IDB WORKING PAPER SERIES Nº (IDB-WP-1009)

Demand-Driven Training and Job Turnover

The Effects of Brazil's Pronate-MDIC at Firm and Worker Level

Rodrigo E. Quintana
Túlio A. Cravo

Inter-American Development Bank
Labor Markets Division

June 2019

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Quintana, Rodrigo.
Demand-driven training and job turnover: the effects of Brazil's Pronatec-MDIC at firm and worker level / Rodrigo E. Quintana, Túlio A. Cravo.
p. cm. — (IDB Working Paper Series ; 1009)
Includes bibliographic references.
1. Employees-Training of-Brazil. 2. Labor turnover-Brazil. 3. Human capital-Government policy-Brazil. I. Cravo, Túlio. II. Inter-American Development Bank. Labor Markets Division. III. Title. IV. Series.
IDB-WP-1009

http://www.iadb.org

Working Paper | IDB-WP-1009

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Rodrigo E. Quintana[i] Túlio A. Cravo [ii]

Abstract

This paper explores for the first time the impact of a demand-driven training program on labor turnover at both firm and worker level. Launched in 2014 by the Ministry of Development, Industry and Trade (MDIC in Portuguese), Pronate-MDIC allows firms to demand courses which some of their workers apply to. Difference-in-difference estimates find that workers who enroll in the courses demanded by their employers increase their job tenure by 8.89 months compared to non-enrolled peers. However, those who complete the training stay in the job 3.36 months less, on average, than those who do not. At firm level, results show that having a course approved is associated with higher turnover in the short run when considering subgroups of workers who participate in Pronate-MDIC. The effect dissipates in the third year, suggesting that it takes time for firms to adjust their labor stock after course demand.

Keywords: Education and Training, Turnover, Human Capital.

JEL Codes: J24, J63, P46.

[i] Rodrigo E. Quintana, Consultant at Inter-American Development Bank, rodrigoq@iadb.org
[ii] Tulio A. Cravo, Senior Labor Market Specialist at the Inter-American Development Bank, tcravo@iadb.org

Acknowledgments: We are grateful to the anonymous reviewer for the comments. We would like to thank Marcelo Neri, Paulo Jacinto and Eduardo Pontual Ribeiro for their comments on earlier drafts of this paper. Synthia Santana, Leandro Justino and Claudia Tufani provided excellent research assistance. Rafael Menezes, Jose Henrique Videira Menezes Luis Gustavo Montes, Mateus Branco, Victor Botelho, Mario Neto from MDIC helped understanding Pronated-MDIC design and data. This paper is an extension of 'Can demand-driven training diminish labor turnover at worker and firm level?' by Quintana et al., (2018) presented at ANPEC 2018.

I. Introduction:

Two features of the labor market in Brazil are high job turnover and stagnant labor productivity. Recent evidence shows that labor productivity has been slowly growing at 1.1% per year in the past decade (IPEA, 2015) and that 49.5% of formal workers switched jobs in 2013 (Corsair, Pero and Da Rocha, 2018). Turnover in Brazil is high even compared to international standards (Corsair et. al., 2006; Gonzaga, 2003) and it has been increasingly high for young workers[3] (Corsair et al., 2013). Thus, the launch of the *Program Nacional de Ensino Técnico* (Pronate) in 2011, the training program where participants choose the courses they wish to pursue, raised expectations on the impact of a massive program of technical education that might affect turnover and productivity.

This paper intends to contribute to the literature by assessing for the first time how skill enhancement is associated to turnover at firm and worker level. It does so by evaluating the impact of the demand-driven training version of Pronate launched in 2014 by the Ministry of Development, Industry and Trade (Pronate-MDIC), which allows firms to demand courses taken by their workers. Specifically, we look at how turnover may affect firms and generate spillover effects for workers.

There is widespread theoretical recognition that skill enhancement within a firm can contribute to minimize turnover and increase productivity. The theory of learning by doing suggests that as workers get trained on the job, they absorb firm-level knowledge, accumulate experience, stay longer in a firm and become more productive (Arrow, 1962; Becker, 1993). This pathway may provide firms incentives to invest in training as a means to diminish turnover and increase firm-level productivity. But empirical evidence on the relationship between learning and turnover is still scant (Chiang, 2014; Corsair, Pero and Da Rocha, 2018).

Existing quasi-experimental evaluations of Pronate focus on assessing regular labor market outcomes: employment and wages. An evaluation of Pronate[4] by Barbosa et al. (2015) suggests it is ineffective in putting students to work. Workers who complete the training do not present higher employment probability or returns than those who do not get confirmation. The launch of Pronate-MDIC in 2014 by the Ministry of Development, Industry and Trade (MDIC

[3] High youth turnover is concentrated in younger workers (ages 18 - 24) with low schooling (up to lower secondary school) who earn low wages, which makes them easily substitutable. The proportion of young workers' separations due to substitutions for workers of the same age group was 65% in 2010 compared to 53% in 1996 (Corseuil et al., 2013).

[4] Between 2014 to 2016, the most common Pronatec enrolled 1,261,434 students while Pronatec-MDIC enrolled 172,023 students. In the case of apprenticeship law 402,683 workers were hired under this scheme in 2014 compared to 367,900 in 2016.

in Portuguese) furthered the debate. O'Connell et al. (2017) show that allowing employers to signal course demands increases employment probability but do not induce major wage gains.

Despite these initial efforts to evaluate Pronate, none of the studies explores the impact of training on labor turnover at firm and worker level. The evidence on labor turnover in Brazil is limited to Corsair, Foguel, and Gonzaga (2018)[5], who find fewer dismissals and admissions of workers after completing an apprenticeship program compared to other temporary workers.

This paper aims to fill this gap. It measures the impact of having a course approved on labor turnover at firm level, and of course enrollment and completion on job tenure at worker level. We assessed the possibility of creating treated and control groups based on random exogenous reasons (non-participation due to class cancellation or oversubscription) but individuals who apply to the program might not participate for reasons arguably correlated to their personal characteristics. Additionally, at firm level, there is no clear criteria to approve course demands. Firms more likely to be selected are, on average, large and may have an incentive to secure workers trained by them. To minimize this selection bias, we employ Propensity Score Matching (PSM) (Heckman et al., 1997) and difference-in-differences (DID) estimations to compare firms and workers that demand and participate in the training program to those with similar characteristics who do not. We also control for time and unit effects for firms and workers.

To this end, we match the administrative data of Pronated-MDIC applications of firms and workers for the years 2014-2016 to the Annual Report of Social Information (annual labor registry and RAIS in Portuguese) from 2011 to 2017[6]. Putting together this dataset was no small achievement. It required merging course demand and approval from 2014-2016 at firm and student level that called for clinical examination of dates, status, and differentiating duplicates from errors. The biggest challenge – and what sets apart this database from O'Connel et al.'s (2017) – was to map class IDs created from firm's demands, allowing us to link the specific firm demand to the training class consequently created and to workers who took it. Once mapped, we use the dataset to link class IDs with student IDs and their employment records using RAIS for 2011-2017. The result is a comprehensive database that enables us to track employment and firm dynamics before and after Pronatec participation between 2014 and 2016 at firm and workers level.

