Bank Financing in Times of Crisis: Evidence from RDD Time Series Estimates*

Giacomo Rodano† Nicolas Serrano-Velarde‡ Emanuele Tarantino§

Bank of Italy *Bocconi University* *University of Bologna*

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Abstract

We employ a repeated regression discontinuity design together with loan level data on Italian small and medium sized firms to identify changes in credit conditions due to the bank lending channel between 2004 and 2011. Our regression discontinuity design is based on fact that firms are allocated to one of the most important credit risk indicators for Italian banks exclusively on the basis of a continuous variable. Firms marginally close to the threshold are economically identical, except that those firms that fell below the cutoff are perceived to be significantly more risky. We document three distinct periods in the supply of bank lending to Italian SMEs. First, between 2004.Q1 to 2007.Q4 firms marginally above and below the threshold obtain similar amount of bank financing but at 10% higher interest rates for firms marginally considered worse risk. Second, between 2008.Q1 and 2009.Q4 we find evidence of credit rationning consistent with Stiglitz and Weiss (1981). Finally, the period between the beginning of 2010 and the end of 2011 is characterized by a decrease in quantity differences between the two group of firms around the threshold, and a simultaneous increase in interest rate differences, which are 20% higher for firms marginally below the threshold.

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*We thank XXX.

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

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

§University of Bologna, Piazza Scaravilli 1, 40126 Bologna, Italy; Phone: +390512098885; E-mail: emanuele.tarantino@unibo.it.

1 Introduction

This paper exploits a regression discontinuity design to measure differences in bank lending conditions borne by Italian SMEs classified in different risk categories, but which are economically identical. More specifically, we estimate a time series of regression discontinuity coefficients to document how differences in lending conditions evolved during the 2004-2011 period. Credit conditions of firms bearing different degree of risk might be simultaneously determined by demand and supply side effects. The channel that operates via the demand side emphasizes that it is firms' characteristics that crucially determine banks' decisions (firms' balance sheets channel), the channel that operates via the supply side stresses the role of banks characteristics (bank lending channel). Our goal is to identify across-time differences in bank lending conditions that operate via the bank lending channel, thus disentangling the impact of the bank lending channel from the impact of firms' balance sheets channel (Bernanke and Gertler, 1995; Tirole, 2006, chapter 13).

The theories that emphasize the role of the *bank lending channel* stress that shifts in the supply of funds offered by financial intermediaries might be driven by differences in intermediaries capital position and balance strength (e.g., Kashyap and Stein, 1994; Kashyap and Stein, 2000). For example, according to these theories a deterioration in the capital position of financial intermediaries might lead to a reduction in the supply of credit, causing an increase in the cost of debt finance. Instead, the theories that emphasize the role of firms' *balance sheet channel* focus on the relationship between the quality of borrowers' balance sheets and their access to external finance (see, among others, Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997). Our empirical strategy allows us to pin down credit conditions set by banks to small and medium firms, for given characteristics of the borrowers. In other words, we can separate the impact of the *bank lending channel* from the impact of the *balance sheet channel*.

Our regression discontinuity design is based on fact that firms are allocated to one of the most important credit risk indicators in Italy exclusively on the basis of a continuous variable. Firms marginally close to the threshold are economically identical, except that those firms that fell below the cutoff are perceived to be significantly more risky. The idea is therefore to compare total bank lending and interest rates of firms marginally above the thresholds, to those of firms marginally below the threshold. To corroborate the causal interpretation of our findings we assess the internal validity of our methodology by checking for possible manipulation of the assignment variable, balancing of firm characteristics, and falsification tests using placebo experiments.

We document three distinct periods in the supply of bank lending to Italian SMEs. First, between 2004.Q1 to 2007.Q4 firms marginally above and below the threshold obtain similar amount of bank financing but at 10% higher interest rates for firms marginally considered worse risk. Second, between 2008.Q1 and 2009.Q4 we find evidence of credit rationning consistent with Stiglitz and Weiss (1981). Firms marginally below the threshold now receive 50% less bank lending with respect to firms above the threshold. At the same time, interest rates are statistically and economically not significantly different. Finally, the period between the beginning of 2010 until the end of 2011 is characterized by a decrease in quantity differences between the two group of firms around the threshold, and a simultaneous increase in interest rate differences, which are 20% higher for firms marginally below the threshold.

We present very preliminary evidence on the interaction between the bank lending channel and monetary policy. When a tight monetary policy is implemented by the central bank, banks experience a rise in their cost of funding that induces them to shift the supply of loans inward and raise loans' price. Of course, an accommodating interest rate policy triggers a process that works in reverse. The paper plots the RDD time series estimates together with measures of monetary policy. Interestingly, the link between policy rate interventions of the ECB to control firms' borrowing costs broke down after 2007, credit rationning remaining high while policy rates dropped to 0. At the same time, the start of the the Securities Market Programme, to improve intermediaries net worth and in this way stimulate banks' supply of credit, correlates with the redution of quantity rationning.

In the following, we first present the data used for the empirical investigation. Section 3 explains the identification challenge related to disentangling demand and supply in bank lending, and introduces the regression discontinuity framework. Section 4 presents the results, first for one single quarter estimation of the RDD, and then for the time series.

2 Data

Our main data sources for the credit conditions of firms and the characteristics of their loans, are confidential datasets collected by the Bank of Italy as part of its bank supervision duties: Central Credit Register (*Centrale dei Rischi*) and *Taxia*. In addition to this information, we also have balance sheet data for the universe of Italian companies from the *Cerved* database.

The Central Credit Register In order to comply with Italian banking regulations, all financial intermediaries operating in Italy (banks, special purpose vehicles, other financial intermediaries providing credit) have to report financial information to Bank of Italy, on a monthly basis, for each borrower whose aggregate exposure exceeds 75,000 Euros. Thus we can use the central credit register to compute the aggregate financial characteristics of firms. For each borrower-bank relationship we thus have information on financing levels, granted and utilized, for three categories of instruments: term loans, revolving credit lines, and loans backed by account receivables. The information on term loans is supplemented by other non-price characteristics, such as loan maturity, and the presence, or otherwise, of real or personal guarantees.[1]

Taxia Taxia is a subset of the Central Credit Register that covers information on more than 80 percent of total bank lending in Italy. More specifically, this dataset provides us, on a quarterly basis, with detailed information on the interest rates that banks charge to individual borrowers on each newly issued term loan and each outstanding credit line. In addition, the dataset provides information on the maturity and presence of collateral for each newly-issued term loan. The data collection process of Taxia was heavily revised in

[1]This dataset has been used by, among others, Detragiache et al. (2000), Sapienza (2002), Bonaccorsi Di Patti and Gobbi (2007). Data from credit registers have also been used for other countries (Hertzberg et al., 2011; Jiménez et al., 2012).

2004. We therefore have reliable loan-level information starting from the second quarter of 2004.

3 Identification Strategy

3.1 Cerved Score

For our purposes, the most important information about a particular loan is the creditworthiness of the borrower. The firms' credit quality is captured by a summary measure called the *Score*. The availability of the credit rating information in our dataset and its coordinated use by Italian banks is linked to the development of Italy's credit market. At the end of the 1970s, regional chambers of commerce and banks decided to cooperate on the collection of firms' mandatory balance sheet disclosures. Cerved was appointed to collect balance sheet information from firms, and it uses that information to provide risk-assessment tools to banks, most prominently the *Score*.

The *Score* variable computes the likelihood of a firm defaulting over a two year horizon on the basis of multiple discriminant analyses of financial ratios (Altman, 1968; Altman and Varetto, 1994). It is an indicator having values of between one (for those firms least likely to default) to nine (for those that are most likely to default) and is purchased by all major banks from Cerved to be employed as an index of firms' risk levels. The continued acceptance of *Score* in loan applications of firms, indicates that there is a level of comfort with their value in determining default probability differences. Figure 3 documents these two important features.

[**Figure 3 Here**]

The top panel of Figure 3 is taken from Panetta et al. (2007) who, using the same balance sheet and bank data as ours for the period 1988-1998, plot the *Score* variable against an indicator of actual default incidence. The figure shows that the *Score* is an accurate predictor of actual default incidence among Italian firms. Firms with a *Score* of up to four in a given year, have less than a 1% probability of defaulting within the next two years. This probability rises to 10% for firms with a *Score* of 7. The bottom panel plots the *Score* variable against the interest rate on newly issued loans. There is a strong positive relation between *Score* and interest rates on loans. The best (lowest) *Score*, in terms of creditworthiness, is on average associated with a loan interest rate of 4%, whereas the worst (highest) category pays an average loan interest rate of around 5%.

