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Essays on Enviromental and Labour Economics

Bruno Benevit

Pelotas
2022

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Essays on Enviromental and Labour Economics

Dissertação submetida ao Programa de Pós-graduação em Organizações e Mercados da Universidade Federal de Pelotas como requisito parcial para obtenção do título de Mestre em Economia Aplicada.

Orientador: Prof. Dr. Daniel de Abreu Pereira Uhr

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Banca examinadora:

_____

Professor Doutor Daniel de Abreu Pereira Uhr (PPGOM/UFPEL)

_____

Professor Júlia Gallego Ziero Uhr (PPGOM/UFPEL)

_____

Professor Paulo Roberto Amorim Loureiro (FACE/UNB)

_____

Professor Rafael Terra de Menezes (FACE/UNB)

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Summary

1. General introduction

This master's thesis applied two microeconometric techniques. We analyzed the influence of entrepreneurship on human capital and the effectiveness of policies to combat deforestation in Brazil. The first essay analyzes the impact of parents' entrepreneurial attitude on their children's educational decisions based on the 2015 National Household Sample Survey (PNAD) complex survey database. We used several matching methods for this analysis according to Dehejia and Wahba's (2002) selection criteria. Additionally, we consider the adjustment for complex samples proposed by Austin, Jembere and Chiu (2016) for propensity score matching methods. We also tested the robustness of the results through placebo testing, propensity score weighting, entropy balancing, and heterogeneous effects analysis. In the second essay we analyzed the effects of the first phase of Action Plan for the Prevention and Control of Deforestation in the Legal Amazon - PPCDAm, a set of policies to combat deforestation in the Brazilian Legal Amazon implemented in 2004. We analyzed the period from 2002 to 2007 using longitudinal data from Project for Monitoring Deforestation in the Legal Amazon (PRODES) in conjunction with other data sources. We utilized the Triple Difference method to identify the PPCDAm's causal effect on the deforestation rates observed in the period from 2002 to 2007. Further, the robustness of the results were checked through placebo tests for the treatment and the outcome variable, heterogeneous effect analysis, and the flexibility of the composition of the groups.

The first essay results indicate an increase in the probability of entrepreneurs' children studying at private schools and universities. The heterogeneous analysis indicates heterogeneous effects conditioned to the gender of the children and parents. This evidence suggests that the entrepreneurial activity affect the entrepreneur's family decisions. Such findings can guide future public policies aimed at incentivizing entrepreneurial activity and fostering the human capital development. The second essay results indicates a deforestation reduction of 10,293 km^2 and a stock of 498 million tons of CO_2 between 2004 and 2007. Such results show the vulnerability of regions isolated from major centers and the importance of policies aimed at curbing environmental degradation in regions of the entire Brazilian Legal Amazon.

2. Parents' entrepreneurial attitude and its influence on children's educational choices: evidence from Brazil

Abstract

This study utilizes the propensity score matching method with survey weights adjustment to identify the parents' entrepreneurial attitude effects on children's years of schooling, probability of studying at private schools, and probability of studying at a university (general, public, and private). The micro data employed is from the National Household Sample Survey of 2015. The study also presents a series of robustness strategies and heterogeneous treatment effect analysis. Our findings suggest that entrepreneurial parents are more willing to enroll their children in private schools. These effects are greater when both parents are entrepreneurs. The results also indicate that children of entrepreneurial parents are more likely to study at universities, which are mainly directed to private universities. The heterogeneous treatment effect analysis highlights that the gender of the children and entrepreneurial parents impacts the magnitude of the treatment.

Keywords: family structure, human capital, intra-household allocation, entrepreneurship, propensity score matching

JEL: J12, J24, L26.

Resumo

Este estudo utiliza o método de pareamento por escore de propensão com ajuste de pesos amostrais para identificar os efeitos da atitude empreendedora dos pais nos anos de escolaridade, probabilidade de estudar em escolas particulares e probabilidade de estudar em universidade (geral, pública e privada) dos filhos. Os microdados utilizados são da Pesquisa Nacional por Amostra de Domicílios de 2015. O estudo também apresenta uma série de estratégias de robustez e análise dos efeitos heterogêneos do tratamento. Nossos resultados sugerem que os pais empreendedores estão mais dispostos a matricular seus filhos em escolas particulares. Esses efeitos são maiores quando ambos os pais são empreendedores. Os resultados também indicam que os filhos de pais empreendedores são mais propensos a estudar em universidades, e este efeito é direcionado principalmente para universidades privadas. A análise do efeito do tratamento heterogêneo destaca que o gênero dos filhos e do pai empreendedor impacta na magnitude do tratamento.

Palavras-chave: estrutura familiar, capital humano, alocação intrafamiliar, empreendedorismo, pareamento por escore de propensão

JEL: J12, J24, L26.

2.1. Introduction

Entrepreneurship is understood as a determining factor for the economic development of society, driving the creation of jobs, innovation, and reduction of inequalities (Gries and Naudé, 2010; Kimhi, 2010; Naudé, 2010). However, the flourishing of initiatives of this nature depends on the quality of institutions, credit lines, reduction of bureaucracy, and social context (Anderson and Jack, 2002; Bosma *et al.*, 2018; Elam and Terjesen, 2010; Terjesen and Amorós, 2010). Individual preferences explain part of the choice to undertake a business, where the profile of entrepreneurs is usually less averse to risk (Brachert, Hyll, and Sadrieh, 2020; Caliendo, Fossen and Kritikos, 2009; Wickstrøm, Klyver, and Cheraghi-Madsen, 2020). Depending on the gender of the individual, the entrepreneurial attitude may be motivated by different reasons (Bönte and Piegeler, 2013; Caliendo *et al.*, 2014; Fossen, 2012). The social context of individuals is an essential aspect of entrepreneurship (Anderson and Jack, 2002; Korsgaard and Anderson, 2011). At the same time, the social background is also a relevant factor in the accumulation of human capital (Guimarães and Sampaio, 2013; Heckman, 2008; Johnson and Heringer, 2015; Sahoo, 2017), potentially affecting both cognitive and noncognitive skills (Cunha, Heckman, and Schennach, 2010).

In this sense, the entrepreneurial attitude of the heads of a family can affect other family members in various ways, for example, regarding the children's choice of undertaking the family business (Caballero, 2017; Honig and Davidsson, 2000; Parker, 2004), and also the level of the children's human capital (Brandt *et al.*, 2017; Gevrek and Gevrek, 2010; Parikh and Sadoulet, 2005; Randerson *et al.*, 2015). This study aims to evaluate the impact of parents' entrepreneurial attitude on their children's education. With the development of new ethical and work values arising from their employment status (Anderson and Smith, 2007; Korsgaard and Anderson, 2011), the entrepreneurial experience can potentially influence the noncognitive skills of parents and, consequently, their children (Cunha *et al.*, 2010; Heckman, 2008; Johnson, 2002; Mortimer and Kumka, 1982). Thus, we analyze whether children of entrepreneurs reach higher levels of education and if there is a predilection for public or private education.

We employed microdata from the National Household Sample Survey (PNAD) of the Brazilian Institute of Geography and Statistics (IBGE) for 2015. This dataset allows us to

identify the characteristics of Brazilian families. We identify each member of the household, whether the heads of the family are entrepreneurs and the educational situation of the children. The 2015 PNAD is a secondary database with a complex sample structure. Thus, to achieve our goal, we employ the *propensity score matching* (PSM) method utilizing the sample weights adjustment for complex samples (Austin, Jembere, and Chiu, 2016). We estimate the influence of parents' entrepreneurial attitude on different educational metrics of the children, considering the presence of an entrepreneurial head of the family or entrepreneurial spouse of the head of the family as the treatment. As a robustness strategy, we conduct the Placebo test, Propensity Score Weighting (PSW), Entropy Balancing, Heterogeneous Treatment Effect (HTE) analysis, and the Rosenbaum sensitivity analysis.

The results indicate that underage children of entrepreneurial parents are more likely to attend private schools, but no impact is identified on those children's schooling years. Children of entrepreneurial parents are also more likely to study at universities, which is majorly driven by enrollment at private universities. The robustness strategies corroborate the results found. This study is important for at least three reasons. First, due to the gap and dissident evidence that relates the parents' entrepreneurial labor conditions and the children's human capital in the literature. Second, this study provides evidence of the influence of parents' work background in deciding which type of school their children are enrolled in. Third, the results can help develop future public policies for educational and entrepreneurial areas.

The remainder of this paper is organized as follows. Section two reviews the literature. Section three presents the database and the variables' construction details. Section four depicts the method utilized. Section five presents the results. Section six describes the robustness strategy and presents its results. Finally, section seven concludes this study.

2.2. Literature Review

2.2.1. Entrepreneurship in emerging economies and its social framework

Entrepreneurship is a means for economic growth and social transformation for countries and families (Bosma *et al.*, 2018; Coulibaly, Erbao, and Metuge Mekongcho, 2018;

Naudé, 2010). The literature also highlights that entrepreneurship can impact different magnitudes depending on the countries' per capita income and development. (Stel, Carree, and Thurik, 2005; Wennekers *et al.*, 2005).

There are several perspectives on understanding the term entrepreneur in the literature: analyzing what motivates the decision to undertake a business, dividing them into entrepreneurs by opportunity and entrepreneurs by necessity (Elam and Terjesen, 2010; Terjesen and Amorós, 2010), or observing potential entrepreneurs as nascent entrepreneurs (Bönte and Piegeler, 2013; Verheul *et al.*, 2012; Wennekers *et al.*, 2005). According to Cressy (1992), entrepreneurs by opportunity follow a line of analysis of costs and gains along with entrepreneurial activity, which is associated with a learning process through experience. The concept of entrepreneurship by necessity can be understood as an entrepreneurial attitude on the part of the individual driven by survival in response to some kind of economic insufficiency (Fajnzylber, Maloney and Rojas, 2006; Gries and Naudé, 2010; Larsson and Thulin, 2019; Terjesen and Amorós, 2010). In a less restricted way, other authors consider self-employed workers as entrepreneurs, differentiating those from waged and salaried employees (Caliendo *et al.*, 2014; Fossen, 2012; Gindling and Newhouse, 2014; Verheul *et al.*, 2012).

