Lending Standards Over the Credit Cycle*

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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, banks relax lending standards by narrowing the interest rate spreads between substandard and performing firms. 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 interbank market is an important factor determining the change in bank lending standards.

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1 Introduction

Credit fluctuations play a crucial role in the propagation and amplification of macroeconomic shocks (e.g., among others, Schularick and Taylor, 2012; Baron and Xiong, 2014; Mian, Sufi and Verner, 2015). Moreover, recent empirical evidence shows that narrowing credit spreads and the deterioration of credit quality can predict future economic and financial busts (e.g., Greenwood and Hansen, 2013; Lopez-Salido, Stein and Zakrajšek, 2015; Krishnamurthy and Muir, 2015). Banks contribute to these aggregate fluctuations by determining the lending standards that borrowers with different risk profiles must meet. However, empirically identifying lending standards implications for credit and real allocations is challenging for three reasons. First, credit policies are likely to simultaneously reflect a firm's demand for and the bank's supply of credit. Second, lending standards can vary, often suddenly, over the cycle (e.g., Ruckes, 2004; Dell'Ariccia and Marquez, 2006; Gorton and He, 2008). Finally, most of the available evidence relies on loan officer surveys (e.g., Maddaloni and Peydró, 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 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 to 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.

We exploit the institutional features of the Italian credit market for small and medium-sized enterprises (SMEs) to reproduce this ideal setting. First, for historical reasons, the credit risk assessment of SMEs performed by Italian banks relies on a common credit rating (the *Score*) that banks purchase 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 *Score*, we document empirically that they set their lending standards using the discrete value of the rating.

The presence of 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 corporate lending standards by studying the differences in the credit conditions 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. These threshold differences inform us about the tightness of banks' lending standards, holding constant the demand for credit.

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 approximatively 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 featured interest rate differences but little (if any) difference in the total amount of credit granted. A firm marginally classified into the performing class payed up to 10% (or 60 basis points) lower interest rates on new term loans than a firm marginally classified into the substandard class. The interest-rate spreads disappeared during the cycle's boom phase in 2007. These findings suggest that banks gradually relaxed 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 reported 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 obtained up to 60% more credit than comparable firms in the substandard class.

Third, we trace the implications of lending standards for firms' real activity. We show that periods of relatively lax standards imply that firms at the threshold do not differ in the value of production and input choices. When lending standards tighten, however, production and investment of ex-ante economically comparable firms significantly diverge. A firm marginally above the threshold in the performing class produced 30% to 50% more between 2008 and 2010 than a firm below the threshold in the substandard class. This difference in production stemmed 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 implemented when tightening their lending standards in 2008 and 2009. First, in 2008 banks reduced the amount of lending to substandard firms by renegotiating their commitments in revolving credit lines. Later, in 2009, they began rejecting the loan applications of new borrowers in the substandard class. This last finding is consistent with reports by loan officers in the European Central Bank (ECB) Bank Lending Survey that 2009 was the peak of strict bank lending standards to Italian SMEs.

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 2BE per year to banks compared to performing firms. The subsequent tightening of lending standards then translates into a drop in the supply of bank financing to substandard firms of approximately 208BE, or 1.2ME per firm. This contraction in the supply of credit resulted in a 10.6% lower value of production for these firms.[1]

The literature suggests two possible channels to explain the shift in lending standards. The first emphasizes the importance of bank capital (e.g., Kashyap and Stein, 2004; Repullo and Suarez, 2013), which could have become more costly during the crisis. As a consequence, banks decided to tighten lending standards to avoid a violation of capital requirements. The second hinges on the importance of bank liquidity (e.g., Allen and Carletti, 2008; Diamond and Rajan, 2011): Banks highly exposed to the interbank market were affected by the pressure on the wholesale market in late 2007. 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 in credit supply among 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.[2]

Our empirical findings about firms at the threshold rely on the presence of rating segmentation in the Italian credit market for SMEs. The fact that we do observe discontinuous changes in financial contracts at the threshold confirms that banks primarily use the categorical value of the *Score* to assess SMEs risk and determine credit conditions. In our institutional setting, segmentation is market driven, since external investors monitor banks by pricing their portfolios based on the reported volume of bank lending by categories of credit risk.[3] We find robust support for this mechanism in the data, by

[1] These computations assume that the threshold estimates influence all substandard firms with the same intensity. Since we expect that firms further away from the threshold should receive even worse financing conditions than firms at the threshold, we believe that our calculations represent a lower bound estimate for the aggregate effects on credit and real allocations.

[2] Finally, our results cannot be explained by the implementation of the Basel II agreements. First, a minority of banks switched to the internal rating-based methods for credit risk assessment. Second, the transition to Basel II did not imply a differential change in the risk weights applied to the SMEs in our sample, as they belong to the retail portfolio.

[3] It can also be implemented strategically by banks to mitigate loan officers' agency problems (Stein, 2002). Supporting this theoretical intuition, evidence from the 2006 Bank of Italy survey of Italian

relating the cost of banks' borrowing conditions to the exposure to substandard firms in their portfolios.

We also confirm the internal validity of our results by presenting three additional robustness checks to our empirical design. Given the importance of the credit rating system to 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 it 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 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' annual reports and Altman's (2003) risk classifications suggest that distinguishing between performing and substandard firms is important for risk management policies. To provide further evidence on the relevance of the threshold, we estimate our baseline specification at all the other six thresholds associated with the categorical value of the *Score*.

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. The historical accounts of the credit cycle analyze the relationship between the time-varying nature of credit spreads and the quality of credit originated. Greenwood and Hansen (2013) show that the deterioration of credit quality during booms forecasts low excess returns to bondholders. Similarly, Lopez-Salido,

banks shows that large banks are more inclined to adopt standardized rating methods for making lending decisions. 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.

Stein and Zakrajšek (2015) show that elevated credit sentiment is associated with a more aggressive pricing of risk and a subsequent contraction in economic activity. Consistent with these studies, we provide evidence of narrowing spreads during the boom phase. We contribute to this literature in three distinct ways. First, we rely on a quasi-experimental design to obtain a measure of lending standards that is not biased by demand heterogeneity. Second, we quantify lending standards using the direct information contained in the contracts signed between financial intermediaries and SMEs. This allows us to extend the analysis of lending standards beyond the case of market-level data. Finally, we show that in the contractionary phase of the cycle banks tighten their standards by adjusting the amount of credit available to firms, which affects firms' production and input choices.

Our paper is also related to the body of work on empirical banking. This literature 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 used in this type of research, as proposed by Khwaja and Mian (2008), keeps all borrower characteristics constant and focuses on differences in bank balance sheet characteristics. Our paper studies variation in credit policies resulting from a discontinuous change in the perceived credit risk of otherwise identical firms. Importantly, this approach allows us to directly measure the aggregate effects of bank lending policies, irrespective of how many relationships with different banks a firm may have.[4]

From a methodological point of view, the paper is closely related to the recent literature on household finance exploiting FICO credit scores. Keys, Mukherjee, Seru, and Vig (2010) examine the screening process for household mortgages exploiting a discontinuous variation in the ease of securitization due to a change in the value of the score. Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015) use discontinuous credit limits of households in order to identify their marginal propensity to borrow, and the associated bank's marginal propensity to lend. Similarly to these studies, we exploit rating segmentation in the Italian credit market. We exploit the repeated nature of our discontinuity framework in order to identify variation in lending standards over time.

2 Lending to Italian SMEs

This section describes the institutional features of the Italian credit market for SMEs and then presents our empirical framework. The main empirical challenge in quantifying lending standards is that differences in credit conditions might simultaneously reflect

[4]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.

heterogeneity in the demand for credit. To address this challenge, we exploit the fact that bank lending to Italian SMEs features rating segmentation. Our 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 used to assess SMEs' credit risk.

In 2004, the share of credit granted to SMEs by banks subscribing to the *Score* rating system was 73%. Evidence from the 2006 Bank of Italy survey of Italian banks indicates that 90% of the banks using the firm's rating find it important when deciding on whether to process a loan application, 76% of them use the rating to set the amount of lending, and 62% use it to formulate an interest rate offer.

The *Score* takes integer values ranging from 1, for firms that are the least likely to default, to 9, for those 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 estimate of the expected likelihood of a firm's default within one year. The continuous variables, in contrast, do not provide the bank with a direct estimate of the firm default probability (Altman, 2003).[5] 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 announce their corporate credit exposure by classifying firms in their portfolios based on their categorical *Score* values (e.g., Unicredit, 2008).

The Italian credit market for SMEs features rating segmentation, which means that banks primarily use the categorical value of the *Score* to assess counterparty risk and determine credit conditions. Segmentation is market driven, since external investors monitor banks by pricing their portfolios based on the reported volume of bank lending by categories of credit risk. In Subsection 5.3, we will provide evidence consistent with this

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

source of segmentation.

