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What drives drivers? Switching, learning, and the impact of claims in car insurance

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ABSTRACT

People rarely change their service provider, and they generally stick instead with the incumbent. This inertia is usually interpreted as market friction that is mainly due to search or switching costs, or is explained by learning about an intangible good. The actual triggers for learning are less studied, especially whether the learners' own behavior triggers the learning. We analyze field data on choices made about car insurance renewal, in which all the features offered and chosen, including claims details, are known. We follow an expected utility approach, and by controlling for individual factors we find that the decision to switch insurers is mainly driven by the direct monetary gains that result from changes within choice sets rather than changes in the default good. The learning effects are present, and, surprisingly, there is a difference in consumer behavior. Consumers at fault for a claim tend to switch significantly less than those who suffered a third-party-induced claim or made a claim with other causes.

1. Introduction

The loyalty of consumers can be observed in many different contexts. We usually go to the same hairdresser, we buy groceries from the same supermarket, and we use the same washing powder. Even though there can be a cheaper alternative of the same quality, many people carry on in the way they are used to and so lose some money.

The same is true in the insurance market. Many studies of U.S. health insurance (Abaluck & Adams-Prassl, 2021; Handel, 2013) show that people choose options that cost them more than alternatives of similar quality. Market frictions have mainly been used to explain this deviation from the rational behavior of *homo economicus*, as it is either too expensive to search for the information needed to make rational choices, or too costly to switch service provider because of the direct cost or the effort that doing so requires. Insurance is an exciting product to study because it takes time for the customer to understand their preferences or learn about the quality of the good or service on offer. This learning starts with an insured event that leads them to claim an indemnity from the insurer. Some studies use claims as a trigger for learning and switching, like Israel (2005), but we are not aware of any studies that use comprehensive datasets and investigate the causes of claims made on car insurance.

This study looks into the auto insurance market, and our interest is in the choice by car drivers to change their insurance provider. We contribute to the literature on the intertemporal consumer choice of experience goods in two ways. The first novel feature is that we study switching behavior within a single category of goods using a unique dataset from the Estonian market.

Motor insurance in Estonia is always provided under two separate policies, where Motor Third-Party Liability (MTPL) covers the damages caused to other people, and Motor Own Damage (MOD) covers the losses suffered by the insured person. The first is mandatory and fully standardized, and the consumer cannot learn from it because the claims service is not experienced by the person who bought the cover. The second policy is also standardized in our setting, but it allows the policyholder to learn from the claims service experience.

A common feature of most of the earlier studies is that the researcher cannot directly observe all of the goods and their characteristics that the

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consumer has considered. Many excellent studies use laboratory experiments or surveys or indirectly derive some features of the choice sets (Honka, 2014), though some studies use actual field data. These studies mainly consider U.S. health insurance (Abaluck & Adams-Prassl, 2021; Handel, 2013) and a few other areas like television providers (Shcherbakov, 2016), utility contracts (Hortascu et al. 2017), and pension fund management (Luco, 2019). Another feature of many earlier studies is that their data come from just one service provider, so the incentives for switching are hypothetical or unobserved.

The second novel feature of our study is that it looks at the triggers of the learning and service experience. In insurance, the consumer learns after experiencing an insured event and claiming the indemnity. The study by Israel (2005) looked at how quickly consumers learn after a claims experience and how much of their learning they incorporate into subsequent buying decisions. He used data from one insurer on the departures of consumers before and after they made car insurance claims. Our data contain the dates and explanations of claims from several insurers against a standardized cover feature set. We have sorted the claims into three categories for who caused the accident. The categories are Self-Induced for claims caused by the driver; Third-Party Induced, which includes theft, vandalism, and collisions where a third-party is at fault; and Other, which covers incidents like fire, broken windscreens, and wild animal collisions. By using claims causes we can depict the decision to switch and the learning in a novel and more precise way.

Our method was to exploit a setting where consumers make a forced choice between standardized alternatives when they enter the first insurance contract in year one, and then they are presented with the same choice with all the other options again the next year. However, if the consumer is satisfied with their previous choice or ignores the renewal option, the contract will continue with the same service provider that they had in the previous year. In contrast to other consumer switching studies, we observe actual choice sets of prices and product features offered, and the choices made over five years. We do not need to impute any significant inputs.

Our setting does not involve any direct monetary costs for search or switching. Our data cover insurance contracts for leased cars and the leasing company prescribes what cover is needed, so there is no need to search for the right cover. In addition, the panel of choices on offer that is presented to the customer includes most of the options available in the market. The potential outside good for the whole consideration set is unlikely to be better in its cover or premiums than the policies in the choice set. The frequency of choice is exogenous, so we need not address the endogeneity of the timing of decisions. The primary data come from the largest insurance broker in Estonia and include pricing data on all the offers made, the actual choices and claims.

We set up an econometric model of choice that describes the likelihood of the consumer switching insurance provider and captures different triggers for switching and their magnitudes, together with product characteristics like prices, the brand preference for the customer's given insurer, and demographic characteristics. It also captures claims, and controls for customer preferences towards a particular insurer to see the learning effects from one period to another. We use the number and monetary value of the claims and all the details about their causes.

We estimate the model using individual-level choice data in an unbalanced panel covering the full years 2012-2017, and find that inertia plays a significant role in this choice context. We can separate previously tested determinants like age, gender and product characteristics, and add different triggers for learning about product quality in the form of switching triggers. As expected, changes in pricing play a significant role. When the incumbent increases its prices by 1% from the year before, the likelihood of switching increases by 0.2 percentage point, whereas a price difference of 1% between the offer of the incumbent insurer and the cheapest alternative available increases the probability of switching by 2 percentage points from the base value. In most of the models estimated, we show that if the consumer merely experiences any type of claim, it has no impact on switching and learning. Once we control for specific claim types, we see that consumers are less likely to switch when they are at fault. Their propensity to switch increases when a third party was the reason for the claim, but not with the other reasons for an accident, hinting at a behavioral implication of our study.

The rest of the paper proceeds as follows. We begin by giving an overview of the related literature in Section 2. Section 3 describes the data and the choice context that creates the data for our research. Section 4 introduces the model used. Section 5 continues with the estimation results and discussion, Section 6 contains robustness checks, and Section 7 concludes.

2. Previous literature on consumer switching

Neoclassical economic theory posits that consumers are homo economicus, meaning they maximize their utility, and they use all the information available in doing so. Consumers are also assumed to process that information appropriately, and their preferences are assumed to be time-consistent and affected only by their payoffs and not by the decision frames.

