Online Appendix

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

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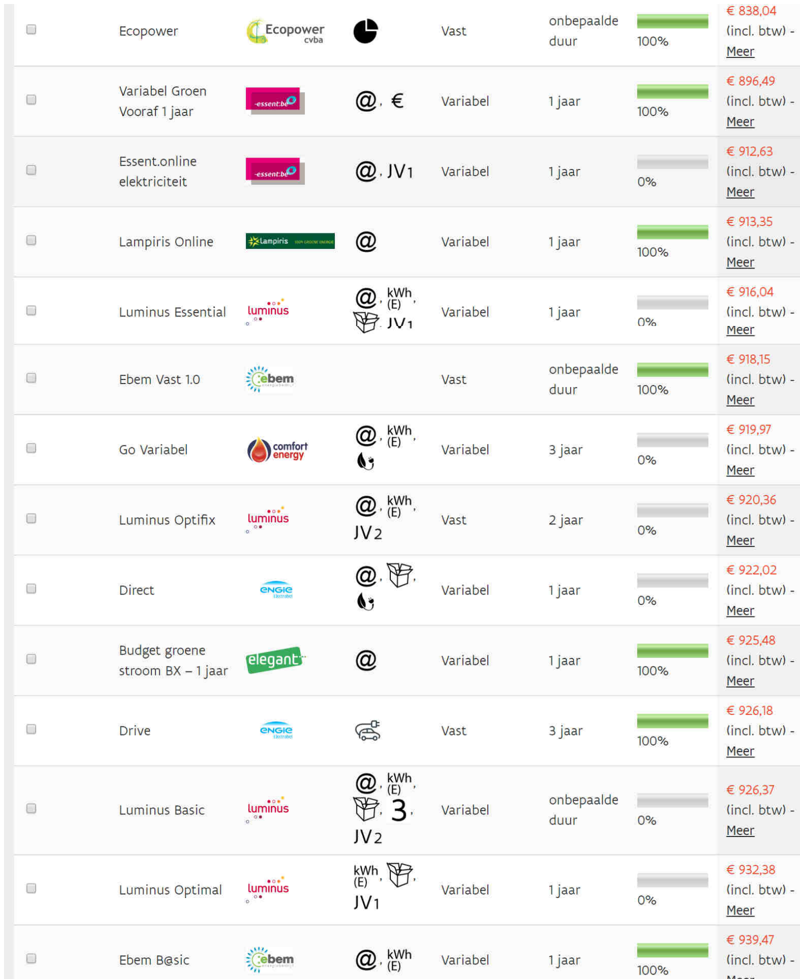
A Additional Descriptive Evidence

Figure A.1: Example screenshot of electricity contract comparison on V-test website

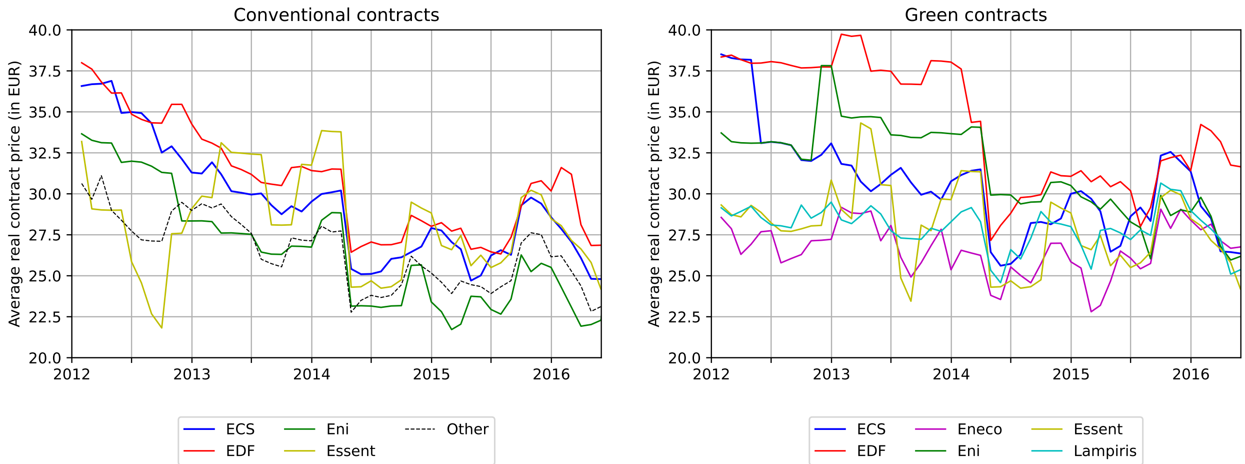


Ecopower	Ecopower cvba		Vast	onbepaalde duur	100%	€ 838,04 (incl. btw) - Meer
Variabel Groen Vooraf 1 jaar	essent.be	@, €	Variabel	1 jaar	100%	€ 896,49 (incl. btw) - Meer
Essent.online elektriciteit	essent.be	@, JV1	Variabel	1 jaar	0%	€ 912,63 (incl. btw) - Meer
Lampiris Online	Lampiris	@	Variabel	1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

Source: VREG, V-test®, `www.vtest.be`, accessed on 30 August 2018.

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

Figure A.2: Monthly prices by contract type over time, supplier averages, in 2012-EUR.



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

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

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

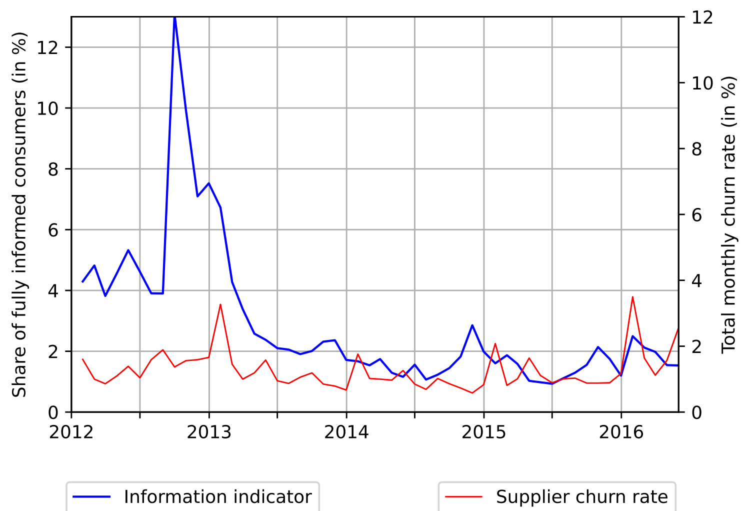
Notes: Other includes all contracts offered by electricity suppliers with an average market share below 1% over the 5 years considered in the analysis. Market shares are recorded in terms of electricity access points. Prices are represented as a twelfth of the yearly expenditure for electricity paid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

Table A.2: Yearly advertisement expenditure in Flanders (in EUR million)

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

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

Figure A.3: Information indicator and churn rates



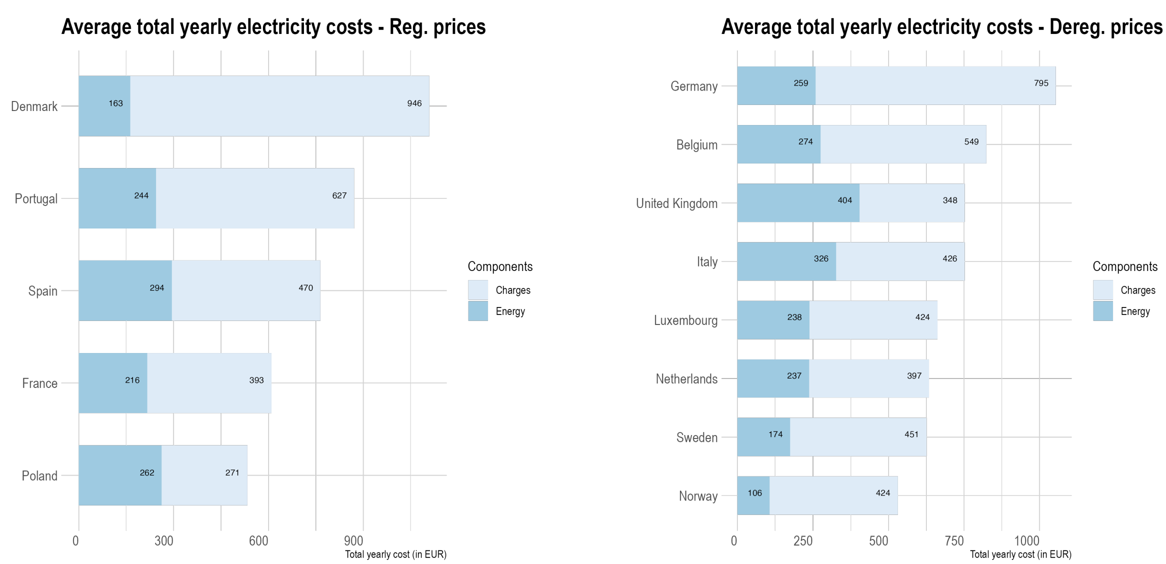
Notes: The figure plots the evolution of the monthly share of fully informed consumers (defined as the share of PCW users in a given month) over time and the total monthly churn rate (aggregated over all suppliers). Monthly churn rates range between 0.6% and 3.5% throughout our sample. During our sample period, there are several churn peaks with the most pronounced ones in January 2013 (3.3%) and January 2016 (3.5%). Comparing the monthly churn rate to our information indicator over our sample period reveals a positive correlation of 0.6.

A.1 Evolution of markups in European electricity markets

In this appendix, we provide more details on the magnitude of markups observed in retail electricity markets in several European countries during our sample period.

Throughout the paper, we define markups as $MU = (p - w)/w$, where p and w denote the *energy component* of the retail price and a measure of the wholesale spot price, respectively. The energy component p is only the payment for buying electricity from the retailer, which is composed of a fixed monthly fee and a per-kWh price for a each unit of electricity.[1] For our discussion of markups and the graphs presented in this appendix, we exclude all taxes and fees, such as network charges, regulated distribution costs or taxes.[2] Our wholesale price

Figure A.4: Total electricity costs for different countries



Notes: The figure displays the yearly electricity bill for an average household averaged over the years 2015-2018 in various representative countries. *Energy* denotes the cost for buying the electricity from the retailer, *Charges* captures all surcharges and taxes (network, RES, VAT, and other taxes and surcharges) levied on electricity consumption. The left and right panel illustrate the decomposition for several representative countries with regulated and deregulated retail electricity prices, respectively. Data source: ACER (2020a).

measure is the electricity price from the spot market at the Belgian power exchange Belpex.

