Do Mergers Improve Information? Evidence from the Loan Market*

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Abstract

We examine the informational effects of M&As investigating how bank mergers affect the pricing of loan contracts. Our test is based on the principle that informational improvements should lead to a closer correspondence between the risk of each firm and its loan rate. We find evidence of these informational effects. Furthermore, our evidence indicates that these improvements derive from improvements in information processing resulting from the merger, rather than from explicit information sharing among the parties in a merger.

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1 Introduction

The unprecedented merger wave observed in the last decade is reshaping the corporate landscape in most countries, in mature and innovative sectors alike. According to Thomson Financial, between 1990 and 2001 there were 54,143 M&As in the major industrial countries, with total value equal to $9,526 billion. A large body of empirical work has investigated the pricing effects of mergers, considering mainly changes in market power and efficiency and the ensuing net variations in average prices induced by the merger (see, for example, Barton and Sherman (1984), Kim and Singal (1993), Focarelli and Panetta (2003)).

However, market power and efficiency are hardly the only important channels through which M&As can affect the pricing policy of the merging company. In many industries, mergers allow companies to enlarge their information set and improve their knowledge of important characteristics of the markets in which they operate. For example, the acquisition of a firm operating abroad might be motivated by the need to gain knowledge and expertise about a foreign market. Further, a consolidated company might asses more precisely characteristics of its suppliers (i.e., their ability to satisfy an unexpected increase in demand) or customers (i.e. their creditworthiness) that are relevant for its pricing policy, and modify its prices accordingly.

Unlike the standard market power and efficiency effects, the price impact of the informational changes induced by a merger could then differ across customers. This is a point that, to our knowledge, has been overlooked by the previous literature. To gain insight on its relevance, we consider a market in which information effects are likely to be particularly important: bank loans. As the theoretical literature in banking has long recognized (see the review in Freixas and Rochet (2000)), loan contracts are affected both by moral hazard and adverse selection problems, making information about the borrowers a particularly important issue. Mergers might modify the ability of banks to asses the riskiness of their customers, thus inducing changes in their pricing policy above and beyond those implied by the market power and efficiency effects. By focusing on how the price effects of a merger can differ across the merging parties' customers, we uncover effects that may have been overlooked to date.

The data needed to analyze the informational effects of bank mergers are generally not available. However, they turn out to be available for Italy. For this country we have access to a unique data set with information on individual loan contracts for a nearly complete sample of Italian borrowers over a long time span (from 1986 to 1998) and the occurrences of all bank mergers in this period. For each loan contract, we observe the interest rate and the characteristics of the bank and the firm involved, so that we can analyze the rate changes for different types of borrowers (e.g., according the their riskiness) and lenders (large and small banks). We also have data on the characteristics of the markets in which the merging banks operate, allowing us to carefully control for the role of local market structure. The availability of this data set has prompted us to focus on Italy to quantify the effects that changes in information caused by the merger have on the interest rates charged to borrowers.

The Italian loan market constitutes a natural laboratory for studying these effects for three reasons. First, in the last decade technological innovation and thorough-going deregulation prompted an unprecedented merger wave that cut the number of Italian banks by nearly 25 percent between 1988 and 1998. Second, the Italian economy is mainly composed of small and unlisted firms, for which the problems posed by asymmetric information are likely to be important, so that, if mergers did indeed result in informational efficiencies, we are most likely to detect them in this market. Third, Italian companies secure almost all their external financing through credit lines, which are highly homogeneous products and can be meaningfully compared over time and across different banks.

Consistent with previous studies of the price effects of bank M&As (Sapienza 2002), we find that mergers lead to a decrease in the average loan rate, an indication that efficiency effects are stronger than market power ones. However, we find – to our knowledge for the first time – that mergers influence market rates also through an improvement in banks' informational processing, so that after the merger the interest rate curve – the relation between the riskiness of each firm and its loan rate – becomes steeper. Thus, while for the high-quality (low-risk) borrowers the decline in the loan rate is larger than average, for the riskier borrowers – which before the merger benefited from underpriced loans, due to the informational inefficiencies of their lenders – the loan rate actually rises. This finding is consistent with the hypothesis that consolidation improves banks' abilities to discriminate among low- and high-quality borrowers, and is robust to a number of alternative interpretations. It also indicates that an important source of efficiency gain in mergers comes from improvement in information processing and in risk assessment.

We investigate the sources of these informational gains by exploiting the fact that Italian companies often borrow from multiple banks (Detragiache, Garella and Guiso 2000). We find that the increase in the slope of the interest rate curve is broadly similar for the companies that before the deal were borrowing from only one of the merging parties (the bidder *or* the target) and for those that were borrowing from both merging parties (the bidder *and* the target). This finding suggests that the potential gains from explicit *pooling* of firm-specific information - that can only emerge when both the bidder and target banks were lending to the company before the consolidation - has negligible effect on the interest rate curve. Instead, our result are consistent with the view that the informational efficiencies arise from an improvement in banks' ability (or an increase in their incentives) to process a given information set. In fact, this type of informational change should affect all firms, irrespectively of whether before the deal they were borrowing from one or both the merging partites.

Our results carry important implications for the controversy on the welfare redistributions associated with consolidations. The previous studies look only at the effect of M&As on the average level of market prices, ignoring potentially important consequences for higher moments of the price distribution. We show that mergers may affect different categories of customers in different ways and increase the variance of market prices: even if some customers benefit from the consolidation, others could be harmed by the merger. Moreover, if consolidation leads to a better pricing of risk, the welfare effects might be stronger than those obtained by considering average price changes only. This implication, which is likely to hold also in other markets, implies new challenges for the antitrust authorities, because it excludes the possibility of using Paretian criteria to asses the welfare effects of mergers. In this sense, our findings complement those of the previous studies that show that mergers are complex events, where efficiency gains may emerge only in the long-run (Focarelli and Panetta 2003), and depend on the characteristics of the merger, such as the market share of the target firm (Sapienza 2002) and the product lines involved in the transaction (Kahn, Pennacchi and Sopranzetti 2000).

The rest of the paper is organized in the following way. In the next section we analyze the related literature and present a simple model to illustrate the main idea of the paper. In Section 3 we introduce the data and describe our empirical approach. In Section 4 we present and discuss our main empirical findings as to the presence and magnitudes of informational effects deriving from a mergers. We consider various explanations for these informational effects in Section 5, and conclude in Section 6.

2 Mergers, Prices and Information

The effect of consolidation on market prices is *a priori* ambiguous. On the one hand, mergers can increase efficiency (through economies of scale and scope or an improvement in managerial x-efficiency), potentially decreasing prices. On the other, if the merging companies have significant market overlap, their market power might increase, leading to adverse price changes for consumers. Several early papers found that mergers increase market power, harming consumers. Kim and Singal (1993) analyze the price effects of M&As in the US airline industry. They find that the merging firms raised airfares by 9.44 percent relative to the routes unaffected by the merger. Prager and Hannan (1993) find that bank mergers that violate the US Department of Justice merger guidelines substantially reduce the deposit rates paid by the merged banks.

Recent studies, however, have found that after taking into consideration important features of the transaction, mergers lead to better prices for consumers. In an analysis of bank mergers in the US, Kahn, Pennacchi and Sopranzetti (1999)find that the price effects depend on the products involved: mergers lead to greater market power in the pricing of personal loans but reduce automobile loan rates. Sapienza (2002) examines the market for bank loans in Italy, and finds that mergers increase market power only when the target bank has a large local market share. Focarelli and Panetta (2003) analyze the Italian deposit market, and find that, although consolidation does generate adverse price changes, these are temporary. In the long run the efficiency gains dominate over the market power effect, leading to more favorable prices for consumers.

One problem with these studies is that they only consider the market power and efficiency effects of consolidation, ignoring other factors that might affect the pricing policy of the merged companies. One such factor is information. For example, by taking over its rivals the company could obtain valuable information to assess the reliability of potential suppliers or their ability to meet unexpected demands. The consolidation could also improve the information available on key characteristics of consumers, such as their tastes or their credit record. Of course, these informational gains could have significant effects on the pricing policy of the merged company.

Unlike the standard market power and efficiency effects, the price impact of the informational improvements need not be the same for all customers. For example, while the average market price could fall substantially, for some customers prices could actually decrease less, or even increase.

The informational effects from consolidation are likely to be particularly important in markets where adverse selection and moral hazard play an important role, such as insurance and credit markets. In this paper, we consider the market for bank loans. A number of papers has emphasized the unique role of banks in managing the problems resulting from imperfect information on borrowers (see for example the seminal papers of Leland and Pyle (1977) and Diamond (1984) and the review in Gorton and Winton (2003)). Empirical contributions have confirmed the specific role of banks in producing information on borrowers (see, for example, James (1987)).