[5] Corseuil, Foguel, and Gonzaga (2018) assess the impact of training on labor turnover but limited to the context of the apprenticeship law and restricted to young workers with no prior experience. Launched in 2000, the law provides a 6-percentage point tax break in payroll to firms that offer 2-year contracts to young individuals between 14 and 24 years of age while promoting in-class and on-the-job training conditioned on offering the program to between 5% and 15% of their workforce.

[6] Annual Social Information Report (RAIS), from the Brazilian Ministry of Labor (MTE).

The remainder of the paper is structured as follows. In section two we discuss the literature on the impact of skill enhancement on labor market outcomes, with a special focus on labor turnover. In the third section we briefly describe the statistics of firms and workers that apply to the program. In the fourth section we delved into the methodology and present the results in the fifth section. Finally, we conclude and provide policy implications for technical education policy design in Brazil.

II. Background

The main conclusion arising from the literature is that supply-driven training programs yield heterogeneous results (Card et al., 2010). In 1986, the U.S. Department of Labor created the largest randomized evaluation of a supply-driven training, the Job Training Partnership Act (Doolittle et al., 1993). This study spearheaded efforts to generate a credible estimate of what would happen to beneficiaries receiving training in the absence of it. Its focus was to assess the impact of training on two common labor market outcomes: employment and wages. In this case, having access to training increased the percentage of women employed by 2.1 p.p. and that of men by 2.8 p.p., 18 months after the program ended. It also rose the 18-month wages of adult women by 7.2 percent, but not that of adult men (Bloom et al., 1993).

In Latin America, randomized evaluations of hybrid programs in the short-, medium-, and long-term have taken place in Colombia, the Dominican Republic, Uruguay and Argentina. In Colombia, Attanasio et al. (2011) found that participating in *Jóvenes en Acción*, a 3-month vocational training combined with a 3-month apprenticeship, increases the probability of formal employment and higher wages in the short term. A subsequent study shows that unemployed poor female workers aged between 18 to 25 earn sustained higher wages 10 years after the intervention. Program participation of men has similar effects on employment but does not induce higher wages (Attanasio et al., 2015).

In the Dominican Republic, participating in *Juventud y Empleo*, a program consisting in technical and vocational courses followed by an internship, led to positive impact on wages but not on employment one year later (Card et al., 2011). More recently, the program documents persistent effects on the formality of employment 6 years after graduating but did not find effects on overall employment (Ibarrarán et al., 2015). Finally, it finds a widening employability gap between participating male students, which obtain an 8 p.p. increase in employment but see no wage gains. Women do not experience any impact in either outcome.

In line with these results, a medium-term RCT of *Entra21*, a program in Cordoba, Argentina which combines technical and life-skills training with internships, estimates employment increases of 8 p.p. with wages being 40 percent higher than the control group 1.5 years after the program (Alzúa et al., 2015). However, the effects remain stable for men but dissipate for women 3 years later. A study in Uruguay also estimates that participating in *Yo Estudio y Trabajo*, a 1-year apprenticeship program in public enterprises, increases the probability of finding a job within 2 years after, but only for a specific age cohort (Araya and Rivero, 2016). Students aged between 18 or 19 who did not hold a formal job before were 9 p.p. more likely to find employment.

For the case of Brazil, an initial evaluation of the supply-driven version of Pronatec, which does not consider market demand, indicates that it is ineffective in inserting unemployed workers in the labor market. Barbosa et al. (2015) estimate the reinsertion probability of workers who were unemployed in 2011 and graduate from short-term (FIC) Pronatec courses. It finds that access to training does not affect positively the employment probability of students who complete training vis-à-vis those who register but do not receive enrollment confirmation. As said before, supply-driven training has heterogenous impact.

Demand-driven training, on the other hand, responds to the needs of the market and adjusts to the needs of trainees. It allows firms and beneficiaries to suggest and select the training they wish to be delivered and even select providers that better suit their needs. The few evaluations which have explored the effect of demand-driven training in Brazil have also assessed employment probability and earnings with favorable results. O'Connel et al. (2017) exploits the program design of Pronatec-MDIC and employ a difference-in-differences strategy. They find that participation increases the probability of employment by 2 to 3 percentage points in the year after program completion without affecting earnings.

The literature on the impact of training focuses on the impact on workers rather than on firms and scant evidence is available on the effect of training on firms (Woodruff, 2018). One of the few studies is Corseuil, Foguel, and Gonzaga (2018) who assessed the impact of changes in the Apprenticeship Law on total turnover[7]. The law states that firms can hire young workers under a two-year apprenticeship contract and indicate which intensive in-classroom courses they should take in exchange of payroll subsidies. Exploiting a change in the eligible age criteria and employing partially fuzzy regression discontinuity design (RDD) and adjusted matching method, the authors find that demand-driven training decreases turnover at worker

[7] From 2000-2005 only individuals 14 to 17 years of age were eligible to the program. From 2005 onward, individuals 14 to 24 years old became eligible.

level in the short and medium term. After controlling for determinants of program participation, the number of dismissals decreases by 37.9% after 2-3 years and by 20.9% after 3-5 years. Similarly, hiring was 16.7% lower than temporary contracts 2-3 years after and 20.6% lower 4-5 years later.

Evidence of whether Pronatec beneficiaries switch jobs more quickly is non-existent to the best of our knowledge. This paper intends to fill this gap by assessing the impact of Pronatec-MDIC on worker turnover at firm level and understand the possible interplay between turnover and productivity in Brazil suggested by Corseuil, Pero and Da Rocha (2018). Estimating whether training influences this relationship is important to understand the implications on firm-level productivity.

Models of job turnover claim that turnover does not necessarily generate bad outcomes according to Jovanovic (1979a, 1979b). It can either improve job matching as information about the job and the candidate is revealed in the first months after placement. Or it can worsen the possibility of accumulating human capital difficult to teach in classrooms such as firm-specific and non-cognitive skills.

Regardless of that, firms with higher levels of turnover may compromise the learning accumulation of their workers and their productivity as a consequence. High turnover may be associated with low levels of commitment and training, from both the workers' and firms' side. Thus, if firms invest in their employees, they may have fewer incentives to dismiss them and replace them for other workers, allowing them to stay longer.

However, the opposite can be true. A recent paper by Rasul et al. (2017) shows that demand-driven vocational training for youth induces higher rates of job-to-job offers in the manufacturing and service sectors, potentially increasing labor turnover. Whether investing in training of workers diminishes turnover, be it is positive or not, is an important empirical question this study seeks to analyze.

III. Data and descriptive statistics

A main part of the data is from Pronatec-MDIC. Pronatec was established in 2011 to promote the inclusion of lower income workers in the formal labor market through vocational and technical education. The MDIC version of Pronatec was launched in 2014 to align course supply to the demand of firms in the manufacturing, trade, and service industries. As summarized in **annex I**, the program protocol involves several steps, from the moment firms and students apply for the program separately to the moment students complete the courses.

Firms submit course demands and report their tax ID, the course ID, the municipality where they wish the course take place, the number of people the companies wish to train, and in some cases, the occupations for which they demand the courses. In our data, 6,006 firms demanded courses between 2014 and 2016. Around 4,683 firms submit applications in at least one year; 1,115 in two years; and 208 in at least 3 years as observed in **table A1** in the annex.

