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The impact of public credit guarantees on the economic outcomes of SMEs: Evidence from Portugal

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Abstract

Public credit guarantees attributed to SMEs as a way of boosting credit access have been widely implemented in developed countries. However, literature often focuses on financial additionality. This paper investigates, for Portugal's case, the impact of these guarantees on the economic outcomes of firms – we study economic additionality. We utilize firm-level data provided by Banco de Portugal and rely on propensity score matching methods to derive causal results. We find evidence that public credit guarantees have incremental effects on credit, employment, total assets, and fixed assets. There is no evidence of effects on total factor productivity, wages, or profitability.

JEL Classification: D82, G28, H43, H81

Keywords: SMEs, Public Credit Guarantees, Economic Outcomes, Propensity Score Matching

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1 Introduction

Micro, Small, and Medium Enterprises (SMEs) often face credit-constraints due to their difficulty to post appropriate collateral, making risk assessment a necessity.

The incapacity to provide detailed financial reports makes the risk assessment process harder, consequently impacting the ability to monitor the firms, and thus making SMEs even riskier from the banking system perspective. Moreover, access to credit is key for SMEs to develop (OECD, 2020). Credit Guarantee Systems (CGSs) exist as a public policy response to this problem in most developed countries, including Portugal. Finally, tangible evidence of credit constraints for Portuguese SMEs has been reported by Farinha and Félix (2015).

For Portugal's case, the mutual guarantee system is the main policy in usage. It is conducted mainly by the Portuguese Society for Mutual Guarantees (SPGM, 2018b). The current outstanding guarantees represented 1.8% of the GDP as of 2017, which by itself makes the case for the need of scrutiny. The policy is mutualist: SPGM buys a share of the benefited company and the benefited company is obliged to buy and hold a share of SPGM for as long as the operation takes place. This risk-sharing aspect is crucial, as it heavily increases the screening of firms that access the guarantees. Since the firms become shareholders of the society themselves, there is a common shared goal of prosperity of SPGM – a bankruptcy of the society becomes a negative outcome for every firm involved.

These policies help credit-constrained firms in obtaining necessary financial means towards their activity, through the access to government-funded guarantees posted to the banking system. And for firms that could already access the financial system beforehand, this policy allows access to better financing conditions – such as lower interest rates and longer maturities -, which may be crucial towards the company's performance. Enhanced access to financing is also of major importance for dealing with external shocks – the liquidity buffer may be crucial to help viable firms withstand exogenous shocks.

The available research on the effectiveness of such policies often focuses on financial additionality – the improvement in the participating firms' financial outcomes: access to funds, interest rates, and the improvement on their debt structure. However, improved financing conditions are not an end in itself – they are a means to an end. The end, or goal, is for firms to achieve economic performance that they would not be able to otherwise.

Are public credit guarantees in Portugal effective in boosting the economic performance of SMEs? This is the research question that we will tackle in this work project.

The economic outcomes we are most interested in are firm productivity (we will look at both labor productivity and total factor productivity), total assets, fixed assets, employment, wages, and EBITDA. Beforehand, we will also analyze if the policy is effective in providing extra credit to these firms, as that is a crucial condition to impact the variables mentioned above. These outcomes will be analyzed by comparison with similar firms that were eligible for the policy but did not receive it (either because they did not apply or because they were not accepted). The intent is to measure the economic additionality from the policy.

If the policy is not effective, then there is a distinct chance that public funds are not being efficiently allocated. Furthermore, consequences at the level of Schumpeterian creative destruction are also a concern, alongside with policy design that requires improvement.

It is only by examining economic outcomes that it is possible to assert if credit guarantees are an efficient policy, or a poor form of allocation for public funds.

By relying on firm level data and employing matching techniques, we find evidence of positive effects on growth rates of credit, total assets, fixed assets and employment. We find no evidence of any changes in total factor productivity, wages, or profitability (through EBITDA). Results also point towards slightly diminished labor productivity growth.

2 The Portuguese Entrepreneurial Scenario

In 2018, SMEs in Portugal represented 99% of the total number of companies in Portugal. The criteria for this definition are number of employees (maximum of 250) and business volume (maximum of 50 million euros) (European Commission, 2020). These firms are responsible for 57% of the total business volume in Portugal. They are also the most dynamic in terms of creation and destruction rates over the years, with no pre-existing firms reaching the large-firm definition by 2018, but with 13 SMEs being created for each group of 10 that ceased their activity.

The financial autonomy of SMEs in 2018 was on average 37%, marginally larger than the ratio for large firms – 35%.

When looking at equity, the concerns are easier to spot. In 2018, 10% of small and medium enterprises had negative own equity, and microenterprises stand even worse in that ratio at 28%. On the other hand, only 4% of large firms suffered from this problem (Central de Balanços, 2019). The focus on public support to SMEs comes from the state aid rules defined by the European Comission following the Great Recession (Comission, 2009), and are the main reason why the public guarantees programs took on a much more prominent role after 2008. This fact supports why the study of the impacts is now so important.

It is possible to see on the 2015 survey on the access to finance of enterprises in the euro area (SAFE), by ECB (2015), that particularly micro and small firms still struggled to find financing

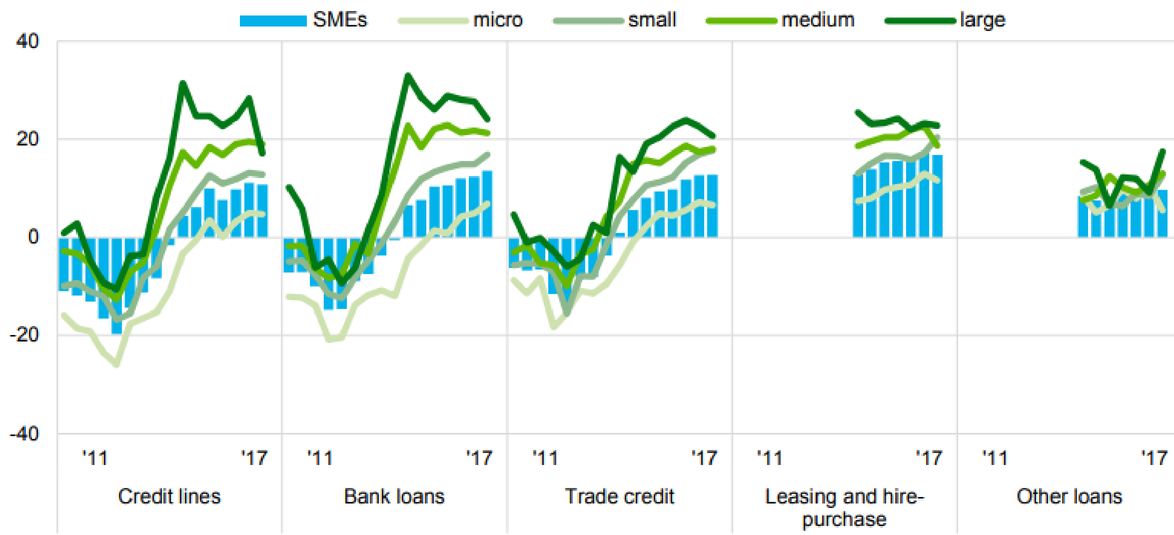

Figure 1: Perception of the change in availability of external financing for euro area enterprises: 2011 to 2017. (ECB, 2018)

in the form of bank loans in the period ranging from 2013 to 2015, with the SAFE survey from October 2017 to March 2018 (ECB, 2018) showing still the same difficulties for micro enterprises to access bank loans and credit lines until the trend changes closer to 2017.

The information gathered so far highlights the need to look closely into the challenges being faced by medium, small and microenterprises, and the role of the policies put in place to help them.