Two further distinct characteristics of the *Score* are worth highlighting. Firstly, unlike U.S. credit ratings, the *Score* is unsolicited and available for all Italian firms, hence its availability is not the result of strategic considerations on the part of the firms themselves. Secondly, the *Score* of a firm for any given year is computed, due to accounting rules and data collection requirements, on the basis of lagged balance sheet information. This implies that the credit rating is not based on forecasted demand conditions.

We focus on firms active in the manufacturing sector. We drop all new loans with an amount smaller than 10,000 Euro and extreme percentiles of the term loan interest-rate distribution. We drop firms with incomplete balance sheets and profit and loss accounts, missing *Score*, with leverage above one or below 0. The final dataset is of a quarterly frequency, and runs from the second quarter of 2004 to the last quarter of 2011, comprising a total of XX distinct manufacturing firms and XX banks.

3.2 The Identification Challenge

Policy makers and regulators typically try to measure the existence and extent of credit cyles by comparing lending conditions between firms belonging to different risk categories. The underlying assumption is that the difference in financial contracts represents how investors price risk. For Italian firms it is possible to compute an indicator, based on *Score*, of credit conditions to firms in high and low risk categories. Firms in risk categories 1 to 4 are labeled by CERVED as "safe", whereas firms in risk categories 5 to 7 are labeled as "vulnerable", and firms in risk categories 8 and 9 as "risky". It is therefore possible to define as a possible cutoff definition for high and low risk categories, $S^{High/Low}$, firms in categories 1 to 4 as opposed to firms in categories 5 to 9. Measuring differences in financial conditions to these two group of firms involves the estimation of the following model by ordinary least squares (OLS):

$$y_i = \alpha + \beta^{High/Low} S_i^{High/Low} + u_i \tag{1}$$

where we define y_i to be two measures of financing conditions. The first measure we consider is the log of total banking finance granted to firm i in a given quarter. The second measure we consider is the log of the interest rate on newly issued term loans to firm i in a given quarter. In this model, α is a constant and $\beta^{High/Low}$ is the average treatment effect, understood as the difference in financing conditions due to a higher risk rating.

[Figure 2 Here]

Figure 2 plots the time series of $\beta^{High/Low}$ coefficients obtained from estimating equation 1 for each quarter between 2004 and 2011. The top panel plots coefficients obtained using the log of granted banking finance as the dependent variable. Higher positive values of $\beta^{High/Low}$ indicate a larger amount of banking finance granted to firms considered as better risk. At the beginning of the sample period, quantity differences are stable around 20%, before significantly dropping in 2006 and remaining low (even negative) between 2007 and 2010. The bottom panel plots coefficients obtained using the log of interest rates on newly issued term loans as the dependent variable. Higher negative values of $\beta^{High/Low}$ indicate a higher interest rate to firms considered as worse risk. Again differences are at first stable, around 12%, before becoming successively smaller until the end of 2009. At the end of 2008 interest rate differences shoot up to approximately 23% in 2010.

Unfortunately, our results using model 1 are unlikely to disentangle demand and supply side effects. Neither the firms in the treatment group, nor those in the control group can be considered random samples. The risk assessment of the firm directly depends on the financial and economic health of the firm, which in turn affects credit demand and credit conditions provided by the bank. Consequently the error term u_i is likely to be correlated with the regressor $S^{High/Low}$.

To isolate changes in the supply of credit by banks from changes in the demand of credit by firms we would ideally like to measure, for the same firm, differences in credit conditions only due to a marginal increase in perceived default risk. Such a measure would capture how banks price risk for the same intrinsic demand. To approximate this experiment we exploit the fact that firms are allocated to the categorical *Score* indicator on the basis of an underlying continuous variable. The proposed identification strategy measures contractual differences in bank lending of firms marginally above and below the threshold of two risk categories.

3.3 Identification by Regression Discontinuity

We take advantage of the fact that firms are allocated to *Score* categories on the basis of a continuous variable, denoted s. The continuous variable s is constructed by Cerved on the basis of multiple discriminant analysis of financial ratios, and the algorithm underlying the construction of the continuous variable is a business secret. Cerved also determines the support of the continuous variable for each of the discrete *Score* categories. Thus, firms not only ignore the value of their own continuous *Score*, but also cannot self-select into a specific category. Banks have access to both sources of information, but mostly use the discrete *Score* indicator in their pricing decisions.

The key identifying assumption of the proposed sharp RDD is that firms are assigned to risk categories solely on the basis of the observed, continuous measure s, called the assignment variable. This assumption holds since the assignment variable is a real valued function of several variables, observed on both sides of the threshold. The observations that fall below the deterministic cutoff $\bar{s}$ are placed in the control group, which is denoted by a categorical indicator, S_i, equal to zero. Observations on or above that point are placed in the treatment group, that is, $S_i = 1$. In other words,

$$S_i = S(s_i) = 1\left\{s_i > \bar{s}\right\} \tag{2}$$

This assumption can be formally restated as,

$$\begin{aligned} lim_{s\downarrow\bar{s}} \quad Pr(S_i = 1|s_i) &= 1 \\ lim_{s\uparrow\bar{s}} \quad Pr(S_i = 1|s_i) &= 0 \end{aligned} \tag{3}$$

A second identifying assumption is the local continuity assumption. This assumption requires the potential outcomes to be continuous in the assignment variable s_i at $\bar{s}$. This implies that taking the difference between the left and right limits in s around the threshold yields the causal estimate,

$$
\begin{aligned}
lim_{s\downarrow\bar{s}} - lim_{s\uparrow\bar{s}} &= \beta\left(lim_{s\downarrow\bar{s}}E(S_i|s_i) - lim_{s\uparrow\bar{s}}E(S_i|s_i)\right) \\
&+ \left(lim_{s\downarrow\bar{s}}E(u_i|s_i) - lim_{s\uparrow\bar{s}}E(u_i|s_i)\right) \qquad (4) \\
&= \beta
\end{aligned}
$$

where the second line follows by continuity of $E(u_i|s_i)$. This last step is crucial. Estimation of the naive regression model implies that many of the determinants of y_i are contained in u_i. The continuity assumption therefore states that none of those determinants discontinuously changes at $\bar{s}$. To infer β we estimate, for each quarter between 2004 and 2011, the following model:

$$
y_i = \alpha + \beta S_i + f(s_i - \bar{s}) + S_i \cdot g(s_i - \bar{s}) + u_i \qquad (5)
$$

where $f(\cdot)$ and $g(\cdot)$ are continuous functions and β is the difference in intercepts at the threshold point. To simplify the analysis we restrict $f(\cdot)$ and $g(\cdot)$ to be of the same polynomial order, determined by minimization of the Akaike information criterion. As before, s_i is the continuous assignment measure for firm i, $\bar{s}$ is the deterministic cutoff for the categorical risk indicator, and S_i is the categorical indicator equal to one for a lower risk category. The dependent variable, y_i, is the log of total granted banking finance to firm i or, alternatively, the log interest rate of loans to firm i. Finally, the inclusion of covariates in the regression discontinuity design potentially serves two purposes. It indirectly tests the validity of the local continuity condition and potentially improves the precision of the RDD estimates by absorbing residual variation.

We focus on the threshold that divides firms into *Score* categories 6 and 7. The support of the continuous variable s for *Score* categories 6 and 7 ranges from 1.5 to -0.6, and the threshold lies at 0.15. Below the threshold, a firm's *Score* is 7. Above the threshold, a firm's *Score* is 6. The reason to focus on this threshold is that falling in category 7 triggers an important change in the firm risk as perceived by the bank. Indeed, a firm in category 6 is classified as "vulnerable", whereas a firm in category 7 is classified as "risky" and potentially prone to default.

Note that it is possible to assess the internal validity of the regression discontinuity approach based on the idea that, around the threshold, we obtain conditions close to a randomized experiment. An implication of the local continuity condition is that firms close to, but on different sides of the threshold should have similar potential outcomes. This suggests that we can test for whether these firms are comparable in terms of characteristics related to the outcome, but logically unaffected by the threshold. Relatedly we will discuss and test for the possibility of firms to manipulate their assignment variable, and therefore self-select into treatment status. Finally, given the setup of the design, one can also implement falsification tests in order to reinforce the assertion that the estimated effect is not due to a coincidental discontinuity. We will address all these issues.