In our empirical framework, we exploit the distinction between the performing and the substandard class of credit risk. Anecdotal evidence from banks' annual reports suggests that this distinction is of major importance for Italian banks' risk management policies. The performing class consists of the firms with a *Score* category between 1 and 6, and the substandard class comprises firms with a *Score* between 7 and 9. To understand the consequences for firms of this classification in terms of S&P's ratings, note that a *Score* of 6 corresponds to class B, and a *Score* of 7 to class CCC (Altman, 2003). In Section 6.3, we will provide further empirical evidence on the relevance of this threshold.

2.2 Empirical Framework

Our empirical framework exploits rating segmentation as a tool to identify banks' lending standards and their evolution over time. As we will show in our data section, a simple comparison of credit allocations to firms in different rating classes is likely to not only reflect banks' lending standards, but also 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 of the distinction between performing and substandard credit risk to banks' risk management. We run a regression discontinuity design that compares the credit conditions applied to the firms at the threshold between the performing and substandard classes, as implied by the value of the *Score* continuous variable. 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:

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

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:

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

The dependent variable capturing the supply of bank financing is the (log) total value of bank lending 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 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 or express interest rates in terms of basis point differences, and we obtain the same results.[6]

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 a value of 1 if $s_i \geq 0$ and 0 otherwise. Functions $f(\cdot)$ and $g(\cdot)$ correspond to flexible sixth-order homogeneous 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.[7]

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.

[6]Using the change in the amount of bank financing over time as the dependent variable would complicate the interpretation of our results. The reason is that this alternative dependent variable introduces a joint dependence on past lending standards and past rating histories of firms. In addition, banks' risk management policies are generally formulated on the basis of total exposure to a given credit risk, rather than on individual firms' changes in banks lending conditions.

[7]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 and 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.

2.3 Discussion of the Identifying Assumptions

The empirical interpretation of the β coefficient relies on several identifying assumptions about the discontinuity design. In this section, we discuss these assumptions and later provide the associated empirical tests in Section 6.

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. We also show that the distribution of firms that enter rating categories 6 or 7 in any given year is balanced 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 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. Finally, we estimate our baseline specification at all the other six thresholds associated with the categorical value of the rating system.

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.

This section first documents the presence of substantial heterogeneity across rating classes. This heterogeneity 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, because the resulting 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, documenting the significant effects of the financial crisis on the 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). Columns (2) and (3) show corresponding results for the group of performing and substandard firms, and columns (4) and (5) show the same for categories 6 and 7. Finally, column (6) reports the mean difference between the values of the variables in categories 6 and 7.

[Table I Here]

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 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 credit, as short-term loans account for around two-thirds of the total value of 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) of Panel C shows that the heterogeneity in firm characteristics extends to rating categories 6 and 7. The cost and availability of bank financing suggests significantly tighter conditions 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 obtaining a measure of lending standards that is not biased by demand heterogeneity.

Time Series Descriptive Statistics In Figure 1 we next document the variation in financial contracts across time.

[**Figure 1 Here**]

The upper panel illustrates 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, showing 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, the top panel shows 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% but it rose by 29% for substandard firms. This evidence is consistent with the historical account of credit booms by Greenwood and Hanson (2013), who show that the quality of credit deteriorates as aggregate credit increases.

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 the leading indicators of monetary policy (plotted in the bottom panel): the Euro overnight index average rate (EONIA). The middle panel also indicates that the spread between interest rates applied to performing and substandard firms increased 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 between 2006 and 2011 from Bank of Italy.

[Figure 2 Here]

The figure has three main takeaways. First, it shows that the Italian banking system was substantially exposed to the shock that dried up the interbank market 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 before picking 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 that was 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 2006 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 illustrates 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, 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, the SMEs in our sample belong to the retail portfolio, so 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—specifically, differences in the interest rates and in the total amount of bank financing—for firms at the threshold between the performing and the substandard classes. We then explore whether differences in credit conditions give rise to differences in real outcomes in terms of production and input choices.

4.1 Results on Credit Allocations

Figure 3 plots 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 loans are shown in the bottom panel. Table D1 in Online Appendix D reports 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 early 2007. In line with the findings in Greenwood and Hanson (2013), during the boom phase the deterioration of the quality of credit documented in Figure 1 is accompanied by narrowing interest rate spreads at the threshold. We next show that the sudden reversion to the bust phase in early 2008 leads to stark differences in the amount of lending at the threshold.

Through 2008 and 2009, the financial crisis that hit the Italian banking sector led to a tightening of lending standards. Tight standards translate into differences in the quantity of lending. The difference in the amount of total credit supplied to similar firms across the threshold is statistically significant and ranges from 50% to 60% (or 9 percentage points in terms of the debt-to-assets ratio). At the same time, interest rate differences remain

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

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

close to zero. The timing suggests that the drying up of the interbank market in 2007 played a crucial role in 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 gradually disappearing. 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 differences in the interest rate and the quantity of credit throughout the cycle. Our discontinuity design shows that 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.

The literature suggests two possible channels to explain the time-varying risk premia set by financial intermediaries.[10] The first channel stresses the importance of bank capital (e.g., Kashyap and Stein, 2004; Repullo and Suarez, 2013). Bank capital becomes more costly with the crisis, and the fear of violating capital requirements induces intermediaries to tighten lending standards. The second emphasizes the importance of bank liquidity (e.g., Allen and Carletti, 2008; Diamond and Rajan, 2011): Banks with exposure to the interbank market are affected by the pressure on the wholesale market for funds. We test the relative merits of these two channels in Subsection 5.2.

We conclude this section by discussing the aggregate implications of our estimates.[11] To compute the higher value of the repayments due by substandard firms when compared to the performing firms, we use the interest rate spread estimated by our discontinuity design and apply it to substandard firms' volume of lending. Between 2004 and 2006, we find a higher aggregate transfer of roughly 2BE per year, corresponding to 15,000 Euros paid by each substandard firm to banks. Because of the larger spreads in 2010–2011, the value of these transfers increased to 4.7BE 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 1.2ME per firm. This suggests that, at the aggregate level, bank financing

[10] These channels emphasize the link between the strength of banks' balance sheet and banks' pricing of risk, along the lines of Bernanke and Gertler (1989), Holmström and Tirole (1997), and Kiyotaki and Moore (1997).

[11] To compute the 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 firms that are rated by the agency using information from simplified balance sheets.

was 208BE lower than that available for the performing class. This figure represents 14.3% of total bank financing in the Italian economy.[12]

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, when our results at the threshold feature quantity differences and no interest rate differences. We divide the domain of s into mutually exclusive bins of size 0.03.[13] 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 in 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 by focusing on the second quarter of 2011 when 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

[12]These calculations are based on a partial equilibrium exercise that does not account for other aggregate factors. They also assume that the threshold estimates influence all substandard firms with the same intensity.

[13]Our results remain the same 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.

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 bottom 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 estimated value of γ as a function of the distance from the threshold. The dashed lines are 90% confidence bands.[14]

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 over 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 provides evidence on 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 expenditures in investment, employment, and intermediates.

[Table II Here]

[14]Specifically, the procedure starts with a value of h equal to 0.01. Thus, 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.

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 to the firms at the threshold 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 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 700KE per-substandard firm drop in production, representing 231BE 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. 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 tightened their lending standards through changes of terms and conditions of credit. We find a significant reduction in the volume of revolving credit lines in 2008 for the SMEs that marginally fall in the substandard class. Moreover, we find a significantly higher loan application rejection rate 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 provide evidence that supports the market-driven motive behind rating segmentation in our institutional setting.[15]

5.1 Loan Terms and Loan Applications

To adjust their lending standards in 2008 and 2009, banks could renegotiate their commitments on revolving credit lines or raise the new loan rejection rate.

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. *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 of the lending standards tightening phase, we observe a threshold difference amounting to about a 50% larger volume of revolving credit lines granted by banks to performing-class firms. The second row lists the threshold estimates regarding loan rejections. While the likelihood of being denied credit by new banks is similar across rating classes in 2008, it jumps by 10 percentage points in 2009. This increase in the likelihood of rejection among new substandard applicants 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 the tightening of lending standards in 2008 and 2009: First, banks reduced the amount of lending to substandard firms by renegotiating their commitments in revolving credit lines. Subsequently, they raised the application rejection rate among new borrowers in the substandard class.

[15] See, e.g., Kisgen and Strahan (2010) and Chernenko and Sunderam (2012) for the analysis of market and regulatory driven segmentation in the United States.

5.2 Bank Liquidity and Capital

In line with the theoretical literature that studies fluctuations in bank balance sheet strength over the cycle (e.g., Holmström and Tirole, 1997; Kiyotaki and Moore, 1997), we analyze two potential channels to explain banks' decision to tighten lending standards. First, bank capital could have become more scarce with the crisis (Kashyap and Stein, 2004; Repullo and Suarez, 2013). 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 (e.g., among others, Allen and Carletti, 2008; Diamond and Rajan, 2011).

To explore the relative merits of these two channels in determining the tightenining of lending standards, we use data from the Bank of Italy and split banks in our sample according to the median of pre-crisis capital ratios and exposure to the interbank market. 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 a median of 14% of their asset base through this channel. The European interbank market dried up in late 2007, leading these banks to allocate up to 60% more credit to firms in the performing class in both 2008 and 2009.