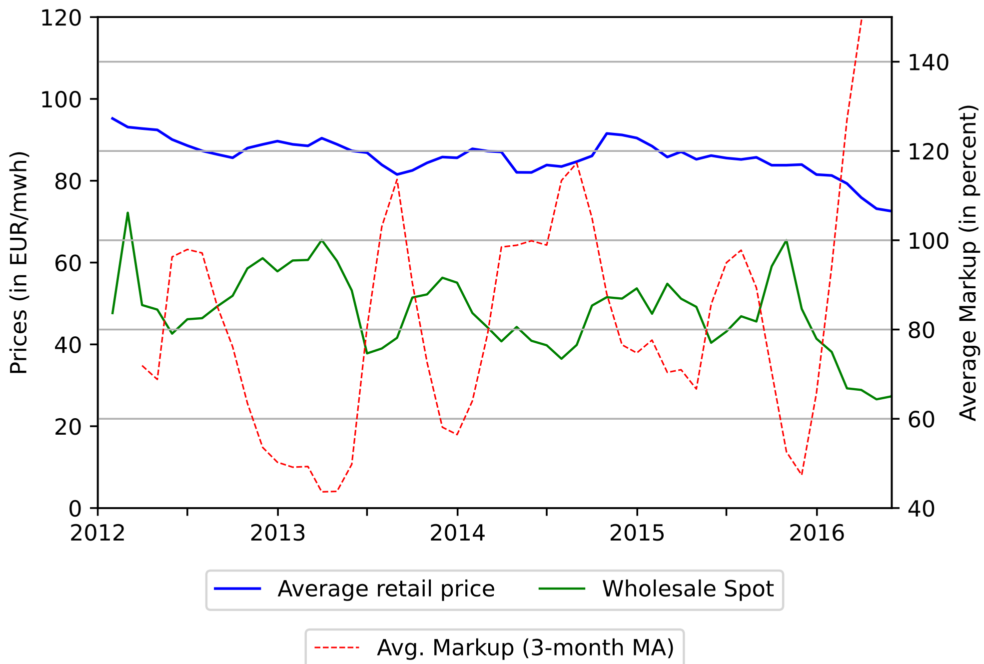
[1] In the estimation we also add VAT to the energy component and a few charges for renewable energy that vary over suppliers and therefore could have an effect on supplier choice.

[2] We present a comparison of the energy component and the taxes and charges component of an average electricity bill for several European countries in Figure A.4. The measure of retail price that we use in the estimation, i.e., energy component plus VAT, accounts for roughly 40% of the consumer's final electricity bill.

We compute the spot price for a given month as the average of the quarter-hourly electricity price during the day, i.e., between 7 am and 8 pm, within that month.

Figure A.5 plots the average retail price (energy component), the wholesale price, as well as the implied markups over time. The average observed markup in Flanders during our sample period is 86% and varies substantially over time between (40% and 130%).

Figure A.5: Evolution of retail prices, wholesale prices, and markups

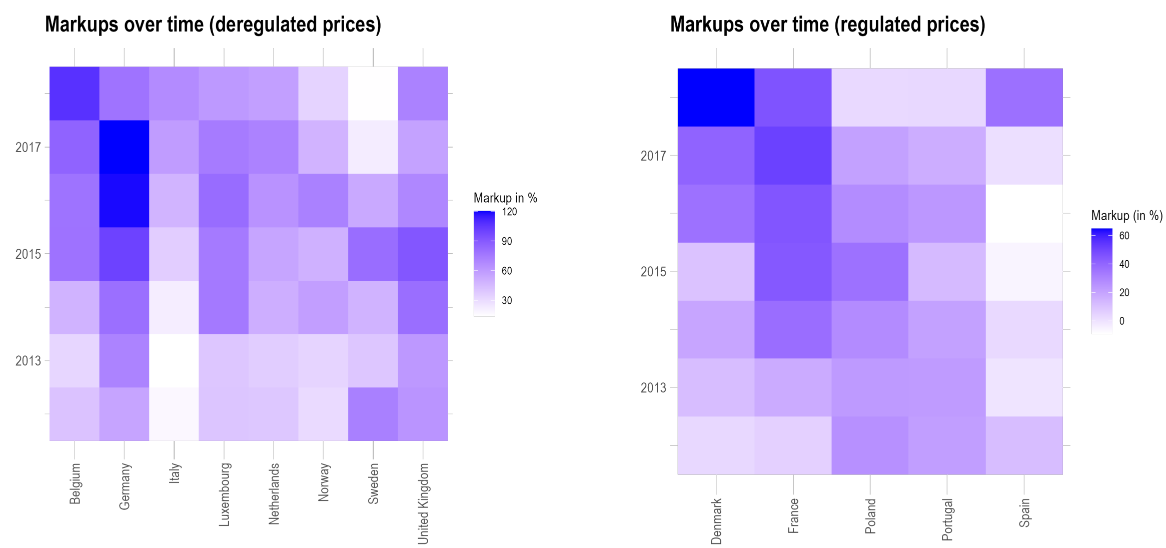


Notes: The figure displays the evolution of retail prices (market share-weighted average across contracts), wholesale spot prices (average quarter-hourly between 7 am and 8 pm, and markups (defined as retail price over wholesale price minus 1 times 100) over time. Data source: ACER (2020b).

It is important to keep in mind that these markups represent gross margins. They do not account for operating costs related to staffing, IT and billing systems, marketing expenses, costs of capital, etc., which can be substantial and are often fixed costs. Also the effective price paid by a retailer (*sourcing costs*) for electricity can vary over time and suppliers, as procurement strategies vary, for example, due to differences in suppliers' own-production portfolios and hedging strategies against volatile day-ahead prices. Since we do not model the supply side, we cannot compute the typical markup measures relative to suppliers' economic marginal costs.

Similar markups as the ones we observe in the Flemish data are reported for Belgium as a whole and for many European countries in a descriptive analysis by ACER (ACER/CEER, 2019). ACER is the European Union's Agency for the Cooperation of Energy Regulators and publishes an *Annual Report on the Results of Monitoring the Internal Electricity and Gas Markets*. The 2019 version of the report contrasts markups in the residential electricity market across European countries, which we summarize in Figure A.6. Even though there

Figure A.6: Evolution of markups over time for different countries

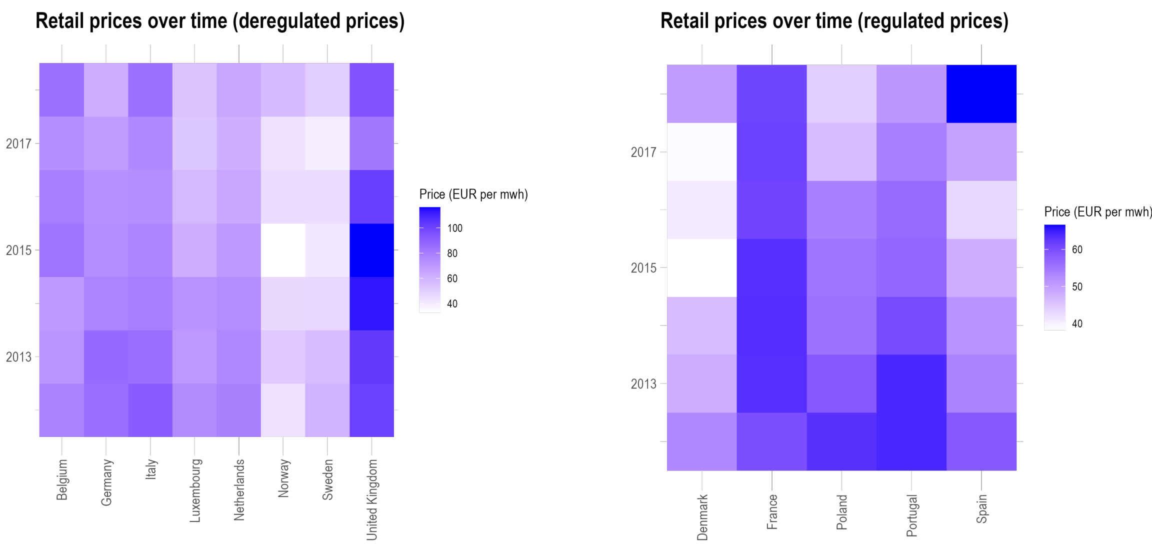


Notes: The figure displays the heatmap of the evolution of average markups, defined as $(p - w)/w$, over the years 2012-2018 for several representative countries that offer non-regulated or some form of regulated retail prices in the left and right figure, respectively. Data source: ACER/CEER (2019).

is also heterogeneity in the wholesale price across different countries, most of the variation in markups is driven by heterogeneous retail price levels across countries, see Figure A.7 and Figure A.8. Similarly to our measure of the retail price, the ACER statistics capture only the energy component of retail prices, and exclude network and regulated distribution charges. Therefore, these data should be comparable to our data from Flanders.

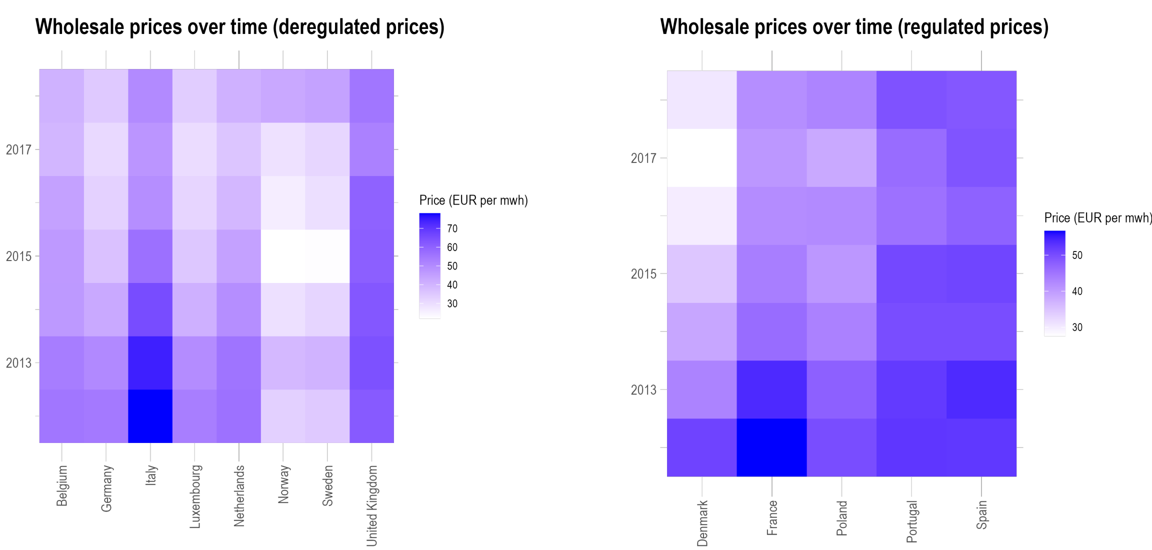
In general, markups in Belgium are on the higher end compared to some other European countries and Flanders exhibits slightly higher markups than the numbers that ACER uses to represent Belgium, which are based on prices in the capital region of Brussels. However, our computed markups are overall in line with what is observed in other European countries with non-regulated retail prices, for example, Germany, Luxemburg, the Netherlands, and the United Kingdom. Interestingly, markups in countries with liberalized retail markets,

Figure A.7: Evolution of retail prices over time for different countries



Notes: The figure displays the heatmap of the evolution of average retail prices (per MWh) over the years 2012-2018 for several representative countries that offer non-regulated or some form of regulated retail prices in the left and right figure, respectively. Data source: ACER/CEER (2019).

