Collana Ricerche

Multiple banking relationships and credit market competition: what benefits the firm?

Research Department

October 2007

MULTIPLE BANKING RELATIONSHIPS AND CREDIT MARKET COMPETITION: WHAT BENEFITS THE FIRM?*

Virginia Tirri**

Abstract 3

1. Introduction 3

2.Theoretical Underpinnings and Related Empirical Studies 5

3. Hypotheses and Research Design 9

3.1 Data description 11

4. Estimation results 15

5.Conclusions 20

References 23

October 2007

* *This is a totally revised and updated version of a paper previously circulated under the title: "The effect of market structure and relationship lending on the likelihood of credit tightening". I am sincerely grateful, without implicating, to Arnoud Boot, Elena Carletti, Riccardo De Bonis, Mark Flannery and Fabrizio Guelpa for helpful discussions, comments and suggestions. I also thank Jacob Arendt and Raoul Minetti for useful insights on methological issues, participants at the 2007 EFA meeting (Ljubljana), the University of Ancona conference on "The changing geography of banking" (Ancona, Italy – September 2006), to Andreas Hackethal and participants at the 2006 EFMA conference (Madrid) and the 2006 FMA conference (Stockholm). Any remaining errors or inaccuracies are my own. This paper is the sole responsibility of its author and the opinions expressed here do not necessarily reflect those of Intesa Sanpaolo.*

** *Intesa Sanpaolo, Research Department; P.tta G. Dell'Amore, 3 – 20121 MILAN (ITALY) Telephone: +39-02-87962149; Fax: +39-02-80215422 - email: virginia.tirri@intesasanpaolo.com*

Abstract

This paper empirically addresses the question of which are the benefits for a firm to borrow from multiple banks, by explicitly correcting the potential endogeneity of the firm's decision of whether to rely on (and on how many) multiple relationships through a two-stage conditional maximum likelihood (2SCML) estimation technique. The estimation procedure also allows an in-depth analysis of the determinants of the multiple banking choice.

The results are consistent with the hypothesis that the likelihood of quantity credit tightening is lower for firms having more lending relationships, and located in less concentrated credit markets. Banking power at firm level and at market level is detrimental to the firm, as it increases the probability of credit constraints. However, firms that engage in multiple relationships benefit from competition among lending banks in terms of a lower probability of tightening, though such competition does not fully outweigh the marginal effect of local banking market power. As for the multiple banking choice, larger, riskier, less profitable and more opaque firms prefer more lending ties, and the number of relationships is also positively correlated with credit market concentration.

I interpret the findings as providing evidence that a key reason why firms rely on multiple banking is their desire to reduce the consequences of hold-up and the risk of being credit constrained.

Keywords*:* multiple banking relationships, credit tightening, credit market competition, two-stage conditional maximum-likelihood estimation

JEL: G21, C33

1. Introduction

Strong theoretical explanations provide ground for the existence and value of single lending relationship or multiple bank relationships with two banks, but less clear are the rationales for multiple banking involving more banks and its measurable benefits. This paper empirically addresses the question of which are the benefits for a firm to borrow from multiple banks, by explicitly recognizing that the decision of whether to rely on (and on how many) multiple relationships is an endogenous choice. As multiple relationships can be seen as an induced form of banking competition at the firm level that may complement or substitute for banking competition at the market level, the analysis as well assesses the effects of bank market structure both on credit availability and on the multiple banking choice.

So far, the existing empirical evidence on the effect of multiple banking relationships on credit conditions is mixed, and not conclusive. Cross-sectional analyses of SMEs samples in the US banking market (Petersen and Rajan, 1994 and 1995; Cole, 1998), Germany (Harhöff and Körting, 1998; Brunner and Krahnen, 2004) and Belgium (de Bodt et al., 2005) suggest that borrowing from multiple lenders increases the cost of credit and the likelihood of credit rationing, especially in situations of financial crisis, and reduces the probability of workout success. On the contrary, other evidence from both large listed companies (Houston and James, 1996) and private firms (Foglia et al., 1998; D'Auria et al., 1999) support the hypothesis that multiple banking reduces the informational lock-in and benefits the firm in terms of better credit conditions, lower liquidity risk

(Detragiache et al., 2000) and lower likelihood of financial distress (Carmignani and Omiccioli, 2007).

However, none[1] of these studies explicitly addresses the potential endogeneity of the decision to rely on multiple relationships or to establish a long-lasting close financing tie with a single bank while testing the effect of such a choice on credit conditions.

By using a two-stage conditional maximum likelihood (2SCML) estimation technique, this paper analyzes the impact of multiple banking on the probability of credit tightening, that is the probability of lower supply of credit compared to the firm's demand. The estimation procedure also allows an in-depth analysis of the determinants of the multiple banking choice. The analyses contribute to the existing empirical literature by providing tests that specifically examine (1) firm-specific characteristics and banking market features affecting the number of lending relationships, (2) whether having more lending relationships translates into a higher or lower probability of being credit tightened, (3) whether the market structure does directly affect the probability of tightening, and (4) whether multiple lending and local credit market competition are alternative or complementary forms of competition influencing credit availability.

The hypotheses are tested on a unique panel data set including more than 11,000 firms borrowing from at least one Italian bank at the end of any year between 1997-2004.

The results are consistent with the hypothesis that the likelihood of credit tightening is lower for firms having more lending relationships, after controlling for the potential endogeneity of the number of relationships, the firm riskiness and profitability, and for other firm-specific characteristics. Furthermore, all else being equal, the probability of tightening is higher in more concentrated credit markets. Firms that engage in multiple relations benefit from competition among lending banks in terms of greater availability of credit, though such competition does not outweigh the marginal effect of bank market power. There is no evidence that lending relationships reduces the probability of credit constraints more/less in highly competitive than in concentrated markets. As for the multiple banking choice, larger, more profitable firms prefer more lending ties, and the number of relationships is also positively correlated with market concentration. The findings above may be interpreted as evidence that firms use multiple banking to reduce the consequences of hold-up and the risk of credit tightening, though they would benefit more from banking market competition.

The results may help explain the large diffusion of multiple banking relations in Italy and in many other European countries (Ongena and Smith, 2001).

This paper adds to the literature on multiple lending relationships and bank market power along three main dimensions. The first contribution comes from the methodology, that properly accounts for the potential endogeneity of the multiple banking choice. The 2SCML estimation technique is not new, but – to the best of my knowledge - it has rarely been applied in the context of financial intermediation studies[2].

Second, to the best of my knowledge, no other study has yet examined the individual and joint effects of multiple relationships and credit market competition on credit tightening in a comprehensive framework, and in an European banking

1 *Carmignani and Omiccioli (2007) acknowledge the potential reverse causality between creditor concentration and the probability of financial distress, and address the issue by using a two-stage instrumental variable procedure as a robustness check.*

2 *A notable exception is the paper by Herrera and Minetti (2007).*

market. Italian data are very well-suited to such analysis. Italian firms, as well as most European firms, heavily rely on bank financing, but the use of multiple banking is more widespread – even among very small firms – (Foglia et al., 1998; Detragiache et al., 2000) and intense than in other countries (Ongena and Smith, 2001). The banking market is segmented into many small local markets characterized by different level of concentration, and thus offers a variety of market structures. Furthermore, an important feature of the banking institutional framework is the presence of a Central Credit Register, that provides a compulsory mechanism of information sharing. Pagano and Jappelli (2000) thoroughly discuss the effects of private information sharing, which may reduce the benefits of inside information for each lending bank and, consequently, the incentive for the banks to establish close lending relationships[3]. Therefore, multiple banking seems to be a natural consequence, whose costs and benefits for the borrowing firms have to be empirically assessed.

Finally, the extremely rich data set used in the analysis allows the construction of meaningful proxies for bank credit constraints and firm risk profile, and a more robust panel econometric analysis.

The remainder of the paper is outlined as follows. Section 2 briefly discusses the theoretical background of the testable predictions and the main conclusions of related empirical studies. Section 3 describes the main hypotheses and the research design. Major results are discussed in section 4, as are the results of the robustness tests. Conclusions are presented in section 5.

2. Theoretical Underpinnings and Related Empirical Studies

This paper draws on different strands of literature. The most relevant - and strictly interrelated - are the studies modelling the multiple banking choice, and the literature on credit market power. I am not aware of theoretical papers that discuss the substitutability between ex ante competition for relationships (i.e., multiple banking) and ex post competition in the market in a unified framework. The following two subsections review the background, while subsection 2.3 briefly summarizes the main results of related empirical analyses.

2.1 The optimal number of banks

Contemporary theory of financial intermediation (Diamond, 1983; Kahn and Mookherjee, 1998; von Thadden, 1992 and 2004; Thakor, 1996; Detragiache et al., 2000; Carletti, 2004; Carletti et al., 2007, among others) and corporate finance theory (Berglöf and von Thadden, 1994; Dewatripont and Maskin, 1995;

3 *However, a high number of multiple banking relationships does not necessarily exclude relationship lending. Drawing on a very extensive and detailed cross-section database of bank-firm relationships, Bonaccorsi di Patti (2003) shows that bank relationships in Italy are skewed:* "the average relationship weights 45% of the total credit of the firm, but 25% of the relationships in the sample are single relationships"*. Single bank financing is indeed an exception rather than the rule, but the evidence suggests that there is asymmetry in multiple bank financing, and a relationship lender may well cohesist with less informed arm's-lenght banks. Multiple banking does not imply the absence of informed financing, though a negative correlation between the number of banks and the incidence of relationship lending seems plausible. Multiple but asymmetric lending has been recently well documented not only in Italy (Carmignani and Omiccioli, 2007), but also in U.S. (Minetti and Guiso, 2004) and other countries with strong bank-firm relationships, like Germany (Ongena et al., 2006, among others).*

Bolton and Scharfstein, 1996; Park, 2000) address directly and indirectly the issue of the optimal number of lenders, and provide insightful arguments as to why firms should opt for single-bank or multiple banking relationships[4].

In a context of costly information asymmetry between lenders and borrowers a single bank arises as the optimal mechanism for channeling loans to firms (Diamond, 1984; Rajan, 1992; Kahn and Mookherjee, 1998, among others). In a static framework, a single bank most efficiently performs the monitoring, screening and renegotiation activities, which result in cheaper financing for the firm; on the contrary, the resulting equilibrium in a context of non-exclusive contracts (multiple banking) implies more rationing and increased prices.

However, a single bank will also have monopoly access to private information about the borrowing firms, resulting in potential hold-up costs. In a dynamic setting, a bank can exploit its monopoly power, either by charging higher interest rates on new loans or by threatening the firm not to extend further credit. Sharpe (1990), Rajan (1992), and von Thadden (1992 and 2004) demonstrate that a firm can avoid or reduce hold-up costs by establishing a relationship with another bank. In this context, two lending relationships can restore competition among banks and limit ex-post rent extraction, though - if monitoring is discretionary and costly - free rider problems or duplication of monitoring costs can reduce the effectiveness of multiple banking relationships.

However, in a framework of adverse selection and costly financial screening, an increase in the number of banks increases the ex post probability of credit rationing (Thakor, 1996). Rationing arises naturally from the screening costs banks incur. Therefore, in equilibrium, each borrower approaches multiple banks, but faces a positive probability of being rationed by each bank.

Multiple banking is costly for the borrowing firm also because it implies significant transaction costs and can affect both the cost of capital and the quality of the investment projects in different ways. Each lender invests in monitoring the borrower fewer resources than she would do in the case of an exclusive long-term relationship. Screening and monitoring activities may be duplicated or, if banks free ride on other lenders' efforts, too little screening or monitoring may result. In these situations, valuable investment projects might be rejected, and firms may use their debt to engage in risky activities without being properly monitored by the credit system. Moreover, in the absence of long-term commitment, no bank is willing to support the firm in financial distress and a *winner's curse* problem can arise (von Thadden, 1995 and 2004), and debt renegotiation is likely to be more complex when many creditors are involved.

