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A Microeconometric Investigation into Bank Interest Rate Rigidity

by Ben R. Craig and Valeriya Dinger

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Using a unique dataset of interest rates offered by a large sample of U.S. banks on various retail deposit and loan products, we explore the rigidity of bank retail interest rates. We study periods over which retail interest rates remain fixed (“spells”) and document a large degree of lumpiness of retail interest rate adjustments as well as substantial variation in the duration of these spells, both across and within different products. To explore the sources of this variation we apply duration analysis and calculate the probability that a bank will change a given deposit or loan rate under various conditions. Consistent with a nonconvex adjustment costs theory, we find that the probability of a bank changing its retail rate is initially increasing with time. Then as heterogeneity of the sample overwhelms this effect, the hazard rate decreases with time. The duration of the spells is significantly affected by the accumulated change in money market interest rates since the last retail rate change, the size of the bank and its geographical scope.

Key words: interest rate rigidity, interest rate pass-through, duration analysis, hazard rate

JEL codes: E43, E44, G21

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1. Introduction

Most macroeconomic models assume that retail bank interest rates adjust immediately to changes in monetary policy and money market interest rates. Some empirical research (see de Graeve et al. 2007 for a review) has challenged this assumption by showing that banks react incompletely and with a delay to monetary policy rate changes. However, existing research into this finding has so far focused on the incompleteness of the adjustment during an exogenously given time period rather than on the timing of the adjustment. Since a convincing model of monetary policy transmission would require information on both the incompleteness and the timing of the adjustment, solid micro-founded empirical evidence on the timing of interest rate adjustments is lacking. This is especially true after the global financial crises of 2007-2009 underscored the pitfalls of omitting financial market frictions in macroeconomic modeling.

In this paper we provide a first step in this direction by presenting a microeconometric analysis of the timing of retail interest rate changes and the determinants of that timing. First, we present descriptive evidence on the lumpiness of bank retail interest rate adjustments. Second, we apply duration analysis to retail interest rate dynamics. We use duration analysis to study periods over which retail interest rates remain fixed ("spells") and the sources of variation in the duration of these spells both across and within different products.

The existing literature on retail interest rate dynamics focuses either on the probability of a bank keeping its retail interest rates unchanged for a certain exogenously chosen period of time (Berger and Hannan 1991, Neumark and Sharpe 1992, and Mester and Sounders 1995) or on the incompleteness of retail interest rate adjustments to changes in monetary policy (see Hofmann and Mizen 2004, de Graeve et al. 2007, Kleimeier and Sander 2006, etc). The major disadvantage with the former is that its focus on exogenously given time periods (usually a month or a quarter) ignores the short- and long-term dynamics of retail interest rates. The latter strand of the literature is challenged by the fact that it uses techniques, such as vector autoregression analysis, that were originally designed for use with the time series structure of aggregate data. The smooth adjustment assumptions are too strong when imposed upon micro-level data, so that robustness of the results is not guaranteed. In particular, the linearity of cointegration implies a quadratic cost of adjusting the interest rate[1]. The validity of this assumption has not been verified for the banking industry, but it has been rejected for numerous other industries in favor of a nonconvex adjustment costs assumption (see Caballero and Engel 2007 for a survey). The rejection of the quadratic adjustment costs assumption raises concerns about the reliability of cointegration-based estimates of price dynamics and has encouraged the implementation of alternative methodologies such as duration analysis for prices in industries other than banking (Alvarez et al. 2005, Nakamura and Steinsson, 2009). A detailed discussion of the functional form of interest rate adjustment costs and the related lumpiness of retail interest rate adjustments is to our knowledge still absent in the empirical banking literature.[2]

Our approach and data set allow us to investigate the form of adjustment costs, the hazard function of retail banking rate changes, and the dependency of the timing of rate changes on market structure as well as the dynamics of wholesale funding markets. By summarizing the descriptive statistics of micro-level retail interest rate dynamics, we document that retail interest rate adjustments for a broad set of retail bank products are very infrequent and large when they occur (much larger than the average magnitude of price changes for goods and services). The infrequency and large magnitude of retail rate changes suggest a high degree of lumpiness consistent with nonconvex adjustment costs.

Moreover, the results of the duration analysis uncover a hump-shaped hazard function for changing an interest rate spell (for a range of deposit and loan products). This form of the estimated hazard function suggests that the conditional probability of changing the rate is

[1] Hofmann and Mizen (2004) and De Graeve et al. (2007) relax the linear cointegration assumption and estimate nonlinear error-correction models as robustness checks. These still assume continuous adjustment, which is inconsistent with menu cost models.
[2] Arbatskaya and Baye (2004) is the only study we are aware of that employs hazard functions for the analysis of interest rate rigidity. These authors, however, focus only on mortgage rates offered online.

increasing within the first few months after a change and decreasing afterwards, which is consistent with a fixed cost of interest rate adjustment.[3] In addition, the estimated covariate coefficients suggest (consistent with Berger and Hannan 1991, Neumark and Sharpe 1992) that banks' reactions to changes in the money market rate or the monetary policy rate are strongly asymmetric: a drop in the wholesale rate accelerates a bank's decision to change deposit rates, while a rise in the wholesale rate does not accelerate the decision to re-price deposit rates. The opposite is true for retail loan rates. This result suggests that market structure might affect retail interest rate inflexibility in addition to adjustment costs.

Our data set provides a wide variety of variables with which we can measure not only the effect of market structure on interest rate adjustment, but also the dynamics of a change in market structure on the behavior of the adjustment, as the change in market structure is slowly incorporated into the policies of the affected banks. We find that the geographical scope of the bank (the number of markets where the bank operates) has a robust rigidity-increasing effect, while the effects of market share and bank size are mixed. Finally, we also take advantage of our high-frequency data to measure the effects of the volatility of money market interest rates and market expectations as reflected in the yield curve. These have been previously ignored in the analysis of retail interest rate dynamics, and we show them to be as important in determining the duration of an interest rate spell as the cumulated change in the market rates or their level.

We make three contributions to the literature. First, we precisely describe the lumpiness of bank retail interest rate adjustments. The implications of lumpy micro-level interest rate adjustments are not only relevant for understanding bank-level dynamics but they are also crucial for the estimation of the aggregate response to a monetary policy shock[4]. Second, we contribute to the interest rate pass-through literature by confirming its key micro-level results

[3] Berger and Hannan (1991) propose a menu cost of interest rate adjustment, and, although menu costs can lead to a fixed cost of adjustment, by no means are they the only possible source.

[4] See Caballero, Engel, and Halitwanger (1995) for a discussion on the aggregate effect of lumpy micro level adjustments.

using a less restrictive framework. Unlike the cointegration approach currently used to study interest rate dynamics, the use of the hazard functions involved in duration analysis implies less strict assumptions about the time series properties of the adjustment process and is thus closer to a structural approach. Also, the duration analysis allows us to include more control variables than we could within a cointegration framework. In particular, we can include changes in the levels of the monetary policy rate and money market rates, the volatility of these rates, and expectations about future interest rate levels manifested in the yield curve. Our third contribution is to the literature on price dynamics in general, which we make by analyzing a market with unusually broad data availability. To start with, data about prices (interest rates) are available on the bank-market level for a wide range of retail deposit and loan products. Next, those products (e.g., checking account deposits, MMDAs, credit card credit lines) are relatively homogeneous, but they are offered by multiple (and potentially heterogeneous) firms.[5] Moreover, the identification of input price shocks is more trivial in banking than in other industries, since interest rates in wholesale money markets (a widely used benchmark for bank funding costs) are publicly observable. And finally, interest rates are especially well suited to studying the asymmetry of price adjustments, since changes in monetary policy rates might go in either the upward or the downward direction.

The rest of the paper is structured as follows. In Section 2 we present a description of the frequency and duration of retail deposit and loan rate spells (that is, periods in which rates don't change). In Section 3, we use hazard functions to analyze the duration of individual price spells, focusing in particular on the impact that changes in wholesale rates have on the probability that retail interest rates will change, bringing a spell to an end, and how this reaction is modified by bank and local market characteristics. Section 4 concludes.

[5] We are therefore less concerned about misspecifications in the estimation of the price-duration models due the heterogeneity of the products (see Alvares et al. 2005 and Nakamura and Steinsson 2009 for a discussion).

2. Empirical Framework

a. Data

Our dataset contains the deposit rates of 624 U.S. banks in 164 local markets (a total of 1,738 bank-market groups) and the loan rates of 86 U.S. banks in 10 local markets (a total of 254 bank-market groups) for the period starting September 19, 1997, and ending July 21, 2006. These rates are obtained from *Bank Rate Monitor*. Note that our deposit rate data encompasses by far the largest sample that has so far been employed in the study of the price dynamics of homogenous products. The loan rate data sample available to us is much smaller (though we are not aware of studies using larger samples of loan rates). Our loan rate sample encompasses only rates offered by the largest U.S. banks in the 10 largest banking markets (the MSAs of Boston, Chicago, Dallas, Detroit, Houston, Los Angeles, New York, Philadelphia, San Francisco, and Washington, D.C.). Because of the small sample size, bank and local market characteristics are likely to vary much less in our loan rate data than in our deposit rate sample.

The time span of our data is the longest employed so far in a study of retail interest rate dynamics. The period encompasses a full interest rate cycle. The substantial upward and downward changes in the federal funds rate within this time period allow us to study the connection between retail and wholesale rate dynamics during a period with substantial wholesale rate variation.

Bank Rate Monitor reports a comprehensive set of retail deposit products (checking accounts, money market deposit accounts, and certificates of deposits with maturities of three months to five years) and retail loan products (personal loans, fixed and variable rate credit cards, mortgages, home equity lines of credit (heloc), auto loans, etc.). Note that rates for these products are those offered to customers with the best credit rating with no other relation to the bank. Rates on products offered to existing customers might vary from the ones reported by *Bank Rate Monitor*.

Interest rates for each product are given at a weekly frequency. The availability of weekly data allows us a more precise differentiation of the speed of adjustment compared to previous studies of interest rate rigidity (Berger and Hannan 1991 and Neumark and Sharpe 1992) and price rigidity (Bils and Klenow 2004 and Nakamura and Steinsson 2008), which use data at monthly or bimonthly frequencies.[6]

We enrich the dataset with a broad range of control variables for individual banks, taken from the *Quarterly Reports of Conditions and Income* (*call reports*). These are given with quarterly frequency (the end of each quarter). We also include control variables for the local markets. These data are taken from the *Summary of Deposits* and are available only at an annual frequency (reporting date is June 30).

