BANCA D'ITALIA
EUROSISTEMA

Temi di Discussione

(Working Papers)

Does credit scoring improve the selection of borrowers and credit quality?

by Giorgio Albareto, Roberto Felici and Enrico Sette

October 2016

Number 1090

BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working papers)

Does credit scoring improve the selection of borrowers and credit quality?

by Giorgio Albareto, Roberto Felici and Enrico Sette

Number 1090 - October 2016

ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

DOES CREDIT SCORING IMPROVE THE SELECTION OF BORROWERS AND CREDIT QUALITY?

by Giorgio Albareto*, Roberto Felici* and Enrico Sette*

Abstract

This paper studies the effect of credit scoring by banks on bank lending to small businesses by addressing the following questions: does credit scoring increase or decrease the propensity of banks to grant credit? Does it improve the selection of borrowers? Does credit scoring improve or reduce the likelihood that a borrower defaults on its loan? We answer these questions using a unique dataset that collects data from both a targeted survey on credit scoring models and the Central Credit Register. We rely on instrumental variables to control for the potential endogeneity of credit scoring. We find that credit scoring does not change the propensity of banks to grant loans to the generality of borrowers but helps them select borrowers. We also find that credit scoring reduces the likelihood that a borrower defaults, in particular for smaller borrowers and for banks that declare to use credit scoring mainly as a tool to monitor borrowers. These results are homogeneous across bank characteristics such as size, capital, and profitability. Overall our results suggest that credit scoring has a positive effect on the selection of borrowers and on credit performance.

JEL Classification: G21.
Keywords: credit scoring, credit supply, bank risk-taking, loan defaults.

Contents

* Bank of Italy, Directorate General for Economics, Statistics and Research.

1 Introduction[1]

A crucial role played by banks is the efficient use of information to screen and monitor borrowers. In particular, banks use different lending technologies characterized by the relative importance of hard and soft information (Berger and Udell, 2002). Advances in information and communication technology, more adapt at transmitting and processing information, and competitive pressure, which pushes banks to compress costs, have increased incentives and opportunities for employing lending technologies which rely more intensively on hard information (Petersen, 2004). Among these, credit scoring, which involves the standardization of information in the form of a credit score, represents a key example of hardening of soft information used to screen and monitor borrowers.

As a consequence, the adoption of credit scoring may have large effects on the way banks originate and monitor loans, and in turn on credit supply and the default rates of borrowers. First, the availability of additional (possibly more precise) information may induce banks to lend more and to better assess borrowers' creditworthiness (Frame, Srinivasan, and Woosley, 2001; Berger, Frame and Miller, 2005). Second, the adoption of credit scoring can generate cost savings to the extent that the information produced by scoring models substitutes the collection of soft information by local branch managers (see, among others, Berger and Udell, 2002; Berger, Frame and Miller, 2005). In this case, the adoption of credit scoring may allow banks to lower rates, granting credit to previously marginal borrowers, which may end up defaulting more. Third, if the quantitative information provided by credit scoring models substitutes the soft information traditionally collected by loan officers, banks can stop lending to borrowers for which the quantitative information needed for scoring models is not available. Finally, the standardization of credit allowed by the adoption of credit scoring is a prerequisite for securitization (Temkin and Kormendi, 2003). This can affect credit standards to the extent that securitized loans are riskier than loans that are not securitized (Keys, Mukherjee, Seru and Vig, 2010).

This paper sheds light on these issues by addressing the following questions: does the adoption of credit scoring affect the propensity of banks to grant a loan? Does the adoption of credit scoring affect the propensity of banks to grant a loan to ex-ante riskier borrowers? Does the adoption of credit scoring affect the likelihood that a borrower defaults on its loans? We an-

[1]We are grateful to Scott Frame, Matteo Piazza, Andrea Polo, seminar participants at the Bank of Italy and two anonymous referees for helpful comments. All errors are our own. The views expressed in this paper are solely of the authors and do not necessarily reflect those of the Bank of Italy or of the Eurosystem.

swer these questions using a unique dataset based on a survey on the adoption of credit scoring models by Italian banks matched with the Italian credit register, which provides information on individual loan applications and on the status (performing or non-performing) of loans granted by Italian banks. Our data cover loans to small businesses. This is important because: i) credit scoring models are mostly used for lending to small firms and households; ii) the market of loans to small firms is especially relevant, as these firms represent about 70 per cent of value added in Italy; iii) small firms are dependent on banks for outside finance, so studying bank loans implies studying their overall access to external finance.

We find that the adoption of credit scoring does not change the propensity of banks to grant loans to the generality of borrowers, but it allows banks to select safer borrowers. We also find that the adoption of credit scoring reduces the likelihood that a borrower defaults. These results are homogeneous across bank characteristics such as size, capital, profitability. The effect of the adoption of credit scoring in reducing the probability that a loan defaults is stronger for banks that declare to use credit scoring mainly as a tool to monitor borrowers and for smaller borrowers. We interpret these results as suggesting that the quantitative information provided by credit scoring helps banks to monitor borrowers after the loan is originated, allowing them to better manage the lending relationships, in this way reducing the likelihood the borrower defaults. In fact, the application of credit scoring to monitor the evolution of borrowers' creditworthiness and of lending relationships allows risk management practices based on hard information, which facilitate the decisions taken by loan officers about loans already granted, particularly inside complex banking organizations (Stein, 2002).

Studying the effects of the adoption of credit scoring on lending and borrower quality poses several identification challenges. First, banks adopting credit scoring may be different from banks not adopting credit scoring, and the difference may not be captured by observable bank variables. Second, the timing of adoption may reflect developments in the loan portfolio of banks: for example, banks may decide to adopt credit scoring because they face an increase in the default rate of their borrowers. We address these identification challenges using a difference-in-difference model which includes bank fixed effects and in which we instrument the decision to adopt credit scoring for small businesses with the decision to adopt credit scoring for loans to households 2 or more years before. Hence, our model compares the probability of accepting loan applications and the probability of default of individual loans of banks adopting credit scoring with those of banks not adopting credit scoring, controlling for all bank observable and unobservable characteristics thanks to the inclusion of bank fixed effects. The instrument takes care of the potential endogeneity of the timing of adoption, and it is based on the observation that the adoption of credit scoring for loans to household typically precedes the adoption for small business loans, since the former are more standardized (Mester, 1997). The fulfilment of the exclusion restriction is plausible, because the adoption of credit scoring in the household loan market reasonably has no effect on the supply of loans in the small business loan market since the two markets are segmented.

Our findings contribute to the literature in several ways. Early works focus on the effect of the adoption of credit scoring on the growth of loans. Frame, Srinivasan and Woosley (2001) study the effect of adopting credit scoring on lending in a simultaneous equations model which accounts for the endogeneity of credit scoring adoption. They find that credit scoring adoption increases lending to small businesses. Frame, Padhi and Woosley (2004) find that the increase in lending following the adoption of credit scoring is more pronounced in low and moderate income areas. Berger, Frame and Miller (2005) extend the previous results and also study the impact of the adoption of credit scoring on credit quality; they find that after the adoption of credit scoring banks increase lending and credit quality deteriorates. De Young, Glennon and Nigro (2008) show that credit scoring is associated with higher default probabilities; they explain this result with the production efficiencies related to the use of credit scoring, which would encourage adopters to expand output by making riskier loans at the margin. Berger, Cowan and Frame (2011) show no change in the quality of the loan portfolio for community banks. Hasumi, Hirata and Ono (2011) find that the ex-post probability of default of small firms increases after non-primary banks adopted credit scoring; they find the opposite result if the bank adopting credit scoring is the main lender.

The effects of small business credit scoring (from now on SBCS) appear to differ markedly depending on how a bank implements the technology. In particular, different effects could depend on the importance credit scoring does have in the decision to grant credit: if it is used automatically and it is the main factor influencing that decision (rules) or if it is just one ingredient among others (discretion). According to Berger, Frame, Miller (2005) for "rules" banks SBCS is associated with more lending, higher prices, and greater loan risk. By contrast, for "discretion" banks they find no statistically significant increase in credit availability, larger increases in loan prices relative to rules banks, and diminished loan risk. These results suggest that when SBCS is used as complement to another lending technology, lending costs may be increased, but the improved accuracy in credit evaluation may reduce risk.

All the previous works use data aggregated at the bank level and treat at different depth the issue of the endogeneity of credit scoring adoption. We complement and extend these findings by using detailed data at the loan level. This is useful for at least two reasons: first, it allows us to control for industry and location of the borrower, which are potential important determinants of both credit supply and credit quality; second, it allows us to use the probability that a loan application is granted as a measure of credit supply, which is a better measure than the volume of loans granted, in that it is less affected by demand factors (Jimenez et al. 2014). Moreover, we account for the potential endogeneity of credit scoring adoption. Other works do not fully control for this relevant issue, with the exception of Frame, Srinivasan and Woosley (2001), who do not study the effect of credit scoring adoption on credit quality. Finally, we also provide first evidence on the channels (screening versus monitoring) through which credit scoring affects lending and credit quality. Concerning the empirical strategy, our paper is strictly related to Einav, Jenkins and Levin (2013) who use data from a seller of used cars to study how the adoption of credit scoring affects loan origination, loan terms, and default rates. The adoption is randomized across different selling outlets of the same company to account for endogeneity. They find that after adoption the lender rations riskier borrowers more through tightening the terms of the loan, and that default rates drop significantly. The difference between our results and those of the prior works may be due to our focus on a different country than the US or Japan, but they could also reflect the use of a different, more robust, identification strategy.

More broadly, our work contributes to the literature on the consequences of the interaction between hard and soft information when banks use credit scoring. Brown, Schaller, Westerfeld and Heusler (2012) show that loan officers use their autonomy in over-riding scoring models more frequently when the borrower has a tighter credit relationship with the bank. Brown, Degryse, Hower, and Penas (2012) show that banks' use of external credit scores do affect the availability of credit for start-up firms, but that banks rely less on external rating information in their decision making for high-tech start-ups than low-tech start-ups. Cerqueiro, Degryse, and Ongena (2011) find that the use of discretion on loan rate setting in small business lending decreased over time, consistently with a higher use of hard information made possible by the increased adoption of scoring techniques. Karapetyan and Stacescu (2014) show that sharing of hard information implies higher benefit from investing in the soft information.

The rest of the paper is structured as follows: section 2 describes the adoption and usage of credit scoring by Italian banks; section 3 describes the data; section 4 discusses the identification strategy; section 5 presents the results; section 6 concludes.

2 The Adoption and Usage of Credit Scoring

The pattern of diffusion of credit scoring differs according to the characteristics of banks and borrowers. Usually credit scoring is adopted for loans of small amount, for which the unit costs of collecting information are very high, or for standardized loans. In fact, credit scoring was firstly adopted in the US for consumer credit; subsequently it has been used for mortgages and small business loans (Mester, 1997). Large banks with broad networks of branches which can fully exploit scale economies usually adopt credit scoring earlier.

We collect data on the adoption and usage of credit scoring from a survey of commercial banks operating in Italy (from now on "the survey") administered by the Bank of Italy. The survey contains a questionnaire aimed at gathering qualitative information on the organizational aspects of the lending process. In the second part of the questionnaire the questions explore the adoption of statistical-quantitative techniques for evaluating firms, their use in setting terms and conditions of loans, as well as in monitoring borrowers. Next, the survey includes questions on the extent to which quantitative and qualitative information is used in evaluating new loan applicants.[2]

The survey was submitted to banks during 2007 through the Bank of Italy's network of regional branches. The response rate has been very high, likely because the Bank of Italy is the banking supervisor. The sample of surveyed banks has been selected to ensure adequate coverage, both geographically and by type of bank, by size, and governance structure (commercial banks and mutual banks). The survey includes 333 banks and 306 responses concerning the adoption and use of credit scoring. The banks included in the survey account for 83 per cent of the total amount of outstanding loans to non-financial firms in 2007.