In the bottom panel, we split our sample based on a measure of bank capitalization, the equity-to-asset ratio. This ratio is 6% before 2008 for less capitalized banks compared to 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 and the performing classes 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 Bank Cost of Financing

To understand how external investors price banks' lending portfolios, we use a confidential dataset from the Bank of Italy. The dataset provides us with information on the amount and interest rate at which Italian banks raise financing from repo markets, households, and firms at a monthly frequency between 2004 and 2011.

We estimate the relationship between a bank's cost of financing and its lending portfolio using OLS, and report our results in Table V.[16]

[Table V Here]

In columns (1) and (2) of Table V we show that external investors monitor banks by pricing lending portfolios based on banks' exposure by credit risk classes. The dependent variable is the (volume) weighted average interest rate at which banks raised financing across different types of investors during the sample period. The estimate in column (1) implies that a 25% higher share of substandard lending in the bank portfolio is associated with 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. The coefficient on the share of substandard loans remains significant and economically identical to the first specification. In contrast, the coefficients on the values of the continous variables are neither statistically nor economically significant. Our evidence is therefore consistent with the presence of rating segmentation in the Italian credit market for SMEs.

In columns (3) and (4) we focus on the cost of financing in the repurchase market, the primary source of funds for the securitized banking system. Gorton and Metrick (2012) describe the crisis as a "run on repo" that was triggered by concerns about bank solvency. We therefore re-estimate our pricing equation separately for the period before and after 2008. In the boom phase of the credit cycle, the correlation between interest rates on the repurchase markets and the lending portfolio of the bank is low and statistically non-significant. During the bust phase of the cycle the correlation is positive and economically significant, implying an increase in the interest rate premium required by banks that are relatively more exposed to substandard credit risk.

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

[16]The specification also includes a vector of issuance characteristics like amounts, maturity, and investor composition, and a vector of bank characteristics like size (in terms of total assets), the value of the tier 1 capitalization ratio, and the bank's liquidity ratio. Standard errors are clustered at the bank level.

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 its exact algorithm is a business secret. Nevertheless, manipulation can be detected empirically: It would result in 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. In Table VI we test for the presence of a discontinuity in firm 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 year-by-year plots associated with these tests.

We confirm the lack of manipulation, suggested by the tests in Table VI plotting 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 new 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 further 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**]

In Panel A of Table VII, the dependent variables are 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-firm relationships at the threshold. The first row in the table focuses on the banks' probability of reporting nonperforming loans. If there were 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' geographic 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.[17]

6.3 Empirical Relevance of the Threshold

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

[17] Table D4 of Online Appendix D shows the results of additional balancing tests.

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 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* 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 Rating Thresholds

Finally, as in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), we investigate whether banks use alternative ratings' cutoffs to formulate lending standards. We estimate our baseline specification at all the other six thresholds associated with the categorical value of the rating system.[18] 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.

[Table VIII Here]

Table VIII shows that the threshold between substandard and performing firms is of major importance for formulating banks' risk management policies. Most of our estimates on alternative thresholds are not statistically significant.

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, banks relax lending standards by narrowing the interest rate spreads between substandard and performing firms. Moreover, in this phase there is no difference in the total 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 substandard firms losing 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 in input choices.

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A Tables and Figures

Table I: DESCRIPTIVE STATISTICS

	All	Performing	Substandard	Score 6	Score 7	6-7 Comparison
	(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	253,502	188,026	65,475	49,265	60,326	109,591
			Panel B: Aggregate Financing Information			
All Bank Financing Granted	8,503	9,237	6,167	7,542	6,392	1,150***
	(37,200)	(40,600)	(23,100)	(24,600)	(21,100)	
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	543,855	414,041	129,754	63,722	104,253	167,975
			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	143,953	108,353	35,600	16,432	27,350	43,782

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 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 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 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 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 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

Year	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	5,951	5,875	6,097	6,512	5,549	5,358	4,307	4,109
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	5,085	5,116	5,033	4,104	4,952	4,491	3,677	3,614
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	5,852	5,786	6,013	6,398	5,454	5,275	4,256	4,061
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	2,911	2,846	2,980	3,137	2,623	2,386	2,148	1,922

Notes: The table reports estimates from regressions that use either *Sales*, *Investment*, *Intermediates*, or *Employment* in logs as a dependent variable for each year between 2004 and 2011. Standard errors are reported in brackets. 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 a 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 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: Revolving Credit Lines and Rejections

Year	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	5,611	5,609	5,825	6,224	5,309	5,079	4,087	3,935
Rejected	.02	-.01	.02	-.03	.02	-.1*	-.02	.11
	(.05)	(.06)	(.05)	(.05)	(.06)	(.06)	(.09)	(.1)
N	3,947	4,028	4,419	4,673	3,817	3,503	3,078	2,670

Notes: The table reports estimates from regressions that use *Revolving* and *Rejected* as the dependent variables for each year between 2004 and 2011. *Revolving* is the (log) total amount of revolving credit lines granted. *Rejected* is a binary variable equal to one if any noncurrent 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. 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 a 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: Bank Liquidity and Bank Capitalization

Year	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	3,605	3,656	3,988	4,362	3,491	3,329	2,733	2,713
High Exposure	.08	.15	.05	.03	.49**	.46**	.32	.1
	(.23)	(.19)	(.16)	(.18)	(.2)	(.2)	(.23)	(.24)
N	5,369	5,359	5,601	5,981	5,081	4,828	3,776	3,499
				Equity Ratio				
Low Ratio	.04	.07	-.02	.03	.49***	.17	.2	.1
	(.25)	(.22)	(.15)	(.19)	(.18)	(.21)	(.22)	(.25)
N	5,411	5,413	5,625	5,947	5,119	4,845	3,751	3,577
High Ratio	0	.07	-.07	-.05	.8***	.2	.15	.17
	(.23)	(.24)	(.18)	(.21)	(.21)	(.19)	(.22	(.27)
N	3,291	3,293	3,518	4,578	3,334	3,292	2,789	2,379
				Bank Size				
Large Banks	.14	.29	-.04	-.05	.51**	.41**	.17	.15
	(.22)	(.21)	(.16)	(.18)	(.21)	(.2)	(.22)	(.24)
N	5,494	5,491	5,700	6,102	5,189	4,938	4,018	3,837
Small Banks	.13	.09	.07	-.16	.38*	.1	-.02	-.18
	(.2)	(.24)	(.21)	(.19)	(.21)	(.21)	(.25)	(.23)
N	3,860	3,872	4,093	4,423	3,817	3,653	3,016	2,936

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 (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*, 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. 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 a 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

			Pre 2008	Post 2008
	(1)	(2)	(3)	(4)
Substandard to Total Credit	1.26***	1.24*	-.37	1.34**
	(.46)	(.66)	(.29)	(.68)
Continuous Variable 1		-.2		
		(.15)		
Continuous Variable 2		.09		
		(.31)		
Bank Characteristics	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
R-squared	.76	.76	.85	0.54
N	4,788	4,728	2,233	2,212

Notes: The table reports estimates from regressions that use as a dependent variable the interest rate at which Italian banks raise financing. In columns (1) and (2), the dependent variable is the (volume) weighted average interest rate at which banks raised financing across different types of investors (repo, markets, households, firms) between 2004 and 2011. In columns (3) and (4), we re-estimate our pricing equation for the period before and after 2008, respectively. Accordingly, the dependent variable is the interest rate at which banks raised financing on repurchase markets before 2008 in column (3) and after 2008 in column (4). *Substandard to Total Credit* 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 the tier 1 capitalization ratio, and the bank's liquidity ratio. The specification includes monthly fixed effects, with standard errors clustered 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 Rating Categories 6 and 7

Year	2004	2005	2006	2007	2008	2009	2010	2011
McCrary Density Estimate	.10	.13	.02	.08	.3***	-.00	.08	.17
	(.06)	(.07)	(.07)	(.06)	(.07)	(.08)	(.10)	(.10)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

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

Year	2004	2005	2006	2007	2008	2009	2010	2011
				Panel A: Presample Characteristics				
Leverage	0	.01	-.04	-.03	.05	-.01	-.04	.01
	(.03)	(.04)	(.03)	(.03)	(.04)	(.04)	(.05)	(.06)
N	3,967	3,636	3,595	3,678	2,888	2,705	2,168	2,024
Return to Assets	0	0	0	-.01	-.02	0	0	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)
N	5,306	4,844	4,750	4,836	3,776	3,504	2,721	2,508
Investment to Assets	.02	.02	.01	.02	.02	-.02	-.03	-.02
	(.01)	(.02)	(.01)	(.02)	(.02)	(.02)	(.03)	(.02)
N	4,501	4,136	4,083	4,174	3,353	3,100	2,414	2,237
				Panel B: Bank Balancing Characteristics				
Nonperforming		.01	0	.01	0	-.01	0	-.03
		(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.03)
N		5,736	5,944	6,358	5,411	5,276	4,235	4,045
Asked	.02	0	-.02	-.07	-.03	.04	.03	-.07
	(.04)	(.05)	(.04)	(.05)	(.04)	(.04)	(.05)	(.05)
N	5,687	5,677	5,889	6,306	5,370	5,264	4,217	4,030
Bank Size	-.12	-.05	-.02	.23**	.1	.09	.04	.23
	(.14)	(.14)	(.11)	(.12)	(.14)	(.17)	(.19)	(.18)
N	5,652	5,641	5,855	6,287	5,356	5,108	4,105	3,937
				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	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Location: Top 5 Cities	.06	.03	.05	-.06	.02	-.01	.07	.05
	(.06)	(.06)	(.06)	(.06)	(.06)	(.06)	(.08)	(.07)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