Figure A.8: Evolution of wholesale prices over time for different countries



Notes: The figure displays the heatmap of the evolution of average wholesale prices (per MWh) over the years 2012-2018 for several representative countries that offer non-regulated or some form of regulated retail prices in the left and right figure, respectively. Data source: ACER/CEER (2019).

but some form of retail price regulation tend to be significantly lower, see the right panel of Figure A.6.[3]

Northern European countries (Finland, Norway, and Sweden) experience much lower markups. These may be driven by differences in the Nordic electricity generation mix[4], infrastructure, the institutional and regulatory environment or economic conditions affecting the electricity industry. ACER/CEER (2019) discusses that retail electricity markets in Finland, Norway, and Sweden also stand out in that their retail tariffs are often linked to the wholesale spot price, for example, in the form of wholesale-plus-fixed markup retail contracts, which is not generally the case in other European countries.

[3]We follow (ACER/CEER, 2019) and classify countries as having *regulated prices* if they impose at least some form of regulation on end-user prices for residential consumers beyond those that protect economically vulnerable consumers.

[4]For example, Norway nearly exclusively produces electricity from hydro.

B Additional Reduced Form Evidence

In this appendix, we present more detailed results of our reduced form regressions to motivate our structural model and justify several of of our assumptions and specification choices.

Evidence for state dependence using aggregate data. In order to provide empirical evidence for the importance of state dependence, we run several reduced form regressions similarly to Shcherbakov (2016). Specifically, we regress contemporaneous contract-level market shares, s_{jt}, on contemporaneous contract attributes and other controls (including price), X_{jt}, and lagged market shares

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

Throughout, prices are instrumented using Hausman instruments and the electricity price at the wholesale spot market as a cost shifter.

Table B.1: Reduced form evidence for state dependence using macro data

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

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

Table B.1 summarizes the results. When we ignore lagged market shares in the estimation, we obtain implausible coefficients on almost all of the regressors, see Column (1). For example, the price coefficient is positive and insignificant and green electricity has a negative significant coefficient. When including the lagged market share as regressor, most of the coefficients revert to the expected signs, see Column (3). In order to mitigate the likely endogeneity problem of the lagged market share, we first run the same regressions with firm-level fixed effects, see Column (4). The qualitative pattern remains the same but we generally get less significance. Finally, we instrument lagged market shares with lagged exogenous shifters as suggested by Shcherbakov (2016). This IV approach accounts for the potential presence of serially uncorrelated unobservables that could affect contract choices over time. As displayed in Column (5), the coefficient on (instrumented) lagged market share is positive and significant, which points to significant state dependence in electricity contract choices.

Importance of informational frictions and transactional switching costs. Table B.2 illustrates that there is significant heterogeneity in the probability of being fully informed about all available contracts across different consumer types. We estimate a binary Probit model using a dummy (*Fully informed*) that is equal to 1 if the consumer has used the PCW in the recent past as a dependent variable and a series of demographic characteristics as regressors. Throughout the different specifications, seniors and women use the PCW much less. Less educated consumers are less likely to be informed; high-income and highly educated consumers use the PCW significantly more. Finally, we include a dummy that is equal to 1 if the consumers states that energy costs constitute an important part of the household's budget. The negative coefficient indicates that those consumers for which energy costs are important are less likely to be informed and might therefore leave money on the table; however, the coefficient is only weakly significant. In Column (2), we add a time trend (*Year*), whose positive coefficient indicates that, ceteris paribus, PCW usage is increasing over time among the survey respondents. Finally, we add a dummy describing whether the consumer is on a green contract. The positive and highly significant coefficient highlights that a preference for renewable energy is associated with the consumer being better informed.

Table B.3 reveals that fully informed consumers tend to sign up for cheaper electricity contracts compared to consumers who do not use the PCW. We regress the monthly energy bill (*Average Price*) that a survey respondent would pay given her supplier and contract choice on the respondent's socio-demographic characteristics and her awareness status.[5] The dummy variable *Fully informed* takes the value 1 if the respondent has used the PCW and 0 otherwise. Socio-demographic characteristics include continuous variables, such as household size, family net income, a linear time trend, and dummy variables indicating whether the

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

respondent is a woman, a senior and whether the respondent stated that energy costs play an important part in the household's budget.

Not surprisingly, ceteris paribus, fully informed consumers tend to pay less for electricity. This is a first indication that full information about available contracts can lead to better choices saving the average consumer roughly EUR 7 per month, which represents 25% of the monthly bill. Throughout the different specifications, seniors tend to pay more, although the coefficient is not statistically significant, and high income households pay significantly less. A striking observation is that households who report that energy costs are important pay significantly more for electricity. Specifically, they pay EUR 8 more per month than households who state that energy costs are not important to them. This coefficient can be interpreted as first evidence that liberalized electricity markets may have regressive distributional effects because low-income households seem to not take advantage of the liberalized market environment. The last column adds the number of past supplier switches by the consumer as an additional regressor. The negative coefficient indicates that consumers who switch save significantly. Each additional switch is associated with an EUR 8 decrease in the consumer's monthly electricity bill.

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

Empirical evidence for relation between advertising, internet penetration rates, and PCW usage. In the following, we provide supporting reduced form evidence for the assumptions that help us in identifying the PCW search cost. We analyze whether PCW usage, Internet penetration, and supplier advertising are associated with each other by regressing both the share of consumers using the PCW in a given month and suppliers' advertising expenditure on our potential shifters of search costs and benefits, as well as a series of controls.

Table B.2: Limited awareness is unequally distributed across the Flemish population.

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

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

Table B.3: Fully informed consumers tend to subscribe to cheaper contracts.

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

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

Table B.4: Socio-demographic characteristics of (non-)switchers

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

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

Table B.5 summarizes the associated results. Column (1) regresses the share of consumers using the PCW in a given month on Internet penetration[6], a dummy for the periods when the government conducted an extensive information campaign, and the aggregate monthly supplier advertising expenditure. In addition, we control for seasonal effects in the form of month-of-the-year dummies and the average retail price, and the standard deviation of prices across suppliers and months within a year.

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

	(1) PCW usage	(2) Ad spending
Retail price (SD)	0.028**	
	(0.011)	
Retail price (mean)	0.002	0.005
	(0.001)	(0.011)
Internet penetration	1.842*	-1.853
	(0.920)	(2.674)
Regulator campaign	0.031***	0.075
	(0.008)	(0.063)
Ad spending	-0.040**	
	(0.017)	
Wholesale price		0.003
		(0.002)
R2	0.717	0.627
Observations	54	378
Firm FE	No	Yes
Month-of-Year FE	Yes	Yes

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

Notes: Column (1) summarizes the results from an OLS regression of the monthly aggregate share of PCW users on various potential shifters of the expected benefits and costs of search. Column (2) summarizes the results from an OLS regression of monthly firm-specific advertising on a similar set of shifters. All regressions include month-of-year fixed effects. Column (2) also incorporates firm fixed effects. Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

PCW usage is affected positively and significantly by both Internet penetration and the information campaign dummy which indicates that both seem to facilitate the use of the

[6]We use the share of households connected to a fixed-line broadband Internet connection as a measure for Internet penetration from OECD (2018).

PCW. In addition, firms' advertising has a negative effect on consumers' PCW usage which is consistent with advertising informing consumers and thereby decreasing their expected benefits from using the PCW.

In Column (2) we regress firm-specific advertising in a given month on our PCW cost shifters, i.e., Internet penetration and the information campaign dummy, as well as a series of controls, in particular, firm fixed effects, month-of-the-year fixed effects, and the electricity wholesale price. We find that neither Internet penetration nor the information campaign dummy has a significant effect on a firm's advertising expenditure. In fact, most of the variation in advertising expenditure can be explained by firm fixed effects and seasonal effects.

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

Table B.6: Supporting reduced form evidence for Hausman IV assumptions

	(1) Elec FL	(2) Elec WL	(3) Gas WL	(4) Gas WL	(5) Gas WL
Natural Gas Wholesale NL	-0.063	-0.093*	-0.049	-0.031	-0.030
	(0.094)	(0.045)	(0.182)	(0.176)	(0.176)
Natural Gas Wholesale GER	0.569***	0.574***	1.870***	1.850***	1.842***
	(0.140)	(0.113)	(0.293)	(0.296)	(0.298)
Elec. Wholesale Spot	0.063***	0.062***	-0.009	-0.005	0.002
	(0.017)	(0.013)	(0.043)	(0.045)	(0.053)
Post-Regulator Campaign 3	-1.258**	-1.372**	-0.065		
	(0.511)	(0.398)	(1.543)		
Post-Regulator Campaign 6				-0.392	
				(0.997)	
Post-Regulator Campaign 12					-0.482
					(1.017)
Observations	594	594	270	270	270

Notes: The table summarizes regression results to provide supporting evidence for the validity of our Hausman IV.

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

C Discussion of Modelling Assumptions

In this appendix, we discuss additional details to justify several of our modeling assumptions.

Consumption homogeneity assumption and linear prices. In the following, we discuss that prices in the Flemish electricity retail market are reasonably linear so that our assumption of consumption homogeneity should not have a significant effect on our model of discrete supplier choice.

Nonlinearities in the electricity rate structure can arise from two different sources. First, they may arise because pricing structures are usually a two-part tariff. In particular, there is a fixed monthly fee per tariff (charged in EUR) and a variable rate for the energy delivered (charged in EUR cent per kWh). Both components vary over tariffs and suppliers. The fixed monthly fee brings in a non-linear element to the otherwise linear kWh-rate.

