Società italiana di economia pubblica
XVI CONFERENZA

POLITICHE PUBBLICHE, SVILUPPO E CRESCITA

Pavia, Università, 7 - 8 ottobre 2004

THE ROLE OF LOCAL REAL AND FINANCIAL VARIABLES IN BANKING INDUSTRY CONSOLIDATION: THE CASE OF ITALY

LUCA COLOMBO, GILBERTO TURATI

pubblicazione internet realizzata con contributo della

COMPAGNIA di San Paolo

The Role of Local Real and Financial Variables in Banking Industry Consolidation: The Case of Italy*

Luca Colombo
Catholic University - Milano

Gilberto Turati
Università di Torino

Abstract

We use probit and count data (ZIP) models to study the consolidation process of the Italian banking industry. Our empirical analysis highlights three main findings. First, we document an important role for the interplay between real and financial variables in driving the consolidation process in Italy. Second, we emphasize the importance of competition in local banking markets, suggesting that more competition renders more likely the presence of acquiring banks. Third, we show that an excess of loans over deposits collected in a given region has an impact on the presence of acquiring banks. This last result suggests that, beside the benefits in terms of efficiency stemming from banking consolidation, there could also be some costs often overlooked.

1 Introduction

Following the experience of other countries, the Italian banking industry has undergone an unprecedented wave of M&As in the last decade of the past century. The restructuring process has reduced the total number of banks while increasing their average size. Most of the literature dealing with banks' consolidation has stressed the importance of financial variables at the bank level as the main driver of the observed M&As, with more efficient banks taking over less efficient ones (see Focarelli *et al.*, 2002, for the Italian case, and Berger *et al.*, 1999, for a survey). However, this conclusion may hinder the role of other variables as engines of the

*We would like to thank Bank of Italy for making available data on bank branches and Maria Serena Caroppo for invaluable research assistance. We are grateful to participants at the 59th IIPF Congress (Prague), the XII International "Tor Vergata" Conference on Banking and Finance, and to Fabio Bagliano, Angelo Baglioni, Sijbren Cnossen, Mario Pagliero, Giovanni Petrella, Massimiliano Piacenza, Alessandro Sembenelli and Virginia Tirri for their comments on previous versions of the paper. Usual disclaimers apply.

consolidation process. In particular, the higher level of efficiency of active (i.e. acquiring) banks might be due not only to better managerial choices, but also to a more favorable macroeconomic environment.

In this paper, we argue that geographical factors — in particular the existence of differences in economic conditions at the local level — as well as the interplay of real and financial variables are major driving forces affecting the consolidation process of banks operating in distant markets. This is particularly evident in Italy where, in most of the observed M&As, banks from the richer Northern part of the country have taken over banks operating in the less developed Southern regions. The data released by the Bank of Italy in its latest annual report show that approximately 70% of the loans originated in the South are from banks headquartered in Northern regions.

We study the factors lying behind this process by using a unique data set on acquiring banks (active) and target banks (passive), and we show that the level of GDP, the degree of concentration of the banking industry, and the demand of financial resources within a certain area are all important factors in shaping the consolidation process of the banking industry.

While the M&As wave that shaped the current Italian banking market is an example of a consolidation process guided by differences in economic conditions *within* a country, we conjecture that our claims are of a greater generality, as our analysis can be extended to encompass situations in which the differences in economic conditions are *across* countries. In this respect, important case studies are those of the Central - Eastern European and of the Latin American banking markets. In both cases, acquiring banks from more developed countries gained market shares (both in the deposits and loans markets) at the expenses of local (resident) banks. For instance, Gros (2003), investigating Eastern European banking industries, reports that "by 2001 foreign banks had more than half of deposits in all of these countries, and in some of the larger ones (e.g. Poland, Hungary, Czech Republic) the share of foreign banks is around two thirds". Furthermore, De Haas and van Lelyveld (2002) show that, in 1999, 36% of total loans in Brazil were originated by foreign banks, and this percentage increases to 58% and 72% when one considers Argentina and Hungary, respectively.

There is little doubt that this process can be positive from an efficiency point of view. As foreign banks are shown to be more efficient than local banks, it is generally argued that improvements in management and credit policies following acquisition would induce efficiency gains and boost economic development. However, it can also raise concerns for policy makers. In particular, M&As between banks operating in distant markets may originate processes of savings reallocation (that may take place at the expenses of credit availability at the local level), possibly determining credit rationing phenomena. Witnessing the importance of the point, the U.S. legislator has taken care of these issues by enacting the Community Reinvestment Act in 1977, requiring a merger's authorization to be subordinated to the guarantee that the acquiring bank takes care of the financial needs of local communities. A way to avoid deposit siphoning at the local level.

The remainder of the paper is structured as follows. In Section 2 we outline some stylized facts on the consolidation of the Italian banking industry. In Section 3 we present our empirical methodology, the data and our main results. Section 4 concludes.

2 The consolidation of the Italian banking industry

There is one evident feature of the Italian banking industry consolidation process that has taken place since the beginning of the 1990s: as shown in Table 1, the great majority of active banks involved in the process are typically located in the northern regions of the country, while passive (target) banks are located both in the North and in the South. Mergers and acquisitions dealing with geographically distant markets are particularly interesting because of the significant differences between the degrees of development and the structural characteristics of local economies in the two areas of the country. Between 1990 and 2001 the number of banks headquartered in southern regions reduced by one half, and the ownership of intermediaries representing about two thirds of total activities has changed, mostly in favour of banks located in northern regions (see Panetta, 2003). Given the size of the phenomenon and its policy implications, it is important to assess the determinants and consequences originating from the decisions of northern banks to acquire credit institutions located in the South.

The interplay of real and financial variables in explaining growth and development has been emphasized in the literature (see, for instance, Levine, 1997). We argue that a similar interplay had an important role in shaping the restructuring of the Italian banking industry, characterized by marked differences in the conditions of local (regional) economies, both in terms of real and financial variables. In order to isolate the main differences between regional economies and assess their influence on the banking consolidation process, we identify four classes of variables (see Section 3) aimed at capturing the dynamics and the levels of development of the real economy, the efficiency and the institutional structure of the regional banking industry, and the determinants and consequences of banks' credit policies.

As for the effects of the M&A wave, there are several elements confirming the relevance of the efficiency arguments typically invoked. As documented by Panetta (2003), benefiting from the superior capital and managerial resources of northern banks, target banks in the South have improved their profitability and increased their array of services since 1996. Since the mid-1990s the fraction of savings collected by southern institutions and used to finance local activities has also increased. Moreover, the resources lent in the South by banks headquartered in central-northern regions have been higher than the deposits collected by those banks in the southern regions. In the market for loans, over the same period, the spread in the cost of short-term debt between Center-North and South diminished to 0.9 percentage points — when one accounts for all the size and sectorial differences among borrowers —, reflecting the higher credit risk of southern regions. Furthermore, the increase in the volume of banks' loans, once corrected for the incidence of bad loans, has been similar in the Center-North and in the South since 1990. Finally, in the market for deposits, Focarelli and Panetta (2003) show the beneficial impact of M&As for consumers.

All this evidence strengthens the appeal of a justification based on efficiency gains to the consolidation process of the banking industry. Although efficiency is certainly playing an important role, there is a further point that deserves consideration. As shown in Table 2, the ratio between loans and deposits is higher than 100% in the Center-North, but it is lower than this value in the South. If the table confirms that northern banks lend more than southern banks in the South, it also indicates that northern banks use more resources than they generate (and increasingly so as the ratio has been increasing in the late nineties). Panetta (2003), among others, argues that much of the funds' shortage experienced by northern banks is filled through financial resources coming from foreign banks. Given the volumes involved, this is certainly true. However, the loans-deposits ratio in the South has been (weakly) decreasing over the second half of the 1990s and it can not be excluded that, beside the doubtless advantages of consolidation in terms of efficiency, the M&A wave of the 1990s has induced some sort of deposit drain. It is well possible, as argued by Panetta (2003), that a lower loans-deposits rate in the South with respect to the Center-North reflects structural characteristics of the southern local economies (in terms, for example, of the lower quality of borrowers, the government transfers directed to the area, or the different degree of efficiency of the local justice), but the issue seems to deserve additional investigation.

Bonaccorsi di Patti and Gobbi (2001), for instance, highlight the existence of a reduction — although likely not to be permanent — in the volume of credit to small and medium sized firms following the consolidation of the banking industry. Similarly, Ferri and Inzerillo (2002) document a strengthening of financial constraints suffered by local firms (possibly again of a temporary nature only) — that ensues from the interruption of credit relationships caused by the changes in the ownership structure determined by the concentration of the banking industry — increasing the probability that a firm considers itself as credit rationed. Along the same lines, Focarelli *et al.* (2002) and Sapienza (2002) report a decrease of the volume of credit accruing to small and medium size firms following consolidation. All these contributions do not exclude, and conversely to some extent support, the view that banking consolidation can imply — at least temporarily — some forms of distortions in credit allocation, mitigating the efficiency gains of concentration.[1]

3 The empirical analysis

We now turn to the empirical identification and to the assessment of the role of real and financial variables at the local level in shaping the direction and consequences of the banking industry consolidation process. In order to do so, we need both to identify the sets of variables to be considered in investigating the phenomenon at hands, and to deal with the issues related to the choice of the econometric model to be used in the analysis. As for the latter, our goal is twofold. First we propose to characterize the determinants of the *probability* to observe an active (passive) bank by means of a standard probit model. Second we aim to improve our understanding of the phenomenon by focusing on count data models, that allow us to study the factors affecting the *number* of banks involved (either as an active or passive subject) in a merger or acquisition. In the following we focus on each of the above issues in turn.

The choice of the relevant variables. Consistently with our analysis in the previous section, we identify four groups of variables that are likely to be important determinants of banking industry consolidation: (a) the dynamics of the real economy, (b) the degree of development and efficiency, as well as (c) the institutional structure of the regional banking industry, and (d) the role of banks' credit policies. For all group of variables, we focus on regional data following the Italian Antitrust Authority definitions, as regions constitute the relevant geographic dimension in banking, at least for the loans market.