The data show that the introduction of scoring techniques for granting loans to firms by Italian banks has been gradual, accelerating sharply since 2003. According to the survey, in 2000 less than 10 per cent of the banks were using credit scoring, against almost 25 per cent in 2003, and 57 per cent in 2006 (Figure 1; for an analysis of the results of the survey see Albareto et al., 2011). In 2009 around 70 per cent of Italian banks adopted credit scoring for

[2]The appendix shows the questions of the survey concerning the adoption and use of credit scoring employed in the paper.

small business lending (see Del Prete, Pagnini, Rossi and Vacca, 2013). The adoption of credit scoring models for assessing households' creditworthiness has generally preceded their adoption for small business lending. According to the survey, both weighted and unweighted frequencies of banks adopting credit scoring models for granting credit to households are always higher than for granting credit to firms (see Rossi, 2008). The adoption of credit scoring was not uniform across banks: adoption is higher among larger banks whose extensive networks of branches allow them to exploit economies of scale (Bofondi and Lotti, 2005).

Credit scoring models may be internally developed, or acquired by external providers. As of December 2006, more than 50 per cent of the banks that had introduced credit scoring models had participated actively in their development, either alone or in cooperation with other institutions. The survey also contains data on what information feeds the scoring models in the case of small business lending. Mutual and small banks report that the most important information is the financial statement, followed by the credit history of firms with the bank and with the rest of the banking system.[3] Larger banks, by contrast, assign greater importance to the firm's past credit performance than to its accounting data.

As mentioned in the introduction, the effect of credit scoring on lending and on the selection of borrowers also depends on its degree of complementarity with other lending technologies: if it is used automatically for granting credit (rules) or if it is just a complementary lending technology with respect to others (discretion; see, among the others, Berger, Frame and Miller, 2005). According to the survey, credit scoring models play a key role in the decision whether or not to grant a loan. Apart from mutual banks, the percentage of the other types of banks for which the score is decisive or very important is above 50 per cent (Figure 2).[4] The relative importance of quantitative techniques is definitely greater among larger banks and decreases with bank size. For loans to SMEs, scoring models are assigned high importance more frequently by larger banks, less frequently by smaller ones, while mutual banks report they assign high importance to qualitative information, too. Credit scoring models are rarely employed to set interest rates and loan maturities (Figure 3). By contrast, they are widely used to monitor the situation of firms, both large and small, and the status of loans and accounts.

[3]In the survey, the question on this matter was phrased in ordinal terms, asking respondents to rank the various pieces of information feeding the scoring models by importance (see the appendix).

[4]In the survey, the question on this matter was phrased in ordinal terms, asking respondents to rank the various factors used in deciding whether or not to grant a loan by importance (see the appendix).

3 Data and Descriptive Statistics

3.1 Sources of credit and bank data

Credit data come from the Credit Register (CR) managed by the Bank of Italy, containing detailed information on all loan contracts granted to each borrower whose total debt from a bank exceeds 75,000 euros (no threshold is required for bad loans). Credit data refer to all loans granted to small firms (we define a firm as small if it has less than 20 employees). At each reporting date (end of the month), banks provide information on credit committed by type of loan, the amount of credit actually disbursed, whether the loan is collateralized or not. The loan types are: i) loans backed by account-receivables, ii) term loans, iii) revolving credit lines. Loan application data also are from the Credit Register of the Bank of Italy, which records monthly all information requests posted by banks on prospective borrowers. In particular, banks file requests only for loan applications from firms that are currently not borrowing from them. By matching the set of corresponding loan applications with the loans actually granted by the banks we obtain a measure of loan application acceptance in a given time window (as in Jimenez et al. 2014).

Bank balance sheet data are from the Supervisory Reports submitted by banks to the Bank of Italy, the banking supervisor in the country.

3.2 The sample

As a first step to build the dataset we have identified the years with the highest adoption rate by banks. These turn out to be 2003, 2004 and 2005, for a total of 85 banks adopting SBCS.[5] These are the "treated" banks, while the control group is composed of all the banks included in the survey which haven't adopted SBCS in the sample period (126 banks). Overall, our sample includes 211 banks.

The construction of the sample aims at obtaining a dataset which can be used for both the "loan acceptance" and the "credit performance" analysis.

For the sample used to study the effect of the adoption of credit scoring on credit performance (probability of default) the dataset includes small firms which accessed the credit market for the first time (cohorts). The use of cohorts allows a better assessment of the evolution of credit

[5]Inclusion of year 2006, the last year of the survey, which shows a high number of SBCS adoptions, would entail the inclusion of data on credit performance until 2009 (see hereafter), making it more difficult to control for the consequences of the financial crisis.

relationships, which are followed since their beginning; besides that, the monitoring of borrowers is less influenced by the information shared in the Credit Register, which refers to firms which have already accessed the credit market (Pagano and Jappelli, 1993; Padilla and Pagano, 1997); for this reason the assessment of firms' creditworthiness is more relevant and as a consequence the impact of the introduction of SBCS could be higher. The sample also includes information on the status of the loans (default or not) during the three years after they are granted. The choice of this time period is based on the observation that for Italian banks on average most of the defaults happen during the first three years of the credit relationship.[6] The pre-adoption cohorts are chosen to avoid an overlap of the periods before and after the adoption of SBCS; for example, if the year of adoption is 2004, the pre-adoption cohort is 2000, while the post-adoption cohort is 2005. This is important because the adoption of SBCS may influence the ability of the bank to both screen and monitor borrowers. If we chose data for the pre-adoption period one year before adoption, the probability that the loan defaults within three years may be affected by the subsequent adoption of SBCS.

The sample used to analyze the effect of the adoption of credit scoring on the acceptance of loans includes all the applications from small firms, both from firms which had already been granted credit in previous periods from other banks, and from firms which entered the credit market for the first time, so that credit history was not available for these firms. The inclusion of the former, not included in the sample used for the analysis of credit performance, is necessary to identify riskier borrowers (see below). In particular, in the analysis of riskier borrowers we focus only on firms that have been in the Credit Register for at least 1 year precisely to ensure that some credit history on them was available to identify those having some past-due loans. We select small firms applying for credit using the same structure as for the credit performance analysis (see above): i.e. for a bank adopting SBCS in 2004, we select applicants in 2000 and 2005. We then check in the CR whether the applicant was granted credit within 3 months of the application date. For computational reasons, the dataset includes a random sample of all small firms included in the CR, based on the CR borrower code (we choose firms whose last digit of the CR code is either 4 or 9).

Overall, the dataset used for the credit performance analysis contains data on about 20,000 credit relationships; the one used for the loan application analysis contains data on almost

[6]See the on-line Bank of Italy Statistical Database, Table TDB30540 (Historical default rates for borrower cohorts).

250,000 credit relationships. The two datasets don't include exactly the same firms. The reason is that firms that are not granted credit are not in the credit performance analysis. Moreover, some firms that are included in the credit performance analysis do not appear in the loan applications dataset because banks chose not to check the applicant status in the CR.[7] We find an overlap for about 10,000 relationships (7,600 firms).

3.3 Description of the variables

To assess the impact of the adoption of credit scoring on banks' decision to grant loans we introduce a dummy variable based on the information contained in the CR concerning loan applications by firms. The dummy variable is equal to one if the loan application has been accepted in the subsequent 3 months, 0 otherwise. We also define a similar variable to study the decision to grant a loan to ex-ante riskier borrowers. In this case we construct a dummy variable which is equal to one if the loan application posted by a borrower which recorded non-performing loans in the prior two years has been accepted in the subsequent 3 months, 0 otherwise.[8]

The dependent variable for the analysis of the effect of SBCS adoption on credit performance is a dummy variable equal to 1 if the credit granted to a single firm defaults during the three years after the beginning of the relationship.

The main explanatory variable concerns the use of SBCS, constructed on the basis of the answers reported by the banks participating to the survey.[9] In particular, we define a dummy variable equal to one if the bank reports that it has adopted SBCS in 2003, 2004, or 2005.

In some regressions we also include relationship-specific and bank balance-sheet controls. The log of the volume of credit committed measures the exposure of the bank to each firm at the beginning of the credit relationship. The strength of the relationship is measured by the number of lenders at its beginning. As highlighted in the introduction, the adoption of credit scoring techniques can be related to the securitization of loans, sometimes concerning non-performing loans. Therefore, we introduce a dummy variable which identifies the securitizied

[7] Checking firms' status in the CR is not compulsory, and banks may decide to dispense with it, especially if the firm is very small and if the applicant declares that it was the first time she applied for credit, as it is the case with the firms included in the dataset for credit performance analysis.

[8] In this case the sample only includes firms that were already recorded in the CR before, so that they had a credit history.

[9] The reliability of the answer to this question is supported by multiple pieces of evidence: the lending process by Italian banks is guided by "credit manuals" (guidelines for loan officers) in which the use of SBCS is explicitly envisaged. The amount of loans which can be granted in autonomy by each loan officer is linked to the results of the application of SBCS. The electronic procedure which governs the lending process envisages procedural blocks which activate if a loan has not been previously evaluated by the SBCS.

loans; in particular, the dummy variable is equal to one if at least part of the loan granted to a firm has been securitized during the 3 years after the establishment of the credit relationship. Finally, bank balance-sheet variables include capital, total profit, all scaled by total assets, and the geographical concentration of deposits.[10]

3.4 Descriptive statistics

We start showing descriptive statistics of the main variables used to proxy for credit supply and credit quality (Table 1). In particular, the mean of the dummy for the acceptance of loans in the post-adoption period (2004, 2005, 2006) is slightly larger than in the pre-adoption period (1999, 2000, 2001) for adopters, while it is smaller for non-adopters (column 1 of Table 1). The mean of the dummy for the acceptance of applications by riskier borrowers is higher in the post-adoption period for both adopters and non-adopters. Default rates after the adoption of SBCS decrease slightly for adopters, while they increase for non-adopters.

While this aggregate evidence suggests that the differences between adopters and non-adopters are somewhat limited, it does not take into account the potential endogeneity of the adoption decision, or differences in industry and geographical location of borrowers, which are likely to matter in the regression analysis.

Descriptive statistics of bank characteristics in the period before the adoption of SBCS show that the only statistically significant difference between adopters and non-adopters concerns size: adopters are on average larger (Table 2). Other bank balance-sheet variables like capital and total profit, scaled by assets, and geographical concentration of deposits do not differ statistically between adopters and non adopters in the period before adoption. This evidence supports the hypothesis that non-adopters are a valid counterfactual for adopters.

Statistics on borrowers (Table 3) show that these are mainly located in the Northern regions and operate mainly in retail, manufacturing and construction; more than half of the sample firms are sole proprietorships. Loan size is on average 109,000 Euros, the median is about 88,000. This indicates that we are covering a sample of small, but not micro firms. These are not included in the sample due to the reporting threshold of the Credit Register, set at 75,000 Euros during our sample period.

[10]This variable captures the extent to which a bank concentrate its activity in a few provinces.

4 Empirical Strategy

To assess the effect of the adoption of SBCS on credit supply and on the probability that a borrower defaults, we estimate the following model:

$$y_{ibt} = \alpha + \beta * CreditScoring_b * Post_t + \lambda_t + \gamma_b + size_i + industry_i + province_i + \epsilon_{ibt} \quad (1)$$

where y_{ibt} is the outcome variable, alternatively: i) a dummy variable equal to one if bank b accepts a loan application from borrower i in year t; ii) a dummy variable equal to one if bank b accepts a loan application from a risky borrower i in year t; iii) a dummy variable equal to 1 if borrower i obtaining a loan by bank b in year t defaults on the loan within the following three years.

The key explanatory variable is $CreditScoring_b * Post_t$, the interaction term between the dummy variable identifying banks which have adopted SBCS in the period 2003-2005 ($CreditScoring_b$) and the dummy variable which identifies the period after the year of adoption of SBCS ($Post_t$).

