Do alert the inert! Switching costs vs. limited awareness in retail electricity markets*

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Abstract
Regulators in many countries spend substantial resources on educating consumers about switching possibilities in retail electricity markets to fight consumer inertia. In order to target these activities efficiently, one needs to have a clear picture on the main sources of inertia. In a structural discrete-choice model of the retail electricity market, we investigate three potential inertia sources: consumer preferences, switching costs and limited awareness about available contracts. We estimate the model using a novel and unique data set on the Belgian electricity market from 2012 to 2016. We combine contract-level market share and price data with supplier advertising data as well as individual-level surveys on consumer information sets and switching considerations. We find that the three potential sources of inertia are present in our data: Seniors have a strong preference for the incumbent supplier and consumers value electricity produced from renewable energy. Switching costs are highly significant amounting to 82 EUR per switch, which corresponds to 20-30% of the yearly electricity expenditures of an average household. Supplier advertising significantly affects consumer awareness. Finally, we conduct counterfactual analyses to investigate the relative importance of switching costs and limited awareness in market outcomes. We find a more balanced market structure when switching costs are reduced or awareness is raised as consumers migrate from the incumbent supplier to the cheaper, new entrants.

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1 Introduction

Enabling an active participation of electricity consumers is necessary to release the full potential of liberalized electricity markets and to ensure effective competition. More than 25 years into electricity market liberalization, gains of the reforms remain often muted. In particular in retail markets, high concentrations of supplier market shares persist and in most countries incumbents still capture the largest share of the consumer base (ACER, 2015). Therefore, policy makers and regulators around the world aim at overcoming inertia of electricity consumers to switch contracts.\(^1\) However, to fight consumer inertia effectively one needs to capture its actual drivers and design policy intervention accordingly. We contribute to this important goal, by quantifying the relative importance of three potential sources of consumer inertia: consumer preferences, switching costs and limited awareness about available electricity contracts. We build a structural discrete-choice model of the retail electricity market that allows us to separately identify the inertia effect of switching costs from limited awareness, while accounting for preference heterogeneity of consumers towards the incumbent supplier and towards electricity generated from renewable sources of energy.

Switching costs may lead to state dependence in electricity contract choices. They are not necessarily limited to monetary switching costs, such as early termination fees, but can also represent a consumer’s opportunity costs of time for organizing the switch, the hassle to switch, or misperceived (although often abolished) contract termination fees. Limited awareness about contract alternatives arises for example from informational frictions. The complex nature of the retail electricity market, quickly changing contract offers and unclear procedures are not conducive for consumers to be fully informed about all details of the available contracts. Price comparison websites (PCW) tackle the awareness problem directly as they enable consumers to compare all available contracts in an easy and transparent way. The importance of PCWs in retail electricity markets is growing - not least because of increasing internet penetration rates and new regulation mandating the provision of PCWs.\(^2\) However, not all consumers make use of PCWs. Consequently, they are aware about available contracts mainly as a result of direct advertising by electricity suppliers and individual consumer search. We define PCW users as being fully informed and non-PCW users as being partially informed about the electricity contract offer. Finally, also preference heterogeneity affects consumer inertia. Although electricity is a physically homogeneous product, consumers perceive and value specific aspects in the generation and the supply of electricity. For example, switching decisions can be the result of a specific preference for electricity produced from renewable energy. From a different angle, con-

\(^1\)For example, one pillar of the European Commission’s “Clean Energy for all Europeans” Package (Winter Package) published in November 2016, which proposes a major overhaul of the European Union’s energy market legislation, 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).

\(^2\)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).
sumers might stay with the incumbent supplier because they fear that a competitor will offer unreliable services.

The contribution of our analysis is twofold: First, we provide more detailed insight into the reasons of consumer inertia in retail electricity markets, a topic that is at the center of policy and regulatory debate. To the best of our knowledge, we are the first in the electricity retail market literature to separately identify the inertia effect related to heterogeneous preferences, switching costs and limited awareness. Due to data limitations, previous research has often analyzed only a subset of these factors. However, models that consider reasons for inertia in isolation may yield biased estimates that are less pertinent for policy recommendation. Our data enables us to quantify the arguably most important potential reasons for inertia, which we then use to evaluate potential future policy interventions, for example to contrast the effect of information campaigns and policies or supplier interventions that reduce or compensate for switching costs.

Second, methodology-wise our analysis augments the classic discrete choice model with random coefficients (Berry, Levinsohn and Pakes, 1995: BLP) by both a switching costs and a limited awareness component. We incorporate switching costs similarly to Shcherbakov (2016). However, we solve the identification challenge slightly differently because we observe more detailed data, in particular churn rates. Our model of the awareness component is similar in spirit to Sovinsky Goeree (2008) and Honka (2014), but we adapt their estimation strategies to our data. In contrast to Honka (2014), who relies on a small individual survey, we combine choice data both at the consumer- and the market-level. Compared to Sovinsky Goeree (2008), our data has the advantage that we partly observe individual consumers’ awareness sets which allows us to model the awareness process directly without relying solely on media exposure as instrument for awareness.

Embedding the consumer choice problem in a structural model has two main advantages. First, by combining several data sets, in particular market share data on aggregate contract choices and survey data on individual choices, it enables us to combine multiple sources of identification and estimate parameters that could not be easily identified previously, when similar data sets were analyzed separately. Second, a structural model derived from a consumer’s utility maximization allows us to run counterfactual analyses: We investigate the effectiveness of different policy interventions and the market structure that would arise if either the limited awareness problem was reduced and more consumers were perfectly informed about all available contracts or if switching costs were reduced.

To estimate the structural model, we use data covering the retail electricity market in the Belgian region of Flanders between 2012 and 2016. The dataset combines a monthly panel of market share distributions with price and contractual information at the electricity contract level, monthly advertisement expenditures of all electricity suppliers in the market, monthly click data on the main Flemish price comparison website, as well as a cross-section of detailed individual-level surveys on consumer awareness, choice and demographic characteristics. We estimate the model by a general method of moments (GMM) routine with simulated consumers and simulated choice sets, in which we match observed aggregate
market shares to model predictions similar to the seminal framework by Berry et al. (1995). These classic BLP-moments are complemented with information on market-level churn rates and micro-moments, which match observed and predicted contract choices at the consumer level, similar in spirit to Petrin (2002), Berry et al. (2004) and Sovinsky Goeree (2008).

The central identification challenge of our model arises due to the interlinkage of inertia effects from preference heterogeneity, switching costs, and limited awareness about contract alternatives. In a nutshell, separate identification of these three potential sources of inertia is ensured because of different layers of variation in our data: First, as in BLP, heterogeneous consumer preferences are identified because we observe variation in contract configurations as well as aggregate choice and substitution patterns. Second, we are able to identify switching costs by observing a panel of aggregate market shares over time. Observing market shares today and their covariation with exogenous shifters in previous periods is informative about state dependence and so switching costs. Finally, the effect of limited awareness can be disentangled because we observe the individual contract choices of a large repeated cross-section of consumer types with different characteristics and awareness status.

Our estimation confirms that the three potential sources of inertia are present in our data. We find that preferences have a significant effect on electricity contract choice. Seniors prefer the incumbent supplier over alternatives and are willing to pay a premium of 21 EUR per month on average. The average Flemish consumer values electricity produced from renewable energy sources at 2 EUR per month, but preferences vary across consumers. This amount is in line with what suppliers generally charge for green electricity on top of conventional contracts. Switching costs have a highly significant effect on the supplier choice of consumers. They amount to 82 EUR per supplier switch, which represents between 20% and 31% of the yearly electricity expenditures of an average Flemish household. Simple calculations show that a consumer who switches from the most expensive to the cheapest electricity contract would be compensated for these switching costs within 6.5 months by savings on the electricity bill. Furthermore, advertising expenditures of electricity suppliers significantly affect awareness and consumer choice sets.

To investigate the effectiveness of different policy measures and the relative importance of switching costs and limited awareness, we perform counterfactual analysis ceteris paribus. Our results suggest that the market structure becomes more balanced when switching costs are reduced or awareness is raised. Although more consumers migrate from the incumbent supplier to the cheaper new entrants under a policy which reduces switching costs (but holding awareness fixed) than under a policy which increases awareness (but holding switching costs fixed). Raising awareness prompts consumers to switch towards cheaper suppliers as well, but the effect is attenuated due to switching costs that keep some newly aware consumers at the incumbent supplier.

Only a very limited number of studies quantifies reasons for consumer inertia in retail electricity markets, but generally does so by modelling one or two potential reasons in
isolation. Giulietti et al. (2014) use a panel of supplier prices, market shares and input costs to measure consumer search costs in relation to the pricing behavior of electricity suppliers in the UK during 2002-2005. They estimate an equilibrium supply model and find that search costs must have been relatively high to explain supplier mark-ups. Hortaçsu et al. (2017) study the inertia effect from search frictions (i.e. inattention) and consumer bias towards the incumbent using a panel of supplier choice data at the meter level in Texas during 2002-2006. The authors find that both sources of inertia played a significant role, and in particular so within census tracks characterized by low average income and education levels and a high share of senior citizens. This paper is closest to our analysis. Our study provides additional insight by studying more recent data (more than ten years after market liberalization), by merging aggregate choice with precise consumer-level data, by studying market shares and prices at the contract (instead of the supplier) level and by disentangling a broader set of potential reasons for consumer inertia, namely switching costs, limited awareness and consumer preferences (not only for the incumbent but also for green electricity and dependent on each consumer’s age and income level). This allows for a more detailed understanding of consumer inertia.

Many other studies explore potential reasons for inertia in energy markets with no attempt to quantifying them (Giulietti et al., 2005; Wieringa and Verhoef, 2007; Giulietti et al., 2010; Sitzia et al., 2014; He and Reiner, 2015; Daglish, 2016; Six et al., 2016) or determine correlations between consumer characteristics and switching activity (Ek and Söderholm, 2008; Waddams Price et al., 2013, 2014; He and Reiner, 2015). Our study goes one step further and quantifies reasons for electricity consumers not to switch contracts, thereby providing the basis for counterfactual policy analyses.

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 dataset and provide first reduced-form evidence for informational frictions and state-dependence to motivate our structural model. Sections 5 and 6 present the economic model and develop the identification strategy. The estimation procedure is outlined in Section 7. We present estimation results of the structural model and the counterfactual analysis in Sections 8. Section 9 concludes.

