SWITCHING COSTS IN LOCAL CREDIT MARKETS

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Abstract

This paper examines the existence of switching costs in local credit markets. Two conjectures from the theoretical literature are empirically investigated. First, banks price discriminate between new and old borrowers by charging lower interest rates to the former in order to cover switching costs. Second, these costs augment state dependence in bank-firm relationships. Using matched bank-firm data regarding four Italian provinces we find that lending rates are significantly lower for borrowers changing their main credit supplier. This result is robust with respect to a number of checks, including selectivity bias and the definition of a switching occurrence. Moreover firms' choice of their main bank show a significant state dependence, even after controlling for unobserved heterogeneity of borrowers' preferences across lenders.

JEL Classification: C25, G21, L13.

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1. Introduction

Credit markets are replete with the presence of switching costs. Closing a previous lending relationship and starting a new one would involve several types of switching costs. First, there are transaction costs of closing the accounts with the current lender and opening new ones with another bank. Second, there exist learning costs such as costs of switching to a new bank following specific rules and practices in its lending activity after learning different rules adopted by the old lender. Third, due to asymmetric information, lending relationships may generate benefits for the borrowing firm that would be lost if this firm

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decided to change its previous bank and borrow from a different intermediary.

Whatever their origin, switching costs have far reaching consequences on the working of credit markets. They increase borrowers lock-in and grant the incumbent bank an ex post monopoly power over its current customers. The cost of attracting rival banks' borrowers will rise since the interest rate cut required to capture an additional borrower must cover switching costs. In turn, this will augment the stability of lender-borrower relationships through time or reduce borrowers' mobility across banks. Switching costs may also explain why banks might prefer to maximise their current market share, the so called battle for market shares. In fact, having a large base of borrowers today will increase future profits, given customers lock-in. Finally, switching costs might also have an impact on the height of entry barriers.

Despite their relevance on a priori grounds, there are still few empirical contributions dealing with switching costs in business lending markets. Almost all papers examine deposit or credit card markets where transactions are not as replete with informational problems as those in business loan markets.

Sharpe (1997) tests the predictions of Klemperer (1987) and looks at the interest rates set in local deposit markets where there are large flows of new customers. Given that these depositors had no previous relation with the local banking industry, they should be able to obtain higher interest rates on their deposits. Empirical results confirm this prediction. Shy (2002) finds also evidence in favour of the presence of switching costs in the Finnish deposit market.

For the credit card market, Ausubel (1991) explains the persistence of rents with the consumer inertia caused by search costs or switching costs. Stango (2002) shows that credit card issuers' pricing is positively correlated with some proxies for switching costs.

As far as we know, Kim *et al.* (2001) is the only empirical paper dealing with switching costs in loan markets. The authors propose a methodology where the magnitude of these costs is indirectly estimated through the observation of aggregate market shares held by Norwegian banks. Credit demand and supply are modelled and simultaneously estimated. Their point estimate of the average switching cost is about 4%, one third of the average interest rates on loans. The analysis considers Norway as a unique market implying that borrowers can costless move across differently located bank branches.

The goal of our paper is that of contributing to the empirical literature on switching costs in business lending markets. To do that, we propose an econometric analysis aimed at detecting state dependence in bank-firm relationships and finding evidence on banks price discrimination between new and old borrowers. The propensity of firms to repeat the choice of their main lender through time is an immediate consequence of switching costs. Moreover, an interest rate reduction offered to switching firms is consistent with the results of a recent theoretical literature dealing with pricing decisions in markets with non anonymous transactions and switching costs.

To carry out this analysis we use a data set reporting very detailed information on individual bank-firms relationships and interest rates for four Italian local credit markets. The features of this data set as well as the econometric methods used allows us to offer a more direct test on the relevance of switching costs in credit markets than what was done in other contributions.

Our results show that there is wide evidence of state dependence in bank-firms relationships in the Italian local markets, even after controlling for unobserved heterogeneity of firms' preferences across banks. Moreover, we find that firms with an exclusive bank relationship exhibit a lower propensity to change their main lender with respect to firms resorting to multiple bank financing. This result is consistent with the possibility that an exclusive relationship could lock-in borrowing firms. We also find evidence that banks price discriminate between their new and old customers by charging lower interest rates to the former. In other words, banks will pay rivals' borrowers to switch. This finding is also a test of the importance of switching costs as compared to other alternative explanations of banks price discrimination based on adverse selection.

The rest of the paper is organized as follows. Section 2 establishes a link between switching costs theory and the following empirical analysis. Sections 3 and 4 describe the data and our empirical strategy. The econometric findings derived from the interest rate equation are shown in section 5. Section 6 discusses results on state dependence in bank-firm-relationships obtained from the mixed logit model, while Section 7 compares these results for firms with a single bank relationships with the those resorting to multiple lending.

Concluding remarks are discussed in the final section.

2. Switching costs in credit markets

In markets with switching costs a customer faces economies of scope when she chooses the same supplier over time. Thus, one of the effect of these costs is that of augmenting the state dependence in repeated purchase decisions. This can be defined as a genuine causal relationship between vendor-buyer matches over time and imply that the probability of observing a customer choosing a certain supplier in a period increases given that the same choice was made in previous period[1]. Switching costs also grant the incumbent supplier with an ex post monopoly power on its customer base. This affects pricing decisions and, through them, has an additional and indirect effect on the stability of seller-buyer matches.

To adapt the literature on switching costs to the banking sector, one must discuss the non anonymity of credit market transactions and the issue of informational problems in lending activity.

Banks directly deliver their services to customers and hence they are able to know whether a borrower is one of its pre existing clients and price discriminate on the basis of this knowledge. With anonymous transactions, a price reduction decided by the supplier would have the advantage of attracting new customers, but this would come at cost of extending this discount to all the captive customers[2]. Chen (1997) and Taylor (2003) recently analyzed models with heterogeneous switching costs and customer recognition. Gerigh and Stembacka (2004) explicitly refer these models to credit markets. The main conclusions of this strand of literature can be summarized as follows: *(i)* in equilibrium some borrowers with switching costs below a certain threshold will change their credit supplier and the remaining ones will stay with their previous lender; *(ii)* banks will price discriminate between their pre-existing customers and rival's borrowers by offering a discount to the latter (poaching strategies). This is due to the fact that banks are aware of the existence of switching costs and therefore have to tease new customers by offering low

[1] See Klemperer (1995) and Farrell and Klemperer (2004) for a general survey.
[2] See Beggs and Klemperer (1992).

introductory prices in order to attract them. In other words, banks "will pay customers to switch".