Given the high costs of multiple banking with two banks, both for the borrower and the lenders, even less clear are the motivations for multiple banking consisting of many banks. Existing information-based theories do not completely explain the observed number of relationships which firms – even small and medium ones – maintain, especially in some European countries (Ongena and

4 *In this paper the firm's viewpoint is assumed. However, it may well be in the bank's self interest that the firm establishes multiple relationships: von Thadden (1992) shows that, if incentive compatibility precludes an exclusive monitor from passing future monopoly profits on to the firm through interest reductions, banks will optimally give up exclusivity and offer contracts with duplicated monitoring. Also Carletti et al. (2007) show that there are cases in wich benefits dominate the costs of multiple banking. For examples, smaller banks have more incentives to enter in a pool of multiple lenders, given that they cannot reach an acceptable degree of diversification. By lending to many more entrepreneurs, smaller banks are able to achieve a higher degree of diversification, thus committing to a higher level of monitoring.*

Smith, 2000). Arguments not related to the hold-up problem may help justify multiple lending relationships.

Dewatripont and Maskin (1995) show that a relationship bank may refinance unprofitable projects, thus reducing firms' incentive to prevent default. By complicating the refinancing process and making it less profitable, multiple bank lending enables banks to commit not to extend further inefficient credit. Increasing the number of creditors also has a positive incentive effect in the model developed by Bolton and Scharfestein (1996), as it reduces the incentive for a manager to strategically default on a loan. The authors derive an expression for the optimal number of creditors[5], which trades off the benefits of preventing strategic defaults with the cost of foregoing an efficient liquidation. In equilibrium, high quality firms and firms whose assets are specific are better off with two creditors than one[6].

Detragiache, Garella and Guiso (2000) provide a rationale for a firm to seek multiple lenders by considering the costs it may incur when it is denied credit for bank's fragility. They provide a diversification argument: firms may have the incentive to diversify across many bank relationships or across many financing sources, when the risk of losing one relation is high. Firms use multiple banking to reduce the risk that a profitable investment is prematurely liquidated.

The optimal number of lenders, as well as the optimal debt structure, may be explained by the borrower's moral hazard problem (Park, 2000). If the borrower's moral hazard problem is very severe, the bank has the appropriate incentive to monitor the firm only if it the sole lender financing the whole project or the only lender in the most senior class. The observed structure of debt contracts and the choice of number of creditors, seniority, covenants and maturities can all be explained as a way to maximize the senior lenders' incentive to control the borrower's moral hazard problem. But, when this problem is not very severe, the benefits from optimal monitoring may be overcome by hold-up costs. A direct implication of the model is that, when the borrower has fewer opportunities to behave opportunistically, multiple bank relationships does not prevent lending, and may reduce informational rents.

Finally, in contrast to the literature based on the hold-up and the soft budget constraints arguments, Carletti (2004) develops an alternative theoretical model predicting the firm's choice between single-bank and two-bank lending. The optimal choice balances the benefit of monitoring in terms of higher expected success probability of the investment project, lower expected private return and higher monitoring costs. According to the model, the attractiveness of two-bank lending is increasing in the firm's expected profitability and private benefit, and the cost of monitoring.

2.2 The recent literature on market power

The literature on credit market power[7] provides foundations for two competing hypotheses concerning the impact of banking market competition on credit availability.

---

5 *More precisely, Bolton and Scharfestein (1996) derive the conditions in which the optimal number of creditors is one or two only.*

6 *However, in their model creditors are not necessarily relationship lenders.*

7 *Carbò-Valverde et al. (2006) provide a comprehensive review of the literature both on relationship lending and competition, and on proxies of market power.*

The traditional "market power view" is based on the structure-conduct-performance paradigm and postulates a direct connection between concentration and performance. A high degree of market concentration may generally be associated with non-competitive behaviour (higher price and lower availability of credit).

However, an alternative view has emerged, that argues that the impact of competition on credit conditions may be related to the level of asymmetric information in the market (Dell'Ariccia et al., 1999; Dell'Ariccia and Marquez, 2004). According to models incorporating asymmetric information between lenders and borrower, credit market competition reduces banks' incentives to invest in soft information and, therefore, in relationship lending[8]. The implications are consistent with those developed, for instance, by Petersen and Rajan (1995), who suggest that lending relationship is less valuable to a firm in competitive markets. While in a competitive market the lender does not expect to share future profits and has to break even period by period, a monopolistic creditor is able to extract rents from the firm's future profits and, therefore, may be willing to offer credit even to risky firms and to smooth rates intertemporally. This mechanism is also efficient, since it can avoid or reduce credit rationing towards young/risky firms and relatively more firms should be able to obtain credit in more concentrated markets.

A recent theoretical paper also offers a model that includes both the traditional and the so called "informational effects" of credit market power (de Mello, 2004). The net effect crucially depends on the cost of information access and the availability of public information about the borrowing firms. Which of the two effects does prevail has to be empirically assessed.

The extent to which the benefits of multiple relations outweigh their costs, and the interaction between multiple banks and credit market competition are, ultimately, empirical issues.

2.3 Related empirical evidence

The empirical evidence on the impact of multiple banking is scant and mixed. Petersen and Rajan (1994) find that firms with multiple relations pay higher interest rates and are more credit constrained than those with a single relationship are. Other studies (Petersen and Rajan, 1995; Cole, 1998; Harhoff and Körting, 1998) also find that firms with multiple relationships are more credit constrained than those with a single relation are, in accordance with the prediction of Kahn and Mookherjee (1998) and Thakor (1996). Houston and James (1996) find evidence that suggest the opposite, but their data set includes large listed companies with a well established track record.

While single relationships dominate among small US and German firms, they are uncommon in many European countries, especially in Italy and other Mediterranean countries. Foglia et al. (1998), D'Auria et al. (1999), Ongena and Smith (2000), Detragiache et al. (2000), Bonaccorsi di Patti (2003), Carmignani and Omiccioli (2007) document an average number of bank relationships maintained by Italian firms - even small businesses - significantly high.

D'Auria et al. (1999) find that local credit market concentration has a negative impact on interest rates (in less competitive markets, firms are charged higher

8 *An alternative theoretical model developed by Boot and Thakor (2000) suggests, on the contrary, that increased competition either among banks, types of debt and from outside sources, drives banks to invest more in relationship lending.*

interest rates), while firm level competition is beneficial, as for a new bank granting credit the interest rate charged by each bank decreases. The most plausible explanation for the use of multiple-credit relationships seems to be the hold-up argument: firms induce competition among lending banks to reduce the informational lock-in effect, and thus lower the average cost of debt. The analysis of the Italian banking industry is complemented by Foglia et al. (1998), who study the correlation between firm riskiness and multiple banking relationships. When a large number of lenders is involved, monitoring of the borrower tends to be weaker and to induce fragility in the firm’s balance sheets; furthermore, the average cost of bank loans for the individual borrower decreases as the number of lending banks increases.

As far as the effect of market power, there is evidence broadly supporting the information view. Petersen and Rajan (1995), Petersen (1999) and Zarutskie (2006) find that young[9] firms are more likely to obtain bank financing in concentrated markets, while older firms are less influenced by the concentration of the local credit market. However, recent papers cast doubts on such conclusions. By drawing on a large sample of Spanish SMSs, Carbò-Valverde et al. (2006) show that the association between market power and credit availability is highly sensitive to the measure of credit market power, and it is positive if a measure of concentration is used, but it turns negative if the Lerner Index is used to measure market power. de Mello (2004) also documents - from three years Surveys of Small Businesses Finances in the United States - that the balance between the traditional (negative) and informational (positive) effects has shifted in favour of the former.

Other results are consistent with the neoclassical prediction that competition increases the general welfare of small firms (Scott and Dunkelberg, 2003), and improves credit conditions (Degryse and Ongena 2005, among others) and access to credit (Boot and Thakor, 2000).

3. Hypotheses and Research Design

The main objective of this study is to investigate at micro level the effects of multiple banking relationships and bank market power on credit availability. More specifically, the dependent variable is modelled as a binary variable measuring the ex post probability of (quantity) credit tightening,. In this section I set out a brief discussion of the main testable hypotheses, describe the methodology and define the variables used in the empirical analysis.

The theoretical literature described in section 2 provides the background for three main testable hypotheses:

1. having more lending relationships translates into a higher (or lower) probability of being credit tightened;
2. the market structure does directly affect the probability of tightening: if the traditional market power effect outweighs the informational effect, the likelihood of credit tightening is higher for firms in concentrated than in competitive markets. The reverse is true if the informational effect does prevail;
3. the marginal impact of multiple banking is higher (or lower) than the marginal effect of market concentration, and it is different for firms in highly

9 *In these papers age is a proxy for credit quality.*

concentrated/competitive markets. In other words, multiple lending and local credit market competition may be alternative or complementary forms of competition influencing credit availability.

Along with the effect of multiple banking and market competition, the analyses also shed light on the determinants of the number of lending relationships.

Before turning to detailed data and variables description, the econometric setting of the analyses is described.

Consider the following model where the parameters of Eq. (1) are of primary focus, while Eq. (2) is the reduced form for the explanatory variable which is endogenous:

$$y^* = \alpha_1 x + z_1 \delta_{11} + u_1 \qquad \text{Eq. (1)}$$

$$x = z_1 \delta_{21} + z_2 \delta_{22} + u_2 \qquad \text{Eq. (2)}$$

where *y** is the probability of tightening, *x* is a proxy for the multiple banking choice, z_1 denotes a vector of controls, and u_1 is the residual. In Eq. (2), z_1 refers to the control variables in (1), z_2 is the vector of instruments and u_2 is the residual.

The equations' errors comprise random individual-specific time-invariant heterogeneity and individual-specific time-variant random disturbance, which are assumed to be independent across individuals.

More specifically: $u_2 = u_{it} = \alpha_i + \upsilon_{it}$; the components are assumed to be normally distributed and any form of autocorrelation in υ_{it} is excluded.

Using a two-stage procedure, I estimate the probit model:

$$P(y=1 \mid x, z_1, u_2) = \Phi\left[\left(\alpha_1 x + z_1 \delta_{11} + \vartheta_1 u_2\right) / \left(1-\rho_1^2\right)^{\frac{1}{2}} \right] \qquad \text{Eq. (3)}$$

where: $\vartheta_1 = \left(\mathrm{cov}(u_2, u_1)/\tau_2^{\ 2}\right)$; $\tau_2^{\ 2} = \mathrm{var}(u_2)$; $\rho_1 = corr(u_2 . u_1)$.

Probit estimation of eq. (3) without correcting for endogeneity would most likely result in biased coefficients and incorrect inference about the actual effect of multiple banking. The determination of the number of relationships can be endogenous to the probability of tightening. In other words, a firm fearing to be credit constrained could choose to originate new credit lines from incumbent banks to preserve financial flexibility or minimize both the hold-up costs and the risk of credit tightening. In these cases, the observed correlation between the probability of credit tightening and the multiple banking measure may be driven by the response of the lending banks to the number of relations and/or by the sensitivity of the latter to the likelihood of credit constraints.

There exist a number of estimation methods to avoid the pitfalls of endogeneity and consistently identify the true impact from "seemingly" reciprocal relationship between the dependent and the (potentially endogenous) independent variable in limited dependent variable (LDV) models. Nonetheless, according to the results of Monte Carlo simulations, two-stage conditional maximum likelihood (2SCML) estimators are consistent and asymptotically efficient, and perform better than two-stage instrumental variable (2SIV) and generalized least square (GLS) estimators (Rivers and Vuong, 1988; Alvarez and Glasgow, 1999).

The 2SCML estimation procedure has been suggested and discussed by the econometrics literature to correct the endogeneity problem of either a binary dependent variable with a continuous endogenous regressor or a continuous dependent variable with a binary endogenous regressor (Rivers and Vuong, 1988; Vella and Verbeek, 1999; Wooldridge, 2002; Arendt, 2002; Arendt and Holm, 2006). Furthermore, the technique provides a convenient implementation of exogeneity test. To the best of my knowledge, except Vella and Verbeek (1999) and Arendt (2003) none has applied the 2SCML to panel data estimation. I will strictly follow Vella and Verbeek (1999) to specify the econometric model, as their application shows it is possible to include dynamics too.

The 2SCML estimation is implemented in two stages. First, the reduced form equation (eq. 2) for the multiple banking variable is estimated using generalized least squares (the reduced form for the binary variable is estimated via random effect probit analysis). The parameters from the reduced-form equation are then used to generate the residuals, which are included in the structural equation (eq. 1) as an additional variable with a corresponding parameter to be estimated at the second stage. The 2SCML approach produces consistent and asymptotically efficient estimates, and the probit *t-stat* on the residuals coefficient provides a direct test of the null hypothesis that the variable is endogenous (Wooldridge, 2002). The estimation procedure is therefore appealing, because it also allows an in-depth analysis of the determinants of the multiple banking choice.