2 Institutional Background

The Belgian electricity market is composed of three regional markets, Brussels-Capital, Flanders and Wallonia, and was totally liberalized in January 2007. The liberalization of the retail market consists of two main changes: First, consumers are now free to choose their electricity supplier. Second the Intercommunales$^3$, traditionally responsible for both

$^3$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,
distribution and sale of electricity to consumers, are charged with the non-liberalized parts of the markets only (such as the management of the distribution network, technical installation, 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 mio), has the highest per capita income (6.7% above average in 2016) and forms one linguistic community. The liberalization of the Flemish regional electricity market was accomplished first, in July 2003 (Brussels-Capital and Wallonia followed in 2007), which puts Flanders into the early waves of electricity market liberalization in Europe. Only six other European countries liberalized earlier (ACER, 2015). As a consequence, Flemish consumers had time to become familiar with the market to turn active and we are confident that the market is in a mature state during the time period that we analyze.

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. Second, by international comparison, Flemish consumers are very active in switching electricity suppliers. In 2014, 11.7% of consumers have switched supplier, which make Flanders score among the top six European countries in terms of supplier switching rates. Despite these positive trends, market concentration remains high. In 2016, the incumbent suppliers, Electrabel and EDF, still serve more than half of the market - though this incumbent share is amongst the lowest across European countries. Furthermore, many Flemish consumers remain with expensive electricity contracts and forgo savings that could be made by switching to cheaper contracts. 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 competitiveness of the national electricity and gas markets and to defend 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

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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)

4 Data was collected from www.statbel.fgov.be/.


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

7 Incumbent market shares are lower only in the UK and Portugal (ACER, 2015).
regulators take an active role in enhancing switching and increasing awareness of electricity consumers in Belgium, with the aim to increase market competition. For example in September 2012, they supported the Federal Ministry of Economic Affairs in the campaign "Dare to compare" which aimed at incentivizing electricity consumers to switch their electricity contract by giving instructions on how to compare tariffs. Furthermore, the three regional regulators are in charge of running and promoting the main price comparison website in each region (BruSim in Bruxelles-Capital, Vtest in Flanders, CompaCWaPE in Wallonia). 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.

Additionally, several legislative or regulatory changes have been implemented at the federal level to protect consumers and to enhance switching. For example, in September 2012 a change in the Belgian national legislation abolished contract termination fees imposed on electricity retail customers. This is to say, domestic 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 supplier, it is enough to sign a contract with another supplier, who will organize the switch for the consumer. Anecdotal evidence shows that most suppliers anticipated this change and slashed contract termination fees much before. 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 much harder to quantify.

Despite the legislative change abolishing monetary switching costs and the efforts of the regulators to increase market transparency and enhance switching, switching reluctance of retail electricity consumers remains an issue in Flanders. Our survey data reveals that consumer switching in 2012-2016 may be affected by all three potential reasons for inertia that we analyze. First, there is evidence for switching costs: On average 47% of the survey respondents, who have not switched supplier yet, state the high efforts involved with switching as a reason for their inertia. Even consumers who visit price comparison websites (PCW) and therefore 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 as well: The market share distributions differ according to the awareness status of a consumer. Those consumers who have used a price comparison tool and are fully aware about all available contracts, exhibit a different, more balanced, supplier choice than consumers with limited awareness who tend to choose the incumbents more often.

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8During 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 price comparison websites 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 price simulators available.

9For example, between April and December 2012 the indexation of electricity tariffs with a variable structure was capped. In January 2013 a safety net regulation was implemented which asks CREG to monitor and guide the indexation of these variable tariffs.
Third, preference heterogeneity for green electricity and the reliability of the incumbent is present as well: On average 42% of those respondents that have already switched supplier, based their choice on considerations for green electricity. On average 44% of all survey respondents, who have already switched supplier, have chosen their supplier on the basis of (what each consumer interprets as) the supplier’s reliability.

3 Data

Our analysis combines data on the Flemish residential electricity market from different sources into a novel and unique dataset. The data cover a period of 54 months (January 2012 - June 2016) and include information on contract choices and contract attributes at the aggregate and the consumer level, on supplier advertisement and on consumer characteristics and awareness status.

3.1 Aggregate data

We use a monthly panel of aggregate market shares at the contract level to construct classic BLP moment conditions which allow us to quantify mean consumer preferences and switching costs. Observing market shares at the contract-level, allows us to include product differentiation in the three arguably most important dimensions: contract price, the origin of the electricity (green vs. conventional), and the supplier offering the contract.

First, monthly market shares for all major residential electricity suppliers in Flanders are publicly available at 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\footnote{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 does not vary within one trimester.} to split the aggregate supplier shares in two contract categories: green and conventional contracts. Green contracts are defined as contracts that offer exclusively electricity generated from renewable sources of energy.\footnote{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.} The conventional category comprises all other contracts.

Second, the contract market shares are merged to the corresponding monthly contract price, which we collected from the tariff information sheets that the Belgium regulator for electricity and gas (CREG) collects from any electricity supplier. In order to keep the model tractable we ignore consumption heterogeneity and follow the literature in assuming an average consumption of electricity across individuals (Giulietti et al., 2014). We construct the monthly contract “price” as a twelfth of the yearly expenditure of an average Belgian consumer.
household who signs up for the specific contract in the given month. Following CREG, we assume an average yearly electricity consumption of 3,500 kWh per year metered at a single rate. If a supplier proposes more than one contract in each contract category (green or conventional) we use the average price.

Our price data represents the component of a household’s electricity bill that is associated with the consumption of electricity only. It includes VAT but excludes other important electricity bill components, such as the price for transporting and distributing electricity and other fees or taxes. Transport and distribution charges are location specific but do not differ across electricity supplier or contract. Because these components are linear and constant across contracts, they will cancel out in the choice probabilities and therefore not bias our model predictions. The pure electricity component of the final bill reflects the margin at which electricity suppliers can compete, making it the appropriate element to study in our model. According to CREG, the electricity component accounts for 20-40% of the final electricity bill of a consumer who pays the average electricity price in Flanders.

We record contract market share and price information only for those suppliers with an aggregate market share above 1% on average over the 54 month considered in the analysis. The contracts of all other suppliers are pooled into an outside option. We disregard access points that are with a social contract or the distribution network operator. According to VREG (2012), consumers are supplied by these contracts or operators 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 six suppliers and one outside option. The six commercial suppliers are: Electrabel Customer Solution (ECS), Electricité de France - Luminus (EDF), Eneco, Eni, Essent, and Lampiris. All six suppliers offer green contracts, whereas only four also propose conventional contracts. We treat a contract/month as one observation, yielding 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 shows the average market share by supplier in each year together with the average monthly price per contract type throughout the entire period. The Flemish retail electricity market in 2016 (i.e. 13 years after its full liberalization) is still rather concentrated with ECS and EDF accounting together for 60% of the total market on average. The ECS share experienced a continuous decline over the last five years. The part of the market that opened up to new suppliers between 2012 and 2016 spreads evenly over the main new entrants in 2016. Average contract prices of ECS and EDF exceed those of the new

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12 Throughout the analysis, we deflate all prices to 2012 EUR.
13 Source: [http://www.creg.be/fr/professionnels/fonctionnement-et-monitoring-du-marche/tableau-de-bord-marche-de-gros-et-de-detail](http://www.creg.be/fr/professionnels/fonctionnement-et-monitoring-du-marche/tableau-de-bord-marche-de-gros-et-de-detail)
14 Eni acquired Nuon Belgium in January 2012 and merges with Distriegas in November 2012 to become Eni gas & power.
entrants (with one exception, the green contract offered by Eni). Excluding Essent, suppliers that offer both green and conventional contracts charge a higher price for contracts delivering green electricity on average. Suppliers that offer only green electricity contracts are amongst the cheapest on average.

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

<table>
<thead>
<tr>
<th>Supplier</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>Average Price (in Euro)</th>
<th>Market Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>conventional green</td>
<td></td>
</tr>
<tr>
<td>ECS</td>
<td>0.54</td>
<td>0.44</td>
<td>0.43</td>
<td>0.41</td>
<td>0.40</td>
<td>29.31 30.46</td>
<td></td>
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<tr>
<td>EDF</td>
<td>0.21</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>30.71 34.28</td>
<td></td>
</tr>
<tr>
<td>Eneco</td>
<td>0.02</td>
<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>26.63</td>
<td></td>
</tr>
<tr>
<td>Eni</td>
<td>0.10</td>
<td>0.11</td>
<td>0.12</td>
<td>0.12</td>
<td>0.14</td>
<td>26.53 31.39</td>
<td></td>
</tr>
<tr>
<td>Essent</td>
<td>0.05</td>
<td>0.08</td>
<td>0.08</td>
<td>0.09</td>
<td>0.07</td>
<td>28.15 27.92</td>
<td></td>
</tr>
<tr>
<td>Lampiris</td>
<td>0.03</td>
<td>0.06</td>
<td>0.05</td>
<td>0.06</td>
<td>0.06</td>
<td>27.94</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>0.06</td>
<td>0.07</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
<td>26.43</td>
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</tr>
</tbody>
</table>

*Other* includes all contracts offered by electricity suppliers with an average market share below 1% over the five 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 1 presents 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 1). Prices of green contracts remain rather stable for the small green suppliers, Eneco and Lampiris. Prices of the traditional Belgian suppliers, ECS and EDF, and suppliers that belong to an incumbent group in other European markets (ENI in Italy; Essent, i.e. RWE, in Germany) decline substantially over time, which reduces the price spread across green contracts.

3.2 Individual data

A pooled cross-section of individual choice data complements our aggregate choice dataset. The data ties chosen contract attributes, such as contract type (i.e. green vs. conventional) and supplier, to consumer characteristics, in particular age and income, as well as the consumer awareness status (fully vs. partially informed). The individual data forms the basis for the micro-moments used in the estimation.
The individual data come from an extensive consumer survey that VREG conducts every year across a stratified random sample of 1,000-1,500 Flemish households. The survey data cover a wide range of topics linked to a household’s attitude towards energy markets. Households provide answers to about 100 questions about the energy market in general, supplier and contract choices, previous switching behavior and future switching intentions, reasons for switching or non-switching, awareness, socio-demographic characteristics, and many more.

We exploit five years of this individual data (2012-2016) mainly to investigate the awareness process of individuals, as we can track which consumer has used the VREG price comparison website every year (i.e. 20-33% per year in our sample). We interpret these consumers as being fully informed about the electricity contract offer. On the one hand, the yearly survey information allows us to create an individual-level dataset to construct micro-moments for our estimation. We use the respondent’s age (i.e. whether the respondent is retired or not) and income band to create different consumer groups.

In addition, we build a monthly information indicator to measure the share of fully informed consumer per month. We combine the yearly share of fully informed survey respondents with information on the number of clicks on the VREG price comparison website (PCW). More precisely, the yearly share of fully informed consumers from the survey is weighted by the share of monthly clicks on the website in the total number of yearly clicks. The number of clicks reported refer to clicks made in the last step of the price comparison and is therefore informative about the number of times a user finished the price comparison and becomes fully informed about all available contracts.\textsuperscript{15} We also keep track of other survey replies to justify some of our assumptions and to perform preliminary reduced form regressions.