We denote with $\mathbf{X}$ the vector of all relevant variables, a precise definition of which is introduced in Section 3.1. We further specify year and quarter dummies together with three macro-area dummies (North, Center, South and Islands) to provide a rough control for fixed effects of time and geographical location.

Probit model specification. As noticed above, we first concentrate on the probability to observe an active (AB) — passive (PB) — bank by means of a standard Probit model

$$\Pr(AB_{it} > 0) = \Phi\left[ka_{it}\left(\boldsymbol{\beta}'\mathbf{X}_{it} + \boldsymbol{\gamma}'\mathbf{Y}_{it} + \boldsymbol{\delta}'\mathbf{Q}_{it} + \boldsymbol{\lambda}'\mathbf{R}_{it}\right)\right], \tag{1}$$

where $i = 1, \ldots, 20$ is an index for regions, $t = 1, \ldots, 24$ is an index for quarters, the dependent variable is a dummy variable assuming value one when at least

[1] This perspective would indeed be further reinforced by broadening the scope of the analysis noticing that, even if northern banks use foreign resources to finance their credit needs instead of draining resources from southern regions, the issue of deposit siphoning is far from resolved. Except that now it invests primarily foreign countries' economies and not the South of Italy, and poses a broader policy problem, investing supra-national regulatory authorities. We leave this issue for future research, focusing instead on the Italian banking market.

one active (passive) bank in region i at time t is observed, and zero otherwise, $ka = 2AB - 1$, $\mathbf{X}$ is the vector of territorial determinants and, finally, $\mathbf{Y}$, $\mathbf{Q}$, and $\mathbf{R}$ denote respectively year, quarter, and regional dummies. Estimates of Equation (1), by showing how the probability to observe an active (passive) bank in a given region is affected by the economic variables discussed above, provides a first representation of the macroeconomic determinants of the M&As wave occurred in Italy during the 1990s.

Count data models. As a second step in the empirical specification of the problem, knowing that some regions (for instance, Valle d'Aosta) have not been touched by the M&As process, and that almost all active (passive) banks have been concentrated in a relatively small subset of regions, we further refine our analysis and explore the determinants of the M&As wave by using count data models characterizing the *number* of banks involved in the M&As observed in a given region. The theoretical econometric literature has introduced several classes of count data models that can do the job. Given the presence of overdispersion in our data (described in Section 3.1), we restrict our attention to three such models, that are often used in applications (e.g. Cameron and Trivedi, 1998): the zero inflated Poisson (ZIP) model, the hurdle model and the negative binomial model. In order to choose the best performing one, we compare the three models by means of the Akaike information criterion (AIC), showing that the ZIP model always scores better than the others (as it will be shown in Section 3.2). The Vuong Statistics further confirms the choice of using a model that accounts for overdispersion.

ZIP model specification. Given that we mainly focus on Zero Inflated Poisson models — that is sequential models in which a regime choice model is combined with a count data model — it is worth to discuss their characteristics in some details (for a brief discussion of the hurdle and negative binomial model see the technical Appendix A). The regime choice model splits observations between two alternative groups, one in which the phenomenon is never observed and one in which the outcome is an integer number (ranging from zero to n). Given the choice of the latter regime, the count data model explains the number of occurrences by means of a Poisson distribution. Formally, the zero outcome can be the result of two alternative regimes indexed by z: one in which the outcome is always zero ($z = 0$), and one in which the outcome $AB = 0$ (or $PB = 0$) obtains as a random draw from a Poisson distribution ($z = 1$). In the former case, the outcome zero describes a structural phenomenon; in the latter case, it is a result of the sampling distribution. The probability of regime $z = 0$ to occur is modeled as a standard Probit. Given regime $z = 1$, the probability of $AB_{it} = n$ follows a Poisson distribution with parameter λ. The general model can thus be written as:

$$\Pr[z_{it} = 0] = f(\mathbf{w}, \boldsymbol{\gamma}) \tag{2}$$

$$\Pr[AB_{it} = n > 0 | z_{it} = 1] = \frac{e^{-\lambda_{it}} \lambda_{it}^n}{n!} \tag{3}$$

where the splitting model (Equation 2) is defined by the set of covariates $\mathbf{w}$ and the vector of parameters $\boldsymbol{\gamma}$, while the parameter λ characterizing the Poisson regression (Equation 3) is a linear combination of a vector of regressors $\mathbf{x}$ (including time and macro area fixed effects) and parameters $\boldsymbol{\beta}$ to be estimated. We specify the same set of covariates w and x for the two dependent variables AB and PB, in order to ensure an homogeneous investigation of their economic determinants.

3.1 Data and variables definition

Our dependent variables are defined by means of a dataset built using information on mergers and acquisition in the banking industry published by the Italian Antitrust Authority, and spanning the period 1995-2000. We consider all operations among Italian banks occurred in the sample period, classifying both active and passive banks according to the region they are headquartered in. We exclude from the analysis all intra-group operations. Moreover, since we focus on the regional (local) determinants and effects of banking consolidation, we also neglect all operations involving banks whose activity (before the merger or the acquisition) has a national extent. This last limitation concerns very few operations only (13) over the sample period, and it has no impact on our results, even though it is relevant in terms of intermediated resources.

The dependent variable AB includes all active banks observed in the period under investigation. As for the variable PB, we distinguish three possible cases, including, respectively, all passive banks in the sample (the *whole sample* case), only passive banks that have been acquired by a bank not located in a neighboring region only (the *out-of-market* case), and only passive banks acquired by a bank located in a neighboring region (the *in-market* case). Splitting passive banks in these three sub-samples allows us to better account for the relationships between banks M&As and the characteristics of local economies and, in particular, to better understand the possibly different mechanisms governing acquisitions in contiguous versus distant regional markets. Appendix Table 1 displays the distribution of dependent variables, controlling for geographical location.

The set of covariates $\mathbf{X}$ includes proxy variables for each of the four groups of determinants that have been discussed in the previous section. The list of variables and the corresponding data sources are summarized in Appendix Table 2. As for *real economy indicators*, we consider the level of GDP, that of fixed investments and the growth rate of the total number of firms . The level of *GDP* (in per capita terms) proxies residents' personal wealth. A higher level of GDP per capita is an indicator of a stronger real economy, and this in turn is typically associated with a more efficient and healthy banking industry. Hence, we expect the level of GDP to be positively (negatively) correlated with active (passive) banks.[2] Notice that we loosely refer to "banks", and not to either the probability or the number of banks (as it should be when distinguishing between Probit and ZIP models), since our goal here is just to assess the expected impact of each determinant based on economic intuition. Hence, by expecting a positive correlation between active (passive) "banks" and a variable x, we mean that: 1) the probability to observe at least one active (passive) bank is increasing with x; 2) the probability to observe regime $z = 1$ is increasing with x (or, which is the same, the probability to observe regime $z = 0$ is decreasing with x); 3) the number of active (passive) banks is increasing with x.

The level of per capita fixed investments INV is an indicator of the growth rate of the real sector of the economy, and can be taken as a proxy for the demand of financial resources inside each region. It is thus expected to be positively (negatively) correlated with active (passive) banks. An alternative measure of the real growth rate of the economy is defined by the growth rate of the number of firms ($FIRMS$). Similarly to INV, also $FIRMS$ influences the demand of financial capital within each region. Hence, we expect the growth rate of the number of firms to be positively (negatively) correlated with active (passive) banks. As different economic sectors show different degrees of correlation with the business cycle, we further decompose $FIRMS$ into four components, namely $MANIF$, $BUILD$, $COMM$, and $SERV$, illustrating the growth rate in the number of firms in the manifacturing, construction, commerce and services sectors of the economy, respectively. Moreover, we also test for the possible impact of different firms ownership structures, decomposing $FIRMS$ into individual firms ($INDIV$), stock companies ($STOCK$) and partnerships ($PARTN$).

We consider the percentage of bad loans out of total loans (the variable BAD) as a measure of the *efficiency of credit policies* at the local level. The higher the efficiency in discriminating among potential borrowers, the lower the percentage of bad loans. We then expect BAD to be negatively (positively) linked with active (passive) banks. One can further argue that what matters for the decision to acquire a bank is not the stock of bad loans, but the flow of *new* bad loans. To check this point, we thus consider the growth rate of the share of bad loans out of total loans ($dBAD$) as well.

In order to assess the *degree of development* of the banking sector, as well as the *impact of credit policies* on the process of M&As, we define the variable $DIFF$, that measures the difference between loans and deposits within a region in per capita terms. Clearly, when $DIFF > 0$, regional banks are not able to raise enough funds through deposits to fulfill the demand of loans by local

[2] In order to further proxy residents' personal wealth, we also retrieved data on the volume of financial assets managed by banks on behalf of their clients. However, as these data are available at the regional level only starting from 1998 (third quarter), we obtain only imprecise estimates of the parameters, inducing us to drop them from the empirical analysis.

entrepreneurs. Hence, they need to collect funds outside their region. Among other options, acquiring a bank located in a region where the demand for loans is lower, or savings allocated to deposits are higher, might be an appealing strategy. On the contrary, when $DIFF < 0$, regional banks raise funds in excess of loans, that can be reallocated through the interbank market or the investment in other financial assets. We expect, therefore, active banks to be positively correlated with $DIFF$, while we do not have a clear *a priori* on the correlation between $DIFF$ and passive banks. On the one hand, a negative correlation might suggests the weaknesses of the local economy in which target banks are operating; on the other hand, a positive correlation signals the existence of potential gains accruing from the restructuring of credit policies. In this respect, to further evaluate the role of credit policies, we split the variable $DIFF$ in its components, namely loans ($LOANS$) and deposits (DEP) measured in per capita terms.

