Public subsidies, TFP and Efficiency: A tale of complex relationships

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Abstract: This paper evaluates the impact of subsidies on the different components of TFP for granted firms' long-term growth. The impact of capital subsidies is captured by a quasi–experimental method (Multiple RDD), exploiting the conditions for a local random experiment created by an Italian industrial policy. Results show that capital subsidies negatively affect TFP growth in the short term, and signals of positive effects appear only after 3-4 years. This positive medium-long term impact comes especially through technological change and not through scale impact change, as may have been expected.

Keywords: Policy evaluation, Public subsidies, TFP decomposition, Stochastic frontier model, Regression discontinuity design

JEL codes: H71, R38, 033, C14

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1. Introduction

Given the increasing amount of financial resources devoted to regional policies supporting private enterprises since the mid-1970s in Europe and abroad, a large and growing body of literature has investigated the policy contribution to growth and competitiveness of subsidized firms. However, the empirical evidence has provided mixed, if not contradictory, results. A recent review promoted by the European Commission to inform preparation of the 2014-20 programs (Mouqué, 2012) notes that while financial support to SMEs in lagging regions has been effective in increasing investment and creating jobs of good quality and longevity, productivity in subsidized firms has basically stayed the same. Ultimately, the main effect of the grant schemes examined is to make subsidized enterprises larger rather than more efficient.

The result is not unexpected. In fact, policy makers use the financial incentive to change firm preferences and to push the firm to invest in projects that, without incentive, would normally be abandoned. The reason is that the social cost of the investment (and of the new employment) is lower than the cost for the firm because there are positive externalities in the less developed areas (Bernini and Pellegrini, 2011). The results might be different if the incentives were to overcome failure in the credit market. In this case, incentives could support projects with high productivity. This point is crucial for a regional policy: efficiency and competitiveness are the main factors for endogenous growth and long-term catch up by lagging regions. The risk is the policy of the lame duck that subsidizes firms that are unable to stay in the market (Mouqué, 2012).[1]

[1] Indeed, capital subsidies may impede the Schumpeterian process of "creative destruction" that creates growth in the economy by shifting resources from low- to high-productivity plants (Moffat, 2014).

From an empirical point of view, the relationship between public subsidies and efficiency and productivity of subsidized firms is complex and not unique. However, only a few studies address the effect of capital subsidies on total factor productivity (TFP) (see Bergstrom, 2000; Harris and Trainor, 2005; Bernini and Pellegrini, 2011; Moffat, 2014; Criscuolo et al., 2016). Growth of TFP is a productivity measure that reflects the increase in total output that is not explained by the increase in capital and labor. Indeed, while labor productivity (output per worker) may grow simply because of the capital deepening induced by the subsidies, the efficiency with which all inputs are used (measured by TFP) may not increase at all. Then, TFP can be considered the most relevant productivity measure for analyzing the efficiency of a subsidized firm. However, one major drawback of this literature is that it does not provide results about the determinants of the changes in TFP caused by the subsidies. The analysis of the variation in the technical or allocative efficiency or in the dynamics of technological change among subsidized firms can explain the sources of the impact on TFP and sheds light on the mechanism that links subsidies to efficiency and competitiveness. For instance, we expect that public incentives increase the propensity to invest in new and more up-to-date capital, augmenting the rate of technological progress of the firm. On the other hand, firms can choose not to pursue the allocative efficiency if the increase in the use of one factor (for instance, labor) augments the probability of obtaining the subsidy. The overall effect of both behaviors on TFP is ambiguous and can be determined only by empirical analysis.

The main contribution of this paper is to show that a suitable decomposition of TFP can be applied to a large sample of subsidized firms for a relevant period of time, allowing an evaluation of the impact of subsidies on either the roles of technological progress and technical efficiency change or scale and allocative efficiency change as determinants of granted firms' long-term growth. We measure and decompose TFP using a Stochastic Frontier Analysis (SFA). Besides SFA, which is a parametric method, two other non-parametric methods are widely used in estimating TFP, Growth Accounting and Data Envelopment Analysis. The advantage of SFA is that it allows for the presence of idiosyncratic shocks, which are widely expected in our framework and can be used to investigate the determinants of technical inefficiency and thus those of TFP. SFA also has the great advantage of decomposing productivity change into parts that have a straightforward economic interpretation. Differently from Bernini and Pellegrini (2011), who used a simplified production function, the stochastic frontier model used in this study assumes that technical inefficiency evolves over time, which enables productivity changes to be decomposed into the change in technical efficiency (i.e., measuring the movement of an economy toward or away from the production frontier) and technological progress (i.e., measuring shifts in the frontier over time). Moreover, because a flexible technology is used, the SFA makes it possible to evaluate the presence of scale efficiency, as well as measure changes in allocative efficiency (i.e., the Bauer-Kumbhakar decomposition; see Kumbhakar, 2000; Kumbhakar and Lovell, 2000; Brümmer et al., 2002).

Note that, unlike Obeng and Sakano (2000) and Skuras et al. (2006), we are able to capture the impact of capital subsidies on the different components of TFP by a quasi-experimental method. In fact, another important novelty of the paper is that we analyze the causal effect of capital subsidies on firm productivity by exploiting the conditions for a local random experiment created by Law 488/92 (L488), which has been an important policy instrument for reducing territorial disparities in Italy. In particular, L488 aims at boosting private investment in industrial structure development and job creation in the less-developed areas of Italy, i.e. in the southern regions. Then, the analysis of the effects of technological innovation and efficiency in these regions has a relevant importance for the local governance. As for the L488 mechanism, this policy has been characterized by a rigorous and transparent selection procedure. Each year, subsidies are allocated to a broad range of investment projects through regional "calls for tenders", which mimic an auction mechanism. In each regional "call for tender", the investment projects are ranked on the basis of a score that depends on a number of (known) characteristics of both the project and the firm. Projects receive subsidies according to their position in the ranking system until the financial resources granted to each region are exhausted. The presence of sharp discontinuities in the L488 rankings makes it possible to use a quasi-experimental method deriving from a regression discontinuity design (RDD) approach, enabling us to identify the causal effect of subsidies on components of firms' TFP.

Finally, a further novelty of the work is the timing used for the evaluation. We scrutinize the impact of the subsidy for each year, from the first to the fifth year, starting from the beginning of the investment. This way, we can capture effects that appear later, after the adjustment period of the subsidized firm, which could have a different sign from the first ones. Even this approach is quite unusual in the literature.

The rest of the paper is organized as follows: the next section summarizes the literature, while Section 3 describes the TFP decomposition and presents the evaluation method. In Section 4, we describe the policy and the data in more detail. The results are discussed in Section 5, while Section 6 assesses their robustness. Section 7 concludes the paper.

2. Literature review

In the literature, there is considerable variation in the estimated impact of investment subsidies, which, among others, reflects differences in circumstances between countries, regions, sectors and firms, differences in the design of policy and delivery (policy implementation details) and differences in the quality of the data and the analytical methods used in the empirical studies (Brandsma et al., 2013).

A large part of this literature has focused on the incentives to R&D (see Bronzini and Piselli, 2016; Dimos and Pugh, 2016), the Enterprise Zones (EZs) program (see Neumark and Kolko, 2010; Reynolds and Rohlin, 2015), and the effectiveness of investment incentives for firms located in lagging areas. Among the latter studies, the empirical evidence, although sketchy, suggests a positive impact of capital subsidies on financed firms' employment, investment and plant survival prospects but a negligible or negative effect on productivity (see, among others, Bernini and Pellegrini, 2011; Bondonio and Greenbaum, 2014; Cerqua and Pellegrini, 2014; Criscuolo et al., 2016).

Among this stream of research, a few papers have considered the impact of capital subsidies on TFP. Having estimated a production function, Bergstrom (2000) investigates the role of subsidies as a determinant of TFP growth. The author finds that after the first year, the more money a firm has been granted, the worse TFP growth develops. The results suggest that subsidization can influence growth, but there seems to be little evidence that the subsidies have affected productivity and hence competitiveness (i.e., growth is achieved simply by using more inputs but not by improving their usage). Harris and Robinson (2004) find opposite results by using a policy off/policy on model in which capital grants are treated as an input of the production function (i.e., TFP is defined as any change in output not due to changes in factor inputs). The analysis shows that assistance does improve productivity compared with average levels; however, when the comparison group is defined more restrictively to only include other plants within Assisted Areas, assistance does not appear to significantly improve plant productivity. The analysis also indicates that this is not a uniform finding across all regions and that for plants located in Scotland as well as those in a small number of industries, the assistance does improve TFP.

In a subsequent paper, Harris and Robinson (2005) break down TFP into different components (entry, exit, within plant, between plant, and cross-plant effects), applying a decomposition approach. The analysis is carried out by comparing non-assisted firms with firms assisted by different types of grants. They find that financed plants experienced negative TFP growth, mostly due to plants with low TFP that increase their market share during the period, suggesting that capital is being substituted for labor.

A different decomposition procedure is used in Skuras et al. (2006). After having estimated a production frontier in which the subsidy is treated as a new input, the authors decompose the TFP into three components, which are technological change, technical efficiency change, and scale efficiency change. They find that capital subsidies to the food manufacturing sector are not fully additional and affect TFP growth mostly through technological change. Combining the above decomposition with a cost function approach, Obeng and Sakano (2000) find negative contributions of subsidies to TFP growth through subsidy-induced factor augmentation.

Only a few papers have investigated the role of subsidies in TFP in a policy evaluation framework. Bernini and Pellegrini (2011), by means of a matching diff-in-diffs approach, show that growth in output, employment and fixed assets is higher in the subsidized firms. Conversely, TFP of subsidized firms shows a smaller increase than that in non-subsidized firms. The positive temporary effects of regional policy contrast with the expected negative impact on long-term productivity and growth. However, in this paper the TFP is identified by the use of a simplified production function, and therefore cannot explain if changes in TFP can derive from adjustments in the use of factors or technology embodied in the subsided capital. Criscuolo et al. (2016) investigate the effects of the Regional Selective Assistance (RSA) by using a combination of IV and plant- or firm-level fixed effects. They find a positive program treatment effect on employment, investment and net entry but not on TFP. The treatment effect is confined to smaller firms with no effect for larger firms; moreover, the policy raises area-level manufacturing employment mainly through significantly reducing unemployment. Moffat (2014) examines whether receipt of a RSA grant has a causal impact on plant TFP. To tackle the problem of self-selection into the treatment group, propensity score matching is employed. Similar to Criscuolo et al. (2016), for high-tech and medium high-tech manufacturing, the effect is not statistically significant. However, for medium low-tech and low-tech manufacturing, receiving an RSA reduces TFP. Results suggest that RSA grants lead plants in low-tech manufacturing, the sector that received the highest number of grants, to employ an inefficiently high level of inputs. Without such grants to compensate them for employing a sub-optimally high level of inputs, they would employ fewer inputs but have higher levels of TFP.

In sum, several studies have focused on the role of subsidies on firms' TFP, mainly considering grants as an additional input in the production process or a determinant of TFP. Conversely, there are a few attempts to estimate the causal impact of capital subsidies on both TFP growth and their components by means of accurate counterfactual analysis. To our knowledge, no studies have yet investigated the role of capital subsidies on productivity and efficiency by means of a causal model.

3. Method

3.1 SFA and TFP decomposition

In the literature, studies on productivity growth have measured productivity as a residual after controlling for input growth, interpreting the improvements in productivity as determined by technological progress. This interpretation is correct only if firms are technically efficient (i.e., firms are operating on their production frontiers and realizing the full potential of the technology). Because firms do not usually operate on their frontiers, TFP measured in this way can reflect both technological innovation and changes in efficiency. Therefore, technological progress may not be the only source of total productivity growth, and it will be possible to increase factor productivity by improving technical efficiency (Jin et al., 2010).