The validity of these assumptions has been studied extensively, especially in behavioral and experimental economics. A common feature in the research has been to establish that there is inertia in updating choices over time. The literature on applied economics has in the past decade documented significant default effects (DellaVigna, 2009). Consumers often do not search for better options, meaning they do not use all of the available information or do not seek information in order to make a new choice from time to time. Moreover, even if the information is available, they do not process it correctly in a way that would let them choose better options. They stick with their previous decision rather than deciding anew and switching when new information arrives.

Consumer inertia as a deviation from rational behavior has mainly been explained by two types of market friction. The first is the cost of searching for the optimal solution, which was described in a seminal article by Stigler (1961). This idea is that the information needed is not readily available and it takes time to search for it, which has an opportunity cost. The second type of friction is related to switching, as there may be direct or indirect costs from switching the current service provider. These approaches mean that seemingly non-optimal behavior can be rationalized by the adjustment cost from search and switching costs.

Early studies in this field like Berger et al. (1989) focus on either search or switching costs. Some subsequent studies such as Schlesinger and Schulenburg (1993) examine both types of cost in decisions to switch car insurers using surveys and various parameters for insurer quality or develop implications on competition and welfare like Wilson (2012). Einav et al. (2010) describe switching decisions in the car insurance context and find that the inertia explained by market frictions is substantial. They also stress the need to have individual-level data when studying general insurance choices, because contract terms and prices are highly customized for each consumer.

Individual-level data have mainly been used to study consumer switching in health insurance markets. Handel (2013) tries to quantify inertia in health insurance choices in the U.S. and finds that it causes $2000 of financial loss per year on average relative to the optimal solution in employer-sponsored health insurance. The study by Ho et al.

(2017) has an annual savings estimate in Medicare D choices of around $1050 for the average consumer. They identify this from the variation in the data on actual choices. Many other studies document choice inefficiencies and inertia in health insurance (Abaluck & Adams-Prassl, 2021; Bhargava et al., 2017, and Ho et al., 2017) and recent attempts have been made to separate inattention to the choice from switching costs, like Heiss et al. (2021).

Outside of the United States, Boonen et al. (2016) examine the propensity to switch based on the price to consumers, service quality, and information search in the competitive Dutch health insurance market. They find that the switching propensity depends negatively on the quality of insurance contracts, positively on price and education, and negatively on age. Searching increases the propensity to switch. There are also studies on pure behavioral aspects of switching like Schmitz and Ziebarth (2017), who consider the willingness to switch depending on how the switching decision is framed.

There are fewer studies that use field data to study insurance types other than health insurance. Honka (2014) estimates the costs of both search and switching for car insurance in the U.S., but she does not incorporate learning effects. She finds that the average switching cost is around $40 per consumer, with the cost of the search ranging from $35 over the internet to $170 when a local agent is used. Unlike our study, she used comprehensive consumer survey data and pricing data to reconstruct implied choice sets in order to estimate the magnitude of the search and switching costs. Her dataset contained fewer than 1000 consumers. Kiss (2019) uses data on the Hungarian insurance market for Motor Third Party Liability, finding the search and switching cost to be between €60 and €110 per policy, and uses general pricing sheets to recover the implied choice sets for individual choices.

Sims (2003) proposes that individuals have limited capacity for processing information, which is an approach that is closely related to the adjustment cost explanation. In this case, it might be rational for consumers not to spend much time trying to understand different choices if they believe their choices would ultimately remain the same.

One particular type of information processing argument appears in the learning literature (or Evans et al., 2001, Sargent, 1993 for example). Learning has a specific form with insurance, since insurance is an intangible good. Only when an indemnity is claimed does the consumer experience the quality of the product, especially if the products are otherwise of sufficient quality and meet expectations. Israel (2005) studies learning using the departure decisions of consumers. He estimates a learning model and lock-in from the data from one insurer and uses market averages to aggregate other offers. We depart from this setup by adding the attributes of competing offers and new choices. Switching has also been studied from field data in the context of moral hazard (Liu et al., 2020).

Osborne (2011) incorporates both learning and switching costs for a packaged consumer good that is bought frequently. He finds that both learning effects and switching costs are present and that consumers learn about their tastes by purchasing new products. He also argues that leaving out one or the other effect may lead to significant biases.

Miravete and Palacios-Huerta (2014) study consumer switching decisions in a U.S. local phone market. In doing so, they distinguish between two effects, which are the impact of past endogenous experience and learning, and the impact of pure inertia. They conclude that consumers can learn from bad choices and make better decisions in the next period. In subsequent work, Hortaçsu et al. (2017) look at switching decisions in the Texas residential electricity market using monthly consumption data for households. They estimate a two-stage discrete choice model to separate inattention to decisions from brand and other preferences, and they conclude that people consider switching their service supplier once every 4-5 years.

3. Data and context

3.1. Institutional and choice context

The Estonian motor insurance market has some specific features that should be borne in mind when interpreting the setup of our study in a broader international context. Like those in several other Central and Eastern European countries, customers in Estonia usually buy two motor policies for their cars. Having an MTPL policy is mandatory, and every vehicle driven on public roads has to have this cover. The MOD policy is optional, and a lot of car owners choose to buy it, more often for newer cars and always for leased ones. The older a vehicle gets, the less likely it is to have a Motor Own Damage policy, except in the case of leased cars, where leasing companies set it as a requirement. Our interest in studying learning effects means that we only use Motor Own Damage policies.

The Motor Insurance Bureau collects all statistics on claims made under MTPL insurance, which is the most common type of car insurance and is compulsory. Each insurer can use information on all previous claims in their MTPL pricing. However, there is no central database for MOD claims and no market-wide no claims bonus for MOD policies. When an MOD policy is signed, no insurer asked for any previous claims history during our sample period. Some insurers use information on MTPL claims as one of the pricing inputs, but there is no generally accepted best practice for doing this, and even if there is, it only covers the damage caused to other vehicles, not the damage done to the customer's car.

The decisions made by the consumers in the dataset represent insurance choices related to around 30% of the total volume of leases issued in Estonia in 2012-2017. Leasing companies require lessees to have two types of cover for their leased cars, with the Motor Third Party Liability that is compulsory by law, and Motor Own Damage, where the leasing company sets the minimum cover level. This means that all leasing customers must have comprehensive motor cover, which Motor Own Damage is part of, with standardized features set by the leasing company. They can buy cover from different insurers and can buy their insurance policies on a stand-alone basis or through the insurance broker who works for the leasing company.

