# Estimating the lock-in effects of switching costs from firm-level data

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**Abstract**

This paper proposes a simple method for estimating the lock-in effects of switching costs from firm-level data. We compare the behavior of already contracted consumers to the behavior of new consumers as the latter can serve as contrafactual to the former. In panel regressions on firms' incoming and quitting consumers, we look at the differential response to price changes and identify the lock-in effect of switching costs from the difference between the two. We illustrate our method by analyzing the Hungarian personal loan market and find strong lock-in effects.

Keywords: switching costs, lock-in, panel data

JEL codes: C33, D12, L13

## 1 Introduction

Switching costs can increase firms' market power by locking in consumers and thereby decreasing the residual elasticity of demand, which might lead to price increases in later periods. Consumer lock-in can also contribute to barriers of expansion for rival firms, which might help incumbent firms conserve their strong market position. Due to these theories of harm,[1] lock-in is an important concern for competition authorities and sectoral regulators alike, and specific regulatory policies were designed to decrease switching costs in most network industries.[2]

From a practical point of view, three issues are of main empirical importance: the presence and magnitude of switching costs, their effect on lock-in and the resulting effects on prices. Most empirical papers analyzed the third question,[3] and some look at the first (see later for more discussion). However, empirical evidence on the lock-in effects is scarce, even though it is the latter that are emphasized in the theoretical literature, because the identification and quantification of lock-in effects present multiple methodological challenges. One such challenge is data availability. Consumer-level data on actual switchers and non-switchers would offer the best opportunities for estimations, but such data are expensive and rarely available.[4]

This paper proposes a simple method for estimating the lock-in effects of switching costs in a direct way. Our approach has two practical advantages, First, it stays within a reduced-form demand analysis framework and can avoid strong assumptions on market structure. Second, it requires firm-level data, which are less expensive and easier to collect than consumer-level data, and most regulatory bodies have the legislative power to acquire them.

We develop a method that compares the reactions of new consumers to the reaction of old consumers with respect to price changes. A new consumer is defined as someone making

[1] The theoretical literature is thoroughly reviewed by Farrell and Klemperer (2007).

[2] An important example is mobile telephone number portability. See Maicas et al. (2009), and the references therein, on estimating the effect of number portability on switching costs and consumer mobility.

[3] See Farrell and Klemperer (2007) for a detailed discussion.

[4] Switching costs were estimated from individual-level data for example in the online brokerage industry by Chen and Hitt (2002), for breakfast cereals by Shum (2004), for Internet portals by Goldfarb (2006) and for mobile telephone subscriptions by Grzybowski (2008).

her first purchase decision on the market, while an old consumer is already a customer of a firm. The difference between their reactions can give some indication on the firms' market power over old consumers. The basis of our identification is the idea that the behavior of new consumers describes the behavior of old consumers in the absence of switching costs. As a result, the group of new consumers can serve as a counterfactual group, in the spirit of the program evaluation literature (see, for example, Imbens and Wooldridge, 2009).[5] The treatment group versus control group approach requires similarity of the two groups. In our case, old and new consumers should be similar in terms of their price elasticity and switching behavior. In principle, this assumption allows for more informed or more patient consumers entering the market as long as that heterogeneity is controlled for or it is unrelated to switching behavior. The latter is may be satisfied in developed markets with relatively homogenous goods, in which entering the market may be the reason of exogenous shocks. Examples for such markets include loan contracts - which we analyze in our application -, consumer utilities, some standard telecommunication services, etc.

When we have ideal data at hand, our empirical model is a system of two panel regressions, estimated in first differences. Both equations measure the effect of a change in the relative price of a given firm. The dependent variable in first the equation is the market share in terms of consumers who are new to the market, so that its changes can be interpreted as changes in the probability of a new consumer choosing the firm. The dependent variable in the second equation is the probability of the firm's old consumers staying loyal to the firm. These specifications are in the spirit of traditional demand analysis as applied by, for example, Hausman, Leonard and Zona (1994). The lock-in effects of switching costs

[5] A simple thought experiment can be given with two identical consumers *New* and *Old* who differ only in that *Old* has been the customer of firm $j$ for some time. Suppose that at current prices *New* would also buy from firm $j$, but there is a change in the relative price of firm $j$ that is large enough to make *New* choose another firm. If there were no switching costs, *Old* would react in the exact same way to this price change and would switch. If switching costs are sufficiently large, though, *Old* might stay locked in with firm $j$.

are measured by comparing these two effects of the same price change. The difference of the two responses is the fraction of old consumers who would have switched firm if they had been new consumers but were prevented from doing so because of switching costs.[6] The identification strategy is very similar to a "difference-in-differences" approach, in which one compares the behavioral response of a group that may be subject to switching costs to the behavioral response of another group that is not subject to switching costs. Such a method is used, for example, by Madrian (1994) who tests for the "job-lock" effect of employer-provided health insurance plans by comparing the effect of medical expenditures on the job switching behavior of those with insurance plans to those without such plans.

With appropriate data on individuals, this counterfactual method could be used in a relatively straightforward fashion. Unfortunately, though, information on consumers who are new to the market and old consumers who switch to other firms are typically not available in firm-level data. Therefore we implement the method using the number of consumers joining or leaving a specific firm and construct proxy variables for changes in the fraction of new and old consumers.[7] We address the potential biases due to the use of such proxy variables, and we develop an easy-to-implement formula that corrects for the biases under conservative assumptions. Data on prices and the number of consumers joining and leaving firms are usually available in markets with long-term contracts such as consumer credits, utilities and telecommunication services, and these are exactly those liberalized network industries where the competition-hindering effects of switching costs are usually feared. The panel data methods we apply can also control for firm-specific fixed effects and trends (e.g. brand loyalty) and common changes in firms' environment (e.g. market structure or outside

[6] Schiraldi (2009) uses a similar counterfactual approach in order to estimate transaction costs (relative to prices) in the Italian car market. He compares the share of consumers holding a car to the share of consumers buying the same car in the same period. He uses individual data to estimate a structural dynamic model of consumer demand and finds large variation in transaction costs.

[7] There are a few empirical papers on switching that also use proxies in their empirical implementation, but they use proxies directly for the unobservable switching costs. See for example Sharpe (1997).

options). The models aim at estimating responses of consumer demand, so they require exogenous variation in prices (or endogeneity biases in the two equations that are equal).

There are few papers that use firm-level data to estimate switching costs, and they focus on the magnitude of switching costs compared to prices as opposed to the lock-in effects.[8] We know about two structural studies, which derive a specific model of competition in the presence of switching costs and then estimate equilibrium conditions for prices or market shares. Shy (2002) builds a static model in which firms' prices are set at given switching costs such that nobody has any incentives to undercut their rivals. By construction, his model predicts no switching and stable market shares and it is used as a benchmark for identifying the existence of switching costs. As an illustration, Shy (2002) estimates that switching costs are 35-50% of average price on the Israeli cellular phone market, and vary between 0 and 11% of the average balance on the Finnish bank deposit market. Kim et. al. (2003) model consumers' transitions and banks' intertemporal decision-making in a dynamic framework and apply it to the Norwegian loan market: their estimated switching costs are 4% of the average loan's value. Both papers measure switching costs in terms of prices, but they do not provide direct estimates for the lock-in effect of switching costs. Because of the structural approach, they also need correctly specified models of competition, in contrast to our counterfactual approach.

The idea that a reduced-form model can capture how the presence of switching costs alters consumers' price responsiveness is of course not completely new. For example, in a homogenous good industry small cross-price elasticity estimates across firms may indicate large switching costs because price increases do not result in significant losses to competitors.[9] Our method requires more data (two measures of quantity as opposed to one), but it has the additional advantage of identifying the magnitude of the lock-in effects of switching costs,

[8] There are additional papers that analyse the impact of switching costs on prices, see Farrell and Klemperer (2007, Section 2.2) for an overview.

[9] See, e.g. NERA, 2003, Appendix B.

and it is also applicable to differentiated goods industries.

As an illustration, we apply the estimation method to the market of personal loans in Hungary. The endogeneity of prices According to our estimates, a one percentage point increase in interest rates leads to a 0.43 to 0.61 percentage points decrease in demand among new consumers, compared to a 0.13 percentage points decrease among the banks' old consumers. Old consumers' responsiveness is therefore 70 to 79 per cent lower than new consumers' responsiveness. Our results imply substantial lock-in effects. We can reject the hypothesis of perfect consumer mobility, while the hypothesis of complete consumer lock-in (as assumed in many theoretical models) cannot be rejected. As a result of the banking sector inquiry of the Hungarian Competition Authority in which this method was applied, several regulatory recommendations were made to facilitate the switching of consumers.

# 2 Underlying economic framework

Although we do not explicitly model firms' behavior, the industry structure we assume is very close to the theoretical framework of Beggs and Klemperer (1992). This classic paper analyzes dynamic competition in the presence of switching costs, and studies the main trade-off between charging high prices to rip-off locked-in consumers versus low prices to attract new ones.

Both our and Beggs and Klemperer's setup have $J$ firms offering a contract for a good (or service) lasting for $T$ periods with required payments $p_{jt}$ in each period.[10] Each consumer demands at most one good, which might be homogenous or differentiated. We assume that both new and old customers of a given firm face the same price $p_{jt}$.[11] In each period $t$,

[10]Technically, there is no problem with allowing the entry of new firms (so $J$ should not be fixed) or the supply of multiple services by firms. Of course in such cases appropriate data is needed on all components.

[11]While this assumption is correct in the context of our empirical application, in some other markets it is common industry practice to charge different prices to old and new consumers. In such cases one should measure two prices as well as two quantities or address the potential bias resulting from differences in prices.

some new consumers enter the market who are drawn from the same population as new consumers in $t-1$, and some old consumers leave the market because of expiring contracts. Both consumers and firms maximize the discounted sum of per-period utilities and profits, respectively.

If an old consumer would like to leave firm $j$ for firm $k$ because of a better price offer, she faces switching costs. Switching costs include both monetary and non-monetary transaction costs that are related to switching, including entry, search and exit costs.[12] However, while Beggs and Klemperer assume that switching costs are so large that they prohibit consumers from switching in equilibrium,[13] we allow switching costs to take any value, so that some fraction of old consumers may still switch.[14]

When solving for equilibrium, Beggs and Klemperer analyze affine strategies in which each firm's price is a linear function of its market share plus some firm-specific constants. Our main equations to estimate are of a similar form, as we study the relationship between prices and choice probabilities (derived from market shares), with additional fixed effects.