Stochastic Frontier Analysis (SFA) is a widely used approach to study production efficiency. SFA makes it possible to estimate technical efficiency in addition to technological change, which is captured by a time trend and interactions of the inputs with time (Aigner et al., 1977; Meeusen and van Den Broeck, 1977; Battese and Coelli, 1992).

The general stochastic production frontier model is described as

$$y_{it} = f(t, L_{it}, K_{it}; \beta)e^{(v_{it} - u_{it})} \tag{1}$$

where y_{it} is the output of the i^{th} firm (*i: 1,...,N*) in period *t* (*t:1,...,T*), $f(\cdot)$ is the production technology, L_{it} and K_{it} are the inputs (i.e., labor and capital, respectively), *t* is the time trend variable, and β is the vector for the parameters defining the production technology. The variables v_{it} refer to the random part of the error, while u_{it} are downward deviations from the production frontier. Thus, $f(t, L_{it}, K_{it}; \beta)e^{(v_{it})}$ represents the stochastic frontier of production, and v_{it} capture the random effects of measuring errors and exogenous shocks that cause the position of the deterministic nucleus of the frontier, $f(t, L_{it}, K_{it}; \beta)$, to vary from firm to firm. The level of technical efficiency (TE_{it}), that is, the ratio of observed output to potential output (given by the frontier), is captured by the component $e^{(-u_{it})}$ and, therefore, $0 \leq TE_{it} \leq 1$.

Following Bauer (1990), Brümmer et al. (2002), Kumbhakar (2000), and Kumbhakar and Lovell (2000), after a production frontier function has been estimated, it is possible to compose the rate of TFP change from the results. In particular, the authors suggested a productivity decomposition that goes beyond the division of productivity changes to a catch-up effect and a technical innovation effect, also accounting for scale effects and efficient allocation of productive factors.

The components of productivity change can be derived from the deterministic part of the production frontier depicted in (1) combined with the usual expression for the productivity change Divisia index[2]:

$$g_{TFP} = \dot{y} - s_K \dot{K} - s_L \dot{L} \tag{2}$$

where dots over variables indicate the rate of change for those variables, g_{TFP} denotes the rate of TFP growth, s_K and s_L are the shares of capital and labor in aggregate income,

[2] Subscripts *i* and *t* are omitted to avoid notational clutter.

$s_K = \dfrac{p_K K}{p_K K + p_L L}$ and $s_L = \dfrac{p_L L}{p_K K + p_L L}$, where p_L and p_K denote the price of labor and capital, respectively.

Totally differentiating the logarithm of y in (1) with respect to time, we have

$$\dot{y} = \frac{\partial \ln f(t, L, K; \beta)}{\partial t} + (\varepsilon_K \dot{K} + \varepsilon_L \dot{L}) - \frac{\partial u}{\partial t} \tag{3}$$

where ε_K and ε_L are the output elasticities with respect to the factors of production. The overall productivity change (equation 3) is affected by either technological progress and changes in input use or change in technical efficiency.

By substituting equation (3) into equation (2), we have

$$g_{TFP} = \frac{\partial \ln f(t, L, K; \beta)}{\partial t} + (RTS - 1)[\lambda_K \dot{K} + \lambda_L \dot{L}] + [(\lambda_K - s_K)\dot{K} + (\lambda_L - s_L)\dot{L}] - \frac{\partial u}{\partial t} \tag{4}$$

where RTS denotes returns to scale with $RTS = \varepsilon_K + \varepsilon_L$, and λ_K and λ_L are defined as normalized shares of capital and labor in income, i.e. $\lambda_K = \varepsilon_K / RTS$ and $\lambda_L = \varepsilon_L / RTS$.

Then, equation (4) decomposes the growth in TFP into four additive components: trends in productivity change, change in the degree of the input-specific return to scale, change in cost and technical efficiencies. The decomposition suggests the intuitive result that advances in both technological progress and technical efficiency increases TFP growth; while the scale component measures TFP changes due to variation in scale of operations. The $(\lambda_K - s_K)\dot{K} + (\lambda_L - s_L)\dot{L}$ component in equation (4) accounts for inefficiency in resource allocation resulting from deviation of input prices from the value of their marginal product.

In details, these four components are defined as:

(i) technological change (TC), measured by $\partial \ln f(t, L, K; \beta) / \partial t$;

(ii) change in technical efficiency (TE), denoted by $-\partial u / \partial \mathrm{t}$;

(iii) change in the scale of production (SC), given by $(RTS - 1)[\lambda_K \dot{K} + \lambda_L \dot{L}]$;

(iv) change in allocative efficiency (AE), measured by $[(\lambda_K - s_K)\dot{K} + (\lambda_L - s_L)\dot{L}]$.

Technological change (TC) is the increase in the maximum output that can be produced from a given level of inputs, thus capturing the upward shift in the production function. Technical efficiency (TE) change is the change in a firm's ability to achieve maximum output given its set of inputs; then, it measures the changes in TFP because of a movement toward the production function. The scale component (SC) accounts for TFP changes due to variations in the scale of operations, its contribution depending both on technology and factor accumulation. The presence of constant returns to scale (RTS=1) cancels out the SC. In the case of increasing returns to scale (RTS > 1) and an increase in the amount of productive factors, the firm shows a higher rate of productivity growth. If the amounts of production factors diminish, the firm would have a reduction in the rate of productivity change. An inverse analogous reasoning can be made for decreasing returns and a reduction (increase) in the amount of productive factors. Allocative efficiency (AE) change is the change in a firm's ability to select a level of inputs to ensure that the input price ratios equal the ratios of the corresponding marginal products. Because $\lambda_K + \lambda_L = 1$, the distances $(\lambda_K - s_K)$ and $(\lambda_L - s_L)$ are symmetric and have opposite signs. Therefore, a factor reallocation that, say, increases the intensity of labor and reduces that of capital will necessarily bring a change in allocative efficiency.

The three components SC, TC and TE are called the *connected to technology* part of the TFP change, which can be calculated using the estimated production technology (i.e., the parameters in the output distance function and the technical efficiency estimates of equation 1). The allocative component AE is caused by the violations of the first-order conditions for profit maximization. These violations might occur if market imperfections exist (i.e., transaction costs, risk, quantitative restrictions, incomplete information, or mark-ups) or if the implied assumption of profit maximization behavior is not adequate. Because these effects are caused by market or behavioral conditions (i.e., they represent the part of the TFP change that is not determined technologically), the allocative component AE is referred to as the *connected to market* part of the TFP change. Obviously, it accounts for the differences between the Divisia index and the three technology-connected components, i.e., $AE = g_{TFP} - (SC + TC + TE)$ (Brümmer et al., 2002; Zhu et al., 2006).

3.2 The multiple RDD

Support programs usually select firms in a non-random manner, and L488 is no exception. However, we can build a reliable counterfactual using data for the firms that applied for the incentives but were not financed because they scored too low in the L488 ranking.[3] Unlike in randomized experiments, this control group is not random, but we can use a "sharp" RDD approach to address selection bias issues. We have a "sharp" RDD since the treatment variable is a deterministic function of the forcing variable as it solely depends on whether the forcing variable is above or below the assignment threshold. In the sharp RDD framework, subsidy assignment can be considered locally random around the

[3] These non-treated firms are willing to invest and have a valid investment project as checked by a preliminary screening. As a consequence, within each ranking, we can consider these firms as the best control group available; in fact, as suggested by Brown et al. (1995), they show a propensity for investment very similar to that of subsidized firms.

threshold of the forcing variable (Lee and Lemieux, 2010), here the sum of the five indicators normalized presented in Section 4. Then, any differences in outcomes between firms who are just below and just above the threshold can be attributed to the causal effect of the subsidies.

To estimate the effect of subsidies on TFP components, we use an approach which takes into account the presence of many regional "calls for tender". Therefore, we first re-center each forcing variable threshold at zero, and then pool in the same ranking firms belonging to the same technological group. Indeed, the analysis is conducted separately for four industry sub-groups defined according to firms' technology. Following Harris and Moffat (2013), industries were classified based mostly on Eurostat definitions, as high-tech (HT), medium high-tech (MHT), medium low-tech (MLT), and low-tech manufacturing firms (LT). Such a disaggregation is necessary because different sectors will operate with different production technologies, and the impact of capital subsidies on TFP is therefore likely to differ across sectors (Moffat, 2014). As L488 was directed also at a subset of non-manufacturing firms (NM), we include them in a separate analysis.[4] We then run the following equation:

$$y_{irt} = a_{rt} + b_0\left(x_{ir}\right) + \tau_{rt}^{SRDD} \cdot D_{ir} + b_1\left(x_{ir}\right) \cdot D_{ir} + \varepsilon_{irt} \tag{5}$$

where y_{irt} is the TFP component (TC, SC, AE, TE, or TFP) of the i^{th} firm at time t *(t:1,…,5)* in technological group r (HT, MHT, MLT, LT, and NM), x_{ir} is the forcing variable (in our

[4] The non-manufacturing category is made up by wholesale trade and commission trade, real estate activities, computer and related activities, sewage and refuse disposal activities and recreational, cultural and sporting activities.

case, x_{ir} is the sum of the indicators normalized for firm *i* in technological group *r*), D_{ir} is the binary indicator variable for treatment which is unity in case of treatment of firm *i* in technological group *r* and zero else, and ε_{irt} is the error term. The evaluation problem consists of estimating the local average treatment effect (LATE)[5] τ_{rt}^{SRDD} of the treatment (subsidy assignment) on the TFP components at time *t* in technological group *r*. The key identification assumption that underlies the RDD strategy is that $b_0(.)$ and $b_1(.)$ are smooth functions of x_{ir}. Under this assumption, the treatment effect τ_{rt}^{SRDD} is obtained by estimating the discontinuity in the empirical regression function at the point where the treatment variable switches from 0 to 1.

Because of its local nature, RDD average treatment-effects estimators are usually constructed using local regression techniques. We follow standard practice and use local polynomial non-parametric regression to estimate the equation (5). This kernel-based estimator requires a bandwidth for implementation, with observations outside the bandwidth receiving zero weight in the estimation. We select an optimal bandwidth that minimizes mean-squared-error using the robust confidence intervals developed by Calonico, Cattaneo, and Titiunik (2014b) and a triangular kernel.[6] To check the robustness of the results, we also use a parametric estimator with a 3rd order polynomial in the forcing variable, which is allowed to differ on the left and the right of the cut-off point to account for non-linearity in the outcome variable.

[5] While the ATT gives the average treatment effect for the treated firms, in the sharp RDD framework the LATE gives the average treatment effect for those firms ranked around the assignment threshold.

[6] See Calonico, Cattaneo, and Titiunik (2014a) for more details on the implementation of the RDD estimates and the Stata module rdrobust.ado.

After estimating the causal effect of L488 with respect to each TFP component via the RDD for each of the technological groups of firms, we aggregate the treatment effects to obtain the global treatment effect of the policy under analysis.[7] The aggregation of different estimates is not a trivial problem because it is not easy to find an objective criterion to choose the weights of the estimates. For non-parametric estimates, we use the number of treated firms in each ranking with a forcing variable value within the optimal bandwidth selector (see Calonico, Cattaneo and Titiunik, 2014b);[8] however, in Section 6, we check the robustness of this aggregation procedure.