Another important feature of credit markets is related to the strategic interaction between more and less informed banks. By lending an incumbent bank may obtain additional information on a borrower's quality. If this information cannot be credibly communicated to an outside bank, a switching firm would pay a lemon's premium. The outside bank would in fact suspect that the switcher could be a bad quality borrower to which the incumbent bank denied credit. In that case one could end up with a mixed strategy equilibrium as described in von Thadden (1998) where only few firms switch and outside banks charge higher interest rates to these borrowers due to adverse selection[3].

Apart from its effects on interest rates, adverse selection may also discourage potential switchers through more severe credit conditions (request of more collateral, lower credit availability, etc.). In this perspective adverse selection is a further source of borrowers' lock-in and is not distinguishable from other kinds of switching costs. Thus it is possible to state the following proposition:

(P1) the higher will be switching costs the higher will be the share of borrowers sticking to their host bank or the more intense will be state dependence in lender-borrower matches. Hence existence and intensity of switching costs can be inferred by measuring state dependence in lending relationships.

Regarding price discrimination between new and old borrowers switching costs and adverse selection will have opposite (and testable) implications. If the strength of adverse selection outweighs that of switching costs, switching firms would pay higher interest rates than those charged to the captive borrowers. On the contrary, if switching costs prevail, banks would offer a discount to the rival's customers with respect to the interest rates charged to their old borrowers. Hence, adverse selection and switching costs can be considered as two forces

[3] Gerigh and Stembacka (2004) introduce adverse selection in their model with customer recognition and heterogeneous switching costs. Model predictions *(i)* and *(ii)* hold conditionally to a moderate degree of adverse selection but, within these limits, adverse selection had no effect on pricing. The latter result is not general and only depends on quite restrictive modelling assumptions. For a loan market model combining adverse selection and switching costs in a less restrictive way, see Vesala (2005).

pushing in opposite directions as far as their effects on interest rates charged to captive versus unattached borrowers are concerned.

Moreover, apart from adverse selection, other forces may lead to higher costs of credit for the unattached customers. Boot and Thakor (1994) show that in a context of infinitely repeated games with discounting borrowers are requested to pledge collaterals and pay higher costs of credit at the beginning of a relationship. As time goes, they are offered unsecured loan and pay declining interest rates after they have demonstrated some project success. As a consequence, an entrepreneur switching to a new bank would pay higher interest rates with respect to established customers and will be also forced to pledge a collateral. This outcome is due to the fact that new borrowers are without track records and does not necessarily depend on the learning developed within the lending relationship.

Previous models generate a clear cut theoretical prediction concerning prices. In particular:

(P2) Other things being equal, a negative (positive) new-old borrowers interest rate differential will reveal that switching costs effects on banks pricing are stronger (weaker) than those derived from adverse selection or from other alternative explanations of lenders and borrowers behaviour.

In what follows we will first empirically test if banks price discriminate between new and old borrowers. According to (P2) if a low introductory pricing strategy turned out to be at work, it would signal the existence of switching costs and their relevance with respect to other forces driving banks pricing behaviour. Following (P1) state dependence in bank-firm relationships is then measured to infer existence and intensity of switching costs.

3. Data description

3.1. Data sources and sample construction

The data come from two sources. The first and most important one is the Survey on lending rates carried out by the Bank of Italy. Data at our disposal refers to the reports of about 300 Italian banks participating in the Survey. This sample includes the main Italian banks and is representative of credit markets at provincial level[4]. The data refer to single bank-borrower relationships. For each record matched, revocable and term loans and the interest rates charged on these operations are reported. The data also include information on borrower characteristics (sector of economic activity, legal form and municipality where the firm is located) and are available at two dates: March 2004 and March 2005 (throughout the paper we refer to them as period $t-1$ and t, respectively). The second source comes from Bank of Italy supervisory reports and consists of information on bank characteristics, including branch locations and loans granted to customers located in different provincial markets.

We restrict our analysis to business lending. Borrowers reporting bad loans are dropped from the sample, as well as those that were not present in both dates[5].

The structure of our database is particularly well-suited to analyse local credit markets and this is a distinguishing feature with respect to the existing literature[6]. Local corporate lending markets are assumed to coincide with Italian provinces. We restrict our sample to lending relationships between one of the top 15 banks operating in a province and the borrowers located in the same area[7]. As it will become clear in Section 4 this condition is motivated by the fact that random utility models, to be empirically manageable, require a limited number of alternatives in the choice set (see equation 3 below).

The analysis is focused on four local markets: Turin, Bologna, Rome and Naples. These provinces have been chosen since they cover different areas of the country with sharp differences in per capita income, sectoral specialization, quality of the local institutions, size and concentration of the credit market, etc. For all the provincial markets the sample includes about 79,000 bank-firm relationships and 50,000 borrowers. Table 1 contains a

[4] Italy is divided into 103 provinces.

[5] The latter choice has been carried out to address a threshold effect: to be included in the Survey on lending rates, in fact, a loan has to be above 75.000 euro; accordingly, single bank-firm relationships can enter or exit the sample due to reasons we could not control for.

[6] It is well known that business lending usually shows a very limited geographical scope (see Petersen and Rajan, 2002, for the USA and Degryse and Ongena, 2005, for the Belgian loan market). Kim *et al.* (2003)'s paper is subject to this criticism as the authors consider the Norwegian loan market at national level. To get around this problem, they run different estimations by splitting their sample according to bank size (measured by the number of branches). This is hardly a solution as small banks are assumed to compete in the same national market.

detailed description of the variables included in our sample while Tables 2 and 3 show summary statistics.

