Lending Standards Over the Credit Cycle*

Giacomo Rodano† Nicolas Serrano-Velarde‡ Emanuele Tarantino§

Bank of Italy *Bocconi University* *University of Mannheim*

October 2015

Abstract

We empirically identify the lending standards applied by banks to small and medium firms over the cycle. We exploit an institutional feature of the Italian credit market that generates a sharp discontinuity in the allocation of comparable firms into credit risk categories. Using loan-level data, we show that during the expansionary phase of the cycle, lax standards mean that substandard firms pay significantly higher interest rates. During the contractionary phase of the cycle, the abrupt tightening of lending standards leads to the exclusion of substandard firms from credit. These firms then report significantly lower production, investment, and employment. Finally, we find that the drying up of the European interbank market is an important factor determining the change in bank lending standards.

JEL classification: G21, G32.

Keywords: Lending Standards; Credit Cycle; Financial Contracts; Real Allocations.

---

*We thank Klaus Adam, Steve Bond, Elena Carletti, Antonio Ciccone, Decio Coviello, Andrew Ellul, Carlo Favero, Nicola Gennaioli, Simon Gilchrist, Martin Hellwig, Nobuhiro Kiyotaki, Rocco Macchiavello, Tommaso Nannicini, Steven Ongena, Marco Pagano, Nicola Pavanini, Nicola Persico, Andrea Polo, Manju Puri, Amit Seru, Enrico Sette, Andrei Shleifer, Javier Suárez, Michele Tertilt, Franco Varetto, Egon Zakrajšek, and participants in the Bank of Italy, Bocconi, Max Planck Institute (Bonn), CSEF, EIEF, HEC Montreal, Mannheim, Goethe University, IFN (Stockholm) seminars and in the NBER Summer Institute (Capital Markets and the Economy), Swiss Conference on Financial Intermediation, Annual Bank Research Conference FDIC/JFSR, European Winter Finance Summit, ESSFM, Csef-Igier Symposium on Economics and Institutions, Petralia Workshop and 4Nations Cup conferences for helpful comments. The views expressed are those of the authors and do not necessarily reflect those of the Bank of Italy.

†Bank of Italy, Via Nazionale 91, 00192 Roma, Italy; Phone: +39064792-2745; E-mail: giacomo.rodano@bancaditalia.it.

‡Bocconi University, Via Roentgen 1, 20135 Milan, Italy; Phone: +390258365851; E-mail: nicolas.serranovelarde@unibocconi.it.

§University of Mannheim, L7 3-5, 68131 Mannheim, Germany; Phone: +49(0)6211813072; E-mail: tarantino@uni-mannheim.de.

1 Introduction

An important role that banks play in financial intermediation is to determine the creditworthiness of borrowers. To perform this task, banks set lending standards that potential borrowers must meet. The theoretical literature highlights the importance of lending standards in explaining the dynamics of aggregate fluctuations (e.g., Martin, 2008), and the consensus is that lax standards lead to downturns (e.g., Dell'Ariccia and Marquez, 2006). Yet, empirically identifying corporate lending standards and their implications for credit and real allocations is challenging for three reasons. First, credit policies are likely to simultaneously reflect a firm's demand and the bank's supply for credit. Second, lending standards can vary, often suddenly, over the cycle (Ruckes, 2004; Gorton, 2008). Finally, most of the available evidence relies on loan officer surveys (e.g., Maddaloni and Peydro, 2011; Bassett, Chosak, Driscoll and Zakrajšek, 2014) rather than on direct information from firm-bank credit contracts.

This paper addresses these challenges and provides a direct measure of a bank's corporate lending standards over the cycle. We exploit the institutional features of the Italian credit market for small- and medium-sized enterprises (SMEs) to conduct a quasi-natural experiment that resembles key aspects of the following ideal laboratory setting: A bank interacts with two ex-ante economically identical firms. Firm A is randomly allocated into the investment grade category of credit risk, and firm B is assigned the speculative category. In such an environment, demand-side characteristics are kept constant, and differences in financial contracts only reflect the bank's lending policies with respect to credit risk as measured by the rating class. Due to the time-varying nature of these policies, an ideal experiment would then repeat this analysis across time.

Our quasi-natural experiment relies on two key institutional features. First, for historical reasons, the credit risk assessment of SMEs performed by Italian banks relies on a common credit rating that is purchased by banks from an external agency (*Centrale dei Bilanci*, or *CEBI*). This rating, which is constructed following Altman's (1968) methodology, is not solicited by firms and is computed based on lagged balance sheet information. Second, within this rating methodology, firms are allocated into two main rating classes—performing and substandard—based on the value of a continuous variable. While banks might observe both the continuous and categorical values of the ratings, as we document empirically, the presence of rating segmentation implies that banks set their lending standards using the discrete value of the rating.

Rating segmentation allows us to replicate the ideal experiment described above by exploiting the sharp discontinuity in the allocation of firms into risk classes. We measure differences in credit allocations between a firm marginally classified into the performing class and a firm marginally classified into the substandard class based on the value of the rating's continuous variable. The differences in financial contracts will therefore inform us regarding the tightness of banks' lending standards.

To run our empirical analysis, we use a unique loan-level dataset collected by the Italian central bank. We evaluate contractual differences in terms of the total quantity of credit granted and the per-loan interest rate charged by financial intermediaries. Our sample is composed of about 144,000 firm-year observations in the manufacturing sector and 253,000 funding contracts, covering the period between 2004 and 2011. Like other OECD economies, Italy was experiencing a credit cycle during this time that reached its peak in 2006–2007 (Drehmann, Borio, and Tsatsaronis, 2012; Giovannini, Mayer, Micossi, Di Noia, Onado, Pagano, and Polo, 2015).

Our analysis yields three major results. First, we show that during the expansionary phase of the cycle (2004–2006), lending to firms at the threshold features interest rate differences but little (if any) difference in the total amount of credit granted. A firm marginally classified into the performing class pays up to 10% (or 60 basis points) lower interest rates on new term loans than a firm marginally classified into the substandard class. This interest-rate premium disappears during the cycle's boom phase in 2007. These findings suggest that banks gradually relax lending standards between 2004 and 2007.

Second, we find that in the aftermath of the turmoil affecting interbank markets in late 2007, banks tightened their lending standards. We show that through 2008 and 2009 firms at the threshold report differences in the total amount of credit granted by banks and no differences in the interest rate set on new term loans. More specifically, firms in the performing class obtain up to 60% more credit than comparable firms in the substandard class. We also show that a simple comparison between the average values of our outcome variables for firms further away from the threshold would produce biased results.

These first two findings can be interpreted within a demand-supply framework featuring rating segmentation and asymmetric information in the bank-firm relationship. Segmentation implies that two comparable firms in different risk classes face different supply curves. However, it is not sufficient to generate the absence of interest rate differences, and the contemporaneous sizeable quantity differences in 2008 and 2009. These patterns can be rationalized within standard models of moral hazard or adverse selection (e.g., Holmström and Tirole, 1998; Bolton and Dewatripont, 2006) by the contemporaneous contraction of the supply of credit and the exacerbation of the asymmetric information problem.

Third, we trace the implications of lending standards for firms' real activity. We show that periods of lax standards imply that firms at the threshold do not differ in the value of production and input choices. When lending standards tighten, instead, production and investment of ex-ante economically comparable firms significantly diverge. A firm marginally above the threshold in the performing class produces 30% to 50% more between 2008 and 2010 than a firm below the threshold in the substandard class. This difference in production stems from a significant reduction in firms' investments, intermediate purchases, and employment.

Our contract-level data also allow us to document the changes in the terms and conditions of credit that banks operate to implement the tightening of their lending standards in 2008 and 2009. First, in 2008 banks reduced the amount of lending to substandard firms by renegotiating the commitments in revolving credit lines. Only subsequently, in 2009, they rejected the applications made by new borrowers in the substandard class. This last finding is consistent with the evidence on the peak of the exacerbation of lending standards applied by banks to Italian SMEs in 2009 as reported by loan officers in the ECB Bank Lending Survey (BLS).

Our results confirm the importance of lending standards in explaining aggregate financial and real fluctuations. At an aggregate level our estimates imply that during the pre-crisis period substandard firms paid additional interest payments for 2 BE per year to banks compared to performing firms. The subsequent tightening of lending standards then accounts for a fall in the supply of bank financing to substandard firms of approximately 208 BE, or 1.2 ME per firm. This contraction in the supply of credit resulted in a 10.6% lower value of production for these firms.

We also investigate the two main channels that can explain banks' decision to tighten lending standards (e.g., Allen and Carletti, 2008; Diamond and Rajan, 2011; Kashyap and Stein, 2004; Repullo and Suarez, 2013). Bank capital could have become more scarce with the crisis. Alternatively, banks with higher interbank market dependance to fund liquidity needs could have expected the cost of capital to rise in the near future. To explore the relative merits of these two mechanisms, we use data from the banking supervisory authority and split banks in our sample according to their pre-crisis capital ratios and exposure to the interbank market. Consistent with the recent empirical banking literature (e.g., Iyer, Peydró, da-Rocha-Lopes, and Schoar, 2014), we find that the reduction of credit supply to substandard firms in 2008 and 2009 was mainly driven by banks that were highly exposed to the dry up of the European interbank market in late 2007.

To confirm the internal validity of our results, we present several robustness checks to our empirical design. Given the importance of the credit rating system for banks' credit decisions, a natural question to ask is whether firms are able to manipulate their assignment and self-select into a safer category. Manipulation of the rating is unlikely, not only because the rating is not solicited by firms and is computed based on firms' past balance sheets, but also because its exact algorithm is a business secret. Nonetheless, we test empirically for the presence of a systematic discontinuity in firm distribution at the threshold due either to the absence of observations near the threshold or to the presence of clusters of observations on the side of the threshold assigning a firm to the safer category. We do not find any systematic or significant evidence of manipulation.

The second identifying assumption in our empirical setting is that close to the threshold firms are as if randomly sampled. If firms were nonrandomly sorted, we would expect firm characteristics to differ systematically at the threshold. We test this assumption by running balancing tests on a set of invariant and pre-treatment firm characteristics. The results suggest no statistically or economically significant difference in firms' characteristics. Importantly, we directly test and reject the hypothesis that differences in credit at the threshold capture a discontinuity in the probability of a firm having a credit event.

The third and most important assumption in our research design relates to the relevance of the threshold that assigns firms to the performing and substandard classes. We first show that our estimates are not consistent with the results obtained at randomly placed thresholds along the support of the assignment variable. Banks reports and Altman's (2003) risk classifications suggest that distinguishing between performing and substandard firms is important for risk management policies. To provide systematic evidence confirming this intuition, we estimate our baseline specification at all the seven thresholds associated with the categorical value of the rating system and find no evidence of systematic discontinuities in lending policies.

This paper contributes to the macro-finance literature that studies the dynamics of credit over the cycle. Consistent with our results, this literature finds that the flow of credit (e.g., Covas and Den Haan, 2011; Jermann and Quadrini, 2012; Becker and Ivashina, 2014) and the value of credit spreads (Gilchrist, Yankov, and Zakrajšek, 2012) are both highly procyclical. Our institutional setting allows us to empirically identify lending standards' evolution over the cycle.[1] By relying on contract-level information, we show that in the expansionary phase of credit cycles banks change their lending standards by adjusting the cost of credit. In the contractionary phase of the cycle banks tighten their standards by adjusting the amount of credit available to firms, with consequences on firms' production and input choices.

The recent empirical literature in banking exploits multi-bank lending to identify the linkages between monetary policy and bank risk taking over the cycle (e.g., Jiménez, Ongena, Peydró and Saurina, 2012 and 2013). The methodology, as proposed by Khwaja and Mian (2008), keeps all borrower characteristics constant and focuses on differences in

[1] Other papers have analyzed the effects of banks' supply shocks on credit conditions and firm real activity (e.g., among others, Peek and Rosengren, 2000; Ashcraft, 2005; Chodorow-Reich, 2014), however they exploit one-time quasi-experimental settings and thus do not inform us about the cyclical behavior of lending standards.

bank balance sheet characteristics. Instead, our paper studies variation of credit policies resulting from a discontinuous change in the perceived credit risk of otherwise identical firms. This approach also allows us to directly measure the aggregate effects of bank lending policies, irrespective of the number of a firm bank relationships.

From a methodological point of view, the paper is closely related to Keys, Mukherjee, Seru, and Vig (2010), who study the screening process of household mortgages in the United States.[2] They exploit a rule of thumb in the household rating system to obtain variation in the ease of securitization. We exploit rating segmentation generated by the Italian credit market institutional features, and we are able to exploit the repeated nature of the framework to identify lending standards over the credit cycle.

2 Lending to Italian SMEs

In this section, we first describe the institutional features of the Italian credit market for SMEs, and then present our empirical framework. To empirically measure corporate lending standards, we follow the theoretical literature (e.g., Dell'Ariccia and Marquez, 2006) and study the credit allocations applied to borrowers with different credit risk profiles.

The main empirical challenge threatening the quantification of lending standards is that differences in credit conditions might simultaneously reflect heterogeneity in the demand for credit. To address this challenge, we exploit the fact that bank lending to Italian SMEs features rating segmentation. This implies that the credit supply curves of two, albeit comparable firms in different rating classes is different. The identification strategy is therefore based on a regression discontinuity design that compares credit conditions applied to firms that marginally fall into different risk classes.

2.1 Institutional Background

For historical reasons, Italian banks rely on a common credit rating produced by Centrale dei Bilanci (*CEBI*) when making decisions about lending to SMEs. *CEBI* was founded in 1983 as a joint initiative of the Italian Central Bank and the Italian Banking Association to record and process firms' financial statements. According to Standard & Poor's (2004), "banks are the main users of the outputs of *CEBI*," referring to the *Score* rating produced by *CEBI* as the major tool for the assessment of SMEs' credit risk.

In 2004, the share of credit granted to SMEs by banks subscribing to the *Score* rating system amounted to 73%. Evidence from the 2006 Bank of Italy survey on Italian banks'

[2]Relatedly, Kara, Marques-Ibanez, and Ongena (2015) study the link between bank lending standards and securitization using a dataset of European banks.

lending organization indicates that 90% of these banks find the firm's score important to decide on whether to process a loan application, 76% of them to set the amount of lending, and 62% to formulate an offer for the interest rate.

The *Score* takes integer values ranging from 1, for those firms that are the least likely to default, to 9, for those that are the most likely to default. To construct the *Score*, *CEBI* employs a two-step algorithm that uses multiple discriminant analyses of firm balance sheet information to generate two continuous variables (Altman, 1968). Based on predetermined thresholds, the first continuous variable is used to allocate the firms between one of the first five rating categories (1–5), the second to allocate firms into categories 6 to 9.

The categorical values of the *Score* provide an accurate estimate for the expected likelihood of a firm's default within one year. The continuous variables, instead, do not provide the bank with a direct estimate of the firm default probability (Altman, 2003).[3] In addition, the continuous variables are difficult to interpret because their value is industry specific. These features of the rating system explain why in annual reports to external investors Italian banks typically display their corporate credit exposure by classifying firms based on the categorical value of firms' score (e.g., Unicredit, 2008).

In our empirical framework, we exploit the distinction between the performing and the substandard class of credit risk. The performing class includes the firms with a *Score* category between 1 and 6, while the substandard class includes firms with a *Score* between 7 and 9. To grasp the relevance of this classification, note that a *Score* of 6 corresponds to class B, and a *Score* of 7 to class CCC, in S&P's ratings (Altman, 2003).

The Italian credit market for SMEs features rating segmentation, which means that banks use primarily the categorical value of the *Score* to assess counterparty risk and determine credit conditions. Segmentation arises for two main reasons. It is market driven, since external investors monitor banks by pricing their portfolio based on the reported volume of bank lending by categories of credit risk. It can also be implemented strategically by banks, in order to mitigate loan officers' agency problems (Stein, 2002).[4] In Subsection 5.3 we will provide evidence consistent with these two sources of segmentation.

2.2 Empirical Framework

Our empirical framework exploits ratings rating segmentation as a tool to identify banks' lending standards and their evolution over time. In the absence of segmentation we should

[3]Descriptive statistics on firms' distribution in the rating categories, and the associated default frequencies can be found in Online Appendix C (Figure C1).