3 Literature Review

Public credit guarantees, provided by credit Guarantee Systems in order to assure bank loans to micro, small, and medium enterprises, are widely implemented in developed nations, with 33 OECD countries reporting use of such mechanisms (OECD, 2020). This instrument, that results in a transfer away from banks of part of the associated risk of lending to SMEs, is intended to correct a market failure, as smaller firms are costly to monitor and, additionally, tend to be undercollateralized and to produce less-detailed financial information (Beck et al., 2008). Without the public guarantee, the amount of credit to viable SMEs would be too low from a social point of view. This is reflected on empirical data, with findings of higher financing constraints on SMEs when compared to large firms (Beck et al., 2005).

CGSs have been built as one possible answer to a framework of financial markets with imperfect information leading to credit rationing due to moral hazard and adverse selection issues (Stiglitz and Weiss, 1981). Credit constraints may in fact be so relevant that SMEs see themselves denied from access to any credit at all without these mechanisms (Berger and Udell, 2006). Different lending technologies may improve this situation.

While theoretically sound, most of the schemes do not have precise goals, resulting in difficulties in conducting cost-benefit analysis (Honohan, 2010). The political cycles and short—termist hazard of policy design also compromises their effectiveness (Honohan, 2010). There is evidence that the role of the government in these mechanisms is important in respect to funding and management, but less so in credit risk assessment and recovery (Beck et al., 2008). Adding to that, even when state intervention in the credit markets may be welfare-enhancing, it is very contingent on a careful policy design (Arping et al., 2010). Thus, the impact of credit guarantees on market outcomes, both on the intensive (e.g. productivity) and extensive margin (e.g. default rates), becomes an empirical question.

In Portugal, for the years following the financial crisis (2010-2012), Farinha and Félix (2015) find evidence of SMEs being partially (15% of firms with bank loans) or even totally credit constrained (32% of firms with no bank loans). Younger and smaller firms were more affected. Adding to this, evidence is also presented by Félix (2018) that partially credit-constrained firms in 2010-2012 were less likely to survive (-1.61 pp), with a negative impact on investment as well (-2.7 pp).

A recent impact-assessment research conducted by SPGM (2018b) reports that firms benefiting from the mutual guarantees policy show improvements in total investment rates (+7.5 pp), export rates (+0.14 pp), job creation (+0.6 pp) and survival rates (+17 to +19 pp). The use of these guarantees also lowers the cost of debt to the median firm (-0.57 pp). Spain follows the same trend, with reports of increased productivity, higher added value per employee, and higher financial resources (Garcia-Tabuenca and Crespo-Espert, 2010).

In Italy, earlier research points toward positive results in limiting default rates, attributed to well-focused policy design that eases credit rationing for the SMEs that need it the most (Zecchini and Ventura, 2009). More recent research, however, finds no positive impacts of the implemented schemes, except for a change in the debt structure. Increased probability of default is found, which may be linked to the fact that the policy failed to reach credit-constrained firms (D'Ignazio and Menon, 2020). The same applies for France: the firms targeted by credit guarantee policies are more likely to default (Lelarge et al., 2010).

For South Korea, Oh et al. (2009) found that the credit guarantee policy in place affected positively the growth of sales, employment, wage levels and survival rate of participant firms; on the other hand the participant firms have lower productivity and that does not change over time, with the authors recognizing that the Schumpeterian process of creative destruction is disrupted by the policy.

The empirical research results are not always consistent, perhaps indicative of the importance of proper policy design and of accounting for country-specific characteristics.

While most of the defense for CGSs comes from positive financial additionality, a closer look at economic additionality is necessary, through the outcome variables mentioned in the introduction.

"Improvement of firms' financing terms is not an end in itself, it is expected to lead to improved economic performance." (SPGM, 2018b).

4 Policy Definition and Framework

The Portuguese Mutual Guarantee System was formed in 1994, as SPGM was founded. It served as a pilot test to the relevance of a CGS in Portugal. SPGM eventually branched out into four Mutual Guarantee Societies (MGS) – Norgarante, Lisgarante, Garval (regional) and Agrogarante (not regional; exclusively dedicated to the agriculture and forestry sector). It became especially relevant after the 2008 financial crisis. SPGM is the main guarantee provider in Portugal, although others do exist.

These MGSs oversee access to guarantees, risk assessment and management, and interact with both local business and the banking system in their designed regions/sectors.

SPGM evolved from being a direct intervenient to becoming a holding company of the four MGSs, also managing the Mutual Counter-Guarantee Fund (MCGF) which reduces the risk incurred by the MGSs through public funding that ensures a counter-guarantee of 50% of the capital debt. SPGM also has a supportive role in promoting the guarantees system and provides shared services (e.g., legal aid, business counselling) as support to the four MGSs.

The eligibility criteria[1] for access to guarantees provision for SMEs, or firms that are not SMEs by definition but have a turnover equal to or lesser than €150 M and are not part of business groups whose consolidated revenue is over €200 M, are as follows:

- Present a positive net worth in the most recent approved balance sheet;

[1]The full document can be found in SPGM's webpage (SPGM, 2018a). The document available only details the 2018 program, but the conditions were identical in the years of our analysis.

- Have no unsolved incidents with the banking system at the time of the emission of the agreement between both parties;

- Have a regularized situation with the banking system, Fiscal Administration and Social Security;

Applying firms must also provide access to all relevant information for the correct evaluation of the operation in terms of risk classification (solvency ratio, leverage ratio, amount of revenues of the firm). The firms are subject to a double financial screening: by the banking institution granting the loan, and the MGS that provides the collateral to ensure the loan.

Firms that gain access to the provision of guarantees must also acquire MGS stock, in a value equal to 2% of the guarantee value (this constitutes the mutualization aspect). This stock can only be sold after the relationship between the two parties is terminated (SPGM, 2018a).

5 Data Description

Microdata on firms was obtained using the Portuguese Simplified Corporate Information Survey (Informação Empresarial Simplificada, IES), provided by Bank of Portugal's Microdata Investigation Laboratory (BPLIM, 2020). This dataset contains detailed balance-sheet data, as well as profit and loss data on all of Portugal's non-financial firms. The years considered for analysis range from 2007 to 2018.

Information about public credit guarantees was provided by the Credit Register Central (Central de Registo de Crédito - CRC) of Bank of Portugal (BPLIM, 2019). It provides information on current outstanding public guarantees for 2014, 2015, 2016 and 2017.[2]

[2]Ideally, data on when the guarantees were originally granted would be most relevant for the analysis, but this information was not available.

In the context of the limitations of our data, a firm is considered treated, i.e., benefiting from public guarantees, if it has an outstanding guarantee in any year between 2014 and 2017.[3] Since credit guarantee programs usually last more than one year, it is likely that companies that have outstanding guarantees in more than one year present this characteristic precisely due to the policy we are analysing. With this key assumption, we have 453 treated firms. However, precautions were taken to ensure that this method is not a major problem. As SPGM (2018b) writes, *"The Portuguese Mutual Guarantee System (...) gained a more prominent status with the 2008 financial crisis, (...). After an incremental development during the first half of its existence, the crises years witnessed an exponential growth in the activity of the system, reaching record highs in 2009 and 2010."* To guarantee that our treated firms were not treated in the period of matching, we go the farthest back possible, to 2007, and perform our match there. This is the furthest back in time we can go with available data, and as such it should provide an adequate way of matching. It is highly unlikely, taking into consideration the quote above, that most of the treatment group firms were treated in 2007. This year also has the added bonus of being prior to the Great Recession, preventing any further distortions introduced by the event.

We follow a production function approach and thus the study of the impact of the credit guarantee system is conducted on eight outcome variables: financial additionality (credit), total assets, fixed assets (capital), labor productivity, total factor productivity, employment (labor), wages, and EBITDA (profitability). Our analysis is performed on the additionality of the respective variables.