The banking literature presents some evidence that multimarket banks tend to offer uniform rates across local markets (Radecki 1998). However, in our sample we observe substantial variation in the deposit and loan rates offered by banks in different local markets. We therefore use the bank-market as the pricing unit and employ the variation of multimarket bank rates across local markets to identify the effect of market structure on interest rate dynamics[7].

b. Spells

We set up the analysis of retail interest rate durations by defining an interest rate spell and the individual quote lines. We define the quote-line$_{i,j,p}$ as the set of interest rates offered by bank *i* in local market *j* for (deposit or loan) product *p*. The interest rate spell is defined as a subsection of the quote line for which the interest rate goes unchanged. The definition of the interest rate spell assumes that if the same interest rate is reported in two consecutive weeks, it

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[6]To our knowledge, studies based on scanner data are the only ones with higher than monthly frequency. They, however, employ data from only a single retailer, although possibly in different markets (Eichenbaum, Jaimovich, and Rebello 2008).

[7] A bias can arise in the estimation if a bank-specific pricing effect impacts the pricing behavior in all local markets, since in this case the assumption of spherical standard errors can no longer be sustained. We account for potential bank-specific effects by estimating the hazard functions using a shared frailty technique (see Nakamura and Steinsson 2008 for a similar approach applied to control for heterogeneity across product groups).

has not changed between observations. We define the number of weeks for which the interest rate goes unchanged as the duration of the interest rate spell.

To avoid left censoring, we include only spells for which we can identify the exact starting date (the week for which a particular rate was offered for the first time). That is, for each bank-market we exclude all observations before the rate changes for the first time. A spell ends with either a change of the interest rate or with the exit of the bank-market unit from the observed sample. In the latter case, the issue of right censoring arises, which we will discuss later. *Bank Rate Monitor* reports rates offered by smaller banks only if the quoted rate deviates from the rate quoted in the preceding week. To control for this, we assume that an interest rate spell "survives" through the weeks until the next observation is reported (if the next reported rate is in week t, we assume the rate has "survived" until week t-1). However, a few instances are present in our sample in which the bank-market unit exits the sample for a longer period (up two a few years) and re-enters the sample again. In this case, the assumption that observations are missing only because no change in the interest rate is observed is too strong. We control for this by treating an unreported rate as an unchanged rate only if the period of missing observations is less than 52 weeks[8].

c. Descriptive Statistics

The average duration and the average change in the retail rates for each of the deposit and loan product categories are presented in Table 1. The data in this table illustrate the substantial variation that exists in the average duration of interest rates across different bank products, with checking account rates and money market deposit account rates being the most inflexible deposit rates[9] and personal loan rates and credit card rates being the most inflexible consumer loan rates. The average duration of checking account rates is 17.71 weeks (roughly

[8] We did a few robustness checks here. For example, for the checking account rates our approach identifies 204 spells for which the rate was not observed for a few weeks but reappeared with a changed value within 52 weeks. If we account only for rates that reappear within 26 weeks, we will identify 191 spells. If we impose no cut-off point with regard to the number of weeks a price was not observed, we have a total of 311 spells.
[9] The same has been found in the interest rate pass-through literature (see de Graeve et al. 2007).

four months). Similarly, money market deposit account rates, personal loan rates, and fixed credit card rates change on average roughly every three months.

An additional signal of the lumpiness of interest rate adjustments is the size of the average interest rate change. The second column of Table 1 presents the average absolute value of the interest rate change given a nonzero rate change.

This average change in the rates is more informative when put into relation to the average value of the respective interest rate (e.g., the average change in the checking account rate seems very low in absolute value, 0.16, but this represents roughly a third of the average checking account rate). The fourth column of Table 1 presents the average absolute value of the changes relative to the average rates. For checking account rates the average size of the interest rate change is 30%. This average size of the interest rate change is much higher than the average price change documented for any good or service categories (excluding sales, see Nakamura and Steinsson 2008, who find the that highest average magnitude of regular price changes across all product groups is 21.6 %—for the product group "travel"). Similarly, the average size of money market deposit account rate changes is also very high, 24%. The average size of loan rate adjustments is likewise relatively high (12%), which also supports the notion of lumpy interest rate adjustment.

Note that the average duration and change in the rates presented in Table 1 reflect all interest rate changes observed in the data. An important measurement issue in the analysis of price dynamics is the treatment of temporary price changes. In the price dynamics literature, temporary price reductions (sales) are considered an important link in the chain of the price-setting mechanism (Bills and Klenow 2004 and Nakamura and Steinsson 2008). With regard to interest rate setting, the issue of temporary interest rate changes is more subtle. Whereas a change in the price of goods and services that is reversed after a few periods is usually classified as a sale, such automatic labelling is more controversial when applied to interest rates. To illustrate this subtlety, consider the case in which a bank has been slow to adjust its retail rates to an upward trend in wholesale rates, and it raises its retail rates only shortly before wholesale rates start declining. In this case, the reversion of the retail interest rate to its previous level can simply reflect the reaction to changes in the wholesale rate rather than a "sale." Note that because interest rate values are usually rounded at 25 basis points, the probability of returning to exactly the same interest rate after a reversal in the level of the aggregate interest rate trend is high. Therefore, labelling any interest rate change reversed after a few weeks as a sale could be misleading. Nevertheless, we do observe a substantial number of interest rate changes which are reversed after a relatively short time. These could probably be considered "sales" in the classical price dynamic sense. With this in mind, we assume that only those changes that are reversed within four weeks are sales. The number of changes reversed within five, six, seven, and eight weeks is substantially lower, and we treat these as regular price changes (implying the end of an interest rate spell). Table 2 illustrates the number of temporary interest rate changes for some of the deposit and loan products. Note that the proportion of price spells reversed after a week is particularly high. It suggests that we might be dealing with measurement errors, due to misreporting of the rate in a particular week, rather than a de facto change in the interest rate.

The distribution of the duration of spells for checking account and money market deposit account rates and personal loan and fixed credit card rates is presented in Chart 1 to Chart 4. In each of the charts the first panel shows the distribution when all interest rate changes are treated as the end of the spell (no reversals are excluded). The next panel shows the distribution when changes reversed within a week are not treated as the end of the spell (again, these reversals might reflect sales or measurement errors). The last panel excludes changes that are reversed within four weeks as an end to the spell.

The distributions uncover the heterogeneity of the duration of interest rate spells within each deposit and loan product category. For all types of interest rates shown on these charts most have spell durations of less than year. However, for both deposit and loan rates a substantial portion of the spells last for two years and even longer. For example, if we focus on the second panel of the distribution charts (which does not treat rates reversed in one week as spell-ending), 237 out of 7,456 checking account rate spells last for more than 104 weeks. These are offered by 78 different banks. In the case of money market deposit account rates, 197 out of 12,833 spells survive for more than two years. These are offered by 76 banks. For personal loan rates there are only 8 spells (out of 663) which last for more than two years, and these are offered by 8 different banks. And finally, 7 fixed credit card rate spells (out of 630) last longer than two years, and these are again offered by 7 different banks. Note that whereas some banks repeatedly offer very rigid rates for deposit accounts, this is not the case for loan rates. This difference could be due to our sample sizes. While the sample of banks for which we have deposit rates is relatively comprehensive, it is limited to the biggest banks in the case of loan rate data, and these banks are certainly less heterogeneous.

We can summarize the descriptive statistics presented in this section in three key facts about retail interest rate dynamics. First, the variation of the mean duration of interest rates across different deposit and loan products is very high. While rates on certificate of deposits and mortgages change frequently, those on purely retail service products such as checking accounts, money market deposit accounts, personal loans, and credit cards are quite inflexible.

In the rest of the paper we will focus on the dynamics of these less flexible deposit and loan rates. Note that these products are not of marginal importance for banks and consumers: with regard to deposits, checking accounts and money market deposit accounts are the major source of retail funding for U.S. banks; with regard to loans, personal loans and credit cards are the ones most closely related to private consumption of non-housing items.

Second, the variation in the duration of interest rate spells is high within the individual deposit and loan products. A large share of spells end within one month, while a substantial share of the spells last for two and more years.

Third, the average magnitude of an interest rate change is very large (much larger than the average magnitude of price changes for goods and services). This again supports the notion of lumpy interest rate adjustments[10].

These findings square well with key findings about price rigidity (e.g., as summarized by Nakamura and Steinsson 2008) and point to some important similarities between price and interest rate adjustment.

d. Duration analysis

We now turn to the analysis of hazard rates, which capture the probability of a given interest rate changing at a certain point in time. The hazard rate can be used to assess whether rates that have changed more recently are more likely to change than rates which have not changed for a long time. In other words, the hazard function plots the functional dependence between the time since the last interest rate change and the probability of a change of the rate. Formally, the hazard rate is expressed as:

$$h(t) = P(T = t | T \geq t)$$

where $P(T = t | T \geq t)$ gives the probability that the retail interest rate will change in period t if it has survived until t-1. The hazard rate, also known as the conditional failure rate, is computed as:

$$h(t) = \frac{f(t)}{1 - F(t)}$$

where $f(t)$ denotes the probability density function and $F(t)$ denotes the cumulative distribution function.

The hazard rate's property of plotting the functional relation between the conditional probability of a change in a price and the time since the latest price change has made it the

[10] Unfortunately, we cannot compare our findings about interest rate rigidities with similar results from other countries or time periods since none are available at this time.

preferred empirical technique in the recent literature on price dynamics. Surprisingly, however, hazard rates have not yet been applied to interest rate dynamics[11].

As mentioned in the introduction, existing studies on interest rate dynamics are based on either probit estimations of the probability of an interest rate change within an exogenously given time period or on estimating the cointegration between monetary policy and retail interest rates (Hofmann and Mizen 2004, de Graeve et al. 2007, Kleimeier and Sander 2003, etc). Compared to probit estimation of the probability of an interest rate change within an exogenously given time period, the hazard function provides richer information on the probability of a change within different subperiods of the "life" of an interest rate spell. It therefore avoids concerns about the choice of the period within which a change in the rate is observed. As already mentioned, the duration model imposes also less stark assumptions than cointegration frameworks. In particular, we do not have to assume quadratic adjustment costs, whereas this is a necessary cointegration assumption. The duration model therefore does not exclude by assumption the notion of a lumpy adjustment scheme (e.g., adjustment with menu costs of adjustment).