A possible way to see that our competition framework with switching costs fits the industry studied, one can check observable market facts against some of the main theoretical results of Beggs and Klemperer. These include the following: entry should be attractive despite the presence of switching costs; growth in demand should cause prices to fall; and initially larger firms should set higher prices and therefore lose market shares.

We assume that consumers are heterogenous in their reservation prices and possibly in some taste parameters. If a consumer $i$ is new to the market in period $t$, let $n_{ijt}$ denote the probability that she buys the product from firm $j$ under existing prices. Similarly, if

[12] As we allow these switching costs to vary across individuals, there is no loss of generality in assuming that switching costs are fixed, i.e. they do not depend on the value of the transaction.

[13] In their model, consumers of firm $j$ enter in a long-term relationship with the firm and pay $p_{jt}$ in subsequent periods.

[14] In most markets characterized by switching costs some switching occurs in fact, although it may be of small magnitude. This is the case in our application as well, which we study later.

consumer $i$ is an old customer of firm $j$ (that is she bought from firm $j$ in period $t-1$), let $l_{ijt}$ denote the probability of this consumer to stay loyal to firm $j$ (so she continues to buy from firm $j$). The share of new consumers and old consumers of firm $j$ who choose firm $j$ in period $t$ is denoted by $n_{jt}$ and $l_{jt}$, respectively.

We are interested in how an increase in the price of firm $j$ affects these choice probabilities. $\Delta n_{jt}/\Delta p_{jt}$ and $\Delta l_{jt}/\Delta p_{jt}$ are likely non-positive. By our most important assumption, the effect of a price increase on the behavior or new and old customers would be the same in the absence of switching costs. If if switching costs are high enough, they will increase the threshold value of a price increase that induces a reaction for some consumers. Such consumers would not switch if the actual price increase is lower than this threshold even though they would have chosen another firm if in the absence of switching costs. These consumers are locked in because of switching costs. As a result, the average effect of the same price increase is likely to be smaller for old consumers than for new consumers, i.e. $|\Delta n_{jt}/\Delta p_{jt}| \geq |\Delta l_{jt}/\Delta p_{jt}|$. Ideally, these two properties could be derived from a more structural discrete choice framework with switching costs. The full analysis of these decision problems is beyond the scope of our paper, but in Appendix A we derive an illustrative model that deliver the assumptions behind our counterfactual approach.

Guided by this intuition, we aim to identify the lock-in effects of switching costs from the difference of the effects of the same price increase on the choice probability of new consumers and the loyalty probability of old consumers:

$$\delta_{jt} = \left|\frac{\Delta n_{jt}}{\Delta p_{jt}}\right| - \left|\frac{\Delta l_{jt}}{\Delta p_{jt}}\right| = \frac{\Delta l_{jt}}{\Delta p_{jt}} - \frac{\Delta n_{jt}}{\Delta p_{jt}}. \tag{1}$$

Indicator $\delta_{jt}$ shows how much more likely it is that a consumer switches away from firm $j$ in response to a small increase in $p_{jt}$ if she is new to the market than if she is already a customer of firm $j$. In a frequentist interpretation, this difference shows the fraction of old consumers who are prevented from leaving firm $j$ in period $t$ but would have switched in the absence of switching costs. If no old consumer is constrained by switching costs then

$\delta_{jt} = 0$, while if switching costs are prohibitive for all customers of firm $j$ in period $t$, then $\delta_{jt} = |\Delta n_{jt}/\Delta p_{jt}|$.

Naturally, the value of $\delta_{jt}$ depends on the distribution of demand parameters and switching costs, as well as on the period-specific market position of firm $j$. In empirical applications, an average value of $\delta$ is likely to be the best absolute indicator of industry lock-in effect.

However, different markets can be characterized by different demand elasticities and market structures (e.g. the number of the firms affects choice probabilities), therefore $\delta$ is not necessarily comparable across markets. For comparisons, it is more convenient to use a normalized version of $\delta_{jt}$:

$$\theta_{jt} = \frac{|\Delta n_{jt}/\Delta p_{jt}| - |\Delta l_{jt}/\Delta p_{jt}|}{|\Delta n_{jt}/\Delta p_{jt}|} = \frac{\Delta n_{jt}/\Delta p_{jt} - \Delta l_{jt}/\Delta p_{jt}}{\Delta n_{jt}/\Delta p_{jt}}. \tag{2}$$

This relative indicator of the lock-in effect shows the fraction of consumers prevented from switching from among the consumers who would have switched in the absence of switching costs. By this definition, $\theta_{jt}$ might take values between 0 (nobody is constrained by switching costs) and 1 (all of those who would have switched without switching costs are constrained by the existence of switching costs).

Using the estimated $\theta$ and its sampling distribution, one is able to test the hypothesis of two polar cases. The hypothesis of $\theta = 0$ corresponds to perfect consumer mobility (no lock-in of any degree), while the hypothesis of $\theta = 1$ corresponds to complete lock-in (this is the assumption used by many theoretical models, including Beggs and Klemperer, 1992).

## 2.1 Discrete choice background

The reduced form approach we take can be grounded in a more structural discrete choice framework with switching costs. Although we do not give a full analysis of the decision problem, we can show that the model confirms the two most important assumptions behind our counterfactual approach. The derivations are relegated to Appendix A.

We first show that, without switching costs, the effect of a price increase $\Delta p_{jt} > 0$ on the choice probability is the same for individual $i$ if she is new and if she is old.

We also show that switching costs make the effect smaller on average in absolute value for old consumers. Switching costs decrease the threshold value for the price increase of other firms in order for the consumer to stay loyal to the firm of her original choice. As a result, the same price increase will induce switching with a smaller probability. In the presence of consumer heterogeneity, this translates to a smaller fraction of consumers switching to other firms than the fraction without switching costs would be.

# 3 Empirical strategy

## 3.1 Measurement of the variables

The goal of our empirical analysis is to estimate $\delta$ and $\theta$, which are functions of the probability responses $\Delta n_{jt}/\Delta p_{jt}$ and $\Delta l_{jt}/\Delta p_{jt}$. We argue that estimating them is feasible using panel data on all firms and with information on prices and two quantities: the number of consumers joining each firm and leaving each firm. In order to see the relationship of these quantities to $n_{jt}$ and $l_{jt}$, we need to understand in detail how they are measured.

Let $S_{jt}$ denote the stock of all consumers who buy from firm $j$ in period $t$. We denote the number of incoming consumers to firm $j$ by $IN_{jt}$ and the number of outgoing consumers from firm $j$ by $OUT_{jt}$ . If we can separate the number of consumers whose contract is expiring with firm $j$ (that is they do not face explicit exit costs) from the outgoing consumers, we denote this number by $X_{jt}$ - in this case, $OUT_{jt}$ measures consumers who deliberately terminated their ongoing purchasing relationship with firm $j$. The evaluation of firm $j$'s stock is therefore:

$$S_{jt} = S_{jt-1} + IN_{jt} - OUT_{jt} - X_{jt}. \tag{3}$$

Incoming consumers can be further separated in two categories: completely new consumers $N_{jt}$ and switchers from other firms $F_{jt}$. Outgoing consumers also belong to two potential groups: $Q_{jt}$ quit the market for good (likely because of a change in an individual factor like income) and $T_{jt}$ switch to other firms (likely because of a price change). Therefore, we have

$$S_{jt} = S_{jt-1} + (N_{jt} + F_{jt}) - (Q_{jt} + T_{jt}) - X_{jt}. \tag{4}$$

To illustrate these decompositions, let us take an example from the market of banking loans, to which we shall return in our application. The stock $S_{jt-1}$ is the number of consumers having a loan contract with bank $j$ in the beginning of period $t$. The stock may change in three ways: by $IN_{jt}$ new loans signed, $OUT_{jt}$ loans repaid earlier, and $X_{jt}$ loans expiring in the respective period. Consumers $Q_{jt}$ repay their loans before those would expire and quit the market, while $T_{jt}$ consumers refinance their loan with another bank. Finally, the bank's incoming consumers consist of consumers who are new to the market ($N_{jt}$) and refinancing consumers ($F_{jt}$) arriving from other banks.

In certain market contexts, we might measure all variables in the value of contracts or revenues instead of the number of consumers. If one can measure both variables, like in our banking example, one might want to work with both in order to check the robustness of the results.

The important measurement problem to deal with is that although we would need decomposition (4) in order to ideally implement our thought experiment, firm-level aggregates usually allow us to track back decomposition (3). We shall address this problem later when we discuss feasible estimation.

A new consumer's realized probability of joining firm $j$ is

$$n_{jt} = \frac{N_{jt}}{\Sigma_k N_{kt}},$$

which is simply firm $j$'s market share from new consumers in period $t$. At the beginning of period $t$, firm $j$ has $S_{jt-1}$ old consumers. From among them, $X_{jt} + Q_{jt}$ leave the firm without switching, and an additional $T_{jt}$ leave due to switching. The pool of potential switchers is therefore $S_{jt-1} - X_{jt} - Q_{jt}$, and from them $T_{jt}$ choose to switch. The realized probability of staying loyal to firm $j$ is therefore

$$l_{jt} = 1 - \frac{T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}}.$$

This probability equals the fraction of consumers loyal to firm $j$ from among all consumers who could have been loyal to it.

Measurement of prices is more straightforward but it is not without problems. In principle, we should keep the prices of other firms ($\mathbf{p}_{kt}$) constant . In our application, we shall make the simplification of including the price of firm $j$ relative to other prices in a single variable, instead of entering all other prices. Depending on the specific market context, relative prices might be defined as differences, ratios or log differences, with at least two possible benchmark prices: the best possible offer (smallest price) or the market average. Comparing to the smallest price is consistent with perfectly informed and rational consumers. This might be better for markets where prices are relatively easy to acquire and compare, like internet subscriptions. Comparing to the average price is consistent with consumers who cannot collect and process all price information available, so they compare the price of firm $j$ to only a few competitors.[15] This latter might be better for markets where search costs are likely to be significant, like banking or telephone services.

