurable goods and Honka et al. (2017) for advertising in the banking industry.

[41] Conceptually, out model is similar to a Heckman-selection model: Our PCW usage stage can be interpreted as a selection equation and our contract choice stage corresponds to the outcome equation. Nonparametric identification of such selection models –when only observing outcome data– typically requires that there is at least one variable that enters only one of the equations but not both.

use of PCWs; therefore, it is unlikely to have altered consumer preferences. On the other hand, we observe exclusive shifters of the benefits of search. For example, in our model, firm-specific advertising affects a consumer's expected benefit from search by shifting her fallback choice set when not searching the PCW. Supplier advertising does not convey information about the PCW of the regulator, so that it is unlikely to affect consumers' cost of using the PCW.

An implied restriction that we make here is that advertising expenditures of electricity suppliers are at least partially driven by features of the advertising market which are exogenous to the retail electricity market and potentially by consumers' preference shocks but not by factors that shift exclusively consumers' search cost, in particular, Internet penetration rates and the regulator's information campaign. Therefore, observing how consumers' PCW usage changes in response to the aggregate level of advertising of all firms should also be informative about the base level of consumers' PCW search cost.[42]

We provide empirical evidence to support these assumptions in Appendix B. Specifically, we illustrate graphically and using reduced form regressions that Internet penetration rates positively affect the number of consumers using the PCW, and that larger advertising expenditures by suppliers are associated with a decrease in aggregate PCW usage. There does not seem to be a statistically significant relationship between supplier advertising and Internet penetration rates or the regulator campaign, however.

In our survey data, we do not only observe PCW usage data but also the demographics of individual consumers along with their contract choices. This unique combination allows us to apply the above argument separately for each demographic consumer type observed in the survey. Consequently, we are able to identify both demographic-specific PCW search costs and heterogeneous consumer preferences. In addition, because we assume that preferences are time-invariant, it is straightforward to allow the PCW search cost κ to vary over time. Guided by anecdotal industry evidence and concerns of the Flemish regulator, we model the PCW search cost as a function of a constant, the Internet penetration rate, a dummy for the months in which the regulator conducted its information campaign, and we allow seniors to have a different PCW search cost than non-seniors.

6.2 Estimation

We estimate the model using the generalized method of moments (GMM). In a nutshell, the estimation involves, first, the simulation of a number of consumers and the time series of their awareness sets and their choices over all months considered in the analysis for a given parameter guess. Second, we integrate over the simulated consumers to predict the aggregate

[42]Note that our identification argument for the switching cost does not interfere with the identification of the search cost parameters. Since we observe the PCW usage status of each consumer, we can apply our argument to identify switching costs to two periods in which not only contemporaneous contract characteristics are the same but also the search behavior in the two periods is identical. As before, observing a panel of aggregate market shares and lagged exogenous shifters of consumers' choices are sufficient for identification, since we can condition on the observed PCW usage behavior.

contract market share distribution for each month, which we match to the observed market shares in our data as in the well-known BLP approach, see Step (1) below. This allows us to compute the structural demand errors that form the basis for our moment conditions. Moreover, we compute additional moments based on the choice probability predictions for individual consumers, similarly to Petrin (2002), Berry et al. (2004) and Sovinsky Goeree (2008). Additional step-by-step details of the estimation routine are presented in Appendix C.

The parameters to estimate are the consumer preferences for contract attributes $(\bar{\alpha}, \alpha_y, \bar{\beta}, \beta_i)$, the switching cost (ψ), the parameters of the advertising-awareness process (α^A) and the PCW search cost κ.

(1) Mean utility levels For a given guess for the vector of parameters, we start by backing out the mean utility levels δ for each contract-month combination by matching aggregate observed market shares S_{kt} to the model predictions s_{kt} for all contracts k and periods t. During this step, market share predictions s_{kt} are calculated repeatedly based on Equation (6) as a function of the nonlinear parameters $(\theta_2, \kappa, \alpha^A)$ and the mean utilities δ. For a given value of the nonlinear parameters, we update the vector of mean utilities $\delta(\cdot)$ such that predicted and observed market shares are equal.

For this, we rely on a mapping similar to BLP. In contrast to the standard BLP contraction mapping, current shares depend on the shares in the previous period because of the switching cost component. Therefore, we have to solve for market share predictions recursively, i.e., period-by-period. The mapping works similarly to the one of dynamic demand models in the style of Gowrisankaran and Rysman (2012). More specifically, the mean utilities are computed by iteratively updating according to

$$\delta^{'}_{kt}(S_t, S_{t-1}; \theta_2, \kappa, \alpha^A) = \delta_{kt} + \log S_{kt} - \log s_{kt}(S_{t-1}, \delta_t; \theta_2, \kappa, \alpha^A). \tag{7}$$

A central issue in models with preference heterogeneity and state dependence is how to handle the initial conditions problem. A key advantage of our data is that we observe the market share distribution in the first period of our data (January 2012) for every demographic consumer type, i.e., for different age and income groups. We use these type-specific distributions as the initial conditions and estimate our model from February 2012 onwards. The only dimension of unobserved heterogeneity in our model relates to the preference for green electricity. For simplicity, we assume that the initial conditions and the distribution of the preference for green electricity are independent. A computationally much more involved approach that is more flexible regarding unobserved heterogeneity would be to simulate the initial conditions such that they are consistent with the estimated model parameters starting from the beginning of the deregulated market in January 2003.

(2) Moments Upon convergence, Equation (7) yields a vector of mean utilities that can be used to compute a variety of moments for our GMM objective function.

(a) Macromoments to identify consumer preferences The first set of moment conditions consists of classical BLP moments. The mean utilities contain a contract-month-specific unob-

served quality shock ξ_{kt}, that represents a structural error term and can be backed out by decomposing δ into the mean utility from observed contract characteristics and the unobserved shock

$$\xi_{kt} = \delta_{kt}(\cdot) - X_{kt}\bar{\beta} - \bar{\alpha}p_{kt}. \tag{8}$$

We impose orthogonality conditions of the following form

$$\mathbb{E}[G_1(\xi_{kt})] \equiv \mathbb{E}[\xi_{kt}Z_{1kt}] = 0, \tag{9}$$

where Z_1 denotes appropriate instruments. In our model, Z_1 contains exogenous product characteristics, i.e., a dummy for the incumbent supplier, a dummy for green electricity contracts and a constant. Because unobserved contract attributes ξ_{kt} are likely to be correlated with contract price, we instrument prices. Following the literature, we use both cost shifters and Hausman instruments, i.e., prices of the same supplier in different markets. Our instruments include monthly wholesale electricity prices on the spot market that are interacted with each supplier's sensitivity to wholesale markets (as discussed in Section 3), and the supplier's monthly average price for gas contracts in Wallonia. Cost shifters, such as the wholesale electricity price, should be correlated with contract prices but excluded from the contemporaneous demand equation and are therefore valid instruments. Under the assumption that cost shifters across regions are correlated, but demand shocks are uncorrelated across regions, the Walloon gas price is a valid instrument as well. Given the different languages and the regional competencies in energy policy, it seems reasonable that the Walloon and Flemish regional markets exhibit uncorrelated demand shocks. The first stage regressions for our endogenous variable (contract price) on the instruments exhibits a large F-statistic of 79, so that we conclude that our proposed instruments are indeed relevant shifters of prices.

(b) Churn rate moments and lagged moments to identify switching costs

We use the choice probabilities predicted by our model to compute the churn rate prediction error ζ_t as the difference between the observed churn rate, C_t, and the predicted one, $c_t(\cdot)$, for every month t

$$\zeta_t \equiv C_t - c_t(\cdot). \tag{10}$$

Based on this churn rate prediction error we construct additional moments that capture the above intuition on the identification of state dependence.

$$\mathbb{E}[G_2(\zeta_t)] = \mathbb{E}[(C_t - c_t)Z_{2kt}] = 0. \tag{11}$$

As the churn rate prediction error does not have a structural interpretation, we can interact it with a generic set of instruments, for example, just dummies or the superset of all our instruments. In our main specification, Z_{2kt} contains only a constant. In addition, we construct moments by interacting lagged exogenous cost shocks with contemporaneous demand shocks into the classical BLP moment conditions in Equation (9). In our application, we capture firms' lagged cost shocks by variation in lagged electricity wholesale prices interacted with each supplier's sensitivity to these prices. The underlying assumption for this instrument to work is that suppliers immediately pass through some of the wholesale cost changes to retail consumers, so that a firm-specific wholesale price shock in period t shifts retail prices already in the same period.

(c) Micromoments to identify preference heterogeneity and awareness

The micromoments from the survey are especially helpful for identifying the effect of demographics and limited awareness. As in Sovinsky Goeree (2008), we use our individual-level survey data to calculate the $K \times 1$ vector η_{1it} that describes the difference between the observed contract choice b_{it} and our model predictions B_{it} for consumer i in market t.[43] The model's prediction errors for the contract choices of consumer i in market t are then given by

$$\eta_{it}(\cdot) = b_{it} - B_{it}(\cdot). \tag{12}$$

Based on this, we construct our first set of micromoments

$$\mathbb{E}[G_3(\eta_{1it})] = \mathbb{E}[\eta_{1it}(\delta, \theta_2, \kappa, \alpha^A)] = 0. \tag{13}$$

Observing individuals with particular characteristics D_i (age, income and PCW usage status) and their choice of contract allows us to match the model predictions for consumers with specific demographics to the observed data. These moments are typically very powerful in identifying preference heterogeneity, in particular, demographic-specific coefficients, see, for example, Petrin (2002) and Berry et al. (2004). Furthermore, these moments allow us to match the choice probabilities conditional on whether the consumer is fully or partially informed, which enables us to identify the parameters of the advertising-awareness process (α^A).