As a result, the global LATE of L488 (τ_t^{MRDD}) and the standard errors (σ_t) at time t are computed as follows:

$$\tau_t^{MRDD} = \sum_{r=TechGroup} N_r * \tau_{rt}^{SRDD} / N ; \tag{6}$$

$$\sigma_t = \sqrt{\sum_{r=TechGroup} N_r^2 * \sigma_{rt}^2 / N^2} ; \tag{7}$$

where, τ_{rt}^{SRDD} represents treatment in technological group *r* at time *t*, σ_{rt} is the standard error of the LATE estimate in technological group *r* at time *t*, N_r is the number of treated firms inside the bandwidth interval in technological group *r*, and N is the total number of treated firms inside the bandwidth interval.

4. Data

[7] In order to reduce the influence of extreme values, we recoded the extreme values of each dependent variable to lowest or highest reasonable values (the value of the 2nd centile and the value of the 98th centile, respectively). The truncation procedure was used for all tables reporting MRDD estimates.

[8] For parametric estimates, we still use the number of treated firms in each ranking, but they are not limited to the observations within the optimal bandwidth selector.

L488 has been the main policy instrument for reducing territorial disparities in Italy during the period 1996-2007. L488 operates in the less-developed areas of Italy, i.e., the areas designated as Obj. 1, 2 or 5b for the purpose of EU Structural Funds. L488 has financed firms in both the Center-North (Objective 2 or 5b) and South regions (Objective 1) of the country;[9] however, Objective 1 regions receive transfers that are substantially higher in magnitude than transfers under all other lines of the EU's Structural Funds program (Becker et al., 2013).[10] This is why our focus is on the southern regions; nevertheless, Section 5.4 reports a separate analysis for the firms localized in the Center-North regions.

L488 makes available grants on capital account for projects designed to build new productive units in less-developed areas or to increase production capacity and employment, increase productivity or improve ecological conditions associated with productive processes, technological updates, restructuring, relocation and reactivation. After receiving an application form that includes a technical report and a business plan, the relevant authority performs a preliminary screening, evaluating the funding eligibility of the project. The amounts awarded are paid out in three equal instalments. L488 allocates subsidies through a rationing system based on regional competitive auctions. In each auction, the investment projects are ranked with respect to five objectives and predetermined criteria: 1) the share of owners' funds in total investment; 2) the new job

[9] In the southern regions, L488 has been financed not only with national funds but also with the EU Structural Funds (the southern regions were the only eight Objective 1 Italian regions in the 1994-1999 cycle of EU regional policies).

[10] In particular, for the L488, the medium-large subsidized firms located in Objective 2 or 5b areas received capital grants that support up to 10-20% of the total investment expenditures, but the medium-large subsidized firms located in Objective 1 areas received capital grants that support up to 40-50% of the total investment expenditures (plus an additional 15% for small firms).

creation by unit of investment; 3) the ratio between the subsidy requested by the firm and the highest subsidy applicable; 4) a score related to the priorities of the region in relation to location, project type and sector; 5) a score related to the environmental impact of the project. The criteria carry equal weight: the values related to each criterion are normalized, standardized and added up to produce a single score that determines the place of the project in the regional ranking (this normalized score is the forcing variable). The rankings are drawn up in decreasing order of the score awarded to each project, and the subsidies are allocated to projects until funding granted to each region is exhausted. Several checks are made to establish whether subsidized firms have respected their targets. If a treated firm does not reach its goals, the subsidy is entirely or partially revoked.

L488 auctions have been conducted on a yearly basis. Our analysis refers to the period 1995-2003 and focuses on three of the four L488 auctions that were taken up by 1998.[11] This time-span makes it possible to analyze the TFP disaggregation dynamics for the 5 years following the subsidy assignment. The data for the auctions derive from two datasets: the administrative L488 dataset of the Ministry of Economic Development, a financial statement dataset that collects data from AIDA,[12] and other sources of financial information.[13] After

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[11] Firms subsidized in auction 2 received the first installment in July 1997, while firms subsidized in auctions 3 and 4 received the first installment in October 1998 and May 1999, respectively. Then each subsidized firm received the remaining installments in the following two years. However, in many cases, administrative complications and technical and economic problems have increased the time span of the project (estimated at 3.6 years by Bernini and Pellegrini, 2011).

[12] AIDA is a large dataset that contains the budgets delivered by a subset (mostly corporate enterprises) of over 500,000 Italian firms to the Chambers of Commerce.

[13] The estimation results we present below rely on the assumption that there are no other governmental programs correlated with the allocation of L488 funding. Actually, a feature of L488 minimizes the extent of this bias by requiring that firms that apply for the incentives renounce any other public subsidies even without any guarantee of receiving the L488 funds. Besides, a recent study (Cerqua and Pellegrini, 2015) shows some

cleaning and merging the data, we have 1074 firms localized in the South (377 in the treatment group and 697 in the control group) and 800 firms localized in the Center-North (264 in the treatment group and 536 in the control group), which applied for the L488 funds in at least one of the auctions considered (auction 2, auction 3, and auction 4).[14] Exploiting the MRDD features, we have tested whether the pre-treatment characteristics of the financed firms are similar to those of the control group. As shown in Table 1, we find no evidence of statistically significant pre-treatment differences at 5% level around the cut-off point between subsidized and non-subsidized firms in terms of each TFP component and other firm-related covariates. This holds for each technological group and for the aggregated sample.

Insert Table 1

modest evidence of negative spillover effects reporting how the employment growth in subsidized firms is in part determined to the detriment of the untreated firms. However, there is no evidence of substantial spillovers concerning turnover, investment, and TFP. The latter finding mitigates the risk of a substantial violation of the Stable Unit Treatment Value Assumption (SUTVA) assumption (Rubin, 1986), which would cast doubts on the validity of our results.

[14] We considered only firms which had been operating since at least 2 years before the subsidy assignment, whereas we excluded projects that presented anomalies and irregularities. Concerning duplicate projects, i.e., applications for more than one auction, we decided to exclude the non-financed projects if the referring firm had already received L488 funds in a previous auction.

5. Results

5.1 Production frontiers estimates

The components of the TFP change were estimated within an SFA framework. The frontier models are specified for panel data, with both a stochastic frontier production function and a technical inefficiency model (Battese and Coelli, 1995). In particular, a flexible functional form as the translog production function is used:[15]

$$\ln y_{it} = \alpha + \beta_L \ln x_{Lit} + \beta_K \ln x_{Kit} + \frac{1}{2}\beta_{LL} \ln x_{Lit}^2 + \frac{1}{2}\beta_{KK} \ln x_{Kit}^2 + \beta_{LK} \ln x_{Lit} \ln x_{Kit} + \beta_t t + \frac{1}{2}\beta_{t2} t^2 + \\ + \beta_{Lt} \ln x_{Lit} t + \beta_{Kt} \ln x_{Kit} t + (v_{it} - u_{it}); \quad i = 1,..,N; \; t = 1,..,T \qquad (8)$$

where $\ln y_{it}$ is the natural logarithm of the value added of firm *i* in year *t* and $\ln x_{kit}$ is the logarithm of input *k*, where *k* = *L, K* represent the two inputs, cost of labor and fixed assets, respectively.[16] The production frontier may shift over time according to the values of the parameters β_t and β_{t2}. The $v_{it}s$ are random variables that are assumed to be independent and identically distributed $N(0;\sigma_V{}^2)$, while the technical inefficiency variables (u_{it}) are assumed to be independently distributed, such that u_{it} is the truncation (at zero) of the

[15] For a detailed discussion of the model selection, parameter estimates and specification tests, see Appendix A.

[16] AIDA does not contain information about human capital, preventing us to control the production frontier for this potential input. Assuming that human capital may be proxied by the average wage (i.e., defined as the ratio between the cost of labor and the number of employees), we verify that there are not significant differences among firms classified with respect to the technological level. This finding suggests that human capital might not capture significant differences in the production process of firms. We thank an anonymous Reviewer for underlying this issue.

$N(\mu_{it};\sigma^2)$ distribution. It is also assumed that the $v_{it}s$ and $u_{it}s$ are independent among each other.

Following Battese and Coelli (1992), μ_{it} may be assumed as a function of observable explanatory variables. To account for time-varying technical inefficiency, we suggest modeling u_{it} by means of yearly dummy variables D_year_t as

$$\mu_{it} = \delta_0 + \sum_t \delta_t D\_year_t + w_{it} \tag{9}$$

where δ_i are the unknown parameters and w_{it} is a random error term.

To account for the different technological sets within the industries, several frontiers were estimated separately. First, we considered firms applying to the different Auctions as separate groups; within each Auction, we also distinguished firms operating in the Center and North of Italy from those located in the South. The choice was motivated by either the specific characteristics of each auction or distinctive features of L488 in the Center-North regions. Furthermore, the industry sub-groups defined in Section 3.2 were considered.[17] A detailed definition of all variables used in the estimated frontier models is reported in Table A1 of Appendix A.

The maximum likelihood estimates of the parameters in the stochastic frontier model for the different auction groups confirm heterogeneity in the production function due to the auction as well as firms' technology (see Table A2 and Table A3 of Appendix A; all other model estimates are available upon request from the authors). Likelihood ratio (LR) tests confirm the identification of 18 firm groups, corresponding to different production frontiers.

[17] High-tech (HT) and medium high-tech (MHT) firms were pooled because of small sample size issues.

5.2 Estimates of TFP decomposition

The TFP and its components were calculated by using the estimated frontiers and the Divisia decomposition illustrated in Section 3.1, for every firm and period. In particular, having estimated the translog frontier function in equation (8) the technical efficiency level of firm *i* at time *t* (TE_{it}) is calculated as the ratio of the actual output to the potential output as

$$TE_{it} = e^{-u_{it}} \tag{10}$$

The elasticity of output with respect to the k^{th} input is obtained by

$$\begin{aligned} \varepsilon_L &= \beta_L + \beta_{LL} \ln x_L + \beta_{LK} \ln x_K + \beta_{Lt} t \\ \varepsilon_K &= \beta_K + \beta_{KK} \ln x_K + \beta_{LK} \ln x_L + \beta_{Kt} t \end{aligned} \tag{11}$$

and *RTS* is calculated as *RTS* = $\varepsilon_K + \varepsilon_L$.

Then, the scale of production (SC) and allocative efficiency (AE) are estimated respectively as

$$SC = (\varepsilon_K + \varepsilon_L \text{-}1)\left[\frac{\varepsilon_K}{\varepsilon_K + \varepsilon_L}\dot{K} + \frac{\varepsilon_L}{\varepsilon_K + \varepsilon_L}\dot{L}\right] \tag{12}$$

$$AE = \left(\frac{\varepsilon_K}{\varepsilon_K + \varepsilon_L} - \frac{p_K K}{p_L L + p_K K}\right)\dot{K} + \left(\frac{\varepsilon_L}{\varepsilon_K + \varepsilon_L} - \frac{p_L L}{p_L L + p_K K}\right)\dot{L} \tag{13}$$

Finally, the rate of *TC* is defined by

$$TC = \beta_t + \beta_{2t} t + \beta_{Lt} \ln x_{Lt} + \beta_{Kt} \ln x_{Kt} \tag{14}$$

In the estimation of equations (11-14), output elasticities and *TC* are functions of input levels and are estimated at the sample means of input levels.

Because each auction operates on a different time span, we identified some typical dates, using as the first period the year when the firm starts to receive the grant (i.e., the fifth period corresponds to four years after the first-year installment). This strategy makes it possible to correctly aggregate and compare TFP components across auctions, irrespective of the calendar years.