We also include a full set of year dummies, λ_t, that capture business cycle effects and of bank dummies, γ_b, which control for systematic differences across banks, including, importantly, bank specific (time invariant) factors affecting credit supply, as well as the initial condition of the loan portfolio. Finally, we include fixed effects for the industry and province of residence of borrowers, and for borrower size classes (single proprietorships and partnerships below 5 employees, between 5 and 20, above 20, further distinguished into craftsmen and others; craftsmen, such as carpenters, locksmiths, etc. are identified separately as they may obtain credit at special conditions). We don't include firm fixed effects because our sample covers only small firms; for each of them there exist only very few applications in our sample; in particular, observations concerning firms which apply for both adopters and non adopters (necessary for identification) amount to 19 per cent of the total.

The identification of the coefficient of the effect of the adoption of credit scoring (Credit Scoring*Post), β, is based on a difference-in-difference approach in which we instrument the adoption of credit scoring. We compare the change in the outcome variable for adopting banks before and after adoption with the change in the outcome variable of non-adopting banks before and after the adoption, conditional on all controls. The coefficient β identifies the causal effect of the adoption of credit scoring on loan application acceptances/credit performance only if certain conditions are fulfilled. First, the decision of banks to adopt credit scoring may be endogenous. Despite the presence of bank fixed effects, the timing of adoption may depend upon some bank time-varying unobservable characteristics. To address this issue we instrument the dummy *CreditScoring* using a dummy which equals one if the bank was already adopting credit scoring models for consumer loans or household mortgages at least 2 years before the reference date. The instrument is based on the idea that banks that already adopted credit scoring techniques for mortgages and consumer credit gained useful experience which makes them more likely to extend the usage to SBCS. As shown in section 2, banks usually adopt credit scoring for standardized loans such as mortgages and consumer credit first, and later extend it to small business loans. Our identification hypothesis holds conditional on bank fixed effects, and thus on bank time-invariant characteristics such as initial composition and quality of the loan portfolio, geographical scope and specialization. Table 4 shows the distribution of the dummy adopters and of the instrument. Overall, 30 banks out of 85 adopted credit scoring for consumer loans and mortgages at least 2 years prior of the adoption for small business loans.[11]

Second, banks that don't adopt credit scoring should represent a good counterfactual for banks that adopt. We argue that this is the case since the main difference across adopters and non-adopters is size (Table 2). Once size is taken into account, adopters have similar profitability and capital as non-adopters. Then, since we also control for the log of bank assets, we are able to control for systematic differences in size across adopters and non-adopters.

Third, the adoption of credit scoring for consumer loans and mortgages should not have a direct effect on small business lending (exclusion restriction). A potential violation of this condition could occur if an easier access to mortgages allows small entrepreneurs to buy a home and this provides good collateral for small business loans. There is no evidence of this phenomenon in the data: figure 4 shows that the dynamics of mortgages is not different for banks adopting and not adopting SBCS. Moreover, an overall exposure of 75,000 Euros towards the same bank is the condition for a firm to be included in the Credit Register in our sample period. This implies that our sample includes small but not micro-firms (see the average and median loan size in Table 3); for this reason the use of personal wealth such as housing is not likely as the firms included in our sample will have other assets pledgeable as collateral. Furthermore, home equity extraction instruments were (and still are) not available in the Italian market, which limits the extent to which entrepreneurs can use housing wealth to obtain loans

[11] Identification in difference in difference models requires that the dependent variable follows a common trend before adoption (the "event" or "shock") across adopters and non-adopters (the treated and control group, respectively). This condition is satisfied provided that the instrument is a valid instrument.

for their business.

Finally, the decision to adopt credit scoring should not create spillovers on non-adopters. For example, banks adopting credit scoring may better select borrowers, and as a consequence non-adopters face a higher proportion of lower quality borrowers (or vice-versa). We take care of this possibility controlling for province*time fixed effects to capture changes in the conditions of local credit markets over time, including possible changes in the proportion of low quality borrowers applying for loans to non-adopters in a local credit market. We assume that the relevant local credit market is a province. This is reasonable since local credit markets in Italy for SMEs can be defined at the province-level (Banca d'Italia, 1992; Bofondi and Gobbi, 2006; Gobbi and Lotti, 2005).

5 Results

5.1 Adoption of SBCS and probability of accepting a loan application

We start showing the results of the regressions on the probability a loan application is granted. We estimate equation (1) using as dependent variable either D(Accept), a dummy equal to one if the loan application at time t has been accepted within the following 3 months, or D(Accept Risk), a dummy equal to one if the loan application at time t from a borrower who had non-performing loans[12] in the previous two years has been accepted within the following 3 months. The specification also includes fixed effects for banks, provinces in which firms are located, firms' size classes, firms' industry and time fixed effects (for the year in which the loan application has been posted). In all regressions we cluster standard errors at the bank level. OLS estimates show that the adoption of credit scoring has a positive effect on the probability of acceptance of loan applications by the generality of borrowers; the result concerning the riskier borrowers is not statistically significant (table 12).

Columns 1 and 2 of Table 5 show 2SLS estimates of the baseline model. The first stage has the expected sign and is highly statistically significant: banks which have adopted credit scoring for loans to households since at least two years are more likely to adopt credit scoring for small business lending. The second stage, shown in column 1, indicates that after the adoption of SBCS the probability of accepting a loan application has not changed significantly: the coefficient of the interaction between the dummy CreditScoring and the dummy Post is negative, but not

[12]Non-performing loans include bad loans and restructured loans.

significant (p-value 0.32). By contrast, the adoption of SBCS has a negative and significant effect on the probability that a loan application posted by riskier borrowers is accepted; this drops by about 1.8 percentage points after the bank starts using credit scoring. The effect is also economically significant, as the average probability of accepting a loan application from a riskier borrower is 5%, so that the adoption of SBCS reduces it by more than one third.

Columns 3 and 4 show the results of the regressions including province*time fixed effects, which control for province specific trends in business cycle and also for changes in local market conditions (and thus for potential spillovers from banks adopting credit scoring to banks not adopting). Interestingly, the estimated effect of credit scoring is unchanged and the size of the coefficients is very similar to the baseline. Finally, columns 5 and 6 show regressions including bank balance sheet controls and results are analogous to those of the baseline regression.

Overall these results indicate that the introduction of SBCS has not led banks to relax credit standards. First, the propensity to grant loans to the average applicant does not seem to be affected by the adoption of SBCS. Second, banks seem to be less willing to grant loans to borrowers that had non-performing loans in the past, arguably riskier borrowers. These results suggest that the adoption of SBCS helps banks to become more selective in their lending policy.

5.2 Adoption of SBCS and credit performance

We now turn to exploring whether the adoption of SBCS affects credit quality. We measure credit quality by the probability that a borrower defaults within 3 years since the beginning of the credit relationship (see par. 3.3).

A priori the effect of the adoption and use of SBCS on credit performance is not obvious. The adoption of SBCS could just entail a lowering of operating costs and the granting of loans to marginal clients characterized by higher risk, thus causing a worsening of credit performance; differently, the adoption of SBCS can improve the accuracy in the evaluation of firms' creditworthiness, resulting in a better credit performance. The results from the previous section suggest that the selectivity of banks does not decrease after the adoption of SBCS, and if anything it even increases.

According to the OLS estimate the adoption of SBCS causes a decrease in the probability of default of the loans granted to firms which for the first time have accessed the credit system, but the result is not statistically significant (table 12). The results of the 2SLS estimates are shown in Table 6 and indicate that the adoption of SBCS has a positive effect on credit performance.[13] The first stage has the expected sign and is highly statistically significant: banks adopting credit scoring for loans to households in the prior two years are more likely to adopt credit scoring for small business lending. The coefficient of the interaction term CreditScoring*Post is negative and statistically significant (column 1). The effect is sizable: the probability of loan defaulting within three years after the establishment of the credit relationship decreases by 2.8 percentage points after a bank adopts SBCS, and the average share of loans defaulting within three years in the post adoption period is 2.5% (with a standard deviation of 15%). This result is robust to several checks. Column 2 shows estimates including loan-level and firm-level controls: the size of the granted loan, a dummy for whether the loan was securitized and the number of bank relationships. The initial size of the loan has no effect on the probability of defaulting. Interestingly, the dummy for securitized loans is negative and significant, suggesting that loans that are securitized are less likely to default.[14] Finally, the initial number of bank relationships is associated with a higher probability of defaulting within 3 years.[15]

Column 3 shows estimates of the main regression including province*time fixed effects, and results are unchanged. Finally, column 4 shows estimates of the main regression including bank-level controls. Again, CreditScoring*Post has a negative and significant coefficient. Importantly, the estimated effect of the adoption of SBCS is very similar in size across specifications, suggesting a low correlation with borrower and bank characteristics.

5.3 The overlapping sample

As discussed in Section 3, the firms included in the two samples used respectively for the loan acceptance and the credit performance analyses are not the same. This is mainly due to the fact that the sample for the analysis of credit performance only includes firms which access for the first time the credit system (cohorts), while the sample for the loan acceptance analysis also includes firms which had already been granted credit in the previous periods. Besides that, not all the firms which have requested credit (included in the loan acceptance sample) do succeed in accessing the credit market. Finally, banks don't request information to the CR for all the firms

[13] Again, regressions include bank fixed effects, industry, province, size class, and year (this corresponds to the cohort, i.e. the year in which the firm first entered the Credit Register and started the relationship with the bank) fixed effects.

[14] This is in line with the findings of Bonaccorsi di Patti and Felici (2008) and Albertazzi et al. (2011).

[15] Yet, only 1,503 firms out of 20,564 have more than one relationship within the first year of entry in the Credit Register.

which apply for credit, especially if they demand credit for the first time. For these reasons the overlapping sample includes around 7,600 firms for about 10,100 observations (for the loan acceptance analysis).

We perform the estimate of the benchmark equation for both the loan acceptance and the credit performance on the firms included in both samples ("overlapping sample"). The results indicate that the adoption of SBCS doesn't affect the probability of granting credit to small firms: the sign of the coefficient related to the generality of borrowers is numerically very close to that of the benchmark equations, but it is not statistically significant (table 7).[16] The adoption of SBCS does still lower the probability that a borrower defaults; the effect is slightly stronger than that associated to the whole sample.

Overall the results of the estimates on the overlapping sample mainly confirm those discussed in the previous paragraphs.

5.4 Extensions

In this section we test whether the effects of the adoption of SBCS described so far are heterogeneous across banks and borrowers. Tables 8 and 9 show results of 2SLS estimates of the baseline model including interactions between the dummy CreditScoring, the dummy Post and dummies for bank characteristics. These are: size, capital, profitability, the concentration of deposits of the bank across provinces, all measured as of the year before the reference year.[17] The size of banks can be considered a proxy for lending technologies in the pre-adoption period; in particular, a small size can be associated with the "relationship lending technology", and a large size with other technologies.[18] We use dummies to identify small/large banks, banks with high/low capital, high/low ROA, high/low concentration of deposits, and interact these dummies with the interaction CreditScoring*Post. Results indicate that the effect of SBCS is mostly homogeneous across bank characteristics both for the loan acceptance (table 8) and for the credit quality (table 9) regressions, with only two exceptions: the adoption of credit scoring is less effective for banks with higher concentration of deposits by province (for the generality

[16]By construction riskier borrowers are not included in the overlapping sample.

[17]If the outcome (acceptance or probability of defaulting in the following three years) refers to 1999, the bank-level variables are measured as of the end of 1998, and so on.