There are two ways in which M&As may improve banks' information about the customers' risk profile. First, the merger may improve banks' ability to process information. In fact, information processing is likely to be characterized by increasing returns to scale. For example, the implementation of internal rating systems or the construction of detailed customer databases may require large fixed costs that need to be allocated over a large volume of output; moreover, the accuracy of the predictions of the rating procedures will increase with the number of customers in the database. As a consequence, the larger banks that result from consolidation may invest more heavily in such activities and install expensive technologies that were not convenient for the merging parties before the deal. The improvements in processing information may also derive from the transfer of superior managerial skills, especially when the bidder is more efficient than the target.

Second, the informational gains may result from pooling information that before the deal was only available separately to each of the merging parties. Even when both merger parties have a business relationship with the company, they might have access to different sources of information. For example, by assisting the firm in its international activity one bank could obtain promptly information on the company's performance abroad, while the other bank could manage the company's checking account and thus obtain privileged information on its sales in the domestic market. This means that the consolidated bank, by pooling these different sources of information, could improve its knowledge of the company relative to each of the merger parties.[1]

Of course, these two hypotheses are not mutually exclusive, as mergers could influence both the information processing and the information pooling skills of the consolidated bank. Below, we will also attempt to disentangle these two types of informational effects for the Italian loan market.

The intuition which underlies our empirical approach is simple. The general idea is that banks with more information about a firm's risk type will charge an interest rate which is

[1] See Broecker (1990), Vives (1999) (chap. 10)) for theoretical discussions of information sharing in oligopoly, and Genesove and Mullin (1999) for empirical evidence from the sugar industry.

more "sensitive" to a measure of the risk type. Hence, the empirical exercise is to examine whether in fact the interest rates charged by merged banks are more sensitive (relative to non-merged banks) to measures of a firm's risk type.

As a benchmark, consider the case were the bank is fully informed about a borrower's failure probability $p \in [0, 1]$. In this case, the "fair" interest rate sets the expected return from a loan to zero:$(1-p)*(1+r) = 1$, so that the fair interest rate $r = \frac{p}{1-p}$. In markets where banks have perfect information about p, the interest rate profile (the relationship of r to p) should resemble the "fair" profile. In the presence of imperfect information, and adverse selection of firms, banks have difficulties distinguishing low p firms from high p firms, and should set an interest rate profile which is flatter in p.

If a merger leads to informational efficiencies, then banks should have better information about p. Therefore, after the merger the interest rate profile of merged banks should become steeper in p. Determining whether the interest rate profiles of merged banks is steeper than the profiles charged by non-merged banks is the main empirical exercise of this paper.

2.1 An Illustrative Model

As an illustrative theoretical example of how improvements in screening ability can lead to a steeper interest rate profile, we consider a case where the probability of failure of a generic firm is a $p \sim \beta(a, b)$, a beta distribution between $[0, 1]$. Hence, the average probability of failure in the population of firms is given by $\bar{p} = \frac{a}{a+b}$. With only prior information, and setting expected return to zero, get $(1-\bar{p})*(1+r) + \bar{p}*0 - 1 = 0$, or $1 + r = \frac{1}{1-\bar{p}}$, or, $r = \frac{\bar{p}}{1-\bar{p}}$.

Banks get binary signals $s = \{0, 1\}$ drawn from the same distribution as that of the project: $\Pr\{s = 0|p\} = p$. We model the screening capacity of banks with the number of signals they get, n: no screening capacity means $n = 0$ and perfect capacity to asses the probability of success is $n = \infty$. The family of Beta distributions is a conjugate family from samples from a Bernoulli distribution (DeGroot 1970): the posterior from n trials with y failures is a $\beta(a + y, b + n - y)$, so that the posterior mean is

$$E(p|n, y) = \frac{a + y}{a + b + n},$$

implying that the optimal zero-profit interest rate is

$$r = \frac{a + y}{b + (n - y)}. \tag{1}$$

In Figure 1, we plot the average zero-profit interest rate, for different values of n, p_0 and (a,b).[2] (Note that when $n=0$, $r=\frac{a}{b}$ identically for all p_0; when $n\to\infty$, $r\to\frac{p_0}{1-p_0}$.) For all pairs of (a,b), we see that the average interest rate becomes steeper as the bank becomes better informed (*i.e.* as n increases).

3 Methodology and Data

3.1 Sources

We have four main sources of data. (1) Interest rate data and data on outstanding loans come from the Italian *Centrale dei Rischi*, or Central Credit Register. (2) The firm-level balance sheet data come from the *Centrale dei Bilanci* database. (3) Banks' balance sheet and income statement information come from the Banking Supervision Register at the Bank of Italy. (4) Data on the mergers and acquisitions are drawn from the Census of Banks (SIOTEC). We describe the first two data sources in some detail.

The Central Credit Register (hereafter CR) is a database housed at the Bank of Italy that contains detailed information on all individual bank loans extended by Italian banks. Banks must report, to the CR, data at the individual borrower level on the amount granted and effectively utilized for all loans exceeding a given threshold[3], with a breakdown by type of the loan (credit lines, financial and commercial paper, collateralized loans, medium and long term loans and personal guarantees). In addition, a subgroup of 95 banks (accounting for more than 80 percent of total bank lending) have agreed to file detailed information on the interest rates they charge to individual borrowers on each type of loan. We define the interest rate as the ratio of the payment made in each period by the firm to the bank to the average amount of the loan. The interest payment includes the fixed expenses charged by the bank to the firm (e.g. which encompasses the cost of opening the credit line or the cost of mailing the loan statement). These data are highly confidential and are made available to individual banks to monitor the total exposure of their customers.

The *Centrale dei Bilanci* (hereafter CB) collects yearly data on the balance sheets and income statements of a sample of about 35,000 Italian nonfinancial and non-agricultural firms. This information is collected and standardized by a consortium of banks interested

[2] Specifically, we plot $E\left[\frac{a+y}{b+(n-y)}|n;a,b,p_0\right]$, where the expectation is over the conditional distribution $y|n;a,b,p_0$.

[3] The threshold was 41,000 euros (U.S. $42,000) until December 1995 and 75,000 euros thereafter.

in pooling information about their customers. The data regarding each year is released with a delay of approximately 15 months: for example, the information on the balance sheets for 1995 were released at the end of March 1997. A company is included in the CB sample if it borrows from at least one of the banks in the consortium. The database is highly representative of the Italian nonfinancial sector[4].

The unique feature of the CB data set is that, unlike other widely used data sets on individual companies (such as the Compustat database of US companies), it has a wide coverage of small (less than 50 employees) and medium (between 50 and 250 employees) companies; moreover, almost all the companies in the CB sample are unlisted. The coverage of these small firms makes the data set particularly well suited for our analysis, since informational asymmetries are potentially strongest for these firms so that, if mergers did indeed result in informational efficiencies, we are most likely to detect them for these firms.

In addition to collecting the data, the CB computes an indicator of the risk profile of each company (which we refer to in the remainder of this paper as the SCORE). The SCORE represents our measure of company risk, and plays a crucial role in the analysis. Therefore, before turning to the econometric tests and discussing the empirical evidence it is necessary to describe in detail the computation, timing of the release and the characteristics of the SCORE.

The SCORE is computed using discriminant analysis, according to the methodology suggested by Altman (1968) and described in Altman, Marco and Varetto (1994). Each year the SCORE is released to all banks in the consortium with the information on firms' balance sheet and income statement. As for the SCORE, the CB classifies firms into four categories: the first one includes safe firms (SCORE=1,2), the second one includes solvent firms (SCORE=3,4), while the third and fourth categories include, respectively, vulnerable firms (SCORE=5,6) and risky firms (SCORE=7,8,9).

Two characteristics of the SCORE are key for our analysis. First, the SCORE for company j in period t only becomes available after approximately 15 months (that is, during year t+2). Thus, it represents information that is not yet available to banks when they set the loan rate at time t. Second, the SCORE is computed by the *Centrale dei Bilanci* ex post, using actual balance sheet data, so that it represents a good proxy of the "true" quality of the company. Therefore, a finding that after a merger the loan rates of the

[4]According to a recent analysis (see Centrale dei Bilanci, 1999) based on a subset of 5,249 firms included in the database, the CB sample represented 49.4 per cent of the total sales reported in the national accounting data for the Italian non-financial, non-agricultural sector.

consolidated banks become more correlated with the SCORE than the loan rates of the banks not involved in mergers (after controlling for the proxies of company risk that are observable, such as leverage or size) would be consistent with the hypothesis that the deal increases banks' ability to screen borrowers. Below, we test the robustness of our results to the use of alternative measures of a company's risk.

3.2 Sample

We restrict our attention to short term credit lines, which have features which are ideal for our analysis. First, the bank can change the interest rate on the loan at any point in time; the borrower, in turn, can close the credit line without notice. This means that (i) a change in the merging banks' ability to process firm-specific information can have almost immediate repercussions on the pricing of the loans; and (ii) differences between the interest rates on loans are not influenced by differences in the maturity of the loan. Second, the loan contracts included in the Central Credit Register are homogeneous products, so that they can be meaningfully compared across banks and firms. Third, short term bank loans are the main source of borrowing of Italian firms. For example, in 1994 they represented 53 percent of the total debts according to the Flow of Funds data.