3.1 Data description

The hypotheses are tested on a unique data set resulting from the merger of a time series-cross section of more than 11,000 firms[10] for which accounting data is available over the years 1997-2004, with data on total exposure to the banking system from the Central Credit Register (CR) for the entire time period.

The original sample includes firms borrowing from at least one Italian bank at the end of any sample year between 1997 and 2004[11][12]. Pure financial holding companies, financial firms and intermediaries, agricultural and real estate companies are dropped from the sample, which is reduced to 9,500 non-financial, for-profit firms per year.

The distribution of sample firms by geographical area and industry broadly reflects the distribution of Italian firms population, though firms based in Northern regions (68%) and manufacturing firms (67%) are slightly over-represented. Almost all sample firms (98%) are corporations, and only 5% of them are based in industrial district areas.

The database is composed of (1) year-end annual balance sheet and income statement data; (2) other information on sample firm characteristics, such as date of incorporation, governance structure, industry, location; (3) year-end data on debt exposure vis-à-vis the banking system, and number of lending banks; (4)

10 Sample firms have been randomly selected from the corporate customer base of Banca Intesa (now Intesa Sanpaolo). Over the years 1997-2004, Banca Intesa was the largest Italian banking group by total assets, total loans and deposits; it operates throughout Italy. However, the analysis does not focus on Banca Intesa lending policies, as the hypotheses are tested only on data from the so called "return information flows", i.e., on data returned to each reporting bank by the Credit Register referring to the exposure towards the banking system as a whole, and not on the exposure of sample firms towards Banca Intesa.

11 The sample period starts from 1997, as the reporting structure of the Central Credit Register was radically changed in 1996 and previous data are not comparable, and ends in 2004 because the most updated available annual balance sheets referred to fiscal year 2004 when the data sets were matched.

12 The sample may be affected by a form of survivorship bias towards firms having longer relationships with the banking system.

data on local banking market concentration; (5) data on the structure of the Italian banking system in 1936.

Accounting data and information are drawn from the Italian Company Account Register (Centrale dei Bilanci - CeBi) archives, which also provide the other information on firm-specific characteristics and identification data, allowing matches with the CR data. The CeBi sample is highly representative of Italian non-financial industries, but it is tilted towards medium-large companies.

Data on individual firm exposure towards the banking system comes from the CR archives. The CR collects from Italian banks monthly data on the individual credit exposures (the reporting threshold is 75,000 Euro[13]) of their borrowers and returns to contributing banks information on their customers' total exposure vis-à-vis the whole banking system. The information collected by CR refers to credit lines and overdrafts (drawn and undrawn amount), mortgages, subordinated loans, repos, leasing and factoring. For each type of instrument, maturity, risk-mitigating guarantees and collateral are also reported. Other information include taxpayer identification numbers, industry of activity, geographical location. Elementary data on individual instrument is aggregated to obtain total outstanding credit and the drawn amounts by firm. For the purpose of the analysis, all forms of financing with a fixed maturity and a defined amortization plan (e.g. mortgage loans, leasing) are dropped from the sample. The main reason for focusing on credit lines only is that other forms of financing are not callable, their level of "credit usage" is necessarily much higher - because the credit drawn is equal to the credit granted - and not discretionary. Therefore, the ratio of credit drawn to credit granted would be a meaningless measure of credit tightening[14].

To conclude, the Bank of Italy Economics and International Relations Department provided the raw data on individual Italian banks' branch network, which have been used to construct the Herfindahl index of branch concentration and the total number of new bank branches opened in each province; instrumental variable measures as well come from the Italian Central Bank[15].

3.2 Description of variables

The empirical analysis encompasses the use of several explanatory measures, described in table 1. All variables are widely accepted and used by the related empirical literature. Therefore, I limit the discussion to the dependent variable, independent variables of interest and the instrumental variables - as their use is unique to the analyses of the Italian market - and refer to table 1 for the remaining ones.

The dependent variable is modelled as a binary variable measuring the ex post probability of credit tightening. To proxy for credit tightening, the dummy OVERDRAFT is used. It takes the value of 1 if the ratio of credit drawn to bank credit granted exceeds 100%. As a robustness check, all regressions are also

---

13 As of December 2001 the Credit Register included over 1,500,000 individuals and 710,000 firms. The total outstanding amount covered 96% of loans to enterprises and 40% of loans to households. For a detailed description of the CR database see Foglia (2002).

14 Besides, I discussed the issue with some credit loan officers, and all of them agreed that (1) when a bank wants to limit credit supply quickly, an effective way to do so is to reduce the credit lines available to the firm, and (2) firms showing an abnormal increase in the credit lines usage are unlikely to get any other (collateralized or not) forms of financing.

15 "Struttura funzionale e territoriale del sistema bancario italiano 1936-1974", Bank of Italy, Rome, 1978.

tested on a weaker definition of credit constraints (CONSTRAINT equal 1 if the credit drawn to credit granted ratio is higher than 90%, 0 otherwise). The credit drawn to credit granted ratio is an inverse measure of credit tightening (Del Colle et al., 2006; Finaldi Russo and Rossi, 2001; among others), assuming that – under normal conditions - the loan market is supply-driven and firms constrained by banks can either access alternative sources of financing or increase the use of available credit lines[16]. This variable potentially varies between 0 and infinity, as firms can overdraw on their credit lines, though at a very high cost in terms of both fees and interest rate it must pay. Normally, borrower draw from their credit lines within the available maximum balance, and tend to maintain substantial excess credit lines when their liquidity needs are low rather than taking the risk of overdrawing in the future (Bonaccorsi di Patti and Gobbi, 2007). Therefore, firms that do overdraw or use the available credit lines up to the limit may be considered credit (quantity) constrained[17]. According to the above measures of tightening, only 3% (6%) of sample firms are subject to the strong (weak) form of credit constraints.

Based on the available data, the primary measure of multiple banking is the (natural log of) number of lending banks (LNBANKS). Since for privacy reasons the Central Credit Register reports such variable only if it is strictly higher that three, an alternative proxy for the number of relationships is constructed: BANKMIN3 is a categorical variable, equal 1 if the number of banks is lower than (or equal to) three, 0 elsewhere. Therefore, BANKMIN3 measures the firm's choice for concentrated lending relationships[18]. Only 5% of the sample firms have concentrated relationships, while multiple banking relationships are widespread, as suggested by the mean and median number of banks (10) from which sample firms borrow. Summary statistics are consistent with previous evidence from the Italian banking market (Ongena and Smith, 2000; Foglia et al., 1998; D'Auria et al., 1999), and even small businesses have fragmented lending relationships.

The other independent variable of interest is bank market power. In what follows, the concentration of the local market proxies for the lenders' market power. It is well known that market concentration is an imperfect measure of market power: high concentration is compatible with very competitive market structures, and low concentration is also compatible with little competitiveness. This notwithstanding, concentration has been extensively used in the banking literature as a proxy for market power. Concentration is measured by the Herfindahl index of banking group branches (HHI) at province level[19].

---

16 A similar argument underpins the use in several empirical studies (Kaplan and Zingales, 1997; Houston and James, 1996, among others) of the unused line of credit both in absolute value and in percentage of total credit granted (which is the inverse of the pecentage of credit drawn to credit granted).

17 Nevertheless, a supply shift may well occur mainly via higher interest rates or a worsening of other terms and conditions.

18 In the context of this paper, lending relationships are defined as "concentrated" when they involve only few banks. Concentration is not a synonym of asymmetry. Firms may have few and equally weighted relationships, or many, but skewed relations.

19 Most analyses perfomed on Italian data assume provinces as relevant banking markets for small and medium enterprises, according to the Italian Antitrust Authority guidelines. The Italian industrial structure is characterised by many SMEs, which almost entirely rely on bank loans as a source of financing. These firms are locally based and are not likely to access banking services provided in areas different from those in which they operate: Bonaccorsi di Patti (2003) provides evidence that 82.5% of bank-firm relationships are established between banks and companies located in the same province, and 50% in the same municipality.

I now turn to the description of instrumental variables, i.e. a set of variables which affect the number of multiple banking relationships, but not – at least directly – the likelihood of credit tightening. Following Guiso et al (2004 and 2006) and Herrera and Minetti (2007), I identify five variables measuring the (potential) shocks to the supply structure of local banking markets. Four of them refer to structural characteristics of Italian banking markets in 1936: (a) number of savings banks; (b) number of cooperative banks; (c) number of bank branches and (d) number of branches belonging to local banks (in percentage of total bank branches), while the fifth one is (e) the number of new bank branches - net of closed branches - opened yearly in each province by both incumbent and new banks (i.e., banks not already operating in the province) from 1997 to 2004.

Guiso et al. (2006) thoroughly discuss the instruments[20] and provide evidence that the structure of the banking system in 1936 significantly contributes to explain the degree of bank competition at the province level until the deregulation in late 1980s. The provinces where the regulation was tighter experienced smaller increases in the local supply of banking services until the late 1980s, and more after that, than the provinces where it was looser. The 1936 regulation also directly constrained banks' potential to open new branches in the local markets and explain provincial variation in the number of bank branches after the deregulation.

Therefore, the four measures referred to 1936 capture the local tightness of regulation, while the yearly number of new branches reflects the greater (lower) inflows of branches after the deregulation and directly proxy for potential shocks to the supply structure of local banking markets. I do not have prior on the relation between the number of multiple banking and the instruments, as the extant literature discussed in section 2 offers conflicting prediction on the impact of increased availability of financing opportunities on the number of relationships (and on the strength of such relationships; see Herrera and Minetti, 2007; Boot and Thakor, 2000).

When testing the hypotheses, it is also necessarily to control for firm-specific characteristics and changes in riskiness, which are likely to affect the probability of the firm being credit tightened. Firm-specific explanatory variables are intended to jointly capture borrower riskiness and profitability, asset liquidity, the availability of pledgeable collateral, and information asymmetry between a firm and its lenders. Each firm is also assigned a credit risk score, based on a scoring model[21]. Appendix A.2 shows the variables and ratios used to specify the model, estimated using multinomial logistic regression. For practical purposes, the predicted probability of default is associated with a discrete score, ranging from 1 (very safe) to 100 (highest risk). To avoid endogeneity problems, all firm-specific variables are lagged one year.

Finally, year, industry and location dummy variables are introduced into the regression analyses. Industry dummies are included to further control for the specific riskiness of the industry[22].

---

20 They also describe the history of the Italian banking regulation.

21 The scoring model has been elaborated and tested for internal use by Banca Intesa, to estimate the probability of default of customer firms.

22 In the regression analysis, only industry dummy variables not controlled for in the credit scoring model are included.

Beside the geographical dummies, one additional location control variable is the DISTRICT dummy: it equals 1 if the firm is located in an industrial district area23, 0 otherwise24.

Theoretical models (Stiglitz, 1994; Banerjee et al., 1994) acknowledge the role played by peer monitoring - exerted by other firms - and ex-post verification – exerted by local banks - in reducing moral hazard and free riding in industrial clusters, and consequently in improving credit conditions for district firms. The lending relationship literature also highlights the role of soft information and banking relationships in reducing credit constraints. Empirical studies (Finaldi Russo and Rossi, 2001, for example) show that firms located inside industrial districts may have an advantage in terms of financial relations with the banking system (lower cost of credit and lower probability of encountering financial constraints). Contra, industrial district firms may be more liable to tightening if (local) lending banks are not well diversified. The potential effect of DISTRICT has therefore to be empirically assessed.

4. Estimation results

As discussed in previous sections, I address the potential endogeneity of the multiple banking choice by instrumenting this variable. The results of instrumental variable estimates (first-stage regressions of eq. (2)) are presented in the next paragraph, while second-stage estimations of eq. (1) are pointed out in section 4.2.