[18]The effects of the use of SBCS can be different according to the type of lending technology adopted by the single banks in the period preceding the adoption of SBCS. We can hypothesize that the adoption of SBCS has a stronger effect on the lending process if in the previous period the bank adopted a "relationship lending" technology. In this case the effect on credit performance should be negative, since the "relationship lending technology" should allow a better assessment of small firms' creditworthiness with respect to the "credit scoring technology".

of borrowers; table 8, column 7) and for banks with higher concentration of loans by industry (for the riskier borrowers; table 8, column 10). Both results are coherent with the hypothesis that credit scoring is more effective for banks less reliant on soft information (measured by their prior exposure to local markets or certain industries).

Next, we turn to test whether the effect of SBCS varies according to characteristics of the borrower. Unfortunately, our sample does not allow us to merge the identity of the borrower with her balance sheet information, so we can exploit a few borrower characteristics. One of the most important is size. As a proxy for the size of the borrower we use the size of the loan, because it is a more detailed measure of size than the size classes used to construct the set of dummies included in the regressions. The lack of information on borrower balance sheet also implies that we cannot run this test on the data for the acceptance of loan applications, since we only observe loan size when a loan is granted.

Results are shown in Table 10. Column 1 contains an interaction term between CreditScoring*Post and a dummy equal to one if the loan is below the median of the size distribution of loans. The coefficient of the interaction term is not statistically significant. Columns 2 and 3 show sample splits across the median loan size. Interestingly, the coefficient of CreditScoring*Post is negative and statistically significant only in the subsample of smaller loans. This is consistent with the idea that SBCS is more effective for smaller firms, for which collecting information is difficult and costly. The adoption of credit scoring reduces the cost of obtaining information on these borrowers, resulting in lower defaults. In column 4 we test the possibility that the effect of SBCS on small loans is especially strong when a large bank adopts SBCS; in fact, since larger banks may be less equipped in gathering and processing soft information, SBCS may be especially effective for this class of banks, in particular when dealing with loans of small size. Our results, though, do not support this hypothesis.

Overall, these findings indicate that the effect of the adoption of SBCS is homogeneous across banks. It is instead stronger in reducing the probability of ex-post default on smaller borrowers.

5.5 The Channels

In this section we provide evidence about the channels through which SBCS adoption affects the probability of accepting a loan application (in general and from riskier borrowers) and the probability that a loan defaults. These channels are related to the different uses of SBCS and to its importance in the lending process. In particular, we focus on two different uses of SBCS, for the decision of granting a loan to a firm (screening) and to monitor borrowers (monitoring), and on the degree of SBCS complementarity with respect to other lending technologies (rules vs. discretion).[19]

We exploit information contained in the Bank of Italy survey on the adoption of SBCS to identify banks that use SBCS mainly as a tool to screen borrowers or mainly as a tool to monitor them.[20] Results are shown in Table 11. It can be seen that there is no evidence of heterogeneous effects of SBCS on the probability of accepting a loan application across banks that use SBCS mainly for screening or monitoring. By contrast, the effect of SBCS on the probability a loan defaults is stronger for banks that use SBCS mainly as a tool to monitor borrowers.

This result suggests that SBCS is a more effective tool in monitoring existing borrowers, than to screen new clients. In fact, the adoption of a lending technology which is characterized by the processing of hard information and which attributes a key role to the credit history of borrowers facilitates and makes the monitoring process more effective.

Finally, results (available upon request) show that the effect of SBCS does not differ across banks which use SBCS as the main factor supporting the decision of granting credit ("rules banks") or as a complement with respect to other evaluation factors ("discretion banks").[21]

6 Conclusions

How does the adoption and use of credit scoring affect bank lending to small business? The widespread diffusion of credit scoring technologies across banks during the last twenty years and the increased relevance of the assessment of borrowers' creditworthiness after the global financial crisis make this question crucial for policy purposes.

Our paper sheds light on this important issue assessing the impact of SBCS on the propensity of banks to grant credit, on the selection of borrowers and on the probability that a borrower defaults on its loan. Our findings show that the adoption of SBCS does not lead banks to relax

[19] SBCS can also be used to determine interest rates. According to the results of the survey this usage is quite rare among the banks in our sample (see par. 2). Results, available from the authors, confirm that the adoption of SBCS has no effect on the distribution of interest rates charged.

[20] In particular, banks indicate the relative importance of different uses assigning a number from 1 to 5, where 1 indicates "decisive". Banks which use SBCS mainly to screen borrowers report 1 for the question concerning the use of SBCS for "loan approval", banks which use SBCS mainly to monitor borrowers report 1 for the question concerning the use of SBCS for "monitoring" (see the Appendix for further details).

[21] This information is also derived from a specific question of the survey. In particular, banks are asked to make a ranking out of 7 specific evaluation factors reported in the questionnaire (see Appendix for details): the assessment of credit scoring as a "decisive" or "very important" factor in the lending process identifies the "rules banks".

credit standards: first, the propensity to grant loans to the generality of borrowers is not affected by the adoption of SBCS; second, banks are less willing to grant loans to riskier borrowers. The effect on credit performance is positive: SBCS reduces the probability that a loan defaults, and the effect is stronger for the banks using SBCS mainly as a tool for monitoring borrowers and for smaller borrowers.

Our findings bear several important implications. From a theoretical perspective they indicate that the process of hardening of soft information in lending associated to the advances in communication technology involves mainly advantages for banks, facilitating the decision process about granting credit and the monitoring of borrowers' creditworthiness. From a policy perspective, the Basel II regulatory framework allowed the possibility for banks to rely on internal models of borrower rating to compute their capital ratios. The new, stricter, Basel III capital requirements and the adoption of stress tests for the assessment of the capacity of banks' balance sheet to bear adverse macroeconomic scenarios have further spurred banks to improve their credit scoring techniques. Yet, some of the early empirical evidence on the consequences of the adoption of credit scoring showed that it would imply a reduction in the costs associated to lending, but also a lower accuracy in the assessment of clients' creditworthiness, with negative consequences on credit quality. Taking for granted the decrease in the costs of the lending activity allowed by the use of credit scoring techniques, the results of our paper suggest that the concerns on the potential unintended consequences of the adoption of credit scoring may be overstated, and that actually the adoption of credit scoring leads to an increase in credit quality with an overall positive impact on the performance of banks.

References

[1] G. Albareto, M. Benvenuti, S. Mocetti, M. Pagnini, P. Rossi (2011), The organization of lending and the use of credit scoring techniques in Italian banks: results of a sample survey, Journal of Financial Transformation, Capco Institute, 32, pp. 143-157.

[2] U. Albertazzi, G. Eramo, L. Gambacorta, C. Salleo (2011), Securitazion is not that evil after all, Bank of Italy, Working Papers, n.796.

[3] Banca d'Italia (1992), La tutela della concorrenza nel settore del credito, Roma, settembre.

[4] A.N. Berger, A.M. Cowan and W.S. Frame (2011), The surprising use of credit scoring in small business lending by community banks and the attendant effects on credit availability, risk and profitability, Journal of Financial Services Research, 39, pp. 1-17.

[5] A.N. Berger, W.S. Frame and N.H. Miller (2005), Credit scoring and the availability, price, and risk of small business credit, Journal of Money, Credit and Banking, 37, pp. 191-222.

[6] A.N. Berger and G.F. Udell (2002), Small business credit availability and relationship lending: the importance of bank organisational structure, Economic Journal, 112, pp. F32-F53.

[7] M.Bofondi and G. Gobbi (2006), Informational barriers to entry into credit markets, Review of Finance, 10, pp. 39-67.

[8] M. Bofondi and F. Lotti (2005), Innovation in the retail banking industry: the diffusion of credit scoring, Review of Industrial Organization, 28, pp. 343-358.

[9] E. Bonaccorsi, R. Felici (2008), Il rischio dei mutui alle famiglie in Italia: evidenza da un milione di contratti, Bank of Italy Occasional Papers, n. 32.

[10] M. Brown, M. Schaller, S. Westerfeld, and M. Heusler (2012), Information or Insurance? On the Role of Loan Officer Discretion in Credit Assessment," Working Papers on Finance 1203, University of St. Gallen, School of Finance.

[11] M. Brown, H. Degryse, D. Hower, and F. Penas (2012), How do banks screen innovative firms? Evidence from start-up panel data," ZEW Discussion Papers 12-032.

[12] Cerqueiro, G., H. Degryse, and S. Ongena (2011), Rules versus discretion in loan rate setting, Journal of Financial Intermediation, 20, Issue 4, pp 503-529.

[13] R. De Young, D. Glennon, P. Nigro (2008), Borrower-lender distance, credit scoring, and loan performance: Evidence from informational-opaque small business borrowers, Journal of Financial Intermediation 17, pp. 113-143.

[14] S. Del Prete, M. Pagnini, P. Rossi, V. Vacca (2013), Organizzarsi per prestare in tempi di crisi. Risultati di un'indagine sulle banche, Bank of Italy Occasional Papers, n. 154.

[15] L. Einav, M. Jenkins and J. Levin (2013), The impact of information technology on consumer lending, RAND Journal of Economics, 44, pp. 249-274.

[16] W.S. Frame, M. Padhi and A. Woosley (2004), The Effect of Credit Scoring on Small Business Lending in Low- and Moderate-Income Areas, Financial Review, 39, pp. 35-54.

[17] W.S. Frame, A. Srinivasan and A. Woosley (2001), The Effect of Credit Scoring on Small-Business Lending, Journal of Money, Credit and Banking, 33, pp. 813-825.

[18] G. Gobbi and F. Lotti (2005), Entry decisions and adverse selection: an empirical analysis of local credit markets, Journal of Financial Services Research, December.

[19] R. Hasumi, H. Hirata and A. Ono (2011), Differentiated use of small business credit scoring by relationship lenders and transactional lenders: evidence from firm-bank matched data in Japan, RIETI Discussion Papers 11-E-070.

[20] A. Karapetyan and B. Stacescu (2014), Information Sharing and Information Acquisition in Credit Markets, Review of Finance 18, pp. 1583-1615.

[21] Keys, B., T. Mukherjee, A. Seru and V. Vig (2010), Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, Quarterly Journal of Economics 125, pp. 307-362.

[22] Jimenez, G., S. Ongena, J.L. Peydro', J. Saurina (2014), Hazardous Times for Monetary Policy: What do 23 Million Loans Say About the Impact of Monetary Policy on Credit Risk-Taking?, Econometrica, 82, 463-505.

[23] L.J. Mester (1997), What's the point of credit scoring? Business Review, September/October, pp. 3-16.

[24] A.J. Padilla, M. Pagano (1997), Endogenous Communication among Lenders and Entrepeneurial Incentives, Review of Financial Studies, 10, pp. 205-236.

[25] M. Pagano e T. Jappelli (1993), Information sharing in credit markets, Journal of Finance, 48, pp. 1693-1718.

[26] M.A. Petersen (2004), Information: hard and soft, mimeo.

[27] P. Rossi (2008), L'offerta di mutui alle famiglie: caratteristiche, evoluzione e differenze territoriali. I risultati di un'indagine campionaria, Bank of Italy Occasional Papers, n. 13.

[28] J. Stein (2002), Information Production and Capital Allocation: Decentralized versus Hierarchical Firms, The Journal of Finance, 57, pp. 1891-1921.

[29] K. Temkin and R.C. Kormendi (2003), An exploration of a secondary market for small business loans, SBA Office of Advocacy, April.

Figures

Figure 1: Introduction of credit scoring for small business lending (percentage values)

The figure shows the share of banks adopting credit scoring for small business lending in each year, distinguishing between banks of different size, structure (part of groups or stand-alone), and governance (mutual banks). Data are from the Survey on the adoption of credit scoring run by the Bank of Italy.