Furthermore, by applying duration analysis to the dynamics of retail interest rates, we present results comparable to those from recent studies on the dynamics of prices of goods and services, which heavily rely on the estimation of the hazard functions to uncover price dynamics. The main challenge of this price dynamics literature has been the treatment of heterogeneity. The problem is that studies using micro-level price data in their quest for representative samples typically include heterogeneous products, some of which change prices frequently and some of which do not. The hazard rate in the first few periods will be high, reflecting the high risk of change in the flexibly priced product prices. The hazard rate drops after a few periods when all flexible prices have changed and the subsample of relatively sticky prices remains. In this case, the estimated hazard rate is downward sloping,

[11] Arbatskaya and Baye (2004) is the only example presenting the hazard function of interest rate spells (in their case, online posted mortgage rates) we are aware of.

whereas theories predict a flat or increasing hazard function. In our framework we have the advantage of exploring the “prices” (interest rates) of relatively homogenous products that still have a broad macroeconomic impact. Downward-sloping hazard functions might, however, still arise due to heterogeneity across bank pricing strategies (if we have a set of banks which reprice very often and some which reprice very infrequently, after a few periods we will be left with the long-lived spells of the infrequently adjusting banks and the form of the hazard function will be downward sloping).

3. Results

A. Unconditional duration dependence

We start the examination of interest rate spell durations by presenting the nonparametric Kaplan-Meier estimation of the hazard functions for each of the more rigid deposit and loan rates. Chart 5 illustrates the nonparametric hazard rate estimation for the checking account, money market deposit account, the personal loan, and the fixed credit card rates, respectively[12]. Despite the differences across the average duration of the spells across these products, a few similarities are obvious. For all four types of interest rates we observe an initially increasing hazard rate. After roughly half a year, hazard rates reach a local maximum and slowly decline before heading to a new maximum after roughly one and one-half years for credit card rates and roughly two years for personal loan, checking account, and money market deposit account rates.

We interpret the estimated hump-shaped form of the hazard function as follows: during the first roughly six months the hazard of changing the interest rate is increasing. This is consistent with models of price dynamics with menu costs, which imply increasing hazard functions (see Nakamura and Steinsson 2009 and Alvarez et al. 2006 for a review of various

[12] For the sake of parsimony we only present the hazard rates estimated on the samples that do not consider interest changes reversed after one week as ends of the interest rate spells. Estimates using the full sample of interest rate changes and those excluding sales with a duration of less than four weeks are qualitatively very similar to the presented hazard rates.

hazard functions derived from alternative price-setting models)[13]. After a period of roughly six months the largest portion of the spells in our sample has ended, the heterogeneity effect among the remaining spells dominates the menu cost effect and the hazard of changing the retail interest rate goes downward.

The hump-shaped form of the hazard is not only relevant as evidence of a lumpy adjustment of interest rates (thus challenging the micro-foundations of partial adjustment models, which assume smooth rather than lumpy adjustment), but it also provides one of the few empirical examples of an increasing hazard function for a price change.

Note that in these baseline estimations, we control for neither bank heterogeneity (across banks) nor changes in wholesale market interest rates. In the next section, we control for these by fitting a shared frailty model, and we present the resulting impact on estimated hazard rates.

B. Wholesale market rates and the probability of changing retail interest rates

In this section, we explore the impact of wholesale interest rate dynamics - as a proxy for the dynamics of the marginal costs of bank products[14]- on the hazard of changing individual bank rates. We use two different rates to represent the wholesale rate. First, we use the rate on 3-month T-bills. Next, we employ the average effective federal funds rate as an alternative wholesale rate. The former is widely employed as a measure of the costs of bank wholesale funding (Berger and Hannan 1991, Neumark and Sharpe 1992, and Hutchison and Pennacchi

[13] A menu cost model assumes that an interest rate change is delayed until the deviation of the current retail interest rate offered by the bank from the optimal retail interest rate goes beyond a trigger point, which is related to the menu cost of adjusting the retail interest rate. The probability that a bank will change a given retail interest rate is increasing in the menu cost model since the deviation of the current interest rate from an optimal interest rate is likely to increase with time.

[14] Simple theoretical models of banking predict a positive dependence between bank retail deposit and loan rates and wholesale money market rates (see Kiser 2003). These models assume that loans are the output in a production function that uses retail and wholesale funds as inputs. In other words, the effect of wholesale rate changes on loan rates is similar to the effect of changing input prices on the prices of final goods. The effect of wholesale rate changes in deposit rates is motivated by the substitutability of retail deposits and wholesale funds. An alternative view of the production function of the bank assumes that banks issue deposits and sell the accumulated funds in the wholesale market. In this case, the wholesale rate is the price of output, whereas the retail rate is the input price. In both frameworks, an exogenous rise in the wholesale rate is related to an increase in the optimal retail deposit and loan rates offered by the bank.

1996). The latter is a proxy of the monetary policy rate and thus more relevant one from monetary policy transmission point of view.

The Kaplan-Maier estimations presented in the preceding subsection are exclusively focused on the time dependency of retail interest rate changes. Time since the latest rate change can be strongly correlated with cumulated changes in observed and unobserved variables, reflecting a state-dependent interest-rate-setting mechanism. Therefore, we could only indirectly interpret the initially increasing hazard as consistent with state-dependent menu costs models. By including the cumulative changes of the wholesale interest rates as covariates, we introduce the first step in developing a model that explicitly controls for state-dependent interest rate setting[15]. State-dependent-pricing schemes typically assume that the probability of a price change is determined by the deviation of the actual price from the optimal price.

Because we do not observe the optimal price in practice, we use the change in the wholesale rate since the last observed change in the retail interest rate as a proxy for the deviation of the current rate from the optimal rate. Again, the wholesale rate serves as a proxy for the change in input costs, and, as is standard in S,s models, we assume that if a bank adjusts the interest rate, it adjusts to the optimal rate. An alternative approach assumes that the bank has an implicit optimal mark-up or mark-down of the retail interest rate relative to the wholesale rate and changes the retail rate when the deviation from this optimal mark-up is large enough.

In our baseline model, we use the cumulative change of the wholesale rate (normalized by the value of the wholesale rate) since the last change of the retail rate (*absolute change T-Bill rate or absolute change fed funds rate*)[16] as a proxy for the deviation of the observed retail interest rate from the optimal retail interest rate. As a robustness check, we have rerun the estimations using the mark-up/mark-down (the difference between the wholesale and the retail rate) as a

[15] In a follow-up project we focus on the state dependency of retail interest rate setting and explore its implications for aggregate interest rate dynamics.

[16] We plan to extend the analysis to modeling the nonlinearities in the reaction of the probability of changing retail rates to wholesale rate changes, as suggested by an S,s price adjustment, using splines of the wholesale rate change. This approach will allow us to estimate different coefficients of the hazard function covariates for different subsets of wholesale rate changes.

proxy for the deviation of the observed from the desired interest rate. Results do not change qualitatively. To account for the asymmetry of adjustment (for the possibility that a positive wholesale rate effect has a different impact from a negative wholesale rate effect as shown by Berger and Hannan 1991), we generate dummy variables for positive changes in the wholesale rate in the loan rate regression (*positive change dummy*) and for negative changes in the wholesale rate in the deposit rate regressions (*negative change dummy*). We include these dummies together with their cross-products with the absolute cumulative change of the wholesale rate as covariates in the estimation of the hazard rate.

The cumulative change of the wholesale rate is only a rough proxy for the deviation from the optimal retail interest rate. Other determinants of this optimal rate might be the level of the wholesale rate as well as its volatility and the expectation of the wholesale rate level in the future. We include these as additional covariates: the T-bill or fed funds rate as a proxy for the wholesale rate; the difference between the 10-year T-bill rate and the 3-month T-bill rate as a proxy for the expected interest rate (we term this difference the *yield curve* proxy) and the volatility of the wholesale rate, which is derived from a GARCH (1,1) model run on weekly observations of the wholesale rate[17]. The importance of these other factors related to wholesale rate dynamics has so far been ignored in empirical analyses of retail interest rate dynamics, since they have focused on the response to changes in wholesale rates. We estimate the hazard functions using a lognormal hazard model. The choice of this parameterization is motivated by the nonmonotonic (first increasing and then decreasing) Kaplan-Maier estimates (see Chart 5), as well as the nonmonotonic baseline hazard function estimated from a semiparametric Cox model, including the full set of covariates, and the Akaike information criterion. (The results of the auxiliary estimations are very much like the parametric estimation results and are available from the authors upon request.) We estimate the

[17] The GARCH process is estimated for the differences in logarithms of the rates, and in each case, all parameters are highly significant and are measured tightly. GARCH-estimated parameters are available from the authors on request.

parametric hazard models with shared frailty at the bank level to control for the possibility of bank-specific random effects in the interest-rate-changing mechanism[18].

The results of these hazard estimations[19] are illustrated in Table 3 to Table 6. The most obvious implication of the estimation results is that there is a substantial difference in the reaction of deposit and loan rates to changes in the wholesale rate. In the case of deposit rates (both checking account rates and money market deposit account rates), the negative coefficient of the cross-product between the absolute change of the wholesale rate and the dummy for a negative wholesale rate change suggests that the probability of changing the deposit rate is increasing with the absolute value of negative wholesale rate changes[20]. On the other hand, when wholesale rates are changing in an upward direction, banks are less likely to change their deposit rates (they postpone the adjustment). These results present very strong evidence of the asymmetric adjustment of deposit rates and confirm the implications of earlier studies based on simple probit and partial-adjustment models (Berger and Hannan 1991; Neumark and Sharpe 1992). They are consistent with a state-dependent adjustment to negative changes of the wholesale market rate[21].

In the case of loan rates, the effect of the absolute value of the cumulative change in the wholesale rate is insignificant. The cross product of the cumulative change and the dummy for positive wholesale rate changes is statistically significant and points to a delayed adjustment.

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[18] Results of the estimations do not significantly change if we do not account for the bank-specific effect and if we include a bank-market random effect rather that a bank random effect.

[19] Here we present only estimation results based on the samples in which a spell is assumed to continue if it changes in week t but reverses to the same level in week t+1. The distribution of the spell durations and the nonparametric hazard estimations for these samples are presented in the middle subpanels of Charts 1 to 8. We have rerun all regressions using the full sample of failures and the sample of failures that are not reversed within four weeks. Results, which are qualitatively the same as the ones presented in the text, are available from the authors upon request.