The Ministry of Development, Industry and Trade (MDIC) filters course demands based on relevance and need. About half of the demands are filtered out in this stage (O'Connel et al., 2017). MDIC then submits the demands to the Ministry of Education (MEC) which compiles and approves demands from other ministries based on budget and complementarity. Similar demands from ministries are aggregated and approved. As summarized in **table 1**, 28.52% of firms that demand courses get approval and 21.38% of vacancies demanded are accepted.

Table 1
Demands and approvals of firm-requested courses (2014-2016)

	Demands	Approvals	% approved
Firms	6,006	1,713	28.52
Courses	43,714	6,994	15.99
Vacancies	1,087,924	232,605	21.38

Source: Calculations of authors using administrative data from Pronatec-MDIC

Once all courses are approved, MEC opens course registration and subsequent enrollment for students. **Table 2** shows that between 2015 and 2016, 23,619 students register at least once for the program, but only 55.97% receive confirmation and enroll thereafter. Of those who receive confirmation, 8,463 (64%) complete and 4,181 (31.62%) do not complete the course. Of those who do not complete the course, 0.26% did so for administrative reasons (class cancellation and oversubscription) as observed in **table A2** in the annex**.**

Table 2
Students who apply at least once to firm-requested courses and Employment history of students who apply to firm-requested courses (2015-2016)

variable	Percentage	N
applicants		23,619
enroll	0.5597	13,221
complete	0.3582	8,463
incomplete	0.1770	4,181
no status	0.2447	577
employed at course onset	0.4714	11,134
employed at course onset by a demanding firm	0.3032	7,163
employed at course onset by a demanding firm whose request is approved	0.1750	6,736
employed at course onset by a demanding firm and enrolled in firm-approved course	0.1594	3,767
employed at course onset by a demanding firm and completed firm-approved course	0.1102	2,605
employed at course onset by a demanding firm but not completed because dropout	0.0450	1,063
employment duration if completed firm-approved course (months)		17.85
employment duration if not completed firm-approved course because dropout (months)		14.82

Source: Calculations of authors using administrative data from Pronatec-MDIC

The Pronatec-MDIC dataset is complemented by the RAIS 2011-2017. The RAIS is an annual administrative dataset that contains information on employment and earnings of all the formally-employed workers of formally-registered firms[8]. In the RAIS, we were able to match the information of 84.55% of firms that request a course at least once between 2014-2016 and of 72.24% of students who apply to the program at least once in the same timeframe. Unmatched student data in the RAIS could occur because the student was not formally employed within the 2011-2017 period. Combining both datasets allows us to trace the employment history of students before and after program registration, enrollment and completion rates, including their job tenure rates.

Unlike O'Connel et al. (2017) who use a probabilistic model to match the class created from firm demand to the class the student is registered for, we manage to create a direct link. This match was possible as we obtained a unique class ID for 2015-2016 from MEC linking firms demands to class; that is, each class the MEC opens as a result of the course demanded by

[8] The RAIS includes detailed information on the employer and the employee (including their tax IDs), and their work relationship (wage, tenure, type of employment, hiring and dismissal date, and reason for dismissal).

the firm. From the pool of students registered in these courses, we filtered their first applications, whether they are employed by the demanding firm at the time the course starts. We also censored those who were given priority to enroll[9] and those employed in two simultaneous jobs for a better identification of the effect.

Once consolidated, we use the dataset to link class IDs to firm and student IDs; retrieve course application, acceptance and rejection proportions; and completion and dropout rates. The matched data result in a balanced panel which traces the employment information of workers who are employed by the firms that demand the course. **Table 2** shows that of the 23,619 students who apply for firm-requested courses, 11,133 are employed at course onset. Of those employed, 6,736 work in firms whose course demand is approved. Out of those, almost half enroll in a firm-approved course, 2,605 complete the course and 1,063 do not because they drop out. Finally, those working for requesting firms and enrolled in the requested course stay employed, on average, for 17.85 months from the moment the course starts. On the other hand, those employed by the requesting firm but who do not complete the course because they drop out remain employed for 14 months.

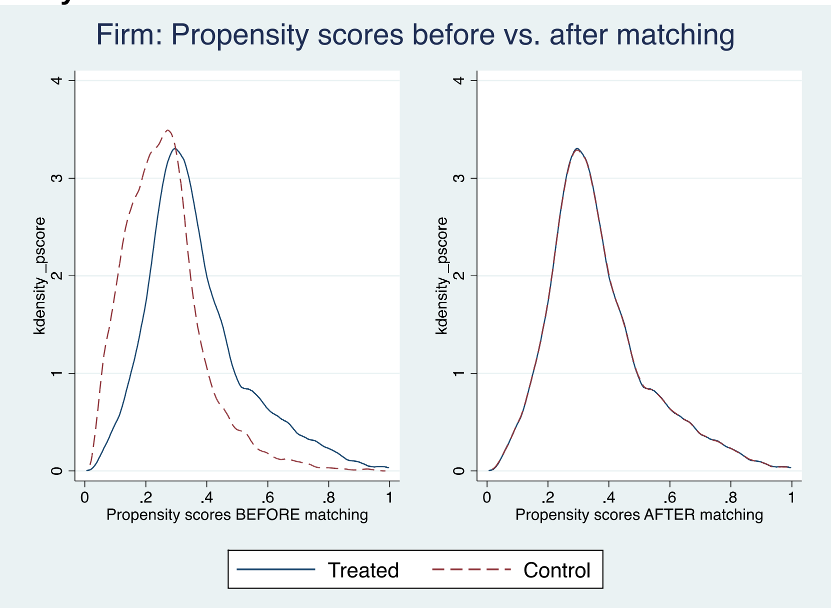
IV. Methodology

A. Firm level

We match the probability of course approval of firms that demand and obtain training confirmation with firms of similar characteristics that demand but do not obtain confirmation. The matching is built on a logit model that captures the likelihood of course approval based on its pre-treatment features such as the location, economic activity and size of the firm as well as the mean gender, race, occupation, educational level, job tenure and wage of workers[10]. We obtained good matching as can be seen in the Kernel densities (**figure 1**) showing the propensity scores for the two groups before and after the matching.

[9] Unemployment insurance recipients, ex-prisoners, Bolsa Familia beneficiary, among other beneficiaries of social assistance.
[10] Location is divided in regions (North, Northeast, Center-west, Southeast, and South) and firm size is the total number of workers per firm. Educational level is broken down by primary, secondary and tertiary education, while occupation and economic activity are listed at one digit. Wage takes the form of the log mean of the monthly-averaged wage between the year the worker was admitted and the year it was separated, deflated using December 2016.