Table 2 shows the average values of the TFP growth rate components for both treated and non-treated firms located in the South of Italy and separately for each technology level.[18,19] On the whole, the analysis reveals a slight decay of TFP in non-treated firms across all the periods. Treated firms reduce TFP until the third year after the subsidy is granted; while TFP improves by 2% in the fourth year, the increase is positive but negligible in the last period. The growth in treated firms, when decomposed, is mainly due to TC and AE. More specifically, the TC index grows by 1.15% during the first year after the subsidy is granted and rises to 5.81% in the fifth period. This indicates that firms adopt technologies that allow them to be more productive. In addition, non-treated firms grow over the period, but with lower intensity (0.8 – 4.0%). The allocative inefficiency results when factor prices are not equal to their marginal product. The estimates of AE for treated firms show the

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[18] All results, related to auctions, size, geographical area and technological sets, are available upon request from the authors.

[19] The complexity of the analysis limits the analytic derivation of the standard errors of estimates reported in Table 2. Indeed, these estimates are obtained by combining frontier parameter estimates with input mean values. Being the frontier parameters all statistically significant at the 1% level, we are confident that all the estimates presented in Table 2 are statistically different from 0. We thank an anonymous Reviewer for underlying this point.

existence of allocative inefficiency in the years immediately after the grants, while in the last part of the observed period, AE turns out to be positive, indicating the presence of adjustment lags and *connected to market* effects for the subsidized firms. Conversely, untreated firms show a continuous decline in their AE for all periods. The contribution of TE is relevant but negative for all the firms and over (almost) all the periods; the intensity is slightly higher in the sample of treated firms. This decrease may be caused either by internal cost of adjustment (organizational changes) or by transaction costs arising from the adoption of the new quantity of inputs. Conversely, the SC effect is negligible, for both treated and untreated firms. The expected boost of capital subsidies on scale efficiency, due to the new capital and consequent additional employees, has not been realized.

Insert Table 2

This evidence suggests that subsidized capital does not really increase the scale of operation, but it substitutes the capital to be invested by the firm under conditions of no subsidization. Being that the SC is similar between granted and not financed firms, it may be attributed to a simple extrapolation of past trends and not to the effect of subsidization.

These effects are quite similar between the different technological groups but with different intensities. TC is higher for firms operating in the low-technology industries, suggesting that in the observed period, all these firms (i.e., treated and untreated firms) have improved their technology. Conversely, non-manufacturing firms show the lowest TC effect, which becomes null for the untreated firms of these industries. Medium-high and high-technological firms show a continuous decline in TFP, mainly due to a negative effect of AE for all the periods.

5.3 Multiple RDD estimates

In this section we compute point estimates and standard errors of the effects of subsidies on each TFP component for the South of Italy.[20] Columns from (1) to (5) of Table 3 report the MRDD non-parametric estimates for the effect of the subsidies on each TFP component for each of the five years following the subsidy assignment; while columns from (6) to (10) report the MRDD parametric estimates. Formula (5) is used to derive all RDD estimates, while Formulae (6) and (7) are used to aggregate them and obtain the global LATE of L488 with the corresponding standard errors. For all coefficients, a positive sign means that the subsidy assignment has a positive effect on the TFP component, while a negative sign means the opposite. Coefficients significantly different from zero at the 90% statistical confidence level are marked with one asterisk; those significant at the 95% level with two asterisks; those significant at the 99% level with three asterisks. The estimates should be interpreted as the percent change in TFP component between treated and untreated firms, e.g. a coefficient of 0.01 corresponds to a 1% increase of the TFP component in the treated relative to the control firms.

[20] Before adopting the MRDD, we used the coarsened exact matching technique (see Iacus et al., 2011), which is a formal preliminary matching procedure to produce better balanced treatment and comparison groups. In particular, we matched exactly on three pre-treatment variables (tangible capital, labor cost per employee, and ROE) using their tertiles as cut-points. This data-preprocessing technique led to the loss of a limited number of observations (about 2%). Besides, as suggested by Lee and Lemieux (2010), we subtract from each dependent variable its pre-treatment value. This is done because differenced outcomes should have a sufficiently lower variance than the level of the outcome to lower the variance in the RDD estimator.

The most interesting result relates to the difference in TFP growth between subsidized and non-subsidized firms: considering the non-parametric approach, in the first three years the difference is negative, indicating that TFP grows more in non-subsidized firms; on the contrary, over the last two years, TFP growth is greater in subsidized firms, with a differential equal, on average, to approximately 9%. This differential is significant from a statistical point of view in the first two years (at 5%, with negative coefficients), less so in the remaining years.[21] Therefore, there are signals that dynamics of TFP growth rate in subsidized firms could be linked to the process of learning and concluding the implementation of the investment. The sign reversal also could explain the mixed results achieved in the literature. The decomposition analysis allows us to identify the components that are responsible for this sign reversal.

In the first place, the TC component gives a positive contribution to the TFP growth gap: in subsidized firms, the growth rate of TC is always higher than in non-subsidized firms, and the differential is statistically significant for two out of five years. On the other hand, the contribution of TE is always negative and statistically significant for two out of five years. The contribution of SC is mixed and always not statistically significant. Finally, the contribution of AE switches sign during the period: it is negative in the first two years and positive in the last three years (it is strongly statistically significant in year 4). The results using the parametric approach are basically the same, even if slightly less statistically significant.[22]

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[21] Note that a similar coefficient pattern emerges when considering different subgroups of firms and following various robustness tests reported in Section 6.

[22] Estimation of the parametric model using the 1st or the 2nd order polynomials in the forcing variable leads to quantitatively similar estimates.

The results suggest that public subsidies could help firms to improve their technological assets, mostly by increasing the technological content embedded in the (new) capital. The new capital bought with incentives augments the rate of technological progress of the firm. It is plausible that the TC component incorporates some element of technical efficiency, which could be underestimated in subsidized firms. Moreover, during the 5-year period, the firm adjusts the production factors to be more efficient: actually, if in the first years the subsidized firm chooses not to pursue allocative efficiency because a higher intensity in the use of one factor (for instance, labor) could increase the chance to obtain the subsidy, in the following years, the firm has the opportunity to move toward a more efficient configuration. However, these technological improvements are slow in offsetting the negative impact, due to complexity in the management of the new resources. The overall effects of subsidies on TFP in the medium term are slightly negative: after a sizable drop during the first three years, there is a clear trend reversal in TFP in years 4 and 5.

The results are similar also for the subsample of small firms (Table 4). The differences in TFP growth rate in the last two years are slightly larger (10%), whereas the differences in the technological progress growth rate are smaller and statistically not significant. The scale component is interesting; in this case, it is negative and statistically significant. A plausible interpretation is that using the subsidies, the firms move toward market niches, which are more profitable but where the scale economies are unfeasible or not essential.

Insert Table 3

Insert Table 4

Looking at the productivity differential by technological sector, we find that the differential in TFP for the low-tech manufacturing firms is higher than the average in the last two years (more than the 14%), even if not statistically significant. The differential in AE is very high in the last two years, where the TC growth rate differential is also positive only in the same period. Both explain the higher TFP growth differential. For the medium-low, medium-high and high-tech firms the picture is different. The TFP growth of subsidized firms is higher with respect to non-subsidized firms only in the fourth year (third and fourth years for the medium-low tech firms). Even if the contribution of the TC component is always positive, the contribution of AE is lower and sometimes negative. In the non-manufacturing firms, the TFP growth differential is positive in the last two years but lower than the average (5%). In addition, the positive contribution of TC is lower than the average.[23]

The conclusion of the analysis is that the TFP differential is basically dominated by two factors: TC and AE. In sectors where the TC growth induced by the subsidies through new capital overcomes the negative effect on TE (related to the new enterprise organization and management, entry in new market and so on), the TFP tends to be positive. However, this is realized when the impact of the AE differential induced by the subsidies becomes positive. The subsidized firms, usually after three years, are able to make a more efficient use of the productive factors finally exploiting the new capital. On the other hand, in sectors where the TC gain is lower or the AE catch-up is modest the impact of the subsidies on TFP is nil or negative.

5.4 What effects on TFP had the subsidies to firms located in the Center-North regions?

[23] The estimates by technological sector are available upon request from the authors.

We also estimated the effect of the L488 on TFP for the firms located in the Center-North regions, which are much wealthier that the regions in the South, after testing for statistically significant pre-treatment differences (see Table B1 of Appendix B). The areas where the firms could apply for the L488 subsidies were small (limited to few provinces) and the intensity of the subsidies was much lower than in the South. Therefore, we expect that the impact of L488 in these areas was less important. Actually, the differences in TFP growth between subsidized and not subsidized firms are statistically not significant (Table B2 of Appendix B). The impact on TFP growth differential is positive in four years out of five. The same is also true for technical efficiency. Technical growth and allocative efficiency are always positive. Estimates of TFP by technology for the firms located in the Center-North regions are affected by the smaller sample dimension. However, TFP growth differentials are always positive and often statistically significant in medium-low tech manufacturing firms, where the main contribution comes from improvement in the allocative efficiency, and mostly in non-manufacturing sectors, where it is important the contribution of scale economies. In the other sectors the picture is more complex, however the effects are negligible.

6. Robustness

We assess the validity and the robustness of our results on the South adopting various specification tests. First, we use a falsification test of the RDD named McCrary test (McCrary, 2008). One often violated criterion for a valid RDD is that the density of the forcing variable be smooth on either side of the discontinuity. The violation of this condition suggests that the score may be manipulated in ways that bias estimates of impact. In our context, the RDD analysis requires that the normalized score density be smooth on either side of the subsidy assignment threshold. The McCrary test is implemented as a Wald test of the null hypothesis that the discontinuity is zero and it fails to reject for each ranking. In Figure C1 of Appendix C we graphically present the negative results of this test in the rankings split by auction and by technological group.

Additionally, we assess the robustness of our parametric results by estimating the models on a "narrow-band" sample around the cut-off, equal to the optimal bandwidth above and below the cut-off. These parametric estimates are very close to those reported in the paper. Moreover, as valid estimates based on the Multiple RDD rely on the assumption that the discontinuity in the outcome can be attributed to the discontinuity in treatment, we tested if there were jumps in the value of other exogenous covariates at the cut-off point. No variables showed a significant jump at the discontinuity.

We also need to check if the adoption of another weighting procedure will deliver different estimates. To do so, we adopt the weighting by inverse variance, which gives more weight to the LATE estimates with smaller variances. Formulae (15) and (16) reported below, show how τ_t^{MRDD} and σ_t are computed:

$$\tau_t^{MRDD} = \left(\sum_{r=TechGroup} \tau_{rt}^{SRDD} * 1/\sigma_{rt}^2 \right) / \left(\sum_{r=TechGroup} 1/\sigma_{rt}^2 \right); \qquad (15)$$

$$\sigma_t = \sqrt{1/\left(\sum_{r=TechGroup} 1/\sigma_{rt}^2 \right)}. \qquad (16)$$

Table C1 of Appendix C shows that this weighting scheme produces estimates very close to the ones reported in Table 3.

Finally, to investigate the role of the technical inefficiency modeling, we also considered the time-variant specification of u_{it} proposed by Battese and Coelli (1992), which is reported in equation (A4) of Appendix A. Table C2 reports the Multiple RDD estimates using the dynamic specification of u_{it}; the results show no relevant differences with respect to the baseline estimates, except for the absence of statistically significant effects for TE using the non-parametric estimator.

7. Conclusions

Understanding the effects of the subsidy policies for private firms is crucial to assessing the effectiveness of public actions to stimulate regional growth. In fact, regional policies that do not lead to an increase in productivity and thus competitiveness are destined to fail in the long run. The purposes of this article were to analyze the impact of a regional policy on TFP growth and decompose the effect among technological change, scale component, technical or allocative efficiency.

The main new element of our analysis is the evaluation design, based on a quasi-experimental approach (Multiple RRD) that allows capturing the causal effect of the subsidies on TFP and its components. Therefore, investigating the estimated effects for five years after the assignment of the subsidies, we can identify the way subsidies can positively affect TFP and determine the processes by which the incentives act on the productivity and efficiency of subsidized firms.