4 Results

We first illustrate our RDD framework by focusing on the second quarter of 2004. We then repeat the estimation procedure for all 32 quarters between 2004 and 2011, and directly plot the associated treatment effects.

4.1 RDD Results

4.1.1 RDD Estimates for Q2 of 2004

Figure 4 provides a graphical representation of the discontinuities in financial contracts induced by the risk categorization. Each point represents, for the second quarter of 2004, the mean and 90% confidence interval over a bin of width (.04), whereas the line plots the fitted sixth-order polynomials on each side of the discontinuity. The top panel plots the log of granted banking finance and the bottom panel plots the log interest rate on newly issued term loans.

[**Figure 4 Here**]

The top panel shows an economically relevant difference of 25% in the financing granted by banks to firms marginally above and below the threshold. The bottom panel shows that among the firms who took out a loan in the second quarter of 2004 the interest rate charged was 9% higher for firms marginally below the threshold. The figures thus illustrate that our polynomial is correctly picking up variations financial contracts occuring directly at the threshold. Note that plots using narrower bin widths (.02) provide very similar conclusions.

4.1.2 Time Series of RDD Estimates

Figure 5 directly plots the magnitude and 90% confidence intervals of the RDD estimate in each quarter. The top panel plots estimates using the log of granted banking finance as dependent variable, the bottom panel plots estimates using the log of interest rates on newly issued term loans as dependent variable.

[**Figure 5 Here**]

The top panel indicates that firms marginally above the threshold got access to a higher amount of banking finance between 2004 and 2005. Although not statistically significant, the estimates are large in magnitude, indicating quantity differences around 25%. This period of weak quantity differentiation is followed by eight quarters of uniform access to bank financing. Indeed differences between firms marginally above and below the threshold fall and are in magnitude and statistical significance indistinguishable from 0. This period of ample supply ends in 2008 when differences in quantities spike to 50% differences in quantities allocated to economically identical firms. The crunch remains large in magnitude and statistically significant until the end of 2009.

The bottom panel plots the RDD estimates related to price differences on newly issued loans. Interest rate differences consistently track quantity differences up until 2008. Between 2004 and 2005 firms marginally above the threshold obtained on average loans at 10% lower interest rates. These differences again shrink in the period 2006 to 2007. An interesting feature arises in 2008 and 2009 when quantity differences are at their peak. Interest rates on newly issued loans remain very similar between the two group of firms, even though with larger volatility as suggested by the widening confidence intervals. It is precisely when quantity differences vanish that the pricing of loans becomes again sensitive to the risk category of the firms. Indeed interest rates on new loans of firms below the threshold are 20% higher with respect to loans of firms above the threshold.

4.1.3 Time Series of RDD Estimates And Monetary Policy

Figures 6 and 7 associate the RDD estimates on supply side effects in bank lending, together with information on monetary policies implemented in the Eurozone area. As previously mentionned, we consider two types of policy instruments, the EONIA rate (top panels) and the Securities Market Programme (SMP, bottom panels).

[**Figure 6 Here**]

Figure 6 focuses on how quantity differences correlate with monetary policy. The top panel shows that Eonia rates were raised from 2% to 4% between 2006 and 2007. The 2008 financial crisis triggered a succession of reductions in the Eonia rate but with seemingly little impact on quantity differences, which remained significant until 2010. The bottom panel shows the association between the introduction and rapid increase in the SMP programme in mid-2009, and the reduction in quantity differences for firms marginally below the threshold.

[**Figure 7 Here**]

Figure 7 associates the policy interventions with RDD estimates on interest rate differences in new loans. Conventional policy interventions again do not seem to signficantly have affected the pricing of loan contracts, since price differences remained at the same level in 2009 as in 2008. Even more strikingly, historically low Eonia rates seem not to bear any relation with widening interest rate differences in 2010 and 2011. A similar picture arises when considering the unconventionnal monetary policy.

4.2 Tesing the Validity of the Identification Strategy

4.2.1 Self-Selection

An identifying assumption of the RDD framework is that the assignment variable, s, has a positive density in a neighborhood of the cutoff $\bar{s}$. This assumption rules out manipulation of the forcing variable, which might result in either no observations near the threshold or bunching of observations on one side of the threshold. In the spirit of McCrary (2008) one can formally test for the presence of a density discontinuity at the threshold by running kernel local linear regressions of the log of the density on both sides of the threshold $\bar{s}$. Note that some manipulation of the assignment variable can be tolerated before identification is compromised.

[**Figure 10 Here**]

In nearly all years there is no evidence that firms sort just above - as opposed to just below - the threshold. This is consistent with the institutional framework presented before: the continuous value of the *Score* is ignored by firms. Even if the loan officer was to communicate to them their value of s and the associated threshold, they would be unable to understand the element used to compute and weight the risk indicator. Only in 2008 does the McCrary procedure find evidence of a discontinuous density. To rule out that this discontinuity is due to manipulative sorting on the side of the firms or of the rating agency we need to implement a further test.

4.2.2 Manipulative Sorting

We further check for manipulative sorting by performing balance tests on the available invariant and pre-treatment characteristics of firms. If there were non-random sorting, on the side of firms or of the rating agency, we should expect some of these characteristics to differ systematically between treated and untreated firms around each threshold. The invariant characteristics we look at are the activity of the firm (measured by the SIC code), agglomeration effects (measured by whether there are more than 100 firms within the same postcode), and average employment of firms. To do so we re-estimate our baseline specification using these characteristics as dependent variables for each year.[2]

Figure 8 illustrates the empirical strategy to detect a discontinuity by plotting the data and the polynomial for 2004.

[**Figure 8 Here**]

Whether one looks at activity in terms of the probability to be in the automobile industry (top left) or in the food industry (top right) , we, visually and statistically, fail to detect any significant discontinuity. The same conclusion holds when assessing the pre-treatment characteristics on the basis of geography or employment. We now plot the the time series of RDD estimates in terms of pre-treatment characteristics for each year.

[**Figure 9 Here**]

No invariant or pre-treatment characteristic shows a significant discontinuity at the threshold in any year. This is especially reassuring for the 2008 sample, as this means that the discontinuity in the density of firms is unlikely to be the result of manipulative sorting. In addition we also fail to recognize any clear time trends in the estimates, i.e., increasing share of food firms or larger firms on one side of the threshold.

4.2.3 Placebo Estimates

We implement falsification tests to alleviate concerns that the estimated relation is spurrious. To do so we draw J randomly distributed placebo thresholds on the support of *Score* 6 and 7. We denote each new value of threshold $j = 1, ...J$ as $\bar{s}^{placebo_j}$, and correspondingly re-define the binary variable $S_i^{placebo_j}$. We re-estimate for each placebo threshold j the series of 32 RDD estimates:

[2] Indeed the values of the categorical *Score* and the underlying continuous variable are updated each year.

$$y_i = \alpha + \beta S_i^{placebo_j} + f(s_i - \bar{s}^{placebo_j}) + S_i^{placebo_j} \cdot g(s_i - \bar{s}^{placebo_j}) + u_i \quad (6)$$

The top figures in each of the panels plot the share of placebo estimates which are statistically significant at the 10% level, as well as the share of placebo estimates which are significant but of the opposite sign with respect to the true threshold. The top left hand panels plot all the drawn placebo thresholds, while the right hand panels restrict the plot to placebo thresholds further away from the true threshold.[3] The bottom figures of each panel plot the RDD estimates from two randomly drawn placebo thresholds on each side of the distribution of the continuous variable.

[**Figure 11 Here**]

We draw 23 placebo thresholds for the quantity series and obtain 736 RDD quarter estimates. On average a randomly drawn threshold has 7.7% probability to be statistically significant in a given quarter. Instead, the true threshold yields a statistically significant estimate in 22% of the cases. Out of the 57 statistically significant RDD estimates, only 13 correspond also to a statistically significant RDD estimate obtained from the true threshold. The top left figure in panel A shows that the probability of a significant threshold is highest in 2008 and 2011. However half of the significant estimates in 2011 have the wrong sign, i.e., estimate a negative quantity difference between both groups. The right hand figure of panel A shows that significant placebo estimates in 2008 and beginning of 2009 are mostly due to thresholds placed at the extremes of the distribution of the continuous assignment variable. The bottom figures of panel A complement the analysis by analysing patterns within a given placebo threshold series. The magnitudes of coefficients do not seem consistent with the observed patterns using the true threshold.

