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

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

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Abstract: This paper shows 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 technical 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). The impact of capital subsidies on the different components of TFP is captured by a quasi–experimental method (Multiple RDD), 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. The main findings from the case study are twofold. First, capital subsidies positively affect TFP growth in the medium-long term and not in the short term. The main reason is that allocative efficiency has a positive effect only after 2-3 years. Second, the positive impact comes especially through technical progress and not through scale impact change, as may have been expected.

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 & 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]

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 & Trainor, 2005; Bernini & Pellegrini, 2011; Criscuolo et al., 2012; Moffat, 2014). 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)

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[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, 2013).

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 technical 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 technical 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. 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 technical progress (measuring shifts in the frontier over time). Moreover, because a flexible technology is used, the SFA make 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 & Lovell, 2000; Brummer et al., 2002).

Note that, unlike Obeng & 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. 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 policy and the data in more detail. In Section 4, we describe the TFP decomposition and present the evaluation method. 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 Cerulli, 2012; Becker, 2014), the Enterprise Zones (EZs) program (see, among others, Ham et al., 2011; Busso et al., 2013), 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 & Pellegrini, 2011; Criscuolo et al., 2012; Bondonio & Greenbaum, 2014; Cerqua & Pellegrini, 2014a).

Among this stream of research, a few papers have considered the impact of capital subsidies on the total factor productivity (TFP). Having estimated a production function, Bergstrom (2000) investigated 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). Moreover, by transferring resources to firms, which become less productive, the subsidies have also disfavored non-subsidized firms because they have been forced to partly finance the subsidies, with negative effects on regional as well as national growth. Harris & Robinson (2004) found 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 for all manufacturing, real gross output would have been 7-10% per annum lower if SFA had not been in operation; while capital grants seem to have a positive impact on TFP compared with the other forms of grant aid. Using a similar approach, Harris & Robinson (2004) found 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 & 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 (i.e., Regional Selective Assistance and Small Firm Merit Awards for Research and Technology). 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. Then, plants in receipt of RSA generally experience market share growth despite having relatively lower productivity.

A different decomposition procedure was used in Skuras et al. (2006). After having estimated a production frontier in which the subsidy is treated as a new input, the authors decomposed the TFP into three components, which are technical 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 technical change. Combining the above decomposition with a cost function approach, Obeng & Sakano (2000) found 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 & Pellegrini (2011), by means of a matching diff-in-diffs approach, showed 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. Criscuolo et al. (2012) investigated 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. Recently, 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. (2012), 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 was found to reduce 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. Data

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 northern (Objective 2 or 5b) and southern regions (Objective 1) of the country;[2] 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).[3] 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.

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[2] 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).

[3] 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).

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.[4] 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 used in the following analysis). 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.

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 (see Bronzini and de Blasio, 2006, for the timing of the assistance). 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[5], and other sources of financial information.[6] After 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).[7] Table A1 in Appendix A displays for both

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[4] 1) The share of owners' funds in total investment; 2) the new job 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. For a detailed description of each criterion and other aspects of L488, see Section 3 in Bernini & Pellegrini (2011).

[5] 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.

[6] 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 & Pellegrini, 2014b) shows some 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 and investment.

[7] We considered only firms having a meaningful balance sheet 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.

treated and control firms the medians for a number of baseline covariates referring to the year before subsidy assignment.

4. Method

4.1 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 technical 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, technical 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 make it possible to estimate technical efficiency in addition to technical change, which is captured by a time trend and interactions of the inputs with time (Aigner et al., 1977; Meeusen & van den Broeck, 1977; Battese & Coelli, 1992).

The general stochastic production frontier model is described as

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

where y is the vector for the quantities produced by the various firms, L and K are the vector for production factors used, t is the time trend variable and β is the vector for the parameters defining the production technology. The variable v refers to the random part of the error, while u is a downward deviation from the production frontier. Thus, $f(t, L_{it}, K_{it}; \beta) \exp(v_{it})$ represents the stochastic frontier of production, and v captures 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), that is, the ratio of observed output to potential output (given by the frontier), is captured by the component $\exp(-u_{it})$ and, therefore, $0 \le TE \le 1$.

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There are several specifications to account for time-varying technical inefficiency u_{it} (Kumbhakar, 2000). Battese & Coelli (1995) proposed a specification for the technical inefficiency effect in the stochastic frontier production function, $\mu_{it} = z_{it}\delta + w_{it}$, where 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 $\mu_{it} = \delta_0 + \delta_1 t + \delta_2 t^2 + w_{it}$. The time trend variable controls for time varying, systematic unobserved factors. Alternately, yearly dummy variables D_t can be used; then, the model for the inefficiency term becomes $\mu_{it} = \delta_0 + \sum_t \delta_t D_t + w_{it}$. Following Battese and Coelli (1992), the technical inefficiency component can also be considered time-variant, assuming that $u_{it} = \exp(-\eta(t - T))u_i$, $u_{it} \geq 0$, $i=1, . . .,N$, $t \in \tau(i)$. $\tau(i)$ represents the T_i periods of time for which we have available observations for the i-nth firms 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 efficiency over time; the sign of η dictates the behavior of technical inefficiency over time. Moreover, the estimated value for η/δ is the same for all firms in the sample, which means that the pattern of inefficiency rise or reduction is the same for all firms.

Following Bauer (1990), Brummer et al. (2002), Kumbhakar (2000) and Kumbhakar & Lovell (2000), after a production frontier function has been estimated, it is possible to compose the rate of total factor productivity 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 inefficient allocation of productive factors.

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

$$g_{TFP} = \frac{\dot{y}}{y} - s_K \frac{\dot{K}}{K} - s_L \frac{\dot{L}}{L} \qquad (2)$$

where dots over variables indicate time derivatives, g_{TFP} denotes the rate of TFP growth, s_K and s_L are the shares of capital and labor in aggregate income, and ε_K and ε_L are output elasticities with respect to the factors of production.

From the deterministic part of (2), we have

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

Combining (2) and (3), it follows that

$$g_{TFP} = TP - \dot{u} + (RTS - 1)\left[\lambda_k g_K + \lambda_L g_L\right] + \left[(\lambda_k - s_K)g_K + (\lambda_L - s_L)g_L\right] \qquad (4)$$

where RTS denotes returns to scale with RTS=ε_K+ε_L, g_K is the growth rate of capital ($\dot{K}/K$) and g_L is the growth rate of labor ($\dot{L}/L$); λ_K=ε_K/RTS and λ_L=ε_L/RTS are defined as normalized shares of capital and labor in income.

Then, the growth in TFP can be split into four elements:

(i) technical progress, measured by $\partial \ln f(t,K, L,B)/\partial t$;

(ii) change in technical efficiency, denoted by $-\dot{u}$;

(iii) change in the scale of production, given by (RTS−1) $\cdot[\lambda_K \cdot g_K + \lambda_L \cdot g_L]$;

(iv) change in allocative efficiency, measured by $[(\lambda_K - s_K) \cdot g_K + (\lambda_L - s_L) \cdot g_L]$.

Technical 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 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

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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., parameters in the output distance function and the technical efficiency estimates of Eq. 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 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., $AE = T\dot{F}P - (SC + TC + TE)$ (Zhu et al., 2006; Brummer et al., 2002).

4.2 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.[8] Unlike in randomized experiments, this control group is not random, but we can use a sharp RDD approach to address selection bias issues.

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[8] 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.

In a potential-outcomes framework, let $Y_{ir}(1)$ and $Y_{ir}(0)$ denote the potential outcomes of firm i in technological group r. Moreover, let treatment assignment depend only on whether the level of the pre-treatment variable X_{ir} (in our case, X_{ir} is the sum of the indicators normalized for firm i in technological group r) is above or below the referring threshold $(\bar{s}_r)$. Estimation in a sharp RDD naturally focuses on the local average treatment effect (LATE)

$$\tau_r^{SRDD} = E[Y_{ir}(1) - Y_{ir}(0) \mid X_{ir} = \bar{s}_r] \qquad (5)$$

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 two separate regression functions above and below the cut-off. 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 (MSE) using the robust confidence intervals developed by Calonico, Cattaneo, & Titiunik (2014b) and a triangular kernel.[9] 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.

Our main approach consists of pooling in the same ranking firms belonging to the same technological group. Indeed, the analysis is conducted separately for low-tech, medium-low tech, and medium-high and high-tech manufacturing firms. 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, we include them in a separate analysis. After estimating the causal effect of L488 with respect to the TFP components via the RDD for each of the 4 groups of firms, we aggregate the treatment effects to obtain the global treatment effect of the policy under analysis (see

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

Cerqua & Pellegrini, 2014a for a wider discussion on multiple RDD).[10] 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 & Titiunik, 2014b);[11] however, in Section 6, we check the robustness of this aggregation procedure.

As a result, the global LATE of L488 $\left(\tau^{MRDD}\right)$ and the standard errors $\left(\sigma\right)$ are computed as follows:

$$\tau^{MRDD} = \sum_{r=TechGroup} N_r * \tau_r^{SRDD} / N ; \qquad (6)$$

$$\sigma = \sqrt{\sum_{r=TechGroup} N_r^2 * \sigma_r^2 / N^2} ; \qquad (7)$$

where, τ_r^{SRDD} represents treatment in technological group r, σ_r is the standard error of the LATE estimate in technological group r, 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.

Furthermore, policymakers are particularly interested in exploring the impact of different treatment levels on policy outcomes as this may uncover heterogeneities along different amounts of financial aids and provide some information on the optimal level of incentives (Bia & Mattei, 2012). As L488 allows for different levels of subsidies depending on the investment project, the firm dimension, the region and also the firms' choice, in Section 5.4, we explore the relationship between subsidy intensity and TFP growth. To do so, we adopt a modified version of the HLATE RDD framework proposed by Becker et al.