Figure 1
Propensity scores of treatment and control firms before and after PSM



Source: Calculations of authors using administrative data from Pronatec-MDIC

We then follow the labor turnover of firms from 2011 until 2017, for which we calculate two different rates for each establishment *i* at the end of year *t*:

$$R_{1it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right) \quad (1)$$

$$R_{2it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right) - abs\left|\left(\frac{H_{it}-S_{it}}{AE_{it}}\right)\right| \quad (2)$$

where;

H_{it} = admissions in firm i at time t

S_{it} = separations in firm i at time t

$AE_{it} = \frac{(E_{iet}+E_{iet-1})}{2}$; is the average number of workers between two consecutive periods in establishment *i* at time *t*

R_{1it} = is the job flow or the rate at which workers enter and leave an establishment *i* at the end of time *t* (Corseuil et al., 2013)

R_{2it} = is the churning rate at which workers enter and leave an establishment *i* at the end of time *t* because job creation or destruction (Corseuil et al., 2013)

The two turnover rates consider the flow of admissions and separations over the average stock of workers between two consecutive years. However, R_{1it} focuses on the overall flow of workers entering and leaving, while R_{2it} discounts the flow caused by net job creation[11].

[11] These measures are calculated for all workers of the firm and subsets of Pronatec applicants and non-applicants, enrolled and non-enrolled workers, as well as those workers who complete and do not complete the course.

Thus, R_{1it} may come about when firms hire for expansion or separate for contraction while R_{2it} only relates to hiring for replacement, also known as job churn (Lazear and McCue, 2018). Job churn is a less cyclical turnover measure and is thus our preferred indicator.

To estimate the difference in labor turnover of firms which experience the treatment and those not exposed to it, we estimate the following regression:

$$y_{it} = \alpha + \beta \cdot pronatec_{it} + \gamma \cdot post_{it} + \delta \cdot pronatec_{it}{}^{*}post_{it} + \varphi_{ij} + \theta_{it} + u_{it} \quad (3)$$

Where y_{it} is job turnover for the years 2012 to 2017; $Pronatec_{it}$ indicates whether the firm obtains training approval and $post_{it}$ accounts for the follow-up period. In other words, each control and treatment unit has one observation before and one after the course. Before being from 2011 to the first year the course demand is approved; after being from then to 2017. Finally, we used clustered errors at state level φ_{ij} and add a year dummy θ_{it} to control for turnover effects stemming from economic shocks and other exogenous features. We are interested on the δ coefficient, which indicates the causal impact of having a course approved on turnover using different subgroups of workers based on enrollment and completion status.

B. Worker level

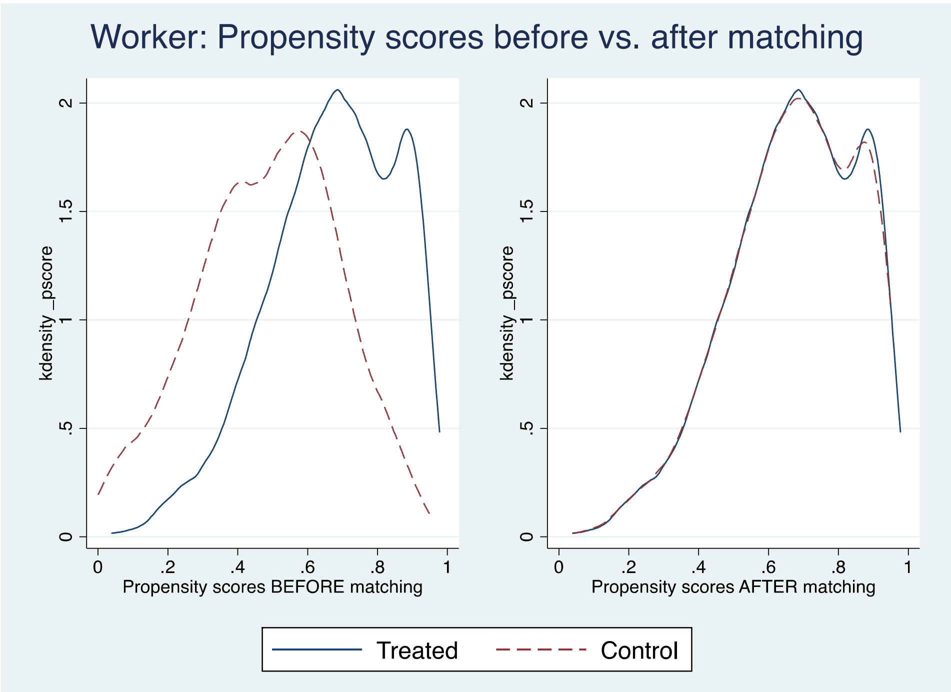
In the case of employees, we wish to measure the impact that enrolling and completing a firm-demanded course has on job tenure. Ideally, we would use administrative constraints as an exogenous source of variation to understand the impact of training on employees. That is, use as counterfactual the employees that apply to courses demanded by the firms, but who are denied access for reasons unrelated to their observed and unobserved characteristics.

However, there is no treatment protocol and the characteristics of employees rejected for administrative reasons are not similar to those of the treatment group, in part because there are few employees that fulfill these conditions (**table A2** in the annex). To construct a comparison group of workers with similar characteristics to minimize a potential self-selection issue, the study uses Propensity Score Matching (PSM) at worker level.

To this end, we match the probability of program enrollment of workers enrolled in courses in 2015-16 demanded by the same firm that employs them with that of workers with similar characteristics who do not enroll but are employed in the same firm. We do the same for workers who complete the courses. That is, we apply Propensity Score Matching (PSM) for both enrolled and graduate workers separately.

The matching is built on a logit model that captures the likelihood that an employee is assigned to treatment based on its pre-treatment characteristics such as age, gender, race, location, education level, occupation, economic activity, job tenure before course onset, wage, number of program registrations, and course enrollments[12]. The match produces treatment and comparison groups that share similar characteristics **(table A3** in the annex**)**. Kernel densities below show that the matching procedure generates similar treatment and control groups for enrolled students as the distribution of the propensity score for the two groups after matching overlaps **(figure 2).** For the distribution of Kernel densities for treatment and control groups for graduate students see **figure A1** in the annex.

Figure 2
Propensity scores of treatment and control of enrolled students before and after PSM



Source: Calculations of authors using administrative data from Pronatec-MDIC

[12] Location is divided in regions (North, Northeast, Center-west, Southeast, and South). Educational level is broken down by primary, secondary and tertiary education while occupation and economic activity are listed at one digit. Wage takes the log mean of the monthly-averaged wage between the year the worker was admitted and the year it was separated, deflated by CPI index (IPCA) using December 2016 as reference date.

We then follow the job tenure of workers until 2017. To estimate job tenure, we calculate the duration of employment from the final day of the course to the dismissal or last day of 2017[13]. To assess the difference in outcomes for workers who enroll or graduate and those who do not, we estimate the following specification:

$$y_{it} = \alpha + \beta \cdot pronatec_{it} + \gamma \cdot post_{it} + \delta \cdot pronatec_{it}{}^{*}post_{it} + \varphi_{ij} + \theta_{it} + u_{it} \qquad (4)$$

Where $y_{i,t}$ is employment duration for the years 2011 to 2017; $pronatec_i$ indicates whether the worker enrolls into or graduate from the course; and $post_t$ accounts for the follow-up period. In other words, each control and treatment unit has one observation before and one after the course. Before being from the first day of the last job, to the first day of the course; after being from there to the dismissal or last day of 2017. Based on the two separated analysis for workers who enroll and for workers that graduate, we hypothesize that while enrollment may have a capital accumulation effect on job tenure, graduation may have a further signaling effect. Finally, we cluster the error at state level φ_{ij} and add a year-monthly dummy θ_{it} using graduation date. We are interested on the δ coefficient, which indicates the causal impact of participating in Pronatec on job tenure. **Table A4** in the annex illustrates the groups of firms and workers used to construct control groups.