The literature shows that entrepreneurship by opportunity, focused on resolving a specific market problem, tends to occur more frequently in developed economies (Fajnzylber, Maloney, and Rojas, 2006; Terjesen and Amorós, 2010). On the other hand, developing countries commonly report higher rates of entrepreneurs compared to developed countries (Amorós and Cristi, 2011; Larsson and Thulin, 2019; Terjesen and Amorós, 2010), establishing a solid relationship with activities with lower industrial productivity (Fajnzylber, Maloney and Rojas, 2006; Terjesen and Amorós, 2010). According to the report conducted by GEM[1] in 2012, total entrepreneurial activity (TEA) rates for the Latin American region have a 15% share for women and 19% for men, while the rates in the developed European countries and the USA are 5% and 10% for women, and 9% and 15% for men, respectively. Other authors point out that women's lower preference for becoming entrepreneurs may be related to discrimination or unfavorable initial conditions (Terjesen and Amorós, 2010; Verheul *et al.*, 2012).

[1] Global entrepreneurship monitor 2012 women's report.

The difference between entrepreneurs and other groups may be related to risk aversion, with the lower risk aversion of the entrepreneurs being one of their most established characteristics in the literature (Bönte and Piegeler, 2013; Brachert, Hyll and Sadrieh, 2020; Caliendo *et al.*, 2014; Fossen, 2012; Mahfud *et al.*, 2020). Risk aversion is also related to the gender of the entrepreneurial person (Bönte and Piegeler, 2013; Caliendo *et al.* , 2014; Fossen, 2012; Verheul *et al.* , 2012). While entrepreneurs commonly devote more hours in the workday (Binder and Coad 2013), they present greater commitment to their current form of employment and demonstrate more appreciation for autonomy and competence. The entrepreneurial activity can also develop specific management and sector activities skills, potentially enhancing behaviors such as proactive attitude, responsible behavior, and task monitoring (Anderson *et al.*, 2000; Anderson and Smith, 2007; Dunn and Holtz-Eakin, 2000; Korsgaard and Anderson, 2011). According to Anderson and Jack (2002), a process develops social capital through entrepreneurship through rules and labels that form and facilitate the functioning of social network structures. Additionally, entrepreneurs must develop social proficiencies to build high levels of trust and credibility with influential social ties and develop personal ties into firm-level relationships and negotiating (Anderson and Jack, 2002; Tocher *et al.*, 2012).

2.2.2. Human capital, parents, and educational institutes in Brazil

The importance of human capital for developing wealth and social and cognitive capabilities are vastly documented across the literature (Cunha *et al.*, 2010; Curi and Menezes-Filho, 2014; Dizon-Ross, 2019; Hansen *et al.*, 2004). Human capital inequality exerts a direct positive effect on income inequality (Castelló-Climent and Doménech, 2021). Further, several economic and social problems are linked with low levels of human capital, entailing crime, teenage pregnancy, high school dropout, and adverse health conditions (Heckman, 2008).

Heckman (2008) addresses human capital as a set of cognitive (IQ and test scores) and noncognitive abilities (perseverance, motivation, time preference, risk aversion, self-esteem, self-control, and preference for leisure). The author emphasizes the importance of family background in human capital development and highlights that children's early

environments are critical to their adulthood outcomes. The parents' education, time involvement, and marital status are determinants of the formation of individuals' human capital (Brandt *et al.*, 2017; Dizon-Ross, 2019; Guryan *et al.*, 2008; Hansen *et al.*, 2004; Heckman, 2008). Dizon-Ross *et al*. (2018) demonstrate that parents with better socioeconomic means have a better perception regarding investing in their children's education. Ural Marchand *et al.* (2013) show that an increase in the number of working hours of mothers in India causes an increase in the education of their children between 7 and 10.

Education metrics such as years of schooling or the highest education degree completed (primary, secondary or tertiary education) are standardly utilized to quantify the human capital of individuals (Castelló-Climent and Doménech, 2021, 2021; Hansen *et al.*, 2004; Heckman, 2008; Psacharopoulos and Patrinos, 2018). Controlled by individuals' latent level of ability, Hansen, Heckman, and Mullen (2004) identifies that schooling increases achievement test scores and is approximately linear across schooling levels. The returns associated with education in low-income and middle-income countries are generally high (Psacharopoulos and Patrinos, 2018; Manacorda, Sanchez-Paramo, and Schady, 2010). At the same time, such countries present high child labor rates (Brandt *et al.*, 2017; de Carvalho Filho, 2012; Kis-Katos, 2012). According to Psacharopoulos and Patrinos (2018), Latin America has the world's highest average private education returns. Utilizing microdata from five Latin American countries over the 1980s and 1990s, Manacorda, Sanchez-Paramo, and Schady (2010) identify that each additional year of schooling incurs a 10 to 20 percent increase in wages and that individuals that completed secondary education are 83% higher than those having completed primary education. In contrast, the school enrollment for children in Brazil is historically low, strongly correlated with high child labor rates, and presents worse child labor statistics than in other Latin American countries (de Carvalho Filho, 2012).

As education provides long-term returns, parents face an investment decision when choosing which school to enroll their children in (Cunha *et al.*, 2010; Dizon-Ross, 2019). Therefore, the quality of the school is an essential factor in this investment decision-making (Hanushek *et al.*, 2007; Sahoo, 2017). Developing countries present significant differences in educational achievements between public and private schools (Cox and Jimenez, 1990; Fuchs and Wößmann, 2007; Singh, 2015). This difference is also perceived in Brazil

(Cavalcanti *et al.*, 2010; Curi and Menezes-Filho, 2013; Oliveira *et al.*, 2013). Curi and Menezes-Filho (2010) identify that the mother's education, family income, the provision of public schools, the cost of education in the state, and the region where they live are the main factors that motivate parents to enroll their children in private schools in Brazil. In a survey conducted for schools in the state of São Paulo, Curi and Filho (2013) show that a 10% increase in the monthly fees of private schools represents a 1.1% improvement in students' National High School Exam (ENEM)[2] scores. Cavalcanti, Guimaraes and Sampaio (2010) identifies that students from private schools perform better in public university admission tests, plus identifying even greater difficulties in entering highly competitive courses for students from public schools.

Regarding the higher education institutes (HEI) in Brazil, public institutes present better quality indicators than private institutes on average, while private institutes present a higher dispersion of their quality indicators (Hoffmann *et al.*, 2014; Johnson and Heringer, 2015). Such logic is different when only considering business courses[3]. Moreover, public universities tend to be located in capital cities or metropolitan areas, while private universities are more dispersed[4], especially in countryside municipalities. Although public universities in Brazil have no tuition fees, historically, the students of these HEIs were majorly high-income white individuals (Johnson and Heringer, 2015). However, adopting affirmative actions and fellowship programs for low-income students drastically changed this scenario (Johnson and Heringer, 2015).

2.2.3. Parents' entrepreneurial attitude on children's human capital

Several authors demonstrate that the parents' occupational choice can potentially influence the investment in their children's education (Dunn and Holtz-Eakin, 2000; Heckman, 2008; Mortimer and Kumka, 1982). The entrepreneurial attitude could influence

[2] Similarly to Scholastic Aptitude Test (SAT), ENEM is widely used as a university admission test in Brazil.
[3] According to the Preliminary Course Concept of 2018 ("*Conceito Preliminar de Curso contínuo para 2018"* – CPC 2018), the nine best rated courses in administration and economic sciences in Brazil were in private education institutions. In addition, 46 of the top 50 rated management courses in Brazil are also taught by private education institutions.
[4] According to CPC 2018, there are 381 municipalities in Brazil with public education institutions and 665 municipalities with private education institutions.

the parents' perception of education returns through new values from their employment status and work background (Anderson and Smith, 2007; Johnson, 2002; Korsgaard and Anderson, 2011; Mortimer and Kumka, 1982). For example, the noncognitive skills of entrepreneurial parents could potentially affect children's education in two ways: (i) through the personality of parents (Checchi, Fiorio, and Leonardi, 2014), where parents who are more risk averse have a lower propensity to invest in the higher education of their dependent children; and (ii) through risk aversion of the children themselves (Belzil and Leonardi, 2007, 2013), granted that parents shape their children's noncognitive preferences (Heckman, 2008), they could be more likely to attend higher education.

The evidence related to the effects of entrepreneurial parents on the accumulation of children's human capital is divergent. Regarding the human capital of school-age children, Parikh & Sadoulet (2005) identified that children of self-employed parents in Brazil's urban areas are more likely to work. However, no reduction in school attendance was identified. Analyzing family businesses, Marchisio *et al.* (2010) indicate that corporate business initiatives increase the human capital of family members of the next generation. Brandt *et al*. (2017) found positive effects on attending the school of daughters of non-agricultural entrepreneurs in a study conducted in Tanzania, indicating heterogeneous effects based on children's gender. However, Gevrek and Gevrek (2010) identify that children of self-employed workers in Turkey showed a reduction in both intention and finishing of their college studies.

2.3. Data

The database used is the National Household Sample Survey (IBGE/PNAD) for 2015. The PNAD-2015[5] presents 356,904 observations, distributed in 117,939 households throughout Brazil, and contains demographic and socioeconomic variables. The database is representative of the Brazilian population through a complex survey design. Complex surveys employ a stratified cluster sampling technique. The target population is split into mutually exclusive strata, and each stratum is divided into clusters. In the case of nationally

[5] The microdata from PNAD 2015 can be obtained directly from the website: https://www.ibge.gov.br/estatisticas/sociais/rendimento-despesa-e-consumo/9127-pesquisa-nacional-por-amostra-de-domicilios.html?=&t=downloads

representative surveys, such strata can represent geographical regions of the country, while each stratum may represent municipalities or other geographic regions.

