Differential Effects of Partial Credit Guarantee Schemes

A Dose-Response Function Approach

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Differential Effects of Partial Credit Guarantee Schemes:

A Dose-Response Function Approach

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Abstract

I fondi per le garanzie di credito emettono garanzie parziali, ossia coprono fino ad una certa percentuale del debito contratto dalle imprese, allo scopo di alleviare i problemi di stabilità del fondo stesso e prevenire comportamenti opportunistici da parte delle imprese. Malgrado il ruolo centrale ricoperto dalle garanzie parziali, la letteratura ha considerato le imprese come completamente garantite. In questo saggio si stima una funzione dose-risposta, ossia si calcola l'effetto prodotto dalle garanzie parziali per ogni livello di copertura. L'analisi evidenzia per l'Italia una funzione a forma di U rivoltata, con un massimo intorno al 70% e assenza di effetto sotto o sopra il 50% e l'80%, rispettivamente. Questo approccio è particolarmente informativo perché consente ai policy maker di ottimizzare l'intervento a seconda dello specifico valore della garanzia parziale.

Credit Guarantee Schemes issue partial guarantees, i.e. they cover up to a certain share of the loan borrowed by firms, in order to mitigate financial stability and moral hazard problems on the part of the guaranteed firms. Although guarantees play a key role in relaxing financial constraints, existing studies have largely focused on firms having received a guarantee, and ignored the magnitude of the partial guarantee. This article takes this issue into account and estimates a dose-response function, namely a different treatment effect for each value of the coverage ratio. For Italy, an inverse-U shaped relationship is found with the maximum of the effectiveness around 70% and no effects below and above 50% and 80%, respectively. This approach is quite informative as allows the policy makers to tailor the policy according to the specific value of the ratio.

Contents

Introduction

The existence of a financial gap for for Small and Medium sized Enterprises, SMEs, unfortunately, is a well known and documented phenomenon, meaning that there are significant numbers of SMEs that could use funds productively if they were available, but cannot obtain finance from the formal financial system (OECD, 2006; OECD, 2007). The provision of collateral can lessen credit rationing (Beck et al., 2010; Berger and Udel, 1998) and for this reason, many countries have established public Credit Guarantee Schemes, CGSs, as an instrument providing guarantees to the bank system on behalf of the indebted SMEs. Guarantees become a substitute collateral, and are considered as being superior to physical collateral that SMEs and micro borrowers cannot offer or offer in sufficient quantities to secure a loan. The guarantee offered by a third party is both secure and liquid. Should the loan default, the guarantee is easily and quickly called by the lender under the terms of a legal contract that specifies how the lender can recover his money. Moreover, the third party guarantee is not subject to the problems presented by physical collateral, such as its maintenance in good condition, verification of its value and safekeeping (Grudger, 1998).

The theoretical principle upon which the mere existence of CGSs is rooted refers to the seminal work by Stiglitz and Weiss (1981), that underlines the existence of failures in financial markets, due to asymmetric information and agency problems. In particular, banks have difficulties in distinguishing good risks from bad risks and in monitoring borrowers once funds have been advanced. They will hesitate to use interest rate increases to compensate for risk, in the belief that, by driving out lower-risk borrowers, high interest rates may lead to a riskier loan portfolio, thus setting in motion a process of adverse credit selection. Therefore, they have an incentive to engage in credit rationing. CGSs are intended to address this market failure, nevertheless they are not free from problems. First of all they are risky institutions and their financial stability may be problematic. In addition, public guarantees may induce moral hazard behaviours on the part of the firms. Mitigation of these problems comes from the fact that **the guarantees delivered are partial**, indeed **CGSs cover up to a certain percentage of the borrowed amount** (Honohan, 2010; Beck et al., 2010).

From a financial stability perspective, the coverage ratio, namely the ratio between guaranteed and borrowed amount, constitutes an important instrument of risk minimization by limiting moral hazard problems for both borrowers and lenders. As noticed by Boschi et al (2014), in spite of the key role played by the partial coverage ratio, its impact is largely a neglected issue. A thorough analysis of the impact of CGSs, measured in terms of partial coverage ratio, is of great help to foster learning by policy makers and other stakeholders, identify good practices, opportunities and challenges to improve design and implementation of partial credit guarantee measures. For this reason, **this work aims at estimating a differential effect of the partial coverage ratio for each value of the ratio.** To this aim, we apply a new methodology that, to the best of our knowledge, has never been applied to the subject under scrutiny. **In this new set up, referred to as dose-response function, the partial coverage ratio is regarded as a measure of the exposure (or dose) to the treatment delivered** by CGSs. Since the treatment is continuous (over the interval 0− 100) we estimate and plot a curve showing the relationship between bank debt and partial coverage ratio. The interesting thing comes from the fact that this curve is not linear, but rather an inverse U-shaped curve, meaning that treatment effectiveness increases as the coverage ratio increases up to a certain value (70% in our case), beyond that point treatment effectiveness decreases. Moreover, the confidence intervals show no significant effects below 50% and above 80%, where the latter bound is mainly attributable to the risk of moral hazard.

The empirical case under scrutiny is the Italian Central Guarantee Fund for SMEs (henceforth the Fund), a public CGS funded by the Italian Government.[1] The Italian case is particularly interesting due to a number of structural peculiarities the country suffers from, which make the Fund as a sort of benchmark. First, in spite of the dominant share of SMEs (99.9% of the total number of firms employing 79.6% of total employment, against 66.9% in the EU) Italian firms are severely rationed, as recently documented by the EU Commission (2015, pp. 11) and by many other works over the past years, Guiso (1998), Finaldi Russo and Rossi (2001); Becchetti and Trovato (2002); Trovato and Alfò (2006); Minetti and Zhu (2011); Albareto and Finaldi Russo (2012), among others. Second, the aforementioned study of the EU Commission reports that in Italy it takes 113.33 days to cash a credit, against 56.73 on average in the EU.

As the effectiveness of collateral also depends on the effectiveness of legal procedures for loan recovery (Berger and Udell, 1998) Italy is a very interesting case study. Third, the available microdata can be easily merged with provincial and sectoral data, which in the preprocessing phase help to reduce model dependency, controlling for possible mis-specification problems (King and Zeng, 2006; Ho et al., 2007). Finally, probably thanks to the structural peculiarities of Italy, the Italian CGS is the most studied in the literature (Zecchini and Ventura, 2009; Boschi et al., 2014; D'Ignazio and Menon, 2013; De Castris and Pellegrini, 2015; de Blasio et al, 2017), and knowledge about it is deeper than that of other CGSs, thus our study wants to push the knowledge frontier ahead so as to provide a sort of guideline for other cases.