We draw 61 series of placebo threshold for the price series and obtain 1952 RDD quarter estimates. On average a randomly drawn threshold has 10% probability to be statistically significant in a given quarter. Instead, the true threshold yields a statistically significant estimate in 44% of the quarters. Out of the 854 statistically significant RDD estimates, only 78 correspond also to a statistically significant RDD estimate obtained from the true threshold. The time series of placebo price estimates is therefore significantly less likely to yield similar conclusions with respect to the true threshold.

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A Tables and Figures

Figure 1: Aggregate Lending to SMEs

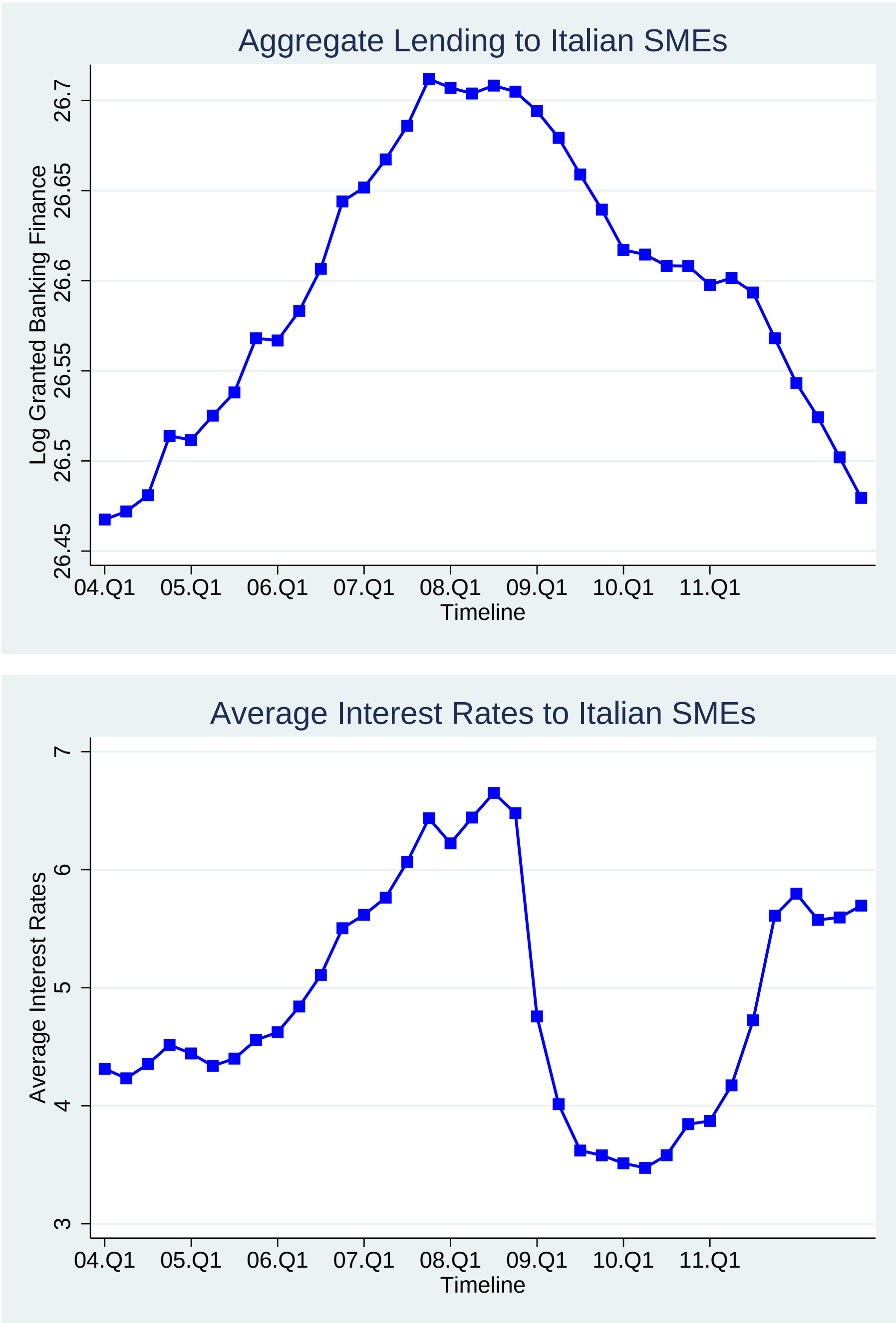


Figure 2: Naive Quantity and Price Effects

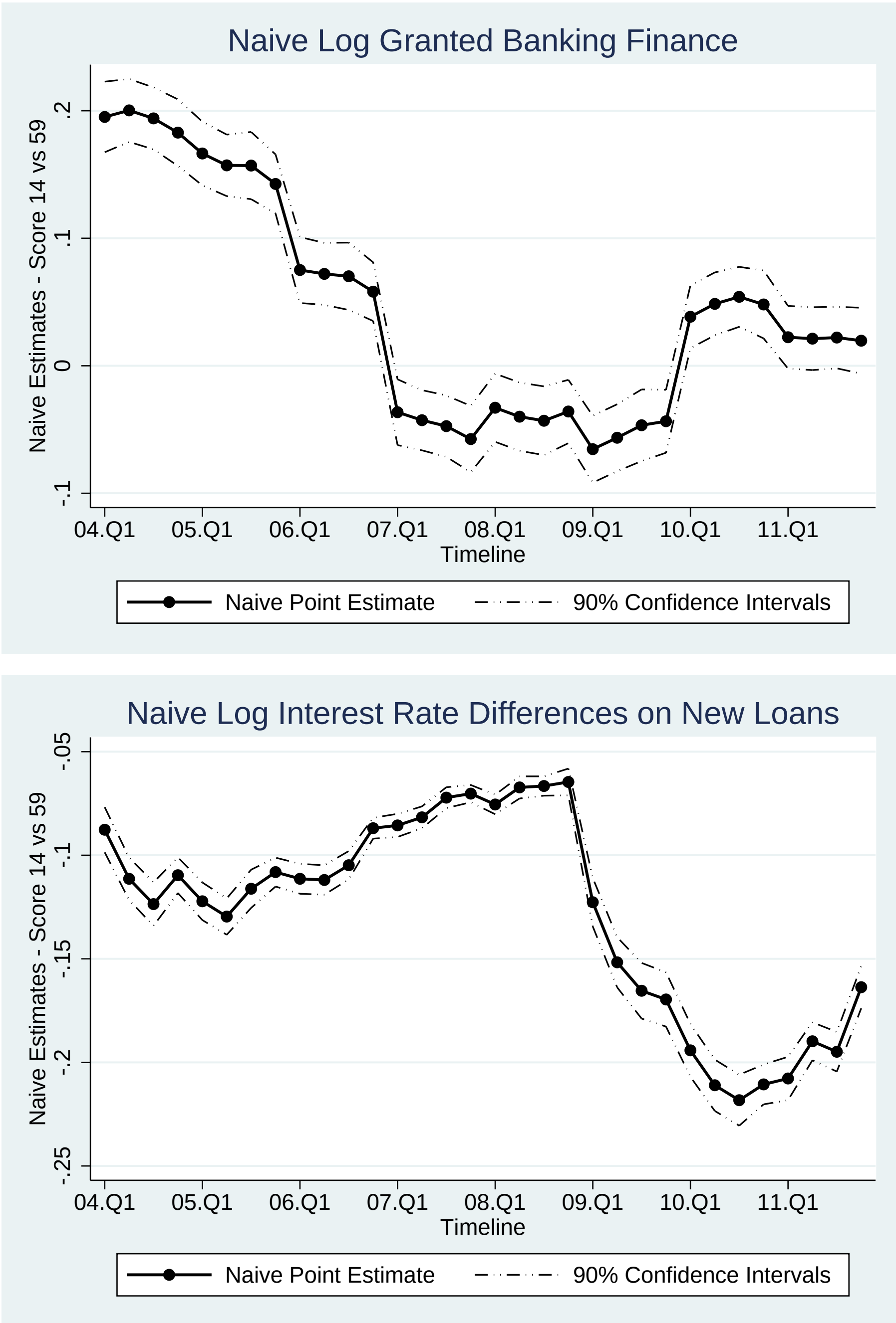
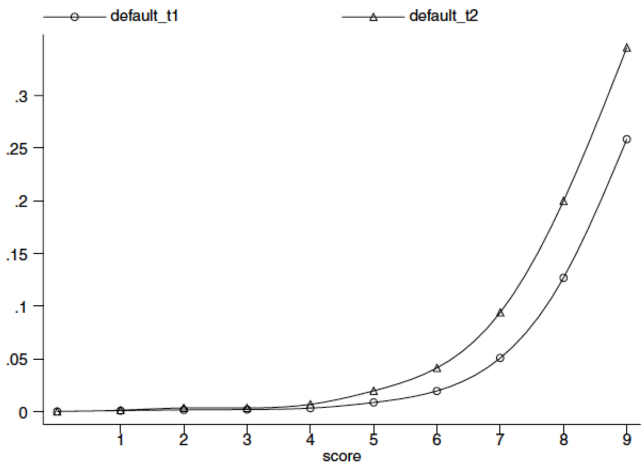
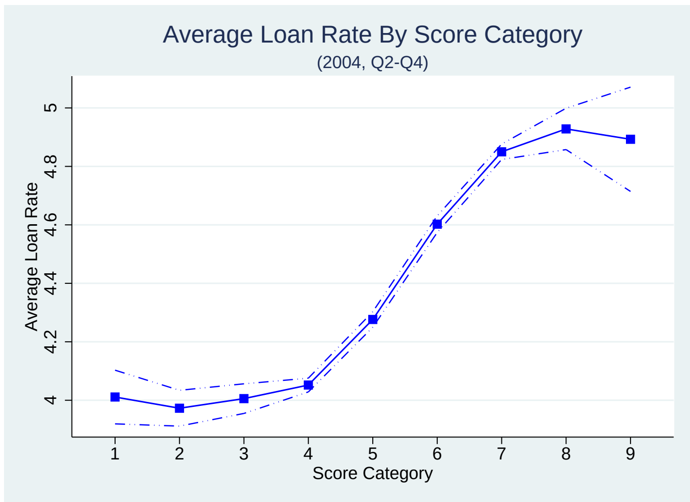