Summary statistics for the banks that report interest rates are shown in Table 1. In Panel A we report data for all banks in our sample. Over the entire period the median bank size (as proxied by total assets) is about 3,700 million euros and 1,137 employees. The ratio of operating costs to gross revenues (a standard indicator of efficiency) is 33.1 percent, while the ratio of bad loans to total lending (a proxy for riskiness) is 4.9 percent. Software expenses per employee are equal to about 1,100 euros.

In Panels B and C we distinguish banks on the basis of their participation in a merger during the period 1988-98. In particular, we classify a bank as a "bidder" if it acquired another bank during our sample period, and a "target" if it was acquired by another bank. Note that a bank could actually be both a bidder and a target, if it acquired another bank before being acquired itself during the sample period. The bidder banks are larger than average (the median size is 9,049 million euros and the number of employees is 2,789). The cost-income ratio, the ratio of bad loans to total loans and the software expenses per employee are similar to the rest of the sample. The target banks are similar to the bidders, except that they are smaller (the median size is 4,999 million euros).

Summary statistics on the firms included in the Centrale dei Bilanci are shown in Table 2.

The median firm in the sample has total assets equal to 0.78 million euros, 31 employees, a return on sales of 8 percent, and leverage of 60 percent. Short term debt represents the largest component of total debt (81 percent).

As for bank-firm relationships, the median firm borrows from 4 banks. As we noted before, this feature of the Italian loan market makes it appropriate not only to examine the informational consequences of bank mergers, but also to disentangle these effects into those arising from explicit information pooling among the merging banks, and those which arise when the consolidated bank is able to exploit economies of scale in information processing. Finally, for the median firm the ratio between credit utilized and credit granted is 38.2 percent.

In table 3 we group firms according to their SCORE. As expected, the leverage is higher for riskier firms, ranging from 15 percent for safe firms (SCORE=1,2) to 81 percent for risky firms (SCORE=7,8 and 9). Another interesting difference emerges in the pattern of bank-firm relationships. In particular, the credit lines are more likely to be exhausted for riskier firms: the proportion of companies recording an overdraft (i.e. a credit line for which utilized credit exceeds credit granted) increases from 4 percent for safe firms to 31 percent for risky firms. A consistent pattern emerges for the interest rates, that range from 13.2 percent for companies with low credit risk to 14.7 percent for the firms in worst shape (SCORE=7,8,9).

The banks reporting detailed interest rate data range from 68 in 1997 to 88 in 1989. In total, we have 863 bank-year observations (see Panel A of Table 4). These reporting banks are larger than average, and they account for more than two thirds of total banking industry loans. The number of bank-year observations affected by a merger ranges from 6 in 1990 to 26 in 1995. Our sample includes 1,300,000 bank-firm-year observations (see Panel B). Of these observations, 43 percent of the observations refer to companies borrowing from bidder banks, 2.8 percent of the observations refer to companies borrowing from the target banks, and 0.7 percent to companies borrowing from both merger parties (the bidder *and* the target banks). Hence, just more than half of the observations refer to firms which do not borrow from a bank which merges during our sample period.

3.3 Test Design

In this section we describe the econometric methodology used in the empirical study and our basic test. We investigate whether bank M&As improve a bank's informational position in pricing loan contracts. If a deal improves informational efficiency, then the interest rate banks charge to borrowers should become more sensitive to the borrower's risk. Thus, the curve linking linking the risk of each firm to its loan rate (the interest rate curve) should become steeper for the merging banks relative to the non-merging ones.

Most of our empirical work is based on the following basic regression for bank i, firm j, and time period t:

$$\begin{aligned} r_{ijt} &= \beta_0 + \beta_1 * MERG_{it} + \beta_2 * SCORE_{jt} + \beta_3 * (SCORE_{jt} * MERG_{it}) \\ &\quad + \beta_4 * FIRM_{j,t-1} + \beta_5 * BANK_{i,t} + \beta_6 * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \tag{2}$$

In the above equation r_{ijt} is the relative interest rate on credit lines charged by bank i to firm j in year t, measured by the difference between the bank's loan rate and the 3-month interbank interest rate. $MERG_{it}$ are dummy variables that equal 1 if bank i was involved in a merger in a period prior to period t. $SCORE_{jt}$ is the credit-worthiness measure contained in the CB for firm j in period t. $FIRM_{j,t-1}$ and $BANK_{i,t}$ are, respectively, a set of time-varying firm- and bank-specific control variables. To control for changes in market concentration that are unrelated to consolidation, we include the Herfindahl-Hirschman Index (HHI) of the local market for bank loans ($CONC_t$). u_j is a firm-specific fixed effect and d_t is a time dummy. Finally, we include a zero-mean random error e_{ijt}.

Within the framework of Eq. (2), β_1 captures the price effect of the merger, i.e. the effect of the deal on the loan rate charged by the consolidated bank. A positive value would imply that the market power effect prevails over the efficiency effect, harming the borrowers, while a negative value would indicate that the efficiency gains outweigh the increase in market power, leading to a reduction in the loan rate (see Focarelli and Panetta (2003)). The value of β_2 represents the slope of the interest rate profile, i.e. the risk-return relationship prevailing in the market for bank loans. We expect a positive value for this parameter.

The hypothesis that mergers improve banks' informational efficiency translates into a testable prediction on the value of β_3, which represents the effect of the merger on the steepness of the interest rate profile. A positive value for β_3 would be consistent with the hypothesis that a merger leads to informational efficiencies, in the form of a steeper interest rate profile.

Our specification of the interest rate equation is similar to Pagano, Panetta and Zingales (1998) and Sapienza (2002). In particular, by using a fixed effect model we are using a firm before the merger as a control for itself after the merger. Moreover, by including a calendar-year fixed effect we control for the cyclical patterns common to all firms and banks. The firm variables capture the relation between the loan rates and firms' characteristics that are not captured by the *SCORE* (to avoid simultaneity, all variables are lagged one year). We include size (the log of total assets), leverage (the ratio of debt to the sum of debt plus capital) and profitability (the return on sales). We also control for bank-specific variables that might influence the loan rates. We include size (proxied with total assets) and the cost-income ratio (a standard proxy for efficiency). To check whether our results are sensitive to the chosen specification, we have also estimated richer models, including additional firm and bank characteristics (see below). Further, as previously noted, we check the robustness of our results to the use of alternative measure of a company's risk.

Before presenting our results, it is worthwhile to discuss a potential endogenous selection problem that we face in estimating our regression: the banks that merged have chosen to do so, and the decision could be related to the bank's record in credit management. However, this is unlikely to affect our results significantly. In fact, previous research on bank M&As in Italy (Focarelli, Panetta and Salleo 2002) has shown that the decision to merge is not related to credit management.[5] Moreover, the selection problem could be solved using a two-stage procedure, where the first stage involves estimating a model of the decision to merge. Unfortunately, this model would have very limited explanatory power (see Focarelli, Panetta and Salleo, 2002), eliminating the practical relevance of this procedure.

3.4 Preliminary evidence

Because the interpretation of our results depends critically on the idea that high-quality information implies a higher sensitivity of the loan rate to the risk characteristics of the firm (i.e., a steeper interest rate curve), before presenting the main empirical results we examine the validity of this assumption. Namely, we analyze whether the data support the view that a bank's responsiveness to the SCORE is correlated to its informational ability. To this end, we examine how the slope of the interest rate curve differs between banks which we *a priori* classify as having better information or information processing ability, and those banks which have worse information. If our assumption is valid, banks which are better informed should have a steeper interest rate curve.

We consider two proxies of a bank's informedness. One is the length of the bank-firm relation, measured by the number of consecutive years that a bank has had a lending relationship with a given firm. The potential informational benefits of long-term bank-

[5]Focarelli, Panetta and Salleo show that the decision to merge can be traced back to strategies aimed at increasing the bank's revenues from services (e.g., the sale of mutual funds).

firm relationships are analyzed by Rajan (1992). The empirical evidence has shown that the length of the relationship affects the availability and the cost of credit.[6] We estimate Eq. (2), replacing the dummy $MERG$ with this proxy. The coefficient of the interaction between the SCORE and our indicator represents the increase in the slope of the interest rate curve resulting from an increase in the duration of the relationship, so that we expect a positive value. The results, reported in Panel A of Table 5, are consistent with our view. In particular, the coefficient of the interaction term is positive (equal to 0.0191) and statistically significant. The coefficients of the SCORE is also positive and significant, as expected.[7]

Our second proxy is the amount of expenditure in computer software per employee, a standard indicator of a bank's information processing capabilities. As in the previous case, we estimate equation (2) replacing the dummy $MERG$ with our proxy (see Panel B of Table 5). Again, the results are consistent with the hypothesis that more informed banks exhibit a steeper interest rate curve: the coefficient of the interaction between the SCORE and software expenditure is positive (equal to 0.0246) and statistically significant (the coefficient of the SCORE is also positive and statistically significant).

