BAD LOANS AND ENTRY INTO LOCAL CREDIT MARKETS

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Abstract

This paper explores the link between entry into local credit markets and default rates of the loans granted by the entrants. Economic theory suggests that entrants may experience high default rates because of a winner's curse effect and because of their lack of information about the local economic conditions. Using a unique database of 7,275 observations on 729 individual banks' lending in 95 Italian local markets, we find that both the winner's curse and the informational disadvantage play a significant role in explaining entrants' loan default rates.

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1. Introduction[1]

Geographical restrictions and legal barriers to entry into banking markets have been steadily relaxed since late 1970s in the United States, in Europe, both at country and European Union level[2], and in many other countries. The lifting of regulatory constraints has been followed by an increase in competition that led to substantial gains in terms of consumers welfare.[3] However, U. S. banks have been slow to move into new markets and cross-border banking in Europe is still limited, particularly in the retail market.[4] Meanwhile, banking crisis that have erupted in several countries around the world have been traced directly or indirectly to the repeal or relaxation of regulatory entry barriers.[5]

Is there anything special in the case of banking services that makes entrants face additional entry costs, different from those paid by entrants in other markets, even when regulatory restrictions are lifted? Were the social benefits derived from increased competition, in terms of higher efficiency, higher deposit rates and lower loan rates, a free ride? Answering these questions is very important for policy reasons. If entry barriers inherently linked with the nature of credit markets do exist, then geographic segmentation is likely to be a persistent feature of financial markets, regardless of deregulation and technological advances.[6] This implies that allowing for market free entry may not be sufficient to help local financial development, which has been proved to play a fundamental role in supporting and fostering economic growth (King and Levine, 1993;

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2 See Berger et al. (1995) and Vives (1991) for a survey of the major regulatory changes in the U.S. and in the European Union respectively.

3 Hannan and Praeger, (1998) and Angelini and Cetorelli (2003).

4 As documented in Buch (2002) and Danthine et al. (1999).

5 Demirgüç-Kunt and Detragiache (1998), analyzing a sample of 53 countries, show that financial liberalization increases the probability of a bank crisis. Caprio and Klingebiel (2000) document a recent increase in the frequency of crises, attributing it at least in part to the lifting of structural controls. Pesola (2001) finds that market liberalization had a substantial role in bank crisis in the Scandinavian countries during the early 1990s.

6 Petersen and Rajan (2002) document that distance still plays a major role in the provision of credit to small firms, even though its importance is diminishing with the growth of remote banking facilities.

Guiso et al. 2003). Moreover, even if entry barriers are not too high to block entry, they may nevertheless add to systemic risk, should some of the entrants default.

In this paper we address these issues through an empirical study of the Italian experience in the early 1990s. Regulatory reforms introduced in the late 1980s allowed a substantial increase in the number of banks operating in each local market. The 1992-93 recession caused an unprecedented surge in non-performing loans, followed by severe losses for a large number of banks. Thanks to a unique database, we investigate individual banks' loan default rates in each local market.

Economic theory suggests that asymmetric information can work as a barrier to entry into credit markets and that incumbents' market power can be shielded to some extent from potential competition from outsiders. This view is supported by two main arguments. The first one, known in the auction theory as the winner's curse hypothesis, is related to the possibility that entry enables previously rejected applicants to apply for loans at additional banks. Insofar as borrowers' creditworthiness is assessed through screening procedures that are not fully revealing and are imperfectly correlated across banks, a larger number of banks increases the probability that a bad risk will be considered creditworthy by at least one of them (Broecker, 1990). Adverse selection is greater for new entrants because their pool of applicants is likely to include would-be borrowers who were previously rejected by mature banks in the market. To our knowledge, Shaffer (1998), very close in spirit to our paper, is the only study that empirically tests the winner's curse hypothesis.

The second argument highlights the informational advantages of the incumbents on market-specific characteristics. A substantial amount of the information used by banks for screening loan applicants and monitoring borrowers is generated through repeated interaction with their customers and the local business community (Dell'Ariccia et al., 1999). Many theoretical and empirical studies have documented that long-term relationships between lenders and borrowers are an important feature of most bilateral credit markets (i.g. Sharpe, 1990; Rajan, 1992; Boot, 2000). A considerable amount of valuable information can be acquired only on a market-specific "learning-by-doing" basis, thus implying that incumbents' creditworthiness tests may well be more accurate than those of the entrants.

We test these hypotheses by investigating the variance in individual banks' default rates. As predicted by theory, we find evidence that, controlling for the level of information on local market conditions, entrants are more exposed to bad loans than incumbents, since they have to deal with the backlog of previously rejected applicants. Subsequently, we distinguish between two different ways in which a bank enters a local market. The first consists in granting loans from branches or the headquarters outside the local market. The second is to open a local branch. We argue that the two types of entry differ substantially in terms of the information gap vìs-à-vìs incumbents. Having on site-branches allows banks to monitor borrowers more rigorously and to acquire a deeper knowledge of the local economy. Moreover, entry with branches is usually anticipated by entry with outside lending. We find that banks that entered with relatively more information, i.e. by opening a branch, experienced a lower default rate than those that entered without branches. There is also a positive relation between the loan default rate and the number of banks operating in a market, as predicted by the winner's curse hypothesis. As a general result, we find that the sub-optimal effects of entry on loan quality are mitigated when entrant banks are among the top performers of the industry. Borrowers of banks that are well-capitalized, efficient and have above-average profits show substantially lower default rates.

The remainder of this paper is organized as follows. In Section 2 we survey some theoretical and empirical contributions in this field. In Section 3 we illustrate our empirical specifications, and in Section 4 we discuss our data and explain how the relevant variables have been constructed. Section 5 presents our results and Section 6 draws the conclusions.

2. Related literature

The possibility that an increase in banking competition may have sub-optimal allocative effects has long been recognized, but only recently has the argument been cast in formal models. The backbone of most of these is an application of the theory of common value first-bid auctions (Milgrom and Weber, 1982). When banks compete in prices (i.e. interest rates) and have an imperfect knowledge of the would-be borrowers' ability to repay their debts, they face an externality caused by the decisions of the other banks.[7] The screening procedure used by banks may be thought of as a not fully revealing test of the quality of the applicant. Depending on the result of the test, banks make an interest rate offer or denies credit. The borrower chooses to sign the credit contract with the bank that offers the lowest interest rate. If the tests run by different banks are not perfectly correlated, there is a positive probability that an applicant's creditworthiness will be assessed differently by different lenders. This implies that the probability that a high-risk borrower will be found creditworthy is positively correlated with the number of tests run. It follows that the average quality of the pool of successful borrowers (and consequently the expected losses from bad loans) declines (increases) as the number of banks in the market increases (decreases).

This idea was formalized by Broeker (1990) using credit-scoring tests with binary outcome. Competition is modeled in two different ways – as a one-stage game and as a two-stage game – obtaining different results for the existence and the characterization of the equilibrium solutions. In both cases an increase in the number of banks can have negative effects on the average ability to repay the loan of those who are granted credit. A similar result was obtained by Riordan (1993) in a model where banks are able to run creditworthiness tests delivering continuous signals. An increase in the number of banks raises the threshold value of the signal above which the loan is granted, but this effect can be offset by the higher probability that at least one bank will observe a "high-quality" signal screening a "low-quality" applicant. In Riordan's model the entry of new banks into a credit market is associated with a more restrictive supply stance. For a non-trivial set of parameters, the equilibrium default rate in the market is also positively correlated with the number of active banks.

This basic framework has been extended in several ways. For instance Gehrig, (1998) allows the banks to choose the precision of their binary creditworthiness test and

[7] As stressed by Dell'Ariccia et al. (1999) in order to obtain a winner's curse effect asymmetric information

models the integration of two previously separated credit markets as a sequential entry game. Entry, if it ever occurs, has no effect on the incumbents' screening intensity choice, while the entrant, facing an adversely selected pool of applicants, substitutes higher interests rates for less accurate screening.

As auction theory has long recognized, additional insight may be gained when information about the value of the object being sold is asymmetrically distributed among participants (Wilson 1967, 1977). Dell'Ariccia et al. (1999) analyze an entry model where the incumbent has an informational advantage thanks to his long-term relationship with part of his customers. This advantage is greater the lower is the customer turnover in the market. They characterize the equilibrium under Bertrand duopoly and show that the adverse selection of the pool of borrowers blocks entry. Marquez (2002) proposes a two-period model assuming that borrowers' characteristics are observable by banks only after a loan has been granted and that there is some turnover among borrowers. In the second period banks will refuse to continue financing borrowers revealed to be bad. Since information is proprietary, these borrowers remain as part of the pool of customers unknown to all other banks. In this framework an increase in the number of banks disperses borrower-specific information, reducing banks' screening ability. Incumbents' informational advantage may also act as a barrier to entry if borrower turnover is low.

The role of relationship lending in magnifying entrants' vulnerability has been extensively studied. Relationship lending generates informational rents accruing to the banks; "captured" firms can try to escape looking for better deals in the credit market. Sharpe (1990) has shown that if an uninformed outsider bank offers a competitive interest rate (e.g. reflecting the average credit quality), only bad borrowers would prefer to switch.[8] The information asymmetries on the same side of the market (the supply side) created by relationship lending is therefore most likely to add to the adverse selection problems faced by a new entrant (Nakamura, 1993). Furthermore, when assessing the credit worthiness of a loan applicant, banks usually refer to their past experience with

between lenders and borrowers about the borrowers' type is not strictly necessary.

similar borrowers in similar markets. This may imply that when a bank expands in a new market or sector, the negative effects of a lack of expertise may overcome the benefits from risk diversification (Winton 1997).