(d) Moments to identify PCW search costs

In order to estimate the PCW search cost parameters, we rely on additional micromoments based on our survey data about the PCW usage of individual consumers. Analogously to the moment conditions in Equation (13), define η_{2it} as the prediction error for individual i's PCW usage in period t, i.e., the difference between her actual usage (either 0 or 1) and the probability of PCW usage predicted by the model for consumer i in period t. For our final set of moment conditions, we assume that this PCW usage prediction error is orthogonal to the consumer's demographics and several market characteristics. This results in the following moment conditions

$$\mathbb{E}[G_4(\eta_{2it})] = \mathbb{E}[\eta_{2it}(\delta, \theta_2, \kappa, \alpha^A) Z_{4it}] = 0, \tag{14}$$

where Z_4 contains a constant, indicators for the consumer's age and income group, the aggregate Internet penetration rate and a dummy for the periods when the regulator conducted the information campaign.

[43] Element k of b_{it} equals 1 if consumer i chooses contract k and 0 otherwise. B_{it} is a vector of predicted choice probabilities with elements strictly between 0 and 1.

(3) Objective function Finally, the four sets of moments are stacked and aggregated to the objective function. The population moment conditions are assumed to equal zero at the true values of the parameters θ^* so that

$$\mathbb{E}[G(\theta^*)] = \begin{pmatrix} E[G_1(\xi_{kt})|\theta^*] \\ E[G_2(\zeta_t)|\theta^*] \\ E[G_3(\eta_{1ikt})|\theta^*] \\ E[G_4(\eta_{2it})|\theta^*] \end{pmatrix} = 0. \tag{15}$$

Our GMM estimate is the value of θ that minimizes the sample analogue of the moments

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \; \bar{G}(\theta)' Z \Phi^{-1} Z' \bar{G}(\theta), \tag{16}$$

where Φ^{-1} is the GMM weighting matrix. In a first stage, we use a block-diagonal 2SLS weighting matrix. In the second stage, we compute an estimate of the asymptotically efficient weighting matrix based on the first stage results.

7 Results

In this section, we first discuss the estimation results from the structural demand model. Afterwards, we analyze counterfactual scenarios to study the effects of potential policy interventions. We start by investigating the relative importance of reducing switching costs and limited awareness for the market structure and consumer welfare. Moreover, we evaluate the welfare gains from the information campaign conducted by the regulator in the fall of 2012. Finally, we address the broader question of quantifying the relative merits of a liberalized electricity market with retail choice and market frictions compared to a regulated industry that is operated by a monopolist.

7.1 Estimation Results

Table 2 and 3 display the estimated parameters from our baseline specification in which we assume that all consumers have the same PCW search cost. Table 2 summarizes the coefficients describing consumer preferences. Table 3 presents the parameter estimates determining consumers' PCW search cost and the advertising-awareness process. Standard errors are reported in parentheses.

Most of the coefficients have the expected sign and are highly significant. The mean price coefficient is negative and statistically significant at the 1%-level. The interaction term on income and price is positive, which points towards richer households being less price sensitive. Several observations on the magnitudes of specific coefficients are noteworthy.

First, seniors[44] place a high premium on being with the incumbent supplier compared to an alternative supplier, roughly EUR 12 per month, which is statistically significant at the 1%-

[44]We define *seniors* as consumers older than 65 years, and *non-seniors* as consumers younger than 65 years.

Table 2: Baseline model (homogeneous PCW search costs) - consumer preferences

	Mean	Sigma	Senior	Income
Constant	−0.8390***			
	(0.0236)			
Price	−4.6932***			0.9030***
	(0.1148)			(0.1005)
Incumbent Dummy	−0.0367***		0.5989***	
	(0.0023)		(0.0904)	
Green Electricity	0.0025	0.8300***		
	(0.0199)	(0.0228)		
Switching Costs	0.7711***			
	(0.0322)			

*Notes: Results for preference parameters from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10, 5 and 1 percent level respectively.*

level.[45] Non-seniors have a negative but economically very small preference for the incumbent. The incumbent preference of seniors is similar in magnitude to the findings of Hortaçsu et al. (2017) who estimate that, two years after the market liberalization in Texas, the average monthly incumbent preference was USD 15. Our estimates suggest that, even more than 10 years after the liberalization, a significant share of consumers continues to have a considerable preference for the incumbent supplier.

Second, consumer valuation of green electricity is very low on average, EUR 0.05 per month, and insignificant. As indicated by the large and highly significant variance parameter (*Sigma*) of the random coefficient distribution, there is, however, substantial heterogeneity in the taste for green electricity across consumers and slightly more than 50% of consumers have a positive WTP for green electricity. Our estimate of the switching cost is positive, highly significant and amounts to EUR 16 per supplier switch. These costs represent a consumer's net hassle of switching and captures mostly non-monetary costs given that early termination fees do not exist in our setting.[46] Our model specification assumes that the switching costs coefficient is constant across consumers but since the price coefficient is decreasing in income, richer consumers have higher switching costs than poorer households by construction. The estimated switching costs are roughly equivalent to half a month's average electricity expenditure (excluding other charges and fees; see Table A.1) of an average Flemish household.[47] A simple back-of-the-envelope calculation suggests that switching from the most expensive

[45] Table D.2 in Appendix D displays the monetary WTP along with each parameter estimate.

[46] Recall that any potential welcome bonus that a supplier may pay to new customers will be absorbed into our switching cost estimate.

[47] Other charges and fees, such as network and distribution charges, and taxes made up 60% of the average bill of a Flemish consumer in June 2016. (Source: `http://www.creg.info/Tarifs/Boordtabel-Tableaudebord/Francais/tabbord201606.pdf`.)

Table 3: Baseline model (homogeneous PCW search costs) - PCW search cost and awareness process parameters

	Coefficients
PCW search cost - constant	0.2829***
	(0.0826)
PCW search cost - internet	-1.2301***
	(0.0540)
PCW search cost - campaign	-0.6189***
	(0.0388)
Awareness process - constant	-1.2160***
	(0.0188)
Awareness process - adv. expenditure	4.6802***
	(0.0299)

*Notes: Results for parameter for advertising-awareness process and PCW search costs from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively.*

to the cheapest contract would yield cost savings of EUR 12.70 per month on average. Consequently, the EUR 16 switching costs would be compensated within a period of less than two months.

Table 3 displays the coefficients describing the PCW search cost and the advertising-awareness process. For the estimation, we restrict the PCW search cost κ to be positive by using an exponential transformation, i.e., we model the PCW search cost as

$$\kappa_{it} = \exp(\kappa_0 + \kappa_1 INTERNET_t + \kappa_2 REG_t), \tag{17}$$

where κ_0 to κ_2 correspond to the parameter estimates in the upper panel of Table 3. The estimates reveal that the costs of searching the PCW are highly significant and equivalent to EUR 18 per PCW search. An increase in the Internet penetration decreases search costs, but somewhat surprisingly, only very little. Over the course of our sample period of five years, in which Internet penetration continuously increased, PCW search costs fell by less than EUR 1.[48] The information campaign of the Flemish regulator, however, had a large effect. Our estimates indicate that the PCW search cost was lower by roughly 50% during the information campaign period. In our specifications, we assume that the information campaign had a direct effect on the PCW search cost for 6 months, i.e., for 6 months after the campaign start date κ is lower ceteris paribus. We choose an effective period of 6 months in order to capture that, even though the campaign lasted only for a couple of weeks, consumers typically remember the information conveyed by the campaign for some time. Therefore, they are likely to find

[48]For a graphical illustration, see Figure D.1 in Appendix D.

it easier to use the PCW even after the campaign has ended, but they will eventually forget about it and the campaign effect on κ should wear off.[49] This provides strong evidence that the activities of the regulator were indeed very successful in nudging consumers to use the PCW.

The lower panel of Table 3 reveals that firm advertising has a significant impact on consumers' awareness sets. Higher advertisement expenditures by a supplier strongly increase the probability that consumers are aware of the supplier's contracts (*adv. expenditure*). At the estimated parameter values, our model predicts that in a given month, a consumer is on average informed about 2.7 out of the 7 firms in the market through advertising.