These results are subject to important caveats. For example, our two proxies may be endogenous, correlated with unobservables which also affect the loan rates. But as we do not seek causal effects here, rather just a descriptive measure of how the interest rate sensitivity differs across banks depending on their information characteristics, this does not matter to us. We take these findings as indicating that it is reasonable to interpret the sensitivity of the loan rates to measures of a firm's credit-worthiness (such as SCORE) as an indicator of the informational sophistication of the banks.

4 Empirical results

Before turning to the regression results, we examine raw plots of the data, as contained in figure 1. The two graphs here contain the average and median (across banks) interest rate

[6] See Petersen and Rajan (1994) and Berger and Udell (1995) for the U.S. and Angelini, di Salvo and Ferri (1998) for Italy.

[7] We perform a further check on the relation between the loan rates and the SCORE by dropping from the right-hand side of the regression our proxy of banks' informedness (the length of bank-firm relationships) and the interaction term. The results (unreported) confirm the existence of a positive and significant relation between loan rates and the SCORE.

profile (ie. r vs. the $SCORE$) for banks which merged during the sample period 1988–98, and for banks which did not merge. Clearly, the merged banks exhibit a steeper profile. Furthermore, we see that lending rates are not uniformly lower across all firms: they are lower for the less risky firms (those with a low SCORE measure), but actually higher for riskier firms (those with a high SCORE measure).

The raw data in figure 1 is consistent with the hypothesis that mergers led to informational efficiencies. However, the interest rate curves shown in the graph could merely reflect differences between merged and non-merged banks, or differences in the pool of borrowers. Therefore, we now turn to the regression analysis, to check whether the relation persists once we control for the characteristics of the borrowers and those of the lenders.

The estimates of equation (2), reported in Panel A of Table 6, confirm that after a merger banks' sensitivity to a worsening of the SCORE (i.e. a unit increase in the SCORE value) rises by 8.7 basis points (the coefficient is significant at the 1 percent level). This finding squares with the the graphical evidence from Figure 1 and is consistent with the hypothesis that M&As lead to higher sensitivity of the loan rates to the risk profile of the borrower, so that post-merger banks price loans more efficiently.

The estimate of β_3 is not huge, but the costs for the borrowing companies are not trivial. These costs, to put them in perspective, come to approximately 78 basis points for the worst companies (SCORE=9). However, this calculation does not consider the price effect of the merger, i.e. the effect on the intercept of the interest rate profile. The negative estimate of β_1 indicates that M&As reduce the intercept of the r-$SCORE$ curve by 29.7 basis points, or 2.5 percent of the median loan rate (this result is consistent with the findings of previous research on the Italian banking industry[8]). The increase in the steepness and the lower intercept imply that only the good companies (i.e. those with SCORE below 4) benefit from the merger. In contrast, our results suggest that the consolidation leads to an increase in the loan rate for the low-quality companies.

The other coefficients are all significant and have the expected signs. The loan rates are higher for riskier companies (higher SCORE) and for companies with higher leverage, while they are lower for more profitable firms (higher return on sales) and for larger companies. The loan rate are also higher for inefficient banks (high ratio of costs to gross income). As expected, the loan rate is higher in markets with high market concentration.

[8]Sapienza (2002) finds that the typical merger leads to a rate reduction of about 40 basis points (considering a market share of the target bank of 2.9 percent; see her table III). Focarelli and Panetta (2003) find that mergers lead to a change in the deposit rate of 3.3 percent.

Robustness of the Estimates We undertake several analyses to assess the robustness of results to the inclusion of other control variables and the use of alternative estimation methods. They have negligible effects on the qualitative results.

A potential problem with our results is that unmeasured or poorly measured bank-specific characteristics could result in correlated errors across observations of each bank. In order to address this issue, we re-estimate our model including firm- *and* bank-specific fixed-effects. The results obtained using this alternative specification are similar to those previously reported: the estimate of β_3 is equal to 8.8 basis points and remains strongly significant (see Panel B of Table 6). The other coefficients remain significant and of the expected sign.[9] Throughout the paper, in order to retain the comparability of our results with those of the previous studies, we will continue to use the results obtained using firm-specific fixed effects.

We then run regressions including proxies for bank profitability (the Return on Assets or the Return on Equity) and including other proxies for bank size (e.g., total loans) and the loan-to-assets ratio. We try also additional firm controls (such as the Return on Assets, age and the ratio of intangible assets to total assets) and different definitions of leverage. These variables are in general not significant and do not affect the sign and significance of the interaction term $SCORE * MERG$.

Another possible problem is that, given the increase in the number of mergers over time, the interaction term $SCORE * MERG$ could capture a trend in banks' informational efficiency that is unrelated to the mergers. For example, the improvements in informational efficiency could merely reflect the positive effects of the expansion in banks' ICT spending on their informational efficiency. If such were the case, the positive estimate of β_3 could capture effects that are unrelated to the mergers. In order to examine this issue, we re-estimate our model interacting the $SCORE$ with time fixed-effects (*i.e.* the year dummies). This way trend effects in banks' informational efficiency should be captured by the interaction coefficients. Using this specification – that represents an extreme test of the robustness of our model – the results (unreported) are qualitatively similar to the previous ones. Namely, the coefficient on the SCORE*MERGE interaction does not change much in magnitude and remains statistically significant.[10]

[9] We estimate our model also including only bank-specific fixed effects (unreported). The results do not change.

[10] In another set of unreported results, we addressed the potential endogeneity of the SCORE variable (arising perhaps from firm-year unobservables which might also influence the interest rate that a firm is granted) by fixing SCORE at its pre-merger average, across all firms. This removes all time variation in

Yet another concern is that our results might suffer from a lack of generality, as they could depend on our specific definition of the firms' risk profile (i.e. the SCORE). To address this issue, we reestimate our model using an alternative proxy for risk. We merge our data base with the information available from the Central Credit Register on the companies that have defaulted. We then estimate a probit model on the probability to default and use the predicted probability as an alternative proxy for company risk. Again, the main results (unreported) are similar to the previous ones.

5 Results for sub-samples

In the previous section we ascribed the increase in the slope of the interest rate curve to the informational gains from mergers. In this section we reinforce this interpretation by examining the effect of mergers on sub-samples of firms for which, a priori, the informational gains from consolidation should differ in a predictable way. If we found that our estimates of the change in the slope of the interest rate curve across these sub-samples confirmed our priors, we would take this as evidence in favor of the hypothesis that this change is indeed determined by informational gains and not by other factors.

5.1 Short vs. long bank-firm relationships

First, we consider the duration of bank-firm relationships, i.e. the number of years for which company i has been a customer of firm j. We split our sample into two subgroups: "long relationships", i.e. the bank-firm pairs that have a relationship of 5 years or more; and "short relationships", i.e. those with duration of 4 years or less (we have experimented with alternative splitting point, obtaining similar results).

Because banks develop information over time, through repeated interactions with their customers, longer relationships are likely to be associated with better knowledge of the borrower. Therefore, the merger-related gain in information should be larger for companies with a short relationship with the bank than for companies with long relationships - simply because the characteristics of the latter are likely to be known to the bank even before the merger. Accordingly, we expect the post-merger increase in the slope of the interest rate

SCORE, so that we are not able to estimate the level effect of SCORE (ie., the coefficient β_2 in Eq. (2)) in the presence of firm dummies. However, we can still estimate the important interaction of MERGE and SCORE, and we find that it remains positive and significant.

curve to be larger for short relationships than for long ones.

We re-estimate equation (2) making this distinction. The results, reported in Table 7, are consistent with our hypothesis: the increase in the slope of the interest rate curve (the coefficient of the interaction term MERGE*SCORE) is equal to 6.7 basis points for the short duration sub-sample and to 2 basis points for the companies with long relationships (the difference between the two coefficients is highly significant). Economically this result implies that for companies with short relationships the difference between the lending rate of the worst companies and the best companies (SCORE=1 or 9, respectively) increases by 48 basis points. In contrast, for the companies with long relationships the spread between low- and high-quality firms increases by 16 basis points. The estimates of the other coefficients are generally similar to those reported in Table 6.

This finding also allows us to make a further point. The post-merger increase in the slope of the interest rate curve that we have documented in the previous section may also be consistent with an alternative interpretation, with different welfare implications: in pricing loan contracts smaller, non-merged banks may rely more on "soft" information rather than on the hard information summarized by the SCORE, so that the increased post-merger interest rate sensitivity could merely reflect the fact that mergers destroy soft information.[11] While soft information is difficult to define or measure precisely, it is reasonable to assume that the amount of soft information which a bank possesses about a borrower increases in the length of the lending relationship. Therefore, the result that the slope of the interest rate profile increases *less* for firms with long relationships (which banks presumably have more soft information about) casts some doubt on the hypothesis that our results merely reflect the destruction of soft information.

5.2 Important vs. fringe banks

For the same reasoning that we used for the length of the relation, one should expect that banks should be more informed about firms for which they supply a large share of credit. Therefore, according to our hypothesis the merger-related informational gains (and the increase in the slope in the interest rate profile) should be larger for banks that represent a small proportion of a company's total lending.