4.1 The number of multiple banking relationships

The multiple banking choice is proxied by either a binary variable (BANKMIN3) or a discrete variable[25] (LNBANKS). Therefore, eq. (2) is estimated, respectively, through maximum likelihood (ML) probit (table 2, specifications I and Ia) and random-effects generalized least square (GLS) procedures (table 2, specification II and IIa). For each dependent variable, I estimate two variants of the reduced form equation. In models Ia and IIa, the inclusion of a lagged dependent variable is meant to isolate the role of dynamics and state dependence (Vella and Verbeek, 1999)[26]. Finally, only standard errors adjusted for clustering on firms' id

---

23 *There is no universally accepted definition of either the elements that make up an industrial district (industrial cluster) or the underlying mechanisms that allow the district to successfully compete with other production models. Nevertheless, there is wide consensus in the literature on industrial district as "a socio-geographical entity characterized by the active presence of both a community of people and a population of firms in one naturally and historically bounded area" (Beccattini, 1990). Marshallian or agglomeration economies were the first justification of the benefits the industrial district offered firms, but a more "thickly" defined industrial district includes the abundance of local productive knowledge, strong institutions, and a culture that facilitates cooperation. Industrial clusters are indeed widespread in North-Central Italian regions, but they may be found in South-Western Germany, Spain, Scandinavia, USA (e.g. Silicon Valley) and Japan, as well as in many developing countries (e.g. Brasil, Romania, Cina and India) where many industrial district firms outsource their labour-intensive productions.*

24 *Sixty-two industrial districts are identified according to the Mediobanca – Unioncamere (2003) criterion.*

25 *Although the number of banks is a discrete variable, following Detragiache et al. (2000) and Herrera and Minetti (2007), I treat it as a continuous variable and use GLS estimator in the first stage. Since the number of banks varies between 4 and 35, this should not lead to a significant bias.*

26 *However, in contrast to Vella and Verbeek (1999) I have to estimate the dynamic model treating the number of multiple banks as exogenous, and ignore the initial condition problem. I am aware that the multiple banking choice in the first period is unlikely to be truly exogenous, given the presence of the firm-specific effects.*

are reported, as they correctly account for the unobserved firm effect and produce unbiased estimates (Petersen, 2007).

Several points are worth noting. First, controlling for exogenous firm-specific characteristics and for local banking market concentration, the instrumental variables jointly have a statistically significant impact on the multiple banking choice. As argued in section 2, both the nature of the instruments and the conflicting theoretical predictions suggest that the signs of the instrumental variable coefficients are ambiguous a priori. However, if we accept the argument that the peculiarities of the Italian Banking Law of 1936 affect the degree of competition more than 50 years later (Guiso et al., 2006) and, consequently, the local supply of banking services, the findings reported in table 2 suggest that shocks to the bank credit offer directly influence the firms' choice of the number of banking relationships.

Second, the impact of the lagged variable in columns Ia and IIa is highly significant and suggest the presence of 'state' dependence. The inclusion of the lagged variable impact on the coefficients of the other variables and it generally reduces their magnitude. This is expected as their effect partially operates through the lagged variable, but it also makes the sign of NEWBRANCH reverse in both Ia and IIa specifications. In the latter one, the coefficient is positive and statistically significant: "conditioned" on the previous year choice of the number of lending banks, the number of relations is positively related with the opening of new bank branches in the province. In other words, a potential shock to the supply structure of local banking markets does affect the firm choice of the number of bank lenders.

Third, the random effects GLS model omitting the lagged dependent variable (table II, specification II) attributes approximate 86% of the total variance to the individual effects; the specification IIa, where the contribution of the individual effects reduces approximately to 12%, indicates that this may be due to the failure to account for dynamics. I therefore consider the specification IIa in table 2 and 3 as the reference or preferred model.

The exogenous variables are generally in keeping with expectations and previous empirical studies, and significantly affect the multiple banking choice. Their marginal effect is, however, small. Larger, growing, riskier, less profitable, more indebted and more opaque firms tend to chose a higher number of banking relationships. The opaqueness of firms' assets has the highest (positive) coefficient among the firm-specific characteristics: firms with a high share of intangible assets are more difficult to value and monitor, and perceived to be riskier (all else equal) by banks. Furthermore, intangible assets are less liquid and more specific (or less-redeployable). Opaque firms are, therefore, more likely to suffer from credit constraints and, as a consequence, tend to choose multiple lenders to reduce the risk of being rationed. The evidence is consistent with both theoretical predictions of contractual theories of the firm (e.g., Bolton and Sharfestein, 1996) and financial intermediation model (Carletti, 2004), and with recent analyses on borrowing concentration (Elsas et al., 2004; Ongena et al., 2006). On the contrary, the availability of slack liquidity is negatively (positively) correlated with the number of banks (the likelihood of having less than/or three relationships).

Along with the opaqueness of firms' assets, the credit market concentration measures have the highest marginal impact. The relation between multiple banking choice and concentration is not linear: the probability of having less than four banks is negatively associated with the HHI index, but positively with the square term. The total effect is always negative, i.e. the higher the local credit market concentration the lower the probability of having few lending relationships. Conversely, the sign and total effect of HHI turn out to be positive in regression IIa: if the dynamic is properly taken into account, the relation between number of relations and market concentration is positive, and the total marginal effect strictly increasing in the HHI. Firms located in very concentrated markets seem to induce competition at firm level by entering multiple lending relations. The estimation results of models Ia and II are consistent and, taken together, they support the argument that firms maintain multiple banking relations as a safety net, which may reduce the risk of being tightened and the (potential) negative effects of credit market concentration.

4.2 Multiple banking and credit market competition: what benefits the firm?

As a second step in the 2SCML estimation procedure, the structural equation (1) is estimated after including first stage residuals. In tables 3 and 4 the dependent variable is the likelihood of credit tightening, while the multiple banking choice is proxied, respectively, by BANKMIN3 and LNBANK.

The probit results reported in tables 3 and 4 (specification I), without correction for the potential endogeneity of the multiple banking choice, reveal a significant relationship between the probability of quantity credit tightening and the number of lending banks: such relationship is positive if the firm has less than/or three banks, positive if it has more banks. In other words, firms having few lending relationships are more likely to be constrained, while firms relying on more relations are less likely to be tightened.

The remaining coefficients have the expected sign, but some of them are weakly or not significant. Interestingly, the local market concentration is a significant determinant of the likelihood of tightening, and its coefficient is positive: firms located in highly concentrated markets are more likely to suffer from bank credit constraints.

Columns II-V of tables 3-4 report the result from estimating the tightening equation while correcting for the potential endogeneity of the number of lending banks. The inclusion of the correction term accounts for endogeneity and provides a valid test for it.

A number of features are worth noting from a comparison of the unadjusted estimates (regression I) to those from the corrected specifications.

First, the parameters of the first stage residuals indicate that no form of endogeneity is present: the coefficient on the individual effects u_{it} is always positive, but not significant. The results in columns III incorporate a role for dynamics in the reduced form multiple banking equation, treating the initial value as exogenous. Total residuals are also decomposed into a time-invariant (u_{it}) and a time varying ($\bar{u}_i$) individual effects (column IV), but none of them does affect the probability of tightening. Therefore, I cannot reject the null hypothesis that the number of lending relations is exogenous to the likelihood of bank credit tightening.

The coefficients of the other regressors have the expected sign and are mostly significant. Overall, the probability of credit constraints is increasing both in the firm riskiness and leverage, but decreasing in its asset liquidity and collateral availability. More profitable firms do not suffer from credit constraints, but more opaque firms do. The availability of slack liquid resources also has an economically and statistically meaningful effect on the dependent variable. Firm size and age do not seem to affect the probability of credit tightening: only the age coefficients are statistically significant, but the marginal effect is negligible. The location control variables are consistent with existing evidence from the Italian banking industry: firms located in Northern and Central regions are less likely to be tightened. Though the number of sample district firms is small, the dummy variable DISTRICT - which is never significant in the first stage regressions - turns out to be positively related to the probability of tightening in all regressions controlling for endogeneity (columns II-V, tables 3 and 4). All else equal, firms located in industrial districts are slightly more liable for credit restrictions. The evidence is consistent with former empirical analyses (Baffigi et al., 2000; Pagnini, 2000), though different conclusions are drawn by Finaldi Russo and Rossi (2001). Two main arguments may help explain the results. First, since industrial district firms are more likely to establish lending relationships with local banks - whose loan portfolios are less diversified, - they are also more likely to suffer from credit restrictions. Second, the consolidation process in the banking system may have had a detrimental effect on the supply of credit to district SMEs. However, data do not allow to disentangle the effect of multiple lending relationships with local banks from that of relationships with large/national banks, and deepen analyses of the issue are not possible so far.

Moving to the second hypothesis testing, credit market structure is a statistically significant determinant of the probability of tightening and the traditional effect of market power seems to prevail, as the probability of credit constraints increases with market concentration (but, at a decreasing rate).

The results of the random effects logistic regressions (model V, tables 3 and 4) further support the evidence, as the estimated standard errors do not differ significantly, though the marginal effect of each independent variable is slightly lower.

Taken together, the findings suggest that a key reason why firms engage in multiple relationships is to reduce the consequences of hold-up costs and the risk of being constrained. The probability of tightening is indeed higher for risky, non-profitable firms, located in concentrated banking markets. The results on the effect of market concentration contrast with the empirical evidence documented by Petersen and Rajan (1995), but are consistent with those reported by Houston and James (1996), de Mello (2004) and Carbò-Valverde et al. (2006). It worth observing that the marginal effect of market concentration is higher than the one of multiple banking: market competition would benefit the firm more than banking competition induced by each firm by diversifying its credit sources.

In order to gain more insight into the benefits of multiple lending relationships in different credit markets (third hypothesis), I first construct two new variables by interacting the market concentration index with the measures of multiple banking (LNBANKS and BANKMIN3). I then regress the probability of tightening on the usual set of independent variables, including the new interacting variable. Probit regression results are reported in table 5.

The multiple banks (dummy variable for less than/or three banks) parameter is still negative (positive) and statistically highly significant, but the interaction variable coefficients are not (columns I and II). The HHI coefficient is still positive and significant in regression II, but not in specification I.

To further test the hypothesis that multiple banking may benefit the firm differently, depending on local credit market structure, I construct three binary variables to distinguish the most competitive (DV_MKTCOMP, equal 1 if HHI is lower than or equal to the 25th percentile threshold, 0 otherwise), the most concentrated (DV_MKTCONC, equal 1 if HHI is higher than or equal to the 75th percentile threshold, 0 otherwise) and the middle competition (DV_MIDCOMP; HHI ranging between the 25th and the 75th percentile thresholds) banking markets. I then replace the continuous measure of concentration with the dummy variables. Regression results are reported in table 5, columns III. Since multiple banks might have a different effect in highly competitive and highly concentrated markets, I estimate different intercepts and slopes for each level of market concentration. The intercept are meant to measure the difference between a firm based in the most concentrated and a one located in the most competitive markets. Only the multiple banking coefficient is negative and significant, while the marginal effect of both dummy variables interacted with LNBANKS is not statistically and economically significant. Such results are robust to more stringent definitions of banking competition/concentration: they do not change if the dummy variables distinguish the highest/lowest deciles or fifth percentile of HHI[27].

The main conclusion I draw from these tests is that banking concentration at firm level and at market level is detrimental to the firm, as both forms of concentration increase the likelihood of quantity credit tightening, but the marginal effect of market concentration is higher. However, firms that engage in multiple relationships benefit from competition among lending banks in terms of a lower probability of credit constraints[28], though such competition does not fully outweigh the marginal effect of local banking market power. The (marginal) impact of multiple banking is not statistically different in highly competitive vs concentrated markets.

Nevertheless, as multiple banking is not necessarily an inverse measure of lending relationship, such conclusions do not exclude that an asymmetric distribution of credit among lending banks may benefit the firm more than just relying on many banks (Guiso and Minetti, 2004; Ongena et al., 2006; Carmignani and Omiccioli, 2007).

4.3 Robustness checks

In order to assess the robustness of the second-stage random-effects probit regression results, further tests are performed.

First, alternative regressors are used. The firm-specific variables have been replaced, for example, by firm size and age categorical variables (small, medium, large; young, old), different definition of size (sales), leverage (i.e., total financial liabilities/total assets; debt/equity ratio), liquidity and profitability, but results are qualitatively similar to those discussed in previous sections and are not showed in tables[29].

Second, estimation results are robust to a different definition of the dependent variable (only the preferred specification is reported in table 6). Since overdrawing is a very expensive form of financing, and therefore a symptom of strong tightening, OVERDRAFT is replaced by CONSTRAINT, which is defined as a binary variable equal 1 if the credit drawn/credit granted ratio is higher than

---

27 Data not reported in tables, but available from the author upon request.

28 Due to data availability, I am unable to test if firms benefit from multiple banking in terms of lower probability of credit tightening, but pay higher interest rates or are required to post more collateral.