The remainder of the paper is organized as follows. Section 2 reviews the literature, Section 3 presents the economic and econometric theory upon which our analysis is grounded. Section 4 describes the content of the dataset and presents some descriptive stats, while the results of the econometric exercise are presented in Section 5. Section 6 elaborates on the findings of the previous Section and, finally, 7 concludes.

[1] The institutional features of the Fund are described in Section 8.2.

Review of the literature

In spite of the relevance of CGSs, scholars have started evaluating their impact and effectiveness only in recent years, reaching ambiguous results. Ambiguity is attributable to a number of reasons, such as different methodologies used, different outcome measures used in the assessment of the performances, and mainly different contexts in which the funds operate, i.e. different countries. As far as the methodologies are concerned, it is possible to make a crucial distinction between causal models and non causal ones. Within the first group we find the early works following a non strictly econometric methodology, or at least not referring to the strand of the econometric literature aimed at estimating causal effects, the so called treatment models. For instance, Boocock and Shariff (2005) relying on case studies find little evidence of positive effects of the Malaysian fund. Riding et al (2006) reproduce the banks' decision to reject credit applications by using a credit scoring algorithm and find positive impacts of the Canadian Fund, in terms of financed firms that would have not been financed otherwise. For Korea, Kang and Heshmati (2008) perform survival analysis on pseudo-panel data and find weak evidence in favour of the credit guarantees in alleviating SMEs's difficulty in acquiring finance and stabilizing employment.

The second generation of articles make intensive use of treatment models. In this framework, the CGS is regarded as the "cause" and the effect is measured in terms of an outcome variable, namely a variable likely to be affected by the fund's action.[2]

Roughly speaking, guaranteed firms are considered as treated, where the treatment is delivered by the funds in terms of guarantees, and the performance of treated firms are evaluated by comparing them to a credible counterfactual group. Being the main purpose of funds that of lessening the credit rationing constraints, most of the time a measure of bank debt made available to the firms is used as an outcome variable. In this respect, it is usual to find papers referring to incrementality, or additionality effects, indeed meaning the extra money borrowed by SMEs thanks to the guarantee. Within this more advanced group of models, for Italy Zecchini and Ventura (2009) find a significant impact of the Fund in terms of additionality and lower debt cost. In a follow-up study Boschi et al (2014) refine Zecchini and Ventura's finding by comparing the results attainable under the treatment homogeneity simplification with those attainable under heterogeneity and document an underestimation in the first occurrence. For Korea, Oh et al (2009) report that credit guarantees positively influence firms' ability to maintain their size, and their survival rate, but do not find significant results in terms of growth and productivity. In addition, the authors even find questionable the management of the fund, as due to adverse selection problems, firms with lower productivity were receiv-

[2] For a complete and detailed review of treatment models we refer the interested reader to Angrist and Pischke (2009) and Cerulli (2015).

ing the guarantee. Lelarge et al (2010) reach very similar conclusions to the Italian case, adding also positive effects on firms' output. As for Spain, Garcia-Tabuenca and Crespo-Espert (2010) report positive effects in terms of additionality, but not in terms of financial costs. Cowan et al (2015) in Chile document that guarantees negatively affect firms' incentives to repay loans, but not their long-term performances, in the sense that guaranteed firms are not more likely to default on these loans. In most of these studies treatment status is typically captured by means of a dummy variable, hence all the treated are considered as being equally treated. Actually, treatment varies among treated, as CGSs cover up to different amounts of credit borrowed, giving rise to different treatment intensities. Boschi et al (2014) raise this point and find a threshold (25%) below which guarantees are not effective.

Moving from these premises, we move a step further by estimating a response for each single level of the treatment. To this purpose, we rely on the part of the econometric literature of treatment effects specific to the estimation of dose-response models (Hirano and Imbens, 2004; Adorno et al., 2007; Guardabascio and Ventura, 2013; Cerulli, 2015). Dose-response models are well suited in socio-economic contexts where a "cause" takes the form of a continuous exposure to a certain treatment. In such a setting what matters is not only the binary treatment status (i.e. treated vs. non treated), but also the level of exposure (or "dose") undergone. In other words, this approach is particularly attractive as it allows to estimate a causal response between an outcome variable and each level of the dose delivered, thus plotting a curve, indeed the dose-response curve, or function.

Modelling the effect of the guarantees

The empirical estimation of the differential effect of the Fund is rooted into the economic theory of disequilibrium, whose seminal works date back to Bowden (1978) and the ensuing copious literature. Briefly speaking, according to this view, credit rationing occurs when the demand of funds exceeds supply at the prevailing price in the market, hence the evolution over time of the firm specific lending rate, pit, is the result of demand–supply mismatch,

$$p_{it} = \phi_i(\Delta D_{it}) \tag{1}$$

with ΔD_{it} representing the demand–supply mismatch, i.e. $\Delta D_{it} = X_{it} - Q_{it}$, where X_{it} represents the demand at time t of firm i and similarly Q_{it} for the supply side. Since excess demand drives the price up, $\phi_i(\cdot)$ must be an increasing function, $\phi'_i(\cdot) > 0$, and we can conveniently rewrite (1) in terms of Q_{it} as:

$$Q_{it} = X_{it} - \Delta D_{it} = X_{it} - \varphi_i(p_{it}) \tag{2}$$

where $\varphi_i(\cdot)$ represents the inverse function of ϕ_i, $\varphi_i(\cdot) = \phi_i^{-1}(\cdot)$, with $\varphi'_i(\cdot) < 0$, as the excess demand, ΔD_{it}, decreases as the price increases, implying a positive relationship between Q_{it} and p_{it}, i.e. $[-\varphi'_i(\cdot) > 0]$.