As for the *efficiency of the regional banking industries*, we consider different proxy measures commonly adopted in the (applied) industrial organization literature. A first variable we use is $HERF$, a Herfindhal index defined on the number of bank branches. As is well known, the Herfindhal index is usually considered by Antitrust Authorities as providing information on the level of competition in a market. In particular, a higher value of $HERF$ is a signal of market concentration, hence of a lower level of aggregate efficiency. We expect $HERF$ — interpreted as an efficiency indicator — to be negatively (positively) correlated with active (passive) banks, as a lower level of efficiency is typically associated with a lower level of profits. We also experiment with three other standard and interconnected measures of market power, which we label $SPREAD$, $MKUP$, and $MKDWN$. $SPREAD$ is defined as the difference between the average market rate on loans and the average market rate on deposits. $MKUP$ is the difference between the average market rate applied on loans and a risk free rate (the average monthly market rate on the Italian government bonds, or *Buoni Ordinari del Tesoro*). Finally, $MKDWN$ is defined as the difference between the risk free rate and the average market rate applied on deposits. Quite obviously, the higher the level of competition in a given market, the lower the level of these three variables should be. Hence, as for $HERF$, we expect $SPREAD$, $MKUP$, and $MKDWN$ to be negatively (positively) correlated with active (passive) banks.

Finally, the *institutional structure of local banking markets* is proxied by the weight of different categories of banks in the regional industry, in terms of their ownership structure and of the extent of their relevant markets. First, we look at the share of bank branches owned by cooperative institutions (the so called *Banche di Credito Cooperativo*), by defining the variable $COOP$. These banks, often located in rural areas, provide funds especially to small firms (e.g. Angelini *et al.*, 1998), and are characterized by peculiar institutional features constraining the probability that they can become involved in a merger or acquisition. Hence, we expect $COOP$ to be negatively related with both active and passive banks. Second, by focusing on market size, we consider the share of regional branches owned by different categories of banks defined with respect to the geographical extension of their activity. In particular, using the classification adopted by the Bank of Italy, we let the variables LOC and REG denote the percentage of regional branches owned by banks with a local and a regional network, respectively. We expect the first to be more likely targets of a typical M&A operation, and hence we expect LOC to be negatively (positively) associated with active (passive) banks. Conversely, we expect regional banks to play an active role in a typical M&A operation, and therefore REG to be positively (negatively) associated with active (passive) banks.

3.2 Results

Estimates of the Probit model (1) are shown in Tables 3 to 6.[3] In general, the models on active banks are better identified than those on passive banks. This implies that the characteristics of the local economy are more important in explaining the presence of active banks, and less so in explaining that of passive banks in a given region and time. As can be easily seen in Table 3, collecting the results of the Probit model for active banks, the probability to observe an active bank in a typical M&A operation is increasing in the level of GDP, competition and efficiency of regional banking markets ($SPREAD$ and $HERF$), and — although less strongly — in the strength of the real economy ($FIRMS$), that in turn generates a stronger demand for loans with respect to the ability to generate deposits ($DIFF$, $LOANS$ and DEP). All the coefficients associated to these variables show the expected sign and are statistically significant at the usual confidence levels. Only the coefficient on INV, contrary to basic intuition, shows a statistically significant negative sign, most likely due to multicollinearity problems with other regressors. In terms of the ownership structure and sectors of activity of firms, the presence of stock companies ($STOCK$) and of firms belonging to the construction sector ($BUILD$) positively affects the probability to observe active banks. The structural characteristics of local banking markets (in particular the presence of different banks in terms of proprietary structure and of territorial extension of their network) matter in the process of M&As, with cooperative ($COOP$) and local (LOC) banks reducing the probability to observe active banks and regional (REG) banks increasing it. Since the coefficient on the volume of bad loans (BAD) is never statistically significant, there are no clear effects on the probability to observe an active bank stemming from the efficiency of credit policies at regional level. The flow of new bad loans ($dBAD$) has a negative impact — though not statistically significant — on the probability to observe an active bank in almost all regressions. Year and area fixed effects are

[3] All tables are constructed by first considering a baseline model (our best specification) in col. I, embedding the key regressors. Additional columns provide robustness checks of our best specification.

almost always statistically significant; on the contrary, in most cases quarter fixed effects are not significant.

One possible criticism to the above results is that the typical M&A operation requires a long process, starting with the managerial decision to acquire (or to merge with) another institution and ending with the decision of the Bank of Italy to authorize the proposed operation.[4] This decision comes usually several months after the submission of the request of authorization. Since our dependent variables count active and passive banks in the instant in which a request for authorization is submitted to the Bank of Italy, considering the effect of territorial determinants *contemporaneous* to the request — and not to the actual decision — can be misleading. To overcome this difficulty, we rerun our baseline model by lagging all the regressors one year. All results continue to hold when considering lagged regressors (as shown in Table 3).[5]

Estimates of the Probit model for passive banks are collected in Tables 4-6, reporting estimates based on the whole sample as well as on the two sub-samples focusing specifically on *in-market* and *out-of-market* M&As. Our empirical models show, in fact, that there are significant differences in the regressors affecting the probability to observe a target bank of a M&A (in a given region and time) depending on the specific sample considered. This consideration also suggests that results based on the whole sample should be taken with care, since two different processes are contemporaneously at work. Only the coefficient of credit policies ($DIFF$) is positive and statistically significant both for the whole sample and the two sub-samples. However, decomposing it, the coefficient on $LOANS$ is positive and significant for the whole sample and the in-market case, while the coefficient on deposits (DEP) is negative and significant for the in-market subsample only. Furthermore, limited to the whole sample and the out-of-market case, the probability to observe a passive bank increases the lower the GDP and the level of investments (INV), and the lower the concentration of the banking industry at the regional level ($HERF$). On the other hand, the spread between market rates ($SPREAD$, $MKUP$ and $MKDWN$) — again an indicator of the competitivness of the local banking industry — matter in the whole sample and the in-market cases. Summarizing the above findings, there are clear overall indications that both efficiency and competitivness of local banking markets impact on the probability to observe target banks in a given region and time. Similarly, the structural characteristics of local banking markets matter both for the whole sample — the coefficient on local (LOC) banks is negative and statistically significant — and for the in-market case — the coefficient on cooperative banks

[4]In Italy, contrary to other industrialized countries, the Central Bank is responsible for guaranteeing an adequate level of competition in the banking industry, while the Antitrust Authority is only responsible for providing advice to the Bank of Italy on the consequences of the proposed M&A operation.

[5]The choice of using regressors lagged one year is obviously quite arbitrary. Experimenting with different time lags has, however, shown that our main conclusions remain unaffected.

($COOP$) is positive and significant. The volume of bad loans (BAD) is often significant and with the expected sign for the two sub-samples, but not for the whole sample, while the flow of new bad loans ($dBAD$) matters in the in-market case only. Our main results are again confirmed by lagging one year all regressors.

As discussed above, Probit models study how the probability to observe an active (passive) bank is correlated with a set of variables. However, as the phenomenon we study is highly concentrated in a subset of regions (Table 1), it is worth to further investigate the relationship between the regressors and the number of banks by using count data models. Such models (see Cameron and Trivedi, 1998, for an extensive discussion) require to divide the set of regressors between those that play a role as determinants of a given regime and those that account for the number of active (passive) banks observed given the regime. A natural strategy to do so is to assume that the regime choice component of the model is affected by the characteristics of the real sector of local economies, for the absence (or presence) of active (passive) banks in a given region is likely to be related to the "macroeconomic" characteristics of that region.[6] Furthermore, this specification strategy turns out to be fully consistent with a more "agnostic" view (i.e. not based on *a priori* conjectures) aimed at determining empirically the best model specification by experimenting with different combinations of variables in each subset of covariates as determinants of regime choice, and using the remaining (groups of) regressors to investigate the number of active (passive) banks given the regime.

Finally, in order to select among the three different types of count data models (ZIP, negative binomial and Hurdle-Poisson) typically considered, we estimate our baseline model for all of them, comparing empirically their relative performance by means of the Akaike information criterion. The result of such comparaison — reported in Table 7 for active banks and in Table 8 for passive banks — indicate the use of ZIP models as the most adequate choice given our sample.

Estimates of the ZIP model for active banks are reported in Table 9, and confirm overall the main findings obtained with Probit models. All the real economy indicators included in the regime choice part of the ZIP models matter in explaining that active banks can be observed in a given region and time. On the one hand, the probability to observe regime $z = 0$ (i.e. a regime where the phenomenon is never observed) is negatively correlated with GDP, INV, and $FIRMS$, indicating — as expected — that active banks should be observed in richer regions. On the other hand, given regime $z = 1$ (i.e. one in which the

[6]One might argue that also the conditions of local banking markets (and especially the dynamics of loans and deposits) should be taken as explanatory variables of the regime choice. However, the count-data models we consider turn out to be better specified including these variables as regressors explaining the number of active - passive - banks observed given the regime choice. In any case, according to our estimates, the role played by credit policy indicators in explaining the number of banks is fully consistent with the role that the same variables have in explaining regime choice.

phenomenon can be observed), the number of banks is negatively affected by the efficiency of local banking markets ($SPREAD$ and $MKUP$), and (although marginally insignificant at the usual confidence levels) by the degree of concentration ($HERF$). Credit policies ($DIFF$) and in particular the loans component ($LOANS$) have a positive impact on the number of active banks in almost all our models. The structural characteristics of local banking markets do not matter in explaining the number of banks except for a positive impact of the number of regional banks (REG) operating in the market.

Tables 10-12 show estimates of the ZIP model for passive banks. The choice of regime $z = 0$ (i.e. a regime where passive banks are never observed) is not captured by our models when focusing on the whole sample and on the in-market sub-sample, while it is positively affected by the level of GDP, and the dynamics of the local real economy (INV) for the out-of-market sub-sample. As for the Probit models, the bad performance of our models in identifying the determinants of regime choice, besides reflecting the existence of possible misspecification problems, is to be expected, at least to some extent, as economic intuition suggests the expected signs of the regressors to be often opposite for the in-market and the out-of-market sub-samples. This may explain the lack of statistical significance of the coefficients when the whole sample is considered.