29 All robustness checks not reported in tables are available upon request.

90%[30]. CONSTRAINT is meant to capture a less stringent form of credit tightening.

Turning to the second-stage robustness results, the coefficient on BANKMIN3 is no longer significant, while properly correcting for the endogeneity of the number of banks. The firm-specific variables have the same sign and statistical significance of those in the reference model (table 3, model V). Furthermore, their marginal effect is higher in absolute value. The only coefficient that loses significance is that of the square term of HHI, while HHI is even (statistically and) economically more relevant.

The evidence on the correlation between CONSTRAINT and multiple banks reinforces the findings of the preferred specification: the marginal effect of LNBANKS is negative, statistically significant and much higher that the one reported in table 4. However, its marginal effect is negligible if compared with the one of HHI. Once more, bank credit market power is the most relevant determinant of the probability of constraints. Firms may contrast it by inducing competition among (incumbent or inside) lending banks.

To conclude, I interpret the robustness checks as further support of the hypotheses that also weaker forms of tightening are highly (positively) correlated with the firm risk profile and the local market structure. Relying on few banks does not significantly affect the probability of quantity credit constraints, but multiple banking does benefit the firm by lowering such probability.

5. Conclusions

This paper examines the impact of multiple banking and credit market competition on the availability of credit for a large sample of private Italian firms. Consolidated theoretical arguments underpin the testable hypotheses that multiple relationships may affect the availability of credit for the firm, and that bank market power does affect both the supply of credit and the value of the relationships for the borrowers. The variance of existing empirical findings on the issue, the lack of analyses of the multiple lenders choice (potential) endogeneity and the peculiarities of the Italian banking market motivated the research question.

The analyses of an extensive longitudinal database supports the hypothesis that the estimated (ex post) probability of quantity credit tightening is significantly lower (higher) for firms having more (very few) bank lending relationships, after correcting for the potential endogeneity of the firm’s decision of the number of banks.

While theory does not point a clear picture about how banking market power ought to affect the availability of credit to firms, the empirical analysis suggest some insights. My results are consistent with the idea that the traditional effect of market power outweighs the positive effect of the informational effect, and the likelihood of quantity credit constraints is negatively correlated with the degree of concentration of local banking markets. These findings contrast those of Petersen and Rajan (1995) and Zarutzkie (2006), but are consistent with more recent evidence from USA (de Mello, 2003) and Spain (Carbò-Valverde et al., 2007). Banking concentration both at firm level and at market level is detrimental to the firm, as it increases the probability of tightening. Firms that engage in multiple relationships benefit from competition among lending banks in terms of a lower

30 90% corresponds to the 90th percentile of credit lines usage.

probability of credit constraints, though such competition does not fully outweigh the marginal effect of local banking market power. The two forms of banking competition seem to be alternative, and not complementary.

As for the multiple banking choice, I find that larger, riskier, less profitable and more opaque firms engage in multiple lending, and the number of relations is also positively related with credit market concentration.

The above findings may be interpreted as providing evidence that a key reason why firms rely on multiple banking is their desire to reduce the consequences of hold-up and the risk of being quantity credit constrained.

This paper leaves open some questions for future research. As multiple banking is not necessarily an inverse measure of lending relationship, the results cannot be interpreted in contrast with the hypothesis that a single-bank lending relationship may benefit the firms. Furthermore, the analysis does not shed light on how an asymmetric distribution of credit among lending banks affects the firm's borrowing conditions and credit availability, or on the coexistence of a relationship lender with many other transaction lenders. A literature is developing on the effects of creditor concentration (Carmignani and Omiccioli, 2007; Ongena et al., 2006), and further work on the issue should help explain the persistence of multiple banking in Italy and other European markets that are experiencing a new wave of banking market concentration.

Appendix

Fig. 1 - Credit scoring model

Variables	Ratios	
Capital structure	LEV1	Equity/(Equity + Financial debt)
	LEV2	Equity/Total liabilities
	AUTDE	EBITDA/Total liabilities
	IMMCA	Total fixed assets/(Equity + Long term liabilities)
	DBRPC	Short term financial debt/Liquidity
	OFFA	Interest expenses/Sales
	PRFIF	Interest earnings/Sales
Profitability	ROE	Net profit/Equity
	UTFA	Net profit/Sales
Liquidity	ACID	Current assets/Current liabilities
Industry trend	D(MOL/FATT)	Expected growth of (Industry EBITDA/Industry sales)
	D(FATT)	Expected growth rate of industry sales

Model specification for firms operating in the service industry[31]:

$$SCORE_{serv} = \alpha_1 + \alpha_2(DV\_SOUTH) + \alpha_3(DV\_TRANSPORT) + \alpha_4 LEV2 + \alpha_5 OFFA + \alpha_6 PRFIF + \alpha_7 UTFA$$

Model specification for manufacturing firms:

$$SCORE_{ind} = \alpha_1 + \alpha_2(DV\_SOUTH) + \alpha_3(DV\_ENERGY) + \alpha_4 AUTDE + \alpha_5 IMMCA + \alpha_6 DBRPC + \alpha_7 OFFA + \alpha_8 ROE + \alpha_9 ACID1 + \alpha_{10} LEV1 + \alpha_{11} DMOL/FATT + \alpha_{12} DFATT$$

31 For privacy reasons, the estimated parameters are not reported.

References

Alvarez M. R., G. Glasgow (1999), Two-stage estimation of nonrecursive choice models, *Political Analysis*, 8 (2), 147-165.

Arendt J. N. (2002), Endogeneity and Heterogeneity in LDV Panel Data Models, Institute of Local Government Studies, Copenhagen, Denmark, unpublished manuscript.

Arendt J. N., A. Holm (2006), Probit Models with Binary Endogenous Regressors, Discussion Papers on Business and Economics, 4/2006, Department of Business and Economics, Faculty of Social Sciences, University of Southern Denmark.

Baffigi A., Pagnini M., F. Quintiliani (2000), Localismo bancario e distretti industriali: assetto dei mercati del credito e finanziamento degli investimenti, published in: Signorini L. F. (edited by) "Lo sviluppo locale. Un'indagine della Banca d'Italia sui distretti industriali", Meridiana Libri, Donzelli Ed., Rome.

Banerjee A. V., Besley T., T. W. Guinname (1994), The Neighbor's Keeper: the Design of a Credit Cooperative with Theory and a Test, *Quarterly Journal of Economics*, 109, n. 2, 491-516.

Beccattini G. (1990), The Marshallian indistrial district as a socio-economic notion, in Pyke F., Beccattini G., Sengenberger W. (eds), *"Industrial Districts and Local Economies Regeneration"*, International Institute for Labour Studies, Geneva.

Berglöf E., E. L. Von Thadden (1994), Short-term versus Long-term Interests: Capital Structure with Multiple Lenders, *Quarterly Journal of Economics*, 109, 625-658.

Bolton P., D. S. Scharfstein (1996), Optimal Debt Structure and the Number of Creditors, *Journal of Political Economy*, 104, 1-25.

Bonaccorsi di Patti E. (2003), Preferences in Bank-Firm Relationships, Bank of Italy, unpublished manuscript.

Bonaccorsi di Patti E., G. Gobbi (2007), Winners or Losers? The Effects of Banking Consolidation on Corporate Borrowers, *Journal of Finance*, 62, 2, 669-695.

Boot A. W. A. (2000), Relationship Banking: What Do We Know, *Journal of Financial Intermediation*, 9, 7-25.

Boot A. W.A., A. V. Thakor (2000), Can Relationship Banking Survive Competition?, *Journal of Finance*, 55, n. 2, 679-713.

Brunner A., J. P. Krahnen (2006), Multiple Lenders and Corporate Distress: Evidence on Debt Restructuring, revised, Frankfurt University, Center for Financial Studies w.p. n. 2001/04.

Carbò-Valverde S., Rodriguez-Fernandez F., G. Udell (2006), Bank Market Power and SME Financing Constraints, Kelley School of Business, Indiana University, unpublished manuscript.

Carletti E. (2004), The Structure of Bank Relationships, Endogenous Monitoring, and Loan Rates, *Journal of Financial Intermediation*, 13, 1, 58-86.

Carletti E., Cerasi V., S. Daltung (2007), Multiple-bank Lending: Diversification and Free-riding in Monitoring, *Journal of Financial Intermediation,* 16, 3, 425-451.

Carmignani A., M. Omiccioli (2007), Costs and Benefits of Creditor Concentration: an Empirical Approach, Bank of Italy, unpublished manuscript.

Cole R. A. (1998), The Importance of Relationships to the Availability of Credit, *Journal of Banking and Finance*, 22, n. 6-8, 959-977.

D'Auria C., Foglia A., P. Marullo Reedtz (1999), Bank Interest Rate and Credit Relationships in Italy, *Journal of Banking and Finance*, 23, 1067-1093.

de Bodt E., Lobez F., J.-C. Statnik (2005), Credit rationing, customer relationships and the number of banks. An empirical analysis, *European Financial Management*, 11, n. 2, 195-228.

de Mello J. M. (2003), Market Power and the Availability of Credit: an Empirical Investigation of the Small Firms' Credit Market, Stanford University, unpublished manuscript.

Degryse H., S. Ongena (2005), Distance, Lending Relationships and Competition, *Journal of Finance*, LX, 1, 231-266.

Del Colle D.M., Russo, F.P., A. Generale (2006), The Causes and Consequences of Venture Capital Financing. An Analysis Based on a Sample of Italian Firms, Bank of Italy, w.p. 584

Dell'Ariccia G., Friedman E., R. Marquez (1999), Adverse Selection as a Barrier to Entry in Banking Industry, *Rand Journal of Economics*, 30, n. 2, 515-534.

Dell'Ariccia G., R. Marquez (2004) Information and Bank Credit Allocation, Journal of Financial Economics, 72, 1, 185-214.

Detragiache E., Garella P., L. Guiso (2000), Multiple versus Single Banking relationships: Theory and Evidence, *Journal of Finance*, LV, 3, 1133-1161.

Dewatripont M., E. Maskin (1995), Credit and Efficiency in Centralized and Decentralized Economies, *Review of Economic Studies*, 62, 541-555.

Diamond D. (1983), Financial Intermdiation and Delegated Monotoring, *Review of Economic Studies*, 51, 3, 393-414.

Elsas, R. (2005), Empirical Determinants of Relationship Lending, *Journal of Financial Intermediation*, 14, 32-57.

Finaldi Russo P., P. Rossi (2001), Credit Constraints in Italian Industrial Districts, *Applied Economics*, 33, n. 11, 1469-1477.

Foglia A. (2002), Using Credit Register and Company Account Data for Measuring Credit Risk: a Supervisory Approach, Bank of Italy, unpublished manuscript.

Foglia A., Laviola S., P. Marullo Reedtz (1998), Multiple banking relationships and the fragility of corporate borrowers, *Journal of Banking and Finance*, 22, 1441-1465.

Guiso L. (1998), High-tech firms and credit rationing, *Journal of Economic Behavior & Organization*, 35, 35-59.

Guiso L., R. Minetti (2004), Multiple creditors and information rights: theory and evidence from U.S. firms, CEPR Discussion paper n. 4278.

Guiso L., P. Sapienza, L. Zingales (2004), Does Local Financial Development Matter?, *Quarterly Journal of Economics*, 119, 3, 929-969.

Guiso L., P. Sapienza, L. Zingales (2006), The Cost of Banking Regulation, Chicago Graduate School of Business, unpublished manuscript.

Harhöff D., T. Körting (1998), Lending Relationship in Germany. Empirical Evidence from Survey Data, *Journal of Banking and Finance*, 22, 1317-1353.

Herrera A. M., R. Minetti (2007), Informed Finance and Techonological Change: Evidence from Credit Relationships, *Journal of Financial Economics*, 83, 223-269.

Holmstrom B., J. Tirole (1997), Financial intermediation, loanable funds, and the real sector, *Quarterly Journal of Economics*, 112, 663-691.

Houston J. F., C. M. James (1996), Information Monopolies and the Mix of Private and Public Debt Claims, *Journal of Finance,* LI*,* 5, 1863-1889.

