BAD LOANS AND ENTRY IN LOCAL CREDIT MARKETS

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Abstract

This paper explores the link between entry in local credit markets and default rates of the loans extended by the entrants. Economic theory suggests that high default rates may be experienced by entrants 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' loan default rates 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]

In markets where information is complete and symmetrically distributed among agents and where externalities are absent competition leads to Pareto optimal outcomes. In the case of banking services, more competition should lead to higher efficiency, higher deposit rates and lower loan rates, therefore increasing borrowers' and depositors' welfare (Besanko and Thakor, 1992). However, the existence of financial intermediaries has been since long traced back to market imperfections. In credit markets asymmetries in the distribution of information and externalities influence banks' risk-taking behavior, their ability and their incentives to price risk correctly. In a number of circumstances the heightening competition can exacerbate market distortions making the welfare effects less straightforward.

Economic theory also suggests that asymmetric information can work as a barrier to entry in credit markets and that incumbents' market power can be to some extent shielded from outside potential competition. This view is supported by two main arguments. The first one is related to the possibility that once entry occurred, previously rejected applicants can apply for loans at additional banks. As far as borrowers' credit-worthiness is assessed through screening procedures which are not fully revealing and are unperfectly correlated across banks, a larger number of banks rises the probability that a bad risk is considered as credit worthy by at least one of them (Broecker, 1990). Adverse selection is greater for new entrants because the pool of their applicants is likely to include those potential borrowers previously rejected by mature banks in the market (Shaffer, 1998).

The second argument relates on the informational advantages of the incumbents on market characteristics. A relevant amount of information used by banks for screening loan applicants and for monitoring borrowers is generated through repeated interaction with their customers. Many studies, both of theoretical and empirical nature, have documented

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that long term relationships established between lenders and borrowers are an important feature of most bilateral credit markets (i.e. 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' credit-worthiness tests may well be more precise than those of the entrants.

Empirical evidence on the link between entry and default rates of the loans extended by the entrants is scarce. Several episodes of banking crisis around the world have been directly or indirectly related to the lifting, or relaxation, of the constraints imposed by regulation. Demirguc-Kunt and Detragiache (1998), analyzing a sample of 53 countries, show that financial liberalization rises the probability of a bank crisis. Caprio and Klingebiel (2000) document a recent increase in the frequency of bank crises and argue that it is at least partially due to the lifting of structural controls. Pesola (2001) finds that market liberalization had a substantial role in the bank crisis experienced by the Scandinavian countries during the early 1990s. To our knowledge, Shaffer (1998), which is very close in spirit to our paper, is the only study that empirically tests the winner's curse hypothesis, i. e. the idea that entrants in a credit market are forced to assume too much risk because their pool of borrowers is adversely selected.

This paper contributes to the subject through an empirical study of the Italian outburst of bad loans in the early 1990s. The 1992-93 recession caused an unprecedented upsurge in non-performing loans followed by severe losses for a large number of banks. Thanks to a unique database on loan default rates made available by the Italian Central Credit Register, we investigate individual banks' loan default rates in each local market. The regulatory reforms introduced in the late 1980s allowed a substantial increase in the number of banks operating in each local market (here defined as a province). We distinguish between two different ways in which a bank enters a local market. The first one consists of extending loans from branches or the headquarters outside the local market. The second one is by directly opening of branch. We argue the two types of entry differ substantially with respect to the information gap vìs a vìs the incumbents. Having on site branches allows banks a more rigorous monitoring of the borrowers and a better understanding of the local economy. Moreover entry with branches is usually anticipated by entry with loans extended from outside.

Consistently with the predictions of the theory we find evidence that entrants are more exposed to bad loans than the incumbents, since they have to deal with the backlog of previously rejected applicants. The consequences of entry on the loan default rate vary with the level of information. Those banks entered with relatively more information, i.e. by opening a branch, experienced a lower default rate than those entered without branches. The negative consequences for the entrants are less severe when markets are characterized by a high level of banks' customers turnover. According to our data 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 loans quality are mitigated when entrant banks belong to the top performers of the industry. Borrowers of well capitalized, efficient, and above-average profitable banks are characterized by substantially lower default rates.

