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Economic performance of Brazilian manufacturing firms: a counterfactual analysis of innovation impacts

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Abstract This article assesses if innovators outperform non-innovators in Brazilian manufacturing during 1996–2002. To do so, we begin with a simple theoretical model and test the impacts of technological innovation (treatment) on innovating firms (treated) by employing propensity score matching techniques. Correcting for the survivorship bias in the period, it was verified that, on an average, the accomplishment of technological innovations produces positive and significant impacts on the employment, the net revenue, the labor productivity, the capital productivity, and market share of the firms. However, this result was not observed for the mark-up. Especially, the net revenue reflects more robustly the impacts of the innovations. Quantitatively speaking, innovating firms experienced a 10.8–12.5 percentage points (p.p. henceforth) higher growth on employment, a 18.1–21.7 p.p. higher growth on the net revenue, a 10.8–11.9 p.p. higher growth on labor productivity, a 11.8–12.0 p.p. higher growth on capital productivity, and a 19.9–24.3 p.p. higher growth on their market share, relative to the average of the non-innovating firms in the control group. It was also observed that the conjunction of product and process innovations, relative to other forms of innovation, presents the stronger impacts on the performance of Brazilian firms.

Keywords Technological innovation · Average treatment effect · Propensity score matching

JEL Classifications O31 · O33 · C40 · L26

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1 Introduction

The exposure of Brazilian manufacturing firms to external competition made clear the technological gap faced by them, especially in technology diffusion sectors. As a result, there was a rush toward the adequacy of technological pattern to international practices, mainly through technology imports and imitation that afterward boosted an increase in the industry's productivity. However, this pattern of technological adequacy had a restrictive stamp and tended to limit the evolution path of both the individual firms and the industrial sector as a whole.

Brazilian manufacturing firms suffer from limited technological investment, lack of larger investments in R&D and are extremely centered in the acquisition of embodied technology in machines and equipments. Stimulating solid technological strategies based on the acceleration of R&D investments is one of the necessary conditions to assure long run economic development. Nevertheless, one should assess the economic rationality of technological investments, i.e., if innovating firms indeed show a differentiated performance. In order to assist the comprehension of the possible benefits to firms from different types of innovation, it is interesting to take a clear picture from the impacts of diverse technologic innovation forms at the firm level.

In spite of the wide empirical literature concerned with the relationship between technological innovation and firm performance, results do not provide definitive answers. These answers are, in most cases, contradictory, depending either on the measure of performance adopted or on the firms' characteristics considered.

Benavente and Lauterbach (2006), using the model proposed by Jaumandreu (2003), found a positive relationship between product innovation and employment demand for Chilean firms. Huergo and Jaumandreu (2004) verified that Spanish firms which undertook processes innovation experimented higher growth in their total factor productivity. Kemp et al. (2003) did not observe significant differences between the innovative and non-innovative firms' profitability in Germany. The author also suggests that only sector differences could explain the disparity between innovators and non-innovators. Using data for 228 small British firms from West Midlands region, Freel (2000) found that innovators showed better performance (measured by sales growth, employment, and profit) among fast-growing firms. Finally, in a seminal article with the suggestive title: "*Do innovating firms outperform non-innovators?*" Gerosky and Machini (1992) assessed the relationship between innovative activities and firms' profitability and found positive and significant differences regarding the profit margins of innovative and non-innovative firms.

In Brazil, Goedhuys (2007) showed that innovative activities affect positively the TFP growth, especially in the long run. Additionally, De Negri et al. (2007) evidenced that R&D activities influence the level of physical capital investments, which holds relationship with the long run firm growth.

Given those uncounted results, one may notice how difficult it is to obtain definitive responses about the impacts of innovative activities on firms' performance. It is important to keep in mind that the direction and magnitude of innovation impacts may vary with the period considered. With no intention of providing decisive answers this article wishes to contribute with the enrichment of this discussion.

The question that motivates this work is: *Do Brazilian innovative firms exhibit superior economic performance than non-innovators?* We employed six measures for firms' performance, which are: size, measured by number of employees, net revenue, labor productivity, capital productivity, market share, and markup. To do so, we applied matching methods based on propensity score (PSM), taking the accomplishment of technological innovation during 1998–2000 as the treatment variable, and taking the following 2-year period, 2001–2002, as the comparison period for the impact variables.

We can separate the contributions aforementioned into two different econometric approaches: (i) papers that incorporate innovations in growth/performance equations ad hoc or based on some structural equation derived from theoretical model (for instance, Jaumandreu 2003); (ii) the ones which estimate structural equations systems directly, as in CDM-like models in three stages, made popular first by Crepon et al. (1998) (for instance, De Negri et al. 2007). Our work does not fit in any of those two groups, since we derive possible impacts instead of estimating structural models. We verify the existence (or not) of theses impacts by comparing characteristics of very similar firms in such a way that the only difference between them will be the fact that one succeeded in the innovative activity and the other did not.[1]

This article is organized as follows. Section 2 presents a comparative static exercise concerning the innovative impacts on firm's performance, where we depict some possible results about product and process innovation impacts. In Sect. 3, we are concerned with some methodological aspects related to the estimation techniques, while in Sect. 4 we

[1] It means that the validity of the innovation impacts on firm's performance does not critically depend on the formulation of the structural equations.

describe data sources and information about the sample. Section 5 discusses the econometric results and Sect. 6 concludes the article.

2 Comparative statics of innovation impacts on firm growth

This section intents to present some basic principles of microeconomics to guide the expected results about the impacts of innovative activity on production, employment, profit margin, and market share. The assumption we adopted is that the innovative activity is undertaken in order to obtain profits. Firm's revenue associated to innovation can be derived from three different sources: (i) licensing for those who do not develop new technology; (ii) incorporation of technologic advances in their own products, which lead to the conquer of new markets; (iii) or even from the introduction of new production processes that boost the productivity of production factors, generating cost advantages and consequently profit increases.