To investigate the role of potential nonlinearities arising from the combination of fixed and variable components we identified the cheapest tariff (across suppliers) for each consumption level from 0 to 6,000 kWh. One would be worried about non-linearity effects if at different consumption levels different suppliers offered the cheapest contract; for example, if Electrabel offered the cheapest tariff for 2,000 kWh, but the cheapest tariff for 3,500 kWh is offered by Lampiris. In the overwhelming majority of months we do not find any evidence for this type of nonlinearities. In a given month, the supplier with the cheapest tariff at one consumption levels generally remains the cheapest supplier at all consumption levels.

Second, non-linear rate structures are a common feature in some retail electricity markets in the US. For example, California has a longstanding tradition of using increasing block prices in the residential electricity market, where the price per kWh electricity increases with consumption. The main objective for implementing the progressive rate structure in California is to ensure that less affluent households can afford a basic level of electricity consumption by generating revenues from wealthier households. Increasing block prices are not common in the market that we analyze. Flanders protects less affluent electricity consumers via a means-tested social tariff as opposed to an overall progressive rate structure. Although electricity suppliers in Flanders could in principle offer non-linear price schedules, our data reveals that only a negligible share of consumers is on contracts that feature kWh-prices that vary with consumption levels.

In principle, consumption heterogeneity can be incorporated into our model, for example, by treating an individual's quantity as an additional demographic characteristic in D_{it}.

Role of sticky prices. The fact that we assume that each consumer always pays the current price of a supplier implies that our model abstracts from the issue of sticky prices, i.e., the fact that some contracts may be fixed-price tariffs, for which the consumer always pays the price that prevailed in the initial subscription period. We implicitly assume that all products are variable contracts for which the consumer always pays the current price specified by the supplier. At additional computational costs, our model can accommodate sticky prices and fixed-price contracts. This would not involve the estimation of additional parameters but requires us to keep track not only of a consumer's contract choice but also the time period in which she subscribed to that contract, which increases the computational burden substantially.

D Details of the Estimation Routine

In this appendix, we describe the detailed steps of the estimation algorithm.

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

2. We simulate NS individual consumers. In our main specification, we simulate $NS = 500$ individuals. Each individual is represented by a 3-dimensional vector comprising 2 consumer demographics (age and income) and a taste shock for green electricity. We draw the demographics from the empirical distribution. Data on the age distribution of the Flemish population comes from Statbel (2016). The income distribution in Belgium is from Eurostat (2016). We draw the random green electricity coefficient from a standard normal distribution. These draws remain fixed throughout the estimation. For the green preference parameter we multiply the standard normal draw with our parameter guess for the standard deviation to simulate the logarithm of each consumer's preference for green electricity, i.e., we exponentiate this part of the utility before adding it to the simulated utility.

3. For each consumer and each period we simulate a fallback choice set that consists of the consumer's current supplier's contracts and the contracts that she became aware of through advertising based on Equation (1). We calculate the probability that individual i is informed about supplier j's contracts for a given value of awareness parameters and firms' advertising levels. To transform probabilities into specific simulated choice sets, we draw J random draws from a uniform distribution for each individual i and time period t. If the calculated probability that individual i is informed about supplier j's

contracts exceeds the uniform draw for this supplier, supplier j's contracts are included in i's choice set. Otherwise, they are excluded.

Based on this fallback choice set, we compute the expected benefit of searching the PCW and compare it to the PCW search cost for each consumer i. We compute the expected benefits of PCW search by simulation. For each consumer i, month t and contract j that the consumer is not informed about either through advertising or because it is offered by her existing supplier, we draw 30 draws from the estimated joint price belief distribution and compute the expected benefit of search as the average over the 30 simulated utilities. If the expected search benefits exceed the search costs, the consumer is classified as a PCW user and is therefore fully informed; if the search cost exceeds the expected benefits, the consumer does not use the PCW and remains only partially informed. In practice, we do not rely on a hard 0-1 classification for each simulated consumer. Instead we feed the simulated utilities from using and not using the PCW into a Logit smoother function. This technique substantially helps to improve the convergence properties of our algorithm and is used in a variety of contexts, for example, when simulating choice probabilities for estimating Probit models, see Train (2009, p. 121).[7] Specifically, let u_1 denote the expected utility from using the PCW and u_0 the utility from not using the PCW. Without the Logit smoother, we would classify a consumer as a PCW user if and only if $u_{1it} \geq u_{0it}$. When using the smoother function, we assign a PCW usage probability to consumer i in month t based on

$$Pr(i \text{ uses PCW in } t) = \frac{\exp\left((u_{1it} - u_{0it})/\lambda\right)}{1 + \exp\left((u_{1it} - u_{0it})/\lambda\right)}, \tag{D.1}$$

where λ is a parameter that determines the degree of the smoothing. When $\lambda \to 0$ the smoother function approaches the hard 0-1 classification without any smoothing. When $\lambda \to 1$, we apply maximal smoothing. Unfortunately, there is little theoretical guidance for how to choose this smoothing parameter. On the one hand it should be small in order to not bias the simulated decisions. On the other hand, the smoothed function can behave very similarly to the unsmoothed version if the parameter is chosen too small. We follow standard practice (Train, 2009) and experiment with several different values for λ in the range of 0 to 0.3 and found that the estimates were generally not very sensitive to the choice of the smoothing parameter within this range. For the main specifications, we use $\lambda = 0.15$.[8] One interpretation of the smoothed PCW usage

[7] In an earlier version of this paper, we did not use a smoother function, but used the hard 0-1 classification. This forced us to simulate many more consumers than we do currently in order to obtain a reasonably smooth objective function.

[8] Estimation results for alternative values of λ are available upon request.

probability is that each simulated consumer represents a continuum of consumers of a specific type who experience different shocks which makes them choose different actions, here either using the PCW or not. One could also interpret λ more structurally as capturing misperceptions about the expected benefits and costs of using the website.[9] $\lambda = 0$ corresponds to a setting where consumers are perfectly informed about the expected benefits, while a larger value for λ can be interpreted as consumers making relatively large errors when deciding about their PCW usage.[10]

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

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

6. We average over all individual contract choice probabilities to predict aggregate contract market share distributions.

7. Both predicted and observed market shares are sent into a BLP-style mapping to back out the mean utilities δ for each contract in each period by matching aggregate observed market shares S_{kt} to the model predictions s_{kt} for all contracts k and periods t. During this step, market share predictions s_{kt} are calculated repeatedly based on Equation (6) as a function of the nonlinear parameters $(\theta_2, \kappa, \alpha^A)$ and the mean utilities δ. In contrast to the standard BLP contraction mapping, current shares depend on the shares in the previous period because of the switching cost component. Therefore, we have to solve for market share predictions recursively, i.e., period-by-period. The mapping works similarly to the one of dynamic demand models in the style of Gowrisankaran and Rysman (2012). More specifically, the mean utilities are computed by iteratively updating according to

$$\text{(D.2)} \qquad \delta'_{kt}(S_t, S_{t-1}; \theta_2, \kappa, \alpha^A) = \delta_{kt} + \log S_{kt} - \log s_{kt}(S_{t-1}, \delta_t; \theta_2, \kappa, \alpha^A).$$

[9] A similar approach is taken by De Los Santos, Hortaçsu, and Matthijs R. Wildenbeest (2012). The key difference between their approach and ours is that they estimate the "bias" as a separate parameter, while we set this parameter to a small number and experiment with the sensitivity of the estimation results with respect to this parameter as suggested by Train (2009, p. 121). We opted against estimating the smoothing parameter in the style of De Los Santos, Hortaçsu, and Matthijs R. Wildenbeest (2012) because our current model is already computationally intensive.

[10] Given that our estimation results are not very sensitive within the range of parameters that we explore, one could argue that consumers misperceptions about the benefits and costs of the PCW do not significantly affect our conclusions.

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

8. After convergence of the mean utilities, we back out the contract-month-specific unobserved quality shocks ξ_{kt} by decomposing δ into the mean utility from observed contract characteristics and the unobserved shock ξ.

$$\xi_{kt} = \delta_{kt}(\cdot) - X_{kt}\bar{\beta} - \bar{\alpha} p_{kt}. \tag{D.3}$$

9. Next, we compute the model's predictions for aggregate churn rates and PCW usage rates, as well as choice probabilities for contract choices for each of the simulated consumer types. These predictions are matched to the observed counterparts to complement the BLP moments.

10. Specifically, we construct the following six sets of moments:

    (a) Macromoments (based on aggregate contract-level, and industry-level data):

    i. BLP moments: $\mathbb{E}[G_1(\xi_{kt})] \equiv \mathbb{E}[\xi_{kt} Z_{1kt}] = 0$, where Z_1 contains exogenous product characteristics, specifically, firm fixed effects and a dummy for green electricity contracts and instruments for contract prices, specifically, the natural gas retail price in Wallonia as Hausman IV, the contemporaneous wholesale electricity price weighted with a supplier's sensitivity to the wholesale market, and the 3-months lagged electricity wholesale price weighted with a supplier's sensitivity to the wholesale market as cost shifter.

    ii. Churn rate prediction error moments: $\mathbb{E}[G_2(\zeta_t)] = \mathbb{E}[(C_t - c_t) Z_{2t}] = 0$, where $\zeta_t \equiv C_t - c_t(\cdot)$ denotes the industry-level churn rate prediction error computed as the difference between the observed churn rate C_t and the model prediction $c_t(\cdot)$ and Z_2 contains contains year dummies and quarter-of-the-year dummies.[11]

iii. PCW usage prediction error moments: $\mathbb{E}[G_3(\rho_t)] = \mathbb{E}[(W_t - w_t)Z_{3t}] = 0$, where $\rho_t \equiv W_t - w_t(\cdot)$ denotes the aggregate PCW usage prediction error computed as the difference between the observed PCW usage W_t as measured by the regulator (total number of users completing the price comparison process) and the analogous model prediction $w_t(\cdot)$. Z_3 contains year dummies and quarter-of-the-year dummies, the broadband Internet penetration rate in Flanders, aggregate advertising level by all Flemish electricity suppliers, and a dummy for the months in which we consider the information campaign to have had a direct effect on consumer's PCW search costs. We set this dummy to 1 for the 6 months following the start of the information campaign.[12]

(b) Micromoments (based on individual-level survey data):

i. Individual-level PCW usage moments: $\mathbb{E}[G_4(\gamma_{it})] = \mathbb{E}[\gamma_{it}(\theta)Z_{4it}] = 0$, where γ_{it} denotes an individual-level PCW usage prediction error and is defined as the difference between survey respondent i's reported PCW usage in period t (either 0 or 1) and the corresponding model prediction and Z_4 contains dummies for the consumer's demographic group defined by the interaction of age and income. We classify age into two groups (seniors and non-seniors) and income into 4 groups, which results in 8 demographic groups in total. Moreover we interact the individual-level PCW usage prediction error with year dummies and omit the dummy for the last year to avoid multicollinearity.

ii. Individual-level relative switching propensity moments: $\mathbb{E}[G_5(\nu_{it})] = \mathbb{E}[\nu_{it}(\theta)Z_{5it}] = 0$, where ν_{it} denotes the individual-level relative switching propensity error and is defined as the difference between survey respondent i's relative switching propensity –defined as the ratio of how often i reports to have switched in the past and the average number of switches reported by all consumers in the survey– in period t and the corresponding model prediction. Z_5 contains the same instruments as Z_4, i.e., 8 demographic group dummies and year dummies.

iii. Individual-level contract/firm choice moments: $\mathbb{E}[G_3(\eta_{it})] = \mathbb{E}[\eta_{it}Z_{6it}] = 0$, where the individual-level prediction error for contract choice $\eta_{it}(\cdot) = b_{it} - B_{it}(\cdot)$. Element k of b_{it} equals 1 if consumer i chooses contract k and 0

[11] Where applicable, we omit the dummy for the last quarter of each year to avoid multicollinearity.