We do not have access to information on which firms were eligible to the policy but were denied by SPGM. Therefore, we must build a control group from observational data. Given that we

[3]The reason to join firms treated on different years is derived from our inability to know exactly when the guarantees were issued. Secondly, there are not enough treated companies in one year that were not treated on the year before, from 2014 to 2017, to achieve desirable statistical power.

have access to the entire population of Portuguese firms, we restrict the database following various criteria.

First, given that the focus of our analysis is on SMEs, we exclude Large eligible firms (i.e., those with turnover below 150 000 000 euros), and all other Large firms (not eligible). SMEs that later progressed into being Large were not excluded– as it is entirely possible that the policy benefit may impact dimension. Another criterion for policy eligibility is having a positive net result in the year prior to application, and thus we exclude firms making a loss in any of the years from 2013 to 2016.[4] A third criterion requires firms not having overdue bank debt registered in the year of the application, but we could not request this information in time.

Firms belonging to the autonomous regions of Açores and Madeira are also excluded, as different policies exist for those regions. There are also firms that reported activity in the financial sector or public administration. These are excluded since the policy targets only non-financial SMEs of the private sector. Only firms in operation, with positive assets, sales, and with at least three paid employees in at least one year are kept in the sample.

Several variables are used for a parsimonious look at firm observed heterogeneity. The firm's economic performance is accounted by labor productivity (Gouveia, 2019), total factor productivity[5] (Levinsohn and Petrin, 2003), investment, turnover, employment through EFTW (Equivalent Full-Time Workers), fixed assets, total assets, and wages. Equally important for characterization are the following variables: EBITDA, debt-to-asset ratio, firm sector of activity (using the portuguese code for sectoral activity - *CAE*), firm age, ability to provide collateral, leverage, existence

[4]We do not have access to when the guarantee was provided, but in our framework we consider this a safe and sound proxy.

[5]The estimation of total factor productivity by the Levinsohn and Petrin method is implemented in STATA with the help of the -prodest- software by Rovigatti and Mollisi (2018).

of credit, and share of long-term credit. [6]

On the following page, we provide descriptive statistics on the treated and untreated firms for the year of 2007. A very important point shown in the table is that since we match for 2007 (as explained below), we have between 339 and 359 firms being analysed, depending on the outcome variable. The exception is the analysis of financial additionality, which will be restricted to 148 firms.

[6] Definitions for constructed variables (such as labor productivity, Total Factor Productivity, *EFTW*, or ratios) can be found on Appendix I.

Table 1: Descriptive Statistics - 2007

	Untreated							Treated						
	N	Mean	Std. Dev.	Q1	Q2	Q3	p95	N	Mean	Std. Dev.	Q1	Q2	Q3	p95
Debt	30345	11.2	1.9	10.1	11.2	12.4	14.3	148	11.8	1.6	10.6	11.8	13.1	14.4
ln Total Assets	102746	12.3	1.7	11.3	12.3	13.3	15.1	359	11.5	1.4	12.4	13.3	14.3	15.6
ln Fixed Assets	97952	10.5	2.1	9.3	10.6	11.8	13.8	357	8.3	1.8	10.7	11.7	13.0	14.8
ln Labor Productivity	92039	9.6	0.9	9.2	9.6	10.1	10.9	348	9.9	0.6	9.6	9.9	10.3	10.9
ln Total Factor Productivity	94162	0.4	0.0	0.4	0.4	0.5	0.5	351	0.4	0.0	0.4	0.4	0.5	0.5
ln Wages	92902	8.7	0.7	8.3	8.7	9.1	9.8	339	8.9	0.5	8.6	8.9	9.2	9.7
ln EBITDA	79977	10.3	1.6	9.3	10.3	11.3	13.0	344	11.1	1.4	10.1	11.2	12.1	13.4
Investment	92128	145.9	19585.4	-0.3	-0.1	0.2	3.3	341	5.0	56.9	-0.1	0.0	0.3	3.0
ln Turnover	99312	12.5	1.6	11.4	12.3	13.4	15.2	355	13.5	1.4	12.6	13.5	14.4	15.9
Firm Age	102986	18.5	13.0	10.0	16.0	24.0	42.0	359	23.3	10.5	16.0	20.0	29.0	44.0
In bank debt	102986	0.8	0.4	1.0	1.0	1.0	1.0	359	0.9	0.3	1.0	1.0	1.0	1.0
Share long-term bank debt	102986	0.2	0.4	0.0	0.0	0.4	1.0	359	0.3	0.4	0.0	0.0	0.7	1.0
Equivalent Full-Time Workers	102986	10.7	32.4	3.0	4.5	9.0	37.0	359	17.8	26.9	4.0	8.5	20.0	63.0
Collateral (Tangible Assets/Total Assets)	102774	0.3	0.3	0.1	0.2	0.4	0.8	359	0.3	0.2	0.1	0.3	0.4	0.7
Leverage (Total Debt/Total Assets)	102774	0.4	0.3	0.0	0.2	0.4	1.0	359	0.2	0.2	0.1	0.2	0.4	0.6

6 Methodology

The absence of experimental data does not invalidate, with the available statistical methods, that a robust control group is synthetically built that allows us to infer causal effects. The wealth of data in our databases, which includes information for the entire population of firms in Portugal, is particularly well-suited for the task. With this in mind, we seek a synthetic control group that allows us to make high-quality causal estimations and eases concerns about sample selection effects possibly taking place.

We rely on the Propensity Score Matching (PSM) methods proposed by Rosenbaum and Rubin (1983) to build a control group and estimate the causal Average Treatment on the Treated effect (ATT). The main idea behind matching estimators is that, conditional on a set of observable covariates X, the outcomes for the treated (Y^T) and control group (Y^C) are independent from the treatment assignment T, and thus the selection effect is no longer present. This is called the Conditional Independence Assumption (CIA; also known as unconfoundedness), and it is the first of two main assumptions necessary for employing matching techniques. It can be written as follows:

$$(Y^T, Y^C) \perp T \mid X \tag{1}$$

It is a strong assumption as it relies on the idea that unobserved selection is small or nonexistent. It is more credible when there is a large set of data and preprogram data, which is the case in our setting; and when robustness tests can be performed to lend credibility to the hypothesis that the hidden selection is not a concern.

The second assumption is Common Support: there must be enough comparison observations (i.e., untreated) that are a close match on observed characteristics to the treated observations, to ensure a substantial overlap of propensity score distributions:

$$0 < P\left(T = 1|X\right) < 1 \tag{2}$$

Smith and Todd (2005) argue that when the goal is, as in the present paper, to estimate the ATT, both assumptions can be relaxed, while still maintaining a high-quality matching. Instead of the aforementioned CIA, we can build on:

$$Y^C \perp T \mid X \tag{3}$$

And instead of the Common Support assumption we can build on:

$$Pr(T = 1 \mid X) < 1 \tag{4}$$

With this in mind, the ATT can be theoretically written as:

$$ATT = E[Y^T - Y^C \mid T = 1] \tag{5}$$

As such, the ATT will correspond to the mean difference in outcome between the average treatment effect on the treated and the average treatment effect on the untreated.

An essential part for estimating the ATT is matching, which we conduct based on estimated propensity scores. The Propensity Score is an estimate of the probability of a subject/observation to be treated, $(T_i = 1)$, as a function of the chosen covariates X. *P* represents the propensity score:

$$P = P(X) = Pr[T = 1 \mid X] \tag{6}$$

A crucial part of this, is that matching must satisfy the balancing property $T \perp X \mid P(X)$. If it is satisfied, it means that, regardless of treatment status, observations with the same propensity score have equal distributions both on observed and unobserved characteristics. If this is valid, then assignment to treatment can be considered random. We conduct balancing tests on Section 7 to confirm this.