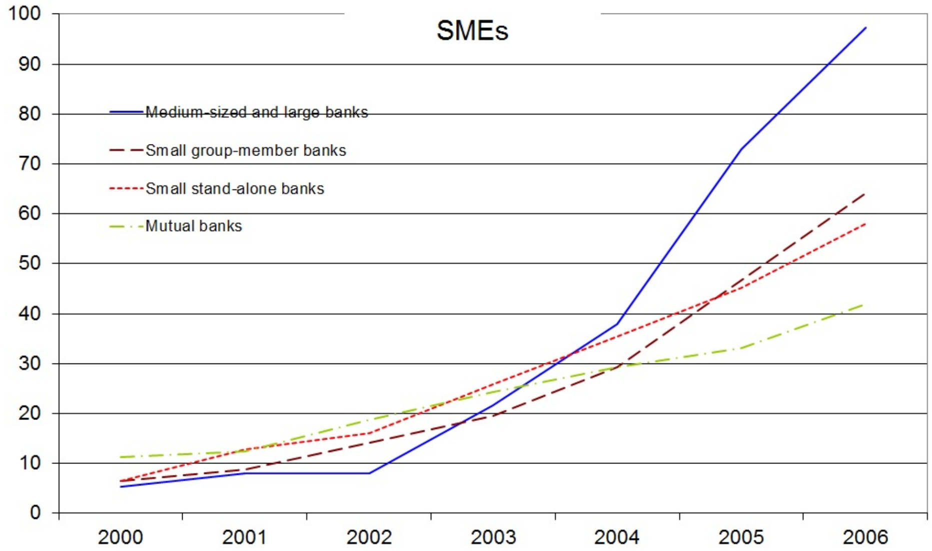


Figure 2: Importance of scoring techniques for lending to SMEs (2006; percentage values)

The figure shows the percent of responses indicating that credit scoring is "very important" or "decisive" for the decision to grant a loan, for its amount, and for monitoring. Data are disaggregated by bank type. Data are from the Survey on the adoption of credit scoring run by the Bank of Italy.

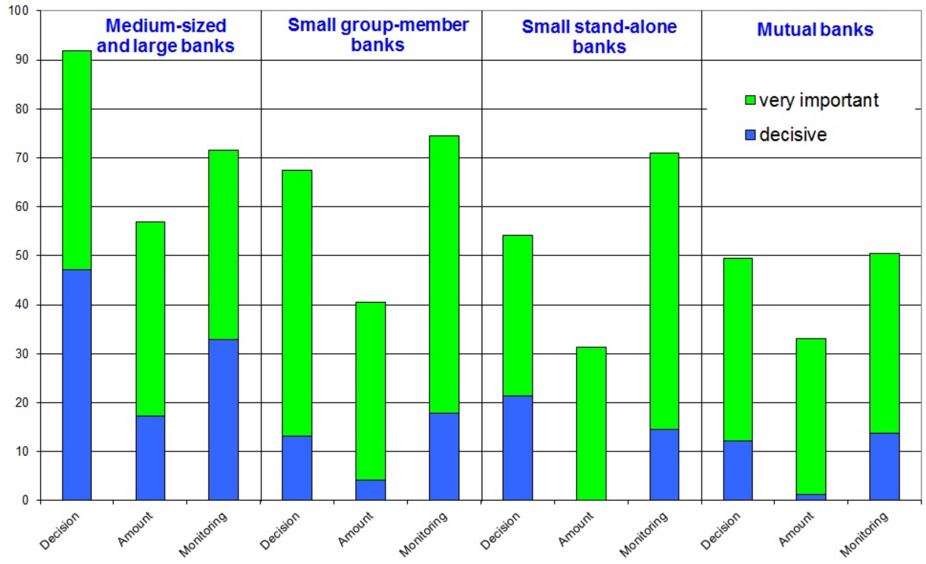


Figure 3: Different uses of SBCS (2006; percentage values)

The figure shows the percent of banks indicating that they use credit scoring mainly for the activity indicated on the horizontal axis. Again, data are disaggregated by bank type class. Data are from the Survey on the adoption of credit scoring run by the Bank of Italy.

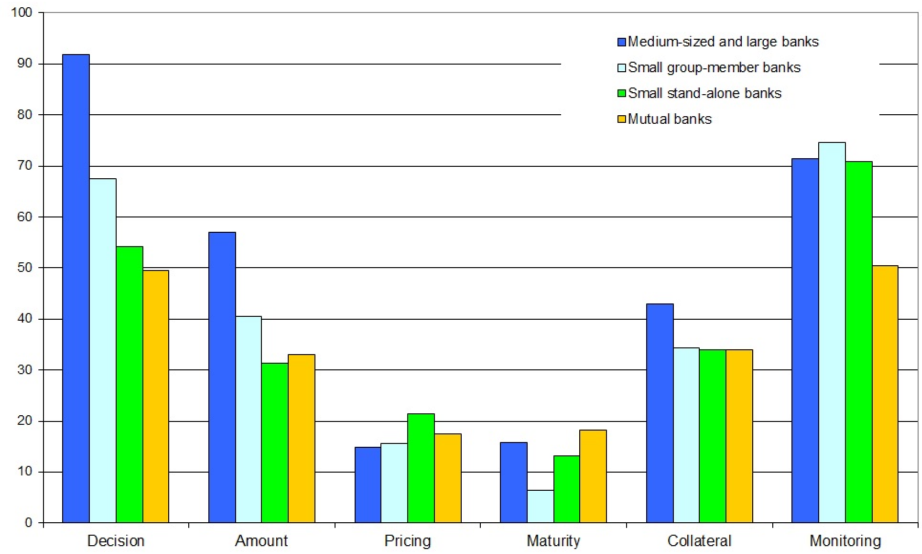
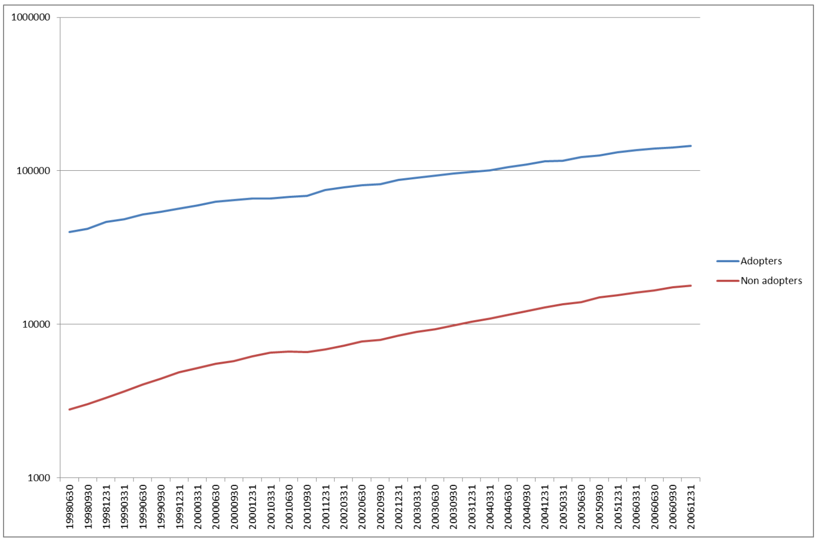


Figure 4: Supply of mortgages to households by adopters and non-adopters (log values)

The figure shows the dynamics of loans to households (mortgages and consumer credit) for banks adopting credit scoring in 2003, 2004, 2005 (adopters) and banks that either did not adopt credit scoring or did so later than 2005 (non-adopters). Data on banks adopting/non adopting credit scoring are from the Survey on the adoption of credit scoring run by the Bank of Italy. Data on loans are from the Supervisory reports.



Tables

Table 1: Mean of the dependent variables by adopters/non adopters and period

The table shows the average of the dependent variables used in the regression analysis in the pre-adoption period (years 1999, 2000, 2001) and in the post adoption period (2004, 2005, 2006), by banks adopting credit scoring in 2003, 2004, or 2005 (adopters), and banks not adopting credit scoring in the sample period. The variable D(Accept) is a dummy variable equal to 1 if a loan application posted by firm i at time t to bank j is accepted within 3 months (measured by observing the presence of positive credit granted by bank j to firm i in the Credit Register). The variable D(Accept risk) is a dummy variable equal to one if the loan application is posted by a firm which recorded non-performing loans in the Credit Register in the 2 years before the loan application. The variable D(Bad loan) is a dummy variable equal to one if firm i is classified as a bad loan by bank j within 3 years from the beginning of the credit relationship. The data refer to a sample of 211 Italian banks, adopting credit scoring in 2003, 2004 or 2005, or non-adopting credit scoring before 2008.

	D(Accept)	D(Accept risk)	D(Bad loan)
Adopters Pre	0.075	0.009	0.027
Adopters Post	0.079	0.015	0.025
Non-Adopters Pre	0.109	0.009	0.016
Non-Adopters Post	0.097	0.015	0.021

Table 2: Descriptive statistics of banks and local markets (1998)

The table shows descriptive statistics of banks, measured as of December 1998. Panel A shows the sample of adopters (85 banks, but for 5 banks we do not observe balance sheet information as of December 1998), panel B the sample of non-adopters (126 banks, but for 9 banks we do not observe balance sheet information as of December 1998). Size is the log of total assets, capratio is the regulatory capital ratio, roa is return on assets, measured as profits divided by total assets, herfindahl deposit is the herfindahl index of deposits in the province where the firm is located, the average share of loans in the same industry is the average share of loans that the banks grant to firms in the same 2-digit ATECO industry.

			Panel A - Adopters			
	Mean	Median	St.Dev.	Min	Max	Obs.
size	8699.43	1355.48	18610.18	9.83	104904.65	80
capratio	10.68	8.44	10.39	3.33	82.04	80
roa	0.965	0.98	0.54	-1.02	2.64	79
herfindahl deposit	0.13	0.12	0.05	0.05	0.25	79
average share of loan in the same industry	13.528	13.47	3.016	1.221	24.822	85
			Panel B - Non-Adopters			
	Mean	Median	St.Dev.	Min	Max	Obs.
size	683.20	301.35	1175.85	36.49	8047.52	117
capratio	10.85	10.22	4.69	4.02	42.57	117
roa	1.25	1.22	1.06	-3.46	9.19	117
herfindahl deposit	0.14	0.12	0.06	0.05	0.29	117
average share of loan in the same industry	13.048	13.031	2.788	4.612	26.157	126

Table 3: Descriptive statistics of borrowers

The table shows the distribution of borrowers according to the macro-area of residence, the industry (2-digit Ateco-Nace 2), the organizational form.

Area		
	Observations	Frequency
North-West	76,863	30.84
North-East	67,313	27.07
Center	47,025	18.91
South	41,315	16.62
Islands	16,301	6.56
Industry		
	Observations	Frequency
Agriculture	26,581	10.69
Construction	33,724	13.56
Hotels and Restaurants	20,588	8.28
Insurance Agents and Brokers	1,730	0.70
Manufacturing	36,989	14.88
Media	3,242	1.30
Mining	207	0.08
Retail	69,688	28.03
Transport	8,945	3.60
Utilities	381	0.15
Other	46,562	18.73
Organizational form		
	Observations	Frequency
Sole Proprietorships	142,100	57.15
Partnerships and Corporations	106,537	42.85
Loan size in Euros (for firms receiving a loan)		
Mean	Median	Std. Dev.
109,090	87,798	267,678

Table 4: Descriptive statistics of the main independent variable and of the instrument

The table shows basic descriptive statistics of the dummy for SBCS adoption (dummy adopters) and the instrument. The dummy adopters equals one if the bank adopts credit scoring in 2003, 2004, or 2005. It equals zero if it did not adopt credit scoring in any year of the sample period and it did not adopt it before the beginning of the sample period. The instrument is a dummy variable equal to 1 if the bank adopted credit scoring for loans to households at least 2 years before the reference year.