V. Results

This section presents the estimations of the effect of Pronatec MDIC at firm and worker level. We first present the results at firm level and assess how having a Pronatec-MDIC course approved affects turnover when compared firms whose demand is not approved. We do so by presenting two types of job turnover rates (job flow (R1) and churning (R2)) at different groups of workers within the firms (all firm workers, Pronatec (non)applicants and workers who enroll and complete the course). Later in the section, the paper assesses the effect at worker level and show whether there is a difference in the effect when a worker employed in a firm whose demand is approved enrolls or completes the course.

A. Firm level

Table 3 shows estimates of equation (3) at firm level for different subgroup of workers. We find that having a course approved in itself is not associated with a change in the labor turnover of firms when considering all workers or non-applicants. Differences start emerging when we

[13] Turnover in Brazil is high and censored data might not change the results. Using data until 2017 allowed us to use a longer time horizon for this analysis.

analyze subgroups of workers who apply, enroll and complete the courses and when considering different time horizons.

Having a course approved is correlated to an overall job flow (R1) and job churning (R2) increase of 0.27 and 0.25 respectively when considering Pronatec applicants (**table 3**). That is, for every 100 workers employed within two consecutive periods after the intervention, 27 and 25 workers extras that were Pronatec applicants are either hired or dismissed when a firm has a course demand approved compared with a similar firm without demand approved. In the same line, having a course demand approved is associated with a labor turnover increase of 0.18 (R1) and 0.16 (R2) for workers who enroll into the course (**table 3**). When considering workers who complete the course, turnover increases by 0.12 (R1) and 0.13 (R2). Almost all of these effects are significant at 1%.

Turnover rate 1: $R_{1it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right)$ | **Turnover rate 2:** $R_{2it} = \left(\frac{H_{it}+S_{it}}{AE_{it}}\right) - abs\left|\left(\frac{H_{it}-S_{it}}{AE_{it}}\right)\right|$

Table 3
Results of job turnover (R1 and R2) before and after course approval

variable	R1	R2
All firm workers (mean annual employment 275.47)		
did_post	-0.022	-0.029
Observations: 4,672	(0.60)	(0.50)
Non-applicants (mean annual employment 263.68)		
did_post	-0.03	-0.03
Observations: 4,656	(0.50)	(0.41)
Pronatec applicants (mean annual employment 23.43)		
did_post	0.27***	0.25***
Observations: 2,432	(0.00)	(0.00)
Enrolled (mean annual employment 20.23)		
did_post	0.18***	0.16***
Observations: 2,161	(0.001)	(0.001)
Completed (mean annual employment 15.93)		
did_post	0.12**	0.13***
Observations: 1,860	(0.02)	(0.009)

Source: Calculations of authors using administrative data from Pronatec-MDIC *** significant at 1%; ** significant at 5%; *significant at 10%; standard errors in ()

The results presented in **table 3** are a first indication that Pronatec affects mainly the turnover of workers who participated in the program. The average turnover, however, might hide the adjustment process within a firm. **Table 4** provides estimates for the first, second and third year after the program presenting a closer look showing that the adjustment in turnover is not immediate and decreases over time.

In the second year after course approval turnover differences spike for workers in firms whose course is approved (0.18 (R1) and 0.11 (R2)), suggesting that the adjustment occurs in the second year after course approval. Turnover differentials then decrease in the third year (-0.11 (R1) and -0.13 (R2)) indicating that turnover decreases with time. The results suggest that having a course approved has an overall effect on turnover for participating firms in spite of their workers. However, the effect is not immediate nor is it maintained overtime.

The adjustment is then reverted in the third year. This effect reversal may be related to changes in productivity as suggested in Corseuil et al (2018). That is, trained (Pronatec) workers might leave to more productive firms in the second year, forcing firms to adjust their labor stock back in the third year. This result similar to what Rasul et. al (2017) find in Uganda, where the size of firms does not change 3.5 years after a training subsidy ends. Alternatively, the turnover increase can also be associated with firms getting rid of less productive workers and retaining more productive (Pronatec) workers. Whether the increase in turnover in the second year is productivity enhancing or not for the treated firm requires further research. The worker level analysis in the following section shed some light on this issue.

Table 4

Results of job turnover (R1 and R2) before and after course approval

All firm workers		
R1		
T1-T0	T2-T1	T3-T2
0.04 (0.43)	0.18** (0.01)	-0.11** (0.02)
R2		
T1-T0	T2-T1	T3-T2
0.04 (0.37)	0.11*** (0.008)	-0.13*** (0.00)
Non-applicants		
R1		
T1-T0	T2-T1	T3-T2
0.03 (0.44)	0.11** (0.01)	-0.11** (0.02)
R2		
T1-T0	T2-T1	T3-T2
0.04 (0.36)	0.11** (0.01)	-0.14*** (0.00)
Applicants		
R1		
T1-T0	T2-T1	T3-T2
0.10 (0.28)	0.10 (0.25)	-0.30*** (0.001)
R2		
T1-T0	T2-T1	T3-T2
0.11 (0.22)	0.15* (0.07)	-0.23*** (0.001)
Enrolled		
R1		
T1-T0	T2-T1	T3-T2
0.07 (0.39)	0.10 (0.22)	-0.22* (0.02)
R2		
T1-T0	T2-T1	T3-T2
0.06 (0.48)	0.14* (0.06)	-0.21*** (0.002)
Completed		
R1		
T1-T0	T2-T1	T3-T2
0.09 (0.32)	0.08 (0.25)	-0.12 (0.216)
R2		
T1-T0	T2-T1	T3-T2
0.08 (0.35)	0.15** (0.02)	-0.16** (0.016)

Source: Calculations of authors using administrative data from Pronatec-MDIC
*** significant at 1%; ** significant at 5%; *significant at 10%

B. Worker level

Table 5 shows estimates of equation (4) to assess the effect of job tenure at worker level. We find evidence that workers who enroll in a course demanded by the employer, stay on average 8.89 months longer in the job than workers from demanding firms who do not enroll (**table 5**). The result is significant and in line with the 8.9 months that graduate workers stay on average from a 6-month, on-the-job training in Uganda (Rasul et al., 2017). Conversely, a worker who enroll and completes the course stays on average 3.36 months less than workers from demanding firms who do not complete the course.