Taking all of the above into account, the ATT is calculated by comparing the outcome of a treated unit with the outcome of an untreated unit with the same propensity score. It can be rewritten as follows:

$$ATT = E_{P(X)|T=1}(E[Y^T \mid T = 1, P(Y^T)] - E[Y^C \mid T = 0, P(Y^C)]) \tag{7}$$

The Propensity Score can be estimated using Maximum Likelihood Estimators: logit or probit, after choosing the X covariates that are deemed most relevant. We use the logit estimator, since it is easier to compute and saves computational processing time. The logistic function is described as follows:

$$F(X) = \frac{exp(X)}{1 + exp(X)} \tag{8}$$

And the probability function:

$$P(T = 1 \mid X) = \frac{1}{1 + exp(-(\alpha + \beta X))} \tag{9}$$

There is no guide or mechanical formula to choose what the most relevant covariates are – they are context specific. We choose covariates following previous literature, also keeping in mind the relevant outcomes we study. Also, the covariates X are not necessarily the same for every outcome variable, as noted by Dehejia (2005). On our work, however, we are able to keep a strong consistency, with few changes in covariates for estimating propensity scores on different outcomes. In practical terms, we match on ability to provide collateral, share of long-term debt, firm age, firm sector of activity as defined by the *CAE*, and debt-to-asset ratio[7].

There are several matching techniques that can be used to match treated and untreated obser-

[7] Debt-to-asset ratio is the only covariate that is not present in all matching procedures.

vations. We are utilizing Propensity Score Matching on nearest-neighbor[8]. Based on the propensity score generated through the logistic distribution, this method searches for the untreated observation with the closest propensity score to the treated observation, forming a "pair" between them. It is one of the most frequently used methods in the literature. There is, however, a caveat: it might be that the untreated "nearest-neighbor" is still very far away in terms of propensity score to the treated observation. This may result in poor matches. To avoid this, we use a caliper together with the nearest-neighbor option, which defines the maximum threshold of difference between propensity scores for two observations to be considered a match. In our specific case, we use a caliper of 0.001. This forces the propensity scores for matched observations to be different from one another by no more than 0.001. We also match with replacement: this means that one untreated observation may be used as a match to more than one treated observation, if it is the case that it also has the closest propensity score to that second treated observation. This may imply that a higher number of untreated observations are dropped, but since we have a very large dataset of untreated observations, we are not concerned by this. Additionally, we impose common support by dropping treated observations with a propensity score higher than the maximum or less than the minimum of the propensity score for untreated observations. Finally, we match on "ties" as well: if there are two or more untreated observations that have identical propensity score to a treated observation, they are used in addition to the nearest neighbor.

As we use a two-step estimation process - first the logit model and then the ATT coefficient estimation -, our standard error estimates should take into account the variance attributable to both steps, as well as the common support imposition. But when going through our estimations,

[8]The only exception to this method is on the credit outcome variable. As a lot of our treated firms did not have any credit in 2007, we lose many treatment-group observations, and thus, lose statistical power. We match on 2 nearest-neighbors to overcome this issue.

theoretically we may end up with bad approximations to the true variation of the estimator. A solution often used is bootstrapping: initially proposed by Efron and Tibshirani (1994), it consists in drawing random sub-samples from the initial sample and reestimating standard errors with each sub-sample. However, bootstrapping has never been proved to be valid in this context, and it is becoming increasingly debatable (Abadie and Imbens, 2008). Given this, instead of bootstrapping we follow Abadie and Imbens (2006) and calculate heteroskedasticity-consistent analytical standard errors.[9]

The practical implementation of this process is done through STATA, utilizing the -psmatch2- software by Leuven and Sianesi (2003). It offers many options together with a range of robustness checks that are important to validate our process.

7 Robustness Checks for assessing matching process quality

These checks are intended to validate our methodology. First, we check the balancing of our covariates' means through a two sample t-test. For good balancing, and thus a robust control group, the t-test between the covariates' means of the treated and control group after matching should show no statistically significant differences (Rosenbaum and Rubin, 1985). After conducting this test, we can verify on Appendix III that the covariates are well-balanced for most outcomes, with notably few exceptions.

Austin (2009) indicates that the variance ratio of covariates for treated and control groups is an additional indicator of good balancing, if the variance ratios are within the 2.5th and 97.5th percentiles. This can also be found on Appendix III, and it is true for the majority of the covariates

[9] Despite this, bootstrapped results are presented in Appendix II for completeness.

for each outcome variable.[10]

Another alternative is suggested by Sianesi (2004) indicating that if we have a high-quality matching, the pseudo-R^2 after matching should be lower than the pseudo-R^2 obtained from the original logit estimation. This is true for all of our outcome estimations, with the pseudo-R^2 falling considerably in all of our results.

Finally, Rubin (2001) proposes "Rubin's B": *"the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group"* and "Rubin's R": *"the ratio of treated to (matched) non-treated variances of the propensity score index"*. The recommendation is that the B is below 25 and the R between 0.5 and 2, in order to conclude that the matched samples are sufficiently balanced (Leuven and Sianesi, 2003). This is verified for all estimation outcomes except for wages on Rubin's B, which is just barely outside the proposed interval.

On Appendix IV we change matching options, from the propensity score matching on nearest neighbor to the propensity score matching on 5 nearest neighbors. Also, we try the no replacement option. We recognize the change in magnitudes and statistical significance for some results, however this is a common inconvenience when changing matching methods. For even more credible analysis, we utilize propensity score matching with radius matching, with two different calipers (0.001 and 0.00001)[11]. Finally, we also use an alternate package, -teffects psmatch-, in order to verify our results are in fact consistent. This package has the advantage of directly computing standard errors taking into account that the propensity scores are estimated.

[10]There are a few exceptions where the variance ratio falls outside the proposed interval by the literature. However, we verified that the covariates scoring outside the interval actually help balance the remaining ones, and that is the reason for not dropping them from the matching process.

[11]Abadie and Imbens (2008)'s criticism of bootstrapping processes also applies for radius matching. Thus, we also perform these estimations using their correction for the standard errors.

All in all, our estimation procedures pass the broad majority of these tests. The bulk of our robustness checks lend credibility to the affirmation that the matching procedure was effective, and that our results are valid.

8 Results

Table 2: Results

	ATT	Std. Error	T - stat	95% Conf. Interval
Credit	0.2009^{+}	0.1034	1.94	[-0.0018 , 0.4036]
Total Assets	0.1097^{**}	0.0411	2.67	[0.0290 , 0.1903]
Fixed Assets	0.0986^{*}	0.0495	2.35	[0.0161 , 0.1811]
Labor Productivity	-0.0734^{+}	0.0430	-1.71	[-0.1576 , 0.011]
Total Factor Productivity	0.0021	0.0025	0.85	[-0.0028 , 0.0070]
Employment	0.0779^{*}	0.0394	1.98	[0.0007 , 0.1551]
Wages	-0.0214	0.0334	-0.64	[-0.0869 , 0.0441]
EBITDA	-0.0805	0.0759	-1.06	[-0.2292 , 0.0683]

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The outcomes of interest analyzed are eight: the impact on credit, labor productivity as defined by Gouveia (2019), Total Factor Productivity as defined by Levinsohn and Petrin (2003), fixed assets, total assets, employment, wages, and EBITDA. For all outcomes, we focus on the ATT growth rate change in percentual points - we define each outcome variable as the difference between the natural logarithm of the variable between 2018 and 2013 (e.g., Credit = ln(Credit2018) - ln(Credit2013)). The results are presented in Table 2.

It is important to mention that, out of the 453 treated firms available[12], 432 are micro or small firms, with only 21 being medium or large. Since we are looking at the average treatment effect on the treated, this information will be important in understanding the results.