The leasing companies set the following minimum requirements for cover, which have been stable over the period we observe:

- the cover is comprehensive cover, or the perils named in it must be: fire, earthquake, explosion, theft, vandalism, windshield, collision with animals, any damage, and loss of the car;
- the insured value must at all times correspond to the amount outstanding under the lease payment schedule
- all damage must be repaired, except in cases of total loss or theft. For all cars that are less than four years old, only original, category A, spare parts may be used for repairs, and these cars must be repaired at the official dealer workshops if the customer demands. B-category spare parts are also allowed for vehicles that are four years old and older, and the repairs do not have to be done at the official dealer workshops;
- the level of deductibles must be either €200 or €300, with some minimal variation allowed, for repairs, and the deductible for theft or total loss can be a maximum of 15% of the insured value.

If a lessee buys motor insurance through the leasing company using the broker, the broker sends a standardized quote request electronically to almost all the insurers operating in the Estonian market. The quote request contains the same list of perils to be insured with equal pricing inputs for all insurers, and quotes are requested for two standardized deductible levels of €200 and €300. The broker combines these quotes

into a panel of choices with the prices from each insurance company for each deductible level. This is sent to the customer alongside the lease offer. After the customer indicates which their preferred insurer is, an insurance certificate is issued. Consumers can equally buy their insurance by applying their own preferences, for a certain brand that is not presented in the panel for example, or by using a discount from a direct online purchase from some insurers. However, most consumers choose to buy insurance from the leasing company and have it managed within the overall leasing arrangement.

The set of choices contains almost all the goods that the consumer can consider, and the insurance companies represented in the panel have a total market share of more than 90%. The leasing companies additionally require all insurers to match the price offered in the leasing insurance panel if they decide to sell the same product through a different sales channel. This means the price of a potential outside good in the choice set cannot be any different to that in the consideration set.

All insurance policies are signed for one year and renewed yearly for the whole duration of the underlying leasing contract. After the first year, the consumer chooses again from the standardized competing offers of different insurers. Consumers are free to stay with their current insurer or switch to another. At the same time, insurers are free to change the price at renewal in response to their claims experience with the customer or for any other commercial reasons. Their choices in this can be tracked.

3.2. Data

We use data from multiple sources. The first source is one of the largest insurance brokers in Estonia, which serves and administers insurance policies for the big car leasing companies. A lease is the most common way of buying a new car in Estonia, and some 80% of all cars newly sold in Estonia in the period observed were leased. Leases are a common substitute for car loans. The data on insurance offers and policies cover the years 2011-2017 and have been combined and anonymized by the broker. We can directly observe all the insurance offers made to customers, including prices and insurance coverage features like deductibles and the perils insured, though the list of perils is standardized. We also observe choices of customers and demographic factors like age and gender, and we use the car data as a proxy for consumer preferences. As our study focuses on switching by consumers, we have excluded all commercial customers from the dataset.

The second data source is insurance claims for all policies in 2012-2017 and their match to policies, with both datasets coming from the same broker. Making a claim might affect the decision to switch as the customer learns directly from the good or bad service they receive when the claim is handled. Switching might equally be impacted by the pricing decision of the incumbent insurer for the next period. We expect the likelihood of switching to be higher if the incumbent insurer raises the price.

We have also gathered a third set of data on the reputations of insurers. It is plausible to assume that each one may have a specific reputation for claims handling and that consumers might consider this when they make their purchase decisions. The data come from the Estonian Insurance Association, which has an ombudsman body that resolves customer disputes with insurers. The reputation variable is the relative reputation against the average market reputation in a given year. The reputation itself measures the number of customer disputes against the number of customers, and it is interpreted that a higher value indicates a weaker reputation.

Combining these datasets gives us an estimation sample that is an unbalanced panel covering data for the full years of 2012-2017. As we only study renewal decisions, 2012 is used for earlier policies that have come up for renewal, and for which we have complete claims records for the previous years.

Two features make the dataset unique. The first is that the insurance offer made together with the leasing offer contains a panel of choices offered by different insurers, with the leasing company standardizing the cover provided in these offers and the deductible levels. This means the choice set is standardized and there is no self-selection bias towards a particular insurer, as might be the case if the study only used data from one insurer. It also means that there is no need to search for information before making the choice as all the offers will comply with the requirements of the leasing company. The second feature is that the offers are highly comparable. The standardization of the cover provided, with the same list of perils and standardized deductibles in each offer, means the offers are essentially the same, with only the prices differing. There might be some slight variation in cover features offered above the minimum, but there is minimal incentive for the insurer to offer those since they may raise the price for the customer and make the offer less attractive than those of competitors.

To give a standardized sample, we have only included customers that take out insurance with a deductible of around €200, and we have omitted all other choices. For the sake of clarity, the customer can switch from a higher deductible to a lower one and the other way. However, no customers in our sample did this during the period observed, and the overwhelming majority of more than 96% of the customers opted for the

Table 1
Summary statistics of the sample.

Variable	Mean	St. dev.	Min	Max
The probability of switching	0.11	0.31	0	1
The probability of switching conditional on no claims	0.10	0.30	0	1
The probability of switching conditional on at least one claim	0.13	0.34	0	1
Consumer characteristics				
Gender (= 1 if the policyholder is male and 0 otherwise)	0.62	0.48	0	1
Age, years	44.72	10.93	20	82
Engine power, in MW	0.09	0.02	0	0.37
Car value, in € 1000	14.43	7.65	0	388.78
Car age, years	3.71	2.28	1	12
Product characteristics				
Actual policy price, in €	393.78	147.13	116.87	3191.25
The relative price change of incumbent insurer at renewal, in %	-2.63	12.18	-73.55	579.75
The relative difference between the incumbent and minimum price offered, in %	8.12	16.39	0	926.14
The relative difference between incumbent insurer offer and mean price offered, in %	-13.15	12.69	-90.25	253.45
Service provider reputation relative to the sector's mean reputation in a given year	-0.15	0.83	-0.98	7.08
The proportion of consumers who actively search for an insurer	0.01	0.12	0	1
The proportion of policies with at least one claim per year	0.20	0.40	0	1
Total claim amount per year, in €	1154.91	1516.35	0	27378.27
The probability of switching by claim type				
Self-Induced claims	0.08	0.27	0	1
Third-Party Induced	0.17	0.38	0	1
Other claims	0.09	0.29	0	1
The number of consumers observed	20,759			
Number of observations	50,553			

Notes: A more comprehensive description of the variables is provided in Appendix 1. Service provider reputation is measured as the share of each insurer's disputes with customers relative to its market share. Self-Induced claims are defined as claims induced by the driver. Third-Party Induced claims are defined as theft, vandalism, and collisions at third-party fault. Other claims are defined as fire, broken windscreens, wild animal collision, breakdown, and all other reasons.

lower deductible level.