Given regime $z = 1$, the number of banks is affected both for whole sample and the two sub-samples only by the efficiency of credit policies at the local level (BAD): positively for the whole sample and the out-of-market sub-sample, and negatively for the in-market case. The degree of concentration and competitiveness of the banking industry at the regional level is important for the in-market sub-sample and for the whole sample, as the coefficients associated to $HERF$ and $SPREAD$ are statistically significant. Splitting the latter into its components, however, $MKDWN$ plays a role for the in-market sub-sample, while $MKUP$ does for the whole sample. Similarly, credit policies ($DIFF$) — and in particular $LOANS$ — are statistically significant in explaining the number of passive banks both for the entire sample and for the in-market sub-sample.[7] Finally, we detect no effects of the structural characteristics of local banking markets, both on the regime choice and on the number of banks.

Summing up, the above analysis highlights three main findings. First, it confirms the relevance of the interplay between real and financial variables as a major driving force behind the consolidation process of the Italian banking industry. Real variables, like the GDP or the level of real investments, have a strong explanatory power in assessing the probability to observe both active and passive banks at the regional level. This finding is consistent with a growing body of literature (e.g. Levine, 1997, for a survey) that stresses the relationship between growth and the characteristics of the financial sector, adding to it the emphasis on the characteristics and the degree of development of local economies

[7] The volume of deposits (DEP) has a negative impact for the in-market sub-sample only.

(as in Guiso *et al.*, 2002).

Second, market structure indicators (like the degree of concentration of the banking industry — as measured by the Herfindhal index — and its efficiency — as measured by the spread between market rates —, or the role of different forms of ownership) seem to matter for acquisition policies: less concentrated local banking industries, being associated to a higher level of efficiency and to less "stable" market shares, are more favorable environments to observe active banks, an effect most likely stemming from the higher level of competition.

Third, active banks are mainly located in regions where raised funds are not sufficient to satisfy the financial needs of the local economy, so that the latter needs financial resources in excess to those that the local financial system is able to generate. Although this does not exclude that banks can raise funds in alternative ways (for example through international borrowing — as stressed by Panetta, 2003 —, international M&As, interbank and bond markets borrowing), it might also indicate the possible relevance of deposit siphoning practices driven by differentials in the profitability of deposit-taking activities and lending opportunities between different areas of a country. In principle, the reallocation of deposits between regions within a country characterized by high differentials in terms of economic conditions should improve efficiency, by equalizing the marginal cost of funds across regions (in this sense, Faini *et al.*, 1993). However, when the possibility of deposit siphoning determines credit rationing in the region where the target bank is located, the reallocation of deposits might undermine the growth potential of that region.

3.3 Explaining the growth rate of loans

To further explore the hypothesis of deposit siphoning, we propose a first tentative analysis to understand if and how the M&As process could affect the growth rate of loans at the regional level. Given that our results show that M&As are strongly characterized at the regional level, we first consider a model in which the growth rate of loans is explained by regional fixed effects only. As can be seen from the results in Table 13 (col. I), this model explains 61% of the dependent variable's total variability. Second, we look for economic variables that account for the information captured by regional fixed effects, trying — at least — to replicate the same level of explained variability. As can be seen from the regressions in Table 13 (col. II and III), where we substitute regional fixed effects with area fixed effects, GDP growth and the rate of growth of bad loans are two such candidates. Overall, the results we obtain show that the economic variables that are important in explaining the growth rate of loans at the regional level are the (growth rate of the) percentage of bad loans out of total loans ($dBAD$) — that has a negative effect — and the amount of fixed investments (INV), as well as the degree of competition and efficiency of local banking markets ($MKUP$) — that have a positive effect. There are no statistically significant effects originating from the structural characteristics of local banking markets ($COOP$ or REG).

Third, to understand the role played by M&As waves, if any, we add to all our specifications the variables AB and PB measuring the number of active and passive banks. In doing so, we detect a strong positive effect of the number of active banks on the rate of growth of loans. Conversely, the presence of passive banks in the process of consolidation (that have been acquired by banks in not-neighboring regions) seem to exert a negative effect that, however, is not statistically significant at the usual confidence levels.

All our results are consistent with the view that the consolidation process is beneficial, since it induces an increase in the overall efficiency of the banking industry and thus improves social welfare (as shown by Focarelli and Panetta, 2003). Nonetheless, the link between loans and active banks suggests a possible consequence of the consolidation processes pointing in the opposite direction, that is often not stressed in the policy debate. Namely, active banks can be interested in reallocating deposits from the local markets of target banks (i.e. the southern regions in our case) to their home markets, in order to employ them more efficiently where the average quality of borrowers is typically higher. This raises the question whether such operations might conceal a geographic savings reallocation process in which southern regions act passively as a market to raise deposits to be lent in more economically sound regions. This does not need to be necessarily negative *per se*. As far as underdeveloped areas have less profitable investment opportunities, a credit policy aimed at improving efficiency should operate a reallocation of savings from weak regions to more developed ones. This would help rationalizing credit policies in the South, with a consequential positive impact on the local economy. However, the consolidation of the banking system, that caused several banks operating in local markets to disappear, might have implied a "de-localization" of banking.[8] As documented in the literature focusing on the Italian case (see e.g. Bonaccorsi di Patti and Gobbi, 2001, Sapienza, 2002, and Focarelli *et al.*, 2002), although generating an improvement in credit policies, the interruption or the weakening of credit relationships could be responsible — at least temporarily — for a strengthening of financial constraints for local firms, especially the smaller ones, more dependent on the conditions of the local banking industry.[9]

The evidence we provide does not permit to conclude whether there have been cases in which the negative consequences of potential deposit siphoning practices

[8] For instance, according to Bank of Italy data, between 1990 and 2001, the number of banks headquartered in the South decreased from 100 to 48. Out of these 48 banks, 26 were owned by credit institutions located in the central-northern regions of the country.

[9] While in the U.S. the legislator took care (to some extent) of these problems already in the late Seventies of the past century with the Community Reinvestment Act, less attention has been devoted to them in evaluating the banking consolidation process in European countries and particularly in Italy, where authorities have focused primarily on the overall stability of the banking industry.

have been dominating the efficiency gains associated to the restructuring of the banking industry. It is, however, sufficient to illustrate the existence of a potential trade-off between the beneficial increase in efficiency associated to the banking consolidation process and its possible negative impact — in terms of deposit siphoning practices and credit rationing — especially for small firms, that is often overlooked in the policy debate.

4 Concluding remarks

In this paper we use probit and count data (ZIP) models to study the consolidation process of the Italian banking industry. We show that local economic conditions played a relevant role in shaping and explaining the number of mergers and acquisitions that have been observed since the early Nineties of the last century.

Our analysis highlights three main issues. First, the links between real and financial variables play an important role as driving forces behind the consolidation process of the Italian banking industry, suggesting the existence of a relationship between growth and the characteristics of the financial sector of the economy. Second, the degree of market concentration is important in explaining the relative position of local banks in the consolidation process, with more competitive local markets rendering more likely the presence of active banks. Third, insufficient financial resources at the local level seem to affect the probability that a bank decides to play an active role in the consolidation process by acquiring or merging with other credit institutions (typically rich in deposits), possibly to raise (at least part of) the funds it needs.

Although the last claim is consistent with a variety of alternative explanations and is often and convincingly motivated in terms of efficiency gains, in the last part of the paper we investigate whether banks acquisition strategies might conceal the existence of deposit siphoning practices, inducing credit rationing and eventually undermining growth possibilities at the local level. Our analysis on this point is still preliminary, but it is aimed to highlight the potential importance of a trade-off between the (sure) benefits of banking consolidation in terms of efficiency and its (possible) costs in terms of credit rationing. Such trade-off, that remains often overlooked especially when considered in an international perspective, raises important policy issues and is related to more general problems such as the design and the duties of regulatory institutions .

References

Angelini P., R. Di Salvo and G. Ferri (1998), Availability and cost of credit for small businesses: Customer relationships and credit cooperatives. *Journal of Banking and Finance*, 22, 925-954.

Berger A. N., R.S. Demsetz and P.E. Strahan (1999), The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future. *Journal of Banking and Finance*, vol. 23, pp. 135-194.

Bonaccorsi di Patti E. and G. Gobbi (2001), The Changing structure of Local Credit Markets: Are Small Businesses Special? *Journal of Banking and Finance*, vol. 25, pp. 2209-2237.

Cameron A. C. and P.K. Trivedi (1998), *Regression Analysis of Count Data*. Econometric Society Monographs n. 30, Cambridge (UK): Cambridge University Press.

De Haas R.T.A. and I.P.P. van Lelyveld (2002), Foreign Bank Penetration and Private Sector Credit in Central and Eastern Europe. *DNB Staff Reports*, n. 91.

Faini R., G. Galli and C. Giannini (1993), Finance and development: the case of Southern Italy, in Giovannini A. (ed.), *Finance and Development: Issues and Experience*. Cambridge: Cambridge University Press.

Ferri G. and U. Inzerillo (eds). (2002), Finanza e internazionalizzazione delle PMI meridionali: primi risultati di un'indagine su un campione di imprese manifatturiere. *Centro Studi Confindustria - Comitato centrale per il Mezzogiorno*, n. 42.

Focarelli D. and F. Panetta (2003), Are Mergers Beneficial to Consumers? Evidence from the Market for Bank Deposits. *American Economic Review*, 93(4), pp. 1152-1172.

Focarelli D., F. Panetta and C. Salleo (2002), Why do banks merge? *Journal of Money, Credit, and Banking*, vol. 34(4), pp. 1047-66.

