On the complementarity between exporting and innovation*

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Abstract

This paper aims to study the complementarity between exporting and innovation in the Brazilian industry. Do firms become more prone to invest in innovation after becoming an exporter? We tackle this issue by analyzing Brazilian firm level data from 1998-2011 linking three databases through a firm identifier.We use propensity score kernel matching combined with difference-in-differences approach to help deal with endogenous exporting, sunk exporting costs and common macroeconomic shocks across industries. The findings show that exporting is associated with further innovation expenditures, although this effect vanishes two years after entry in the export market.

Keywords: innovation; firm-level data; learning by exporting; Kernel propensity score; differences-in-differences.
JEL Classification: D22, F14, F23, O3.

1 Introduction

The literature widely recognizes that exporters are more productive than non-exporters.[1] Two mechanisms explain this asymmetry. First, exporters may be more productive than their domestic counterparts, allowing than to overcome the sunk cost of export and to compete in international markets (Melitz, 2003; Bernard et al., 2003). The second mechanism is related to the ability to learn from foreign markets, enabling firms to gain new knowledge and expertise, improving their level of efficiency (Biesebroeck, 2005). These two non-competing hypothesis (self-selection *versus* learning by exporting) had been extensively tested and surveyed over the last fifteen years, when datasets at firm level all over the world became available.

The role of exporting in shaping a firm's future productivity was surveyed by Wagner (2012), revealing that this debate is far from settled. In fact, innovation is shown as a missing link in the effect of exporting on firm's characteristics. Thus, we explore learning effects from trade through firm innovations, acknowledging that trade does not necessarily translate into immediate TFP (Total Factor Productivity) improvements, but may impact TFP growth or firm survival in foreign markets in the long run.[2] Our approach is silent on the exact theoretical mechanism, which has been

*I am grateful for valueable comments from Emanuel Ornelas, João Paulo Pessoa, Lucas Ferraz, Paulo Furquim Azevedo, Camila Campos and Leandro Veloso. All remaining errors are mine. The IBGE is exempt from any responsibility for the views, information, data and concepts presented in this article, which are solely the responsibility of the author. Access to confidential data provided by process #03605000636_2014_44.

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[1]See Bernard and J. Bradford (1999), Bernard et al. (2003), Melitz (2003), Melitz and Redding (2015).

[2]See Grossman and Helpman (1991) for the role played by innovation in raising productivity and output growth.

outlined by Bustos (2011), who extended Melitz (2003) and shows how trade liberalization through MERCOSUR affects technology upgrading by Argentinian firms.

We find that Brazilian firms are more prone to innovate after export market entry. However, this effect is no longer visible two periods after entry. When examining whether such achievement is due to exporting per se or to the entry into foreign markets, we find that only newly exporting firms increase their innovation expenditure.

Lileeva and Trefler (2010) present firm heterogeneity derived from Canada-US Free Trade Agreement's tariff cuts. They conclude that market size matters for innovation and hence for productivity. Smalls firms increased their labor productivity while productivity gains for high productivity plants are negligible. Bloom et al. (2016) use the removal of product-specific quotas following China's entry into the World Trade Organization in 2001 to assess whether there is trade induced technical change on firms most affected by Chinese imports in their output markets. Finally, Albornoz et al. (2012) argue that firm's uncertainty about their success after export market entry plays an important role to understanding their export pattern, specially regarding destination countries and timing.

The channels that Bustos (2011), Lileeva and Trefler (2010) and Bloom et al. (2016) investigate are slightly different from ours. In fact, they focus on trade liberalization while we remain attention on (newly) export status itself. Do firms become more prone to invest in innovation after becoming exporter? To investigate this channel, we merged three dataset of Brazilian firms linked by its CNPJ tax identifier. This dataset comprises production, exports, imports and innovation gathering all set of information based on international standards over 1998-2011. To soften potential endogeneity issues, we rely on kernel propensity score matching (Abadie and Imbens, 2011) combined with differences-in-differences techniques as proposed by Blundell and Dias (2009) to rule out constant external effects over time. Following Lileeva and Trefler (2010), we allow two sources of heterogeneity: in initial productivity and in the productivity gains from investing (on innovation).

Despite the lack of data on export promotion policies, we argue that APEX's creation on 2003 and some others exports support instruments play an important role in explaining such effect.[3] APEX's goal is to provide training, consulting and advisory services in order to increase the competitiveness and promote the export culture in companies, ultimately preparing them for the challenges of the international market. The Brazil Exporter Program, also launched in 2003, gathers 44 projects under MDIC's coordination (Ministry of Development, Industry and Foreign Trade), some existing, but that have undergone a readjustment on focus, and others were created. The programs are aimed at the adjustment of products and the processes, funding for micro and small enterprises, guarantee funds, among others. In fact, placebo tests for year 2008 confirm the robustness of our findings, showing that starters at 2008 do not innovate more after entry, unlike 2004's entrants.

Following this introduction, the paper is organized as follows. The second section describes the dataset and main procedures, section three presents the methodology and section four discusses the main findings and policy implications. The fifth concludes.

2 Data

The data to evaluate the existence of learning effects from international market entry are originated from three databases[4]: the Secex (collected by SECEX – Secretariat of Foreign Trade)[5], the Annual Industrial Survey (PIA –*Pesquisa Industrial Anual*)[6] and the Brazilian Innovation

[3]APEX is the Brazilian trade and investment promotion agency.

[4]Acess to confidential data provided by process #03605000636_2014_44.

[5]The foreign trade microdata by exporter and/or importer are protected by confidentiality in tax matters according to the National Tax Code, in its articles 198 and 199. For that reason they are unavailable for our purposes.

[6]For details, see
http://www.ibge.gov.br/english/estatistica/economia/industria/pia/atividades/conceitos.shtm.

Survey (PINTEC – *Pesquisa de Inovação Tecnológica*), both collected by The Brazilian Institute of Geography and Statistics(IBGE).[7] We then merged the three databases, through a unique firm identifier, the National Registry of Legal Entities (CNPJ - Cadastro Nacional de Pessoa Jurídica)[8], gathering the firm-level inputs and outputs of Brazilian firms for the period 1998-2011.