Table 1 provides summary statistics for the data available. The definitions of the variables are given in Appendix 1. The first observation from Table 1 is that only about 11% of consumers on average switch their insurance provider in any given year. The probability of switching fluctuates between 7% and 15% over the years, without any trend. The average probability of a switch is 10% if there were no claims during the year, and the probability of switching is 13% if at least one claim was made. It seems that customers who experience a claim tend to switch more often.

Our dataset contains slightly more males than females, and the average age of a customer is 45. We will look at the issues of potential multicollinearity between explanatory variables when developing the model. A more detailed view can be found in Appendix 2, which provides the correlation matrix of the variables.

The average price paid for a Motor Own Damage contract is €394. There is significant variation between the prices offered, and the consumer does not always choose the cheapest option. We have split the price changes into two parts. We start with what the incumbent insurer offers in comparison to what they offered in the previous year. Table 1 shows that the average price for the same consumer fell by 2.6% or approximately €10 if the consumer stayed with their current, incumbent insurer. The second price element is the difference between this price and the cheapest other option available.

Although the incumbent insurer cuts their price from the previous year on average, more affordable options are still available. The average price difference between the incumbent's offer and the cheapest offer is 8.1%, or approximately €32. The incumbent's offer meanwhile is 13.2% or €53 cheaper than the mean price offered in the panel.

The relative reputation of the service provider has a mean value of -0.15 because of the variable's construction. However, the distribution of this variable is skewed towards a couple of insurers that have a relatively large number of disputes relative to the market, while some other insurers have very few. The variable having a positive sign indicates relatively more disputes and a worse reputation than the average.

Only 1.45% of the customers told the leasing company that they would take care of their insurance for themselves and present policies that comply with the requirements of the leasing company every year. These customers have been labeled "Active" in our study. This label is also used for those who have consented to receive the offers from the full panel of different choices and chosen their cover from an insurer presented in the panel. This might be an indication of a very attentive consumer.

Claims can act as triggers or accelerators for learning about the actual quality of service. We use data on the number of claims and their monetary value, and detailed descriptions of each of them. Around 20% of the policies have at least one claim per year, and the average value of the claims was €1155 per year. As there is no established market standard for categorizing claims, we sorted all the claims into three categories from their descriptions.

If a Third Party caused the claim, the consumer could not have avoided the incident that provoked the claim. The second claims category with a dummy for Self-Induced claims means that the customer's behavior caused the claim. This category covers incidents when the insured driver is at fault, like hitting other cars, driving off the road, or hitting other objects. The behavioral implications that impact Self-Induced claims may be different to those affecting the last category. We group other causes of claims where the trigger is neither the driver nor a third party and is primarily natural, such as fire, collision with wild animals, mechanical breakdown, and glass claims, into a third category as a baseline case labeled Other Claims.

Table 1 shows that the probability of switching in the sample is significantly higher if the claim was triggered by a third party than it is with other causes. In our sample, 17% of customers whose cars were damaged by a third party switch their insurer, while 8% of those with self-induced claims do so, and 9% of those whose claims have other causes.

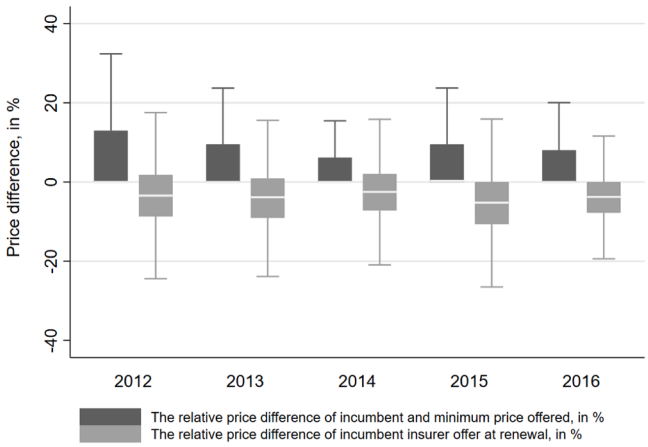

Fig. 1. Box plot of the time dynamics of relative price difference variables, 2012-2016.

There is only a slight variation in the relative price differences over time, as can be seen in Fig. 1. In our sample, the incumbent insurer's price at renewal falls each year because of the institutional setting where the renewal offers are put into a new decision context every year. All the insurers are competing for the same customers again at each renewal. They cannot afford to use dual pricing for new entrants and existing customers, where the renewal price starts to increase afterward. In around 50% of the cases in our dataset, it turns out that the incumbent actually offers the lowest price. There is also a difference against the minimum price for each year, which might indicate customer preferences for a specific insurer or real default inertia that we try to disentangle later.

4. Modeling and identification

Before describing the model, it is essential to emphasize the choice context described in Section 3.1. All customers need to buy an insurance policy because of the requirements set by the leasing company. These requirements mean they do not need to decide which cover they want to buy. This is standardized, and all the insurers are quoting the same parameters in response to the broker's request. The broker combines all the quotes into a standardized panel of different offers to satisfy the leasing company's requirements for the features of the cover. This means there is only a limited reason to search for information as the customers are presented with offers from 90% of the insurance providers in the total market. Insurers in the panel can have no monetary incentive for giving a better price for the reasons explained earlier.

As explained in the previous section, only a tiny fraction of customers, whom we have labeled "active", decide not to use the broker's services and opt to buy a policy themselves. We have also used this feature in the robustness checks as it may be a proxy for eagerness to search. This might give an indication of customer preferences that are not controlled for with the other variables we use.

Since the leasing company sets the search criteria for the coverage needed and the prices, and other observable outside offers cannot be different from the offers made in the broker panel except in their brand

and some limited exceptions that are not priced separately by insurers,[1] we can assume that the search and choice can be modeled simultaneously. In assuming this, we follow Honka and Chintagunta (2017).

Many previous studies like Handel and Kolstad (2015) or Honka (2014) have used the random utility approach. Our setting results in a simplified logistic approach because of the institutional setting explained in Section 3.1. In our case, consumer i can either stay with the current insurer j within period t by obtaining utility U_{ijt}, or can switch insurer to j' and obtain a different utility $U_{ij't}$. The consumer switches their current insurer for a new one whenever $U_{ij't} > U_{ijt}$.