An explicit concern of the regulator is that not all consumers make use of PCWs to the same extent. For example, our survey data shows that seniors use the PCW much less than non-seniors. To investigate this observation formally, we estimate an extended version of our model in which we allow the PCW search cost to vary across different demographic types. Specifically, we model the search cost such that seniors can have a different PCW search cost κ than non-seniors

$$\kappa_{it} = \exp(\kappa_0 + \kappa_1 INTERNET_t + \kappa_2 REG_t + \kappa_3 SENIOR_i). \tag{18}$$

Table 4: Model with heterogeneous PCW search costs - consumer preferences

	Mean	Sigma	Senior	Income
Constant	−0.7672***			
	(0.0390)			
Price	−3.7159***			0.3043***
	(0.1557)			(0.1153)
Incumbent Dummy	−0.0333***		0.2413***	
	(0.0039)		(0.0639)	
Green Electricity	0.0016	0.3563***		
	(0.0327)	(0.0274)		
Switching Costs	0.6642***			
	(0.0309)			

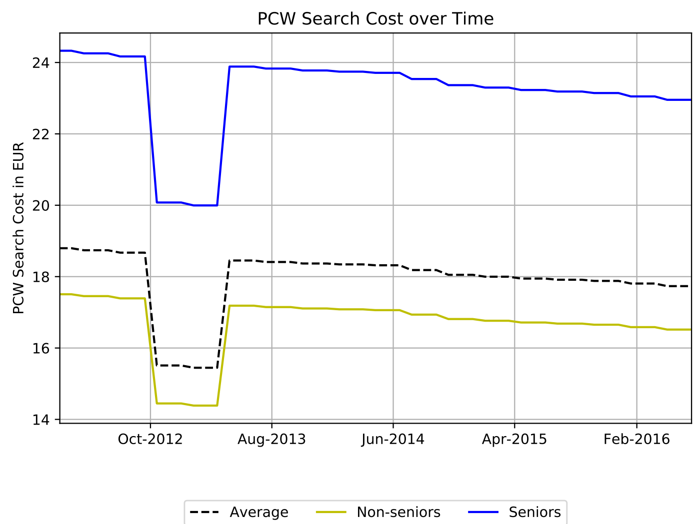
*Notes: Results for preference parameters from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10, 5 and 1 percent level respectively.*

Table 4 and D.5 in Appendix D summarize the associated results. Generally, the estimated parameters are qualitatively identical and similar in magnitude to the baseline model. However, the estimated incumbent preference of seniors drops to approximately EUR 5 per month while still being significant. The estimated switching cost increases slightly from EUR 16 to

[49] Experimenting with different effective lengths of the campaign, such as 2 or 4 months, resulted in similar estimates.

EUR 18. Both models reveal that consumers in our data face both significant search and switching costs, i.e., even if a consumer is fully informed and aware of a better contract, there is a significant probability that she remains with her previous supplier due to switching costs.

Figure 3: Evolution of PCW search costs (heterogeneous κ)



Notes: The figure displays the evolution of the PCW search cost (κ) for different consumer types (senior vs. non-senior) over time. Estimates are based on the model specification with heterogeneous κ as specified in Equation (18) and the parameter estimates in Table D.5.

The parameter estimates for the search cost change as expected. Non-seniors have an average search cost of roughly EUR 17, while seniors incur a cost of approximately EUR 24 per PCW search, see Figure 3 for a graphical illustration. Although still highly significant, in our extended model, the regulator's information campaign generates only a smaller decrease in the PCW search costs of roughly 25% compared to 50% in the baseline model.

7.2 Counterfactuals

Next, we use our parameter estimates to conduct a series of counterfactual policy simulations in order to illustrate the common and differential effects of switching costs and limited awareness.

We start by simulating the market structure if either switching costs or PCW search costs are reduced while holding the other effect fixed. In practice, a reduction in switching costs, can take many forms, for example, implementing standardized switching procedures, regular campaigns informing consumers about how to switch or direct payments to consumers by firms in the form of welcome discounts. A reduction in search costs is typically easily achieved by maintaining reliable PCWs and increasing their ease-of-use, for example, via information campaigns, such as the one conducted by the Flemish regulator in the fall of 2012. To shed light on the effectiveness of this specific campaign we conduct a separate counterfactual.

Finally, we investigate the broader question of how much consumers value a liberalized retail electricity market by comparing the status quo, i.e., a market with product differentiation and choice but switching costs and search frictions, to a scenario in which the market is eliminated and electricity is provided to all consumers by one regulated firm.

In order to evaluate the welfare effects of our counterfactuals, we compute the respective consumer surplus as the expected ex ante utility a consumer obtains from participating in the market. In logit models, the closed-form solution for the surplus of consumer i is given by

$$CS_i = \frac{1}{\alpha_i} \log \left(\sum_j \exp(v_{ij}) \right) + C, \tag{19}$$

where the summation is taken over all contracts in the consumer's choice set, α_i is her price coefficient, $v_{ij} = \delta_j + \mu_{ij}$ is the deterministic part of the utility for consumer i from having contract j and C is a constant coming from the fact that discrete-choice models are only identified up to scale.[50] In models with state dependence consumer surplus also depends on a consumer's choice in the previous period. If type i is subscribed to contract j at the beginning of the period, her surplus is given by

$$CS_{it|j} = \frac{1}{\alpha_i} \log \left(\exp(v_{ijt}) + \sum_{k \neq j} \exp(v_{ikt} - \psi) \right) + C, \tag{20}$$

where ψ denotes the switching cost. The aggregate welfare of all type-i consumers is obtained by integrating over the previous period's market share distribution

$$CS_{it} = \sum_j CS_{it|j} s_{ijt-1} + C. \tag{21}$$

Finally, aggregate welfare in market t is obtained by integrating over all consumer types

$$CS_t = \int_i CS_{it} dD_{it}. \tag{22}$$

A meaningful analysis of the welfare effects from compensating consumers for switching costs requires us to make assumptions about how the compensation is financed. By construction, consumer welfare increases when any kind of cost is reduced. For our simulations, we assume the following. While only consumers who switch or use the PCW benefit from the reduction in search and switching costs through a smaller utility loss, this utility compensation is financed uniformly by all consumers. More specifically, we compute the total churn and total PCW

[50] Consequently, absolute welfare statements are not informative. However, the constant C will cancel out when comparing welfare across different scenarios.

usage in a period to compute the total amount of compensation that is given to consumers who search or switch. This amount is subtracted from the gross welfare gain of the market.[51]

When either type of friction is reduced, market shares become more volatile as consumers respond more actively to demand shifters, for example, price increases. The evolution of market shares over time when either switching costs are reduced by 75%, which is equivalent to EUR 12 for the average consumer, or PCW search costs are reduced by 70%, which is roughly equivalent to EUR 13 for the average consumer, are shown in Figures E.2 to E.3 Appendix E.[52] While averaged over time the market shares remain surprisingly similar, the incumbent loses customers in many periods. Overall, the aggregate market share distribution reacts much more to a decrease in the PCW search costs than a reduction in switching costs.[53]

Reducing switching costs or search costs does not only affect market shares but also a consumer's decision of whether to use the PCW. In our counterfactuals, we find that eliminating either market friction would significantly increase PCW usage. While a reduction in switching costs by 75% increases the monthly share of PCW users by 4 percentage points, or roughly 55%, on average, a reduction in search costs by 70% increases the share of PCW users massively by almost 40 percentage points. Figure E.4 in Appendix E illustrates the observed and counterfactual PCW usage over time.

Typically, policy makers are not concerned about the market structure per se, but primarily about consumer surplus. Therefore, we focus our remaining discussion on welfare statistics. Overall, we find that both market frictions have large effects. Decreasing PCW search costs and switching costs by 70% and 75% respectively results in approximately identical welfare gains. Specifically, each policy measure increases the monthly net surplus of the average consumer by EUR 6.60 which corresponds to roughly 20% of the average monthly electricity bill in Flanders.[54]

One general caveat of our first two counterfactuals is that they do not take into account reactions on the supply side. In reality, one would expect firms to adjust prices and advertising strategies when switching or search frictions are eliminated. Incorporating a full-fledged supply side model in the presence of switching costs and limited awareness would require a dynamic supply model. This goes beyond the scope of the current analysis but is an interesting avenue for future research. In most cases, one would expect that a reduction of market frictions leads to an increase in competition and lower prices. Therefore, it is likely that our welfare predictions are conservative, i.e., they constitute a lower bound on the welfare gains that are likely to be achieved in the real world.

[51] Even though reductions in search and switching costs need not involve monetary payments, conceptually, one can think of reducing search and switching costs as a subsidy to consumers who search or switch; and the paid subsidies are financed by a uniform tax on all consumers.

[52] Simulated market structures for other reduction levels are qualitatively similar and available upon request.

[53] This pattern is in line with theory models that consider both channels. For example, Wilson (2012) shows that, in his model, a marginal reduction in search costs has a larger effect on consumer activity than switching costs. The underlying reasoning is that, while search costs have to be paid independently of whether the consumer finds a better contract or not, switching costs are only incurred when the consumer finds a better contract.

[54] Simulating the welfare gains using different levels of search and switching cost reductions yields similar results and changes in welfare gains are as expected.

In our third counterfactual, we assess the welfare gains from the information campaign conducted by the Flemish regulator in the fall of 2012. We do this by comparing the consumer surplus in our observed data to a simulated surplus assuming that the campaign did not affect the level of the PCW search cost. Our model predicts that in this case, the average monthly consumer surplus would have been EUR 0.19 lower than in the observed data. When aggregating these losses over all 53 months of our sample period, we find that the campaign generated a welfare gain of roughly EUR 10 for the average consumer which is equivalent to a total gross welfare gain for the whole region of Flanders of roughly EUR 27 million.[55] Note that the effects of this intervention are twofold. First, without the campaign, PCW users directly incur a higher cost of using the PCW for several months. Second, in the absence of the campaign, some consumers refrain from using the PCW so that they are likely to be subscribed to a less efficient contract than if the PCW search cost had been lower. We interpret these results as evidence that relatively low-cost measures, such as standard information campaigns, can already generate massive benefits for consumers in markets that are characterized by substantial search and switching costs.