[4]Paravisini and Schoar (2012) provide evidence supporting Stein's (2002) conclusions. Moreover, Berg, Puri and Rocholl (2013) document the presence of agency problems on the loan officers' side within an institutional context in which, differently from ours, the rating's categorical value can be manipulated.

not observe any difference in the credit conditions set to the firms at the threshold. Moreover, as we will show in our data section, a simple comparison of credit allocations to firms in different rating classes is likely to reflect differences in firms' economic characteristics. If firms in better credit risk categories are more profitable, or face better investment opportunities, they are also likely to have a higher demand for bank credit than firms in worse credit risk categories.

To overcome this identification challenge, we exploit the importance for banks' risk management of the distinction between performing and substandard credit risk.[5] We run a regression discontinuity design that compares the credit conditions applied to the firms at the threshold between the performing and the substandard class, as implied by the value of the *Score* continuous variable. The intuition behind this empirical strategy is that, close to the threshold, firms are as if randomly allocated to the two rating classes. This allows us to hold constant demand-side characteristics, and isolate differences in banks lending policies with respect to a change in credit risk.

The support of the continuous variable for categories 6 and 7 ranges between -0.6 and 1.5, and the threshold is 0.15. Below this threshold, a firm's *Score* is 7 and thus the firm falls into the substandard class. Above the threshold, a firm's *Score* is 6 and it is in the performing class. In all of our analyses, we normalize the threshold to 0 and only use the support of the continuous variable that spans between categories 6 and 7. Thus, if s_i is the value of firm i's continuous variable, the allocation of this firm into a rating class takes place according to the following sharp mechanism:

$$Score_i = \begin{cases} 6 \quad \text{i.e. Performing} \quad \text{if} \quad 0 \leq s_i < 1.35 \\ \\ 7 \quad \text{i.e. Sub-Standard} \quad \text{if} \quad -.75 \leq s_i < 0 \end{cases}.$$

Let $\bar{s}$ denote the normalized threshold for allocating firms into rating categories 6 and 7. Then, for each quarter t between 2004 and 2011, we estimate the following sharp regression discontinuity model:

$$y_i = \alpha + \beta S_i + f(s_i - \bar{s}) + S_i \times g(s_i - \bar{s}) + u_i. \quad (1)$$

In our main specification, the dependent variable capturing the supply of bank financing is the (log) total value of bank financing granted to firm i. This measure accounts for the possibility that firms obtain credit from multiple banks. The variable capturing the cost of bank financing is the (log) value of the interest rate applied to a new loan granted to firm i. By estimating our specification at the quarterly level, we control for

[5] In Table VIII, we apply our discontinuity design to other thresholds and find no systematic difference in credit conditions.

the influence that the stance of monetary policy exercises on nominal rates. We also estimate alternative specifications in which we scale the supply of bank financing by assets and express interest rates in terms of basis point differences, and obtain the same results.

Because below $\bar{s}$ a firm is in the substandard class (i.e., its *Score* is 7 or larger) and above $\bar{s}$ it is in the performing class (i.e., its *Score* is 6 or lower), the indicator S_i takes value of 1 if $s_i \geq 0$ and 0 otherwise. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth order polynomials whose goal is to fit the smoothed curves on either side of the cutoff as closely to the data as possible. Function $f(\cdot)$ is estimated from 0 to the left, whereas the $S_i \times g(\cdot)$ term is estimated from 0 to the right. To simplify the analysis, we restrict $f(\cdot)$ and $g(\cdot)$ to be of the same polynomial order. Finally, u_i is a mean-zero error term clustered at the firm level.[6]

Since we normalize the threshold $\bar{s}$ to 0, at the cutoff the $f(\cdot)$ and $g(\cdot)$ polynomials are evaluated at 0 and drop out of the calculation. This allows us to interpret β as the magnitude of the discontinuity in credit conditions at the threshold. Importantly, this coefficient should be interpreted locally, in the immediate vicinity of the rating threshold.

2.3 Discussion of the Identifying Assumptions

The empirical interpretation of the β coefficient relies on several identifying assumptions about the discontinuity design. First, we need to rule out the concern that firms are able to manipulate their continuous rating. To this end, we show in Table VI that, based on the test proposed by McCrary (2008), there is no evidence of a systematic discontinuity in firms' distribution at the threshold.

The second identifying assumption is that close to the threshold firms are as if randomly sampled. In the presence of non-random sorting, one would expect firm characteristics to differ systematically around the threshold. We test this assumption by running balancing tests on a set of invariant and pre-treatment firm characteristics. The results of these tests are reported in Table VII.

The third and most important assumption in our research design relates to the relevance of the threshold that assigns firms to the performing and substandard classes. We first show that our estimates are not consistent with the results obtained at randomly

[6]Our results are not sensitive to the choice of the polynomial order, or of the estimation method. We also estimate the model using polynomial functions with degree of between 4 to 7. Moreover, in Table D3 (Appendix D) we estimate our discontinuity model by means of a local polynomial regression. There, the estimator is linear with a local-quadratic bias correction, and a triangular kernel. The bandwidth is chosen following Imbens and Kalyanaraman (2012), but is robust to the use of alternative measures based on cross validation. Consistent with Calonico, Cattaneo, and Titiunik (2014), we present conventional discontinuity estimates with a conventional variance estimator, bias-corrected estimates with a conventional variance estimator, and bias-corrected estimates with a robust variance estimator. All our results are robust to these empirical checks.

placed thresholds along the support of the assignment variable. Finally, we estimate our baseline specification at all the seven thresholds associated with the categorical value of the rating system and find no evidence of systematic discontinuities in lending policies.

3 Data Preview and Economic Environment

We use confidential datasets from the Bank of Italy that contain information on the financial contracts signed between banks and SMEs, and firm and bank balance sheets. Our final sample is composed of about 144,000 firm-year observations in the manufacturing sector and 253,000 funding contracts signed between the first quarter of 2004 and the last quarter of 2011. Further details on the dataset and its organization can be found in Appendix B.[7]

In what follows, we first document the presence of substantial heterogeneity across rating classes. This suggests that a naïve comparison between the credit conditions of firms in different rating classes would likely yield misleading conclusions on the pattern of lending standards. The reason is that the credit differences could simply reflect differences in firms' demand for credit. Then, we show the patterns of firms' financial contracts over time, which document how the phases of the credit cycle that Italy experienced between 2004 and 2011 affect financial allocations. Finally, we present key developments in the Italian banking environment that occurred during our sample period, showing the significant effects of the financial crisis on wholesale funding and capitalization of Italian banks.

3.1 Firm Financing Environment

We begin by presenting the sources of cross-sectional heterogeneity in our dataset and the time-series variation in firm financial contracts.

Cross-sectional Descriptive Statistics Table I provides the cross-sectional characteristics of the full sample in column (1), for the group of performing and substandard firms in columns (2) and (3), and for the firms in categories 6 and 7 in columns (4) and (5), respectively. Finally, in column (6) we report the mean difference between the values of the variables in categories 6 and 7.

[Table I Here]

[7] Data from the Italian Central Credit Register have been used by, e.g., among others, Sapienza (2002) and Rodano, Serrano-Velarde, and Tarantino (forthcoming).

The table shows that there is significant heterogeneity among firms across different risk profiles, not only with respect to financial characteristics, but also in terms of balance sheet characteristics.

More specifically, Panel A of Table I shows that important differences arise in the characteristics of financial contracts granted to firms in different *Score* classes (performing and substandard) and categories (1–9). In the full sample, the average nominal interest rate charged for a loan is 4.57%. However, the interest rates applied to performing and substandard firms are 4.32% and 5.3%, respectively. Although the average loan in the sample is approximately 816,000 Euro, it is about 617,000 Euro for a firm in the substandard class. Moreover, the maturity structure of the loans in our sample is biased towards short term, as short-term loans account for around two-thirds of the total granted loans.

Panel B reports the aggregate financing characteristics of the firms in our sample. On average, total bank lending amounts to 8.5ME per firm, 35% of which is in the form of loans. While firms in the performing class receive bank financing that adds up to about 9.2ME, firms in the substandard class receive an average of 6ME.

Panel C provides an overview of the main balance sheet characteristics of Italian manufacturing firms based on unique firm-year observations. Firms in our sample are relatively small. On average, they employ 92 workers, with firms in the performing class being relatively larger than those in the substandard class. While the investment-to-asset ratio is stable across classes, the values of leverage and return to assets are not. The leverage ratio increases from 0.61 for firms in the performing class to 0.86 for those in the substandard class. Moreover, return on assets decreases from 0.07 to zero for firms in these two classes.

Finally, in column (6) we show that the heterogeneity in firm characteristics extends to rating categories 6 and 7. The cost and availability of bank financing suggests significantly tighter standards for firms in category 7 as opposed to category 6. For instance, interest rates for firms in category 6 are 50 points lower than those of firms in category 7. At the same time, these firms are again significantly different in terms of characteristics related to the demand for credit, such as the value of investment and profitability.

Taken together, the descriptive statistics show the importance of disentangling the evolution of (supply-driven) lending standards from other (demand-related) factors, through our regression discontinuity design.

Time Series Descriptive Statistics Figure 1 documents the variation in financial contracts across time.

[**Figure 1 Here**]

In the upper panel we illustrate that, like other OECD economies (Drehmann, Borio, and Tsatsaronis, 2012; Giovannini, Mayer, Micossi, Di Noia, Onado, Pagano, and Polo, 2015), between 2004 and 2011 Italy was experiencing a credit cycle that reached its peak in 2007. The middle panel focuses on firms' nominal average interest rates: It shows that nominal rates mirrored the pattern of the indicators for the monetary policy of the ECB, which are plotted in the bottom panel.

More specifically, in the top panel we show that the time series of the amount of bank financing to Italian SMEs features a humped shape. From the first quarter of 2004 to the fourth quarter of 2007, bank financing increased by 18%, on average. It then decreased by 11% through the end of the sample period. Although this pattern is qualitatively similar across risk classes, the variation in bank financing is larger for substandard firms: Between 2004 and 2008 bank financing to performing firms increased by only 13%, by 29% for substandard firms.

The middle panel of Figure 1 shows that nominal interest rates increased from 4.3% in 2004 to 6.11% in late 2008. This pattern closely follows the changes in two leading indicators of monetary policy (plotted in the bottom panel): The Euro overnight index average rate (EONIA) and the ten-year Italian government bond interest rate. The middle panel also shows that the spread between interest rates applied to performing and substandard firms increases from 63 basis points at the beginning of 2004 to 90 basis points at the beginning of 2008. In the fourth quarter of 2011, the last in our sample period, the spread reached about 160 basis points.

3.2 Banking Environment

In Figure 2 we illustrate the key developments in the Italian banking environment that occurred during our sample period. We use bank balance sheet data from Bank of Italy.

[**Figure 2 Here**]

The figure has three main takeaways. First, it shows that the Italian banking system was largely exposed to the shock that dried up wholesale funding in late 2007 (e.g., Brunnermeier, 2009). Second, it shows that the financial crisis had an impact on Italian banks' capitalization, which fell between late 2007 and early 2008 to pick up in the following years. Both features are shared by the banking systems of other European countries during the same time interval (Giovannini, Mayer, Micossi, Di Noia, Onado, Pagano, and Polo, 2015). Finally, the figure illustrates the Italian banking sector regulatory environment prevailing during our sample period.

As shown in the top panel of Figure 2, the Italian banks experienced a dramatic reversal in their access to the interbank market. Between 2005 and 2007, the amount of financing raised by banks on the interbank market represented up to 16% of their total assets. Dependence on the interbank market is also reflected in the pattern of Italian banks' funding gap: The difference in the amount lent by banks and their deposits increased from 100BE in 2004 to more than 300BE in 2007 (Angelini, Nobili and Picillo, 2011). Not surprisingly, following the interbank market turmoil, the share of bank assets funded through the interbank market plummeted to 6% in 2008 and 2009.

The middle panel of Figure 2 provides evidence regarding the capitalization of Italian banks: We compute the tier 1 capital ratio for the five largest banks in our sample by dividing banks' tier 1 capital by their total assets. The figure shows that the average value of banks' capital ratio at the beginning of the financial crisis period was approximately 4.5%. In 2008 the ratio fell to around 3.6%, before rising above 5% towards the end of the sample period.

The bottom panel of Figure 2 provides evidence on the implementation of the Basel II agreements. Credit risk capital allocations account for more than 100% of total capital requirements through 2008 and 2010, implying that credit risk management was critical for Italian banks during our sample period. Moreover, the transition from Basel I to Basel II is unlikely to drive the evolution of lending standards during our sample period. First, because the fraction of capital allocations calculated using internal rating systems hovers around 20%. Therefore, most of the Italian banks relied on the standardized approach to comply with capital regulations. Second, because the SMEs in our sample belong to the retail portfolio, so that the transition from Basel I to Basel II did not equate to a differential change in the risk weights applied to firms falling into different rating classes.[8]

4 Results

In this section, we present the results on the differences in credit conditions, interest rate, and quantity of bank financing, for firms at the threshold between the performing and the substandard class. We then explore whether differences in credit conditions give rise to differences in real outcomes in terms of production and input choices. Finally, we analyze the aggregate implications of our results.

4.1 Results on Credit Allocations

In Figure 3 we plot the time series of the coefficients for the differences in credit conditions at the threshold (parameter β in equation (1)). The estimates related to the total amount of granted bank financing are in the top panel, and those for the interest rates on new

[8]For additional details on Basel II implementation, see Bank of Italy (2006:45).

loans are in the bottom panel. In Table D1 of Online Appendix D, we report the details of the regression results.

[Figure 3 Here]

Figure 3 shows that banks gradually relax lending standards between 2004 and 2007. In 2004 and 2005, differences in the total amount of lending granted to the firms at the threshold are positive but not significant. During the same period, firms in the substandard class are charged up to 10%, or 60 basis points, higher interest rates on new bank loans than similar firms in the performing class.[9] Consistent with the timing of the peak of the credit cycle, the differences in the interest rate and the quantity of credit vanish in late 2006 and 2007.

Through 2008 and 2009, the financial crisis that hit the Italian banking sector implies a tightening of lending standards. Remarkably, tight standards translate into differences in the quantity of lending. Indeed, the difference in the amount of total credit supplied to similar firms across the threshold is statistically significant, and ranges between 50% and 60% (or 9 percentage points in terms of the debt-to-assets ratio). At the same time, interest rate differences remain close to 0. The timing suggests that the drying up of the interbank market in 2007 played a crucial role in explaining the abrupt change in lending standards.

Between 2010 and 2011 our estimates are consistent with a recovery in bank lending, with differences in the quantity of credit that gradually disappear. During this period, lending standards translate into a 20%, or 120 basis points, interest rate spread between comparable firms in different rating classes.

By controlling for demand heterogeneity, our empirical strategy delivers novel results on the adjustment of lending standards over the cycle. The aggregate patterns in Figure 1 suggest that firms in different rating classes and categories display positive and significant interest rate and quantity differences throughout the cycle. Instead, by allowing to tease out demand and supply our regression discontinuity design shows that, when setting their lending standards, banks use the interest rate and the quantity margin differentially over the cycle. In the expansionary phase of the cycle banks change their lending standards by adjusting the cost of credit. In the contractionary phase of the cycle banks tighten their standards by adjusting the amount of credit supplied to firms.

Our results are consistent with an increase in banks' aversion to the risk of losses during the 2008–2009 financial crisis. Guiso, Sapienza and Zingales (2013) provide experimental evidence on financial investors' time-varying risk aversion in Italy. The literature

[9] To obtain the exact percentage changes associated with the value of $\hat{\beta}$, we compute $\left(exp^{\hat{\beta}} - 1\right)$.

suggests two possible channels to explain the shift in lending standards. The first has regulatory underpinnings (e.g., Kashyap and Stein, 2004; Repullo and Suarez, 2013). Since bank capital could have become more costly with the crisis, banks' fear to violate capital requirements induced them to tighten the lending standards. The second hinges on the importance of bank liquidity (e.g., Allen and Carletti, 2008; Diamond and Rajan, 2011): Those banks with higher interbank market exposure feared the pressure on the wholesale market for funds. We test the relative merits of these two channels in Subsection 5.2.

We conclude by discussing the aggregate implications of our estimates.[10] For the impact of lending standards on interest repayments, we consider the amount of bank financing granted to firms with a substandard rating. To determine the increased value of the repayments due by substandard firms when compared to the performing firms, we take the interest rate spread estimated by our discontinuity design at the threshold. Between 2004 and 2006, we find a higher total transfer of roughly 2 BE per year, or 15,000 Euros paid by each substandard firm to banks. Because of the larger spreads in 2010–2011, these transfers from substandard firms to banks increased to 4.7 BE per year, or 27,000 Euros per firm.