To test this hypothesis we compute w_{ijt}, the proportion of total lending to company i

[11] Evidence that smaller banks (which are more likely to be the target banks in a merger) tend to rely to a larger extent on soft information is presented in Cole, Goldberg and White (2000) using US data.

provided by bank j and split our bank-firm observations into two subsamples. The first sub-sample includes all observations for which w_{ijt} is below the median (15 percent)[12]; the second, those with w_{ijt} above the median. Results, reported in Table 8, are consistent with our hypothesis: the increase in the sensitivity of the loan rate to the SCORE score is higher for firm-bank relations with a low share of credit, where we expect informational gains to be stronger (the difference is statistically significant) Again, we find this result to be robust to alternative splitting points.

As a further check, we have also used a measure of firm-bank distance, splitting according to the fact that both the firm and the bank headquarters are in the same region, on the presumption that geographical proximity improves the bank's information about the firm, so that less should be gained from the merger. Results, not reported for brevity sake, again indicate that the increase in the sensitivity is higher when the firm and the bank are located in different regions, suggesting larger informational gains. All in all, we find this evidence remarkably supportive of the hypothesis that mergers increase the banks' screening ability.

5.3 Is it price discrimination?

If the merging banks have significant local market overlap, the merger could lead to an increase in market power. Therefore, we consider the alternative explanation that the effects we have documented may be attributed to market power: specifically, a merged bank, with enhanced monopoly power, may be able to exercise more price discrimination among its customers.

While the market power hypothesis is consistent with the steeper interest rate profile, and increase interest rate dispersion, resulting from a merger, it has difficulty explaining the decrease in rates for the less risky firms.[13] On the other hand, if the merger had both market power and cost-reduction effects, then our observed results could still be consistent with the explanation that the market power effect dominated for the risky firms, resulting

[12]Our data set contains the amount of credit utilized at the end of each period. Therefore, for the banks that have lent to the company only during the period the value of w_{ijt} is equal to zero. To avoid the bias induced by this feature of our data, we compute the median of w_{ijt} by excluding the bank-firm observations with end-of-period credit utilized equal to zero.

[13]For instance, the literature on competition and third-degree price discrimination shows that a monopoly tends to raise prices to *all* consumers, relative to the duopoly case. See Stole (2002), section 2 and Holmes (1989). Also see Borenstein (1989) and Busse and Rysman (2001) for empirical work on the effects of competition on price discrimination.

in higher interest rates,[14] but the cost-reduction effects dominated for the less risky firms, leading to the lower interest rates observed in the data. In order to test this hypothesis, we divide the mergers in our sample into *in-market* and *out-of-market* mergers. An in-market merger is defined as the event where both the acquiring and acquired parties to a period t merger were already active lenders in a given province during period $t-1$, and an out-of-market merger as one where only one of the parties was already lending in the province.[15]

Since an increase in local market concentration only occurs for the in-market sample, if the market power interpretation of our results is correct, then the slope of the interest rate profile should increase only for in-market mergers; in contrast, for the out-of-market sub-sample the sensitivity of the loan rate to the SCORE should not be affected by the merger. We re-estimate the basic regression for the two sub-samples separately. The results from this regression, reported in Table 9, indicate that the regression results are similar for the in-market and out-of-market subsamples. Indeed, not only the the interest rate curve becomes steeper in both sub-samples, but the increase in the slope is larger for out-of-market mergers than for in-market mergers (the SCORE*MERG interaction coefficient is equal to 11.9 and 6.6 basis points, respectively), which is exactly the opposite result that one would expect under the market power interpretation of our result.

6 Characterizing the mechanisms of informational benefits from mergers

Since we found little evidence in the previous section to support several alternative explanations of the steepening of the interest rate curve, we turn next to characterizing *how* the informational benefits of a merger were realized. As we have already mentioned in Section 2, the informational gains from mergers may reflect three non-mutually exclusive hypothesis: (i) a general improvement in merged banks' abilities to process information; (ii) a transfer of capabilites from a more efficient acquiring to a less efficient aquired bank (iii) the benefits from pooling information that before the deal was only available separately to each of the

[14]For instance, if firms with high SCORE have a less elastic demand curve for loans, due to difficulties in obtaining funding from alternative sources, then a monopolist may exploit this situation by raising interest rates to these borrowers.

[15]Italy is divided into 103 provinces that by and large correspond to U.S. counties. In previous research, local markets have been identified with the provinces by \citeasnoun
{sapienza} and Focarelli and Panetta (2003)

merging parties. Therefore, in this section we test between these hypothesis.

6.1 Information processing or information pooling?

We create three merger-related dummy variables, $BIDDER_{ijt}$, $TARGET_{ijt}$, and $BIDTAR_{ijt}$. The first dummy is equal to 1 if the observation refers to a firm that before the merger was borrowing only from the bidder, or acquiring bank. Analogously, the dummy $TARGET_{ijt}$ refers to companies that before the consolidation were borrowing only from the acquired bank. Finally, $BIDTAR_{ijt}$ is equal to one if before the deal the firm was borrowing from both the bidder and target banks in a given merger. We then estimate the following regression:

$$\begin{aligned} r_{ijt} &= a_0 + a_1 * BIDDER_{ijt} + a_2 * TARGET_{ijt} + a_3 * BIDTAR_{ijt} + a_4 * SCORE_{jt} + \\ &\quad a_5 * (SCORE_{jt} * BIDDER_{ijt}) + a_6 * (SCORE_{jt} * TARGET_{ijt}) + \\ &\quad a_7 * (SCORE_{jt} * BIDTAR_{ijt}) + a_8 * FIRM_{j,t-1} + a_9 * BANK_{i,t} + \\ &\quad a_{10} * CONC_t + u_j + d_t + e_{ijt}. \end{aligned} \tag{3}$$

Even if the three hypothesis above are not mutually exclusive and could be operating simultaneoulsy, we show that by comparing the size of the interaction coefficients we can easily discriminate among them. The hypthesis that informational gains arise from a general improvement in the merged banks' ability (or an increase in their incentives) to process information implies that all firms borrowing in from a bank involved in an M&A should be affected: $a_5 > 0, a_6 > 0, a_7 > 0$; moreover, if this is the only source of informational gain, we should find that the increase in the steepness is similar across observations: $a_5 = a_6 = a_7$. If gains derive from a more efficient bidder transfering its information processing capabilities to a less efficient target, we should find that $a_6 > a_5$, because the reassesment of the loan portfolio of the acquired bank would bring interest rates more in line with the true riskiness of firms only for the formerly badly priced loans of the target bank. Finally, *pooling* the borrower-specific private information available separately to the bidder *and* the target before the merger could also be a source of informational gains. This effect only applies to $BIDTAR$ observations, and should therefore generate a stronger increase in the steepness for these subset of observations: $a_7 > a_{5,} a_7 > a_6$. The results, reported in Table 10, show that for the companies borrowing from only one of the merger parties - the bidder *or* the target - the interest rate curve becomes steeper. For the loans that refer to the bidder banks, the estimate of the coefficient of the interaction term (a_5 in equation 3) is equal to about 9 basis points using both firm-specific fixed effects (see Panel A of the Table) and bank- and firm-specific effects (see Panel B). In economic terms, this implies that the spread between the worst and best firms (with SCORE equal to 9 and 1) increases by approximately 70 basis points. The estimate of a_6 (i.e. the increase in the slope of the interest rate curve for target banks) ranges from 7.6 to 8.6 basis points (using firm-specific and firm and bank-specific dummies, respectively). The fact that the gains are similar for the bidder and target banks (an F-test indicates that the difference between a_5 and a_6 is not significant) suggests that the merger does not result in a transfer of managerial skills from one party to the other, but instead improves the operations of both banks. This result is in line with the findings of Focarelli et al. (2002) discussed in Section 3.3, according to which the merger decision is driven by other factors that differences in credit management capabilities.

The estimate of a_7 (the coefficient of the $SCORE * BIDTAR$ term) is slightly smaller than a_5 and a_6: it is equal to 3.9 basis points with firm fixed-effects to 5.5 basis points with firm and bank fixed effects. This result is somewhat puzzling, although the difference between a_7 on one side and a_5 and a_6 on the other is small. As already mentioned, in principle the gains that result from a more efficient processing of information should also apply to the $BIDTAR$ companies, so that a_7 should not be smaller than a_5 and a_6. A possible explanation for the slightly lower coefficient on $SCORE * BIDTAR$ is firm selection. Indeed, the probability of having a loan from both a bidder and target bank is presumably higher for large companies, that have more bank relationships than small companies. This conjecture is supported by the data: the $BIDTAR$ firms are twice as large in terms of total assets than the others, and have a larger number of bank relations. These factors imply that, due to the sample desing, $BIDTAR$ firms tend to be informationally more transparent that $BIDER$ or $TARGET$ firms, so that the informational gains from the merger are likely to be small.

Summing up, our results provide little evidence that the merging banks succesfully pool their information on individual borrowers. Instead, our results are consistent with the view that the consolidated banks improve the way they handle information.