Regarding the sample of subjects, they are randomly selected from each cluster, which is randomly selected from each stratum. A sampling weight is related to each sampled subject and indicates the number of subjects in the target population represented by the sampled subject. Thus, it is required to incorporate the sampling weights into the analyses to estimate population standard errors and confidence intervals (Austin, Jembere and Chiu, 2016). In order to homogenize our sample, we removed from the sample households where at least one of the parents was a statutory civil servant[6] or in the armed forces. We constructed two samples, one for children under 18 and another for children between 18 and 30 years old.

The five outcome variables were constructed as follows: (i) *YearsSchooling* indicates the years of schooling of the children; (ii) *PrivateSchool* indicates if the child studies at a private school (primary or secondary education); (iii) *AnyUniversity* indicates if the children studies at a university; (iv) *PublicUniversity* indicates if the children studies at a public university; and (v) *PrivateUniversity* indicates if the children studies at a private university. The variables (i) and (ii) were constructed for the sample with children aged under 18 years, while the variables (ii), (iv), and (v) were constructed for the sample with children aged between 18 and 30 years. We consider entrepreneur employers and self-employed workers with active company registration (*"Cadastro Nacional de Pessoas Jurídicas"* - CNPJ) (Caliendo *et al.*, 2014; Fossen, 2012; Gindling and Newhouse, 2014; Verheul *et al.*, 2012). We create one treatment variable that indicates whether there is at least one entrepreneur in the reference couple of the household (*EntrepreneurialParent*). PNAD individuals are identified by kinship with the head of the family. We consider the head of the family and the spouse of the head of the family (reference couple) as parents.

Regarding the covariates, we create specific variables for children and households. For the children's covariates: *Gender* assumes a value of 1 for men and 0 for women; *Age* indicates the age; *Race* assumes a value of 1 if the individual is white or yellow, and zero otherwise; *Marriage* indicates if the individual lives with a spouse; *Migration* indicates if the individual was born in the municipality of the household. The variables *Gender, Age, Race, Marriage,* and *Migration* follow the same logic for the characteristics of the head of the

[6] Statutory civil service positions are permanent work posts in Brazil.

family (*HeadGender*, *HeadAge*, *HeadRace*, *HeadMarriage*, and *HeadMigration*). We create five education level covariates for the reference person: the covariable *HeadEducation1* indicates if the head of the family has not completed elementary school; the covariable *HeadEducation2* indicates if the head of the family has completed elementary school or not finished high school; the covariable *HeadEducation3* indicates if the head of the family has completed high school or incomplete higher education, and the covariable *HeadEducation4* indicates the head of the family has a complete higher education. Furthermore, we construct general household variables: *Siblings* indicates the number of siblings in the household; *Residents* indicates the number of people in the household; *OwnDweling* indicates if the dwelling is owned. We create four covariates to identify the household income level: the covariable *IncomeLevel1* indicates if the household income per person is equal to or below ½ minimum wage, the covariable *IncomeLevel2* indicates if the household income per person is between ½ and one minimum wage, the covariable *IncomeLevel3* indicates if the household income per person is between 1 and 3 minimum wage, and the covariable *IncomeLevel4* indicates if the household income per person is above three minimum wage. Finally, we consider the indicative variables: *Metropolitan* indicates if the household is in the metropolitan region; *Urban* indicates if the household is in the urban region; the geographical region of Brazil (*North, Northeast, Midwest, Southeast,* and *South*); and the 27 federal units of Brazil (*FederalUnit*).

The mean and the standard deviation of the variables used in this study are arranged in Table 1, considering the groups (treated and control) and the total samples. The sample weights weighted the covariate statistics. Observations with missing data on any of the covariates were disregarded. The sample for children under 18 years old has 69,212 observations, of which 6,302 are children of entrepreneurs (9.2%). The sample for children between 18 and 30 years old presents 2,878 children of entrepreneurs, representing 9.1% of the 31,445 total observations.

Table 1 – Descriptive Statistics

Variables	Children under 18 years old						Children between 18 and 30 years old					
	Treated		Control		Sample		Treated		Control		Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outcome Variables												
YearsSchooling	3.221	3.409	2.976	3.276	2.999	3.291						
PrivateSchool	0.265	0.432	0.069	0.254	0.088	0.283						
AnyUniversity							0.340	0.461	0.151	0.358	0.169	0.374
PublicUniversity							0.075	0.257	0.039	0.193	0.042	0.201
PrivateUniversity							0.265	0.430	0.112	0.315	0.127	0.332
Treatment Variable												
EntrepreneurialParent	1.000	0.000	0.000	0.000	0.095	0.294	1.000	0.000	0.000	0.000	0.096	0.293
Covariates												
Gender	0.515	0.490	0.513	0.502	0.513	0.501	0.553	0.484	0.567	0.495	0.565	0.494
Race	0.644	0.469	0.407	0.494	0.430	0.496	0.654	0.463	0.428	0.494	0.449	0.495
Age	9.132	5.022	9.207	5.141	9.200	5.130	22.461	3.385	22.700	3.634	22.677	3.610
Marriage	0.000	0.017	0.002	0.046	0.002	0.44	0.038	0.186	0.063	0.242	0.060	0.237
Migration	0.846	0.354	0.840	0.368	0.841	0.367	0.757	0.417	0.785	0.410	0.783	0.411
HeadGender	0.749	0.425	0.632	0.485	0.643	0.480	0.733	0.431	0.545	0.497	0.563	0.494
HeadRace	0.580	0.483	0.357	0.481	0.378	0.486	0.639	0.468	0.397	0.488	0.420	0.492
HeadAge	40.409	7.883	38.614	9.305	38.785	9.190	50.971	6.981	51.834	8.910	51.752	8.740
HeadMarriage	0.064	0.240	0.202	0.403	0.188	0.392	0.138	0.336	0.341	0.473	0.322	0.465
HeadMigration	0.497	0.490	0.534	0.501	0.530	0.500	0.431	0.482	0.459	0.498	0.457	0.496
HeadEducation1	0.172	0.370	0.452	0.500	0.425	0.496	0.253	0.423	0.558	0.496	0.529	0.497
HeadEducation2	0.146	0.346	0.193	0.397	0.189	0.392	0.152	0.350	0.148	0.354	0.148	0.354
HeadEducation3	0.451	0.487	0.298	0.460	0.313	0.465	0.385	0.474	0.229	0.419	0.244	0.428
HeadEducation4	0.230	0.412	0.057	0.232	0.073	0.261	0.210	0.396	0.066	0.248	0.080	0.270
Siblings	1.046	0.900	1.454	1.365	1.415	1.331	1.027	0.879	1.211	1.248	1.193	1.217
Residents	4.107	1.052	4.432	1.550	4.401	1.511	4.175	1.177	4.379	1.691	4.360	1.648
OwnDwelling	0.750	0.424	0.675	0.471	0.682	0.467	0.848	0.349	0.818	0.385	0.821	0.382
IncomeLevel1	0.094	0.286	0.528	0.502	0.487	0.501	0.040	0.192	0.289	0.454	0.266	0.441
IncomeLevel2	0.265	0.433	0.305	0.463	0.301	0.460	0.178	0.374	0.340	0.474	0.325	0.468
IncomeLevel3	0.474	0.490	0.150	0.359	0.180	0.386	0.537	0.488	0.331	0.471	0.350	0.476
IncomeLevel4	0.167	0.366	0.017	0.130	0.031	0.174	0.244	0.420	0.040	0.197	0.059	0.236

Note: This table reports the means and standard deviation of the treated, controls, and all observations from both samples. The sample weight adjusts all descriptive statistics. The first three columns report the sample's descriptive statistics for children under 18 years. The last three columns present the sample's descriptive statistics for children between 18 and 30. The variables of regions and federative units were omitted due to space.

2.4. Method

In this work, we want to test the effect of parents' entrepreneurial attitudes on their children's education in Brazil. We can model the relationship in the econometric specification as follows:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \varepsilon_i \quad (1)$$

where Y_i represents one of the five possible outcome variables (*YearsSchooling*, *PrivateSchool*, *AnyUniversity*, *PublicUniversity*, *PrivateUniversity*). The treatment variable T_i represents the existence of an entrepreneurial parent (*EntrepreneurialParent)*, a binary variable that indicates if there is at least one entrepreneur on the household's reference couple. The vector X_i represents all covariates with characteristics of children, parents, and household. Finally, ε_i represents the stochastic term.

It is only possible to identify the influence of parents' entrepreneurial attitude on their children if we eliminate the sources of bias. The direct comparison between treatment and control groups would be enough under a random experiment. However, we cannot assume that the parents' entrepreneurship choice occurs randomly. Thus, the control group could not be comparable to the counterfactual group in observational studies, creating sources of bias in the estimates.

In order to approximate our analysis to a random experiment, we utilize the matching methods approach to eliminate any source bias. Consider the potential outcomes framework proposed by Rosenbaum and Rubin (1983). Each child *i* has a pair of possible outcomes, $Y_i(0)$ and $Y_i(1)$. The individual cannot be in both conditions at the same time. The influence of parents' entrepreneurial attitudes cannot be estimated directly at the individual level. Therefore, we estimate the Average Treatment Effect on Treated (ATT), $E[Y_i(1) - Y_i(0)|T_i = 1]$. The idea of a matching method is to construct a control group similar to the treatment group in the observable variables, and it has two assumptions. First, the observable selection hypothesis assumes that observable variables contain all the information participation in the treatment group. Second, the common support hypothesis asserts that individuals in the treatment group have at least one pair in the control group. Rosenbaum and

Rubin (1983) suggest that a function of vector X can summarize all the information contained in vector X and maintain the orthogonality of the treatment variable. In formal terms:

$$(Y_i(1), Y_i(0)) \perp T_i | p(X) \quad (2)$$

Conditional on the propensity score $p(X)$By approximating the characteristics of children, parents, and household between the treatment and control groups, matching methods enables the identification of a proper counterfactual for children of entrepreneurial parents. Thus, only the treatment assignment will differentiate both groups.