The simplest estimable version of (2) consists in a linear form, such as:

$$q_{it} = \alpha + \beta' x_{it} + \gamma p_{it} + \varepsilon_{it} \tag{3}$$

where q_{it} is the outcome variable of firm i at time t, α is the constant term, x_{it} is a $k \times 1$ vector of proxies for the demand side, β its conformable coefficient vector, p_{it} is the idiosincratic cost of lending, γ its coefficient and, finally, ε is an error term. The outcome variable in the left-hand-side can be measured in terms of (log of) bank loans. As for the proxies of credit demand, we follow the consolidated practice in the literature (Zecchini and Ventura, 2009; Boschi et al, 2014; and Pozzolo, 2004), so that the vector x_{it} contains: firm size given by (the log of) total sales and the number of employees, and (the log of) fixed assets, as a variable aimed at assessing to what extent the presence of assets raise the firm's ability to borrow. To account for $\varphi_i(p_{it})$ we use balance sheet data on financial costs, given that, *caeteris paribus*, higher interest rates bore are immediately mirrored into higher financial costs, so that the positive relationship between q_{it} and financial costs, p_{it}, is preserved.

In order to extend eq. (3) to a counterfactual setting, we define a binary treatment indicator w, taking value 1 when a firm accesses the Fund, and 0 otherwise. Thus, it is possible to rewrite (3) in the two treatment states:

$$\begin{cases} w = 0 : q_{it,0} = \alpha_0 + \beta'_0 x_{it} + \gamma_0 p_{it} + \varepsilon_{it,0} \\ w = 1 : q_{it,1} = \alpha_1 + \beta'_1 x_{it} + \gamma_1 p_{it} + \varepsilon_{it,1} \end{cases} \tag{4}$$

where the function $h(s_{it})$ is the additional (or extra) lending appearing only in the treated status (i.e. when the firm is allowed to access the Fund), and s_{it} is the coverage ratio granted by the Fund.

The potential outcome model implied by (4) is the building block to obtain the dose-response function, following the model provided by Cerulli (2015), which extends the Regression Adjustment model proposed by Wooldridge (2010, p. 915–920) to a continuous treatment setting. The econometric technicalities of this model are beyond the aim of this paper, and for this reason they are reported in the Appendix. However, to our purpose, it is important to rigorously define the dose-response function as the "Average Treatment Effect (ATE), given the level of the treatment", that is:

$$\text{ATE}(s) = \text{E}[q_{it}(s) — q_{it}(0)] \tag{5}$$

in words, the dose-response in (5) is an ATE computed at each value of the treatment s. Without going into the details, hereafter we report the baseline regression derived from (4). This is obtained by using Rubin's potential outcome model, and Conditional Mean Independence (CMI). Its estimation allows to identify both the overall effect of the Fund, i.e. the ATE, and the dose-response function in (5), namely:

$$q_{it} = \alpha + w_{it} \cdot \text{ATE} + \beta'_0 x_{it} + w_{it} \cdot (x_{it} - \bar{x})\beta + \gamma_0 p_{it} + w_{it} \cdot (p_{it} - \bar{p})\,\gamma + w_{it} \cdot (h(s_{it}) - \bar{h}) + \eta_{it} \tag{6}$$

where: $\alpha = \alpha_1 - \alpha_0$ is a constant; ATE is directly obtained as the coefficient of w_{it}; $\beta = \beta_1 - \beta_0$; $\gamma = \gamma_1 - \gamma_0$; $\bar{h}$ is the sample mean of $h(s_{it})$; and η_{it} represents an error term. In a panel data context, we can consistently estimate (6) by fixed effects, once one allows for the error term to contain both a time fixed effect (λ_t), and a firm specific fixed effect (θ_i). This way, we can relax the selection-on-unobservable assumption (typical of Regression Adjustment models), by allowing for parameters consistent estimation also in the presence of possible unobservable confounders.

By assuming a third-degree polynomial approximation of $h(s)$, it can be proved that the dose-response function is equal to (see the Appendix):

$$\widehat{ATE}(s_{\mathrm{j}}) = w \cdot \left[\widehat{\mathrm{ATET}} + \hat{a}\left(s_j - \frac{1}{N}\sum_{j=1}^{\mathrm{N}} s_j\right) + \hat{b}(s_{\mathrm{j}}^2 - \frac{1}{N}\sum_{j=1}^{\mathrm{N}} s_{\mathrm{j}}^2) + \hat{c}(s_{\mathrm{j}}^3 - \frac{1}{N}\sum_{j=1}^{\mathrm{N}} s_{\mathrm{j}}^3)\right] + (1-w)\widehat{ATENT} \tag{7}$$

where: ATET is the Average Treatment Effect on Treated; ATENT the Average Treatment Effect on the non treated; *a*, *b*, *c*, polynomial coefficients; *j*, used in place of the double index *it*. A plot of $\widehat{ATE}(s_{\mathrm{j}})$ against *s* retrived from this equation provides a consistent estimation of the dose-response function of eq. (5). This function is plotted along with the pattern of its confidence interval in order to detect possible regions of statistical significance.

To our knowledge, the use of a dose-response approach in the context of partial credit guarantees is an absolute novelty. This makes it possible to go beyond the identification of just the “single” average effect of the policy, by displaying such effect at different policy intensity (i.e. different coverage ratio). This is a considerable advance offered by this method over traditional program evaluation as: (i) the interpretation of the results becomes clearer, (ii) the understanding of the policy functioning/effectiveness appears more evident, also thanks to suitable graphical representations; (iii) policy interpretation and recommendations can be tailored for each value of the treatment intensity. Broadly speaking, the use of a dose-response model helps to have a more efficient management of the policy instrument and an accurate overview of policy outcomes.