[20] The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate.

[21] State-dependent price adjustment implies that microlevel price rigidity will not be reflected in delayed adjustment on the aggregate level (Caplin and Spulber 1987). Mojon (2000) presents evidence that aggregate deposit rates almost immediately adjust to negative changes in the money market rate.

Although striking at a first glance, this adjustment path can be interpreted as a preference of banks to delay upward adjustments to personal loan and credit card rates. This preference could be caused by the substantial influence that high retail loan rates have on the probability of loan repayment, which might make banks cautious about the total effect of loan rate increases on expected returns from the loans (see Mester 1994 for a theoretical model on the rigidity of uncollateralized loan rates).

For both deposit and loan rates, the effect of the level of the wholesale rate and its expected trend have a statistically significant impact with the predicted sign. So, for example, when wholesale rates are high or when a rise in the wholesale rates is expected, banks are less likely to adjust their deposit rates and more likely to adjust the loan rates. The volatility of the wholesale rate has a significant impact only on the probability of changing deposit rates, and this impact works in the direction of accelerated adjustment time.

In sum, state-dependent adjustment could only be confirmed for deposit rates (and only for the case of adjusting to negative wholesale rate changes). The adjustment of loan rates to changes in wholesale market rates is particularly delayed when wholesale rates are increasing. Note that this delayed adjustment of loan rates to positive changes in the wholesale market rate, which is consistent with the theoretical model of Mester 1994, has not been emphasized in the existing empirical research. It implies the necessity of a more structural approach, which would incorporate the effect of interest rate changes on both loan demand and loan riskiness, which is a planned extension of this project.

C. Bank market structure and the probability of changing retail interest rates

One of the potential sources for the heterogeneity of the reaction of interest rates to changes in the wholesale rates is market power. Models of price adjustment (e.g., Barro 1972 and Rotemberg and Saloner 1987) predict a higher frequency of price changes in markets with more competition because firms therein face more elastic demand. For the banking industry, Berger and Hannan (1991) model the positive relationship between market concentration and menu costs (and interest rate rigidity). Empirically, the positive relationship between market concentration and price rigidity has been shown in the case of markets for goods and services by Carlton (1986), Caucutt, Ghosh, and Kelton (1999), and Bils and Klenow (2004). In the case of bank retail interest rates, Berger and Hannan (1991), Neumark and Sharpe (1992), Mester and Saunder (1995), and de Graeve et al. (2007) present evidence of a positive relationship between market concentration and interest rate rigidity. A common result of these empirical studies using banking data is that market power allows banks to slow down the adjustment of deposit rates to positive wholesale rate changes and of loan rates to negative wholesale rate changes.

To our knowledge the impact of market structure on the hazard of changing the price has not been explored yet. In this subsection we close this gap for the case of banking and extend the analysis from the previous exercise to include the impact of market characteristics on the duration of bank interest rate spells. The purpose is to reassess the robustness of the results of earlier studies on interest rate and price rigidity using the hazard rate rather than the probability of change within an exogenously given time period as a measure of price rigidity.

We not only employ a new technique to the analysis, we also use a much richer set of data on market structure relative to earlier studies. The richness of our dataset allows us to distinguish between different proxies of market structure and market power in the estimation, whereas most of the literature uses a single market structure proxy (e.g., concentration ratio or Herfindahl index). In particular, we include the market share of the bank in the respective local market, as measured by the share of the bank's retail deposits collected in the local market relative to the total volume of retail deposits issued by all banks in this local market. This is to control whether banks with a dominant market power adjust their interest rates less frequently. We also control for market concentration in each of the local markets, since market structure can affect the price setting of all banks operating in a market. To this end, we include the Herfindahl index as a covariate in the hazard function estimation. Moreover, we control for potential nonlinearities in the reaction of the hazard rates to market concentration and split the sample into interest rates in highly concentrated bank markets and less-concentrated markets. The split is based on the Herfindahl index threshold of 1800 basis points, which is employed by the U.S. Department of Justice for the evaluation of the concentration effect of bank mergers. We also control for the number of local markets in which a bank operates. This is to control for the effect of the so-called linked oligopoly hypothesis, which posits that firms operating in numerous markets will adjust prices in each market less frequently, fearing revenge from competitors in all other markets.

We also control for a number of bank characteristics which might affect the speed of interest rate adjustment. In particular, we control for the total size of the bank, measured by the national logarithm of its total assets. The effect of bank size can be ambiguous. On the one hand, if menu costs have a lump-sum component at the bank level, larger banks may be more likely to frequently adjust prices. On the other hand, larger banks bundle different sets of products, and the customers' switching costs away from a larger bank may be higher, so the size of the bank can have an additional pro-rigidity effect apart from the market share. On the bank level, we also include the equity-to-total-assets and the liquid-to–total-assets ratios as controls because, as argued in the credit channel literature, better capitalized and more liquid banks might react less to monetary policy contractions (Kashyap and Rajan 2000)[22]. To avoid endogeneity concerns, all bank variable values stem from the Call Report of the preceding quarter and all market variables from the previous year's Summary of Deposits.

In the estimation of the effect of market structure and bank characteristics on the probability of changing interest rates, we build upon the model presented in subsection A and add the market structure and bank-specific variables to the set of covariates. As in the previous subsection, we estimate a parametric duration model, assuming a lognormal distribution of the

[22] De Graeve et al. (2007) find that both liquidity and capitalization significantly affect the cointegration relation between bank retail and wholesale market rates.

baseline hazard rate. Again, we control for bank-specific random effects by estimating the model with shared frailties at the individual bank level.

The results of the estimation are presented in Table 7 to Table 10. With regard to the estimations of the probability of changing the deposit rate, we find that the number of markets significantly decreases the probability. Adding an additional market "slows" the time to the change in the retail rate by roughly 1.3%. In other words, banks which operate in numerous local markets have stickier prices than banks with a more narrow geographic scope. This result is consistent with the linked oligopoly hypothesis, which argues that firms operating in many markets adjust prices less frequently. Bank size has no significant impact on the probability of changing money market deposit account rates and mildly increases the probability of changing the checking account rate. This result could be caused by the opposite effect of a lump-sum component of the adjustment costs and the unwillingness of larger banks to reprice products because of product bundling. The positive impact of market share on price rigidity is confirmed in the case of MMDA rates: banks with a larger market share adjust their MMDA rates less frequently. However, the economic significance of this effect is small (10 percentage points of difference in market share imply a deceleration of the time to change by about 1.36%). The effect of market concentration is economically more important: 10 percentage points of difference in the Herfindahl index imply a deceleration of the time to change by about 7.3%). Checking account rate hazard rates do not react to market share and market concentration.

Note that the coefficients of the bank and market variables are insignificant in the loan rate regressions. We presume that this is the case because our loan rate sample is much smaller than our deposit rate sample. Also, because the sample covers only very large banks in major banking markets, the variation in terms of bank size, market share, number of markets, and market concentration is not sufficient to for tight coefficient estimation. However, it could also be due to an intrinsic difference between loan- and deposit-rate-setting processes. To shed more light on the most likely source of this deviation (significant impact of market structure on the deposit rate dynamics, no effect of market structure on loan rate dynamics) we re-estimate the hazard rates for checking and money market deposit account rates but only for the subsample of banks and markets for which we have loan rate observations. In this experiment, all wholesale rate variables turned out with statistically significant coefficients, similar to those estimated from the full deposit-rate sample. However, none of the banks or local market characteristics entered with a statistically significant coefficient. These variables' lack of significance is, therefore, most likely due to the limited scope of the sample. The comparison of the estimations based on the different samples underscores the importance of using comprehensive samples and casts doubt on the results of studies which only focus on subsamples of the market, e.g. Hofmann and Mizen, 2004.

In sum, our results suggest that standard bank and market variables explain some of the heterogeneity of deposit rate adjustments. However, the effect of these variables on the frequency of adjustment is much smaller than the one predicted by earlier studies (Berger and Hannan 1991 predict that the probability of changing the rate within a month is roughly 60% smaller if the market share increases by 10 percentage points, but we find that time to change is decelerated by a mere 1.3%). In our sample, the rigidity of retail rates depends on the concentration of the market rather than on the market share of the individual bank. Due to the limited scope of the sample, we find no evidence on the effect of bank and market characteristics on loan-rate dynamics.

D. Bank mergers and the probability of changing retail interest rates

In this subsection we extend the analysis of the impact of bank market structure on interest rate duration by exploring the effect of bank mergers on the hazard of changing the retail interest rate. Focusing on the effect of mergers can strengthen the identification by easing concerns about the endogeneity of market structure with regard to interest rate dynamics as well as concerns about an omitted variable bias.

In the estimation of the effect of bank mergers on the hazard of changing retail interest rates we adopt the approach presented in Craig and Dinger (2009). Due to degree-of-freedom limitations, we perform only the estimations for checking account and money market deposit account rates where we have a sufficient number of spell observations and variation of market and bank characteristics. Data on bank mergers are drawn (as in Craig and Dinger 2009) from the Supervisory Master File of Bank Mergers and Acquisitions.

Bank mergers can affect interest rate dynamics by changing the size of the bank, its market share in markets where both the acquiring and the target banks were previously active, as well as by expanding the number of markets in which a bank operates. To estimate the impact of the merged banks' size (*target's size*), we include the volume of total assets of the target bank[23] (normalized to the acquirer's total assets) in the regression. To control for the effect of changes in market share, we include the *change of market share* (CMS) caused by the merger. Because we do not have precise data on changes in market share directly related to individual mergers for each of the affected local markets, we have to approximate them with changes in market share realized in the year of the merger. That is, we approximate changes in market share caused by a merger as the difference between a bank's market share in the years before and after a merger and normalize by the market share of the acquiring bank before the merger[24]. In order to estimate the effect of the market-extension dimension of the mergers, we include the *change in the number of local markets* (CNM), divided by the number of markets prior to the merger as a regressor. As with the CMS, we have to approximate the CNM, which we do with the ratio of the number of markets in which a bank operates in the years before and after the merger.

[23] The *Supervisory Master File of Bank Mergers and Acquisitions* provides data for the target banks' ID. Given these, we match the acquiring banks' data with the target banks' data from the *Call Report*.
[24] *Summary of Deposits* publishes market shares as of June 30; therefore, we define the year in this case as the period July 1 to June 30.