The utility gain from switching is modeled as the difference between these two utilities $U^*_{it} = U_{ij't} - U_{ijt} = \boldsymbol{X}'\boldsymbol{\beta}_i + \boldsymbol{Y}'\boldsymbol{\beta}_{it} + \boldsymbol{Z}'\boldsymbol{\beta}_{it} + \varepsilon_{it}$.

Vector $\boldsymbol{X}$ contains consumer characteristics, vector $\boldsymbol{Y}$ contains the utility attributes of the products, and vector $\boldsymbol{Z}$ contains effects from learning about the insurance provider's service over time, which is triggered by claims. We will explain the variables in more detail below. The random terms ε_{it} represent elements that are known to the customer, but which the researcher cannot observe.

It seems appropriate to take a simplified logistic approach to investigating switching behavior that follows both Boonen (2016) and Kiss (2019). We aim to estimate the probability of the customer switching insurer, where the dependent variable is the decision to switch insurer at renewal. Switching means having a different insurer in period t to that in period t-1. In the logistic approach, this will be

$$Pr_{it}(switch = 1) = \frac{exp(\beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{Y}_{i,t} + \beta_3 \boldsymbol{Z}_{i,t})}{1 + exp(\beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{Y}_{i,t} + \beta_3 \boldsymbol{Z}_{i,t})}$$

Like Honka (2014), we include different sets of variables. In order to control for any observable heterogeneity in consumer characteristics that may explain switching, the vector $\boldsymbol{X}_i$ contains factors like age and gender. As we have a setting where cars are leased and the value of the car is transformed into a monthly installment, we use car value or car age as a proxy for consumer income. Appendix 2 shows that car age and car value are correlated with each other. We also use engine power as a proxy for consumer preferences.

The vector $\boldsymbol{Y}_{i,t}$ contains observable product characteristics such as direct monetary gains from switching, and controls for consumer preferences with dummies for the insurer and the make of car, and the engine power of the leased car. Following Handel and Kolstad (2015) among others, the differences in price between the different options play a significant role as a driver for switching. As explained in the previous section, we have divided the potential gain into two parts.

The incumbent insurer can change the price at each renewal, and it is on average 2.6% lower in year t than in the previous year t-1, but there was significant variation within this. The variable is "The relative price change of the incumbent insurer".

There is potential endogeneity in pricing because the incumbent's renewal price may depend on claims made in previous periods by customers, and the incumbent insurer uses its own experience from the claims in its pricing. To control for the effect of the incumbent insurer's renewal offer price changing as a result of a claim, we interact the claim type and the difference in the incumbent insurer's price in some specifications. This helps to separate out the monetary effect of experience pricing from other monetary incentives.

We also include the relative price difference between the incumbent's offer at renewal time t and the minimum price in the choice set at the same renewal. It is reasonable to assume that this price difference plays a role in switching. The other benefit of dividing the potential impact of pricing on the switching decision into two parts is that it can ascertain whether there is a difference between the total monetary gain and the different elements that may depend on the monetary gain or loss resulting from a claim with the incumbent insurer.

Many price differences turn out to be zero, especially the difference between the incumbent renewal offer and the cheapest offer. About a third of the incumbent offers in our dataset were the cheapest offer made, as also depicted in Fig. 1. To capture the maximum amount of information for the estimation and so as not to lose the observations where the price was no different to either the incumbent's price from the previous year or to the minimum price offered, we use the inverse hyperbolic sine (IHS) transformation[2] for price differences, as IHS is defined for zero differences. It can be interpreted similarly to log transformations, as explained in Burbidge et al. (1988).

We also want to control for insurer brand preferences. We proxy this by the length of the relationship in years since the first contract for a given car between the incumbent insurer and the given owner.

The vector $\boldsymbol{Z}_{i,t}$ contains variables that describe the learning effect. To examine the learning effects for insurance as an intangible good following Israel (2005), we add a dummy for having at least one claim during the period before renewal. We later replace this general claim dummy with dummies for different claims categories in order to capture potential behavioral drivers in some specifications. We also want to control for two different effects on learning. The first is the indirect word-of-mouth and publicly available information that the consumer may use without having experienced the service after an accident. We control for this by adding the reputation indicator we constructed from the number of customer disputes for the insurer relative to its market share. This variable enters the model with a lag. As explained earlier, we want to separate out learning effects that result from a claim, and so we interact the lagged claims with the price differences of the incumbent. Finally, $\varepsilon_{i,t}$ captures the unobservable elements of utility, and for later modeling, $\varepsilon_{i,t}$ is assumed to follow Extreme Value Type I distribution.

Before proceeding, we want to understand the potential multicollinearity between the different factors. The correlation coefficients are provided in Appendix 2. The only notable correlation coefficients are between car age and car value, which are negative as would be expected, and between car value and engine power, which have a positive sign. This is also expected as more powerful cars are usually more expensive.

We use a panel logit regression with random effects in the estimation, as we want to estimate gender and some proxies for preferences that are time-invariant, like engine power and brand dummies for make of car or insurer. The specification choice for a panel with random effects was validated with the Hausman test. We also use a linear probability model with fixed effects to separate individual preference effects from those already mentioned. Many customers do not have any claims during the estimation period, and many variables of interest are time-invariant. As a result, we would lose a lot of information if we used the fixed-effects model, as it cannot capture the effect of time-invariant variables. Therefore the linear probability model with fixed effects is the main model used to validate the main findings.

5. Results

We analyze several specifications that contain consumer characteristics, the utility attributes of the products, and indicators for learning. We add the event of a claim in the previous period as a dummy or use the monetary value of a claim instead. We later explore the role that

[1] As there is electronic quoting, all the insurers respond to the same set of parameters that are used for pricing. However, some insurers might decide to include extra features in their cover for which pricing input parameters are not required, and which are consequently not priced separately. This feature might eventually create additional heterogeneity that is not reflected in the prices we observe but that may be salient to the customer if they work carefully through the wordings of all the competing offers.

[2] The variable will be transformed as $\text{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$.

Table 2
Switching probabilities in baseline models, marginal effects (except the last column).