2.1 Process innovations

Formally, some impacts of process innovation on firm performance can be represented by the technological parameter, A—also known as total factor productivity or Solow residual—which represents a symmetric increase in the marginal productivity of both factors of production, labor and capital. In order to analyze the set of impacts suggested, it may be worthy to model the industry-level effects of innovation. Therefore, we derive initially the Stackelberg model of duopoly according to which firms produce a homogeneous product. The leader firm, 1, is the innovative one, while firm 2 is the follower, and, at least in this stage, does not innovate. Thus, consider a maximization problem of usual conditional cost, assuming a CES (Constant Elasticity of Substitution) production function, as follows:

$$\text{Min } C_i = wL_i + rKi$$

Subject to

$$q_i = A_i(\delta L_i^{-\rho} + (1-\delta)K_i^{-\rho})^{\frac{-1}{\rho}}, \text{ with } i = 1,2 \tag{1}$$

In the problem above, w is the wage, r is the capital cost, L is labor factor, K is capital factor, A is the efficiency parameter (Hicks neutral), δ is the distribution parameter, with $0 < \delta < 1$, and ρ is the substitution parameter, with $-1 < \rho < \infty$. Assuming w and r fixed, or given by the market, and allowing that labor and capital are adjustable, one should notice that the capital–labor ratio is constant and given by:

$$k_i = \frac{K_i}{L_i} = \left(\frac{(1-\delta)}{\delta}\frac{w}{r}\right)^{\frac{1}{1+\rho}} \tag{2}$$

Consequently $L_i = \left((1-\delta)\left(\frac{(1-\delta)}{\delta}\frac{w}{r}\right)^{\frac{-\rho}{1+\rho}} + \delta\right)^{\frac{1}{\rho}} \frac{q_i}{A_i} = \Psi q_i A_i^{-1}$. Assuming an inverse demand curve given by $p = a - b(q_1 + q_2)$, with $a, b > 0$, the profits maximization problem of the follower firm is given by:

$$\text{Max Profit}_2 = pq_2 - (w + rk_2)\Psi\frac{q_2}{A_2} \tag{3}$$

The derivative of (3) with respect to q_2 allows the attainment of firm's 2 reaction function, given by:

$$q_2 = \Gamma - \frac{q_1}{2} \tag{4}$$

with $\Gamma = \dfrac{a - \frac{(w+k_2r)\Psi}{A_2}}{2b}$, so that $\Gamma > 0$ if $a > \text{Cmg}_2$.

As we notice in (4), the follower firm has its supplied quantity negatively related to the quantity supplied by the leader firm. The solution to leader firm's similar problem, using (4) to represent q_2, produces q_1's supply equation that can be written as:

$$q_1 = \frac{a}{b} - \Gamma - \left(\frac{(w + k_1r)\Psi}{bA_1}\right) \tag{5}$$

Starting with the above equations, it is possible to derive some propositions regarding the possible impacts of process innovation.

Proposition 1 *For the leader firm that accomplishes process innovation, the technologically neutral impact of technological progress on the produced quantity will be positive.*

Proof Deriving (5) with respect to the technological progress, A_1 and notice that the derived is always positive, that is:

$$\frac{\mathrm{dq_1}}{\mathrm{d}A_1} = \frac{(w + k_1r)\Psi}{bA_1^2} > 0$$

Proposition 2 *The impact of process innovation on employment of the leader firm will be positive, since* *the increase in production more than compensates the reduction in labor demand resulted from the supposition of constant production.*

Proof Combining (5) with the labor demand equation (4), it is possible to derive the labor demand equation in order to get:

$$\frac{\mathrm{dL}_1}{\mathrm{d}A_1} = \frac{(w + k_1 r)\Psi^2}{bA_1^3} - \frac{\Psi\left(\frac{a}{b} - \Gamma - \frac{(w+k_1 r)\Psi}{bA_1}\right)}{A_1^2}$$

Corollary 1 *The impact of process innovation will be negative on production and on employment of the follower firm.*

Proof Using (4) and letting $L_2 = \Psi q_2 A_2^{-1}$, it is directly observable that the impact on output and employment will be both negative for the follower firm.

Corollary 2 *Assuming a market with constant size, there will be an increase in the market share of the innovative firm, contrasting with a decline in the market share of the non-innovative firm. This impact will be greater the higher the elasticity of demand.*

Proof The Corollary 2 follows directly from the Proposition 1 and the Corollary 1.

For this model, if we assume a linear demand curve in which the elasticity of demand depends on the produced quantity, it is possible that the mark-up (given by the price-to-the-marginal-cost ratio) also changes with the technical progress event. In fact, since the total cost curve of i firm given by $C(q_i) = (w + k_i r)\Psi q_i A_i^{-1}$, with i = 1, 2, it is clear that the shift in A_1 might produce only a reduction in the marginal cost of the leader firm. Meanwhile, the price reduction will be noticed by both firms with the same intensity. Hence, we have the following proposition:

Proposition 3 *The leader firm's mark-up increases with process innovation, since* $(a - b\Gamma) > 0$, *while the mark-up of the follower firm always falls.*

Proof It is only necessary to use the mark-up formula as the ratio of price (given by the inversed demand) and marginal cost and then differentiate with respect to A_1. Intuitively, it happens that the price decrease is a function of the quantity variation below the increase in the production of the leader firm in function of the follower firm. This leads to an increase in the profit margin of leader firm and a reduction in the profit margin of follower firm, that is[2]:

$$\frac{\mathrm{dmkup}_1}{\mathrm{d}A_1} = \frac{(a - b\Gamma)}{2(w + k_1 r)\Psi} > 0 \text{ since } (a - b\Gamma) > 0$$

$$\frac{\mathrm{dmkup}_2}{\mathrm{d}A_1} = -\frac{(w + k_1 r)A_2}{2(w + k_2 r)A_1^2} < 0$$

2.2 Product innovations

For product innovations it is convenient to alter the setting of the model previously adopted in such way that we incorporate the imperfect substitution between goods produced by the leader and the follower firms. Using linear demand functions we get:

$$p_1 = \alpha_1 - \beta_1 q_1 - \varphi q_2 \tag{6a}$$

$$p_2 = \alpha_2 - \varphi q_1 - \beta_2 q_2 \tag{6b}$$

In the equations above, parameters α_1, α_2, β_1, β_2, and φ are all larger than zero. Conveniently, we assume quadratic curves to total costs, given by $TC_1 = 0.5cq_1^2$ and $TC_2 = 0.5cq_2^2$, so that c is constant and positive. Thus, it is possible to replicate the profit maximization exercise showed above and find the following reaction function for the follower firm:

$$q_2 = -\frac{\varphi q_1 - \alpha_2}{c + 2\beta_2} \tag{7}$$

That reaction function will have a negative slope if $\varphi q_1 > \alpha_2$, which is a plausible hypothesis considering the reasonable amount of output and/or the existence of a non-negligible parameter φ. Inserting this result in the profit maximization problem of the leader firm, we obtain the produced quantity in equilibrium, expressed as:

[2] In comparison with an alternative specification of the model, based on a constant elasticity curve for the inversed demand function, given by $p = H(q_1 q_2)^{-1/\eta}$ and on a Cobb-Douglas production function $q_i = A_i\ L^a K^b$, i = 1, 2, the only different result is the one for the mark-up variable, if respected the conditions of decreasing returns to scale. In the second alternative specification, the mark-up becomes, obviously, invariant given the supposition of constant elasticity of demand.

$$q_1 = \frac{(c+2\beta_2)\alpha_1 - \varphi\alpha_2}{c^2 - 2\varphi^2 + 2c\beta_2 + 2\beta_1(c+2\beta_2)} \quad (8)$$

The impact of a product innovation could be represented by a positive shift in the demand, or even by the supposition that changes in attributes reduce price sensitivity to demanded quantity by shifting the slope of the demand function ($d\beta_1 < 0$). Under these hypotheses, we can also derivate a set of possible impacts from product innovation, similarly as we did with process innovations:

Proposition 4 *Product innovations have a positive impact on leader firm's production.*

Proof By hypothesis, the impacts of product innovations can be the result of changes in both parameters α_i and β_i. It is also possible to see that both these impacts are positive on production if the denominators in the two following equations are positive:

$$\frac{dq_1}{d\alpha_1} = \frac{(c+2\beta_2)}{c^2 - 2\gamma^2 + 2c\beta_2 + 2\beta_1(c+2\beta_2)} > 0$$
$$\frac{dq_1}{d\beta_1} = -\frac{2(c+2\beta_2)(\alpha_1(c+2\beta_2) - \gamma\alpha_2)}{(2\beta_1(c+2\beta_2) + c^2 + 2c\beta_2 + 2\beta_1 - 2\varphi^2)^2} > 0$$

Corollary 3 *Product innovations have positive impact on innovative firms' employment as well as on their market share. The opposite occurs with the follower firms.*

Proof Considering the demand function for labor and the reaction function of the follower firm, it is directly inferred that the effects on both leader firm's production and follower firm's production as well as on employment are similar than those observed in the case of process innovation. Consequently, assuming a constant size market, it is also verified that an increase in the market share of leader firm in detriment of follower firm's participation.

Proposition 5 *The mark-up of leader firm increases with product innovation, while the mark-up of the follower falls.*

Proof As before, defining mark-up as the ratio of price to marginal cost and considering the particularities of the linear model described here, it is possible to derive some results regarding the impacts of product innovation on leader and follower firm's mark-up. The mark-up' can be written as:

$$\mathrm{mkup}_1 = \frac{p_1}{\mathrm{Cmg}_1} = \frac{\alpha_1 + \frac{\varphi\alpha_2}{c+2\beta_2} + 2q_1\left(\frac{\varphi^2}{c+2\beta_2} - \beta_1\right)}{cq_1}$$
$$\mathrm{mkup}_2 = \frac{p_2}{\mathrm{Cmg}_2} = \frac{\alpha_2 - 2\beta_2 q_2 - \varphi q_1}{cq_2}$$

Considering the expressions above, it is straightforward that $\frac{\mathrm{dmkup}_1}{d\alpha_1} = \frac{1}{cq_1}$ and $\frac{\mathrm{dmkup}_1}{d\beta_1} = -\frac{2}{c}$. Hence, the leader firm's mark-up will experience a positive impact associated not only with the increase in α_1, but also with the decrease in β_1. However, the impact of a shift of α_1 depends on the output level, and it is lower and as larger as the leader firm's output level, while the impact of β_1 does not depend on the produced quantity. On the other hand, the follower firm's mark-up depends on the quantity supplied by the leader firm, and does experience a decrease if the leader firm increases its production. As shown above, it might occur either due to an increase in α_1 or to a decrease in β_1.

3 Estimation strategy[3]

In this article, we aim to analyze if there was any effect from innovation on the several aforementioned measures of firms' performance, such as labor productivity, capital productivity, market share, and mark-up. Let $\mathrm{INOV}_{it} \in \{0,1\}$ be the indication of innovation by firm i and $y^1_{i,t+s}$ the measure of the firm performance at $t+s$, with $s \geq 0$, following innovation. Additionally, denote $y^0_{i,t+s}$ as the measure of firm performance in the case when i does not innovate in t. The causal effect of innovation of firm i at period $t+s$ is then defined as $y^1_{i,t+s} - y^0_{i,t+s}$.

The main problem of causal inference in this case is that $y^0_{i,t+s}$ is not observed for firms that have innovated (i.e., those for which we observe $y^1_{i,t+s}$). Hence, nothing can be said about the causal impact without some hypothesis about the value of $y^0_{i,t+s}$. This hypothetical value is called counterfactual. Here, we conduct an inference based on the comparison of the factual outcome with the counterfactual outcome which is conventionally named in the literature as treatment evaluation. Specifically here,

[3] This section is based on papers of Dehejia and Wahba (1998), Abadie et al. (2001) and Cameron and Trivedi (2005).

we analyze the average treatment effect on the treated unit (ATET), defined as:

$$\begin{aligned}\text{ATET} &= E\left(y^1_{i,t+s} - y^0_{i,t+s} | \text{INOV}_{\text{it}} = 1\right) \\ &= E\left(y^1_{i,t+s} | \text{INOV}_{\text{it}} = 1\right) - E\left(y^0_{i,t+s} | \text{INOV}_{\text{it}} = 1\right)\end{aligned} \tag{9}$$

The unobservability problem of $E\left(y^0_{i,t+s} | \text{INOV}_{\text{it}} = 1\right)$ is solved by the construction of a control group and by the estimation a function such as $E\left(y^0_{i,t+s} | \text{INOV}_{\text{it}} = 0\right)$. The average output for the non-innovative group identifies the counterfactual average output for the innovative group, in the absence of innovation. Once we consider technological innovation as a result of firm's choice, we could not attend innovation as a random event. Hence, estimating causal effects of innovation on firm's performance by comparing directly the treatment and control groups will produce biased results. The endogeneity of firm's choice arises from the fact that firm's decision to attempt innovations is correlated with observable and unobservable characteristics, which describes a problem of sample selectivity. In order to correct this problem of "*selection on observables*," we employed matching methods based on propensity score (PSM).