Starting by credit, we find statistically significant evidence of an increase in the growth rate of obtained credit of 20 pp. This result goes in line with what would be expected: treated firms have access to more credit. Also, we argue that there may be one other mechanism helping treated firms obtain credit: treated firms undergo thorough assessment by SPGM, and when they receive access to the credit guarantee they are signaled to all of the banking system as relatively safer then their untreated counterparts. What this means is that aside from the direct effect of the financial additionality these firms enjoy, an indirect effect of positive signalling contributes to making it relatively easier for them to find financing in future occasions that are independent from the treatment program. This is an educated guess at a possible mechanism, but we do not prove this in our analysis.

Total assets growth rate for treated firms increases on average 11 pp. Given the increase in credit, it is logical to see an increase in the acquisition of total assets by the treated firms.

Fixed assets are positively affected as well. We find an increase in the growth of fixed assets compared to control group firms of about 10 pp. The result is statistically significant, and it follows closely the change in growth rate for total assets.

Turning to labor productivity, we see a decrease on the treated group of 7 pp. The negative coefficient had us question the results. Thus, we checked the results for the average treatment effect, and the average treatment effect of the untreated, and it turns out both are also negative.

[12] This number reports to the total treated firms we dispose in our database in 2018, and not the 2007 total. They differ because in 2007 some firms that are in our treatment database did not exist yet, or because they have missing values on the outcome variables. This has been highlighted in the Data Description section, where we present the total number in 2007 as being around 350, depending on the outcome variable.

This provides clues that suggest the existence of downward drivers of Portugal's labor productivity not related to the program being analysed. This will be discussed in the conclusion section.

As for Total Factor Productivity growth ratio, the ATT coefficient is positive, but it is not statistically significant. Since productivity measures are some of the most important economic outcomes, finding negative impact on labor productivity and no impact on total factor productivity is a concern to keep in mind. As mentioned in the literature review in citing Oh et al. (2009), the policy may be impairing the process of creative destruction.

Employment manifests a statistically significant increase of 8 pp for the treated firms. This policy, thus, leads to extra job creation.

The growth rate of the wages of employees are not affected by the program. This is coherent with our findings that labor productivity is not positively impacted on firms that receive the policy.

The earnings before interest, taxes, depreciations and amortizations - EBITDA - present no statistically significant increase, and a negative coefficient: -8 pp.

As a concluding note, we make a remark on the magnitude of our estimates, going back to the second paragraph of this section. We are looking mostly at firms of very small dimension, where apparently small variations in absolute totals translate into high relative changes.

9 Conclusion

The attribution of public credit guarantees to SMEs increased greatly after the Great Recession (2008-2009) and the sovereign debt crisis (2011-2013). Seen as a way of preventing credit rationing to SMEs, the focus on the evaluation of such policies is often the financial additionality. This paper mainly analyzed the economic additionality of the policy and the conclusions are mixed - mimicking available literature for other countries. On the one hand, there is a positive impact on access to credit (i.e., there is financial additionality), total assets, fixed assets and job creation. There seems to be a negative effect on labor productivity. On the other hand, the policy is not effective in impacting the growth rate of total factor productivity, wages, and EBITDA. Looking back at the literature review, our results are closer to the evidence from countries like Italy, France, or South Korea, than the results found for Spain or Portugal.

Our data has limitations that we have highlighted over our work. We do not have information to determine exactly when the credit guarantee was attributed, so we develop a method to overcome this, by estimating propensity scores for firms in 2007 and matching them in that same year. Since SPGM (2018b) itself describes that the credit guarantee attributions only became truly relevant after the 2008-09 period, this seems like a relatively safe identification strategy for us.

Adding to this, we trust our point estimates, but must recognize that our confidence intervals are considerably large - a result stemming from having a relatively small number of treated firms available to work with, and also of employing a quantitative analysis strategy that relies on two-step estimations.

Here, we will discuss our results at a 10% significance level. We find that treated firms grow on assets and create more employment. They show no signs of growing on productivity. The report by OECD (2019) provides a deep analysis into the issue of productivity. It details how employment has been rising across OECD countries but mainly in low productivity and low wage jobs, bringing with it a decrease in the overall labor productivity. This is even more relevant in our context as we are dealing with mainly micro and small firms. The report also offers detail into Portugal's own situation: the labor productivity growth shows, on average, a decreasing trend from 2010 to 2018 - with barely existent labor productivity growth from 2014 to 2018. For what the OECD defines as *Multifactor Productivity*, it can also be seen that Portugal is stagnant on that measure. The figures that show this can be seen on Appendix V. Although the OECD relies on different methodologies for estimating productivity measures, their findings are similar to ours. And it is worth noting that OECD's findings account for the whole of portuguese firms - not just SMEs. So, as it stands, this seems to be a structural problem of the portuguese economy, and not particularly related to the policy at hand.

Is the process of creative destruction being impaired by these policies? Should firms that do not contribute towards overall economic productivity growth and wages growth continue to be supported, even if they create employment? These are questions that future research could address, with a focus on what is most suitable for the overall macroeconomic scenario. Additional research for Portugal is necessary to understand what are the root causes for low-to-none productivity growth, and possible guides for future policy making.

Finally, it becomes clear that an increase in independent policy evaluation is necessary. Access to more complete data on future researches is fundamental for better policy evaluation. Further questions of cost-effectiveness should also be addressed, along with the analysis of default rates of treated firms.

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Appendixes

Appendix I - Variables Definition

$$\text{Credit} = ln(\text{Long-term Credit}_{2018}) - ln(\text{Long-term Credit}_{2013}) \tag{1}$$

$$\text{Total Assets} = ln(\text{Total Assets}_{2018}) - ln(\text{Total Assets}_{2013}) \tag{2}$$

$$\text{Fixed Assets} = ln(\text{Fixed Assets}_{2018}) - ln(\text{Fixed Assets}_{2013}) \tag{3}$$

$$\text{Labor Productivity} = \frac{\text{VAB}_{it}}{\text{EFTW}_{it}} \tag{4}$$

$$\text{VAB}_{it} = \text{Production}_{it} - \text{Intermediate Costs}_{it} + \text{Operating Subsidies}_{it} - \text{Indirect Taxes}_{it} \tag{5}$$

$$\begin{aligned}\text{Production}_{it} = \text{Turnover}_{it} + \text{Changes in stocks}_{it} + \text{Own work capitalised}_{it} + \\ + \text{Supplementary income}_{it}\end{aligned} \tag{6}$$

$$\begin{aligned}\text{Intermediate Costs}_{it} = \text{Cost of goods sold and materials consumed}_{it} + \\ \text{External supplies and services}_{it}\end{aligned} \tag{7}$$

$$\text{Equivalent Full - Time Workers}_{it}(\text{EFTW}) = \text{Full-time workers}_{it} + 0.5 * \text{Part-time workers}_{it} \tag{8}$$

Total Factor Productivity: See Levinsohn and Petrin (2003) (9)

$$\text{Employment} = ln(\text{ETI}_{2018}) - ln(\text{ETI}_{2013}) \tag{10}$$

$$\text{wages} = ln(\frac{\text{Employee Salaries}_{2018}}{\text{EFTW}_{2018}}) - ln(\frac{\text{Employee Salaries}_{2013}}{\text{EFTW}_{2013}}) \tag{11}$$

$$\text{EBITDA} = ln(\text{EBITDA}_{2018}) - ln(\text{EBITDA}_{2013}) \tag{12}$$

$$\text{Collateral} = \text{Ability to provide collateral} = \frac{\text{Fixed Tangible Assets}_{it}}{\text{Total Assets}_{it}} \tag{13}$$

CAE: Portuguese definition of economic activity sectors. See INE (2007) (14)

Age = Firm age = Number of years since firm constitution (15)

$$\text{Debt-to-asset ratio} = \frac{\text{Total Debt}}{\text{Total assets}} \tag{16}$$

$$\text{Share of long-term debt} = \frac{\text{Long-term debt}}{\text{Total debt}} \tag{17}$$