Jappelli T., M. Pagano (2000), Information sharing in credit markets: a survey, CSEF w.p. n. 36, University of Salerno.

Kahn C. M., D. Mookherjee (1998), Competition and Incentives with Nonexclusive Contracts, *Rand Journal of Economics*, 29, n. 3, 443-465.

Mayer C. (1988), New Issues in Corporate Finance, *European Economic Review*, 32, 1167-1188.

Ongena S., D. C. Smith (2000), Bank Relationship: A Review, in Harker P., S. A. Zenios (eds.), *"The Performance of Financial Institutions"*, Cambridge Univ. Press.

Ongena S., D. C. Smith (2001), What determines the number of number of bank relationships? Cross-country evidence, *Journal of Financial Intermediation*, 9, 26-56.

Ongena S., Tümer-Alkan G., N. Westernhagen (2006), Creditor concentration: an empirical investigation, Tilburg University, unpublished manuscript.

Park C. (2000), Monitoring and Structure of Debt Contracts, *Journal of Finance*, 55, n. 5, 2157-2195.

Pagnini M. (2000), I vincoli finanziari per le imprese distrettuali: un'analisi su dati bancari, published in: Signorini L. F. (edited by) "Lo sviluppo locale. Un'indagine della Banca d'Italia sui distretti industriali", Meridiana Libri, Donzelli Ed., Rome.

Petersen M. A. (2007), Estimating standard errors in Finance Panel Dat Sets: Comparing Approaches, Kellogg School of Management, Northwestern University, unpublished manuscript.

Petersen M. A., R. G. Rajan (1994), The Benefits of Lending Relationship: Evidence From Small Business Data, *Journal of Finance*, 49, 1, 3-37.

Petersen M. A., R. G. Rajan (1995), The Effect of Credit Market Competition on Lending Relationships, *Quarterly Journal of Economics*, n.110, 407-443.

Rivers D., Vuong Q., (1988), Limited Information Estimators and Exogeneity testing for Simultaneous Probit Models, *Journal of Econometrics*, 39, 347-366.

Scott J. A., W. C. Dunkelberg (2003), Bank Mergers and Small Firm Financing, *Journal of Money, Credit and Banking*, 35, 6, 999-1017.

Sharpe S. A. (1990), Asymmetric Information, Bank Lending and Implicit Contracts: A Stylized Model of Customer Relationships, *Journal of Finance*, 45, n. 4, 1069-1087.

Stiglitz J. E. (1994), Peer Monitoring in Credit Markets, *World Bank Economic Review*, 4, n. 3, 351-366.

Thakor A. V. (1996), Capital Requirements, Monetary Policy and Aggregate Bank Lending: Theory and Empirical Evidence, *Journal of Finance*, 51, 279-324.

Vella F., M. Verbeek (1999), Two-step Estimation of Panel Data Models with Censored Endogenous Variables and Selection Bias, *Journal of Econometrics*, 90, 239-263.

von Thadden E. L. (1992), The Commitment of Finance, Duplicated Monitoring and the Investm,ent Horizon, CEPR Discussion paper n. 27, London.

von Thadden E. L. (1995), Long-Term Contracts, Short-Term Investment and Monitoring, *Review of Economic Studies*, 62, 4, 557-575.

von Thadden E. L. (2004), Asymmetric Information, Bank Lending and Implicit Contracts: the Winner's Course, *Finance Research Letters*, 1, 11-23.

Wooldridge J. M. (2002), *Econometric analysis of cross-section and panel data*, The MIT Press, Cambridge, Massachusetts.

Zarutskie R. (2006), Evidence on the effects of bank competition on firm borrowing and investment, *Journal of Financial Economics*, 81, 503-537.

Table 1 - *Variable description and main summary statistics*

This table reports the definition and summary statistics for the variables included in the regression analysis

VARIABLES	DESCRIPTION	LABEL	DESCRIPTIVE STATISTICS					
DEPENDENT VARIABLES			MEAN	SD	25th pct	50th pct	75th pct	95th pct
OVERDRAFT	Dummy variable: one if the Credit drawn/Credit granted ratio is greater than 100%, and zero otherwise	OVERDRAFT	0.03	0.16	0.00	0.00	0.00	0.00
FINANCIAL CONSTRAINTS	Dummy variable: one if the Credit drawn/Credit granted ratio is greater than 90%, and zero otherwise	CONSTRAINT	0.06	0.24	0.00	0.00	0.00	1.00
INDEPENDENT VARIABLES								
NUMBER OF LENDING BANKS	(Ln) Number of lending banks (truncated variable, reported if the number of banks is greater than three)	LNBANKS	2.30	0.48	1.95	2.30	2.64	3.09
NUMBER OF LENDING BANKS LOWER THAN THREE	Dummy variable: one if the number of lending banks is lower than/equal three, and zero otherwise	BANKMIN3	0.05	0.22	0.00	0.00	0.00	1.00
BANKING MARKET CONCENTRATION	Herfindahl index of concentration of bank branches network, computed at province level	HHI	0.10	0.05	0.08	0.10	0.12	0.18
FIRM SIZE	(Ln) Total book assets	LOGTA	9.56	1.17	8.76	9.39	10.19	11.66
AGE	(Ln) Number of years since the firm was founded	LOGAGE	2.91	0.73	2.56	3.00	3.37	3.95
IDLE COLLATERAL	Tangible assets/bank debt	IDLECOLL	7.03	32.39	0.26	1.07	2.70	17.64
LEVERAGE	Bank debt/total financial liabilities	LEVERAGE	0.85	0.26	0.82	0.99	1.00	1.00
ASSET LIQUIDITY	Current assets/Total assets	ASSLIQUI	0.74	0.18	0.63	0.77	0.88	0.97
SLACK RESOURCES	Liquidity/Total assests	SLACK	0.06	0.09	0.01	0.02	0.07	0.23
GROWTH	y/y Growth rate of sales	SALESGR	4.69	20.51	-5.84	3.53	13.27	38.91
PROFITABILIY	Gross operating margin/sales	PROFIT	0.08	0.08	0.04	0.07	0.12	0.22
OPAQUENESS	Intangible assets/Total book assets	OPAQ	0.03	1.05	0.00	0.01	0.02	0.09
RISK SCORE	Credit risk score	SCORE	38.71	21.41	22.56	39.58	53.66	73.71
DELTA SCORE (DSCORE)	y/y Variation of credit risk score; if DSCORE is positive, the credit risk score is higher (the firm is riskier); if DSCORE is negative, the credit risk score is lower (the firm is safer)	DSCORE	0.42	0.49	0.00	0.00	1.00	1.00
INSTRUMENTAL VARIABLES								
SAVINGS BANKS IN 1936	Number of savings banks/ 1000 inhab., in 1936 (province level)	SAVINGS	0.03	0.06	0.01	0.01	0.03	0.10
COOPERATIVE BANKS IN 1936	Number of cooperative banks/ 1000 inhab., in 1936 (province level)	COOP	0.01	0.01	0.00	0.01	0.01	0.02
BRANCHES OF LOCAL BANKS IN 1936	Number of branches of local banks/Total bank branches, in 1936 (province level)	LOCBRANC	65.44	33.09	39.00	68.00	96.00	115.00
BANK BRANCHES IN 1936	Number of total bank branches/ 1000 inhab., in 1936 (province level)	BRANC1936	0.21	0.08	0.16	0.19	0.24	0.35
NEW BRANCHES	Number of branches opened (net of branches closed)/1000 inhab. (province level)	NEWBRANC	2.01	1.24	1.29	1.78	2.64	3.97
OTHER CONTROL VARIABLES								
DISTRICT	Dummy variable: one if the firm is located in an industrial district area, zero otherwise	DISTRICT	0.13	0.34	0.00	0.00	0.00	1.00
NORTH/SOUTH	Dummy variable: one if the firm is located in Northern/Southern regions, zero otherwise	NORTH	0.86	0.34	1.00	1.00	1.00	1.00

Table A.1 *- Correlation matrix of regressors*

	OVERDRAFT	LNBANKS	SAVINGS	COOP	LOCBRANC	BRANC1936	NEWBRANCH	LOGTA	LOGAGE	IDLECOLL	LEVERAGE	ASSLIQUI	SLACK	SALESGR	PROFIT	OPAQ	SCORE	DSCORE	HHI	HHI^2	DISTRICT
OVERDRAFT	1.000																				
LNBANKS	-0.030	1.000																			
SAVINGS	-0.012	0.020	1.000																		
COOP	-0.008	0.049	-0.012	1.000																	
LOCBRANC	-0.018	0.022	0.437	0.282	1.000																
BRANC1936	-0.024	0.092	0.659	0.067	0.378	1.000															
NEWBRANCH	-0.025	0.070	0.084	0.302	0.266	0.219	1.000														
LOGTA	-0.024	0.514	0.006	-0.027	-0.057	0.015	-0.021	1.000													
LOGAGE	-0.024	0.075	-0.018	-0.032	-0.050	0.011	-0.064	0.124	1.000												
IDLECOLL	-0.025	-0.071	-0.007	-0.024	-0.022	-0.003	-0.009	0.114	0.037	1.000											
LEVERAGE	0.018	0.051	0.019	0.042	0.060	0.036	0.035	-0.200	-0.012	-0.282	1.000										
ASSLIQUI	-0.006	-0.094	-0.020	0.012	0.015	0.010	0.017	-0.297	-0.067	-0.051	0.094	1.000									
SLACK	-0.034	-0.092	-0.012	0.021	0.001	0.020	0.024	-0.043	-0.005	0.106	0.002	0.131	1.000								
SALESGR	0.001	0.066	0.016	0.012	0.003	-0.001	0.043	0.099	-0.035	0.002	-0.012	0.046	0.021	1.000							
PROFIT	-0.051	0.003	-0.007	-0.009	0.006	0.018	0.050	0.149	0.027	0.097	-0.010	-0.303	0.111	0.136	1.000						
OPAQ	0.022	0.057	0.000	-0.032	-0.060	-0.003	-0.032	0.103	-0.050	-0.007	-0.061	-0.197	-0.054	0.018	0.022	1.000					
SCORE	0.135	0.131	-0.023	0.023	-0.038	-0.061	-0.036	-0.134	-0.058	-0.217	0.050	0.156	-0.214	-0.069	-0.422	0.062	1.000				
DSCORE	0.008	0.001	0.004	0.003	0.014	0.013	0.026	-0.012	-0.017	-0.012	0.004	-0.002	0.002	-0.032	-0.006	0.001	0.068	1.000			
HHI	0.020	-0.043	-0.152	0.050	0.193	-0.112	0.060	-0.069	-0.095	-0.021	0.027	-0.034	-0.006	0.007	0.002	-0.056	0.029	0.009	1.000		
HHI^2	0.014	-0.048	-0.096	-0.020	0.084	-0.119	0.088	-0.052	-0.062	-0.014	0.008	-0.034	-0.007	0.009	-0.007	-0.041	0.028	0.003	0.896	1.000	
DISTRICT	0.000	0.004	-0.037	0.080	0.053	0.085	0.083	-0.036	-0.022	-0.013	0.055	0.038	0.029	-0.030	0.006	-0.040	-0.031	0.025	0.024	-0.007	1.000

Table 2 - *First stage estimation results*

This table reports the results of the first stage estimation of the multiple banking choice. In models I and Ia, the dependent variable is the dummy variable BANKMIN3, which equals 1 if the firms has less than three lending banks, 0 otherwise. The dependent variable in specifications II and IIa is the continuous variable LNBANKS (natural log of the number of lending banks). The set of instrumental variables alternatively includes the t-1 lagged value of LNBANKS. dy/dx is for discrete change of dummy variables from 0 to 1. For continuous variables dy/dx is computed at the variable mean value. Standard errors are adjusted for clustering on firm's id.