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[10] Before carrying out the analyses, we used a truncation method, wherein extreme values (observations in the first two and last two centiles) are recoded to lowest or highest reasonable values (the value of the 2nd centile and the value of the 98th centile, respectively) to the relative dependent variable.
[11] 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.

(2013),[12] plotting 3D graphs that clearly display the interaction between the forcing variable, the subsidy intensity, and the TFP growth.[13]

5. Results

The components of the TFP change were estimated within an SFA framework, where the time-varying production frontier is specified in translog form; the inefficiency term is modelled by using year dummies, allowing the temporal pattern of TE to be completely flexible (all parameter estimates and specification tests are reported in Appendix A).

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 Centre 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 Northern regions[14]. Furthermore, four industry sub-groups defined according to firms' technology were considered.[15] Following Harris & Moffat (2013), industries were classified based mostly on Eurostat definitions, as high-tech and medium high-tech, medium low-tech, low-tech manufacturing and other non-manufacturing firms. The last classification was applied in all the territorial-auction groups, with the exceptions of Auctions 2 and 4 in the North (in these areas, the small sample size prevented consistent statistical estimates of production frontiers with respect to technology).

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[12] The HLATE RDD allows estimating the LATE for different values of a covariate Z different from the forcing variable. The main assumption underlying the validity of this approach is that Z is uncorrelated with the error term in the outcome equation, conditional on the forcing variable. In the context of our application, this assumption states that, conditional on the sum of the normalized score that determines the subsidy assignment, firms with different intensities do not differ in unobserved dimensions that are relevant for the TFP growth. We do not pursue this approach as there are reasons for considering this assumption "hard to hold" in our context. The main one is that subsidy intensity is not randomly assigned, but rather, it has a decreasing relationship with respect to firm size.

[13] Notice that information on the subsidy intensity requested by non-subsidized firms is crucial for investigating such a relationship.

[14] L488 has financed firms in both northern (Objective 2 or 5b) and southern regions (Objective 1) of the country; however, the subsidy intensity is by far higher in the latter areas, following the map of state aid delineated by the European Commission (De Castris & Pellegrini, 2012).

[15] High-tech and medium high-tech firms were pooled because of small sample size issues. 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.

Finally, 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 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 2-3-4 Auction groups, respectively).

5.1 Estimates of TFP decomposition

The TFP and its components were calculated by using the estimated frontiers and the Divisia decomposition illustrated in Section 4, for every firm and period. 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 1 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[16]. 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 1.5% during the first year after the subsidy is granted and rises to 5.8% 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 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-the-market" effects for the subsidized firms. Conversely, untreated firms show a continuous decline in their AE for all periods.

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

Table 1. Dynamics in TFP components

| | South | | | | | | | | | |
| | 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

South – 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

South - 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

South - 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

South - 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).

The contribution of TE is relevant but negative for all the firms and over (almost) all

the period; 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.

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.

5.2 Multiple RDD estimates

As suggested by Lee & 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 RD estimator.

The main outcomes are presented in Table 2, which provides the decomposition for all subsidized firms in the South. 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 8%. This differential is significant from a statistical point of view for three out of five years. The dynamics of TFP growth rate in subsidized firms appears to 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 technical progress (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 five years. On the other hand, the contribution of technical efficiency (TE) is always negative and statistically significant for two out of five years. The contribution of scale effect (SE) is mixed and always not statistically significant. Finally, the contribution of allocative efficiency (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.

The results suggest that public subsidies 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 component of technical progress 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.

The results are similar also for the subsample of small firms (Table 3). The differences in TFP growth rate in the last two years are slightly larger (9%), whereas the differences in the technical progress growth rate are smaller and statistically not significant. The scale effect 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.

We also report the productivity differential by technological sector in the South (Appendix B). In this case, the number of firms by subsample is considerably lower, affecting the statistical significance of the estimates. The differential in TFP for the low-tech manufacturing firms is higher than the average in the last two years (more than the 15%), even if not statistically significant. The differential in the allocative efficiency is very high in

the last two years, where the technical progress 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 technical progress is always positive, the contribution of the allocative efficiency 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 the technical change is lower than the average.

The conclusion of the analysis is that the TFP differential is basically dominated by two factors: Technical change and allocative efficiency. In sectors where the technical change growth induced by the subsidies through new capital overcomes the negative effect on technical efficiency (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 allocative efficiency differential induced by the subsidies becomes positive. The subsidized firms, usually after three years, are more efficient in the use of the productive factors and can finally fully exploit the new capital. On the other hand, in sectors where the technical progress gain is lower or the allocative efficiency catch-up is modest the impact of the subsidies on TFP is nil or negative.

Table 2. 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	0.00336 (0.00236)	0.00483 (0.00429)	0.00677 (0.00645)	0.01424 (0.00802)*	0.02207 (0.00963)**	0.00190 (0.00235)	0.00196 (0.00424)	0.00346 (0.00608)	0.00936 (0.00807)	0.01532 (0.00999)
Scale Effect	0.00740 (0.00809)	0.00026 (0.00803)	-0.00184 (0.00755)	0.00336 (0.00844)	-0.00488 (0.00967)	0.01143 (0.00852)	0.00726 (0.00944)	0.00593 (0.00792)	0.00710 (0.00833)	0.00446 (0.00959)
Allocative Efficiency	-0.07780 (0.05903)	-0.14907 (0.06395)**	0.01913 (0.06070)	0.14988 (0.06219)**	0.05747 (0.05980)	-0.11246 (0.05418)**	-0.14263 (0.06117)**	0.02241 (0.05718)	0.10644 (0.05604)*	0.03601 (0.05665)
Technical Efficiency	-0.06462 (0.03768)*	-0.06115 (0.04373)	-0.07372 (0.03477)**	-0.01823 (0.04023)	-0.10946 (0.04536)**	-0.04444 (0.03495)	-0.03621 (0.03526)	-0.03894 (0.03293)	-0.02353 (0.04027)	0.01820 (0.04565)
Total Factor Productivity	-0.16239 (0.08136)**	-0.18189 (0.08996)**	-0.06630 (0.08197)	0.13483 (0.07229)*	0.03542 (0.09941)	-0.13678 (0.07803)*	-0.15656 (0.07735)**	-0.01832 (0.07636)	0.11586 (0.07023)*	0.11123 (0.08649)

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 & 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%.

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

Dependent variable	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	0.00209 (0.00546)	0.00457 (0.01081)	0.00780 (0.01556)	0.00792 (0.02123)	0.01006 (0.02676)	-0.00587 (0.00423)	-0.01057 (0.00852)	-0.01353 (0.01249)	-0.01898 (0.01695)	-0.02288 (0.02135)
Scale Effect	-0.00927 (0.01006)	-0.00731 (0.00858)	-0.00515 (0.00706)	-0.02503 (0.01246)**	-0.01714 (0.00802)**	-0.00382 (0.00845)	-0.00480 (0.00783)	0.00069 (0.00667)	-0.00896 (0.00999)	-0.00371 (0.00695)
Allocative Efficiency	-0.04763 (0.05219)	-0.08000 (0.06275)	0.00206 (0.06854)	0.14095 (0.05339)***	0.08884 (0.05520)	-0.02197 (0.04784)	-0.05920 (0.05859)	0.04389 (0.05693)	0.13850 (0.04929)***	0.04731 (0.05133)
Technical Efficiency	-0.09257 (0.03036)***	-0.05964 (0.03378)*	-0.08369 (0.03669)**	-0.00565 (0.04195)	-0.10459 (0.05346)*	-0.04002 (0.02876)	0.01231 (0.03214)	0.00221 (0.03174)	0.03835 (0.04225)	0.02551 (0.04689)
Total Factor Productivity	-0.23133 (0.07663)***	-0.13327 (0.06904)*	-0.00933 (0.07632)	0.13552 (0.06299)**	0.05782 (0.08530)	-0.10696 (0.06283)*	-0.06812 (0.06657)	0.06256 (0.06832)	0.15820 (0.06595)**	0.07006 (0.08954)

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 & Titiunik (2014b). Estimation is implemented in the Stata package rdrobust by Calonico, Cattaneo & 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%.

5.3 What effects on TFP had the subsidies to firms located in the Centre-North regions?

We also estimated the effect of the L488 on TFP for the firms located in the Centre-North regions, that are wealthier that the regions in the South. 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 4). 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 Centre-North regions are affected by the smaller sample dimension. However, TFP growth differential 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. Appendix C presents the productivity differentials by technological sector in the Centre-North regions.