The PSM method allows the correction of sample bias when it pairs an innovative firm from the treatment group, with a non-innovative firm from the control group, in such a way that both firms are similar regarding their observable characteristics, which allows the comparison between their performances. Hence, indentifying $\boldsymbol{x}_i$ as the set of covariates composed by firm's observable characteristics observed in the pre-treatment period, it is possible to predict the decision to innovate, $\text{p}(\text{x}_i) = Pr\left(\text{INOV}_{\text{it}} = 1 \middle| x_{i,t-1}\right)$. Allowing for overlaps in subsamples of innovators and non-innovators, each innovative firm is paired to a non-innovative one, conditionally on their observable pre-innovation characteristics. The non-innovative firms that are paired to innovative ones define the control group. Hence, it is possible to ensure that the output does not determine participation, which allows the estimation of ATET.[4] To estimate $p(x)$ we used a logit model where x_i is composed by the following covariates: employment, or the number of employees on December 31st (log), average years of schooling of the labor force (log), average wage (log), labor productivity (log of the ratio of gross value of firm's production to number of employee), capital productivity (log of the ratio of gross value of firm's production to capital stock), market share (% ratio of firm's net revenue to total sector's net revenue), markup (ratio of net revenue to operational costs), export activity (dummy equals 1 if firm have exported in 1996 or 1997), foreign ownership participation (dummy equals 1 if foreign ownership is greater than 50%), sector control variables (CNAE—two digit), and representative variable of inverse Mills ratio (Mills^{-1}) from the Heckman's selection equation estimated for firms' survivorship probability model.[5] Continuous variables are, in fact, the average value observed in both years before treatment (innovation), which are 1996 and 1997. This guarantees the non-simultaneity between treatments and firm's initial conditions.[6] Logit results are shown in the Appendix.

Let p_i denote the predicted probability of the firm i undertaking innovation and let this firm belong to the group of firms that effectively innovated (INOV $= 1$). Also, denote p_j as the predicted probability of firm j in the control group (defined here as $C(x_i)$). The ATET general expression is written as:

$$\Delta^M = \frac{1}{N} \sum_{i \in \text{INOV}=1} \left(y^1_i - \sum_{j \in C(x_i)} \omega(i,j) y^0_j \right) \tag{10}$$

where $0 < \omega(.) \leq 1$ and $\omega(.)$ is the function that assigns weight to the jth firm corresponding to counterfactual from the ith innovative firm, according to the matching algorithm. In this article we estimate the ATET by applying two methods:

(a) radius matching, which defines $C(x_i)$ as $C(x_i) = \left\{ p_j \middle| \left\| p_i - p_j \right\| < r \right\}$, where r indicates the radius with dimension $\boldsymbol{\omega}(.) = 1$[7] and;

[4] This is called independence of treatment assignment. The output for the control group (not treated) is $y^0 \perp \text{INOV} | x_i$. The PSM relies on this assumption.

[5] The construction of the capital stock variable is based on the method of perpetual inventory, using data from Annual Survey of Manufacturing firms (PIA). The survivorship probability model is similar to the one described in De Negri et al. (2007).

[6] According to Ashenfelter (1975) and Ashenfelter and Card (1985) *apud* Dehejia and Wahba (1998), the use of more than one pretreatment period is essential to an improved estimation of treatment effect.

[7] The *radius matching* assumes that observations have fixed weights that disable the adoption of sample weighting in ATET

(b) *kernel matching*, where $\omega(i,j) = \frac{K\left[\frac{p_i - p_j}{h}\right]}{\sum_{i \in C(x_i)} K\left[\frac{p_i - p_j}{h}\right]}$, K is a Gaussian kernel and h is the bandwidth parameter.[8]

PSM methods are useful under the assumption of "selection on observables." However, it is possible that the innovation decision is a function of individual firm's heterogeneity, so that the unobservable factors could partially define the output and also the decision to innovate. Supposing those unobservable factors are time invariant, it would be interesting to associate matching estimators with difference-in-differences method (DID). This would eliminate differences in performance's measures between innovators and non-innovators due to unobservables that have not been eliminated by the matching estimator. Because of this, we estimated ATET not using the variables in levels, but in their differences. Defining Δy_i^1 as $\Delta y_i^1 = y_{i,t+s}^1 - y_{i,t}^1$ and Δy_i^0 as $\Delta y_i^0 = y_{i,t+s}^0 - y_{i,t}^0$, the matching estimator associated with difference-in-differences can be expressed by:

$$\Delta^{M,\mathrm{DID}} = \frac{1}{N} \sum_{i \in \mathrm{INOV}=1} \left(\Delta y_i^1 - \sum_{j \in C(x_i)} \omega(i,j) \Delta y_j^0 \right) \quad (11)$$

Finally, it is important to mention three features regarding the matching estimation conducted here. We estimated matching with replacement and one single match for each innovative firm, chartering the bias reduction in detriment of variance reduction. We also ran tests for balancing properties, that is, we tested using t-test of differences of covariates' means in each quartile of each variable. These tests showed no differences in the distribution of covariates between innovative firms and non-innovative ones in the control group. Additionally, we imposed a restriction of common support of probability of innovation in order to make the matching estimation more accurate. This restriction implies that the tests for balancing properties—and ATET and DID estimates—were only run for the firms whose propensity scores fell within the ranges determined by the propensity scores of innovators and control groups.

4 Data source and sample features

Information employed in the empirical analysis conducted here was extracted from five different datasets: Technological Innovation Survey of Manufacturing Firms (Pintec), provided by the Brazilian Institute Geography and Statistics (IBGE), the Annual Survey of Manufacturing firms (PIA), provided by IBGE, Foreign trade data (SECEX) provided by the Ministry of Development, Industry and Foreign Trade; Annual Report of Social Information (RAIS) provided by the Ministry of Labor and Employment; and the Foreign Capital Census (CCE) provided by the Brazilian Central Bank (BACEN). By matching those datasets using firm's identification number (CNPJ) as the key variable, it was possible to construct the samples for our analysis.

The strategy adopted to draw the sample is mainly based on the Pintec-2000 survey, which covers the period from 1998 to 2000, denoted as the period t. This period establishes the moment of innovation, and innovation may happen in any year of the 1998–2000 period. With the firm's CNPJ comprised by Pintec, we matched the PIA, SECEX, RAIS, and CCE databases in the years of 1996–1997 and 2001–2002. Therefore, two more periods were defined: the pre-innovation period, $t-1$, comprised by the years 1996 and 1997 and the pos-innovation period, $t+1$, comprised by the years 2001 and 2002.