## 3.2 Ideal estimation

Suppose for a moment that we can observe all terms in equation (4) and can therefore compute $n_{jt}$ and $l_{jt}$.We are interested in the changes of these probabilities in reaction to price changes, which we estimate from the following basic system of two equations:

$$\Delta n_{jt} = \alpha_n + \beta^* \Delta p_{jt-1} + u_{njt}, \text{ and} \tag{5}$$

$$\Delta l_{jt} = \alpha_l + \gamma^* \Delta p_{jt-1} + u_{ljt}. \tag{6}$$

[15] The average may be weighted by previous market shares, but in a regression of market shares on prices such weighting may lead to endogeneity.

where star superscripts denote estimations in an ideal situation in which the $n$ and $l$ variables are observed. Recall that we measure prices $p$ relative to the market average. A more sophisticated way of keeping other prices constant would be to control for each of the prices. The measurement model is easily generalizable to that more sophisticated case. We stay within the simpler framework both because of notational simplicity and because the more sophisticated approach would require long time series, which are not always available.

We argue that in most applications it makes sense to relate changes in consumer decision to lagged price changes. Search for best prices takes time, and in many applications, transactions follow consumer decisions with a considerable lag. In such cases, unless the frequency of observations is low (i.e. time periods are wide), we can expect price changes in one period to affect measured transactions in the next period. Entering price changes with a lag also alleviates the problem of the endogeneity of price changes (see the next section for more details).

Now suppose that the following two conditions hold:

**Condition 1** *New and old consumers are similar in terms of characteristics that matter for demand changes.*

This first condition is necessary for new consumers to serve as valid counterfactuals for old consumers, that is to adequately describe what the reactions of old consumers would be without switching costs. This property is more likely to be satisfied on a stable market with relatively homogenous goods. Note, however, that the fact that more (or less) informed, sophisticated or impatient consumers enter the market in earlier periods does not matter as long as these different consumer cohorts' behavioral reactions to price changes is similar regarding which firm to choose.

The similarity of new and old consumers is required in terms of the price changes they face as well. This is obviously satisfied if firms cannot charge different prices to new and old consumers. It may also be satisfied, however, if such price discrimination is feasible as long

$\Delta p$ is the same for new and old consumers. Examples for the latter include fixed discounts or free complementary items for new consumers if prices are entered in levels, or proportional discounts if prices are entered in logarithmic form in the regressions.

**Condition 2** *Price changes are exogenous to demand.*

The second condition is needed to identify changes in demand.

Under these two conditions, OLS regressions of (5) and (6) consistently estimate the theoretical $\beta$ and $\gamma$ coefficients.[16] As a result,

$$\hat{\delta} = \hat{\beta}^* - \hat{\gamma}^*, \text{ and} \tag{7}$$

$$\hat{\theta} = \frac{\hat{\beta}^* - \hat{\gamma}^*}{\hat{\beta}^*} \tag{8}$$

are consistent estimators of $\delta$ and $\theta$ as defined in (1) and (2) because of their continuity in the consistent $\hat{\beta}^*$ and $\hat{\gamma}^*$ estimators. Their sampling distribution involves the joint sampling distribution of $\hat{\beta}^*$ and $\hat{\gamma}^*$. $\hat{\theta}$ is also nonlinear in the regression estimators. Therefore, estimating confidence intervals is probably best done by bootstrapping or using other simulation-based methods.

Firm-specific time-invariant heterogeneity in market share in new contracts ($n_{jt}$) and loyalty probabilities ($l_{jt}$) are filtered out in the regressions because they are specified in first differences. Similarly, as we estimate the evolutions of shares, the specifications take care of the shocks affecting all firms in the same way (although this is strictly true only for $n_{jt}$). For this latter reason it may be advisable to include time fixed effects in the regressions, and additional cross-section fixed-effects could be also included in order to control for firm-specific trends.

[16] (5) and (6) define a seemingly unrelated regression (SUR) system. Since each equation includes the same right-hand side variables equation-by-equation OLS is identical to GLS and therefore there is no efficiency loss.

Note that time fixed-effects control for everything that is common to all firms in a given time period, including the potential benchmark price, whether it is the average or the minimum. As a result, the theoretically important distinction of using absolute versus relative prices becomes empirically irrelevant if time fixed-effects are included.[17] Time fixed effects can also control, to some degree, for changes in market structure or the outside option.

## 3.3 Potential econometric problems

In order to meet Conditions 1 and 2, regression models (5) and (6) may in general include other variables. As we noted previously, it may be a good idea to include firm and time fixed-effects. Note that the model is defined in first differences so firm-specific time-invariant factors in market share and loyalty are automatically controlled for. Including additional firm fixed-effects amount to controlling for firm-specific (possibly stochastic) trends.

Condition 2 requires exogenous variation in prices. Such exogeneity is best ensured by natural experiments or the use of valid instrumental variables. Note, however, that finding valid instruments are difficult in these applications even more than in general. It is standard in the empirical industrial organization literature to use the competitors' characteristics as instruments. That is obviously ruled out here as the competitors' behavior is likely to affect switching (and thus $\Delta l$) directly. Another set of usual variables are "cost shifters." Since our application looks for variation in prices within the same market, cost shifters are likely to be extremely weak instruments because they are likely to affect competitors in similar ways. In

[17] Naturally, $\hat{\beta}$ and $\hat{\gamma}$ are estimated from responses to price changes that are observed in the data. Generalization to price changes that are outside the observed range may be problematic. If, for example, switching costs have a common lower bound across consumers and firms keep their price increases below that lower bound, no consumer would switch. As a result, we would estimate $\hat{\theta} = 1$, implying that switching costs are prohibitive for everyone. This is of course true for the observed price changes but would not be true for larger ones. Note that this problem is not unique to our method but applies to *any* regression-based estimation of switching costs, including those using individual data.

fact, any instrument that is likely to affect all firms within the market in similar ways would be wrong candidates.

An alternative, although typically an imperfect alternative, to instrumental variables is the use of proxy variables for endogenous price changes. Note that in our model the behavioral effects are captured by lagged price changes on the right-hand side ($\Delta p_{jt-1}$) in order to allow for delays in the responses. An important potential source of endogeneity is the reaction of firms to changes in new demand or the stock of their consumers. Lagged prices are free of this endogeneity since firms cannot change their prices retroactively. As a result, $\Delta p_{jt-1}$ the $u_{jt}$ variables are uncorrelated in the absence of serial correlation. Serial correlation may lead to endogeneity if it affects both unobservables ($u$) and price changes ($\Delta p$). Serial correlation in unobservables can in part be captured by controlling for firm-specific trends. Including contemporaneous price changes $\Delta p_{jt}$ can capture serial correlation in the right-hand side variables, which can make the coefficient on $\Delta p_{jt-1}$ be consistent for demand responses even under serially correlated unobservables. The latter approach is sometimes called as a proxy variable solution to endogeneity.

Comparing switching costs in different regimes is straightforward by comparing $\hat{\delta}$ and $\hat{\theta}$ estimated from separate samples. Such estimation may be more efficient if carried out in a pooled sample with appropriate interactions with $\Delta p_{t-1}$. Indeed, a typical difference-in-differences estimation method would use such a pooled sample. We keep the two samples separate for the estimation only for expositional reasons. The coefficient estimates from the two regressions are combined anyway in an explicit way in $\hat{\delta}$ and $\hat{\theta}$.

Similar interactions may be helpful in assessing the role of observable firm-specific switching cost components. By interacting their level with price changes in regressions (5) and (6), one can estimate switching costs $\hat{\delta}$ and $\hat{\theta}$ at different levels of observed cost components. Note however, that interactions with firms-specific cost components can be problematic as they are choice variables to firms. In our example of banking loans, loan termination fees are potentially observed firm-specific cost components. If banks see an exogenous increase in early repayment of loans, they may increase the termination fee in order cover possibly convex costs associated with such repayments. This can be problematic especially if $\Delta n_{jt}$ and $\Delta l_{jt}$ are not measured but are approximated, which is going to be our case (see next subsection). Firms' behavior would create a correlation between termination fees and the discrepancy between $\Delta l_{jt}$ and its measured counterpart (see the next section), resulting in biased estimates. Moreover, termination fees may respond to switching itself, leading to additional simultaneity bias.

The problems listed above may or may not occur in specific applications, and they need to be assessed on a case by case basis.

### 3.4 Potential data problems in firm-level analysis

In a typical application on firm-level data, the ideal left-hand side variables in (5) and (6) are unobserved: aggregate data on the status of the consumer in previous time periods are seldom available. However, the number of incoming and outgoing consumers from decomposition (3) is often available in certain markets, and we argue that these can be used as proxies in our estimations.

We denote the proxy of $n$ by $m$ and the proxy of $l$ by $k$, and define them as follows:

$$m_{jt} = \frac{IN_{jt}}{\Sigma_k IN_{kt}}, \tag{9}$$

$$k_{jt} = 1 - \frac{OUT_{jt}}{S_{jt-1} - X_{jt}}. \tag{10}$$

By using these proxies, our regressions to estimate become:

$$\Delta m_{jt} = \alpha_m + \beta \Delta p_{jt-1} + u_{mjt} \tag{11}$$

$$\Delta k_{jt} = \alpha_k + \gamma \Delta p_{jt-1} + u_{kjt}. \tag{12}$$

The principal question is how estimators $\hat{\beta}$ and $\hat{\gamma}$ are related to the ideal estimators $\hat{\beta}^*$ and $\hat{\gamma}^*$, respectively. This depends on whether the discrepancies between proxy and ideal variables are correlated with (lagged) price changes, the right-hand side variable of each regression. Formally, we would need $Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right) = 0$ and $Cov\left(\Delta d_{kjt}, \Delta p_{jt-1}\right) = 0$ to hold, where $d_{mjt} = m_{jt} - n_{jt}$ and $d_{kjt} = k_{jt} - l_{jt}$. We argue that the second covariance condition is likely to be satisfied, but the first is not.