The remaining of this paper is organized as follows. In Section 2 some theoretical and empirical contributions in this field are surveyed. In section 3 we illustrate our empirical specifications, while in Section 4 we discuss our data and explain how the relevant variables have been constructed. Results are presented in Section 5 and section 6 draws the conclusions.

2. Related literature

The possibility that an increase in competition in the banking industry may have sub-optimal allocative effects has been recognized since long, but only recently the argument has been cast in formal models. The backbone of most of them 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.[2] Before granting a loan a bank needs to assess the credit-worthiness of the applicant. The screening procedure may be thought as a not fully revealing test of the quality of the applicant. Conditional on the result of the test the bank offers an interest rate 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 credit-worthiness is assessed differently by different lenders. This implies that probability that a high risk borrower is assessed as credit-worthy is positively correlated with the number of tests that are run. It follows that the average quality of the pool of borrowers that obtain a loan (and consequently the expected losses from bad loans) declines (increases) as the number of banks in the market increases.

This idea has been 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 concerning the existence and the characterization of the equilibrium solutions. In both cases the intuition that an increase in the number of banks may have negative effects on the average ability to repay the loan of those who are granted credit holds true. A similar result was obtained by Riordan (1993) in a model where banks are able to run credit-worthiness tests delivering continuous signals. An increase in the number of banks rises the threshold value of the signal above which the loan is granted, but this effect can be offset by the increase in the probability that at least one bank observes 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 also the equilibrium default rate in the market is positively correlated with the number of active banks.

This basic framework has been extended by several papers. Gehrig (1998) allows the banks to choose the precision of their binary credit-worthiness test and models the integration of two previously separated credit markets as a sequential entry game and as

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[2] As stressed by Dell'Ariccia et al. (1999) in order to obtain a winner's curse effect asymmetric information between lenders and borrowers about the borrowers' type is not strictly necessary.

simultaneous duopoly. In the first case entry, if it ever occurs, doesn't have any effect on the incumbent's screening intensity choice, while the entrant, facing an adversely selected pool of applicants, substitutes a less accurate screening with higher interests rates.

As auction theory has recognized since long, additional insights 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 on the entrant since he has a long-term relationship with part of his customers. This advantage is greater the lower is the customers turnover in the market. They characterize the equilibrium under Bertrand duopoly and show that the adverse selection of the borrowers' pool causes entry to be blockaded. Marquez (2002) proposes a two periods model assuming that borrowers' characteristics are observable by banks only once 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 from which "captured" firms can try to escape searching 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.[3] The information asymmetries on the same side of the market (the supply side) induced by relationship lending is therefore most likely to add to the adverse selection problems faced by a new entrant banks (Nakamura, 1993). Furthermore, when assessing the credit worthiness of a loan applicant, banks usually refer to their past

[3] As pointed out by Von Thadden (2001) Sharpe's analysis is slightly incorrect since it is assumed that a pure strategy equilibrium in interest rates exists, when this is not true. Nevertheless, the informed bank still earn positive informational rents, therefore Sharpe's intuition is correct.

experience with 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).

Comparing with the abundance of theoretical papers on the subject, the empirical work has been rather limited. 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 regress 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 the presence of a learning process of an inexperienced lender), he concludes that adverse selection appears the main cause of the observed phenomenon. 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 linkage between gross chargeoff rates and the total number of banks in each MSA.

Hedricks and Porter (1988) investigate the links between the winners' 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 its superior information. They also test these theoretical conclusions examining data from the federal offshore oil and gas drainage lease sales finding that both types of buyers actually behave consistently with the Bayesian-Nash equilibrium.

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, as compared to the incumbents.