We also compute the additional amount of lending that would have been granted to substandard firms, with respect to performing firms, had lending standards not tightened in 2008 and 2009. On average, we estimate a fall in the supply of bank financing of approximately 1,2 ME per firm. This suggests that, at the aggregate level, bank financing was 208 BE lower than that available for the performing class. This figure represents 14.3% of total bank financing in the Italian economy.

These calculations need to be interpreted with some caution. First, they are based on a partial equilibrium exercise that does not account for other aggregate factors. Second, our aggregate calculations implicitly assume that the threshold estimates influence all substandard firms with the same intensity. However, it is reasonable to believe that firms lying further away from the threshold receive worse financing conditions than the firms at the threshold. Consequently, our aggregate calculations provide a lower bound estimate for the aggregate impact of lending standards.

4.1.1 Nonparametric Plots

We next confirm the local interpretation of our estimates, by providing nonparametric plots of the outcome variable as a function of the continuous assignment variable.

In the top panel of Figure 4, we focus on data from the second quarter of 2009, in which our results at the threshold feature quantity differences and no interest rate differences.

[10] To compute our aggregate estimates, we use data from all Italian limited liability firms between 2004 and 2011. We extend the sample to include firms from all sectors of activity. We also consider those firms that are rated by the agency using information from simplified balance sheets.

We divide the domain of s into mutually exclusive bins of size 0.03.[11] For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's midpoint. The fitted red line shows how close the sixth order polynomial approximates the variation of bank financing conditions at the threshold.

[**Figure 4 and 5 Here**]

The top left panel of Figure 4 shows that a clear discontinuity arises in the total amount of bank financing close to the threshold. The magnitude of this discontinuity can be quantified by comparing the mean value of the variable of interest in the two bins next to the threshold. Immediately to the left of the threshold, the average value of (log) granted credit is approximately 14.6, whereas immediately to the right this value is 15, implying that the estimated value of β captures the variation arising directly at the threshold. The top right panel of Figure 4 repeats this exercise for the interest rates on new bank loans. It shows that when there is no discontinuity in the value of the conditional regression function at the threshold, the polynomial fit does not display any significant discontinuity: In the figure, the value of the average interest rate is not significantly different when comparing the value corresponding to the bins next to the threshold.

The top panel of Figure 5 confirms this analysis focusing on the second quarter of 2011, in which our results at the threshold feature significant interest rate differences and no quantity differences.

4.1.2 Simple Averages Comparison

We next turn to the question of how our threshold analysis improves on a simple comparison between the average values of the financial conditions computed using all the observations in categories 6 and 7.

We estimate a simple mean difference specification for increasingly larger bins around the threshold:

$$y_i = \delta + \gamma S_i + u_i \quad \text{for} \quad \bar{s} - h \leq s_i \leq \bar{s} + h, \tag{2}$$

with S_i equal to 1 if $s_i \geq 0$, and 0 otherwise. We are interested in studying how the value of the estimate of γ changes as we increase the size of the bin. In the middle panels in Figures 4 and 5, the estimate of γ is reported on the vertical axis and the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the

[11] The results of the empirical analysis remain identical when plotting bins of different size, like 0.02 or 0.01. For the ease of the exposition, we only report the results obtained using bins of 0.03.

estimated value of γ as a function of the distance from the threshold. The dashed lines are 90% confidence bands.[12]

The figures show that the estimates from the specification in (2) above are biased for larger values of h around the threshold, and that the direction of this bias varies with time. For example, in the second quarter of 2009 estimates directly at the threshold show that lending standards translate into differences in the quantity of credit granted to firms. Instead, a simple comparison between the interest rates applied to the firms within the categories would have also produced a statistically significant spread of approximately 11%.

In the second quarter of 2011, our threshold estimates for β indicate that firms obtain a similar amount of bank financing and significantly different interest rates. Instead, the values of the coefficient γ estimated using an increasingly larger value of h imply a significant difference in the quantity of total bank financing and in the interest rate on new bank loans.

4.2 Implications for Firms' Real Activity

Do differences in credit conditions produce real effects? We address this question by applying our regression discontinuity analysis to firm-level balance sheet variables that measure firms' expenditures in production inputs and the value of production. The balance sheet information we use is reported in end-of-the-year statements; thus, it reflects a firm's lending conditions throughout the year. This analysis will identify the relationship between lending standards and firms' real decisions.

Table II reports the results of our baseline regression in (1) using as dependent variables the log of firms' sales and expenditure in investment, employment, and intermediates.

[Table II Here]

We first find that in periods of relatively lax lending standards the value of production reported by firms at the threshold is not significantly different. This is consistent with the fact that lending contracts feature similar amounts of bank financing and only interest rate differences. Although the marginally substandard firms pay a higher price to the bank than the marginally performing firms, this interest rate difference is unlikely to constrain production choices. Our second finding highlights the importance of shifts in lending standards across the cycle. We show that the production choices of firms at the

[12]Specifically, the procedure starts with a value of h equal to 0.01. So the starting bin has a support given by $[-0.01; +0.01]$. In each further step we increment h by 0.01 until we reach the $[-0.50; +0.50]$ interval.

threshold diverge, especially during the periods when access to credit is limited for the marginally substandard firms.

In 2008 and 2009, the marginally performing firms report up to a 50% larger value of production than the marginally substandard ones. The economic magnitude of these estimates suggests that differences in the amount of credit translate into a (close to) one-on-one difference in the value of production. Repeating the aggregation exercise in Subsection 4.1, we find that the contraction in credit provision led to a 700 KE per-substandard firm drop in production, representing 231 BE, or 10.6% of the value of total production in the economy.

To further investigate the implications of lending standards for firm real activity, we also report the differences in input choices made by the firms at the threshold over time. We estimate our discontinuity design using as dependent variables the value of firms' investment in capital, expenditures in intermediates, and employment. Again, we find no statistically or economically significant difference in the input choices of firms at the threshold between 2004 and 2007.

Between 2008 and 2010 input choices diverge significantly. During that period, the most economically significant differences arise in the purchase of intermediates.[13] This result is intuitive given that unless a firm is able to substitute bank financing with trade credit, the reduction in bank financing immediately transmits into a reduction of intermediates. The value of investment also reacts to the tightening of lending standards. In 2008, marginally performing firms invest nearly twice as much as marginally substandard firms. An analogous result arises when differences in employment are considered, although with a lag: In 2010, firms in the substandard class report 50% lower employment than comparable firms in the performing class. This lag can be explained by the rigidities of the Italian labor market during that time.

5 Economic Mechanism

In this section, we study how banks implemented the tightening of their lending standards through changes of terms and conditions of credit. We find a significant reduction of the volume of revolving credit lines in 2008 for the SMEs that marginally fall in the substandard class. Moreover, we find a significantly higher rejection rate of loan applications in 2009 for the firms in the substandard class. We proceed by investigating the channel of transmission of lending standards from the supply side to the demand side. Our results point to the crucial role of banks' exposure to the interbank market. Finally, we give evi-

[13]The results are statistically significant at the 5% level for 2008 and 2009, but slightly above the 10% significance level in 2009.

dence that supports the market-driven and strategic motives behind rating segmentation in our institutional setting.

5.1 Loan Terms and Loan Applications

To implement the adjustment of their lending standards in 2008 and 2009, banks can renegotiate the commitments on revolving credit lines or raise the rejection rate of firms' applications for new loans.

We take advantage of the fact that the Italian credit register distinguishes between term loans and revolving credit lines. The latter are an important source of short-term financing in which banks maintain the right to modify the contractual conditions. The variable *Revolving* measures the total amount of revolving credit lines granted by banks to a firm. Moreover, the Italian register records the banks' monthly requests for information regarding the credit merit of new borrowers.[14] *Rejected* is a binary variable that is equal to one if a bank requested information on a new borrower, but did not grant credit to the applicant within the next two quarters.

Table III reports the estimates of the baseline specification in equation (1) using *Revolving* and *Rejected* as dependent variables.

[**Table III Here**]

In 2008, the first year in lending standards' tightening phase, we observe a threshold difference amounting to about a 50% larger volume of revolving credit lines granted by banks to the firms in the performing class. The second row lists the threshold estimates regarding loan rejections. While the likelihood to be denied credit by new banks is similar across rating classes in 2008, it jumps by 10 percentage points in 2009. The result that banks are more likely to reject new applicants that fall in the substandard class is consistent with the theoretical result in Dell'Ariccia and Marquez (2006) that in times of tight standards banks cut down on lending to unknown borrowers.

These estimates suggest the following mechanism behind lending standards' tightening process in 2008 and 2009. First, banks reduced the amount of lending to substandard firms via the renegotiation of the commitments in revolving credit lines. Subsequently, they rejected the applications made by new borrowers in the substandard class.

5.2 Bank Liquidity, Capital, and Regulation

Two channels can explain banks' decision to tighten lending standards (e.g., among others, Allen and Carletti, 2008; Diamond and Rajan, 2011; Kashyap and Stein, 2004; Repullo

[14] Recall that banks receive on a monthly basis only the information related to the financial position of their current borrowers.

and Suarez, 2013). First, bank capital could have become more scarce with the crisis. Alternatively, banks could have expected the cost of bank capital to rise in the near future, especially those with interbank market dependance to fund liquidity needs. To explore the relative merits of regulatory capital and liquidity in determining the tightness of lending standards, we use data from the Bank of Italy and split banks in our sample according to their pre-crisis capital ratios and exposure to the interbank market. We also discuss whether our results can be explained by the implementation of Basel II agreements.

We divide the banks in our sample between those that lie above and below the median of the distribution of pre-2008 bank capital and interbank exposure ratios. Accordingly, the dependent variable is the amount of lending a firm takes out from banks with high and low interbank market exposure and capital ratios. The results are reported in Table IV.

[**Table IV Here**]

The banks with low exposure to the interbank market funded approximately 3% of their asset base through loans from other banks, at the median. We find that these banks significantly cut the lending granted to substandard firms only in 2008. In sharp contrast, banks that were highly exposed to the interbank market funded, at the median, 14% of their asset base through this channel. The European interbank market dry up in late 2007 led these banks to allocate up to 60% more credit to the firms in the performing class in both 2008 and 2009.

In the middle and bottom panels, we split our sample based on a measures of bank capitalization, the equity-to-asset ratio, that features an economically significant cross-sectional variation. This ratio is 6% before 2008 for less capitalized banks, while it is 11% for highly capitalized banks, at the median. However, these cross-sectional differences do not seem to explain why firms at the threshold between the substandard class and the performing class were offered different levels of credit. We find that the banks in both groups restricted access to financing disproportionally more to the firms in the substandard class in 2008 only. In 2009, we see neither an economically nor a statistically significant difference in the amount of lending at the threshold.

5.3 Rating Segmentation

The empirical interpretation of the threshold coefficients relies on the presence of rating segmentation in the Italian credit market for SMEs. Segmentation implies that banks primarily use the categorical value of the *Score* to set their lending standards. The fact that we observe a discontinuous change in financial contracts at the threshold confirms the presence of segmentation, and we next give direct evidence on the mechanisms through which segmentation arises in our institutional setting.

5.3.1 Bank Cost of Financing

To show that external investors price banks' portfolio based on the amount of lending by classes of credit risk, we use a confidential dataset from the Bank of Italy. The dataset provides us with information on the the amount and interest rate at which Italian banks raise financing from repo markets, households, and firms at a monthly frequency. For the period between 2004 and 2011, we estimate by OLS the following specification, where i indexes banks and t indexes months:

$$\bar{r}_{it} = \alpha + \delta \times \left(\frac{Substandard}{Total} \right)_{it-1} + \Phi_1 \times I_{it} + \Phi_2 \times B_{it-1} + \lambda_t + u_{it}. \tag{3}$$

Variable $\bar{r}_{it}$ is the (volume) weighted average interest rate at which banks raised financing across different types of investors during the sample period. $\left(\frac{Substandard}{Total}\right)_{it-1}$ is the share of a bank's volume of lending to SMEs with substandard rating relative to total SME lending. Finally, I_{it} is a vector of issuance characteristics including amounts, maturity, and investor composition, and B_{it-1} a vector of bank characteristics including size (in terms of total assets), the value of tier 1 capitalization ratio, and the bank's liquidity ratio. Standards errors are corrected for clustering at the bank level. Table V reports the results we obtain.

[Table V Here]

Column 1 confirms that the share of substandard lending significantly affects the rate at which banks can obtain financing from external investors. The estimate implies that a 25% higher share of substandard lending in the bank portfolio is associated to an increase in the banks' interest rate of approximately 28%, or 31 basis points. Column 2 extends the baseline specification by including the continuous values produced by the rating system. We find that the coefficient on the share of substandard loans remains significant and economically identical to the first specification. Instead, the coefficients on the values of the continous variables are neither statistically nor economically significant.

These results suggest that, consistent with the anecdotal evidence in Subsection 2, differences in the continuous values of the rating are not priced by external investors.

5.3.2 Large and Small Banks

We next provide evidence suggesting that rating segmentation can have strategic motives. Data from the 2006 Bank of Italy survey on Italian banks' lending organization indicate that there is a positive and significant correlation between the use of scoring methodologies and the size of the bank. This correlation is consistent with the results in Stein (2002), who shows that large banks are more inclined to adopt standardized rating methods when taking lending decisions.[15] To test this prediction, we compare the contractual differences arising at the threshold when splitting our sample in large and small banks. The measure of size we use is based on the value of total financing granted to SMEs as computed at the beginning of the sample period.[16]

The bottom panel of Table IV shows that the differences in the quantity of lending offered by large banks to the firms at the threshold are large in 2008 and 2009. Instead, the differences in the quantity of lending offered by small banks to the firms at the threshold are small, if not negligible, through our sample period, except for 2008. That is, small banks seem to offer the same contract to the firms at the threshold even in 2009, when large banks restricted credit to firms falling in the sub-standard class.[17]

This evidence is in line with the conclusions in Stein (2002). Although the empirical results in Table IV can be explained by other differences between the banks in the two groups, the fact that our results are consistent with the evidence on the use of scoring methodologies by Italian banks gives us confidence that we are capturing differences in the incentive schemes within large and small banks.

6 Empirical Tests and Importance of the Threshold

In this section, we test the three identifying assumptions underlying our empirical setting. First, we show that firms do not seem to manipulate their ratings to self-select into more favorable categories. Second, we show that firms at the threshold are balanced in terms of their economic characteristics. Finally, we present placebo tests showing that estimates of the discontinuity obtained at the true threshold are not due to coincidental variation that occurs along the support of the continuous variable.

6.1 Manipulation of the Score and Self Selection

Given the importance of the *Score* in bank credit decisions, a natural question to ask is whether firms are able to manipulate their credit rating and self-select into a better category. Manipulation of the rating is very unlikely, not only because the *Score* is unsolicited by firms and is computed based on firms' past balance sheets, but also because

[15] The intuition is that, because of their centralized decision-making structure, in large banks the loan officer's agency problem is more binding than in small banks.

[16] We verify that the balancing characteristics presented in Section 6 hold in the subsamples.

[17] Although they are not reported in the table, analogous patterns holds for interest rate differences, as larger banks systematically charge higher spreads at the threshold.

its exact algorithm is a business secret. Nevertheless, manipulation can be detected empirically: It would result into a systematic discontinuity of firms' distribution at the threshold, due either to the absence of observations near the threshold or to the presence of clusters of observations on the side of the threshold assigning a firm to the safer category. Since our empirical analysis focuses on the threshold separating the performing from the substandard class, in Table VI we test for the presence of a discontinuity of the firms' density at that threshold.

[**Table VI Here**]

Following McCrary (2008), for each year we run a kernel local linear regression of the log of the density on both sides of the threshold separating substandard firms in category 7 from performing firms in category 6. Table VI shows that, with the exception of 2008, there is no evidence of significant discontinuities in the distribution of firms at the threshold. The discontinuity in 2008 is most likely coincidental for two reasons. First, if firms had discovered the exact formula of the *Score* and how to manipulate their assignment, a discontinuity should emerge systematically in every year following 2008. Second, had strategic manipulation occurred, it would mean that firms had anticipated by at least one year the financial crisis and the associated benefits of being classified as marginally performing entities. Figure D3 in Online Appendix D provides the plots associated to these tests.

The lack of manipulation, as suggested by the tests in Table VI, is confirmed by inspection of the plots of the distribution of firms that enter rating categories 6 or 7 in any given year. If firms were able to determine the value of their own continuous variable, then we should observe a disproportionate number of firms clustering just above the threshold, in category 6. Figure D4 of Online Appendix D shows that a significant mass of firms enters the sample with a value of the continuous variable that lies just below the threshold, in category 7. This confirms that manipulation of the assignment variable is highly unlikely.