In the applied estimation model outlined in this section, the proxy of $n_{jt}$ is $m_{jt}$, the market share in all new loans issued in period $t$ as defined in (9). This proxy variable errs by potentially including switchers $F_{jt}$ from other banks : $IN_{jt} = N_{jt} + F_{jt}$. Therefore the discrepancy between the ideal variable and the measured one, $d_{mjt} = m_{jt} - n_{jt}$, may include switchers. If price changes induce any switching, an increase in firm $j$'s price may discourage switchers as well as new consumers. As a result, the estimated reaction of new consumers is biased downwards (looks stronger than it is). Formally, we have that

$$\begin{aligned} \mathrm{p}\lim \hat{\beta} &= \mathrm{p}\lim \hat{\beta}^{*} + \frac{Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)} = \mathrm{p}\lim \hat{\beta}^{*} + bias \\ bias &= \frac{Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)} < 0 \end{aligned}$$

The bias is due to changes in switching consumers as a response to price changes, and is therefore related to $\gamma^{*}$. If switching costs prevent everybody to change firms, there is no bias in $\hat{\beta}$. An immediate consequence of this fact is that the bias has no effect on the consistency of a test for $H_0 : \theta = 1$ (i.e. complete lock-in).

The bias is likely to be larger the stronger the switching response, and therefore the larger $\gamma^{*}$ is. In Appendix B, we show that an upper bound to the bias can be approximated as proportional to $\gamma^{*}$, where the proportionality factor is the average of the ratio of firm-level stocks (minus exiting consumers) to the sum of all incoming consumers:

$$\begin{aligned} bias &\leq a\gamma^{*} \\ a &\approx E_{j,t}\left[\frac{S_{jt-1} - X_{jt}}{\Sigma_k IN_{kt}}\right] \end{aligned}$$

The proxy of $l_{jt}$ is $k_{jt}$ as defined in (10), based on contract terminations (loan repayments in our example) before due date. Recall that this variable is meant to proxy the fraction of consumers who did not switch after the price change. It errs on two counts. First, the numerator is $OUT_{jt} = T_{jt} + Q_{jt}$ instead of $T_{jt}$. It therefore includes consumers $Q_{jt}$ who repay their loans before due date but do not refinance at other banks. Second, the denominator is $S_{jt-1} - X_{jt}$ instead of $S_{jt-1} - X_{jt} - Q_{jt}$, which again includes $Q_{jt}$. The discrepancy $d_{kjt} = k_{jt} - l_{jt}$ is due to these two facts: the numerator and the denominator of $l$ are both increased by the same $Q_{jt}$. The discrepancy is positive, since the numerator of $l$ is smaller than the denominator.

Contrary to the discrepancy for new consumers, this one is unlikely to lead to an estimation bias. The question is whether (normalized) non-refinancing terminations $Q_{jt}$ are correlated with price changes in the previous period. We have no reasons to think that they are, because these terminations are typically due to positive income shocks, which are typically unrelated to price movements. Therefore, we can assume that $Cov\left(\Delta d_{kjt}, \Delta p_{jt-1}\right) = 0$. So estimates of $\gamma$ are consistent for the same parameter as estimates of $\gamma^*$ would be under ideal circumstances: $p\lim \hat{\gamma} = p\lim \hat{\gamma}^*$.As a result, if Conditions 1 and 2 are satisfied,

$$\begin{aligned} \beta^* &\leq \mathrm{p}\lim \hat{\beta} \leq \beta^* + a\gamma^* \\ \mathrm{p}\lim \hat{\gamma} &= \gamma^* \end{aligned}$$

Consistency of $\hat{\gamma}$ allows us to obtain a simple bias-corrected version of $\hat{\beta}$ and thus the switching cost estimators:

$$\hat{\delta}_{corrected} = \left(\hat{\beta} - a\hat{\gamma}\right) - \hat{\gamma} \tag{13}$$

$$\hat{\theta}_{corrected} = \frac{\left(\hat{\beta} - a\hat{\gamma}\right) - \hat{\gamma}}{\hat{\beta} - a\hat{\gamma}} \tag{14}$$

In absolute value, the corrected estimators are the lower bounds of the true parameters $\delta$ and $\theta$, respectively. The stronger the estimated switching response (the larger $\hat{\beta}$) is, the larger the effect of the bias correction will be. But the effect is different for $\delta$ and $\theta$, and a smaller effect is expected in terms of the latter.

# 4 Illustrative application

In this section we present an application in order to show how our measurement model can be put to work. This application was part of the retail banking sector inquiry of the Hungarian Competition Authority (GVH) that started in 2007. The inquiry explored switching costs in relation to current accounts and bank loans, and it made recommendations to improve the effective functioning of competition in this sector. Many of the recommendations aimed at facilitating the switching of consumers and constraining the market power of banks in terms of ex-post price changes by unilateral contract modifications.[18]

We focus on the market of personal loans between 2002 and 2006, i.e. loans for undetermined use that can in principle be either unsecured or secured by a mortgage. In Hungary, personal loans can be denominated either in home currency or foreign currencies, the latter mostly in Swiss Franc and Euro. Our application focuses on unsecured loans denominated in home currency. This segment was the largest and most developed of the personal loan products in the sample period (the volume of foreign currency denominated loans started to grow only after 2005). Old consumers are clients already having a loan contract at one of the banks. In any period (quarter) they can stay at their original bank or terminate the loan contract and refinance it by the loan of another bank at a more favorable rate. The latter behavior is the switching we are interested in. There is no price discrimination between old and new consumers of a certain bank concerning personal loans.

The overall dataset covers the nine largest banks in Hungary that hold at least a one per cent market share on the personal loan market. Together, they cover over 90 per cent of the market for all personal loans. We use quarterly data on prices and the number

[18]The full report including the estimation results of this Section is avalaible in Hungarian at the GVH's homepage: http://www.gvh.hu/domain2/files/modules/module25/777170A574AD8E91.pdf

An English executive summary can be also found at

http://www.gvh.hu/domain2/files/modules/module25/8801AA394BE9C1EF.pdf and contract value of new contracts and terminated contracts. Of the nine banks, seven provided adequate data on the number of consumers and six on the value of terminated contracts. Nonrespondents were among the smaller banks. Prices $p_{jt}$ are measured by the annual percentage rate (APR) of the banks' most popular (modal) product in terms of loan value and duration. Most banks had a single product in the personal loan market during the period. According to Hungarian financial regulations, APR includes all entry costs but not the termination costs. Table 1 shows the most important data for the market using our sample.

Table 1. Features of the personal loan market in Hungary (unsecured leans)

| | 2002 | 2003 | 2004 | 2005 | 2006 |
|---|---|---|---|---|---|
| Number of consumers ($'000$) | 50 | 78 | 222 | 413 | 506 |
| Value of contracts (billion HUF) | 23 | 42 | 100 | 167 | 187 |
| Number of firms | 7 | 7 | 9 | 9 | 9 |
| Average interest rate (APR), per cent | 26.8 | 25.8 | 28.4 | 25.9 | 24.3 |

Note. Number of consumers and value of contracts are measured as yearly averages.

The market grew dynamically during the observed time period, its growth rate slowing down somewhat after 2005. Meanwhile, the number of firms participating in the market increased, a fact that is in line with the Beggs and Klemperer (1992) framework that implies entry despite of potentially large switching costs. Another implication of their framework is also broadly in line with what we see in this market: a growth in demand leads to falling prices Furthermore, the Beggs and Klemperer framework implies that larger firms should charge higher prices and have declining markets, a fact that is also present in our data (but not detailed for confidentiality reasons).

The main explanatory variable is the APR relative to the market average, lagged by one period. Lagging makes sense because changes are advertised only after they are made and thus consumers are likely to react with some time lag. We estimate regressions (11) and (12) and include bank and time period fixed effects. Including bank fixed-effects ensures that potential bank-specific trends do not interfere with the identification. Including time period (quarterly) fixed effects ensures that common effects on all banks do not interfere with the identification. In particular, the effects of potential changes in the outside option, business cycle or seasonality are filtered out (to the extent of a linear approximation). We do not have credible instruments for price changes nor clean natural experiments that would ensure that variation in prices is exogenous to consumer demand. Instead, in the spirit of our discussion of econometric problems above, we include contemporaneous price changes $\Delta p_{jt}$ next to the main variable $\Delta p_{jt-1}$ as a proxy variable for potential endogeneity.

In the main text we present the OLS estimates of the coefficients $\beta$ and $\gamma$ and the estimates of $\delta$ and $\theta$ based on those OLS coefficients. We return to the bias-corrected estimates later. Summary statistics and the complete set of parameter estimates and regression statistics are in Appendix C (Tables C1 and C2). We present boostrap confidence intervals on the $5^{th}$ and $95^{th}$ percentiles. These are estimated by block-bootstrap (i.e. re-sampling of complete firm histories as opposed to individual firm-year observations) in order to account for serial correlation. While the confidence intervals contain only 90 per cent of the sampling distribution, they are nevertheless rather conservative. This can be seen by comparing the bootstrap standard errors of the $\hat{\beta}$ coefficients to their analytical standard errors shown in Appendix C: the bootstrap standard errors are significantly larger.

Table 2 shows the estimates of the regression parameters and the switching cost parameters assuming no bias in $\hat{\beta}$.

Table 2. Estimates of lock-in for unsecured personal loans assuming no bias in $\hat{\beta}$

| | # consumers | value |
|---|---|---|
| Response of new consumers ($\beta$) | $-0.61$ | $-0.74$ |
| (bootstrap SE) | (0.22) | (0.23) |
| (confidence interval) | $(-0.93, -0.14)$ | $(-0.99, -0.22)$ |
| Response of old consumers ($\gamma$) | $-0.13$ | $-0.18$ |
| (bootstrap SE) | (0.06) | (0.07) |
| (confidence interval) | $(-0.18, -0.01)$ | $(-0.24, -0.00)$ |
| Switching costs: difference ($\delta$) | 0.48 | 0.56 |
| (confidence interval) | $(0.13, 0.87)$ | $(0.22, 0.81)$ |
| Switching costs: normalized ($\theta$) | 0.79 | 0.76 |
| (confidence interval) | $(0.66, 1.00)$ | $(0.68, 1.00)$ |

Block-bootstrap confidence intervals ($5^{th}$ and $95^{th}$ percentiles) based on 2000 iterations.