Compared with the abundance of theoretical papers on the subject, empirical work has been rather limited. Keeley (1990) finds indirect evidence of increasing credit risk as a consequence of entry. Analyzing U. S. data from the period 1970-86, he shows that banks with more market power have a lower default risk as reflected in lower risk premiums on large, uninsured CDs. Shaffer (1998) tests empirically the prediction that *de novo* banks should suffer higher loan losses due to the adverse selection effect. He considers all U.S. commercial banks during the period 1986-1995 and regresses the net chargeoff ratio versus annual age dummies for each of a bank's first 10 years, controlling for business cycle and other macroeconomic effects, including quarterly calendar time dummies. He finds that the net chargeoff rates are strongly and significantly higher from year 3 on. After discussing alternative explanations of this pattern (such as the seasoning of a new portfolio or learning by an inexperienced lender), he concludes that adverse selection is the main cause. Shaffer also estimates a cross-sectional model using data from mature banks, each operating in a single geographic market (MSA). He finds a strong positive link between gross chargeoff rates and the total number of banks in each MSA.

Hedricks and Porter (1988) investigate the links between the winner's curse and asymmetric information among bidders in auctions. They show that in equilibrium the uninformed buyer makes zero profits, while the informed buyer makes positive profits thanks to superior information. They also test these theoretical conclusions with data from federal offshore oil and gas drainage lease sales, finding that both types of buyers actually behave consistently with the Bayesian-Nash equilibrium.

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[8] As pointed out by Von Thadden (2001) Sharpe's analysis is slightly incorrect since it assumes the existence of a pure strategy equilibrium in interest rates, which is not true. Nevertheless, informed banks still earn positive informational rents and so Sharpe's intuition is correct.

3. Empirical strategy

The purpose of this paper is to test whether entrants in a local credit market are systematically subject to higher loans default rates than incumbents. If this is the case, we argue that it is a consequence of asymmetric information between banks.

The loan default rate is defined as the ratio between new bad loans at time T and the stock of performing loans at time $T-1$ granted to firms by a bank in a given local market. Loans are attributed to markets on the basis customer location. The loan default rate is an ex-post measure of risk and thus depends on the states of nature that trigger defaults. In normal times defaults tend to be highly idiosyncratic according to the many characteristics of the borrowers, so that it can be empirically very difficult to test differences in banks' choices. We therefore choose to measure default rates in the aftermath of an economic downturn affecting all borrowers. Figure 1 summarizes the sequence of events that we try to capture. Given some initial conditions for banks and local markets, reforms are introduced lowering the barriers to entry into local markets. This facilitates entry and banks react in different ways to the new environment. Finally, a strong macroeconomic shock occurs and the magnitude of risks in banks' portfolios is revealed.

T_0 ____________________ T_1 ____________________ T_2

Initial period ⇑ ⇑ ⇑ Final period

Market entry — Macroeconomic shock — Bad loans upsurge

Fig. 1

3.1 The basic econometric model

We model the loan default rate of a bank in a given local market as a function of entry and information, plus two sets of dummy variables for banks' and markets' characteristics. We expect entrants to face more severe problems of adverse selection, since they will receive applications from all the firms that have been previously rejected by the incumbents. Moreover, the adverse selection effect faced by the incumbents should be inversely correlated with their knowledge of the local markets. We estimate the following equation by weighted least squares logit regression for grouped data: [9]

$$y_{ij,T_2} = \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \gamma ENTRY_{ij} + \varphi_j P_j + \varepsilon_{ij} \tag{1}$$

where y_{ij,T_2} is the log-odds transformation of the default rate of bank i's loans in market j at time T_2. Local market characteristics are accounted for by the dummy P_j, while B_i is bank's i fixed effect. The variable $ENTRY_{ij}$ is a dummy that assumes a value of 1 when bank j enters market i in the period between T_0 and T_1. Entry is defined as the shift from a market share of zero to a positive one. Finally, we chose the loan market share in the initial period as a proxy for the amount of information about market characteristics.[10, 11]

The comparative disadvantage of entrants should be mitigated by a high turnover of banks' customers. In each period the pool of potential borrowers is composed of the backlog of those previously rejected and of first-time applicants. The higher is the latter component, the lower the informational disadvantage of the entrants. We test this hypothesis by introducing in our regression an interaction variable between the entry dummy a dummy identifying high turnover markets:

$$\begin{aligned} y_{ij,T_2} &= \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \gamma ENTRY_{ij} + \\ &+ \tau\, ENTRY_{ij} * TURNOVER_j + \varphi_j P_j + \varepsilon_{ij} \end{aligned} \tag{2}$$

we expect a negative coefficient for the interaction variable and a stronger effect of the entry dummy on the default rate than in equation (1).

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[9] This estimation method is chosen because we are dealing with proportion data, i.e. the fraction of loans in a local market that defaults in a given time interval. The dependent variable is continuous and ranges from zero to one. Applying the logistic transformation to the dependent variable allows it to range over all real values (the logistic transformation of p is given by ln(p/1-p)). Since the variance of the default rate is inversely correlated with the size of total bank lending in the market under consideration, weighted least square estimation is needed in order to avoid heteroskedasticity problems (Greene, 1993).

[10] A large market share may also be associated with monopolistic power, which in turn may affect risk-taking. The exertion of market power, however, depends on the overall market structure, for which we control through the dummies P_j.

[11] The choice of the market share as a proxy for information is justified by the conclusions drawn by Sharpe (1990), Dell'Ariccia et al. (1999) and Marquez (2002).

3.2 Different definitions of entry and different levels of information

The definition of entry we have used so far is very broad; the acquisition of a positive market share may be episodic and not necessarily reflect a strategic entry decision. In our definition the borders of local markets are those of local governments for which a satisfactory set of statistics exists. Bonaccorsi di Patti and Gobbi (2001b) argue that provinces are also good approximations for local credit markets. On average, 80 per cent of borrowing by residents in a given province is from bank branches in the same province. Nonetheless, the proportion of credit granted from outside is not negligible. A natural alternative definition of entry is the opening of a new branch. When a bank enters a market by opening a new branch, it presumably has more of information about the local market conditions and its potential new borrowers than when it enters simply by granting loans from outside. This difference in knowledge may be due to the fact that the bank already had some customers in that market or to preliminary market research.[12] Opening a new branch implies sunk costs that must be justified by the expectation of reaching a critical mass of loans, and these expectations must be supported by information. Moreover, when a bank opens a new branch it is likely to provide payment services to its borrowers. Black (1985) and Fama (1985) argue that this may greatly help banks in their monitoring activity. Mester et al. (2001) provide empirical evidence that checking account information actually improves monitoring. We therefore compare the effects on the loan default rate of different types of entry characterized by different levels of information. Equations (1) and (2) are modified as follows:

$$\begin{aligned} y_{ij,T_2} &= \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \phi ENTRY\_BR_{ij} + \\ &\quad + \nu ENTRY\_LOA_{ij} + \rho OUTLOANS_{ij} + \varphi_j P_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

where $ENTRY\_BR_{ij}$ indicates if bank i opened a branch in market j, $ENTRY\_LOA_{ij}$ indicates that bank i entered market j acquiring at least one new customer but without

[12] In our sample 452 out of 493 episodes of entry with branches refer to banks that were already lending in that markets. Moreover, an ANOVA analysis (not reported) shows that in the year preceding entry banks that entered with branches had been granting, on average, a larger quantity of loans than those that did not open branches.

opening a branch, and, finally, $OUTLOANS_{ij}$ is a dummy that is equal to one if bank i is an incumbent in market j but never opened a branch. We expect all three dummies to have positive coefficients. In particular, the effect on the default rates should be larger for banks that entered a market by lending from outside than for those that opened a branch.

Again we test whether high customer turnover mitigates the adverse selection effect by interacting the entry dummies and $OUTLOANS_{ij}$ with the high turnover market indicator. In what follows we refer to this specification as equation (4).

Theory suggests that we should obtain higher coefficients than those of equation (3) for the entry dummies and $OUTLOANS_{ij}$, while the interaction variables are expected to have a negative effect on the default rate.

The difference between entry with and without branches suggests a further possible test. The informational disadvantage of the entrants with branches should be lower if they were already granting loans in the market they entered. This reduction of the informational disadvantage should be smaller the larger the market share (our proxy for information) they had before entry. By the same reason also the default rate of the incumbents without branches should be lower the larger the market share. We test this hypothesis interacting $ENTRY\_BR_{ij}$ with the pre-entry market share ($PRE\_MKT\_SHARE_{ij}$) and $OUTLOANS_{ij}$ with the initial period market share.

$$\begin{aligned}
(5)\qquad y_{ij,T_2} &= \alpha_i B_i + \beta MKT_SHARE_{ij,T_0} + \\
&+ \phi ENTRY_BR_{ij} + x\ ENTRY_BR_{ij} * PRE_MKT_SHARE_{ij} \\
&+ \nu ENTRY_LOA_{ij} + \\
&+ \rho\ OUTLOANS_{ij} + \eta\ OUTLOANS_{ij} * MKT_SHARE_{ij,t} + \varphi_j P + \varepsilon_{ij}
\end{aligned}$$

Introducing the interactions should reduce the value of the coefficient associated with the market share and increase those of $ENTRY\_BR_{ij}$ and $OUTLOANS_{ij}$, as compared with equation (3). At the same time the two interactions are expected to have a negative effect on the default rate.

As a final test we specify a model where both the turnover and the pre-entry information effect are present. In what follows we refer to this specification as equation (6).