The loan default rate is defined as the ratio between new bad loans at time T and the stock of performing loans at time $T-1$ extended to firms by a bank in a given local market. Loans are attributed to a certain market on the basis of the location of the customer. Loans' default rate is an ex-post measure of risk and thus it depends on the states of nature that trigger debtors' defaults. In normal times these events tend to be highly idiosyncratic according to the many characteristics of the borrowers and consequently 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 which is a common shock to all borrowers. Figure 1 summarizes the sequence of events that we try to capture. Given some initial conditions for banks and local markets, a set of reforms relaxing the barriers to entry in local markets occurs. This facilitates entry and banks react in different ways to the new environment. Finally, a strong macroeconomic shock follows and the magnitude of risks in banks' portfolios are revealed.

T_0 ____________________________________ T_1 ________________________________ T_2

Initial period ⇑ ⇑ ⇑ Final period

Market Entry Macroeconomic shock Bad Loans Outburst

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 intended to capture banks' and markets' characteristics. We expect entrants to face more severe problems of adverse selection, since they will receive applications from all those firms that have been previously rejected by the incumbents (Shaffer, 1998). Moreover, the adverse selection effect faced by the incumbents should be inversely correlated with their knowledge of the local markets (Dell'Ariccia et al., 1999; Marquez, 2002). We estimate the following equation by weighted least squares logit regression for grouped data: [4]

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

where y_{ij,T_2} is the log-odds transformation of the default rate of bank i 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 assume value 1 when bank j enters in market i in the period between T_0 and T_1. Entry is defined as the shift from a market share equal to 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.[5, 6]

The comparative disadvantage of entrants should be mitigated by a high turnover of banks' customers (Dell'Ariccia et al., 1999; Marquez, 2002). In every period the pool of potential borrowers is composed by the backlog of those who were previously rejected and by those who apply for a loan for the very first time. The higher is the latter component, the lower the disadvantage in terms of information suffered by the entrants. We test this hypothesis introducing in our regression an interaction variable between the entry dummy a dummy identifying high turnover markets:

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

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[4] This estimation method is chosen because we are dealing with proportion data, i.e. the fraction of loans in local market which defaults in a given time interval. The dependent variable is continuous and included between zero and 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 rates 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).

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

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

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).

3.2 Different definitions of entry and different levels of information

The definition of entry we 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 from residents in a given province comes from banks' 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 opening a new branch, it presumably has a greater amount of information about the local market conditions and its potential new borrowers than when it enters simply 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 activity.[7] Opening a new branch implies some 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 also payment services to its borrowers. Black (1985) and Fama (1975) argued 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:

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

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

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

Again we test whether a high turnover of the banks' customers helps in mitigating the adverse selection effect interacting the entry dummies and $OUTLOANS_{ij}$ with the high turnover market indicator:

$$
\begin{aligned}
(4)\qquad y_{ij,T_2} = {} & \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \\
& + \phi ENTRY\_BR_{ij} + \varsigma\, ENTRY\_BR_{ij} * TURNOVER_j + \\
& + \nu ENTRY\_LOA_{ij} + \zeta\, ENTRY\_LOA_{ij} * TURNOVER_j + \\
& + \rho\, OUTLOANS_{ij} + \sigma\, OUTLOANS_{ij} * TURNOVER_j + \varphi_j P_j + \varepsilon_{ij}
\end{aligned}
$$

The theory suggests that we should obtain higher coefficients, as compared to those of equation (3), associated to 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.

(5)
$$\begin{aligned} y_{ij,T_2} &= \alpha_i B_i + \beta MKT\_SHARE_{ij,T_0} + \\ &+ \phi ENTRY\_BR_{ij} + x\ ENTRY\_BR_{ij} * PRE\_MKT\_SHARE_{ij} \\ &+ \nu ENTRY\_LOA_{ij} + \\ &+ \rho\ OUTLOANS_{ij} + \eta\ OUTLOANS_{ij} * MKT\_SHARE_{ij,t} + \varphi_j P + \varepsilon_{ij} \end{aligned}$$

The introduction of the interactions should reduce the value of the coefficient associated to the market share and increase those of $ENTRY\_BR_{ij}$ and $OUTLOANS_{ij}$, as compared to 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. The new specification is:

(6)
$$\begin{aligned} y_{ij,T} &= \alpha_i B_i + \beta MKT\_SHARE_{ij,t} + \\ &+ \phi ENTRY\_BR_{ij} + \\ &+ \varsigma\ ENTRY\_BR_{ij} * TURNOVER_j + x\ ENTRY\_BR_{ij} * PRE\_MKT\_SHARE_{ij} \\ &+ \nu ENTRY\_LOA_{ij} + \\ &+ \zeta ENTRY\_LOA_{ij} * TURNOVER_j + \\ &+ \rho\ OUTLOANS_{ij} \\ &+ \eta\ OUTLOANS_{ij} * MKT\_SHARE_{ij,t} + \sigma\ OUTLOANS_{ij} * TURNOVER_j + \varphi_j P_j + \varepsilon_{ij} \end{aligned}$$

3.3 Bank and market characteristics

As an extension of basic model we substitute the banks' fixed effects and the local market dummies with appropriate controls. The purpose is to have insights on bank and market characteristics that affect the loan default rate. Moreover, it allows us to test two additional hypotheses. The first one is a direct consequence of the independence of the credit-worthiness tests, namely that the average quality of loans decreases as the number of banks in the market increases. The second is instead related with information: a high borrowers turnover, though mitigating the relative disadvantage of the entrants, should be positively correlated with the average default rate by increasing the share of borrowers known only through the credit-worthiness 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 substituted 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 occurred 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 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 loans' market shares in the province. There are several reasons for introducing this variable. First, high competition can have a disruptive effect on relationship banking therefore lowering information reusability and returns; this reduces the incentives to information gathering and, consequently the accurateness of the credit-worthiness 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. Also, we need to control for the level of competition in order to use banks' market shares as proxies for information. Finally, as it 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 relatively riskier projects have been financed and therefore they are expected to be positively correlated with ex-post default rates. In Italy courts proceedings take long time to settle (Generale and Gobbi, 1996; Bianco et al., 2001). Differences in courts efficiency in enforcing bankruptcy procedures may be reflected in opportunistic behavior on behalf 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 therefore 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 $OUTPUT\_SHOCK$.

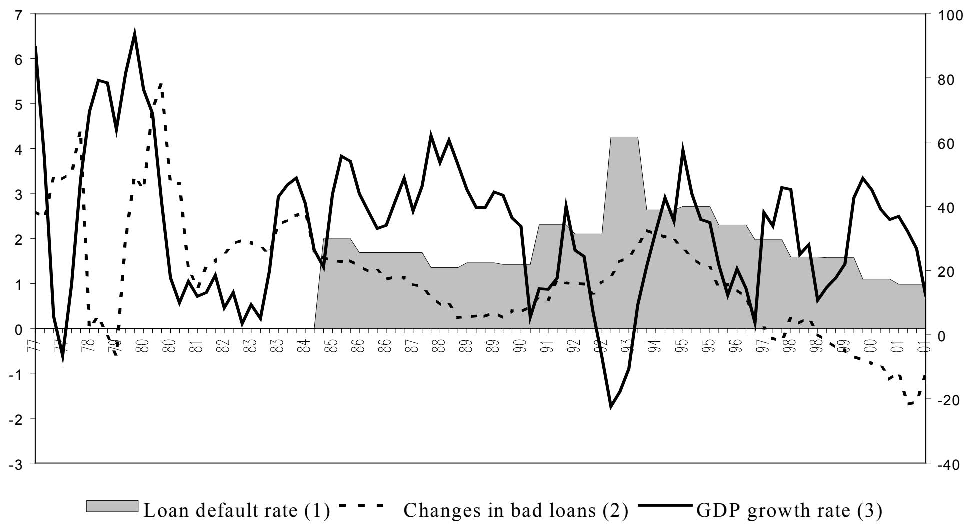
Regarding banks' characteristics we control for size, efficiency and leverage. A bad management may have poor skills in credit scoring, be unable to appraise the value of collateral and have difficulty in monitoring. Those banks that had a high proportion of bad loans in the initial period ($BANK\_BADL$) are likely to experience a high default rate also in later periods. The overall efficiency is approximated 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 occurred in the period between time T_0 and time T_1 are captured by the two variables $DBANK\_CAPITAL$ and $DBANK\_PROFIT$. An increase of the leverage should be positively linked to the default rate due to the regulator's intervention. The expected sign of the coefficient associated to $DBANK\_PROFIT$ is less straightforward. An increase in the bank profits may have two interpretations. On one hand it may be that banks' overall efficiency 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 credit-worthiness evaluation, in order to obtain high short run returns at the price of higher loan losses in the future (Berger and De Young, 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. saving and loans institutions, special credit institutions, cooperative banks or community banks). We expect the coefficients of the dummies associated to cooperative and community banks to be negative, because of the high level of information that this kind of institutions have about their customers, as documented by previous studies (e.g. Angelini et. al., 1998).[8]