3.2. Managing multiple lending

The literature on switching costs is usually based on the implicit assumption that a customer will buy a product or service from only one seller. This is at odds with the evidence featuring Italian as well as other European credit markets where lending from more than one bank is a quite common strategy even for small business financing. Multiple lending adds further complexity to the analysis of switching behaviour. For instance, a single-bank firm in $t-1$ could start getting credit from a new bank in t without breaking its pre-existing relationship. To address this and other similar problems, switching is defined as the change of the main bank, i.e. the bank granting the largest amount of credit. This choice is motivated by the special role played by the main bank. In our data, financing through these lenders represents on average 87 per cent of total bank credit extended to each firm. Even considering exclusively firms lending from more than one bank, this percentage amounts to 67 per cent of a firm bank debt. Thus, given this strong concentration, it is likely that a relationship with the main bank will generate stronger benefits for the borrower and, consequently, increases its lock-in. Moreover transactional and learning costs might also be larger in the case of main bank change. Finally, the pivotal role of the main bank can also be justified on a theoretical ground even when multiple lending occurs[8].

4. Empirical design

4.1. Price discrimination between old and new borrowers

In order to test if banks offer teasing prices to new clients (see proposition P2) we run the following reduced form regression:

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[7] These banks are defined as those that are at the top in the ranking based on the number of customers they have in each local market. On average, these banks represent about 70 per cent of the total loans in each province.

[8] Elsas, Heinemann and Tyrell (2004) show that a concentrated credit offering in which a main lender coexists with many other small arm's-length banks does emerge as an optimal solution to the firm financing problem. The presence of a main bank will reduce coordination costs of the other arm's-length lenders while the latter help mitigating the hold up problem generated by the privileged position enjoyed by the main bank.

$$INTRATE_{ijt} = \alpha + \xi' \, DUMMIES + \varphi MS_{jp(i)t-1} + \pi' \, X_{it-1} + \beta_p DNEW_{ijt} + \mu_{ijt} \qquad (1)$$

where $INTRATE_{ijt}$ is the interest rate charged by bank j to firm i in march 2005 and μ_{ijt} is an error term with the usual properties. To avoid simultaneity all time-varying regressors but $DNEW_{ijt}$ are taken with one-year lag. To estimate equation (1) we pool data referring to the four provinces. Right hand side variables in equation (1) are defined as follows:

(i) *DUMMIES* include bank fixed effects (38 banks) controlling for any bank-specific factor such as marginal cost of funding, bank efficiency and other unobservable supply factors, provincial fixed effect (4 provinces) capturing the local market structure and sectoral fixed effects (187 sectors) controlling for the idiosyncratic risk tied to different economic activities;

(ii) $MS_{jp(i)t\text{-}1}$ is the market share of bank j in the province where firm i is located; it should account for banks' local market power and its expected sign is positive;

(iii) $X_{it\text{-}1}$ is a vector of firm-specific variables including size ($LSIZE_{it\text{-}1}$), a dummy variable set equal to one for single-bank firms ($MONO_{it\text{-}1}$) and a dummy set equal to one for limited liability enterprises ($DLTD_{it\text{-}1}$). We expect the interest rate to be negatively correlated with $LSIZE_{it\text{-}1}$ and $DLTD_{it\text{-}1}$ while the effect of $MONO_{it\text{-}1}$ is unclear on a priori ground. $X_{it\text{-}1}$ also includes the composition of a firm bank debt in terms of matched and term loans shares ($SHM_{it\text{-}1}$ and $SHT_{it\text{-}1}$, respectively); these variables control for the possibility that the cost of credit varies with different loan characteristics (maturity, collateral requirements and other technical details);

(iv) $DNEW_{ijt}$ is a dummy set equal to one when bank j is firm i's main lender in t and it was not in $t - 1$ and zero otherwise.

Our test is based on parameters β_p which are allowed to vary with provinces. The hypothesis that banks poach rivals' customers would imply that $\beta_p < 0$.

4.2. State dependence in bank-firm matching

The second piece of evidence on the existence of switching costs is drawn from the demand side. Switching costs are inferred from state dependence in firms' choices of its main lender. This genuine state dependence in bank-firm relationships can be observationally equivalent to the phenomenon of heterogeneous firm preferences across banks. In the latter case, a pre existing banking relationship would have no casual link with borrower's current bank choice. Rather a borrower would go on choosing the same bank because of idiosyncratic and time invariant preferences for it.

To give an intuition of the difference between the two concepts, suppose that a bank announced a sharp but temporary reduction in its lending rates. If there is state dependence a relevant share of newly acquired borrowers would stick to the host bank even after the price returned to normal. By contrast, if unobserved heterogeneity was prevalent most borrowers would leave that bank after the price reduction was no longer in effect.

In what follows we will show how to address unobserved heterogeneity by using, within a discrete choice model, a mixed logit specification.

A firm located in a province is assumed to choose its main bank among N potential lenders operating in the same area[9]. The net indirect benefit firm i obtains from choosing bank j at date t is given by:

$$\Pi_{ijt} = V_{ijt} + \delta W_{ijt} + \varepsilon_{ij} = \alpha_j + \lambda_j ' Z_{it-1} + \gamma' X_{ijt} + \delta W_{ijt} + \varepsilon_{ijt} \tag{2}$$

where $Z_{it\text{-}1}$ is a vector of firm characteristics, X_{ijt} is a set of variables varying with firm and bank identity and W_{ijt} is a variable set equal to -1 if in $t-1$ bank j was not firm i's main lender and zero otherwise, α_j, γ, λ_j and δ are parameters to be estimated and ε_{ijt} are random terms i.i.d. according to type I extreme value distribution. The deterministic part of the net benefit includes the following variables:

(i) α_j are bank fixed effects estimating the utility each bank can provide indifferently to all borrowers;

(ii) $Z_{it\text{-}1}$ is a vector of firm characteristics including four dummies for the sector of economic activity (agriculture, industry, constructions and services), $LSIZE_{it\text{-}1}$ and $MONO_{it\text{-}1}$. Note that the effect of each variable in $Z_{it\text{-}1}$ on Π_{ijt} varies with j[10];

(iii) X_{ijt} is a vector of firm-bank varying variables including $INTRATE_{ijt}$ and the lender-

[9] In our setting $N = 15$ as explained in Section 3.

borrower physical distance ($DIST_{ij}$). Both regressors are expected to have a negative effect on Π_{ijt}; $DIST_{ij}$ is included because traditional shoe-leather costs, screening and monitoring costs as well as other specific relational investment expenditure will all increase with it.