Greene W.H. (1997). *Econometric Analysis*. Upper Saddle River (NJ): Prentice Hall.

Gros D. (2003), Who needs foreign banks. *CESifo Working Paper*, n. 998.

Guiso L., P. Sapienza and L. Zingales (2002), Does Local Financial Development Matter? *mimeo*, Northwestern University.

Levine R. (1997), Financial Development and Economic Growth: Views and Agenda. *Journal of Economic Literature*, vol. 35(2), pp. 688-726.

Panetta F. (2003), Evoluzione del sistema bancario e finanziamento dell'economia nel Mezzogiorno. *Moneta e Credito*, LVI, 222, Roma, BNL.

Sapienza P. (2002), The Effects of Banking Mergers on Loan Contracts. *Journal of Finance*, vol. 57(1), pp. 329-367.

A Technical Appendix

Consider a random variable $Y = y_i$ measuring the number of banks, that takes on non-negative values only. Assuming that $Y \sim Poisson\,(\mu)$ implies that $E(Y) = Var(Y) = \mu$. The high occurrence of the zero outcome in a sample indicates that $E(Y) \neq Var(Y)$, signalling the presence of overdispersion. There are different ways to deal with such overdispersion. One possibility is to use a mixed Poisson distribution such that $Y \sim Poisson\,(\mu V)$, where V is a random variable (e.g. following the negative binomial distribution, NB). In this way, $E(Y) = \mu$ and $Var(Y) = \mu + \alpha\mu^2$, with α denoting the overdispersion parameter. Other possibilities are to assume that there are two random processes at work, one that generates the zero outcome only (i.e. a process for "structural" zeros), and the other that generates the positive counts. An "hurdle" Poisson (HP) model — in the case positive counts are modeled using a truncated Poisson distribution — is one in which

$$\Pr\left(Y=y_i\right)=\begin{cases}\pi_0 & y=0\\ \frac{(1-\pi_0)e^{-\lambda}\lambda^y}{\left(1-e^{-\lambda}\right)y!} & y>0\end{cases}$$

Note that — by using a simple Probit model — only "structural" zero outcomes are originated with probability π_0.

When the zero outcome can be originated also as a random draw from a Poisson distribution we have a Zero Inflated Poisson (ZIP) model in which

$$\Pr\left(Y=y_i\right)=\begin{cases}\omega+(1-\omega)\,e^{-\lambda} & y=0\\ (1-\omega)\,\frac{e^{-\lambda}\lambda^y}{y!} & y>0\end{cases}$$

Note that in this case, differently from the HP model, "structural" zero outcomes are originated with probability ω, while "sampling" zero outcomes follow a Poisson distribution. Clearly, when $\omega+(1-\omega)\,e^{-\lambda}=\pi_0$, ZIP and HP models provide the same results.

Table 1. Mergers and acquisitions by region (1990-2000)

		Active Bank																			
	REGION	Piemonte	Lombardia	Trentino	Friuli-VG	Veneto	Liguria	Emilia	Toscana	Umbria	Marche	Abruzzo	Molise	Lazio	Campania	Puglia	Basilicata	Calabria	Sicilia	Sardegna	Total
Passive Bank	Piemonte	2	5	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
	Lombardia	1	16	0	0	5	0	3	1	0	0	0	0	0	0	0	0	0	0	0	26
	Trentino	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
	Friuli-VG	0	0	0	0	9	0	2	0	0	0	0	0	0	0	0	0	0	0	0	11
	Veneto	1	1	0	0	15	1	2	0	0	0	0	0	0	0	0	0	0	0	0	20
	Liguria	0	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	Emilia	0	5	0	0	3	1	9	1	0	0	0	0	0	0	0	0	0	0	0	19
	Toscana	0	4	0	0	1	1	0	3	0	0	0	0	0	0	0	0	0	0	0	9
	Umbria	1	2	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	7
	Marche	0	1	0	0	0	0	1	0	0	5	0	0	0	0	0	0	0	0	0	7
	Abruzzo	0	3	0	0	0	0	4	0	0	0	0	0	0	0	0	1	0	0	0	8
	Molise	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	3
	Lazio	0	5	0	0	1	0	2	1	0	1	0	0	0	0	0	0	0	0	0	10
	Campania	1	5	0	0	1	0	6	0	0	0	0	0	1	0	0	0	0	0	0	14
	Puglia	1	2	0	0	2	1	5	1	0	0	0	0	0	0	4	0	0	0	0	16
	Basilicata	0	0	0	0	0	0	5	0	0	0	0	0	1	0	0	0	0	0	0	6
	Calabria	0	1	0	0	2	1	7	0	0	0	0	0	0	0	0	0	0	0	0	11
	Sicilia	1	10	0	0	4	3	6	1	0	0	0	0	1	0	0	0	0	2	0	28
	Sardegna	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	3
	Total	8	65	1	0	48	9	54	9	1	6	0	0	4	0	4	1	0	2	2	214

Note: excluded all operations involving banks whose activity (before M&A) had a national extent; excluded all intragroup operations.

Table 2. Ratio between loans in a given area and collected funds in the same area (%)

Geographical area	1998	1999	2000	2001	2002	Average
Northern-Centre Regions	100,1	107,6	118,7	120,1	116,9	112,7
Southern Regions	82,1	86,2	87,6	83,4	83,1	84,5
of which:						
Banks headquartered in the North-Centre	*93,4*	*96,4*	*94*	*89,2*	*88*	*92,2*
Banks headquartered in the South	*68,8*	*66,3*	*62,6*	*54,9*	*57*	*61,9*

Source: Bank of Italy Annual Report 2002, Tab. E22. Collected funds include both deposits and bonds.

Table 3. Probit models: active banks

	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII (a)
GDP	0.08**	0.06*	0.08***	0.16***	0.09**	0.07**	0.18***	0.14***	0.16***	0.11***	0.08***	0.17***
	(2.539)	(1.724)	(2.621)	(3.863)	(2.505)	(2.308)	(3.996)	(3.849)	(4.143)	(4.621)	(2.715)	(3.700)
INV							-0.30***					
							(-3.040)					
FIRMS	0.03*			0.03*	0.03*	0.03*	0.03*	0.03*	0.03*	0.02*	0.03*	-0.04
	(1.826)			(1.680)	(1.830)	(1.777)	(1.816)	(1.744)	(1.673)	(1.666)	(1.825)	(-1.153)
STOCK			5.16***									
			(2.946)									
PARTN			0.13									
			(1.525)									
INDIV			0.02									
			(0.732)									
OTHER			0.01									
			(0.327)									
MANIF		-1.23										
		(-0.888)										
BUILD		3.76**										
		(2.043)										
COMM		-0.27										
		(-0.277)										
SERV		-0.77										
		(-1.391)										
HERF	-1.52	-1.80	-1.60	-1.95	-1.33	0.39	-2.26	-6.69***	-6.43***	-4.71**		-4.72**
	(-0.866)	(-0.992)	(-0.917)	(-1.004)	(-0.728)	(0.211)	(-1.131)	(-2.710)	(-2.631)	(-2.511)		(-1.999)
SPREAD	-0.95***	-0.88***	-0.95***	-1.13***	-0.96***	-1.03***	-0.76***	-0.59***	-0.45**		-0.98***	-0.86***
	(-5.137)	(-4.879)	(-4.996)	(-5.504)	(-5.219)	(-4.794)	(-3.971)	(-2.615)	(-1.927)		(-5.461)	(-2.983)
BAD					0.02							
					(0.549)							
dBAD						-0.83						
						(-0.659)						
DIFF	0.06***	0.07***	0.05***		0.06***	0.06***	0.04***	0.04*	0.03	0.04***	0.06***	0.05**
	(3.977)	(4.267)	(2.836)		(3.972)	(3.222)	(2.813)	(1.950)	(1.414)	(3.185)	(4.115)	(2.118)
LOANS				0.08***								
				(4.685)								
DEP				-0.24***								
				(-3.953)								
COOP								-0.04***				-0.39***
								(-3.494)				(-2.784)
LOC									-0.33***			
									(-3.531)			
REG								0.03***	0.03**			0.03**
								(3.075)	(2.550)			(2.405)
Constant	0.87	0.21	1.86	1.42	0.44	0.85	-1.70	-3.37*	-4.62**	-4.61***	0.76	-2.66
	(0.547)	(0.131)	(1.072)	(0.781)	(0.249)	(0.475)	(-0.968)	(-1.651)	(-2.147)	(-4.535)	(0.488)	(-1.036)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	480	480	480	480	400	480	400	400	480	480	320
Time period	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	97(1) - 00(4)
Pseudo R-sq.	0.62	0.62	0.96	0.65	0.62	0.63	0.63	0.67	0.66	0.54	0.63	0.70
Model Chi-sq.	149.40	154.14	162.45	159.74	149.70	130.92	159.30	157.73	160.81	115.64	148.57	134.76
[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log-L	-144.76	-142.39	-138.23	-139.59	-144.61	-115.30	-139.81	-101.89	-100.36	-161.64	-145.17	-77.87

MLE; asymptotic t-ratios in parentheses

(a) All variables lagged 1 yr.