We describe below each of the datasets.

PINTEC The Brazilian Innovation Survey was launched in 2000, 2003, 2005, 2008 and 2011 comprising national and regional indicators of the technological innovation activities developed in the Brazilian industrial enterprises with 10 or more employees. Some firms were also randomly surveyed by the PINTEC, in which quantitative and qualitative data on R&D expenditures and innovation were gathered. The information collected refers to the firms' characteristics; the product innovations and/or process implemented, incomplete or abandoned; to developed innovative activities; to expenditure on these activities; to finance these expenditures; attributes of internal R&D, skill level and hours devoted; innovation's impact on sales and exports; sources of information used by firm; the cooperative arrangements established with other(s) organization(s); government support; patents and other protection methods; the problems faced by firms; and organizational and marketing innovations.

The methodological and conceptual references of PINTEC is based on the third edition of the Oslo Manual (OECD, 2005) and, more specifically, on the model of the Community Innovation Survey – CIS version 2008, proposed by the Statistical Office of the European Communities, which was attended by 15 European Union member states. This ensures quality of information and comparability with international data. PINTEC remains focused on products and processes, but also comprises organizational and marketing innovation.

There are three types of variables on PINTEC database: the original ones from questionnaires, the variables constructed through PINTEC survey, and variables from other sources such as RAIS (Annual List of Social Information, from the Ministry of Labor), PIA and PAS (Annual Services Survey, from IBGE). Original ones do not provide information on which firms are *general* innovators, revealing only who implemented *product* or *process* innovations separately (binary variables on each condition). To define who are the innovative firms, we follow the PINTEC survey structure presented in 1 . Not all firms answer all questions as can be seen in this flowchart. Thus, beyond the process and product innovation, we must account for abandoned and incomplete projects and also correct for zero/missing misassignments. After such modifications, the number of innovative firms matches with official reports for every year.

The variable of interest is *expenditure on innovation activities*, that can be calculated as the sum of reported expenses on: internal R&D, external R&D, acquisition of other external knowledge, software acquisition, purchase of machinery and equipment, training, expenditure on introduction of technological innovations in the market, industrial design and other technical preparations for production and distribution. As can be seen, our definition of Innovation goes beyond R&D activities.

SECEX Administrative records of all exporting and importing companies distributed into five value ranges (US$ FOB). It is collected by Secretary of Foreign Trade (SECEX) of the Ministry of Development, Industry and Foreign Trade (MDIC). We then construct dummy variables regarding foreign orientation.

PIA Survey conducted annually by IBGE that captures basic characteristics of the Brazilian industrial segment. We use the non-random sample of all Brazilian mining and manufacturing firms

[7]The dataset is available at the Brazilian Institute of Geography and Statistics located at Rio de Janeiro, Brazil. The data need to be accessed at the IBGE site and it involves significant red tape. In particular, after the calculations the results need approval by technical and ethic committees under fiscal regulations, before being released.

[8]Previously encoded by IBGE to preserve firms's anonymity in accordance to Standard CDDI (Centre for Documentation and Dissemination of Information) Service Guidelines No. 01/03 of 09/10/2003.

over all federal units (Estrato Final Certo, receiving a complete questionnaire). It has three main groups of variables: i) longitudinal relations across firms; ii) balance sheet and income statement; iii) other economic information such as investment flows, employees and origin of firm's capital. Sectors are reclassified from CNAE 2.0 (Classificação Nacional de Atividades Econômicas 2.0) to International Standard Industries Classification (ISIC) Rev 3.1 for international comparison purposes. See Muendler (2003) for PIA's further characteristics.

Due to time-span limitation, we need to collapse the PIA and SECEX database following PINTEC availability. We then split the sample into five periods (1998-2000, 2001-2003, 2004-2005, 2006-2008, 2009-2011) before merging then. Besides innovation expenditure, an important feature of the merged dataset is that PINTEC allows us to control for state and regions, which is not possible with PIA dataset. Nominal variables were deflated into real values at constant 2012 prices using the IPA/OG index at sector level (wholesale price index), published by Getulio Vargas Foundation. Nominal Wages, in turn, were deflated by national consumer price Index (INPC) at constant 2012 prices. Also, CNAE classification changes after 2007, which requires translation from CNAE 1.0 into CNAE 2.0 from 1996 to 2006. This only applies for PIA and PINTEC dataset (because SECEX export and import ranges is converted into dummies).

The final unbalanced panel contains 42,272 observations distributed along 24 two-digits sector level and five waves, where 45% are exporters, 51% report general innovation and 28% of the companies are in both innovation and exporting activities.[9] Specifically, 32% executed product innovation, 43% invested on process innovation, while 24% reported both innovative types between 1998-2011. The majority of firms rely on low-tech manufacture of food products whilst the less numerous is in the Tobacco's manufacture.

3 Methodology

We have no relevant and intuitively convincing set of instruments for a firm start exporting. To tackle this self-selection issue, we rely on Heckman et al. (1997) and isolate from our sample the group of "exporting-starters" and "non-exporting" firms. Therefore, we wish to know the outcome (y) of treatment obtained by the difference in the innovation expenditure for companies that have experienced the treatment (*starter*) *vs.* those have not been exposed to it. Every period t, the average impact of starting exporting on innovation ($s = \{1, 2, 3\}$ periods ahead) can be computed as:

$$E[{y^1}_{t+s} - {y^0}_{t+s}|starter_{it} = 1] = E[{y^1}_{t+s}|starter_{it} = 1] - E[{y^0}_{t+s}|starter_{it} = 1] \qquad (1)$$

where y^1 and y^0 are potential outcomes from been "starter" and "non-starter", respectively.

In order to infer the impact of "starting exporting" on "innovation expenditure" we need to know what would have happened to the company that entered the export market if it had not done so. That is, we are in pursuit of a counterfactual situation, which of course constitutes a problem as this fact is not observed by the researcher – which is represented by the last term in Equation 1.

To overcome this problem we match each firm that switched into exporting with a derived counterfactual, constructed over the distribution of non-exporting firms. We assume that the self-selection of companies is based on characteristics that are observable *and/or* unobservable but fixed in time. Therefore, the most appropriate strategy to identify the effect of "start exporting" is the combination of Propensity Score Matching with Difference-in-Differences techniques.