[12] In an earlier version of this paper, we experimented with different horizons for the information campaign, such as 3 months and 9 months. Qualitatively, these results were similar.

otherwise. B_{it} is a $K \times 1$ vector of predicted choice probabilities with elements strictly between 0 and 1. The instrument matrix Z_6 contains dummies for a consumer's income and age group[13], as well as firm-specific advertising levels to help us identify the parameters characterizing the advertising-awareness effectiveness. A minor drawback of our surveys is that only half of he survey respondents are asked about their specific contract choice, while the other half is only interviewed about supplier choice. Therefore, we can compute the contract-level moments only for a subset of our survey respondents and we have to rely on supplier-level moments for the rest of our survey sample. In order to deal with this feature of our survey data, we construct this set of moments separately for the two groups of survey respondents. Moreover, we construct separate moments for PCW users and PCW non-users. For each of the 4 groups of survey respondents[14] we interact each of the 6 instruments in Z_6 with each component of the contract (or supplier) choice prediction error η. Ultimately, this results in $6 * 10 * 2 + 6 * 6 * 2 = 192$ moments. Note that η only contains predictions errors for the inside goods, i.e., either 10 contracts or 6 firms, in order to avoid collinearity issues.

11. Finally, our six sets of moments are stacked and aggregated to the final objective function $g(\theta)'Wg(\theta)$, where $g(\theta)$ collects the sample averages across all observations for each moment. The population moment conditions are assumed to equal zero at the true values of the parameters θ^*. Our GMM estimate is the value of θ that minimizes the sample analogue of these moments. We estimate the model using efficient two-step GMM. In the first stage, we use a block-diagonal 2SLS weighting matrix W. In the second stage, we compute an estimate of the asymptotically efficient weighting matrix based on the first stage results.

12. We perform a non-linear search for the parameter values that minimize our GMM objective function. While most of our parameters are non-linear, some (firm fixed effects and the mean preference for green electricity) are linear and can be profiled out following the procedure first suggested by Nevo (2000).

[13] Since we discretize income into four groups and age into two groups, we use 5 demographic group dummies in total in Z_6.

[14] The four groups correspond to: (1) contract-level choice observed and PCW user, (2) firm-level choice observed and PCW user, (3) contract-level choice observed and not PCW user, (4) firm-level choice observed and not PCW user.

E Additional Estimation Results

Table E.1: Comparison of estimation results with and without Hausman IV

	Baseline		**No Hausman IV**	
	Coefficients	WTP in EUR	Coefficients	WTP in EUR
Mean price coefficient	-15.9270*** (0.1816)	-	-15.6100*** (0.1905)	-
Income-price interaction	0.1723*** (0.0146)	-	0.3809*** (0.0153)	-
Incumbent (non-seniors)	-0.6477*** (0.0382)	-4.07	-0.6247*** (0.0362)	-4.00
Incumbent (seniors)	3.8328*** (0.0799)	24.06	3.3085*** (0.0627)	21.20
Mean green coefficient	0.1936*** (0.0433)	1.22	0.1846*** (0.0433)	1.18
Variance green coefficient	0.0509 (0.1088)	-	0.0453 (0.0694)	-
Switching cost	3.5951*** (0.0222)	22.57	3.0712*** (0.0275)	19.68
PCW search	2.7515*** (0.0297)	-	2.3143*** (0.0137)	-
PCW search-Internet	-8.9856*** (0.0813)	-	-7.4296*** (0.0376)	-
PCW search-Campaign	-0.3614*** (0.0134)	-	-0.1700*** (0.0195)	-
Adv. constant	-2.1168*** (0.0059)	-	-2.8842*** (0.0146)	-
Adv. expenditure	0.6264*** (0.0180)	-	0.7851*** (0.0301)	-

*Notes: Results from estimating the demand model using efficient 2-step GMM weighting matrix. The left panel contains our baseline specification that uses our Hausman IV. The right panel contains the same model specification, but does not use the Hausman IV. Both specifications include firm fixed effects. Standard errors in parentheses. *,**,*** denote significance at the 10%, 5% and 1%-level respectively. - denotes non-interpretable willingness-to-pay.*

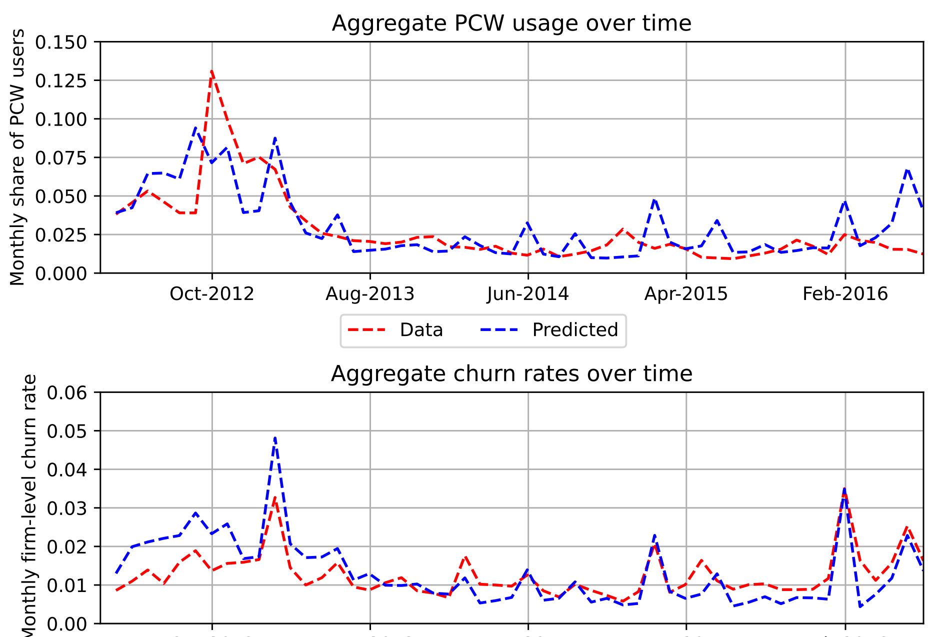
E.1 Goodness-of-Fit

Table E.2: Goodness-of-fit statistics for churn rates and PCW usage by year

Churn rates	2012	2013	2014	2015	2016	Average
Mean (obs)	0.015	0.011	0.010	0.012	0.017	0.013
Mean (pred)	0.023	0.012	0.009	0.009	0.014	0.013
Median (obs)	0.015	0.010	0.009	0.010	0.016	0.010
Median (pred)	0.022	0.011	0.007	0.007	0.012	0.011
PCW usage	2012	2013	2014	2015	2016	Average
Mean (obs)	0.063	0.024	0.016	0.015	0.017	0.028
Mean (pred)	0.061	0.020	0.018	0.020	0.039	0.031
Median (obs)	0.051	0.022	0.015	0.014	0.015	0.020
Median (pred)	0.063	0.018	0.012	0.016	0.032	0.020

Notes: The table displays the goodness of fit of our baseline model regarding industry-level churn rates and PCW usage behavior.

Figure E.1: Illustration of goodness-of-fit: churn and PCW usage predictions



Notes: The figure displays the evolution of the observed aggregate PCW usage and churn rates along with the predictions from our baseline model.

E.2 Comparison with restricted models

Table E.3: Estimation results: Model without switching costs

	Coefficients	WTP in EUR
Mean price coefficient	-27.8830*** (1.6201)	-
Income-price interaction	0.2105** (0.0970)	-
Incumbent (non-seniors)	-0.4720*** (0.0595)	-1.69
Incumbent (seniors)	5.5626** (2.2119)	19.95
Mean green coefficient	-0.0920 (0.0767)	-0.33
Variance green coefficient	0.0613 (0.2305)	-
PCW search	3.0767*** (0.0461)	-
PCW search-Internet	-4.6170*** (0.2297)	-
PCW search-Campaign	-0.1878*** (0.0287)	-
Adv. constant	-2.4524*** (0.0342)	-
Adv. expenditure	0.3075*** (0.0548)	-

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

Tables E.3 and E.4 present the full estimation results from the two restricted models. Table E.5 compares several statistics of the different model specifications. While almost all implied WTPs are consistent for our baseline model (with homogenous PCW search costs and switching costs) and the extended model (with heterogeneous market friction parameters), the two restricted models that abstract either from PCW search costs or switching costs give very different predictions. In particular, the restricted models predict a higher preference for the incumbent firm and a negative willingness to pay for green electricity. As a consequence, basing policy recommendation on a restricted model risks to devalue the benefits from product variety, both in terms of different suppliers and different types of products, such as, green

Table E.4: Estimation results: Model without PCW search costs

	Coefficients	WTP in EUR
Mean price coefficient	-5.9381**	-
	(3.0051)	
Income-price interaction	0.5702	-
	(0.3592)	
Incumbent (non-seniors)	0.3685***	6.21
	(0.0802)	
Incumbent (seniors)	1.7500***	29.47
	(0.1282)	
Mean green coefficient	-0.3085***	-5.19
	(0.0856)	
Variance green coefficient	0.0946	-
	(0.2488)	
Switching cost	3.5690***	60.10
	(0.1445)	
Adv. constant	-1.8930***	-
	(0.2779)	
Adv. expenditure	1.1518*	-
	(0.6048)	

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

Table E.5: Comparison of full and restricted models

Average WTP	Full model	No switching costs	No PCW search costs
Incumbent - non-senior	-4.07	-1.69	6.21
Incumbent - senior	24.06	19.95	29.47
Green electricity	1.22	-0.33	-5.19
PCW search costs - non-senior	4.10	15.15	0.00
PCW search cost - seniors	4.10	15.15	0.00
Switching cost - non-senior	22.57	0.00	60.10
Switching cost - senior	22.57	0.00	60.10

Notes: The table compares the average WTP (across months and consumers) for various product characteristics and consumer types obtained from different model specifications.