As we have shown, however, $\hat{\beta}$ may be a biased estimator of $\beta^*$. In equations (13) and (14), we derived an upper bound to the bias, with a proportionality factor $a$. Table 3 shows the switching cost estimates allowing for this maximum bias.

Table 3: Corrected estimates of switching costs allowing for maximum bias.

| | # consumers | value of contracts |
|---|---|---|
| Switching costs: difference ($\delta$) | 0.33 | 0.31 |
| (confidence interval) | $(0.03, 0.80)$ | $(0.10, 0.61)$ |
| Switching costs: normalized ($\theta$) | 0.70 | 0.63 |
| (confidence interval) | $(0.35, 1.00)$ | $(0.41, 1.00)$ |

Note: The estimated value of the proportionality factor $a$ is 1.4

Block-bootstrap confidence intervals ($5^{th}$ percentile, $95^{th}$ percentile) based on 2000 iterations.

Given the sample size, the estimates are reasonably precise. The confidence interval around the parameter of major interest, $\theta$, is especially tight. When maximum bias is allowed for, the estimates of $\delta$ become significantly smaller. At the same time, however, the bias-corrected estimates of $\theta$ are close to the non-corrected estimates.

According to the point estimates, one percentage point increase in bank $j$'s APR charges leads to an overall 0.61 percentage point decrease in the probability of new consumers choosing bank $j$ (the bias-corrected point estimate would be 0.43). Note that the corresponding elasticity is quite strong: a one per cent increase in the price of the loan (i.e. one percentage points increase in APR) leads to a 4.7 per cent decrease in market shares if we evaluate it at the average market share (the bias-corrected estimate would be $-3.3$).

The same price increase is estimated to induce a mere 0.13 percentage points decrease in the probability of bank $j$'s old consumers to stay loyal. This implies an elasticity of $-0.13$ (evaluated at the average loyalty probability of 0.98). These estimates imply a strong lock-in effect, which obviously increases firms' market power. The corresponding estimates for the value of contracts are somewhat stringer, in line with the presumption that consumers with larger contracts are more price sensitive.

These estimates imply that the lock-in effects of switching costs are substantial, whether measured in terms of choice probabilities or contract values. Point estimates of $\theta$ indicate that due to switching costs, consumers are 79 per cent more likely to stay in their existing personal loan contract than if they were about to choose a new contract. The corresponding bias-corrected estimates are also high, at 70 per cent. Estimated switching costs are somewhat smaller in terms of contract value (they prevent 76 or 63 per cent of contract value to switch). The difference is small but it may indicate that consumers with larger contracts are somewhat less constrained by switching costs, which result is consistent with the presumption that at least a part of switching costs is fixed.

Inspection of the confidence intervals reveals that the null hypothesis of $\theta = 0$ can be rejected, while the null hypothesis of $\theta = 1$ cannot (as independent one-sided tests at 5 per cent significance level). The estimates therefore provide strong evidence for the existence of lock-in effects, to the extent that they can be consistent with complete consumer lock-in.[19]

Tables D1 through D4 in Appendix D show robustness checks from different specifications and different time periods. Based on those results we can conclude that the inclusion of time fixed effects is very important, the bank fixed effects are moderately important (recall that these are bank fixed effects added to panel regressions in first differences), and the contemporaneous and leaded proxy variables are no important.

Tables D5 and D6 in the Appendix show estimates from regressions with the value of the termination fee included. Termination fees are one-time fees to be paid when repaying

[19] The significance of the lock-in effects in this market is supported by other, more circumstanctial evidence. From 2006, the demand for loans denominated in local currency started to decrease so it was not in the bank interests' anymore to vigorously compete for new consumers. In line with such incentives, many banks increased their interest rates significantly, especially after the financial crisis of 2008 that led to a further drop in the number potential new consumers.

a loan before due data and are therefore potentially important elements of switching costs. The results show that the estimated lock-in effect of switching costs increases substantially at higher levels of termination fees. In the richest specifications (fixed effects and proxies all included), $\hat{\delta} = 0.33$ at the $25^{th}$ percentile of termination fees, while $\hat{\delta} = 0.61$ at the $75^{th}$ percentile. At the same time, the corresponding estimates of $\theta$ are practically equal. These results highlight the acute measurement problems with termination fees (they are likely to be endogenous with respect to switching behavior), but they are consistent with the idea that monetary costs are important elements of switching costs but other elements like search costs play an important role as well.

# 5 Conclusions

Based on a simple thought experiment, we proposed a simple model for estimating the lock-in effects of switching costs in a direct way by using firm-level data. The basic idea was to compare demand responses to price changes for consumers who are new to the market and for consumers who are already customers of a given firm, and the difference should attributable to the presence of switching costs. Implementation of the method required proxies for the following two quantities in each period: new transactions on the market and transactions (contracts) terminated by consumers. Using these proxy variables may lead to biased estimates, but we derived a way to correct for these biases.

We illustrated our method with an application to the Hungarian market of unsecured personal loans and found substantial switching costs. Old consumers' responsiveness to price changes is estimated 79 per cent lower than new consumers' responsiveness (70 per cent lower if allowing for the maximum bias due to measurement problems and a bit smaller if estimated in terms of contract value). The results indicate the existence of strong lock-in effects, to the extent that they might be consistent with complete consumer lock-in.

The Hungarian Competition Authority used this method among others in a detailed sector inquiry of the banking sector, and the robust conclusion was that switching costs are substantial enough to significantly raise the market power of banks, especially by ex-post fee increases. Therefore, the sector inquiry made several recommendations to the lawmakers and financial regulators that were partly aimed at facilitating the switching of consumers (developing a product & price comparison website in order to increase transparency, foreign currency risks should be also represented in the APR, early repayment charges should be maximized) and at constraining the market power of banks in terms of ex-post price changes by unilateral contract modifications.

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# Appendices

# A Details of the discrete choice background

The model describes the decision problem of consumer $i$ who enters into a contractual relationship lasting for $S$ periods with one of the $J$ firms.[20] The consumer who starts buying the product from firm $j$ may stay loyal to this firm till the end or switch to another firm $k$ at some period $s^* > 1$. If she switched her service provider, we continue the decision problem from period $s + 1$. The problem ends at $S$ (which may be finite or infinite). Note that since consumers arrive at different periods in terms of calendar time, customers of firm $j$'s product may be at different contract periods $s$ at a given calendar period $t$.

Let $y_{ijs} = 1$ mean that consumer $i$ chooses firm $j$ in period $s$ and $y_{ijs} = 0$ otherwise. The cost of being the customer of firm $j$ in period $s$ will be the observed price $p_{js}$ and an unobserved component $u_{ij}$ that is specific to the match of individual $i$ and firm $j$. We assume that the unobserved component is time-invariant, which captures the idea that many of those match-specific utility components may be persistent (such as taste heterogeneity, regional differences in availability, brand loyalty, etc.). Furthermore, if consumer $i$ switches from firm $\dot{j}$ to firm $k$ in period $s \in [2, S]$(that is if $y_{ij(s-1)} = 1$ and $y_{ijs} = 0$) she faces additional switching costs $C_{ij}$ to be paid at the time of switching. Additionally, we assume that consumers cannot predict future price changes so that $E_s [p_{jr}] = p_{js}$ for $r > s$.[21]

If consumer $i$ is a new consumer at $s = 1$, she will minimize her discounted present value of the expected per-period costs denoted by $e_{ij1} = E_1 \left[ \sum_{r=1}^{S} (p_{jr} + u_{ij}) / (1 + \rho)^r \right]$. She then chooses firm $j$ if $e_{ij1} \leq e_{ik1}$ for $\forall k \neq j$, which condition simplifies to $u_{ij} - u_{ik} \leq p_{k1} - p_{j1}$ for

[20] The outside option may or may not be included among the firms; as we shall see, our empirical implementation handles outside options with the inclusion of period fixed effects.

[21] We think this assumption is justified is many applications. Loan contracts provided to individuals or subscription fees usually specificy the same per-period fixed fee, while future consumption affecting variable payments (like minutes called) can usually be proxied best by current consumption.

$\forall k \neq j$, or in vector notation[22]

$$\mathbf{u}_{ij} - \mathbf{u}_{ik} \leq \mathbf{p}_{k1} - \mathbf{p}_{j1}. \tag{15}$$

Intuitively, the individual should choose firm $j$ if the prices of all other firms exceed firm $j$'s price to a degree that the difference is larger than firm $j$'s subjective costs relative to all other firms' subjective costs.

If we assume that the vector of unobservables is i.i.d. across individuals, the probability of new consumers choosing firm $j$ at calendar time $t$ is

$$n_{jt} \equiv \Pr\left(y_{ijt} = 1 | s = 1\right) = \Pr\left(\mathbf{u}_{ij} - \mathbf{u}_{ik} \leq \mathbf{p}_{kt} - \mathbf{p}_{jt}\right) = F\left(\mathbf{p}_{kt} - \mathbf{p}_{jt}\right) \tag{16}$$

where $F$ is the joint c.d.f. of the unobserved cost differentials $\mathbf{u}_{ij} - \mathbf{u}_{ik}$. Intuitively, an increase in $p_{jt}$ would make some new consumers change their mind and choose another firm instead: these are those for whom at least one element of the threshold (the left-hand side of (15)) is high enough to exceed the corresponding relative price. $n_{jt}$, the fraction of consumers buying from firm $j$, is decreased by the fraction of such consumers. The magnitude is determined by the fraction of such marginal individuals, which is determined by the shape of $F$ at $\mathbf{p}_{kt} - \mathbf{p}_{jt}$.