Specifically, the first-stage logit estimation captures the likelihood that firms become exporters based on observable pre-exporting attributes of the firm. To ensure a good match, it is crucial to identify treatment (starter) and control (always non-exporter for the whole sample) groups with substantial overlapping firm characteristics (common support). Both control and treatment firm

[9] On average, 8454 firms by wave/period.

groups are then assigned to strata according to its propensity score. Kernel regression estimator chooses the weights so that the closest observations receive greater weight.

As proposed by Heckman et al. (1997), matching and diff-in-diff can be combined to accommodate unobserved determinants of the non-treated outcome affecting participation for as long as these are constant over time. This approach can be applied when treated and non-treated are observed over time with at least one observation before and one after the treatment. Blundell and Dias (2009) establish that we can compare the evolution of treated outcomes with that of non-treated over the observation period and assign any difference to the impact of treatment.

After Matching, the diff-in-diff specification we want to estimate on matched sample is:

$$innov\_expend_{i,t+s} = \beta_0 + \beta_1 \cdot starter_i + \beta_2 \cdot post_t + \beta_3 \cdot starter^{*}post_{it} + \beta_k \cdot X_{it} + u_{it} \quad (2)$$

where $innov\_expend_{i,t+s}$ is the self-reported expenditure on innovation (in R$) from PINTEC database. This variable accounts for both product and process innovations and is evaluated up three years after the firm's entry into the international market. *starter* is a dummy that is zero for firms that are domestic (never exports on the whole sample) and equals one when the firm starts exporting. We examine two kind of entry on export market: *starters* when firm i did not export in $t-1$ and export in t; and *entrants* for firms that did not export in $t-1$, export in t and in $t+1$ (entry and remain as exporter). The variable *post* accounts for follow-up period, which we set on 2004. Finally, X refers to baseline covariates which includes a complete set of sector dummies at the two-digit level, state dummies, technological intensity (Table 1), raw materials, size (number of employees), capital, productivity[10] and energy. The full set of year and sector aims to control for common aggregated demand and supply shocks. The very same X vector was previously used for kernel matching first-step procedure. We are interested on the β_3 coefficient, which indicates the causal impact of start exporting on innovation expenditure.

Denoting d as firm's treatment status, y^d_{id} is the outcome for firm i at time t when their treatment status at that time is d: it means that is y^0 when the firm belongs to the non-treated group (never-exporting) or when the time is t_0 (before 2004) and is y^1 when the firm is in the treated group (newly exporting) and the time is t_1 (after 2004). Then, the assumptions are:

a. Conditional on the observables X, the evolution of the unobserved part of y^0 is independent of the treatment status. Thus, controls must evolve from a pre- to a post-program period in the same way treatments would have evolved had they not been treated.

$$(u_{it_1} - u_{it_0}) \perp d_{it_1} | X_i \quad (3)$$

b. Common support hypothesis: all starters firms have a counterpart on the non-exporting population before and after the treatment.

$$P[d_{it_1} | X_{i,t}] < 1 \quad (4)$$

First, we estimate the average treatment effect on the treated (firms that experienced entry on export markets) following Abadie and Imbens (2011). To construct the "control"[11] group we matched each treated to exactly one firm that did not export during the whole sample, allowing us to yearly choose the best match over a multi-dimensional pre-exporting characteristics. The set of pre-treatment variables are: dummies for 2-digit sector, federal units, log(raw materials), technological intensity (ranging from 1 to 4 according Table 1), log(size) proxied by average number of employees during the year, log(capital), log(energy) and log(real wage per worker). We estimate

[10] Productivity is measured alternatively as value added per worker and total factor productivity (see Levinsohn and Petrin, 2003).

[11] Hereafter we use "control group" and "comparison group" interchangeably.

productivity for each 2-digit industry level separately following Levinsohn and Petrin (2003) and use energy and raw material expenses as a proxy, deflated by the IPA-OG (sector-specific). Output is calculated by industrial transformation value in log (manufacturing) and we treat firm's usage of blue and white collar labor as freely variable inputs. Capital is calculated by standard perpetual inventory method (see OECD, 2001a for details). Labor productivity offers a dynamic measure of economic growth, competitiveness, and living standards within an economy. Alternatively, we test a wide variety of (log) labor productivity proxies summarized on Table 2, relying on its basic definition: ratio of a volume measure of output to a measure of input use. Table 3 show the number of treated and non-treated firms. Estimates are conducted on common support.

Although we have no clear intervention, we test if after 2004 (follow-up period) "starters" (treated) become more prone to innovate (outcome variable). This period coincides with a number of policies aimed at improving competitiveness of Brazilian firms. Indeed, we carried out falsification test with year 2008 to test whether there are similar results. If they are, it may suggest that 2004's starters would be similar to 2008's.

4 Results

Under learning by exporting hypothesis, there are efficiency gains immediately after export market entry. These gains stem from a more competitive environment, better supply-chain management, new business practices, adjustments of product portfolio, new processes, among others. Consistently with Bustos (2011), our results indicate that there is a significant correlation between switch to exporting and innovation expenditure in the period after export entry.

Table 4 indicates that becoming exporter is consistent with higher innovation expenditure one year[12] after entry by about R$235 thousand for those firms that enter and remain exporters (variable *entrants*). For *starters*, a less restrictive proxy for entry, this effect is an increase of about R$160 thousand on innovation expenditure (Table 5). Using different productivity measures to provide sensitivity analysis show that results change by about 6% for entrants and 4% for starters. This impact is significant at 10% level of significance. Table 5 shows no statistical significance for the switch's impact two years after entry. However, three years after start exporting, firms decrease its innovation investments by approximately R$246 thousands (more than the amount spent in the first year of international experience). All results should be interpreted as compared to the baseline domestic status (firms who never exported in the whole sample). This suggests that the larger investments are taken before or at last immediately after entry on export markets. Firms that enter and remain exporting do not show any statistically significant change on innovation investments two and three periods after switching status.