(iv) $W_{ijt} = Y_{ijt-1} - 1$ where $Y_{ijt} = 1\{$firm i chooses bank j as its main lender in $t\}$ and $1\{\cdot\}$ is the indicator function that is equal to 1 if the condition in the brackets is satisfied and zero otherwise; W_{ijt} captures the correlation between repeated choices.

Maximum likelihood estimates of parameters in equation (2) are based on the observed choices made by each firm Y_{ijt}. The probability that firm i chooses bank j in period t is given by the standard conditional logit specification:

$$P(Y_{ijt} = 1) = \frac{\exp(V_{ijt} + \delta W_{ijt})}{\sum_k \exp(V_{ikt} + \delta W_{ikt})}^{11}.$$

In this model δ may picks up both state dependence and unobserved heterogeneity. For our purposes it is crucial to distinguish between the two sources of persistence since we want δ to represent the true state dependence (Heckman, 1981) and hence to reflect switching costs. Econometrically, in a dynamic discrete choice model the inclusion of Y_{ijt-1} among regressors may induce inconsistency in estimation if it is correlated with the current error term and this correlation is not modelled. To overcome this difficulty we assume that δ is randomly distributed across borrowers according to $g\ (\delta \mid \theta)$. Resulting choice probabilities are defined according to a mixed logit specification as follows:

$$P(Y_{ijt} = 1) \equiv P_{ijt} = \int \left(\frac{\exp(V_{ijt} + \delta W_{ijt})}{\sum_k \exp(V_{ikt} + \delta W_{ikt})} \right) g(\delta \mid \theta) d\delta \tag{3}$$

where α_j, γ, λ_j, and θ are parameters to be estimated.

Specification (3) allows to isolate the state dependence by modelling the correlation between W_{ijt} and the error term[12]. The expected value of δ will measure only state

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[10] This is a necessary condition to make λ identifiable; however it possesses a meaningful economic interpretation. Consider, for example, a small firm: some banks may be good at deal with it ($\lambda_j > 0$) because, for instance, they are able to manage well soft information while other banks may be not ($\lambda_j < 0$).

[11] See McFadden (1974) and Train (2003).

[12] Individual parameters for W_{ijt} can be expressed as $\delta_i = \delta_{mean} + \eta_i$ where δ_{mean} is the population mean and η_i is

dependence and if some unobserved heterogeneity is present it will be picked up by the variance of δ.

A data issue arises in estimating parameters in (3) because $INTRATE_{ijt}$ is observed only for the bank-firm relationships which are in place, including those with non main banks. Hence we impute lending rates for unselected alternatives with the fitted values of $INTRATE_{ijt}$ obtained by running regression based on equation (1). Model (3) is estimated separately for the four provincial markets (Turin, Bologna, Rome and Naples) and for t equal to march 2005. $g(\delta \mid \theta)$ is specified as a Lognormal distribution[13] since we expect δ to have a non-negative sign.

5. Econometric evidence on poaching strategies

Regression results obtained from equation (1) are shown in Table 4. Note that estimation is carried out on all existing bank-firm relationships including those with non-main lenders. Although provincial, sectoral and bank fixed effects were used in the specification, their estimated parameters were not reported in the same Table. Notably, nearly all the estimated coefficients are significantly different from zero, denoting that, idiosyncratic factors featuring individual banks and provinces will reflect on interest rates.

The market share held by a bank within each provincial market has a positive effect on the cost of credit, consistently with the market power hypothesis advanced before (see Table 4, Column I). Large firms and limited liability companies pay lower interest rates consistently with the expectation that less risky and less opaque firms have favourable credit conditions. Furthermore, our evidence shows that differences in the composition of a firm's credit sources will have an impact on the price of credit. In particular, firms with higher shares of matched and term loans will be charged lower interest rates. This could be explained by a sort of a positive sorting effect according to which firms using long-term and

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the individual stochastic deviation. The effect of previous choice on current benefit is now split in two additive terms: $\delta_{mean}W_{ijt}$ and $\eta_i W_{ijt}$. The random part $\eta_i W_{ijt}$ enters the stochastic portion of Π_{ijt} which now equals ($\eta_i W_{ijt} + \varepsilon_{ijt}$). This term is correlated over alternatives and time due to the common influence of η_i. With this specification the correlation between the lagged dependent variable and the current error term is explicitly modelled and δ_{mean} estimate is no longer affected by the endogeneity bias because, conditional on η_i, W_{ijt} is no more correlated with the error term.

more stable sources of credit are expected to be less risky than others. Finally, firms having a relationship with a unique bank will be offered a discount of nearly 27 basis point. This finding is consistent with Petersen and Rajan (1994) and is at odds with Angelini, Di Salvo and Ferri (1998) who find that firms with multiple bank relationships pay a lower than average cost of credit. Explaining these different results is outside the scope of the present paper. A priori, one could expect opposite effects from multiple lending. As suggested by Petersen and Rajan (1994), having many bank relationships could be a proxy for a firm's quality, signalling low quality borrowers. Hence, this variable could pick up unobserved firm quality effects in our regression, while these effects approximating firm credit worthiness are explicitly captured by the explanatory variables used in Angelini *et al*'s paper.

But the most important result is related to the dummy $DNEW_{ijt}$. All else being equal, those firms that changed their main bank between march 2004 and march 2005 were offered a discount ranging from a minimum of 53 bp in Bologna to a maximum of 84 bp in Naples provincial market. Moreover, estimated parameters are individually significant in each local market.

This finding is consistent with the hypothesis that banks will pay rival's customers to switch by offering low introductory interest rates. As explained in Section 2, evidence on $DNEW_{ijt}$ is also an indirect test on the relevance of switching costs as compared to adverse selection.

As a robustness check we rerun equation (1) dropping all the lending relationships with non main banks. Results are qualitatively similar to those illustrated above and are not reported. The physical distance between lender and borrower is added to the set of explanatory variables. Differently from other papers[14], it turns out that the estimated parameter for this variable is never significantly different from 0. Thus, we do not find evidence of spatial price discrimination in local credit markets. All the other estimated parameters are left unchanged by this additional control.

Up to now, we have examined price discrimination between new and old borrowers in

[13] δ follows a lognormal if ln (δ) is Normal. We parameterize the lognormal distribution is terms of the underlying normal. That is, we estimate the mean and the standard deviation of ln (δ).