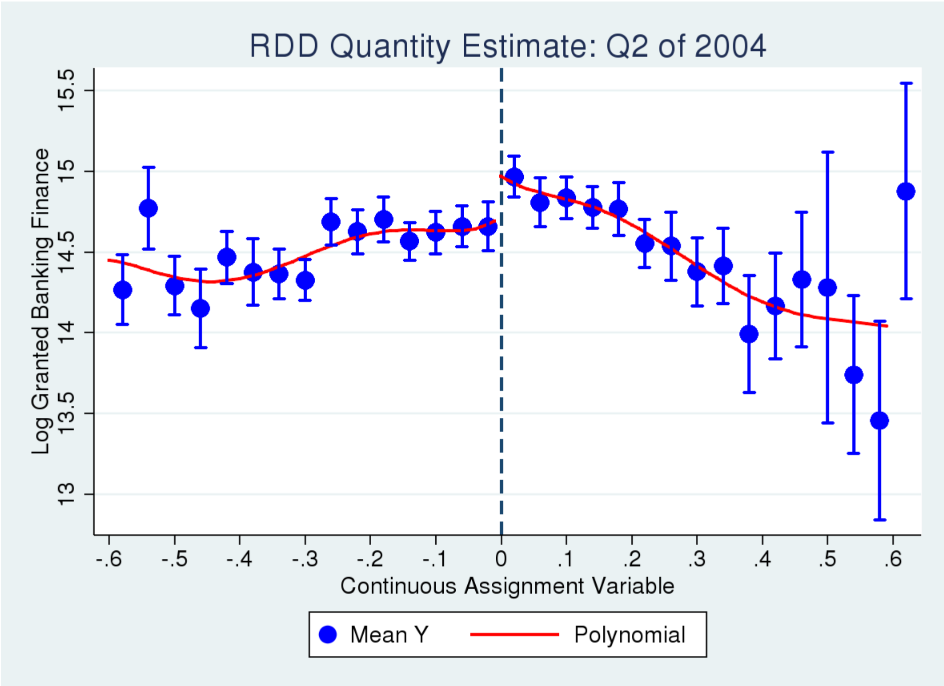
Figure 3: Characteristics of the Score Assignment Variable





The top panel is taken from Panetta et al. (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 middle panel plots, for a representative sample (2004.Q2-2004.Q4), the share of firms within each *Score* category. The bottom panel, computed on the basis of a representative sample (2004.Q2-2004.Q4), plots the *Score* variable against the average interest rate on loans.