	Mean	Median	p25	p75	Std Dev
Dummy Adopters	0.674	1	0	1	0.469
Instrument	0.358	0	0	1	0.479
Number of Adopters (total)	85				
Number of Non-adopters (total)	126				

Table 5: Acceptance of loan applications

The table shows 2SLS regressions of the measures of credit supply, the dummy D(Accept) and D(Accept Risk) (see Table 1), on the dummy Credit Scoring interacted with the dummy Post. The former equals 1 if the bank adopts credit scoring in 2003, 2004, or 2005; the latter equals one if the observation refers to years 2004, 2005, 2006, it equals 0 if the observation refers to 1999, 2000, 2001. The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. Columns 1 and 2 include year and bank fixed effects, and borrower industry, province, and size class fixed effects; columns 3 and 4 include province*year fixed effects; columns 5 and 6 include bank-level controls as described in Table 1. The sample includes loan applications by small firms recorded in the Credit Register. Standard errors clustered at the bank level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	D(Accept)	D(Accept Risk)	D(Accept)	D(Accept Risk)	D(Accept)	D(Accept Risk)
Credit Scoring*Post	-0.0392	-0.0182*	-0.0353	-0.0174*	-0.0285	-0.0185**
	(0.0386)	(0.0103)	(0.0331)	(0.0100)	(0.0322)	(0.00909)
Size					-0.0548*	-0.0147**
					(0.0283)	(0.00695)
Capital Ratio					-0.235*	-0.0924**
					(0.135)	(0.0441)
Roa					-0.600	-0.390**
					(0.898)	(0.165)
Herfindahl Deposits					0.440*	0.0454
					(0.233)	(0.0764)
			First Stage			
Instrument	0.267***	0.267***	0.266***	0.266***	0.304***	0.304***
	(0.094)	(0.094)	(0.076)	(0.076)	(0.082)	(0.082)
Bank FE	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	no	no	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Borrower Size Class FE	yes	yes	yes	yes	yes	yes
Province*Year FE	no	no	yes	yes	no	no
Observations	248636	165056	248632	165049	248598	165035

Table 6: Effect on credit quality

The table shows 2SLS regressions of D(Bad Loan), the probability that a new loan made in year t to a firm first recorded in the Credit Register defaults within the following 3 years (see Table 1), on the dummy Credit Scoring interacted with the dummy Post. The former equals 1 if the bank adopts credit scoring in 2003, 2004, or 2005; the latter equals one if the observation refers to years 2004, 2005, 2006, it equals 0 if the observation refers to 1999, 2000, 2001. The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. Column 1 includes year and bank fixed effects, and borrower industry, province, and size class fixed effects; column 2 includes loan-level and firm-level controls measured at the beginning of the relationship: the log of the size of the loan, a dummy D(securitize) equal to 1 if the loan was securitized within 3 years from origination, and the number of borrower's bank relationships (some firms get loans from more than one bank in the first year in which they enter the credit register), all measured as of the start of the relationship; column 3 includes province*year fixed effects; column 4 includes bank-level controls as described in Table 1. The sample includes loans made to small firms first recorded in the Credit Register. Standard errors clustered at the bank level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) D(Bad Loan)	(2) D(Bad Loan)	(3) D(Bad Loan)	(4) D(Bad Loan)
Credit Scoring*Post	-0.0278**	-0.0245**	-0.0269*	-0.0268**
	(0.0134)	(0.0118)	(0.0153)	(0.0112)
Bank size				-0.0221**
				(0.00949)
Capital Ratio				-0.104
				(0.0703)
ROA				0.0177
				(0.254)
Herfindahl Deposits				0.134
				(0.130)
Loan Size		-0.00214		
		(0.00148)		
D(Securitize)		-0.0174***		
		(0.00475)		
Number of bank relationships		0.00688**		
		(0.00274)		
	First Stage			
Instrument	0.267***	0.267***	0.266***	0.266***
	(0.094)	(0.094)	(0.076)	(0.093)
Bank FE	yes	yes	yes	yes
Province FE	yes	yes	no	yes
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Borrower Size Class FE	yes	yes	yes	yes
Province*Year FE	no	no	yes	no
Observations	20806	19100	20806	20698

Table 7: Overlapping sample

The table shows 2SLS regressions of the dummies for the acceptance of loan applications D(Accept) and for the probability a firm enters into default within 3 years from the loan origination, D(Bad Loan), on the dummy Credit Scoring interacted with the dummy Post (defined in the previous tables). The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. Regressions are run on the sample of bank-firm relationships of firms applying for credit for the first time; in the case of the regression of D(Bad loan) on the subsample of those firms whose loan application was granted. All regressions include year and bank fixed effects, and borrower industry, province, and size class fixed effects. Standard errors clustered at the bank level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(1)	(2)
VARIABLES	D(Accept)	D(Bad Loan)
Credit Scoring * Post	0.0740	-0.0402*
	(0.0952)	(0.0223)
Bank FE	yes	yes
Province FE	yes	yes
Year FE	yes	yes
Industry FE	yes	yes
Borrower Size Class FE	yes	yes
Observations	10132	7661

Table 8: Bank heterogeneity - Acceptance

The table shows 2SLS regressions of the dummies for the acceptance of loan applications D(Accept) and D(Accept risk), on the dummy Credit Scoring interacted with the dummy Post (defined in the previous tables) and with dummies for bank characteristics. The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. Small size, Low Capratio, Low Roa equal 1 if bank assets, capital ratio and Roa, respectively, are in the bottom quartile of the distribution. High Herf Deposits equals 1 if the Herfindahl index of deposits in the province where the borrower is located is above the median. High share of loans in the industry equals one if the share of loans to the industry the firm belongs to is above the median. Each distribution is computed in the reference year. All regressions include year and bank fixed effects, and borrower industry, province, and size class fixed effects. Standard errors clustered at the bank level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Credit Scoring * Post	-0.0387	-0.0213*	-0.0734	-0.0202	-0.0707	-0.0207	-0.0915	-0.0276	-0.0419	-0.0201*
	(0.0416)	(0.0114)	(0.0947)	(0.0185)	(0.0640)	(0.0154)	(0.0599)	(0.0211)	(0.0391)	(0.0105)
Credit Scoring * Post *	-0.00164	0.0106								
Small Bank	(0.0207)	(0.0118)								
Credit Scoring * Post			-0.106	-0.00660						
Low Capital			(0.192)	(0.0407)						
Credit Scoring * Post					0.0228	0.00189				
Low Roa					(0.0408)	(0.00603)				
Credit Scoring * Post							0.0475***	0.00862		
High Herf Dep							(0.0170)	(0.0109)		
Credit Scoring * Post									0.00560	0.00518*
High share of loans in industry									(0.00495)	(0.00272)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Borrower Size Class FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	248608	165041	248608	165041	248608	165041	248598	165035	245536	163006

Table 9: Bank heterogeneity - Credit quality

The table shows 2SLS regressions of the dummy for the probability a firm enters into default within 3 years from the loan origination, D(Bad Loan), on the dummy Credit Scoring interacted with the dummy Post (defined in the previous tables) and with dummies for bank characteristics. The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. Small size, Low Capratio, Low Roa equal 1 if bank assets, capital ratio and Roa, respectively, are in the bottom quartile of the distribution. High Herf Deposits equals 1 if the Herfindahl index of deposits in the province where the borrower is located is above the median. High share of loans in the industry equals one if the share of loans to the industry the firm belongs to is above the median. Each distribution is computed in the reference year. All regressions include year and bank fixed effects, and borrower industry, province, and size class fixed effects. Standard errors clustered at the bank level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)
Credit Scoring*Post	-0.0295	-0.0300**	-0.0174	-0.0248	-0.0132*
	(0.0214)	(0.0123)	(0.0160)	(0.0224)	(0.00689)
Credit Scoring*Post*	-0.00608				
Small Bank	(0.0814)				
Credit Scoring*Post*		0.00685			
Low Bank Capital		(0.0134)			
Credit Scoring*Post*			-0.00934		
Low ROA			(0.00883)		
Credit Scoring*Post*				-0.00473	
High Herf Index				(0.0135)	
Credit Scoring*Post*					0.00243
High share of loans in industry					(0.00722)
Bank FE	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
Borrower Size Class FE	yes	yes	yes	yes	yes
Observations	20702	20702	20702	20698	20381

Table 10: Borrower heterogeneity

The table shows 2SLS regressions of the probability a firm enters into default within 3 years from the loan origination, D(Bad Loan), on the dummy Credit Scoring interacted with the dummy Post (defined in the previous tables). The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. The regression shown in column 1 includes interactions between the dummy Credit Scoring, the dummy Post and a dummy D(small loan) equal to one if the loan is below the median size of loans. The regressions shown in column 2 and 3 are run on sample splits according to the size of the loan being below (column 2) and above (column 3) the median loan. The regression shown in column 4 includes an interaction between the dummy Credit Scoring, the dummy Post, and the dummies D(small loan) and D(large bank). The latter equals one if banks' assets in the year are above median assets. All regressions include year and bank fixed effects, and borrower industry, province, and size class fixed effects. Standard errors clustered at the bank level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
VARIABLES	D(Bad Loan)	D(Bad Loan)	D(Bad Loan)	D(Bad Loan)
		small loans	large loans	
Credit Scoring*Post	-0.0131	-0.0409*	-0.0155	0.00136
	(0.0117)	(0.0228)	(0.0150)	(0.0165)
Credit Scoring*Post*D(small loan)	-0.0327			-0.0322
	(0.0238)			(0.0310)
Credit Scoring*Post*D(large bank)				-0.00561
				(0.0343)
Credit Scoring*Post*D(small loan)*D(large bank)				-0.0224
				(0.0646)
D(small loan)*D(large bank)				0.0226
				(0.0383)
D(small loan)	0.0138			0.0123
	(0.00919)			(0.0100)
Bank FE	yes	yes	yes	yes
Province FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Borrower Size Class FE	yes	yes	yes	yes
Observations	19100	9466	9628	19028

Table 11: Channels: screening vs monitoring

The table shows 2SLS regressions of the dummies for the acceptance of loan applications D(Accept) and D(Accept risk) and for the probability a firm enters into default within 3 years from the loan origination, D(Bad Loan), on the dummy Credit Scoring interacted with the dummy Post (defined in the previous tables) and with dummies which represent the main use of credit scoring techniques by banks. The dummy Credit Scoring is instrumented using a dummy equal to 1 if the bank adopted credit scoring for household loans two years earlier or more. The dummy Screening equals 1 if the bank reports using credit scoring mainly as a screening tool, zero otherwise. The dummy Monitoring equals 1 if the bank reports using credit scoring mainly as a tool to monitor borrowers after the credit relationship is in place, zero otherwise. All regressions include year and bank fixed effects, and borrower industry, province, and size class fixed effects. Standard errors clustered at the bank level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

VARIABLES	(1) D(Accept)	(2) D(Accept Risk)	(3) D(Bad Loan)
Credit Scoring*Post	-0.0127	-0.0118	-0.0207
	(0.0289)	(0.00752)	(0.0196)
Credit Scoring*Post*Screening	0.00138	0.00179	
	(0.0205)	(0.00708)	
Credit Scoring*Post*Monitoring			-0.0247*
			(0.0145)
Bank FE	yes	yes	yes
Province FE	yes	yes	yes
Year FE	yes	yes	yes
Industry FE	yes	yes	yes
Borrower Size Class FE	yes	yes	yes
Observations	224008	149620	18541

Table 12: Baseline regressions - OLS estimates

VARIABLES	(1) D(Accept)	(2) D(Accept risk)	(3) D(Bad loan)
Credit scoring*Post	0.0178*	-0.0023	-0.00670
	(0.00970)	(0.0031855)	(0.00463)
Bank FE	yes	yes	yes
Province FE	yes	yes	yes
Year FE	yes	yes	yes
Industry FE	yes	yes	yes
Borrower Size Class FE	yes	yes	yes
Observations	248636	165056	20801
R^2	0.030	0.011	0.033

The Questionnaire

SECTION B: ASSESSMENT OF CREDITWORTHINESS

B1 – In assessing creditworthiness, do you use automatic scores generated by **statistical/quantitative methodologies** (credit scoring and internal ratings)? Please indicate whether these methods are used for the types of lending listed below, the year they were introduced, whether they were developed internally or purchased from outside, and their importance in the decision whether or not to lend, amount, pricing, maturity, collateral and monitoring.