4. Data

We use data referring to the Italian banking industry during the period ranging from 1986 to 1996 and define local markets as provinces.[9] Starting from the 80's the Italian banking system underwent a sequence of reforms aimed at increasing competition in the market. From 1985 to 1990 the Italian economy experienced a period of growth that ended in 1992 with the strongest 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 changes with respect to the corresponding quarter of the preceding year, data not adjusted for debt cancellations and assignments: right-hand scale. – (3) Percentage changes of constant prices GDP with respect to the corresponding quarter of the preceding year: left-hand scale.

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

[9] Italy is divided in 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.

In particular, the Italian Supervisory Authorities progressively increased the possibility to open new branches and eased the geographical restrictions on lending, lowering in this way the barriers to entry in the local markets. In Italy since the late 1970s the opening of new bank branches was regulated by the “branch distribution plans” issued every four years. Structural control on entry in local credit markets were deemed necessary on the view, widely shared by regulators in those years, that market forces alone would have been unable to marry efficiency and stability. Among the objectives of branch distribution plans there was the one 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 and from March 1990 the establishment on new branches was completely liberalized.

This led to an unprecedented growth of the number of branches: in 1985 there were 13,136 branches, which became 19,786 in 1992. The phenomenon was widespread all over the country, 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 growth in the number of branches, also the credit to GDP ratio increased significantly in the same period. The GDP growth rate started to decline from the end of 1991 and reached the minimum 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 up to 4.2 per cent leading to a strong reduction of banks’ returns that lasted for a few years.[10]

We draw our data from four sources. The default rate and the local market credit variables are from the Italian Central Credit Register (CCR)[11]. Banks’ characteristics are from the Supervisory Reports at the Bank of Italy, which collects data about banks’ balance sheets and income statements. The GDP by province comes from the data constructed by the Istituto Tagliacarne, a research unit of Italian Chamber of Commerce, while the length of the bankruptcy legal procedures is drawn from the Court Statistics maintained by Istat, the Italian official agency 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 borrowers having loans and credit lines totaling to a sum 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.

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 from 1986 to 1996 were considered as if they occurred in 1986. This implies that entry by M&A is not considered in our analysis: when a bank enters a new market by M&A it does not increase the number of banks in that market and it inherits the information held by the acquired. Therefore it is less exposed to the winner's curse.

The sets of dummy variables that we use in our specifications induce 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 from (1) to (6), where entry is defined as passing from a market share equal to zero to a positive one; the partition in Panel B is instead based on the set of dummy variables used in equations from (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 at time T to performing loans at time $T-1$. We chose to take an average ratio in order to avoid a possible bias induced by the different timing at which banks may have put their non-performing loans into the bad loan category. In computing the default rate we considered loans between 130,000 and 26,000,000 euros extended to firms; data below this threshold are rather noisy, while those above refers to loans granted to large firms, that are usually managed by banks'

[10] For an early discussion of the 1993 bank bad loans upsurge in Italy see Focarelli et al. (1997).

[11] A description of the Italian CCR is contained in Miller (2000).

headquarters rather than by local branches. The average ratio was aptly corrected to compute its log-odds ratio.[12]

The variable MARKET_SHARE, intended to capture the level of information about the market economic conditions, is the market share of loans by bank and province. The information acquired before opening a branch in a new market is proxied by the variable PRE_MK_SHARE, that 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 assumes value one if the customers 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 that is the Herfindahl index computed on loans, based on the location of the borrower; LOAN_RATE, that measures the risk of the financed projects as perceived by banks, is the average rate on loans. The intensity of the economic activity is measured by the 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 through. 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 legal procedure over the period 1983-85.