\textsuperscript{15}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.
Figure 2 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. Highest churn rates occur at the start of each year reaching an all-time maximum in January 2013 (3.3%) and January 2016 (3.5%). Comparing the monthly churn rate to our information indicator shows that especially in recent years peaks in awareness precede peaks in churn rates by roughly two months.

Further information about 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. Although we cannot display results for confidentiality reasons, contrasting the distribution of supplier market shares in the group of fully informed consumers to the distribution in the group of partially informed consumers indicates that supplier choice differs 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 about their potential choice set.

Note that in the aggregate, the market share distribution of all consumers interviewed in the survey resembles strongly the distribution constructed on the basis of the aggregate data (see Table 1). Our survey data seems to reflect the real market share distributions well.

Additional data on the empirical distribution of individual demographic characteristics was collected from publicly available sources and is used in the simulation of consumers. First,
yearly data on the proportion of the Flemish population older than 65 years comes from
the Belgian Statistics Office.\textsuperscript{16} Second, the yearly income distribution in Belgium is from
Eurostat.

3.3 Advertising data

To model the awareness process and choice sets of Flemish electricity consumers that
have not used a price comparison website (i.e. partially informed consumers), we combine
our survey data on individual awareness with a monthly panel of supplier advertisement
expenditures.

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.

The advertising expenditures are reported monthly by energy supplier in Belgium, which
leads to two caveats. First, the supplier data is not broken down into specific products such
as electricity or gas. As our analysis focuses on the electricity retail market exclusively,
we exclude advertising spending in the gas market by weighting each supplier’s advertis-
ing expenditures by the supplier’s market share in the retail electricity as opposed to the
retail gas market. Second, as electricity suppliers are often part of a bigger group which
is involved in other segments than the supply of electricity, the Nielsen data may contain
advertisement spending at different stages of the value chain (e.g. advertisement for elec-
tricity production, retail sales). However, we assume that the substantial advertisement
effort in the energy sector is concentrated on the retail market and does not take place at
the production level. 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.

Table 2 shows average advertisement expenditures (in 2012 Euro) by electricity supplier.
Total supplier expenditures are normalized by each supplier’s customer base on gas and
electricity contracts to express expenditure by customer.

\textsuperscript{16}Direction générale Statistique, \url{http://statbel.fgov.be/en/statistics/figures/}.
Table 2: Advertisement expenditure per customer in Euro (Flanders, yearly averages)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ECS</td>
<td>0.29</td>
<td>0.38</td>
<td>0.27</td>
<td>0.23</td>
<td>0.34</td>
</tr>
<tr>
<td>EDF</td>
<td>0.53</td>
<td>0.47</td>
<td>0.53</td>
<td>0.58</td>
<td>0.41</td>
</tr>
<tr>
<td>Eneco</td>
<td>1.59</td>
<td>0.47</td>
<td>0.52</td>
<td>0.34</td>
<td>0.20</td>
</tr>
<tr>
<td>Eni</td>
<td>0.55</td>
<td>0.71</td>
<td>0.24</td>
<td>0.07</td>
<td>0.13</td>
</tr>
<tr>
<td>Essent</td>
<td>0.82</td>
<td>0.54</td>
<td>0.69</td>
<td>0.53</td>
<td>0.39</td>
</tr>
<tr>
<td>Lampiris</td>
<td>1.15</td>
<td>0.68</td>
<td>0.54</td>
<td>0.50</td>
<td>0.27</td>
</tr>
<tr>
<td>Other</td>
<td>0.12</td>
<td>0.12</td>
<td>0.08</td>
<td>0.45</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Source: Nielsen MDB. Yearly advertisement expenditures per supplier in Flanders are divided by the supplier’s yearly customer base. Advertisement expenditures in Flanders are calculated as 60% of the supplier’s expenditures across Belgium reported by Nielsen MDB based on gross tariffs. The yearly customer base per supplier equals the market share in the electricity and gas market multiplied by the total number of customers in the respective market in Flanders as reported by VREG.

3.4 Instruments

Finally, to account for the potential endogeneity between unobserved contract attributes and contract prices, we have collected several additional variables that are used as price instruments in our analysis:

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. Variation across suppliers is introduced 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) to satisfy consumer demand and assumes that those suppliers with lots of own production are less sensitive to wholesale electricity prices. More specifically, it relates the volumes that each supplier delivered to all consumers (professional and residential) in all three regions of Belgium in 2014 (source VREG) to the estimated production of each supplier in Belgium. The production estimate uses current production capacity data from ELIA and capacity factors by energy source from FEBEG.

Second, we use Hausman instruments. Based on our large price dataset collected from the CREG tariff information sheets, we construct average monthly prices for gas contracts offered by each supplier in Wallonia.
4 Reduced-form evidence

As discussed in Section 2, despite major political and regulatory efforts to mobilize Flemish electricity consumers to switch supplier, a quick look at survey statistics reveals that consumer inertia still prevails. Several reasons for consumer inertia seem to be present in Flanders: switching costs, limited awareness and preference heterogeneity for green electricity or the incumbent supplier. In the present section we provide reduced-form evidence for informational frictions leading to limited awareness and state-dependence (i.e. switching costs) in Flanders.

The presence of different potential reasons for consumer inertia in Flanders suggest the use of a structural model, which we present in the next section. Only a structural model allows us to combine different datasets and multiple sources of identification in order to separately identify the different reasons for inertia. The results presented in this section should not be interpreted in a causal sense but as simple correlations. To reveal causal relationships, we use our structural model.

4.1 Evidence for informational frictions

This section presents evidence from our individual survey data showing that limited awareness is indeed an important factor in electricity contract choices of Flemish consumers.

Table 3 shows that fully informed consumers, indeed, tend to sign up for cheaper electricity contracts as opposed to their partially informed counterparts. We regress by OLS the monthly energy bill (Average Price) that a survey respondent would pay given his supplier and contract choice and if he follows average consumption patterns on the respondents’ socio-demographic characteristics and awareness status using our surveys in 2012-2016. The dummy variable, Fully informed, takes the value 1 if the respondent has used a price comparison tool and 0 otherwise. Socio-demographic characteristics include continuous variables, such as household size, family net income and a time trend, as well as dummy variables indicating whether the respondent is a woman, a senior, has a higher-education degree or accomplished only primary education, and whether the respondent stated that energy costs take an important part in the household’s budget.

Ceteris paribus, fully informed consumers tend to pay less for their electricity. This is a first indication that full information about available contracts may lead to better choices and that awareness plays an important role in the switching behavior of Flemish retail electricity consumers. Note that the negative correlation between full information and the yearly electricity bill remains even if we control for consumer preferences for the incumbent supplier or green contracts. The specification in column 2 adds a dummy variable taking the value 1 if the respondent is with the incumbent supplier and 0 otherwise. The specification

\[17\] 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/contract-type choice.
Table 3: Fully informed consumers tend to sign up to cheaper contracts on average

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average price</td>
<td>Average price</td>
<td>Average price</td>
</tr>
<tr>
<td>Fully informed</td>
<td>-4.828***</td>
<td>-3.739***</td>
<td>-3.529***</td>
</tr>
<tr>
<td></td>
<td>(1.052)</td>
<td>(1.044)</td>
<td>(1.466)</td>
</tr>
<tr>
<td>Household size</td>
<td>-1.068**</td>
<td>-0.776*</td>
<td>-1.191***</td>
</tr>
<tr>
<td></td>
<td>(0.423)</td>
<td>(0.419)</td>
<td>(0.602)</td>
</tr>
<tr>
<td>Woman</td>
<td>0.832</td>
<td>0.424</td>
<td>1.503</td>
</tr>
<tr>
<td></td>
<td>(0.957)</td>
<td>(0.945)</td>
<td>(1.314)</td>
</tr>
<tr>
<td>Senior</td>
<td>-1.174</td>
<td>-1.440</td>
<td>-3.286**</td>
</tr>
<tr>
<td></td>
<td>(1.164)</td>
<td>(1.149)</td>
<td>(1.630)</td>
</tr>
<tr>
<td>Higher education</td>
<td>-4.488***</td>
<td>-3.993***</td>
<td>-4.079***</td>
</tr>
<tr>
<td></td>
<td>(1.015)</td>
<td>(1.003)</td>
<td>(1.400)</td>
</tr>
<tr>
<td>Primary education</td>
<td>1.280</td>
<td>1.372</td>
<td>6.097**</td>
</tr>
<tr>
<td></td>
<td>(1.758)</td>
<td>(1.735)</td>
<td>(2.485)</td>
</tr>
<tr>
<td>Family net income</td>
<td>0.775**</td>
<td>0.681*</td>
<td>1.329**</td>
</tr>
<tr>
<td></td>
<td>(0.377)</td>
<td>(0.372)</td>
<td>(0.526)</td>
</tr>
<tr>
<td>Energy costs are important</td>
<td>3.588***</td>
<td>3.973***</td>
<td>4.778***</td>
</tr>
<tr>
<td></td>
<td>(1.089)</td>
<td>(1.076)</td>
<td>(1.489)</td>
</tr>
<tr>
<td>Year</td>
<td>-22.190***</td>
<td>-21.879***</td>
<td>-19.716***</td>
</tr>
<tr>
<td></td>
<td>(0.343)</td>
<td>(0.340)</td>
<td>(0.488)</td>
</tr>
<tr>
<td>Incumbent supplier</td>
<td>9.168***</td>
<td>7.725***</td>
<td>7.152***</td>
</tr>
<tr>
<td></td>
<td>(0.955)</td>
<td>(1.337)</td>
<td>(1.331)</td>
</tr>
<tr>
<td>Green contract</td>
<td>7.152***</td>
<td>7.152***</td>
<td>7.152***</td>
</tr>
<tr>
<td></td>
<td>(1.331)</td>
<td>(1.331)</td>
<td>(1.331)</td>
</tr>
<tr>
<td>R2</td>
<td>0.573</td>
<td>0.584</td>
<td>0.533</td>
</tr>
<tr>
<td>Observations</td>
<td>3421</td>
<td>3421</td>
<td>1645</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

in column 3 adds a dummy variable indicating whether the respondent has signed up for an electricity contract delivering electricity generated from renewable energy sources. Because this question was asked to only 50% of survey respondents (randomly) in each year, the sample size is smaller.