Model		**ML probit**			**ML probit**			**GLS, re**			**GLS, re**	
Dependent variable		**BANKMIN3**			**BANKMIN3**			**LNBANKS**			**LNBANKS**	
		I			**Ia**			**II**			**IIa**	
	dy/dx	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*Coeff.*	*SE*	*P-value*	*Coeff.*	*SE*	*P-value*
Instrumental variables												
SAVINGS	0.005	0.786	0.880	-0.006	1.046	0.041	-0.823	0.141	0.000	-0.030	0.029	0.299
COOP	-0.561	5.743	0.029	-0.046	8.551	0.042	1.324	0.939	0.158	-0.004	0.197	0.983
LOCBRANC	0.000	0.002	0.413	0.000	0.002	0.791	0.001	0.000	0.000	0.000	0.000	0.973
BRANC1936	-0.003	0.569	0.910	0.004	0.727	0.019	0.528	0.095	0.000	0.061	0.020	0.002
NEWBRANC	-0.002	0.020	0.009	0.000	0.033	0.236	-0.001	0.001	0.213	0.002	0.001	0.021
$BANKMIN3_{t-1}$				-0.009	0.227	0.000						
$LNBANK_{t-1}$										0.894	0.003	0.000
Exogenous and control variables												
$LOGTA_{t-1}$	-0.069	0.151	0.000	-0.002	0.358	0.068	0.405	0.039	0.000	0.055	0.011	0.000
$(LOGTA\^2)_{t-1}$	0.003	0.007	0.000	0.000	0.018	0.067	-0.009	0.002	0.000	-0.001	0.001	0.011
$LOGAGE_{t-1}$	-0.012	0.097	0.006	-0.001	0.154	0.134	0.074	0.013	0.000	0.002	0.006	0.695
$(LOGAGE\^2)_{t-1}$	0.002	0.020	0.023	0.000	0.031	0.144	-0.009	0.003	0.001	-0.002	0.001	0.102
$IDLECOLL_{t-1}$	0.000	0.000	0.000	0.000	0.001	0.002	0.000	0.000	0.003	0.000	0.000	0.000
$LEVERAGE_{t-1}$	-0.027	0.093	0.000	-0.001	0.122	0.061	0.086	0.010	0.000	0.045	0.005	0.000
$ASSILIQUI_{t-1}$	0.000	0.170	0.964	-0.001	0.193	0.261	0.080	0.019	0.000	0.019	0.006	0.002
$SLACK_{t-1}$	0.028	0.277	0.023	0.000	0.331	0.652	-0.159	0.026	0.000	-0.072	0.013	0.000
$SALESGR_{t-1}$	0.000	0.001	0.956	0.000	0.002	0.049	0.000	0.000	0.000	0.001	0.000	0.000
$PROFIT_{t-1}$	-0.020	0.377	0.233	-0.003	0.429	0.017	-0.034	0.030	0.254	-0.024	0.015	0.104
$OPAQ_{t-1}$	0.010	0.786	0.783	-0.002	0.742	0.427	0.143	0.064	0.025	0.102	0.029	0.000
$SCORE_{t-1}$	0.000	0.001	0.000	0.000	0.001	0.139	0.000	0.000	0.000	0.000	0.000	0.050
DSCORE	0.000	0.030	0.742	0.000	0.063	0.314	-0.005	0.002	0.025	0.004	0.002	0.048
HHI	-0.173	1.395	0.006	-0.014	1.679	0.002	-1.683	0.218	0.000	0.140	0.055	0.011
$HHI^{\^2}$	0.315	3.518	0.046	0.025	3.188	0.002	2.486	0.595	0.000	-0.451	0.147	0.002
DISTRICT	0.003	0.089	0.458	0.000	0.112	0.913	0.024	0.010	0.018	-0.001	0.003	0.638
CONSTANT		0.002	0.254		1.849	0.000		0.198	0.000		0.055	0.000
Control DV												
DV_YEAR	YES	not significant		YES	not significant		YES	significant		YES	significant	
DV_IND	NO			NO			NO			NO		
NORTH	YES	significant		YES	not significant		YES	significant		YES	significant	
Obs	36115			34647			34943			34362		
Wald chi2(15)	593.54			399.53			4416.43			236121.12		
Prob > chi2	0.000			0.000			0.000			0.000		
Pseudo R2	0.14			0.43								
rho							0.86			0.12		

Table 3 - *Second stage estimation results*

This table reports the second stage regressions results. The dependent variable, OVERDRAFT, is a binary variable equal 1 if the credit drawn/credti granted ratio is higher than 100%, 0 otherwise. Model I reports the parameter and statistical significance of a probit estimation without corrections for the potential endogeneity of the number of banks. Specifications II-V are estimated by two-stage conditional maximum likelihood. u_{it} are the residuals of first stage estimations of the dummy variable BANKMIN3 on instrumental variables and exogenous and control variables (table 2). Dynamic correction means that the first stage estimation does take into account the dynamic in the number of banks (i.e., the lagged variable). Static correction means that the first stage estimation does not take into account such dynamic. dy/dx is for discrete change of dummy variables from 0 to 1. For continuous variables dy/dx is computed at the variable mean value. Standard errors are adjusted for clustering on firm's id.

Model	**ML probit**			**ML probit**			**ML probit**			**ML probit**			**Random-effect probit**		
Dependent variable	**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**		
Correction	**NO**			**YES (static)**			**YES (dynamic)**			**YES (dynamic)**			**YES (dynamic)**		
	I			**II**			**III**			**IV**			**V**		
	dy/dx	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*
exogenous and control vars															
BANKMIN3	0.010	0.081	0.019	0.012	0.111	0.020	0.015	0.140	0.025	0.015	0.140	0.026	0.006	0.074	0.000
u_{it} -I				0.002	0.076	0.571									
u_{it} -II							-0.002	0.017	0.003	-0.001	0.042	0.609	0.000	0.154	0.262
$\bar{u}_i$ - II										-0.001	0.047	0.506	0.000	0.388	0.309
$LOGTA_{t-1}$	-0.001	0.176	0.937	-0.009	0.218	0.251	-0.001	0.201	0.856	-0.001	0.201	0.889	-0.001	0.224	0.920
$(LOGTA\^2)_{t-1}$	0.000	0.009	0.925	0.000	0.010	0.295	0.000	0.010	0.781	0.000	0.010	0.804	0.000	0.011	0.742
LOGAGE	0.007	0.113	0.155	0.014	0.230	0.099	0.015	0.233	0.068	0.015	0.233	0.070	0.006	0.245	0.097
LOGAGE^2	-0.002	0.022	0.045	-0.003	0.041	0.057	-0.003	0.042	0.042	-0.003	0.042	0.042	-0.001	0.043	0.041
$IDLECOLL_{t-1}$	0.000	0.006	0.237	-0.001	0.014	0.078	-0.001	0.016	0.088	-0.001	0.016	0.087	0.000	0.007	0.000
$LEVERAGE_{t-1}$	0.010	0.088	0.011	0.008	0.115	0.044	0.010	0.117	0.014	0.010	0.117	0.013	0.004	0.133	0.038
$ASSILIQUI_{t-1}$	-0.019	0.119	0.000	-0.019	0.135	0.000	-0.018	0.137	0.000	-0.018	0.137	0.000	-0.008	0.147	0.000
$SLACK_{t-1}$	-0.046	0.427	0.012	-0.048	0.482	0.005	-0.048	0.491	0.006	-0.048	0.489	0.005	-0.020	0.386	0.000
$SALESGR_{t-1}$	0.000	0.001	0.683	0.000	0.001	0.637	0.000	0.001	0.470	0.000	0.001	0.517	0.000	0.001	0.773
$PROFIT_{t-1}$	-0.087	0.262	0.000	-0.079	0.301	0.000	-0.078	0.303	0.000	-0.078	0.303	0.000	-0.034	0.332	0.000
$OPAQ_{t-1}$	0.035	0.346	0.018	0.046	0.369	0.001	0.048	0.374	0.000	0.047	0.374	0.000	0.023	0.460	0.000
$SCORE_{t-1}$	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000
DSCORE	0.005	0.029	0.000	0.003	0.036	0.009	0.003	0.037	0.018	0.003	0.037	0.017	0.001	0.045	0.023
HHI	0.094	1.224	0.073	0.097	1.343	0.045	0.104	1.393	0.033	0.105	1.396	0.032	0.047	1.290	0.013
$HHI^{\wedge 2}$	-0.257	3.667	0.103	-0.191	3.781	0.162	-0.212	3.978	0.128	-0.214	3.986	0.125	-0.093	3.423	0.064
DISTRICT	0.003	0.065	0.385	0.006	0.076	0.043	0.007	0.077	0.031	0.007	0.076	0.032	0.003	0.082	0.045
CONSTANT		0.903	0.046		1.167	0.335		1.071	0.035		1.073	0.064		1.201	0.051
Control DV															
DV_YEAR	YES	significant		YES	significant		YES	significant		YES	significant		YES	significant	
DV_IND	YES	not significant		YES	not significant		YES	not significant		YES	not significant		YES	not significant	
NORTH	YES	significant		YES	significant		YES	significant		YES	significant		YES	significant	
Obs	40002			27922			26900			26900			26900		
Wald chi2(15)	431.03			336.27			334.70			334.50			366.70		
Prob > chi2	0.000			0.000			0.000			0.000			0.000		
Pseudo R2	0.07			0.08			0.08			0.08					
Log likelihood ratio test													328.49 (0.000)		

Table 4 - *Second stage estimation results*

This table reports the second stage regressions results. The dependent variable, OVERDRAFT, is a binary variable equal 1 if the credit drawn/credti granted ratio is higher than 100%, 0 otherwise. Model I reports the parameter and statistical significance of a probit estimation without corrections for the potential endogeneity of the number of banks. Specifications II-V are estimated by two-stage conditional maximum likelihood. uit are the residuals of first stage estimations of the number of banking relationships on instrumental variables and exogenous and control variables (table 2). Dynamic correction means that the first stage estimation does take into account the dynamic in the number of banks (i.e., the lagged variable). Static correction means that the first stage estimation does not take into account such dynamic. dy/dx is for discrete change of dummy variables from 0 to 1. For continuous variables dy/dx is computed at the variable mean value. Standard errors are adjusted for clustering on firm's id.

Model	**ML probit**			**ML probit**			**ML probit**			**ML probit**			**Random-effect probit**		
Dependent variable	**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**		
Correction	**NO**			**YES (static)**			**YES (dynamic)**			**YES (dynamic)**			**YES (dynamic)**		
	I			**II**			**III**			**IV**			**V**		
	dy/dx	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*
exogenous and control vars															
$LNBANK_{t-1}$	-0.006	0.048	0.002	-0.009	0.121	0.026	-0.007	0.060	0.001	-0.009	0.070	0.000	-0.004	0.074	0.000
u_{it} -I				0.005	0.122	0.277									
u_{it} -II							0.007	0.131	0.114	0.005	0.139	0.299	0.002	0.154	0.262
$\bar{u}_i$ - II										0.016	0.392	0.240	0.005	0.388	0.309
$LOGTA_{t-1}$	0.007	0.188	0.405	0.000	0.210	0.947	0.000	0.208	0.982	0.001	0.206	0.893	0.000	0.224	0.920
$(LOGTA\text{^}2)_{t-1}$	0.000	0.009	0.443	0.000	0.010	0.870	0.000	0.010	0.884	0.000	0.010	0.932	0.000	0.011	0.742
LOGAGE	0.005	0.112	0.289	0.014	0.231	0.079	0.013	0.233	0.101	0.013	0.234	0.099	0.005	0.245	0.097
LOGAGE^2	-0.002	0.022	0.105	-0.003	0.041	0.047	-0.003	0.042	0.059	-0.003	0.042	0.059	-0.001	0.043	0.041
$IDLECOLL_{t-1}$	0.000	0.007	0.276	-0.001	0.017	0.096	-0.001	0.017	0.102	-0.001	0.017	0.105	0.000	0.007	0.000
$LEVERAGE_{t-1}$	0.010	0.090	0.011	0.008	0.117	0.039	0.009	0.118	0.022	0.010	0.118	0.018	0.004	0.133	0.038
$ASSILIQUI_{t-1}$	-0.017	0.120	0.001	-0.017	0.139	0.000	-0.017	0.140	0.001	-0.016	0.140	0.001	-0.007	0.147	0.000
$SLACK_{t-1}$	-0.045	0.430	0.013	-0.048	0.489	0.005	-0.049	0.502	0.005	-0.050	0.501	0.005	-0.021	0.386	0.000
$SALESGR_{t-1}$	0.000	0.001	0.742	0.000	0.001	0.669	0.000	0.001	0.616	0.000	0.001	0.540	0.000	0.001	0.773
$PROFIT_{t-1}$	-0.083	0.267	0.000	-0.076	0.308	0.000	-0.077	0.308	0.000	-0.078	0.310	0.000	-0.034	0.332	0.000
$OPAQ_{t-1}$	0.045	0.336	0.002	0.049	0.378	0.000	0.049	0.385	0.000	0.050	0.386	0.000	0.024	0.460	0.000
$SCORE_{t-1}$	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000
DSCORE	0.005	0.030	0.000	0.003	0.037	0.009	0.003	0.037	0.012	0.003	0.037	0.012	0.001	0.045	0.023
HHI	0.083	1.264	0.122	0.088	1.377	0.070	0.092	1.357	0.053	0.091	1.348	0.054	0.041	1.290	0.013
$HHI^{\text{^}2}$	-0.248	3.807	0.126	-0.183	3.907	0.183	-0.187	3.789	0.158	-0.185	3.750	0.159	-0.082	3.423	0.064
DISTRICT	0.002	0.067	0.551	0.076	0.077	0.082	0.006	0.077	0.067	0.006	0.077	0.068	0.003	0.082	0.045
CONSTANT		0.967	0.009		1.102	0.050		1.105	0.047		1.097	0.039		1.201	0.051
Control DV															
DV_YEAR	YES	significant		YES	significant		YES	significant		YES	significant		YES	significant	
DV_IND	YES	not significant		YES	not significant		YES	not significant		YES	not significant		YES	not significant	
NORTH	YES	significant		YES	significant		YES	significant		YES	significant		YES	significant	
Obs	38731			26946			26526			26526			26526		
Wald chi2(15)	413.68			315.09			324.03			326.32			346.150		
Prob > chi2	0.000			0.000			0.000			0.000			0.000		
Pseudo R2	0.07			0.08			0.08			0.08					
Log likelihood ratio test													316.81 (0.000)		