6.2 Balancing Tests

In Table VII, we analyze whether firms close to the threshold are as if randomly sampled, a critical identification assumption within regression discontinuity models. If firms are nonrandomly sorted into specific rating classes, we would expect firm characteristics to differ systematically across the threshold. Following the regression discontinuity literature, the firm characteristics we test are those logically unaffected by the threshold but plausibly related to firm financing.

[Table VII Here]

Panel A of Table VII, the dependent variable is a broad set of firm financing, investment, and profitability measures taken in 2003. In the first row, we show that firms at the threshold do not differ in terms of leverage choices in the pre-sample period. Moreover, we find no significant difference in firms' return on assets, or investments.

Panel B tests for differences in bank relationships of firms at the threshold. The first row in the table focuses on the banks' probability to report non-performing loans. If there was a discontinuity in the probability of a firm's credit event at the threshold, then our results could be explained by the fact that banks correctly price this difference. However, we find no statistically or economically significant differences at the threshold. In the second row, the variable *Asked* is a binary indicator equal to one if a bank requests information on a new loan applicant. The estimates suggest that firms at the threshold do not display a different propensity to apply for loans to new banks. The last row of the panel tests for the presence of assortative matching between banks and firms at the threshold. For each firm we compute its banks' average size. Again, we find no evidence of a systematic difference at the threshold.

Panel C focuses on differences in time-invariant firm characteristics. In the first row, the dependent variable is the firms' activity sector proxied by its SIC code. The yearly estimates indicate no statistically or economically significant evidence of firms clustering into sectors such as food industries. Next, we look at time-invariant characteristics related to firms' geographical locations. Geographic location is a particularly interesting dimension to study within this setting because Italian geography is correlated with heterogeneity in economic development, crime rates, and political accountability (Brollo, Nannicini, Perotti and Tabellini, 2013) and could thus be associated with opportunistic manipulation. The variable capturing location in the largest cities or the most entrepreneurial areas does not display a statistically significant discontinuity.[18]

6.3 Empirical Relevance of the Threshold

We now provide further evidence on the relevance of the threshold between performing and substandard firms.

6.3.1 Placebo Tests

Finding a significant discontinuity in lending conditions at the threshold, as shown in Figure 3, might not necessarily establish a causal relationship between the threshold and the design of financial contracts. For example, analogous results might arise when

[18] In Table D4 of Online Appendix D we provide additional balancing tests.

comparing financing conditions borne by firms whose *Score* lies further away from the true threshold. We thus implement the following falsification tests: We draw approximately 100 randomly distributed placebo thresholds along the support of *Score*'s categories 6 and 7, and rerun the baseline specification in (1) for all the quarters in our sample.

To illustrate our results we plot in Figure 6 the distribution of the placebo estimates for the second quarters of 2009 and 2011.

[**Figure 6 Here**]

Figure 6 illustrates that the contractual differences identified by the true threshold estimates (vertical dotted line) are not due to a coincidental discontinuity. If this were the case, then we should observe similar estimates arising when considering randomly placed thresholds. In the top panel, we find that the 100 placebo estimates for the differences in the quantity of bank financing are approximately normally distributed around 0. Only in 6% of the cases we do find placebo estimates that are actually equal to or larger than the true threshold estimate of 0.33. Similarly, the bottom panel shows that in the second quarter of 2011 the interest rate differences of 20% that we find in the main analysis are well outside the normal variation arising from randomly placed thresholds.

In Online Appendix D, Table D2 reports the descriptive statistics about the mean, median, and statistical significance of these placebo tests across all quarters. The estimated values are about zero and are not significant in most of the quarters. Finally, Figure D5 illustrates that a randomly drawn placebo threshold is also unlikely to yield an economically sensible pattern of estimates across time.

This evidence demonstrates the relevance of the categorical value of the *Score* for Italian banks' lending decisions. If financial intermediaries were not using the categorical rating for the allocation of credit in the SME segment, then the threshold should not yield financial outcomes that are significantly and systematically different from those obtained using a randomly set threshold along the support of the continuous variable. Our evidence rejects this claim on the basis of the distribution of placebo estimates within and across the sample period.

6.3.2 Other Thresholds

Finally, we provide evidence showing that the threshold between substandard and performing firms is of major importance for formulating banks' risk management policies. We estimate our baseline specification at all seven thresholds associated with the categorical value of the rating system.[19] In Table VIII, the reported dummy variable is equal to one for firms in the better, i.e., lower value, rating category, and 0 otherwise.

[19] Recall that due to the construction of the *CEBI* rating, the threshold between categories 5 and 6 cannot be used.

[Table VIII Here]

Most of our estimates are not statistically significant. Moreover, across time, the sign of the coefficients is not consistent with the impact of lending standards predicted in Table D1. These estimates suggest that the threshold between categories 6 and 7, i.e., the performing class and the substandard class, is particularly relevant for banks' risk management decisions.

7 Conclusions

We empirically identify the lending standards applied by banks to SMEs over the cycle. We exploit an institutional feature of the Italian credit market that generates a sharp discontinuity in the allocation of firms into credit risk categories. Using loan-level data, we then compare the credit conditions applied to firms marginally classified into the performing class with those marginally classified into the substandard class.

During the expansionary phase of the cycle, we find that lax lending standards imply that substandard firms pay significantly higher interest rates. However, there is no difference in the amount of credit granted to the firms next to the threshold. During the contractionary phase of the cycle, the abrupt tightening of lending standards leads to the exclusion of substandard firms' access to credit. Finally, we show that when lending standards tighten, firms in the substandard class report a significant drop in the value of production and input choices.

References

[1] Allen, F., Carletti, E., 2008, The Role of Liquidity in Financial Crises, 2008 Jackson Hole Conference Proceedings, Federal Reserve Bank of Kansas City, 379-412.

[2] Altman, E. I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, 23(4), 589-609.

[3] Altman, E. I., 2003, Managing Credit Risk: The Challenge for the New Millennium (Presentation Slides Available at http://people.stern.nyu.edu/ealtman/2-%20CopManagingCreditRisk.pdf.

[4] Ashcraft, A., 2005, Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks, *American Economic Review*, 95, 1712-1730.

[5] Bank of Italy, 2006, New Regulations for the Prudential Supervision of Banks (Circular 263 of 27 December 2006).

[6] Bassett, W. F., Chosak, M. B., Driscoll, J. C., Zakrajšek, E., 2014, Changes in Bank Lending Standards and the Macroeconomy, *Journal of Monetary Economics*, 62, 23-40.

[7] Becker, B., Ivashina, V., 2014, Cyclicality of Credit Supply: Firm Level Evidence, *Journal of Monetary Economics*, 62, 76-93.

[8] Berg, T., Puri, M., Rocholl, J., 2013, Loan Officer Incentives and the Limits of Hard Information, NBER Working Paper No. 19051.

[9] Brollo, F., Nannicini, T., Perotti, R., Tabellini, G., 2013, The Political Resource Curse, *American Economic Review*, 103(5), 1759-1796.

[10] Brunnermeier, M. K., 2009, Deciphering the Liquidity and Credit Crunch 2007-2008, *Journal of Economic Perspectives*, 23(1), 77-100.

[11] Chernenko, S., Sunderam, A., 2012, The Real Consequences of Market Segmentation, *Review of Financial Studies*, 25(7), 2041-2069.

[12] Chodorow-Reich, G., 2014, The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-2009 Financial Crisis, *Quarterly Journal of Economics*, 129(1), 1-59.

[13] Covas, F., Den Haan, W. J., 2011, The Cyclical Behavior of Debt and Equity Finance, *American Economic Review*, 101, 877-899.

[14] Dell'Ariccia, G., Marquez, R., 2006, Lending Booms and Lending Standards, *Journal of Finance*, 61, 2511-2546.

[15] Diamond, D., Rajan, R. G., 2011, Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes, *Quarterly Journal of Economics*, 126(2), 557-591.

[16] Drehmann, M., Borio, C. E., Tsatsaronis, K., 2012, Characterising the Financial Cycle: Don't Lose Sight of the Medium Term!, Unpublished Manuscript.

[17] Ellul, A., Jotikasthira, P., Lundblad, C. T., 2011, Regulatory Pressure and Fire Sales in the Corporate Bond Market, *Journal of Financial Economics*, 101, 596-620.

[18] Gilchrist, S., Yankov, V., Zakrajšek, E., 2009, Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets, *Journal of Monetary Economics* 56, 471-493.

[19] Gilchrist, S., Zakrajšek, E., 2012, Credit Spreads and Business Cycle Fluctuations, *American Economic Review* 102(4), 1692-1720.

[20] Giovannini, A., Mayer, C., Micossi, S., Di Noia, C., Onado, M., Pagano, M., Polo, A., 2015, Restarting European Long-Term Investment Finance: A Green Paper Discussion Document, CEPR Press.

[21] Guiso, L., Sapienza, P., Zingales, L., 2013, Time Varying Risk Aversion, EIEF Working Paper No. 22/13.

[22] Iyer, R., Peydró, J.L., da-Rocha-Lopes, S., Schoar, A., 2014, Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007–2009 Crisis, *Review of Financial Studies*, 27(1), 347-372.

[23] Jermann, U., Quadrini, V., 2012, Macroeconomic Effects of Financial Shocks, *American Economic Review*, 102(1), 238-271.

[24] Jiménez, G., Ongena, S., Peydró, J.L., Saurina, J., 2012, Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications, *American Economic Review*, 102(5), 2301–2326.

[25] Jiménez, G., Ongena, S., Peydró, J.L., Saurina, J., 2014, Hazardous Times for Monetary Policy: What do 23 Million Loans Say About the Impact of Monetary Policy on Credit Risk-Taking?, *Econometrica*, 82(2), 463–505.

[26] Kara, A., Marques-Ibanez, D., Ongena, S., 2015, Securitization and Lending Standards: Evidence from the European Wholesale Loan Market, Unpublished Manuscript.

[27] Kashyap, A. K., Stein, J. C., 2004, Cyclical Implications of the Basel II Capital Standards, *Federal Reserve Bank of Chicago: Economic Perspectives*, (1), 18-31.

[28] Keys, B. J., Mukherjee, T., Seru, A., Vig, V., 2010, Did Securitization Lead to Lax Screening? Evidence from Subprime Loans, *Quarterly Journal of Economics*, 125(1), 307-362.

[29] Kisgen, D. J., 2006, Credit Ratings and Capital Structure, *Journal of Finance*, 61(3), 1035-1072.

[30] Kisgen, D. J., Strahan, P. E., 2010, Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital, *Review of Financial Studies*, 23(12), 4324-4347.

[31] Khwaja, A. I., Mian, A., 2008, Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market, *American Economic Review*, 98(4), 1413-1442.

[32] Maddaloni, A., Peydro, J. L., 2011, Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the US Lending Standards, *Review of Financial Studies*, 24(6), 2121-2165.

[33] McCrary, J., 2008, Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test, *Journal of Econometrics*, 142(2), 698-714.

[34] Martin, A., 2008, Endogenous Credit Cycles, Unpublished Manuscript.

[35] Panetta, F., Schivardi F., Shum, M., 2009, Do Mergers Improve Information? Evidence from the Loan Market, *Journal of Money, Credit and Banking*, 41(4), 673-709.

[36] Paravisini, D., Schoar, A., 2013, The Incentive Effect of Scores: Randomized Evidence from Credit Committees, Unpublished Manuscript.

[37] Peek, J., Rosengren, E., 2000, Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States, *American Economic Review*, 90, 30-45.

[38] Repullo, R., Suarez, J., 2013, The Procyclical Effects of Bank Capital Regulation, *Review of Financial Studies*, 26(2), 452-490.

[39] Rodano, G., Serrano-Velarde, N., Tarantino, E., forthcoming, Bankruptcy Law and Bank Financing, *Journal of Financial Economics*.

[40] Ruckes, M., 2004, Bank Competition and Credit Standards, *Review of Financial Studies*, 17(4), 1073-1102.

[41] Sapienza, P., 2002, The Effects of Banking Mergers on Loan Contracts, *Journal of Finance* 57, 329-367.

[42] Stein, J. C., 2002, Information Production and Capital Allocation: Decentralized versus Hierarchical Firms, *Journal of Finance*, 57(5), 1891-1921.

[43] Standard & Poor's, 2004, Credit Risk Tracker Italy, Standard & Poor's Risk Solutions.

[44] Unicredit Bank, 2008, Unicredit S.p.A. 2008 Annual Report.

A Tables and Figures

Table I: Descriptive Statistics

	All	Performing	Sub-Standard	Score 6	Score 7	Naïve 6-7
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Loan Information			
Term Loans: Interest Rate	4.57	4.32	5.3	4.79	5.29	-.48***
	(1.62)	(1.56)	(1.6)	(1.58)	(1.59)	
Term Loans: Amount	816	885	617	451	569	-118
	(9850)	(5156)	(17300)	(1623)	(17700)	
Term Loans: Maturity	.66	.66	.65	.77	.72	.05***
	(.47)	(.47)	(.48)	(.44)	(247)	
N	253502	188026	65475	49265	60326	109591
			Panel B: Aggregate Financing Information			
All Bank Financing Granted	8503	9237	6167	7542	6392	1150***
	(37200)	(40600)	(23100)	(24600)	(21100)	
Share of Term Loans Granted	.35	.35	.36	.33	.35	-.02***
	(.25)	(.25)	(.25)	(.21)	(.25)	
Share of Write-downs	.01	.01	.03	.00	.01	-.01***
	(.09)	(.04)	(.17)	(.05)	(.09)	
N	543855	414041	129754	63722	104253	167975
			Panel C: Balance Sheet Information			
Employment	92	95	76	73	72	1
	(294)	(295)	(290)	(170)	(207)	
Investment to Assets	.05	.05	.04	.04	.039	.001**
	(.06)	(.06)	(.06)	(.06)	(.06)	
Return to Assets	.05	.07	.00	.05	.03	.02***
	(.10)	(.08)	(.13)	(.07)	(.07)	
Leverage	.67	.61	.86	.79	.85	-.06***
	(.19)	(.18)	(.10)	(.10)	(.09)	
N	143953	108353	35600	16432	27350	43782

Notes: All panels use data for the period 2004.Q1–2011.Q4, and monetary values expressed in KE (1,000 Euro). Standard deviations are reported in brackets. The last column reports the difference in means of each variable between categories 6 and 7. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level. Panel A uses pooled loan-level data with observations at the loan-quarter level. *Interest Rate* is the gross annual interest rate inclusive of participation fees, loan origination fees, and monthly service charges. *Amount* is the granted amount of the issued term loan. *Maturity* is a binary variable indicating whether the maturity of the newly issued loans is up to one year, or longer. Panel B uses the credit register data with observations at the firm-quarter level. *All Bank Financing Granted* is the firms' total amount of bank financing granted for all categories (loans, credit lines, backed loans). *Share of Used to Granted Financing* is the firms' total amount of bank financing granted for all categories, divided by the firms' total amount of bank financing drawn down for all categories. *Share of Term Loans Granted* is the firms' total amount of term loans granted, divided by the total amount of bank financing granted for all categories. *Share of Write-downs* is a binary variable indicating whether the firms' total amount of bank financing granted for all categories has experienced write-downs by banks. Panel C uses the balance sheet and cash flow statements at the firm-year level. *Employment* is defined as the firms' average employment over the year. *Investment to Assets* is defined as the firms' investment in material fixed assets over total fixed assets. *Returns to Assets* is defined as the firms' earnings before interest and taxes, over total assets. *Leverage* is defined as the firms' ratio of debt (both short- and long-term) over total assets. In all panels, N corresponds to the pooled number of observations in our sample.