An important aspect considered in our estimations is the sample selection problem. According to the sample drawing, firms that were selected remained in the PIA survey for at least 7 years consecutively (1996–2002). Hence, the fact that a given firm drops out of the data survey during the considered period must be due to three factors: (i) a reduction in the total employment to a size class below 30 workers, in such a way that the firm does not belong to the non-random strata of the PIA survey.[9]

Footnote 7 continued
estimation. In this article the distance (radius) of the neighborhood is 0.01 which is the maximum value allowed for the difference between distances in the propensity *scores* of treated and untreated units.

[8] The unit's weight for kernel function is assigned by the bandwidth parameter between treated and untreated units. However, our sample has its own sampling weight (Pintec-2000), which is also used in the matching procedure and not only in those observations belonging to that distance. This distance was limited to 0.06.

[9] There are two strata in the PIA survey. The first stratum comprises a non-random sample of all Brazilian manufacturing firms with more than 30 employees. The second stratum is a randomly selected sample composed by firms with 5–29 employees.

This can be observed if a firm is not identified in PIA but still remains registered in RAIS (which is a census-type of survey); (ii) a fusion or acquisition by other firm—PIA brings information about structural changes; or (iii) bankruptcy, determined if any of the above options is observed. In order to correct the survivorship bias we estimated a probability model for firm's survivorship, based on the Heckman's model for bias correction (1979), and the variable representing the inverse Mills ratio was later inserted in the propensity score equation, as mentioned previously.[10]

An additional issue concerning the sample construction is the necessity to ensure the non-simultaneity between firm's performance, observed in the period 2001–2002 and the attainment of innovation in the period 2001–2003 (registered in Pintec 2003, posterior to Pintec 2000). In other words, if a given firm has innovated in the 1998–2000 period and also innovated in the following 2001–2003 period, it is possible that its performance during the period of 2001 and 2002 is correlated with the fact that the firm is getting prepared to attempt innovations in this same period. However, some descriptive tabulation using Pintec 2000 indicates that the innovation cycle, defined by the life-time of the main product/process until its substitution, is over than 3 years. More precisely, most firms report that the life-time of its main products or processes is more than 9 years, which may have two reasons: either firms might by facing some difficulty to accomplish technological innovations or firms with longer innovation cycle might be taking advantage of innovation returns for a longer period. Those evidences exceptionally decrease the possibility of simultaneity between performance and innovation during the period analyzed.

Pintec 2000 discriminates the innovations activities by type: product innovation, process innovation, and both product and process innovation; and by extension: market or firm. The definition of the treatment variable was modified in order to refine results and capture further differences between innovative activities. Table 1 presents the definition of those treatment variables and its representativity. It demonstrates that the treatment group composition changes with the specification of the innovation variable, giving rise to different subsamples. The total sample, apart from type or extension, has 11,097 firms. The control group is the same for all sorts of treatment, with 5,473 non-innovative firms. The more restrictive innovative activity is specified, the smaller is the proportion of innovators. Note that the total of firms that undertook process or both product and process innovation are larger than those which conducted solely product innovations. Additionally, we observe that the firm innovations exceed market innovations.

The output variables or firms' performance measures described in Sect. 3, are: employment, net revenue, labor productivity, capital productivity, market share, and markup. Values extracted from PIA were deflated using the wholesale price index, IPA-OG (Índice de Preços por Atacado—Oferta Global calculated by FGV). The advantage of IPA-OG is its availability of sector-specific indices, according to the National Classification of Economic Activity (CNAE) at the three-digit level.

In order to observe the relationship between the different kinds of innovation and firm performance variables, Table 2 presents some descriptive statistics of the performance variable in the pre-innovation period (1996–1997) and post-innovation period (2001–2002).

Initially, it is possible to observe that non-innovative firms exhibit average performance values clearly lower than innovative ones, without any consideration about the innovation categories. If we compare the values among both periods, we observe that non-innovative firms exhibited a decrease in the average value in all performance variables from the pre-innovation to the post-innovation period. However, that decrease was also observed in some others innovation categories like capital productivity, market share, and mark-up. It is important to note that in 2001 and 2002 Brazil faced a period of economic instability, due to the crisis in electric/energy sector, and political instability, engendered by the presidential dispute, which could have reflected the firm's performance values.

5 Econometric results

This section presents the results for ATET with difference-in-differences calculated using radius

[10] Following the survivorship model estimated in De Negri et al. (2007), the identification variable for the selection equation was the log of the ratio of financial expenses (including factoring) to net revenue—this variable was separated in four quantiles categories.

Table 1 Definition of treatment variables

Variable name	Description	No. of firms	p.p. of total firms (%)	Group	p.p. of the group (%)	Obs.
Inov	Innovators	5,624	50.68	–	–	–
Noninov	Non-innovators	5,473	49.32	–	–	–
Inovprod	Product innovators solely	1,060	9.55	–	–	–
Inovproc	Process innovators solely	2,125	19.15	–	–	–
Prodproc	Product and process innovators	2,439	21.98	–	–	–
Inovprodfirm	Product innovators solely, for firm	729	6.57	Group of product innovators (solely)	69	
Inovprodmarket	Product innovators solely, for market (includes product innovators for firm)	330	2.97		31	258 are also product innovators for firm
Inovprocfirm	Process innovators solely, for firm	1,864	16.80	Group of process innovators (solely)	88	
Inovprocmarket	Process innovators solely, for market (includes process innovators for firm)	260	2.35		12	211 are also process innovators for firm
Prodmarkprocmark	Product and process innovators, for market (includes product/process innovators for firm)	410	3.70	Group of product and process innovators	17	122 are also product and process innovators for firm
Prodfirmprocfirm	Product innovators for market and process for firm	412	3.72		17	282 are also product innovators for firm
Prodfirmprocmark	Product innovators for firm and process for market	204	1.84		8	127 are also process innovators for firm
Prodfirmprocfirm	Product and process innovators for firm	1,411	12.72		58	

Obs.: Values calculated according to sampling weights from Pintec 2000. "–" Not available

matching and kernel matching. Each method was employed to one of each six types of performance variables and then the analysis was repeated to each innovation category (treatment). The control group is the same for all estimations and is composed by the non-innovators firms.