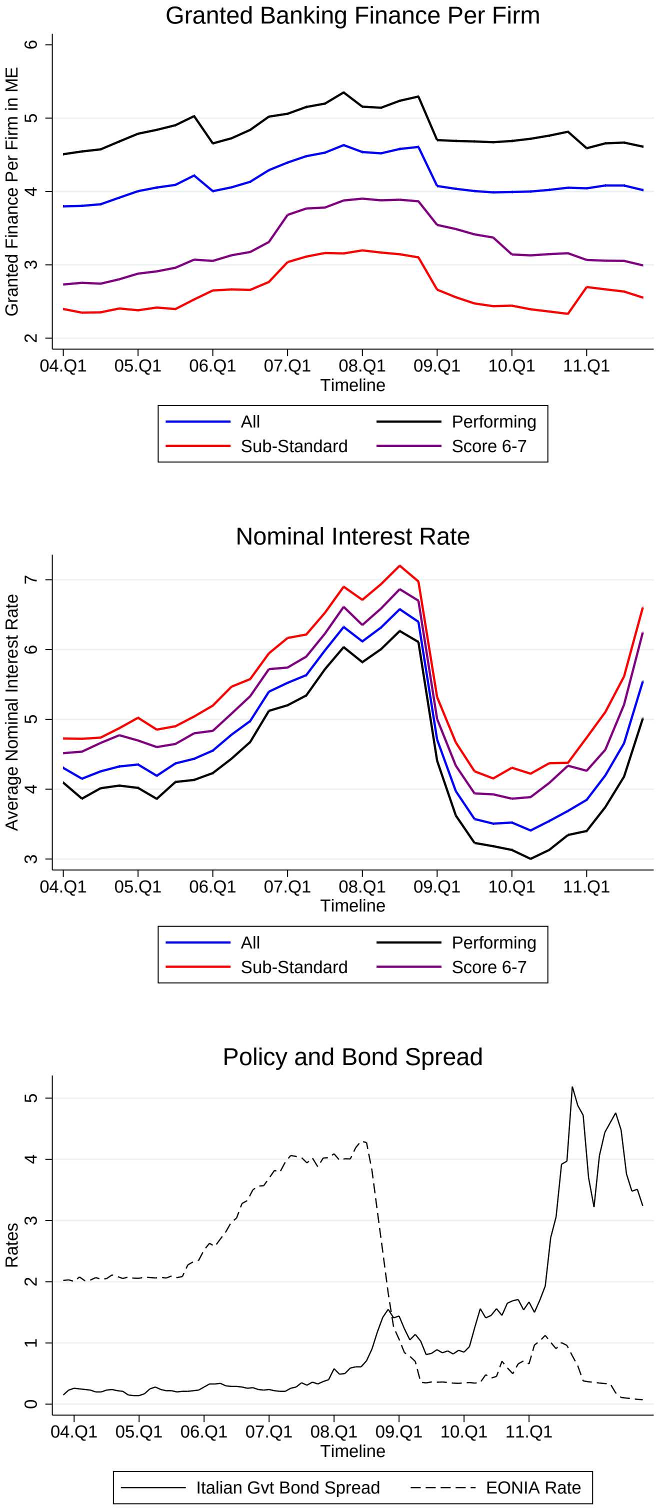
Notes: The table estimates differences in presample firm characteristics at the threshold. We report the standard errors in brackets. In all rows, the dependent variable is measured in 2003. The discontinuity is estimated using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7. The reported estimates refer to S_i, a binary variable that takes a 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. *Nonperforming* is a binary variable equal to one if any of a given firm's banks classified the firm's credit as nonperforming. *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 variable indicating whether the firms' SIC code belongs to the food industry. *Top 5 Cities* is a binary variable indicating whether the firms' headquarters zip code is in one of the largest five 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

Year	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	2,555	2,693	2,648	2,684	2,886	2,975	2,677	2,773
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	2,311	2,508	2,480	2,383	2,265	2,243	2,243	2,375
Price	0	.16	-.1	.01	-.02	-.1	-.23	.7***
	(.13)	(.12)	(.11)	(.08)	(.14)	(.27)	(.22)	(.22)
N	1,099	1,427	1,595	1,702	1,475	1,260	1,406	1,825
			Threshold Between Categories 3 and 4					
Quantity	-.24	-.03	-.14	.29	.11	-.29	-.15	.29
	(.31)	(.3)	(.35)	(.29)	(.33)	(.32)	(.29)	(.3)
N	6,087	6,361	6,371	6,526	6,040	5,968	5,840	6,128
Price	-.03	.03	.09	-.03	-.08	-.01	-.12	-.03
	(.08)	(.09)	(.08)	(.04)	(.06)	(.13)	(.15)	(.12)
N	7,197	9,359	10,255	10,547	9,033	8,625	11,153	13,158
			Threshold Between Categories 4 and 5					
Quantity	-.33	.22	-.44*	-.18	-.2	-.06	-.26	-.41*
	(.24)	(.24)	(.24)	(.21)	(.24)	(.24)	(.24)	(.23)
N	7,019	7,359	7,437	7,616	6,960	6,878	6,711	7,058
Price	0	-.05	.03	-.01	0	-.02	-.23***	.07
	(.05)	(.06)	(.04)	(.03)	(.03)	(.1)	(.08)	(.07)
N	11,072	14,972	16,561	17,056	14,662	13,505	17,687	19,743
			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	4,160	4,136	4,256	4,602	3,752	3,472	2,875	2,688
Price	0	-.2	.1	-.22**	-.08	.35*	-.56	-.12
	(.19)	(.17)	(.11)	(.09)	(.1)	(.2)	(.56)	(.27)
N	6,058	8,394	10,412	13,192	8,280	6,047	5,883	5,791
			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

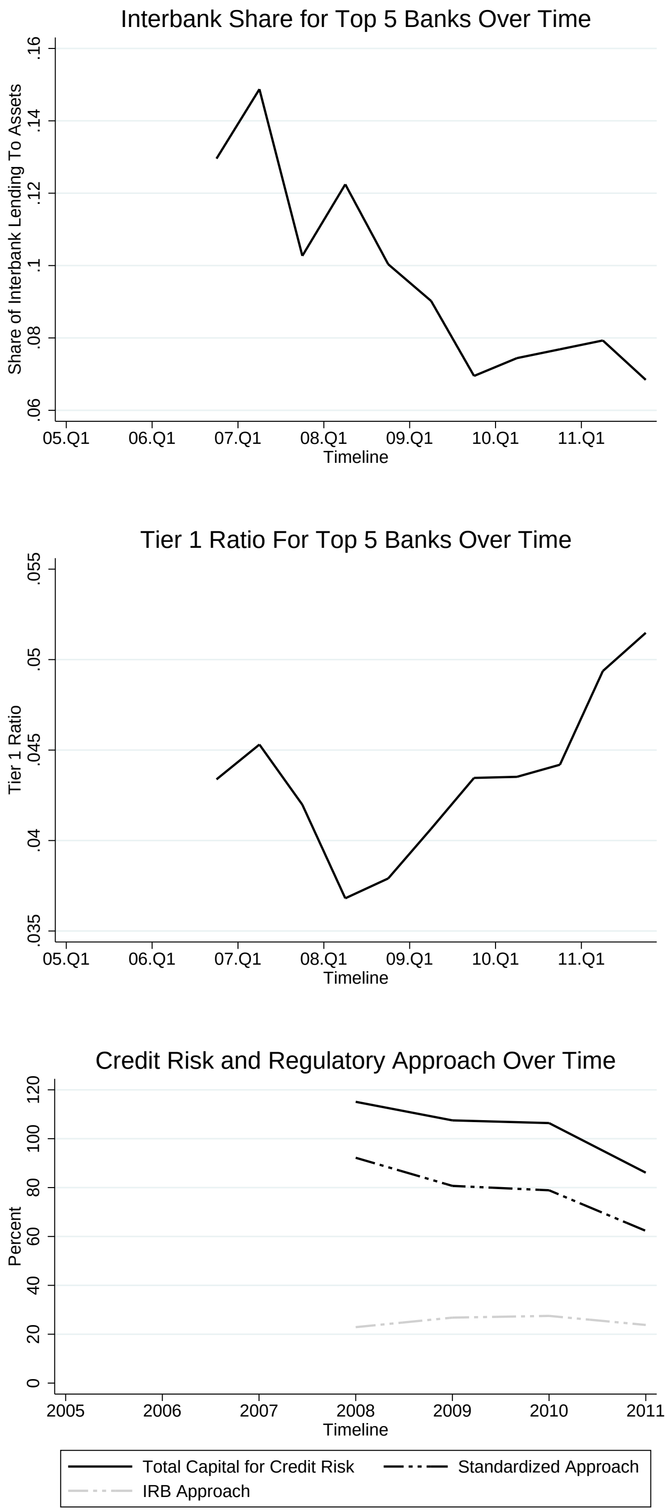
Notes: The table reports estimates from our baseline specification at all the seven thresholds associated with the categorical value of the rating system. We report standard errors in brackets. The dependent variable is either *All Bank Financing Granted* or *Interest Rate* for each year between 2004.Q1–2011.Q4. 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 a 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 other variable definitions. 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