3.3 Bank and market characteristics

As an extension of basic model we replace the banks' fixed effects and the local market dummies with appropriate controls, in order to have insights on bank and market characteristics that affect the loan default rate. Moreover, this procedure allows us to test two additional hypotheses. One, a direct consequence of the independence of the creditworthiness tests, is that the average quality of loans decreases as the number of banks in the market increases. The other, related with information, is that high borrower turnover, though mitigating the relative disadvantage of the entrants, should be positively correlated with the average default rate as it increases the share of borrowers known only through the creditworthiness tests. The empirical models have the same structure of those previously described, and in what follows we refer to them as equations (1a), (2a), (3a), (4a), (5a) and (6a). Their specification can be found in Table IV.

We replaced the markets' fixed effects with two sets of variables, the first intended to control for the initial conditions at time T_0, the second to take into account the changes occurring between time T_0 and time T_1. In our specifications we control for the size of the market and for the level of its overall economic activity through the variables $MARKET\_SIZE$ and $MARKET\_OUTPUT$. The two hypotheses previously described are tested by introducing the dummy $TURNOVER$ and the variable $NUMBER\_BANKS$; both are expected to have a positive coefficient. Market structure is controlled by the Herfindahl-Hirschman concentration index (HERFINDAHL) computed on loan market shares in the province. There are several reasons for introducing this variable. First, high competition can have a disruptive effect on relationship banking, thereby lowering information reusability and returns; this reduces the incentives to gather information and, consequently the accurateness of the creditworthiness evaluation (Chan et al., 1986). Second, the exertion of some market power increases the benefits from providing financial support to firms in temporary distress (Petersen and Rajan, 1995), making borrowers' debt restructuring relatively less costly than default. These two effects should lead to a negative correlation between market concentration and loan default rates. On the other hand, low market concentration is frequently associated with low loan interest rates, as has been shown by many empirical studies (e. g. Berger and Hannan, 1989). It follows that, according to the Stiglitz-Weiss standard result on equilibrium credit rationing, where interest rates are low the pool of borrowers is likely to include a high proportion of low-risk customers. Consequently, market concentration should be negatively correlated with low default rates. Also, we need to control for the level of competition in order to use banks' market shares as proxies for information. Finally, as will be discussed later, measures of concentration were employed by the regulators to set structural controls. We account for the average quality of the borrowers in the market, as perceived by banks, by introducing the variable $LOAN\_RATE$: high loan interest rates in the initial period should signal that riskier projects have been financed and they are therefore expected to be positively correlated with ex-post default rates. In Italy courts proceedings take a long time to reach an outcome (Generale and Gobbi, 1996; Bianco et al., 2001). Differences in courts efficiency in enforcing bankruptcy procedures may be reflected in opportunistic behavior on the part of borrowers (Shleifer and Vishny, 1993). Therefore, we include the variable $BANKRUPTCY$ indicating the average number of days needed to complete a bankruptcy procedure; the expected sign of its coefficient is positive. The changes in the market conditions between T_0 and T_1 are described by the variables $DHERFINDAHL$ and $DLOAN\_RATE$. Finally, we control for the effect of the economic downturn with the variable $OUTPUT\_SHOCK$.

Regarding banks' characteristics, we control for size, efficiency and leverage. A bad management may have poor skills in credit scoring, be unable to appraise the value of collateral and have difficulty in monitoring. Banks that had a high proportion of bad loans in the initial period ($BANK\_BADL$) are also likely to have a high default rate in later periods. Overall efficiency is proxied by gross returns on equity ($BANK\_PROFIT$) and it is expected to have a negative coefficient. The loan default rate may also be affected by banks' moral hazard. Banks with low returns may be tempted to gamble, assuming too much risk in order to remain in the market. This temptation is stronger the higher the leverage, due to the effect of deposit insurance and limited liability (Brander and Lewis, 1986; Dewatripont and Tirole, 1994). The variable $BANK\_CAPITAL$, defined as the ratio of equity capital to total assets, is expected to have a positive coefficient. The changes occurring between time T_0 and time T_1 are captured by the two variables $DBANK\_CAPITAL$ and $DBANK\_PROFIT$. An increase in leverage should be positively linked to the default rate, owing to the regulator's intervention. The expected sign of the coefficient associated with $DBANK\_PROFIT$ is less straightforward. An increase in bank profits may have two interpretations. On one hand, banks' overall efficiency may have improved during the period under consideration, and this would imply a negative coefficient associated with the variable $DBANK\_PROFIT$. On the other hand, short-sighted managers may deliberately choose to skimp on the resources devoted to creditworthiness evaluation, in order to obtain high short-run returns at the price of larger loan losses in the future (Berger and DeYoung, 1997). In this case the coefficient should be positive. We also include a set of dummy variables indicating the institutional status of the bank (i.e. thrift institutions, special credit institutions, cooperative banks or community banks). We expect the coefficients of the dummies associated with cooperative and community banks to be negative, because of the high level of information that these institutions have about their customers, as documented by previous studies (e.g. Angelini et. al., 1998).[13]

3.4 Consequences on incumbents' default rates

A natural extension of the analysis is to assess the consequences of entry on incumbents' default rates. Theory suggests two effects working in opposite directions. The first one is related to incumbents' customers. According to Sharpe (1990), uninformed entrants offer an interest rate that reflects the average credit quality of borrowers in the

[13] Both cooperative and community banks (respectively *banche popolari* and *banche di credito cooperativo*) are actually cooperative institutions, the latter being more strictly tied to relatively small local communities

market. In so doing they attract incumbents' high-risks customers who are charged high interest rates (Sharpe effect). This implies a negative relation between the number of entrants in a given market and incumbents' default rate[14]. The second effect is related to the fist-time loan applicants. Broeker (1990) and Shaffer (1998) predict that entry, by increasing the number of banks, increases the probability that a bad borrower will be found creditworthy by at least one of them (Shaffer effect). Therefore, a high number of entrants should be correlated with higher default rates for incumbents. In order to test which of these two effects prevails, we estimate the following equation:

$$\begin{aligned} y_{ij,T_2} &= \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \eta\, OUTLOANS_{ij} + \\ &+ \phi N\_ENTRANTS_j + \gamma TURNOVER_j + \delta N\_ENTRANTS_j * TURNOVER_j + \\ &+ MARKET\_CONTROLS + \varepsilon_{ij} \end{aligned} \tag{7}$$

where y_{ij,T_2} is the log-odds transformation of the default rate of incumbent bank i's loans in market j at time T_2; $N\_ENTRANTS_j$ is the number of entrants in market j in the period between T_o and T_1 and MARKET _CONTROLS is a set of covariates including market size, the number of existing banks, the Herfindahl index, the average loan rate, the average number of days needed to complete a bankruptcy procedure, the level of economic activity and the output shock. Depending on which of the two effects prevails the variable $N\_ENTRANTS_j$ will have a positive or negative coefficient. Whichever the prevailing effects, incumbents in markets characterized by a high level of turnover should exhibit higher default rates, since in every period there is a larger proportion of borrowers whose risk level can be assessed through the creditworthiness test only. Actually, the Shaffer effect only works on new customers, so that introducing an interaction between the number of entrants and turnover allows us to disentangle the two effects. In order to check for robustness of these specifications, we also estimate the same models considering entry with branches and entry with loans.

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and subject to specific regulation.

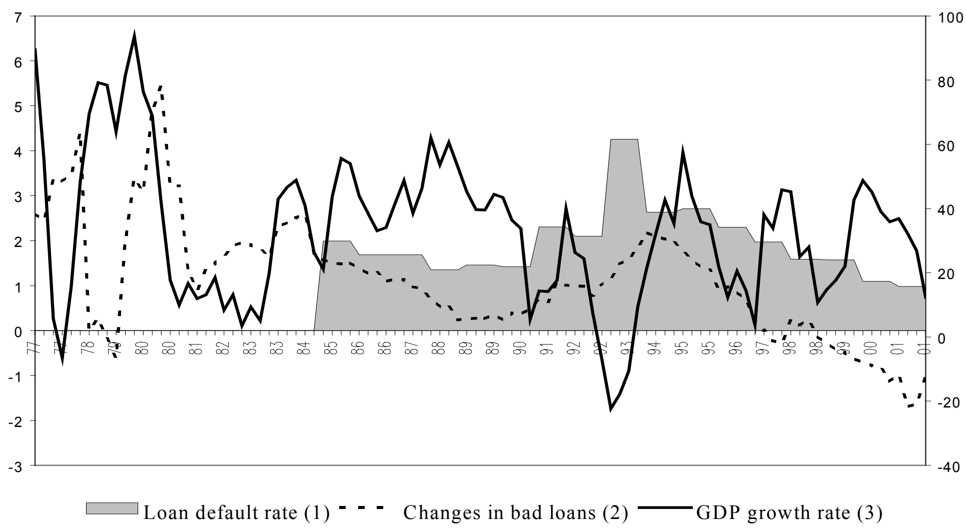
[14] A possible alternative interpretation can be found in Gehrig (1998), where incumbents react to entry by tightening their loan policy.

4. Data

We use data referring to the Italian banking industry for the period from 1986 to 1996 and define local markets as provinces.[15] Beginning in the 1980s the Italian banking system underwent a series of reforms aimed at increasing competition in the market. From 1985 to 1991 the Italian economy enjoyed a period of growth, which ended in 1992 with the deepest recession of the post-war period (see Chart 1).

Chart 1

BAD LOANS OF ITALIAN BANKS
(pecentages and percentage changes)



Sources: Bank of Italy (Central Credit Register and Supervisory Reports) and Istat (National Accounts).
(1) New bad loans as a percentage of the stock of performing loans outstanding at the end of the preceding year: annual data: left-hand scale. – (2) Percentage change with respect to the corresponding quarter of the preceding year, data not adjusted for debt cancellations and assignments: right-hand scale. – (3) Percentage change at constant prices with respect to the corresponding quarter of the preceding year: left-hand scale.