Now suppose that consumer $i$ is an old consumer of firm $j$ in period $s \in [2, S]$, so $y_{ij(s-1)} = 1$. The expected costs of staying loyal is $e_{ijs} = E_s\left[\sum_{r=s}^{S}(p_{jr} + u_{ij}) / (1+\rho)^r\right]$, while choosing another firm $k$ would mean expected costs $e_{iks} = E_s\left[\sum_{r=s}^{S}(p_{kr} + u_{ik} + c_{ij}) / (1+\rho)^r\right]$, where $c_{ijs}$ is the discounted switching cost distributed equally for all subsequent periods so that $C_{ij} = \sum_{r=s}^{S} c_{ijs} / (1+\rho)^r$ (the $s$ subscript in $c_{ijs}$ denotes the time period of switching). Consequently, consumer $j$ would stay loyal to firm $j$ if and only if $u_{ijt} - u_{ikt} \leq p_{ks} - p_{js} + c_{ijs}$ for $\forall k \neq j$, or in vector notation if

$$\mathbf{u}_{ij} - \mathbf{u}_{ik} - \mathbf{c}_{ijs} \leq \mathbf{p}_{ks} - \mathbf{p}_{js} \tag{17}$$

[22] The dimension of the vectors is $(J-1) \times 1$, $\mathbf{u}_{ij}$ is a vector with all elements $u_{ij}$, $\mathbf{p}_{j1}$ is a vector with all elements $p_{j1}$, while $\mathbf{u}_{ik}$ and $\mathbf{p}_{k1}$ are the $(J-1) \times 1$ vectors of the different $u_{ik}$ and $p_{k1}$ entries, respectively $(k \neq j)$.

where $\mathbf{c}_{ijs}$ is a vector with all elements $c_{ijs} \geq 0$.Note that for a given $S$, $c_{ijs}$ is negatively related to $S - s$ (and positively related to $s$): in a forward-looking decision, the longer the remaining time the smaller the role of one-time switching costs. Or, in other words, switching costs are expected to be more prohibitive the closer the end date $S$ (the larger $s$).[23]

In this way we can write down the probability of staying loyal for the old customers of firm $j$ in $s > 1$ by

$$l_{jt} = \Pr\left(y_{ijt} = 1 | y_{ijt-1} = 1\right). \tag{18}$$

This choice probability is conditional on the individual's choice in the previous period. That choice itself was a loyalty decision, too, which was again conditional on the consumer's earlier choice, etc. As a result, the loyalty probability a fairly complicated function of all past prices, and solving the loyalty problem is beyond the scope of our paper. Instead, we focus on some intuitive implications of the loyalty conditions themselves.

The first immediate consequence of condition (17) is that if there are no switching costs, the condition of staying loyal to $j$ is the same as condition (15) for choosing $j$ in the first place. This confirms the intuition behind our reduced-form approach: the price responsiveness of new consumers can be a valid approximation of the price responsiveness of old consumers in the absence of switching costs.

On the other hand, condition (17) shows that switching costs decrease the threshold that other firms' relative prices have to exceed in order for consumer $i$ to stay loyal to firm $j$. One consequence is that for given prices, the loyalty probability is greater than the choice probability of new consumers. The other consequence is that, starting from above the threshold for new consumers (left-hand side of (15)), own prices have to increase more (other firms' prices have to decrease more) in order to pass the threshold for old consumers. In particular, for a given increase in own price ($\Delta p_{jt} > 0$), there are always consumers who

[23] The magnitude of this effect is decreased inif we add period-specific switching costs or costs that are scaled directly to the remaining time (as in cases when incumbent firms make switching consumers pay a sum related to remaining time).

would switch in the absence of switching costs but whose $c_{ijs}$ is high enough to prevent switching. As a result, the same price increase leads to a weaker average reaction of old consumers. The fraction of consumers who are prevented from switching depends on the c.d.f. of switching costs $c_{ijs}$, which in turn depends on the distribution of $C_{ij}$ and heterogeneity in the remaining contract time $S - s$. Since $c_{ijs}$ is increasing in $s$ (decreasing in the remaining contract time $S - s$) we expect more people to switch in growing markets than in stationary markets ceteris paribus.

# B Deriving the bias to $\hat{\beta}$

Our goal is to approximate the upper bound to the bias to $\hat{\beta}$, which is the following:

$$bias \leq \frac{Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)}$$

We start from the definition of the discrepancy $d_m$ :

$$\begin{aligned}
n_{jt} &= \frac{N_{jt}}{\Sigma_k N_{kt}} \text{ and} \\
m_{jt} &= \frac{IN_{jt}}{\Sigma_k IN_{kt}} = \frac{N_{jt} + F_{jt}}{\Sigma_k N_{kt} + \Sigma_k F_{kt}}, \text{ so} \\
d_{mjt} &= m_{jt} - n_{jt} = \frac{N_{jt} + F_{jt}}{\Sigma_k N_{kt} + \Sigma_k F_{kt}} - \frac{N_{jt}}{\Sigma_k N_{kt}} \leq \frac{F_{jt}}{\Sigma_k IN_{kt}}.
\end{aligned}$$

The last result follows from the fact that $\frac{N_{jt}+F_{jt}}{\Sigma_k N_{kt}+\Sigma_k F_{kt}} - \frac{N_{jt}}{\Sigma_k N_{kt}} \leq \frac{N_{jt}+F_{jt}}{\Sigma_k N_{kt}+\Sigma_k F_{kt}} - \frac{N_{jt}}{\Sigma_k N_{kt}+\Sigma_k F_{kt}}$, given that $\frac{N_{jt}}{\Sigma_k N_{kt}} \geq \frac{N_{jt}}{\Sigma_k N_{kt}+\Sigma_k F_{kt}}$.

Assume that the market is stationary in the sense that the number of new consumers is the same in each time period. Therefore, $\sum_j N_{jt} = \sum_j N_{jt-1}$, and so we have that

$$\Delta d_{mjt} = \left(m_{jt} - n_{jt}\right) - \left(m_{jt-1} - n_{jt-1}\right) \leq \frac{\Delta F_{jt}}{\sum_k IN_{kt}}.$$

The switching response to a price increase is captured by $\gamma^*$. Here we expand the definition of $\gamma^*$ in order to connect it to the measure of switchers in the discrepancy term.

$$\begin{aligned}
\gamma^* &= \frac{Cov\left(\Delta l_{jt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)} \text{ and} \\
l_{jt} &= 1 - \frac{T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}}, \text{ so} \\
\Delta l_{jt} &= 1 - \frac{T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}} - \left(1 - \frac{T_{jt-1}}{S_{jt-2} - X_{jt-1} - Q_{jt-1}}\right) \\
&= \frac{T_{jt-1}}{S_{jt-2} - X_{jt-1} - Q_{jt-1}} - \frac{T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}} \\
&\approx \frac{T_{jt-1} - T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}} = -\frac{\Delta T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}}.
\end{aligned}$$

If firms are symmetric and consumers homogenous, the change in switching from bank $j$ and to bank $j$ are equal in absolute value (and they are always of opposite sign):

$$\Delta T_{jt} \approx -\Delta F_{jt}.$$

As a result,

$$\begin{aligned}
\Delta l_{jt} &\approx -\frac{\Delta T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}} \approx \frac{\Delta F_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}} \\
&= \frac{\Delta F_{jt}}{\sum_k IN_{kt}} \frac{\sum_k IN_{kt}}{S_{jt-1} - X_{jt} - Q_{jt}}.
\end{aligned}$$

This leads to a bound to the bias for each firm $j$ in each time period $t$ the following way:

$$\begin{aligned}
Cov\left(\Delta l_{jt}, \Delta p_{jt-1}\right) &\approx Cov\left(-\frac{\Delta T_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}}, \Delta p_{jt-1}\right) \approx Cov\left(\frac{\Delta F_{jt}}{S_{jt-1} - X_{jt} - Q_{jt}}, \Delta p_{jt-1}\right) \\
&= \frac{\sum_k IN_{kt}}{S_{jt-1} - X_{jt} - Q_{jt}} Cov\left(\frac{\Delta F_{jt}}{\sum_k IN_{kt}}, \Delta p_{jt-1}\right), \\
Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right) &\leq Cov\left(\frac{\Delta F_{jt}}{\sum_k IN_{kt}}, \Delta p_{jt-1}\right) \\
&\approx \frac{S_{jt-1} - X_{jt} - Q_{jt}}{\sum_k IN_{kt}} Cov\left(\Delta l_{jt}, \Delta p_{jt-1}\right) \leq a_{jt} Cov\left(\Delta l_{jt}, \Delta p_{jt-1}\right), \text{ where} \\
a_{jt} &= \frac{S_{jt-1} - X_{jt}}{\sum_k IN_{kt}}
\end{aligned}$$

In the last inequality we replaced $\frac{S_{jt-1}-X_{jt}-Q_{jt}}{\Sigma_k IN_{kt}}$ by $a_{jt} = \frac{S_{jt-1}-X_{jt}}{\Sigma_k IN_{kt}}$ because the latter is estimable, while the former is not.

Based on these results, we can approximate the upper bound to the bias in a panel of firms by the average of the $jt$ bias bounding terms:

$$\begin{aligned}
bias &= \frac{Cov\left(\Delta d_{mjt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)} \leq a \frac{Cov\left(\Delta l_{jt}, \Delta p_{jt-1}\right)}{V\left(\Delta p_{jt-1}\right)} = a\gamma^*, \text{ where} \\
a &= E_{j,t}\left[\frac{S_{jt-1} - X_{jt}}{\sum_k IN_{kt}}\right].
\end{aligned}$$

# C Summary statistics and complete results

Table C1. Summary statistics for unsecured personal loans denominated in home currency

| | # consumers | | | contract value | | |
|---|---|---|---|---|---|---|
| | *mean* | *std.dev.* | *obs.* | *mean* | *std.dev.* | *obs.* |
| $m_{jt}$ | 0.13 | 0.18 | 105 | 0.14 | 0.18 | 87 |
| $k_{jt}$ | 0.98 | 0.02 | 105 | 0.97 | 0.02 | 87 |
| $p_{jt}$ | 0.06 | 0.03 | 105 | 0.05 | 0.03 | 87 |
| $\Delta m_{jt}$ | $-0.007$ | 0.049 | 105 | $-0.008$ | 0.051 | 87 |
| $\Delta k_{jt}$ | $-0.001$ | 0.010 | 105 | $-0.001$ | 0.012 | 87 |
| $\Delta p_{jt-1}$ | $-0.001$ | 0.001 | 105 | $-0.001$ | 0.020 | 87 |

Table C2. Complete regression estimates (unsecured personal loans denominated in home currency)

| | # consumers | | contract value | |
|---|---|---|---|---|
| | $m$ | $k$ | $m$ | $k$ |
| $\Delta p_{jt-1}$ | $-0.61$ | $-0.13$ | $-0.74$ | $-0.18$ |
| SE | $(0.14)^{**}$ | $(0.05)^{*}$ | $(0.19)^{**}$ | $(0.06)^{*}$ |
| $\Delta p_{jt}$ | $-0.62$ | 0.11 | $-0.83$ | 0.16 |
| SE | $(0.13)^{**}$ | $(0.04)^{*}$ | $(0.13)^{**}$ | $(0.05)^{*}$ |
| Firm FE | yes | yes | yes | yes |
| Period FE | yes | yes | yes | yes |
| $R^2$ | 0.49 | 0.43 | 0.55 | 0.44 |
| # firms | 7 | 7 | 6 | 6 |
| Observations | 105 | 105 | 87 | 87 |

Analytical standard error estimates (clustered at firm level) in parentheses.