The main findings from the case study are twofold. First, results show that capital subsidies negatively affect TFP growth in the short term, and signals of positive effects appear only after 3-4 years. The negative short term and the positive medium-long term impact can be explained by several reasons: time to learn, time to stay in a larger market, time to adjust factor proportion, the sluggishness in the effects of technological progress. The analysis can explain the differences from the previous literature on L488; actually, the effects on productivity are negative or negligible in several papers on this policy instrument

(Bronzini and De Blasio, 2006; Bernini and Pellegrini, 2011; Bondonio and Martini, 2012; Cerqua and Pellegrini, 2014). However, none of these studies perform such a long year-by-year analysis. Indeed, the effects become positive only after the third year (in the South). In Bernini and Pellegrini (2011), it was noted that firms subsidized by L488 could overshoot the optimal amount of employment to gain a subsidy. It is plausible that after the third year, firms start to reduce the inflated employment and increase allocative efficiency.

Second, the positive impact comes especially through technological change and not through scale impact change, as may have been expected. Following the framework presented by Beason and Weinstein (1996) and Skuras et al. (2006), where industrial policies are classified as Schumpeterian when subsidies aim to support technological progress or Marshallian when subsidies assist economies of scale and/or infant industries, our results support the conclusion that capital subsidies present Schumpeterian and not Marshallian effects on regional growth. This is also the conclusion of Skuras et al. (2006). Therefore, the main channel of the impact of capital subsidies on TFP is through increasing the technological content of the new capital, which sustains the technological upgrade of the subsidized firm.

In conclusion, the result suggested in the previous literature, that the increase in capital stock does not necessarily entail efficient and productive subsidized firms, is only partially confirmed by our empirical evidence, and just in the first years of investment. Even if in the short term firms are induced to overshoot the optimal amount of employment to gain the subsidy, in the long run they can adjust the factor proportion and, sustained by the new technology embedded in the new capital, can achieve long-run efficiency and growth. The analysis of the relationship between subsidy intensities and TFP growth showed that this is especially true for micro and small firms. However, the topic of how the increase in

TFP can influence the competitiveness of subsidized firms in the global economy is left for future research.

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Appendix

Appendix A. Production frontier estimates and specification tests

The stochastic frontier model in (8) is appealing for TFP decomposition as it is quite flexible and it allows for non-neutral technological change. TC is said to be *k*-input using (saving) if β_{kt} is positive (negative); and TC is neutral if all $\beta_{kt}s$ (*k* = L, K) are equal to zero. If all βs are equal to zero ($\beta_{LL} = \beta_{KK} = \beta_{LK} = \beta_{tt} = \beta_{Lt} = \beta_{Kt} = 0$), the production function reduces to the Cobb-Douglas function with neutral TC. Details on variables definition, measurement and expected effects in the production function are presented in Table A1.

Insert Table A1

Another interesting feature regards the capability to model the technical inefficiencies u_{it} which are assumed to be distributed as the truncation (at zero) of the $N(\mu_{it};\sigma^2)$ distribution, where μ_{it} is a function of observable explanatory variables and unknown parameters. There are several specifications to account for time-varying technical inefficiencies u_{it} (Kumbhakar, 2000) which can be used in the TFP decomposition. Battese and Coelli (1995) proposed a specification for the technical inefficiency effect in the stochastic frontier production function

$$\mu_{\mathrm{it}} = \delta_0 + \mathrm{z}_{\mathrm{it}}\delta + w_{\mathrm{it}} \tag{A1}$$

where z_{it} are observable variables assumed to influence the inefficiency of firm *i* at time *t*, δs are parameters to be estimated and the random variable w_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2.

Replacing z_{it} by *t* (time trend), the technical inefficiency function u_{it} can be defined as

$$\mu_{\mathrm{it}} = \delta_0 + \delta_1 t + \delta_2 \mathrm{t}^2 + w_{\mathrm{it}} \qquad \text{(A2)}$$

where the time trend variable controls for time varying, systematic unobserved factors. Alternately, yearly dummy variables D_year_t can be used; then, the model for the inefficiency term becomes

$$\mu_{\mathrm{it}} = \delta_0 + \sum_{\mathrm{t}} \delta_{\mathrm{t}} D\_year_t + w_{\mathrm{it}} \qquad \text{(A3)}$$

Following Battese and Coelli (1992), the technical inefficiency component can also be considered time-variant assuming that

$$u_{it} = e^{(-\eta(t-T))} u_i,\ u_{it} \geq 0,\ i{:}\ 1, .., N,\ \ t \in \tau(i) \qquad \text{(A4)}$$

where $\tau(i)$ represents the T_i periods of time for which we have available observations for the i^{th} firm among the available *T* periods in the panel (i.e., $\tau(i)$ may contain all periods in the panel or only a subset of periods). η represents the rate of change of technical inefficiency over time; the sign of η dictates the behavior of technical inefficiency over time.

To note that the parameters η in equation (A4) and δs in equation (A2 and A3) are assumed to be the same for all firms in the sample, which means that the pattern of inefficiency rise or reduction is the same for all firms. Some generalizations have been provided in literature, as

$$u_{\mathrm{it}} = \alpha_{0\mathrm{i}} + \alpha_{1\mathrm{i}} t + \alpha_{2\mathrm{i}} \mathrm{t}^2 + w_{it} \qquad \text{(A5)}$$

where α_{0i}, α_{1i}, α_{2i} are producer-specific parameters (Cornwell et al., 1990). Since time appears in a linear fashion as a regressor in the production function, as well as in u_{it}, all the parameters associated with the time variable in the production function and in u_{it} cannot, in general, be identified. Then, this specification prevents to separate the effects of technological change and productivity change, limiting its applicability in the decomposition of TFP.

In the analysis, we suggest using yearly dummy variables D_year_t to model the inefficiency term $\mu_{it} = \delta_0 + \sum_t \delta_t D\_year_t + w_{it}$. The use of this approach in modeling the time-varying inefficiency is appealing and well adapts to TFP decomposition. First, this specification allows a greater flexibility compared with the use of deterministic time trends or a time invariant specification. Second, our interest is in modeling the inefficiency term over time and disentangling time-varying inefficiency from dynamics in the production frontier. Models (8) and (A3) allow to specify different dynamics for the frontier and the inefficiency; while the true fixed/random estimators proposed by Greene (2005a,b), which are the main competing approaches used in empirical analyses, do not. Moreover, the Greene estimators suffer of the incidental parameters problem (i.e., the estimator is appropriate only when the length of the panel is large enough, that is T≥10), preventing its use in our analysis (Greene, 2002). Differently from Battese and Coelli (1995), the Greene estimators allow disentangling unit specific time invariant unobserved heterogeneity from inefficiency.

For a robustness check, we also present results of the Multiple RDD when model (A4) is used for the inefficiency term (see Table C2 of Appendix C). Results are similar to those obtained when the model (A3) is implemented.

The parameters of the frontier production function are simultaneously estimated with those of the inefficiency model ($\beta, \delta, \sigma^2, \sigma_V^2$), in which the technical inefficiency effects are specified as a function of yearly dummies (equations 8 and A3). Maximum likelihood estimates of the model parameters are obtained using the program, FRONTIER 4.1, written by Coelli (1996). The variance parameters are defined by $\sigma_S^2 = \sigma_V^2 + \sigma^2$ and $\gamma = \sigma^2 / \sigma_s^2$ originally recommended by Battese and Corra (1977). The log-likelihood function of this model is presented in the appendix of Battese and Coelli (1993). When the variance associated with the technical inefficiency effects converges toward zero (i.e. $\sigma^2 \to 0$) then the ratio parameter, γ, approaches zero. When the variance of the random error (σ_v^2) decreases in size, relative to the variance associated with the technical inefficiency effects, the value of γ approaches one.

The problem of endogeneity in stochastic frontier analysis has been largely discussed in the literature (Amsler et al., 2016). Dealing with endogeneity in our context is not a simple issue because the usual Maximum Likelihood Estimator (MLE) for the standard stochastic frontier model is harder to generalize and the non-linearity of the translog frontier function largely complicates the procedure. Then, we leave the treatment of endogeneity to future research.[24]

The maximum likelihood estimates of the parameters in the panel translog stochastic frontier production function for the different auction groups are given in Table A2. To verify for firms' heterogeneity in the production frontier in each auction, initially the specification

[24] However, we investigate for the possible presence of endogeneity in our production frontier. In particular, we explore the presence of Granger-causality between production factors (capital and labor) and value added within the framework of a VAR model for panel data. The test strongly rejects the null hypothesis of Granger-causality of value added in both labor and capital equations.

of model (8) has been enlarged and a set of controlling variables (in the form of dummy variables) have been introduced. In particular, we investigate if firm dimension (*D_micro*, *D_small,* and *D_medium_and_large*), technological level (*D_HT_and_MHT, D_MLT, D_LT,* and *D_NM*), and region where firm resides (*D_regio*$_i$, *i*: 1,..,17) have a significant influence on production. Coefficients have signs that conform to our expectations: we expected a positive sign if dimension and technological level increases (see Table A1).

Insert Table A2

In Table A3, the results of the various null hypothesis tests associated with the frontier specification and inefficiency effects are reported for the estimated frontiers. Hypotheses can be tested using the generalized likelihood ratio statistic, λ, given by $\lambda = -2[\ln(L(H_0)) - \ln(L(H_1))]$, where $L(H_0)$ and $L(H_1)$ denote the value of the likelihood function under the null and alternative hypotheses, respectively. If the given null hypothesis is true, then λ has approximately a Chi-square (or a mixed Chi-square) distribution. If the null hypothesis involves $\gamma = 0$, then the asymptotic distribution involves a mixed Chi-square distribution (Coelli, 1995).

The first null hypothesis, $H_0: \beta_{jk} = 0 \ \forall j,k$, that the Cobb-Douglas frontier is an adequate representation for firms, is strongly rejected by the data for the whole sample as well as for firms in the second auction. The second null hypothesis, $\beta_t = \beta_{2t} = \beta_{kt} = 0 \ \forall \mathrm{k}$, that there is no TC, is always rejected.

Insert Table A3

We also check, separately, for the presence of neutral TC and other biased TC. The neutral TC leaves the ratio of inputs constant and shifts the production frontier in parallel and outwards. The biased TC is the technological change embedded in at least one of the inputs; it changes the slope of the production frontier and shifts it outwards. The rejection of tests of the null hypotheses $\beta_t = \beta_{2t} = 0$ and $\beta_{kt} = 0 \ \forall \mathrm{k}$ indicate the presence of both two-dimensional technological changes. On average, over the sample period, investment in fixed assets negatively affects the frontier, shifting it downwards; while, on the contrary, labor force positively contributes to an upward movement of the frontier. This means that, on average, firms make lower productive use of fixed assets in their production and a higher productive use of their labor force.

As regards the model efficiency, the LR test of the one sided error for the null hypothesis $\gamma = \delta_i = 0 \, \forall i$ of no technical inefficiency is strongly rejected for all the models. The LR tests are in fact equal to 420.564, 449.620, and 388.747 for the 2nd, 3rd, and 4th action respectively, which exceeds the corresponding upper five per cent point for the mixed Chi-square distribution (Kodde and Palm, 1986). The value of the estimates of the γ parameters are higher than 0.93 for all the models which implies that a significant proportion of the total variability is associated with technical inefficiency of production.

Finally, we plot the distribution of the technical efficiencies for the three auctions (Figure A1). The plots are quite similar, with a thin tail to the left of the distribution, gradually rising to a maximum in the 0.8 to 0.9 interval and then dropping sharply in the 0.9 to 1.0 interval. The fact that the mode of the distribution is not in this final interval supports the use of the truncated normal distributions for the inefficiency effects (Battese and Coelli, 1996), representing a generalization of other distributional forms (Meesters, 2014).