To consider the evolution of a merger effect, we account for a period from one year before the merger date[25] to up to ten years after the merger. We approximate the development of the rates around the merger by linear spline interpolation, the simplest form of spline interpolation[26]. It is equivalent to piecewise linear interpolation, where the function to be modeled is divided into a fixed number of subintervals, and within each of the subintervals the function is linearly approximated. Nonlinearity can, therefore, be modeled by different slopes of the linear functions across the subintervals. The end points of the linearly approximated subintervals are known as "knots."

Algebraically, each spline is a linear function constructed as:

$$f(x) = \frac{x_{i+1} - x}{x_{i+1} - x_i}\alpha_i + \frac{x - x_i}{x_{i+1} - x_i}\alpha_{i+1}, \qquad \text{when } x \in (x_i, x_{i+1}],$$

$$= \qquad 0, \text{ otherwise,} \qquad (12)$$

and where x is the value of the explanatory variable (the time distance to the merger, in our case). The values x_i denote the "knots" of the spline, and the coefficients, α_i, are estimated from the data. In our case, we approximate the impact of a merger on the change in deposit rates by dividing the time period around the merger into several subperiods. We fix the knots, x_i, at six months before the merger date, at the merger date, six months, one year, one and one-half years, two years, three years, and four years after the merger. Through the splines we model the potential nonlinearity of the dependence between deposit-rate changes and time after the merger.

The results of the estimations are presented in Table 11 and Table 12. The estimated coefficients of the wholesale rate and bank and market characteristic variables are

[25] The merger date is the date on which the target bank loses its charter.

[26] See Craig and Santos, 1997.

qualitatively the same as those presented in Table 7 and Table 8. With regard to the merger effects, we find that the expansion in geographical scope (measured by CNM) has a statistically significant effect of reducing the frequency of changing retail rates for both checking accounts and money market deposit accounts. Target size and the change in local market share significantly reduce the probability of changing the rate only in the case of mergers in less-concentrated local markets. This result suggests that the degree of interest rate inflexibility in concentrated markets is not further accelerated by mergers involving major banks. The fact that bank mergers result in less flexible prices is mostly driven by the fact that mergers increase the geographical scope of banks and thus complicate the linkages between multimarket banks' pricing across different local markets. These findings about the effects of mergers square well with the effects of bank size, the number of markets, and market share on retail-rate durations, which we documented in the previous subsection.

With regard to the time to the merger, we find almost no statistically significant effect on the probability to change MMDA rates. The effect of mergers on the hazard of changing checking account rates is negative in the pre-merger period (lower probability of changing rates), mixed in the first two years after the merger, and negative again in the longer-term period.

4. Conclusion

We present results on retail interest rate dynamics that add to the literature in two dimensions, one data related, and one technical. Our data combine weekly observations of individual banks operating in 165 separate markets. Our technique is to analyze the timing of changes in retail interest rates through statistical duration analysis. Our results justify both the richer data and the more sophisticated technique. Most current studies analyze retail interest rate dynamics with cointegration techniques, which rely on the assumption that the process of adjusting interest rates is approximately smooth, especially around periods of no price change.

In other words, the bank usually adjusts its retail rates in each period, even if these adjustments are moderately small.

Our study shows most emphatically that, for some products, retail interest rate adjustments do not occur in the vast majority of periods, and when they do occur, they can be quite large. Given this lumpiness of the adjustment process, we employ more sophisticated hazard-based-estimation techniques to analyze the determinants of the timing of retail rate changes. The hazard-based estimations lead to results that both differ from these studies and are richer.

Our results show that retail interest rates such as checking account rates, money market deposit account rates, personal loan rates, and fixed credit card rates have a mean duration in the range of 3 to 4 months. The form of the estimated hazard function implies an initially increasing slope of the hazard, which is consistent with the lumpy adjustment of interest rates, which in turn challenges the use of partial adjustment and cointegration models in the analysis of retail interest rate dynamics. We confirm (consistent with earlier studies) that the effect of money market interest rates dynamics on retail interest rates is strongly asymmetric. Also, we show a significant impact of previously omitted variables, such as the volatility of money market rates and interest rate expectations.

Our results also show a statistically significant impact of market structure on the speed of adjustment. The economic significance of this impact is, however, much lower than the one suggested by earlier studies based on the estimation of probit models (Berger and Hannan 1991). In turn, the geographical scope of a bank, whose effect on retail interest rate rigidity has not been explored so far, is shown to have a robust rigidity-increasing effect. In particular, the rigidity of retail rates is strongly enhanced after bank mergers, implying broad geographic expansion of the bank.

Our analysis in this paper could be characterized as “reduced form” in the sense that the estimates have few structural interpretations. However, the hazard functions that we estimate provide a point of departure to a variety of continuous time models, which are appropriate to the high-frequency data that we have. Many of our explanatory variables, such as the volatility of the wholesale rate, which we have shown to be important drivers of the price formation process, can be readily modeled in a continuous time context, and these models already have many representatives in the investment literature. The simple probits previously used to estimate cross-sectional effects are less directly translated to the continuous-time behavioral models and are more likely to be sensitive to ad hoc assumptions about the length of an arbitrary time period. Further, because our results suggest an importance of unobserved heterogeneity in the determination of price changes, our estimating approach can easily be expanded to include unobserved heterogeneity of a known parametric form.

All of this suggests that duration analysis, along with our high-frequency data, can be an important first step towards a structural model of the behavior of interest-rate determination. Potentially, these results point to important similarities between the microeconometric properties of price and interest-rate dynamics that can be employed for the modeling of the monetary policy transmission mechanism.

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Table 1: Average duration of interest rate spells and average change of the rate

Product	average duration (in weeks)	average change (in %)	average rate	average change relative to average rate
deposits				
cheching account	17.71	0.16	0.53	0.30
MMDA	12.76	0.26	1.07	0.24
CD 3 months	7.87	0.33	2.33	0.14
CD 12 months	6.08	0.35	2.96	0.12
loans				
auto loan	9.87	0.87	7.67	0.11
arm 1 year	4.88	0.52	3.82	0.14
heloc	8.15	0.60	12.32	0.05
mortgage 15 years	3.34	0.25	5.83	0.04
personal	11.13	1.47	12.32	0.12
fixed credit card	10.08	0.87	7.56	0.12

Source: Own computations based on BankRate Monitor data

Table 2: Number of spells and number of time changes reversed within four weeks

Product	total number of spells	total number of uncensored spells	number of "sales" with one week duration	number of "sales" with 2 weeks duration	number of "sales" with 3 weeks duration	number of "sales" with 4 weeks duration
deposits						
cheching account	8084	5714	628	149	107	70
MMDA	14433	11814	1600	240	257	103
loans						
personal	797	642	134	48	20	12
fixed credit card	709	565	79	21	12	15

Source: Own calculations based on BankRate Monitor data

Table 3: Wholesale rate changes and the hazard of changing the checking account rate: lognormal hazard estimations

	wholesale rate=T-Bill 3 month rate			wholesale rate=Fed funds rate		
	Coefficient		standard error	**Coefficient**		standard error
absolute change wholesale rate	**1.324**	***	0.214	**2.110**	***	0.215
dummy for negative change	**-0.042**		0.043	**0.045**		0.044
negative change*absolute change	**-2.069**	***	0.130	**-4.092**	***	0.256
wholesale rate	**0.199**	***	0.030	**0.099**	***	0.027
yield curve	**0.205**	***	0.041	**0.141**	***	0.040
wholesale rate volatility	**-0.006**	***	0.001	**0.000**	***	0.000
# Observations	**159762**			**2.403563**		
# spells	**7405**			**7405**		
LR Chi(2)	**797.9**			**521.89**		

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate.

Table 4: Wholesale rate changes and the hazard of changing the money market deposit account rate: lognormal hazard estimations

	wholesale rate=T-Bill 3 month rate			wholesale rate=Fed funds rate		
	Coefficient		standard error	**Coefficient**		standard error
absolute change wholesale rate	2.558	***	0.160	3.549	***	0.149
dummy for negative change	0.402	***	0.028	0.493	***	0.029
negative change*absolute change	-2.801	***	0.112	-5.979	***	0.199
wholesale rate	0.096	***	0.018	0.024		0.017
yield curve	0.143	***	0.025	0.092	***	0.025
wholesale rate volatility	-0.007	***	0.000	0.000	***	0.000
# Observations	**184531**			**184531**		
# spells	**12815**			**12815**		
LR Chi(2)	**1392.67**			**944.71**		

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate.

Table 5: Wholesale rate changes and the hazard of changing the personal loan rate: lognormal hazard estimations

	wholesale rate=T-Bill 3 month			wholesale rate=Fed funds rate		
	Coefficient		standard error	**Coefficient**		standard error
absolute change wholesale rate	**0.437**		0.382	**-0.251**		0.323
dummy for positive change	**-0.949**	***	0.094	**-1.070**	***	0.098
positive change*absolute change	**1.864**	***	0.467	**3.175**	***	0.335
wholesale rate	**-0.017**		0.072	**-0.086**		0.064
yield curve	**-0.079**		0.090	**-0.100**		0.085
wholesale rate volatility	**0.001**		0.001	**0.000**		0.000
# Observations	**5582**			**5582**		
# spells	**625**			**625**		
LR Chi(2)	**83.77**			**123.37**		

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if exp(-$x_j\beta_x$)>1, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate.

Table 6: Wholesale rate changes and the hazard of changing the fixed credit card rate: lognormal hazard estimations

	wholesale rate=T-Bill 3 month rate			wholesale rate=Fed funds rate		
	Coefficient		standard error	**Coefficient**		standard error
absolute change wholesale rate	**1.335**	***	0.290	**0.384**	***	0.297
dummy for positive change	**-0.624**	***	0.094	**-0.706**	***	0.104
positive change*absolute change	**3.069**	***	0.560	**15.437**	***	1.527
wholesale rate	**-0.254**	***	0.069	**-0.256**	***	0.066
yield curve	**-0.383**	***	0.098	**-0.387**	***	0.099
wholesale rate volatility	**-0.001**		0.001	**0.000**		0.000
# Observations	**5185**			**5185**		
# spells	**625**			**625**		
LR Chi(2)	**84.11**			**117.76**		

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate.