Table 3 reports the results of the analysis for the three largest categories of innovation, which are: innovators, process innovators, and product innovators. Initially, it is important to notice that both matching results, radius and kernel, are similar, except for the product innovation category. In this last case, radius matching gives statistically significant results, while kernel matching does not. Except for the employment variable for product innovative firms, the market share and the markup variables for process innovators, we observed significant differences in favor of innovative firms for all other innovation categories. More precisely, innovative firms exhibit more significant differences in growth in terms of net revenue and market share. Firms that undertook process innovations are largely benefited by performance differentials, especially in terms of employment, net revenue, and labor productivity. Employment growth was not significant for product innovative firms, although they revealed positive variations in the net revenue, labor, and capital productivity, compared to the control group. From a quantitative point of view, those firms experienced, on an average, growth rates from 10.8 to 12.5 percentage points (p.p.) higher in employment, from 18.1 to 21.7 p.p. higher in net revenue, from 10.8 to 11.9 p.p. higher in labor productivity, from 11.8 to 12.0 p.p. higher in capital productivity, and from 19.9 to 24.3 p.p. higher in market share.

Discriminating firms according to the extension of innovations, Table 4 illustrates the matching results for innovators in process or product solely for the firm or for market. It is very interesting to notice that firms that innovated only in product did not reveal any significant impact on its performance. Although, when we estimate kernel matching, product innovators for the market present positive effects on their net revenue. For process innovators for the firm the

Table 2 Performance variables (mean) and innovative activities at pre- and post-treatment periods

Performance variables	Employment		Net revenue (Thousand Reais)		Labor productivity (Reais)		Capital productivity		Market share (%)		Markup	
Treatment (innovation category)	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Innovators	326 (824)	335 (795)	61,800 (268,000)	72,300 (319,000)	63,531 (71,553)	61,513 (72,466)	1.5 (0.983)	1.17 (0.855)	0.923 (3.1)	0.842 (.93)	0.583 (0.951)	0.507 (0.54)
Non-innovators	161.95 (347.17)	153.3 (327)	20,800 (70,700)	20,600 (88,200)	43,058 (48,203)	36,987 (47,501)	1.4 (1.03)	1.00 (0.834)	0.331 (1.16)	0.266 (0.89)	0.513 (0.554)	0.422 (0.497)
Product innovators	204 (360)	195.8 (321)	43,800 (152,000)	44,900 (787,000)	71,451 (86,093)	62,040 (68,167)	1.62 (0.997)	1.24 (0.921)	0.671 (2.4)	0.507 (1.59)	0.606 (1.52)	0.49 (0.707)
Process innovators	216 (396)	233 (525)	28,000 (71,000)	32,700 (92,200)	48,211 (55,785)	47,643 (62,019)	1.42 (1.02)	1.11 (0.874)	0.453 (1.33)	0.404 (1.17)	0.544 (0.61)	0.486 (0,51)
Product and process innovators	474 (1,154)	485 (1,066)	99,100 (385,000)	119,000 (458,000)	73,443 (74,514)	73,464 (80,290)	1.5 (0.929)	1.21 (0.804)	1.44 (4.2)	1.37 (4.14)	0.606 (0.868)	0.534 (0.476)
Product innovators for firm	179 (313)	172 (273)	37,000 (143,000)	37,500 (199,000)	65,466 (88,456)	53,656 (64,500)	1.61 (1.02)	1.18 (0.909)	0.543 (2.08)	0.389 (1.31)	0.616 (1.8)	0.487 (0.807)
Product innovators for market	259 (442)	246 (403)	57,200 (170,000)	61,100 (155,000)	84,660 (79,318)	80,515 (72,471)	1.67 (932)	1.36 (0.939)	0.952 (2.99)	0.768 (2.06)	0.583 (0.531)	0.498 (0.411)
Process innovators for firm	202 (366)	223 (524)	25,200 (68,800)	29,800 (90,000)	43,909 (49,920)	44,375 (60,232)	1.39 (1.02)	1.09 (0.842)	0.375 (1.1)	0.342 (0.984)	0.529 (0.618)	0.478 (0.521)
Process innovators for market	313 (559)	304 (529)	48,000 (832,000)	54,300 (104,000)	78,987 (80,667)	70,994 (69,404)	1.68 (1.03)	1.26 (1.06)	1.01 (2.37)	0.853 (2.01)	0.652 (0.54)	0.54 (0.425)
Product for market and process for market	1,151 (2.126)	1,075 (1.634)	280,000 (760,000)	330,000 (770,000)	106,914 (98,771)	112,595 (96,807)	1.59 (0.979)	1.15 (0.695)	3.84 (7.59)	3.77 (7.69)	0.622 (0.501)	0.611 (0.496)
Product for firm and process for firm	269 (618)	294 (696)	43,900 (177,000)	58,600 (354,000)	58,658 (58,986)	58,318 (68,766)	1.45 (0.91)	1.19 (0.814)	0.613 (1.69)	0.566 (1.8)	0.576 (0.791)	0.504 (0.469)
Product for market and process for firm	464 (1,002)	482 (1,016)	92,200 (310,000)	110,000 (340,000)	86,721 (76,576)	86,901 (88,241)	1.63 (0.944)	1.32 (0.844)	1.47 (3.5)	1.4 (3.15)	0.692 (1.37)	0.573 (0.492)
Product for firm and process for market	317 (815)	324 (765)	59,400 (265,000)	70,200 (30,200,000)	62,839 (71,026)	61,132 (72,568)	1.5 (0.986)	1.18 (0.856)	0.87 (2.93)	0.797 (2.8)	0.581 (0.962)	0.507 (0.544)

Obs.: Standard deviations in bracket

Table 3 Impacts of innovation (ATET–DID)

Innovation category	Method	Employment	Net revenue	Labor productivity	Capital productivity	Market share	Markup
Innovators	Radius	0.108*** (0.025)	0.181*** (0.027)	0.108*** (0.030)	0.118*** (0.038)	0.199*** (0.068)	−0.001 (0.027)
	Kernel	0.125*** (0.016)	0.217*** (0.021)	0.119*** (0.025)	0.120*** (0.029)	0.243*** (0.044)	0.03 (0.023)
Process innovators	Radius	0.127*** (0.026)	0.192*** (0.034)	0.110** (0.042)	0.091* (0.049)	0.017 (0.046)	−0.023 (0.034)
	Kernel	0.121*** (0.019)	0.200*** (0.025)	0.076*** (0.029)	0.086** (0.034)	0.048 (0.045)	−0.002 (0.025)
Product innovators	Radius	0.055 (0.040)	0.194*** (0.051)	0.174*** (0.053)	0.214*** (0.068)	0.083** (0.136)	0.033 (0.052)
	Kernel	0.013 (0.028)	0.019 (0.037)	0.005 (0.037)	0.043 (0.048)	−0.130 (0.090)	0.025 (0.27)