Do the results stem from entry on export markets? It means, we should ask whether this is a regularity for exporters or a particularity for starters. To answer this question, we carried out one-to-one match for domestics and exporters on the same multi-dimensional set of pre-exporting variables. Now, we assign to "treated group" those firms that are "continuing exporters" (regardless of its experience on international markets, continuing exporters are those firms that export for at least one year, which may include firms that enter, exit or switch status). The comparison group remains the never-exporting firms. Table 6 provides average treatment effects on treated and shows no effect for exporters *vs.* domestic firms. It suggests that it is indeed the first-time firm experience on international market that drives innovation expenditure, not exporting per se.

In addition to the evidence of correlation presented above through matching strategy, we carry out regressions accounting for time-varying external shocks. This double-difference estimator is calculated as the difference in average outcome in the treatment group before and after treatment

[12]In fact our measure of time is not years, but (PINTEC's) waves or periods. Due to PINTEC availability, we needed to collapse the dataset, which left us with five periods.

minus the difference in average outcome in the control group before and after treatment – Equation 2. The follow-up period is set after 2004 because it coincides with some changes on Brazilian exports promotion policies. The "treatment" is *entrants* and *starters*, which represent switching from domestic to exporter status. The outcome is the innovation expenditure in the period following entry $(t+1)$. We carried out kernel propensity score matching, which assigns weights to construct a control group selecting on the same set of firm's pre-exporting characteristics.

Figures 2, 3 and 4 parallel yearly before-after propensity score densities to provide evidence of matching quality. To prevent that missing values affect the quality of control-treatment assignment, we perform matchings for different outcome variables. Balancing tests between control and treatment groups do not reject the null hypothesis of mean equality between the two groups after matching. As matching is carried out for every wave, we show balancing tests for each of them. Table 7 shows the difference-in-differences estimates for *entrants* while Table 8 report results for *starters* as a robustness check.

For those firms that did not export in $t-1$ and start exporting in t, the *starters*, innovation expenditure increases by R$280 thousands compared to baseline situation, ranging approximately 12% depending upon productivity measure used. For those firms that enter export markets and remain as exporter for at least two years (*entrants*), in turn, switching into exporter increases innovation expenditure by R$420 thousands, ranging from R$370 thousands to R$460 thousands across productivity covariates. The result is slightly responsive to the productivity measure used.

As a robustness check we also test if this result is random or even driving by something that we are not accounting for. There is no clear intervention been used as instrument that could cause such increase on innovation expenditure for starters after 2004. Therefore, we conduct a falsification test using 2008 as a placebo follow-up period. In fact, Tables 9 and 10 show no effect of entry on innovation, using *entrants* or *starters*, respectively. Results remain unchanged across the complete set of productivity measures. So, we conclude that newly exporting firms from 2008 does not innovate more after start exporting, while starters from 2004 do.

Hence, we can infer that export market entry indeed causes innovation expenditure in $t+1$ and that policies on 2004-2008 period are imperative for this result. However, this finding can still reveal a combination of two policy outcome targeted by such policies. Because of the acknowledgment of exports' importance for economic growth, the export promotion mechanisms become relevant and settled into its goals both export market entry and product improvements.

5 Concluding remarks

It is extensively argued that only the most productive firms are able to make positive profits from exporting, giving rise to the self-selection mechanism into these markets. However, there is less consensus whether export market entry affects firm performance after entry (learning by exporting). This paper aims to investigate the role played by innovation as a possible channel for such a link.

We control the self-selection bias by restricting the original sample to two comparable subsamples of control and treatment groups. To identify the counterfactual group, it is assumed that all differences between starters and the appropriate comparison group (non-exporters) can be captured by a vector of observables through Kernel propensity score matching. Once we have this counterfactual in hand we use a Difference-in-Differences methodology to assess the impact of export market entry on innovation expenditure up to three years after entry.

We find that entry into international market indeed is correlated with more expenditure on innovative activities such as internal and external R&D, cooperations, training, purchase of machinery and equipment, among others. This effect, however, disappears two periods after entry. When examining if such achievement is due to exporting per se or to the entry into foreign markets, we find that only newly exporting firms increase its innovation expenditure on subsequent period.

Also, comparing starters before/after 2004 with their counterpart non-starters and controlling for common macroeconomic shocks across firms, we find that entrants are more prone to innovate one period after entry. This result is consistent with a falsification test using year 2008 as follow-up period. We thus conclude that 2004-2008 entrants have different incentives to start and innovate after entry. This allows to say that a set of public policies aimed at promoting Brazilian exports abroad after 2003 can be identified as partially responsible for such result. Finally, the main policy implication is that innovation can be viewed as complementary investment for newly exporting Brazilian firms in order to assure competitiveness.

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Table 1: Classification os manufacturing industries into categories based on R&D intensities

Category	Classification	CNAE code
1	Low-technology industries	10, 11, 12, 13, 14, 15, 16, 17, 31, 181, 182, 321, 322, 323, 324, 329
2	Medium-low-technology industries	19, 22, 23, 24, 25, 33, 301, 183
3	Medium-high-technology industries	20, 27, 28, 29, 303, 305, 309, 325
4	High-technology industries	21, 26, 304

Source: Economic Analysis and Statistics Division, OECD.
Notes: CNAE is the Brazilian classification of economic activities. The manufacturing industry lies between CNAE-10 and CNAE-33 and can be detailed into two, three or four digits.

Table 2: Productivity variables description

Productivity	Description
lnpy1	value of manufacturing per employee*
lnpy2	value of manufacturing per worker**
lnpy3	net sales revenue per employee
lnpy4	net sales revenue per worker
lnpy5	gross industrial output value per worker
lnpy6	value added per employee
lnpy7	value added per worker
prod_LP_vti_ma	TFP using manufacturing and raw materials
prod_LP_va_e	TFP using value added and energy (by sector)
prod_LP_va_e_firm	TFP using value added and energy

Notes: All variables in log. TFP is the log value of total factor productivity estimated by the Levinsohn and Petrin (2003) method. Value of manufacturing comes from PIA and is computed as *gross industrial output value* minus *cost of industrial operations*
*employee is computed as average number of employees during the year; **worker is average number of business partner, white and blue collars during the year. We are aware that these two measures can report different values along the sample.