Lastly, we compute consumer surplus for a counterfactual setting in which the liberalized market is removed and electricity is provided to all consumers by one regulated firm. While this scenario eliminates all market frictions, it also terminates potential welfare gains from product differentiation and consumer choice. These simulations reveal that, when all consumers are served by the conventional contract of the incumbent firm at the same price as observed in the data, the average consumer will suffer a welfare loss of approximately EUR 10 per month. We interpret this result as evidence that, in spite of substantial market frictions in the form of search and switching costs, Flemish consumers value a liberalized retail electricity market.[56]

A comprehensive evaluation of the welfare effect of this policy requires determining the counterfactual retail price. Predicting this regulated price goes beyond the scope of this paper since the prevailing price depends on a plethora of factors, for example, local market features, such as the main energy sources used to produce electricity and their origins and the characteristics of the regulated firm, in particular its bargaining power, as well as political considerations. A likely candidate for a regulated pricing structure is a *wholesale plus* contract, which sets the retail price equal to the wholesale spot price plus a fixed markup.

To shed additional light on the welfare effects of eliminating the deregulated market, we simulate the regulated industry for a variety of *wholesale plus* contracts. This exercise reveals that Flemish consumers would be indifferent[57] between a regulated market and the liberalized

[55] These numbers are calculated as follows. Total welfare gain for average consumer = average gain per month $\times$ number of months in sample period = EUR 0.19 $\times$ 53 = EUR 10.07. Total welfare gain for Flanders = Total welfare gain for average consumer $\times$ number of residential electricity access points in Flanders = EUR 10.07 $\times$ 2.7 million = EUR 27.19 million.

[56] Furthermore, there are additional benefits of a deregulated market that our demand model does not capture. In particular, our analysis cannot evaluate the competitive effects on the supply side, such as the firms' incentives to innovate, for example, by offering novel contract types or technologies that can ultimately lead to a better allocation of resources.

[57] We define indifference as yielding the same consumer surplus for the average consumer as in the observed data.

market observed in the data when the markup is set at roughly 30% above the wholesale price.

From a technological perspective, it is very conceivable that it is possible to set the regulated retail price below this threshold while still covering retail costs.[58] During our sample period, however, markups in Belgium consistently range between 50% and 80% (ACER/CEER, 2016).[59] If Belgium were to switch back to a regulated retail market, current markups would need to be reduced by more than 50% compared to current levels to reach the indifference threshold predicted by our simulations. Implementing a regulated price that cuts current markups by such an amount is challenging - not least due to political reasons. If such a decrease in markups cannot be achieved, consumers are better off in the liberalized market with retail choice and market frictions than in a regulated price regime.

8 Conclusion

In this paper, we develop and estimate a structural demand model of the retail electricity market to quantify the importance of different channels of consumer inertia for the welfare gains from a liberalized electricity market. The use of a detailed and novel data set on aggregate and individual-level contract choices and PCW usage data allows us to model consumer behavior in much more detail than the existing literature. Such a detailed model is likely to provide more reliable guidance for specific policy measures than models that ignore at least one of the channels. Specifically, we investigate the role of preference heterogeneity and product differentiation, consumer switching costs and limited awareness about the available contracts. In addition, our model sheds new light on the role of a regulated PCW for consumers' search and switching behavior.

Our model consists of two stages. In the awareness stage, consumers form their consideration sets by deciding whether to use a PCW and so become fully informed. If a consumer decides not to become fully informed, she is forced to remain with her previous supplier or choose among the contracts she became aware of through firm advertising. In the choice stage, each consumer chooses the utility-maximizing contract as a function of her preferences, observed and unobserved contract characteristics and her previous supplier choice.

Our detailed data set allows us to identify the different channels of consumer inertia using a combination of macromoments in the style of BLP and a rich set of micromoments based on consumers' PCW usage behavior and their contract choices conditional on demographic characteristics and their PCW usage.

[58]In several European countries that regulate retail markets, markups are usually less than 20 percent, for example, Denmark, Spain and Portugal. Regulated retail prices in France and Poland, however, tend to exhibit markups of more than 30 percent (ACER/CEER, 2016).

[59]In many other European countries, for example, Germany, the UK and the Netherlands, the magnitudes of markups are similar. Because of several institutional particularities, it is not always straightforward to compare such statistics across countries, however.

We estimate the model using data from the Belgian region of Flanders and a sample period from 2012 to 2016. Since the data required for our estimation can be obtained relatively easily, our empirical strategy can be applied to other countries and potentially other industries as well.

Our empirical results reveal that all three channels in our model play a significant role for the choices of Flemish consumers. First, although electricity is a physically homogeneous product, consumers perceive electricity contracts as differentiated. Our estimates show that seniors have a preference for the incumbent supplier. Depending on the model specification, they are willing to pay up to EUR 12 per month to remain with the incumbent instead of being with another supplier. However, this WTP drops to EUR 5 per month when we allow seniors to also have a different PCW search cost than younger consumers. While the mean consumer does not value electricity produced from renewable sources, our estimates reveal that preferences vary substantially across the Flemish population.

Furthermore, we find evidence for significant market frictions in the form of switching and search costs. A consumer who switches electricity suppliers incurs a switching cost of roughly EUR 17, which is equivalent to half a month's electricity expenditure of an average Flemish household; therefore, the switching cost would be compensated within less two months for a consumer who switches from the most expensive to the cheapest supplier. Searching the PCW is costly too. Our estimates reveal that search costs are approximately as important as switching costs and range from EUR 17 to EUR 24 depending on our model specification. This implies that even a perfectly informed consumer may not switch due to the significant hassle she faces when going through the switching process. The costs to search the PCW do not vary substantially over time, except for the fall of 2012, when an information campaign run by the regulator significantly reduced the PCW search costs by 25% to 50% depending on our model specification.

Finally, we conduct a series of counterfactual simulations. In many European countries and US states, deregulated retail electricity markets share very similar features with the Flemish market; therefore, our counterfactuals are likely to be informative about a series of important policy questions that regulators in many regions face.

First, search and switching costs hinder consumer engagement considerably. If either PCW search costs or switching costs were reduced by 70% and 75% respectively, the monthly surplus of the average consumer would increase by EUR 6.60 (20% of the average monthly electricity bill). Therefore, fully overcoming consumer inertia requires policy makers to ideally act in both dimensions, raising awareness about contract alternatives –in particular about the low price offers– and, at the same time, tackling consumers' switching costs, for example, by implementing standardized switching procedures or regular information campaigns about different aspects of the industry.

Second, we find that relatively low-cost measures can already generate massive gains in consumer surplus. For example, a targeted information campaign by the regulator to increase awareness about its PCW in 2012 generated a total consumer surplus gain of approximately EUR 27 million.

Lastly, we address the broader question of the net welfare gains from deregulated electricity markets by simulating scenarios in which the liberalized market is replaced by one in which a regulated monopolist serves all consumers. These simulations indicate that the welfare of an average Flemish consumer tends to decrease in the regulated market –by about EUR 10 per month if the monopolist charges the same prices as in the data. The results from simulating several *wholesale-plus* contracts are mixed. For the Flemish market we find cautious evidence that the benefits of a liberalized market with retail choice are likely to outweigh its costs, even though regulators can still do a lot to address the issue of consumer inertia. More generally, it is not clear, however, that either a regulated or a liberalized market regime is always welfare-dominating. Instead, specific policy recommendations require a careful analysis of the institutional particularities of the market under consideration, the preferences of local consumers and the objective function of the regulator.

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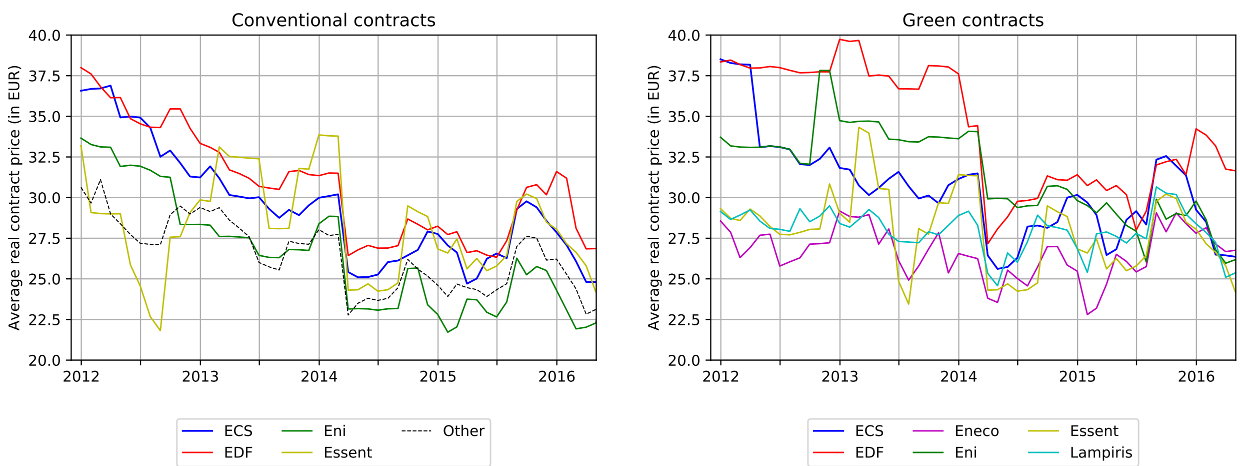
Appendices

Appendix A Additional Descriptive Evidence

Figure A.1: Monthly prices by contract type over time, supplier averages, in 2012-EUR.