Control group: non-innovative firms

*Significant at 10%; **significant at 5%; ***significant at 1%

Standard errors in brackets

Table 4 Impacts of process or product innovation (ATET–DID)

Innovation categories	Method	Employment	Net revenue	Labor productivity	Capital productivity	Market share	Markup
Product innovators for firm	Radius	0.030 (0.042)	−0.001 (0.059)	0.011 (0.065)	0.031 (0.082)	0.091 (0.175)	−0.006 (0.069)
	Kernel	0.039 (0.030)	0.012 (0.042)	−0.005 (0.043)	0.025 (0.056)	−0.044 (0.094)	−0.028 (0.061)
Product innovators for market	Radius	0.045 (0.055)	0.06 (0.065)	0.002 (0.074)	0.103 (0.093)	0.059 (0.090)	−0.010 (0.067)
	Kernel	0.032 (0.041)	0.112** (0.050)	0.066 (0.058)	0.108 (0.072)	0.078 (0.093)	−0.037 (0.047)
Process innovators for firm	Radius	0.117*** (0.027)	0.187*** (0.035)	0.127*** (0.041)	0.090* (0.049)	0.080 (0.092)	0.024 (0.036)
	Kernel	0.102*** (0.020)	0.214*** (0.026)	0.127*** (0.031)	0.112*** (0.036)	0.048 (0.042)	−0.002 (0.027)
Process innovators for market	Radius	0.156*** (0.061)	0.193** (0.089)	0.135 (0.087)	0.192* (0.109)	0.143 (0.128)	0.076 (0.073)
	Kernel	0.110*** (0.038)	0.160*** (0.054)	0.122*** (0.050)	0.095 (0.065)	0.053 (0.108)	0.027 (0.055)

Control group: non-innovative firms

*Significant at 10%; **significant at 5%, ***significant at 1%

Standard errors in brackets

impacts were positive and significant at 5% for employment, net revenue and labor productivity. At level 10% of significance, kernel matching produced positive results of impacts on capital productivity of firms that innovated only for firm. The largest differences in the growth rates were observed, in both methods, for the net revenue variable followed by labor productivity and employment.

Finally, Table 5 reports the matching results for firms which accomplished, jointly, product and process innovations, considering also the 'extension' of innovation (if for the firm of for the market). It is worthy to notice that in this table the significance level for rejection of the null hypothesis in tests for mean differences is, on an average, lower than previous tables. Hence, significant results were

Table 5 Impacts of process and product innovation (ATET–DID)

Innovation category	Method	Employment	Net revenue	Labor productivity	Capital productivity	Market share	Markup
Product for market and process for market Innovators	Radius	0.145*** (0.055)	0.275*** (0.066)	0.185*** (0.068)	0.200** (0.089)	0.279 (0.230)	0.076 (0.067)
	Kernel	0.194*** (0.48)	0.324*** (0.059)	0.161** (0.072)	0.140 (0.086)	0.796*** (0.156)	0.039 (0.059)
Product for firm and process for firm innovators	Radius	0.144*** (0.032)	0.207*** (0.040)	0.124*** (0.046)	0.126** (0.053)	0.139 (0.093)	0.018 (0.046)
	Kernel	0.136*** (0.021)	0.261*** (0.027)	0.167*** (0.031)	0.180*** (0.036)	0.127** (0.058)	0.036 (0.036)
Product for market and process for firm innovators	Radius	0.134*** (0.047)	0.299*** (0.060)	0.105* (0.059)	−40.023 (0.069)	0.350*** (0.150)	−0.004 (0.055)
	Kernel	0.159*** (0.037)	0.276*** (0.045)	0.146*** (0.048)	0.150*** (0.058)	0.257*** (0.090)	0.034 (0.048)
Product for firm and process for market innovators	Radius	0.130* (0.072)	0.244*** (0.093)	0.193** (0.087)	0.222* (0.114)	0.532* (0.275	0.070 (0.083)
	Kernel	0.170*** (0.050)	0.277*** (0.059)	0.178*** (0.060)	0.195** (0.077)	0.721*** (0.228)	0.063 (0.058)

Control group: non-innovative firms

*Significant at 10%; **significant at 5%; ***significant at 1%

Standard errors in brackets

observed for the market share variable in most types of innovations. Additionally, firms that conduct product and process innovations enlarge their market share 79.6 p.p. more than non-innovators[11] according to the kernel matching results. As observed before, the markup variable was not affected by innovations and the average impact on net revenue is increasing. However, in opposition to former results, the capital productivity variable presents observable differences concerning the control group, identifying the most important source of variation in this variable. Yet, the significance level of rejecting the null hypothesis varies between 1 and 10%, and it is not rejected even at 10% of significance in both tests. Thereafter, without any evident order, employment and labor productivity variables appear. Another important observation is that the estimated impacts are, on an average, larger among product and process innovators, in comparison with other types of innovation, conducted solely, independent of the innovation extension.

[11] One must remember that, in general, the growth on the market share of innovators happens at the expenses of the decrease on the market share of non-innovators.

6 Conclusions

The aim of this article was to assess the impacts of different forms of innovation on the performance of Brazilian manufacturing firms. To do so, the methodology adopted was propensity score matching (PSM) associated with difference-in-differences techniques. We estimated the impacts of 13 forms of innovation, defined according to the type of innovation (process, product or both process and product) and extension (firm solely or market), taking as control group the non-innovative firms.

Before stating conclusions about the results, it is necessary to detach some limitations regarding the employment of PSM to our study. First, the PSM analysis was designed to identify a causal effect due to an exogenous intervention (possibly a public policy) on a group of individuals. Whenever this strategy is applicable to observable data, it is possible to reproduce the feature of a quasi-experimental study. Therefore, it is reasonable to ask whether the employment of PSM to technological innovation analysis is appropriate or not. The methodological restrictions take place in the identification hypothesis; specifically the ones regarding the assumption of absence of general equilibrium effects and also the absence of unobservable factors simultaneously correlated with both innovation decision and innovation outputs.

Considering the former supposition, it is important to keep in mind that the study was lead at the firm level, which mitigates the effects of more concentrated industrial sectors. Besides that, the fact that it is a short-term impact analysis, firm's adjustment costs and sunk costs do not allow reactions that cause first or second order effects in such a brief period of time. Regarding the latter hypothesis, it is expected that the unobservable component could be properly represented as a time invariant component, in order to apply difference-in-differences techniques. Nevertheless, it is not possible to exclude the possible wrong designation of the control group by means of the logit model. It is important to mention, although, the effort engaged in the estimation of these models, where we included not only the lagged variables of interest, but also a relevant set of independent variables which represented observable characteristics of the firms.