Table 4. Non-parametric and parametric Multiple RDD estimates (CENTRE-NORTH)

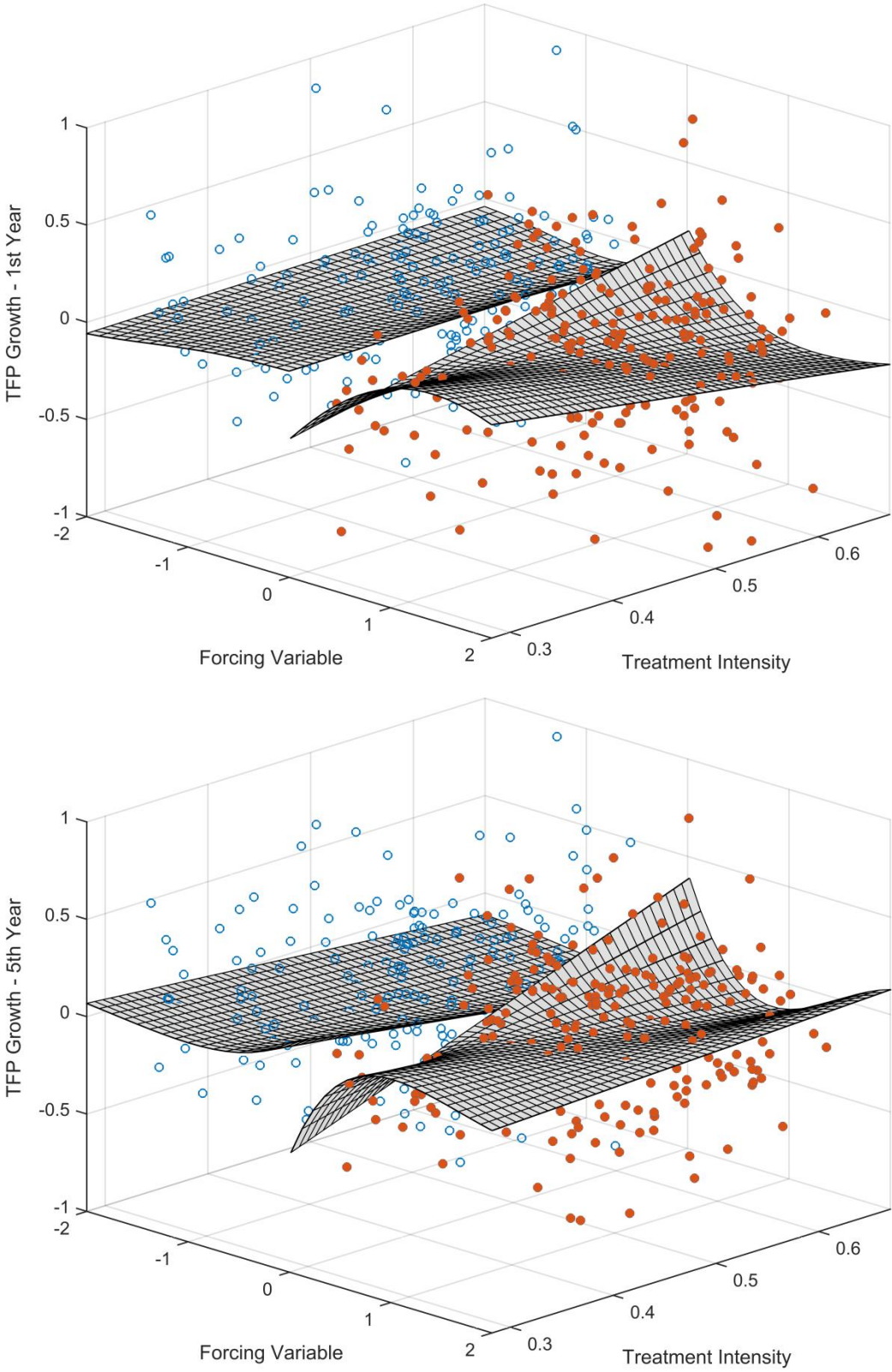| Dependent variable	Weighting scheme: Number of treated firms within the optimal bandwidth									
	Non-parametric estimates					Parametric estimates				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.00065	0.00098	0.00229	0.00347	0.00539	-0.00133	-0.00242	-0.00258	-0.00248	-0.00172
	(0.00139)	(0.00275)	(0.00391)	(0.00501)	(0.00594)	(0.00139)	(0.00262)	(0.00356)	(0.00447)	(0.00517)
Scale Effect	-0.00361	0.00535	-0.00488	-0.00421	-0.03001	-0.01037	0.00241	-0.01752	-0.00119	-0.01706
	(0.00885)	(0.00748)	(0.00729)	(0.00833)	(0.01856)	(0.01222)	(0.01045)	(0.01098)	(0.01013)	(0.01850)
Allocative Efficiency	-0.00160	0.06399	0.06438	0.01382	0.01804	0.01980	-0.00303	0.04733	-0.00033	0.01207
	(0.05609)	(0.06331)	(0.06517)	(0.06509)	(0.06154)	(0.06175)	(0.05897)	(0.05747)	(0.06113)	(0.05557)
Technical Efficiency	0.01202	0.01705	0.03188	0.00977	-0.01039	0.01949	0.01961	0.02817	0.00043	0.01420
	(0.01604)	(0.02008)	(0.01662)*	(0.04032)	(0.04230)	(0.01759)	(0.01935)	(0.01574)*	(0.03730)	(0.04021)
Total Factor Productivity	0.01790	0.03601	0.04494	0.00035	-0.04445	0.03733	0.02659	0.06384	0.01211	0.01979
	(0.05628)	(0.06272)	(0.05384)	(0.08808)	(0.06750)	(0.06174)	(0.06306)	(0.05546)	(0.07837)	(0.06853)

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 & 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%.

5.4 Heterogeneity of the results due to intensity of treatment

The intensity of treatment is strongly heterogeneous across firms, depending on size, region and choices of the firms. We expect that treatment heterogeneity explains some differences in TFP growth across treated firms. The role of heterogeneity is analyzed by a modified version of the HLATE RDD framework proposed by Becker et al. (2013) for scrutinizing the relationship between subsidy intensity and TFP growth (Figure 1). The 3D graph allows a clear display of the interaction between the forcing variable, the subsidy intensity, and the TFP growth (or each TFP component as reported in Appendix D). The solid (hollow) dots indicate firms that received (did not receive) L488 funds. The surfaces represent fifth-order polynomial functions of the forcing variable and linear functions of subsidy intensity. These functions are estimated on both sides of the threshold separately. The top panel in Figure 1 suggests that the year after subsidy assignment, TFP grew at a slower pace for treated firms receiving less than 50% of the total investment (mostly small and medium-large firms) than their counterfactual (very similar untreated firms that basically asked for the same treatment intensities). Observing each TFP components separately (Appendix D), we infer that the slower TFP growth was mainly due to the TE and AE components.

The bottom panel in Figure 1 still shows a negative and wide gap in terms of TFP growth between treated and untreated firms receiving or asking for less than 50% of the total investment. On the other hand, after 5 years of the subsidy assignment, a large TFP premium lies with firms receiving more than 50% of the total investment (mostly micro and small firms). Indeed, the wedges between the two surfaces clearly indicate that the smallest treated firms were those that benefitted the most from the policy in terms of TFP. Looking at Figure E3, we see that this growth is mainly due to the AE component. The effect that we note in the all sample is stronger in the highly subsidized firm: Higher subsidies help to build up larger and up-to-date capital; when these firms, usually after three years, become more efficient in the use of the productive factors, they fully exploit the new capital and increase the dynamics of TFP.

Figure 1. Relationship between TFP growth rate (1st and 5th years), subsidy intensity, and forcing variable

Notes: The upper and lower figures illustrate the relationship between the TFP, forcing variable and subsidy intensity. The solid (hollow) dots indicate firms that received (did not receive) L488 funds. The surfaces represent fifth-order polynomial functions of the forcing variable and linear functions of subsidy intensity. These functions are estimated on both sides of the threshold separately.

6. Robustness analysis

We assess the validity and the robustness of our results on the South adopting various specification tests. First, we rule out possible discontinuities in the conditional density of the forcing variable (the score of the project in the regional ranking), which would indicate evidence of manipulation in the subsidies assignment. The McCrary test (McCrary, 2008) turns out to be negative for each ranking. In Figure F1 of Appendix E, we graphically present the negative results of this test in the rankings split by auction and by technological group.

Additionally, we test whether the TFP components of the financed firms are similar to those of the control group in the year preceding the subsidies assignment. As shown in Table F1 of Appendix F, we find no evidence of statistically significant pre-treatment differences around the cut-off point between subsidized and non-subsidized firms in terms of technological change, scale effect, allocative efficiency, technical efficiency, and TFP. This holds for each technological group and for the aggregated sample.

Following Martorell & McFarlin Jr. (2011), 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 (8) and (9) reported below, show how τ^{MRDD} and σ are computed:

$$\tau^{MRDD} = (\sum_{r=TechGroup} \tau_r^{SRDD} * 1/\sigma_r^2) / (\sum_{r=TechGroup} 1/\sigma_r^2); \quad (8)$$

$$\sigma = \sqrt{1/(\sum_{r=TechGroup} 1/\sigma_r^2)}. \quad (9)$$

Table F2 in Appendix F shows that this weighting scheme produces estimates very close to the ones reported in Table 2.

Finally, to investigate the role of the technical inefficiency modelling, we also considered the time-variant specification of u proposed by Battese and Coelli (1992), that is, $u_{it}=\exp(-\eta(t-T))u_i$, $u_{it} \geq 0$, $i=1,\ldots,N$, $t \in \tau(i)$. Table F3 reports the Multiple RDD estimates using the dynamic specification of u; 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 technical change, scale effect, 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 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, capital subsidies positively affect TFP growth in the medium-long term and not in the short term. The main reason is that the allocative efficiency has a positive effect only after 2-3 years. There are several reasons that explain the finding: Time to learn, time to stay in a larger market, time to adjust factor proportion. 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, 2014a). However, none of these studies perform such a long year-by-year analysis. Indeed, only after the third year are the effects positive and

statistically significant (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 technical progress 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 not confirmed by our empirical evidence. 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 adjust the factor proportion, and sustained by the new technology embedded in the new capital, they 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 A. Descriptive statistics by technological group

Table A1. Descriptive statistics by technological group

	Southern regions		Centre-North regions	
	Treated	**Not-Treated**	**Treated**	**Not-Treated**
Whole sample				
Tangible Capital	478	470	945	542
Value Added	519	541	1305	939
Labor cost	314	324	686	583
# employees	13	13	29	22
ROE	6.84	5.16	9.71	6.01
Net liabilities	485	499	883	482
Cash Flow	123	137	351	198
N	377	697	264	536
Low tech firms				
Tangible Capital	517	525	792	494
Value Added	582	547	1183	828
Labor cost	361	326	648	531
# employees	14	13	30	20
ROE	7.09	4.79	8.27	5.54
Net liabilities	582	533	703	509
Cash Flow	136	141	285	156
N	139	248	90	232
Medium-Low tech firms				
Tangible Capital	544	616	1332	542
Value Added	465	589	1372	951
Labor cost	280	339	698	598
# employees	12	14	27	23
ROE	5.49	4.59	11.02	7.11
Net liabilities	581	544	919	413
Cash Flow	131	153	402	199
N	123	248	88	173
Medium-High and High tech firms				
Tangible Capital	804	655	945	560
Value Added	736	879	1781	1157
Labor cost	392	510	974	723
# employees	17	21	40	25
ROE	9.09	5.39	10.94	7.87
Net liabilities	789	715	1076	540
Cash Flow	204	244	430	273
N	58	97	61	100
Non-Manufacturing firms				
Tangible Capital	131	222	945	658
Value Added	285	298	991	912
Labor cost	154	173	456	627
# employees	7	7	18	23
ROE	8.51	8.21	8.69	3.04
Net liabilities	174	128	967	618
Cash Flow	56	63	325	244
N	57	104	25	31

Note: Amounts of tangible capital, value added, labor cost, net liabilities, and cash flow are expressed in thousands of euros. All euros are measured in 1995 euros.