As PNAD-2015 presents a complex sample structure, this study employs the sample weights in the analysis. Using the sample weights allows the estimation of the Populational Average Treatment Effect on Treated - PATT (DuGoff, Schuler, and Stuart, 2014; Ridgeway et al., 2015; Austin, Jembere, and Chiu, 2016). According to Ridgeway et al. (2015), using sample weights results in treatment effect estimates with the lowest root mean squared error and better fit regarding the balance of the covariates among various scenarios. The authors also warn of the risks of not incorporating the sample weights if they involve unavailable variables to estimate the propensity score. Therefore, this study follows the recommendations of Austin, Jembere, and Chiu (2016), who propose that the survey weights should weight propensity score methods on both treatment and control groups.

According to King and Nielsen (2019), the Propensity Score Methods (PSM) can provide non-robust estimates under certain circumstances, resulting in a "propensity score paradox." The authors recommend potentially more robust methods like Mahalanobis Distance Method (MDM) that directly approach the covariate difference between the treatment and control group. The MDM works by pairing nearby units based on the Mahalanobis distance, a non-scaling Euclidean distance. By finding control subjects close to the treated subjects within the Mahalanobis distance, each pair will have similar covariate values. Conversely, Ripollone et al. (2018) argue that the paradox may occur with some data, but it is not problematic when the pre-matched sample presents a high imbalance. Additionally, while the PSM provided an excellent balance in the covariates, MDM produced a poor balance in the dataset tested by the authors. As there is no preferable method, we will test both MDM and PSM estimators.

2.5. Results

The analysis starts by estimating the propensity scores for both samples (children aged under 18 and children aged between 18 and 30 years) through a Probit model. The propensity scores are estimated considering the presence of an entrepreneurial parent on the reference couple of the household (*EntrepreneurialParent*) as a first stage function of the covariates (results of the Probits are shown in Table A1, appendix). The propensity score distribution for both samples were estimated to find a common support region[7]. The distribution of the propensity scores are shown in Table 2.

Table 2 – Distribution of propensity scores of children

Sample	Mean	Min.	Max.	Observ.	Off support	On support
A. Sample Children under 18						
Treated	0.250	0.001	0.746	6,084	10	6,070
Untreated	0.073	0.000	0.686	62,031	0	62,031
All children	0.089	0.000	0.746	68,115	10	724
B. Sample Children between 18-30						
Treated	0.228	0.001	0.744	2,730	4	2,726
Untreated	0.076	0.000	0.705	27,835	0	27,835
All children	0.090	0.000	0.744	30,561	4	30,561

Notes: Panel A presents the sample's propensity score distribution for children under 18. Panel B presents the sample's propensity score distribution for children between 18 and 30. The means, minimum and maximum values of propensity score distributions are reported in the first three columns. The last three columns present the number of children, the number of children off support region, and the number of children on support region in each sample group.

Table 2 shows that the region of common support for children under 18 sample lies within the interval 0.001 – 0.686, and for children between 18 and 30 lies in the interval 0.001 – 0.705. Thus, children whose propensity score is outside those intervals for their respective sample are not considered (off support) in the matching (Caliendo and Kopeinig, 2008).

We analyze the MDM and the different metrics of the PSM matching algorisms. We adopted the selection criteria suggested by Dehejia and Wahba (2002) based on Pseudo-R2, the balancing test, and the size of the matched sample of each compatibility algorithm. Therefore, it is preferable to match algorisms with good balance in its covariates (low pseudo-

[7] Common support is the region where the propensity score of the treatment and control groups overlaps.

R2) and a larger sample size. Finally, the likelihood ratio-Chi2 and its p-value[8] are also considered. Table 3 reports such statistics for each matching algorism tested. The p-value of the insignificant likelihood ratio test in Table 3 indicates that the PSM Kernel estimators present the best covariate balance for both samples, with the Kernel Epanechnikov algorithm presenting the best fit overall. To improve the robustness of the results, we utilize each kernel algorithm in the analysis: (i) Kernel Gaussian, (ii) Kernel Biweight, (iii) Kernel Tricube, (iv) Kernel Epanechnikov, and (vi) Kernel Uniform.

Table 3 – Performance criteria of matching algorisms

Matching algorism	Pseudo-R2	Sample size	LR-Chi2	p>Chi2
A. Sample Children under 18				
Mahalanobis	0.020	68,115	331.66	0.000
Nearest neighbor	0.002	68,110	41.03	0.717
Caliper	0.002	68,110	41.03	0.717
Radius	0.002	68,110	26.01	0.994
Kernel – Gaussian	0.002	68,110	29.07	0.982
Kernel – Biweight	0.002	68,110	26.19	0.994
Kernel – Tricube	0.002	68,110	26.20	0.994
Kernel - Epanechnikov	0.002	68,110	26.07	0.994
Kernel – Uniform	0.002	68,110	26.01	0.994
B. Sample Children between 18-30				
Mahalanobis	0.020	30,565	154.08	0.000
Nearest neighbor	0.007	30,561	54.17	0.220
Caliper	0.007	30,560	54.15	0.220
Radius	0.002	30,560	13.59	1.000
Kernel - Gaussian	0.002	30,561	14.29	1.000
Kernel - Biweight	0.002	30,560	13.51	1.000
Kernel - Tricube	0.002	30,560	13.51	1.000
Kernel - Epanechnikov	0.002	30,560	13.45	1.000
Kernel - Uniform	0.002	30,560	13.59	1.000

Notes: This table reports the performance criteria for matching algorisms. All matching algorisms consider 58 covariates. All PSM models are weighted by sample weight during propensity score estimation. The nearest neighbor estimator considers one neighbor. The caliper estimator considers a caliper of 0.01. The Radius estimator considers a bandwidth of 0.01. The likelihood ratio test (LR-Chi2) and the p-value associated (p>Chi2) are calculated for the matched sample.

Table 4 presents the balance of the covariates between the treated and control groups for both samples (Kernel Epanechnikov algorithm). The balance of the covariates presents the means of treatment and control groups, the standardized percentage of bias between the

[8] The insignificant likelihood ratio test indicates if treated and untreated children have the same distribution in the covariates after matching.

means, the percentage of bias reduction (after the matching), and the p-value indicating the statistical difference between the groups' mean. The results for both samples before the matching show that most covariates are significantly different between groups (p-value<0.001), indicating that the control group is not comparable to the treatment group due to their difference in observable characteristics. Considering the sample of children under 18 years (Panel A), only the covariates Gender, Age, and Migration are similar in means before the matching (p-value>0.1. For the sample of children between 18 and 30 years (Panel B), only the covariates Gender and HeadEducation2 are similar in means before the matching (p-value>0.1). Therefore, it is not appropriate to analyze this case without considering such a source of bias in the econometric model.

Table 4 – Covariates balance test

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children under 18						
Gender	0.513	0.513	0.904	0.517	0.514	0.723
Race	0.639	0.406	0.000	0.609	0.615	0.531
Age	9.094	9.200	0.162	9.177	9.097	0.393
Marriage	0.000	0.002	0.000	0.000	0.000	0.712
Migration	0.848	0.840	0.164	0.843	0.839	0.486
HeadGender	0.750	0.631	0.000	0.733	0.741	0.356
HeadRace	0.573	0.356	0.000	0.549	0.551	0.818
HeadAge	40.320	38.588	0.000	40.328	40.386	0.709
HeadMarriage	0.064	0.202	0.000	0.069	0.068	0.790
HeadMigration	0.494	0.534	0.000	0.485	0.475	0.250
HeadEducation1	0.176	0.452	0.000	0.172	0.172	0.985
HeadEducation2	0.148	0.194	0.000	0.153	0.141	0.081
HeadEducation3	0.454	0.298	0.000	0.453	0.459	0.506
HeadEducation4	0.222	0.056	0.000	0.222	0.227	0.502
Siblings	1.043	1.450	0.000	1.042	1.018	0.179
Residents	4.100	4.425	0.000	4.101	4.084	0.392
OwnDwelling	0.746	0.673	0.000	0.754	0.753	0.943
IncomeLevel1	0.094	0.528	0.000	0.098	0.100	0.689
IncomeLevel2	0.266	0.305	0.000	0.268	0.263	0.529
IncomeLevel3	0.474	0.150	0.000	0.463	0.471	0.380
IncomeLevel4	0.166	0.017	0.000	0.171	0.166	0.455
B. Sample children between 18 and 30						
Gender	0.557	0.567	0.358	0.557	0.559	0.855
Race	0.649	0.423	0.000	0.610	0.623	0.352
Age	22.686	22.433	0.001	22.463	22.443	0.828
Marriage	0.038	0.062	0.000	0.042	0.043	0.850
Migration	0.757	0.786	0.003	0.756	0.744	0.315
HeadGender	0.739	0.545	0.000	0.727	0.731	0.706

HeadRace	0.631	0.392	0.000	0.591	0.606	0.267
HeadAge	50.883	51.768	0.000	50.935	50.902	0.873
HeadMarriage	0.134	0.342	0.000	0.143	0.141	0.760
HeadMigration	0.427	0.461	0.002	0.409	0.405	0.782
HeadEducation1	0.258	0.560	0.000	0.246	0.250	0.737
HeadEducation2	0.155	0.148	0.378	0.153	0.145	0.404
HeadEducation3	0.385	0.228	0.000	0.403	0.389	0.282
HeadEducation4	0.202	0.064	0.000	0.197	0.216	0.094
Siblings	1.025	1.209	0.000	1.014	1.001	0.628
Residents	4.177	4.373	0.000	4.169	4.171	0.970
OwnDwelling	0.847	0.818	0.000	0.847	0.850	0.737
IncomeLevel1	0.040	0.289	0.000	0.046	0.047	0.826
IncomeLevel2	0.178	0.340	0.000	0.175	0.180	0.661
IncomeLevel3	0.538	0.331	0.000	0.531	0.535	0.817
IncomeLevel4	0.243	0.040	0.000	0.247	0.238	0.442

Notes: This table reports the means of treatment and control groups before and after matching for PSM (Kernel Epanechnikov) and the p-value for the mean difference test. The first three columns report the results before matching. The last three columns report the results after matching. Panel A presents the covariates balance of the sample for children under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching, consider the sample weights. The variables of regions and federative units were omitted for space considerations.