Table 4 gives first evidence that the awareness status of consumers is correlated with switching behavior in Flanders: fully informed consumers are more likely to have switched in the past and to have switching intentions for the future ceteris paribus. It reports results of a simple probit regression using the survey data 2012-2016. The specification in Column 1 regresses a dummy (Past switch) indicating whether the survey respondent has already switched electricity supplier in the past on a respondent’s socio-demographic characteristics and awareness status. Column 2 reports results of a specification where the dependent variable is a dummy (Switching intention) indicating whether or not a respondent mentioned to consider switching electricity supplier in the coming six month.
Table 4: Socio-demographic characteristics of (non-)switchers

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past switch</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully informed</td>
<td>0.566***</td>
<td>0.162***</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.104***</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Woman</td>
<td>-0.134***</td>
<td>-0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Senior</td>
<td>-0.046</td>
<td>-0.247***</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Higher education</td>
<td>0.089*</td>
<td>0.138***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Primary education</td>
<td>0.144*</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Family net income</td>
<td>-0.031*</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Energy costs are very important</td>
<td>0.099*</td>
<td>0.265***</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Year</td>
<td>0.134***</td>
<td>0.037**</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Observations</td>
<td>3367</td>
<td>3421</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

The reduced-form results presented in this section point towards informational frictions in the Flemish retail electricity market that have an effect on switching behavior and contract choice. However, they should be interpreted cautiously, as reported results may be biased due to endogeneity (if full information and switching behavior are correlated with unobservables such as a respondent’s inherent interest in switching, in Table 4) or simultaneity problems (e.g. does full information affect switching intentions or vice versa). However, if informational frictions and limited awareness exist, they need to be accounted for in a consumer choice model of retail electricity markets as presented in Section 5.

4.2 Evidence for state-dependence

Table 5 displays initial evidence for state-dependence in consumer decisions based on our panel of aggregate market shares. Following our arguments on identifying state dependence below, we regress contemporaneous contract market shares, \( s_{jt} \), on contemporaneous contract attributes and other controls, \( X_{jt} \), (including price) 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. Even though one should be careful in giving the parameter estimates causal interpretations, we get strong initial evidence for state dependence.

Table 5: Reduced form evidence for state dependence using macro data

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Market share</td>
<td>Market share</td>
<td>Market share</td>
<td>Market share</td>
<td>Market share</td>
</tr>
<tr>
<td>Price</td>
<td>0.228</td>
<td>-0.018**</td>
<td>0.130</td>
<td>-0.009</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.153)</td>
<td>(0.009)</td>
<td>(0.168)</td>
<td>(0.009)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Incumbent</td>
<td>0.153***</td>
<td>-0.001***</td>
<td>-0.005</td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.000)</td>
<td>(0.010)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Green contract</td>
<td>-0.075***</td>
<td>0.001***</td>
<td>-0.092***</td>
<td>0.002***</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.000)</td>
<td>(0.009)</td>
<td>(0.000)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Advertising</td>
<td>-0.005</td>
<td>0.001**</td>
<td>-0.006</td>
<td>0.001**</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Lagged share</td>
<td>0.999***</td>
<td>0.999***</td>
<td>1.002***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.049)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R2</td>
<td>0.551</td>
<td>0.999</td>
<td>0.603</td>
<td>0.999</td>
<td>0.999</td>
</tr>
<tr>
<td>Observations</td>
<td>594</td>
<td>583</td>
<td>594</td>
<td>583</td>
<td>583</td>
</tr>
<tr>
<td>Lagged Share</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Lagged Share Inst.</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

For example, when ignoring lagged market shares in the estimation (cf. Column 1), we get nonsensical coefficients on almost all of the remaining regressors: the price coefficient is positive but insignificant, the incumbent enjoys a huge brand advantage, advertising enters negatively (but is insignificant) and green electricity has a negative coefficient. When including the lagged market shares (cf. Column 2), most of these revert into sensible signs: price enters negatively, green electricity is valued positively, 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 (cf. Column 3 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), cf. Column 5.
5 Structural model

To analyze the sources of consumer inertia on a structural level, we use a discrete choice model with random-coefficient (Berry et al. (1995), BLP). A simple logit model is likely to be misspecified because individuals may have heterogeneous preferences for specific characteristics of retail electricity. For example, some consumers may prefer electricity generated from renewable sources of energy (green electricity), whereas others are indifferent to the energy source used during electricity generation. In the simple logit model, elasticities are the same for all individuals and depend primarily on market shares which can have counterintuitive implications such as cheaper products charging higher markups.

As discussed above, in the retail electricity market consumer preferences may not be the only channel that affects contract choices. On the one hand, individuals are likely to face switching costs when choosing a contract offered by a supplier different from the individual’s previous supplier. A model that does not account for such costs would attribute too much importance to consumer preferences in determining contract choices. On the other hand, individuals may face different choice sets depending on their information about which electricity contracts are available in each period. A model that does not account for differences in choice sets produces biased estimates of consumer preferences and switching costs. We incorporate switching costs into the classic BLP framework similarly to Shcherbakov (2016). Our model of the awareness component is inspired by Sovinsky Goeree (2008) and Honka (2014).

This section first describes the basic BLP framework and how it applies to our case. It then explains how the switching costs and the awareness component are included.

(1) The classic BLP framework

To introduce the model, assume first that all individuals are fully informed about their choice set and face no switching costs. These two assumptions will be relaxed below.

Consider \( t = 1, \ldots, T \) periods and \( i = 1, \ldots, I \) individuals. In each period, \( t \), individual, \( i \), can choose between \( K \) electricity contracts that are offered by \( J \) suppliers. In our application, we look at monthly contract choices over a period of 54 months. Our preferred frequency is monthly because retail consumers generally receive electricity bills every month, which may prompt them to reconsider their supplier choice. We consider 10 retail electricity contracts (green or conventional) that are offered by 6 suppliers and one outside good.\(^{18}\) The indirect utility of individual \( i \) from choosing contract \( k \) in month \( t \) can be decomposed into a mean utility, \( \delta_{kt} \), that is common to all consumers and a consumer-specific utility, \( \mu_{ikt} \), that is a function of observed demographic characteristics (in particular age and income) and contract specific shocks (i.e. the individual’s taste for

\(^{18}\)We summarize all suppliers that have less than 1% market share on average throughout our sample in the outside good.
green electricity). \( \theta_1 \) and \( \theta_2 \) are vectors of parameters to be estimated.

\[
u_{ikt} = \delta_{kt}(\theta_1) + \mu_{ikt}(\theta_2) + e_{ikt}
\]

\[
= \alpha_{0i}p_{kt} + X_{kt}\bar{\beta} + \xi_{kt} + X_{kt}D_{it}\beta_i + e_{ikt}
\]

We choose a specification in which the level of utility that consumer \( i \) derives from contract \( k \) in month \( t \) is a function of a vector of individual demographics, \( D_{it} \), and a vector of observed and unobserved product attributes \( (p_{kt}, X_{kt}, \xi_{kt}) \). \( p_{kt} \) represents monthly electricity expenditures of the average consumer subscribed to contract \( k \) in month \( t \). \( X_{kt} \) is a vector of observed contract attributes, such as a dummy variable whether the contract delivers green electricity or whether the contract is offered by the incumbent supplier. \( \xi_{kt} \) is a scalar capturing unobservable contract quality valued equally by every consumer.

\( \alpha_{0i} = \bar{\alpha} + \alpha_i\ln\left(\frac{y_{it}}{\bar{y}}\right) \) is individual \( i \)'s marginal disutility from price and depends on the deviations of an individual’s income, \( y_{it} \), from mean income, \( \bar{y} \). \( \bar{\beta} \) is the mean of the marginal utility associated with a contract attribute and \( \beta_i \) is a random (individual-specific) coefficient, which depends on the interaction between consumer preferences and contract attributes. We allow consumers to have heterogeneous preferences in various dimensions. First, we allow for a random coefficient on green electricity. Second, we allow for interactions between price and income as well as between an incumbent-fixed-effect and age. \( e_{ikt} \) is the \( i.i.d. \) error term.

We can calculate analytical market shares for each consumer \( i \), contract \( k \) and month \( t \), under the following two common assumptions: First, consumers choose the utility maximizing contract. That is individual \( i \) chooses contract \( k \) in month \( t \) if and only if \( U(D_{it}, p_{kt}, X_{kt}, \xi_{kt}; \theta) \geq U(D_{it}, p_{mt}, X_{mt}, \xi_{mt}; \theta) \), where \( m \) represents any competing contract including the outside option. Second, as typical for this literature, random shocks in the utility function are distributed \( i.i.d. \) extreme value across individuals, contracts and time.\(^{19}\)

Given these assumptions, the probability that individual \( i \) chooses contract \( k \) in month \( t \) is given by

\[
P_{ikt} = \frac{\exp(\delta_{kt} + \mu_{ikt})}{\sum_{m=0}^{K} \exp(\delta_{mt} + \mu_{imt})}
\]

These contract choice probabilities are used to construct a distribution of predicted market shares for each individual in each month, \( s_{it} \). From there, aggregate contract market shares are calculated by averaging over all individual specific market share distributions. More precisely, to derive the aggregate contract market share distribution we integrate out the choice function over the distribution of demographic characteristics in the population.\(^{20}\)

\(^{19}\)The density function of the extreme value type I distribution is \( f(x) = e^{-x}e^{-e^{-x}} \). It yields a convenient closed-form solution of the choice probabilities.
Let $A_{kt}$ be the set of individual characteristics for which contract $k$ is the utility maximizing choice in month $t$. $A_{kt}$ depends on the observed contract attributes, prices, and mean utilities associated to all contracts available. For a given set of parameters we calculate aggregate contract market shares as a function of contract attributes. Assuming ties occur with zero probability, the predicted market share of contract $k$ in month $t$ is an integral with respect to the population distribution function over the mass of consumers in $A_{kt}$.

$$s_{kt}(p_{kt}, X_{kt}, \xi_{kt}; \theta) = \int_{D_t \in A_{kt}} P_{ikt} dD_t$$

(3)

(2) Switching costs

To explain how switching costs are incorporated into the random coefficient framework described above, we will still assume that all individuals are fully informed about their choice set. This assumption will be relaxed below. Switching costs add a dynamic component to our model. However, we assume individuals continue to be myopic and do not form beliefs about how the electricity market evolves in the future. This is equivalent to a model with static expectations, which is a justifiable approach in a slowly evolving market such as the electricity market, and does not require additional assumption about consumer beliefs.\(^{20}\)

We add a switching component to the indirect utility in equation (1) that includes a switching cost $\psi$, which is constant across individuals and time, and a switching dummy, $1$, which takes the value 0 if individual $i$ chooses the same supplier as in the previous month, and 1 if the individual switches supplier. Let $a_{it} = 0, \ldots, J$ describe individual $i$’s choice of supplier in month $t$.