Table 3: Treatment and Comparison groups

	treated	control
entrants	321	26737
starters	1037	26737
exporters	19144	23128

Notes: Number of observations assigned to Treated and Control groups. Time-span: five periods from (1998-2000) to (2009-2011).

Table 4: Nearest neighbor matching estimation - *entrants*

Outcome: Innovation expenditure						
	value added per worker			TFP		
Treatment: *entrants*	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+1	t+2	t+3
SATT	233,368*	-48,710	-210,043	247,297*	-86,000	-195,511
	(127,223)	(223,601)	(146,015)	(142,190)	(229,161)	(151,418)
Observations	2,293	1,273	544	2,288	1,266	544
m	1	1	1	1	1	1

Notes: Treatment: *entrants* (who did not export in t-1; exported in t; and t+1; zero otherwise.). This table reports Nearest neighbor (exact) matching estimation for average treatment effects for the treated. m specifies the number of matches to be made per observation. Matching is applied according firm's pre-exporting attributes (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). See (Abadie and Imbens, 2011) for further details. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Nearest neighbor matching estimation - *starters*

Outcome: Innovation expenditure						
	value added per worker			TFP		
Treatment: *starters*	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+1	t+2	t+3
SATT	162,166*	25,462	-246,756*	156,351*	16,022	-370,698**
	(94,862)	(153,067)	(134,767)	(102,243)	(158,617)	(177,346)
Observations	2,468	1,398	592	2,463	1,391	592
m	1	1	1	1	1	1

Notes: Treatment: *starters* (who did not export in t-1 and exported in t; zero otherwise.). This table reports Nearest neighbor (exact) matching estimation for average treatment effects for the treated. m specifies the number of matches to be made per observation. Matching is applied according firm's pre-exporting attributes (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). See Abadie and Imbens (2011) for further details. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Nearest neighbor matching estimation - *exporters*

Outcome: Innovation expenditure						
	value added per worker			TFP		
Treatment: *exporters*	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+1	t+2	t+3
SATT	39,281	144,459	202,019	32,624	118,096	-267,804
	(72,719)	(100,788)	(273,300)	(73,559)	(105,469)	(855,100)
Observations	7,140	3,966	1,596	7,123	3,952	1,591
m	1	1	1	1	1	1

Notes: Treatment: *exporters* (assign 1 to firm who export, regardless of its experience on international market; zero otherwise.). This table reports Nearest neighbor (exact) matching estimation for average treatment effects for the treated. m specifies the number of matches to be made per observation. Matching is applied according firm's pre-exporting attributes (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). See Abadie and Imbens (2011) for further details. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

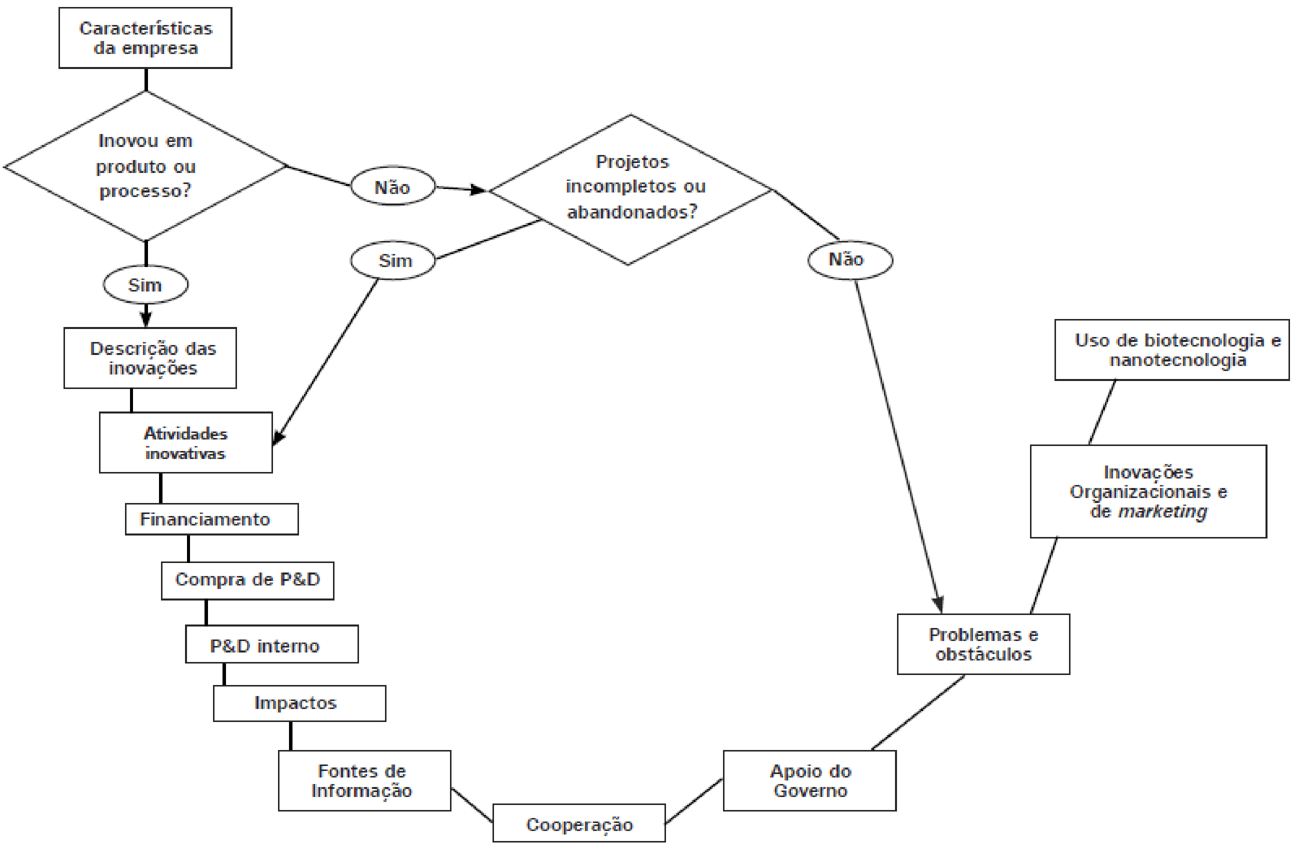


Figure 1: PINTEC's questionnaire structure.