In particular, the Italian Credit Authorities increasingly liberalized branching and eased the geographical restrictions on lending, thereby lowering the barriers to entry into the local markets. From the late 1970s the opening of new bank branches had been regulated by the "branch distribution plans" issued every four years. Structural control on entry into local credit markets were deemed necessary on the view, widely shared by

[15] Italy is divided into 103 provinces, which correspond by and large to U.S. counties. However, since 8 provinces were carved out in 1995, in our sample period we have only 95 local markets.

regulators in those years, that market forces alone could not deliver both efficiency and stability. Among the objectives of branch distribution plans was that of "seeking a more homogenous level of competition in the various areas" (Lanciotti, 1984, p. 229), and measures of market concentration were used to gauge rivalry among banks. The last distribution plan was issued in 1986; from March 1990 the establishment on new branches was completely liberalized.

This led to unprecedented growth in the number of branches: from 13,136 in 1985 to 19,786 in 1992. The phenomenon was nationwide: the province with the largest number of branches went from 891 in 1985 to 1.512 in 1992, the one with the smallest from 13 to 21. Along with the the number of branches, the credit-to-GDP ratio also rose significantly in the same period. The GDP growth started to slacken at the end of 1991 and bottomed out during the first quarter of 1993. The long and severe recession proved to be a hard test for the loans granted in the previous years; the default rate rose to 4.2 per cent, depressing banks' returns for several years.[16]

We draw our data from four sources. The default rate and the local market credit variables are from the Italian Central Credit Register (CCR).[17] Banks' characteristics are from the Supervisory Reports to the Bank of Italy, which collects data about banks' balance sheets and income statements. GDP by province comes from the data constructed by the Istituto Tagliacarne, a research unit of the Italian Chambers of Commerce, while the length of court bankruptcy procedures is drawn from the Court Statistics compiled by Istat, Italy's National Institute for Statistics. The Italian Central Credit Register (CCR) is a department of the Bank of Italy that collects data on borrowers from their lending banks. The reporting banks file detailed information for each borrower with total loans and credit lines above a given threshold, which was about 40,000 euros during the period covered by our data. Bad loans are defined on a customer basis and therefore include all the outstanding credit to borrowers considered insolvent.

[16] For an early discussion of the 1993 surge in banks' bad loans, see Focarelli et al. (1997).
[17] A description of the Italian CCR is contained in Miller (2000).

Our sample has 7,275 observations referring to 729 banks, representing virtually all commercial banks for which data were available during the period under consideration. Mergers and acquisitions that took place between 1986 and 1996 were considered as if they occurred in 1986. This implies that entry by M&A is not considered in our analysis; a bank entering a new market by M&A does not increase the number of banks in that market and inherits the information held by the acquired bank.

The sets of dummy variables that we use in our specifications lead to two partitions of our sample based on the banks' status of incumbent or entrant. Table I describes these partitions. Panel A is based on the dummies used in equations (1) to (6), where entry is defined as passing from a market share equal to zero to a positive one. By contrast, the partition in Panel B is based on the set of dummy variables used in equations (7) to (12), where we distinguish between entry with and without branches.

Table II shows the descriptive statistics for the dependent and the independent variables. We constructed our dependent variable, the default rate, as an average from 1993 to 1996 of the ratios between new bad loans[18] at time T to performing loans at time $T-1$. We chose to take an average ratio in order to avoid a possible bias produced by the different timing with which banks may have classified non-performing loans as bad debts. In computing the default rate we considered loans between 130,000 and 26,000,000 euros granted to firms; data below this threshold are rather noisy, while those above it refers to loans granted to large firms, which are usually managed by banks' headquarters rather than by local branches. The average ratio was appropriately adjusted to compute its log-odds ratio.[19]

The variable MARKET_SHARE, intended to capture the level of information about market economic conditions, is the market share of loans by bank and province. The

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[18] For bad loans we use the "adjusted" statistics provided by the CCR. In the case of a single bank relationship the "adjusted" definition coincides with bad loans, namely all the loans extended to insolvent borrowers. Loans extended to borrowers with multiple bank relationships are all classified among the "adjusted" bad loans when: 1) the borrower is reported as insolvent by a bank which accounts for 70 per cent or more of his exposure toward the banking system; 2) the borrower is reported as insolvent by two or more banks which accounts for at least 10 per cent of its total exposure toward the banking system.

[19] The default rate is p=z/k, where z are the new bad loans and k the stock of performing loans the year before. The correction sets z'=0.001*k whenever z=0 and k'=k+0.001*z whenever k=z.

information acquired before opening a branch in a new market is proxied by the variable PRE_MK_SHARE, which is constructed as the market share of entrants with branches the year before entry.

All the initial conditions for banks and markets characteristics refer to 1986. TURNOVER is a dummy variable that has a value of one if the customer turnover in a market (computed as the ratio between new customers in 1986 to existing customers in 1985) exceeds the 75th percentile of the distribution of turnover over markets. The variable MARKET_SIZE is the log of the province's population, NUMBER_BANKS is the log of the number of banks operating in that market. Concentration is measured by the variable HERFINDAHL, which is the Herfindahl index computed on loans, based on the location of the borrower; LOAN_RATE, which measures the risk of the financed projects as perceived by banks, is the average interest rate on loans. The intensity of the economic activity is measured by per capita value added (MARKET_OUTPUT). DHERFINDAHL and DLOAN_RATE, are the differences of HERFINDAHL and LOAN_RATES respectively in 1991 and 1986. The macroeconomic shock is captured by the variable OUTPUT_SHOCK, the rate of growth of value added in real terms in 1993, the year in which the recession reached its trough. A slightly different approach was used to construct BANKRUPTCY. This variable is the log of the average number of days needed to complete a bankruptcy procedure during the period 1983-85.

The variable BANK_SIZE is constructed as the log of total assets; BANK_CAPITAL is ratio of capital to total assets. BANK_BADL is the ratio between the stock of bad loans and the stock of performing loans. BANK_PROFITS is measured by returns on equity before taxes. The variables accounting for changes in bank's characteristics, DBANK_CAPITAL and DBANK_PROFITS, are computed as the differences between the respective variables in 1991 and 1986. COMMUNITY, COOPERATIVE, SCI and THRIFT are dummy variables indicating whether the bank is, respectively, a cooperative bank, a community bank, a special credit institution or thrift institution.

The variable N_ENTRANTS is the log of one plus the number of entrants during the interval 1986-1991 in a given market. N_ENTRANTS_LOA and N_ENTRANTS_BR are the log of one plus the number of banks that entered a given market with loans and with branches respectively.

5. Results

We estimated equations (1) to (10) using weighted least squares logit regression for grouped data. Estimation results for the fixed effects model are shown in Tables III. The first two columns report the estimated coefficients of the equations where entry is defined as the acquisition of a positive market share during the period 1986-1991. The remaining columns show the estimation results for the equations in which we distinguished between entrants and incumbents with and without branches. The overall pattern of coefficient is consistent across the different specifications.

Our hypothesis on the consequences of entry are confirmed by the data: the entry dummies are positive and strongly significant under both the definitions adopted. The coefficient associated with the market share is negative and significantly different from zero: the greater the information about the local market conditions and the pool of customers, the lower the default rate. The positive coefficient associated with *OUTLOANS* implies that granting loans from outside, i.e. with a small informational endowment, leads to high default rates. Moreover, the introduction of the interactions of the entry dummies with the market share, the pre-entry market share and customer turnover has the expected negative effects, confirming that the informational disadvantage is stronger for complete newcomers and that the adverse selection they face is lower where turnover of customers is high.

As is well known, in a logit regression for grouped data it is not possible to interpret the regression coefficients as the partial derivatives of the conditional expectation of the default rate with respect to the associated independent variables. Furthermore, without further assumptions, we cannot estimate the conditional expectation of the default rate (and consequently of the marginal effects).[20] In order to assess the economic significance of the estimates, we simulate the effects of entry, turnover and information by computing the predicted default rates for different values of the relevant independent variables, following the methodology proposed by Berger et al. (2001). Table IV reports the predicted default rates based on the regression coefficients of equations (1) and (3) (Panels A and B, respectively).

Panel A shows that loans granted by banks that entered a new market (here entry is defined as the acquisition of a positive market share) end up as bad debts with a 10.05 per cent probability, almost three times higher than loans granted by incumbents that had a large market share in the initial period (3.38 per cent). [21] Incumbents with a small market share experienced a default rate lying between the two extremes, though closer to the lower one (4.08 per cent) and still below the sample mean. The difference in the predicted probabilities between the two types of incumbents can be explained by the different endowments of information. The entrants, on the other hand, not only have scarce information about the local market conditions, but they are also more exposed than incumbents to adverse selection.

[20] Assuming independence of the error term and the covariates, one can estimate E(p|x), where p is the default rate and x the set of regressors, using Duan's (1983) methodology. Without this assumption an estimate of the conditional distribution of the errors must be recovered first, but this approach is not robust. On the other hand, one can make an assumption on the conditional distribution of the default rate. Mullahy (1990) suggests that a plausible distribution for fractional response data is the beta distribution. Unfortunately this assumption implies that each value in [0,1] is taken on with probability zero and it is therefore difficult to justify in applications (like ours) where some proportion of the sample is at the extreme values of zero or one. A different estimation approach is suggested by Papke and Wooldridge (1996). They state the problem directly in terms of E(p|x) and propose a quasi-likelihood estimation procedure. Preliminary estimates conducted following this methodology show that the results are consistent with those discussed in the paper.