Appendix B. Production frontier estimates and specification tests

The frontier models are specified for panel data, with both a stochastic frontier production function and a technical inefficiency model (Battese and Coelli, 1995). We use flexible functional forms as the translog production function:

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + \sum_j \sum_{k \geq j} \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t t + \beta_{t2} t^2 + \sum_k \beta_{kt} \ln x_{kit} t + (v_{it} - u_{it});$$

$$i = 1,.., N; \ t = 1,.., T \tag{10}$$

which provides a good local approximation of any twice differentiable arbitrary function, and allows the analysis of the underlying production structure through relatively simple tests on appropriate groups of estimated parameters. The translog form for the terms involving the input levels, x_{kit}, implies that we do not impose any a priori restrictions with respect to the internal return to scale. In (10), $\ln y_{it}$ is the natural logarithm of the value added of firm i in year t. $\ln x_{kit}$ is the logarithm of input k, where k = L, K represent the two inputs, cost of labour and fixed assets respectively. 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, $N(0; \sigma_V^2)$. The nonnegative random variables, (u_{it}), which account for technical inefficiency in production, are assumed to be independently distributed, such that u_{it} is 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. We choose the truncated normal form because of the hypothesis that the market is competitive, that is, the greater proportion of the enterprises operate 'close' to efficiency. It is assumed that the v_{it}s and u_{it}s are independent random variables. Furthermore, yearly dummy variables D_t are used to model the inefficiency term $\mu_{it} = \delta_0 + \sum_t \delta_t D_t + w_{it}$.

The parameters of the frontier production function are simultaneously estimated with those of the inefficiency model (β, δ, σ2, σ2v), in which the technical inefficiency effects are specified as a function of other variables. 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 ML estimates of the parameters in the panel translog stochastic frontier production function for the different Auction groups are given in Table B1. Coefficients have signs and sizes that conform to our expectations. All the other estimate and test by groups are available on request from the authors.

Table B1. 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_{2t}	0.010***	0.006***	0.004***
β_{tL}	0.014***	0.009***	0.001
β_{tK}	-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_ HM2	-0.020	0.033**	0.125***
D_HM3 & HM4	0.079***	0.049***	-0.004
D_HM5	0.054***	0.070***	0.038

	Auction 2	Auction 3	Auction 4
D_Small	0.085***	-0.007	0.019
D_Medium & large	-0.018	0.018	0.032
Inefficiency Model			
δ_0	-8.931***	-5.563***	-4.564***
D_Period2	-3.474*	-1.109***	-0.854***
D_Period3	-1.495*	-2.130***	-2.281***
D_Period4	-3.248*	-3.399***	-3.819***
D_Period5	-1.253**	-3.752***	-3.113***
D_Period6	-0.399	-2.777***	-5.188***
D_Period7	2.344**	-1.540***	-2.083***
D_Period8	-	-0.148**	-2.785***
D_Period9	-	-	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%.

In Table B2, 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 generalised 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, $\beta_t = \beta_{2t} = \beta_{kt} = 0 \ \forall k$, that there is no technical change, is always rejected.

Table B2. 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
$\beta_t = \beta_{2t} = \beta_{kt} = 0 \ \forall k$	46.080***	Rejected	39.69***	Rejected	18.20***	Rejected
$\beta_t = \beta_{2t} = 0$	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%.

We also check, separately, for the presence of neutral technical change and other biased technical change. The neutral technical change leaves the ratio of inputs constant, and shifts the production frontier in parallel and outwards. The biased technical change is the technical 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 $\beta_{kt} = 0 \ \forall k$ indicate the presence of both of the two-dimensional technical changes. On average over the sample period, investment in fixed assets negatively affects the frontier, shifting it downward; while on the contrary, labour 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 labour 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 efficiency is strongly rejected for all the models. The LR tests are in fact equal to 420.564, 449.620 and 388.747 for the second, third and fourth 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.

Appendix C. Non-parametric and parametric RDD estimates for each TFP component by technology

Table C1. Non-parametric and parametric RDD estimates (SOUTH) Low tech firms

Dependent variable	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	-0.00001	-0.00288	-0.00377	0.00824	0.01997	-0.00052	-0.00237	-0.00205	0.00573	0.01404
	(0.00405)	(0.00561)	(0.00865)	(0.00970)	(0.01100)*	(0.00372)	(0.00509)	(0.00695)	(0.00852)	(0.01040)
Scale Effect	0.01523	-0.00904	0.00628	-0.00333	-0.01208	0.01438	0.00213	0.01139	0.00454	0.00255
	(0.01417)	(0.01112)	(0.01173)	(0.01802)	(0.01911)	(0.01431)	(0.01288)	(0.01289)	(0.01638)	(0.01803)
Allocative Efficiency	-0.11206	-0.32236	-0.12252	0.19394	0.12848	-0.11596	-0.23711	-0.01121	0.13721	0.08209
	(0.10485)	(0.11325)***	(0.10750)	(0.12153)	(0.10764)	(0.09803)	(0.10524)**	(0.09053)	(0.10448)	(0.09732)
Technical Efficiency	-0.03332	-0.17961	-0.05878	-0.01933	-0.15516	0.00116	-0.04410	-0.03163	-0.00672	0.16325
	(0.05685)	(0.09129)**	(0.04857)	(0.07113)	(0.11293)	(0.04647)	(0.05438)	(0.04260)	(0.07238)	(0.09674)*
Total Factor Productivity	-0.22021	-0.48297	-0.25708	0.16112	0.15175	-0.15330	-0.23286	-0.03166	0.14774	0.30382
	(0.13188)*	(0.16414)***	(0.15568)*	(0.11397)	(0.21103)	(0.12546)	(0.12604)*	(0.11997)	(0.11904)	(0.17781)*

Note: There are 387 observations (139 treated firms and 248 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 106 (61 T and 45 NT) and 185 (95 T and 90 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%.

Table C2. Non-parametric and parametric RDD estimates (SOUTH) Medium-low tech firms

Dependent variable	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	0.00415	0.00763	0.00989	0.01162	0.01296	0.00235	0.00514	0.00784	0.00918	0.01065
	(0.00306)	(0.00585)	(0.00865)	(0.01127)	(0.01384)	(0.00261)	(0.00502)	(0.00745)	(0.00974)	(0.01201)
Scale Effect	0.00253	-0.00100	0.00020	0.01317	0.00521	0.00936	0.01155	0.01714	0.02457	0.02451
	(0.01131)	(0.01197)	(0.01260)	(0.01039)	(0.01298)	(0.01290)	(0.01346)	(0.01107)	(0.01075)**	(0.01248)**
Allocative Efficiency	-0.05838	-0.03742	0.13405	0.14952	0.05023	-0.04943	-0.01816	0.12349	0.12979	0.06744
	(0.09784)	(0.09281)	(0.10652)	(0.09610)	(0.10407)	(0.10369)	(0.10721)	(0.10983)	(0.10044)	(0.11020)
Technical Efficiency	-0.11860	-0.00725	-0.10205	-0.00110	-0.12354	-0.09090	-0.04993	-0.06949	-0.04724	-0.11713
	(0.06787)*	(0.07551)	(0.06668)	(0.07310)	(0.06380)*	(0.07148)	(0.07752)	(0.07449)	(0.07690)	(0.07024)*
Total Factor Productivity	-0.14470	-0.03227	0.06879	0.17655	-0.06073	-0.08159	-0.06669	0.06269	0.14407	-0.00047
	(0.15415)	(0.15141)	(0.13709)	(0.14173)	(0.14149)	(0.16881)	(0.15511)	(0.14502)	(0.14368)	(0.14468)

Note: There are 371 observations (123 treated firms and 248 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 168 (83 T and 85 NT) and 226 (99 T and 127 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. 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 C3. Non-parametric and parametric RDD estimates (SOUTH) Medium-high or high tech firms

Dependent variable	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	0.00471	0.00882	0.00299	0.01059	0.01993	-0.00159	-0.00538	-0.01238	-0.01229	-0.01185
	(0.00789)	(0.01525)	(0.02194)	(0.03046)	(0.03771)	(0.00840)	(0.01570)	(0.02274)	(0.03156)	(0.03947)
Scale Effect	0.00908	0.01710	-0.00327	0.00115	0.01960	0.01450	0.00932	-0.00111	-0.00108	0.01389
	(0.01931)	(0.02627)	(0.01590)	(0.01677)	(0.01771)	(0.01760)	(0.02621)	(0.01555)	(0.01535)	(0.01731)
Allocative Efficiency	-0.10170	-0.12175	-0.04433	0.01089	-0.09240	-0.24197	-0.20857	-0.08067	0.00766	-0.13739
	(0.11969)	(0.20806)	(0.14867)	(0.14351)	(0.15223)	(0.11058)**	(0.17238)	(0.17116)	(0.13637)	(0.14162)
Technical Efficiency	-0.02169	-0.00285	-0.02919	0.01485	-0.05074	-0.02568	-0.01349	0.03328	0.01092	-0.00027
	(0.10623)	(0.07302)	(0.09760)	(0.07732)	(0.09979)	(0.10272)	(0.07002)	(0.08419)	(0.07534)	(0.08586)
Total Factor Productivity	-0.12583	-0.16440	-0.10795	0.02622	-0.05533	-0.22683	-0.23727	-0.10447	0.02647	-0.04897
	(0.14589)	(0.21550)	(0.21461)	(0.16955)	(0.17820)	(0.13434)*	(0.17905)	(0.23932)	(0.15156)	(0.15946)