$R^2$ include the explanatory power of fixed-effects.

$^{**}$ significant at 1%, $^{*}$ significant at 5%

# D Additional regression results

Table D1. Regression results for the entire sample period (standard errors are clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | M | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -1.06 | -0.06 | -1.17 | -0.10 | -0.73 | -0.12 | -0.89 | -0.17 | -0.62 | -0.12 | -0.77 | -0.17 |
| | (0.25) | -0.03 | (0.28) | -0.06 | (0.21) | (0.04) | (0.23) | (0.06) | (0.14) | (0.04) | (0.16) | (0.06) |
| Obs | 105 | 105 | 87 | 87 | 105 | 105 | 87 | 87 | 105 | 105 | 87 | 87 |
| R-sq | 0.16 | 0.01 | 0.21 | 0.03 | 0.33 | 0.4 | 0.31 | 0.39 | 0.46 | 0.41 | 0.49 | 0.4 |
| Uncorrected point estimates of the structural parameters | | | | | | | | | | | | |
| δ | 1.00 | | 1.07 | | 0.61 | | 0.72 | | 0.50 | | 0.60 | |
| θ | 0.94 | | 0.91 | | 0.84 | | 0.81 | | 0.81 | | 0.78 | |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.61 | -0.13 | -0.74 | -0.18 | -0.60 | -0.11 | -0.70 | -0.17 |
| | (0.13) | (0.04) | (0.17) | (0.06) | (0.13) | (0.05) | (0.17) | (0.05) |
| $\Delta p_{tj}$ | -0.62 | 0.11 | -0.83 | 0.16 | -0.6 | 0.09 | -0.83 | 0.13 |
| | (0.12) | (0.04) | (0.12) | (0.04) | (0.12) | (0.03) | (0.12) | (0.05) |
| $\Delta p_{tj+1}$ | | | | | 0.07 | 0.05 | 0.12 | 0.04 |
| | | | | | (0.11) | (0.04) | (0.07) | (0.03) |
| Obs | 105 | 105 | 87 | 87 | 98 | 98 | 81 | 81 |
| R-sq | 0.49 | 0.43 | 0.55 | 0.44 | 0.48 | 0.44 | 0.54 | 0.48 |
| Uncorrected point estimates of the structural parameters | | | | | | | | |
| δ | 0.48 | | 0.56 | | 0.49 | | 0.53 | |
| θ | 0.79 | | 0.76 | | 0.82 | | 0.76 | |

Table D2. Regression results for the period of 2003 to 2006 (standard errors are clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -1.07 | -0.08 | -1.16 | -0.13 | -0.68 | -0.13 | -0.88 | -0.18 | -0.57 | -0.13 | -0.76 | -0.19 |
| | (0.26) | (0.04 | (0.30) | (0.07 | (0.22) | (0.04) | (0.25) | (0.06) | (0.13) | (0.05) | (0.17) | (0.06) |
| Obs | 89 | 89 | 75 | 75 | 89 | 89 | 75 | 75 | 89 | 89 | 75 | 75 |
| R-sq | 0.16 | 0.01 | 0.21 | 0.03 | 0.33 | 0.4 | 0.31 | 0.39 | 0.46 | 0.41 | 0.49 | 0.4 |
| Uncorrected point estimates of the structural parameters | | | | | | | | | | | | |
| δ | 0.99 | | 1.03 | | 0.55 | | 0.70 | | 0.44 | | 0.57 | |
| θ | 0.93 | | 0.89 | | 0.81 | | 0.80 | | 0.77 | | 0.75 | |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.57 | -0.13 | -0.76 | -0.19 | -0.55 | -0.11 | -0.72 | -0.17 |
| | (0.13) | (0.04) | (0.17) | (0.06) | (0.12) | (0.06) | (0.15) | (0.06) |
| $\Delta p_{tj}$ | -0.41 | 0.1 | -0.55 | 0.14 | -0.38 | 0.08 | -0.55 | 0.11 |
| | (0.10) | (0.03) | (0.12) | (0.05) | (0.10) | (0.02) | (0.12) | (0.05) |
| $\Delta p_{tj+1}$ | | | | | 0.13 | 0.06 | 0.14 | 0.07 |
| | | | | | (0.15) | (0.06) | (0.13) | (0.01) |
| Obs | 89 | 89 | 75 | 75 | 82 | 82 | 69 | 69 |
| R-sq | 0.61 | 0.44 | 0.7 | 0.41 | 0.6 | 0.46 | 0.69 | 0.46 |

Table D3. Regression results for the period of 2004 to 2006 (point estimates and standard errors clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.49 | 0.06 | -0.66 | 0.04 | -0.57 | -0.04 | -0.72 | -0.04 | -0.18 | -0.06 | -0.24 | -0.04 |
| | (0.38) | (0.1) | (0.42) | (0.11) | (0.43) | (0.05) | (0.5) | (0.05) | (0.27) | (0.05) | (0.22) | (0.07) |
| Obs | 69 | 69 | 59 | 59 | 69 | 69 | 59 | 59 | 69 | 69 | 59 | 59 |
| R-sq | 0.03 | 0 | 0.06 | 0 | 0.04 | 0.42 | 0.07 | 0.33 | 0.46 | 0.43 | 0.66 | 0.35 |
| Uncorrected point estimates of the structural parameters | | | | | | | | | | | | |
| δ | 0.55 | | 0.70 | | 0.53 | | 0.68 | | 0.12 | | 0.20 | |
| θ | 1.12 | | 1.06 | | 0.93 | | 0.94 | | 0.67 | | 0.83 | |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.17 | -0.05 | -0.23 | -0.05 | -0.15 | -0.05 | -0.19 | -0.06 |
| | (0.27) | (0.06) | (0.2) | (0.08) | (0.24) | (0.04) | (0.18) | (0.08) |
| $\Delta p_{tj}$ | -0.19 | -0.02 | -0.11 | 0.07 | -0.11 | -0.09 | -0.08 | -0.01 |
| | (0.12) | (0.1) | (0.23) | (0.15) | (0.14) | (0.13) | (0.25) | (0.2) |
| $\Delta p_{tj+1}$ | | | | | 0.25 | 0.11 | 0.17 | 0.08 |
| | | | | | (0.18) | (0.07) | (0.13) | (0.03) |
| Obs | 69 | 69 | 59 | 59 | 62 | 62 | 53 | 53 |
| R-sq | 0.46 | 0.43 | 0.67 | 0.35 | 0.44 | 0.47 | 0.65 | 0.41 |
| Uncorrected point estimates of the structural parameters | | | | | | | | |
| δ | 0.12 | | 0.18 | | 0.10 | | 0.13 | |
| Θ | 0.71 | | 0.78 | | 0.67 | | 0.68 | |

Table D4. Regression results for the period of 2002 to 2005 (standard errors are clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -1.11 | -0.06 | -1.23 | -0.11 | -0.77 | -0.13 | -0.94 | -0.18 | -0.67 | -0.13 | -0.81 | -0.19 |
| | (0.22) | (0.03 | (0.25) | (0.06 | (0.20) | (0.05) | (0.22) | (0.06) | (0.12) | (0.04) | (0.14) | (0.05) |
| Obs | 77 | 77 | 63 | 63 | 77 | 77 | 63 | 63 | 77 | 77 | 63 | 63 |
| R-sq | 0.19 | 0.02 | 0.25 | 0.06 | 0.37 | 0.38 | 0.34 | 0.43 | 0.47 | 0.42 | 0.5 | 0.46 |
| Uncorrected point estimates of the structural parameters | | | | | | | | | | | | |
| δ | 1.05 | | 1.12 | | 0.64 | | 0.76 | | 0.54 | | 0.62 | |
| θ | 0.95 | | 0.91 | | 0.83 | | 0.81 | | 0.81 | | 0.77 | |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.67 | -0.13 | -0.80 | -0.19 | -0.65 | -0.12 | -0.77 | -0.18 |
| | (0.12) | (0.04) | (0.15) | (0.05) | (0.12) | (0.05) | (0.15) | (0.05) |
| $\Delta p_{tj}$ | -0.64 | 0.09 | -0.9 | 0.15 | -0.74 | 0.11 | -0.96 | 0.15 |
| | (0.16) | (0.04) | (0.13) | (0.06) | (0.17) | (0.03) | (0.13) | (0.06) |
| $\Delta p_{tj+1}$ | | | | | -0.02 | 0.05 | 0.07 | 0.06 |
| | | | | | (0.15) | (0.04) | (0.15) | (0.03) |
| Obs | 77 | 77 | 63 | 63 | 70 | 70 | 57 | 57 |
| R-sq | 0.51 | 0.44 | 0.57 | 0.51 | 0.52 | 0.44 | 0.55 | 0.54 |
| Uncorrected point estimates of the structural parameters | | | | | | | | |
| δ | 0.54 | | 0.61 | | 0.53 | | 0.59 | 81 |
| θ | 0.81 | | 0.76 | | 0.82 | | 0.77 | 0.48 |