Table E.6: Average contract valuations: Comparison of full and restricted models

Contract	Full model	No switching costs	No PCW search costs
ECS	0.00	0.00	0.00
ECS (g)	1.22	-0.33	-5.19
EDF	0.80	-1.42	-15.05
EDF (g)	2.02	-1.75	-20.25
Essent (g)	0.47	-1.17	-11.66
ENI	0.42	-1.13	-6.01
ENI (g)	1.64	-1.46	-11.21
Eneco	-2.77	-3.86	-16.21
Eneco (g)	-1.55	-4.19	-21.41
Lampiris (g)	5.08	2.50	-7.79

Notes: The table compares the average contract valuation (across months and consumers) as measured by the sum of the relevant firm fixed effects and the mean preference for green electricity contracts obtained from different model specifications. Valuations are measured in EUR per month relative to the conventional contract of the incumbent firm.

contracts. Table E.6 presents the implied average valuations of the different contracts across the three model specifications. Most contracts by the major entrants are on average valued more than the conventional contract of the incumbent, even though not by much (around 7% of the average monthly electricity expenditure). In contrast, both restricted models imply that almost all entrant contracts are valued less than the incumbent contract. The difference is especially big for a model that ignores the existence of PCW search costs. One potential explanation for this pattern is that when ignoring one market friction, the other friction does not fully absorb the effect of the omitted channel and instead loads its effects onto consumer preferences. As a consequence, the data pattern that many consumers remain with the incumbent cannot fully be rationalized by market frictions and so the model explains the inertia with a higher preference for the incumbent.

E.3 CCP Matrix Estimates

Tables E.7 and E.8 display several representative conditional choice probabilities (CCP) matrices implied by our model. Overall, the numbers make sense and the diagonal is consistent with our aggregate churn rate numbers. The predicted CCP for staying with the green contract of EDF and the conventional contract for Eneco seem relatively low. However, these are overall the least popular contracts in our data and therefore may not be estimated very precisely.[15]

[15] Data confidentiality agreements prohibit us from publishing contract-level market shares, but the market share of these contracts is less than two percent averaged over our whole sample period.

Table E.7: Predicted CCP matrix (contract-level) for representative non-senior consumer type

	ECS	ECS (g)	EDF	EDF (g)	Essent (g)	ENI	ENI (g)	Eneco	Eneco (g)	Lampiris (g)	Other
ECS	0.9787	0.0077	0.0027	0.0010	0.0013	0.0030	0.0020	0.0003	0.0009	0.0012	0.0013
ECS (g)	0.0432	0.9096	0.0079	0.0029	0.0052	0.0058	0.0056	0.0015	0.0051	0.0062	0.0070
EDF	0.0010	0.0004	0.9861	0.0084	0.0002	0.0016	0.0011	0.0001	0.0003	0.0003	0.0005
EDF (g)	0.0312	0.0149	0.0732	0.5583	0.0569	0.0314	0.0310	0.0132	0.0460	0.0712	0.0727
Essent (g)	0.0012	0.0005	0.0027	0.0014	0.9891	0.0023	0.0014	0.0001	0.0004	0.0004	0.0006
ENI	0.0027	0.0010	0.0038	0.0020	0.0008	0.9554	0.0301	0.0002	0.0010	0.0011	0.0019
ENI (g)	0.0021	0.0010	0.0034	0.0013	0.0018	0.0160	0.9691	0.0005	0.0012	0.0018	0.0018
Eneco	0.0093	0.0041	0.0126	0.0044	0.0102	0.0087	0.0108	0.8457	0.0695	0.0109	0.0138
Eneco (g)	0.0018	0.0007	0.0019	0.0012	0.0006	0.0029	0.0029	0.0053	0.9805	0.0010	0.0011
Lampiris (g)	0.0008	0.0003	0.0014	0.0006	0.0003	0.0012	0.0008	0.0001	0.0002	0.9936	0.0008
Other	0.0008	0.0003	0.0015	0.0007	0.0005	0.0016	0.0010	0.0001	0.0005	0.0005	0.9925

Notes: The table displays the predicted conditional choice probabilities (on the contract-level) averaged over time for one representative consumer type.

Table E.8: Predicted CCP matrix (contract-level) for representative senior consumer type

	ECS	ECS (g)	EDF	EDF (g)	Essent (g)	ENI	ENI (g)	Eneco	Eneco (g)	Lampiris (g)	Other
ECS	0.9918	0.0077	0.0001	0.0001	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
ECS (g)	0.0457	0.9529	0.0005	0.0003	0.0000	0.0002	0.0002	0.0000	0.0001	0.0001	0.0001
EDF	0.0148	0.0046	0.9689	0.0079	0.0003	0.0006	0.0010	0.0001	0.0005	0.0004	0.0009
EDF (g)	0.1957	0.0903	0.0458	0.4986	0.0293	0.0170	0.0176	0.0068	0.0241	0.0364	0.0383
Essent (g)	0.0165	0.0063	0.0015	0.0007	0.9709	0.0009	0.0012	0.0001	0.0005	0.0005	0.0010
ENI	0.0405	0.0129	0.0031	0.0016	0.0019	0.9016	0.0271	0.0007	0.0026	0.0022	0.0059
ENI (g)	0.0187	0.0061	0.0021	0.0009	0.0006	0.0162	0.9520	0.0002	0.0008	0.0008	0.0015
Eneco	0.0815	0.0299	0.0083	0.0032	0.0072	0.0055	0.0098	0.7682	0.0613	0.0092	0.0158
Eneco (g)	0.0114	0.0041	0.0015	0.0010	0.0004	0.0009	0.0019	0.0054	0.9718	0.0007	0.0009
Lampiris (g)	0.0158	0.0054	0.0017	0.0010	0.0004	0.0008	0.0012	0.0002	0.0005	0.9715	0.0016
Other	0.0061	0.0022	0.0005	0.0003	0.0001	0.0007	0.0009	0.0001	0.0004	0.0003	0.9885

Notes: The table displays the predicted conditional choice probabilities (on the contract-level) averaged over time for one representative consumer type.

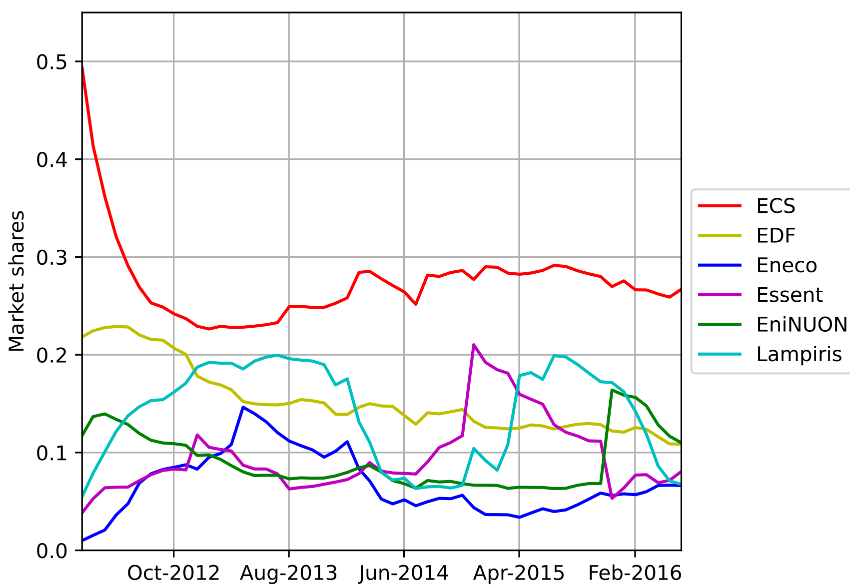
F Additional Counterfactual Results

In this appendix, we present several additional counterfactual results. We discuss the counterfactual market structure from our first set of counterfactuals. We provide a more detailed discussion about how we control for the logit shocks in the regulated monopolist counterfactual and potential supply side reactions when market frictions are reduced. Finally, we compare the counterfactual results from our full model to the results from restricted models that ignore either PCW search costs or switching costs.

F.1 Discussion of counterfactual market structure

In the following, we discuss the simulated counterfactual market structure when either PCW search costs or switching costs are reduced, and the supply side, in particular, contract prices, are held constant. The evolution of market shares over time for each scenario is shown in Figures F.1 and F.2.[16] As a reference, we plot the evolution of the firm-level market shares observed in our data in Figure F.3.

Figure F.1: Counterfactual market shares - Reduced PCW search costs

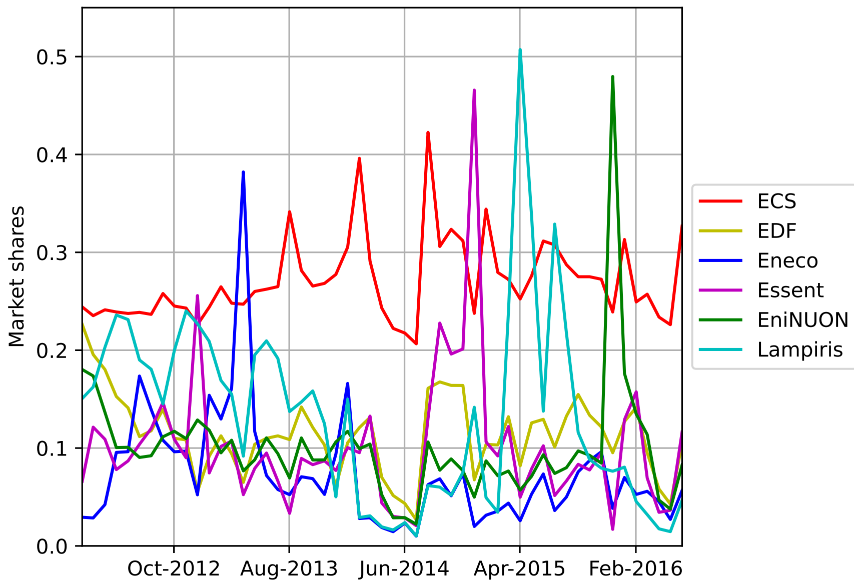


Notes: The figure displays the evolution of supplier-level market shares over our sample period when PCW search costs are reduced by 95% ($\sim$ EUR 4).