VARIABLES	(1) Consumer characteristics and incumbent price change	(2) Consumer characteristics and the price difference to minimum offer	(3) Consumer characteristics and both price differences	(4) Model (3) + sum of claims	(5FX) Consumer characteristics, price differences, consumer FX
Gender (Male=1)	-0.002	-0.001	-0.001	-0.001	
	(0.003)	(0.003)	(0.003)	(0.003)	
Age, in years	-0.001***	-0.001***	-0.001***	-0.001***	-0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)
Engine Power (MW)	0.271***	0.093	0.101*	0.102*	0.390
	(0.063)	(0.058)	(0.058)	(0.058)	(2.004)
Car age, years	0.009***	0.007***	0.007***	0.007***	-0.020
	(0.001)	(0.001)	(0.001)	(0.001)	(0.021)
Lagged relationship length with the incumbent	-0.053***	-0.062***	-0.059***	-0.060***	0.015***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
(Lagged relationship length with the incumbent)^2	0.014***	0.014***	0.014***	0.014***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IHS relative price change of incumbent at renewal, in %	0.013***		0.003***	0.003***	0.005***
	(0.001)		(0.001)	(0.001)	(0.001)
IHS incumbent's price difference from minimum price, in %		0.043***	0.042***	0.042***	0.058***
		(0.001)	(0.001)	(0.001)	(0.001)
The lagged reputation of the incumbent	-0.004**	0.016***	0.015***	0.015***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Lagged Claims (=1 if a claim in the year before renewal)	0.009***	0.002	-0.002		-0.001
	(0.003)	(0.003)	(0.003)		(0.004)
The total sum of claims in				-0.000	
The previous year, €				(0.000)	
Observations	50,551	50,551	50,551	50,551	50,551
Number of consumers	20,759	20,759	20,759	20,759	20,759

Notes: Columns (1)-(4) of this table report marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations. Column (5) contains estimates of a linear probability model with consumer fixed effects. The mean probability of switching is 11%. Marginal effects (models 1-4) and parameter estimates (model 5) are reported with robust standard errors in parentheses.

*** p<0.01.

** p<0.05.

* p<0.1.

different types of claims and their interaction with pricing play in switching decisions. Table 2 summarizes the main findings in terms of marginal effects at mean values, with the exception of model 5.

The first observation is that in all the models 1-4, we see that age has a statistically significant impact on the probability of switching. An age difference of 10 years impacts the likelihood of switching by 1 percentage point relative to the base rate. Gender, however, does not play a role in model 1 or any of the subsequent models. We also include the length of the relationship in models 1-5, as this can be a proxy of the preference for a specific insurer. This is statistically significant in all of our models. The probability of switching decreases with each year that the customer stays with their current insurer. We add a quadratic term for relationship length into our models to explore this further and discover an interesting non-linearity. The coefficient for the quadratic length of the relationship becomes positive, meaning that after four years with the incumbent insurer, the probability of a switch becomes positive[3].

Model 1 uses the price change in the offer of the incumbent against the offer from the previous year only. The pricing action by the incumbent seems to play a role, as the coefficient estimate for it is statistically significant. The probability of the customer switching their current service provider increases by approximately 1 percentage point over the base rate for every price difference of 1% against the price of the previous year at mean levels.[4] The incumbent's average price fell by 2.6 percentage points against that of the previous year on average. Whether there was a claim before renewal seems to be relevant, but the reputation as a control variable for indirect learning is statistically not significant.

The other insurers are not aware of the claim submitted to the incumbent insurer and cannot base their pricing decisions on this, but the incumbent insurer is able to do that. That is why model 2 includes the difference between the incumbent insurer's price and the minimum price offered at renewal. There was an average price difference of about €32 or 8.12%. A difference of 1% in the price increases the likelihood of switching by about 4 percentage points over the base rate. A claim in the previous period does not seem to influence the decision to switch.

In model 3, we add both pricing differences into the model at the same time. The estimated coefficients for the marginal effects indicate that a rise in the price offer from the incumbent company would increase the probability of switching, but by far less than the difference against the minimum price offered does. A difference of 1% between the incumbent renewal offer and the minimum offer increases the switching rate by almost 2 percentage points, whereas a change in the incumbent

[3] An example from model 3 would be to use the estimated coefficients of -0.059 for relationship length and 0.014 for its quadratic term to estimate the chance of switching. The calculation of this would indicate that it takes on average -0.059/-0.014=4.21 years until the probability of the average customer switching becomes positive.

[4] Because of the inverse hyperbolic sine transformation we need to find $\frac{\partial (y)}{\partial (x)} = \frac{\widehat{\beta}}{\sqrt{x^2+1}}$. For example, if $\widehat{\beta}$=0.013 and the mean value of x is -1.08 (the mean value of the respective IHS variable is -0.934, hence the mean value of x would be (exp(x_{IHS})-exp(-x_{IHS})/2=-1.08) , we get $\frac{\partial (y)}{\partial (x)} = \frac{0.013}{\sqrt{-1.08^2+1}} = 0.01$.

Table 3
Impact of causes of claims on switching probability, marginal effects.

VARIABLES	(6) Consumer characteristics, price differences, and claims types	(7) Consumer characteristics, price differences, claims type and price change interacted
Gender (Male=1)	-0.000	-0.000
	(0.005)	(0.006)
Age, years	-0.001***	-0.001***
	(0.000)	(0.000)
Engine Power, MW	0.095	0.108
	(0.101)	(0.105)
Car age, years	0.011***	0.011***
	(0.001)	(0.001)
Lagged relationship length	-0.095***	-0.094***
	(0.009)	(0.009)
(Lagged relationship length)^2	0.017***	0.017***
	(0.002)	(0.002)
IHS price change of incumbent at renewal, in %	0.009***	0.005***
	(0.000)	(0.001)
IHS incumbent's price difference from minimum price, in %	0.041***	0.041***
	(0.002)	(0.002)
The lagged reputation of the incumbent	0.008**	0.008**
	(0.004)	(0.004)
Lagged Third-Party Induced claim	0.079***	0.069***
	(0.006)	(0.007)
Lagged Third-Party Induced Claim x Price difference in %		0.002***
		(0.000)
Lagged Self-Induced claim	-0.023***	-0.031***
	(0.007)	(0.007)
Lagged Self-Induced claim x Price Difference, in %		0.001***
		(0.000)
Observations	9917	9917
Number of consumers	7841	7841

Notes: This table reports the marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations. The past experience of claims is split into different categories and interacted with price changes in model (7). The mean probability of switching is 11%. Marginal effects are reported with robust standard errors in parentheses.
*** p<0.01,]
** p<0.05 * p<0.1.

price only influences the switching probability by 0.2 percentage point over the base rate. This means that while a change in the incumbent's price slightly increases the probability of switching, what matters more is the price difference to other plans.[5]

Again, as in Model 2, a claim in the previous period is not statistically significant. This contradicts the learning hypothesis presented by Israel (2005) for the case of a claims experience and Miravete and Palacios-Huerta (2014) for spending on phone tariff plans.