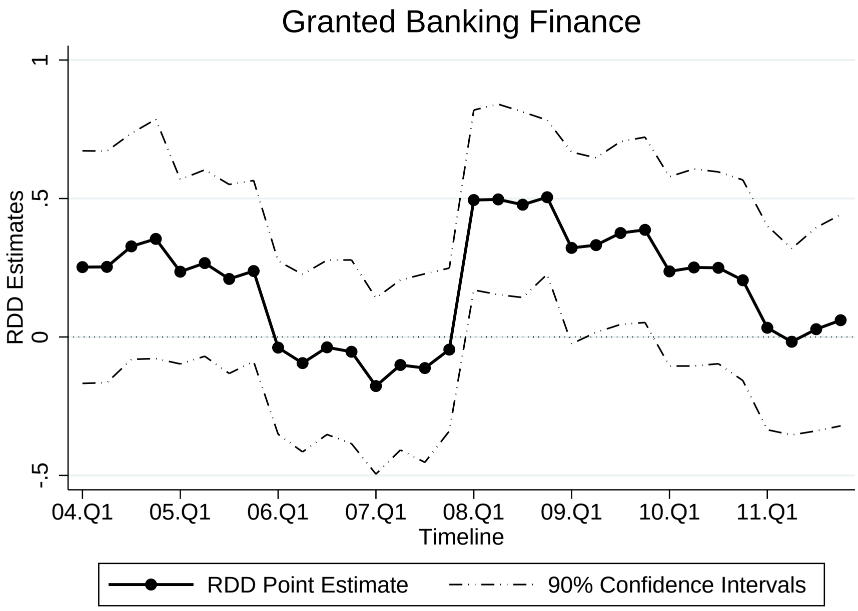
In the upper panel, we plot the per-firm aggregate value of bank financing for different rating categories across time. In the middle panel, we plot nominal average interest rates applied to firms in different rating categories across time. In the bottom panel, we plot the ten-year Italian government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

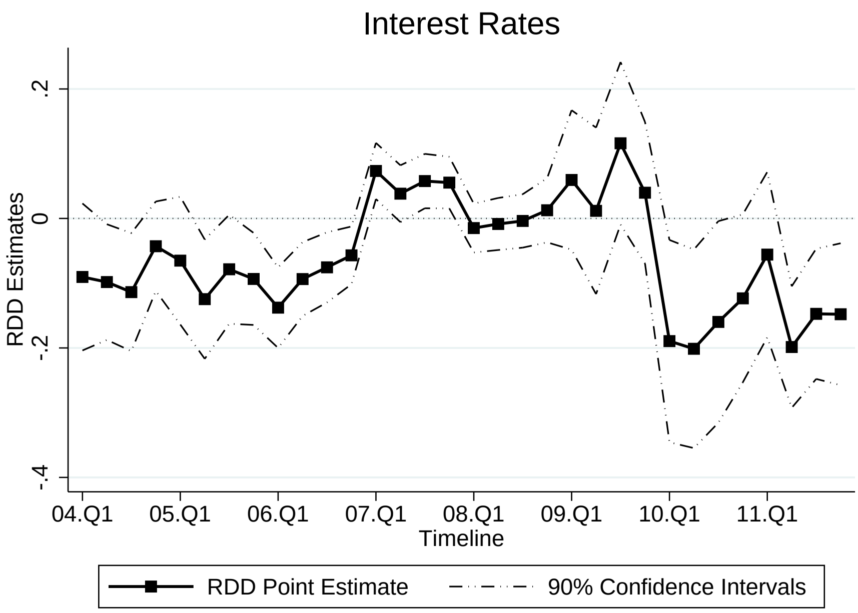
Figure 2: Bank Capital and Credit Risk



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 five 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 black line).

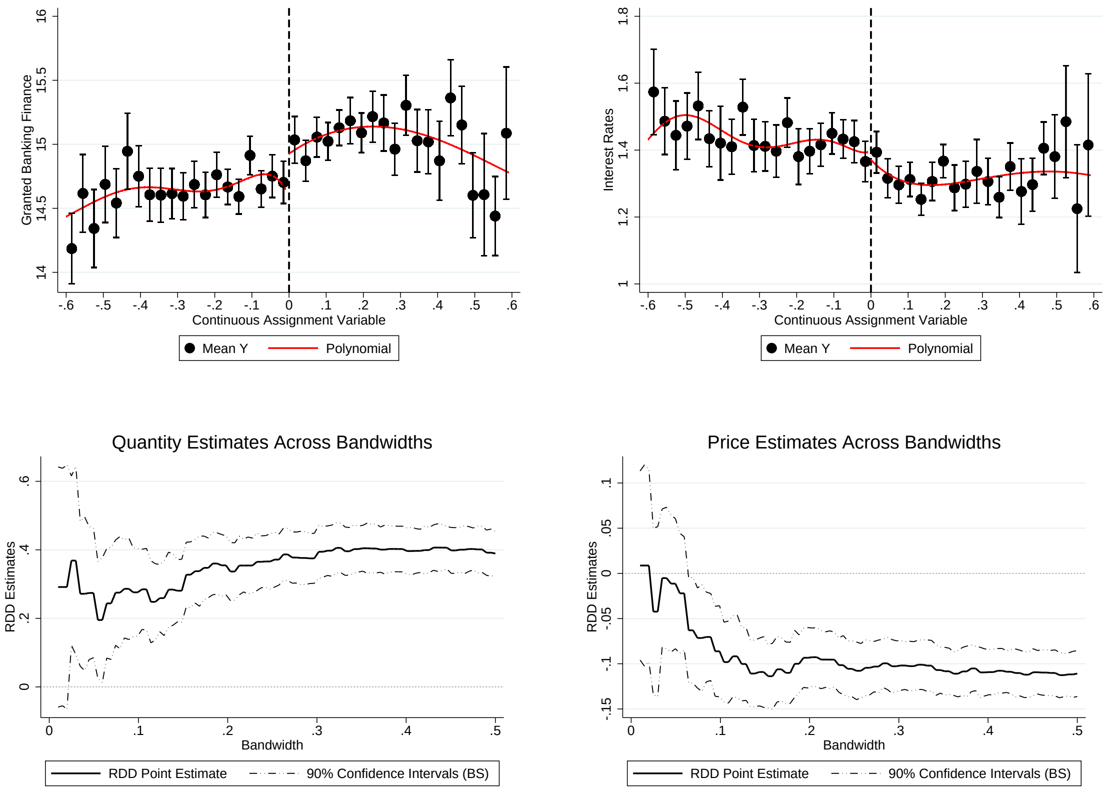
Figure 3: RDD Quantity and Price Treatment Effects