[21] We obtained this estimate as follows. We begin with the mean value of 0.048 for DEF_RATE and calculate the log-odds ratio and then subtract the mean values of MARKET_SHARE and ENTRY (mean values are shown in Table I) multiplied by their respective regression coefficients (shown in the first column of Table III). Doing so we obtained a benchmark log-odds ratio of the default rate of a fictitious incumbent bank with zero market share, average bank's characteristics and operating in an average market. We then add the value of the 90th percentile of MARKET_SHARE times its regression coefficient and convert this new log-odds ratio to a new default rate, obtaining the predicted default rate for incumbents with large market share. Repeating the same calculations using the 10th percentile of MARKET_SHARE, we obtain the default rate for incumbents with small market share. Finally we add to our benchmark the regression coefficient of ENTRY, obtaining the default rate for entrants. Thus we find DEF_RATE(entrants) = 10.05 by calculating DEF_RATE(entrants) = exp(p)/(1 + exp(p)), where p = ln(0.048 / (1-0.048)) – (-3.421*0.012) - (0.964*0.217) + 0.964.

The results reported in Panel B distinguish between banks that entered a new market by opening a branch (possibly already having some customers there) and those that entered by granting loans. The different categories of banks are ranked in ascending order with respect to the predicted default rate of their loan portfolio. This ranking would be exactly the same if we had ordered them according to the amount of information they presumably have about the local market conditions and their borrowers or the possibility they have to monitor borrowers closely. Incumbent banks with a large market share and with branches are best placed to assess the impact of the business cycle on the local economy, to evaluate the creditworthiness of their borrowers and to monitor them once the loan is granted. Their predicted default rate, equal to 2.35 per cent, is far below the sample mean. This informational advantage declines if the market share is small and becomes even smaller if a bank is new in that market: entrants with branches experience a default rate 0.8 percentage points (or 34 per cent) higher than incumbents with branches and large market share. Having a branch on site seems to be very important in order to avoid credit losses. According to our estimates, even incumbent banks with a relatively large market share, but not present with a branch, are likely to have high default rates (5.04 per cent), almost twice as higher as that of incumbents with large market share and branches. An explanation is that higher screening and monitoring abilities are associated with the presence of a branch.[22] Also, opening a branch implies some sunk costs and that require a careful ex ante assessment of the profitability and the risk of the operation. It is therefore reasonable to suppose that banks that decide to open a branch are already quite well informed about the market conditions and the potential risks linked with the winner's curse. If a potential borrower applies for a loan in a bank that is relatively far from his location, it is reasonable to suppose that his application was previously rejected by some, if not all, banks that have branches in his province. The winner's curse is therefore far stronger for those that granted loans from outside. This, plus the scarce information about local market conditions, explains the extremely high default rate (10.03 per cent) on the loan portfolio of those banks that entered without opening a branch.

[22] The presence of a branch is almost a necessary condition for the bank to supply payment services to their borrower in a local market. As shown by Mester et al. (2001) the information gathered through checking accounts makes banks more effective in their monitoring activity.

Table V reports the predicted default rates obtained using the regression coefficients of equation (4) and highlights the role of information in reducing the loan default rate. Entrants with branches and with a small pre-entry market share experienced loan loss rates 10 per cent higher than those with a large pre-entry market share. The difference between incumbents without branches with large and small market share is much smaller (3 per cent), indicating that for such banks the winners’ curse effect dominates the disadvantage of having less information on the local market conditions.

Table VI shows the effect of high customer turnover. Panel A reports the predicted default rates based on the regression coefficients of equation (5). Customer turnover increases the default rate of entrants by 38 per cent. In Panel B, the predicted default rates are based on the regression coefficients of equation (6). Entrants with branches in high turnover markets had a default rate 13 per cent higher than their peers in low turnover markets. Entrants without branches reduced their loan default rate of 64 per cent if they entered a high turnover market instead of a low turnover one. This confirms that entrants without branches are much more exposed to adverse selection and informational disadvantage than entrants with branches.

We show the estimation results for the covariate model in Table VII, organized as Table III. Replacing market and bank fixed effects with the covariates does not alter the sign and the significance of the entry dummies and their interactions with market share, pre-entry market share and customer turnover. Again, the overall pattern of coefficients is consistent across the different specifications. The data support our hypotheses regarding the effects of the number of banks operating in a market and the existence of a high customers’ turnover: both NUMBER_BANKS and TURNOVER have a positive and significant coefficient. Banks operating in markets characterized by a large number of banks experienced higher default rates, as predicted by the theory; high customer turnover increases loan losses because it increases in the share of borrowers known only through the creditworthiness tests. HERFINDAHL has a positive sign which is at odds with most of the theoretical predictions but not with previous empirical studies (Bonaccorsi di Patti and Gobbi, 2001a).[23] There are two possible interpretations. One is that previous regulation on branching tended to shelter from competition more fragile markets. The other is that the inefficiencies associated with lack of competition reverberate on the screening procedures.

All the remaining coefficients on market covariates have the expected signs. Also the hypotheses regarding banks characteristics are confirmed. Banks with high leverage, incapable managers and low efficiency experienced significantly higher default rates, as confirmed by the signs associated with the variables BANK_CAPITAL, BANK_BADL and BANK_PROFITS. The negative coefficient associated with the variable DBANK_PROFITS suggests rejecting the skimping hypothesis and accepting the idea of an improvement in banks' overall efficiency.

Applying the same methodology previously described, we assess the economic significance of the estimates by simulating the effects of entry, information and different values for the banks' and markets' covariates. The results in Table VII are computed using the regression coefficients of equation (1a). The top line of the table shows the predicted default rate for the three types of banks identified in this specification, keeping all the other covariates at their mean values. The rest of the table reports the predicted default rates obtained by setting one regressor at the 25^{th} (75^{th}) percentile, while keeping all the other at the mean. Tables IX and X are similarly organized and report the predicted default rates for banks lending in local markets with and without branches, respectively; the regression coefficients used for the calculations are those of equation (3a). The values obtained keeping all the covariates at their mean are consistent with those reported in Tables IV and V. Banks lending in markets with a large number of banks experienced a default rate more than 25 per cent higher than if they lent in markets with a small number of banks. Efficiency and managers' ability play a crucial role in determining the loan default rate of banks. Overall, ex-ante efficiency reduces the predicted default rate by a almost 18 per cent. As could be expected, specific abilities in assessing creditworthiness

[23] Aware of potential problems due to multicollinearity with other variables we have also estimated equation from 1a to 6a without the variable HERFINDAHL, with no qualitative change and a slight inflation in the standard errors of some coefficients.

and monitoring have an even greater impact. The predicted default rate has a 22 per cent increase if computed at the 25th or 75th percentile of BANK_BADL. Finally, the strong local roots of cooperative and community banks generate relationship information of which lenders seem to take advantage in their screening and monitoring activities. The finding that these intermediaries experience lower than average loan default rates is consistent with other empirical studies performed using different samples and different methodologies (e.g. Cannari and Signorini, 1997).

Table XI reports the results of the analysis of the effects of entry on incumbents' default rate. The first two columns shows the regression coefficients of the estimate of equation (7), with and without the interaction between the number of entrants and turnover. The negative coefficient of the variable N_ENTRANTS indicates that the Sharpe effect is stronger than the Shaffer effect: the improvement of incumbents' default rates deriving from the fact that their riskier customers switch to the entrants more than compensate for the worsening of their loans quality due to the higher probability they have of assessing a high-risk new customer creditworthy. The second column of the table shows, however, that the Shaffer effect does exist and is significant. The coefficient of the interaction between the number of entrants and customers' turnover is positive, while the absolute value of the coefficient of N_ENTRANTS increases. This is consistent with the hypothesis that, as far as first-time loan applicants are concerned,, an increase in the number of banks in the markets causes incumbents' default rate to rise. Finally, this further specification can also be interpreted as a robustness check of the results that reduced distance between banks and their customers helps in keeping the default rates low and that more information reduces the risk level of banks' loans portfolios. Both the coefficients of OUTLOANS and of MKT_SHARE are significant and with the same sign obtained in the previous specifications.

6. Conclusions

This paper has explored the links between entry and default rates of the loans granted by the entrants. Using the estimated coefficients of a log-odds regression for grouped data, we assessed the economic significance of our estimates by simulating the loan default rates for different definitions of entry and for different levels of information about the local market economic conditions. We found a significantly higher default rate for banks that entered local markets than for the incumbents. The default rate is even higher for banks that entered without opening a branch, suggesting that having a branch on site can help in reducing the informational disadvantage. Our results confirm the insights provided by theoretical models which emphasize the role of asymmetric information in determining incentives and costs of entry into credit markets.

Our empirical results have some implications for several issues investigated in the banking literature as well for policy-making. We discuss two of them that are particularly relevant: the welfare effects of a rise in bank competition and the importance of the distance between lenders and borrowers for market integration.

According to our estimates, entry into credit markets can generate substantial costs in term of loan losses. As long as entry accentuates bank rivalry, the result is consistent with other studies emphasizing the sensitivity of relationship lending to competition (e.g. Petersen and Rajan, 1995). Our findings, however, do not warrant any general welfare conclusion about competition in local banking markets for two reasons. First, a well established result in empirical banking studies is the negative correlation between the measure of market competition and loan interest rates (Berger and Hannan, 1989; Hannan, 1991; Berger and Hannan, 1998). Second, lending is only one activity of banks, albeit a very important one; customers other than borrowers are likely to benefit from higher competition in local markets. For instance, Hannan and Praeger (1998) find evidence that in the U.S. the liberalization of state laws restricting inter-state multibank holding company operations caused an increase in deposit interest rates. The analysis of the previous sections suggests that achieving the benefits stemming from more competitive banking entails costs and that these costs are lower when banks are well capitalized and efficient.