The Dataset

1. The dataset

The dataset used in this study is the resulting merge of four different sources: (i) firm level treatment information, collected from the Fund’s book; (ii) firm level financial statement, drawn from AIDA balance sheet databank; (iii) province level data; (iv) sectoral level data. The time span, 1999–2006, covers a relatively homogenous period as in 2007 the Fund's operative framework was changed. The treated group consists of 1, 385 treated firms and the control group contains 235 firms that applied and were rejected. The number of rejected applicants is lower in this dataset than in that of Boschi et al, even though the latter covers a shorter period, 1999–2004. This is due to the fact that some firms rejected before 2004 successfully re-applied the demand in the following two years. One of the main information coming from the first source of data is the continuous treatment variable, given by the coverage ratio, i.e. the ratio between the nominal amount of guarantees provided by the Fund and the guaranteed loan borrowed by the firm. Besides, this dataset provides us with province (NUTS-3) and sectoral (NACE) codes for each firm in the sample, which will turn as key variables to merge the data with dataset (iii) and (iv), as we will explain shortly. The dataset (ii) contains information about total sales, bank debt, total debt, number of employees and financial costs. The first two datasets have been merged by means of the VAT code, and the resulting dataset, in turn, has been merged other two times, first with the dataset (iii), by means of NUTS-3 code, and then with dataset (iv), by means of NACE code. Firm specific information has been coupled with NUTS-3 and NACE level data in order to take full account of the socio-economic context in which the firms operate, enlarging the conditioning set as much as possible and shrinking at a minimum unobservable factors and model dependency by pre-processing the data (King and Zeng, 2006). In detail, we have included variables capturing local labour market conditions (unemployment rate, *unem*; source: Italian National Institute of Statistics, Istat); investment activity (gross fixed capital formation, *gfcf*; source: OECD STAN); wealth conditions (final consumption expenditure over disposable income, *cody*, per-capita value added, *vadl*; source: Istat). The stage of development of local banking system has been captured by bank branches growth rate, *bbrr*, and the share of non-performing loans over total bank loans, *blot* (source: Bank of Italy). Finally, for environmental variables we have included judicial inefficiency, *inef*, measured as the average number of years necessary to complete a first degree trial and a proxy for social capital, *scap*, that is the number of blood bags collected per 1000 inhabitants (source: Guiso et al, 2004).

2. Descriptive stats

Table 1 reports the characteristics of treated and non treated firms prior to their receipt of the guarantee, in order to partially control for endogenous response and focus more on baseline characteristics. Firms that received the guarantee are larger than the non treated, both in terms of turnover and employees, as well as in terms of collateral the firms can pledge (fixed assets) and outcome, i.e. outstanding bank debt. Our treatment variable shows an average intensity around 70%. These descriptive stats are supportive of the view that policies attempting to lessen credit rationing phenomenon are difficult in the sense than they might easily incur in adverse selection problems. Thus, simple Ordinary Least Squares, OLS, comparison of the two groups are likely to overestimate the potential impact of the guarantee. Indeed, in order to mitigate selection problems and to reduce model dependency, we have followed the approach proposed by King and Zeng (2006) and Ho et al (2007) pre-processing the data. This step has been carried out after having extended the firm specific dataset with confounders at sectoral and provincial level, as explained in section 4.1. The descriptive stats of these further confounders are reported Table 2, which shows similar mean values between the two groups. More in detail, in order to adjust the data before the parametric analysis, we have computed the propensity score with the broadest available information set and discarded the units outside of the common support.[3] Such a procedure allows us to be, at least to a certain extent, confident that the results will not suffer from great changes in response to minor modifications in the estimated model. In the Appendix we report the balancing test for the first run of the pre-processing, see Table A1.[4] The table is divided into two parts, in the upper part equality in mean tests on each single covariate are reported, while the lower part reports tests on the overall quality of the pre-processing. Both parts show encouraging results, as for the single covariate tests it is never possible to reject the null of equality in mean between the two groups and, analogously, in the lower part it is not possible to reject the null of the joint test of non-significance of all the covariates after matching.

Table 1. Descriptive stats of firm level variables at 1999

	(1)			
	Non treated		Treated	
	Mean	Std. Dev.	Mean	Std. Dev.
bank debt	914.7	2072.0	1576.3	2869.4
fin. costs	110.4	156.8	153.8	240.9
turnover	4373.5	6197.4	6145.5	8333.5
fixed assets	1212.0	2195.3	1620.2	2640.6
employees	27.10	44.93	34.52	44.82
coverage ratio	0	0	0.754	0.189

Thousands of Euro except for *coverage ratio* and *employees*

[3] The common support has been computed by using the fitted probability from 7 probit regressions, one for each year from 2000 to 2006,

$$w_{it} = F(\beta' X_{it-1} + \theta' Z_i) + u_{it} \qquad \text{for } t = 2000, \dots, 2006 \text{ and } i = 1, \dots, N \tag{8}$$

where the dependent variable, w_{it}, is binary taking 1 if firm i at time t entered the program, X_{it-1} is a vector containing firm specific confounders observed one period before the firm were treated, while Z_i is a matrix of provincial and sectoral variables observed one period before the outset of the policy. At each run, units out of the common support have been discarded for a total of 22, out of which 9 treated.

[4] The other balancing tests for t=2001,. . . ,2006 are made available to the interested reader upon request.

Table 2. Descripive stats of provincial and sectoral level variables at 1999

	(1)			
	Non treated		Treated	
	Mean	Std. Dev.	Mean	Std. Dev.
unem	0.136	0.0706	0.126	0.0702
cody	0.905	0.0838	0.881	0.0878
vadl	15.90	4.707	16.91	5.089
bbrr	0.0253	0.0302	0.0276	0.0230
blot	0.146	0.0921	0.124	0.0899
inef	4.088	1.229	3.910	1.252
scap	0.0212	0.0161	0.0255	0.0200
gfcf	0.0375	0.0266	0.0371	0.0249

Variables defined in Section 4

Results

Table 3 and figures 1 and 2 set out the main econometric results of this study. Table 3 shows the parameters estimates of the baseline regression (6). In this regression, estimated by fixed–effects, the outcome variable is the log of the amount of bank loans, while the main exposure variables are both the binary treatment variable (guaranteed vs. non guaranteed), and the partial coverage ratio. Some control variables are also included in the regression, such as firms' financial burden, size, and the stock of fixed assets, in a lagged form to avoid problems of possible simultaneity.

We comment the results appearing in the first column of Table 3 that we consider as our benchmark, thus considering the results in the subsequent three columns as robustness checks. The coefficient of the binary treatment variable directly returns the ATE, which appears to be positive but not strictly significant, 0.09. The ATET – whose standard errors are obtained by bootstrap – is also positive with a value around 0.10, meaning that on average firms accessing the Fund obtained a 10% larger amount of loans from the bank system. Unfortunately, also this parameter is statistically not significant, thus pushing us to delve into a more accurate analysis of such "average" result to discover whether different levels of the coverage ratio were supportive of a positive and possibly significant effect of the policy in question. This is in line with the methodological philosophy embraced in this paper, which supports the idea of going beyond average results.