Figure 4: RDD Quantity and Price Treatment Effects: Q2.2004



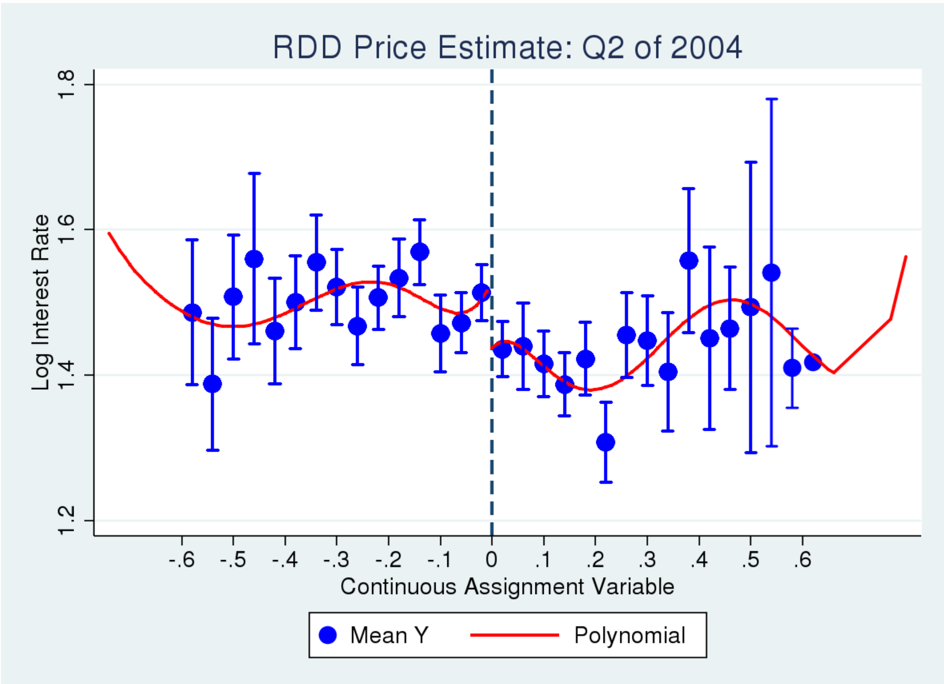


Figure 5: RDD Quantity and Price Treatment Effects

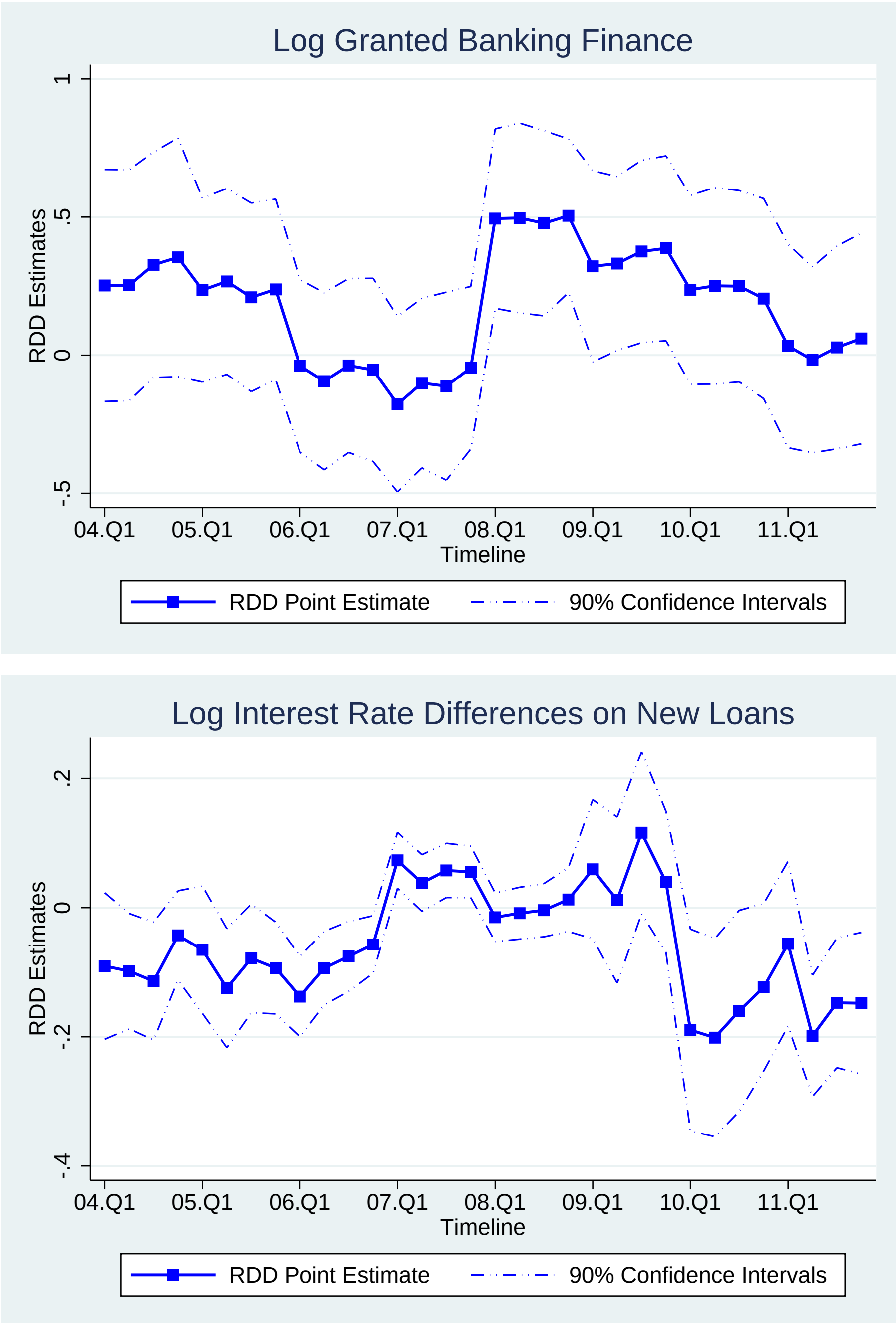
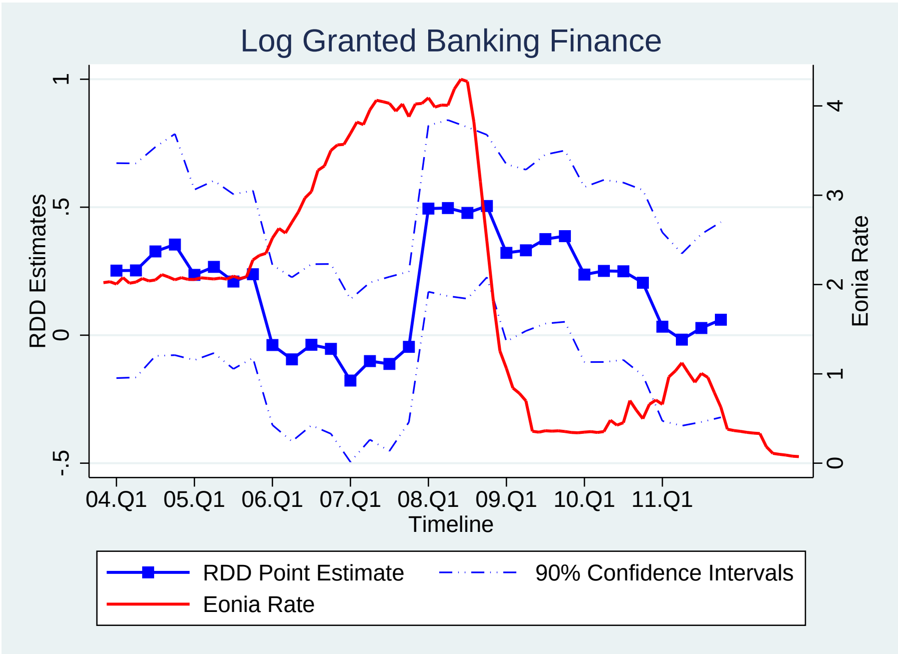