The second issue is the role of distance. One of our key findings is that banks lending in markets where they have branches experience far lower loan default rates than banks lending from distance. The importance of distance in banking has been recently emphasized by a number of papers discussing the impact of technical progress in financial intermediation. Petersen and Rajan (2002) find evidence that in the United States the distance at which banks lend has increased substantially during the last decade. But they also find that informationally opaque firms have closer lenders. Berger et al. (2002) show that large banks, which lend at a greater distance, interact more impersonally with their borrowers and have shorter relationships. In credit markets, where incomplete contracting is widespread, physical proximity is likely reduce the information gap between lenders and borrowers. Geographical markets segmentation is therefore likely to be a persistent characteristics for a significant proportion of borrowers, despite the development of remote banking facilities.

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Table I
Entry into local markets in the 1986-1991 period

The table reports the partition of our sample determined by the two different definitions of entry were used. Panel A displays the number of observations referring to incumbents and entrants, where entry is defined as passing from a zero to a positive market share during the sampling period. Panel B distinguishes between incumbents and entrants with and without branches. Note that the number of incumbents in Panel A is not the sum of the two types of incumbents in Panel B because 452 banks that entered with a branch, but were already granting loans, must be added. Similarly the number of entrants displayed in Panel A is the number of entrants without branches reported in Panel B plus 41 banks that entered a local market where they were not previously granting loans.

Panel A

Partition determined by the dummies used in equation (1), (2), (3), (4), (5) and (6)

ENTRY	Description	No. Obs.
0	Incumbents	5,696
1	Entrants	1,579
	Total	7,275

Panel B

Partition determined by the dummies used in equation (6), (7), (8), (9), (10), (11) and (12)

ENTRY_BR	ENTRY_LOA	OUTLOANS	Description	No. Obs.
0	0	0	Incumbents with branches	1,852
0	0	1	Incumbents without branches	3,392
1	0	0	Entrants with branches	493
0	1	0	Entrants without branches	1,538
			Total	7,275

Table II
Variables' Definitions and Descriptive Statistics

The table displays the descriptive statistics for the dependent and the independent variables. The database has 7,275 observations, referring to 729 banks and 95 local markets. The (0,1) notation indicates a dummy variable. The dependent variable, DEF_RATE, is the default rate of loans granted to firms and is obtained as an average from 1993 to 1996 of the ratio between new bad loans at time *T* to performing loans at time *T-1*. The original default rate was corrected in order to be able to compute its log-odds ratio. The correction was made as follows: denoting the default rate as p=z/k, where z are the new bad loans and k the stock of performing loans the year before, we set z'=0.001*k whenever z=0 and k'=k+0.001*z whenever k=z. All the explanatory variables refer to 1986, except when differently specified. MKT_SHARE is the market share of loans by bank and market; PRE_MK_SHARE is the market share of the entrants with branches the year before entry. The following dummy variables are the indicators for entry and refers to the period 1986-1991: ENTRY indicates if a bank passed from a zero to a positive market share in a given market; ENTRY_BR assumes value one if a bank opened a branch in a market; ENTRY_LOA indicates if a bank passed from a zero to a positive market share in a given market without opening a branch; OUTLOANS assumes value one if a bank was an incumbent in a market, but did not have a branch. TOURNOVER is a dummy variable that assumes value one if the customer turnover in a market (computed as the ratio between new clients in 1986 to existing clients in 1985) exceeds the 75th percentile of the distribution of turnover over markets. The variable MARKET_SIZE is the log of the province's population, NUMBER_BANKS is the log of the number banks in each market. HERFINDAHL is the Herfindahl index computed on loans, based on the location of the borrower; LOAN_RATE is the average interest rate on loans. BANKRUPTCY is the log of the average number of days needed to complete a bankruptcy procedure during the period 1983-85. MARKET_OUTPUT is the log of per capita value added. DHERFINDAHL and DLOAN_RATE are the differences of HERFINDAHL and LOAN_RATES respectively in 1991 and 1986. OUTPUT_SHOCK is computed as growth rate of value added in real terms in 1993. The variable BANK_SIZE is constructed as the log of total assets; BANK_CAPITAL is the ratio of capital to total assets. BANK_BADL is the ratio between the stock of bad loans and the stock of performing loans. BANK_PROFIT is measured by returns on equity before taxes. DBANK_CAPITAL and DBANK_PROFITS, are constructed as the differences between the respective variables in 1991 and 1986. COMMUNITY, COOPERATIVE, SCI and THRIFT are dummy variables indicating whether the bank is, respectively, a cooperative bank, a community bank, a special credit institution or thrift institution.

Symbol	Mean	Min.	Max.	St. Dev.
Dependent Variable				
DEF_RATE	0.048	0.001	0.999	0.106
Explanatory Variables				
Bank - market variables				
MKT_SHARE	0.012	0.000	0.461	0.034
PRE_MKT_SHARE	0.001	0.000	0.223	0.005
ENTRY (0,1)	0.217	0.000	1.000	0.412
ENTRY_BR (0,1)	0.068	0.000	1.000	0.251
ENTRY_LOA (0,1)	0.211	0.000	1.000	0.408
OUTLOANS (0,1)	0.466	0.000	1.000	0.499

Table II - *Continued*

Market variables				
TURNOVER (0,1)	0.292	0.000	1.000	0.455
MARKET_SIZE	13.228	11.433	15.191	0.829
NUMBER_BANKS	4.851	3.296	5.979	0.546
HERFINDAHL	0.083	0.029	0.261	0.042
LOAN_RATE	14.823	12.660	17.960	1.311
BANKRUPTCY	7.652	7.389	8.125	0.177
MARKET_OUTPUT	3.313	1.369	5.122	0.527
DHERFINDAHL	-0.006	-0.122	0.051	0.019
DLOAN_RATE	-0.041	-2.690	1.530	0.764
OUTPUT_SHOCK	-1.580	-4.920	1.737	1.401
Bank variables				
BANK_SIZE	7.798	1.692	11.275	2.050
BANK_CAPITAL	0.059	0.005	0.204	0.033
BANK_BADL	0.063	0.000	0.472	0.034
BANK_PROFIT	0.262	0.012	2.979	0.156
DBANK_CAPITAL	0.014	-0.111	0.230	0.028
DBANK_PROFIT	-0.092	-2.876	1.704	0.165
COOPERATIVE (0,1)	0.197	0.000	1.000	0.397
COMMUNITY (0,1)	0.126	0.000	1.000	0.332
SCI (0,1)	0.195	0.000	1.000	0.397
THRIFT (0,1)	0.204	0.000	1.000	0.403

Table III

Determinants of the loan default rate: the fixed effect model

The table reports regression coefficients and associated standard errors, robust to heteroskedasticity, for the fixed effect model. The regressions are estimated with weighted least square logit for grouped data. Coefficients statistically different from zero, respectively at: *** 99%, ** 95% and * 90% significance level. The (0,1) notation indicates a dummy variable. Dummy variables for banks and markets not reported for brevity. The dependent variable is the log-odds ratio of the loan default rate. The first two columns report the estimated coefficients of the equations where entry is defined as the acquisition of a positive market share during the period 1986-1991. The second column adds to the basic model the interaction between entry and customer turnover. Columns from three to six distinguish between entrants and incumbents with and without branches. The fourth column extends the basic model introducing two interactions: one between the entry dummy and the pre-entry market share (for those entered with branches), the other between the dummy for being an incumbent without branches and the market share. Column five introduces customer turnover, while the last column shows both the effects of market share and turnover.

Equation	(1)	(2)	(3)	(4)	(5)	(6)
CONSTANT	-3.057 ***	-3.056 ***	-3.097 ***	-3.115 ***	-3.085 ***	-3.098 ***
	0.049	*0.049*	*0.046*	*0.046*	*0.046*	*0.046*
MKT_SHARE	-3.421 ***	-3.420 ***	-2.377 ***	-2.159 ***	-2.374 ***	-2.138 ***
	0.120	*0.120*	*0.125*	*0.126*	*0.125*	*0.126*
ENTRY (0,1)	0.964 ***	1.086 ***				
	0.081	*0.098*				
ENTRY * TURNOVER (0,1)		-0.355 ***				
		0.162				
ENTRY * MKT_SHARE						
ENTRY_BR (0,1)			0.187 ***	0.289 ***	0.238 ***	0.362 ***
			0.032	*0.036*	*0.040*	*0.045*
ENTRY_BR * TURNOVER (0,1)					-0.127 **	-0.163 ***
					0.061	*0.061*
ENTRY_BR * PRE_MKT_SHARE				-3.820 ***		-4.050 ***
				0.760		*0.767*
ENTRY_LOA (0,1)			1.392 ***	1.392 ***	1.589 ***	1.588 ***
			0.083	*0.082*	*0.101*	*0.100*
ENTRY_LOA*TURNOVER (0,1)					-0.551 ***	-0.546 ***
					0.162	*0.161*
OUTLOANS (0,1)			0.687 ***	0.775 ***	0.732 ***	0.863 ***
			0.027	*0.029*	*0.032*	*0.035*
OUTLOANS * TURNOVER (0,1)					-0.100 **	-0.185 ***
					0.042	*0.043*
OUTLOANS * MKT_SHARE				-5.331 ***		-5.771 ***
				0.573		*0.584*
Adj. R-squared	*0.623*	*0.624*	*0.659*	*0.664*	*0.659*	*0.666*
N. of observations	7,275	7,275	7,275	7,275	7,275	7,275
N. of local markets	*95*	*95*	*95*	*95*	*95*	*95*
N. of banks	*729*	*729*	*729*	*729*	*729*	*729*

Table IV
Economic significance:
the effect of entry in the fixed effect model

The table reports the quantitative assessment of the effect of entry on the loan default rate. We obtain the predicted default rates shown in Panel A as follows. We begin from the sample mean of DEF_RATE equal to 0.048 and compute the log-odds ratio and then subtract the mean values of MARKET_SHARE and ENTRY (mean values are shown in Table I) multiplied by their respective regression coefficients (shown in the first column of Table III). Doing so we obtained a benchmark log-odds ratio of the default rate of a fictitious incumbent bank with zero market share, average bank's characteristics and operating in an average market. We then add the value of the 90th percentile of MARKET_SHARE times its regression coefficient and convert this new log-odds ratio to a new default rate, obtaining the predicted default rate for incumbents with large market share. Repeating the same calculations using the 10th percentile of MARKET_SHARE, we obtain the default rate for incumbents with small market share. Finally we add to our benchmark the regression coefficient of ENTRY, obtaining entrants' default rate. Thus we find DEF_RATE(entrants) = 10.05 by calculating DEF_RATE(entrants) = exp(p)/(1 + exp(p)), where p = ln(0.048 / (1-0.048)) - (-3.421*0.012) - (0.964*0.217) + 0.964. The results shown in Panel B are obtained using the regression coefficients reported in the third column of Table III.