Some earlier studies like Ho et al. (2017) have used the monetary value of a claim to study the switching decision, so model 4 uses the total sum of claims in euros instead of a claims dummy, but this also turns out to be statistically insignificant. This is why we build upon model 3 for the rest of the analysis.

We only present the marginal effects in Table 2, but the underlying coefficient estimates also have an intercept. Together with the error term, it describes factors that are not attributable to demographic factors or the utility from switching, or that are unobserved. The intercept is statistically significant and sizeable in all versions of our model. Some studies (Honka, 2014; Kiss, 2019) explain the intercept as the cost of search and switching.

In model 5, we validate model 3 by estimating a linear probability model with fixed effects for the combination of a car and its driver. The age of the driver and of the car increase linearly over time depending on the car owner, and their effect becomes statistically insignificant in model 5. Interestingly, the linear term for relationship length changes sign when individual fixed effects are considered, whereas the quadratic term remains similar to that in specifications 1-4. The individual fixed effects suggest the likelihood of switching starts to increase with each year of the relationship. The coefficients for monetary incentives to switch and learning effects are similar in their sign and order of magnitude to what they were in models 2-4.

The effect of age is statistically significant in all our models 1-4, indicating that older people are less likely to switch. This finding is in line with previous research (Boonen, 2016), though the magnitude of this coefficient is small.

We now develop two further models to disentangle the causes of the claims and their potential behavioral impact on switching. Claims are divided into three categories, as described in Section 3, with dummies for two of the categories. Table 3 presents the estimation results.

Model 6 unpicks the claims dummy used previously and splits it into the categories of Self-Induced and Third-Party Induced. The coefficients used in the previous specification remain of the same magnitude and significance, but a surprising effect appears, as a consumer who experienced a Third-Party Induced claim is more likely to switch at renewal. Quite the opposite story unfolds if there was a Self-Induced claim before renewal. If the consumer was at fault for a claim, their probability of switching falls relative to the probability with Other claim types, and the estimated coefficient is statistically significant.

The causes of the claims made with the incumbent insurer are known to the incumbent insurer but not to the other insurers, and so the price offer from the incumbent insurer at renewal might be affected by the claims submitted in previous periods. There is no market standard for no-claims-bonus calculations in Estonia, and in model 7, we consequently interact the difference in the incumbent price at renewal with different claims types. This helps us control for the learning effect separately from any price increases induced by the claims. The results of model 7 are similar to those of model 6, and the coefficient for the Self-Induced claim is even more pronounced than it is in model 6 after interaction terms have been used to control for price changes from previous claims. The interaction terms themselves have the expected signs.

The effect of Self-Induced claims on the probability of switching is negative, surprisingly, while the effect of Third-Party Induced claims is positive. This phenomenon is undoubtedly worth exploring further, especially as some studies indicate that psychological factors influence the switching responses of consumers to service quality. Consiglio and van Osselaer (2019) find for example that consumers with low self-esteem often do not switch when they experience poor service quality. Although the finding is contrary to the empirical findings in the literature on moral hazard, we can find support for this outcome in behavioral and psychology literature. Soscia (2007) for example studies consumer emotions and finds that gratitude is a significant driver of repurchase decisions.

A customer experiencing a Self-Induced claim might feel gratitude if they have a positive experience of the repair service. It could also be inferred from Soscia (2007) that a Third-Party Induced claim might cause feelings of anger, which would contribute to the switching behavior. The exact transmission mechanism of psychological factors in combination with learning remains one avenue for future research.

6. Robustness checks

To test for the robustness of the results, we create other versions of

[5] We thank an anonymous reviewer for the suggestion that we point this finding out more clearly. It has indicated the arguments for *homo economicus* clearer and helped to improve the resulting conclusions.

Table 4
Robustness checks for switching probability, marginal effects.

VARIABLES	(8) Car value[a]	(9) Active search[b]	(10) Price Difference from mean[c]	(11) Car make dummies	(12) Insurer dummies
Gender (Male=1)	-0.001	-0.001	-0.001	-0.003	-0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Age, in years	-0.001***	-0.001***	-0.001***	-0.001***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Engine Power in MW		0.105	0.107*	0.079	0.115
		(0.105)	(0.103)	(0.113)	(0.091)
Car value, in thousands of €	0.014**				
	(0.002)				
Car age, years	0.014***	0.011***	0.011***	0.009***	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged relationship length	-0.093***	-0.092***	-0.090***	-0.089***	-0.069***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
(Lagged relationship length)^2	0.017***	0.016***	0.016***	0.016***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
IHS price change of incumbent, in %	0.005***	0.005***	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IHS incumbent's price difference from minimum price, in %	0.041***	0.041***	0.045***	0.040***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
The lagged reputation of the incumbent	0.008**	0.008**	0.008**	0.006*	
	(0.004)	(0.004)	(0.004)	(0.004)	
Incumbent's price difference from the mean, in %			-0.001**		
			(0.000)		
Lagged Third-Party Induced claim	0.069***	0.068***	0.067***	0.067***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.000)
Lagged Third-Party Induced Claim x Price difference in %	0.002***	0.001***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Self-Induced claim	-0.031***	-0.032***	-0.032***	-0.028***	-0.026***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Lagged Self-Induced claim x Price Difference, in %	0.001***	0.001***	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
				(0.000)	
Active		0.080***			
		(0.019)			
Car make dummies				Yes***	
Insurer dummies					Yes***
Observations	9917	9917	9917	9917	9917
Number of consumers	7841	7841	7841	7841	7841

Notes: This table reports the marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations that have changed the specifications of the previous models as robustness checks.

[a] model (8) uses Car Value instead of Engine Power as a proxy for consumer income.

[b] model (9) includes a small portion of Active customers who have opted to make the insurance decision by themselves. This was 1.45% of the total number of customers in our sample.

[c] model (10) uses the price difference between the incumbent offer and the mean price offered instead of the difference to minimum price offered.

our model 7, and the results are provided in Table 4. As Engine Power correlates positively with the value of the car, we use car value instead of engine power in model 7 to arrive at model 8, which is used for checking robustness. The statistical significance of the coefficients does not change from the earlier estimation results, and the car value itself is statistically significant.