Table 7: Differences in Differences estimates for entrants (R$1000). Outcome: Innovation expenditure 1 year after export market entry.

Year: 2004	lnpy1	lnpy2	lnpy3	lnpy4	lnpy5	lnpy6	lnpy7	prod_LP_vti_ma	prod_LP_va_e	prod_LP_va_e_firm
Baseline										
Control	-21000	-15000	-25000	-20000	-16000	-16000	-21000	3500	5300	6200
Treated	-21000	-16000	-26000	-21000	-17000	-16000	-22000	3200	4700	5600
DIFF(T-C)	-890	-820	-890	-830	-820	-820	-900	-290	-600	-580
	(730)	(710)	(690)	(730)	(730)	(640)	(650)	(730)	(740)	(660)
Follow-up										
Control	-22000	-17000	-27000	-22000	-18000	-18000	-23000	2700	4800	6100
Treated	-19000	-13000	-23000	-18000	-14000	-14000	-20000	6500	7900	9300
DIFF(T-C)	3200	3800	3400	3800	3600	3800	2900	3800	3100	3200
	(2000)	(2000)	(1800)	(2100)	(2100)	(2100)	(2400)	(1900)	(2000)	(2000)
Diff-in-Diff	4.100**	4.600**	4.300**	4.600**	4.400**	4.600**	3800	4.100**	3.700*	3.700*
	(2100)	(2000)	(1900)	(2100)	(2100)	(2100)	(2500)	(1900)	(2200)	(2100)
Observations	9,311	9,311	9,311	9,311	9,311	9,311	9,311	9,311	9,311	9,311

Notes: Treatment: *entrants* (who did not export in t-1; exported in t; and t+1). This table reports estimates using a wide variety of productivity measure as covariate for sensitivity analysis(see Table 2 for definitions). Time-varying propensity scores based on observable pre-exporting attributes of the firm (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). ***p<0.01, **p<0.05, *p<0.1.

Table 8: Differences in Differences estimates for starters (R$1000). Outcome: Innovation expenditure 1 year after export market entry.

Year: 2004	lnpy1	lnpy2	lnpy3	lnpy4	lnpy5	lnpy6	lnpy7	prod_LP_vti_ma	prod_LP_va_e	prod_LP_va_e_firm
Baseline										
Control	-14000	-13000	-17000	-14000	-12000	-16000	-15000	3000	3800	4400
Treated	-15000	-13000	-18000	-15000	-12000	-16000	-16000	2800	3300	4000
DIFF(T-C)	-560	-540	-530	-510	-520	-570	-570	-150	-440	-400
	(550)	(560)	(570)	(570)	(620)	(560)	(600)	(640)	(560)	(590)
Follow-up										
Control	-16000	-14000	-18000	-15000	-12000	-16000	-17000	2200	3800	4600
Treated	-13000	-12000	-16000	-14000	-11000	-15000	-15000	4800	5200	6100
DIFF(T-C)	2300	2000	1700	1700	1900	1400	2100	2500	1400	1400
	(1300)	(1300)	(1400)	(1300)	(1400)	(1500)	(1200)	(1200)	(1400)	(1600)
Diff-in-Diff	2800**	2500*	2200	2200	2400	2000	2700**	2700**	1800	1800
	(1400)	(1300)	(1500)	(1400)	(1600)	(1500)	(1200)	(1300)	(1500)	(1600)
Observations	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437

Notes: Treatment: *starters* (who did not export in t-1 and exported in t). This table reports estimates using a wide variety of productivity measure as covariate for sensitivity analysis(see table x for definitions). Time-varying propensity scores based on observable pre-exporting attributes of the firm (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). ***p<0.01, **p<0.05, *p<0.1.

Table 9: Differences in Differences estimates for entrants (R$1000). Outcome: Innovation expenditure 1 year after export market entry. Falsification test (year: 2008).

Year: 2008	lnpy1	lnpy2	lnpy3	lnpy4	lnpy5	lnpy6	lnpy7	prod_LP_vti_ma	prod_LP_va_e	prod_LP_va_e_firm
Baseline										
Control	-26000	-24000	-27000	-25000	-22000	-23000	-27000	3300	4900	1100
Year: 2008	-24000	-23000	-26000	-24000	-20000	-21000	-25000	5300	6800	2900
DIFF(T-C)	1700	1800	1800	1800	1800	1800	1700	2000	1900	1700
	(1600)	(1500)	(1500)	(1600)	(1900)	(1600)	(1400)	(1700)	(1700)	(1400)
Follow-up										
Control	-27000	-25000	-28000	-26000	-23000	-24000	-28000	2100	4500	960
Treated	-27000	-25000	-28000	-26000	-22000	-24000	-28000	4000	4400	1500
DIFF(T-C)	780	-730	-95	-140	600	570	-100	1900	-71	530
	(1200)	(1600)	(1400)	(1400)	(1500)	(1100)	(1500)	(1200)	(770)	(1400)
Diff-in-Diff	-960	-2500	-1900	-2000	-1200	-1200	-1800	-93	-2000	-1200
	(1900)	(2400)	(2200)	(2100)	(2300)	(1900)	(2000)	(2000)	(1700)	(2100)
Observations	9311	9311	9311	9311	9311	9311	9311	9311	9311	9311

Notes: Falsification test for the year 2008. Treatment: *entrants* (who did not export in t-1; exported in t; and t+1). This table reports estimates using a wide variety of productivity measures as covariate for sensitivity analysis(see table x for definitions). Time-varying propensity scores based on observable pre-exporting attributes of the firm (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 10: Differences in Differences estimates for starters (R$1000). Outcome: Innovation expenditure 1 year after export market entry. Falsification test (year: 2008).