The indirect utility of consumer $i$ from choosing contract $k$ in month $t$ becomes:

$$u_{ikt} = \delta_{kt}(\theta_1) + \mu_{ikt}(\theta_2) - \psi 1_{a_{it} \neq a_{i(t-1)}} + e_{ikt}$$

(4)

Given the same assumptions as above, the conditional probability that individual $i$ chooses contract $k$ in month $t$ if the individual had chosen contract $l$ in the previous month is given by

$$P_{ikt}(k|l) = \frac{\exp(\delta_{kt} + \mu_{ikt} - 1_{a_{it} \neq a_{i(t-1)}} \psi)}{\sum_{m=0}^{K} \exp(\delta_{mt} + \mu_{imt} - 1_{a_{it} \neq a_{i(t-1)}} \psi)}$$

(5)

Where $m$ are all competing contracts to $k$. To keep the model tractable, we assume that switching costs arise from switching supplier not contract.

Individual-specific market shares can then be computed recursively:

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

\(^{20}\)This assumption decreases the computational burden of the model substantially while still being rich enough to investigate a series of interesting counterfactuals.
The distribution of the aggregate contract market shares in month \( t \), given previous contract choices, is again derived by integrating out the choice function over the distribution of demographic characteristics in the population.

\[
(6) \quad s_{kt} = \int_{D_t \in A_{kt}} s_{ikt} dD_t
\]

(3) **Awareness component**

When integrating the awareness component into our model, we relax the assumption that all consumers are fully informed about their choice set. Consider three types of consumers:

First, fully informed consumers are aware of all contracts that are offered in each month. This type of consumer uses price comparison websites (PCWs) which give a quick overview on all available contracts (including prices and other attributes). Our survey data reveals that between 21\% and 33\% of consumers have used a price comparison website every year. The choice problem of this consumer type is identical to the one described above.

Second, partially informed consumers are aware of some, but not all, contracts that are offered in month \( t \). These consumers do not use PCWs. Instead, their information about available contracts comes from advertisement by electricity suppliers and their previous contract choice. We model the awareness process of this type of consumer similarly to Sovinsky Goeree (2008). However, we exploit our detailed data to estimate the awareness process directly instead of having to rely on media exposure and consumer choice data alone. We model individual \( i \)'s probability of being informed about all contracts offered by supplier \( j \) in month \( t \) as a function of \( i \)'s demographic characteristics, \( D_i \) and supplier \( j \)'s advertising intensities, \( W_{jt} \) as a binary probit.

\[
(7) \quad Pr(i \text{ is informed about } j) = \Phi(\alpha_0^A + W_{jt} \alpha_1^A + D_i ECS_j \alpha_2^A + W_{jt} D_i \alpha_3^A + \epsilon_{it}^A)
\]

Where \( \alpha_0^A \) represents supplier fixed effects. \( \alpha_1^A \) measures the information effect of \( j \)'s advertisement on individual \( i \) in month \( t \). \( W_{jt} \) is a moving average of the monthly advertisement expenditure per customer of the economic group to which supplier \( j \) belongs. \( D_i \) is a vector including a dummy indicating whether individual \( i \) is a senior as well as the income of individual \( i \). \( ECS_j \) is the incumbent dummy taking the value 1 for the incumbent supplier ECS and 0 otherwise. The interaction of the demographics vector and the incumbent dummy captures that different consumer types can be differently informed about the incumbent supplier as opposed to new entrants.

In principle, there is a third group of totally unaware consumers who are simply not aware of any alternative to the default electricity contract. Since the liberalization of the Flemish electricity market in 2003, the number of this consumer type shrank tremendously. Our data reveals that across 2012-2016 on average only 1.1\% of all survey respondents did not know about the possibility to switch electricity supplier. Given these low numbers, we do not include this consumer type in our baseline model.
Aggregate contract market shares are again constructed by aggregating over all individuals, but accounting for the potentially heterogeneous choice sets. The probability that individual $i$ chooses contract $k$ in month $t$, given that contract $l$ was chosen previously, is given by

$$P_{ikt}(k|l) = \sum_{\phi \in \Phi_{kt}} P_{ikt}(k|l, \phi) \cdot Pr(i \text{ has awareness set } \phi)$$

where $\Phi_{kt}$ denotes the set of all choice sets that contain contract $k$. $Pr(i \text{ has awareness set } \phi)$ equals 1 for the choice set with all contracts if the individual is fully informed. If the consumer is partially informed, $P_{ikt}(k|l)$ is based on computing the joint probability of a given choice set $\phi$ using the awareness equation (7) for each contract, assuming independence across contracts. Note that the probability that a partially informed consumer is informed about the contract chosen in $t - 1$ equals 1 as well.

6 Identification Strategy

The key identification challenge in evaluating consumer inertia is to disentangle permanent unobserved preference heterogeneity, switching costs and choice set awareness. Indeed, observing that an electricity consumer did not choose a specific contract might be evidence for switching costs, but might also reflect the fact that the consumer was not aware about the specific contract or that the consumer has an unobserved preference for another contract. Throughout this section, we use a simple example to show that our model is identified under the following assumptions (justification of these assumptions are included as we go along):

- The logit shock, $e_{ikt}$ is distributed i.i.d.
- Preferences are constant over time.
- Conditional on demographics, preferences are independent of the awareness status.

As an example, consider two contracts, $A$ and $B$, which share the same attributes (including price) and a third contract, $C$, with different attributes.

Our identification argument proceeds in three steps:

First, assume that all individuals are fully informed about all available contracts and face no switching costs. (These two assumptions will be relaxed below.) Parameters of preference heterogeneity across consumers are identified following Berry et al. (1995) and extensions thereof that have access to choice data at the individual level (Petrin, 2002; Berry et al., 2004). Identification comes from variation in choice sets and is based on the idea that consumers choose electricity contracts according to individual preferences for
contract attributes. Our panel data on monthly market shares, prices and attributes at the contract level are used to establish corresponding moment conditions.

On the one hand, aggregate consumer choices under different available configurations of contract attributes identify the mean preference parameters. In our example, the market share of contract C informs about consumer preferences for contract C’s attributes, whereas market shares of contracts A and B about preferences for the attributes of those contracts. On the other hand, identification of the distribution of preferences (the random coefficients) comes from observed aggregate substitution patterns when contract attributes change. In our example, suppose $p_B$ increases exogenously ceteris paribus. As a result of this price change some consumers quit contract B. If these consumers mainly substitute contract A for contract B, there is evidence for strong preference heterogeneity regarding the attributes that contracts A and B share. If consumers distribute equally over contracts A and C, heterogeneity for those attributes is low.

In addition to the market level data in our panel, we observe individual contract choices conditional on consumer characteristics in our survey dataset to build micro-moments. The consumer-level data enable us to more precisely identify heterogeneous preferences for contract attributes. Observing different demographic types choosing different contract attributes is informative about preferences linked to demographic characteristics.

Second, now assume that some individuals are only partially informed about all contracts although they still face no switching costs. For separating the choice effect of limited awareness from consumer preferences, we rely on the individual choice data. However, just combining individual choices with demographic characteristics will not identify whether contracts with a low market share are simply not popular because of consumer preferences, or whether they might be popular but consumers are not aware of them. In our example, suppose $p_B$ increases exogenously ceteris paribus. Observing an individual choosing contract A and not contract C as a consequence of this price change is evidence that the individual has a preference for the attributes that contracts A and B share if and only if the individual is fully informed about all available contracts. A partially informed individual might well prefer the attributes of contract C, but might not be aware of this contract and therefore choose contract A as well.

We separately identify the choice effect of limited awareness from consumer preferences by comparing contract choices of consumers with same demographic characteristics but different awareness status. Under the assumption that preferences of individuals with same demographic characteristics are orthogonal to awareness, variation in contract choices of consumers with same demographic characteristics can only be explained by differences in awareness. Observing market shares at the consumer-level in the survey data is pertinent, as they associate individual choices not only to consumer characteristics but also to a consumer’s awareness status. The subsample of fully informed consumers will be informative about consumer preferences only, whereas differences in choices between fully and partially informed consumers with same characteristics explain the effect of limited awareness. Our micro-moment conditions compare individual choices of same consumer types but differ-
ent awareness status and thereby "extract" the awareness effect on contract choices in our estimation.

The assumption that preferences of individuals with same demographic characteristics are orthogonal to awareness is arguably restrictive but is supported by evidence in our survey data. We compare how individuals with same demographic characteristics but different awareness status state their preferences by answering specific survey questions (for example, questions about possible reasons to switch electricity supplier or about the level of monetary benefits necessary to motivate a switch) and could not find a statistically significant difference across groups.\(^{21}\) In Appendix A, we present an extension of our baseline model that incorporates a Heckman-style selection equation into our model allowing consumer preferences to be correlated with the decision to use the PCW. Since our data contains information on which consumers use the PCW along with their choices, we can identify the additional parameters by constructing additional micromoments.

Finally, assume that each individual faces switching costs when changing electricity supplier. Separate identification of preference heterogeneity and switching cost parameters follows arguments as in Shcherbakov (2016) and is facilitated because we also observe churn rates (Yang, 2010). Identification is based on variation of exogenous shifters over time and the idea that any correlation between aggregate contemporaneous contract choices and lagged exogenous shifters can only be explained by switching costs.

More precisely, an exogenous one-period change in contract attributes yesterday will affect consumer choice today only if switching costs exist, but will have no influence on today's choice if there are no switching costs. In our example, consider the contracts \(A\) and \(B\) have same attributes today \((t)\) but a different attribute history, e.g. different prices yesterday \((t − 1)\) as a result of an exogenous cost shock. Suppose \(p_A\) decreases exogenously in \(t − 1\), ceteris paribus, and attracts consumers so that the market share of contract \(A\) increases relative to that of contract \(B\). If \(A\)’s market share is still relatively higher in \(t\), when attributes between both suppliers are the same, we have evidence for switching costs. Without switching costs the marginal consumer should be indifferent between contracts \(A\) and \(B\) in \(t\). Therefore, comparing aggregate market shares of contracts with same attributes in \(t\), but different attributes in \(t − 1\) enables us to identify switching costs.

Our argument to separately identify switching costs from preferences assumes that unobserved consumer preferences are i.i.d., the classic logit assumption, and that observed preferences are constant over time. We believe this assumption is justified since we are looking at the electricity market in a relatively mature state, about 10 years after the liberalization.\(^{22}\)

\(^{21}\)Neither under a Chi-square test of independence nor under Fisher’s Exact test can we reject the null hypothesis that the groups of fully and partially informed survey respondents have homogeneous preferences regarding potential reasons for switching electricity supplier in 2012 and 2013. A t-test comparing the distribution of monetary benefits that were cited to be necessary in order to motivate a switch does not reject the null hypothesis of same means across both groups in 2012 and 2013. (No data is available to perform the tests also in later years.)

\(^{22}\)The assumption rules out consumer learning discussed in Dubé et al. (2010).
Going back to the example, under these assumptions consumers who remain with contract A in t after the price change in t – 1 will do so only because of switching costs. The state dependence induced by the change in relative prices cannot be explained by preferences, because contract A and B have same attributes in t and consumer preferences are constant over time. It can neither be explained by limited awareness – at least not in the subsample of consumers that are fully informed. Confounding of switching costs and awareness may only take place when looking at choices of partially informed consumer. As above, we use moments based on consumer-level data to contrast choices of consumers with same demographic characteristics but different awareness status to keep the awareness effect fixed.