Table D5. Regression results with the value of termination fee included as additional regresor (F). (Measured in HUF ’00,000, min=0.02, max=0.35. Entire sample period; standard errors are clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -1.06 | -0.06 | -1.17 | -0.10 | -0.73 | -0.12 | -0.89 | -0.17 | -0.62 | -0.12 | -0.77 | -0.17 |
| | (0.25) | -0.03 | (0.28) | -0.06 | (0.21) | (0.04) | (0.23) | (0.06) | (0.14) | (0.04) | (0.16) | (0.06) |
| $\Delta p_{tj-1} \times F_{tj-1}$ | -2.26 | -0.51 | -3.28 | -0.94 | -0.87 | -0.41 | -2.69 | -0.83 | -1.42 | -0.37 | -3.45 | -0.73 |
| | (2.25 | (0.20) | (1.99 | (0.26) | (2.37 | (0.16) | (2.26 | (0.18) | (2.79 | (0.17) | (2.52 | (0.15) |
| Obs | 69 | 69 | 59 | 59 | 69 | 69 | 59 | 59 | 69 | 69 | 59 | 59 |
| R-sq | 0.03 | 0 | 0.06 | 0 | 0.04 | 0.42 | 0.07 | 0.33 | 0.46 | 0.43 | 0.66 | 0.35 |
| Uncorrected point estimates of the structural parameters at various levels of the termination fee | | | | | | | | | | | | |
| | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ |
| Minimum | 0.60 | 1.11 | 0.54 | 1.26 | 0.50 | 0.96 | 0.29 | 1.13 | 0.25 | 0.87 | -0.06 | 0.91 |
| 25th per cent | 0.82 | 0.99 | 0.84 | 0.99 | 0.56 | 0.89 | 0.53 | 0.88 | 0.39 | 0.82 | 0.30 | 0.77 |
| Median | 0.91 | 0.97 | 0.96 | 0.94 | 0.58 | 0.86 | 0.62 | 0.84 | 0.44 | 0.81 | 0.43 | 0.78 |
| 75th per cent | 1.17 | 0.92 | 1.31 | 0.87 | 0.65 | 0.81 | 0.90 | 0.79 | 0.60 | 0.79 | 0.84 | 0.78 |
| Maximum | 1.17 | 0.92 | 1.31 | 0.87 | 0.65 | 0.81 | 0.90 | 0.79 | 0.60 | 0.79 | 0.84 | 0.78 |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | -0.20 | -0.04 | 0.21 | 0.01 | -0.12 | -0.01 | 0.32 | 0.00 |
| | (0.7 | (0.06 | (0.58 | (0.06 | (0.72 | (0.05 | (0.64 | (0.06 |
| $\Delta p_{tj}$ | -0.62 | 0.11 | -0.84 | 0.16 | -0.98 | -0.04 | -1.22 | 0.18 |
| | (0.13) | (0.04) | (0.14) | (0.04) | (0.32) | (0.13 | (0.47) | (0.13 |
| $\Delta p_{tj+1}$ | -0.11 | 0.00 | -0.03 | 0.00 | 0.01 | 0.02 | 0.07 | 0.00 |
| | (0.04) | (0.01 | (0.08 | (0.01 | (0.26 | (0.06 | (0.39 | (0.01 |
| $\Delta p_{tj-1} \times F_{tj-1}$ | -1.64 | -0.33 | -3.65 | -0.70 | -1.86 | -0.42 | -4.01 | -0.68 |
| | (2.33 | (0.14) | (1.93 | (0.11) | (2.39 | (0.12) | (2.14 | (0.13) |
| $F_{tj}$ | | | | | -0.13 | -0.03 | -0.12 | 0 |
| | | | | | (0.27 | (0.06 | (0.37 | (0.02 |
| $\Delta p_{tj} \times F_{tj}$ | | | | | 1.27 | 0.53 | 1.37 | -0.08 |
| | | | | | (1.01 | (0.43 | (1.42 | (0.4 |
| Obs | 69 | 69 | 59 | 59 | 62 | 62 | 53 | 53 |
| R-sq | 0.46 | 0.43 | 0.67 | 0.35 | 0.44 | 0.47 | 0.65 | 0.41 |
| Uncorrected point estimates of the structural parameters at various levels of the termination fee | | | | | | | | |
| | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ | $\delta$ | $\theta$ |
| minimum | 0.19 | 0.80 | -0.14 | 1.03 | 0.14 | 0.88 | -0.25 | 1.06 |
| 25th per cent | 0.36 | 0.80 | 0.24 | 0.72 | 0.33 | 0.82 | 0.18 | 0.64 |
| median | 0.42 | 0.80 | 0.39 | 0.75 | 0.40 | 0.81 | 0.35 | 0.72 |
| 75th per cent | 0.62 | 0.80 | 0.83 | 0.78 | 0.61 | 0.80 | 0.85 | 0.78 |
| maximum | 0.62 | 0.80 | 0.83 | 0.78 | 0.61 | 0.80 | 0.85 | 0.78 |

Table D6. Regression results with the log of the termination fee included as additional regresor (log(F+!)). (min=7.6, max=10.5. Entire sample period; standard errors are clustered at the bank level)

| | Simplest specification | | | | Time Fixed Effects | | | | Time and Bank Fixed Effects | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | 1.85 | 0.99 | 3.41 | 1.84 | -0.80 | 0.88 | 2.11 | 1.72 | 1.31 | 0.77 | 4.89 | 1.48 |
| | (5.93 | (0.55 | (5.73 | (0.72) | (6.01 | (0.37) | (6.02 | (0.32) | (6.83 | (0.37) | (6.51 | (0.26) |
| $\Delta p_{tj-1} \times F_{tj-1}$ | -0.29 | -0.10 | -0.46 | -0.19 | 0.01 | -0.10 | -0.30 | -0.19 | -0.19 | -0.09 | -0.56 | -0.16 |
| | (0.58 | (0.05 | (0.57 | (0.07) | (0.59 | (0.03) | (0.59 | (0.03) | (0.67 | (0.04) | (0.64 | (0.02) |
| Obs | 105 | 105 | 87 | 87 | 105 | 105 | 87 | 87 | 105 | 105 | 87 | 87 |
| R-sq | 0.17 | 0.02 | 0.23 | 0.05 | 0.33 | 0.4 | 0.32 | 0.4 | 0.48 | 0.41 | 0.5 | 0.41 |
| Uncorrected point estimates of the structural parameters at various levels of the termination fee | | | | | | | | | | | | |
| | δ | θ | δ | θ | δ | θ | δ | θ | δ | θ | δ | θ |
| minimum | 0.58 | 1.65 | 0.48 | 5.57 | 0.84 | 1.17 | 0.45 | 2.62 | 0.22 | 1.64 | -0.37 | 0.58 |
| $25^{th}$ per cent | 0.97 | 1.03 | 1.03 | 1.01 | 0.62 | 0.88 | 0.67 | 0.86 | 0.42 | 0.82 | 0.44 | 0.88 |
| median | 1.02 | 1.00 | 1.10 | 0.96 | 0.59 | 0.84 | 0.70 | 0.81 | 0.45 | 0.79 | 0.55 | 0.84 |
| $75^{th}$ per cent | 1.13 | 0.95 | 1.26 | 0.89 | 0.53 | 0.76 | 0.76 | 0.74 | 0.51 | 0.75 | 0.78 | 0.80 |
| maximum | 1.13 | 0.95 | 1.26 | 0.89 | 0.53 | 0.76 | 0.76 | 0.74 | 0.51 | 0.75 | 0.78 | 0.80 |

| | Time and Bank Fixed Effects, Period t proxy | | | | Time and Bank Fixed Effects, Period t and t+1 Proxies | | | |
|---|---|---|---|---|---|---|---|---|
| | # Consumers | | Contract Value | | # Consumers | | Contract Value | |
| | m | k | m | k | m | k | m | k |
| $\Delta p_{tj-1}$ | 2.29 | 0.59 | 5.99 | 1.28 | 2.56 | 0.87 | 6.37 | 1.29 |
| | (5.56 | (0.34 | (4.86 | (0.26) | (6.07 | (0.33) | (5.67 | (0.38) |
| $\Delta p_{tj}$ | -0.61 | 0.11 | -0.84 | 0.15 | -1.92 | -1.21 | -2.79 | 0.11 |
| | (0.11) | (0.04) | (0.13) | (0.04) | (2.66 | (1.02 | (3.94 | (0.89 |
| $\Delta p_{tj+1}$ | -0.02 | 0.00 | -0.01 | 0.00 | -0.02 | 0.00 | -0.01 | 0.00 |
| | (0.01) | 0.00 | (0.02 | 0.00 | (0.04 | (0.01 | (0.06 | 0.00 |
| $\Delta p_{tj-1} \times F_{tj-1}$ | -0.29 | -0.07 | -0.67 | -0.14 | -0.32 | -0.10 | -0.70 | -0.15 |
| | (0.54 | (0.03) | (0.48 | (0.02) | (0.59 | (0.03) | (0.56 | (0.04) |
| $F_{tj}$ | | | | | 0 | 0 | 0 | 0 |
| | | | | | (0.04 | (0.01 | (0.06 | 0 |
| $\Delta p_{tj} \times F_{tj}$ | | | | | 0.13 | 0.13 | 0.19 | 0 |
| | | | | | (0.26 | (0.1 | (0.38 | (0.09 |
| Obs | 105 | 105 | 87 | 87 | 105 | 105 | 87 | 87 |
| R-sq | 0.51 | 0.43 | 0.56 | 0.44 | 0.51 | 0.44 | 0.57 | 0.44 |
| Uncorrected point estimates of the structural parameters at various levels of the termination fee | | | | | | | | |
| | δ | θ | δ | θ | δ | θ | δ | θ |
| minimum | -0.03 | 0.32 | -0.68 | 0.76 | -0.02 | 0.14 | -0.90 | 0.86 |
| $25^{th}$ per cent | 0.42 | 0.83 | 0.39 | 0.85 | 0.43 | 0.82 | 0.21 | 0.58 |
| median | 0.48 | 0.82 | 0.54 | 0.83 | 0.49 | 0.80 | 0.37 | 0.65 |
| $75^{th}$ per cent | 0.60 | 0.81 | 0.84 | 0.82 | 0.61 | 0.78 | 0.67 | 0.71 |
| maximum | 0.60 | 0.81 | 0.84 | 0.82 | 0.61 | 0.78 | 0.67 | 0.71 |