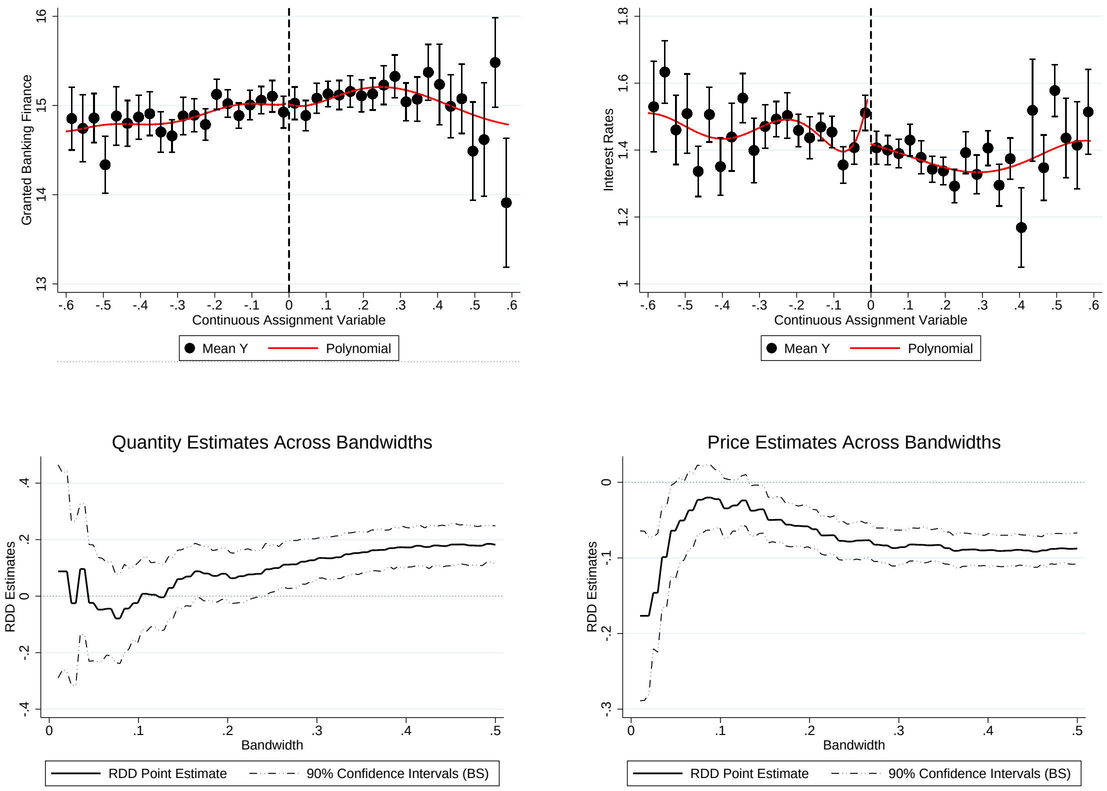
The figure plots the quarterly discontinuity estimates and 90% confidence intervals of specification (1) using either *All Banking Financing Granted* (top panel) or *Interest Rate* (bottom panel) as a dependent variable between 2004.Q1–2011.Q4. The plotted estimates refer to S_i, a binary variable that takes a 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



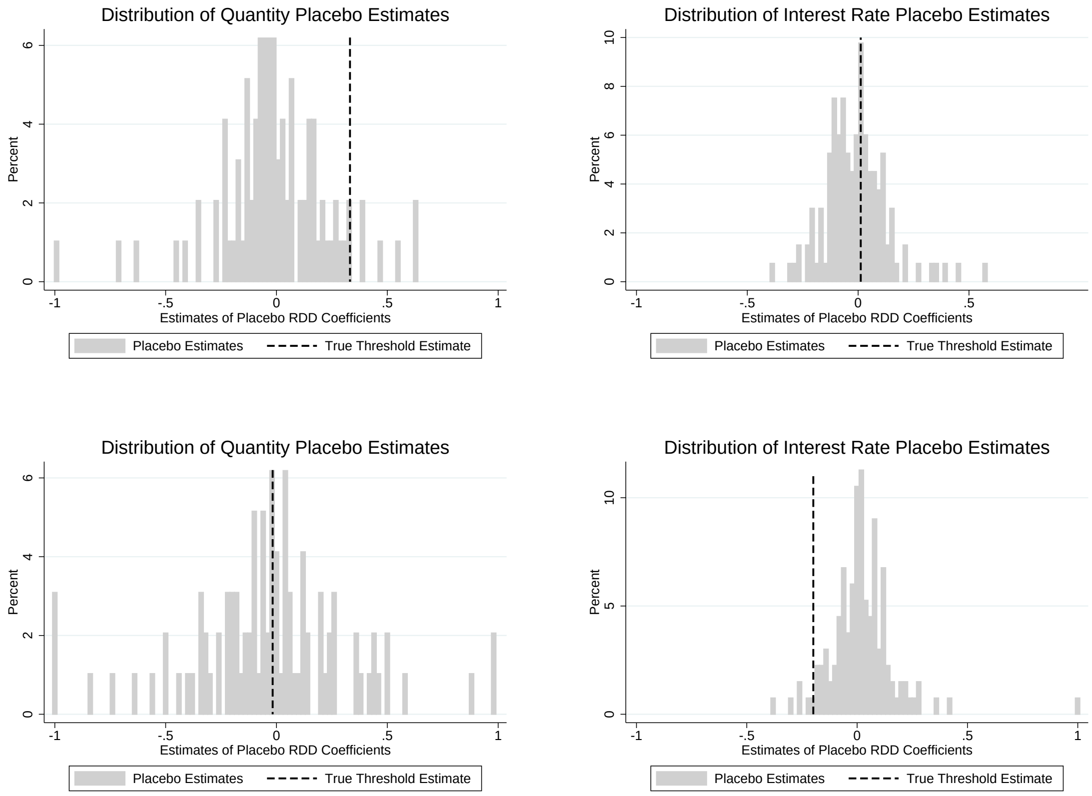
The figure focuses on the second quarter of 2009. The top panel divides the domain of s_i into mutually exclusive bins with a size of 0.03. For each bin, we compute the average and the 90% confidence interval of the outcome variable, and plot these values at the bin's mid-point. The fitted red line shows how closely the sixth-order polynomial approximates the variation in bank financing conditions at the threshold. The bottom 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 a function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors.

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 a 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 in bank financing conditions at the threshold. The bottom 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 a function of the distance from the threshold. The dashed lines are 10% confidence bands calculated using clustered standard errors.

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



The figure plots 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 figures focus 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 define 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.[19] 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, both 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 nonprice characteristics, such as loan maturity and the presence or 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 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. Note that the qualitative nature of our results remains the same when we include the firms that change risk categories in two consecutive years in our empirical sample.

[19] During the sample period, the threshold for the aggregate financial exposure above which banks had to report 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.

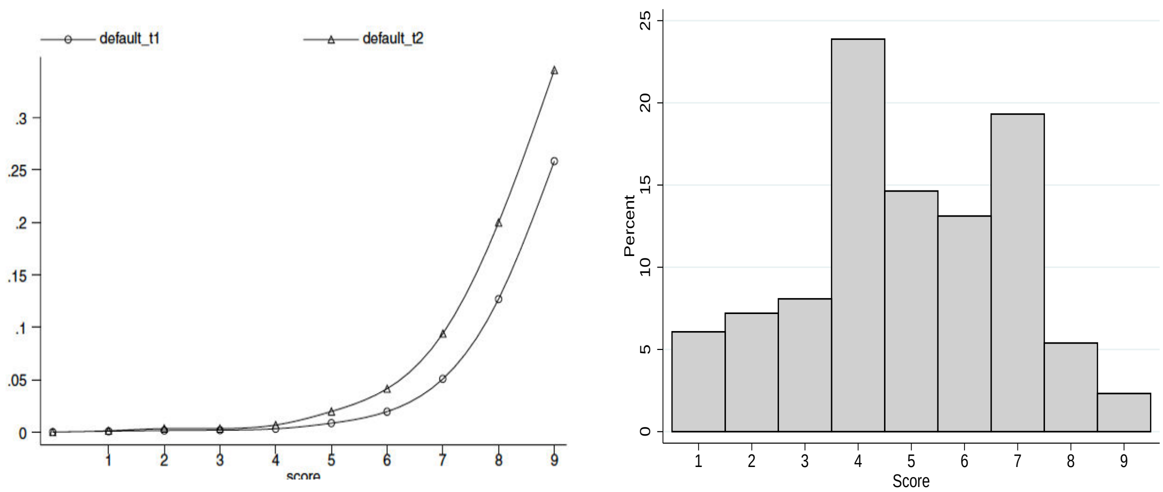
B.3 Definition of Variables

We use information from the Taxia dataset to compute variables describing each bank financing contract. *Loan Interest Rate* is 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.

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.