7 Estimation

To estimate the model parameters, we follow a generalized method of moments (GMM) approach. In a nutshell, the estimation involves, first, the simulation of a number of consumers together with each consumers’ time-series of choice sets over all months considered in the analysis. Second, based on our theoretical model we predict contract market share distributions for each month, which we match to the observed market shares in our data as in the classic BLP moment condition. To identify all our parameters, we compute additional moment conditions similar to Berry et al. (2004), Shcherbakov (2016) and Sovinsky Goeree (2008).

The main parameters to estimate are consumer preferences for product attributes ($\bar{\alpha}, \alpha_i, \bar{\beta}, \beta_i$), the switching costs ($\psi$) and the parameters of the awareness process ($\alpha^A_0, \alpha^A_1, \alpha^A_2, \alpha^A_3$). Under the assumption that the observed data are equilibrium outcomes, the parameters are simultaneously estimated as the parameter values that minimize a GMM objective function.

(1) Mean utility levels

Similar to BLP we start the estimation procedure with backing out the mean utility levels of consumers by matching aggregate observed contract market shares, $S_{kt}$, to the model predictions, $s_{kt}$.

\[
S_{kt} = s_{kt}(\delta, a_{t-1}; \theta_2)
\]

For given values of $\theta_2$ and $\delta$, market shares predictions, $s_{kt}$ are calculated according to our model outlined in section 5. Afterwards, for given values of $\theta_2$, we solve for the vector of mean utilities, $\delta_{kt}(\theta_2)$, that equates predicted and observed market shares. For this, we rely on a contraction mapping similar to BLP. Different from the classic BLP contraction, current choices depend on previous choices because of switching costs and we have to solve for market share predictions recursively, period-by-period. The mapping works similarly to the dynamic demand literature (Gowrisankaran and Rysman, 2012). An algorithm
estimates the mean utilities by adjusting a guessed initial value, $\delta_{kt}$, iteratively by the following formula.\textsuperscript{23}

\begin{equation}
\delta'_{kt}(S_{kt}, S_{kt-1}; \theta_2) = \delta_{kt} + \log S_{kt} - \log s_{kt}(S_{kt-1}, \delta_{kt}; \theta_1).
\end{equation}

(2) Moments  Upon convergence of equation (10) we have backed out a vector of mean utilities that can be used to formulate moment conditions which identify our parameters and which are included in the GMM objective function.

(a) Aggregate choice moments to identify contract specific attributes

The mean utility levels contain, as a structural error term, the average utility that consumers obtain from unobserved product attributes, $\xi_{kt}$. As in BLP, we decompose the vector of mean utilities to compute the structural error term as the difference between the mean utility levels that equate predicted and observed market shares for a given value of $\theta_2$ and the mean utility levels predicted by our model.

\begin{equation}
\xi_{kt} = \delta_{kt}(S_{kt}, S_{kt-1}; \theta_2, \psi) - X_{kt}\bar{\beta}
\end{equation}

Because unobserved contract attributes, $\xi_{kt}$, are likely correlated with contract price, we implement an instrumental variable regression to solve (11). Under the assumption that $Z$ are valid instruments, the following moment is included in the GMM objective function: $E[G_1(\xi_{kt})] = E[\xi_{kt}Z_{kt}]$

Following the literature, we use both cost shifters and Hausman instruments, i.e. prices of same suppliers in different markets. Our instruments include monthly wholesale electricity prices on the spot market that are interacted with each suppliers sensitivity to wholesale markets, and the supplier monthly average price for gas contracts in Wallonia. Cost shifters, such as the wholesale electricity price and lagged exogenous product attributes, are correlated with contract prices but excluded from the contemporaneous demand equation and therefore valid instruments. Under the assumption that cost shifters across regions are common but demand-shocks are uncorrelated across regions, our Walloon gas price instrument is valid as well. Given the different languages and the regional competencies in energy policy, the Walloon and Flemish regional markets are likely exhibiting uncorrelated demand shocks.

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

We use the model predictions for choices probabilities to compute the churn rate prediction error $\zeta_{kt}$ as the difference between the observed, $C_t$, and the predicted, $c_t(\delta, \psi)$, churn rates.

\begin{equation}
\zeta_{kt} = C_t - c_t(\delta, \psi)
\end{equation}

\textsuperscript{23}The algorithm adjusts the initial guess $\delta_{kt}$ until the predicted and observed market shares equate. More precisely, if the value guess leads to predictions that exceed the observed shares, the logarithm becomes negative and adjusts the guessed value downwards. If the value guess leads to predictions that are inferior to observed shares, the logarithm is positive and adjusts the guessed value upward.
We use moments based on churn rates, which capture the above intuition on identification of state-dependence in a reduced form. Churn rates describe the fraction of individuals that switch supplier in each month and equal one minus the probability not to switch supplier. Similarly to above, if no switching costs exist a consumer’s probability not to switch supplier today is independent of previous supplier choices. If, however, switching costs exist, the probability that a consumer does not switch supplier today is relatively higher.

The following moment is included in the GMM objective function: \( \mathbb{E}[G_2(\zeta_{kt})] = \mathbb{E}[(C_t - c_t)Z_{kt}] \). As the churn rate prediction error does not have any structural interpretation, we can interact it with a generic set of instruments (for example just dummies or the superset of all the instruments that we use). Currently, \( Z_{kt} \) is a constant. In addition, we construct moments by interacting lagged exogenous cost shocks with contemporaneous demand shocks. In our application, cost shocks come from variation in lagged electricity wholesale prices that are interacted with supplier sensitivity to these prices.

(c) Individual choice moments to identify correlation between demographic characteristics and particular contract attributes

The micro-moments from the survey are especially helpful for identifying the effect of demographics and limited awareness. As in Sovinsky Goeree (2008), we use our individual data to calculate the individual choice error \( \eta \) as the difference between observed individual contract choices and our model prediction given the vector or mean utilities, \( \delta_{kt}(S_{kt}, S_{kt-1}; \theta_2) \) and parameter guesses. Let \( B_i \) be a \( K \times 1 \) vector of contract choice for individual \( i \), where \( b_i \) is a realization of \( B_i \), and \( b_{ik} = 1 \) if contract \( k \) was chosen.

\[
B_i(\delta, \theta) = b_i - \mathbb{E}(B_i|D_i, \delta, \theta)
\]

The following moments are included in the objective function:

\[
\mathbb{E}[G_3(\eta_{ikt})] = \mathbb{E}[B_i(\delta, \theta)|X, \xi, \psi]
\]

Observing individuals with particular characteristics, \( D_i \), (age, income and awareness status) and their choice of contract allows us to match the model predictions for consumers with specific demographics to the observed data. Most importantly, these micro-moments allow us to compare the choices of fully and partially informed consumers since our survey contains both types of consumers. This enables us to identify limited awareness and estimate the parameters \( (\alpha_0^A, \alpha_1^A, \alpha_2^A, \alpha_3^A) \).

**Objective function** The three sets of moments are stacked in our final objective function. The population moment conditions are assumed to equal zero at the true values of the parameters \( \theta^* \).

\[
\mathbb{E}[G(\theta^*)] = \begin{cases} 
E[G_1(\xi_{kt})|\theta^*] = 0 \\
E[G_2(\zeta_{kt})|\theta^*] = 0 \\
E[G_3(\eta_{ikt})|\theta^*] = 0
\end{cases}
\]
Our estimate is the value of $\theta$ that minimizes the sample analogue of the moments:

\[
\hat{\theta} = \arg\min_{\theta} G(\theta)'Z\Phi^{-1}Z'G(\theta)
\]

Where $\Phi$ is a block-diagonal 2SLS weighting matrix.

**Estimation procedure** Practically, our estimation is implemented as follows: We simulate many consumers. For each consumer, we simulate her time-series of choices given a set of parameter values. Afterwards, we average over the individual consumers to get aggregate market share predictions from which we construct other moment predictions.

Overview:

1. We guess a vector of parameters $\theta$ which contains the preference parameters, switching cost, and parameters of the awareness process.

2. We simulate a set of $NS$ individuals (e.g. $NS = 1,000$ individuals) that belong to two types of consumer groups: fully informed and partially informed consumers. Each individual is represented by a three dimensional vector of consumer demographics (age and income) and taste 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 simulated individual in the group of fully informed consumers, we simulate a time-series of choices for the whole sample period. Because we assume that this consumer type is aware of the full choice set, each individual faces the general discrete choice problem with switching costs. Choice probabilities are given by the typical formulas as in switching cost models, equation (5).

4. For each simulated individual in the group of partially informed consumers, we simulate a time-series of choices in two steps: First, we simulate the individual’s choice set. 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 choice set entries, we draw $J$ supplier variables from a uniform distribution for each individual $i$. 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. Second, given the simulated choice set, each individual faces a discrete-choice problem with switching costs. Choice probabilities are given by the typical formulas as in switching cost models, equation (5) but are conditional on the outcome of the consumer’s awareness process.
5. We average over all individual contract choice probabilities to predict aggregate contract market share distributions. These are, together with the observed market shares, fed into a BLP contraction mapping to back out the mean utilities, $\delta_{kt}$, for each contract in each period.

6. After convergence of the mean utilities, we back out the structural demand errors $\xi$ to compute the BLP moment conditions and compute the churn rate prediction errors.

7. In addition, after convergence of the mean utilities, we compute the model’s choice predictions for each of the consumer types (defined by demographic characteristics and awareness status) and match to the observed choices in the survey. This effectively allows us to compare the behavior of fully and partially informed consumers.

8. Finally, we perform a non-linear search for the parameter values that minimize our objective function.

8 Results

This section describes the estimation results from the random-coefficient model developed in Section 5 and analyses counterfactual scenarios to study the effect of potential policy interventions and to investigate the relative importance of switching costs and limited awareness in market outcomes.

8.1 Structural estimation results

Table 6 displays the estimated parameters. Standard errors are in parenthesis. 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.

The mean price coefficient has the expected negative sign and is statistically significant at the 1% level.\textsuperscript{24} The average consumer is highly price sensitive.\textsuperscript{25} Spending an additional 100 EUR on electricity, reduces utility by 7 units. The interaction term on income and price ($Income\text{-}price$) is positive, as expected. Although not statistically significant, due to relatively high standard errors, the coefficient points towards richer households being less price-sensitive.