Table 7: Market structure and the hazard of changing the checking account rate: lognormal hazard estimations

	full sample								highly concentrated markets								less concentrated markets							
	wholesale rate=T-Bill 3				wholesale rate=Fed				wholesale rate=T-Bill 3				wholesale rate=Fed funds				wholesale rate=T-Bill 3				wholesale rate=Fed funds			
	Coefficient		standard error		**Coefficient**		standard error		**Coefficient**		standard error		**Coefficient**		standard error		**Coefficient**		standard error		**Coefficient**		standard error	
absolute change wholesale rate	**1.344**	***	0.228		**2.459**	***	0.237		**1.733**	***	0.422		**2.622**	***	0.464		**1.424**	***	0.274		**2.421**	***	0.276	
dummy for negative change	**-0.032**		0.045		**0.104**	**	0.049		**-0.022**		0.088		**0.050**		0.092		**-0.081**		0.057		**0.131**	**	0.058	
negative change*absolute change	**-2.013**	***	0.135		**-4.412**	***	0.276		**-1.946**	***	0.239		**-4.382**	***	0.525		**-2.260**	***	0.166		**-4.466**	***	0.325	
wholesale rate	**0.245**	***	0.031		**0.198**	***	0.029		**0.303**	***	0.059		**0.208**	***	0.055		**0.307**	***	0.039		**0.192**	***	0.034	
yield curve	**0.283**	***	0.043		**0.306**	***	0.044		**0.354**	***	0.083		**0.301**	***	0.083		**0.361**	***	0.053		**0.308**	***	0.052	
wholesale rate volatility	**-0.006**	***	0.001		**0.000**	***	0.000		**-76.185**	***	11.368		**0.000**	***	0.000		**-49.060**	***	8.335		**0.000**	***	0.000	
bank size	**-0.060**	**	0.032		**-0.073**	***	0.021		**-0.010**		0.038		**-0.026**		0.038		**-0.078**	***	0.028		**-0.088**	***	0.026	
herfindahl	**-0.457**		0.318		**-0.711**	**	0.283																	
market share	**0.029**		0.226		**0.285**		0.196		**-0.161**		0.267		**-0.115**		0.262		**0.567**	*	0.307		**0.539**	*	0.290	
number of markets	**0.013**	***	0.003		**0.014**	***	0.002		**0.008**	***	0.003		**0.009**	***	0.003		**0.014**	***	0.002		**0.015**	***	0.002	
# Observations	**138652**				**138652**				**40629**				**40629**				**98023**				**98023**			
# spells	**6483**				**6483**				**1967**				**1967**				**4754**				**4754**			
LR Chi(2)	**736.37**				**638.71**				**247.74**				**162.98**				**684.99**				**481.84**			

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index ≥0.18 (following the definition of the Department of Justice).

Table 8: Market structure and the hazard of changing the money market deposit account rate: lognormal hazard estimations

	full sample				highly concentrated markets				less concentrated markets			
	wholesale rate=T-Bill 3		wholesale rate=Fed funds		wholesale rate=T-Bill 3		wholesale rate=Fed funds		wholesale rate=T-Bill 3		wholesale rate=Fed funds	
	Coefficient	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error
absolute change wholesale rate	**2.149** ***	0.170	**3.373** ***	0.161	**1.479** ***	0.403	**3.296** ***	0.345	**1.473** ***	0.242	**3.153** ***	0.213
dummy for negative change	**0.395** ***	0.029	**0.496** ***	0.031	**0.552** ***	0.064	**0.609** ***	0.068	**0.558** ***	0.039	**0.693** ***	0.043
negative change*absolute change	**-2.490** ***	0.114	**-5.752** ***	0.212	**-2.696** ***	0.244	**-6.208** ***	0.461	**-2.677** ***	0.152	**-5.858** ***	0.278
wholesale rate	**0.158** ***	0.020	**0.085** ***	0.018	**0.236** ***	0.040	**0.216** ***	0.036	**0.180** ***	0.025	**0.151** ***	0.022
yield curve	**0.251** ***	0.027	**0.207** ***	0.027	**0.280** ***	0.056	**0.308** ***	0.054	**0.234** ***	0.035	**0.240** ***	0.034
wholesale rate volatility	**-0.008** ***	0.000	**0.000** ***	0.000	**-64.625** ***	7.809	**-2.906** ***	0.547	**-95.511** ***	4.841	**-3.722** ***	0.333
bank size	**0.013**	0.020	**-0.007**	0.019	**-0.057** **	0.024	**-0.049** **	0.023	**-0.057** ***	0.016	**-0.054** ***	0.016
herfindahl	**0.704** ***	0.186	**0.561** ***	0.181								
market share	**0.075**	0.140	**0.136** ***	0.137	**0.765** ***	0.188	**0.669** ***	0.180	**-0.218**	0.187	**-0.177**	0.185
number of markets	**0.007** ***	0.001	**0.006** ***	0.001	**0.010** ***	0.002	**0.008** ***	0.002	**0.010** ***	0.001	**0.009** ***	0.001
# Observations	**160188**		**160188**		**46302**		**46302**		**114211**		**114211**	
# spells	**11216**		**11216**		**3690**		**3690**		**9271**		**9271**	
LR Chi(2)	**1367.56**		**932.27**		**382.13**		**310.69**		**1173.1**		**740.36**	

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index ≥0.18 (following the definition of the Department of Justice).

Table 9: Market structure and the hazard of changing the personal loan rate: lognormal hazard estimations

	full sample				highly concentrated markets				less concentrated markets			
	wholesale rate=T-Bill 3		wholesale rate=Fed		wholesale rate=T-Bill 3		wholesale rate=Fed		wholesale rate=T-Bill 3		wholesale rate=Fed funds	
	Coefficient	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error
absolute change wholesale rate	**0.382**	0.385	**-0.391**	0.338	**0.271**	1.050	**-0.219**	0.778	**0.429**	0.407	**-0.356**	0.366
dummy for positive change	**-0.968** ***	0.100	**-1.108** ***	0.106	**-0.935** ***	0.236	**-1.143** ***	0.252	**-0.996** ***	0.113	**-1.101** ***	0.122
positive change*absolute change	**2.318** ***	0.528	**3.922** ***	0.411	**2.520** **	1.054	**3.662** ***	0.922	**2.158** ***	0.634	**3.979** ***	0.471
wholesale rate	**-0.020**	0.080	**-0.148** **	0.075	**-0.339** **	0.173	**-0.461** ***	0.168	**0.018**	0.092	**-0.132**	0.088
yield curve	**-0.075**	0.103	**-0.204** **	0.105	**-0.517** **	0.229	**-0.627** ***	0.246	**-0.008**	0.119	**-0.157**	0.123
wholesale rate volatility	**0.001**	0.001	**0.000**	0.000	**7.125**	44.942	**0.000**	0.000	**9.863**	15.906	**0.000**	0.000
bank size	**-0.083**	0.076	**-0.069**	0.078	**-0.045**	0.208	**-0.028**	0.210	**-0.034**	0.071	**-0.012**	0.070
herfindahl	**-0.737**	1.031	**-0.695**	1.016								
market share	**0.121**	0.653	**0.046**	0.652	**-0.043**	1.119	**0.554**	1.184	**0.428**	0.753	**0.445**	0.746
number of markets	**-0.002**	0.004	**0.000**	0.005	**-0.004**	0.008	**-0.007**	0.008	**-0.009**	0.003	**-0.010**	0.003
# Observations	**4862**		**4862**		**1032**		**1032**		**3830**		**3830**	
# spells	**532**		**532**		**118**		**118**		**421**		**421**	
LR Chi(2)	**90.79**		**135.67**		**34.04**		**44.21**		**97.88**		**129.34**	

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index ≥ 0.18 (following the definition of the Department of Justice).

Table 10: Market structure and the hazard of changing the fixed credit card rate: lognormal hazard estimations

	full sample				highly concentrated markets				less concentrated markets			
	wholesale rate=T-Bill 3		wholesale rate=Fed		wholesale rate=T-Bill 3		wholesale rate=Fed		wholesale rate=T-Bill 3		wholesale rate=Fed	
	Coefficient	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error
absolute change wholesale rate	**1.361** ***	0.292	**0.498** *	0.284	**0.565**	0.914	**0.736**	0.654	**-0.339**	0.484	**-0.833** **	0.418
dummy for positive change	**-0.628** ***	0.096	**-0.660** ***	0.106	**-0.092**	0.254	**0.132**	0.271	**0.011**	0.151	**-0.216**	0.154
positive change*absolute change	**2.994** ***	0.574	**15.265** ***	1.579	**0.419**	1.088	**-0.511**	3.302	**-0.435**	0.998	**7.252** ***	1.944
wholesale rate	**-0.257** ***	0.072	**-0.250** ***	0.068	**-0.596** ***	0.194	**-0.469** **	0.197	**-0.285** **	0.111	**-0.201** **	0.096
yield curve	**-0.393** ***	0.099	**-0.398** ***	0.101	**-0.360**	0.259	**-0.240**	0.286	**-0.282**	0.154	**-0.184**	0.147
wholesale rate volatility	**-0.001**	0.001	**0.000**	0.000	**6.259**	48.496	**0.000**	0.000	**-27.862** *	15.924	**0.000** **	0.000
bank size	**0.044**	0.059	**0.079**	0.058	**-0.063**	0.279	**0.091**	0.285	**0.279** ***	0.085	**0.290** ***	0.080
herfindahl	**0.234**	0.793	**-0.185**	0.791								
market share	**-0.145**	0.508	**-0.271**	0.506	**-0.465**	1.371	**-1.051**	1.387	**-1.144**	0.847	**-1.321** *	0.798
number of markets	**-0.004**	0.003	**-0.005** *	0.003	**-0.001**	0.010	**-0.007**	0.011	**-0.011** **	0.004	**-0.010** **	0.004
# Observations	**4982**		**4982**		**1035**		**1035**		**3947**		**3947**	
# spells	**604**		**604**		**136**		**136**		**543**		**543**	
LR Chi(2)	**92.03**		**118.19**		**36.82**		**36.24**		**48.3**		**58.27**	

Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index $\geq$0.18 (following the definition of the Department of Justice).