Table 4. Probit models: passive banks (whole sample)

	I	II	III	IV	V	VI	VII	VIII (a)
GDP	-0.07**	-0.09***	-0.07**	-0.07**	-0.03	-0.06*	-0.05	-0.06*
	(-2.419)	(-3.164)	(-2.439)	(-2.172)	(-0.697)	(-1.704)	(-1.490)	(-1.904)
INV					-0.14*			
					(-1.739)			
FIRMS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-0.01
	(1.086)	(0.993)	(0.968)	(1.094)	(1.132)	(0.987)	(0.959)	(-0.909)
HERF	-5.52***	-5.06***	-5.50***	-5.45***	-6.04***	-6.46***	-6.55***	-5.30***
	(-3.310)	(-2.758)	(-3.300)	(-3.264)	(-3.401)	(-2.982)	(-3.073)	(-2.969)
SPREAD	-0.28**	-0.32**		-0.27**	-0.18	-0.25*	-0.20	-0.30**
	(-2.502)	(-2.364)		(-2.269)	(-1.481)	(-1.769)	(-1.363)	(-2.426)
MKUP			-0.26**					
			(-2.215)					
MKDWN			-0.39*					
			(-1.712)					
BAD	0.02		0.02	0.02	0.01	0.02	0.02	0.03
	(0.837)		(0.682)	(0.862)	(0.517)	(0.742)	(0.632)	(1.115)
dBAD		-1.13						
		(-1.316)						
DIFF	0.04***	0.05***	0.04***		0.03**	0.04**	0.03*	0.04***
	(2.891)	(3.080)	(2.935)		(2.109)	(2.207)	(1.941)	(2.854)
LOANS				0.04***				
				(2.657)				
DEP				-0.02				
				(-0.451)				
COOP						-0.01		
						(-1.616)		
LOC							-0.01**	
							(-2.022)	
REG						0.01	0.004	
						(0.774)	(0.641)	
Constant	3.62**	5.05***	4.11**	3.51**	2.67*	3.41**	2.99*	3.47**
	(2.540)	(3.181)	(2.452)	(2.413)	(1.754)	(1.972)	(1.689)	(2.179)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	400	480	480	480	400	400	400
Time period	95(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Pseudo R-sq.	0.48	0.49	0.48	0.48	0.49	0.49	0.49	0.48
Model Chi-sq.	67.48	58.09	67.79	67.61	70.61	60.63	62.46	57.58
[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log-L	-235.08	-190.23	-234.92	-235.01	-233.51	-188.96	-188.04	-190.21

MLE; asymptotic t-ratios in parentheses

(a) All variables lagged 1 yr.

Table 5. Probit models: passive banks (in market)

	I	II	III	IV	V	VI	VII	VIII (a)
GDP	-0.04	-0.05	-0.04	0.004	0.001	0.04	-0.02	-0.01
	(-1.113)	(-1.362)	(-1.078)	(0.082)	(0.017)	(-0.803)	(-0.525)	(-0.309)
INV					-0.14			
					(-1.385)			
FIRMS	0.02	0.02	0.01	0.02	0.02	0.02	0.02	-0.02
	(1.416)	(1.470)	(0.901)	(1.389)	(1.446)	(1.447)	(1.431)	(-1.219)
HERF	-3.53*	-1.27	-3.17	-4.15*	-3.99*	-4.41	-4.63	-2.27
	(-1.687)	(-0.497)	(-1.540)	(-1.867)	(-1.827)	(-1.467)	(-1.535)	(-1.033)
SPREAD	-0.78***	-0.87***		-0.86***	-0.65***	-0.66**	-0.55**	-0.73***
	(-4.056)	(-3.729)		(-4.238)	(-3.078)	(-2.518)	(-2.031)	(-3.552)
MKUP			-0.70***					
			(-3.523)					
MKDWN			-1.37***					
			(-3.617)					
BAD	-0.05		-0.06*	-0.06	-0.07*	-0.07	-0.07	-0.005
	(-1.355)		(-1.718)	(-1.499)	(-1.685)	(-1.517)	(-1.629)	(-0.117)
dBAD		-2.59**						
		(-2.170)						
DIFF	0.05***	0.07***	0.05***		0.04**	0.04**	0.04*	0.04**
	(2.994)	(3.435)	(3.287)		(2.187)	(2.144)	(1.713)	(2.516)
LOANS				0.06***				
				(3.329)				
DEP				-0.15**				
				(-2.395)				
COOP						-0.02*		
						(-1.833)		
LOC							-0.02**	
							(-2.158)	
REG						0.01	0.003	
						(0.515)	(0.221)	
Constant	5.03**	5.60**	7.43***	5.72***	4.05*	4.91*	4.09	3.46
	(2.508)	(2.441)	(3.063)	(2.724)	(1.909)	(1.945)	(1.583)	(1.613)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	400	480	480	480	400	400	400
Time period	95(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Pseudo R-sq.	0.56	0.60	0.58	0.58	0.56	0.58	0.58	0.53
Model Chi-sq.	92.78	86.10	96.36	95.74	94.76	86.97	89.14	76.03
[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log-L	-134.46	-103.72	-132.67	-132.98	-133.47	-103.29	-102.20	-108.63

MLE; asymptotic t-ratios in parentheses

(a) All variables lagged 1 yr.

Table 6. Probit models: passive banks (out of market)

	I	II	III	IV	V	VI	VII	VIII (a)
GDP	-0.13***	-0.17***	-0.13***	-0.18***	-0.05	-0.13**	-0.13**	-0.16***
	(-2.808)	(-3.307)	(-2.794)	(-3.132)	(-0.843)	(-2.347)	(-2.372)	(-2.786)
INV					-0.38**			
					(-2.397)			
FIRMS	0.003	-0.0001	0.003	0.003	0.01	-0.001	-0.001	-0.004
	(0.171)	(-0.004)	(0.165)	(0.138)	(0.274)	(-0.068)	(-0.73)	(-0.196)
HERF	-3.39*	-3.93*	-3.39*	-3.12	-3.21	-2.67	-2.67	-4.32*
	(-1.643)	(-1.684)	(-1.642)	(-1.521)	(-1.426)	(-0.976)	(-0.993)	(-1.668)
SPREAD	0.01	0.07		0.10	0.18	0.07	0.08	0.02
	(0.095)	(0.426)		(0.689)	(1.134)	(0.406)	(0.422)	(0.158)
MKUP			0.01					
			(0.105)					
MKDWN			0.001					
			(0.005)					
BAD	0.04*		0.04*	0.05*	0.03	0.04*	0.04*	0.04
	(1.744)		(1.657)	(1.959)	(1.432)	(1.663)	(1.644)	(1.387)
dBAD		-0.89						
		(-0.875)						
DIFF	0.04**	0.06**	0.04**		0.03	0.05**	0.05**	0.06***
	(2.126)	(2.479)	(2.117)		(1.458)	(2.039)	(2.026)	(2.672)
LOANS				0.03				
				(1.485)				
DEP				0.07				
				(1.007)				
COOP						-0.002		
						(-0.133)		
LOC							-0.002	
							(-0.176)	
REG						-0.01	-0.01	
						(-0.967)	(-0.974)	
Constant	2.97	4.77*	3.03	2.26	1.54	2.70	2.69	4.12
	(1.368)	(1.901)	(1.211)	(1.014)	(0.652)	(1.028)	(1.028)	(1.583)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	400	480	480	480	400	400	400
Time period	95(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Pseudo R-sq.	0.53	0.55	0.53	0.53	0.61	0.53	0.53	0.56
Model Chi-sq.	95.44	79.03	95.44	98.07	101.76	81.69	81.70	83.12
[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log-L	-140.76	-111.19	-140.76	-139.45	-137.60	-109.86	-109.86	-109.02

MLE; asymptotic t-ratios in parentheses

(a) All variables lagged 1 yr.

Table 7. Model choice: active banks

	ZIP	NB	HP
Nr. of banks			
SPREAD	-1.176***	-1.841***	-0.981***
	(-3.887)	(-4.902)	(-3.943)
DIFF	0.058*	0.087***	0.054**
	(1.898)	(2.769)	(2.506)
COOP	-0.030	-0.020	-0.014
	(-0.975)	(-0.577)	(-0.423)
REG	0.030	0.031	-0.018
	(1.454)	(1.517)	(-1.000)
Constant	5.082***	7.436***	2.188*
	(3.400)	(4.084)	(1.756)
Overdispersion parameter	-	0.729**	-
	-	(2.252)	-
Mills ratio	-	-	2.404***
	-	-	(8.690)
Splitting model			
GDP	-0.172***	-	0.075***
	(-5.200)	-	(6.619)
FIRMS	-0.616**	-	0.030*
	(-2.159)	-	(1.921)
Constant	7.067***	-	-3.911***
	(5.316)	-	(-8.834)
Area dummies	yes	yes	yes
Year dummies	yes	yes	yes
Quarter dummies	yes	yes	yes
Nr. Obs.	400	400	400
Time period	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Vuong stat.	5.96	-	-
Pseudo R-sq. (a)	0.49	0.49	0.86
Log-L	-181.49	-189.65	-109.07
Log-L Probit	-	-	-145.01
AIC(b)	392.985	407.304	540.154