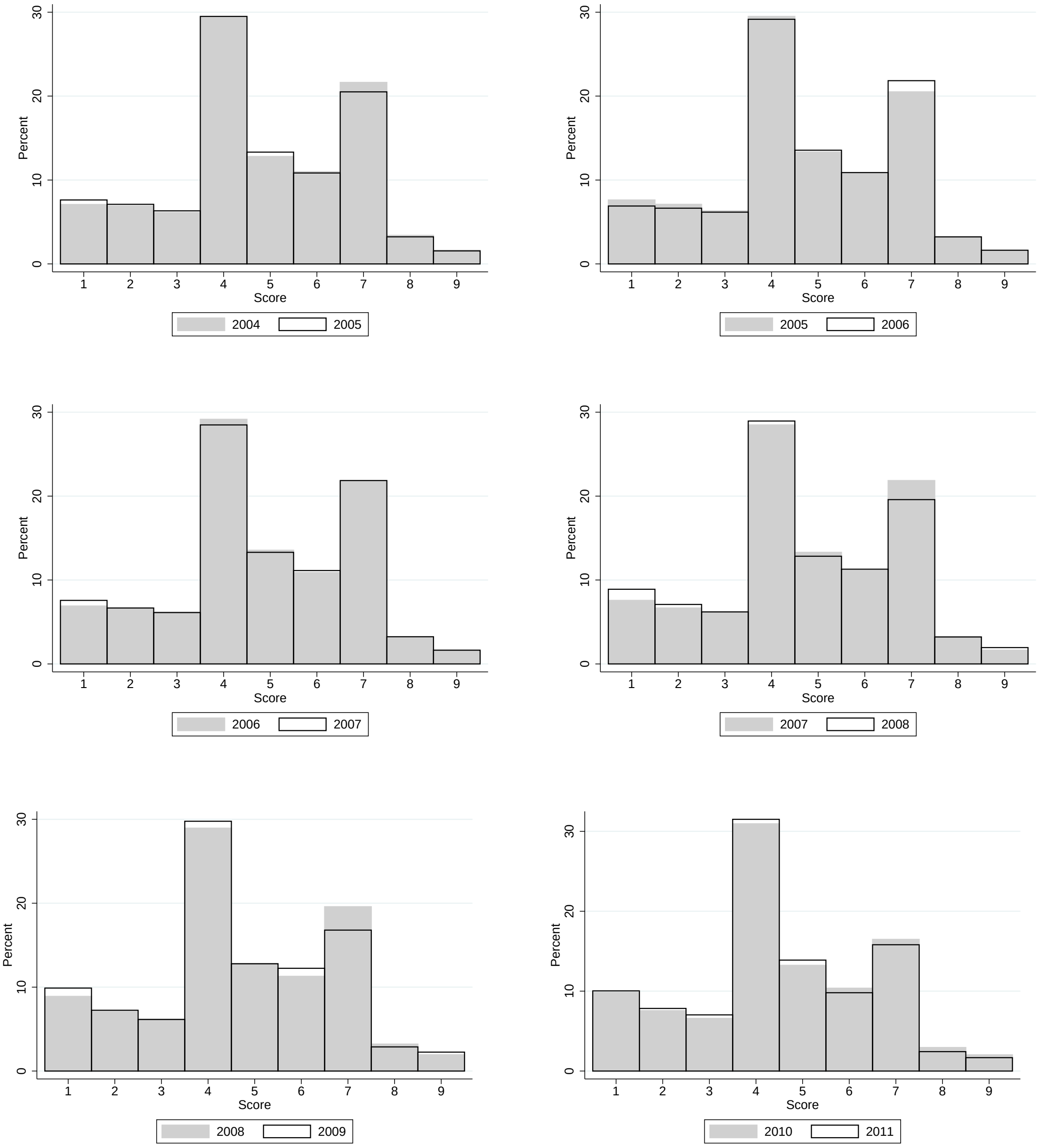
C Online Appendix: Characteristics of the Score Rating System

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



This figure plots 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

Year	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	5,614	5,621	5,621	5,599	5,601	5,608	5,604	5,605	5,822	5,822	5,815	5,829	6,224	6,230	6,237	6,234
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	1,758	1,922	2,229	3,522	3,048	3,177	3,459	4,002	3,318	3,922	4,204	5,123	4,808	4,680	4,921	5,853
Year	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	5,328	5,323	5,330	5,316	5,108	5,106	5,102	5,093	4,105	4,104	4,102	4,098	3,955	3,952	3,942	3,943
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	3,845	3,633	3,431	3,466	2,918	2,884	2,783	3,407	2,542	2,762	2,911	3,299	3,019	2,957	3,120	2,699

Notes: The table reports estimates from regressions that use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1–2011.Q4. 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 that use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each quarter between 2004.Q1 and 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. 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 a value of one if the continuous variable $s_i \geq \bar{s}^{Placebo}$. See Table I for the definitions 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

Year	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	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03**	-.03***	-.05***	-.01	.01	-.02	-.07***	-.02**
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795
				Bias-Corrected				
Quantity	.32***	.12	-.09	-.2**	.19***	.22***	.09	-.06
	(.08)	(.08)	(.06)	(.07)	(.07)	(.07)	(.07)	(.09)
N	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03***	-.03***	-.06***	0	.01*	-.01	-.11***	0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795
				Bias-Corrected and Robust Standard Errors				
Quantity	.32***	.12	-.09	-.2**	.19*	.22**	.09	-.06
	(.11)	(.1)	(.12)	(.09)	(.1)	(.11)	(.11)	(.11)
N	5,657	5,652	5,870	6,274	5,356	5,136	4,126	3,969
Price	-.03**	-.03***	-.06***	0	.01	-.01	-.11***	0
	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)	(.02)	(.02)
N	9,431	13,686	16,567	20,262	14,375	11,992	11,478	11,795

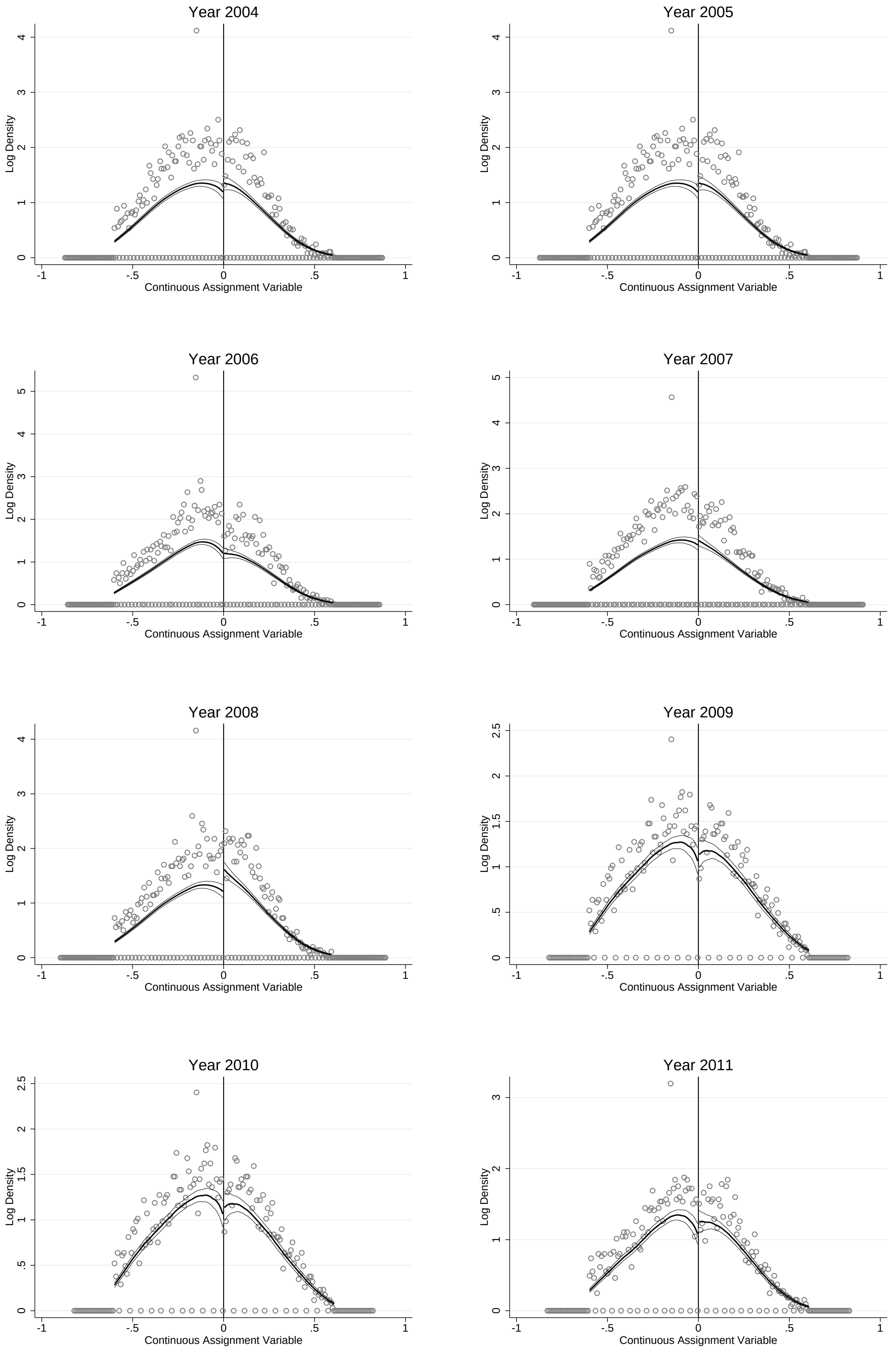
Notes: The table reports estimates from regressions that use either *All Bank Financing Granted* (Quantity) or *Interest Rate* (Price) as a dependent variable for each year between 2004–2011. To estimate the discontinuity ($s_i \geq 0$), we use a local polynomial regression. The estimator is linear with 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 a 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 definitions 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

Year	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	4,750	4,380	4,317	4,364	3,422	3,147	2,487	2,297
Automobile Industry	.01	.02	.00	.00	-.03	.00	.01	-.02
	(.02)	(.02)	(.01)	(.00)	(.03)	(.02)	(.02)	(.02)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Top 10 Cities	.05	.01	.02	-.04	.02	-.02	.11	.07
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.09)	(.08)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110
Firm Clusters	.07	.06	.09	.03	.01	.06	.05	.01
	(.07)	(.07)	(.07)	(.06)	(.07)	(.07)	(.08)	(.08)
N	5,951	5,876	6,098	6,514	5,551	5,360	4,307	4,110