Table 11: Bank mergers and the hazard of changing checking account rates

	full sample of mergers				highly concentrated markets				less concentrated markets			
	wholesale rate=T-Bill 3		wholesale rate=Fed		wholesale rate=T-Bill 3		wholesale rate=Fed funds		wholesale rate=T-Bill 3		wholesale rate=Fed funds	
	Coefficient	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error
absolute change wholesale rate	**1.388** ***	0.256	**2.344** ***	0.262	**2.784** ***	0.496	**1.759** ***	0.470	**1.243** ***	0.304	**2.180** ***	0.306
dummy for negative change	**-0.020**	0.052	**0.172** ***	0.053	**0.136**	0.098	**0.021**	0.093	**-0.037** **	0.063	**0.186** ***	0.063
negative change*absolute change	**-2.225** ***	0.150	**-4.695** ***	0.308	**-5.075** ***	0.582	**-2.092** ***	0.261	**-2.279** ***	0.182	**-4.540** ***	0.360
wholesale rate	**0.299** ***	0.036	**0.179** ***	0.033	**0.202** ***	0.061	**0.310** ***	0.065	**0.291**	0.044	**0.166** ***	0.039
yield curve	**0.342** ***	0.049	**0.278** ***	0.049	**0.309** ***	0.091	**0.365** ***	0.089	**0.331** ***	0.059	**0.266** ***	0.057
wholesale rate volatility	**-58.671** ***	7.411	**0.000** ***	0.000	**0.000** ***	0.000	**-78.993** ***	12.337	**-48.696** ***	9.207	**0.000** ***	0.000
bank size	**-0.035**	0.044	**-0.082** *	0.043	**-0.077**	0.084	**-0.040**	0.084	**-0.034**	0.053	**-0.094** *	0.051
market share	**0.066**	0.211	**0.210**	0.209	**0.227**	0.278	**0.151**	0.279	**0.077**	0.335	**0.254**	0.323
number of markets	**0.011**	0.002	**0.012** ***	0.002	**0.011** ***	0.004	**0.010** ***	0.004	**0.012** ***	0.002	**0.013** ***	0.002
target size	**-0.006**	0.032	**0.019**	0.030	**0.003**	0.065	**-0.012**	0.066	**-0.009**	0.036	**0.024**	0.035
change number of markets	**0.226** ***	0.041	**0.212** ***	0.039	**0.242** ***	0.073	**0.255** ***	0.074	**0.226** ***	0.050	**0.217** ***	0.047
change market share	**0.755**	0.569	**0.507**	0.550	**1.830** **	0.814	**1.776** **	0.789	**-0.229**	0.820	**-0.396**	0.774
spline-0.5	**0.507** ***	0.183	**0.500** ***	0.177	**0.290**	0.300	**0.287**	0.299	**0.615** ***	0.229	**0.565** **	0.219
spline0	**-0.153**	0.112	**-0.117**	0.108	**-0.509** ***	0.185	**-0.554** ***	0.188	**0.025**	0.140	**0.041**	0.133
spline+0.5	**-0.214** **	0.108	**-0.339** ***	0.103	**-0.632** ***	0.179	**-0.460** ***	0.182	**-0.099**	0.134	**-0.223** *	0.125
spline+1	**0.265** **	0.115	**0.310** ***	0.110	**-0.057**	0.194	**-0.057**	0.197	**0.388**	0.141	**0.456** ***	0.133
spline+1. 5	**-0.025**	0.124	**-0.020**	0.120	**-0.411** **	0.212	**-0.401** *	0.212	**0.133**	0.152	**0.127**	0.145
spline+2	**0.586** ***	0.125	**0.607** ***	0.120	**0.439** **	0.210	**0.425** **	0.212	**0.642** ***	0.154	**0.654** ***	0.146
spline+3	**0.419** ***	0.115	**0.426** ***	0.110	**0.032**	0.195	**-0.003**	0.196	**0.597** ***	0.141	**0.571** ***	0.134
spline+4	**0.224** **	0.099	**0.198** **	0.096	**-0.218**	0.186	**-0.116**	0.188	**0.344** ***	0.117	**0.344** ***	0.112
# Observations	**114337**		**114337**		**33432**		**33432**		**80905**		**80905**	
# spells	**5388**		**5388**		**1648**		**1648**		**3939**		**3939**	
LR Chi(2)	**924.33**		**684.46**		**210.88**		**285.36**		**673.27**		**510.24**	

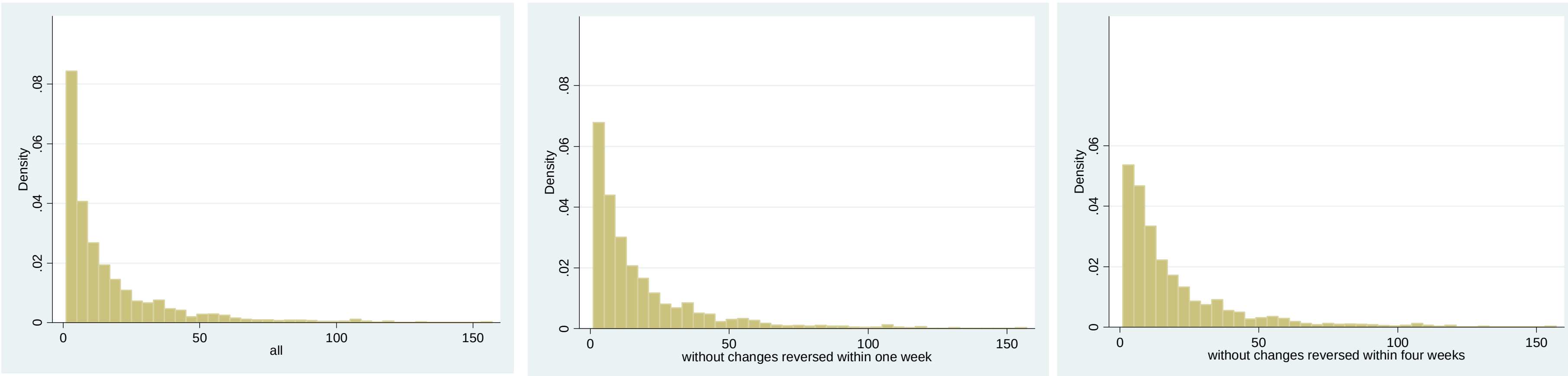
Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index ≥ 0.18 (following the definition of the Department of Justice).

Table 12: Bank mergers and the hazard of changing money market deposit account rates

	full sample of mergers				highly concentrated markets				less concentrated markets			
	wholesale rate=T-Bill 3		wholesale rate=Fed funds		wholesale rate=T-Bill 3		wholesale rate=Fed funds		wholesale rate=T-Bill 3		wholesale rate=Fed funds	
	Coefficient	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error	**Coefficient**	standard error
absolute change wholesale rate	**1.321** ***	0.231	**3.136** ***	0.198	**1.102** **	0.462	**3.187** ***	0.382	**1.388** ***	0.265	**3.096** ***	0.232
dummy for negative change	**0.555** ***	0.037	**0.668** ***	0.040	**0.544** ***	0.073	**0.635** ***	0.076	**0.561** ***	0.043	**0.679** ***	0.046
negative change*absolute change	**-2.739** ***	0.143	**-5.959** ***	0.260	**-2.883** ***	0.282	**-6.543** ***	0.514	**-2.657** ***	0.165	**-5.716** ***	0.301
wholesale rate	**0.166** ***	0.025	**0.146** ***	0.022	**0.175** ***	0.048	**0.173** ***	0.042	**0.162** ***	0.029	**0.138** ***	0.025
yield curve	**0.233** ***	0.033	**0.248** ***	0.032	**0.247** ***	0.065	**0.292** ***	0.062	**0.223** ***	0.039	**0.230** ***	0.038
wholesale rate volatility	**-89.649** ***	4.547	**-3.615** ***	0.315	**-74.417** ***	8.639	**-3.146** ***	0.602	**-95.925** ***	5.348	**-3.821** ***	0.370
bank size	**-0.115** ***	0.029	**-0.111** ***	0.028	**-0.080**	0.060	**-0.061**	0.057	**-0.126** ***	0.033	**-0.121** ***	0.032
market share	**0.546** ***	0.142	**0.563** ***	0.137	**0.897** ***	0.208	**0.767** ***	0.196	**0.096**	0.206	**0.167**	0.203
number of markets	**0.010** ***	0.001	**0.008** ***	0.001	**0.008** ***	0.002	**0.007** ***	0.002	**0.010** ***	0.001	**0.009** ***	0.001
target size	**0.063** ***	0.021	**0.065** ***	0.020	**0.030**	0.047	**0.029**	0.046	**0.071** ***	0.024	**0.073** **	0.023
change number of markets	**0.159** ***	0.027	**0.134** ***	0.026	**0.262** ***	0.057	**0.225** ***	0.054	**0.126** ***	0.031	**0.105** ***	0.030
change market share	**1.017** ***	0.389	**0.871** ***	0.372	**1.159** *	0.608	**1.003** *	0.580	**1.066** **	0.520	**0.847** *	0.499
spline-0.5	**-0.085**	0.112	**-0.059**	0.107	**-0.044**	0.211	**-0.048**	0.201	**-0.115**	0.131	**-0.073**	0.127
spline0	**0.131**	0.080	**0.154** **	0.077	**-0.180**	0.144	**-0.143**	0.136	**0.255** **	0.097	**0.270** ***	0.093
spline+0.5	**-0.290** ***	0.071	**-0.289** ***	0.067	**-0.343** ***	0.133	**-0.378** ***	0.126	**-0.279** ***	0.084	**-0.258** ***	0.080
spline+1	**-0.038**	0.072	**0.055**	0.070	**-0.287** **	0.140	**-0.217**	0.133	**0.066**	0.085	**0.162** **	0.082
spline+1. 5	**-0.283** ***	0.078	**-0.291** ***	0.074	**-0.457** ***	0.147	**-0.462** ***	0.140	**-0.226** **	0.091	**-0.230** ***	0.087
spline+2	**0.110**	0.075	**0.080**	0.072	**0.261** *	0.158	**0.271**	0.151	**0.044**	0.086	**0.012**	0.082
spline+3	**-0.077**	0.075	**0.007**	0.072	**-0.442** ***	0.137	**-0.341** ***	0.131	**0.098**	0.090	**0.171** **	0.087
spline+4	**0.185** ***	0.063	**0.180** ***	0.060	**0.012**	0.130	**0.009**	0.124	**0.259** ***	0.072	**0.253** ***	0.069
# Observations	**132967**		**132967**		**38279**		**38279**		**94707**		**94707**	
# spells	**10375**		**10375**		**2981**		**2981**		**7623**		**7623**	
LR Chi(2)	**1393.61**		**935.04**		**397.33**		**321.11**		**1047.09**		**666.17**	