Table 5
Results of job tenure before and after course

If enrolled						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
enrollment	-2.90	1.39	-2.08	0.051	-5.81	0.015
post	-23.19	1.91	-12.15	0.000	-27.18	-19.19
Pronatec*post (δ)	8.89***	1.83	4.85	0.000	5.06	12.72
_cons	47.55	1.27	37.53	0.000	44.90	50.20
Observations	5,741					
If completed						
job tenure after	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
graduation	5.22	1.35	3.88	0.001	2.38	8.06
post	-11.93	1.93	-6.18	0.000	-16.00	-7.86
Pronatec*post (δ)	-3.36**	1.65	-2.04	0.057	-6.84	0.12
_cons	23.96	0.97	24.82	0.000	21.93	26.00
Observations	3,420					

Source: Calculations of authors using administrative data from Pronatec-MDIC
*** significant at 1%; ** significant at 5%; *significant at 10%

These results are in line to the human capital accumulation model (Becker 1962, 1993) and the job market signaling effect (Spence, 1973) model. On one hand, the 8.89 months differential between enrolled and non-enrolled workers suggests that investing in training that is applied on the job enhances capital accumulation and induces experience. That is, taking the course helps workers accumulate skills, gain experience and stay longer. This longer tenure might be associated with productivity gains at the firm as suggested by Corseuil et al. (2018).

On the other hand, completing the course may discourage workers from staying longer in the firm compared to those who do not complete the course. This may occur because workers realize that finalizing the course may signal differentiable accumulation of skills to other employers. The worker effects may be related to what Rasul et al. (2017) find in their study in Uganda. Trainees who obtain certificates receive more job offers than those who do not.

Whether workers in Brazil who complete the course receive more job offers requires further research. We provide some initial analysis about how workers behave after course completion, which may hint why graduate students stay on the job for fewer months. Workers who complete the course stay 1.03 fewer months unemployed from the moment they exit the job (Annex **table A5**).[14] Put differently, completers who exit the job stay unemployed less afterwards.

Since the hypothesis is that graduate workers leave earlier to look for better opportunities and thus stay unemployed less, we dig deeper and restrict the sample used in this exercise to students who graduate and were reemployed. This restriction allows us to understand whether their salary and tenure differentials justify their exit.[15] We find that workers who complete the course and do switch jobs stay 0.24 months less in their next job (**table A6**). They also earn 3% more than those who do not complete the course. However, none of these results are significant. In sum, course completers stay unemployed less time than non-completers. However, it is uncertain whether they do so because they receive better job opportunities, a question that remains open for future research.

VI. Conclusion and policy implications

The labor market in Brazil is characterized for high labor turnover and stagnant worker productivity. The launch of the demand-driven version of Pronatec in 2014 by the Ministry of Development, Industry and Trade, where firms can demand courses their workers take, raised expectations on whether skill development could diminish turnover and increase productivity.

This paper finds that at firm level, having a course approved is associated with a job turnover increase for participating workers. For every 100 workers hired in two consecutive periods after course approval, 27 and 25 enrolled workers are hired or separated from the job. Nevertheless, results show that the turnover differential is only higher the second year after course approval and decreases a year later, suggesting that it takes time for firms to adjust to the training effect.

[14] This effect is estimated using propensity score to create comparable groups of workers that completed the course and those that did not complete the course and difference-in-difference estimates. Annex X provides more details.

[15] This effect is estimated using propensity score to create comparable groups of workers that separated from the job they had at the time of the enrollment and got reemployment later and that completed the course and those that did not complete the course. The estimated impact provided is based on fixed effect estimations. Annex V provides more details.

At worker level, the job tenure of workers that enroll in courses demanded by their employers increases by 8.89 months, while completing the course may induce workers to stay 3.36 months less. However, it is not clear whether course completers move proportionately more to another job because they receive better job opportunities. All we know is that workers who complete the course stay 1.03 fewer months unemployed from the moment they exit the job.

The combined results hint that demand-driven training affects turnover at both firm and worker level. At worker level, it occurs when they complete the courses. At firm level, turnover in the year following approval might increase as workers leave firms. It remains uncertain why they do so. All we know is that they remain unemployed less after leaving. The decrease in turnover after the third year of participation might be associated with firms keeping more productive workers that enrolled in the program substituting for those who left.

The policy implications of these results are that large scale training programs in Brazil affect turnover. Demand-driven training programs might be productivity enhancing within the firms when worker stay but might also be productivity enhancing outside the firm when workers leave for a more productive job. However, workers motivated enough to complete the course may stay less if they receive other opportunities, which might disincentivize provision of training by the firm.

The fact that only one Ministry employs this demand-driven design out of 21 eligible Ministries provides an opportunity to switch to a demand-driven training model to improve labor productivity in the long run[16], a phenomenon that may be holding back the labor productivity potential of firms in the country. Ultimately, this supply-driven programs spent BRL 2.4 billion annually in 2015[17] while demand-driven programs can be more cost-effective, specially in times of fiscal consolidation.

[16] It is paramount to understand that some supply-driven programs have social objectivities where this statement may not apply like re-insertion of former convicts, insured workers, among others.
[17] Calculated using the federal budget line 20RW

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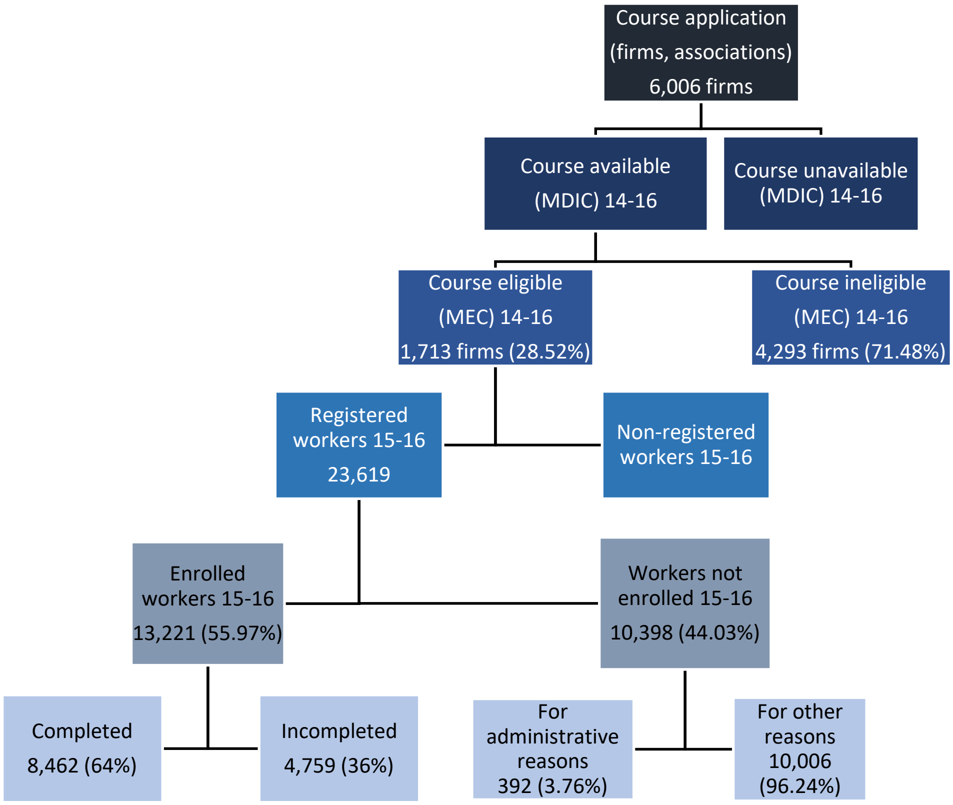
Annex