Table 5 *- The effect of credit market structure*

This table reports the second stage regressions results. The dependent variable, OVERDRAFT, is a binary variable equal 1 if the credit drawn/credti granted ratio is higher than 100%, 0 otherwise. Models I-III are estimated by two-stage conditional maximum likelihood. uit the residuals of first stage estimations of the number of banking relationships on instrumental variables and exogenous and control variables (table 2). Dynamic correction means that the first stage estimation does take into account the dynamic in the number of banks (i.e., the lagged variable). Specifications I and II include an the interaction of the number of multiple banks (or BANKMIN3) with the Herfindahl index. In specification III, LNBANKS is interacted with two dummy variables, euqal 1 if the Herfindahl index is, respectively, higher than the 75th percentile or lower than the 25th. dy/dx is for discrete change of dummy variables from 0 to 1. For continuous variables dy/dx is computed at the variable mean value. Standard errors are adjusted for clustering on firm's id.

Model		**ML probit**			**ML probit**			**ML probit**	
Dependent variable		**OVERDRAFT**			**OVERDRAFT**			**OVERDRAFT**	
Correction		**YES (dynamic)**			**YES (dynamic)**			**YES (dynamic)**	
		I			**II**			**III**	
	dy/dx	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*
exogenous and control vars									
$LNBANK_{t-1}$	-0.009	0.115	0.033				-0.009	0.070	0.000
$BANKMIN3_{t-1}$				0.015	0.131	0.022			
u_{it} -II	0.005	0.139	0.304	-0.001	0.042	0.649	0.005	0.139	0.304
$\bar{u}_i$ - II	0.016	0.392	0.233	-0.001	0.047	0.468	0.016	0.392	0.233
HHI*LNBANKS	0.000	0.898	0.996						
HHI*BANKMIN3				0.010	1.085	0.787			
DV_MKTCONC*LNBANKS							0.000	0.042	0.967
DV_MKTCOMP*LNBANKS							0.000	0.043	0.971
$LOGTA_{t-1}$	0.001	0.206	0.893	-0.002	0.200	0.772	0.001	0.206	0.892
$(LOGTA\^2)_{t-1}$	0.000	0.010	0.938	0.000	0.010	0.689	0.000	0.010	0.939
LOGAGE	0.013	0.233	0.106	0.015	0.236	0.075	0.013	0.233	0.106
LOGAGE^2	-0.003	0.042	0.062	-0.003	0.042	0.046	-0.003	0.042	0.061
$IDLECOLL_{t-1}$	-0.001	0.017	0.107	-0.001	0.016	0.100	-0.001	0.017	0.107
$LEVERAGE_{t-1}$	0.010	0.118	0.017	0.011	0.118	0.007	0.010	0.118	0.017
$ASSILIQUI_{t-1}$	-0.016	0.140	0.001	-0.018	0.139	0.000	-0.016	0.140	0.001
$SLACK_{t-1}$	-0.050	0.501	0.005	-0.048	0.493	0.005	-0.050	0.500	0.005
$SALESGR_{t-1}$	0.000	0.001	0.514	0.000	0.001	0.636	0.000	0.001	0.514
$PROFIT_{t-1}$	-0.078	0.310	0.000	-0.078	0.309	0.000	-0.078	0.310	0.000
$OPAQ_{t-1}$	0.050	0.384	0.000	0.045	0.388	0.001	0.050	0.385	0.000
$SCORE_{t-1}$	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000
DSCORE	0.003	0.037	0.013	0.003	0.037	0.014	0.003	0.037	0.013
HHI	0.027	1.927	0.690	0.035	0.502	0.044	0.028	0.600	0.189
DISTRICT	0.006	0.077	0.060	0.007	0.076	0.017	0.006	0.078	0.062
CONSTANT		1.102	0.054		1.065	0.060		1.096	0.053
Control DV									
DV_YEAR	YES	significant		YES	significant		YES	significant	
DV_IND	YES	not significant		YES	not significant		YES	not significant	
NORTH	YES	significant		YES	significant		YES	significant	
Obs	26526			26680			26526		
Wald chi2(15)	326.22			327.80			325.29		
Prob > chi2	0.000			0.000			0.000		
Pseudo R2	0.08			0.08			0.08		

__Table 6 -__ Robustness check

This table reports the second stage regressions results. The dependent variable, CONSTRAINT, is a binary variable equal 1 if the credit drawn/credti granted ratio is higher than 90%, 0 otherwise. Specifications are estimated by two-stage conditional maximum likelihood. uit are the residuals of first stage estimations of the number of banking relationships on instrumental variables and exogenous and control variables (table 2). Dynamic correction means that the first stage estimation does take into account the dynamic in the number of banks (i.e., the lagged variable). dy/dx is for discrete change of dummy variables from 0 to 1. For continuous variables dy/dx is computed at the variable mean value. Standard errors are adjusted for clustering on firm's id.

Model	**ML probit**			**ML probit**		
Dependent variable	**CONSTRAINT**			**CONSTRAINT**		
Correction	**YES (dynamic)**			**YES (dynamic)**		
		I			**II**	
	dy/dx	*SE*	*P-value*	*dy/dx*	*SE*	*P-value*
exogenous and control vars						
BANKMIN3	0.018	0.121	0.200			
u_{it} -II	-0.005	0.027	0.096			
$\bar{u}_i$ - II	0.005	0.031	0.105			
$LNBANK_{t-1}$				-0.010	0.055	0.076
u_{it} -II				0.006	0.092	0.519
$\bar{u}_i$ - II				0.098	0.318	0.003
$LOGTA_{t-1}$	0.008	0.218	0.744	0.018	0.220	0.444
$(LOGTA\text{^}2)_{t-1}$	0.000	0.011	0.755	-0.001	0.011	0.540
LOGAGE	0.032	0.185	0.105	0.030	0.187	0.125
LOGAGE^2	-0.007	0.033	0.036	-0.007	0.033	0.042
$IDLECOLL_{t-1}$	0.000	0.002	0.107	0.000	0.002	0.116
$LEVERAGE_{t-1}$	0.031	0.080	0.000	0.033	0.081	0.000
$ASSILIQUI_{t-1}$	-0.035	0.111	0.003	-0.030	0.113	0.012
$SLACK_{t-1}$	-0.179	0.410	0.000	-0.181	0.416	0.000
$SALESGR_{t-1}$	0.000	0.001	0.782	0.000	0.001	0.644
$PROFIT_{t-1}$	-0.244	0.249	0.000	-0.244	0.255	0.000
$OPAQ_{t-1}$	0.166	0.346	0.000	0.177	0.360	0.000
$SCORE_{t-1}$	0.001	0.001	0.000	0.001	0.001	0.000
DSCORE*	0.016	0.027	0.000	0.016	0.027	0.000
HHI	0.228	1.036	0.037	0.216	1.031	0.047
$HHI^{\wedge 2}$	-0.391	2.627	0.158	-0.365	2.599	0.182
DISTRICT*	0.017	0.063	0.023	0.015	0.063	0.039
CONSTANT		1.111	0.028		1.120	0.008
Control DV						
DV_YEAR	YES	significant		YES	not significant	
DV_IND	YES	not significant		YES	not significant	
NORTH	YES	significant		YES	significant	
Obs	26900			26526		
Wald chi2(15)	462.42			455.24		
Prob > chi2	0.000			0.000		
Pseudo R2	0.07			0.07		

Ultimi studi apparsi nella “**Collana "Ricerche** "

R00-06 A. Baglioni – R. Hamaui, *The choice among alternative payment systems: the European experience,* Settembre 2000

R01-01 E. Bernini – D. Fantazzini, *Stima di strutture a termine: il caso dei Corporate Spread Finanziari*, Settembre 2001

R01-02 G. De Felice – D. Revoltella, *Towards a multinational bank? European banks’ growth strategies,* Ottobre 2001

R01-03 G. De Felice – F. Guelpa, S*istema moda e prospettive sui mercati internazionali,* Novembre 2001

R01-04 E. Bernini, *Callable convertible bond,* Dicembre 2001

R01-05 E. Bernini, *Obbligazioni indicizzate a fondi e sicav,* Dicembre 2001

R02-01 E. De Riva – L. Noto, *Gli effetti della tassazione sulla struttura a termine dei tassi d’interesse: il caso dei Japanese Govt Bonds,* Febbraio 2002

R02-02 F. Franzina – J. Linon, *La riforma fiscale lussemburghese del 2002. Nuove prospettive per la detenzione e valorizzazione di partecipazioni nel Granducato,* Marzo 2002

R02-03 L. Campanini, *Gli accordi nel settore dei servizi pubblici locali*, Luglio 2002

R02-04 J. Alworth, G. Arachi, R. Hamaui, *Adjusting capital income taxation: some lessons from the Italian experience*, Settembre 2002

R02-05 R. Hamaui – F. Spinelli, *Hedge Funds: cosa insegna la recente letteratura empirica*, Novembre 2002

R03-01 A. Jamaleh – L. Ruggerone, *Modelling Eastern Europe currencies in the run-up to joining the EMU*, Giugno 2003

R03-02 E. Coletti – A. Colombo – G. De Felice – V. Tirri, *Structure and performance of central and eastern european banking sectors* ,Luglio 2003

R04-01 E. Bernini, *Strategies based on Dividends in the Italian Stock Exchange*, Luglio 2004

R04-02 F. Guelpa – V. Tirri, *Market structure and relationship lending: effects on the likelihood of credit tightening in the Italian banking industry*, Luglio 2004

R05-01 F. Guelpa, *Crescita dell’impresa e complessità finanziaria*, Maggio 2005

R05-02 G. Foresti – F. Guelpa - S. Trenti, S*truttura settoriale e dimensionale dell’industria italiana: effetti sull’evoluzione della produttività del lavoro,* Dicembre 2005

R06-01 G. De Felice – V. Tirri, *Financial structure of central and eastern European countries: development trends and role of the banks,* Marzo 2006

R06-02 A. Baglioni – R. Hamaui, *The industrial organization of post-trading,* Ottobre 2006

R07-01 G. Cifarelli – G. Paladino, *The buffer stock model redux? An analysis of the dynamics of foreign reserve accumulation,* Febbraio 2007

R07-02 G. Foresti – F. Guelpa – S. Trenti, *Quali leve per il rilancio dell’industria? La questione dimensionale*, Giugno 2007

R07-03 G. Foresti – F. Guelpa – S. Trenti, *La terziarizzazione dell’economia europea: è vera deindustrializzazione?*, Luglio 2007

R07-04 V. Tirri – *Multiple banking relationships and credit market competition: what benefits the firm?;* Ottobre 2007