The results in Table 4 show that after applying the PSM Kernel (Epanechnikov) method, the majority of the covariates in both samples are similar in means (p-value>0.1). Every covariate in the sample for children under 18 years shows no statistical difference in the means between the treated and control groups (p-value>0.1), except for HeadEducation2 (p-value>0.08). The same occurs for children between 18 and 30 years, with only the covariate HeadEducation4 presenting a p-value<0.1 (p-value>0.09). Thus, the treated and control groups are comparable in both samples as all of the observable characteristics present a p-value>0.05 after the matching procedure.

The magnitudes of parents' entrepreneurial attitude toward children's education indicators are reported in Table 5. Column 1 presents the results for the years of schooling for children aged under 18 years for all models. None of the coefficients are statistically significant for this outcome variable, indicating an absence of effect of the parents' entrepreneurial occupational choice in children's years of schooling. Column 2 presents the results for the probability of studying in a private school for children under 18 years. Under-age children of entrepreneurial parents present an increase between 5.3 and 5.7 percentage points (p.p.) in the probability of studying at a private school (p-value<0.01). Column 3

presents the probability of studying at any university for children aged between 18 and 30 years. The results of all models present a five p.p. increase in the probability of studying at a university (p-value<0.01). Columns 4 and 5 present the results for the probability of studying at a public and a private university for children aged between 18 and 30 years, respectively. The probability of studying at a private university is responsible for a 4.3 p.p. increase (p-value<0.01) of the chance of studying at any university. The results also present no statistically significant influence on the probability of studying at a public university.

Compared to the average outcome variable for children in the control group, children of entrepreneurial parents show a probability of studying at private schools approximately 25% higher. Children of entrepreneurial parents present a statistically significant increase of approximately 17% and 20% in the probabilities of studying at any university compared to the children in the control group.

Table 5 – Results – PSM for Kernel matching algorisms

	(1) Years Schooling[a]	(2) Private School[a]	(3) Any University[b]	(4) Public University[b]	(5) Private University[b]
A. Kernel Gaussian					
Entrepreneur. Parents	0.047	0.057***	0.050***	0.007	0.043***
t-stat	(0.91)	(9.46)	(5.01)	(1.22)	(4.71)
N. on support	68,110	68,110	30,561	30,561	30,561
Average outcome var. for control units	3.182	0.208	0.290	0.072	0.218
B. Kernel Biweight					
Entrepreneur. Parents	0.046	0.053***	0.050***	0.006	0.043***
t-stat	(0.89)	(8.79)	(4.95)	(1.10)	(4.72)
N. on support	68,110	68,110	30,560	30,560	30,560
Average outcome var. for control units	3.183	0.211	0.290	0.072	0.217
C. Kernel Tricube					
Entrepreneur. Parents	0.046	0.053***	0.050***	0.006	0.043***
t-stat	(0.88)	(8.79)	(4.96)	(1.10)	(4.73)
N. on support	68,110	68,110	30,560	30,560	30,560
Average outcome var. for control units	3.183	0.211	0.290	0.072	0.217
D. Kernel Epanechnikov					
Entrepreneur. Parents	0.047	0.053***	0.050***	0.006	0.043***
t-stat	(0.91)	(8.83)	(4.96)	(1.10)	(4.72)
N. on support	68,110	68,110	30,560	30,560	30,560
Average outcome var. for control units	3.182	0.211	0.290	0.072	0.217

E. Kernel Uniform					
Entrepreneur. Parents	0.048	0.054***	0.050***	0.006	0.043***
t-stat	(0.92)	(8.93)	(4.97)	(1.14)	(4.71)
N. on support	68,110	68,110	30,560	30,560	30,560
Average outcome var. for control units	3.181	0.211	0.290	0.072	0.218

Notes: This table reports estimates of the influence of the entrepreneurial attitude of parents on children's education. The superscript *a* indicates that Columns 1 and 2 considered the sample for children aged under 18 years. The superscript *b* indicates that columns 3, 4, and 5 considered the sample for children aged 18 and 30. The estimates consider propensity score matching with kernel matching estimator. Panel A presents the Gaussian Kernel results. Panel B presents the Biweight Kernel results. Panel C presents the Tricube Kernel results. Panel D presents the Epanechnikov Kernel results. Panel E presents the Uniform Kernel results. Covariables were omitted for space considerations. The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. The values in parentheses are t-student statistics.

The results show that entrepreneurial parents are more willing to enroll their children in private schools. Such behavior could be related to a change in the parents' education returns perception (Dizon-Ross, 2019) due to different work values (Tocher et al., 2012; Anderson and Jack, 2002) and noncognitive skills (Cunha, Heckman, and Schennach, 2010) developed through entrepreneurial activities. The results also suggest that entrepreneurs' children over 18 years of age are more prone to seek higher education. Additionally, the results indicate that entrepreneurial parents' risk aversion could be an influential factor (Checchi, Fiorio, and Leonardi, 2014). Another explanation to the probability of studying at universities results could be related to entrepreneurial parents' degree of risk aversion (Checchi, Fiorio, and Leonardi, 2014), given entrepreneurs' lower risk aversion (Brachert, Hyll, and Sadrieh, 2020; Caliendo *et al.*, 2014; Wickstrøm, Klyver, and Cheraghi-Madsen, 2020). The reasons that define which type of university children choose are not trivial to explain. The intention of children to follow their parents' career choices could justify the choice of private universities (Kyrö, 2015; Li, Qu, and Huang, 2018). Moreover, considering our results on the *PrivateSchool* outcome variable and the evidence of private schools students achievements on university admission tests in Brazil (Curi and Menezes-Filho 2010; Cavalcanti, Guimaraes and Sampaio 2010), it is acceptable to assume that children of entrepreneurial parents would attain better scores on admission tests for public universities (and relatively higher enrollment). The effects on public universities enrollment could be underestimated due to the limitations in the database identification of children who do not

live with their parents in the same household. Parents might be willing to finance the living expenses of children studying in other cities or distant campus, incurring in missing observations in such cases[9].

2.6. Robustness Analysis

We conducted a series of five robustness tests to verify the strength of the results found in the previous section. First, we propose the placebo test. The placebo test aims to verify whether the results were due to chance. In other words, if the results of Table 5 were type I errors. This test is a routine for PSM (Cole, 2017; Karhunen and Huovari, 2015; Srhoj *et al.*, 2021). Therefore, we must create placebo treatments. We generate random variables with mean and standard deviation similar to the original treatment variables. In addition, the procedure is to re-estimate the first equation of the PSM with the placebo treatments. The balance of the covariates for the placebo test in Tables A2 (Appendix) shows that the observable variables have similar means between the treatment and control groups after the matching. The panels in Table 6 presents the results of different robustness analysis, and their columns report the treatment coefficients for the outcome variables in the same order as in Table 5. The results of the placebo test are reported in Panel A. All coefficients presented in Panel A are not statistically significant (p-value>0.1). Thus, the results of the placebo test reinforce that our previous estimates are robust and are no Type-I errors.

Our second robustness test consists of the Propensity Score Weighting (PSW) method. This method approximates the treated and control groups using the propensity score as a weight: each subject in the control group is weighted by the inverse probability of not receiving treatment. Further, the PSW utilizes the whole sample to consider subjects outside the common support area. We use the sample weight in both stages of the procedure: first, as a weight in the propensity score model, and second, by multiplying the propensity score weight in the outcome analysis (Ridgeway *et al.*, 2015). Table A3 (Appendix) presents the balance of covariates between the treated and control groups after applying PSW. The p-value statistics indicates no difference in the means of each covariate between the groups,

[9] Although such scenario might be concerning, the proportion of entrepreneurial children under age (9.2%) and children over 18 years (9.1%) are similar.

Table 6 – Results – Robustness tests

	(1) Years Schooling[a]	(2) Private School[a]	(3) Any University[b]	(4) Public University[b]	(5) Private University[b]
A. Placebo Test					
Placebo Entrepreneur. Parents	0.000	-0.001	0.001	0.024	-0.003
t-stat	(0.03)	(0.20)	(0.09)	(0.55)	(0.79)
N. on support	30,565	30,565	30,565	68,115	68,115
Average outcome var. for control units	0.172	0.045	0.126	2.984	0.089
B. Propensity Score Weighting					
Entrepreneur. Parents	0.869***	0.090***	0.053***	0.010	0.043***
t-stat	(15.60)	(12.18)	(4.44)	(1.44)	(3.89)
N. on support	68,115	68,115	30,565	30,565	30,565
Average outcome var. for control units	2.327	0.171	0.288	0.067	0.220
C. Entropy Balancing 1st moment					
Entrepreneur. Parents		0.055***	0.051***	0.009	0.042***
t-stat		(7.18)	(4.27)	(1.38)	(3.74)
N. on support		68,115	30,565	30,565	30,565
Average outcome var. for control units		0.206	0.289	0.068	0.222
D. Entropy Balancing 2nd moment					
Entrepreneur. Parents		0.053***	0.048***	0.008	0.040***
t-stat		(6.78)	(3.99)	(1.18)	(3.56)
N. on support		68,115	30,565	30,565	30,565
Average outcome var. for control units		0.209	0.292	0.069	0.223
E. Entropy Balancing 3rd moment					
Entrepreneur. Parents		0.053***	0.048***	0.008	0.040***
t-stat		(6.82)	(4.00)	(1.20)	(3.56)
N. on support		68,115	30,565	30,565	30,565
Average outcome var. for control units		0.208	0.292	0.069	0.223

Notes: This table reports estimates of the influence of the entrepreneurial attitude of parents on children's education. The superscript *a* indicates that columns 1 and 2 considered the sample for children under 18 years old. The superscript *b* indicates that columns 3, 4, and 5 considered the sample for children between 18 and 30. Panel A considers a placebo test with a random treatment variable utilizing a PSM with Kernel (Biweight) estimator. Panel B considers a propensity score weighting estimator. Panels C, D, and E consider an entropy balancing estimator for the first and second moments, respectively. Covariables were omitted for space considerations. The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. The values in parentheses are t-student statistics.

implying that the groups are comparable. The results of the PSW estimator are reported in Panel B of Table 6. The results in Column 1 demonstrate that the PSW estimator yields a significant increase of 0.869 (p-value<0.01) in the years of schooling of under-age children, representing an increase of approximately 37% compared to the control group. Column 2 results indicate that entrepreneurial parents present an increase of 9 p.p. in the probability of children under 18 studying at a private school (p-value<0.01), presenting a probability 53% higher in comparison to the average outcome of the control group. Results in Columns 3 and 5 present similar coefficients to those found in Table 5, demonstrating that the influence of entrepreneurial parents increases the probability of children studying at university (Column 3) by 5.3 p.p. (p-value<0.01), specifically at a private university (Column 5) by 4.3 p.p. (p-value<0.01). Column 4 shows no statistically significant coefficients regarding the influence on the probability of studying at a public university. The results support the evidence of the positive influence of parents' entrepreneurial attitude on the children's human capital accumulation in the previous section.