Annex I. Overview of the protocol for course request



Source: Built from O'Connel et al., 2017 using authors' own calculations

Annex II. Tables

Table A1
Times firms demand courses (2014-2016)

	Freq.	Percent	Cum.
Demanded once	4,683	77.97	77.97
Demanded twice	1,115	18.56	96.53
Demanded thrice	208	3.46	100
Total	6,006		

Source: Calculations of authors using administrative data from Pronatec-MDIC

Table A2
Reasons for not completing firm-requested courses (2015 - 2016)

student status	Freq.	Percentage	Cum.
dropout	3,901	93.30	93.30
unfulfilled requirements	235	5,62	98.92
transfer	28	0.66	99.58
administrative reasons	11	0.26	99.84
no status	6	0.14	100
Total	4,181	100	

Source: Calculations of authors using administrative data from Pronatec-MDIC

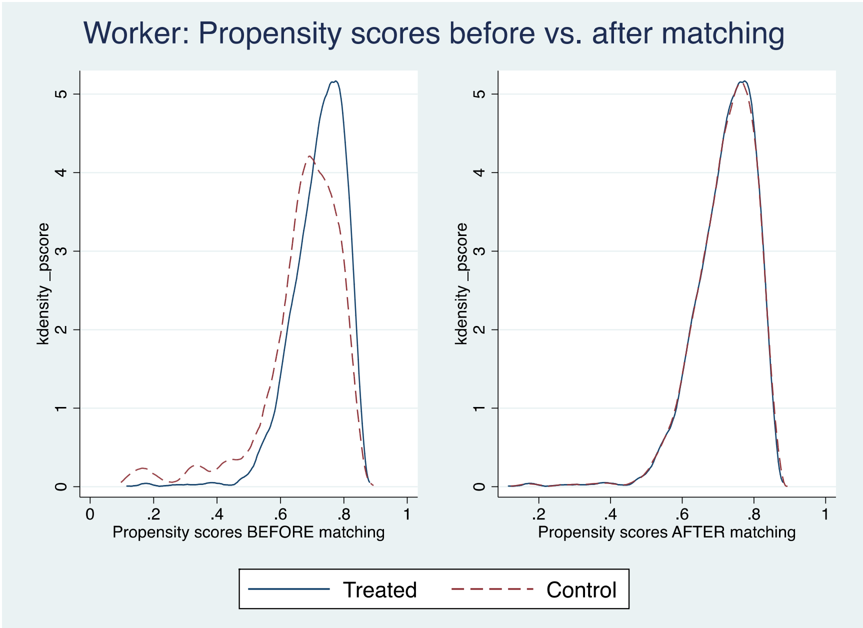
Table A3
Descriptive statistics of control and treatment groups before and after PSM
Enrolled students employed by requesting firm at course onset (2015-2016)

	Unmatched	Mean			t-test		
variable	Matched	T	C	%redact |bias|	t-stat	p-value	V (T) / V ©
age	U	30.551	29.509		4.97	0	1.02
	M	30.551	30.684	87.2	-0.68	0.498	0.86*
male	U	0.9096	0.85086		6.89	0	.
	M	0.9096	0.90813	97.5	0.21	0.834	.
non-white	U	0.567	0.64353		-5.82	0	.
	M	0.567	0.56934	96.9	-0.2	0.845	.
north	U	0.09128	0.20776		-12.71	0	.
	M	0.09128	0.10503	88.2	-1.91	0.056	.
north east	U	0.31246	0.25259		4.92	0	.
	M	0.31246	0.2952	71.2	1.55	0.121	.
south east	U	0.23113	0.34224		-9.31	0	.
	M	0.23113	0.22908	98.2	0.2	0.841	.
south	U	0.22996	0.05129		18.77	0	.
	M	0.22996	0.244	92.1	-1.37	0.172	.
center west	U	0.13517	0.14612		-1.17	0.24	.
	M	0.13517	0.12668	22.5	1.04	0.298	.
illiterate	U	0.00176	0.00043		1.41	0.158	.
	M	0.00176	0.00029	-10.5	1.89	0.059	.
tenure before	U	36.447	37.079		-1.07	0.286	0.69*
	M	36.447	35.508	-48.5	1.75	0.08	0.71*
no. registrations	U	1.0138	1.1172		-14.38	0	0.09*
	M	1.0138	1.0176	96.3	-1.25	0.21	0.76*
log wage	U	7.4821	7.391		7.26	0	0.89*
	M	7.4821	7.4609	76.7	1.82	0.069	0.79*
service & sales	U	0.02575	0.0375		-2.54	0.011	.
	M	0.02575	0.02399	85.1	0.47	0.641	.
agricultural fishery	U	0.06407	0.04871		2.45	0.014	.
	M	0.06407	0.06934	65.7	-0.87	0.383	.
craft workers	U	0.42101	0.41767		0.25	0.802	.
	M	0.42101	0.42013	73.7	0.07	0.941	.
machine operators	U	0.13136	0.1125		2.13	0.033	.
	M	0.13136	0.14775	13.1	-1.95	0.051	.
elementary occu	U	0.21299	0.1431		6.72	0	.
	M	0.21299	0.19514	74.5	1.83	0.067	.
officials & managers	U	0.00439	0.00517		-0.43	0.67	.
	M	0.00439	0.00351	-12	0.58	0.563	.
technicians	U	0.06788	0.13319		-8.36	0	.
	M	0.06788	0.06963	97.3	-0.29	0.774	.
clerks	U	0.05295	0.07888		-3.96	0	.
	M	0.05295	0.0553	91	-0.43	0.669	.
professionals	U	0.0196	0.02328		-0.95	0.342	.
	M	0.0196	0.01521	-19.5	1.39	0.165	.
	U	0.63956	0.73147		-7.34	0.000	
H_than_college	M	0.63956	0.622	80.9	1.50	0.133	.

Source: Calculations of authors using administrative data from Pronatec-MDIC

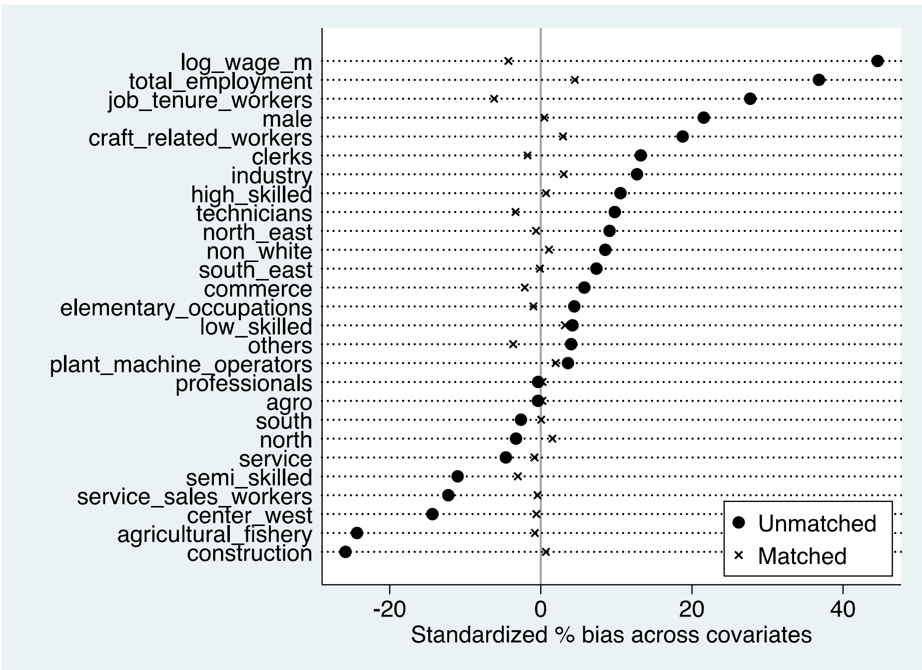
Annex III. Figures

Figure A1
Propensity scores of treatment and control before and after PSM
Graduate students