The variable BANK_SIZE is constructed as the log of total assets; BANK_CAPITAL is the capital to total assets ratio. 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. The variables accounting for changes in the bank

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[12] The default rate is p=z/k, where z are the new bad loans and k the stock of performing loans the year

characteristics, DBANK_CAPITAL and DBANK_PROFITS, are computed as the differences between the respective variables in 1991 and 1986.

5. Results

We estimated the equations from (1) to (6a) 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 we adopted. The coefficient associated with the market share is negative and significantly different from zero: the higher 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 extending loans from outside, therefore having 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 the customers' turnover has the expected negative effects, confirming that the informational disadvantage is stronger for the totally newcomers and that the adverse selection they face is lower where the turnover of banks' customers is high.

As it 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. Furthemore, without further assumptions, we can not estimate the conditional expectation of the default

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before. The correction sets z'=0.001*k whenever z=0 and k'=k+0.001*z whenever k=z.

rate (and consequently of the marginal effects).[13] 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) (Panel A and B, respectively).

Panel A shows that the loans extended by banks that entered in a new market (here entry is defined as the acquisition of a positive market share) have a probability to fall among the bad loans equal to 10.05 per cent, almost three times larger than for those loans issued by incumbents that had a large market share in the initial period (3.38 per cent).[14] Incumbents with a small market share experienced a default rate that lies between the two extremes, though being 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 the adverse selection.

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[13] 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.

[14] We obtained this estimates 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 opening a branch (possibly already having some customers there) and those that entered granting loans. The different types in which we classified the 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 with respect to the amount of information they presumably have about the local market conditions and their borrowers or the possibility they have to closely monitor them. Incumbent banks with a large market share and with branches are those that are in the best conditions to assess the impact of the business cycle on the local economy, to evaluate the credit worthiness 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 100 per cent larger than the one experienced by incumbents with large market share and branches. An explanation is that higher screening and monitoring abilities are associated with the presence of a branch.[15] A second one is connected with the fact that opening a branch implies some costs that are sunk in nature and that require a deep and 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 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 think that his application was previously rejected by some, if not all, banks that have branches in his province. The winners' curse is therefore by far stronger for those that extended loans from outside. This, plus the scarce information about local market conditions, explains the extremely high default rate (10.03

[15] The presence of a branch is an almost 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

per cent) of the loan portfolio of those banks that entered by granting loans, but without opening a branch.

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 losses 10 per cent higher than if they had 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 this type of banks the winners' curse effect dominates the disadvantage of having less information on the local market conditions.

Table VI shows the effect of high customers turnover. Panel A reports the predicted default rates based on the regression coefficients of equation (5). Customers 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 as compared to 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. The substitution of the market and bank fixed effects with the covariates doesn't modify the sign and the significance of the entry dummies and their interactions with the market share, the pre-entry market share and the customers' turnover. Again, the overall pattern of coefficient 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 high number of banks experienced higher default rates, as predicted by the theory; a high customers' turnover increases loan losses because it rises in the share of borrowers known

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checking accounts makes banks more effective in their monitoring activity.

only through the credit-worthiness tests. HERFINDAHL has a positive sign at odds with most of the theoretical predictions, but not with previous empirical studies (Bonaccorsi di Patti and Gobbi, 2001a).[16] There are two possible interpretations. The first one is that previous regulation on branching tended to shelter from competition more fragile markets. The second one 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 a high leverage, poorly skilled managers and characterized by 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 to refuse the skimping hypothesis and accept the one that suggests an improvement in banks' overall efficiency.

Applying the same methodology previously described we assess the economic significance of the estimates 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 25th (75th) 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 characterized by a high 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

[16] Aware of potential problems due 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.

the loan default rate of banks. Overall ex-ante efficiency reduces the predicted default rate by a almost 18 per cent. As it could be expected, specific abilities in assessing credit worthiness and monitoring have an even greater impact. The predicted default rate has a 22 per cent increase if computed at the 25^{th} or 75^{th} percentile of BANK_BADL. Finally, the strong ties with the local communities of cooperative and community banks generate relationship information of which lenders seem to take advantage in their screening and monitoring activities. The result 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).