Appendix II - Bootstrapped Results

Table 3: Bootstrapped Results - 200 repetitions

	ATT	Std. Error	Z - stat	95% Conf. Interval
Credit	0.2009	0.1308	1.54	[-0.0554 , 0.4573]
Total Assets	0.1097+	0.060	1.82	[-0.0087 , 0.2280]
Fixed Assets	0.0992	0.1111	1.08	[-0.0975 , 0.3379]
Labor Productivity	-0.0734	0.048	-1.52	[-0.1681 , 0.0218]
Total Factor Productivity	0.0021	0.0031	0.68	[-0.0040 , 0.0082]
Employment	0.0779+	0.0404	1.93	[-0.0014 , 0.1572]
Wages	-0.0214	0.043	-0.49	[-0.1067 , 0.0638]
EBITDA	-0.0805	0.1011	-0.80	[-0.2786 , 0.1176]

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix III - Balancing Tests

```
**** BALANCING TESTS *****

* CREDIT


Log likelihood = -1476.7812                     Pseudo R2         =     0.0161

--------------------------------------------------------------------------------
   treat14to17 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
  collateral07 |  -.2177492   .2615744    -0.83   0.405    -.7304256    .2949272
longcreditpc07 |   .1609716   .1486454     1.08   0.279    -.1303679    .4523112
          cae3 |  -.0000194   2.96e-06    -6.55   0.000    -.0000252   -.0000136
         age07 |   -.000236   .0051232    -0.05   0.963    -.0102774    .0098053
  debtassetr07 |  -.2807261   .2469456    -1.14   0.256    -.7647305    .2032783
         _cons |  -3.521446    .214183   -16.44   0.000    -3.941237   -3.101655
--------------------------------------------------------------------------------


------------------------------------------------------------------------------
                        |       Mean               |     t-test    |  V(T)/
Variable                | Treated Control    %bias |    t    p>|t| |  V(C)
------------------------+--------------------------+---------------+----------
collateral07            | .30269   .27663     11.2 |   1.44  0.150 |  1.00
longcreditpc07          | .32695   .29049      8.8 |   1.05  0.296 |  1.04
cae3                    |  37802    37949     -0.7 |  -0.09  0.926 |  0.98
age07                   | 23.786   24.562     -7.0 |  -0.79  0.427 |  0.77*
debtassetr07            | .25434   .24284      3.6 |   0.65  0.514 |  0.84
------------------------------------------------------------------------------
* if variance ratio outside [0.79; 1.27]

----------------------------------------------------------------------
Ps R2   LR chi2   p>chi2   MeanBias   MedBias      B       R     %Var
----------------------------------------------------------------------
0.005      3.74    0.587      6.3       7.0      16.5    0.87      20
----------------------------------------------------------------------
* if B>25%, R outside [0.5; 2]
```

*TOTAL ASSETS

Log likelihood = -2083.3085 Pseudo R2 = 0.0193

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	.1197925	.2221053	0.54	0.590	-.3155259	.555111
longcreditpc07	.3071381	.1279497	2.40	0.016	.0563612	.557915
cae3	-.0000213	2.52e-06	-8.47	0.000	-.0000263	-.0000164
age07	-.0037951	.0046019	-0.82	0.410	-.0128146	.0052244
_cons	-4.10162	.1801391	-22.77	0.000	-4.454686	-3.748554

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.29319	.27473	8.0	1.12	0.264	0.91
longcreditpc07	.29759	.26097	9.2	1.22	0.224	1.06
cae3	38264	37525	3.7	0.52	0.601	0.94
age07	23.41	24.017	-5.4	-0.74	0.459	0.86

* if variance ratio outside [0.81; 1.23]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.004	3.63	0.459	6.6	6.7	14.3	1.02	0

* if B>25%, R outside [0.5; 2]

*FIXED ASSETS

Log likelihood = -2000.2397 Pseudo R2 = 0.0181

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	-.0135032	.2302872	-0.06	0.953	-.4648578	.4378514
longcreditpc07	.3190963	.132046	2.42	0.016	.0602909	.5779018
cae3	-.0000205	2.55e-06	-8.03	0.000	-.0000255	-.0000155
age07	-.0043119	.0046719	-0.92	0.356	-.0134687	.004845
debtassetr07	-.0845762	.1806224	-0.47	0.640	-.4385897	.2694373
_cons	-3.99814	.1869652	-21.38	0.000	-4.364585	-3.631695

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.2983	.27924	8.2	1.11	0.268	0.83
longcreditpc07	.30333	.2866	4.2	0.54	0.592	0.97
cae3	38220	37932	1.4	0.20	0.842	0.93
age07	23.552	23.863	-2.8	-0.38	0.703	0.94
debtassetr07	.24311	.23688	1.8	0.36	0.718	0.62*

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.002	1.68	0.891	3.7	2.8	9.9	0.83	20

* if B>25%, R outside [0.5; 2]

*LABOR PRODUCTIVITY

Log likelihood = -2008.3238 Pseudo R2 = 0.0201

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	.1248681	.2297712	0.54	0.587	-.3254751	.5752113
longcreditpc07	.2987633	.1316803	2.27	0.023	.0406747	.5568518
cae3	-.0000217	2.56e-06	-8.48	0.000	-.0000267	-.0000167
age07	-.0044101	.0047197	-0.93	0.350	-.0136605	.0048404
debtassetr07	-.023207	.1449163	-0.16	0.873	-.3072376	.2608237
_cons	-3.993691	.1861726	-21.45	0.000	-4.358583	-3.628799

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.29589	.2668	12.7	1.76	0.078	0.94
longcreditpc07	.2961	.27486	5.3	0.69	0.489	1.00
cae3	37927	37334	2.9	0.41	0.680	0.91
age07	23.402	24.069	-5.9	-0.77	0.444	0.73*
debtassetr07	.24454	.24169	0.8	0.16	0.873	0.56*

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.004	4.09	0.537	5.5	5.3	15.4	0.88	40

* if B>25%, R outside [0.5; 2]

* TOTAL FACTOR PRODUCTIVITY

Log likelihood = -1962.9286 Pseudo R2 = 0.0185

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	-.0160685	.2342249	-0.07	0.945	-.4751409	.4430039
longcreditpc07	.3008215	.1325519	2.27	0.023	.0410244	.5606185
cae3	-.0000208	2.57e-06	-8.07	0.000	-.0000258	-.0000157
age07	-.0044578	.0047358	-0.94	0.347	-.0137399	.0048243
debtassetr07	-.0084631	.1568564	-0.05	0.957	-.3158959	.2989698
_cons	-3.958654	.1883282	-21.02	0.000	-4.327771	-3.589538

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.29803	.29027	3.4	0.47	0.641	0.96
longcreditpc07	.30133	.25922	10.5	1.37	0.171	1.05
cae3	37971	37230	3.6	0.51	0.609	0.94
age07	23.512	24.141	-5.6	-0.72	0.470	0.76*
debtassetr07	.24417	.24993	-1.7	-0.29	0.772	0.42*

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.004	3.43	0.633	5.0	3.6	14.2	1.01	40

* if B>25%, R outside [0.5; 2]