[14] See Degryse and Ongena (2005) and Petersen and Rajan (2002).

their relationships with their main bank. In a new regression, we remove this constraint and rerun equation (1) assuming that all customers starting a new lending relationship with *any* bank may be offered different interest rates with respect to the established borrowers. Accordingly $DNEW_{ijt}$ is replaced by $DNEW_{ijt}'$ that is set to one if in t - 1 firm i did not borrow from bank j, regardless the status of j (main on non main bank, see Table 1). Results are reported in Table 4, Column (II). They are almost equal to those in column (I). So we are confident that our conclusions are not restricted to the mobility of borrowers across their main banks.

Previous results may suffer from a selectivity bias. Interest rates are observed only for the firm-bank relationships that are actually in place, so interest rate equation should be correctly estimated conditional on this information. The probability of observing a given bank-firm matching could depend on unobserved factors that might be correlated with residuals in the interest rate equation. Ignoring this circumstance may produce inconsistency in the estimated results. To tackle this potential shortcoming in our procedure, a Heckman correction is introduced. In the selection equation, the probability of observing a bank-firm matching is estimated as a function of borrower-lender distance and the set of bank and firm characteristics used in equation (1). We exploit previous results on distance and add this variable to the set of regressors used in the selection equation to identify the model. The two equations are simultaneously estimated using a maximum likelihood full information method. Results are reported in Table 4, Column (III).

Unreported evidence on the selection equation shows that distance has a significant and negative effect on the probability of observing a bank-firm relationship. A rho test rejects the independence between the two equations, showing that a selectivity bias may be an issue in our estimates. However, a comparison of estimated parameters with and without selectivity indicates that the main findings remain valid. Selectivity is not an issue in the specification with $DNEW_{ijt}'$ (Table 4, Column IV).

6. Econometric evidence on state dependence

We now turn to the analysis of switching costs based on the state dependence in lending relationships. To this aim, relevant parameters in choice probabilities (3) are estimated using a mixed logit model that allows δ to vary randomly across firms. Results are reported in Table 5. Coefficients for bank fixed effects and for their interactions with firm characteristics are not shown. An oversight of the main findings shows that these do not vary much across different provincial markets.

Note first that the borrower-lender distance has a negative and significant effect on the probability of observing a specific bank-firm relationship. Borrowers whose locations are further off from those of a bank's branches are unlikely to get credit from that bank. As shown in the previous section, banks seem not to price discriminate on the basis of this spatial segmentation. Coefficients on the interest rate are always negative and significantly different from zero in all provincial markets. *Coeteris paribus*, a bank charging higher interest rates with respect to its competitors will reduce the probability of being chosen as a firm's main source of credit. All in all, the observed matching factors used in our specification have a significant impact on the firm's choice of its main banking partner.

The standard deviation of ln (δ) is always highly significant in all provincial markets, denoting that δ does indeed vary in the firm population. This dispersion could reflect both heterogeneity of true state dependence across firms and the fact that some firms are better matched with a specific bank than other firms are (unobserved heterogeneity). Disentangling between the two components is beyond the scope of the present paper. However, the observed matching factors included in V_{ijt} should assure that the variability of δ reflects at least in part genuine differences in state dependence.

The estimated mean of ln (δ) is positive and significantly different from zero in all the provincial markets. This means that the probability of observing a firm choosing j as its main bank at t, given that it made the same choice at t - 1, exceeds the probability of observing the same firm choosing j, given that it chose $k \neq j$ at t - 1. Having controlled for unobserved heterogeneity through mixed logit, this result will reflect a genuine casual link between past and present bank choice. As discussed above, the existence of such casual link can in turn be related to the presence of switching costs in local credit markets.

A joint consideration of equations (1) and (3) implies that a past bank-firm relationship has an indirect impact on P_{ijt} through lending rates[15] and a direct one picked up by δ. Hence the latter parameter captures those (positive) effects on P_{ijt} not channelled through interest rates. They may include the saving on transactional switching costs, greater credit availability, request of less collaterals, increased flexibility and discretion within the lending relationship.

To compare the magnitude of switching costs across provinces δ is divided by the estimated parameter on interest rate, obtaining the willingness to pay (*WTP*). First we derived moments of δ according to standard probability calculus[16]. *WTP* allows also to asses the magnitude of state dependence in money terms.

Point estimates of the main moments of *WTP* are given in Table 5. The median value ranges from 10.7 (Turin) to 16.7 percent (Rome). That means that a firm belonging to, say, Turin's local market is indifferent between changing its current main lender and pay a switching cost, on one hand, and facing an interest rates increased by 10.7 points, on the other[17].

Our data do not include the duration of a lending relationship or its scope i.e. the number and types of financial services and products a bank may offer to a firm. In fact, the way through which we modelled state dependence creates a discretization of duration by distinguishing between relationships existing for one year or longer and the others.

Recent banking literature argued that duration and scope can be strongly correlated with the intensity of lending relationships and hence with borrowers lock-in. Some firms would exhibit a stronger state dependence due to the fact that they have a longer relationship with its main bank or a wider scope of interactions with it. If this correlation were true, it would have the consequence of inflating the variability of δ in our mixed logit model. By no means this would involve a bias in the estimated mean of ln (δ). Hence, the mixed logit

[15] Note that according to equation (1) $INTRATE_{ijt}$ depends on Y_{ijt-1} through $DNEW_{ijt}$.

[16] First we derived moments of δ according to standard probability calculus: if ln $X = Y$ and $Y \sim N(\mu, \sigma^2)$ it holds that $E(X) = \exp\{\mu + (1/2)\sigma^2\}$, $VAR(X) = \exp\{2\mu + 2\sigma^2\} - \exp\{2\mu + \sigma^2\}$ and $MEDIAN(X) = \exp\{\mu\}$. Then *WTP* is given by the ratio between δ and the estimated parameter on interest rate and, consequently, follows a lognormal too. *WTP* it is independent of the unobserved variance of ε_{ijt} (the so-called scale parameter).

[17] The median seems to be a more appropriate location measure than the mean because the latter is more sensitive to the special shape of the lognormal distribution. Lognormals are appealing because they are defined

estimator is sufficiently flexible to accommodate the lack of data on duration and scope of bank-firms relationships.