Several conclusions about consumer preferences can be drawn from the results reported in Table 6. First, consumers have a preference for well-established suppliers in the market as the constant term shows. Electricity contracts offered by one of the six inside firms (ECS,

\textsuperscript{24}Throughout the estimation, we deflate all prices to 2012 EUR.
\textsuperscript{25}In our specification, the average consumer has a disposable income of 2,500 EUR per month.
Table 6: Structural estimation results

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>WTP in EUR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>1.2261***</td>
<td>14.35</td>
</tr>
<tr>
<td></td>
<td>(0.3102)</td>
<td></td>
</tr>
<tr>
<td>Incumbent non-seniors</td>
<td>0.0926</td>
<td>1.08</td>
</tr>
<tr>
<td></td>
<td>(0.1479)</td>
<td></td>
</tr>
<tr>
<td>Mean price coefficient</td>
<td>-8.5476***</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(1.1299)</td>
<td></td>
</tr>
<tr>
<td>Mean green coefficient</td>
<td>0.1700***</td>
<td>1.99</td>
</tr>
<tr>
<td></td>
<td>(0.0432)</td>
<td></td>
</tr>
<tr>
<td>Variance green coefficient</td>
<td>0.1530</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(1.8863)</td>
<td></td>
</tr>
<tr>
<td>Incumbent seniors</td>
<td>1.4637**</td>
<td>17.12</td>
</tr>
<tr>
<td></td>
<td>(0.6928)</td>
<td></td>
</tr>
<tr>
<td>Income-price interaction</td>
<td>2.1906</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(2.1345)</td>
<td></td>
</tr>
<tr>
<td>Switching cost</td>
<td>5.7483***</td>
<td>67.25</td>
</tr>
<tr>
<td></td>
<td>(0.0780)</td>
<td></td>
</tr>
<tr>
<td>Adv. constant</td>
<td>-1.4786*</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.7568)</td>
<td></td>
</tr>
<tr>
<td>Adv. expenditure</td>
<td>7.3856***</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.5215)</td>
<td></td>
</tr>
<tr>
<td>Adv. senior</td>
<td>6.4275*</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(3.4890)</td>
<td></td>
</tr>
<tr>
<td>Adv. income</td>
<td>-0.0623</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(131.7700)</td>
<td></td>
</tr>
<tr>
<td>Adv. exp-senior</td>
<td>3.1147</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(3023.8000)</td>
<td></td>
</tr>
<tr>
<td>Adv. exp-income</td>
<td>2.5135</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(147.9900)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Results from estimating a RC-logit model using first-step GMM. Standard errors in parentheses. *, **, *** denote significance at the 10%, 5% and 1%-level respectively. 0.00 denotes non-interpretable willingness-to-pay.

EDF, Eneco, ENI, Essent, Lampiris) are valued 11.3 EUR per month more than contracts of firms that are pooled into the outside good. Second, seniors place a high premium on being with the incumbent compared to an alternative supplier, roughly 21 EUR per month, which is statistically significant at the 1% level. (Incumbent-seniors takes the value 1 if an individual is retired and has a contract with ECS, and is 0 otherwise.) Conversely, younger consumers have only a low and insignificant preference for the incumbent (Incumbent-non-
seniors). Our survey shows that seniors are less wealthy than the average consumer in Flanders, which implies that their price coefficient is relatively smaller than the one of the mean-income consumer, so the 21 EUR represent an upper bound of their willingness-to-pay for the incumbent. The incumbent bias of seniors is similar in magnitude to the findings of Hortaçsu et al. (2017) who determine an overall incumbent bias of 15-60 USD in Texas during 2002-2006 depending on the time since liberalization. Third, consumer valuation of green electricity is low on average, but there seems to be much variation of taste across consumers. The average consumer is willing to pay 1.95 EUR per month for a contract delivering green electricity (significant at the 5% level). The estimated valuation of green electricity by the average consumers is in line with the price premium on green contracts that is set by some suppliers. As reported in Table 1, ECS, EDF and ENI charge an additional 1 to 4.5 EUR per month for green as opposed to their conventional contracts. Although the estimated variance of the green coefficient is not statistically significant, it points to some variation of green preferences within the Flemish population.

Our estimate for switching costs is highly significant and positive, implying an average switching cost of 82 EUR. These costs represent a consumer’s hassle to switch or other non-monetary switching costs, given that early termination fees do not exist in our setting. Our model assumes that the switching costs coefficient is constant across consumers, but since the price coefficient varies with income, richer consumers have higher switching costs than poorer households by construction. The estimated switching costs represent between 20% and 31% of the average yearly electricity expenditures of an average Flemish household. Simple back-of-the-envelope calculation suggests that switching from the most expensive to the cheapest contract would yield cost savings of 12.7 EUR per month on average. So, the 82 EUR switching costs would be compensated within a period of 6.5 months. A switch from the average to the cheapest contract compensates the estimated switching costs within 11 months.

Not surprisingly, advertisement has a significant impact on awareness and consumer choice sets. Higher advertisement expenditures by a supplier strongly increase the probability that consumers are aware of the supplier’s contracts (Adv. expenditure). The demographics-advertising interactions suffer from large standard errors.\footnote{Standard errors are most likely numerically unstable and large as they are calculated via a numerical differentiation, while being placed in a highly non-linear simulation routine. Experimenting with different differentiation methods as well as running \textit{efficient GMM} should allow us to get lower standard errors.} We include four interaction terms. The positive coefficients on expenditure-senior and expenditure-income suggest that the effectiveness of firm advertising rises with both age and income. When supplier advertising increases, older and richer consumers are more likely to become aware. Incumbent-senior denotes an interaction term capturing the effect that seniors may be more aware of the incumbent than of new entrants, because seniors may be less well informed about the electricity market liberalization. Finally, there does not seem to be a relation between income and higher awareness of the incumbent supplier (incumbent-income).
8.2 Counterfactuals

In this section, we use our structural model to conduct a series of counterfactual simulations. In order to illustrate the common and differential effects of switching costs and limited awareness and to assess the potential outcome of different policy interventions, we simulate the market structure if either switching costs or limited awareness were reduced, while holding the other effect fixed. More specifically, we conduct two exercises. In the first, we simulate the market structure if switchers were compensated for their switching costs, for example through direct payments or a welcome discount by suppliers. In the second, we simulate the market structure when a higher share of consumers is fully informed about contract alternatives, for example via an information campaign or increasing use of price comparison websites.

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Observed shares</th>
<th>Predicted shares</th>
<th>Switching subsidy</th>
<th>Perfect information</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECS</td>
<td>0.4424</td>
<td>0.4426</td>
<td>0.2819</td>
<td>0.3596</td>
</tr>
<tr>
<td>EDF</td>
<td>0.2008</td>
<td>0.2009</td>
<td>0.1673</td>
<td>0.2097</td>
</tr>
<tr>
<td>Essent</td>
<td>0.0421</td>
<td>0.0421</td>
<td>0.0853</td>
<td>0.0597</td>
</tr>
<tr>
<td>ENINuon</td>
<td>0.1145</td>
<td>0.1146</td>
<td>0.1389</td>
<td>0.1247</td>
</tr>
<tr>
<td>Eneco</td>
<td>0.0767</td>
<td>0.0768</td>
<td>0.1217</td>
<td>0.0945</td>
</tr>
<tr>
<td>Lampiris</td>
<td>0.0517</td>
<td>0.0517</td>
<td>0.0871</td>
<td>0.0582</td>
</tr>
<tr>
<td>Other</td>
<td>0.0717</td>
<td>0.0713</td>
<td>0.1178</td>
<td>0.0935</td>
</tr>
</tbody>
</table>

Column 1 in Table 7 reports average market shares by supplier as reported in our data. Averages are built over the entire period of the analysis. For confidentiality reason, we do not split the supplier shares into contract types. Column 2 displays market shares that are predicted by the model and suggests that our model fits the data very well. Column 3 summarizes the results when a switching costs compensation of 50 EUR is paid to customers that switch supplier and Column 4 displays the market share distribution when 85% of consumers are fully informed.27

Two main results emerge from Table 7. First, the benefits from a reduction in switching costs are decreasing in supplier market shares. Large suppliers tend to loose, while small suppliers win when a switching costs compensation is implemented. This result is intuitive as with switching costs, large suppliers can take advantage of state dependence affecting a large customer base. Second, the benefits from an information campaign are decreasing in the advertising expenditures of a supplier. Intuitively, suppliers that spend relatively more on advertising are more likely to be known by prospective customers. Such suppliers benefit less from a policy that makes more consumers aware of all contract alternatives.

27 Simulated market structures for other subsidies or other levels of informedness are qualitatively similar and available upon request.
Conversely, suppliers that spend few on own advertisement tend to win from an increase in information.

More precisely, results of our simulations show that the incumbent, ECS, loses in both scenarios, but more with a switching costs compensation (15 percentage-points) than with an increase in awareness (9 percentage-points). Also EDF, the supplier with the second highest market share, loses from the switching costs compensation, while increasing market shares slightly through an increase in awareness. In total, 17% of customers (net) switch in the presence of a 50 EUR switching costs compensation and 9% (net) when 85% of the population is fully informed about contract alternatives (instead of the current 20-33% reported in the surveys).

In both scenarios, these net switchers migrate to the new entrants (Eneco, ENI, Essent and Lampiris) which propose cheaper contracts on average (see Table 1). With a switching compensation, the new entrants gain in equal parts from the migration (3 to 4 percentage-points each). In the information campaign counterfactual, this gain is unequally distributed across new entrants, depending on own advertising expenditure. For example, the market share of Lampiris remains relatively stable when information is raised which can be explained by Lampiris generally putting a lot of effort in advertising and reaching out to potential customers, so benefitting less from a general awareness increase. Our advertising data shows that Lampiris spends on average 1 EUR per customer on advertisement, nearly two times as much as Eneco, a comparable supplier in Flanders.28 Similarly, the slight increase in the EDF market share under an information campaign may be explained by the persistently higher advertisement of EDF throughout the years. Information campaigns harm EDF relatively less, because of switching costs in the customer base built through persistent advertisement over time. (ECS on the other hand loses customers who become aware of alternative suppliers via the information campaign.)

The monthly market share distributions over time for the baseline and counterfactual scenarios are shown in Appendix C. As expected, in the switching costs compensation counterfactual, market shares become very volatile as the compensation makes switching very attractive for consumers. Therefore, one should be careful in interpreting the time series of market shares. A look at over-time averages (cf. Table 8.2) is more informative about the competitive effects. Interestingly, market shares become more volatile under perfect information as well - though to a smaller extent. This is consistent with firms playing a mixed-strategies equilibrium in prices: high prices to exploit consumer inertia linked to unawareness of some consumers, low prices to attract consumers that are fully informed. In the counterfactual scenario, information asymmetry is nearly eliminated but firms’ price strategies remain the same. So, the increased volatility is not surprising.