	Yes / No	Year of introduction (1)	Internal / external (2)	Importance of the method in decisions on:					
				Loan approval (3)	Amount (3)	Pricing (3)	Maturity (3)	Collateral (3)	Monitoring (3)
Loans to households									
Consumer credit									
Loans to SMEs									
Loans to large firms									

(1) Year when first introduced. – (2) Specify whether: 1 = the methodology was developed exclusively within the bank; 2 = it was developed in cooperation with other institutions or consortia; 3 = it was purchased from an outside company belonging to your group; 4 = it was purchased from an outside company not belonging to your group; 5 = other. – (3) Rank from 1 to 5 in decreasing order of importance: 1 = decisive, 2 = very important, 3 = fairly important, 4 = not very important, 5 = not important at all, NA = not applicable.

B2 – If you use **statistical-quantitative methodologies** for assessing firms' creditworthiness, please **rank** by decreasing order of importance the data considered in your "calculation engine" in assigning the overall score: **1 for the most important, 2 for the next most important, and so on**. No two factors can be given the same rank. If you do not use the factor, answer NA.

	Financial statement data	Geographical area and economic sector	Relations with banks (1)	Other outside data sources (2)	Relations with your bank (3)	Relations with your banking group (3)	Qualitative information (4)	Other (5) ___
SMEs								
Large firms								

(1) Central Credit Register and/or other credit bureaus. – (2) Interbank register of bad cheques and payment cards, Chambers of Commerce, specialized companies, etc. – (3) E.g., loans and deposits of firm with your bank. – (4) Firm's organizational structure, project to finance, etc.. – (5) Specify.

B3 – For the granting of loans to non-financial firms that apply to you for the first time, please rank in decreasing order of importance the factors used in deciding whether or not to grant the loan. 1 for the most important, 2 for the next most important, and so on. No two factors can be given the same rank. If you do not use the factor, answer NA.

	SMEs	Large firms
Statistical-quantitative methods exclusively		
Financial statement data (1)		
Credit relations with entire system (data from Central Credit Register and/or other credit bureaus or public sources, i.e. Interbank register of bad cheques and payment cards, Bulletin of protests, etc. (1)		
Availability of personal guarantees or collateral		
Qualitative information (organizational structure of firm, characteristics of project, etc.) (1)		
Other assessments based on first-hand information		
Other (specify)		

(1) With respect to the statistical-quantitative methodologies referred to in question B2, please answer as regards the use of each source of information <u>outside</u> the algorithms.

RECENTLY PUBLISHED "TEMI" (*)

N. 1062 – *Market timing and performance attribution in the ECB reserve management framework*, by Francesco Potente and Antonio Scalia (April 2016).

N. 1063 – *Information contagion in the laboratory*, by Marco Cipriani, Antonio Guarino, Giovanni Guazzarotti, Federico Tagliati and Sven Fischer (April 2016).

N. 1064 – *EAGLE-FLI. A macroeconomic model of banking and financial interdependence in the euro area*, by Nikola Bokan, Andrea Gerali, Sandra Gomes, Pascal Jacquinot and Massimiliano Pisani (April 2016).

N. 1065 – *How excessive is banks' maturity transformation?*, by Anatoli Segura Velez and Javier Suarez (April 2016).

N. 1066 – *Common faith or parting ways? A time-varying factor analysis*, by Davide Delle Monache, Ivan Petrella and Fabrizio Venditti (June 2016).

N. 1067 – *Productivity effects of eco-innovations using data on eco-patents*, by Giovanni Marin and Francesca Lotti (June 2016).

N. 1068 – *The labor market channel of macroeconomic uncertainty*, by Elisa Guglielminetti (June 2016).

N. 1069 – *Individual trust: does quality of public services matter?*, by Silvia Camussi and Anna Laura Mancini (June 2016).

N. 1070 – *Some reflections on the social welfare bases of the measurement of global income inequality,* by Andrea Brandolini and Francesca Carta (July 2016).

N. 1071 – *Boulevard of broken dreams. The end of the EU funding (1997: Abruzzi, Italy),* by Guglielmo Barone, Francesco David and Guido de Blasio (July 2016).

N. 1072 – *Bank quality, judicial efficiency and borrower runs: loan repayment delays in Italy,* by Fabio Schiantarelli, Massimiliano Stacchini and Philip Strahan (July 2016).

N. 1073 – *Search costs and the severity of adverse selection,* by Francesco Palazzo (July 2016).

N. 1074 – *Macroeconomic effectiveness of non-standard monetary policy and early exit. A model-based evaluation*, by Lorenzo Burlon, Andrea Gerali, Alessandro Notarpietro and Massimiliano Pisani (July 2016).

N. 1075 – *Quantifying the productivity effects of global sourcing,* by Sara Formai and Filippo Vergara Caffarelli (July 2016).

N. 1076 – *Intergovernmental transfers and expenditure arrears,* by Paolo Chiades, Luciano Greco, Vanni Mengotto, Luigi Moretti and Paola Valbonesi (July 2016).

N. 1077 – *A "reverse Robin Hood"? The distributional implications of non-standard monetary policy for Italian households*, by Marco Casiraghi, Eugenio Gaiotti, Lisa Rodano and Alessandro Secchi (July 2016).

N. 1078 – *Global macroeconomic effects of exiting from unconventional monetary policy,* by Pietro Cova, Patrizio Pagano and Massimiliano Pisani (September 2016).

N. 1079 – *Parents, schools and human capital differences across countries*, by Marta De Philippis and Federico Rossi (September 2016).

N. 1080 – *Self-fulfilling deflations*, by Roberto Piazza, (September 2016).

N. 1081 – *Dealing with student heterogeneity: curriculum implementation strategies and student achievement*, by Rosario Maria Ballatore and Paolo Sestito, (September 2016).

N. 1082 – *Price dispersion and consumer inattention: evidence from the market of bank accounts*, by Nicola Branzoli, (September 2016).

N. 1083 – *BTP futures and cash relationships: a high frequency data analysis*, by Onofrio Panzarino, Francesco Potente and Alfonso Puorro, (September 2016).

N. 1084 – *Women at work: the impact of welfare and fiscal policies in a dynamic labor supply model*, by Maria Rosaria Marino, Marzia Romanelli and Martino Tasso, (September 2016).

(*) Requests for copies should be sent to:
Banca d'Italia – Servizio Studi di struttura economica e finanziaria – Divisione Biblioteca e Archivio storico – Via Nazionale, 91 – 00184 Rome – (fax 0039 06 47922059). They are available on the Internet www.bancaditalia.it.

2014

G. M. TOMAT, *Revisiting poverty and welfare dominance*, Economia pubblica, v. 44, 2, 125-149, **TD No. 651 (December 2007).**

M. TABOGA, *The riskiness of corporate bonds*, Journal of Money, Credit and Banking, v.46, 4, pp. 693-713, **TD No. 730 (October 2009).**

G. MICUCCI and P. ROSSI, *Il ruolo delle tecnologie di prestito nella ristrutturazione dei debiti delle imprese in crisi*, in A. Zazzaro (a cura di), Le banche e il credito alle imprese durante la crisi, Bologna, Il Mulino, **TD No. 763 (June 2010).**

F. D'AMURI, *Gli effetti della legge 133/2008 sulle assenze per malattia nel settore pubblico*, Rivista di politica economica, v. 105, 1, pp. 301-321, **TD No. 787 (January 2011).**

R. BRONZINI and E. IACHINI, *Are incentives for R&D effective? Evidence from a regression discontinuity approach*, American Economic Journal : Economic Policy, v. 6, 4, pp. 100-134, **TD No. 791 (February 2011).**

P. ANGELINI, S. NERI and F. PANETTA, *The interaction between capital requirements and monetary policy*, Journal of Money, Credit and Banking, v. 46, 6, pp. 1073-1112, **TD No. 801 (March 2011).**

M. BRAGA, M. PACCAGNELLA and M. PELLIZZARI, *Evaluating students' evaluations of professors*, Economics of Education Review, v. 41, pp. 71-88, **TD No. 825 (October 2011).**

M. FRANCESE and R. MARZIA, *Is there Room for containing healthcare costs? An analysis of regional spending differentials in Italy*, The European Journal of Health Economics, v. 15, 2, pp. 117-132, **TD No. 828 (October 2011).**

L. GAMBACORTA and P. E. MISTRULLI, *Bank heterogeneity and interest rate setting: what lessons have we learned since Lehman Brothers?*, Journal of Money, Credit and Banking, v. 46, 4, pp. 753-778, **TD No. 829 (October 2011).**

M. PERICOLI, *Real term structure and inflation compensation in the euro area*, International Journal of Central Banking, v. 10, 1, pp. 1-42, **TD No. 841 (January 2012).**

E. GENNARI and G. MESSINA, *How sticky are local expenditures in Italy? Assessing the relevance of the flypaper effect through municipal data*, International Tax and Public Finance, v. 21, 2, pp. 324-344, **TD No. 844 (January 2012).**

V. DI GACINTO, M. GOMELLINI, G. MICUCCI and M. PAGNINI, *Mapping local productivity advantages in Italy: industrial districts, cities or both?*, Journal of Economic Geography, v. 14, pp. 365–394, **TD No. 850 (January 2012).**

A. ACCETTURO, F. MANARESI, S. MOCETTI and E. OLIVIERI, *Don't Stand so close to me: the urban impact of immigration*, Regional Science and Urban Economics, v. 45, pp. 45-56, **TD No. 866 (April 2012).**

M. PORQUEDDU and F. VENDITTI, *Do food commodity prices have asymmetric effects on euro area inflation*, Studies in Nonlinear Dynamics and Econometrics, v. 18, 4, pp. 419-443, **TD No. 878 (September 2012).**

S. FEDERICO, *Industry dynamics and competition from low-wage countries: evidence on Italy*, Oxford Bulletin of Economics and Statistics, v. 76, 3, pp. 389-410, **TD No. 879 (September 2012).**

F. D'AMURI and G. PERI, *Immigration, jobs and employment protection: evidence from Europe before and during the Great Recession*, Journal of the European Economic Association, v. 12, 2, pp. 432-464, **TD No. 886 (October 2012).**

M. TABOGA, *What is a prime bank? A euribor-OIS spread perspective*, International Finance, v. 17, 1, pp. 51-75, **TD No. 895 (January 2013).**

G. CANNONE and D. FANTINO, *Evaluating the efficacy of european regional funds for R&D*, Rassegna italiana di valutazione, v. 58, pp. 165-196, **TD No. 902 (February 2013).**

L. GAMBACORTA and F. M. SIGNORETTI, *Should monetary policy lean against the wind? An analysis based on a DSGE model with banking*, Journal of Economic Dynamics and Control, v. 43, pp. 146-74, **TD No. 921 (July 2013).**

M. BARIGOZZI, CONTI A.M. and M. LUCIANI, *Do euro area countries respond asymmetrically to the common monetary policy?*, Oxford Bulletin of Economics and Statistics, v. 76, 5, pp. 693-714, **TD No. 923 (July 2013).**

U. ALBERTAZZI and M. BOTTERO, *Foreign bank lending: evidence from the global financial crisis*, Journal of International Economics, v. 92, 1, pp. 22-35, **TD No. 926 (July 2013).**

R. DE BONIS and A. SILVESTRINI, *The Italian financial cycle: 1861-2011*, Cliometrica, v.8, 3, pp. 301-334, **TD No. 936 (October 2013).**

G. BARONE and S. MOCETTI, *Natural disasters, growth and institutions: a tale of two earthquakes*, Journal of Urban Economics, v. 84, pp. 52-66, **TD No. 949 (January 2014).**

D. PIANESELLI and A. ZAGHINI, *The cost of firms' debt financing and the global financial crisis*, Finance Research Letters, v. 11, 2, pp. 74-83, **TD No. 950 (February 2014).**