MLE; asymptotic t-ratios in parentheses

(a) Pseudo R-sq. from the Poisson model

(b) AIC = - 2 logL + 2k

Table 8. Model choice: passive banks

	Whole sample			Out of market			In market		
	ZIP	NB	HP	ZIP	NB	HP	ZIP	NB	HP
Nr. of banks									
SPREAD	-0.344**	-0.334*	-0.089	0.049	0.122	0.180	-1.064***	-1.027***	-0.359
	(-2.028)	(-2.226)	(-0.626)	(0.241)	(0.506)	(1.093)	(-2.639)	(-2.939)	(-1.154)
DIFF	0.048***	0.044***	0.002	0.037	0.022	-0.004	0.071**	0.064**	0.003
	(2.671)	(2.928)	(0.101)	(1.458)	(0.848)	(-0.156)	(2.187)	(2.417)	(0.121)
HERF	-7.086**	-7.231***	0.584	-4.802	-4.879	3.913	-6.159	-7.112*	-1.949
	(-2.521)	(-2.749)	(0.224)	(-1.067)	(-0.920)	(1.160)	(-1.401)	(-1.745)	(-0.439)
BAD	0.055**	0.061***	0.024	0.089***	0.109***	0.064**	-0.071	-0.076	-0.139
	(2.295)	(2.661)	(1.093)	(2.870)	(2.710)	(2.529)	(-0.960)	(-1.156)	(-2.098)
Constant	1.177	0.703	-5.406***	-2.666*	-4.218	-9.001***	5.166***	4.534***	-3.043
	(1.465)	(1.068)	(-3.265)	(-1.901)	(-3.072)	(-5.301)	(3.005)	(3.262)	(-1.070)
Overdispersion parameter	-	0.093	-	-	1.00 (c)	-	-	0.262	-
	-	(0.344)	-	-	-	-	-	(0.553)	-
Mills ratio	-	-	4.368***	-	-	3.909***	-	-	4.449***
	-	-	(4.174)	-	-	(4.037)	-	-	(2.586)
Splitting model									
GDP	0.020	-	-0.015**	0.091*	-	-0.015**	-0.030	-	-0.015**
	(0.655)	-	(-2.251)	(1.825)	-	(-2.251)	(-0.742)	-	(-2.251)
FIRMS	-0.835	-	0.008	-1.693	-	0.008	-0.566	-	0.008
	(-1.544)	-	(0.907)	(-1.276)	-	(0.907)	(-0.952)	-	(0.907)
Constant	-1.092	-	-0.172	-2.655	-	-0.172	0.964	-	-0.172
	(-0.929)	-	(-0.711)	(-1.413)	-	(-0.711)	(0.596)	-	(-0.711)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	480	480	480	480	480	480	480	480
Time period	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)
Vuong stat.	2.69	-	-	3.71	-	-	2.49	-	-
Pseudo R-sq. (a)	0.16	0.16	0.96	0.28	0.28	0.83	0.30	0.30	0.83
Log-L	-311.19	-315.63	-136.66	-180.26	-188.70	-96.65	-173.06	-172.71	-90.17
Log-L Probit	-	-	-264.75	-	-	-264.75	-	-	-264.75
AIC(b)	654.38	661.26	836.78	392.52	407.40	756.76	371.30	375.42	743.8

MLE; asymptotic t-ratios in parentheses

(a) Pseudo R-sq. from the Poisson model

(b) AIC = - 2 logL + 2k

(c) Parameter fixed to solve convergence problems; experimenting with different values leave results unchanged

Table 9. ZIP model: active banks

	I	II	III	IV	V	VI	VII	VIII
ZIP Model								
GDP	-0.17***		-0.17***	-0.17***	-0.16***	-0.17***	-0.16***	-0.08***
	(-5.200)		(-4.505)	(-4.557)	(-4.553)	(-4.145)	(-4.326)	(-3.486)
INV		-1.06***						
		(-3.925)						
FIRMS	-0.62**	-0.85*	-0.65*	-0.60*	-0.62*	-0.62*	-0.61*	-0.29
	(-2.159)	(-1.873)	(-1.853)	(-1.758)	(-1.712)	(-1.828)	(-1.698)	(-1.461)
Constant	7.07***	7.21***	6.68***	6.52***	6.61***	6.65***	6.51***	3.41***
	(5.316)	(3.958)	(4.472)	(4.525)	(4.525)	(4.104)	(4.306)	(3.497)
Poisson model								
HERF			-9.34					
			(-1.476)					
SPREAD	-1.18***	-0.60*	-0.57*	-1.00***		-0.87***	-0.69**	-0.94***
	(-3.887)	(-1.930)	(-1.788)	(-2.731)		(-2.635)	(-2.196)	(-4.278)
MKUP					-0.83**			
					(-2.312)			
MKDOWN					-0.80*			
					(-1.710)			
BAD						0.05		
						(0.511)		
dBAD							-2.86	
							(-1.080)	
DIFF	0.06*	0.08**	0.05		0.07**	0.07**	0.08**	0.08***
	(1.898)	(2.521)	(1.446)		(2.075)	(2.324)	(2.572)	(3.499)
LOANS				0.10**				
				(2.505)				
DEP				-0.18*				
				(-1.883)				
COOP	-0.03	-0.03	-0.04	-0.03	-0.03	-0.03	-0.03	
	(-0.975)	(-1.143)	(-1.273)	(-0.786)	(-0.987)	(-0.867)	(-1.003)	
LOC								
REG	0.03	0.06***	0.06**	0.05**	0.05**	0.05**	0.05**	
	(1.454)	(2.851)	(2.453)	(2.133)	(2.105)	(2.253)	(2.240)	
Constant	5.08***	2.19	2.64*	5.84**	3.25**	3.08**	2.66*	4.50***
	(3.400)	(1.426)	(1.703)	(2.047)	(2.071)	(1.961)	(1.691)	(4.458)
Area dummies	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	400	400	400	400	400	400	400	480
Time period	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	95(1) - 00(4)
Vuong stat.	5.96	4.02	4.86	4.68	4.83	4.93	4.51	4.75
Pseudo R-sq.	0.49	0.54	0.55	0.55	0.54	0.54	0.55	0.47
Log-L	-181.49	-173.59	-173.86	-174.43	-175.90	-175.69	-174.99	-240.85

MLE; asymptotic t-ratios in parentheses

Table 10. ZIP model: passive banks (whole sample)

	I	II	III	IV	V	VI
ZIP Model						
GDP	0.02	0.02	0.02		-0.03	-0.03
	(0.655)	(0.662)	(0.591)		(-0.545)	(-0.608)
INV				0.31		
				(1.596)		
FIRMS	-0.83	-0.83	-0.86	-0.81	-1.69	-1.77
	(-1.544)	(-1.533)	(-1.580)	(-1.371)	(-1.572)	(-1.556)
Constant	-1.10	-1.11	-1.02	-2.70*	0.43	0.56
	(-0.929)	(-0.929)	(-0.870)	(-1.653)	(0.277)	(0.351)
Poisson model						
HERF	-7.08**	-7.08**	-7.16**	-8.10***	-7.93**	-8.02**
	(-2.521)	(-2.520)	(-2.542)	(-2.953)	(-2.341)	(-2.372)
SPREAD	-0.34**		-0.37*	-0.28*	-0.26	-0.20
	(-2.028)		(-1.776)	(-1.777)	(-1.246)	(-0.891)
MKUP		-0.34*				
		(-1.898)				
MKDOWN		-0.38				
		(-1.008)				
BAD	0.05**	0.05**	0.05**	0.04**	0.06**	0.03*
	(2.295)	(2.144)	(2.139)	(1.982)	(2.132)	(1.820)
dBAD						
DIFF	0.05***	0.05***		0.04***	0.04**	0.03*
	(2.671)	(2.668)		(2.677)	(2.011)	(1.805)
LOANS			0.05**			
			(2.292)			
DEP			-0.07			
			(-0.918)			
COOP					-0.02	
					(-0.943)	
LOC						-0.02
						(-1.241)
REG					-0.003	-0.004
					(-0.290)	(-0.371)
Constant	1.18	1.31	1.67	1.02	0.88	0.69
	(1.465)	(0.848)	(0.844)	(1.378)	(0.868)	(0.673)
Area dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	480	480	480	400	400
Time period	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Vuong stat.	2.69	2.68	2.71	3.17	2.38	2.39
Pseudo R-sq.	0.16	0.16	0.16	0.16	0.17	0.18
Log-L	-311.19	-311.18	-311.12	-309.12	-244.61	-243.39

MLE; asymptotic t-ratios in parentheses

Table 11. ZIP model: passive banks (out of market)

	I	II	III	IV	V	VI
ZIP Model						
GDP	0.09*	0.09*	0.1*			
	(1.825)	(1.746)	(1.882)			
INV				0.81*	0.64**	0.63**
				(1.900)	(2.219)	(2.113)
FIRMS	-1.69	-1.71	-1.48	-2.05	0.003	0.003
	(-1.276)	(-1.287)	(-1.261)	(-1.621)	(0.044)	(0.045)
Constant	-2.65	-2.59	-2.93	-4.26	-4.09*	-4.06*
	(-1.413)	(-1.374)	(-1.454)	(-1.622)	(-1.848)	(-1.764)
Poisson model						
HERF	-4.80	-4.77	-4.97	-4.81	-5.06	-5.22
	(-1.067)	(-1.055)	(-1.063)	(-1.090)	(-0.823)	(-0.844)
SPREAD	0.05		0.11	0.09	0.16	0.15
	(0.241)		(0.390)	(0.424)	(0.455)	(0.443)
MKUP		0.01				
		(0.028)				
MKDOWN		0.27				
		(0.490)				
BAD	0.09***	0.09***	0.09***	0.08***	0.09**	0.09**
	(2.870)	(2.755)	(2.783)	(2.548)	(2.351)	(2.260)
dBAD						
DIFF	0.04	0.04		0.03	0.03	0.04
	(1.458)	(1.366)		(1.327)	(0.981)	(0.994)
LOANS			0.03			
			(1.026)			
DEP			0.02			
			(0.127)			
COOP					0.03	
					(0.445)	
LOC						0.02
						(0.454)
REG					-0.02	-0.02
					(-1.164)	(-1.094)
Constant	-2.67*	-3.57	-3.84	-2.59*	-3.35*	-3.32*
	(-1.901)	(-1.376)	(-1.274)	(-1.951)	(-1.848)	(-1.841)
Area dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	480	480	480	400	400
Time period	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Vuong stat.	3.71	3.75	4.06	5.56	5.37	5.04
Pseudo R-sq.	0.28	0.28	0.28	0.28	0.32	0.32
Log-L	-180.26	-180.09	-180.14	-175.81	-139.79	-139.79

MLE; asymptotic t-ratios in parentheses

Table 12. ZIP model: passive banks (in market)