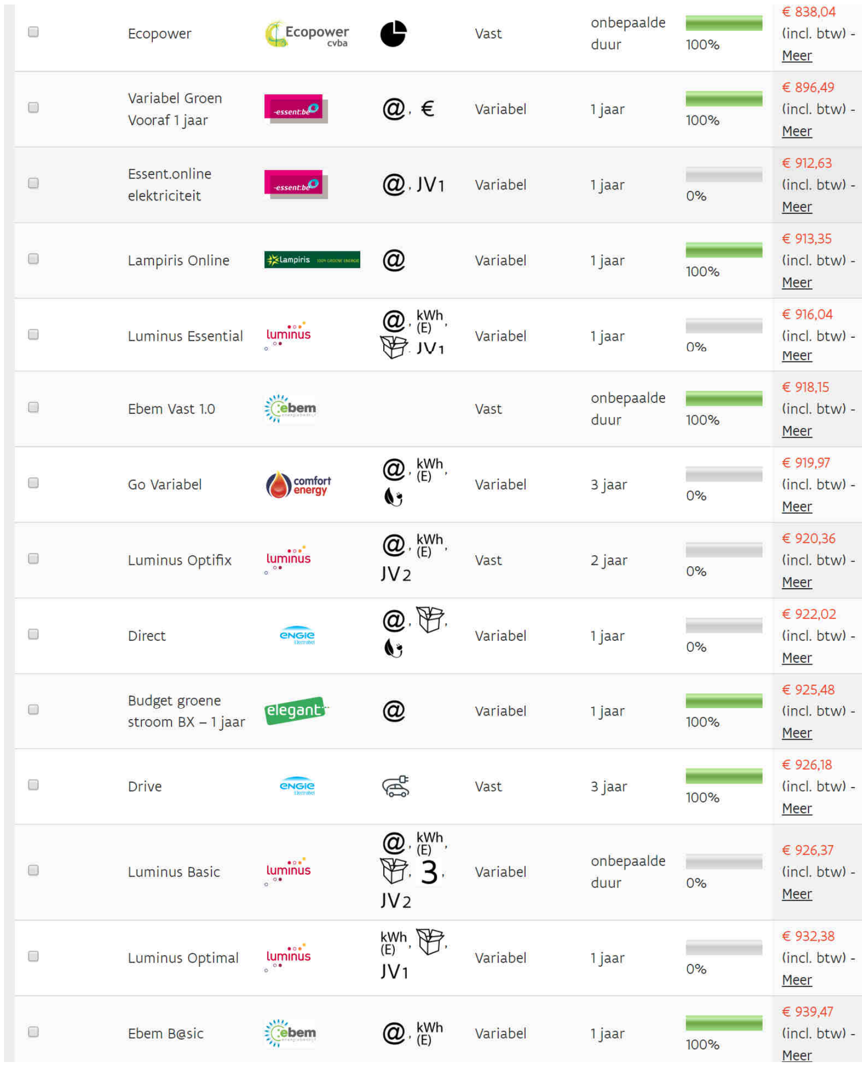
Notes: Prices are represented as a twelfth of the yearly expenditure for electricity paid by an average Belgian household consuming 3,500 kWh per year. Prices are averaged across contracts if a supplier offers more than one contract in each category. All prices are deflated to 2012 Euros. The decline of prices in April 2014 is due to a change in the VAT rate that was reversed in September 2015.

Table A.1: Yearly advertisement expenditure in Flanders (in million EUR)

	2012	2013	2014	2015	2016
ECS	13.75	13.96	9.88	8.16	5.69
EDF	8.81	7.5	8.65	9.84	3.42
Eneco	2.59	2.21	2.54	1.45	.41
Eni	7.73	7.06	2.52	.68	.79
Essent	3.65	4.26	5.36	4.46	1.26
Lampiris	4.43	3.98	3.09	3.03	.79
Other	.55	.67	.47	2.91	1.17

Notes: Advertisement expenditures in Flanders are calculated as 60% (share of Belgian advertising in Dutch language) of the supplier's expenditures across Belgium (gross tariffs). Data source: Nielsen MDB.

Figure A.2: Example screenshot of electricity contract comparison on V-test website



Ecopower	Ecopower cvba		Vast	onbepaalde duur	100%	€ 838,04 (incl. btw) - Meer
Variabel Groen Vooraf 1 jaar	essent.be	@, €	Variabel	1 jaar	100%	€ 896,49 (incl. btw) - Meer
Essent.online elektriciteit	essent.be	@, JV1	Variabel	1 jaar	0%	€ 912,63 (incl. btw) - Meer
Lampiris Online	Lampiris	@	Variabel	1 jaar	100%	€ 913,35 (incl. btw) - Meer
Luminus Essential	luminus	@, kWh (E), JV1	Variabel	1 jaar	0%	€ 916,04 (incl. btw) - Meer
Ebem Vast 1.0	ebem		Vast	onbepaalde duur	100%	€ 918,15 (incl. btw) - Meer
Go Variabel	comfort energy	@, kWh (E)	Variabel	3 jaar	0%	€ 919,97 (incl. btw) - Meer
Luminus Optifix	luminus	@, kWh (E), JV2	Vast	2 jaar	0%	€ 920,36 (incl. btw) - Meer
Direct	ENGIE	@	Variabel	1 jaar	0%	€ 922,02 (incl. btw) - Meer
Budget groene stroom BX – 1 jaar	elegant	@	Variabel	1 jaar	100%	€ 925,48 (incl. btw) - Meer
Drive	ENGIE		Vast	3 jaar	100%	€ 926,18 (incl. btw) - Meer
Luminus Basic	luminus	@, kWh (E), 3, JV2	Variabel	onbepaalde duur	0%	€ 926,37 (incl. btw) - Meer
Luminus Optimal	luminus	kWh (E), JV1	Variabel	1 jaar	0%	€ 932,38 (incl. btw) - Meer
Ebem B@sic	ebem	@, kWh (E)	Variabel	1 jaar	100%	€ 939,47 (incl. btw) - Meer

Source: `www.vtest.be`, accessed on 30 August 2018.

Notes: Prices are represented as the yearly bill of a Belgian household living in Hasselt (postal code 3500) consuming 3,500 kWh per year. All bill components are included: price for electricity, network and distribution tariffs, taxes and other charges.

Appendix B Additional Reduced Form Evidence

In this Appendix, we provide supporting evidence for the assumptions that help us in identifying the PCW search cost. Figure B.1 indicates that consumers' PCW search behavior is plausibly affected by supplier advertising. Fewer consumers tend to use the PCW when advertising expenditure by suppliers increases. This is consistent with the argument that

Table B.1: Limited awareness is unequally distributed across the Flemish population.

	(1) Fully informed	(2) Fully informed	(3) Fully informed
Household size	0.024	0.023	0.032
	(0.022)	(0.022)	(0.033)
Woman	-0.294***	-0.299***	-0.321***
	(0.049)	(0.049)	(0.072)
Senior	-0.260***	-0.258***	-0.270***
	(0.063)	(0.063)	(0.095)
Higher education	0.324***	0.336***	0.359***
	(0.050)	(0.051)	(0.074)
Primary education	-0.584***	-0.559***	-0.626***
	(0.126)	(0.127)	(0.198)
Family net income	0.135***	0.129***	0.132***
	(0.019)	(0.020)	(0.029)
Energy costs important	-0.080	-0.073	-0.133*
	(0.055)	(0.055)	(0.080)
Year		0.036**	0.043
		(0.018)	(0.027)
Green contract			0.482***
			(0.070)
Observations	3422	3422	1645

Data source: VREG surveys 2012-2016.
Notes: The table summarizes results from probit regressions with a dummy for a consumer having used the PCW on consumer characteristics. *Household size* is the number of people living in the household. *Woman* and *Senior* are dummies for female consumers and respondents older than 65, respectively. *Higher education* and *Primary education* are dummies for consumers with a higher education degree and primary education degree only, respectively. *Family net income* is the monthly net household income. *Energy costs important* denotes consumers who state that energy costs are an important part of their budget. *Green contract* indicates consumers who currently receive energy only from renewable sources. *Year* captures a linear time trend.
Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ad spending informs consumers and consequently decreasing their benefits of searching the PCW.[60]

Figure B.2 illustrates that the number of consumers searching the PCW increases with Internet penetration.[61]

[60]Naturally, one should be careful in interpreting this relationship as necessarily causal. Figure B.1 could also indicate the reverse, namely that firms reduce advertising when PCW usage is high. However, it seems plausible that this channels is not very important because firms do not have access to the usage statistics of the PCW operated by the regulator so that it is arguably difficult for them to adjust their advertising expenditure based on this information.

[61]We use the share of households connected to a fixed-line broadband Internet connection as a measure for Internet penetration. When using a measure of mobile broadband penetration, we obtain similar results.

Table B.2: Fully informed consumers tend to subscribe to cheaper contracts.