Table II: Real Effects

Period	2004	2005	2006	2007	2008	2009	2010	2011
Sales	.21	.22	.23	.07	.51***	.42**	.40**	.13
	(.21)	(.18)	(.17)	(.17)	(.18)	(.18)	(.20)	(.21)
R-squared	.04	.04	.04	.03	.04	.04	.02	.01
N	5951	5875	6097	6512	5549	5358	4307	4109
Investment	.31	.19	-.28	.43	.71**	.19	-.01	.2
	(.30)	(.30)	(.28)	(.31)	(.32)	(.32)	(.32)	(.35)
R-squared	.01	.01	.01	.01	.01	.00	.00	.00
N	5085	5116	5033	4104	4952	4491	3677	3614
Intermediates	.15	.23	.15	.00	.54***	.29	.38*	.06
	(.22)	(.19)	(.18)	(.18)	(.19)	(.19)	(.21)	(.22)
R-squared	.04	.03	.03	.03	.04	.03	.02	.01
N	5852	5786	6013	6398	5454	5275	4256	4061
Employment	-.01	-.14	.04	.14	.25	-.09	.4*	-.23
	(.22)	(.20)	(.19)	(.17)	(.22)	(.25)	(.23)	(.27)
R-squared	.01	.01	.01	.01	.01	.01	.00	.01
N	2911	2846	2980	3137	2623	2386	2148	1922

Notes: The table reports estimates from regressions which use either *Sales*, *Investment*, *Intermediates*, *Employment* in logs as a dependent variable for each year between 2004–2011. Standard errors are reported in brackets. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s \geq 0$, i.e., if the firm is allocated to the performing class as opposed to the substandard class. *Sales* corresponds to the total value of production.*Investment* is the value of the firm's the investment in material assets. Finally, we analyze the value of the *Intermediates* factors of production. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table III: Revoling Credit Lines and Rejections

Period	2004	2005	2006	2007	2008	2009	2010	2011
Revolving	.26	.13	.02	-.04	.43**	.17	.17	.07
	(.25)	(.20)	(.05)	(.18)	(.18)	(.19)	(.21)	(.22)
N	5611	5609	5825	6224	5309	5079	4087	3935
Rejected	.02	-.01	.02	-.03	.02	-.1*	-.02	.11
	(.05)	(.06)	(.05)	(.05)	(.06)	(.06)	(.09)	(.1)
N	3947	4028	4419	4673	3817	3503	3078	2670

Notes: The table reports estimates from regressions which use *Revolving*, and *Rejected* as a dependent variable for each year between 2004–2011. *Revolving* is the (log) total amount of revolving credit lines granted. *Rejected* is a binary variable equal to one if any non-current bank requested information on the firm, but did not grant credit to the applicant within the next two quarters. We report the standard errors in brackets. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the normalized threshold between each continguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the lower credit risk category as opposed to the higher credit risk category. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table IV: Credit Allocation Based, Bank Liquidity and Bank Capitalization

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Exposure to Interbank Market				
Low Exposure	.03	-.23	.01	-.2	.75***	.02	.28	-.1
	(.2)	(.22)	(.18)	(.2)	(.22)	(.24)	(.23)	(.26)
N	3605	3656	3988	4362	3491	3329	2733	2713
High Exposure	.08	.15	.05	.03	.49**	.46**	.32	.1
	(.23)	(.19)	(.16)	(.18)	(.2)	(.2)	(.23)	(.24)
N	5369	5359	5601	5981	5081	4828	3776	3499
				Equity Ratio				
Low Ratio	.04	.07	-.02	.03	.49***	.17	.2	.1
	(.25)	(.22)	(.15)	(.19)	(.18)	(.21)	(.22)	(.25)
N	5411	5413	5625	5947	5119	4845	3751	3577
High Ratio	0	.07	-.07	-.05	.8***	.2	.15	.17
	(.23)	(.24)	(.18)	(.21)	(.21)	(.19)	(.22	(.27)
N	3291	3293	3518	4578	3334	3292	2789	2379
				Bank Size				
Large Banks	.14	.29	-.04	-.05	.51**	.41**	.17	.15
	(.22)	(.21)	(.16)	(.18)	(.21)	(.2)	(.22)	(.24)
N	5494	5491	5700	6102	5189	4938	4018	3837
Small Banks	.13	.09	.07	-.16	.38*	.1	-.02	-.18
	(.2)	(.24)	(.21)	(.19)	(.21)	(.21)	(.25)	(.23)
N	3860	3872	4093	4423	3817	3653	3016	2936

Notes: The table reports estimates from regressions that split the sample according to the credit conditions granted to a firm by a bank with higher (respectively, lower) exposure to the interbank market, capital ratio, size. *Exposure to Interbank Market* is measured as the ratio of interbank financing divided by total assets. Bank capitalization is measured as *Equity Ratio*, which is constructed as the ratio of book equity to total assets. These bank balance sheet variables are measured at the end of the second quarter of 2007. *Bank Size* is defined on the basis of total bank financing granted to SMEs, with *Large Banks* belonging to the top decile of the distribution. The dependent variable *All Bank Financing Granted* (Quantity) refers to financing from each category of banks between 2004–2011. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the normalized threshold between each continguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the lower credit risk category as opposed to the higher credit risk category. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table V: Banks' Cost of Financing and Rating Segmentation

	Cost of Financing	
	(1)	(2)
Substandard to Total Credit	1.26***	1.24*
	(.46)	(.66)
Continuous Variable 1		-.2
		(.15)
Continuous Variable 2		.09
		(.31)
Bank Characteristics	Yes	Yes
Monthly Fixed Effects	Yes	Yes
R-squared	.76	.76
N	4788	4728

Notes: The table reports estimates from regressions which use as a dependent variable the (volume) weighted average interest rate at which banks raised financing across different types of investors (repo markets, households, firms) between 2004 and 2011. $\left(\frac{Substandard}{Total}\right)_{it-1}$ is the share of a bank's volume of lending to SMEs in the "substandard" rating class relative to total lending. *Continous Variable 1* denotes the mean of the continuous variable of firms in rating categories 1 to 5. *Continous Variable 2* denotes the mean of the continuous variable of firms in rating categories 6 to 9. The specification includes a vector of bank and issuance characteristics. Issuance characteristics include amounts raised, maturity, and investor composition. Bank characteristics include size (in terms of total assets), the value of tier 1 capitalization ratio, and the bank's liquidity ratio. The specification includes monthly fixed effects, with standards errors are corrected for clustering at the bank level. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VI: Self Selection Into Ratings 6 and 7

Period	2004	2005	2006	2007	2008	2009	2010	2011
Mc Crary Density Estimate	.10	.13	.02	.08	.3***	-.00	.08	.17
	(.06)	(.07)	(.07)	(.06)	(.07)	(.08)	(.10)	(.10)
N	5951	5876	6098	6514	5551	5360	4307	4110

Notes: The table reports, at a yearly level, the McCrary density estimates of the continuous variable's distribution. For each year we run a kernel local linear regression of the log of the density on both sides of the threshold, separating substandard firms in category 7 from performing firms in category 6. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VII: Model Diagnostics - Balancing Checks

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Panel A: Pre-Sample Characteristics				
Leverage	0	.01	-.04	-.03	.05	-.01	-.04	.01
	(.03)	(.04)	(.03)	(.03)	(.04)	(.04)	(.05)	(.06)
N	3967	3636	3595	3678	2888	2705	2168	2024
Return to Assets	0	0	0	-.01	-.02	0	0	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)
N	5306	4844	4750	4836	3776	3504	2721	2508
Investment to Assets	.02	.02	.01	.02	.02	-.02	-.03	-.02
	(.01)	(.02)	(.01)	(.02)	(.02)	(.02)	(.03)	(.02)
N	4501	4136	4083	4174	3353	3100	2414	2237
				Panel B: Bank Balancing Characteristics				
Non Performing		.01	0	.01	0	-.01	0	-.03
		(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.03)
N		5736	5944	6358	5411	5276	4235	4045
Asked	.02	0	-.02	-.07	-.03	.04	.03	-.07
	(.04)	(.05)	(.04)	(.05)	(.04)	(.04)	(.05)	(.05)
N	5687	5677	5889	6306	5370	5264	4217	4030
Bank Size	-.12	-.05	-.02	.23**	.1	.09	.04	.23
	(.14)	(.14)	(.11)	(.12)	(.14)	(.17)	(.19)	(.18)
N	5652	5641	5855	6287	5356	5108	4105	3937
				Panel C: Time Invariant Characteristics				
Activity: Food Industry	.03	-.04	.03	-.01	.05	.04	.06	-.06
	(.04)	(.05)	(.04)	(.04)	(.04)	(.04)	(.06)	(.06)
N	5951	5876	6098	6514	5551	5360	4307	4110
Location: Top 5 Cities	.06	.03	.05	-.06	.02	-.01	.07	.05
	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.08)	(.07)
N	5951	5876	6098	6514	5551	5360	4307	4110

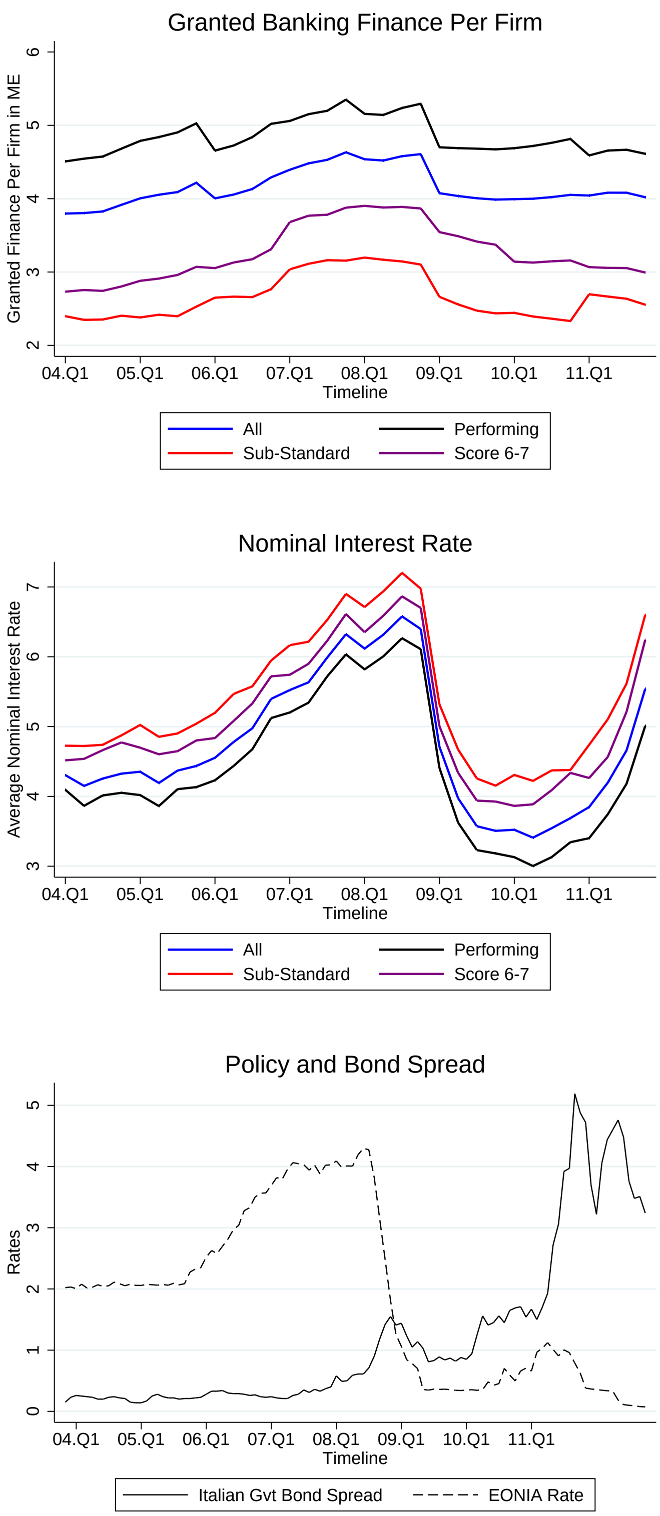
Notes: The table estimates differences in pre-sample firm characteristics at the threshold. We report the standard errors in brackets. In all rows, the dependent variable is measured in 2003. The discontinuity is estimated using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing class as opposed to the substandard class. *Non Performing* is a binary variable equal to one if any of a given firm's banks classified the firm's credit as non-performing. *Asked* is a binary variable equal to one if any non-current bank requested information on the firm during the year. *Food Industry* is a binary variables indicating whether the firms' SIC code belongs to the food industry. *Top 5 Cities* is a binary variable indicating whether the firms' headquarter zip code is in one of the largest 5 cities. See Tables I, and IV for the definition of the other variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table VIII: Yearly RDD Estimates - Other Thresholds

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Threshold Between Categories 1 and 2				
Quantity	-.3	-.15	.07	.17	-.28	-.19	-.3	-.32
	(.24)	(.26)	(.26)	(.31)	(.27)	(.25)	(.23)	(.21)
N	2555	2693	2648	2684	2886	2975	2677	2773
Price	.04	.13	.08	.03	-.12	-.23	-.04	-.22
	(.11)	(.12)	(.11)	(.08)	(.08)	(.2)	(.18)	(.22)
N	583	716	782	815	715	712	832	775
				Threshold Between Categories 2 and 3				
Quantity	-.12	-.19	-.45	-.3	-.25	-.2	-.45	-.51
	(.39)	(.4)	(.39)	(.35)	(.41)	(.34)	(.36)	(.35)
N	2311	2508	2480	2383	2265	2243	2243	2375
Price	0	.16	-.1	.01	-.02	-.1	-.23	.7***
	(.13)	(.12)	(.11)	(.08)	(.14)	(.27)	(.22)	(.22)
N	1099	1427	1595	1702	1475	1260	1406	1825
				Threshold Between Categories 3 and 4				
Quantity	-.24	-.03	-.14	.29	.11	-.29	-.15	.29
	(.31)	(.3)	(.35)	(.29)	(.33)	(.32)	(.29)	(.3)
N	6087	6361	6371	6526	6040	5968	5840	6128
Price	-.03	.03	.09	-.03	-.08	-.01	-.12	-.03
	(.08)	(.09)	(.08)	(.04)	(.06)	(.13)	(.15)	(.12)
N	7197	9359	10255	10547	9033	8625	11153	13158
				Threshold Between Categories 4 and 5				
Quantity	-.33	.22	-.44*	-.18	-.2	-.06	-.26	-.41*
	(.24)	(.24)	(.24)	(.21)	(.24)	(.24)	(.24)	(.23)
N	7019	7359	7437	7616	6960	6878	6711	7058
Price	0	-.05	.03	-.01	0	-.02	-.23***	.07
	(.05)	(.06)	(.04)	(.03)	(.03)	(.1)	(.08)	(.07)
N	11072	14972	16561	17056	14662	13505	17687	19743
				Threshold Between Categories 7 and 8				
Quantity	-.25	-.28	-.29	-.06	-.36	-.63	1.44*	1.01
	(.48)	(.51)	(.55)	(.55)	(.63)	(.66)	(.73)	(.88)
N	4160	4136	4256	4602	3752	3472	2875	2688
Price	0	-.2	.1	-.22**	-.08	.35*	-.56	-.12
	(.19)	(.17)	(.11)	(.09)	(.1)	(.2)	(.56)	(.27)
N	6058	8394	10412	13192	8280	6047	5883	5791
				Threshold Between Categories 8 and 9				
Quantity	-.9	.18	.51	-1.31	-1.26	-.42	-.97	-1.68
	(1.4)	(1.16)	(1.12)	(1.36)	(1.09)	(1.24)	(.95)	(1.2)
N	596	649	598	646	595	668	517	616
Price	-1.29	-.01	.21	.09	-.02	.07	.4	-.31
	(54.98)	(.53)	(.26)	(.27)	(.13)	(.5)	(.47)	(.4)
N	380	494	655	761	518	701	471	489