6.2 Disentangling improvements in information processing

Having established that improvements in information processing appear to be the prevalent channel through which the informational benefits from a merger were realized, we proceed to distinguish between two types of improvements in information processing. First, a merger might allow the larger bank to gain more information about its borrowers, so that a merger actually increases the generation of new information. Second, the merger may provide incentives to use existing information more effectively.

We are able to disentangle these two components of information improvements — generation of new information vs. more effective use of existing information — by exploiting the peculiar timing features of the SCORE variable. As discussed above, we observe SCORE a full year before the banks in our dataset do. As such, in a given year t, we proxy the existing information about firm i that banks possess with $SCORE_{t-1}$, while we estimate the "new" information about firm i that appears between year $t-1$ and t with the residual from a pooled (across all banks, firms, and years) AR(1) regression of $SCORE_t$ on $SCORE_{t-1}$.[16] Therefore, we amend the basic regression (Eq. (2)) by using $SCORE_{t-1}$ instead of $SCORE_t$, and by including the period t residual $resid_{i,t} \equiv SCORE_{i,t} - \hat{\rho}_0 - \hat{\rho}_1 SCORE_{i,t-1}$ (where $\hat{\rho}_0$ and $\hat{\rho}_1$ denote, respectively, the intercept and slope coefficient from the pooled AR1 regression). We also interact $resid_{i,t}$ with the merger dummies.

The regression results are reported in Table 11. In the first column of results, the coefficients on both of the interactions $MERGE * SCORE_{t-1}$ and $MERGE * resid_t$ are positive and significant (with point estimates of 0.092 and 0.035, respectively), indicating that a merger not only leads to acquisition of new information, but also leads to better use of existing information.

In the second set of results reported in Table 11 we break down the merger effects into those which occur to the $BIDDER$ firms, the $TARGET$ firms, and the $BIDTAR$ firms. The coefficients of the interaction with $SCORE_{t-1}$ and $resid_t$ are positive and significant for both the $BIDDER$ and $TARGET$ firms, suggesting that after the merger these firms are affected by both types of informational changes (production of new information and better use of existing information). In contrast, for the $BIDTAR$ firms only the $SCORE_{t-1}$ interaction is positive and significant, while $resid_t$ interaction is insignificant. This indicates that for these firms a merger's informational benefits arise only from more efficient use of existing information (as captured by$SCORE_{t-1}$). Again, this result could reflect firm selection, indicating that for large and well established firms (such as the $BIDTAR$ firms) the production of new information is much more difficult than for the other companies.

[16]This pooled panel AR1 regression was run without firm dummies, because we already include firm dummies in the basic regression (Eq. (2)).

7 Concluding remarks

In this paper, we have documented evidence in favor of the hypothesis that an important effect of bank mergers is to improve banks' ability to screen lenders. Consistently with the information hypothesis, we find that merged banks exhibit a closer correspondence between the price of loans and the risk of each firm than unmerged banks, resulting in a steeper interest rate profile. Our results indicate that the pricing effects of mergers differ across firms: specifically, only high-quality firms benefit from the merger; in contrast, for the riskier firms the loan rate actually increases after the merger.

We attribute these effects to improvements in information processing rather than explicit information pooling between the merging parties. We uncover a striking asymmetry in the information improvements between the acquiring and acquired banks: while acquired banks improve by making better use of existing information (thus suggesting the importance of managerial improvements in these banks), acquiring banks become more adept at both using existing information as well as gaining new information.

These results raise other interesting questions for future research. First, we wish to investigate the "portfolio reassessment" hypothesis, which claims that mergers trigger a one-time reassessment of a bank's loan portfolio, so that any merger effects should be short-lived. Given our access to detailed data on changes in firms' SCOREs at the beginning of a lending relationship, and at the time of a merger, this hypothesis could be directly tested. Second, we wish to expand our notion of information pooling after a merger, by testing whether merging banks share information regarding industrial sectors and/or geographic regions which they specialized in before the merger.

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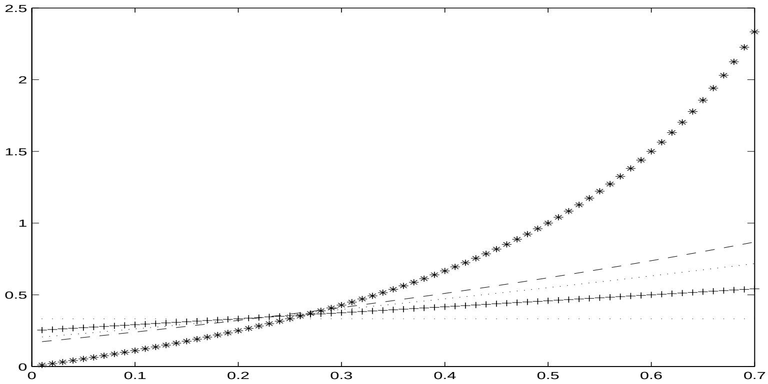
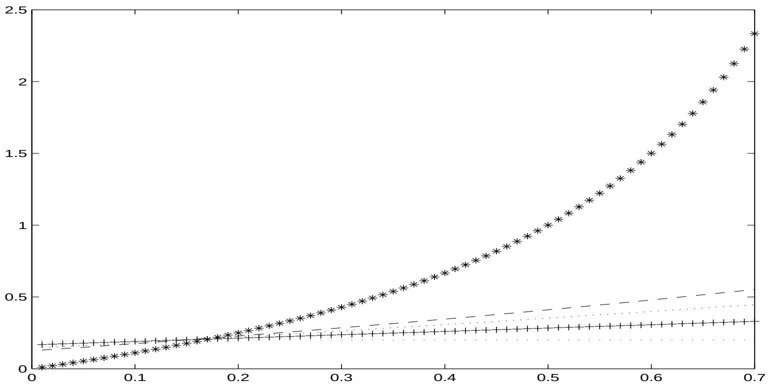
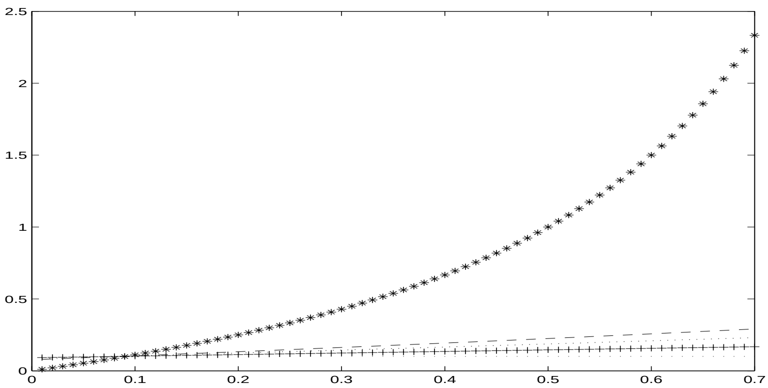
Figure 1: Average interest rate in theoretical model



$a = 1,\ b = 3$



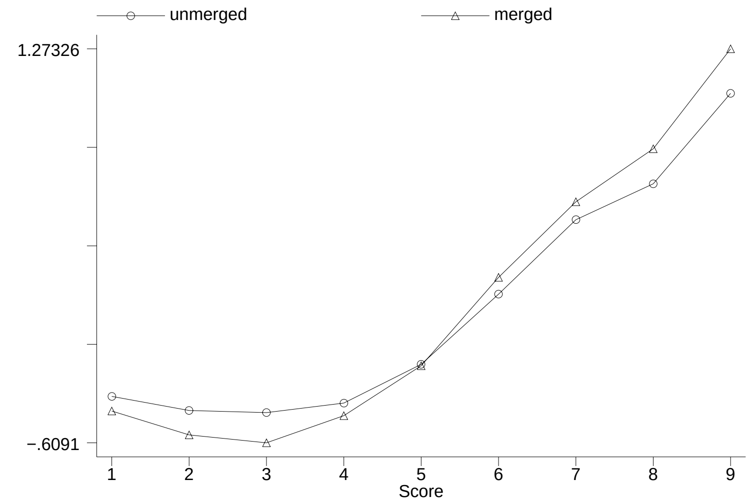
$a = 1,\ b = 5$



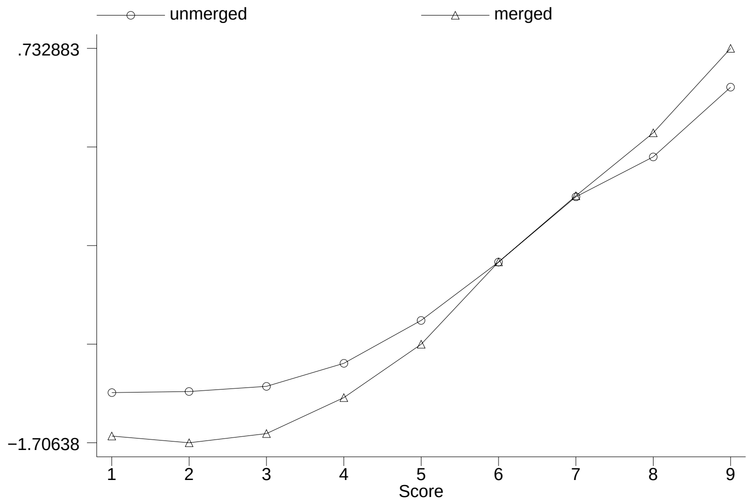
$a = 1,\ b = 10$

Legend: +++: $n = 1$ +++: $n = 2$ +++: $n = 3$ ***: $n = \infty$

Figure 2: Interest rate profiles: merged vs. unmerged banks



Average interest rate vs. SCORE



Median interest rate vs. SCORE

Table 1

Summary Statistics: the Bank Sample

The summary statistics of Panel A refer to all banks that report the interest rates charged on credit lines. Panel B to the banks that were bidders in a merger. Panel C to the banks that were target in a merger. The number of observations is the number of bank-years. Size is the bank's total assets in millions of euros. Employees is the number of employees at the end of the year. Bad loans is a percentage of total loans. Cost-income ratio is the ratio of overhead to gross income (in %). Software per employee is the ratio of expenses in software to the number of employees, expressed in thousands euros.