Year: 2008	lnpy1	lnpy2	lnpy3	lnpy4	lnpy5	lnpy6	lnpy7	prod_LP_vti_ma	prod_LP_va_e	prod_LP_va_e_firm
Baseline										
Control	-22000	-21000	-23000	-21000	-19000	-21000	-22000	2900	4300	710
Treated	-21000	-20000	-22000	-20000	-18000	-20000	-21000	4200	5500	1800
DIFF(T-C)	1100	1100	1100	1100	1200	1100	1100	1300	1200	1100
	(1200)	(1300)	(1200)	(1200)	(1300)	(1200)	(1200)	(1300)	(1200)	(1200)
Follow-up										
Control	-23000	-22000	-25000	-23000	-19000	-22000	-22000	3500	3600	620
Treated	-23000	-22000	-24000	-22000	-20000	-22000	-23000	2800	3500	370
DIFF(T-C)	-1900	-340	-2200	-2100	-2300	-1900	-2000	-2000	-1700	-2100
	9437	9437	9437	9437	9437	9437	9437	9437	9437	9437
Diff-in-Diff	-1200	-1400	-720	-640	-2000	-1200	-2000	-2000	-1200	-1300
	(1500)	(1600)	(1700)	(1500)	(1800)	(1500)	(1900)	(1900)	(1300)	(1600)
Observations	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437	9,437

Notes: Falsification test for the year 2008. Treatment: *starters* (who did not export in t-1 and exported in t). This table reports estimates using a wide variety of productivity measure as covariate for sensitivity analysis(see table x for definitions). Time-varying propensity scores based on observable pre-exporting attributes of the firm (sector dummies at the two-digit level, state dummies, technological intensity, raw materials, size (number of employees), capital, real wage per worker and energy). ***p<0.01, **p<0.05, *p<0.1.

Table 11: Brazil Export Program

Program/Project	Description	Agency
Support to SMEs	Financing the Local Productive Arrangements' Strengthening	BNDES
Guarantee Fund for Micro and Small Enterprises - FAMPE	Granting collateral in financing for production and sale for export market	SEBRAE
Export financing	ACC/ACE, BNDES-EXIM	BNDES /Bank of Brazil
Export financing	Direct funding and equalization of interest rates	Bank of Brazil
Income tax reduction incurring on shipments for trade promotion of Brazilian products abroad	Reduction of income tax	SECEX / Interministerial group
Financing of Export Credit Insurance	Granting of credit insurance for exports to the small businesses	SBCE /APEX / SECEX
Financing trade promotion	Credit line (with FAT resources) to working capital for micro and small exporting companies or potential exporter.	Bank of Brazil

Source: MDIC.

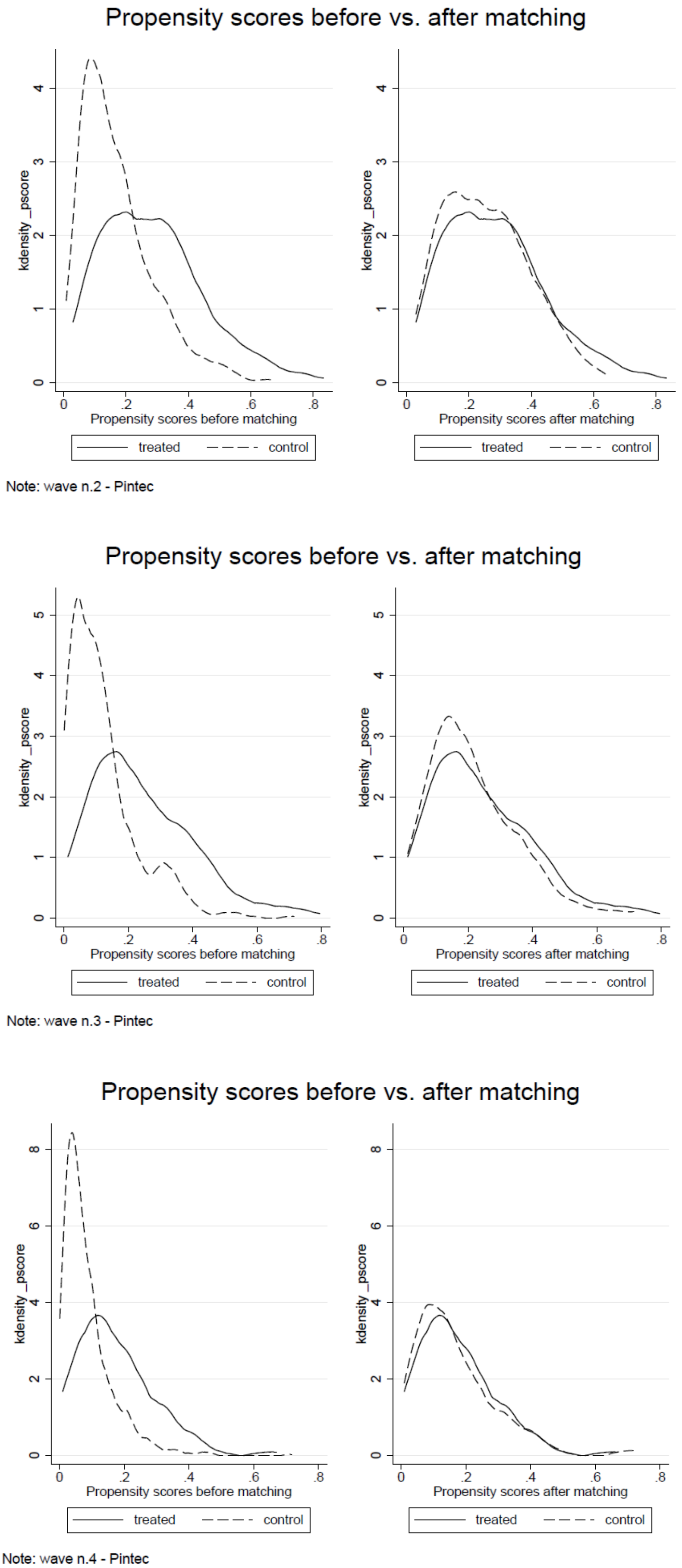
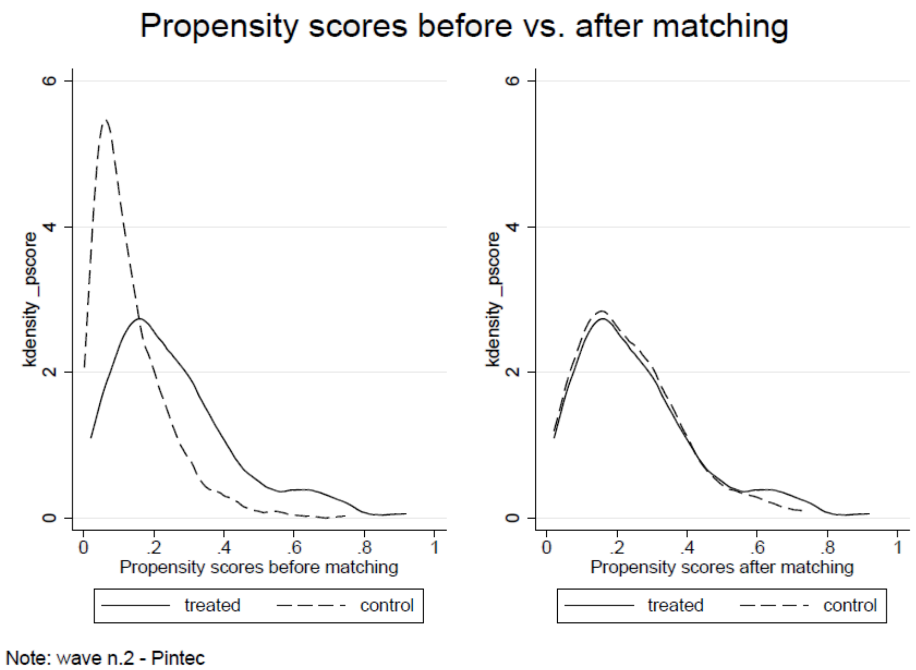