Figure 6: RDD Quantity Treatment Effects and Monetary Policy



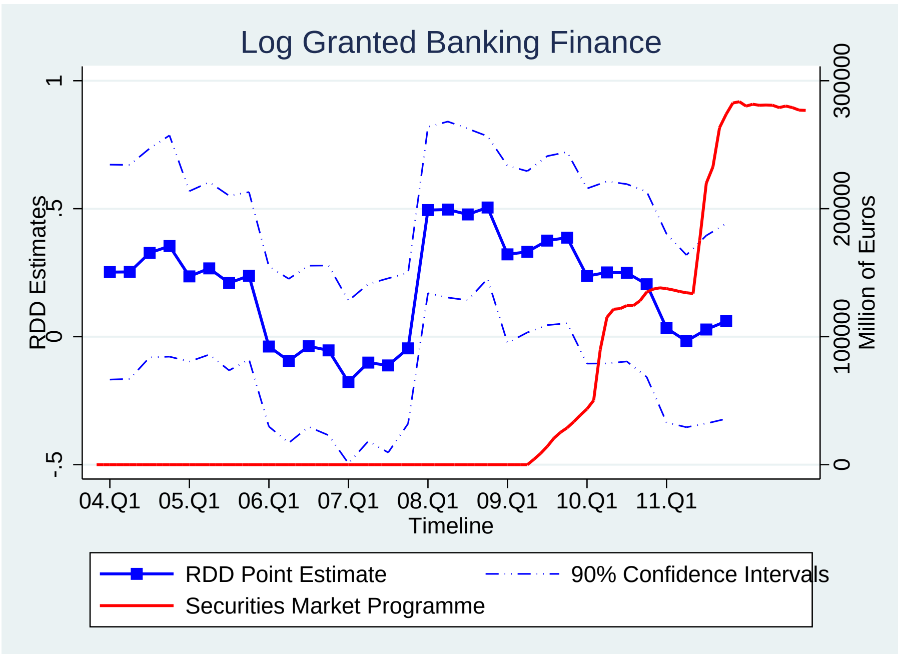


Figure 7: RDD Price Treatment Effects and Monetary Policy

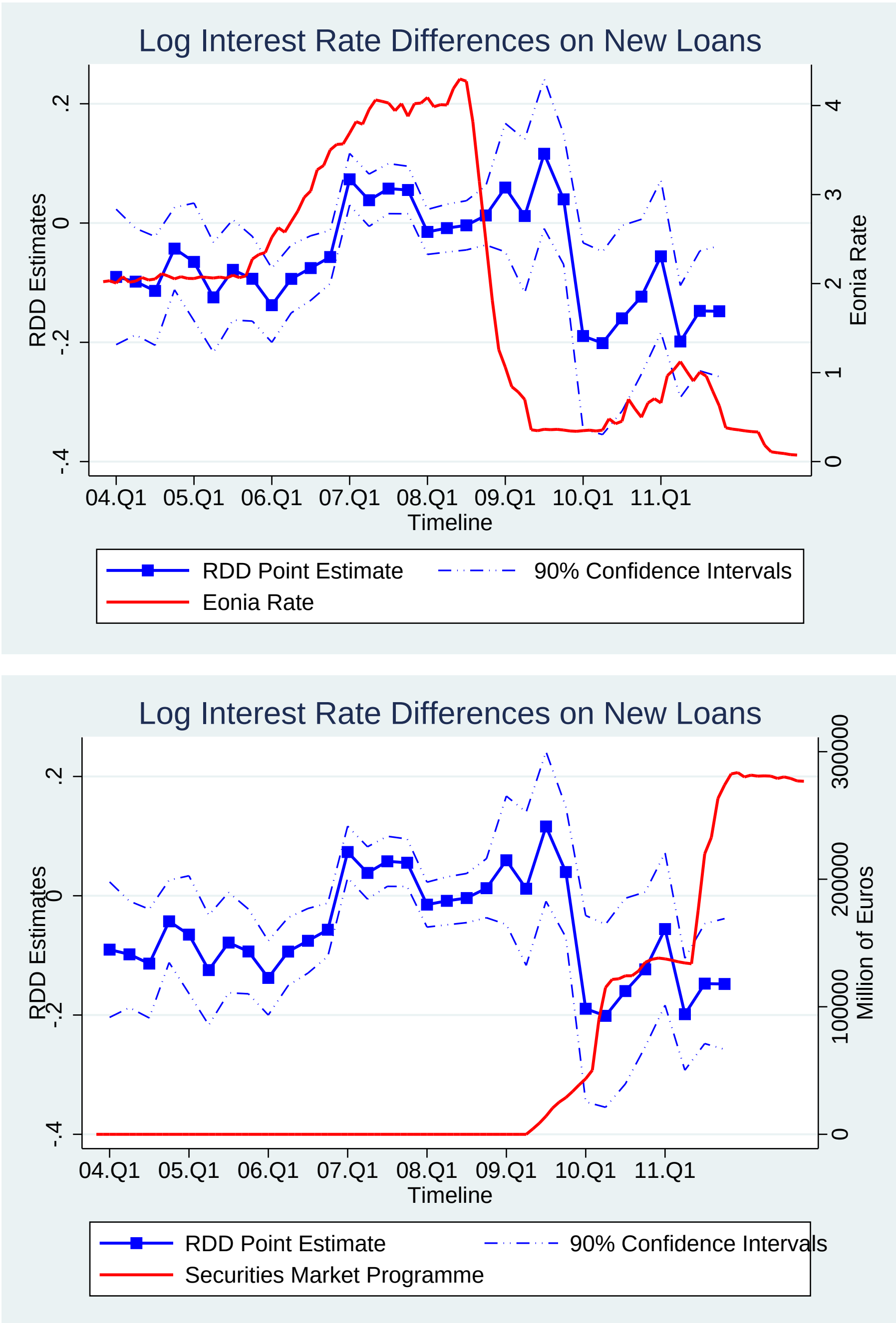


Figure 8: Balancing Characteristics Test For 2004

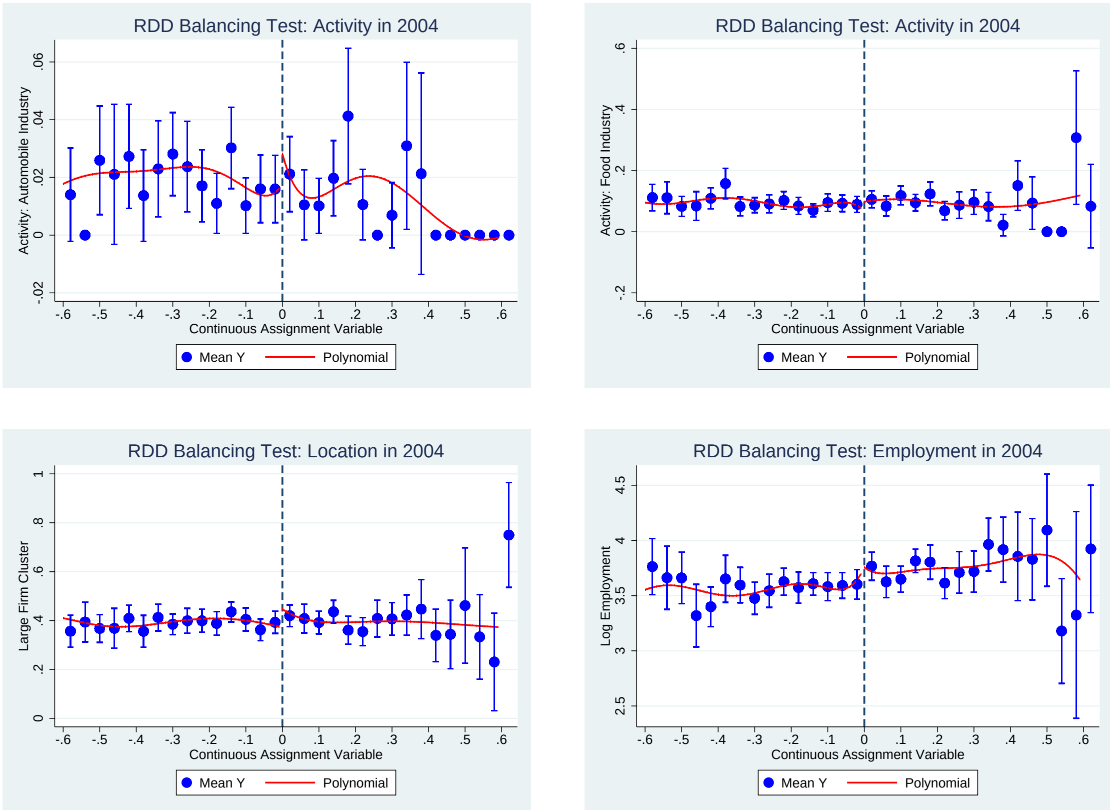


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Figure 9: Balancing Characteristics Test

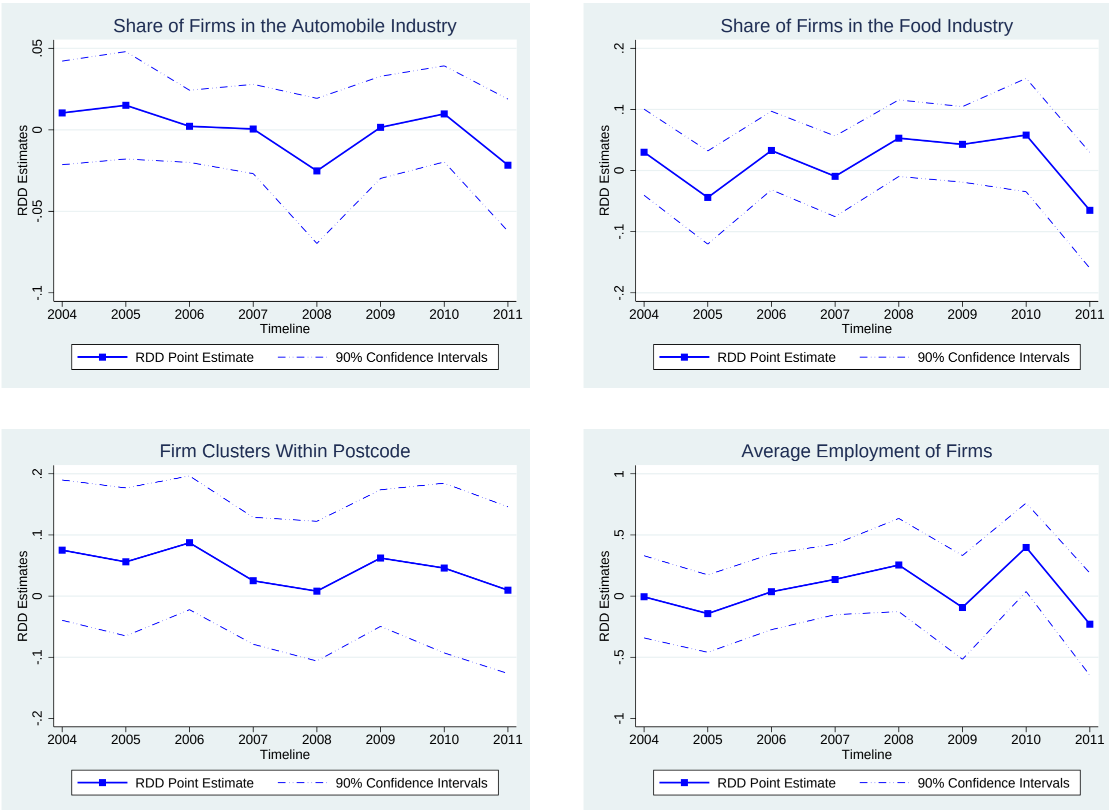

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Figure 10: Mc Crary Self-Selection Test