In this spirit, Figure 1 shows the distribution of the "ATE given the covariates", both for treated, untreated, and for the whole sample (i.e. ATET($\mathbf{x}$), ATENT($\mathbf{x}$) and ATE($\mathbf{x}$), respectively). As expected, these distributions show that there is a larger probability mass for positive values of our outcome variable. Thus, this first in-depth analysis is consistent with the evidence of the positive ATE previously found, although not significant. The distribution of ATENT($\mathbf{x}$) seems to be slightly shifted on the right with respect to that of ATET($\mathbf{x}$), indicating that untreated firms would have produced a greater outcome if treated.

More interestingly, Figure 2 sets out the plot of the dose-response function. The nonlinear form of its shape is evident, as a cubic polynomial seems to fit the data rather well in this case. This is analytically confirmed by the significance of the polynomial parameters reported in Table 3, i.e. *a*, *b* and *c*. More precisely, **what clearly emerges** from such a figure, **is a region of positive and significant effects between a dose of 50% and one of 80%, where an inverted U-shaped pattern appears, with a maximum and significant effect around a dose of 70**%. This means that a too low (below 50%) coverage ratio does not produce substantial effects. A partial guarantee is shown to have a positive impact on bank loans only in the range 50%-80%. Although our results delve into what is hidden behind an "average" finding, they are consistent with what some literature (Boschi et al. (2014), Zecchini and Ventura (2009)) had previously found. Indeed, by considering the average value of the derivative of the dose-response function (not reported here), we find an additional supply of bank lending of around 13% as a result of the Funds guarantees.

Finally, as robustness checks, we tried three other specifications of the baseline regression model. The first in Table 3, ROB1, considers contemporaneous (rather than lagged) control variables; the second, ROB2, uses as non treated units also non-applicant firms, rather than rejected; and the last one, ROB3, uses winsorized variables to take into account possible outliers. Interestingly, ROB2 still presents a non significant ATE, but now with the flipped sign. The result is due to the greater unobservable heterogeneity left in the data which introduces larger noise in the estimation. Overall, ROB1 and ROB3 confirm the results in the estimation of the benchmark and even more importantly from our point of view, the dose-response function is rather stable over all these different specifications, including ROB2.

Implications of our analysis

The empirical results show the presence of an interval over the support of the treatment variable for the effectiveness of the Fund, i.e. doses of treatment outside the interval do not bring about the desired effect. While it is self-evident that **low guarantees are likely not to sufficiently alleviate the lending banks from risks**, the explanation of why "too" high guarantees are not effective may seem counter intuitive. Actually, **too high guarantees are likely to be perceived as a bad signal and provide a scant incentive (or even at all) to mitigate moral hazard behaviours.** Bad signalling means that high coverage ratios make envisage riskier activities financed. Thus, if on the one hand, almost total guarantees may seem attractive to banks, on the other hand, they signal a high probability of default and/or moral hazard. Yet, in order to obtain the guarantee the payment of a fee is required, that varies between 1% and 0.125% of the guaranteed sum according to the type of operation (loans, participation loans, equity), the size of the firm and its location. The more disadvantaged the SME, the

Table 3. Baseline and robustness regressions for the effect of the Fund for Guarantees

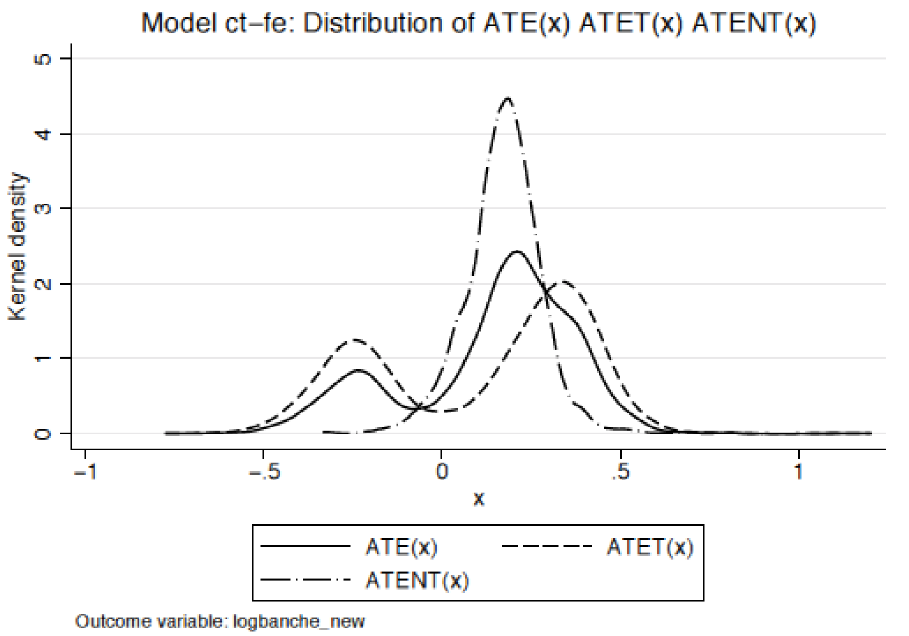
	(1) BENCH	(2) ROB1	(3) ROB2	(4) ROB4
ATE	0.09	0.14	-0.13	0.01
	(0.38)	(0.27)	(0.39)	(0.26)
ATET	0.10			
	(.08)			
Financial costs (t-1)	0.33***		0.25***	
	(0.07)		(0.03)	
Turnover (t-1)	0.05		0.04	
	(0.12)		(0.04)	
Fixed assets (t-1)	0.13*		0.15***	
	(0.07)		(0.03)	
Parameter a	-0.08**	-0.06**	-0.03	-0.05*
	(0.03)	(0.03)	(0.03)	(0.03)
Parameter b	0.00***	0.00***	0.00*	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Parameter c	-0.00***	-0.00***	-0.00**	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Financial costs		0.65***		
		(0.07)		
Turnover		-0.04		
		(0.07)		
Fixed assets		0.33***		
		(0.07)		
W_Financial costs (t-1)				0.29***
				(0.06)
W_Turnover (t-1)				0.09
				(0.08)
W_Fixed assets (t-1)				0.11**
				(0.05)
N	5270	6054	21361	5270
adj. R^2	0.042	0.100	0.028	0.055
R^2	0.04	0.10	0.03	0.06
F-test	6.21***	19.46***	12.53***	8.12***