Note: There are 155 observations (58 treated firms and 97 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 58 (31 T and 27 NT) and 96 (45 T and 51 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. 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 C4. Non-parametric and parametric RDD estimates (SOUTH) Non-manufacturing firms

Dependent variable	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	0.00935	0.01268	0.02490	0.04066	0.05349	0.01036	0.01315	0.02356	0.04064	0.05615
	(0.00653)	(0.01579)	(0.02228)	(0.02931)	(0.03613)	(0.00738)	(0.01616)	(0.02317)	(0.03068)	(0.03788)
Scale Effect	-0.00462	0.00876	-0.03283	-0.00541	-0.05369	0.00559	0.00838	-0.02440	-0.01603	-0.04376
	(0.03224)	(0.02765)	(0.03036)	(0.02530)	(0.03196)*	(0.02934)	(0.03684)	(0.03054)	(0.02561)	(0.03253)
Allocative Efficiency	0.01025	-0.01874	0.08064	0.22436	0.06449	-0.10818	-0.11373	-0.00885	0.08155	0.03227
	(0.10441)	(0.14281)	(0.08221)	(0.07498)***	(0.06727)	(0.09240)	(0.11631)	(0.08819)	(0.07885)	(0.08224)
Technical Efficiency	-0.06414	-0.05394	-0.08444	-0.11355	-0.05612	-0.07451	-0.01045	-0.06430	-0.04843	-0.02470
	(0.07417)	(0.05947)	(0.06103)	(0.08661)	(0.08138)	(0.07668)	(0.06112)	(0.05898)	(0.07973)	(0.06991)
Total Factor Productivity	-0.08840	0.00595	-0.00657	0.06457	0.10603	-0.12397	-0.08234	-0.07296	0.11213	0.04561
	(0.15089)	(0.15393)	(0.10359)	(0.09922)	(0.12379)	(0.14613)	(0.14851)	(0.11063)	(0.10761)	(0.12427)

Note: There are 161 observations (57 treated firms and 104 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 59 (23 T and 36 NT) and 87 (34 T and 53 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. 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 D1. Non-parametric and parametric RDD estimates (CENTRE-NORTH) Low tech firms

Dependent variable	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	-0.00066 (0.00254)	0.00007 (0.00409)	-0.00273 (0.00634)	-0.00129 (0.00782)	-0.00044 (0.00933)	-0.00534 (0.00268)**	-0.00753 (0.00443)*	-0.01159 (0.00603)*	-0.01251 (0.00760)*	-0.01497 (0.00895)*
Scale Effect	-0.00882 (0.01357)	-0.00291 (0.01105)	-0.01094 (0.00910)	-0.01545 (0.01490)	-0.02576 (0.01822)	-0.00547 (0.01566)	0.01962 (0.01151)*	-0.00538 (0.01034)	0.00232 (0.01404)	0.00005 (0.01406)
Allocative Efficiency	0.08468 (0.08329)	0.01998 (0.09126)	-0.05317 (0.07791)	-0.12527 (0.10822)	-0.06239 (0.08403)	-0.00504 (0.07755)	-0.10845 (0.08420)	-0.08104 (0.07179)	-0.12614 (0.10090)	-0.13898 (0.06531)**
Technical Efficiency	0.01740 (0.03448)	0.03796 (0.02572)	0.01096 (0.02605)	0.11421 (0.09416)	-0.12493 (0.10377)	0.03194 (0.03255)	0.02448 (0.02581)	0.00727 (0.02588)	0.10304 (0.08249)	-0.09755 (0.08293)
Total Factor Productivity	0.07110 (0.08942)	0.02330 (0.09146)	-0.07053 (0.08199)	0.01421 (0.15348)	-0.25213 (0.12547)**	0.02152 (0.08568)	-0.07401 (0.09668)	-0.08478 (0.08024)	0.00580 (0.13498)	-0.25719 (0.11465)**

Note: There are 322 observations (90 treated firms and 232 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 77 (47 T and 30 NT) and 144 (61 T and 83 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%.

Table D2. Non-parametric and parametric RDD estimates (CENTRE-NORTH) Medium-low tech firms

Dependent variable	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	-0.00028	0.00194	0.00716	0.00805	0.01058	-0.00040	-0.00015	0.00166	0.00185	0.00298
	(0.00208)	(0.00438)	(0.00618)	(0.00765)	(0.00997)	(0.00187)	(0.00356)	(0.00449)	(0.00560)	(0.00692)
Scale Effect	0.00346	0.00712	-0.01173	0.00595	0.00455	0.00499	0.00291	-0.01305	0.00585	0.00024
	(0.00969)	(0.00785)	(0.01271)	(0.00698)	(0.00811)	(0.00886)	(0.00851)	(0.01038)	(0.00744)	(0.01167)
Allocative Efficiency	0.04601	0.21188	0.24962	0.29050	0.19756	0.08872	0.06512	0.16935	0.19361	0.19021
	(0.09255)	(0.13140)	(0.14701)*	(0.13983)**	(0.11752)*	(0.10752)	(0.11333)	(0.11896)	(0.11631)*	(0.11438)*
Technical Efficiency	0.03667	-0.01568	0.01866	0.02307	0.02102	0.03837	0.00595	0.02110	0.01853	0.04339
	(0.01391)***	(0.03271)	(0.02051)	(0.02727)	(0.03365)	(0.01800)**	(0.02313)	(0.02363)	(0.02797)	(0.03957)
Total Factor Productivity	0.11376	0.15184	0.24785	0.34521	0.26112	0.15826	0.10301	0.19550	0.24783	0.27808
	(0.09761)	(0.12187)	(0.13764)*	(0.15067)**	(0.13800)*	(0.11660)	(0.11780)	(0.11996)	(0.13110)*	(0.13712)**

Note: There are 261 observations (88 treated firms and 173 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 62 (39 T and 23 NT) and 117 (58 T and 59 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%.

Table D3. Non-parametric and parametric RDD estimates (CENTRE-NORTH) Medium-high or high tech firms

Dependent variable	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	0.00194 (0.00287)	0.00148 (0.00573)	0.00312 (0.00735)	0.00502 (0.01002)	0.00826 (0.01253)	0.00134 (0.00277)	0.00240 (0.00551)	0.00354 (0.00711)	0.00685 (0.00933)	0.01138 (0.01148)
Scale Effect	0.00007 (0.01635)	-0.01693 (0.01750)	-0.01427 (0.01444)	-0.03288 (0.02223)	-0.03124 (0.01816)*	-0.00360 (0.01823)	-0.01102 (0.01784)	-0.00980 (0.01417)	-0.01010 (0.01898)	-0.00935 (0.01769)
Allocative Efficiency	-0.21653 (0.11493)*	-0.20059 (0.11538)*	-0.12298 (0.10388)	-0.17350 (0.10062)*	-0.14335 (0.09995)	-0.13820 (0.10675)	-0.15851 (0.10177)	-0.08752 (0.09167)	-0.19122 (0.09483)**	-0.12169 (0.09736)
Technical Efficiency	-0.00261 (0.01834)	-0.00681 (0.02232)	0.06482 (0.04360)	-0.09423 (0.05983)	0.03672 (0.04241)	0.00235 (0.01808)	-0.01531 (0.02328)	0.03898 (0.03410)	-0.05200 (0.05209)	0.02868 (0.04471)
Total Factor Productivity	-0.20380 (0.11391)*	-0.23549 (0.12555)*	-0.09791 (0.07795)	-0.36408 (0.16502)**	-0.09555 (0.08942)	-0.14155 (0.10606)	-0.18243 (0.10490)*	-0.07180 (0.07459)	-0.29016 (0.14210)**	-0.06106 (0.09171)