*EMPLOYMENT

```
Log likelihood = -2025.1617                     Pseudo R2         =     0.0200

--------------------------------------------------------------------------------
   treat14to17 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
  collateral07 |   .0948394   .2287639     0.41   0.678    -.3535297    .5432084
longcreditpc07 |   .3072734   .1315711     2.34   0.020     .0493987     .565148
          cae3 |  -.0000216   2.55e-06    -8.49   0.000    -.0000266   -.0000167
         age07 |  -.0046492   .0046993    -0.99   0.322    -.0138596    .0045612
  debtassetr07 |  -.0503745   .1599363    -0.31   0.753    -.3638439     .263095
         _cons |  -3.991129   .1856192   -21.50   0.000    -4.354936   -3.627322
--------------------------------------------------------------------------------
```

```
------------------------------------------------------------------------------
                        |       Mean               |     t-test    |  V(T)/
Variable                | Treated Control    %bias |    t    p>|t| |  V(C)
------------------------+--------------------------+---------------+----------
collateral07            | .29449   .28414      4.5 |   0.60  0.546 |  0.81
longcreditpc07          | .29727    .2618      8.9 |   1.17  0.244 |  1.03
cae3                    |  37966    37346      3.1 |   0.43  0.665 |  0.91
age07                   | 23.411   23.664     -2.2 |  -0.30  0.765 |  0.79*
debtassetr07            | .24328    .2503     -2.0 |  -0.33  0.739 |  0.34*
------------------------------------------------------------------------------
* if variance ratio outside [0.81; 1.23]
```

```
----------------------------------------------------------------------
Ps R2   LR chi2   p>chi2   MeanBias   MedBias      B       R     %Var
----------------------------------------------------------------------
0.002      2.31    0.805      4.1       3.1      11.5    0.90      40
----------------------------------------------------------------------
* if B>25%, R outside [0.5; 2]
```

*WAGES

Log likelihood = -1959.9048 Pseudo R2 = 0.0191

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	.1069661	.2328801	0.46	0.646	-.3494706	.5634028
longcreditpc07	.330467	.1327455	2.49	0.013	.0702906	.5906434
cae3	-.0000209	2.58e-06	-8.09	0.000	-.0000259	-.0000158
age07	-.004848	.0047471	-1.02	0.307	-.0141522	.0044561
debtassetr07	-.0467747	.1628573	-0.29	0.774	-.3659691	.2724196
_cons	-3.989954	.1884462	-21.17	0.000	-4.359302	-3.620606

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.29647	.27457	9.6	1.32	0.187	0.96
longcreditpc07	.30348	.28674	4.2	0.53	0.596	0.97
cae3	37992	37331	3.3	0.46	0.648	0.94
age07	23.537	25.171	-14.4	-1.77	0.076	0.64*
debtassetr07	.24136	.19895	12.1	2.72	0.007	0.88

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.012	11.44	0.043	8.7	9.6	26.0*	0.70	20

* if B>25%, R outside [0.5; 2]

*EBITDA

Log likelihood = -1926.7631 Pseudo R2 = 0.0189

treat14to17	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
collateral07	.1125562	.2325204	0.48	0.628	-.3431754	.5682879
longcreditpc07	.2962204	.1356177	2.18	0.029	.0304146	.5620262
cae3	-.000021	2.60e-06	-8.08	0.000	-.0000261	-.0000159
age07	-.0067377	.0049551	-1.36	0.174	-.0164496	.0029742
debtassetr07	-.0831817	.1789018	-0.46	0.642	-.4338228	.2674595
_cons	-3.973149	.191998	-20.69	0.000	-4.349459	-3.59684

	Mean			t-test		V(T)/
Variable	Treated	Control	%bias	t	p>|t|	V(C)
collateral07	.29779	.27945	7.9	1.08	0.278	0.94
longcreditpc07	.29616	.26986	6.6	0.84	0.403	1.00
cae3	38382	38116	1.3	0.18	0.855	0.93
age07	23.124	22.703	3.8	0.52	0.606	0.91
debtassetr07	.24138	.22403	4.9	0.75	0.456	0.28*

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.003	2.44	0.785	4.9	4.9	12.2	0.86	20

* if B>25%, R outside [0.5; 2]

Appendix IV - Other Matching Methods

Table 4: Nearest-Neighbor Matching: 5 Neighbors

	ATT	Std. Error	T - stat	95% Conf. Interval
Credit	0.1976*	0.085	2.31	[0.0302 , 0.3650]
Total Assets	0.0800**	0.0303	2.64	[0.0205 , 0.1395]
Fixed Assets	0.0695+	0.0738	1.86	[-0.0709 , 0.2185]
Labor Productivity	-0.0856**	0.0327	-2.62	[-0.1497 , -0.0215]
Total Factor Productivity	0.0029	0.0020	1.44	[-0.0011 , 0.0069]
Employment	0.0659*	0.0295	2.24	[0.0082 , 0.1237]
Wages	-0.0303	0.0260	-1.17	[-0.0812 , 0.0206]
EBITDA	-0.0458	0.0549	-0.83	[-0.1534 , 0.0619]

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Nearest-Neighbor Matching without replacement

	ATT	Std. Error	T - stat	95% Conf. Interval
Credit	0.0275	0.1199	0.23	[-0.2075 , 0.2623]
Total Assets	0.1097**	0.0411	2.67	[0.0292 , 0.1901]
Fixed Assets	0.0814	0.0954	1.53	[-0.041 , 0.3328]
Labor Productivity	-0.0719+	0.0419	-1.72	[-0.1541 , 0.0102]
Total Factor Productivity	0.0024	0.0024	1.00	[-0.0023 , 0.0072]
Employment	0.0770*	0.0392	1.97	[0.0003 , 0.1538]
Wages	-0.0214	0.0338	-0.63	[-0.0876 , 0.0448]
EBITDA	-0.0701	0.0742	-0.94	[-0.2157 , 0.0753]

+ p <0.10, * p <0.05, ** p <0.01, *** p <0.001

Table 6: Radius Matching with 0.001 caliper

	ATT	Std. Error	T - stat	95% Conf. Interval
Credit	0.2103**	0.0739	2.85	[0.0655 , 0.3551]
Total Assets	0.0898***	0.0270	3.32	[0.0368 , 0.1428]
Fixed Assets	0.0755	0.0954	1.53	[-0.0247 , 0.2377]
Labor Productivity	-0.0669*	0.0303	-2.21	[-0.1262 , -0.0076]
Total Factor Productivity	0.0038*	0.0018	2.07	[0.0002 , 0.0074]
Employment	0.0479+	0.0266	1.80	[-0.0042 , 0.1001]
Wages	-0.0213	0.0234	-0.91	[-0.0672 , 0.0246]
EBITDA	-0.0351	0.0481	-0.73	[-0.1293 , 0.0592]

+ p <0.10, * p <0.05, ** p <0.01, *** p <0.001

Table 7: Radius matching with 0.00001 caliper

	ATT	Std. Error	T - Stat	95% Conf. Interval
Credit	0.1715*	0.0778	2.21	[0.0191 , 0.3239]
Total Assets	0.0857**	0.0275	3.12	[0.0318 , 0.1396]
Fixed Assets	0.0694	0.0680	1.51	[-0.0307 , 0.2357]
Labor Productivity	-0.0709*	0.0307	-2.31	[-0.1310 , -0.0108]
Total Factor Productivity	0.0033+	0.0019	1.79	[-0.0003 , 0.0070]
Employment	0.0571*	0.0270	2.11	[0.0041 , 0.1101]
Wages	-0.0200	0.0238	-0.84	[-0.0666 , 0.0266]
EBITDA	-0.0323	0.0488	-0.66	[-0.1280 , 0.0633]

+ p <0.10, * p <0.05, ** p <0.01, *** p <0.001

Table 8: Using -teffects psmatch- with Abadie-Imbens Standard Errors

	ATT	Std. Error	Z - stat	95% Conf. Interval
Credit	0.2009*	0.0120	1.97	[0.0010 , 0.4009]
Total Assets	0.0804+	0.0437	1.84	[-0.0053 , 0.1661]
Fixed Assets	0.0721	0.0920	1.31	[-0.0602 , 0.3005]
Labor Productivity	-0.0734+	0.0435	-1.69	[-0.1586 , 0.0118]
Total Factor Productivity	0.0021	0.0024	0.87	[-0.0027 , 0.0069]
Employment	0.0779*	0.0386	2.02	[0.0022 , 0.1536]
Wages	-0.0214	0.0330	-0.65	[-0.0861 , 0.0433]
EBITDA	-0.0805	0.0763	-1.06	[-0.2300 , 0.0690]