Standard errors in parentheses 14

All variables are in logs except ATE, a, b and c

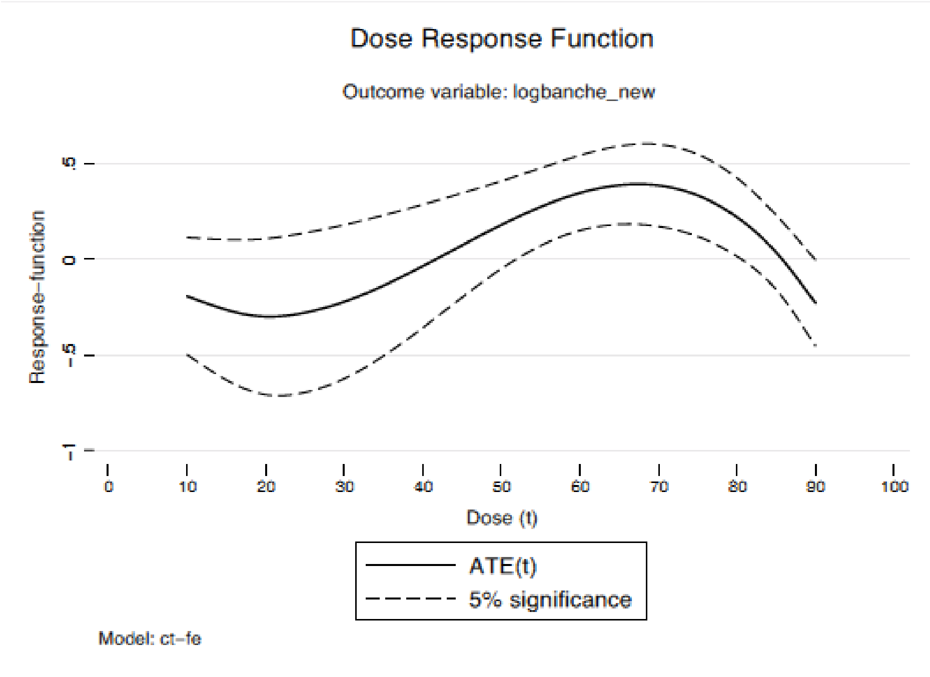
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1. Distribution of the effects



lower the fee, up to the limit case of no fee for SMEs located in 107.3c zones, i.e. southern regions. Thus, priority sectors being more disadvantaged are riskier, but pay a lower fee, making the moral hazard opportunity cost even lower. Last, but not least, Boschi et al describe a complex procedure for recovery procedures of the defaulted sums on the part of the lending banks, this last occurrence may contribute to discourage banks to finance those operations with high coverage ratios. Of course, the estimated results are case specific. In particular, the bounds of the interval can be affected by institutional and country specific peculiarities. Nevertheless, we reckon some results likely to be common to other contexts, i.e. to a certain extent they have external validity. Indeed, from a macro perspective, the inverse U-shaped curve can be regarded as abiding by for the very general economic principle of non explosive, or even decreasing, returns to scale, thus there is room to believe the result to bring out a general feature of CGS. In this line, we dare putting forth **two conjectures**. **First, repeating the analysis on other countries, *mutatis mutandis*, we expect to find a similar pattern of the dose-response function**. **Second,** and even more interestingly, comparing the bounds of the effectiveness region between countries, **it could be possible to find a meaningful correlation with some structural features of the country**. For

Figure 2. Dose-response function



instance, in countries with stronger effectiveness of legal procedures for loan recovery the upper bound can be higher or even disappear. In general, the width of the interval can be positively correlated to the strength of the enforcement system. Finally, other features may play a relevant role in shaping the curvature of the dose-response, which are hard to predict and only empirical applications can provide some insights, such as the business cycle phase or the bank system features.

Conclusion and further research

This work has moved a step further into the knowledge of CGSs with particular reference to the Italian case, the most studied in the literature. The work shifts attention from the estimation of an average effect to the estimation of a causal effect for each level of the treatment. This approach leads to very interesting results, such as the inverse U-shaped curve and the confidence bounds, but the potential implications of the findings are even more interesting, such as the supposed stability of the shape of the dose-response across countries and the positive correlation between the width of the effectiveness region and the strength of the enforcement systems, should one repeat the analysis on other countries. We urge further research on these points which seem promising and may provide with a better knowledge and use of the policy instrument.

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Appendix

1. The econometric model

In this appendix we briefly present the dose-response model employed in the paper, which in turn, draws on the econometric model developed by Cerulli (2015), which also includes a Stata implementation via the user-written command ctreatreg.

Consider two different and exclusive outcomes: one referring to unit i when it is treated, y_{1i}; and one referring to the same unit when it is non treated, y_{0i}. Define w_i as the treatment indicator, taking value 1 for treated and 0 for non treated units, and $\mathbf{x}_i = (x_{1i}, x_{2i}, x_{3i}, \ldots, x_{Mi})$ as a row vector of M exogenous and observable characteristics (confounders) for unit $i = 1, \ldots, N$. Let N be the number of units involved in the experiment, N_1 be the number of treated units, and N_0 the number of non treated units with $N = N_1 + N_0$.

Let us define two distinct functions, $g_1(\mathbf{x}_i)$ and $g_0(\mathbf{x}_i)$, as the unit i's responses to the vector of confounding variables, $\mathbf{x}_i$, when the unit is treated and non treated, respectively. Assume also μ_1 and μ_0 to be two scalars, and e_1 and e_0 two random variables having zero unconditional mean and constant variance. Finally, let us define $s_i \in [0; 100]$ as the continuous treatment indicator, and $h(s_i)$ as a general derivable function of s_i. In what follows, in order to simplify notation, we will get rid of the subscript i when defining population quantities and relations.