Insert Figure A1

Based on these results, we account for the different technological sets within the industries by estimating several frontiers separately. First, we considered firms applying to the different auctions as separate groups; within each auction, we also separated firms operating in the Center-North of Italy from those located in the South. Furthermore, four industry sub-groups defined according to firms' technology were considered (Harris and Moffat, 2013). Then, 18 firm groups were identified and 18 production frontier models estimated (8 for auction 3; 5 for both auctions 2 and 4). LR tests support our identification strategy, strongly rejecting the null hypothesis of homogenous production functions among the above groups (LR tests are 539.89 (p-value=0.00), 920.47 (p-value=0.00), and 480.89 (p-value=0.00) for the auction groups 2, 3 and 4, respectively).

Appendix B. Policy effects in the Center-North regions

Insert Table B1

Insert Table B2

Appendix C. Robustness tests

Insert Table C1

Insert Table C2

Insert Figure C1

Table 1. Multiple RDD estimates of the pre-treatment differences in TFP components and other covariates between subsidized and non-subsidized firms (SOUTH)

Dependent variable	SOUTH REGIONS				
	Low tech	Medium-low tech	Medium-high and high tech	Non-manufacturing	Whole sample
	(1)	(2)	(3)	(4)	(5)
Technological Change	-0.00301	0.00052	-0.02425	-0.03124	-0.00756
	(0.00948)	(0.00736)	(0.03174)	(0.02270)	(0.00684)
Scale Component	-0.00567	-0.01583	0.01283	0.01308	-0.00528
	(0.00987)	(0.00852)*	(0.01304)	(0.02339)	(0.00580)
Allocative Efficiency	0.03011	-0.03065	0.11052	-0.02342	0.01170
	(0.06324)	(0.07835)	(0.14312)	(0.05784)	(0.04513)
Technical Efficiency	0.03965	0.04929	-0.00014	0.08031	0.04149
	(0.02863)	(0.04406)	(0.07618)	(0.05862)	(0.02640)
Total Factor Productivity	0.06863	0.04470	0.12050	-0.00403	0.05825
	(0.09140)	(0.09956)	(0.15467)	(0.07949)	(0.05579)
Tangible Capital	-346.34	-1144.92	137.50	-441.81	-661.32
	(467.51)	(733.04)	(579.09)	(405.99)	(359.15)*
Value Added	200.47	-1110.81	195.31	57.59	-357.31
	(337.93)	(647.75)*	(464.03)	(481.22)	(275.66)
Labor Cost per Employee	2941.45	1570.89	-834.03	-3396.91	848.15
	(1611.03)*	(1646.25)	(2880.67)	(2735.46)	(1019.65)
# Employees	-1.67	-22.70	5.83	4.65	-10.50
	(11.12)	(14.38)	(14.70)	(11.84)	(7.22)
ROE	-4.10	2.11	-2.38	16.06	0.66
	(9.85)	(13.72)	(14.83)	(10.88)	(7.05)
Net liabilities	-958.01	-1820.73	707.36	-140.52	-916.55
	(501.23)*	(1085.59)*	(559.55)	(343.31)	(481.35)*
Cash Flow	-70.78	-323.52	142.15	-157.65	-149.64
	(120.43)	(239.25)	(250.27)	(198.15)	(110.58)

Note: For the aggregated estimates (5) we used the weighting scheme based on the number of treated firms within the optimal bandwidth. Results are from local linear regression with triangular kernel using the robust confidence intervals and CCT implementation of mean-squared-error optimal bandwidth selector developed by Calonico, Cattaneo & Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo & Titiunik (2014a). Bias is estimated with a quadratic polynomial. 95% robust confidence intervals are in brackets. Monetary values are expressed in constant euros, year 2000. Significant at *10%, **5%, and ***1%.

Table 2. TFP components growth rates (SOUTH)

	All firms									
	Treated					Not treated				
	TC	SC	AE	TE	TFP	TC	SC	AE	TE	TFP
Year 1	0.0115	0.0006	-0.0615	-0.0358	-0.0831	0.0081	-0.0024	-0.0142	-0.0138	-0.0162
Year 2	0.0217	-0.0014	-0.1064	-0.0252	-0.1086	0.0160	0.0026	-0.0259	-0.0056	-0.0137
Year 3	0.0333	0.0050	-0.0331	-0.0379	-0.0349	0.0244	0.0059	-0.0400	-0.0294	-0.0393
Year 4	0.0456	0.0045	0.0166	-0.0434	0.0238	0.0321	0.0053	-0.0303	-0.0233	-0.0156
Year 5	0.0581	0.0084	0.0241	-0.0954	0.0035	0.0396	0.0143	-0.0376	-0.0884	-0.0787
	Low-tech firms									
	Treated					**Not treated**				
	TC	SC	AE	TE	TFP	TC	SC	AE	TE	TFP
Year 1	0.0176	-0.0016	-0.0398	-0.0462	-0.0551	0.0172	0.0001	-0.0161	-0.0480	-0.0274
Year 2	0.0343	-0.0006	-0.1119	-0.0027	-0.0853	0.0351	0.0052	-0.0118	-0.0155	0.0058
Year 3	0.0532	0.0064	-0.0095	-0.0524	-0.0084	0.0531	0.0113	-0.0360	-0.0393	-0.0181
Year 4	0.0725	0.0053	0.0132	-0.0413	0.0517	0.0691	0.0095	-0.0463	-0.0303	0.0054
Year 5	0.0924	0.0096	0.0244	-0.1557	-0.0283	0.0863	0.0123	-0.0182	-0.1450	-0.0702
	Medium-low tech firms									
	Treated					**Not treated**				
	TC	SC	AE	TE	TFP	TC	SC	AE	TE	TFP
Year 1	0.0086	-0.0029	-0.0460	-0.0215	-0.0690	0.0048	-0.0023	-0.0220	0.0174	0.0035
Year 2	0.0170	-0.0064	-0.0457	-0.0257	-0.0471	0.0094	0.0000	-0.0234	0.0379	0.0277
Year 3	0.0247	0.0005	-0.0301	-0.0447	-0.0522	0.0141	0.0023	-0.0627	-0.0256	-0.0675
Year 4	0.0323	0.0023	0.0260	-0.0294	0.0277	0.0187	0.0045	-0.0311	0.0084	0.0023
Year 5	0.0399	0.0080	0.0543	-0.0572	0.0558	0.0236	0.0092	-0.0534	-0.0596	-0.0815
	Medium-high and high-tech firms									
	Treated					**Not treated**				
	TC	SC	AE	TE	TFP	TC	SC	AE	TE	TFP
Year 1	0.0099	0.0059	-0.1344	-0.0519	-0.1734	0.0051	-0.0046	0.0194	-0.0542	-0.0469
Year 2	0.0172	-0.0058	-0.1952	-0.0614	-0.2492	0.0091	-0.0015	-0.0471	-0.0779	-0.1149
Year 3	0.0250	-0.0040	-0.1004	-0.0426	-0.1162	0.0137	-0.0026	-0.0162	-0.0633	-0.0760
Year 4	0.0354	-0.0053	-0.0096	-0.0747	-0.0519	0.0189	0.0036	-0.0115	-0.0873	-0.0862
Year 5	0.0452	0.0000	-0.0627	-0.0991	-0.0956	0.0223	0.0013	-0.0364	-0.1061	-0.1396
	Non-manufacturing firms									
	Treated					**Not treated**				
	TC	SC	AE	TE	TFP	TC	SC	AE	TE	TFP
Year 1	0.0027	0.0116	-0.0841	-0.0251	-0.0980	-0.0003	-0.0059	-0.0164	0.0086	-0.0191
Year 2	0.0012	0.0176	-0.1612	-0.0488	-0.1905	-0.0014	0.0073	-0.0451	-0.0402	-0.0815
Year 3	0.0062	0.0269	-0.0296	0.0373	0.0421	-0.0004	0.0101	-0.0088	0.0079	0.0166
Year 4	0.0134	0.0220	0.0335	-0.0525	0.0215	-0.0004	0.0001	-0.0097	-0.0403	-0.0502
Year 5	0.0213	0.0175	0.0435	-0.0139	0.0749	-0.0027	0.0417	-0.0386	-0.0311	-0.0423

Note: Statistics computed only using the 536 observations (255 treated firms and 281 control firms) closest to the forcing variable threshold (scores within -1.5 and +1.5). Abbreviations: TC, technological change; SC, scale component; AE, allocative efficiency; TE, technical efficiency; TFP, total factor productivity.

Table 3. Non-parametric and parametric Multiple RDD estimates (SOUTH)

Dependent variable	Weighting scheme: Number of treated firms within the optimal bandwidth									
	Non-parametric estimates					Parametric estimates				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.0040	0.0047	0.0053	0.0137	0.0212	0.0027	0.0024	0.0039	0.0103	0.0167
	(0.0024)	(0.0043)	(0.0063)	(0.0080)*	(0.0093)**	(0.0024)	(0.0042)	(0.0061)	(0.0077)	(0.0096)*
Scale Component	0.0049	-0.0086	-0.0057	0.0046	-0.0032	0.0089	0.0066	0.0041	0.0070	0.0038
	(0.0076)	(0.0079)	(0.0077)	(0.0081)	(0.0091)	(0.0083)	(0.0094)	(0.0079)	(0.0083)	(0.0090)
Allocative Efficiency	-0.0813	-0.1387	0.0256	0.1369	0.0833	-0.1069	-0.1331	0.0203	0.1080	0.0610
	(0.0545)	(0.0653)**	(0.0584)	(0.0608)**	(0.0555)	(0.0533)**	(0.0618)**	(0.0566)	(0.0547)**	(0.0539)
Technical Efficiency	-0.0501	-0.0120	-0.0550	-0.0022	-0.0663	-0.0488	-0.0300	-0.0474	-0.0075	0.0165
	(0.0372)	(0.0407)	(0.0326)*	(0.0390)	(0.0391)*	(0.0356)	(0.0346)	(0.0329)	(0.0399)	(0.0466)
Total Factor Productivity	-0.1549	-0.1736	-0.0237	0.1349	0.0465	-0.1380	-0.1546	-0.0090	0.1165	0.1170
	(0.0771)**	(0.0853)**	(0.0791)	(0.0727)*	(0.0855)	(0.0765)*	(0.0775)**	(0.0801)	(0.0731)*	(0.0855)

Note: There are 1074 observations (377 treated firms and 697 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 415 (205 T and 210 NT) and 544 (260 T and 284 NT) (it depends on the dependent variable and the year analyzed). Results are from local linear regression with triangular kernel using the robust confidence intervals and CCT implementation of mean-squared-error optimal bandwidth selector developed by Calonico, Cattaneo and Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo and Titiunik (2014a). Bias is estimated with a quadratic polynomial. 95% robust confidence intervals are in brackets. Parametric regressions include a third-order polynomial in the forcing variable. These functions are estimated on both sides of the threshold separately. Significant at *10%, **5%, and ***1%.