After acknowledging some possible methodological restrictions, it is interesting to notice that, in a general way, results are consistent with theoretical predictions presented in Sect. 2. It is clearly noticed that innovation positively affected manufacturing firm's performance, reflected in terms of increases in employment, net revenue, productivity, and oftentimes, market share, during the 2-year period following innovation. The most robust results were observed for the net revenue variable. On the other hand, it was not possible to capture significant innovation impacts on firm's profitability, suggesting that technological innovations can boost an increase in profits via rising revenue, but keeping constant the marginal profit.

More deeply, the comparative results showed that process innovation solely tends to produce a higher impact in terms of performance indicators than product innovation solely. This evidence is important and demonstrates that, in spite of being technologically narrow, this innovation strategy is individually profitable for firm and its adoption requires better rationalization. These results help us to comprehend the information provided by the Pintec survey about the high innovative levels embedded in acquisitions of machines and equipment, one of the larger sources of innovation among Brazilian manufacturing firms.

The results presented here also suggest that solid technological strategies, which involve the incorporation or development of new process allied with the introduction of new products, are definitely the ones with more extended impacts. These impacts are translated into effective increases in market share that leads to a stronger firm's development in the long-run.

The implications of these results in terms of policy making are obvious. The development of a robust industrial structure requires the increase in competitiveness through technological innovation. The rise in competitiveness, as we demonstrated here, occurs in several levels, but the ones with a more prosperous future are those based in solid technological strategies and pronounced investments in R&D&I. The translation of these microeconomics impacts into macroeconomics impacts is straightforward. In accordance with various theoretical views and their growth models, our results suggest that some efforts must be made in order to stimulate entrepreneurial conscience regarding the importance of innovation and to strengthen the national innovation system itself.

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Appendix

Logit model results: probability of the firm assigns treatment—innovation activity and covariates (mean 1996–1997, $t-1$)

Dependent variable/ covariates ($t-1$)	Inov	Inovproc	Inovprod	Inovprod mark	Inovprod firm	Inovproc mark	Inovproc firm	Prodmark procmark	Prodfirm procfirm	Prodmark procfirm	Prodfirm procmark
Employment (log)	0.204***	0.12	0.151	0.314*	0.087	−0.004	0.142*	0.851***	0.182**	0.449***	0.279
	(0.063)	(0.079)	(0.111)	(0.161)	(0.127)	(0.157)	(0.084)	(0.156)	(0.090)	(0.148)	(0.244)
Years of education (log)	0.468*	0.113	0.911***	2.02***	0.423	0.149	0.068	1.48***	0.782*	1.13***	0.813*
	(0.170)	(0.194)	(0.306)	(0.487)	(0.326)	(0.453)	(0.202)	(0.390)	(0.255)	(0.412)	(0.418)
Labor productivity (log)	0.271***	0.077	0.240**	0.469**	0.177	0.575***	0.032	0.616***	0.356**	0.821***	0.358
	(0.072)	(0.075)	(0.103)	(0.184)	(0.112)	(0.173)	(0.078)	(0.141)	(0.141)	(0.160)	(0.243)
Capital productivity (log)	0.126*	0.004	0.020	0.068	−0.006	0.402**	−0.040	0.160	−0.250**	−0.036	−0.021
	(0.075)	(0.079)	(0.111)	(0.210)	(0.122)	(0.171)	(0.082)	(0.205)	(0.114)	(0.161)	(0.204)
Market share	0.040*	−0.013	0.002	−0.012	0.029	0.038	−0.043	0.041	0.005	0.034	0.088***
	(0.020)	(0.026)	(0.025)	(0.030)	(0.032)	(0.038)	(0.032)	(0.030)	(0.027)	(0.031)	(0.032)
Markup	0.026	−0.028	−0.018	−0.306	0.025	−0.309	0.068	−0.037	0.098	0.054	0.041
	(0.049)	(0.097)	(0.078)	(0.281)	(0.075)	(0.250)	(0.101)	(0.231)	(0.098)	(0.074)	(0.193)
Export activity (*dummy*)	0.206**	0.095	0.402**	0.964***	0.231	0.632***	0.018	0.513*	0.07	0.602***	0.657**
	(0.089)	(0.112)	(0.158)	(0.282)	(0.183)	(0.243)	(0.120)	(0.281)	(0.131)	(0.226)	(0.330)
Foreign ownership (*dummy*)	−0.071	0.122	−0.274	−0.178	−0.485	0.226	−0.010	0.124	−0.457**	−0.477*	0.013
	(0.146)	(0.185)	(0.244)	(0.304)	(0.310)	(0.308)	(0.204)	(0.263)	(0.209)	(0.273)	(0.318)
$(\text{Mills})^{-1}$	−0.534*	−0.900**	0.285	1.09	0.138	−1.97***	−0.793**	−1.50	−0.641	−0.408	−1.26
	(0.285)	(0.349)	(0.454)	(0.717)	(0.528)	(0.686)	(0.369)	(0.979)	(0.493)	(0.609)	(1.06)
Constant	−4.44***	−2.13**	6.94***	−14.65***	−5.11***	−8.94***	−1.82*	−16.95***	−6.85***	−16.27***	−9.08***
	(0.890)	(0.965)	(1.39)	(2.11)	(1.49)	(1.81)	(1.013)	(1.98)	(1.62)	(1.97)	(2.83)
P score (mean)	0.568	0.319	0.214	0.105	0.159	0.082	0.279	0.151	0.270	0.143	0.129
	(0.156)	(0.092)	(0.162)	(0.125)	(0.121)	(0.078)	(0.086)	(0.215)	(0.138)	(0.162)	(0.169)
Observations	5,002	3,112	2,485	2,132	2,316	2,247	2,964	2,344	2,824	2,279	2,230
Pseudo R^2	0.0742	0.0285	0.136	0.222	0.105	0.121	0.027	0.417	0.073	0.24	0.169
Log-likelihood	−3,209.3	−1,791.62	−968.225	−380.309	−765.011	−365.851	−348.619	−1,329.15	−447.616	−287.934	
Treated	2.908	1.015	382	169	311	148	867	295	732	255	131
Non-treated	2,103	2,103	2,103	2,103	2,103	2,103	2,103	2,103	2,103	2,103	2,103
No. of blocks	7	7	8	8	5	5	5	7	7	5	7

*Significant at 10%; **significant at 5%; ***significant at 1%

Standard error in brackets

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