Not surprisingly, the incumbent loses customers in most periods, and market shares become much more symmetric than in the status quo, see Table F.1. Overall, the aggregate market

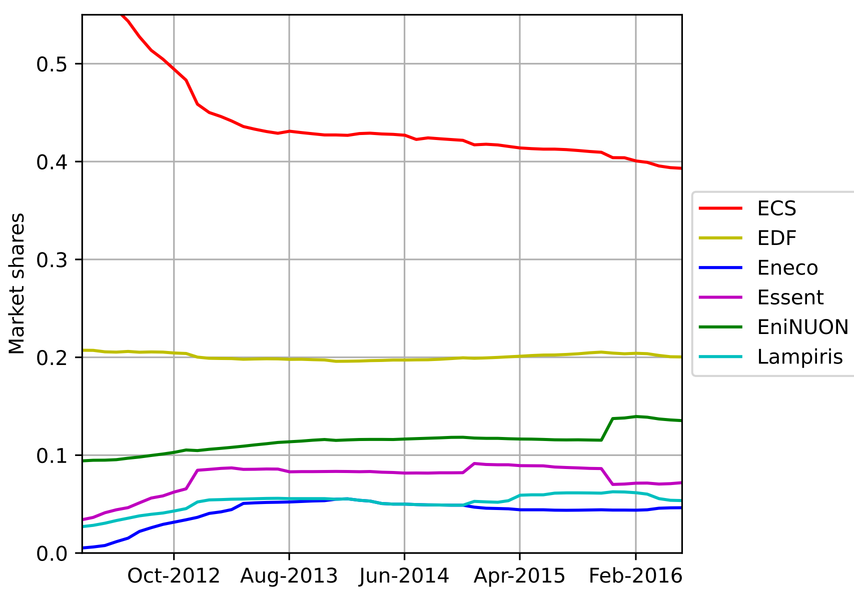
[16]Simulated market structures for other reduction levels are qualitatively similar and available upon request.

Figure F.2: Counterfactual market shares - Reduced switching costs



Notes: The figure displays the evolution of supplier-level market shares over our sample period when consumer switching costs are reduced by 95% (∼ EUR 20).

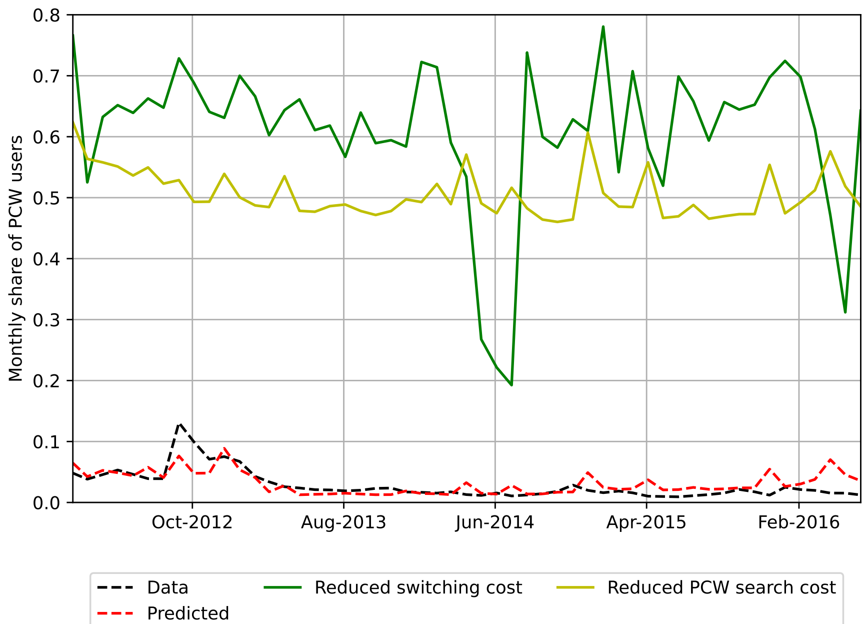
Figure F.3: Observed market shares



Data source: VREG (2017b). *Notes:* The figure displays the evolution of supplier-level market shares over our sample period.

share distribution reacts very similarly to the elimination of the PCW search costs and the reduction in switching costs. Reducing switching costs or search costs does not only affect market shares but also a consumer's decision of whether to use the PCW. In our counterfactuals we find that eliminating either market friction would massively increase PCW usage from 2% to 5% to 50% to 70%. Figure F.4 illustrates the observed and counterfactual PCW usage over time.

Figure F.4: Observed vs counterfactual PCW usage: Baseline model



Notes: The figure contrasts the observed PCW usage with the one predicted by the counterfactuals that reduced switching costs and PCW search costs, respectively.

Table F.1: Counterfactual market shares: Baseline model

	Observed	Predicted	Switching Cost Reduction	Search Cost Reduction	No Info Campaign	Inc. All	Inc. All WH+
ECS	0.44	0.44	0.27	0.27	0.46	0.27	0.29
EDF	0.20	0.20	0.11	0.15	0.20	0.13	0.22
Essent	0.04	0.04	0.07	0.07	0.04	0.08	0.05
ENINuon	0.11	0.11	0.10	0.09	0.12	0.12	0.13
Eneco	0.08	0.08	0.10	0.10	0.07	0.12	0.09
Lampiris	0.05	0.05	0.13	0.14	0.04	0.12	0.08
Other	0.07	0.07	0.21	0.18	0.07	0.16	0.14

Notes: The table summarizes observed (Column 1) and counterfactual (Columns 3 to 7) firm-level market shares averaged over all time periods. Column 1 and 2 compare market shares as observed in the data and predicted by our model. Column 3, 4, 5, 6, 7 display market shares from the switching costs reduction, the PCW search cost reduction, the no information campaign, the hypothetical monopolist offers all contracts at observed prices, the hypothetical monopolist offers all contracts at the indifference markup counterfactuals, respectively.

F.2 Role of logit shocks for consumer surplus in monopolist counterfactuals

In this appendix, we discuss additional details of how we compare consumer surplus under the deregulated status quo with 11 contracts to the regulated monopolist counterfactual with only 2 contracts. Moreover, we discuss consumer surplus changes for a scenario in which we do not correct the surplus changes for the different number of logit shocks.

When using a logit model to compare consumer surplus across scenarios with a different number of products, it is important to compare the two scenarios in a fair manner considering the properties of the logit welfare formula that generates "too much taste for products", see Ackerberg, Rysman, et al. (2005) for a detailed discussion. Therefore, we conduct additional robustness checks to isolate the welfare effects of the logit shocks from the consumer surplus gains from actual product variety.

In addition to computing consumer surplus under a setting with just 2 contracts offered by the monopolist, we also compute the surplus under the regulated monopolist for a "logit-corrected" scenario in which we assume that the incumbent offers identical copies of its conventional and green contract such that its portfolio has the same size as the status quo (5 conventional contracts and 6 green contracts). We argue that the surplus from this logit-corrected calculation is more comparable to the status quo, because consumers receive the same number of logit shocks. Our results are qualitatively unaffected by the logit-correction but they can provide additional insights about the magnitude of the gains from actual product variety in this market.[17] We summarize the different steps of the regulated monopolist counterfactual in the bottom panel of Table 3 and describe the details in the following.

1. Row *Incumbent only* shows that the average consumer loses surplus of around EUR 1 per month when there are only the incumbent contracts (1 conventional and 1 green) in the market.[18] This surplus reduction could be driven either by the elimination of true gains from variety from the entrants' contracts or by the higher number of logit shocks in the deregulated status quo.

[17] Given that we observe the same number of products in each market, the problem of a varying number of products is not relevant for our estimation, but only for our regulated monopoly counterfactuals. Therefore, we argue that our step-by-step approach, in which we illustrate the role of the logit shocks directly, is more informative than an estimation-based approach in the spirit of Ackerberg, Rysman, et al. (2005). We are also aware of alternative discrete-choice models that avoid this problem, in particular, Berry and Pakes (2007). In light of the well-known difficulties in taking the pure characteristics model to the data, we do not explore this route.

[18] Note that the surplus reduction is the net effect of the elimination of market frictions, which increases consumer surplus, and the elimination of surplus-enhancing products from the entrant firms.

2. In order to quantify the importance of the logit shocks, we compute consumer surplus for a setting in which the incumbent offers 5 identical copies of its conventional contract together with 6 identical copies of its green contract, so that the incumbent's portfolio has the same size as the choice set in the status quo. The only difference across the contract copies is that each contract receives a separate and independent logit shock. In this setting, in which the number of products is identical to the status quo, the welfare-increasing effect of the logit shocks should be controlled for, which allows for a better comparison. Row *Incumbent only (logit corr.)* reveals that the net surplus change is still negative for the average consumer and relatively close to the *Incumbent only* case, which does not control for the higher number of logit shocks.

3. It is important to keep in mind that for this case we still assume that consumers pay a switching cost when switching contracts within the incumbent.[19] To better isolate the effect of (contract-specific) switching costs, we next compute surplus changes when consumers can switch freely across the 11 contract copies of the incumbent, see row *Incumbent only (logit corr. and no SC)*. In this case, consumer surplus increases significantly, by EUR 7 to EUR 12 depending on the model specification, which amounts to 25% to 40% of the average monthly electricity bill. On the one hand, comparing the rows *Incumbent only (no SC)* and *Incumbent only (logit corr. and no SC)* reveals that the logit shocks seem to drive a large part of the simulated welfare gains from variety in our application. On the other hand, the comparison between *Incumbent only (logit corr.)* and *Incumbent only (logit corr. and no SC)* reveals that (contract-specific) switching costs have a substantial negative effect on consumer surplus.

4. To obtain a measure of the magnitude of the welfare gains from actual product variety, we compare consumer surplus under the scenario *Incumbent only (logit corr. and no SC)* with a best-case scenario, in which the incumbent offers all contracts available under the status quo and eliminates all market frictions (including contract-specific switching costs), see row *Incumbent all (no SC)* for the results. This reveals that the best-case scenario yields surplus gains that are 10% to 30% higher compared to the case *Incumbent only (logit corr. and no SC)*. These numbers indicate that the entrants' contracts indeed are valued by consumers, even though one could argue that the gains from variety are relatively modest in our application.

[19] This is the reason why the logit-corrected specification can yield smaller surplus than the *Incumbent only* scenario. In the logit-corrected version there is more opportunities for costly contract switching than in the baseline scenario with only two contracts.