Variables	Obs.	Mean	Stand. Dev.	5^{th} pctile	Median	95^{th} pctile
			Panel A: All Banks			
Size	900	10,726.8	16,965.6	481.3	3,709	54,354.1
Employees	896	3,179.9	4,582.5	206	1,137	14,038
Bad loans	893	6.2	6.3	1.9	4.9	15.8
Costs-income ratio	893	34.5	6.1	25.4	33.1	43.2
Software per employee	792	1.3	1.1	0.1	1.1	3.2
			Panel B: Bidder Banks in Mergers			
Size	107	19,386	23,902	1,193	9,049	75,096
Employees	106	5,325	5,733	365	2,789	18,987
Bad loans	107	6.2	4.7	2.0	5.6	15.1
Cost-income ratio	106	33.6	6.8	25.2	33.2	44.3
Software per employee	91	1.4	1.3	0.4	1.1	3.9
			Panel C: Target Banks in Mergers			
Size	28	7,254	7,804	144	4,999	26,952
Employees	28	2,270	2,769	67	1,551	10,014
Bad loans	28	9.3	13.4	1.2	4.2	50.0
Cost-income ratio	24	34.0	8.9	23.6	31.9	51.6
Software per employee	23	1.1	0.8	0.1	1.1	3.1

Table 2

Summary Statistics: the Firms Sample

The summary statistics in the table refer to the company sample. Total assets are expressed in million euros. Employees is the number of employees at year-end**.** Short term debt is expressed as a proportion of total debt. The SCORE is the indicator of the risk of the company computed each year by the *Centrale dei Bilanci* (higher values indicate riskier companies). Number of lenders is the number of banks from which the company borrows. Utilized credit is expressed as a proportion of credit granted.

Variable	Obs.	Mean	Stand. Dev.	5^{th}pctile	Median	95^{th}pctile
Total Assets	329,622	3.6	119.9	0.04	0.78	8.4
Employees	293,281	73.7	637.9	3	31	224
Leverage	329,611	55.3	30.1	0.1	60.3	96.0
Return on Sales	328,650	9.1	9.9	4.3	8.6	20.4
Short term debt	304,440	70.2	31.9	0.2	81.0	100.0
SCORE	318,645	5.1	1.8	2	5	8
No. of lenders	329,623	4.4	3.3	1	4	11
Utilized credit	319,792	50.2	54.3	0	38.2	138.4

Table 3

Firm Characteristics by Risk Class

The summary statistics refer to the company sample. Companies have been grouped on the basis of the risk indicator computed each year by the *Centrale dei Bilanci* (the SCORE: higher values indicate riskier firms). Panel A refers to safe firms (SCORE=1,2). Panel B refers to solvent firms (SCORE=3,4). Panel C refers to vulnerable firms (SCORE=5,6). Panel D refers to risky firms (SCORE=7,8,9). Employees is the number of employees at year-end. Average loan rate is the average interest rate paid by the company on credit lines. Number of lenders is the number of banks from which the company borrows. Percentage of overdrafts is the proportion of firms with at least one credit line with credit utilized exceeding credit granted.

Variable	Obs.	Mean	Stand. Dev.	5th pctile	Median	95th pctile
			Safe firms (SCORE=1,2)			
Employees	26,954	80.7	292	5	34	261
Leverage	29,317	19.2	16.8	0.5	15.2	50.7
Average loan rate	23,906	14.3	4.0	10.2	13.2	22.2
No. of lenders	29,317	2.8	2.3	1	2	7
Percentage of overdrafts	29,317	4.2	14.1	0	0	29.8
			Solvent firms (SCORE=3,4)			
Employees	88,841	85.5	539.5	6	35	254
Leverage	98,047	40.2	21.7	0.3	42.1	73.6
Average loan rate	91,022	14.2	3.4	10.4	13.5	20.4
No. of lenders	98,047	4.1	3	1	3	10
Percentage of overdrafts	98,047	8.3	18.9	0	0	50.2
			Vulnerable firms (SCORE=5,6)			
Employees	90,115	70.1	650.1	4	31	212
Leverage	101,195	63.3	24.1	0.4	68.8	92.3
Average loan rate	98,595	14.5	3	10.8	14.0	20.0
No. of lenders	101,198	5	3.5	1	4	12
Percentage of overdrafts	101,198	15.7	25.9	0	0	75.2
			Risky firms (SCORE=7,8,9)			
Employees	78,135	57.0	487.8	2	24	177
Leverage	90,076	74.3	26.7	0.6	81.4	103.8
Average loan rate	88,627	15.1	3	11.1	14.7	20.4
No. of lenders	90,083	4.8	3.4	1	4	11
Percentage of overdrafts	90,083	31.0	33.5	0	20.2	100

Merger Activity: Overall Sample

Panel A: Bank-year Observations

Number of banks is the number of bank-year observations in the sample of banks that report detailed information on the loan rates to individual borrowers (the reporting banks). Percentage of loan market is the ratio between the loans of the reporting banks and total banking industry loans. Number of bidders (targets) is the number of reporting banks that in each year was involved in a merger as a bidder (target).

Year	No. Of Banks	No. of bidders	No. Of targets
1988	87	7	0
1989	88	13	0
1990	87	5	1
1991	84	12	4
1992	81	11	4
1993	79	5	2
1994	75	8	0
1995	73	22	4
1996	71	8	3
1997	68	7	2
1998	70	8	1
Total	863	106	21

Panel B: the bank-firm-year observations

A firm is classified as a borrower of a bidder, a target or both for the 5 years following the merger if the firm was borrowing from the merging bank in the year before the merger. Number of observations is the number of bank-firm-year observation in our sample.

Year	No. Of observations	% of firms that borrow from a bidder	% of firms that borrow from a target	% of firms that borrow from a bidder & target
1988	96,353	10.1	0,0	0,0
1989	95,648	25.4	0,0	0,0
1990	105,073	27.7	0.1	0.1
1991	112,088	33.0	1.8	0.9
1992	116,942	39.3	6.0	0.5
1993	122,606	40.1	4.5	0.4
1994	134,037	48.9	3.6	0.3
1995	128,549	69.7	4.2	0.5
1996	116,307	61.9	4.0	1.4
1997	143,844	50.3	3.2	1.3
1998	126,075	53.9	2.0	1.6
Total	1,297,522	43.3	2.8	0.7

Table 5

The Effect of Information on the Slope of the Interest Rate Curve: Preliminary Evidence

In this table we report the results of estimating equation (1) of the paper replacing the *MERG* dummy with two proxies of the quality of the information that banks produce on their borrowers. The first proxy is the length of the bank-firm relationship (Panel A). The second is the bank's computer software expenditures per employee (see Panel B). The dependent variable is the bank-firm-specific interest rate on credit lines. The equations includes firm-specific fixed effects and time dummies. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent..