+ p <0.10, * p <0.05, ** p <0.01, *** p <0.001

Appendix V - OECD Productivity figures

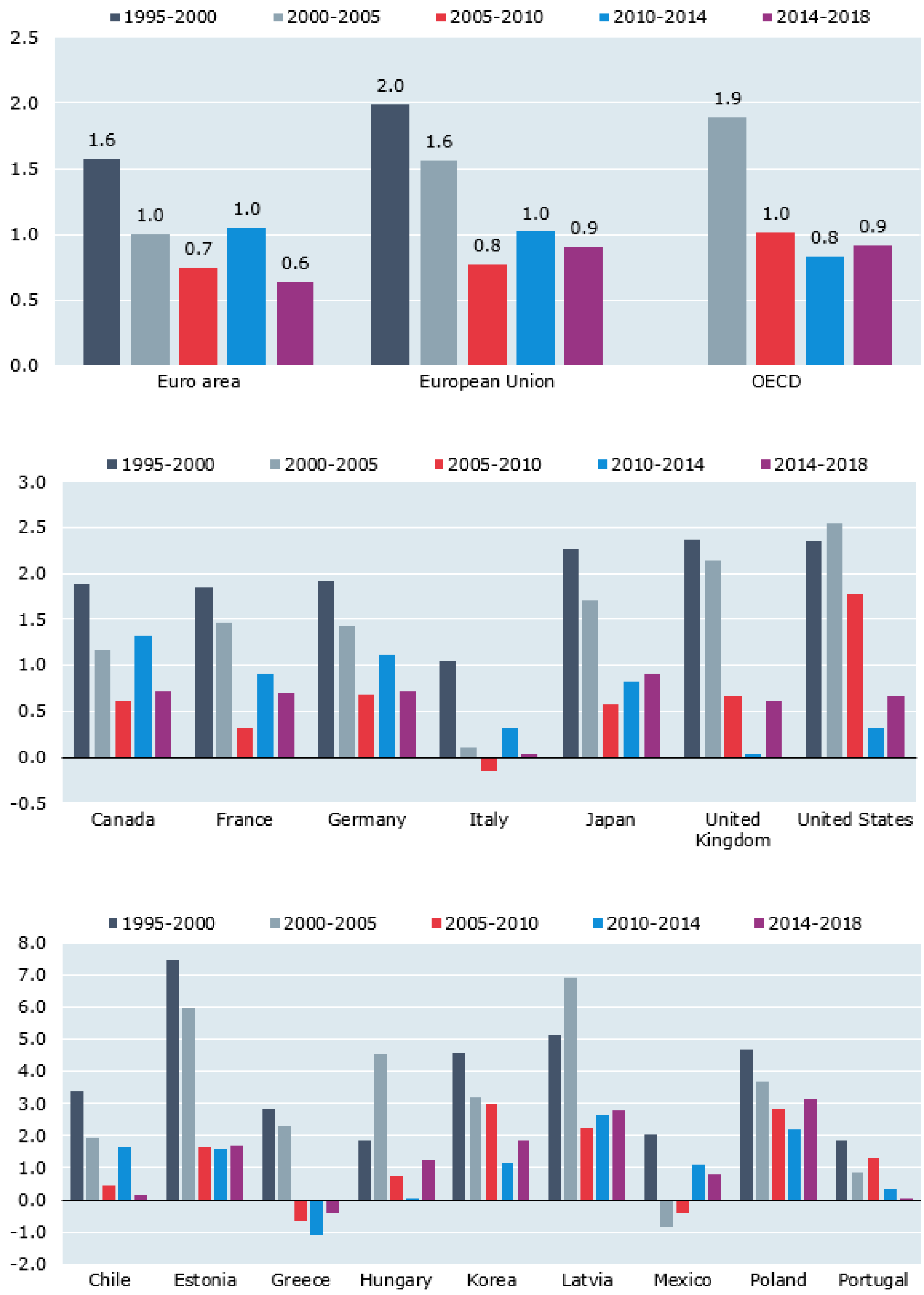

Figure 2: Labour productivity growth in the OECD (OECD, 2019)

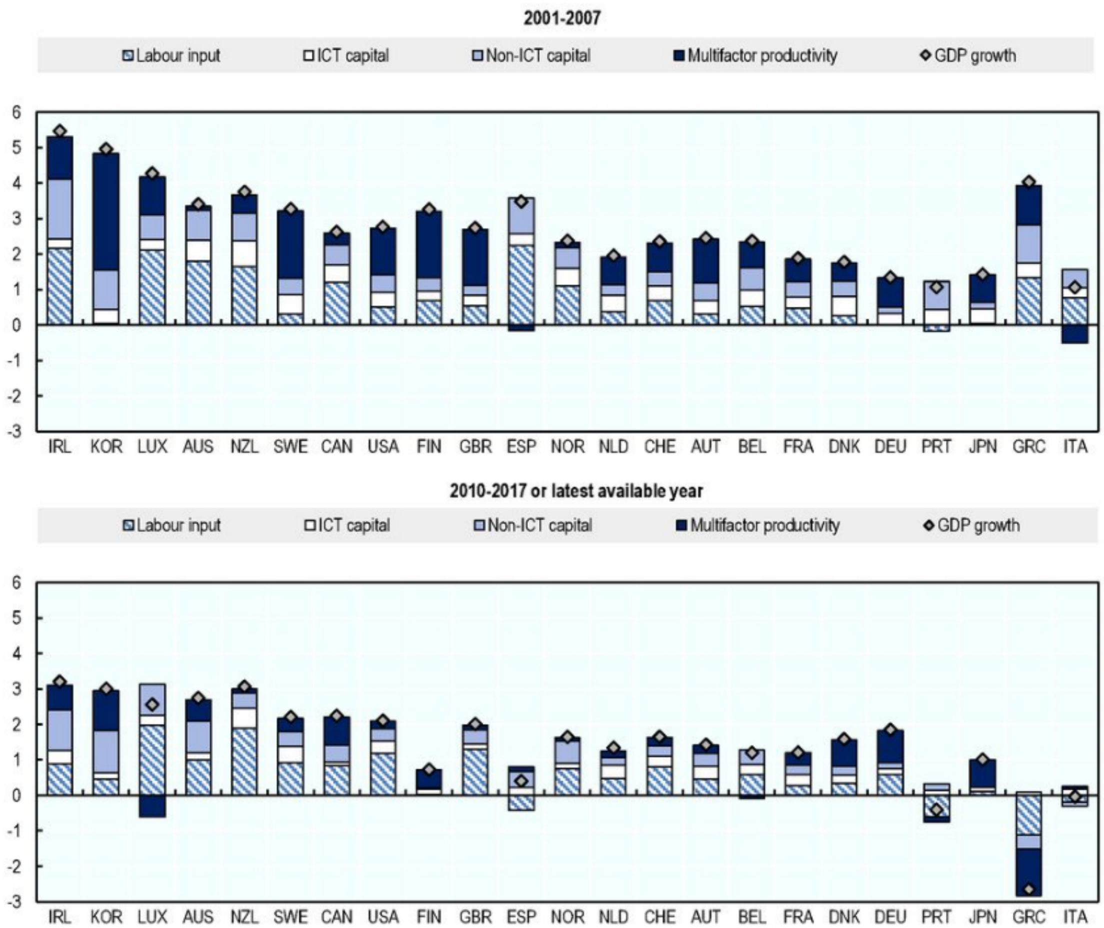

Figure 3: Multifactor productivity growth in the OECD (OECD, 2019)