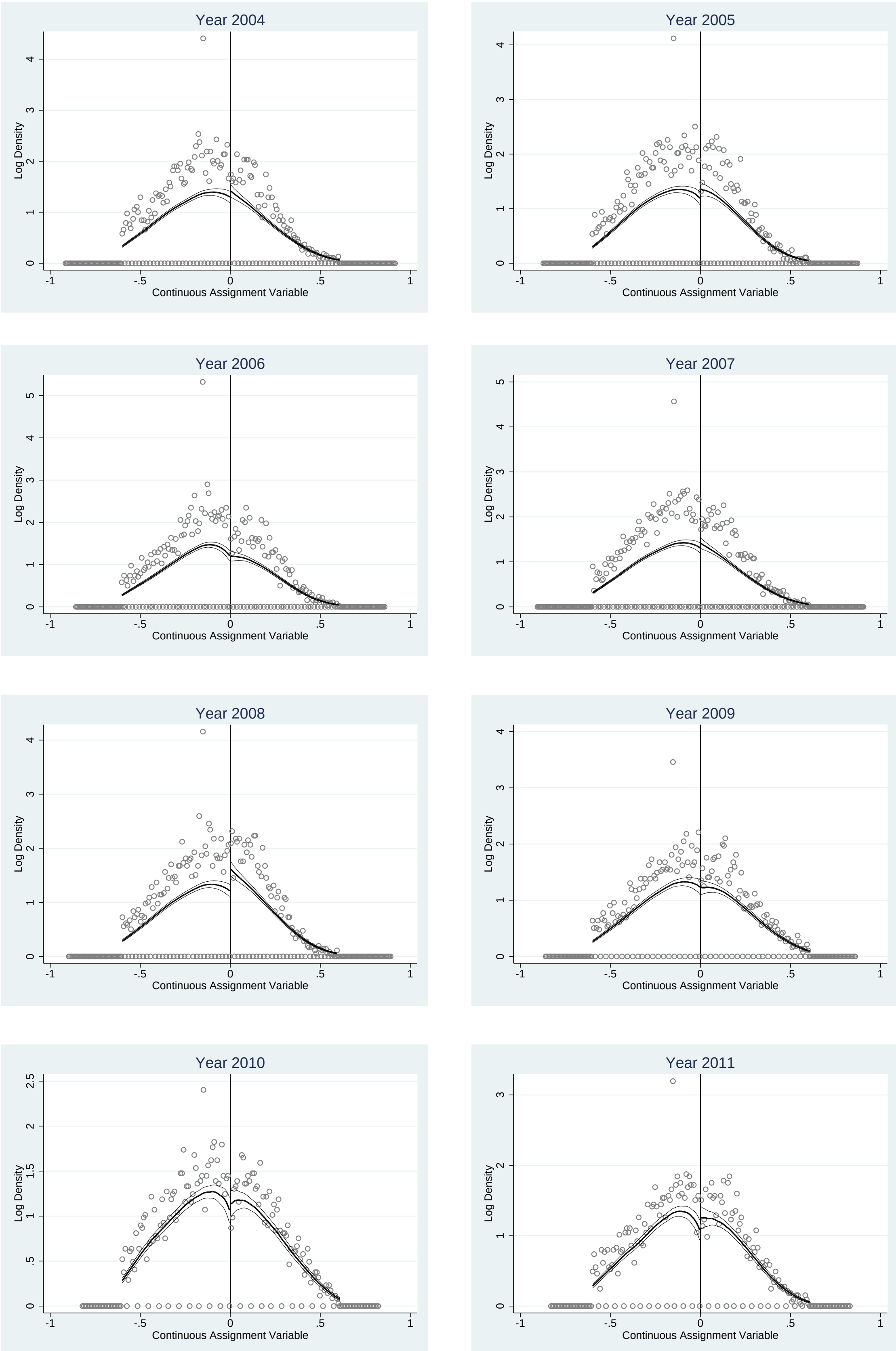

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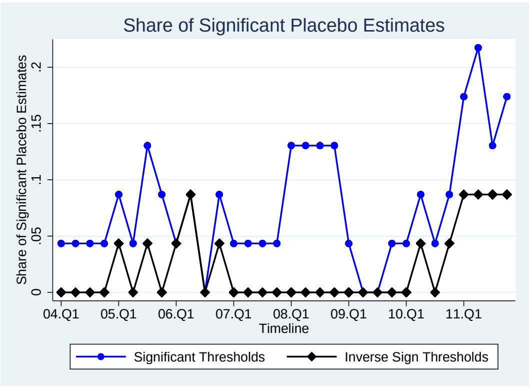
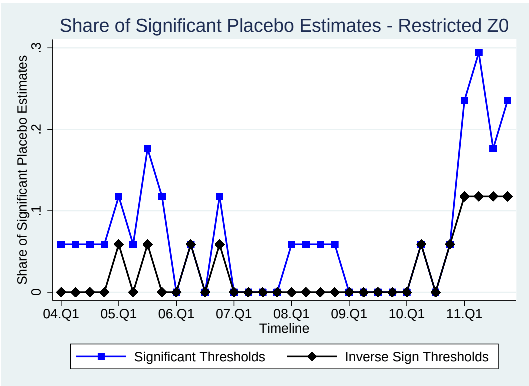
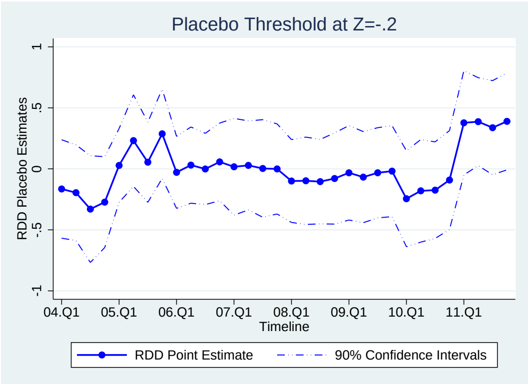
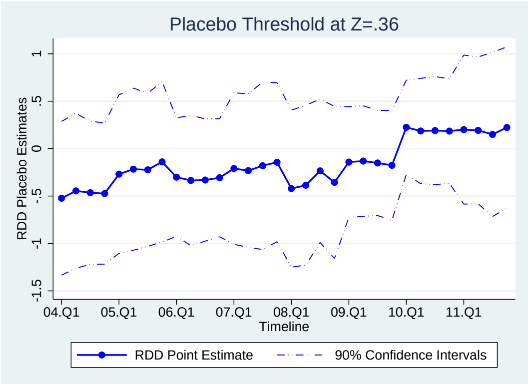
Figure 11: Placebo Threshold Test

Panel A: Quantity Differences

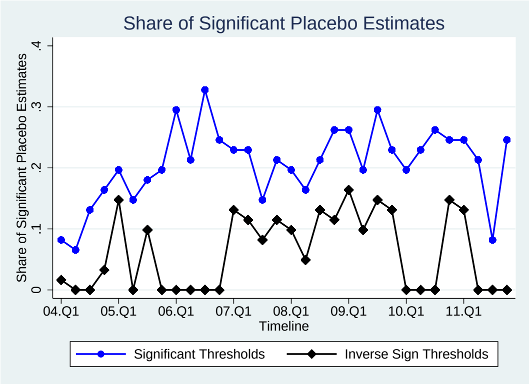


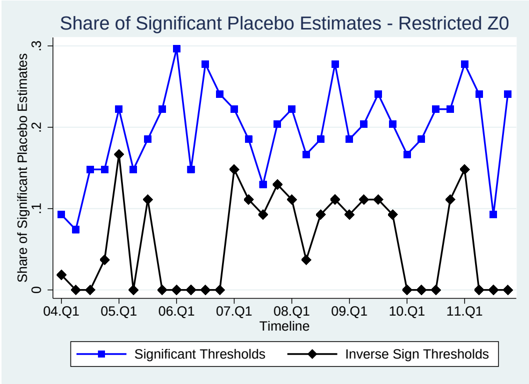


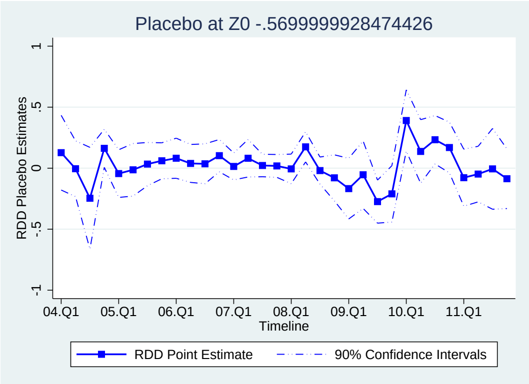


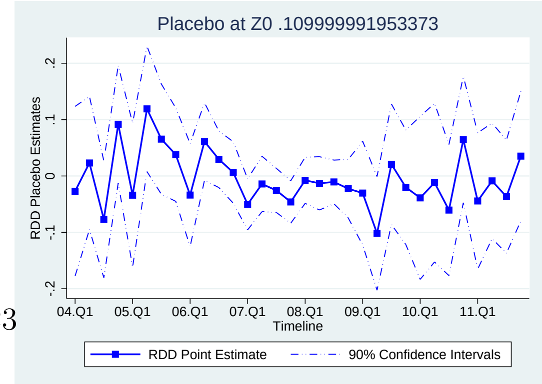


Panel B: Price Differences









xxx.