Panel A

	Predicted default rate
Incumbents with large market share	3.38
Incumbents with small market share	4.08
Entrants	10.05

Panel B

	Predicted default rate
Incumbents with large market share and with branches	2.35
Incumbents with small market share and with branches	2.70
Entrants with branches	3.15
Incumbents with large market share and without branches	5.04
Incumbents with small market share and without branches	5.22
Entrants without branches	10.03

Table V
Economic significance:
the effect of information in the fixed effect model

The table reports the quantitative assessment of the effect of information on the loan default rate based on the regression coefficients shown in the fourth column of Table III. The computation technique is the same used in Table IV.

	Predicted default rate
Incumbents with large market share and with branches	2.36
Incumbents with small market share and with branches	2.60
Entrants with branches and with a large pre-entry market share	3.05
Entrants with branches and with a small pre-entry market share	3.37
Incumbents without branches and with a large market share	5.25
Incumbents without branches and with a small market share	5.42
Entrants without branches	9.70

Table VI
Economic significance:
the effect of turnover in the fixed effect model

The table reports the quantitative assessment of the effect of customer turnover on the loan default rate based on the regression coefficients shown in the fifth column of Table III. The computation technique is the same used in Table IV.

Panel A

	Predicted default rate
Entrants in high turnover markets	8.11
Entrants in low turnover markets	11.18

Panel B

	Predicted default rate
Entrants with branches in high turnover markets	2.89
Entrants with branches in low turnover markets	3.27
Incumbents without branches in high turnover markets	4.83
Incumbents without branches in low turnover markets	5.31
Entrants without branches in high turnover markets	7.17
Entrants without branches in low turnover markets	11.82

Table VII
Determinants of the loans default rate: the covariate model

The table reports regression coefficients and associated standard errors, robust to heteroskedasticity, for the covariate model. The regressions are estimated with weighted least square logit for grouped data. Coefficients statistically different from zero, respectively at: *** 99%, ** 95% and * 90% significance level. The (0,1) notation indicates a dummy variable. Dummy variables for thrift and special credit institutions not reported for brevity. The dependent variable is the log-odds ratio of the loan default rate. The first two columns report the estimated coefficients of the equations where entry is defined as the acquisition of a positive market share during the period 1986-1991. The second column adds to the basic model customer turnover. Columns from three to six distinguish between entrants and incumbents with and without branches. The fourth column extends the basic model introducing two interactions: one between the entry dummy and the pre-entry market share (for those entered with branches), the other between the dummy for being an incumbent without branches and the market share. Column five introduces customer turnover, while the last considers both the effects of market share and turnover.

Equation	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
CONSTANT	-12.822 ***	-10.411 ***	-13.617 ***	-13.163 ***	-11.103 ***	-10.810 ***
	0.603	*0.612* ***	*0.586*	*0.581*	*0.594*	*0.588*
MKT_SHARE	-2.150 ***	-2.141 ***	-1.278 ***	-0.940 ***	-1.247 ***	-0.898 ***
	0.131	*0.129* ***	*0.135*	*0.137*	*0.132*	*0.134*
ENTRY (0,1)	0.918 ***	1.037 ***				
	0.101	*0.123* ***				
ENTRY * TURNOVER (0,1)		-0.451 ***				
		0.205				
ENTRY * MKT_SHARE						
ENTRY_BR (0,1)			0.281 ***	0.329 ***	0.310 ***	0.391 ***
			0.038	*0.043*	*0.048*	*0.055*
ENTRY_BR * TURNOVER (0,1)					-0.089 ***	-0.126 *
					0.072	*0.073*
ENTRY_BR * PRE_MKT_SHARE				-1.020 ***		-1.676 ***
				0.798		*0.803*
ENTRY_LOA (0,1)			1.368 ***	1.370	1.542 ***	1.548 ***
			0.105	*0.104*	*0.129*	*0.128*
ENTRY_LOA * TURNOVER (0,1)					-0.561 ***	-0.566 ***
					0.209	*0.207*
OUTLOANS (0,1)			0.688 ***	0.849 ***	0.719 ***	0.949 ***
			0.033	*0.035*	*0.039*	*0.043*
OUTLOANS * TURNOVER (0,1)					-0.010	-0.191 ***
					0.052	*0.054*
OUTLOANS * MKT_SHARE				-7.691 ***		-7.611 ***
				0.624		*0.639*
TURNOVER (0,1)		0.370 ***			0.397 ***	0.406 ***
		0.023			*0.024*	*0.024*
MARKET_SIZE	0.128 ***	0.040	0.174 ***	0.169 ***	0.082 ***	0.081 ***
	0.027	*0.027*	*0.026*	*0.026*	*0.026*	*0.026*
NUMBER_BANKS	0.359 ***	0.284 ***	0.338 ***	0.316 ***	0.260 ***	0.246 ***
	0.056	*0.055*	*0.054*	*0.054*	*0.053*	*0.053*
HERFINDAHL	6.426 ***	6.996 ***	6.377 ***	6.063 ***	7.004 ***	6.730 ***
	0.353	*0.349*	*0.343*	*0.342*	*0.339*	*0.338*
LOAN_RATE	0.309 ***	0.258 ***	0.302 ***	0.297 ***	0.249 ***	0.247 ***
	0.014	*0.014*	*0.013*	*0.013*	*0.014*	*0.014*

Table VII - *Continued*

BANKRUPTCY	0.335 ***	0.334 ***	0.350 ***	0.325 ***	0.349 ***	0.329 ***
	0.060	*0.059*	*0.058*	*0.057*	*0.057*	*0.056*
MARKET_OUTPUT	-0.126 ***	-0.200 ***	-0.072 *	-0.078 **	-0.150 ***	-0.154 ***
	0.040	*0.039*	*0.039*	*0.038*	*0.038*	*0.038*
DHERFINDAHL	2.696 ***	2.968 ***	2.970 ***	2.953 ***	3.302 ***	3.384 ***
	0.714	*0.702*	*0.694*	*0.692*	*0.680*	*0.679*
DLOAN_RATE	0.216 ***	0.189 ***	0.210 ***	0.217 ***	0.182 ***	0.186 ***
	0.017	*0.017*	*0.017*	*0.017*	*0.017*	*0.016*
OUTPUT_SHOCK	-0.072 ***	-0.044 ***	-0.076 ***	-0.070 ***	-0.048 ***	-0.044 ***
	0.007	*0.007*	*0.007*	*0.007*	*0.007*	*0.007*
BANK_SIZE	-0.058 ***	-0.059 ***	-0.061 ***	-0.059 ***	-0.063 ***	-0.063 ***
	0.009	*0.009*	*0.008*	*0.008*	*0.008*	*0.008*
BANK_CAPITAL	-4.156 ***	-4.115 ***	-4.005 ***	-4.302 ***	-3.967 ***	-4.204 ***
	0.477	*0.469*	*0.463*	*0.462*	*0.454*	*0.453*
BANK_BADL	3.831 ***	3.904 ***	3.920 ***	3.893 ***	3.953 ***	3.971 ***
	0.411	*0.404*	*0.399*	*0.396*	*0.392*	*0.389*
BANK_PROFIT	-1.610 ***	-1.518 ***	-1.671 ***	-1.571 **	-1.572 ***	-1.481 ***
	0.128	*0.126*	*0.124*	*0.123*	*0.122*	*0.121*
DBANK_CAPITAL	2.571 ***	2.249 ***	2.118 ***	2.030 ***	1.774 ***	1.634 ***
	0.533	*0.525*	*0.518*	*0.513*	*0.509*	*0.504*
DBANK_PROFIT	-0.277 **	-0.209 **	-0.407 ***	-0.302 ***	-0.336 ***	-0.261 **
	0.133	*0.131*	*0.129*	*0.128*	*0.127*	*0.126*
COOPERATIVE (0,1)	-0.070 ***	-0.069 ***	-0.086 ***	-0.090 ***	-0.084 ***	-0.089 ***
	0.034	*0.033*	*0.033*	*0.032*	*0.032*	*0.032*
COMMUNITY (0,1)	-0.451 ***	-0.410 ***	-0.384 ***	-0.357 ***	-0.342 ***	-0.321 ***
	0.087	*0.086*	*0.085*	*0.084*	*0.083*	*0.082*
Adj. R-squared	*0.332*	*0.355*	*0.372*	*0.385*	*0.397*	*0.409*
N. of observations	7,275	7,275	7,275	7,275	7,275	7,275
N. of local markets	*95*	*95*	*95*	*95*	*95*	*95*
N. of banks	*729*	*729*	*729*	*729*	*729*	*729*

Table VIII
Economic significance:
the effect of entry in the covariate model

The table reports the quantitative assessment of the effect of entry by acquiring a positive market share on the loan default rate. We obtain the predicted default rates shown in the first column as follows. We begin from the sample mean of DEF_RATE equal to 0.048 and compute the log-odds ratio and then subtract the mean values of MARKET_SHARE and ENTRY (mean values are shown in Table I) multiplied by their respective regression coefficients (shown in the first column of Table VII). Doing so we obtained a benchmark log-odds ratio of the default rate of a fictitious incumbent bank with zero market share, average bank's characteristics and operating in an average market. We then add the value of the 90^{th} percentile of MARKET_SHARE times its regression coefficient and convert this new log-odds ratio to a new default rate, obtaining the predicted default rate for incumbents with large market share. Repeating the same calculations using the 10^{th} percentile of MARKET_SHARE, we obtain the default rate for incumbents with small market share. Adding to our benchmark the regression coefficient of ENTRY, we obtain the default rate for entrants. The default rates associated with the banks and markets characteristics were computed subtracting to the value shown in the first line the mean value of the respective variable times its coefficient and then adding respectively its 25^{th} or 75^{th} percentile times its coefficient.