Given the previous notation, we assume a specific population generating process for the two exclusive potential outcomes.[5]

$$\begin{cases} w = 1 : y_1 = \mu_1 + g_1(\mathbf{x}) + h(s) + e_1 \\ w = 0 : y_0 = \mu_0 + g_0(\mathbf{x}) + e_0 \end{cases} \tag{9}$$

where the $h(s)$ function is different from zero only in the treated status. By defining the treatment effect as the difference TE $= (y_1 - y_0)$, we can define the causal parameters of interests as the population ATEs conditional on $\mathbf{x}$ and s, that is:

$$\begin{aligned} &\text{ATE}(\mathbf{x}; s) = \text{E}(y_1 - y_0 | \mathbf{x}, s) \\ &\text{ATET}(\mathbf{x}; s > 0) = \text{E}(y_1 - y_0 | \mathbf{x}, s > 0) \\ &\text{ATENT}(\mathbf{x}; s = 0) = \text{E}(y_1 - y_0 | \mathbf{x}, s > 0) \end{aligned} \tag{10}$$

[5] Such a model is the representation of a treatment random coefficient regression as showed by Wooldridge (1997; 2003). See also Wooldridge (2010, Ch. 18).

where ATE, ATET and ATENT are as in the main text. By the law of iterated expectations (LIE), we know that the population unconditional ATEs are obtained as:

$$\begin{aligned} &\text{ATE} = \mathrm{E}_{(\mathbf{x};s)}\{ATE(\mathbf{x};\ s)\} \\ &\text{ATET} = \mathrm{E}_{(\mathbf{x};s>0)}\{ATE(\mathbf{x};\ s>0)\}) \\ &\text{ATENT} = \mathrm{E}_{(\mathbf{x};s=0)}\{ATE(\mathbf{x};\ s=0)\} \end{aligned} \tag{11}$$

where $\mathrm{E}_z(\cdot)$identifies the mean operator taken over the support of a generic vector of variables z. By assuming a linear-in-parameters form for $g_0(\mathbf{x}) = \mathbf{x}\delta_0$ and $g_1(\mathbf{x}) = \mathbf{x}\delta_1$, the ATE conditional on $\mathbf{x}$ and s becomes:

$$\text{ATE}(\mathbf{x}, s, w) = w \cdot [\mu + \mathbf{x}\delta + h(s)] + (1 - w) \cdot [\mu + \mathbf{x}\delta]$$

where $\mu = (\mu_1 - \mu_0)$, $\delta = (\delta_1 - \delta_0)$, and the unconditional ATE related to model (9) is equal to:

$$\text{ATE} = p(w = 1) \cdot \left(\mu + \bar{\mathbf{x}}_{s>0}\delta + \bar{h}_{s>0}\right) + p(w = 0) \cdot (\mu + \bar{\mathbf{x}}_{t=0}\delta) \tag{12}$$

where $p(\cdot)$ is a probability, and $\bar{h}_{s>0}$ is the average of the response function taken over $s > 0$. Since by LIE, we have that ATE $= p(w = 1) \cdot$ ATET $+ p(w = 0) \cdot$ ATENT, we obtain from the previous formula that:

$$\begin{cases} \text{ATE} = p(w = 1)\left(\mu + \bar{\mathbf{x}}_{s>0}\delta + \bar{h}_{s>0}\right) + p(w = 0)(\mu + \bar{\mathbf{x}}_{s=0}\delta) \\ \text{ATET} = \mu + \bar{\mathbf{x}}_{s>0}\delta + \bar{h}_{s>0} \\ \text{ATENT} = \mu + \bar{\mathbf{x}}_{s=0}\delta \end{cases} \tag{13}$$

defining the dose-response function as the ATE given the level of the treatment, it can be obtained by averaging ATE($\mathbf{x}$, s) over $\mathbf{x}$:

$$\text{ATE}(s) = \begin{cases} \text{ATET} + \left(h(s) - \bar{h}_{s>0}\right) \text{ if } s > 0 \\ \text{ATENT if } s = 0 \end{cases} \tag{14}$$

that is a function of the treatment intensity s.

Now, we consider the conditions for a consistent estimation of the causal parameters defined in (10) and (11), and thus of the dose-response function in (14). What it is firstly needed, however, is a consistent estimation of the parameters of the potential outcomes in (9), that we call here "basic" parameters as both ATEs and the dose-response function are functions of these parameters. Under the previous definitions and assumptions, the form of the potential outcomes in eq. (9), can be substituted into Rubin's potential outcome equation $y_i = y_{0i} + w(y_{1i} - y_{0i})$, giving rise to a baseline random-coefficient regression (Wooldridge, 2003; Wooldridge, 1997):

$$y_i = \mu_0 + w_i \cdot \text{ATE} + \mathbf{x}_i\delta_0 + w_i \cdot (\mathbf{x}_i - \bar{\mathbf{x}})\delta + w_i \cdot \left(h(s_i) - \bar{h}\right) + \eta_i \quad (15)$$

where:

$$\eta_i = e_{0i} + w_i \cdot (e_{1i} - e_{0i})$$

The equation sets out in (15), provides the baseline regression for estimating the basic parameters (μ_1, μ_0, δ_1, δ_0), and the ensuing ATEs. Both a semi-parametric or a parametric approach can be employed as soon as a parametric or a non-parametric form of the function *h*(*s*) is assumed. In both cases, however, in order to get a consistent estimation of the basic parameters, we need some additional hypotheses. In particular, we assume Unconfoundedness or CMI, as a sufficient condition able to provide consistent estimates. Unconfoundedness states that, conditional on the knowledge of the true exogenous confounders **x**, the conditions for randomization are restored and causal parameters become identifiable. Given the set of random variables $y_{1i}, t_i, w_i, \mathbf{x}_i$ as defined above, Unconfoundedness (or CMI) implies that:

$$\text{E}(y_{ji} | w_i, t_i\mathbf{x}_i) = \text{E}(y_{ji}|\mathbf{x}_i) \; with \; j = \{0,1\} \quad (16)$$

Under this condition, OLS can be used to retrieve consistent estimation of all parameters. Once a consistent estimation of the parameters in (15) is obtained, the ATE can be estimated directly from this regression, and ATET, ATENT and the dose-response function can be obtained by plugging the estimated basic parameters into formula (12) and (13). This is possible because these parameters are functions of consistent estimates, and thus consistent themselves. Moreover, the standard errors for ATET and ATENT can be correctly obtained via bootstrapping (Wooldridge, 2010, pp. 911–919).

To complete the identification of ATEs and that of the dose-response function, we finally assume a parametric form for *h*(*t*):

$$h(s_i) = as_i + bs_i^2 + cs_i^3$$

where *a*, *b*, and *c* are parameters to be estimated in regression (15).