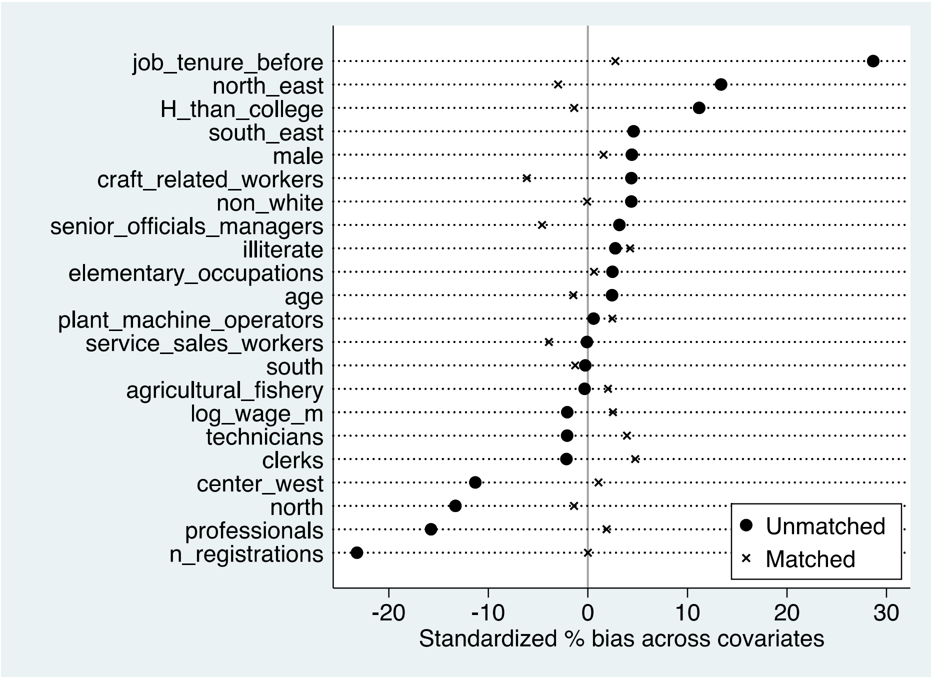
Source: Calculations of authors using administrative data from Pronatec-MDIC

Figure A2
Means difference of control and treatment groups at firm level (2014-2016)
before and after propensity score matching (PSM)



Source: Calculations of authors using administrative data from Pronatec-MDI

Figure A3
Means difference of control and treatment groups of graduate workers (2014-2016) before and after propensity score matching (PSM)



Source: Calculations of authors using administrative data from Pronatec-MDI

Annex IV. Construction of treatment and control groups at firm and worker level

Table A4
Treatment and control groups for firms and workers

<table>
<tr><td rowspan="5">demanding firm = hiring firm</td><td colspan="6">firm whose demand is approved</td><td colspan="6">firm whose demand is not approved</td></tr>
<tr><td colspan="6">Worker</td><td colspan="6">Worker</td></tr>
<tr><td colspan="4">Apply (A)</td><td colspan="2">Not apply (B)</td><td colspan="4">Apply (C)</td><td colspan="2">Not apply (D)</td></tr>
<tr><td colspan="2">Enrolled (A.1.)</td><td colspan="2">Not enrolled (A.2.)</td><td colspan="2">Not enrolled (B.2.)</td><td colspan="2">Enrolled (C.1.)</td><td colspan="2">Not enrolled (C.2.)</td><td colspan="2">Not enrolled (D.2.)</td></tr>
<tr><td>Complete</td><td>Incomplete</td><td>C</td><td>I</td><td>C</td><td>I</td><td>C</td><td>I</td><td>C</td><td>I</td><td>C</td><td>I</td></tr>
</table>

Annex. V. Workers who complete the course

Knowing what happens to students after course completion in terms of unemployment spell may help understand what makes them rotate. To estimate unemployment time after treatment for graduate students, we count the number of months the worker stays unemployed from the moment of dismissal until the last day of 2017[18]. To construct a comparison group of workers with similar characteristics and estimate difference in unemployment spell, we replicate PSM and DID methodology in section IV.B (see **figure A1 and table A4 in the annex**). We matched workers that completed the course to workers that did not complete the course and present DID estimates in **table A5**.

Table A5
Results of unemployment time and rate until 2017 after course
If completed

	Coef.	Std. Err.	z	P>t	[95% Conf. Interval]	
Unemployed time (months)	-1.03***	0.16	-6.28	0.000	-1.35	-0.71
Observations	3,422					

Source: Calculations of authors using administrative data from Pronatec-MDIC
*** significant at 1%; ** significant at 5%; *significant at 10%

The hypothesis is that graduate workers leave earlier to look for better opportunities and thus stay unemployed less. We thus restrict our student sample to graduate students reemployed[19]. This restriction allows us to understand whether their salary and tenure differentials justify their exit. To estimate job tenure in the next job, we calculate the time between rehire and final dismissal or last day of 2017. Lastly, wage growth is estimated taking the proportional wage differential between the new and former job.

To assess the difference in these outcomes, we estimate a fixed effect model after employing a logit model for matching. The match is carried out with groups of students who enroll, complete the course and find reemployment (treatment) with students who enroll, do not complete the course but find reemployment (control). The simple regression uses the following specification:

$$y_{it} = \alpha + \beta \cdot pronatec_{it} + \theta_{it} + u_{it} \qquad (5)$$

[18] We censored the timeline at 2017 to allow for a longer time horizon for this analysis assuming that turnover in Brazil is high and censored data is unlikely to change the results.

[19] Students who i) were employed at course onset, ii) who finish the course, iii) who exit after course completion, and iv) find another job.

Where $y_{i,t}$ are the outcomes for the years 2015 to 2017 and $pronatec_i$ indicates whether the worker graduate from the course. We then add a year-monthly dummy θ_{it} using the graduation date. We do not use difference-in-difference model given that we cannot observe re-employment before graduation, only after.

Table A6
Results of job status of course completers who switch jobs (months)

	Coef.	Std. Err.	z	P>t	[95% Conf. Interval]	
Job tenure in next job (months)	-0.24	0.40	-0.60	0.551	-1.02	0.54
Salary growth rate (mean monthly rate)	0.03	0.11	0.28	0.781	-0.18	0.24
Observations	454					

Source: Calculations of authors using administrative data from Pronatec-MDIC
**** significant at 1%; ** significant at 5%; *significant at 10%*