	INCUMBENTS WITH LARGE MKT SHARE		INCUMBENTS WHITH SMALL MKT SHARE		ENTRANTS	
Mean values	3.61		4.07		9.60	
	25° perc.	75° perc.	25° perc.	75° perc.	25° perc.	75° perc.
BANKS	2.94	3.76	3.32	4.24	7.92	9.98
HERFINDAHL	3.14	4.50	3.54	5.05	8.42	11.77
LOAN_RATE	2.99	5.53	3.37	6.22	8.03	14.24
BANKRUPTCY	3.43	3.82	3.86	4.30	9.14	10.13
MARKET_OUTPUT	3.83	3.55	4.31	4.00	10.13	9.46
DHERFINDAHL	3.52	3.71	3.97	4.18	9.38	9.85
DLOAN_RATE	3.17	3.92	3.57	4.41	8.49	10.36
OUTPUT_SHOCK	3.85	3.43	4.33	3.86	10.20	9.14
BANK_CAPITAL	3.80	3.38	4.27	3.81	10.06	9.03
BANK_BADL	3.21	3.90	3.62	4.39	8.61	10.31
BANK_PROFITS	3.99	3.27	4.49	3.68	10.54	8.74
DBANK_CAPITAL	3.56	3.78	4.00	4.26	9.46	10.03
DBANK_PROFIT	3.65	3.52	4.11	3.96	9.69	9.37
COOPERATIVE		3.42		3.85		9.12
COMMUNITY		2.47		2.78		6.69

Table IX
Economic significance:
the effect of entry with branches in the covariate model

The table reports the quantitative assessment of the effect entry with branches on the loan default rate, based on the regression coefficients shown in the third column of Table VII. The computation technique is the same used in Table VII.

	INCUMBENTS WITH LARGE MKT SHARE AND BRANCHES		INCUMBENTS WITH SMALL MKT SHARE AND BRANCHES		ENTRANTS WITH BRANCHES	
Mean values	2.47		2.66		3.40	
	25° perc.	75° perc.	25° perc.	75° perc.	25° perc.	75° perc.
BANKS	2.03	2.56	2.19	2.76	2.81	3.54
HERFINDAHL	2.14	3.07	2.31	3.31	2.96	4.23
LOAN_RATE	2.05	3.77	2.21	4.05	2.83	5.17
BANKRUPTCY	2.33	2.62	2.52	2.82	3.22	3.61
MARKET_OUTPUT	2.55	2.44	2.75	2.63	3.52	3.37
DHERFINDAHL	2.40	2.54	2.58	2.74	3.31	3.51
DLOAN_RATE	2.17	2.67	2.34	2.88	2.99	3.68
OUTPUT_SHOCK	2.64	2.33	2.85	2.51	3.64	3.22
BANK_CAPITAL	2.59	2.31	2.79	2.49	3.57	3.19
BANK_BADL	2.19	2.67	2.36	2.87	3.02	3.68
BANK_PROFITS	2.74	2.22	2.95	2.39	3.77	3.07
DBANK_CAPITAL	2.43	2.56	2.62	2.76	3.36	3.54
DBANK_PROFIT	2.50	2.37	2.70	2.56	3.45	3.27
COOPERATIVE		2.30		2.48		3.18
COMMUNITY		1.78		1.92		2.46

Table X
Economic significance:
the effect of entry without branches in the covariate model

The table reports the quantitative assessment of the effect entry without branches on the loan default rate, based on the regression coefficients shown in the third column of Table VII. The computation technique is the same used in Table VII.

	INCUMBENTS WITH LARGE MKT SHARE AND NO BRANCHES		INCUMBENTS WITH SMALL MKT SHARE AND NO BRANCHES		ENTRANTS WITHOUT BRANCHES	
Mean values	5.06		5.15		9.69	
	25° perc.	75° perc.	25° perc.	75° perc.	25° perc.	75° perc.
BANKS	4.18	5.25	4.26	5.35	8.08	10.05
HERFINDAHL	4.41	6.26	4.50	6.38	8.50	11.86
LOAN_RATE	4.21	7.62	4.30	7.76	8.14	14.24
BANKRUPTCY	4.79	5.36	4.89	5.47	9.21	10.25
MARKET_OUTPUT	5.22	5.01	5.32	5.11	9.99	9.61
DHERFINDAHL	4.92	5.21	5.02	5.31	9.44	9.97
DLOAN_RATE	4.46	5.47	4.55	5.57	8.59	10.43
OUTPUT_SHOCK	5.41	4.79	5.51	4.88	10.33	9.19
BANK_CAPITAL	5.30	4.75	5.40	4.84	10.14	9.13
BANK_BADL	4.50	5.46	4.58	5.56	8.66	10.42
BANK_PROFITS	5.60	4.57	5.70	4.66	10.67	8.79
DBANK_CAPITAL	4.99	5.25	5.09	5.35	9.57	10.04
DBANK_PROFIT	5.13	4.87	5.23	4.96	9.82	9.35
COOPERATIVE		4.73		4.83		9.10
COMMUNITY		3.67		3.74		7.13

Table XI
Effect of entry on incumbents' default rate

The table reports regression coefficients and associated standard errors, robust to heteroskedasticity, for equations (7) to (10). The regressions are estimated with weighted least square logit for grouped data. Coefficients statistically different from zero, respectively at: *** 99%, ** 95% and * 90% significance level. The (0,1) notation indicates a dummy variable. Dummy variables for banks and markets not reported for brevity. The dependent variable is the log-odds ratio of the loan default rate of incumbents. The first two columns report the estimated coefficients of the equations where entry is defined as the acquisition of a positive market share during the period 1986-1991. The second column adds to the basic model the interaction between entry and customer turnover. Columns from three to four distinguish between entrants with and without branches. The fourth column introduces the interactions of the two types of entry with customer turnover.

Equation	(7)	(8)	(9)	(10)
CONSTANT	-8.458 ***	-8.043 ***	-8.198 ***	-7.602 ***
	0.620	*0.654*	*0.623*	*0.648*
MKT_SHARE	-2.442 ***	-2.420 ***	-2.390 ***	-2.363 ***
	0.152	*0.153*	*0.153*	*0.153*
OUTLOANS	0.674 ***	0.675 ***	0.677 ***	0.681 ***
	0.033	*0.033*	*0.033*	*0.033*
N_ENTRANTS	-0.191 ***	-0.224 ***		
	0.036	*0.040*		
N_ENTRANTS_LOA			-0.111 ***	-0.100 ***
			0.028	*0.037*
N_ENTRANTS_BR			-0.133 ***	-0.161 ***
			0.023	*0.024*
N_ENTRANTS*TURNOVER		0.100 *		
		0.051		
N_ENTRANTS_LOA*TURNOVER				0.044
				0.042
N_ENTRANTS_BR*TURNOVER				0.172 ***
				0.043
TURNOVER (0,1)	0.337 ***	0.004 **	0.344 ***	-0.115
	0.025	*0.170*	*0.025*	*0.146*
MARKET_SIZE	0.071 **	0.038	0.067 **	-0.017
	0.030	*0.034*	*0.029*	*0.036*
NUMBER_BANKS	0.199 ***	0.232 ***	0.227 ***	0.282 ***
	0.056	*0.059*	*0.057*	*0.059*
HERFINDAHL	4.785 ***	4.733 ***	4.965 ***	4.451 ***
	0.351	*0.352*	*0.352*	*0.373*
LOAN_RATE	0.107 ***	0.108 ***	0.091 ***	0.115 ***
	0.011	*0.011*	*0.012*	*0.013*
BANKRUPTCY	0.350 ***	0.357 ***	0.319 ***	0.344 ***
	0.060	*0.060*	*0.060*	*0.060*
MARKET_OUTPUT	-0.111 **	-0.140 ***	-0.088 *	-0.160 ***
	0.044	*0.046*	*0.044*	*0.048*
OUTPUT_SHOCK	-0.016 **	-0.014 *	-0.019 ***	-0.006
	0.008	*0.008*	*0.008*	*0.008*
Adj. R-squared	*0.586*	*0.586*	*0.587*	*0.588*
N. of observations	*5,244*	*5,244*	*5,244*	*5,244*
N. of local markets	*95*	*95*	*95*	*95*
N. of banks	*726*	*726*	*726*	*726*