6. Conclusions

This paper has explored the links between entry and default rates of the loans extended by the entrants. Using the estimated coefficients of a log-odds regression for grouped data, we assessed the economic significance of our estimates 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 those banks that entered in local markets as compared to the incumbents. The default rate is even higher for those banks that entered without opening a branch suggesting that having a branch on place 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 in credit markets.

Our empirical results bear 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 in credit markets can generate substantial costs in term of loan losses. As long as entry heightens 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 measure of market competition and loan interest rates (Berger and Hannan, 1989; Hannan, 1991; Berger and Hannan, 1998). Second lending is only one, albeit very important, among the several activities of banks: 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 interest rates paid to depositors. The analysis of the previous sections suggests the achievement of 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 in the banking industry. One of our major results 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 substantially increased during the last decade. But they also find that informationally opaque firms have closer lenders. Berger et al. (2002) shows that large banks, which lend to 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 in local markets in the 1986-1991 period

The table reports the partition of our sample induced by the two different definitions of entry that 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 in which they were not previously granting loans.

Panel A

Partition induced 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 induced 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 means that the variable is a dummy. The dependent variable, DEF_RATE, is the default rate of loans extended to firms and is obtained as an average from 1993 to 1996 of the ratio between new bad loans in year *T* to performing loans in year *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 didn't have branches. TOURNOVER is a dummy variable that assumes value one if the clients 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 rate on loans. BANKRUPTCY is the log of the average number of days needed to complete a bankruptcy legal procedure over the period 1983-85. MARKET_OUTPUT is the log of the 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 1993. The variable BANK_SIZE is constructed as the log of the banks' total assets; BANK_CAPITAL is the capital to total assets ratio. 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 S&L are dummy variables indicating whether the bank is, respectively, a cooperative bank, a community bank, a sic or a saving and loans.

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
ICS?? (0,1)	0.195	0.000	1.000	0.397
S&L (0,1)	0.204	0.000	1.000	0.403

Table III
Determinants of the loans 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 means that the variable is a dummy. Dummy variables for banks and markets not reported for brevity. The dependent variable is the log-odds ratio of the loans default rate. The first two columns report the estimated coefficients of the equations that use as definition of entry 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 the turnover of banks' clients. Columns from three to six distinguish between entrants and incumbents with and without branches. The fourth column extends the basic model introducing two interactions: the first between the entry dummy and the pre-entry market share (for those entered with branches), the second between the dummy for being an incumbent without branches and the market share. Column five introduces the banks' customers turnover, while the last considers both the effects of the market share and the 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 loans 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 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. 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 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 loans 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 customers turnover on the loans 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 means that the variable is a dummy. Dummy variables for saving and loans and special credit institutions not reported for brevity. The dependent variable is the log-odds ratio of the loans default rate. The first two columns report the estimated coefficients of the equations using as definition of entry the acquisition of a positive market share during the period 1986-1991. The second column adds to the basic model the turnover of banks' clients. Columns from three to six distinguish between entrants and incumbents with and without branches. The fourth column extends the basic model introducing two interactions: the first between the entry dummy and the pre-entry market share (for those entered with branches), the second between the dummy for being an incumbent without branches and the market share. Column five introduces the banks' clients turnover, while the last considers both the effects of the market share and the 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 acquisition of a positive market share in the covariate model

The table reports the quantitative assessment of the effect of entry by acquiring a positive market share on the loans 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 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. 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 time its coefficient and then adding respectively its 25th or 75th percentile time 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 for banks with branches in local markets in the covariate model

The table reports the quantitative assessment of the effect entry for banks with branches in local markets on the loans 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 IX
Economic significance:
the effect of entry for banks without branches in local markets in the covariate model

The table reports the quantitative assessment of the effect entry for banks without branches in local markets on the loans 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