Table 4. Non-parametric and parametric Multiple RDD estimates (SOUTH) - Small firms

	Weighting scheme: Number of treated firms within the optimal bandwidth									
	Non-parametric estimates					Parametric estimates				
Dependent variable	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.0026 (0.0057)	0.0048 (0.0106)	0.0093 (0.0158)	0.0121 (0.0210)	0.0183 (0.0229)	-0.0029 (0.0043)	-0.0091 (0.0088)	-0.0073 (0.0123)	-0.0115 (0.0169)	-0.0150 (0.0207)
Scale Component	-0.0079 (0.0101)	-0.0070 (0.0083)	-0.0064 (0.0067)	-0.0227 (0.0128)*	-0.0167 (0.0079)**	-0.0055 (0.0088)	-0.0051 (0.0079)	0.0004 (0.0065)	-0.0135 (0.0094)	-0.0059 (0.0067)
Allocative Efficiency	-0.0612 (0.0526)	-0.0789 (0.0623)	0.0324 (0.0689)	0.1428 (0.0537)***	0.0913 (0.0550)*	-0.0475 (0.0490)	-0.0478 (0.0587)	0.0255 (0.0563)	0.1404 (0.0507)***	0.0624 (0.0519)
Technical Efficiency	-0.0885 (0.0317)***	-0.0568 (0.0336)*	-0.0616 (0.0368)*	-0.0135 (0.0433)	-0.0968 (0.0531)*	-0.0467 (0.0280)*	-0.0094 (0.0316)	-0.0031 (0.0318)	0.0149 (0.0424)	0.0170 (0.0486)
Total Factor Productivity	-0.1776 (0.0763)**	-0.1277 (0.0690)*	-0.0108 (0.0755)	0.1303 (0.0624)**	0.0692 (0.0836)	-0.1285 (0.0629)**	-0.0916 (0.0660)	0.0411 (0.0679)	0.1460 (0.0665)**	0.0827 (0.0890)

Note: There are 504 observations (169 treated firms and 335 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 166 (86 T and 80 NT) and 265 (127 T and 138 NT) (it depends on the dependent variable and the year analyzed). Results are from local linear regression with a triangular kernel using the robust confidence intervals and CCT implementation of the mean-squared-error optimal bandwidth selector developed by Calonico, Cattaneo and Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo and Titiunik (2014a). Bias estimated with quadratic polynomial. 95% robust confidence intervals are in brackets. Parametric regressions include a third order polynomial in the forcing variable. These functions are estimated on both sides of the threshold separately. Significant at *10%, **5%, and ***1%.

Appendix

Appendix A. Production frontier estimates and specification tests

Table A1. Variables information and measurement

Variable	**Type**	**Measurement**	**Expected effects**
y	Output	Value added (€)	
x_1	Labor input	Cost of labor (€)	+
x_2	Capital input	Fixed Assets (€)	+
t	Trend	Time	+/-
D_year_t	Trend	Yearly dummies, t: 1,...,9	+/ -
D_regio_r	Covariate	Regional dummies, r: 1,...,17	+/-
D_micro *D_small* *D_medium_and_large*	Covariate	Firm size dummies	+
D_MHT_and_HT *D_MLT* *D_LT*	Covariate	Manufacturing technological level dummies	+
D_NM	Covariate	Non-manufacturing firms dummy	+/-

Table A2. Maximum Likelihood estimates for parameters of the stochastic frontier with inefficiency effects model

Coefficient	Auction 2	Auction 3	Auction 4
Stochastic Frontier			
β_0	1.994***	2.528***	2.467***
β_L	0.573***	0.169***	0.359***
β_K	0.110***	0.387***	0.174***
β_{LL}	0.041***	0.050***	0.049***
β_{KK}	0.033***	0.023***	0.013***
β_{LK}	-0.054***	-0.048***	-0.031***
β_t	-0.129***	-0.0936***	-0.048***
β_{t^2}	0.010***	0.006***	0.004***
β_{Lt}	0.014***	0.009***	0.001
β_{Kt}	-0.009**	-0.005***	-0.003
D_regio2	-0.193***	-0.145***	-0.052
D_regio3	-0.162***	-0.076***	-0.117***
D_regio4	-0.082***	-0.060***	0.029
D_regio5	0.037	0.022	-
D_regio6	-	-0.028	0.117***
D_regio7	-	0.058**	-
D_regio8	-	0.086***	0.016
D_regio9	-0.04	0.036	0.013
D_regio10	0.144***	0.235***	-0.013
D_regio11	-	0.082***	-
D_regio12	-0.158***	-0.096***	-0.133***
D_regio13	-0.140***	-0.257***	-0.182***
D_regio14	-	-0.049**	-0.025
D_regio15	-	0.087***	0.120***
D_regio16	-0.036	0.043*	-0.011
D_regio17	-	0.013	-
D_MLT	-0.020	0.033**	0.125***
D_MHT_and_HT	0.079***	0.049***	-0.004
D_NM	0.054***	0.070***	0.038
D_small	0.085***	-0.007	0.019
D_medium_and_large	-0.018	0.018	0.032
Inefficiency Model			
δ_0	-8.931***	-5.563***	-4.564***
D_year2	-3.474*	-1.109***	-0.854***
D_ year3	-1.495*	-2.130***	-2.281***
D_ year4	-3.248*	-3.399***	-3.819***
D_ year5	-1.253**	-3.752***	-3.113***
D_ year6	-0.399	-2.777***	-5.188***
D_ year7	2.344**	-1.540***	-2.083***
D_ year8	-	-0.148**	-2.785***
D_ year9	-	-	0.089
Variance Parameters			
σ_S^2	2.576***	1.382***	1.498***

γ	0.946***	0.929***	0.939***
Loglikelihood Function			
LL	-2327.870	-3336.724	-1397.143
LR test of the one sided error	420.564	449.620	388.747
Number of restrictions	8	9	10
Number of iterations	100	62	54
Number of cross-sections	527	1024	366
Number of time periods	7	8	9
Total number of observations	3689	8192	3294

Note: Significant at *10%, **5%, and ***1%. The reference category for size is D_micro (firms with less than 10 employees), while the reference category for technology is D_LT (low-tech manufacturing firms).

Table A3. Hypotheses testing for the functional form of the stochastic production function

	Auction 2		Auction 3		Auction 4	
H_0	λ	Decision whit respect to H_0	λ	Decision whit respect to H_0	λ	Decision whit respect to H_0
$\beta_{jk} = 0 \ \forall j, k$	128.456***	Rejected	390.68***	Rejected	133.36***	Rejected
$\beta_t = \beta_{t^2} = \beta_{kt} = 0 \ \forall k$	46.080***	Rejected	39.69***	Rejected	18.20***	Rejected
$\beta_t = \beta_{t^2} = 0$	20.522***	Rejected	5.91**	Rejected	2.64	Not Rejected
$\beta_{kt} = 0 \ \forall k$	12.851***	Rejected	21.40***	Rejected	1.70	Not Rejected
$\gamma = \delta_0 = \delta_1 = \delta_2 = 0$	415.629***	Rejected	449.62***	Rejected	388.747***	Rejected

Note: Significant at *10%, **5%, and ***1%.

Appendix B. Policy effects in the Center-North regions

Table B1. Multiple RDD estimates of the pre-treatment differences in TFP components and other covariates between subsidized and non-subsidized firms (CENTER-NORTH)

Dependent variable	CENTER-NORTH REGIONS				
	Low tech	Medium-low tech	Medium-high and high tech	Non-manufacturing	Whole sample
	(1)	(2)	(3)	(4)	(5)
Technological Change	-0.00394	-0.00565	0.00660	0.00423	-0.00059
	(0.01303)	(0.00889)	(0.01549)	(0.03533)	(0.00737)
Scale Component	0.00303	-0.01016	0.01684	-0.02820	-0.00048
	(0.00709)	(0.00433)	(0.01782)	(0.03861)	(0.00627)
Allocative Efficiency	0.03990	-0.10558	0.13599	-0.30894	-0.01613
	(0.07715)	(0.09138)	(0.08997)	(0.20669)	(0.05047)
Technical Efficiency	-0.01503	-0.00864	0.00638	-0.05216	-0.00893
	(0.01942)	(0.01492)	(0.01919)	(0.02713)*	(0.00972)
Total Factor Productivity	0.04231	-0.14109	0.18477	-0.26439	0.00358
	(0.06633)	(0.09630)	(0.10657)*	(0.14449)*	(0.04745)
Tangible Capital	505.22	-578.47	-4794.22	-1561.93	-1255.93
	(2326.67)	(1272.41)	(5237.28)	(1961.78)	(1645.52)
Value Added	-3952.10	-289.84	-8021.70	-2120.12	-3722.82
	(4596.86)	(439.29)	(7330.42)	(988.45)**	(2532.68)
Labor Cost per Employee	-3209.93	-2231.42	-2918.15	622.11	-2569.87
	(1755.34)*	(1158.49)*	(4073.33)	(3291.76)	(1329.67)*
# Employees	-97.33	2.64	-25.12	-16.67	-47.52
	(106.75)	(10.87)	(51.67)	(20.84)	(46.73)
ROE	-6.93	-14.58	9.75	7.33	-3.59
	(8.64)	(12.29)	(9.10)	(16.78)	(6.42)
Net liabilities	963.83	176.71	-12985.57	-1825.00	-2351.60
	(1937.09)	(442.34)	(9456.18)	(1147.75)	(2065.25)
Cash Flow	-148.65	-103.29	-4494.63	-798.79	-1121.80
	(884.50)	(161.14)	(3429.07)	(326.24)	(829.59)

Note: See notes of Table 1.

Table B2. Non-parametric and parametric Multiple RDD estimates (CENTER-NORTH)

	Weighting scheme: Number of treated firms within the optimal bandwidth									
	Non-parametric estimates					Parametric estimates				
Dependent variable	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.0006 (0.0014)	0.0010 (0.0027)	0.0023 (0.0039)	0.0035 (0.0050)	0.0054 (0.0059)	-0.0013 (0.0014)	-0.0024 (0.0026)	-0.0026 (0.0036)	-0.0025 (0.0045)	-0.0017 (0.0052)
Scale Component	-0.0036 (0.0089)	0.0053 (0.0075)	-0.0049 (0.0073)	-0.0042 (0.0083)	-0.0300 (0.0186)	-0.0104 (0.0122)	0.0024 (0.0104)	-0.0175 (0.0110)	-0.0012 (0.0101)	-0.0171 (0.0185)
Allocative Efficiency	-0.0016 (0.0561)	0.0640 (0.0633)	0.0644 (0.0652)	0.0138 (0.0651)	0.0180 (0.0615)	0.0198 (0.0617)	-0.0030 (0.0590)	0.0473 (0.0575)	-0.0003 (0.0611)	0.0121 (0.0556)
Technical Efficiency	0.0120 (0.0160)	0.0171 (0.0201)	0.0319 (0.0166)*	0.0098 (0.0403)	-0.0104 (0.0423)	0.0195 (0.0176)	0.0196 (0.0193)	0.0282 (0.0157)*	0.0004 (0.0373)	0.0142 (0.0402)
Total Factor Productivity	0.0179 (0.0563)	0.0360 (0.0627)	0.0449 (0.0538)	0.0004 (0.0881)	-0.0444 (0.0675)	0.0373 (0.0617)	0.0266 (0.0631)	0.0638 (0.0555)	0.0121 (0.0784)	0.0198 (0.0685)

Note: There are 800 observations (264 treated firms and 536 control firms); however, for non-parametric estimates the actual number of observations within the bandwidth ranges between 259 (142 T and 117 NT) and 341 (172 T and 169 NT) (it depends on the dependent variable and the year analyzed). Results are from local linear regression with triangular kernel using the robust confidence intervals and CCT implementation of mean-squared-error optimal bandwidth selector developed by Calonico, Cattaneo and Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo and Titiunik (2014a). Bias is estimated with a quadratic polynomial. 95% robust confidence intervals are in brackets. Parametric regressions include a third-order polynomial in the forcing variable. These functions are estimated on both sides of the threshold separately. Significant at *10%, **5%, and ***1%. The estimates by technological sector are available upon request from the Authors.