Figure 2: Propensity score kernel density - before vs. after matching. Outcome: innovation expenditure in t+1



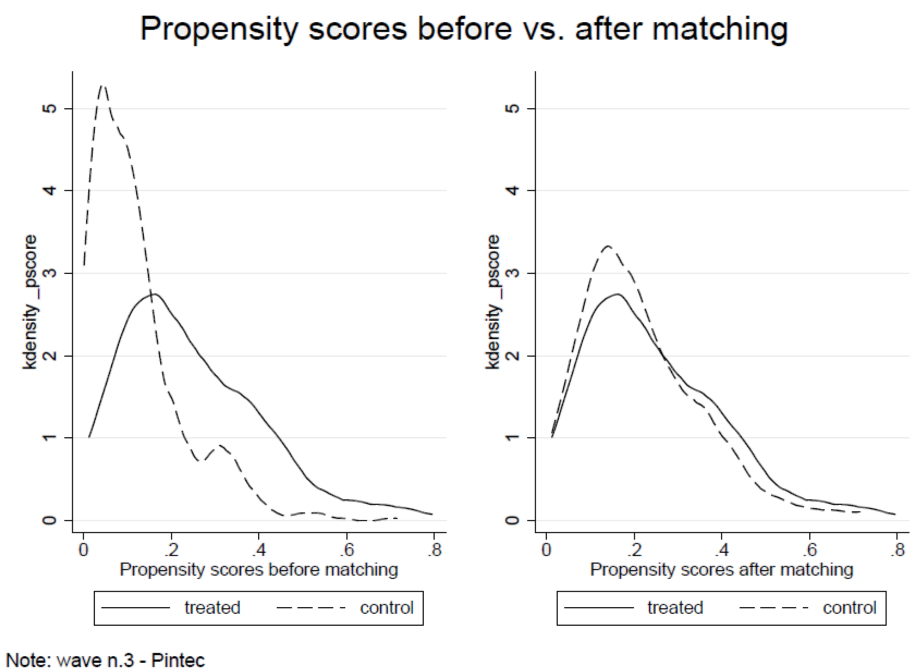


Figure 3: Propensity score kernel density - before vs. after matching. Outcome: innovation expenditure in t+2

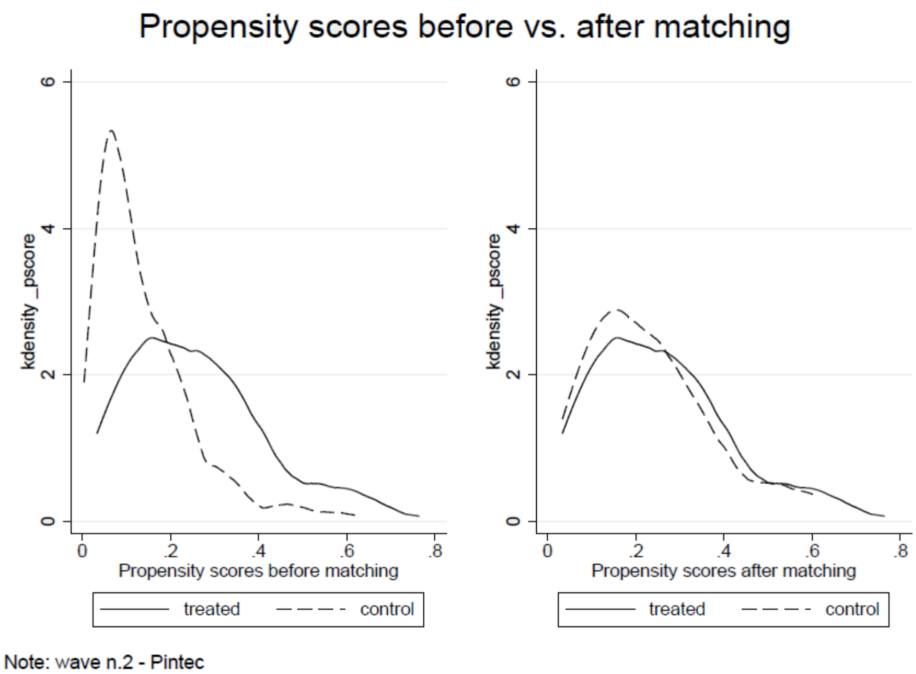


Figure 4: Propensity score kernel density - before vs. after matching. Outcome: innovation expenditure in t+3