Note: There are 161 observations (61 treated firms and 100 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 55 (33 T and 22 NT) and 90 (47 T and 23 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%.
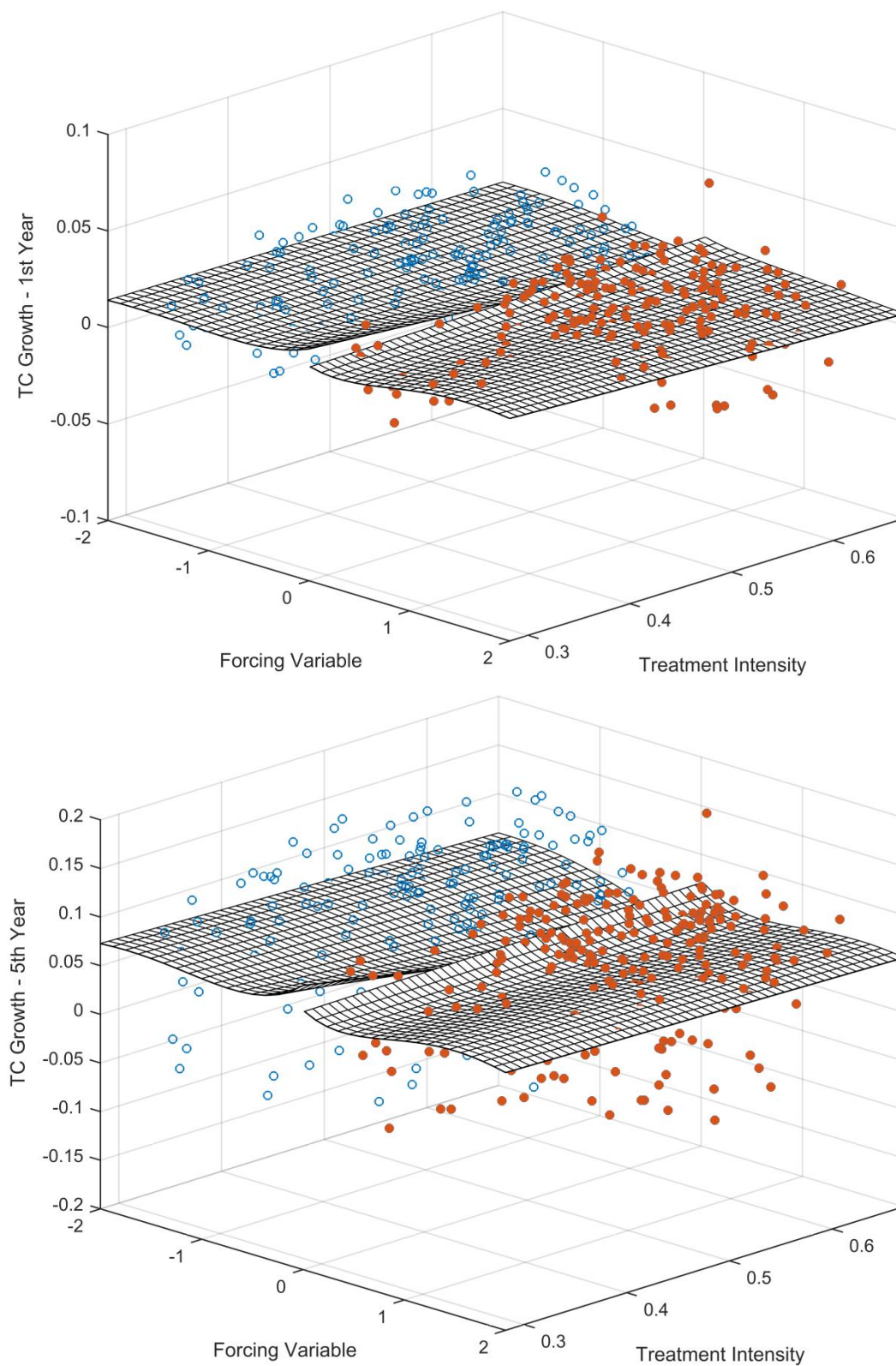
Table D4. Non-parametric and parametric RDD estimates (CENTRE-NORTH) Non-manufacturing firms

Dependent variable	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	0.00613	-0.00173	0.00112	-0.00057	-0.00096	0.00336	-0.00378	-0.00002	-0.00437	-0.00248
	(0.00651)	(0.01456)	(0.02014)	(0.02561)	(0.02170)	(0.00590)	(0.01322)	(0.01974)	(0.02403)	(0.02366)
Scale Effect	-0.02434	0.13414	0.11376	0.10706	-0.17050	-0.09858	-0.02854	-0.09574	-0.01684	-0.15834
	(0.07144)	(0.06191)**	(0.05563)**	(0.04927)**	(0.17447)	(0.10262)	(0.08752)	(0.09757)	(0.07781)	(0.17907)
Allocative Efficiency	0.11074	0.55586	0.38723	0.21040	0.22965	0.25213	0.51601	0.40897	0.23568	0.25522
	(0.28629)	(0.24645)**	(0.26545)	(0.21848)	(0.26787)	(0.36908)	(0.27403)*	(0.27602)	(0.24029)	(0.26551)
Technical Efficiency	-0.05884	0.16619	0.07573	-0.25383	0.18023	-0.04994	0.13538	0.10197	-0.30480	0.27846
	(0.12454)	(0.16785)	(0.08085)	(0.18348)	(0.23167)	(0.12176)	(0.15256)	(0.07137)	(0.20281)	(0.24466)
Total Factor Productivity	0.07837	0.58029	0.47934	-0.12899	0.02553	0.10509	0.62975	0.46638	-0.05743	0.30500
	(0.24876)	(0.27684)**	(0.18681)**	(0.34355)	(0.26538)	(0.30727)	(0.29125)**	(0.21937)**	(0.33999)	(0.26513)

Note: There are 56 observations (25 treated firms and 31 control firms); however, for non-parametric estimates, the actual number of observations within the bandwidth ranges between 19 (9 T and 10 NT) and 48 (22 T and 26 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%.
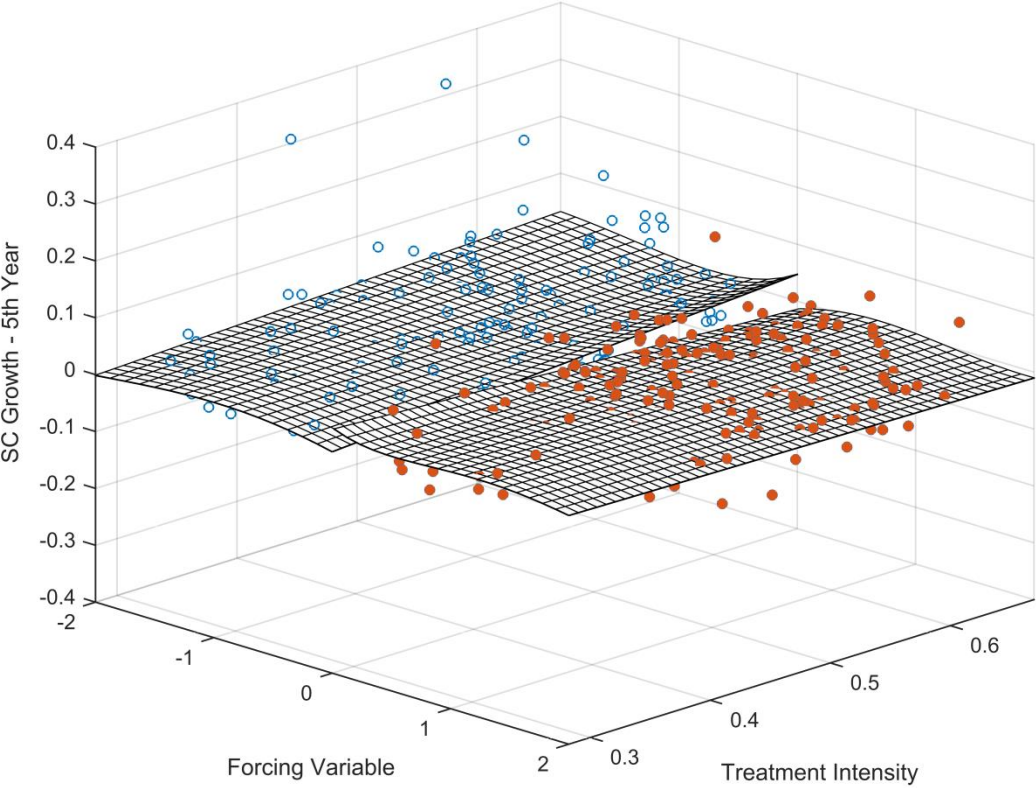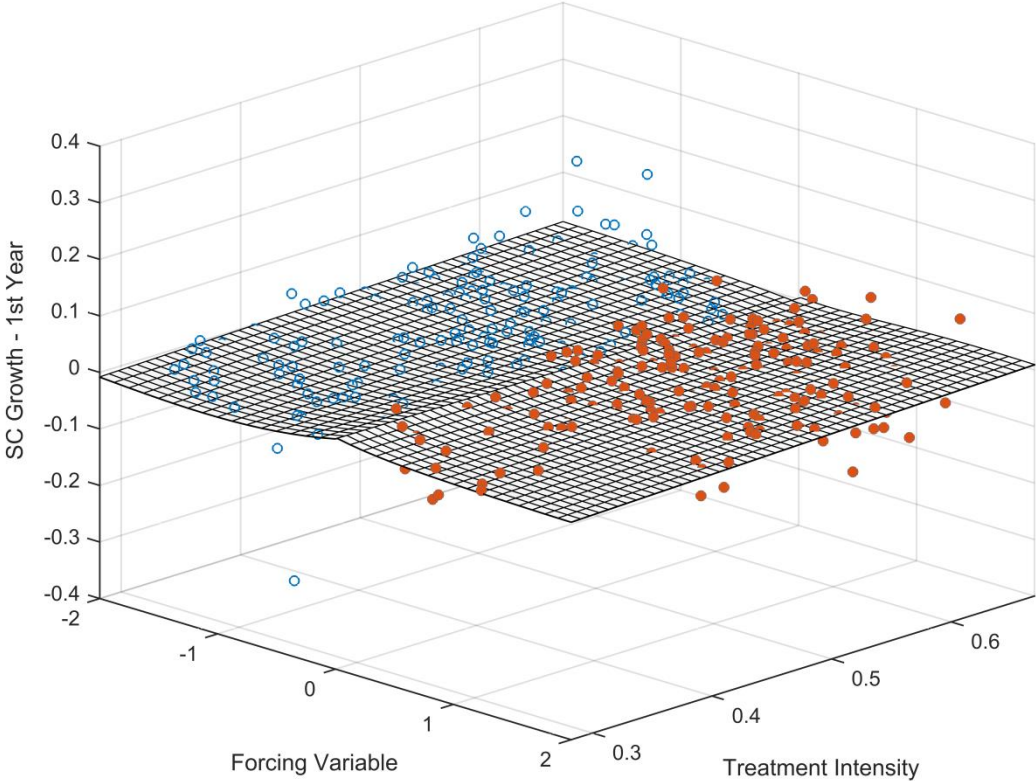
Appendix E. Heterogeneity of the results due to intensity of treatment (TC, SC, AE, TE)