Under CMI, an OLS estimation of equation (15) produces consistent estimates of the parameters. With these parameters at hand, we can finally consistently estimate the dose-response function as:

$$\widehat{ATE}(s_\text{i}) = w \cdot \left[\widehat{\text{ATET}} + \hat{a}\left(s_i - \frac{1}{N}\sum_{i=1}^{\text{N}} s_i\right) + \hat{b}(s_\text{i}^2 - \frac{1}{N}\sum_{i=1}^{\text{N}} s_\text{i}^2) + \hat{c}(s_\text{i}^3 - \frac{1}{N}\sum_{i=1}^{\text{N}} s_\text{i}^3)\right] + (1-w)\widehat{ATENT} \quad (17)$$

where:

$$\widehat{\text{ATET}}(s_i) = \widehat{\text{ATE}}(s_i)_{s_i>0} \tag{18}$$

A simple plot of (18) over the support of s returns the pattern of the dose-response function. Moreover, for each level of the dose s, it is also possible to calculate the α-confidence interval around the dose-response curve. Indeed, by defining $S_1 = s - \mathrm{E}(s)$, $S_2 = s_2 - \mathrm{E}(s_2)$ and $S_3 = s_3 - \mathrm{E}(s_3)$, the standard error of the dose-response function is equal to:[6]

$$\hat{\sigma}_{\widehat{\text{ATE}}(s)} = \left\{S_1^2\hat{\sigma}_a^2 + S_2^2\hat{\sigma}_b^2 + S_3^2\hat{\sigma}_C^2 + 2S_1S_2\hat{\sigma}_{a,b} + 2S_1S_3\hat{\sigma}_{a,C} + 2S_1S_3\hat{\sigma}_{b,c}\right\}^{1/2}$$

This means that the α-confidence interval of $\widehat{\text{ATE}}(s)$ for each s is then given by:

$$\{\widehat{ATE}(s) \pm Z_{\alpha/2} \cdot \hat{\sigma}_{\widehat{\text{ATE}}(s)}\} \tag{20}$$

that can be usefully plotted along the dose-response curve for visually detecting the statistical significance of the treatment effect along the support of the dose *s*.

2. Institutional features of the Fund

The Italian CGS, i.e. the Fund, operates since 2000, issuing more than 600,000 guarantees to SMEs up to the first quarter of 2017. Firms operating in the sector of: manufacturing, construction and services are eligible, while are excluded those operating in the agriculture, automobile and finance sector, because of the limitations imposed by EU regulation on competition. Any kind of financial operation and any kind of maturity and typology granted to SMEs by banks and financial intermediaries are in principle admissible. Guarantees can be either direct guarantees, i.e. to the lender to cover outstanding loans, or counter-guarantees, i.e. indirect guarantees to the lender through a guarantee of the main guarantor. Applicants undergo a double risk assessment. The first one is carried out by the financial intermediary, as a potential lender, or the Credit Guarantee Consortia, as a first guarantor. Only if passed through this first step the firm application is sent through to the Fund manager (Mediocredito Centrale, MCC), which formulates the second risk assessment. The final decision is taken by the Managing Committee. Thanks to this double layer risk assessment only a tiny fraction of applicants are rejected by the Fund, around 2%. The evaluation carried out by MCC is made on the basis of a set of balance-sheet indices referring to the last two years of activity, which varies according to the economic sector. For each index an "optimum level" and a range of admissible values have been fixed, based on historical data. Depending on those values a final rating is assigned (AA, BA, AB,CA, AC, BB, CB, BC, CC) and the consequent admission or rejection is submitted to the Managing Committee.

[6] This comes from the variance/covariance properties where S_1, S_2 and S_3 are taken as constant and *a*, *b* and *c* as random variables.

As explained in Section 1, the Italian fund has been the object of several works in the literature, and the Fund's operating system has already been described at length. For this reason here we recall only the main features of the policy instrument, referring the interested reader to the aforementioned literature. In particular, for a focus on the scoring system see de Blasio et al (2017), for a detailed description of recovery procedures see Boschi et al (2014), for the economic performance of the Fund see Zecchini and Ventura (2009).

Figure 3. Table A1. Balancing test of the covariates for treated units at time t=2000

Panel A: single covariates

Variable	Unmatched / Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|
Financial costs	U	11.321	10.935	28.1		2.47	0.014
	M	11.326	11.315	0.8	97.1	0.09	0.930
Turnover	U	15.193	14.733	38.4		3.40	0.001
	M	15.198	15.242	-3.6	90.5	-0.42	0.671
Fixed assets	U	13.391	12.81	35.1		3.15	0.002
	M	13.415	13.248	10.1	71.3	1.10	0.272
Intangible	U	10.561	10.048	28.3		2.46	0.014
	M	10.576	10.662	-4.8	83.1	-0.51	0.607
Unem	U	.10618	.12739	-31.1		-2.76	0.006
	M	.1058	.10283	4.4	86.0	0.50	0.614
cody	U	.86339	.89455	-34.0		-2.92	0.004
	M	.86321	.86363	-0.5	98.7	-0.05	0.962
vadl	U	18.444	16.786	34.1		3.02	0.003
	M	18.477	18.57	-1.9	94.4	-0.21	0.831
bbrr	U	.03021	.02772	9.8		0.87	0.387
	M	.03024	.03259	-9.2	5.6	-0.99	0.324
blot	U	.10035	.13426	-38.3		-3.42	0.001
	M	.09956	.09255	7.9	79.3	0.92	0.356
inef	U	3.5813	3.9909	-33.1		-2.97	0.003
	M	3.5694	3.5731	-0.3	99.1	-0.03	0.973
scap	U	.03204	.02235	50.9		4.35	0.000
	M	.03216	.03284	-3.6	92.9	-0.36	0.721
gfcf	U	.03718	.03887	-6.9		-0.61	0.541
	M	.03704	.03733	-1.2	82.6	-0.12	0.902

Panel B: joint test

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias
Unmatched	0.076	33.48	[0.001]	30.7	33.6
Matched	0.012	7.30	[0.837]	4.0	3.6

Note: Panel A: The standardised % bias is the % difference of the sample means in the treated and non treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (formulae from Rosenbaum and Rubin, 1985). Panel B: Pseudo R2 from probit estimation of the propensity score on all the variables in the pre-processing on raw sample and matched sample before and after matching.Corresponding P-values of the likelihood-ratio test of the joint insignificance of all the regressors before and after matching in square brackets

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