Appendix C. Robustness tests

Table C1. Non-parametric and parametric Multiple RDD estimates (SOUTH) using an alternative weighting scheme

	Weighting scheme: Inverse-variance weighting									
	Non-parametric estimates					Parametric estimates				
Dependent variable	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.0042 (0.0026)	0.0064 (0.0047)	0.0081 (0.0068)	0.0164 (0.0090)*	0.0249 (0.0102)**	0.0023 (0.0019)	0.0021 (0.0033)	0.0036 (0.0049)	0.0097 (0.0063)	0.0172 (0.0076)**
Scale Component	0.0053 (0.0084)	-0.0071 (0.0082)	-0.0046 (0.0082)	0.0047 (0.0091)	0.0105 (0.0105)	0.0116 (0.0078)	0.0048 (0.0085)	0.0038 (0.0069)	0.0108 (0.0075)	0.0122 (0.0086)
Allocative Efficiency	-0.0825 (0.0619)	-0.1312 (0.0662)**	-0.0088 (0.0657)	0.1389 (0.0646)**	0.0912 (0.0635)	-0.1207 (0.0525)**	-0.1366 (0.0604)**	0.0289 (0.0513)	0.1170 (0.0498)**	0.0511 (0.0530)
Technical Efficiency	-0.0463 (0.0283)	-0.0580 (0.0435)	-0.0587 (0.0373)	-0.0106 (0.0412)	-0.0925 (0.0442)**	-0.0367 (0.0326)	-0.0331 (0.0323)	-0.0390 (0.0290)	-0.0285 (0.0372)	-0.0193 (0.0387)
Total Factor Productivity	-0.1362 (0.0800)*	-0.1681 (0.0864)*	-0.0691 (0.0987)	0.1394 (0.0732)*	0.0479 (0.0989)	-0.1494 (0.0689)**	-0.1561 (0.0729)**	-0.0116 (0.0659)	0.1118 (0.0635)*	0.0750 (0.0747)

Note: See notes of Table 3.

Table C2. Non-parametric and parametric Multiple RDD estimates (SOUTH) using a time-variant specification of u_{it}

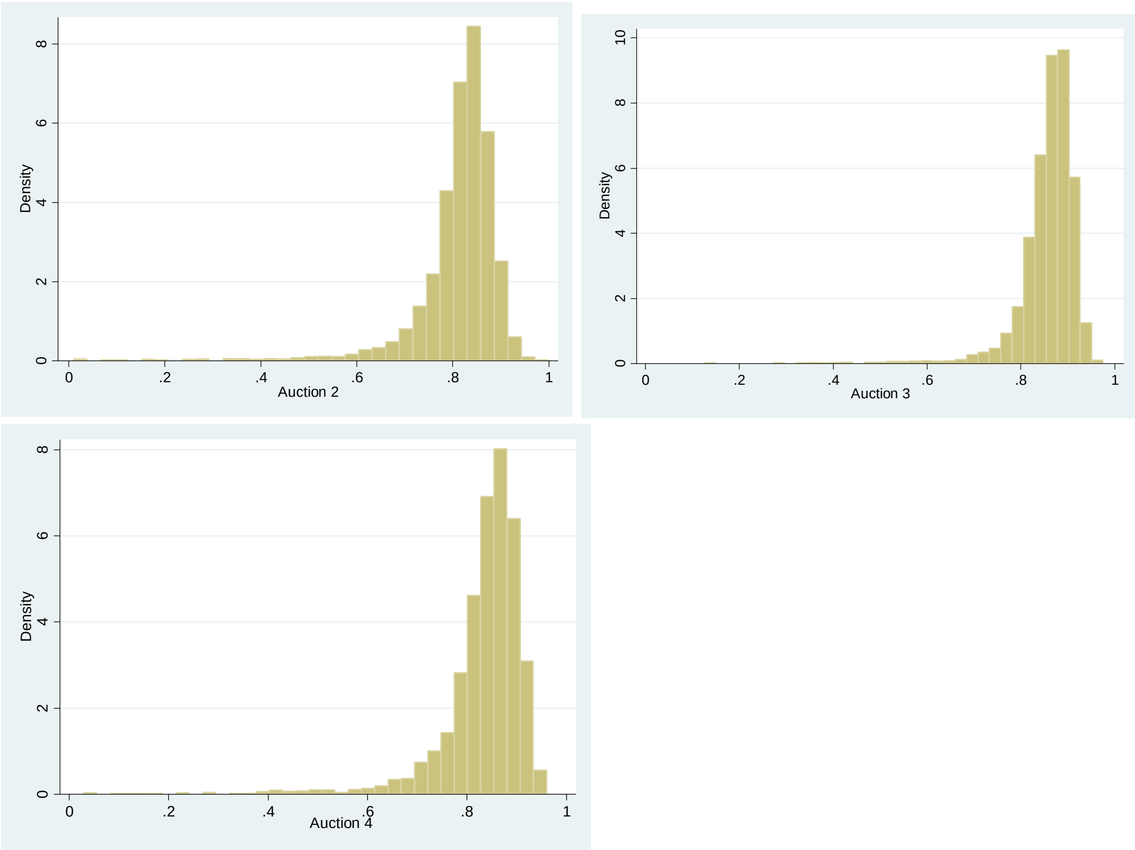
Dependent variable	Non-parametric estimates					Parametric estimates				
	Weighting scheme: Number of treated firms within the optimal bandwidth									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.0009 (0.0014)	-0.0003 (0.0019)	-0.0005 (0.0028)	0.0029 (0.0034)	0.0067 (0.0040)*	0.0005 (0.0014)	-0.0008 (0.0019)	-0.0010 (0.0026)	0.0016 (0.0033)	0.0048 (0.0040)
Scale Component	0.0077 (0.0112)	0.0083 (0.0116)	0.0020 (0.0113)	0.0116 (0.0139)	0.0022 (0.0130)	0.0172 (0.0113)	0.0190 (0.0124)	0.0114 (0.0113)	0.0164 (0.0123)	0.0107 (0.0129)
Allocative Efficiency	-0.0627 (0.0692)	-0.1446 (0.0725)**	0.0345 (0.0714)	0.1723 (0.0737)**	0.0768 (0.0743)	-0.1299 (0.0647)**	-0.1576 (0.0722)**	0.0344 (0.0679)	0.1236 (0.0643)*	0.0359 (0.0669)
Technical Efficiency	-0.0003 (0.0004)	-0.0006 (0.0008)	-0.0008 (0.0012)	-0.0009 (0.0015)	-0.0009 (0.0019)	-0.0002 (0.0005)	-0.0002 (0.0009)	-0.0003 (0.0013)	-0.0003 (0.0016)	-0.0002 (0.0019)
Total Factor Productivity	-0.0531 (0.0646)	-0.1478 (0.0703)**	0.0140 (0.0661)	0.1816 (0.0687)***	0.0833 (0.0691)	-0.1032 (0.0623)*	-0.1474 (0.0693)**	0.0396 (0.0644)	0.1379 (0.0607)**	0.0561 (0.0635)

Note: There are 1074 observations (377 treated firms and 697 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 463 (228 T and 235 NT) and 541 (255 T and 286 NT) (it depends on the dependent variable and the year analyzed). Results are from local linear regression with triangular kernel using the robust confidence intervals and CCT implementation of mean-squared-error optimal bandwidth selector developed by Calonico, Cattaneo & Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo & Titiunik (2014a). Bias is estimated with a quadratic polynomial. 95% robust confidence intervals are in brackets. Parametric regressions include a third-order polynomial in the forcing variable. These functions are estimated on both sides of the threshold separately. Significant at *10%, **5%, and ***1%.

Appendix

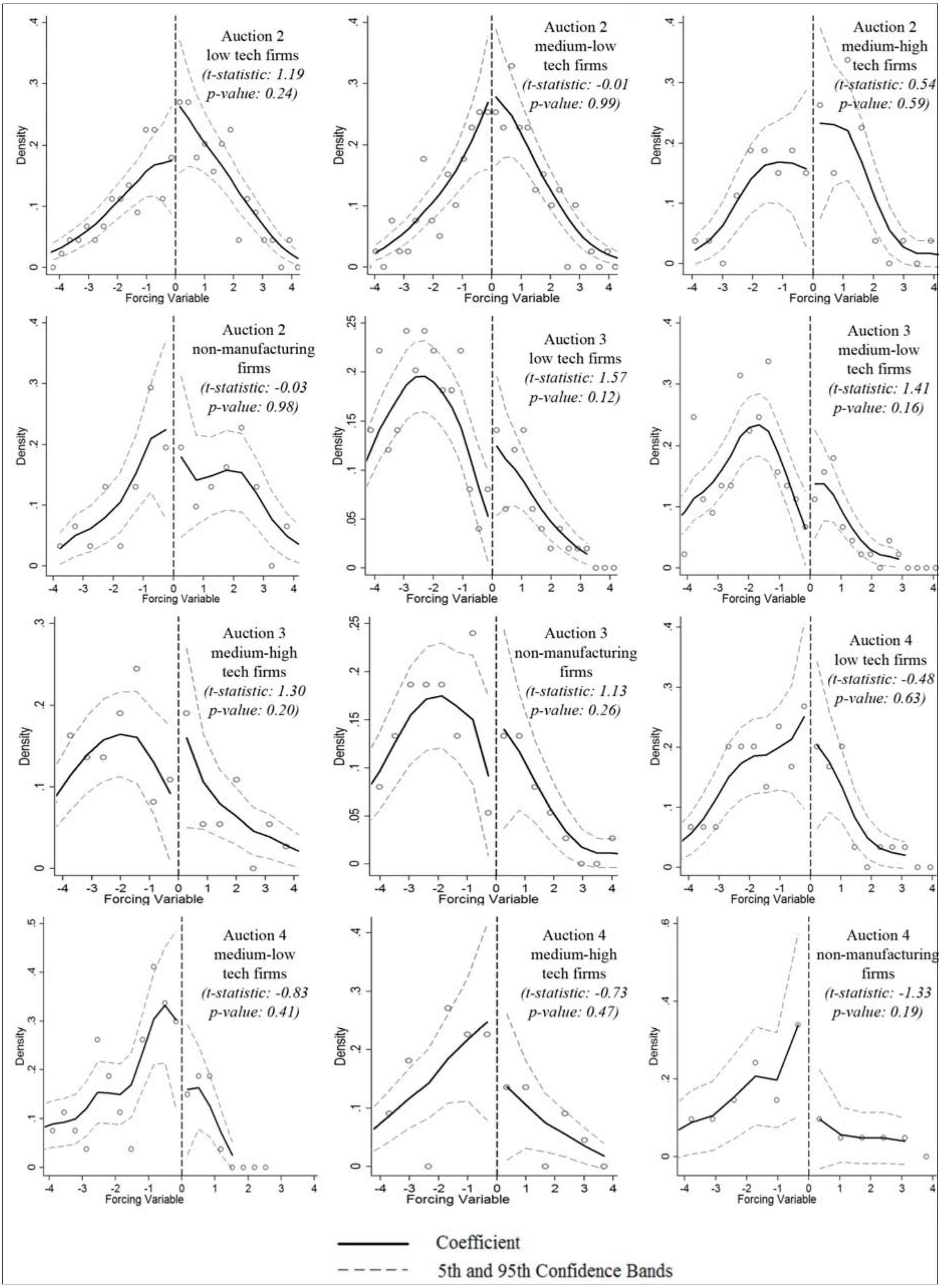
Appendix A. Production frontier estimates and specification tests

Figure A1. Technical efficiency distributions



Appendix C. Robustness tests

Figure C1. McCrary test for the analyzed rankings



Note: This test is based on an estimator for the discontinuity at the cut-off in the density function of the forcing variable. The test is implemented as a Wald test of the null hypothesis that the discontinuity is zero.