	I	II	III	IV	V	VI
ZIP Model						
GDP	-0.03		-0.03			
	(-0.742)		(-0.956)			
INV		3.85		0.90	-1.33	-1.27
		(0.150)		(1.053)	(-1.325)	(-1.375)
FIRMS	-0.57	0.57	-0.63	-1.08	-1.72	-1.68
	(-0.952)	(0.136)	(-1.165)	(-0.637)	(-1.111)	(-1.115)
Constant	0.96	-40.06	1.18	-8.42	8.39	8.08
	(0.596)	(-0.148)	(0.885)	(-1.021)	(1.410)	(1.459)
Poisson model						
HERF	-6.16	-12.60***	-9.50**	-11.46***	-9.72	-10.05
	(-1.401)	(-3.053)	(-2.050)	(-2.805)	(-1.335)	(-1.369)
SPREAD	-1.06***		-1.40***	-0.63*	-0.42	-0.28
	(-2.639)		(-2.596)	(-1.848)	(-0.777)	(-0.511)
MKUP		-0.36				
		(-1.101)				
MKDOWN		-1.37**				
		(-2.205)				
BAD	-0.07	-0.2***	-0.12*	-0.15**	-0.10	-0.13
	(-0.960)	(-2.882)	(-1.659)	(-2.333)	(-0.878)	(-1.055)
dBAD						
DIFF	0.07**	0.05*		0.05*	0.04	0.03
	(2.187)	(1.845)		(1.657)	(1.108)	(0.901)
LOANS			0.11***			
			(2.621)			
DEP			-0.28**			
			(-2.058)			
COOP					-0.04	
					(-0.976)	
LOC						-0.04
						(-0.923)
REG					0.01	0.01
					(0.512)	(0.314)
Constant	5.17***	7.12***	10.71***	3.92***	2.82	2.46
	(3.005)	(2.813)	(2.627)	(2.824)	(1.267)	(1.077)
Area dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes
Nr. Obs.	480	480	480	480	400	400
Time period	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	95(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)
Vuong stat.	2.50	4.34	2.86	3.45	3.84	3.74
Pseudo R-sq.	0.30	0.31	0.31	0.30	0.33	0.35
Log-L	-169.65	-161.86	-166.57	-166.25	-126.29	-124.85

MLE; asymptotic t-ratios in parentheses

Table 13. The impact of M&As on loans

Dependent variable: d LOANS

	I	II	III	IV	V	VI	VII	VIII	IX	X
PB		-0.004	-0.01**	-0.007	-0.007	-0.006	-0.006	-0.006	-0.007	-0.003
		(-0.807)	(-2.097)	(-1.518)	(-1.367)	(-1.227)	(-1.209)	(-1.174)	(-1.356)	(-0.504)
AB		-0.0007	0.006***	0.006***	0.005***	0.004**	0.004**	0.004**	0.004**	0.002
		(-0.381)	(3.935)	(3.682)	(2.601)	(2.247)	(2.346)	(2.368)	(2.163)	(1.249)
d DEP		0.03	-0.01	-0.01	-0.007	0.007	0.01	0.01	0.12**	-0.09
		(0.708)	(-0.236)	(-0.190)	(-0.113)	(0.110)	(0.209)	(0.206)	(2.291)	(-1.227)
d BAD		-0.14***	-0.21***	-0.21***	-0.20***	-0.19***	-0.20***	-0.20***	-0.18***	-0.24***
		(-4.141)	(-7.472)	(-7.153)	(-6.657)	(-6.743)	(-6.791)	(-6.774)	(-6.550)	(-7.608)
d GDP		0.05	0.13	0.03	0.04	0.04	0.04	0.04	0.03	0.16*
		(0.646)	(1.456)	(0.351)	(0.417)	(0.457)	(0.452)	(0.443)	(0.284)	(1.743)
INV				0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.005***
				(6.533)	(6.849)	(7.089)	(7.180)	(7.278)	(6.391)	(5.232)
SPREAD					-0.007**					
					(-2.574)					
MKUP						-0.01***	-0.009***	-0.009***	-0.009***	-0.01***
						(-3.788)	(-3.428)	(-3.422)	(3.436)	(-5.034)
MKDOWN							0.006	0.006	0.02***	-0.01*
							(1.095)	(1.087)	(3.089)	(-1.868)
HERF								0.003	-0.01	0.03
								(0.113)	(-0.367)	(1.087)
d COOP									-0.014	
									(-1.112)	
d LOC										0.007
										(0.822)
d REG										0.02
										(1.552)
Constant	0.05***	0.05***	0.07***	0.03***	0.06***	0.06***	0.04*	0.04*	0.007	0.06***
	(3.705)	(4.078)	(8.423)	(2.825)	(3.548)	(4.258)	(1.848)	(1.845)	(0.377)	(2.702)
Regional dummies	yes	yes	no	no	no	no	no	no	no	no
Area dummies	no	no	yes	yes	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Nr. Obs.	400	400	400	400	400	400	400	400	400	320
Time period	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	96(1) - 00(4)	97(1) - 00(4)
Adj. R-sq.	0,61	0.65	0.54	0.56	0.56	0.57	0.57	0.57	0.55	0.63
Model F	25,42	25.17	34.54	35.04	33.46	34.27	32.35	30.47	28.50	29.63
[p-value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Log-L	776.32	799.98	735.13	744.87	747.29	750.12	750.75	750.76	742.96	611.52

OLS; t-ratios in parentheses (SE corrected using the White procedure)

Appendix Table 1

Distribution of dependent variables

Vbs.	***0***	***1***	***2***	***3***	***more than 3***
Active Banks	398 (83%)	43 (9%)	19 (4%)	9 (2%)	11 (2%)
AB|North	122 (73%)	22 (13%)	10 (6%)	6 (4%)	8 (4%)
AB|Center	113 (78%)	17 (12%)	8 (6%)	3 (2%)	3 (2%)
AB|South	163 (97%)	4 (2%)	1 (1%)	0 (0%)	0 (0%)
Passive Banks (all)	362 (76%)	88 (18%)	26 (5%)	4 (1%)	0 (0%)
PB|North	127 (75%)	33 (20%)	7 (4%)	1 (1%)	0 (0%)
PB|Center	113 (78%)	22 (15%)	8 (6%)	1 (1%)	0 (0%)
PB|South	122 (73%)	33 (20%)	11 (6%)	1 (1%)	0 (0%)
Passive Banks (out of market)	415 (87%)	48 (10%)	14 (3%)	0 (0%)	0 (0%)
PB|North	163 (97%)	5 (3%)	0 (0%)	0 (0%)	0 (0%)
PB|Center	127 (88%)	13 (9%)	4 (3%)	0 (0%)	0 (0%)
PB|South	126 (75%)	31 (18%)	11 (7%)	0 (0%)	0 (0%)
Passive Banks (in market)	421 (88%)	47 (9%)	10 (2%)	2 (1%)	0 (0%)
PB|North	132 (78%)	28 (17%)	7 (4%)	1 (1%)	0 (0%)
PB|Center	128 (89%)	13 (9%)	2 (1%)	1 (1%)	0 (0%)
PB|South	161 (96%)	6 (3%)	1 (1%)	0 (0%)	0 (0%)

Definitions:

North: Valle d'Aosta, Piemonte, Lombardia, Trentino A. A., Friuli Venezia Giulia, Veneto, Liguria

Center: Emilia Romagna, Toscana, Umbria, Marche, Abruzzo, Lazio

South: Campania, Molise, Puglia, Calabria, Basilicata, Sicilia, Sardegna

Appendix Table 2

Variables definition and descriptive statistics

Vbs.	*Mean*	*Std. Dev.*	*Min*	*Max*	*Description*
Real Economy Indicators					
GDP	34,38	9,09	18,1	51,15	GDP per capita (mln ITL lire)
					Yearly data. Source: ISTAT
INV	6,52	2,06	3,24	13,97	Fixed investment per capita (mln ITL lire)
					Quarterly data. Source: ISTAT
FIRMS	1,23	7,92	-105,97	104,97	Growth rate total nr. firms x 1000 inhab.
MANIF	0,01	1,12	-16,96	16,77	Growth rate nr. firms x 1000 inhab. (sector D ISTAT Economic Activities class.
BUILD	0,07	0,8	-11,67	11,78	Growth rate nr. firms x 1000 inhab. (sector F ISTAT Economic Activities class.
COMM	0,0003	1,63	-24,33	23,98	Growth rate nr. firms x 1000 inhab. (sector G ISTAT Economic Activities class.
SERV	0,08	1,25	-17,45	17,48	Growth rate nr. firms x 1000 inhab. (sector H, I, K ISTAT Economic Activities class.
INDIV	0,95	7,24	-67,71	66,17	Growth rate nr. firms x 1000 inhab. (individual firms)
STOCK	0,12	0,87	-13,31	13,71	Growth rate nr. firms x 1000 inhab. (joint stock companies)
PARTN	0,16	2,02	-23,29	23,37	Growth rate nr. firms x 1000 inhab. (partnerships)
					Quarterly data. Source: Unioncamere - Movimprese
Market structure - efficiency					
HERF	0,12	0,08	0,03	0,48	Herfindhal index defined considering the number of bank branches
					Yearly data. Source: Bank of Italy
SPREAD	5,31	1,39	2,67	9,91	Difference between average rate on loans and average rate on deposits
MKUP	3,28	1,45	-0,49	7,33	Difference between average rate on loans and average rate on 1-month Govt. Bond
MKDWN	2,02	0,99	0,46	4,81	Difference between average rate on 1-month Govt. Bond and average rate on dep
					Quarterly data. Source: Bank of Italy
Credit policies					
BAD	12,21	7,53	1,99	33,73	% bad loans out of total loans
					Quarterly data. Source: Bank of Italy
DIFF	3,89	7	-7,65	28,04	Difference between loans and deposits per capita (mln ITL lire)
LOANS	19,87	10,32	6,8	55,66	Loans per capita (mln ITL lire)
DEP	15,98	5,37	7,56	27,61	Deposits per capita (mln ITL lire)
					Quarterly data. Source: Bank of Italy
Institutional structure					
COOP	11,73	11,8	0,15	60,62	% regional bank branches owned by cooperative banks
					Yearly data. Source: ISTAT
LOC	18,37	17,58	0,63	88	% regional bank branches owned by local banks
REG	16,88	14,97	0,21	68,71	% regional bank branches owned by banks with regional diffusion
					Quarterly data. Source: Bank of Italy