	(1) Average price	(2) Average price	(3) Average price	(4) Average price
Fully informed	-7.769***	-7.937***	-7.615***	-3.630**
	(1.555)	(1.562)	(1.558)	(1.536)
Senior	1.965	0.823	0.670	0.577
	(1.646)	(1.730)	(1.724)	(1.673)
Family net income	-3.277***	-2.980***	-2.455***	-2.370***
	(0.461)	(0.523)	(0.532)	(0.516)
Household size		-1.152*	-1.579**	-0.907
		(0.627)	(0.630)	(0.613)
Woman		-1.495	-2.225	-3.333**
		(1.427)	(1.429)	(1.388)
Energy costs important			8.146***	9.095***
			(1.623)	(1.576)
No of past switches				-8.185***
				(0.559)
Observations	3421	3421	3421	3421

Data source: VREG surveys 2012-2016.
Notes: The table summarizes results from OLS regressions of a consumer's average monthly electricity expenditure on consumer characteristics. *No of past switches* captures how often a consumer has already switched suppliers. The remaning regressors are defined as in Table B.1. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In addition, we investigate in reduced form regressions, whether PCW usage, Internet penetration and supplier advertising are associated with each other. We regress both the share of consumers using the PCW in a given month and suppliers' advertising expenditure on our potential shifters of search costs and benefits, as well as a series of controls. Table B.5 summarizes the associated results. Column (1) regresses the share of consumers using the PCW in a given month on Internet penetration, a dummy for the periods when the regulator conducted an extensive information campaign and the aggregate monthly supplier advertising expenditure. In addition, we control for seasonal effects in the form of month-of-the-year dummies and the average retail price and the wholesale electricity spot price. PCW usage is affected positively and significantly by both Internet penetration and the regulator campaign dummy which indicates that both seem to facilitate the use of the PCW. In addition, firms' advertising has a negative effect on consumers' PCW usage which is consistent with advertising informing consumers and thereby decreasing their expected benefits from using the PCW. In Column (2), we regress firm-specific advertising in a given month on our PCW cost shifters, i.e., Internet penetration and the regulator campaign dummy, as well as a series of controls, in particular, firm fixed effects and month-of-the-year fixed effects. We find that neither Internet penetration nor the regulator campaign dummy has a significant effect on a firm's advertising expenditure. In fact, most of the variation in advertising expenditure can

Table B.3: Socio-demographic characteristics of (non-)switchers

	(1) Past sw.	(2) Past sw.	(3) Past sw.	(4) Intention	(5) Intention	(6) Intention
Fully informed	0.581***	0.580***	0.581***	0.193***	0.191***	0.181***
	(0.051)	(0.051)	(0.052)	(0.051)	(0.051)	(0.052)
Senior	-0.109**	-0.101*	-0.025	-0.260***	-0.257***	-0.221***
	(0.053)	(0.053)	(0.056)	(0.057)	(0.057)	(0.061)
Family net income	0.029**	0.013	-0.021	0.014	0.010	0.004
	(0.015)	(0.015)	(0.018)	(0.016)	(0.016)	(0.019)
Year		0.127***	0.132***		0.031*	0.034**
		(0.017)	(0.017)		(0.017)	(0.017)
Household size			0.103***			0.022
			(0.021)			(0.021)
Higher education			0.086*			0.133***
			(0.049)			(0.051)
Primary education			0.138			-0.032
			(0.086)			(0.094)
Energy costs imp.			0.091*			0.254***
			(0.051)			(0.053)
Observations	3367	3367	3367	3421	3421	3421

Data source: VREG surveys 2012-2016.
Notes: The table summarizes results from probit regressions with a dummy for whether a consumer has switched in the past (Columns 1-3) or intends to switch supplier (Columns 4-6) on consumer characteristics. The definition of the regressors is as in Table B.1. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

be explained by firm fixed effects and seasonal effects. For example, advertising expenditures seem to systematically increase in May and in November.

In conclusion, we take these results as evidence in support of our assumptions that allow us to treat advertising expenditure as an exclusive shifter of consumers' expected benefits of searching the PCW, and Internet penetration and the regulator campaign dummy as exclusive shifters of consumers' PCW search cost.

Appendix C Additional Details of the Estimation Routine

The estimation algorithm is implemented as follows.

1. We guess a vector of parameters θ, which contains the preference parameters, switching cost, PCW search costs and parameters of the advertising-awareness process.

Table B.4: Reduced form evidence for state dependence using macro data

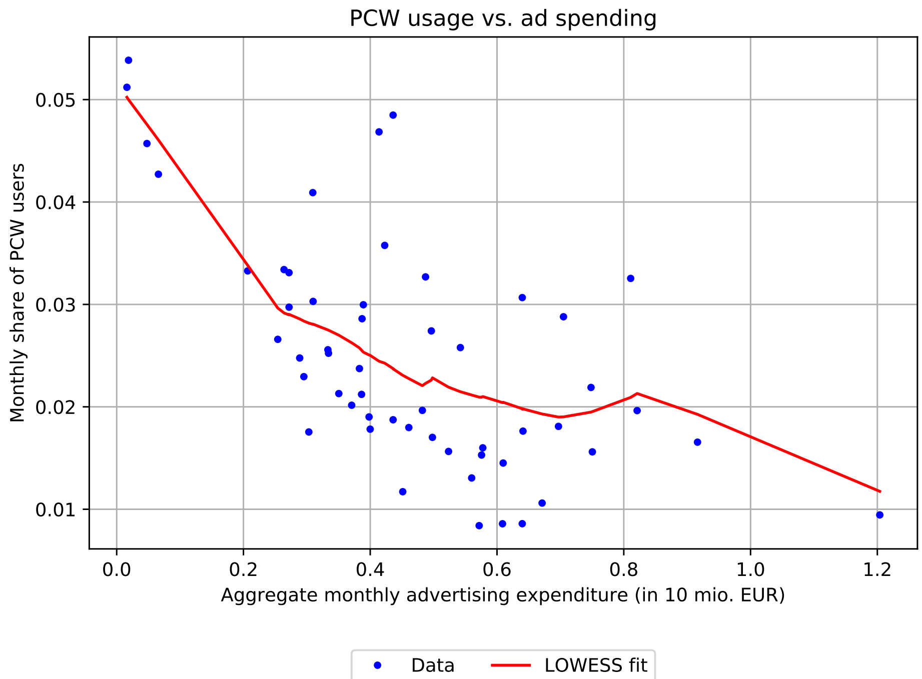
	(1) Market share	(2) Market share	(3) Market share	(4) Market share	(5) Market share
Price	0.227	0.139	-0.018*	-0.009	-0.003
	(0.155)	(0.170)	(0.009)	(0.009)	(0.011)
Incumbent	0.153***		-0.001***		0.005*
	(0.011)		(0.000)		(0.003)
Green contract	-0.075***	-0.093***	0.001***	0.002***	-0.002
	(0.007)	(0.009)	(0.000)	(0.000)	(0.001)
Advertising	-4.645	-6.723	0.634*	0.585*	0.179
	(3.995)	(4.527)	(0.328)	(0.316)	(0.369)
Lagged share			0.999***	0.999***	0.956***
			(0.002)	(0.002)	(0.018)
R2	0.551	0.603	0.999	0.999	0.998
Observations	594	594	583	583	583
Lagged Share	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes	No
Lagged Share Inst.	No	No	No	No	Yes

Data source: Panel (2012-2016) of contract-level market shares provided by VREG.
Notes: The table summarizes results from regressing contract-level market shares on contract characteristics and lagged market shares.
Standard errors in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2. We simulate NS individual consumers. In our main specification, we simulate $NS = 1,000$ individuals. Each individual is represented by a 3-dimensional vector comprising 2 consumer demographics (age and income) and a taste shock for green electricity. We draw from the empirical distribution of demographics and a random green electricity coefficient from a standard normal distribution.

3. For each consumer and each period, we simulate a fallback choice set that consists of the consumer's previous contract and the contracts that she became aware of through advertising based on Equation (1). We calculate the probability that individual i is informed about supplier j's contracts for a given value of awareness parameters and firms' advertising levels. To transform probabilities into specific simulated choice sets, we draw J random draws from a uniform distribution for each individual i and time period t. If the calculated probability that individual i is informed about the specific supplier j's contracts exceeds the uniform draw for this supplier, supplier j's contracts are included in i's choice set. Otherwise, they are excluded.
   Based on this fallback choice set, we compute the expected benefit of searching the PCW and compare it to the PCW search cost for each consumer i. We compute the expected benefits of PCW search by simulation. For each consumer i, month t and contract j that the consumer is not informed about either through advertising or because it is her previous contract, we draw 25 draws from the estimated joint price belief distribution and compute the expected benefit of search as the average over the

Figure B.1: Empirical evidence: Advertising affects PCW usage



Data source: Nielsen MDB and VREG.

Notes: The figure illustrates the relationship between the aggregate monthly PCW usage and supplier ad spending in the raw data.

25 simulated utilities from search. If the expected search benefits exceed the search costs, the consumer is classified as a PCW user and is therefore fully informed; if the search cost exceeds the expected benefits, the consumer does not use the PCW and remains only partially informed.

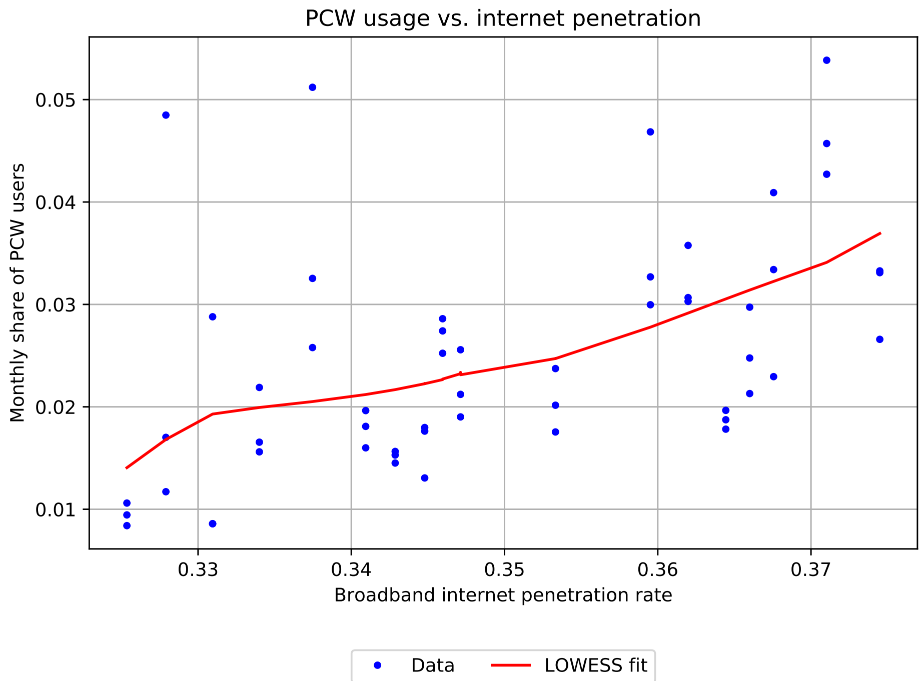
4. If a consumer is fully informed in a given month, we compute her contract choice based on the full awareness set. Choice probabilities are given by Equation (5).