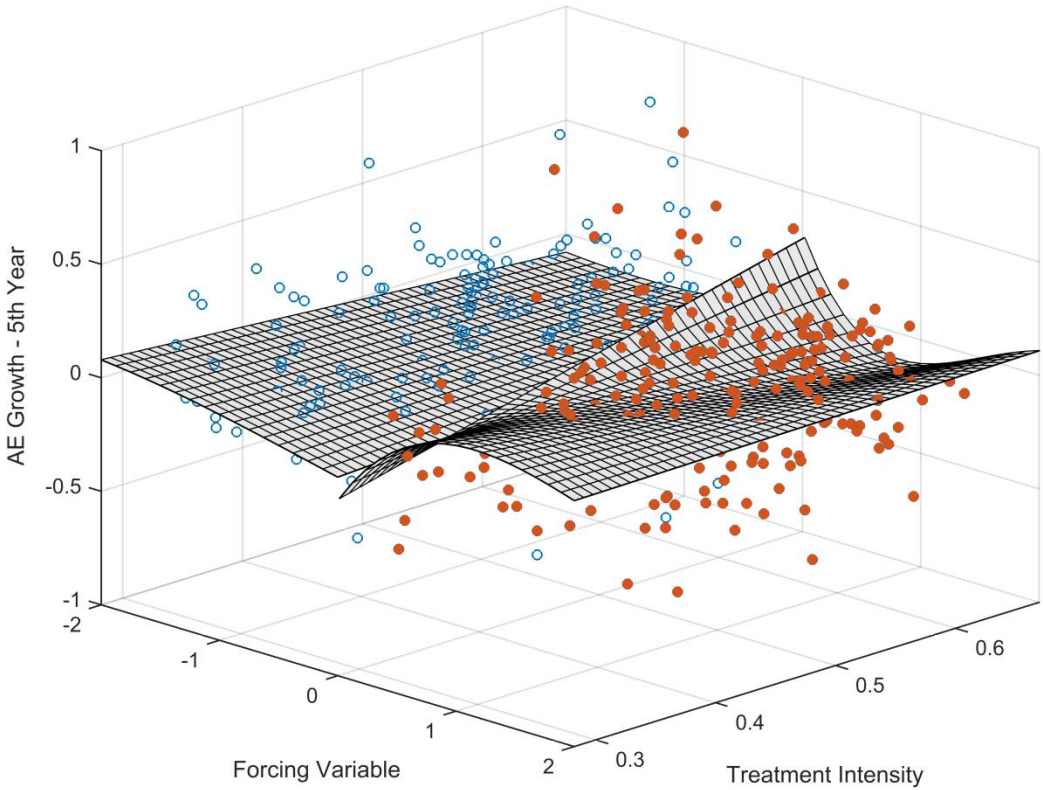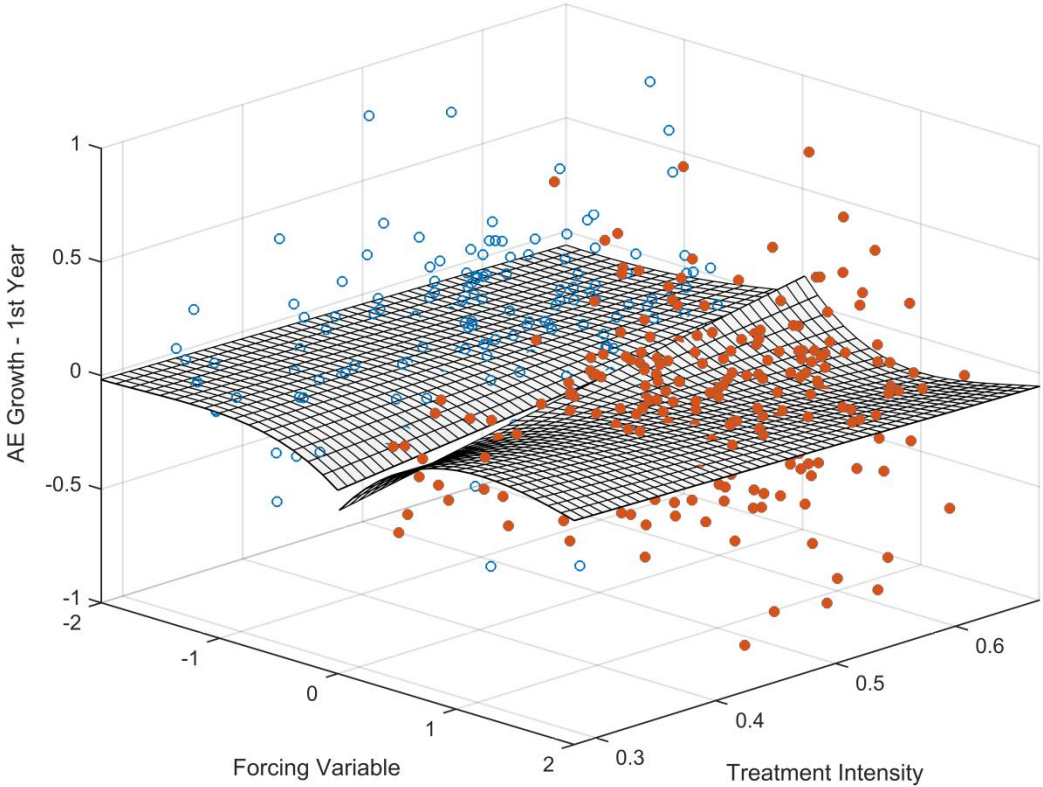**Figure E1. Relationship between TC growth rate (1st and 5th years), subsidy intensity, and forcing variable**

Notes: See notes of Figure 1.

Figure E2. Relationship between SE growth rate (1st and 5th years), subsidy intensity, and forcing variable
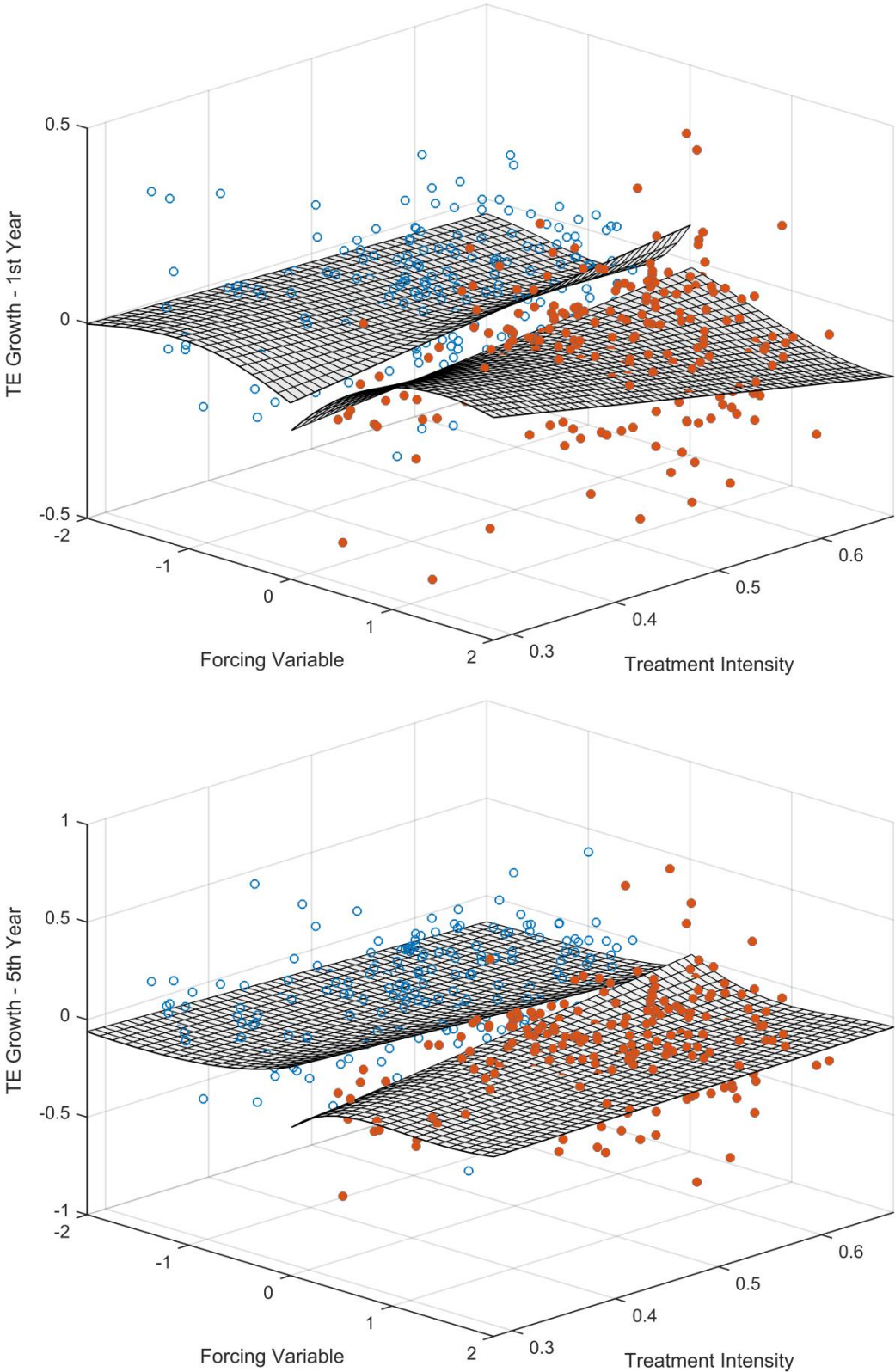

Notes: See notes of Figure 1.

Figure E3. Relationship between AE growth rate (1st and 5th years), subsidy intensity, and forcing variable

Notes: See notes of Figure 1.

Figure E4. Relationship between TE growth rate (1st and 5th years), subsidy intensity, and forcing variable

Notes: See notes of Figure 1.