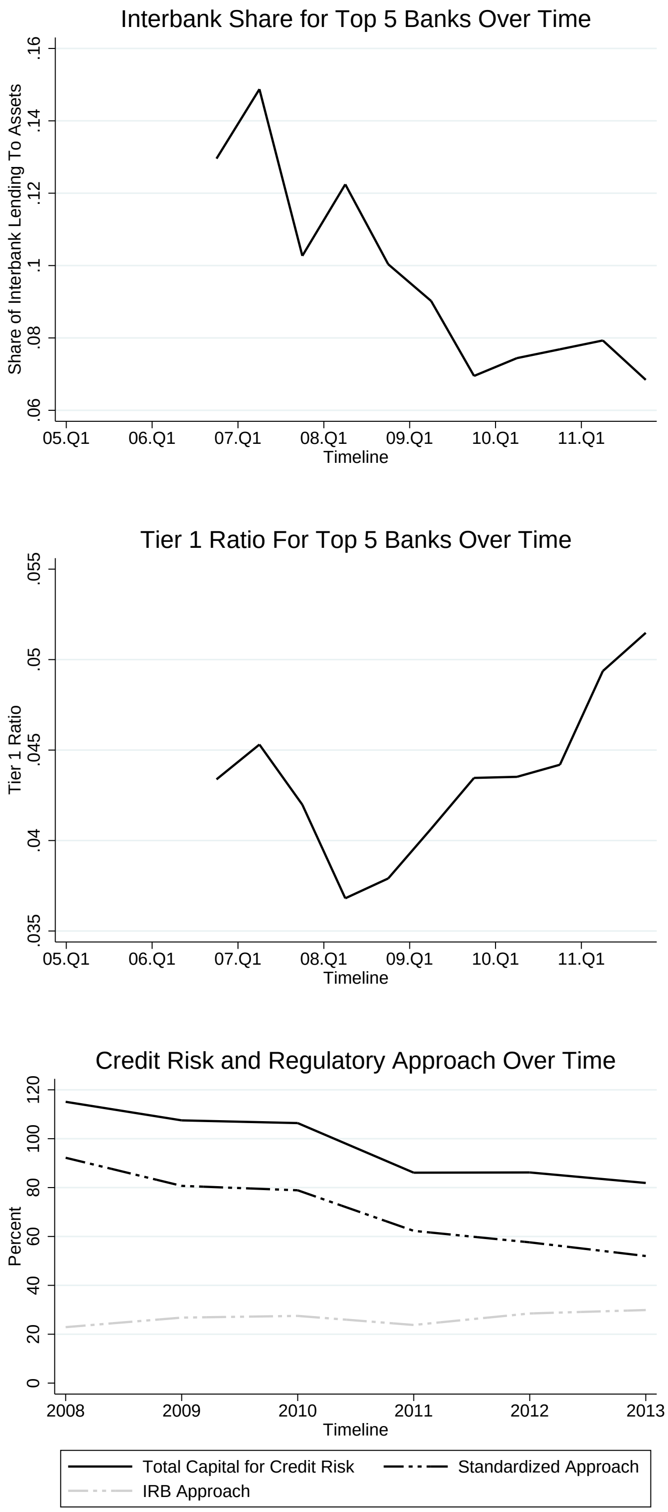
Notes: The table reports estimates from our baseline specification at all the seven thresholds associated to the categorical value of the rating system. We report standard errors in brackets. The dependent variable we use is either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each year between 2004.Q1–2011.Q4. We estimate the discontinuity ($s_i \geq 0$) using a flexible sixth-order polynomial on either side of each normalized threshold between each contiguous *Score* category, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the lower credit risk category as opposed to the higher credit risk category. See Table I for the definition of the variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Figure 1: Descriptive Statistics Across Time



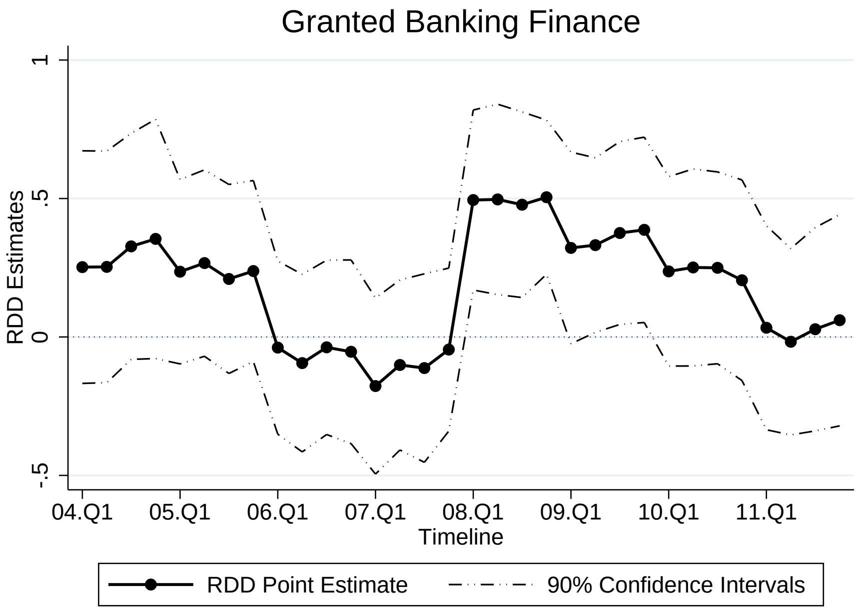
In the upper panel we plot the per-firm aggregate value of bank financing for different rating categories across time. In the middle panel we plot nominal average interest rates applied to firms in different rating categories across time. In the bottom right panel we plot the ten-year Italian government bond interest rate together with the Euro overnight index average rate.

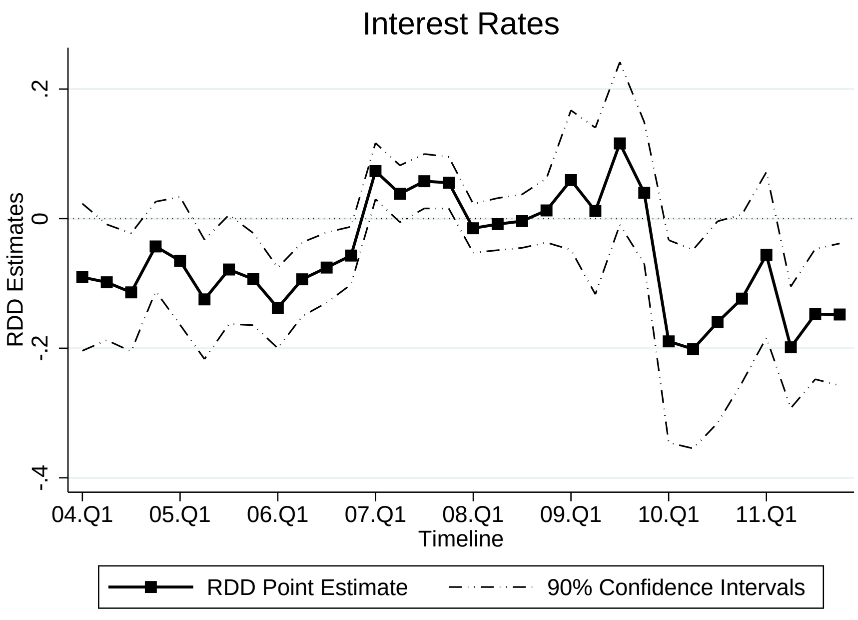
Figure 2: Bank Capital and Credit Risk



In the top panel we plot the amount of financing raised by Italian banks on the interbank market as a fraction of their total assets. In the middle panel we plot the tier 1 capital ratio for the 5 largest banks in our dataset across time. In the bottom panel we use data from the ECB statistical data warehouse to plot the credit risk capital allocations over total capital requirements (black line), the fraction of capital allocations computed using the standardised approach (grey line) and the fraction computed using the internal rating based approach (dashed line).

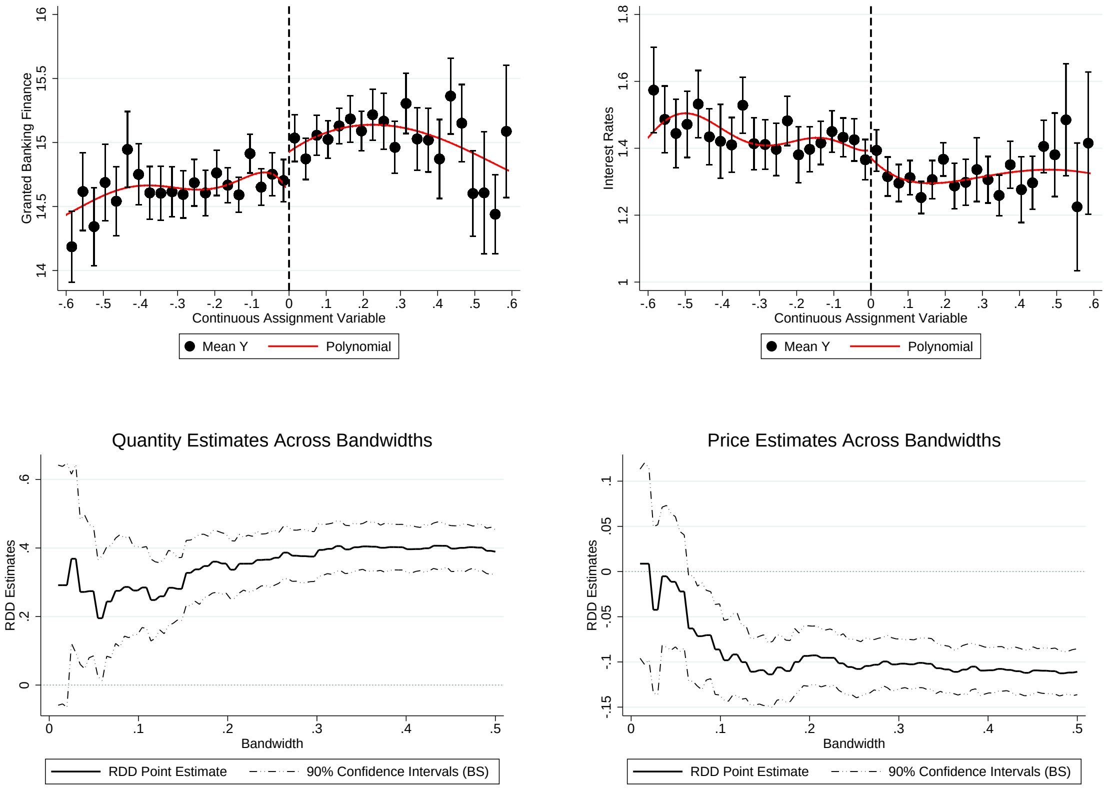
Figure 3: RDD Quantity and Price Treatment Effects





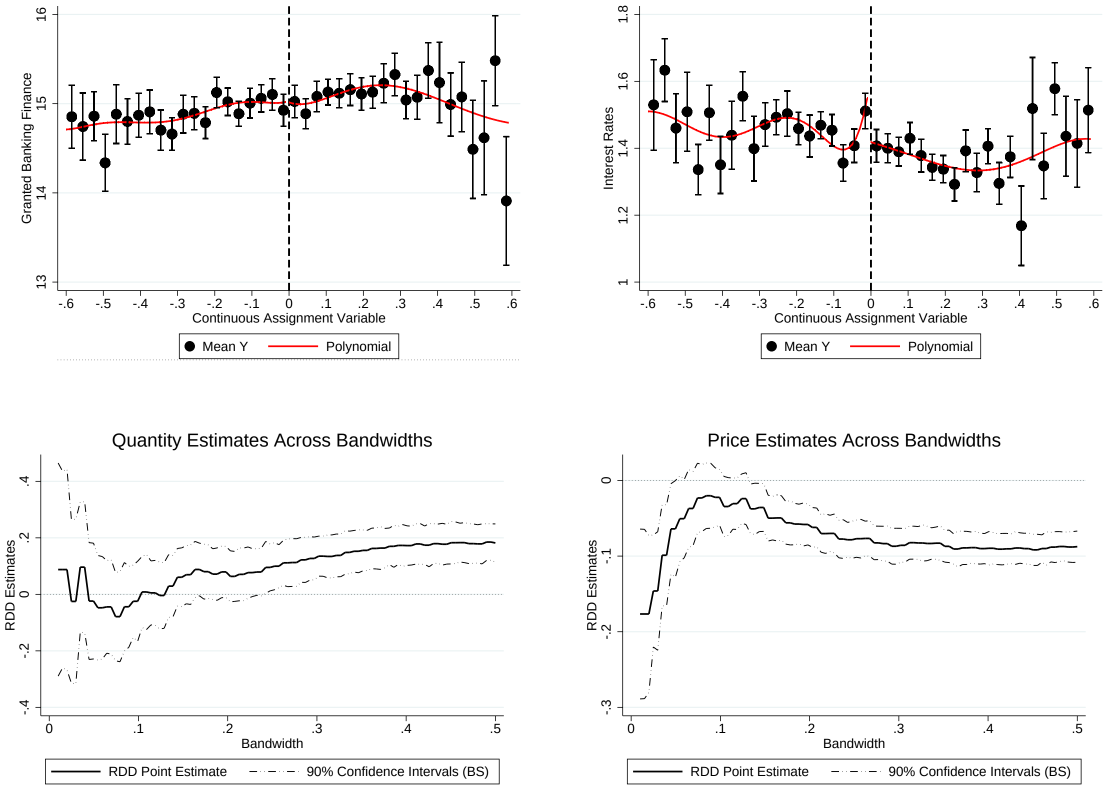
The figure plots the quarterly discontinuity estimates and 90% confidence intervals of specification (1) using either *All Banking Financing Granted* (top panel) or *Interest Rate* (bottom panel) as a dependent variable between 2004.Q1–2011.Q4. The plotted estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing class as opposed to the substandard class.

Figure 4: 2nd Quarter of 2009



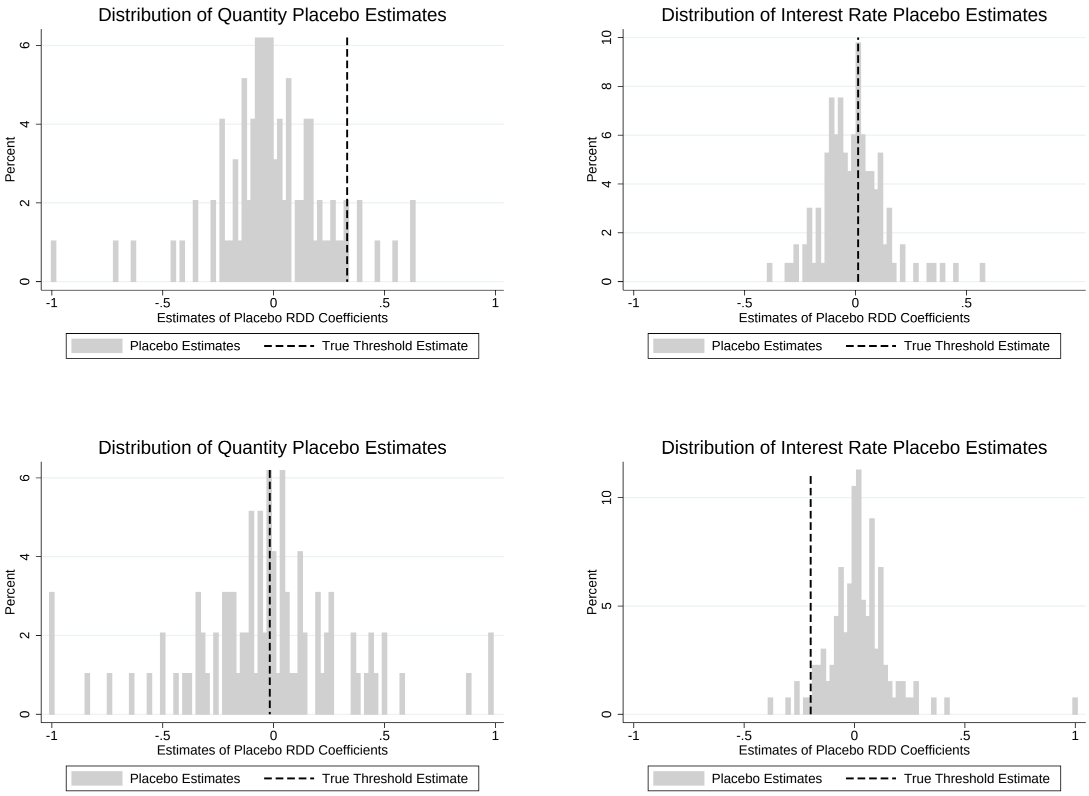
The figure focuses on the second quarter of 2009. The top panel divides the domain of s_i into mutually exclusive bins with size of 0.03. For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth order polynomial approximates the variation of bank financing conditions at the threshold. The middle panels estimate a simple mean difference specification for increasingly larger bins ($\pm h$) around the threshold. The value of γ is reported on the vertical axis, while the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the estimated value of γ as function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors. The bottom panels plot the empirical distribution of estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold.

Figure 5: 2nd Quarter of 2011



The figure focuses on the second quarter of 2011. The top panel divides the domain of s_i into mutually exclusive bins with size of 0.03. For each bin, we compute the average and the standard deviation of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth order polynomial approximates the variation of bank financing conditions at the threshold. The middle panels estimate a simple mean difference specification for increasingly larger bins ($\pm h$) around the threshold. The value of γ is reported on the vertical axis, while the width of the bins around the threshold is reported on the horizontal axis. The solid line represents the estimated value of γ as function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors. The bottom panels plot the empirical distribution of estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold.

Figure 6: Placebo Estimates - 2nd Quarters of 2009 (top panel) and 2011 (bottom panel)



The figure plot the empirical distribution of estimates based on approximately 100 randomly drawn placebo thresholds. The vertical dotted line represents the estimate obtained from the true threshold. The top panel figure focuses on the second quarter of 2009, while the bottom panel focuses on the second quarter of 2011.