5. If a consumer is only partially informed, she chooses a contract only from her fallback choice set which is determined by firm advertising and her previous contract. Choice probabilities are given by Equation (5) but the summation is only taken over the contracts in the consumer's consideration set.

6. We average over all individual contract choice probabilities to predict aggregate contract market share distributions. These are, together with the observed market shares, send into a BLP-style mapping to back out the mean utilities δ for each contract in each period.

7. After convergence of the mean utilities, we back out the structural demand errors ξ based on Equation (8). This allows us to compute the BLP moment conditions and the churn rate prediction errors as a function of our parameter guess.

Figure B.2: Empirical evidence: Internet penetration affects PCW usage



Data source: OECD and VREG.

Notes: The figure illustrates the relationship between the aggregate monthly PCW usage and Internet penetration rates in the raw data.

8. Afterwards, we compute the model's choice probability predictions for contract choices and PCW usage for each of the consumer types, defined by demographic characteristics and awareness status, and match them to the observed choices in the survey to compute our micromoments.

9. Finally, we perform a non-linear search for the parameter values that minimize our GMM objective function given by Equation (16).

Table B.5: Reduced form relationship between PCW usage, ad spending and Internet penetration

	(1) PCW usage	(2) Ad spending
Internet penetration	0.261*	-1.853
	(0.147)	(2.674)
Regulator campaign	0.008**	0.075
	(0.004)	(0.063)
Ad spending	-0.028***	
	(0.007)	
Retail price	0.001	0.005
	(0.001)	(0.011)
Wholesale price		0.003
		(0.002)
R2	0.687	0.627
Observations	54	378
Firm FE	No	Yes
Month-of-Year FE	Yes	Yes

Data source: VREG surveys 2012-2016 and Nielsen MDB.

Notes: Column (1) summarizes the results from an OLS regression of the monthly aggregate share of PCW users on various potential shifters of the expected benefits and costs of search. Column (2) summarizes the results from an OLS regression of monthly firm-specific advertising on a similar set of shifters. All regressions include month-of-year fixed effects. Column (2) also incorporates firm fixed effects. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D Additional Estimation Results

Tables D.1 and D.2 summarize the estimation results from our baseline model with homogeneous PCW search costs. The last column translates the point estimates into marginal willingness-to-pay per month using the marginal utility of money that was derived from the estimated price coefficient for a mean-income consumer. In our specification, the average consumer has a disposable income of EUR 2,500 per month. Tables D.3 and D.4 illustrate the results for our extended model with heterogeneous PCW search costs.

Table D.1: Estimation results for model with homogeneous PCW search costs (first stage GMM)

	Coefficients	WTP in EUR
Constant	-0.8343*** (0.1710)	-18.12
Mean price coefficient	-4.6034*** (0.3568)	-
Income-price interaction	0.9090 (1.7903)	-
Incumbent (non-seniors)	-0.0379 (0.0322)	-0.82
Incumbent (seniors)	0.7170 (0.4524)	15.58
Mean green coefficient	0.0038 (0.2707)	0.08
Variance green coefficient	0.8534*** (0.3312)	-
Switching cost	0.9969** (0.4550)	21.66
PCW search	0.3288 (0.7080)	-
PCW search-Internet	-1.1948 (0.9979)	-
PCW search-Campaign	-0.7873*** (0.2074)	-
Adv. constant	-1.0612*** (0.4108)	-
Adv. expenditure	4.5122*** (0.3875)	-

*Notes: Results from estimating a RC-logit model using GMM with block-diagonal 2SLS weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively. - denotes non-interpretable willingness-to-pay.*

Table D.2: Estimation results for model with homogeneous PCW search costs (efficient second stage GMM)

	Coefficients	WTP in EUR
Constant	-0.8389*** (0.0236)	-17.88
Mean price coefficient	-4.6932*** (0.1148)	-
Income-price interaction	0.9030*** (0.1005)	-
Incumbent (non-seniors)	-0.0367*** (0.0023)	-0.78
Incumbent (seniors)	0.5989*** (0.0904)	12.76
Mean green coefficient	0.0025 (0.0199)	0.05
Variance green coefficient	0.8300*** (0.0228)	-
Switching cost	0.7711*** (0.0322)	16.43
PCW search	0.2829*** (0.0826)	-
PCW search-Internet	-1.2301*** (0.0540)	-
PCW search-Campaign	-0.6189*** (0.0388)	-
Adv. constant	-1.2160*** (0.0188)	-
Adv. expenditure	4.6802*** (0.0299)	-

*Notes: Results from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively. - denotes non-interpretable willingness-to-pay.*

Table D.3: Estimation results for model with heterogeneous PCW search costs (first stage GMM)

	Coefficients	WTP in EUR
Constant	-0.7962*** (0.0662)	-21.56
Mean price coefficient	-3.6925*** (0.6953)	-
Income-price interaction	0.3887 (12.0670)	-
Incumbent (non-seniors)	-0.0328 (0.0261)	-0.89
Incumbent (seniors)	0.2472*** (0.0822)	6.70
Mean green coefficient	0.0036 (0.0903)	0.10
Variance green coefficient	0.4645*** (0.0605)	-
Switching cost	0.8700*** (0.0652)	23.56
PCW search	0.0012 (0.0375)	-
PCW search-Internet	-1.1488*** (0.1493)	-
PCW search-Campaign	-0.6679*** (0.1035)	-
PCW search-Senior	0.4164** (0.1661)	-
Adv. constant	-0.9057*** (0.0538)	-
Adv. expenditure	4.5712*** (0.1729)	-

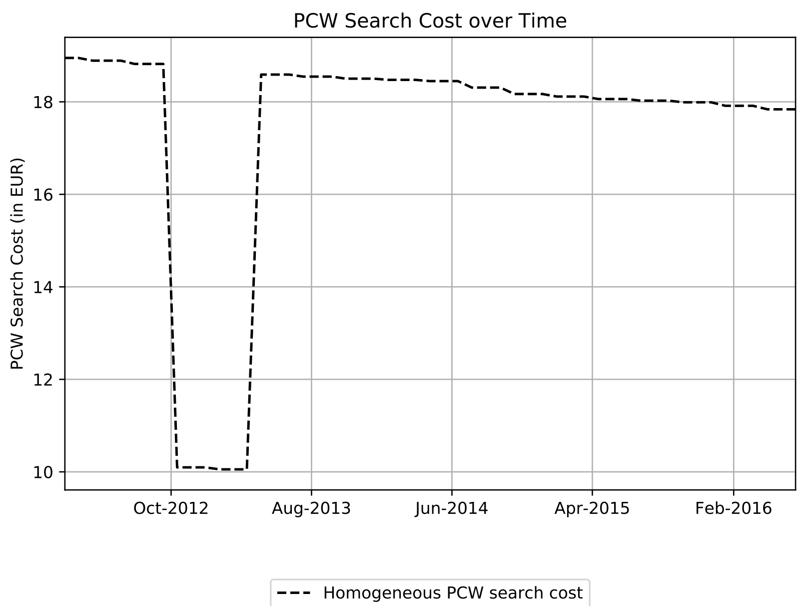
*Notes: Results from estimating a RC-logit model using GMM with block-diagonal 2SLS weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively. - denotes non-interpretable willingness-to-pay.*

Table D.4: Estimation results for model with heterogeneous PCW search costs (efficient second stage GMM)

	Coefficients	WTP in EUR
Constant	-0.7672*** (0.0390)	-20.65
Mean price coefficient	-3.7159*** (0.1557)	-
Income-price interaction	0.3043*** (0.1153)	-
Incumbent (non-seniors)	-0.0333*** (0.0039)	-0.90
Incumbent (seniors)	0.2413*** (0.0639)	6.49
Mean green coefficient	0.0016 (0.0327)	0.04
Variance green coefficient	0.3563*** (0.0274)	-
Switching cost	0.6642*** (0.0309)	17.87
PCW search	-0.0448 (0.0363)	-
PCW search-Internet	-1.1839*** (0.0714)	-
PCW search-Campaign	-0.1819*** (0.0408)	-
PCW search-Senior	0.3291*** (0.0319)	-
Adv. constant	-0.7226*** (0.0053)	-
Adv. expenditure	4.9187*** (0.0174)	-

*Notes: Results from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively. - denotes non-interpretable willingness-to-pay.*

Figure D.1: Evolution of PCW search costs (homogeneous κ)



Notes: The figure displays the evolution of consumers' PCW search cost (κ) over time. Estimates are based on the model specification with homogeneous κ as specified in Equation (17) and the parameter estimates in Table 3.