F.3 Effects of switching costs on pricing strategies

In this appendix, we provide a more detailed discussion of our conjecture that in our application the consumer surplus gains computed assuming a fixed supply side could well be conservative, i.e., surplus gains from removing market frictions could be larger if reactions on the supply side are taken into account.

Our discussion is based on both the earlier literature on switching costs surveyed by Farrell and P. Klemperer (2007) and more recent theory papers that re-examine the effects of switching costs on equilibrium prices.[20]

From a theoretical perspective it is not clear whether switching costs increase or decrease equilibrium prices because firms face a trade-off between harvesting its existing consumers by charging a high price and investing into a future installed base by charging a low price today. There is a large theory literature on the effects of switching costs on equilibrium prices, but the predictions often depend on the details of the model setup and the parameter values.

In many traditional theory models switching costs lead to higher prices because it can be shown that the motivation to harvest locked-in consumers outweighs the incentive to invest in new consumers (P. D. Klemperer, 1995, p. 516). This is especially true when switching costs are large so that consumer lock-in is perfect, see Beggs and P. Klemperer (1992).

The more recent theory literature on switching costs arrives at somewhat different conclusions and emphasizes the pro-competitive effects of switching costs. However, even the most recent theory models analyze relatively stylized settings. A typical setup considers a duopoly with symmetric firms and consumers that are distributed uniformly across a Hotelling line, consumers receive an iid draw from the Hotelling line in each period, and each period a share of new consumers who do not face any switching costs enters.

For such a setting Rhodes (2014) shows that switching costs decrease prices in the long-run, if firms are sufficiently patient relative to consumers and if switching costs are not too large. Given the assumption of a duopoly with symmetric firms, the central insight of Rhodes (2014) describes a steady state in which both firms have identical market shares. However, if market shares are sufficiently asymmetric[21] he shows that for the incumbent with a large

[20]With the notable exception of Wilson (2012) we are not aware of any theory paper that models search costs and switching costs separately. Therefore, for this discussion we do not distinguish between the effects of PCW search costs and switching costs on pricing strategies and follow the literature in treating switching costs as a black-box that can capture a variety of channels, among others, transactional switching costs or informational switching costs created by search frictions. The model setup of Wilson (2012) is static and features symmetric firms and consumers that have to engage in (sequential) search and also face a switching cost when choosing a different product than their current one. For this relatively stylized setting he shows theoretically that both switching costs and search costs lead to higher equilibrium prices.

[21]Given the assumption of symmetric firms, Rhodes (2014) refers to this situations as the *short-run*.

market share the harvest incentive dominates, which leads to higher average prices than without switching costs.

For a similar setting, i.e., duopoly with symmetric firms, Cabral (2016) and Fabra and Garcia (2015) arrive at similar conclusions: Switching costs are more likely to be pro-competitive when market shares are symmetric, but the more market shares are asymmetric, the less likely switching costs are to decrease prices.

The general consensus from the more recent theory literature is that small switching costs are pro-competitive, especially when market shares are fairly symmetric, while large switching costs are likely to be anti-competitive.

We argue that our application is more similar to a setting for which theory models find relatively little support for the pro-competitive effects of switching costs. In our data market shares are very asymmetric. Even at the end of our sample period the incumbent captures over 40% of the market and entrants typically have less than 10% market share. Moreover, our switching cost estimates are relatively high. Monthly firm-level churn rates are around 1% in our data and the sum of our PCW search cost and switching cost estimates amounts to almost 100% of the average monthly electricity expenditure of the average consumer.

Based on the theory literature alone, it is extremely hard to make clear predictions for our application because it is unclear to what extent the theoretical predictions carry over to a real-world setting with multiple firms[22], differentiated products, correlated preferences over time, and a setting where there are virtually no unattached consumers, because the market started in a setting where all consumers were with the incumbent. Whether the harvest or investment motive dominates firms' pricing in practice is therefore an empirical question. An important implication of the theoretical predictions is that eliminating switching costs completely may not be desirable since small switching costs may decrease equilibrium prices. Consequently, empirical studies on the magnitude of the switching costs are important, because they provide an essential input into empirical supply models.

The empirical literature that finds pro-competitive effects of switching costs mostly analyzes markets that are quite different from retail electricity markets; therefore, insights from this literature do not necessarily carry over to our application. Dubé, Hitsch, and Rossi (2009) is a prominent example that uses data on consumer packaged goods (CPG) industries, specifically for orange juice and margarine. Their setting differs from ours in at least two important

[22] Pearcy (2016) shows for his setup that the number of firms in the market can determine whether switching costs are pro-competitive or anti-competitive.

aspect: First, CPGs are much more differentiated than retail electricity contracts, for which we find some but not very large differentiation.[23]

Second, in CPG industries consumers tend to be locked in less than in our application.[24] Table 1 and Figure 1 in Dubé, Hitsch, and Rossi (2009) suggest that consumers switch orange juice or margarine products on average 20% of the time. This contrasts sharply with the switching rates of only 1-2% in our application. The fact that consumers are relatively more likely to switch can make it profitable for firms to compete for new customers without having to sacrifice a lot of profit from the locked-in consumers, i.e., in such a setting the investment motive can outweigh the harvest motive and so decrease equilibrium prices. For levels of switching costs that result in lock-in rates on the order of 99% –which is similar to what we observe in our setting–, Dubé, Hitsch, and Rossi (2009) also find that switching costs do not decrease equilibrium prices, see Dubé, Hitsch, and Rossi (2009, Figure 1 and Table 1).

In line with the argument that large enough switching costs are more likely to have anti-competitive effects, Viard (2007) finds empirically that in the market for 0800-numbers services, an industry were switching costs are finite but relatively large, removing switching costs led to lower prices.

In addition to affecting firms' pricing strategies, reducing switching costs can also affect firm entry. We conjecture that in our application reducing market frictions is likely to increase net entry, which should result in additional competition and larger welfare gains than a counterfactual with a constant supply side. It is well established that switching costs can make small scale entry easy, if there is a sufficient share of unattached consumers in each period (Farrell and P. Klemperer, 2007, p. 1998).

In our application, however, there are virtually no unattached consumers. Therefore, we judge it unlikely that small scale entry is a viable source of competition. On the flip side, large scale entry in industries with switching costs is difficult, because it is very hard to attract consumers that are already locked-in. Furthermore, in practice, entrants are faced with an adverse selection problem: Only consumers who are relatively less loyal, i.e., have a low switching cost, will be attracted by the entrant. If an entrant can only attract high-frequency switchers, the entrant might not find it profitable to attract these consumers,

[23]In the limit case where products are fully homogeneous switching costs are usually anti-competitive (Rhodes, 2014, p. 163).

[24]Switching costs in CPG industries are likely to be mostly psychological rather than transactional. When going to the supermarket the cost of picking a different product from the same shelf is plausibly much lower than the hassle from transferring a subscription contract. Arie and Grieco (2014) analyze a similar setting theoretically and also find pro-competitive effects of small switching costs.

because it knows that it will not be able to lock-in and harvest these consumers in the future (Farrell and P. Klemperer, 2007, p. 2000).

Furthermore, we argue that reducing market frictions is relatively unlikely to lead to significant firm exit. This could happen if lowering switching costs decreases prices and margins, so that fewer firms can survive in the market. As a consequence, some firms exit, competition will decrease and equilibrium prices could rise again. In light of the fairly large wholesale-retail margins of around 80% observed in our data[25] we believe that it is unlikely that lower switching costs would lead to significant firm exit. Therefore, we expect the effect of lowering switching costs on net entry to be positive.

Finally, there are more subtle effects that we judge likely to increase welfare in our application further when switching costs are reduced. For example, even if switching costs do not affect equilibrium prices on average, market frictions can prevent consumers from reacting to preference shocks which results in less efficient matching of consumers and products.

In light of these points, it is conceivable that our consumer surplus gains from eliminating market frictions are a lower bound for the consumer surplus gains that could be realized in practice when the supply side reacts to the reduced frictions. Answering this important question more rigorously with a full-fledged supply model is a challenging but important topic for future research.

F.4 Comparison of full and restricted models

Lastly, we compare the counterfactual results from our full models to the ones based on restricted models that either ignore switching costs or PCW search costs. Table F.2 summarizes the results. Theoretically it is hard to predict how the counterfactuals change when the restricted models are used. In our application, we find that some consumer surplus predictions differ significantly from the ones obtained from the full models. For example, the gains from reducing switching costs are underestimated by 50% when PCW search costs are ignored (EUR 3.80 vs. EUR 7.99), while the gains from reducing PCW search costs are overestimated by more than 100% when switching costs are ignored (EUR 5.43 vs. EUR 1.73). Most importantly, and in line with our results for the average contract valuation discussed in Section 6, restricted models consistently underestimate the gains from product variety, and therefore overestimate the welfare gains from abolishing retail competition in favor of a regulated monopolist. For example, when we evaluate the consumer surplus effects of a hypothetical monopolist and use the restricted model without switching costs, the logit-

[25] For a detailed discussion of the observed markups, see Appendix A.1.

corrected monopolist generates practically the same surplus as the best-case scenario (EUR 5.91 vs. EUR 6.14). When we evaluate the regulated monopolist using a restricted model without PCW search costs, the (logit-corrected) monopolist generates even higher surplus than a firm that offers all available contracts without any frictions (EUR 39.52 vs. EUR 32.73).

Table F.2: Comparison of selected counterfactual results: Full vs. restricted models

	Baseline	Extension	No switching costs	No PCW search costs
Reduced switching costs	7.99	7.77	0.00	3.80
Reduced PCW search costs	1.73	2.30	5.43	0.00
Automatic lowest price	-7.48	-7.23	-8.14	-17.15
Incumbent only	-1.34	-1.00	0.00	1.98
Incumbent only (no SC)	1.92	0.80	0.00	10.39
Incumbent only (logit corr.)	-0.57	-1.18	5.91	4.22
Incumbent only (logit corr. and no SC)	12.41	7.44	5.91	39.52
Incumbent all (no SC)	13.25	10.00	6.14	32.73

Notes: The table compares the welfare results from several couterfactual simulations for both the baseline model with homogeneous market frictions and the model extension with heterogeneous PCW search cost and switching cost, as well as the restricted models that either ignore switching costs (ψ) or PCW search costs (κ). For all counterfactuals, the numbers indicate the welfare gain in EUR/month for the average consumer. Row Incumbent all (no SC) *indicates the best-case scenario in which one firm offers all currently available contracts without any market frictions.*

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