In the third robustness strategy, we estimate the influence of the parents' entrepreneurial on children's education with an Entropy Balancing procedure (Hainmueller, 2012). The Entropy Balancing enables the balance of covariates in observational studies with binary treatments through pre-processing data. The method utilizes a maximum entropy reweighting procedure that calibrates the unit weights such that the reweighted treatment and control group satisfy a large set of pre-specified equilibrium conditions that incorporate information about the first, second, or higher moments of the covariate distribution. This recalibration effectively adjusts for systematic and random inequalities in representation. Additionally, the Entropy Balancing utilizes the whole sample. We use the sample weights and calibrate the unit weights for both groups to construct entropy weights for the first, second, and third moments (respectively, mean, variance, and skewness of the covariates). Thus, we create three models weighted by each of the entropy weights to estimate the influence of the entrepreneurial attitude of parents on the education binary outcome variables. Tables A4 and A5 (appendix) presents the balance of covariates between the treated and control groups before and after applying the entropy weights. The p-value statistics indicates no differences between groups in the means of each covariate after weighting by the entropy weights, demonstrating the comparability of the groups. The results of the Entropy Balancing

estimators are reported in Panel C, D, and E of Table 6. The results of the entropy models for all outcome variables are similar in magnitude to those found in Table 5. Column 2 results indicate that children under 18 with entrepreneurial parents increase between 5.3 and 5.5 p.p. in the probability of studying at a private school (p-value<0.01). Results in Columns 3 and 5 demonstrate that children of entrepreneurial parents are between 4.8 and 5.1 p.p. likely to study at a university (p-value<0.01), mainly at private universities with a coefficient between 4 and 4.2 p.p. (p-value<0.01). Column 4 presents no statistically significant influence of entrepreneurial parents on the children's probability of studying at a public university. The results indicate that the entrepreneurial attitude of parents positively influences the children's human capital accumulation.

As a fourth robustness strategy, we test whether there are heterogeneous treatment effects (HTE) on the entrepreneurial attitude of parents. Therefore, we establish five restricted subsamples: (i) a sample considering only boys for the HTE analysis on boys; (ii) a sample considering only girls for the HTE analysis on girls; (iii) a sample considering only households with at least one man in the reference couple for the HTE analysis when only the father is an entrepreneur; (iv) a sample considering only households with at least one woman in the reference couple for the HTE analysis when only the mother is an entrepreneur; and (v) a sample considering only households with the presence of a spouse in the reference couple for the HTE analysis when both parents are entrepreneurs. Then, we disaggregate the treatment variable into three specific groups: (a) only the man of the reference couple is an entrepreneur, (b) only the woman of the reference couple is an entrepreneur, and (c) both parties in the couple are entrepreneurs. The analysis for the subsamples (i) and (ii) considers the presence of an entrepreneurial parent in the reference couple of the household as the treatment variable (*EntrepreneurialParent*). The analysis for the subsamples (iii), (iv), and (v) considers the disaggregated treatment variables (a), (b), and (c), respectively. We use the PSM with Epanechnikov Kernel type for all heterogeneous treatment effect analyses. Tables A6 to A10 (appendix) reports the balance of the covariates between the treated and control groups before and after the matching for the five HTE analysis. All models presents an appropriate covariates balance between groups after the matching procedure. The results of the HTE analysis are reported in Table 7. Panels A to E presents the results of the HTE

analysis in the same order of subsamples (i) to (v), and the columns report the treatment coefficients for outcome variables in the same order as in Table 5.

Table 7 – Heterogeneous analysis of the influence of entrepreneurial parents

	(1) Years Schooling[a]	(2) Private School[a]	(3) Any University[b]	(4) Public University[b]	(5) Private University[b]
A. Influence on sons					
Entrepreneur. Parents	0.094	0.061***	0.038***	0.008	0.030**
t-stat	(1.30)	(7.21)	(2.92)	(1.09)	(2.55)
N. on support	35,116	35,116	17,239	17,239	17,239
Average outcome var. for control units	3.155	0.202	0.257	0.064	0.193
B. Influence on daughters					
Entrepreneur. Parents	-0.002	0.045***	0.063***	0.006	0.057***
t-stat	(0.03)	(5.08)	(3.99)	(0.69)	(3.86)
N. on support	32,992	32,992	13,314	13,314	13,314
Average outcome var. for control units	3.208	0.223	0.330	0.081	0.250
C. Only father entrepreneur					
Only Father Entrep.	-0.009	0.053***	0.036***	0.004	0.032***
t-stat	(0.14)	(8.83)	(2.82)	(0.52)	(2.76)
N. on support	54,144	54,144	20,761	20,761	20,761
Average outcome var. for control units	3.076	0.211	0.284	0.073	0.211
D. Only mother entrepreneur					
Only Mother Entrep.	0.100	0.025**	0.082***	0.017*	0.064***
t-stat	(1.04)	(2.23)	(4.60)	(1.67)	(3.92)
N. on support	62,271	62,271	27,477	27,477	27,477
Average outcome var. for control units	3.423	0.213	0.275	0.070	0.205
E. Both parents entrepreneurs					
Both Parents Entrep.	0.093	0.088***	0.042 [θ]	-0.015	0.057**
t-stat	(0.71)	(5.20)	(1.62)	(1.07)	(2.31)
N. on support	50,065	50,065	18,113	18,113	18,113
Average outcome var. for control units	3.349	0.304	0.347	0.089	0.258

Notes: This table reports estimates of the analysis of the heterogeneous influence of the entrepreneurial attitude of parents on children's education. The superscript *a* indicates that columns 1 and 2 considered the sample for children under 18 years. The superscript *b* indicates that columns 3, 4, and 5 considered the sample for children between 18 and 30. All estimates consider propensity score matching with an Epanechnikov kernel matching estimator. Panel A presents the coefficient of the influence of the entrepreneurial attitude of parents on sons (boys). Panel B presents the coefficient of the influence of the entrepreneurial attitude of parents on daughters (girls). Panel C presents the coefficient of the influence of entrepreneurial attitude when only the father is an entrepreneur. Panel D presents the coefficient of the influence of entrepreneurial attitude when only the mother

is an entrepreneur. Panel E presents the coefficient of the influence of entrepreneurial attitude when both parents are entrepreneurs. Covariates were omitted for space considerations. The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. The superscript θ represents a statistical significance of 11%. The values in parentheses are t-student statistics.

The results in Panels A and B (Table 7) indicate the presence of heterogeneity in the influence of entrepreneurial parents related to the children's gender. Column 2 results demonstrate that the treatment coefficient for the boys' probability of studying at a private school is 1.5 p.p. higher than for girls (6.1% for boys and 4.5% for girls, p-value <0.01). Compared to the control units' average outcome, the treatment incurs an increase of approximately 30% for boys and 20% for girls. Columns 3 and 5 demonstrate that the treatment coefficients for girls are 2.5 p.p. higher for the probability of studying at a university and 2.7 p.p. higher for the probability of studying at a private university. Column 2 shows that children of households where only the father is an entrepreneur present a treatment coefficient of 2.8 p.p. higher for the probability of studying at a private school than when only the mother is an entrepreneur (5.3% for fathers and 2.5% for mothers).

Conversely, the results in Columns 3, 4, and 5 show a greater effect on the probability of studying at a university when only the mother is an entrepreneur, presenting treatment coefficients of at least twice the magnitude of those estimated when only the father is an entrepreneur. Further, the treatment considering only the mother as an entrepreneur is the only specification that presented a statistically significant coefficient on the probability of studying at a public university (an increase of 1.7 p.p., p-value<0.1). Lastly, Panel E presents the results for the HTE analysis when both parents are entrepreneurs. Column 2 results indicate that children of entrepreneur couples have an increase of 8.8 p.p. (p-value<0.01) in the probability of studying at a private school, an increase of approximately 28% compared to the average probability of the control group children. Column 3 presents an increase of 4.2 p.p. (p-value<0.11) in the probability of studying at a university. Column 5 shows an increase of 5.7 p.p. in the probability of studying at a private university. All panel results in Column 1 report no statistically significant coefficients for the years of the schooling outcome variable.

Finally, our last robustness strategy relies on Rosenbaum's sensitivity analysis. This analysis is not definitive regarding the existence of unobservable confounding variables.

However, it indicates how close the estimates of a pairing method are to violating the assumption of selection in observables. The test establishes the critical point for the null hypothesis of the randomness of treatment (*EntrepreneurialParent*) after pairing. The sensitivity parameter gamma (Γ) is considered to represent the degree of distance from the randomness of the treatment, wherein Γ=1, the effect of treatment is free of bias.