But the association between duration and the intensity of lending relationships came recently under attack. Some authors found that duration has a negative effect on the probability of continuation for a bank-firm relationship[18]. This could be consistent with the hypothesis that borrowers strategically react to the threat of being excessively locked-in by breaking their previous relationship. In this circumstance, one would observe that a pre-existing partnership with a bank would be a favourable pre-condition for switching to another lender, the opposite of what we have been assumed up to now. Although, it is unlikely that this attitude involves the entire firm population, it could be relevant for those firms that have a moderate level of transactional switching costs and at the same time are particularly vulnerable to hold-up problems.

Another criticism that can be raised against our methodology concerns the possibility for which firms were forced to switch because they were credit rationed by their previous lender.

All in all, these remarks imply that some firms in the population might show negative values for δ. With the assumption of a log normal distribution we cannot obviously test the possibility that this parameter takes on different signs across firm population. Therefore we remove the previous assumption and re estimate the mixed logit model assuming that δ is normally (instead of log normally) distributed. Unreported evidence clearly indicates that the share of firms in the population with negative δ is rather small in all provincial markets. Thus we conclude that only few firms seem to strategically react to the possibility of being excessively locked into a relationship or are forced to switch because their main bank denied credit.

7. Single versus multiple lending relationships

A bunch of theoretical papers recently examined the costs and benefits accruing to

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on the non negative domain; however they typically have a very long right-hand tail which may inflate *WTP* calculations. The provincial ranking of *WTP* among provinces is not affected by the location measure.

[18] See Ongena and Smith (2001).

firms that lend from a single bank as compared to those related to firms getting credit from many banks[19]. The empirical literature mainly dealt with the question of the optimal number of banking relationships, analyzing for which firms is likely that costs of multiple lending outweighed benefits and vice versa. Few papers examined the impact of multiple lending within a dynamic setting and no contribution explicitly referred this phenomenon to switching[20].

This theme has several implications in terms of switching behaviour. If an exclusive relationship increases a borrower's lock-in, then single-bank firms will be expected to face higher switching costs. By contrast, if single-bank firms strategically react to the threat of a future hold-up and bear moderate transactional switching costs, they will switch more often than what it is observed for firms with many banks. Moreover, if multiple lending is a signal of low borrowers' credit worthiness, a multiple-bank firm would encounter additional problem when trying to switch to another lender. Thus, a priori one obtains conflicting predictions that can be empirically investigated.

To this aim, we explicitly compare switching costs for firms with a unique lending relationship and firms with multiple banks by estimating model in equation (3) separately for these two sets. The comparison between the two groups is carried out in terms of willingness to pay. It turns out that firms with an exclusive bank relationship have a higher *WTP* for all the provincial markets (Table 6). Differences are huge: the ratio between single-bank and multiple-bank firms *WTP* ranges from two to six.

Firms resorting to multiple lending in t - 1 may switch either to a main bank with which they had no previous relationship or to a bank from which they already got credit in t - 1 but that was not their main lender. In the latter case, these firms are expected to bear

[19] On the one side, the improvement in the information setting of the incumbent bank may translate for the borrower into lower interest rates, more credit availability, request of less collaterals, increased flexibility and discretion within the lending relationship. On the other, the borrower will incur into the risk of being locked-in into the relationship and hence of being exposed to ex post opportunism and monopoly power exerted by the incumbent bank. In this circumstance, the informational advantage of the inside bank would not be entirely passed on to the borrowing firm. With multiple lending, a firm could limit the hold-up problem generated by an exclusive relationship and also be less exposed to liquidity risk connected to the financial position of the unique lender. However, multiple lending would involve duplicated screening and monitoring costs with a consequent reduced incentive for the lenders to invest into the relationship. Moreover, the presence of many creditors could increase the costs of debt renegotiation.

much lower switching costs. In turn, this circumstance might fully explain why single-bank firms do exhibit higher *WTP*.

To control for this, we split the set of switchers with multiple banking relationships into those switching toward a completely new main bank (let G1 denote this group) and those moving to a main bank already known to them (group G2)[21]. In unreported evidence we show that firms belonging to G2 have a lower *WTP* than G1-type firms as expected. However, the estimated δ for G2 is positive and significantly different from zero. This is a clear indication of the special role played by the main bank. In particular, moving to a new main lender is costly even for firms that already interacted with that bank in the past.

Finally, we compare the single-bank and many-bank firms, by excluding G2 firms from the latter set. These results fully confirm previous findings: in three provinces out of four firms with a unique relationship exhibit a much higher persistence in the choice of their bank partner (see the last row in Table 6). We also controlled for the possibility that these differences reflected the fact that firms resorting to multiple lending are usually larger than the others. A further split of the previous two samples based on firm's size show that this is not the case[22].

At last, our findings show that an exclusive bank relationship is an obstacle to the mobility of borrowers across lenders while multiple lending would facilitate this mobility. This is consistent with the possibility that firms will be locked-in into a relationship when dealing with a unique bank and that this hold-up problem can be partially mitigated by the presence of other lenders. These results can also shed some light on the debate on relational lending. Consistently with other recent findings[23], they suggest that a crucial aspect of relational lending is related to the concentration of a firm's borrowing across lenders and not to other dimension like the duration of a relationship.

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[20] Ongena and Smith (2001) studied the probability for a firm to end a bank relationship as a function of its duration and of multiple lending. Farinha and Santos (2002) examined the likelihood of a firm substituting a single relationship with multiple relationships as a function of duration of that relationship.

[21] We estimate parameters in equation (3) on two overlapping sub-samples of multiple-bank firms. The first one includes borrowers that do not switch and G1, while the second comprehends again those that do not switch and G2.

[22] Small (large) firm are those whose *LSIZE* is below (greater than) the median value.

[23] In an interesting contribution, Elsas (2005) shows that banks in Germany are more likely to qualify as hausbank when their share of borrower debt financing is higher and when the number of bank relationships is lower, while duration of a relationship has no effect.

8. Concluding remarks

Lending markets are an ideal setting for the study of switching costs. The complexity of bank-firm contracts as well as the asymmetries of information surrounding these contracts enhances the probability of borrowers' lock-in. Furthermore, the non anonymity of transactions within credit markets introduces the possibility for the banks to tease rivals' customers by offering lower interest rates with respect to those charged to their established borrowers. Adverse selection, that is typically associated with bank competition, enriches further this picture by offering alternative predictions in terms of pricing behaviour.