	Proxy of the degree of banks' informedness:	
Variables	Panel A	Panel B
	Length of bank-firm relationship	Software expenses
SCORE	.010 *	.047 ***
	(.006)	*(.004)*
Length of relationship	-.019 **	—
	(.007)	
SCORE*Length of relationship	.019 ***	—
	(.001)	
Software expenses	—	-.077 ***
		(.010)
SCORE*software expenses	—	.024 ***
		(.002)
Firm Controls:		
Size (log value)	-.005	-.010 ***
	(.004)	*(.004)*
Return on Sales	-.073	-.060
	(.048)	*(.044)*
Leverage	.170 ***	.183 ***
	(.021)	*(.020)*
Bank Controls:		
Size (log value)	.034 ***	.036 ***
	(.012)	*(.011)*
Cost-Income ratio	2.459 ***	2.653 ***
	(.065)	*(.058)*
Market concentration	2.549 ***	2.575 ***
	(.284)	*(.274)*
No. of Observations	811,945	965,696
R-Square	61.5	60.6

Table 6

Effect of M&As on Banks' Information

In Panel A we report the results of estimating equation (2) of the paper. In Panel B we report the results of estimating equation (2) of the paper using firm- and bank-specific fixed effects. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:		Panel B:	
Variables	Firm fixed effects		Bank *and* firm fixed effects	
SCORE	.036	***	.032	***
	(.004)		*(.004)*	
MERGE*SCORE	.087	***	.088	***
	(.004)		*(.004)*	
MERGE	-.297	***	-.347	***
	(.021)		*(.021)*	
Firm Controls:				
Size (log value)	-.019	***	-.019	***
	(.004)		*(.004)*	
Return on Sales	-.003		-.007	
	(.043)		*(.042)*	
Leverage	.191	***	.186	***
	(.020)		*(.020)*	
Bank Controls:				
Size (log value)	-.033	***	-.012	
	(.011)		*(.048)*	
Cost-Income ratio	2.962	***	.017	
	(.053)		*(.089)*	
Market Concentration	1.937	***	1.737	***
	(.271)		*(.271)*	
No. of Observations	1,061,785		1,061,785	
R-Square	58.4		60.2	

Effect of Mergers on Information: Long vs. Short Bank-Firm Relations

In Panel A we report the results of estimating equation (2) of the paper for firm-bank relations with a length less than 5 year, while in Panel B for relations of 5 years or more. Difference Test is the value of an F-test on the difference between the coefficients for the short and long relations. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	Panel A: Short bank-firm relations	Panel B: Long bank-firm relations	Panel C: Difference test (long vs. short relations)
SCORE	0.035 ***	0.060 ***	0.003 ***
	(0.004)	*(0.007)*	
MERGE*SCORE	0.067 ***	0.020 ***	0.001 ***
	(0.005)	*(0.006)*	
MERGE	-0.179 ***	-0.0294	0.001 ***
	(0.029)	*(0.035)*	
Firm Controls:			
Size (log value)	-0.013 ***	-0.007	0.450
	(0.004)	*(0.007)*	
Return on Sales	0.077	-0.189 ***	0.002 ***
	(0.051)	*(0.072)*	
Leverage	0.171 ***	0.228 ***	0.160
	(0.024)	*(0.034)*	
Bank Controls:			
Size (log value)	-.0710 ***	0.069 ***	0.000 ***
	(0.014)	*(0.018)*	
Cost-Income ratio	3.155 ***	2.543 ***	0.000 ***
	(0.067)	*(0.092)*	
Market Concentration	2.302 ***	2.417 ***	0.826
	(0.381)	*(0.398)*	
No. of Observations	669,877	391,908	
R-Square	59.3	63.8	

Effect of Mergers on Information: Important vs. Fringe Banks

In Panel A we report the results of estimating equation (2) of the paper for firm-bank relations where the bank account for less that 15% of the total loan of the firm, while in Panel B for more than 15%. Difference Test is the p-value of an F-test on the difference between the coefficients for the short and long relations. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	Panel A: Less than 15% of total loans	Panel B: More than 15% of total loans	Panel C: P-value for the null: less = more
SCORE	.052 ***	.050 ***	0.26
	(.005)	*(.005)*	
MERGE*SCORE	.101 ***	.079 ***	0.003 ***
	(.005)	*(.006)*	
MERGE	-.314 ***	-.255 ***	0.176
	(.030)	*(.033)*	
Firm Controls:			
Size (log value)	-.019 ***	-.038 ***	0.045 **
	(.005)	*(.010)*	
Return on Sales	.023	-.106 **	0.097 *
	(.065)	*(.053)*	
Leverage	.263 ***	.123 ***	0.000 ***
	(.030)	*(.026)*	
Bank Controls:			
Size (log value)	-.117 ***	-.140 ***	0.315
	(.015)	*(.017)*	
Cost-Income ratio	2.509 ***	2.648 ***	0.211
	(.071)	*(.086)*	
Market concentration	1.552 ***	1.890 ***	0.488
	(.395)	*(.351)*	
No. of Observations	607,285	385,615	
R-Square	58.4	70.9	

Effect of Mergers on Information: In-Market vs. Out-of-Market Mergers

In Panel A we report the results of estimating equation (2) of the paper for in-market mergers, i.e. mergers where both the acquiring and acquired parties to a period t merger were already active lenders in a given province during period t-1. In Panel B we report the results of estimating equation (2) of the paper for out-of-market mergers, i.e. mergers where only one of the merging parties (the acquiring *or* the acquired bank) to a period t merger was already active lender in a given province during period t-1. In Panel C report the results of estimating equation (2) of the paper for the pooled sample, letting the coefficient of the MERGE*SCORE variable to differ for in and out of market mergers (the INMKT coefficient represents the deviation from the out of market one). Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	**Panel A: In market mergers**	**Panel B: Out of market mergers**
SCORE	.044 ***	.046 ***
	(.004)	*(.004)*
MERGE*SCORE	.065 ***	.119 ***
	(.004)	*(.005)*
MERGE	-.364 ***	-.241 ***
	(.025)	*(.030)*
Firm Controls:		
Size (log value)	-.016 ***	-.020 ***
	(.004)	*(.004)*
Return on Sales	-.036	.070
	(.045)	*(.048)*
Leverage	.188 ***	.212 ***
	(.021)	*(.023)*
Bank Controls:		
Size (log value)	.036 ***	.211 ***
	(.012)	*(.014)*
Cost-Income ratio	3.008 ***	2.355 ***
	(.056)	*(.059)*
Market Concentration	2.071 ***	*2.615* ***
	(.288)	*(.368)*
No. of Observations	891,449	815,865
R-Square	59.3	58.1

Whence Informational Improvements: Information Pooling

In Panel A we report the results of estimating equation (3) of the paper. In Panel B we report the results of estimating equation (3) of the paper using using firm- and bank-specific fixed effects. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Panel A:	Panel B:
Variables	Firm fixed effects	Bank *and* firm fixed effects
SCORE	.035 ***	.032 ***
	(.004)	*(.004)*
BIDDER*SCORE	.091 ***	.090 ***
	(.004)	*(.004)*
TARGET*SCORE	.073 ***	.086 ***
	(.010)	*(.010)*
BIDTAR*SCORE	.039 *	.055 ***
	(.020)	*(.020)*
BIDDER	-.294 ***	-.343 ***
	(.022)	*(.020)*
TARGET	-.445 ***	-.445 ***
	(.059)	*(.060)*
BIDTAR	-.306 ***	*-.416* ***
	(.116)	*(.114)*
Firm Controls:		
Size (log value)	-.018 ***	-.019 ***
	(.004)	*(.004)*
Return on Sales	-.002	-.006
	(.043)	*(.042)*
Leverage	.192 ***	.187 ***
	(.020)	*(.020)*
Bank Controls:		
Size (log value)	-.032 **	.003
	(.010)	*(.048)*
Cost-Income ratio	2.970 ***	.013
	(.053)	*(.088)*
Market Concentration	1.938 ***	1.747 ***
	(.271)	*(.270)*
No. of Observations	1,061,785	1,061,785
R-Square	58.4	60.0

Table 11

Disentangling Improvements in Information Processing

In Panel A we report the results of estimating eq. (2) of the paper by using SCORE(t-1) instead of SCORE (t) and including RESID(t), defined as the period t residual of a pooled (across banks, firms and years) AR(1) regression of SCORE on SCORE(t-1). In Panel B we report the results of estimating eq. (3) by using SCORE(t-1) instead of SCORE (t) and including RESID(t) among the regressors. Standard errors adjusted for clustering over firm-year are reported in parentheses. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	Panel A: No distinction between bidder and target banks	Panel B: Distinguishing bidders from targets
SCORE(t-1)	0.099 ***	0.099 ***
	(0.005)	*(0.005*
RESID(t)	0.045 ***	0.044 ***
	(0.004)	*(0.004)*
MERGE*SCORE (t-1)	0.087 ***	—
	(0.004)	
BIDDER*SCORE (t-1)	—	0.092 ***
		(0.0043)
TARGET*SCORE (t-1)	—	0.059 ***
		(0.010)
BIDTAR*SCORE (t-1)	—	0.064 ***
		(0.021)
MERGE*RESID(t)	0.038 ***	—
	(0.005)	
BIDDER*RESID(t)	—	0.041 ***
		(0.005)
TARGET*RESID(t)	—	0.043 ***
		(0.013)
BIDTAR*RESID(t)	—	-0.033
		(0.030)
MERGE	-0.345 ***	—
	(0.022)	
BIDDER	—	-0.344 ***
		(0.022
TARGET	—	-0.455 ***
		(0.062
BIDTAR	—	-0.466 **
		(0.119
Firm Controls:		
Size (log value)	-0.019***	-0.019***
	(0.005)	*(0.005)*
Return on Sales	-0. 031 ***	-0.031
	(0.047)	*(0.047)*
Leverage	0.096 ***	0.098 ***
	(0.022)	*(0.021)*
Bank Controls:		
Size (log value)	-0.050 ***	-0.041
	(0.011)	*(0.113)*
Cost-Income ratio	2.943 ***	2.955 ***
	(0.055)	*(0.055)*
Market Concentration	1.846 ***	1.843 ***
	(0.288)	*(0.288)*
No. of Observations	973,237	973,237
R-Square	56.6	58.9