The p-value indicates the rejection of the null hypothesis. We applied two Rosenbaum test methods. We conducted the Wilcoxon test (DiPrete and Gangl, 2004) for the continuous outcome variable *YearsSchooling.* Regarding the binary outcome variables (*PrivateSchool, AnyUniversity, PublicUniversity,* and *PrivateUniversity*), we follow the recommendations of Becker and Caliendo (2007) to conduct the Mantel–Haenszel test. The sensitivity analysis results are presented in Table 8. The Wilcoxon test indicates that *YearsSchooling* is sensitive to unobservable confounding variables (Γ=1). The Mantel-Haenszel test for the binary outcome variables indicates that *PrivateSchool, AnyUniversity* and *PrivateUniversity* results are strongly robust at 75% hidden bias (Γ=1.75, p-value<0.001), while the *PublicUniversity* results presents robustness with p-value<0.1 until Γ=1.75. In general, the sensitivity analysis results demonstrates that the statistically significant estimates identified in Table 5 presents low sensitivity for unobservable confounding variables and reinforce their robustness.

Table 8 – Rosenbound sensibility analysis

Outcome variable	Bound	Γ = 1	Γ = 1.15	Γ = 1.3	Γ = 1.45	Γ = 1.6	Γ = 1.75
YearsSchooling	Upper	0.927	1.000	1.000	1.000	1.000	1.000
YearsSchooling	Lower	0.927	0.001	0.000	0.000	0.000	0.000
PrivateSchool	Upper	0.000	0.000	0.000	0.000	0.000	0.000
PrivateSchool	Lower	0.000	0.000	0.000	0.000	0.000	0.000
AnyUniversity	Upper	0.000	0.000	0.000	0.000	0.000	0.000
AnyUniversity	Lower	0.000	0.000	0.000	0.000	0.000	0.000
PublicUniversity	Upper	0.000	0.000	0.000	0.000	0.004	0.072
PublicUniversity	Lower	0.000	0.000	0.000	0.000	0.000	0.000
PrivateUniversity	Upper	0.000	0.000	0.000	0.000	0.000	0.000
PrivateUniversity	Lower	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table reports the p-values of the Rosenbound test for hidden bias due to unobservable confounding variables. The Wilcoxon statistic test analyzes the *YearsSchooling* outcome variable. The Mantel-Haenszel statistic test analyzes the *PrivateSchool, AnyUniversity, PublicUniversity,* and *PrivateUniversity.*

2.7. Discussion and Final Remarks

This study aimed to analyze the influence of parents' entrepreneurial attitude on the educational decisions of their children related to the likelihood of studying at private schools and attending a university (general, public, and private). We used a matching procedure to utilize the micro data complex sample from PNAD 2015. After testing the goodness of fit of the models, we employed a PSM Kernel of Epanechnikov type with sample weights adjustment.

Our findings provide new evidence for the interactions between parents' work decisions and their children's education. The results indicate that the parents' entrepreneurial attitude positively affects their children's chances of studying at private schools. These results can happen through a change in parents' perception regarding the returns associated with their children's education, reflected in the search for better quality schools in the private sector. Further, the results show that entrepreneurial parents' children have more chances of studying at universities, especially at private universities. Such results could be related to the intergenerational transmission of values that can encourage the children of entrepreneurs to value higher education. All robustness strategies strengthen the results identified. The HTE analysis highlights the existence of heterogeneous magnitudes for the influence of the parents' entrepreneurial attitude related to the children's and entrepreneurial parent's gender. The HTE analysis also indicates that when both parents are entrepreneurs the magnitude of the treatment increases.

The results must be carefully analyzed. First, as the microdata is a cross-section, applying fixed effect control methods is impossible. Additionally, the database restricts the analysis to children who live in the same household. Although private schools provide better academic results in Brazil, our study cannot state whether entrepreneurs allocate more financial resources to their children's education and do not consider the number of public and private schools near the households. Another important question concerns the graduation rate and children's performance in different universities and graduate majors. Answers to these questions would provide a better understanding of the academic performance of entrepreneurs' children and information to guide future public policies that incentivize entrepreneurial activity while looking for educational spillovers, as well as policies that aim for better usage of resources in the development of human capital.

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Appendix

Table A1 – First stage Propensity Score results (Probit)

Covariates	Coefficient	Stand. Error	T-stat	P-value
A. Sample children aged under 18 years				
Gender	-0.014	0.026	(0.53)	0.597
Race	0.095***	0.033	(2.91)	0.004
Age	-0.014***	0.004	(3.22)	0.001
Marriage	-0.065	0.068	(0.95)	0.343
Migration	-0.068**	0.032	(2.10)	0.036
HeadGender	0.228***	0.034	(6.69)	0.000
HeadRace	0.181***	0.033	(5.52)	0.000
HeadAge	-0.015***	0.002	(8.37)	0.000
HeadMarriage	-0.409***	0.043	(9.61)	0.000
HeadMigration	0.001	0.028	(0.03)	0.977
HeadEducation1	-0.368***	0.047	(7.88)	0.000
HeadEducation2	-0.150***	0.051	(2.96)	0.003
HeadEducation3	-0.035	0.044	(0.80)	0.425
HeadEducation4	Omitted	.	.	.
Siblings	0.010	0.024	(0.40)	0.693
Residents	0.041**	0.019	(2.14)	0.032
OwnDwelling	0.071**	0.035	(2.01)	0.045
IncomeLevel1	-1.702***	0.067	(25.26)	0.000
IncomeLevel2	-1.188***	0.051	(23.46)	0.000
IncomeLevel3	-0.677***	0.043	(15.79)	0.000
IncomeLevel4	Omitted	.	.	.
B. Sample children aged between 18 and 30 years				
Gender	0.012	0.026	(0.68)	0.597
Race	0.118***	0.033	(5.41)	0.004
Age	0.001	0.004	(0.58)	0.001
Marriage	-0.475	0.068	(1.45)	0.343
Migration	0.025	0.032	(0.97)	0.036
HeadGender	0.074***	0.034	(3.36)	0.000
HeadRace	0.044**	0.033	(2.02)	0.000
HeadAge	0.004***	0.002	(3.41)	0.000
HeadMarriage	-0.501***	0.043	(13.69)	0.000
HeadMigration	0.004	0.028	(0.20)	0.977
HeadEducation1	-0.343***	0.047	(9.74)	0.000
HeadEducation2	-0.166***	0.051	(4.70)	0.003
HeadEducation3	0.004	0.044	(0.15)	0.425
HeadEducation4	Omitted	.	.	.
Siblings	0.097***	0.024	(4.44)	0.693
Residents	-0.018	0.019	(0.92)	0.032
OwnDwelling	0.109***	0.035	(5.43)	0.045
IncomeLevel1	-1.872***	0.067	(40.79)	0.000
IncomeLevel2	-1.236***	0.051	(30.89)	0.000
IncomeLevel3	-0.617***	0.043	(16.51)	0.000
IncomeLevel4	Omitted	.	.	.

Notes: This table reports coefficient, standard errors, T-stat and p-value for the covariates of the propensity score model. The propensity score considers a Probit algorithm with sample weight adjustment. Panel A

presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years.The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. The variables of regions and federative units were omitted for space considerations.

Table A2 – Covariates balance for Placebo Test

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.515	0.513	0.767	0.515	0.516	0.913
Race	0.439	0.429	0.147	0.401	0.406	0.546
Age	9.196	9.235	0.603	9.2297	9.1971	0.722
Marriage	0.001	0.002	0.217	0.001	0.001	0.209
Migration	0.837	0.841	0.376	0.835	0.838	0.705
HeadGender	0.642	0.643	0.866	0.624	0.629	0.546
HeadRace	0.381	0.378	0.663	0.345	0.353	0.356
HeadAge	38.879	38.775	0.445	38.736	38.687	0.770
HeadMarriage	0.185	0.189	0.462	0.192	0.190	0.764
HeadMigration	0.523	0.531	0.237	0.512	0.519	0.440
HeadEducation1	0.437	0.424	0.072	0.434	0.429	0.566
HeadEducation2	0.184	0.189	0.338	0.189	0.190	0.872
HeadEducation3	0.307	0.314	0.302	0.310	0.312	0.837
HeadEducation4	0.073	0.073	0.882	0.067	0.069	0.616
Siblings	1.402	1.417	0.455	1.4275	1.4247	0.908
Residents	4.390	4.402	0.572	4.4166	4.4131	0.900
OwnDwelling	0.679	0.682	0.689	0.691	0.689	0.821
IncomeLevel1	0.494	0.487	0.334	0.512	0.505	0.421
IncomeLevel2	0.293	0.302	0.177	0.292	0.293	0.890
IncomeLevel3	0.183	0.180	0.618	0.168	0.173	0.458
IncomeLevel4	0.030	0.031	0.720	0.028	0.029	0.717
B. Sample children aged between 18 and 30 years						
Gender	0.541	0.568	0.013	0.547	0.546	0.900
Race	0.460	0.448	0.276	0.429	0.416	0.320
Age	22.837	22.662	0.027	22.786	22.806	0.841
Marriage	0.059	0.060	0.717	0.065	0.064	0.807
Migration	0.792	0.782	0.245	0.783	0.788	0.689
HeadGender	0.571	0.562	0.406	0.558	0.553	0.730
HeadRace	0.435	0.418	0.120	0.404	0.390	0.284
HeadAge	51.981	51.789	0.174	51.699	51.753	0.818
HeadMarriage	0.328	0.321	0.463	0.332	0.341	0.499
HeadMigration	0.481	0.454	0.014	0.465	0.468	0.832
HeadEducation1	0.527	0.529	0.878	0.521	0.523	0.899
HeadEducation2	0.149	0.148	0.868	0.153	0.152	0.964
HeadEducation3	0.242	0.244	0.873	0.249	0.249	0.978
HeadEducation4	0.081	0.079	0.757	0.077	0.076	0.894
Siblings	1.145	1.198	0.028	1.1848	1.171	0.672
Residents	4.318	4.364	0.170	4.3801	4.3635	0.714
OwnDwelling	0.826	0.820	0.496	0.834	0.833	0.897

IncomeLevel1	0.252	0.267	0.112	0.272	0.268	0.793
IncomeLevel2	0.325	0.325	0.998	0.333	0.333	0.975
IncomeLevel3	0.356	0.349	0.532	0.333	0.337	0.765
IncomeLevel4	0.067	0.059	0.145	0.063	0.062	0.871