In this paper we offered evidence that is consistent with the presence of switching costs in the Italian local credit markets. Through a mixed logit model, we show that firms tend to iterate their choice of the main bank over time. We also show that this finding is not related to unobserved and time invariant firms' preferences across banks. This bundling of past and current choices is exactly the sort of effects stemming from the presence of switching costs. Our findings also show that firms do not seem to react to threat of a future hold-up in the relationship with their main bank and that single-bank firms are likely to face higher switching costs than those beard by firms resorting to multiple lending. Finally, it turns out that banks offer lower interest rates to their new customers, consistently with the tenets of literature on switching costs with customer recognition and contrary to what was predicted by adverse selection models.

In general, our results put emphasis on the relevance of switching costs for the analysis of bank-firm relationships and competition in credit markets. Moreover, they call for a stronger integration between the traditional topics of the banking literature like adverse selection, moral hazard and asymmetric information and those typical of theoretical and empirical contributions dealing with switching costs.

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Tables

TABLE 1 – VARIABLES DEFINITION

The table describes the variables used in the paper. Subscripts *i*, *j* and *t* are referred to firm, bank and time, respectively; *t* is equal to march 2004 or march 2005. Variables used in econometric models are in *italic*.

Variable	Description/*Definition*
Firm varying	
Identity	The identity of a firm is given by a unique crypto graphed code
Location	Municipality where the firm's headquarter is located and province which the municipality belongs to
Sector of economic activity	187 sectors belonging to agriculture, industry, constructions and services and broadly corresponding to the three digits ISIC (International Standard Industrial Classification of all Economic Activities) classification
Number of lenders	Total number of banks sampled in the Survey on lending rates which grants loans to the firm
$LSIZE_{it}$	Natural logarithm of the sum of loans extended to firm *i*. The sum is over all the bank-firm relationships recorded in the Survey on lending rates and regarding firm *i*
$DLTD_{it}$	Dummy variable equal to 1 if firm *i* is a limited liability company and zero otherwise
$MONO_{it}$	Dummy variable equal to 1 if firm *i* is a single-bank borrower and zero otherwise
SHM_{it}	Share of matched loans in firm *i*'s bank debt portfolio
SHT_{it}	Share of term loans in firm *i*'s bank debt portfolio
Bank varying	
Identity	The identity of a bank is given by a unique code
Branch locations	Number of branches for each municipality
Firm-bank varying	
$INTRATE_{ijt}$	Interest rate charged by bank *j* to firm *i* in period *t*. It is computed as a weighted average of interest rates charged on matched, term and revocable loans
$MS_{jp(i)t}$	Loan market share in period *t* of bank *j* in the province *p(i)* where firm *i* is located
Y_{ijt}	It is set equal to 1 if firm *i* chooses bank *j* as its main lender in *t* and zero otherwise. Formally $Y_{ijt} = 1\{$firm *i* chooses bank *j* as its main lender in *t*$\}$ and $1\{\cdot\}$ is the indicator function that is equal to 1 if the condition in the brackets is satisfied and zero otherwise
$DNEW_{ijt}$	Dummy variable equal to one when bank *j* is firm *i*'s main lender in *t* and it was not in $t-1$ and zero otherwise. It holds that $DNEW_{ijt} = Y_{ijt}\,(1 - Y_{ijt-1})$
$DNEW_{ijt}'$	Dummy variable equal to one when bank *j* is one of firm *i*'s lenders in *t* and it was not in $t-1$ and zero otherwise
$DIST_{ij}$	Physical distance between firm *i* and bank *j*. It has been computed as kilometres between the municipality where the firm is located and the municipality where the bank has the nearest branch to that firm. For some bank-firm relationship distance is zero because the bank has at least one branch in the municipality where the firm's headquarter is located. To circumvent this problem we substitute zeros with the ray of the circumference with the same area of that of the municipality. It is equivalent to approximate the municipality surface with a circumference and to assume that branches are located in the centre of the circumference while firms are uniformly distributed on the boundaries. This seems to be a reasonable assumption since branches are usually located where the population density is higher while firms are generally sited far from cities centres. With such a substitution it may happen that the distance within a municipality is greater than some of the distance between municipalities. In this case we pick up the minimum of the two distances.
W_{ijt}	It is equal to zero if in $t-1$ bank *j* is firm *i*'s main lender and -1 otherwise It holds that $W_{ijt} = Y_{ijt-1} - 1$;

TABLE 2 – SWITCHING RATES AND MARKET CHARACTERISTICS

	TURIN		*BOLOGNA*		*ROME*		*NAPLES*	
	No. of firms.	Switching rate	No. of firms	Switching rate	No. of firms	Switching rate	No. of firms	Switching rate
				SWITCHING RATES				
Number of lender banks								
One	9,462	3.8	6,356	3.9	11,243	3.1	5,374	4.3
Two or more	5,100	27.9	4,112	26.9	4,777	23.0	2,915	28.0
Total loan size of borrower								
75,000-249,999 euros	7,231	5.1	4,635	5.7	7,480	4.1	3,699	5.2
250,000-999,999 euros	4,822	16.1	3,715	16.4	5,473	11.4	2,892	16.3
1 mln euros and above	2,509	25.4	2,118	22.7	3,067	16.7	1,698	22.4
Total number of borrowers	14,562	12.2	10,468	12.9	16,020	9.0	8,289	12.6

MARKET CHARACTERISTICS

	North-West	North-East	Centre	South
Per capita real GDP (000 euros) - 2002	19.7	22.2	20.1	10.6
Size (loans extended to firms, millions euros) – December 2003	22,649.47	16,017.59	64,520.73	11,183.90
Herfindhal index on loans	0.0605	0.0582	0.0352	0.0595