B Online Appendix: Data Organization

We first describe the characteristics of the datasets used in the empirical analysis, and then provide the definition of the variables that we construct from these sources.

B.1 The Central Credit Register

Each month all financial intermediaries operating in Italy (banks, special purpose vehicles, other financial intermediaries providing credit) report financial information to the Bank of Italy for each borrower whose aggregate exposure exceeds 75,000 Euro.[20] Thus, we can use the central credit register to compute the aggregate financial characteristics of firms. For each borrower-bank relationship, we have information on financing levels, granted and utilized, for three categories of financial instruments: term loans, revolving credit lines, and loans backed by account receivables (advances on trade credit). The information on term loans is supplemented by other non-price characteristics, such as loan maturity and the presence or the absence of real and personal guarantees.

B.2 Taxia

Taxia is a subset of the Central Credit Register that covers information on more than 80% of total bank lending in Italy. More specifically, this dataset provides us with detailed quarterly information on the interest rates that banks charge to individual borrowers on each newly issued term loan. In addition, the dataset provides information on the maturity and presence of real collateral for each newly issued term loan.

Our analysis focuses on limited liability firms in the manufacturing sector in the 32 quarters between the beginning of 2004 and the end of 2011. We drop all new loans with an amount smaller than 10,000 Euro and the extreme percentiles of the term loan interest-rate distribution. Finally, we focus on those firms that fall in the same rating category for two consecutive years. This ensures that our results do not simply capture the effect of a firm's upgrade or downgrade over time. Yet, the qualitative nature of our results remains the same when we include the firms that change risk categories in two consecutive years in the sample used to run our empirical analysis.

[20]During the sample period, the threshold for the aggregate financial exposure above which banks had to report the borrower information to the Bank of Italy changed for administrative reasons. To keep the scope of the sample constant across time, we focus on firms whose aggregate exposure exceeded 75,000 Euro across our sample period.

B.3 Definition of Variables

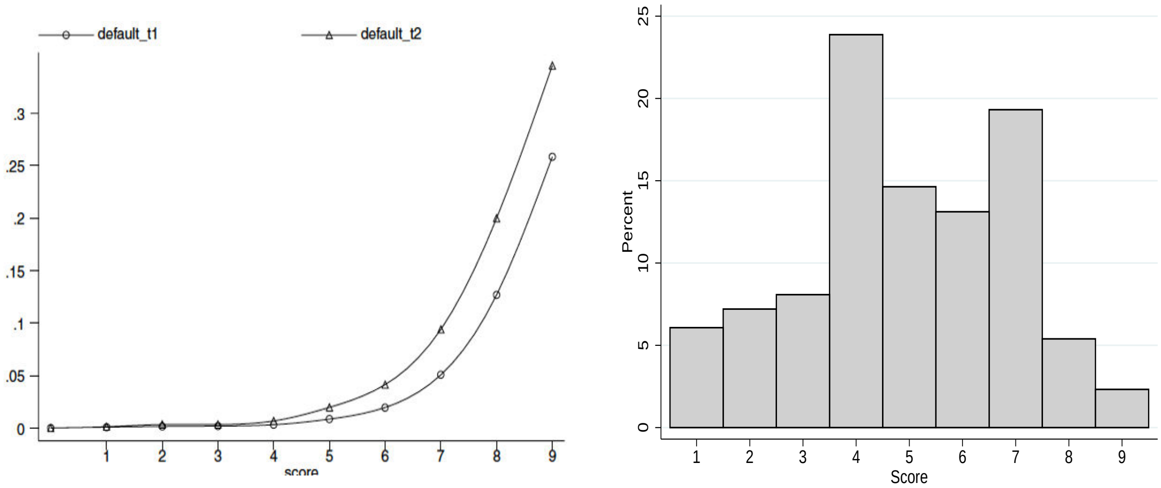
We use information from the Taxia dataset to compute variables describing each bank financing contract. *Loan Interest Rate* computes the gross annual interest rate for each newly issued term loan, inclusive of participation fees, loan origination fees, and monthly service charges. This rate is calculated so that the present value of loan installments equals the present value of payments at loan origination. We also have information on the following term loan characteristics: *Amount* is the granted amount of the issued term loan and *Maturity* is a set of binary variables indicating whether the maturity of the newly issued loan is up to one year, between one and five years, or more than five years.

We use information from the Credit Register to compute aggregate variables describing the financial structure of firms. *All Bank Financing Granted* is the firm's total bank financing granted including term loans, credit lines and advances on trade credit. *Share of Used to Granted Financing* is the firm's total used bank financing, divided by the total granted bank financing to the firm. *Share of Term Loans Granted* is the firm's total term loans, divided by the total amount of bank financing granted to the firm. *Share of Write-downs* is the firm's total bank financing that has been written down by banks, divided by the total amount of bank financing granted to the firm.

We use information in the *CEBI* database to compute firm's balance sheet characteristics. *Employment* is the firm's number of employees at the beginning of the year. *Investment to Assets* is the firm's investment in material fixed assets divided by material fixed assets. *Return to Assets* is the firm's earnings before interest and depreciation divided by total assets. *Leverage* is defined as the ratio of debt (both short and long term) to total assets.

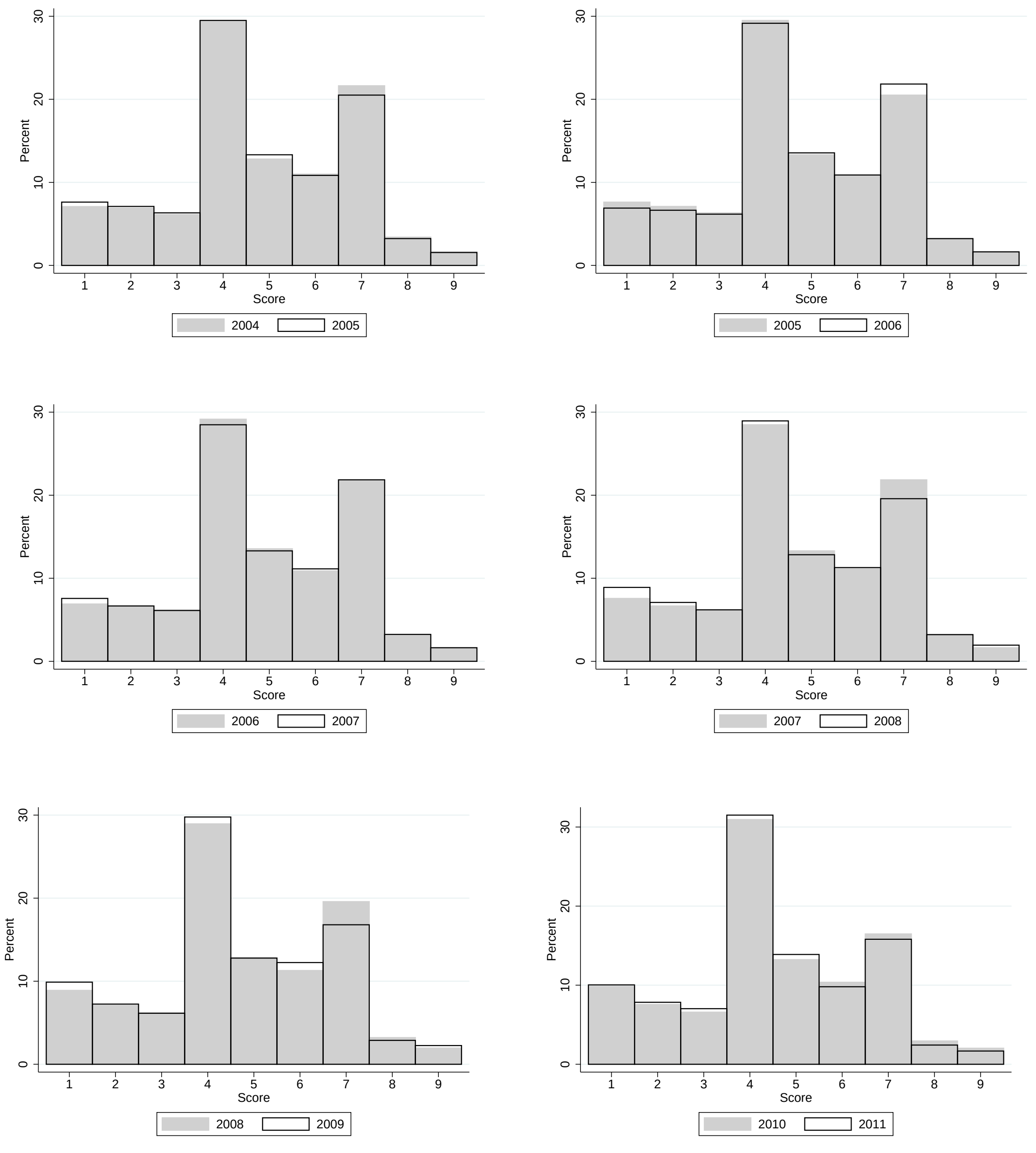
C Online Appendix: Characteristics of the Score Rating System

Figure C1: Characteristics of the Score Assignment Variable



The left panel is taken from Panetta, Schivardi and Shum (2007) who, using the same balance sheet and bank data for the period between 1988 to 1998, plot the *Score* variable against an indicator of default within the next one (circle) and two years (triangle). The right panel plots the share of firms within each *Score* category between 2004 and 2011.

Figure C2: Distribution of Firms in *Score* Rating Categories Over Time



In the figure, we plot of the share of firms within each *Score* category in two consecutive years for the period between 2004 and 2011.

D Online Appendix: Additional Results

Table D1: Credit Allocation

Period	04.Q1	04.Q2	04.Q3	04.Q4	05.Q1	05.Q2	05.Q3	05.Q4	06.Q1	06.Q2	06.Q3	06.Q4	07.Q1	07.Q2	07.Q3	07.Q4
Quantity	.25	.25	.33	.35	.24	.27	.21	.24	-.04	-.09	-.04	-.05	-.18	-.10	-.11	-.04
	(.24)	(.25)	(.25)	(.26)	(.20)	(.21)	(.19)	(.19)	(.20)	(.18)	(.21)	(.20)	(.20)	(.18)	(.19)	(.19)
R-squared	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.03	.03	.02	.02	.02	.02
N	5614	5621	5621	5599	5601	5608	5604	5605	5822	5822	5815	5829	6224	6230	6237	6234
Price	-.09	-.10**	-.11**	-.04	-.07	-.13***	-.08*	-.09**	-.14***	-.09***	-.07***	-.06**	.07**	.04	.06**	.05**
	(.07)	(.05)	(.06)	(.05)	(.06)	(.05)	(.05)	(.04)	(.04)	(.04)	(.03)	(.03)	(.03)	(.03)	(.03)	(.02)
R-squared	.17	.18	.18	.16	.15	.17	.17	.19	.17	.15	.14	.15	.14	.14	.13	.12
N	1758	1922	2229	3522	3048	3177	3459	4002	3318	3922	4204	5123	4808	4680	4921	5853

Period	08.Q1	08.Q2	08.Q3	08.Q4	09.Q1	09.Q2	09.Q3	09.Q4	10.Q1	10.Q2	10.Q3	10.Q4	11.Q1	11.Q2	11.Q3	11.Q4
Quantity	.49**	.50***	.48***	.51***	.32	.33*	.37*	.39**	.23	.25	.25	.21	.03	-.02	.03	.06
	(.19)	(.18)	(.18)	(.19)	(.21)	(.20)	(.20)	(.20)	(.21)	(.22)	(.22)	(.20)	(.25)	(.22)	(.23)	(.23)
R-squared	.02	.02	.02	.02	.02	.03	.03	.03	.02	.02	.02	.02	.01	.01	.01	.01
N	5328	5323	5330	5316	5108	5106	5102	5093	4105	4104	4102	4098	3955	3952	3942	3943
Price	-.02	-.01	-.00	.01	.06	.01	.11	.04	-.19*	-.20**	-.16*	-.12	-.06	-.20***	-.15***	-.15**
	(.02)	(.02)	(.02)	(.03)	(.06)	(.07)	(.08)	(.07)	(.10)	(.10)	(.09)	(.08)	(.08)	(.06)	(.06)	(.08)
R-squared	.13	.10	.13	.12	.09	.07	.08	.09	.08	.11	.10	.13	.14	.15	.13	.10
N	3845	3633	3431	3466	2918	2884	2783	3407	2542	2762	2911	3299	3019	2957	3120	2699

Notes: The table reports estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1–2011.Q4. In order to estimate the discontinuity ($s_i \geq 0$) we use a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7, allowing for a discontinuity at 0. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing class as opposed to the substandard class. See Table I for the definition of the variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table D2: Model Diagnostics - Placebo Threshold Estimates

Period	04.Q1	04.Q2	04.Q3	04.Q4	05.Q1	05.Q2	05.Q3	05.Q4	06.Q1	06.Q2	06.Q3	06.Q4	07.Q1	07.Q2	07.Q3	07.Q4
True Threshold: Quantity Estimates	.25	.25	.33	.35	.24	.27	.21	.24	-.04	-.09	-.04	-.05	-.18	-.10	-.11	-.04
Mean of Placebo Estimates	.08	.11	.10	.11	-.09	-.09	-.09	-.03	.011	.03	.01	.03	-.09	-.09	-.09	-.08
Median of Placebo Estimates	.07	.09	.09	.06	-.06	-.02	-.06	-.03	.00	.03	.04	.08	-.03	-.02	-.01	.00
Fraction of Significant Placebo Estimates	.10	.10	.12	.11	.12	.15	.14	.11	.04	.08	.06	.08	.04	.06	.07	.07
Fraction of Placebo Estimates with Opposite Sign	.04	.03	.03	.03	.08	.08	.08	.06	.01	.02	.01	.02	.01	.02	.03	.03
Number of Placebos	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97
True Threshold: Price Estimates	-.09	-.10**	-.11**	-.04	-.07	-.13***	-.08*	-.09**	-.14***	-.09***	-.07***	-.06**	.07**	.04	.06**	.05**
Mean of Placebo Estimates	-.03	.00	-.01	-.01	-.01	.02	-.20	.07	-.01	-.13	1.03	-.01	-.00	.02	-.00	.02
Median of Placebo Estimates	-.00	.02	-.01	-.00	.00	.01	.00	.01	.00	.00	.00	.00	-.00	.01	.00	.00
Fraction of Significant Placebo Estimates	.13	.14	.11	.16	.25	.15	.20	.15	.24	.21	.26	.22	.23	.23	.15	.20
Fraction of Placebo Estimates with Opposite Sign	.05	.00	.00	.08	.15	.00	.11	.00	.00	.00	.00	.00	.12	.10	.07	.10
Number of Placebos	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133

Period	08.Q1	08.Q2	08.Q3	08.Q4	09.Q1	09.Q2	09.Q3	09.Q4	10.Q1	10.Q2	10.Q3	10.Q4	11.Q1	11.Q2	11.Q3	11.Q4
True Threshold: Quantity Estimates	.49**	.50***	.48***	.51***	.32	.33*	.37*	.39**	.23	.25	.25	.21	.03	-.02	.03	.06
Mean of Placebo Estimates	.06	.07	.07	.10	-.00	-.00	.00	.01	.05	.04	.02	.03	-.04	-.04	-.07	-.07
Median of Placebo Estimates	.04	.03	.03	.03	-.02	-.02	.00	-.01	.03	.03	.03	.01	-.04	-.03	-.02	-.02
Fraction of Significant Placebo Estimates	.11	.12	.10	.08	.06	.07	.06	.10	.09	.08	.06	.08	.12	.08	.06	.09
Fraction of Placebo Estimates with Opposite Sign	.02	.02	.01	.00	.04	.05	.04	.05	.04	.03	.02	.03	.05	.04	.03	.04
Number of Placebos	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97	97
True Threshold: Price Estimates	-.02	-.01	-.00	.01	.06	.01	.11	.04	-.19*	-.20**	-.16*	-.12	-.06	-.20***	-.15***	-.15**
Mean of Placebo Estimates	.05	.01	-.02	.07	-.02	-.01	.00	-.02	-.02	-.13	-.05	.01	-.00	.02	-.05	-.04
Median of Placebo Estimates	.00	.00	.00	.00	-.01	-.01	-.01	-.01	-.02	-.02	-.01	.01	-.00	.01	.00	-.00
Fraction of Significant Placebo Estimates	.20	.17	.20	.21	.21	.20	.23	.16	.23	.26	.23	.20	.24	.17	.11	.21
Fraction of Placebo Estimates with Opposite Sign	.09	.04	.11	.09	.14	.10	.11	.09	.00	.00	.00	.11	.11	.00	.00	.00
Number of Placebos	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133	133