We include a further dummy in model 9 describing whether the customer decided to take care of the insurance themselves. The proportion of consumers in our sample who did so was tiny at only 1.45%. This dummy is statistically significant. The probability of customers in the Active category switching is 8% higher than the probability for non-active consumers. No other coefficients change their statistical significance or their signs.

We also wanted to test whether the price difference from the mean value of all the offers made has an impact on switching. It turns out in model 10 that it is statistically significant, but the coefficient implies a minimal sensitivity to the difference in price over the mean value.

We add dummies for the make of car in model 11 for the makes that represent 5% or more of the total insured portfolio. These makes were statistically significant at the 99% level, with a few exceptions. However, adding dummies for the make of car into the model does not change the coefficient values or signs for the main explanatory variables. The main change is that the coefficient for the age of the car might correlate with the make of the car.

In model 12, we control for insurer dummies, since these might capture similar aspects to insurer reputation. We have left insurer reputation out of this specification. We can see that the impact of stand-alone dummies for claims is smaller than in model 7, indicating that insurer-specific effects are important.

The results in models 8-12 for the impact of demographic characteristics, price differences, other proxies for consumer preferences such as engine power or car age, and learning effects over time remain the same as in model 7.

The impact of demographic characteristics, price differences, other proxies for consumer preferences like engine power and car age, and learning effects remain the same across the different specifications in the robustness checks. These results are in line with the findings presented in Section 5.

7. Conclusions

This study provides empirical evidence for the probability of customers switching their car insurance provider in response to demographic and utility factors, and learning about the insurer's service quality. We ask how much such switching is driven by direct monetary effects, how much is attributable to characteristics of the car indicating brand preferences, and how much can be explained by the customer learning about the quality of the service.

In general, there is inertia, and the average probability of a customer switching service provider at renewal is 11%, while the average difference between the price of the option chosen and the cheapest offer was 8%. The triggers for switching reveal that a minor role is played by consumer characteristics like age, or like the age or value of the car as proxies for income. A consumer who is ten years older is one percentage point less likely to switch than the base rate.

As expected, direct monetary gains drive switching behavior, and the customer responses are as expected. A change in the price offered by the incumbent from that of the previous year is statistically significant. However, the difference between the price offered by the incumbent and the cheapest alternative has much more impact. A rise in price of 1% at renewal from the incumbent insurer makes switching 0.2 percentage points more likely on average than the base rate. Simultaneously, the difference between the incumbent offer and the cheapest option available increases the likelihood of switching by two percentage points over the base value. Even if the overall switching rate is not very high, the responses to changes within the choice set are more pronounced than those to changes in the default option. If consumers see their current price change, they might think about switching. They then compare that price with those of other plans and they only switch if they can actually save money by switching because there is a much cheaper option. Our study shows inertia to be smaller than earlier studies of adjustment costs have found, and *homo economicus* is more visible in our setting.

There was no direct cost involved from search and switching, so the main theoretical arguments for inertia would come from information processing, and learning as a particular case of it. Insurance is an intangible good, and consumers can only experience it directly when a claim happens. However, we did not find any universal relationship between a claim in the previous period and the probability of switching. After classifying claims into different categories, we find that consumers facing a renewal decision after a claim caused by a Third Party are more likely to switch than those who have experienced Other claims. If the claim were Self-Induced, the consumers are more likely to stick with their previous choice, even after interaction terms are used to control for the price impact of the claim. This outcome deserves further research into the psychological factors behind it and their impact on information processing.

Data availability

Stata dataset and do-file attached

Appendix 1. Glossary of the variables used

Variable	Definition
The probability of switching	= 1 if the service provider was changed in a given year and 0 otherwise
The probability of switching conditional on no claims	= 1 if the service provider was changed in a given year when no claims were handled and 0 otherwise
The probability of switching conditional on at least one claim	= 1 if the service provider was changed in a given year when at least one claim was handled and 0 otherwise
Consumer characteristics	
Gender	= 1 if policyholder is male and 0 otherwise
Age	years
Engine power	MW. Although commonly stated in kW, recalibrated into MW for better salience of the estimated effects
Car value	€ 1000
Car age	years
Active	The proportion of consumers who actively search for an insurer (= 1 if the consumer decided to deal with insurance themselves and 0 otherwise)
Product characteristics	
The relative price change of the incumbent insurer at renewal	in % against the price from last year
The relative difference between the incumbent and the minimum price offered	in %
The relative difference between the incumbent insurer offer and the mean price offered	in % against the mean price in the panel of offers
Service provider reputation relative to the sector's mean reputation in a given year	Reputation is measured as the difference between the number of consumer disputes relative to the market share of the insurer. To calculate relative reputation, the market average reputation is subtracted for a given year for a specific insurer.
The proportion of policies with at least one claim per year	= 1 if at least one claim was handled and 0 otherwise
Total claim amount per year	In € across all claims made under the policy in a given year
The probability of switching by claim type	
Self-Induced claim	= 1 if the claim was induced by the driver and 0 otherwise
Third-Party Induced claim	= 1 if the claim was induced by theft, vandalism, and collisions at third party fault and 0 otherwise
Other claims	= 1 if the claim was induced by fire, broken windscreens, wild animal collision, breakdown, or all other reasons and 0 otherwise

Appendix 2. Correlation coefficients for selected variables.

	Switch	Gender (Male = 1)	Age	Engine Power	Car age	Price change of incumbent	Incumbent price diff from min price	Lagged relative reputation	Lagged indication of at least one claim per year	Car value	Active search	Incumbent price diff from mean price
Switch	1											
Gender (Male = 1)	0.00	1										
Age	-0.04	0.03	1									
Engine Power	0.03	0.16	-0.11	1								
Car age	0.08	0.01	-0.13	0.11	1							
Price change of the incumbent, in %	0.15	-0.00	0.04	0.01	-0.02	1						

(*continued on next page*)

(*continued*)

Incumbent price diff from min price, in %	0.24	0.00	0.03	0.05	0.04	0.39	1					
Lagged relative reputation	0.01	0.02	-0.17	0.12	0.25	-0.01	-0.11	1				
Lagged indication of at least one claim per year	0.04	-0.00	-0.03	0.06	0.00	0.18	0.00	-0.02	1			
Car value	-0.02	0.09	0.04	0.40	-0.60	0.02	-0.17	-0.05	0.02	1		
Active search	0.09	-0.00	-0.01	0.03	0.04	0.01	0.01	0.02	-0.01	-0.01	1	
Incumbent price diff from mean price, in %	0.17	-0.02	0.07	-0.01	-0.01	0.39	-0.14	-0.09	0.13	0.06	-0.01	1

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