One general caveat of our counterfactual analysis is that it does not take into account reactions on the supply side. In reality, one would expect firms adjusting prices and advertising strategies when switching is subsidized or informational frictions are eliminated. Incorpor

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28 Average advertising expenditures per customer are as follows: ECS 0.44 EUR, Eneco 0.56 EUR, EDF 0.72 EUR, ENI 0.8 EUR, Essent 0.87 EUR, Lampiris 1 EUR.
rating a full supply side model in the presence of switching costs and limited awareness would require a dynamic model of firm pricing where firms set both advertising level and prices. This goes beyond the scope of the current paper, but could be an interesting avenue for future research.

Welfare implications Typically, regulators are not concerned with market share distributions per se, but rather consumer surplus. In our model, we can compute consumer surplus as the expected ex-ante utility a consumer gets from participating in the market. In logit models, the closed-form solution for the surplus of consumer $i$ is:

$$CS_i = \frac{1}{\alpha_i} \log \left( \sum_j \exp(\tilde{u}_j^i) \right) + C$$

where $\alpha_i$ is $i$’s price coefficient, $\tilde{u}_j^i = \delta_j + \mu_j^i$ is the deterministic utility for consumer $i$ from having contract $j$, and $C$ is an arbitrary constant coming from the fact that discrete-choice models are only identified up to scale.\(^{29}\) In models with state-dependence, consumer surplus also depends on a consumer’s choice in the previous period. For type $i$ subscribed to contract $j$ at the beginning of the period, it is given by:

$$CS_{it|j} = \frac{1}{\alpha_i} \log \left( \sum_{k\neq j} \exp(\tilde{u}_{ik}^i - \psi^i) + \exp(\tilde{u}_{ij}^i) \right) + C$$

where $\psi^i$ denotes $i$’s switching cost. The aggregate welfare of all type-$i$ consumers is obtained by integrating over previous period’s choices:

$$CS_{it} = \sum_j CS_{it|j}s_{jt-1} + C$$

Aggregate welfare in market $t$ is obtained by integrating over all consumer types:

$$CS_t = \sum_i CS_{it}$$

Note that the welfare of fully informed and partially informed consumers differs only because the summation is taking over different sets of products. Therefore, the surplus of partially informed consumers is strictly smaller than that of a fully informed consumer (conditional on having the same preferences).

We find that both our counterfactuals have very large effects on consumer surplus. When informing a partially informed consumer perfectly about all available contracts, her welfare increases by $107\%$ on average.\(^{30}\)

\(^{29}\)Consequently, absolute welfare statements are not informative. However, the constant $C$ will cancel out when comparing welfare across different scenarios.

\(^{30}\)By construction, welfare of the perfectly informed is unchanged.
A meaningful analysis of the welfare effects of a switching subsidy requires us to make assumptions about how the subsidy is financed. By construction, consumer welfare will increase when any kind of subsidy is paid out. For our setting, we assume the following. While the subsidy is only paid to consumers who actually perform a switch, the subsidy is financed by a uniform tax on all consumers (i.e. a uniform price increase of all contracts). More specifically, we compute the total churn in a period to compute the total amount of subsidy paid to consumers. This amount is subtracted from the gross welfare gain in the market.

Under this assumption, the average surplus of an informed consumer increases by 130% while an uninformed consumer loses on average 119%. The differential effect on informed and uninformed consumers is very large, but not surprising. Informed consumers have a larger choice set and are therefore able to benefit much more from a switching subsidy resulting in a larger welfare gain. In contrast, partially informed consumers might have a much smaller choice set so that they may not find it attractive to switch. Put differently, in our setting, fully informed consumers have much higher expected benefits from the switching subsidy than partially informed consumers, but through the uniform tax, both segments pay equally for the subsidy.

9 Conclusion

Current retail electricity markets are characterized by consumer inertia. Although large monetary benefits are available from choosing another contract, many consumers decide not to switch. Regulators and policy makers around the world spend substantial resources to fight consumer inertia in order to achieve effective competition in retail electricity markets. To yield the desired result, these resources need to be targeted carefully towards the actual sources of inertia.

In this paper, we develop a structural discrete choice model for the Flemish retail electricity market to quantify different reasons that may prevent consumers from switching and to support policy makers and regulators designing activities that target the main sources of consumer inertia. We estimate the relative importance of the three most important reasons for inertia: consumer preferences, switching costs and limited awareness about available contracts. Our results confirm that all of these reasons play a significant role in the supplier and contract choice of retail electricity consumers in Flanders.

First, preferences have a significant effect on the decision process of consumers. On the one hand, our estimations show that seniors have a preference for the incumbent supplier. They are willing to pay up to 21 EUR per month to stay on an incumbent contract instead of switching to another supplier. On the other hand, we find that the mean consumer values electricity produced from renewable sources of energy by roughly 2 EUR per month.

31These numbers can be recomputed for other mechanisms of raising the switching subsidy in a straightforward way.
but preferences vary across the Flemish population. The 2 EUR are in line with the
price premiums that most electricity suppliers charge for green as opposed to conventional
contracts. Second, switching costs in the Flemish retail electricity market have a highly
significant effect on supplier choice. We find that a consumer who switches electricity
supplier incurs a switching cost of 82 EUR ceteris paribus, which represents between 20%
and 31% of the yearly electricity expenditures of an average Flemish household. Simple
calculations suggest that these switching costs would be compensated within 6.5 months
for a consumer who switches from the most expensive to the cheapest supplier and within
11 months when switching from the average to the cheapest supplier. Third, we find that
supplier advertising significantly affects the choice set of those consumers that are only
partially informed about alternative contracts.

To investigate the effectiveness of different policy interventions aiming at overcoming con-
sumer inertia, we study the relative importance of switching costs and limited awareness in
retail electricity markets through counterfactual analyses. We simulate the market struc-
ture if either switching costs or limited awareness are reduced, while holding the other
effect fixed. We find that an intervention which reduces switching costs or compensates
consumers during a switch, e.g. through direct payments or welcome discounts, initiates
relatively more consumers to migrate towards cheap, new entrants than an intervention
which raises awareness. Raising consumer awareness, e.g. through information campaigns
or an increased use of price comparison websites, will prompt switches from the incumbent
towards new entrants as well – though to a smaller extent because of switching costs. More
specifically, our results suggest that compensating switching costs favors cheap entrants
that could otherwise not attract consumers who stick to their previous supplier because
of high switching costs. Conversely, increasing information about alternative contracts
favors those entrants that spend relatively few on advertising activities at the expense of
incumbents which benefit most from limited awareness.

Our analysis shows that both switching costs and limited awareness play an important role
in the switching behavior of electricity consumers. Policy makers and regulators that aim at
overcoming switching inertia in the retail electricity market need to act in both dimensions,
raising awareness about contract alternatives - in particular the low price offers - but at
the same time tackling the high switching costs of consumers.

Our counterfactual analysis should be interpreted with care, as it simulates market struc-
tures under different policy scenarios without taking into account potential feedback effects
on the supply side. One would expect firms adjusting prices or advertising expenditures
in response to policies that reduce switching costs or increase awareness. Incorporating a
full dynamic supply side model in our analysis could be an interesting direction for future
research. Furthermore, we currently interpret our model of limited awareness as a reduced
form of an underlying consumer search model and that differences in awareness status
of consumers come from heterogeneity in search costs. Future research could extend our
model by a search costs module, for example by adding a stage in which consumers decide
whether or not to become fully informed about all available contracts. Such an extension would allow to structurally quantify consumer search costs along with switching costs.

References


### A Controlling for endogenous PCW usage

In this appendix, we discuss how our baseline model can be extended to control for consumers selecting into using the PCW. In our baseline model, we assume that consumer’s decision of becoming active, i.e. using the PCW is exogenously given. However, consumers are likely to decide endogenously whether to use the PCW or not. For example, consumers
who expect to benefit more from switching suppliers, are more likely to use the PCW. Assuming that PCW usage is exogenous is likely to bias our estimation results.

Therefore, we model consumers’ decision of using the PCW to control in the spirit of a Heckman-selection model. After having observed the market structure, but before making a contract choice, each consumer decides whether to use the PCW in a given month or not. We assume that the probability of becoming active (using the PCW) can be described by a binary probit equation:

$$ Pr(\text{active}|X_a) = \Phi(X_a\gamma_a) $$

$X_a$ contains regressors shifting a consumer’s probability of becoming active in a given month. In our main specification, $X_a$ includes:

- Constant
- Age (senior dummy)
- Income
- Consumers green preference shock
- Internet/mobile internet penetration
- Regulator’s information campaign dummy

The last two regressors are crucial for the identification since it is likely that they do not affect consumers’ preferences, but only their costs of becoming active. Therefore, they satisfy the exclusion restriction for identifying the activity process.

**Estimation** The main difference in the estimation algorithm is that we now simulate whether a consumer belongs to the informed or uninformed segment of the market explicitly based on the outcome of the activity equation. The estimation algorithm proceeds in the following steps:

1. Simulate consumers all of which start as being uninformed.
2. At beginning of model evaluation, compute predicted probability of becoming active based on $Pr(\text{active}|X_a) = \Phi(X_a\gamma_a)$. Compare this to uniform draw, in order to classify consumer as active or passive.
3. Split simulated consumers in active and passive market segment.
4. Compute model predictions for aggregate and micro-level choices as in the baseline model.
5. In order to identify the new parameters in the activity equation, we construct additional micromoments by matching the models predicted probabilities of becoming active for each consumer to the observed survey data. A special regressor in the activity process is the preference for green electricity since it is unobserved. We identify this parameter by constructing an additional micromoment that interacts “Choice of green supplier” with “Choose to be active”. The intuition is that if people with high green preference are more likely to become active we should see a strong correlation between the becoming active and choosing green.  

6. Include the new set of micromoments into the objective function and minimize.

### B Detailed estimation results

<table>
<thead>
<tr>
<th></th>
<th>Point Estimates</th>
<th>Standard Error</th>
<th>P-Values</th>
<th>Magnitude in EUR</th>
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</thead>
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<tr>
<td>Constant</td>
<td>1.2261</td>
<td>0.3102</td>
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<td>Incumbent non-seniors</td>
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<td>0.1479</td>
<td>0.5313</td>
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<td>1.1299</td>
<td>0.0000</td>
<td>-100.0000</td>
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<tr>
<td>Mean green coefficient</td>
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<td>Variance green coefficient</td>
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<td>0.0000</td>
<td>67.2504</td>
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<td>0.9992</td>
<td>36.4394</td>
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</table>
| Adv. exp-income                | 2.5135          | 147.9877       | 0.9864   | 29.4059          

32 This requires the assumption that the advertising process is not structurally different for conventional and green suppliers.
C Counterfactual market share graphs

Figure C.1: Observed market shares
Figure C.2: Counterfactual market shares (I)
Figure C.3: Counterfactual market shares (II)