Appendix F. Robustness tests

Table F1. RDD estimates of the pre-treatment differences in TC, SE, AE, TE, and TFP between subsidized and non-subsidized firms

Dependent variable	Non-parametric estimates					Parametric estimates				
	Low tech	Medium-low tech	Medium-high and high tech	Non-manufact uring	All	Low tech	Medium-low tech	Medium-high and high tech	Non-manufact uring	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	-0.00301	0.00052	-0.02425	-0.03124	-0.00756	-0.00224	0.00062	-0.00245	-0.03246	-0.00591
	(0.00948)	(0.00736)	(0.03174)	(0.02270)	(0.00684)	(0.00984)	(0.00665)	(0.03165)	(0.02545)	(0.00751)
Scale Effect	-0.00567	-0.01583	0.01283	0.01308	-0.00528	-0.01390	-0.01482	-0.00463	-0.00217	-0.01100
	(0.00987)	(0.00852)*	(0.01304)	(0.02339)	(0.00580)	(0.01119)	(0.00978)	(0.01497)	(0.02349)	(0.00672)
Allocative Efficiency	0.03011	-0.03065	0.11052	-0.02342	0.01170	0.02832	-0.04434	0.14428	0.00849	0.01946
	(0.06324)	(0.07835)	(0.14312)	(0.05784)	(0.04513)	(0.06446)	(0.08388)	(0.12344)	(0.06305)	(0.04201)
Technical Efficiency	0.03965	0.04929	-0.00014	0.08031	0.04149	-0.02109	0.06410	-0.01278	0.04451	0.01790
	(0.02863)	(0.04406)	(0.07618)	(0.05862)	(0.02640)	(0.02304)	(0.05311)	(0.07026)	(0.05432)	(0.02359)
Total Factor Productivity	0.06863	0.04470	0.12050	-0.00403	0.05825	0.03307	0.01268	0.12179	0.03142	0.03982
	(0.09140)	(0.09956)	(0.15467)	(0.07949)	(0.05579)	(0.08914)	(0.11275)	(0.13100)	(0.08368)	(0.05477)

Note: For the aggregated estimates (5) and (10) 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. 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 F2. Non-parametric and parametric Multiple RDD estimates (SOUTH) using an alternative weighting scheme

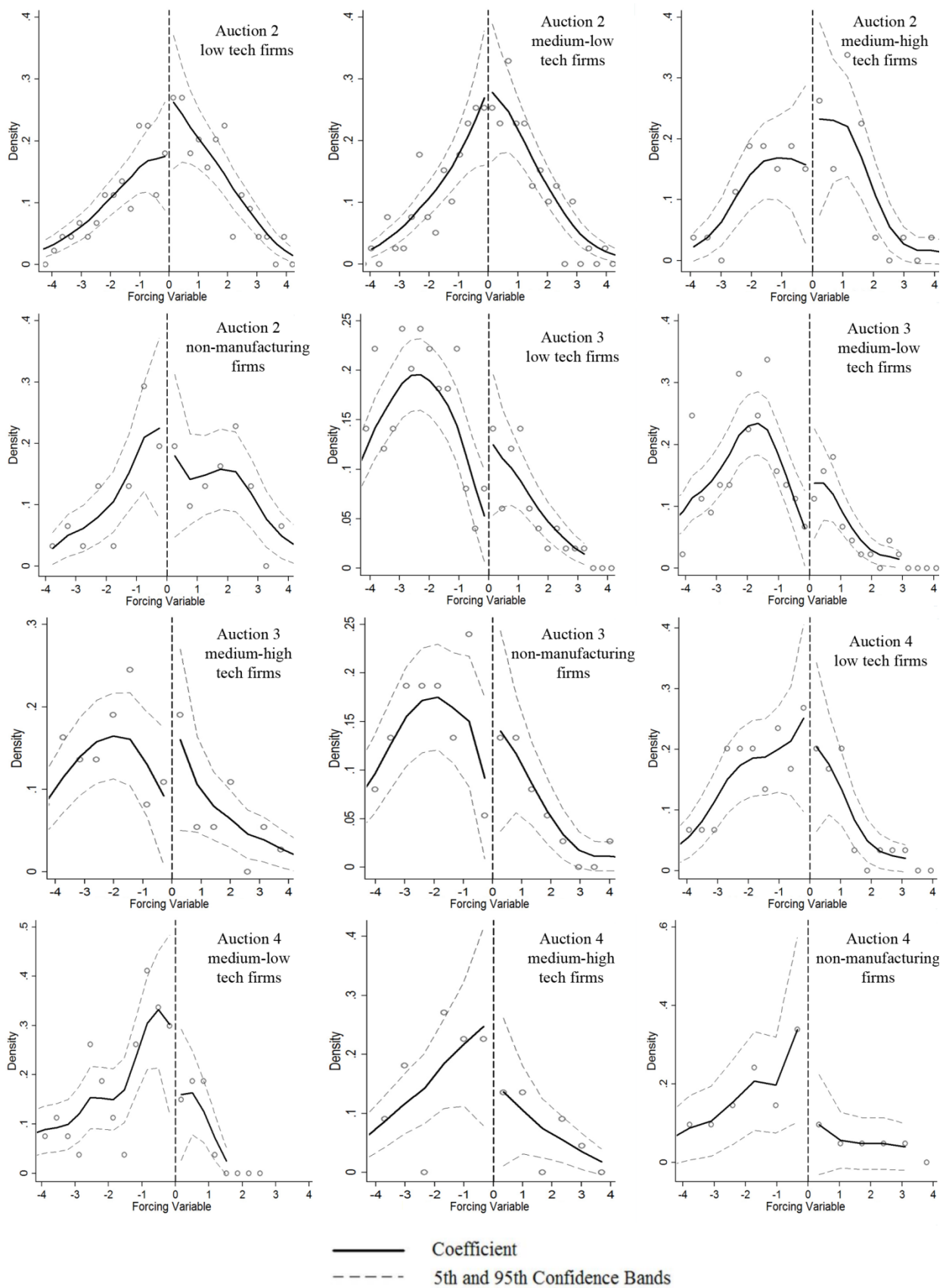| Dependent variable	Weighting scheme: Inverse-variance weighting									
	Non-parametric estimates					Parametric estimates				
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 1	Year 2	Year 3	Year 4	Year 5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Technological Change	0.00356 (0.00220)	0.00318 (0.00380)	0.00448 (0.00570)	0.01146 (0.00694)*	0.01924 (0.00818)**	0.00189 (0.00199)	0.00163 (0.00340)	0.00279 (0.00485)	0.00783 (0.00616)	0.01343 (0.00756)*
Scale Effect	0.00702 (0.00780)	-0.00246 (0.00749)	-0.00009 (0.00733)	0.00615 (0.00757)	0.00060 (0.00883)	0.01176 (0.00809)	0.00702 (0.00853)	0.00917 (0.00718)	0.01105 (0.00742)	0.01235 (0.00852)
Allocative Efficiency	-0.06289 (0.05293)	-0.12476 (0.06129)**	0.03028 (0.05214)	0.17335 (0.04985)***	0.05870 (0.04752)	-0.12406 (0.05025)**	-0.13485 (0.05925)**	0.01355 (0.05216)	0.09612 (0.04967)*	0.03149 (0.05092)
Technical Efficiency	-0.06229 (0.03543)*	-0.00504 (0.03614)	-0.07200 (0.03128)**	-0.02434 (0.03820)	-0.09746 (0.04168)**	-0.03503 (0.03290)	-0.02947 (0.03201)	-0.03771 (0.02936)	-0.02158 (0.03797)	-0.01752 (0.03923)
Total Factor Productivity	-0.1499 (0.07245)**	-0.15659 (0.08320)*	-0.04730 (0.06911)	0.10893 (0.06165)*	0.03281 (0.07689)	-0.15422 (0.07056)**	-0.15777 (0.07432)**	-0.03240 (0.06801)	0.10835 (0.06339)*	0.05785 (0.07383)

Note: See notes of Table 2.

Table F3. Non-parametric and parametric Multiple RDD estimates (SOUTH) using a time-variant specification of *u*

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	0.00088	-0.00033	-0.00045	0.00290	0.00669	0.00053	-0.00076	-0.00101	0.00164	0.00482
	(0.00147)	(0.00191)	(0.00278)	(0.00344)	(0.00402)*	(0.00139)	(0.00194)	(0.00264)	(0.00328)	(0.00399)
Scale Effect	0.00770	0.00832	0.00200	0.01162	0.00217	0.01716	0.01897	0.01136	0.01641	0.01068
	(0.01122)	(0.01157)	(0.01128)	(0.01395)	(0.01302)	(0.01128)	(0.01240)	(0.01133)	(0.01231)	(0.01292)
Allocative Efficiency	-0.06269	-0.14462	0.03447	0.17234	0.07682	-0.12989	-0.15761	0.03439	0.12363	0.03595
	(0.06922)	(0.07253)**	(0.07139)	(0.07369)**	(0.07426)	(0.06475)**	(0.07225)**	(0.06788)	(0.06430)*	(0.06693)
Technical Efficiency	-0.00032	-0.00056	-0.00075	-0.00087	-0.00089	-0.00016	-0.00025	-0.00028	-0.00025	-0.00015
	(0.00042)	(0.00082)	(0.00118)	(0.00153)	(0.00186)	(0.00046)	(0.00087)	(0.00126)	(0.00161)	(0.00195)
Total Factor Productivity	-0.05306	-0.14778	0.01396	0.18161	0.08330	-0.10325	-0.14740	0.03957	0.13792	0.05610
	(0.06465)	(0.07029)**	(0.06607)	(0.06869)***	(0.06915)	(0.06230)*	(0.06934)**	(0.06442)	(0.06075)**	(0.06351)

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%.

Figure F1. 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.