Notes: The table reports placebo estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1–2011.Q4. The placebo threshold $\left(\bar{s}^{Placebo}\right)$ is randomly drawn from the support of the continuous variable in *Score* categories 6 and 7. In order to estimate the placebo discontinuity $\left(s_i \geq \bar{s}^{Placebo}\right)$ we use a flexible sixth-order polynomial on either side of the threshold $\left(\bar{s}^{Placebo}\right)$, allowing for a discontinuity at $\left(\bar{s}^{Placebo}\right)$. The reported estimates refer to the placebo variable $S_i^{Placebo}$, a binary variable that takes value of one if the continuous variable $s_i \geq \bar{s}^{Placebo}$. See Table I for the definition of the variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level

Table D3: Local Polynomial Regression

Period	2004	2005	2006	2007	2008	2009	2010	2011
				Conventional				
Quantity	.29***	.15**	.07	-.13*	.22***	.27***	-.01	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03**	-.03***	-.05***	-.01	.01	-.02	-.07***	-.02**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9431	13686	16567	20262	14375	11992	11478	11795
				Bias-Corrected				
Quantity	.32***	.12	-.09	-.2**	.19***	.22***	.09	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03***	-.03***	-.06***	0	.01*	-.01	-.11***	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9431	13686	16567	20262	14375	11992	11478	11795
				Bias-Corrected and Robust Standard Errors				
Quantity	.32***	.12	-.09	-.2**	.19*	.22**	.09	-.06
	(.11)	(.1)	(.12)	(.09)	(.1)	(.11)	(.11)	(.11)
N	5657	5652	5870	6274	5356	5136	4126	3969
Price	-.03**	-.03***	-.06***	0	.01	-.01	-.11***	0
	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)
N	9431	13686	16567	20262	14375	11992	11478	11795

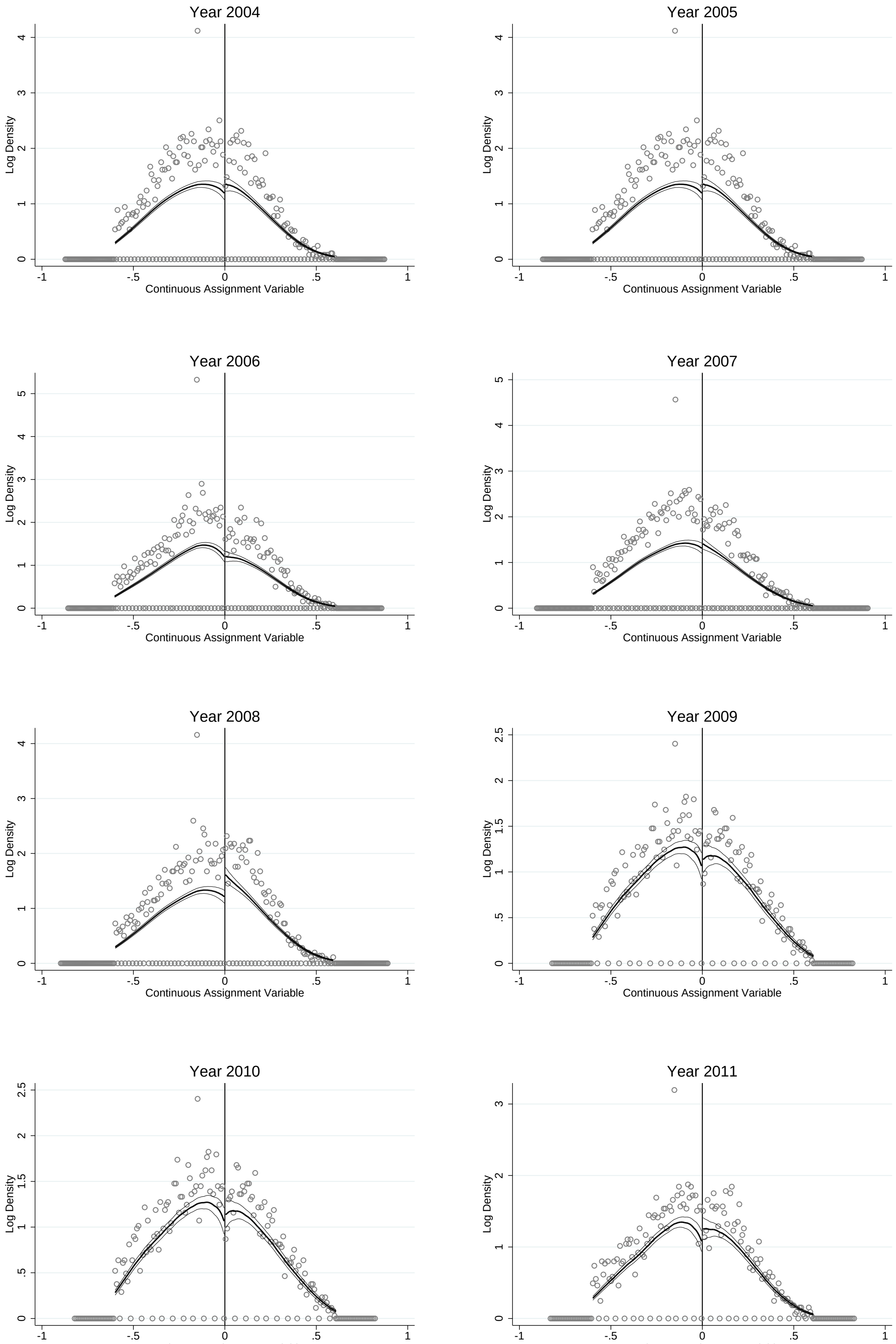
Notes: The table reports estimates from regressions which use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each year between 2004–2011. In order to estimate the discontinuity ($s_i \geq 0$) we use a local polynomial regression. The estimator is linear with a local-quadratic bias correction and a triangular kernel. The bandwidth is chosen following Imbens and Kalyanaraman (2012). Consistent with Calonico, Cattaneo, and Titiunik (2014), we present conventional discontinuity estimates with a conventional variance estimator, the bias-corrected estimates with a conventional variance estimator, and the bias-corrected estimates with a robust variance estimator. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the lower credit risk category as opposed to the higher credit risk category. See Table I for the definition of the variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Table D4: Model Diagnostics - Additional Balancing Checks

Period	2004	2005	2006	2007	2008	2009	2010	2011
Cash Holdings	.02	0	.01	.01	-.01	-.04	-.02	0
	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)	(.03)	(.03)
N	4750	4380	4317	4364	3422	3147	2487	2297
Automobile Industry	.01	.02	.00	.00	-.03	.00	.01	-.02
	(.02)	(.02)	(.01)	(.00)	(.03)	(.02)	(.02)	(.02)
N	5951	5876	6098	6514	5551	5360	4307	4110
Top 10 Cities	.05	.01	.02	-.04	.02	-.02	.11	.07
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.09)	(.08)
N	5951	5876	6098	6514	5551	5360	4307	4110
Firm Clusters	.07	.06	.09	.03	.01	.06	.05	.01
	(.07)	(.07)	(.07)	(.06)	(.07)	(.07)	(.08)	(.08)
N	5951	5876	6098	6514	5551	5360	4307	4110

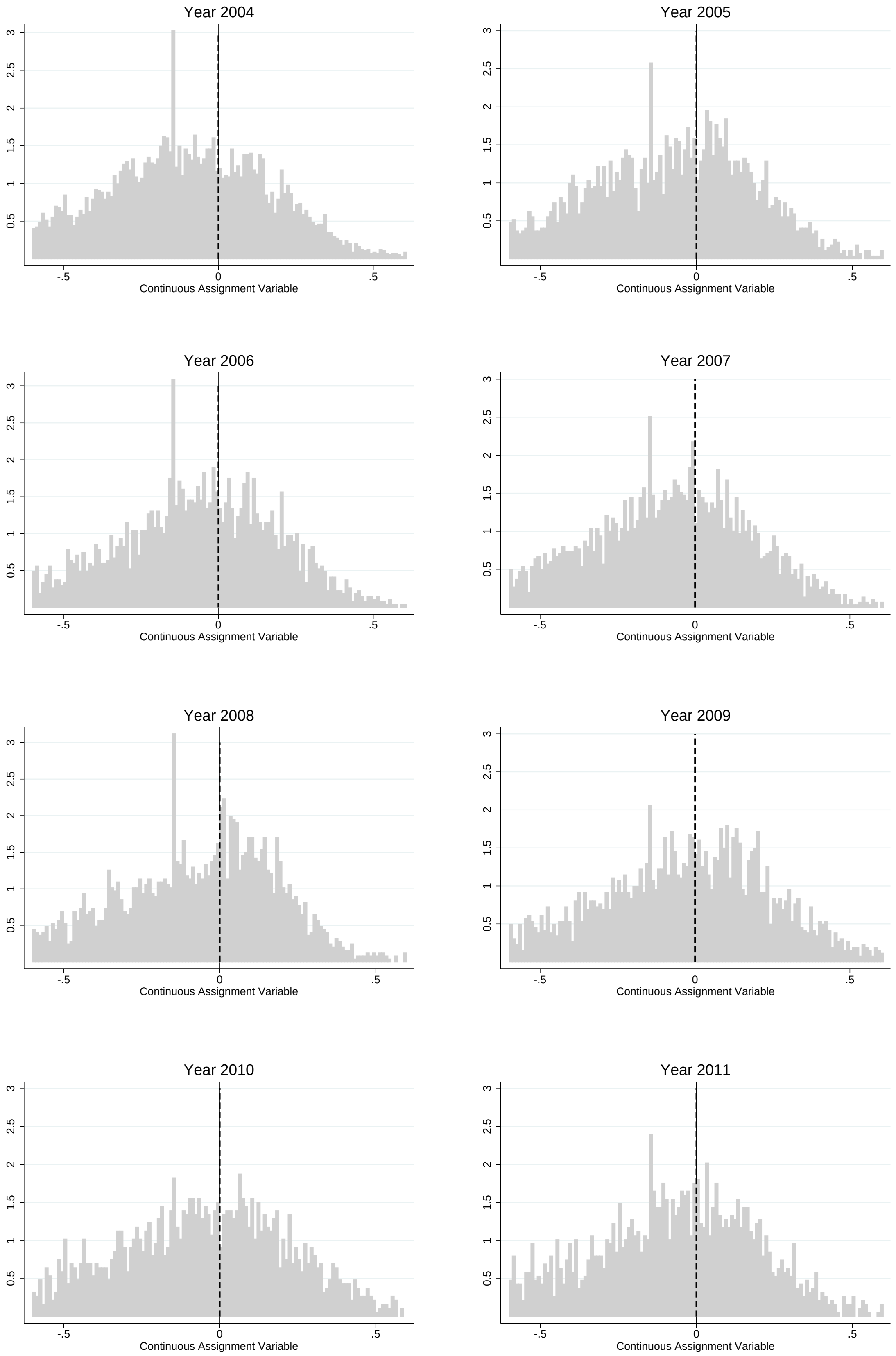
Notes: The table estimates differences in pre-sample firm characteristics at the threshold. We report the standard errors in brackets. In all rows, the dependent variable is measured in 2003. The discontinuity is estimated using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7. The reported estimates refer to S_i, a binary variable that takes value of one if the continuous variable $s_i \geq 0$; i.e., if the firm is allocated to the performing class as opposed to the substandard class. *Cash Holdings* are defined as cash over total assets. *Automobile Industry* is a binary variables indicating whether the firms' SIC code belongs to the automobile industry. *Top 10 Cities* is a binary variable indicating whether the firms' headquarter zip code is in one of the largest 10 cities. *Firm Clusters* is a binary variable indicating whether the firms' headquarter is in a zip code containing more than 100 other industrial firms. See Tables I, and IV for the definition of the other variables. One star denotes significance at the 10% level, two stars denote significance at the 5% level, and three stars denote significance at the 1% level.

Figure D3: McCrary Self-Selection Test



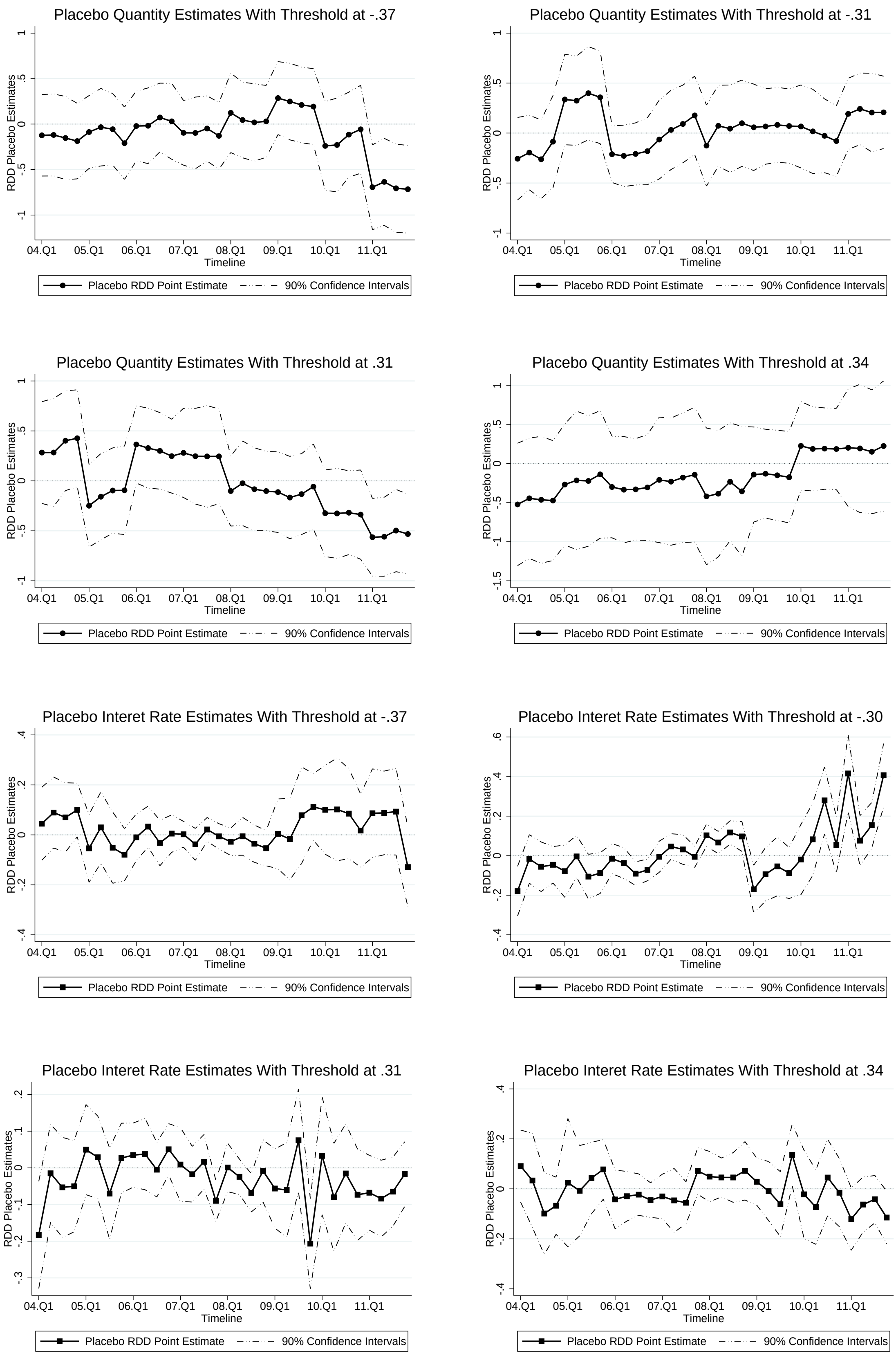
In the figure, we plot the distribution of firms along the support of the continuous variable (s_i) between *Score* rating categories 6 and 7. The solid line is a fitted kernel local linear regression of the log of the density on both sides of the threshold separating firms in category 7 from firms in category 6.

Figure D4: Firms' Inflow Into Score Categories 6 and 7



In the figure, we plot the yearly distribution of firms entering each year into categories 6 and 7 along the support of the continuous variable s_i.

Figure D5: Sequence of RDD Estimates for Placebo Thresholds



The panels plot the sequence of discontinuity estimates obtained running specification (1), and the associated 90% confidence intervals, on a fixed and randomly drawn placebo threshold.