TABLE 3 –DESCRIPTIVE STATISTICS OF EXPLANATORY VARIABLES

Variable	No. of Obs.	Mean	Std. Deviation	Minimum	Maximum
			TURIN		
DIST	218,430	7.755	6.757	0.706	76.338
INTRATE	23,964	6.105	2.176	0.001	19.127
LSIZE	14,562	11.944	1.525	0.000	20.169
SHM	14,562	0.229	0.323	0.000	1.000
SHT	14,562	0.466	0.417	0.000	1.000
MS	15	0.045	0.044	0.011	0.150
			BOLOGNA		
DIST	157,020	8.282	6.192	1.395	51.610
INTRATE	17,794	4.866	1.644	0.842	15.660
LSIZE	10,468	12.037	1.578	0.000	19.658
SHM	10,468	0.269	0.339	0.000	1.000
SHT	10,468	0.471	0.410	0.000	1.000
MS	15	0.043	0.044	0.011	0.168
			ROME		
DIST	240,300	8.529	10.136	0.003	60.497
INTRATE	23,357	6.945	2.526	0.001	19.520
LSIZE	16,020	12.064	1.721	0.000	20.968
SHM	16,020	0.159	0.287	0.000	1.000
SHT	16,020	0.459	0.442	0.000	1.000
MS	15	0.031	0.029	0.005	0.100
			NAPLES		
DIST	124,335	41.944	98.981	0.524	399.447
INTRATE	13,792	7.041	2.532	0.743	18.226
LSIZE	8,289	12.035	1.635	0.693	18.276
SHM	8,289	0.185	0.298	0.000	1.000
SHT	8,289	0.416	0.425	0.000	1.000
MS	15	0.047	0.040	0.014	0.147

TABLE 4 – INTEREST RATE REGRESSION

(standard error in brackets)

The table reports results from estimating equation (1). The dependent variable is $INTRATE_{ijt}$. In columns (I) and (III) $DNEW_{ijt} = 1$ if in $t - 1$ bank j was not firm i's main lender. In columns (II) and (IV) $DNEW_{ijt} = 1$ if in t - 1 firm i did not borrow from bank j. Columns (I) and (III) report OLS estimates for equation (1). Columns (II) and (IV) report full information maximum likelihood estimates for equation (1) with Heckman correction. All regressions include bank, sector and province fixed effects. Estimates for these variables are not reported. All time varying explanatory variables, apart from $DNEW_{ijt}$, are taken at date $t - 1$. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Explanatory variables	(I)		(II)		(III)		(IV)	
MS	1.754	***	1.523	***	1.598	***	1.494	***
	(0.371)		*(0.373)*		*(0.355)*		*(0.357)*	
LSIZE	- 0.138	***	- 0.126	***	- 0.138	***	- 0.127	***
	(0.005)		*(0.005)*		*(0.005)*		*(0.005)*	
SHM	- 1.481	***	- 1.475	***	- 1.481	***	- 1.475	***
	(0.029)		*(0.029)*		*(0.029)*		*(0.029)*	
SHT	- 2.807	***	- 2.802	***	- 2.809	***	- 2.806	***
	(0.024)		*(0.024)*		*(0.023)*		*(0.024)*	
MONO = 0	0.275	***	0.202	***	0.270	***	0.198	***
	(0.018)		*(0.018)*		*(0.018)*		*(0.018)*	
DLTD = 0	0.243	***	0.237	***	0.240	***	0.237	***
	(0.016)		*(0.016)*		*(0.016)*		*(0.016)*	
DNEW = 1								
TURIN	- 0.768	***			- 0.739	***		
	(0.048)				*(0.049)*			
BOLOGNA	- 0.535	***			- 0.510	***		
	(0.055)				*(0.056)*			
ROME	- 0.640	***			- 0.605	***		
	(0.053)				*(0.054)*			
NAPLES	- 0.844	***			- 0.811	***		
	(0.063)				*(0.063)*			
$DNEW_{ijt}' = 1$								
TURIN			- 0.443	***			- 0.517	***
			(0.047)				*(0.077)*	
BOLOGNA			- 0.170	***			- 0.246	***
			(0.057)				*(0.084)*	
ROME			- 0.207	***			- 0.283	***
			(0.050)				*(0.079)*	
NAPLES			- 0.282	***			- 1.232	***
			(0.060)				*(0.122)*	
Rho					-0.026		0.016	
					(0.006)		(0.013)	
Prob (*Rho* = 0)					0.000		0.219	
Number of obs.	78,907		78,907		78,907		78,907	
Adj R^2	0.340		0.336					
Log Likelihood					-214,040		-214,263	

TABLE 5 – MIXED LOGIT MODELS

(standard error in brackets)

The table reports maximum likelihood estimates for models defined in equations 3. The dependent variable is P_{ijt}. Each observation represents a firm-bank combination. All the specifications include bank fixed effects and their interactions with firm characteristics. Estimates for these variables are not reported. All time varying explanatory variables, apart from interest rates, are taken at date $t - 1$. *** indicates significance at 1% level, ** indicates significance at 5% level, * indicates significance at 10% level.

Variable	*TURIN*	*BOLOGNA*	*ROME*	*NAPLES*
INTRATE	- 0.667 ***	- 0.504 ***	- 0.510 ***	- 0.662 ***
	(0.017)	*(0.021)*	*(0.014)*	*(0.019)*
DIST	- 0.078 ***	- 0.179 ***	- 0.038 ***	- 0.045 ***
	(0.009)	*(0.012)*	*(0.008)*	*(0.013)*
W				
Mean of ln(δ)	1.961 ***	1.928 ***	2.143 ***	2.018 ***
	(0.052)	*(0.082)*	*(0.082)*	*(0.075)*
Std. dev. of ln(δ)	0.886 ***	0.892 ***	0.808 ***	0.918 ***
	(0.060)	*(0.097)*	*(0.077)*	*(0.085)*
Log Likelihood	- 8,689	- 6,940	- 8,153	- 5,341
Likelihood ratio index	0.780	0.755	0.812	0.762
Number of obs.	14,562	10,468	16,020	8,289
Number of cases	218,430	157,020	240,300	124,335
WTP				
Median	10.654	13.632	16.735	11.368
Mean	15.774	20.290	23.203	17.328
Std. dev.	17.222	22.370	22.283	19.935

TABLE 6 – MEDIAN OF *WTP*

WTP are computed on the basis of model (3) parameters estimates on three sub-samples. The first one includes all single-bank firms; the second one comprises all multiple-bank firms; the third one is obtained from the second one excluding those firms switching to a main bank already known to them.

Sub-sample	*TURIN*	*BOLOGNA*	*ROME*	*NAPLES*
Single-bank firms	15.241	29.486	24.085	17.944
Multiple-bank firms	5.732	4.870	10.826	5.596
Multiple-bank firms switching toward a completely new main bank	13.371	12.204	27.867	9.886