J. LI and G. ZINNA, *On bank credit risk: sytemic or bank-specific? Evidence from the US and UK*, Journal of Financial and Quantitative Analysis, v. 49, 5/6, pp. 1403-1442, **TD No. 951 (February 2015).**

A. ZAGHINI, *Bank bonds: size, systemic relevance and the sovereign*, International Finance, v. 17, 2, pp. 161-183, **TD No. 966 (July 2014).**

G. SBRANA and A. SILVESTRINI, *Random switching exponential smoothing and inventory forecasting*, International Journal of Production Economics, v. 156, 1, pp. 283-294, **TD No. 971 (October 2014).**

M. SILVIA, *Does issuing equity help R&D activity? Evidence from unlisted Italian high-tech manufacturing firms*, Economics of Innovation and New Technology, v. 23, 8, pp. 825-854, **TD No. 978 (October 2014).**

2015

G. DE BLASIO, D. FANTINO and G. PELLEGRINI, *Evaluating the impact of innovation incentives: evidence from an unexpected shortage of funds*, Industrial and Corporate Change, , v. 24, 6, pp. 1285-1314, **TD No. 792 (February 2011).**

M. BUGAMELLI, S. FABIANI and E. SETTE, *The age of the dragon: the effect of imports from China on firm-level prices*, Journal of Money, Credit and Banking, v. 47, 6, pp. 1091-1118, **TD No. 737 (January 2010).**

R. BRONZINI, *The effects of extensive and intensive margins of FDI on domestic employment: microeconomic evidence from Italy*, B.E. Journal of Economic Analysis & Policy, v. 15, 4, pp. 2079-2109, **TD No. 769 (July 2010).**

U. ALBERTAZZI, G. ERAMO, L. GAMBACORTA and C. SALLEO, *Asymmetric information in securitization: an empirical assessment*, Journal of Monetary Economics, v. 71, pp. 33-49, **TD No. 796 (February 2011).**

A. DI CESARE, A. P. STORK and C. DE VRIES, *Risk measures for autocorrelated hedge fund returns*, Journal of Financial Econometrics, v. 13, 4, pp. 868-895, **TD No. 831 (October 2011).**

G. BULLIGAN, M. MARCELLINO and F. VENDITTI, *Forecasting economic activity with targeted predictors*, International Journal of Forecasting, v. 31, 1, pp. 188-206, **TD No. 847 (February 2012).**

A. CIARLONE, *House price cycles in emerging economies*, Studies in Economics and Finance, v. 32, 1, **TD No. 863 (May 2012).**

D. FANTINO, A. MORI and D. SCALISE, *Collaboration between firms and universities in Italy: the role of a firm's proximity to top-rated departments,* Rivista Italiana degli economisti, v. 1, 2, pp. 219-251, **TD No. 884 (October 2012).**

A. BARDOZZETTI and D. DOTTORI, *Collective Action Clauses: how do they Affect Sovereign Bond Yields?*, Journal of International Economics , v 92, 2, pp. 286-303, **TD No. 897 (January 2013).**

D. DEPALO, R. GIORDANO and E. PAPAPETROU, *Public-private wage differentials in euro area countries: evidence from quantile decomposition analysis*, Empirical Economics, v. 49, 3, pp. 985-1115, **TD No. 907 (April 2013).**

G. BARONE and G. NARCISO, *Organized crime and business subsidies: Where does the money go?*, Journal of Urban Economics, v. 86, pp. 98-110, **TD No. 916 (June 2013).**

P. ALESSANDRI and B. NELSON, *Simple banking: profitability and the yield curve*, Journal of Money, Credit and Banking, v. 47, 1, pp. 143-175, **TD No. 945 (January 2014).**

M. TANELI and B. OHL, *Information acquisition and learning from prices over the business cycle*, Journal of Economic Theory, 158 B, pp. 585–633, **TD No. 946 (January 2014).**

R. AABERGE and A. BRANDOLINI, *Multidimensional poverty and inequality*, in A. B. Atkinson and F. Bourguignon (eds.), Handbook of Income Distribution, Volume 2A, Amsterdam, Elsevier, **TD No. 976 (October 2014).**

V. CUCINIELLO and F. M. SIGNORETTI, *Large banks,loan rate markup and monetary policy*, International Journal of Central Banking, v. 11, 3, pp. 141-177, **TD No. 987 (November 2014).**

M. FRATZSCHER, D. RIMEC, L. SARNOB and G. ZINNA, *The scapegoat theory of exchange rates: the first tests*, Journal of Monetary Economics, v. 70, 1, pp. 1-21, **TD No. 991 (November 2014).**

A. NOTARPIETRO and S. SIVIERO, *Optimal monetary policy rules and house prices: the role of financial frictions,* Journal of Money, Credit and Banking, v. 47, S1, pp. 383-410, **TD No. 993 (November 2014).**

R. ANTONIETTI, R. BRONZINI and G. CAINELLI, *Inward greenfield FDI and innovation,* Economia e Politica Industriale, v. 42, 1, pp. 93-116, **TD No. 1006 (March 2015).**

T. CESARONI, *Procyclicality of credit rating systems: how to manage it,* Journal of Economics and Business, v. 82. pp. 62-83, **TD No. 1034 (October 2015).**

M. RIGGI and F. VENDITTI, *The time varying effect of oil price shocks on euro-area exports*, Journal of Economic Dynamics and Control, v. 59, pp. 75-94, **TD No. 1035 (October 2015).**

2016

E. BONACCORSI DI PATTI and E. SETTE, *Did the securitization market freeze affect bank lending during the financial crisis? Evidence from a credit register*, Journal of Financial Intermediation , v. 25, 1, pp. 54-76, **TD No. 848 (February 2012).**

M. MARCELLINO, M. PORQUEDDU and F. VENDITTI, *Short-Term GDP forecasting with a mixed frequency dynamic factor model with stochastic volatility*, Journal of Business & Economic Statistics , v. 34, 1, pp. 118-127, **TD No. 896 (January 2013).**

M. ANDINI and G. DE BLASIO, *Local development that money cannot buy: Italy's Contratti di Programma,* Journal of Economic Geography, v. 16, 2, pp. 365-393, **TD No. 915 (June 2013).**

F BRIPI, *The role of regulation on entry: evidence from the Italian provinces*, World Bank Economic Review, v. 30, 2, pp. 383-411, **TD No. 932 (September 2013).**

L. ESPOSITO, A. NOBILI and T. ROPELE, *The management of interest rate risk during the crisis: evidence from Italian banks*, Journal of Banking & Finance, v. 59, pp. 486-504, **TD No. 933 (September 2013).**

F. BUSETTI and M. CAIVANO, *The trend–cycle decomposition of output and the Phillips Curve: bayesian estimates for Italy and the Euro Area,* Empirical Economics, V. 50, 4, pp. 1565-1587, **TD No. 941 (November 2013).**

M. CAIVANO and A. HARVEY, *Time-series models with an EGB2 conditional distribution,* Journal of Time Series Analysis, v. 35, 6, pp. 558-571, **TD No. 947 (January 2014).**

G. ALBANESE, G. DE BLASIO and P. SESTITO, *My parents taught me. evidence on the family transmission of values,* Journal of Population Economics, v. 29, 2, pp. 571-592, **TD No. 955 (March 2014).**

R. BRONZINI and P. PISELLI, *The impact of R&D subsidies on firm innovation,* Research Policy, v. 45, 2, pp. 442-457, **TD No. 960 (April 2014).**

L. BURLON and M. VILALTA-BUFI, *A new look at technical progress and early retirement,* IZA Journal of Labor Policy, v. 5, **TD No. 963 (June 2014).**

A. BRANDOLINI and E. VIVIANO, *Behind and beyond the (headcount) employment rate,* Journal of the Royal Statistical Society: Series A, v. 179, 3, pp. 657-681, **TD No. 965 (July 2015).**

A. BELTRATTI, B. BORTOLOTTI and M. CACCAVAIO, *Stock market efficiency in China: evidence from the split-share reform,* Quarterly Review of Economics and Finance, v. 60, pp. 125-137, **TD No. 969 (October 2014).**

A. CIARLONE and V. MICELI, *Escaping financial crises? Macro evidence from sovereign wealth funds' investment behaviour,* Emerging Markets Review, v. 27, 2, pp. 169-196, **TD No. 972 (October 2014).**

D. DOTTORI and M. MANNA, *Strategy and tactics in public debt management,* Journal of Policy Modeling, v. 38, 1, pp. 1-25, **TD No. 1005 (March 2015).**

F. CORNELI and E. TARANTINO, *Sovereign debt and reserves with liquidity and productivity crises,* Journal of International Money and Finance, v. 65, pp. 166-194, **TD No. 1012 (June 2015).**

G. RODANO, N. SERRANO-VELARDE and E. TARANTINO, *Bankruptcy law and bank financing,* Journal of Financial Economics, v. 120, 2, pp. 363-382, **TD No. 1013 (June 2015).**

S. BOLATTO and M. SBRACIA, *Deconstructing the gains from trade: selection of industries vs reallocation of workers,* Review of International Economics, v. 24, 2, pp. 344-363, **TD No. 1037 (November 2015).**

A. CALZA and A. ZAGHINI, *Shoe-leather costs in the euro area and the foreign demand for euro banknotes,* International Journal of Central Banking, v. 12, 1, pp. 231-246, **TD No. 1039 (December 2015).**

E. CIANI, *Retirement, Pension eligibility and home production,* Labour Economics, v. 38, pp. 106-120, **TD No. 1056 (March 2016).**

L. D'AURIZIO and D. DEPALO, *An evaluation of the policies on repayment of government's trade debt in Italy*, Italian Economic Journal, v. 2, 2, pp. 167-196, **TD No. 1061 (April 2016).**

FORTHCOMING

S. MOCETTI, M. PAGNINI and E. SETTE, *Information technology and banking organization*, Journal of Financial Services Research, **TD No. 752 (March 2010).**

G. MICUCCI and P. ROSSI, *Debt restructuring and the role of banks' organizational structure and lending technologies,* Journal of Financial Services Research, **TD No. 763 (June 2010).**

M. RIGGI, *Capital destruction, jobless recoveries, and the discipline device role of unemployment,* Macroeconomic Dynamics, **TD No. 871 July 2012).**

S. FEDERICO and E. TOSTI, *Exporters and importers of services: firm-level evidence on Italy*, The World Economy, **TD No. 877 (September 2012).**

P. BOLTON, X. FREIXAS, L. GAMBACORTA and P. E. MISTRULLI, *Relationship and transaction lending in a crisis*, Review of Financial Studies, **TD No. 917 (July 2013).**

G. DE BLASIO and S. POY, *The impact of local minimum wages on employment: evidence from Italy in the 1950s,* Regional Science and Urban Economics, **TD No. 953 (March 2014).**

A. L. MANCINI, C. MONFARDINI and S. PASQUA, *Is a good example the best sermon? Children's imitation of parental reading,* Review of Economics of the Household, **TD No. 958 (April 2014).**

L. BURLON, *Public expenditure distribution, voting, and growth,* Journal of Public Economic Theory, **TD No. 961 (April 2014).**

G. ZINNA, *Price pressures on UK real rates: an empirical investigation,* Review of Finance, **TD No. 968 (July 2014).**

U. ALBERTAZZI, M. BOTTERO and G. SENE, *Information externalities in the credit market and the spell of credit rationing,* Journal of Financial Intermediation, **TD No. 980 (November 2014).**

A. BORIN and M. MANCINI, *Foreign direct investment and firm performance: an empirical analysis of Italian firms,* Review of World Economics, **TD No. 1011 (June 2015).**

R. BRONZINI and A. D'IGNAZIO, *Bank internationalisation and firm exports: evidence from matched firm-bank data,* Review of International Economics, **TD No. 1055 (March 2016).**