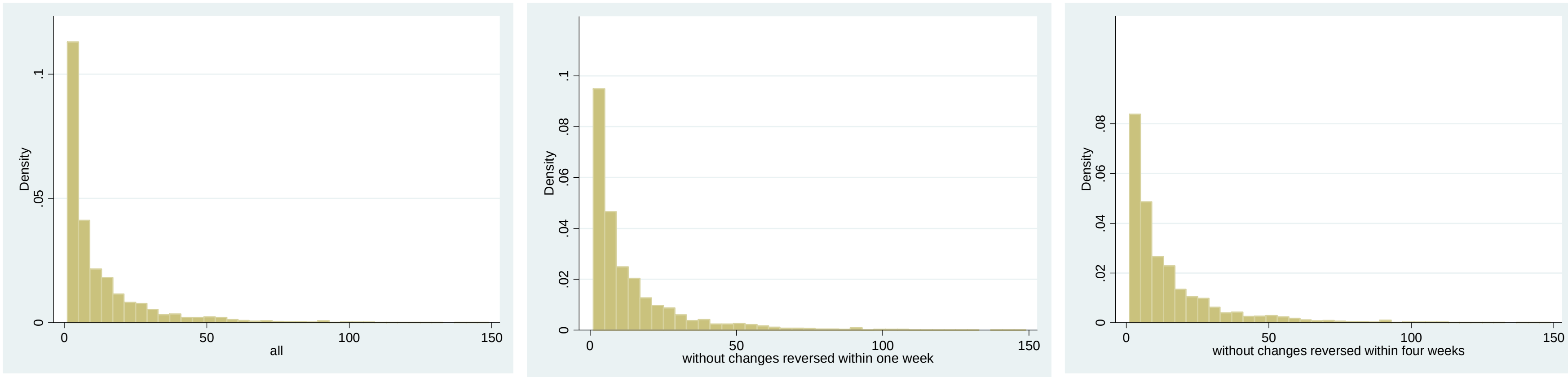
Note: Lognormal parametric estimation of the hazard of changing the retail rate based on a sample of spells considering only changes which are not reversed within one week as spell "ends". The lognormal hazard model is an accelerated time-to-failure model, in which coefficients of the covariates are interpreted as follows: if $\exp(-x_j\beta_x)>1$, then time passes more quickly for the subject; in other words, the probability of changing is higher. Given positive values of x_j, a negative coefficient β_x implies an increased probability of changing the retail interest rate. Highly concentrated markets are defined as markets with Herfindahl index ≥ 0.18 (following the definition of the Department of Justice).

Chart 1: Distribution of checking account rate durations



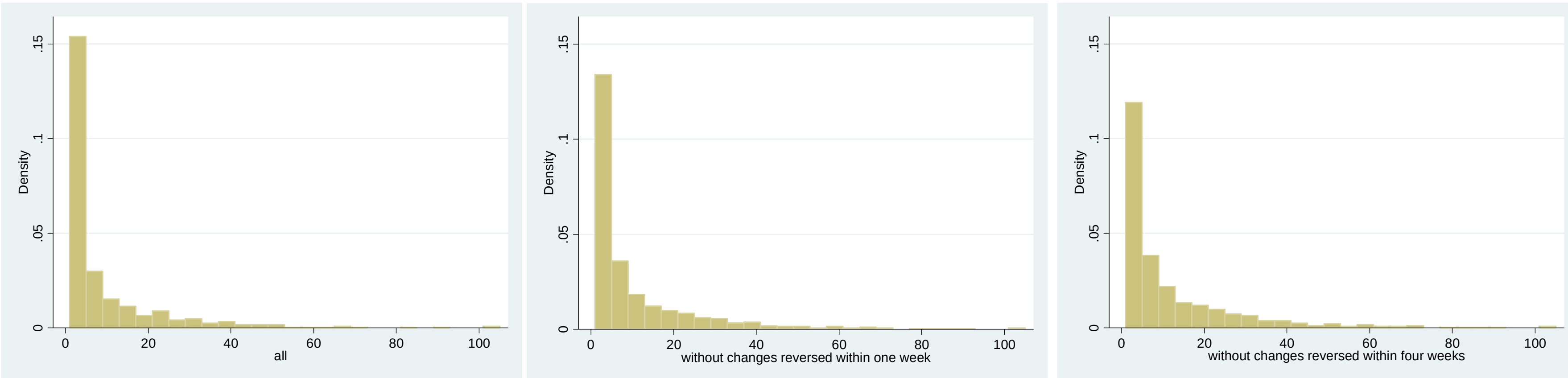
Note: Distribution of the duration of retail rates in weeks.

Chart 2: Distribution of money market deposit account rate durations



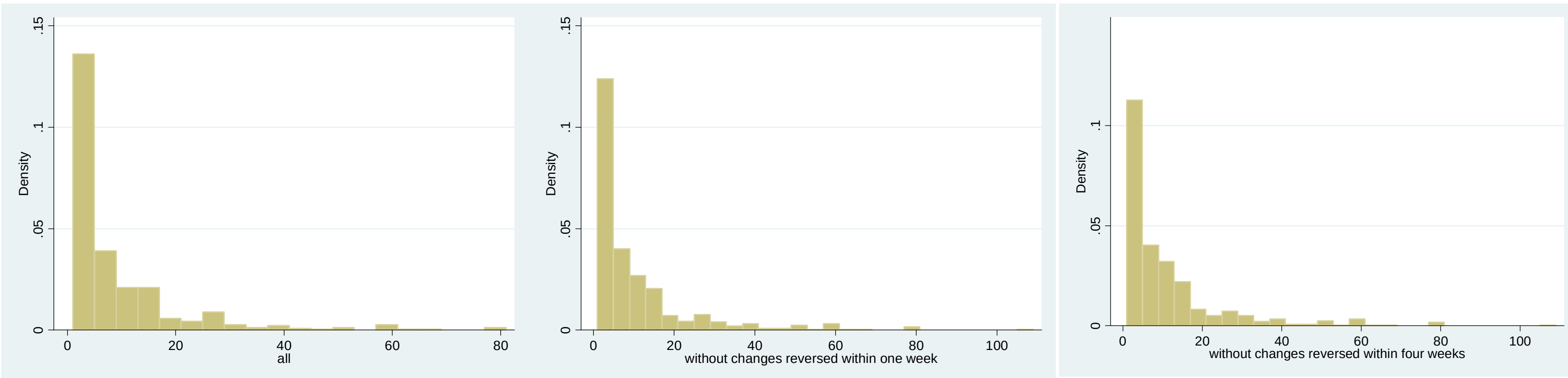
Note: Distribution of the duration of retail rates in weeks.

Chart 3: Distribution of personal loan rate durations



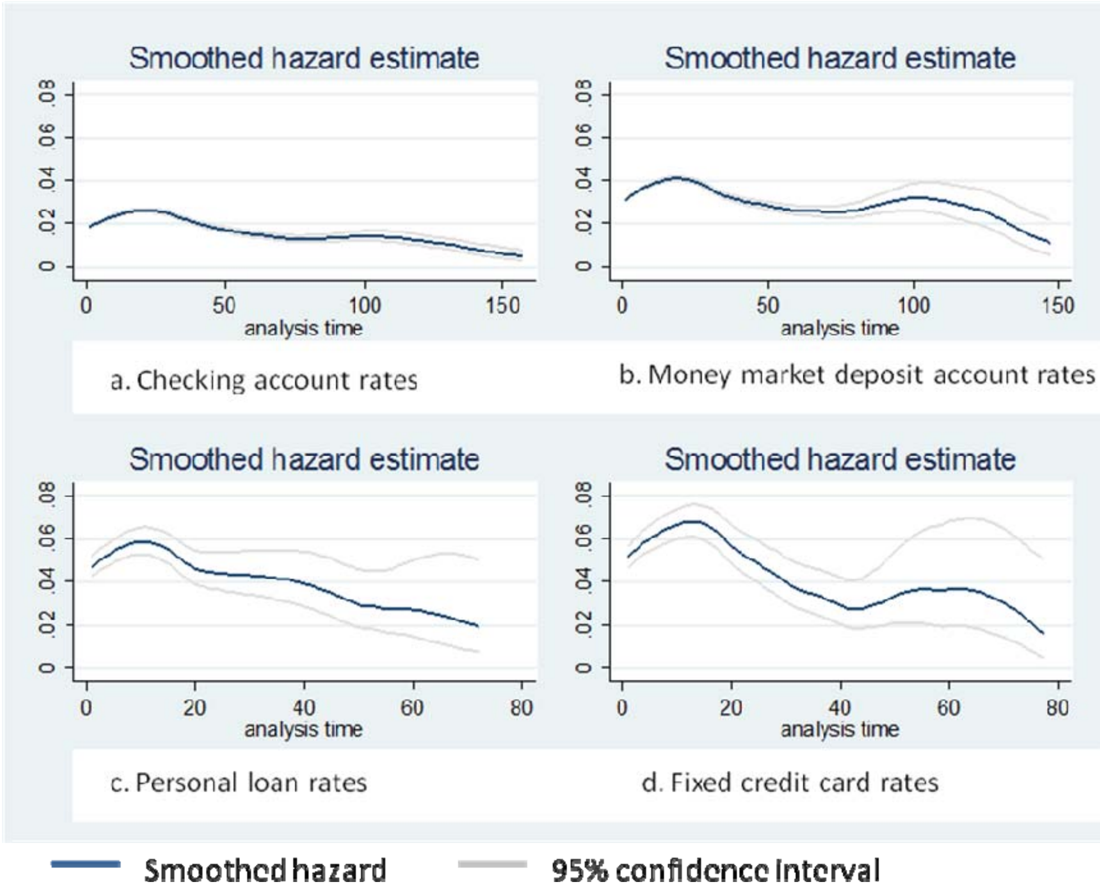
Note: Distribution of the duration of retail rates in weeks.

Chart 4: Distribution of fixed credit card rate durations



Note: Distribution of the duration of retail rates in weeks.

Chart 5: Kaplan-Maier hazard function estimates



Note: Nonparametric Kaplan-Maier smoothed hazard estimates based on samples considering only interest rate changes that are not reversed within one week as ends of the spells.