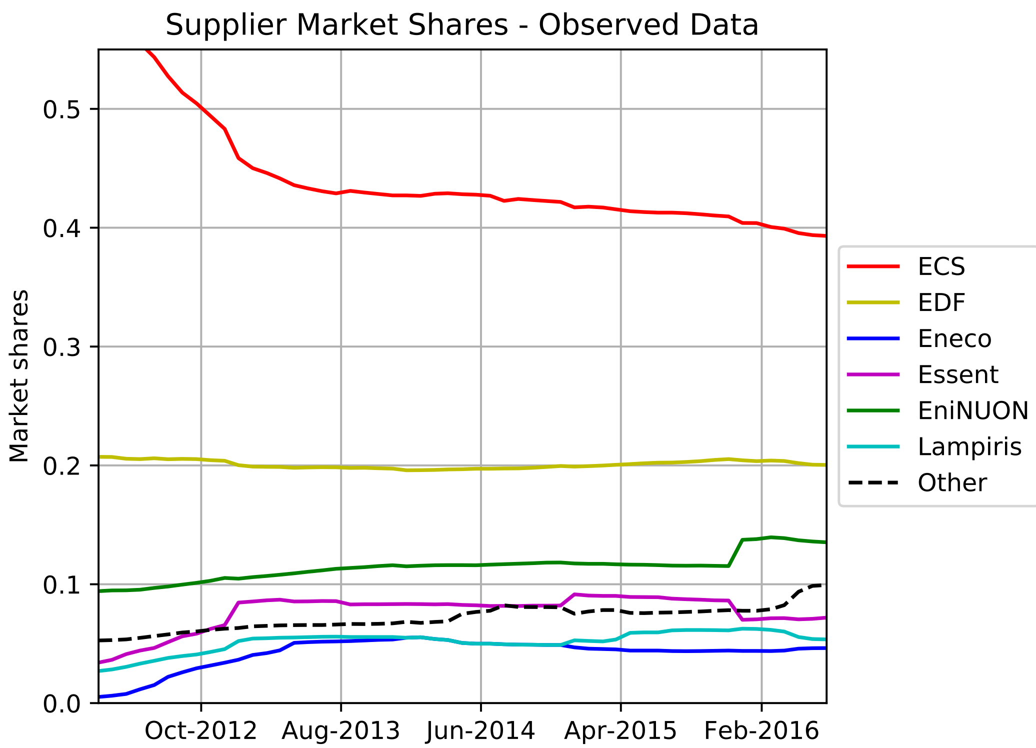
Table D.5: Model with heterogeneous PCW search costs - PCW search cost and awareness process parameters

	Coefficients
PCW search cost - constant	-0.0448 (0.0363)
PCW search cost - internet	-1.1839*** (0.0714)
PCW search cost - campaign	-0.1819*** (0.0408)
PCW search cost - senior	0.3291*** (0.0319)
Awareness process - adv. expenditure	-0.7226*** (0.0053)
Adv. expenditure	4.9187*** (0.0174)

*Notes: Results for parameter for advertising-awareness process and PCW search costs from estimating a RC-logit model using 2-step GMM with efficient weighting matrix. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively.*

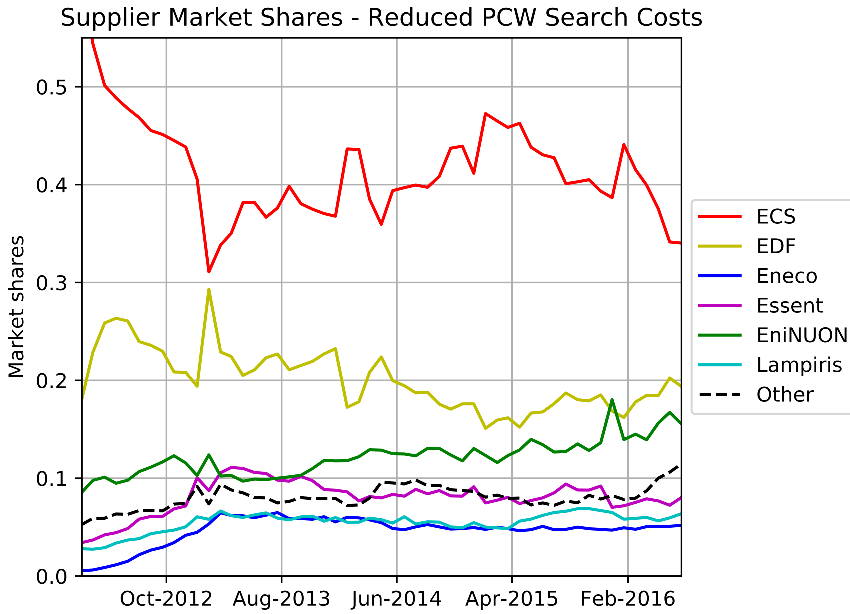
Appendix E Additional Counterfactual Results

Figure E.1: Observed market shares



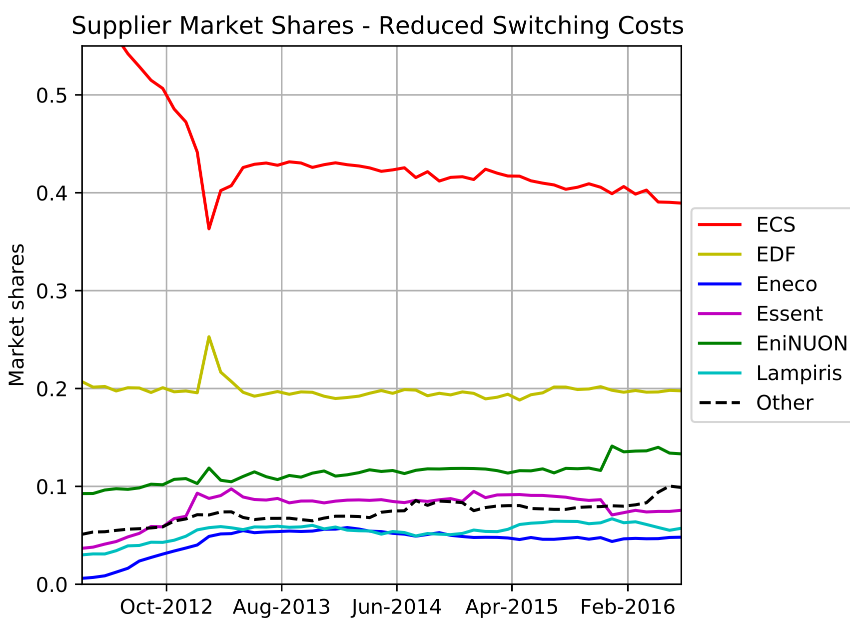
Data source: VREG. *Notes:* The figure displays the evolution of supplier-level market shares over our sample period.

Figure E.2: Counterfactual market shares (I)



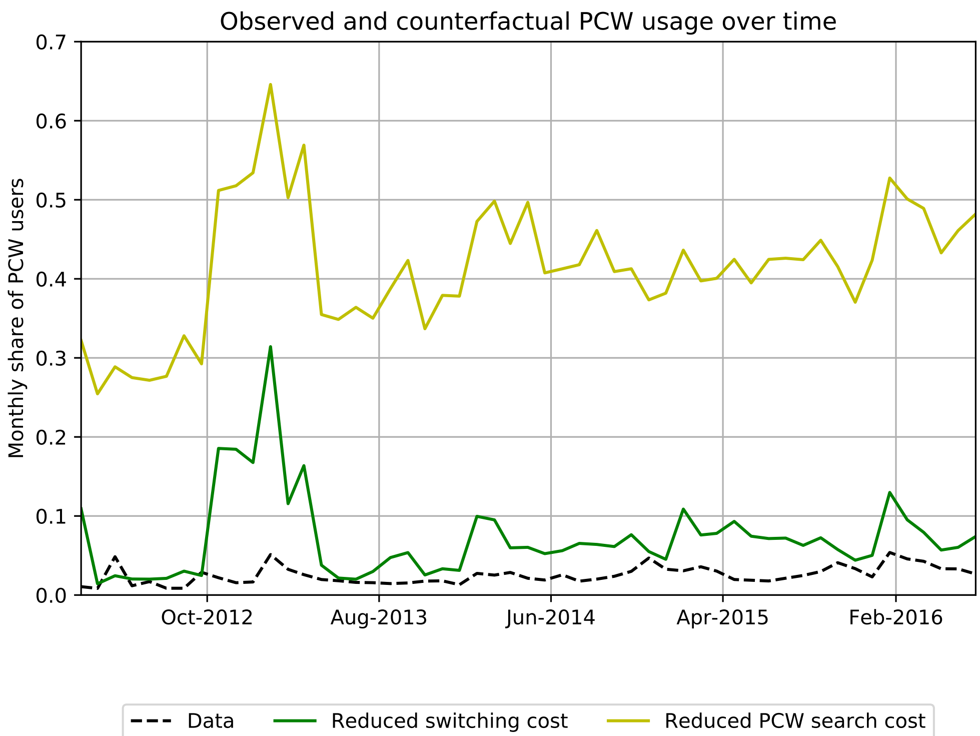
Notes: The figure displays the evolution of supplier-level market shares over our sample period when PCW search costs are reduced by 70% (∼ EUR 13).

Figure E.3: Counterfactual market shares (II)



Notes: The figure displays the evolution of supplier-level market shares over our sample period when consumer switching costs are reduced by 75% (∼ EUR 12).

Figure E.4: Observed and counterfactual PCW Usage



Notes: The figure compares the evolution of the aggregate monthly PCW usage over time in the observed data and in counterfactual simulations when either PCW search costs or switching costs are reduced by 70% and 75% respectively.