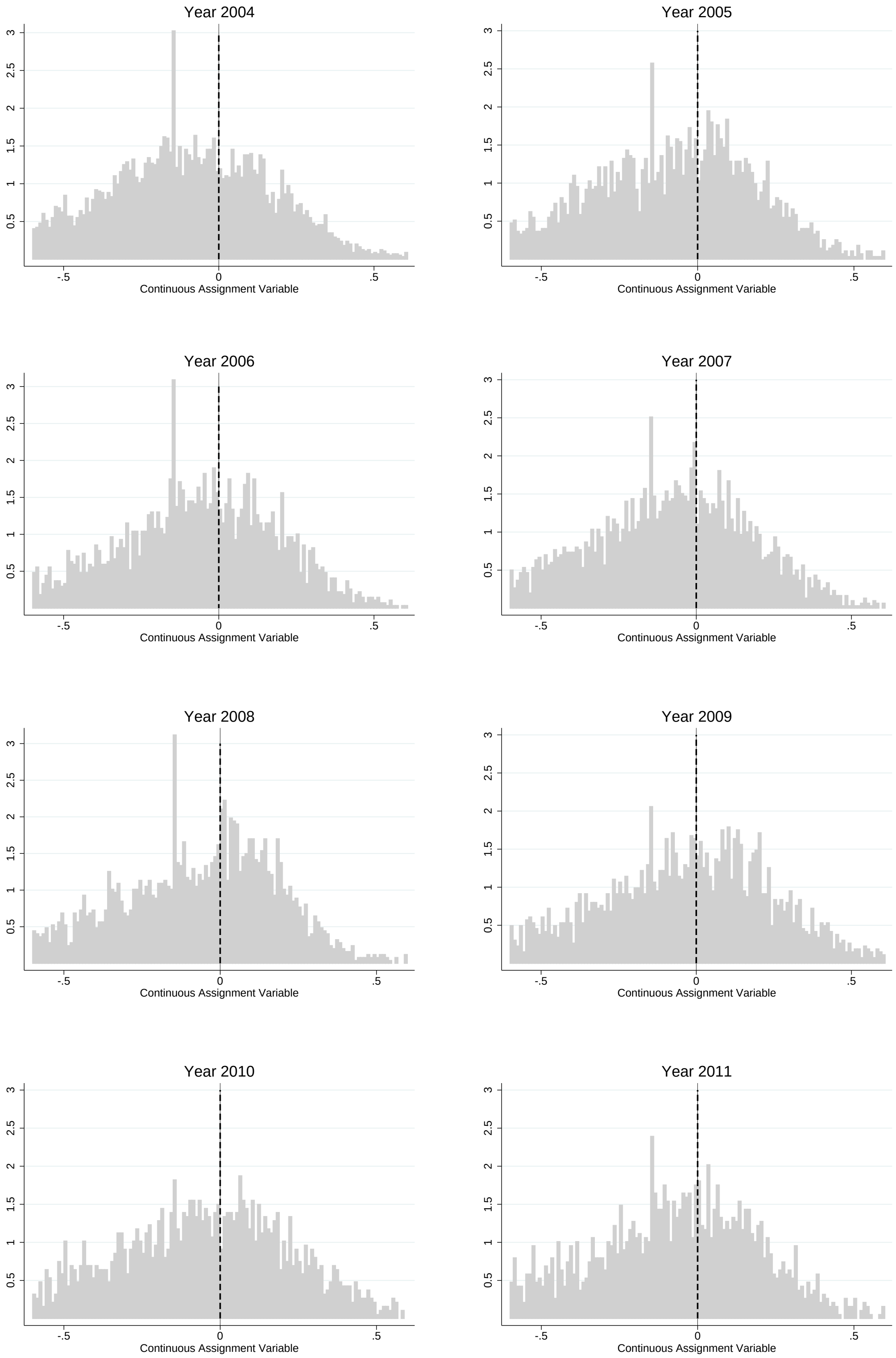
Notes: The table estimates differences in presample firm characteristics at the threshold. We report the standard errors in brackets. In all rows, the dependent variable is measured in 2003. The discontinuity is estimated using a flexible sixth-order polynomial on either side of the threshold between *Score* categories 6 and 7. The reported estimates refer to S_i, a binary variable that takes a 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 variable indicating whether the firms' SIC code belongs to the automobile industry. *Top 10 Cities* is a binary variable indicating whether the firms' headquarters zip code is in one of the largest 10 cities. *Firm Clusters* is a binary variable indicating whether the firms' headquarters is in a zip code containing more than 100 other industrial firms. See Tables I and IV for the definitions 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



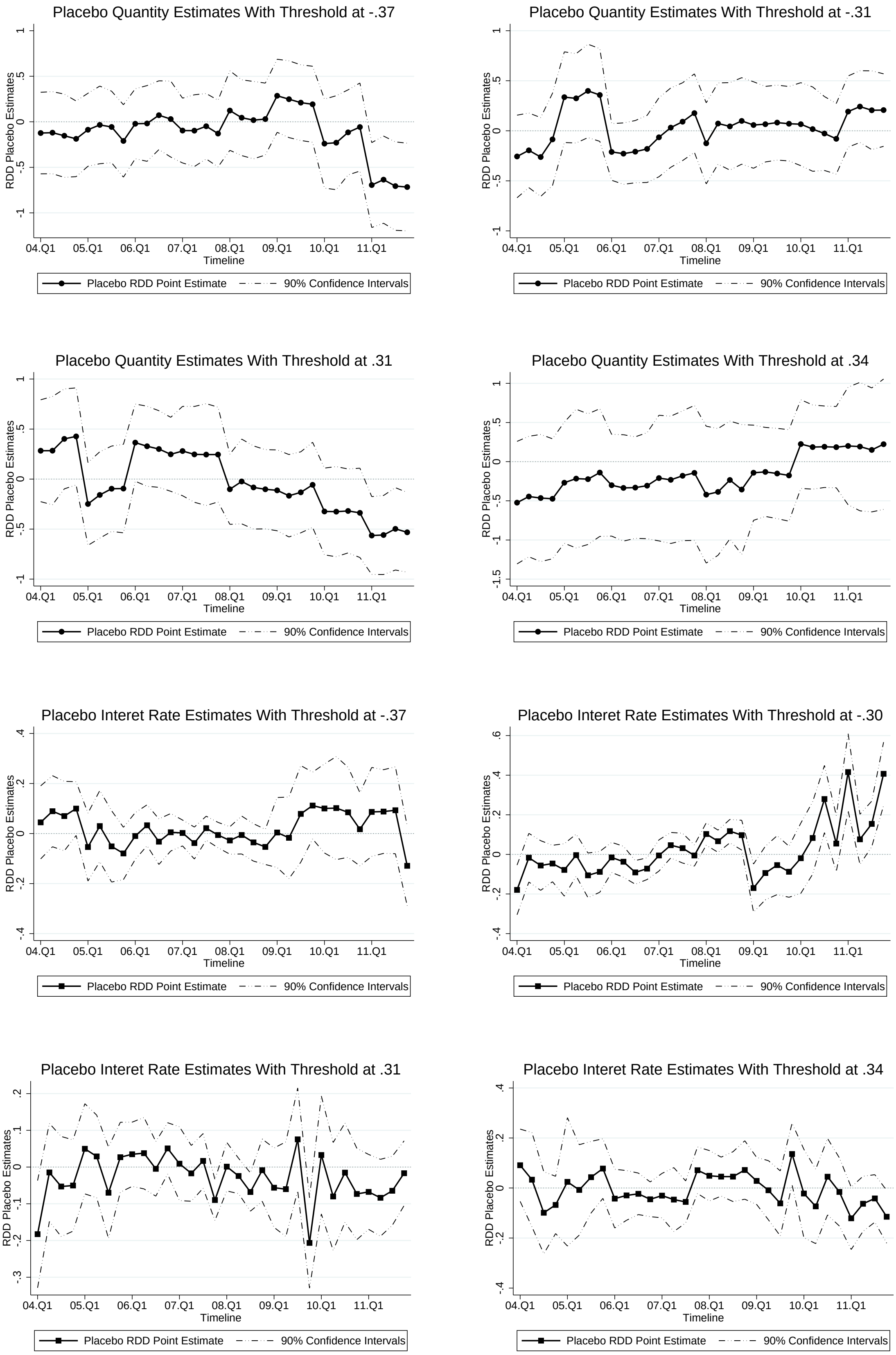
In the figure, we plot the distribution of firms along the support of the continuous variable (s_i) between *Score* rating categories 6 and 7. The solid line is a fitted kernel local linear regression of the log of the density on both sides of the threshold separating firms in category 7 from firms in 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), along with the associated 90% confidence intervals, on a fixed and randomly drawn placebo threshold.