Notes: This table reports the means of the placebo treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value for the difference in means. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A3 – Covariates balance test after PSW

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.515	0.513	0.770	0.514	0.512	0.896
Race	0.644	0.407	0.000	0.639	0.645	0.417
Age	9.132	9.207	0.315	9.098	9.071	0.759
Marriage	0.000	0.002	0.000	0.000	0.000	0.739
Migration	0.846	0.840	0.297	0.848	0.841	0.275
HeadGender	0.749	0.632	0.000	0.750	0.752	0.732
HeadRace	0.580	0.357	0.000	0.574	0.580	0.475
HeadAge	40.409	38.614	0.000	40.331	40.419	0.529
HeadMarriage	0.064	0.202	0.000	0.064	0.065	0.897
HeadMigration	0.497	0.534	0.000	0.494	0.481	0.112
HeadEducation1	0.172	0.452	0.000	0.176	0.170	0.307
HeadEducation2	0.146	0.193	0.000	0.148	0.142	0.259
HeadEducation3	0.451	0.298	0.000	0.454	0.457	0.738
HeadEducation4	0.230	0.057	0.000	0.223	0.232	0.226
Siblings	1.046	1.454	0.000	1.044	1.003	0.006
Residents	4.107	4.432	0.000	4.102	4.067	0.044
OwnDwelling	0.750	0.675	0.000	0.746	0.747	0.874
IncomeLevel1	0.094	0.528	0.000	0.094	0.094	0.969
IncomeLevel2	0.265	0.305	0.000	0.265	0.263	0.788
IncomeLevel3	0.474	0.150	0.000	0.474	0.474	0.912
IncomeLevel4	0.167	0.017	0.000	0.167	0.168	0.922
B. Sample children aged between 18 and 30 years						
Gender	0.553	0.567	0.210	0.557	0.561	0.755
Race	0.654	0.428	0.000	0.650	0.656	0.614
Age	22.461	22.700	0.002	22.429	22.463	0.690
Marriage	0.038	0.063	0.000	0.038	0.041	0.555
Migration	0.757	0.785	0.002	0.757	0.748	0.383
HeadGender	0.733	0.545	0.000	0.740	0.741	0.895
HeadRace	0.639	0.397	0.000	0.631	0.637	0.603
HeadAge	50.971	51.834	0.000	50.877	50.955	0.653
HeadMarriage	0.138	0.341	0.000	0.133	0.135	0.831
HeadMigration	0.431	0.589	0.007	0.428	0.417	0.363

HeadEducation1	0.253	0.558	0.000	0.527	0.256	0.912
HeadEducation2	0.152	0.148	0.567	0.155	0.148	0.416
HeadEducation3	0.385	0.229	0.000	0.385	0.385	0.992
HeadEducation4	0.210	0.066	0.000	0.203	0.211	0.441
Siblings	1.027	1.211	0.000	1.025	0.989	0.095
Residents	4.175	4.379	0.000	4.177	4.143	0.224
OwnDwelling	0.848	0.818	0.000	0.847	0.848	0.925
IncomeLevel1	0.040	0.289	0.000	0.040	0.042	0.741
IncomeLevel2	0.178	0.340	0.000	0.178	0.177	0.883
IncomeLevel3	0.537	0.331	0.000	0.537	0.539	0.926
IncomeLevel4	0.244	0.040	0.000	0.244	0.243	0.917

Notes: This table reports the means of treatment and control groups and p-value for the mean difference after the PSW procedure. Panel A presents the covariates balance of the sample for children aged under 18 years are reported in the first three columns. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A4 – Covariates balance - Entropy Bal. for children under 18 years

Covariates	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
	A. Before matching			**B. After Entropy Matching 1**		
Gender	0.515	0.513	0.770	0.514	0.514	0.999
Race	0.644	0.407	0.000	0.639	0.639	0.964
Age	9.132	9.207	0.315	9.098	9.099	0.997
Marriage	0.000	0.002	0.000	0.000	0.000	0.965
Migration	0.846	0.840	0.297	0.848	0.848	0.998
HeadGender	0.749	0.632	0.000	0.750	0.750	0.987
HeadRace	0.580	0.357	0.000	0.574	0.574	0.967
HeadAge	40.409	38.614	0.000	40.331	40.329	0.990
HeadMarriage	0.064	0.202	0.000	0.064	0.064	0.962
HeadMigration	0.497	0.534	0.000	0.494	0.494	0.987
HeadEducation1	0.172	0.452	0.000	0.176	0.176	0.934
HeadEducation2	0.146	0.193	0.000	0.148	0.148	0.994
HeadEducation3	0.451	0.298	0.000	0.454	0.454	0.975
HeadEducation4	0.230	0.057	0.000	0.223	0.222	0.973
Siblings	1.046	1.454	0.000	1.044	1.045	0.936
Residents	4.107	4.432	0.000	4.102	4.103	0.949
OwnDwelling	0.750	0.675	0.000	0.746	0.746	0.998
IncomeLevel1	0.094	0.528	0.000	0.094	0.095	0.804
IncomeLevel2	0.265	0.305	0.000	0.265	0.265	0.968
IncomeLevel3	0.474	0.150	0.000	0.474	0.473	0.948
IncomeLevel4	0.167	0.017	0.000	0.167	0.167	0.978
	C. After Entropy Matching 2			**D. After Entropy Matching 3**		
Gender	0.514	0.514	0.999	0.514	0.514	1.000
Race	0.639	0.639	0.956	0.639	0.639	0.995
Age	9.098	9.098	0.999	9.098	9.098	0.997
Marriage	0.000	0.000	0.964	0.000	0.000	0.999
Migration	0.848	0.848	0.999	0.848	0.848	0.996

HeadGender	0.750	0.750	0.982	0.750	0.750	0.996
HeadRace	0.573	0.574	0.960	0.574	0.574	0.967
HeadAge	40.331	40.328	0.982	40.331	40.330	0.993
HeadMarriage	0.064	0.064	0.960	0.064	0.064	0.999
HeadMigration	0.494	0.494	0.987	0.494	0.494	1.000
HeadEducation1	0.176	0.176	0.923	0.176	0.176	0.994
HeadEducation2	0.148	0.148	0.994	0.148	0.148	0.996
HeadEducation3	0.454	0.453	0.969	0.454	0.454	0.999
HeadEducation4	0.223	0.222	0.971	0.223	0.223	0.992
Siblings	1.044	1.046	0.904	1.044	1.044	0.996
Residents	4.102	4.103	0.926	4.102	4.102	0.999
OwnDwelling	0.746	0.746	0.996	0.746	0.746	0.996
IncomeLevel1	0.094	0.095	0.790	0.094	0.094	0.995
IncomeLevel2	0.265	0.265	0.966	0.265	0.265	0.996
IncomeLevel3	0.474	0.473	0.944	0.474	0.473	0.992
IncomeLevel4	0.167	0.167	0.977	0.167	0.167	0.997

Notes: This table reports the means of treatment and control groups and p-value for the mean difference for the entropy balancing analysis considering the sample for children aged under 18 years. Panel A reports the results before matching. Panels B, C and D reports the results after the entropy balancing procedure for the first moment, second and third moments, respectively. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A5 – Covariates balance - Entropy Bal. for children between 18 and 30 years

Covariates	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
	A. Before matching			B. After Entropy Matching 1		
Gender	0.553	0.567	0.210	0.557	0.557	1.000
Race	0.654	0.428	0.000	0.650	0.650	0.999
Age	22.461	22.700	0.002	22.429	22.429	0.999
Marriage	0.038	0.063	0.000	0.038	0.038	1.000
Migration	0.757	0.785	0.002	0.757	0.757	1.000
HeadGender	0.733	0.545	0.000	0.740	0.740	1.000
HeadRace	0.639	0.397	0.000	0.631	0.631	0.999
HeadAge	50.971	51.834	0.000	50.877	51.877	0.999
HeadMarriage	0.138	0.341	0.000	0.133	0.133	1.000
HeadMigration	0.431	0.589	0.007	0.428	0.428	1.000
HeadEducation1	0.253	0.558	0.000	0.257	0.257	0.998
HeadEducation2	0.152	0.148	0.567	0.155	0.155	1.000
HeadEducation3	0.385	0.229	0.000	0.385	0.385	0.999
HeadEducation4	0.210	0.066	0.000	0.203	0.203	0.999
Siblings	1.027	1.211	0.000	1.025	1.025	0.998
Residents	4.175	4.379	0.000	4.177	4.177	0.998
OwnDwelling	0.848	0.818	0.000	0.847	0.847	1.000
IncomeLevel1	0.040	0.289	0.000	0.040	0.040	0.990
IncomeLevel2	0.178	0.340	0.000	0.178	0.178	0.999
IncomeLevel3	0.537	0.331	0.000	0.537	0.537	0.998
IncomeLevel4	0.244	0.040	0.000	0.244	0.244	0.999

	C. After Entropy Matching 2			D. After Entropy Matching 3		
Gender	0.557	0.557	0.996	0.557	0.557	0.997
Race	0.650	0.650	0.994	0.650	0.650	0.994
Age	22.429	22.427	0.982	22.429	22.427	0.985
Marriage	0.038	0.038	0.999	0.038	0.038	0.999
Migration	0.757	0.757	0.995	0.757	0.757	0.993
HeadGender	0.740	0.740	0.994	0.740	0.740	0.993
HeadRace	0.631	0.631	0.994	0.631	0.631	0.994
HeadAge	50.877	51.872	0.979	50.877	51.873	0.982
HeadMarriage	0.133	0.133	0.999	0.133	0.133	0.994
HeadMigration	0.428	0.428	0.999	0.428	0.428	0.997
HeadEducation1	0.257	0.257	0.998	0.257	0.258	0.993
HeadEducation2	0.155	0.155	0.999	0.155	0.155	0.994
HeadEducation3	0.385	0.385	0.998	0.385	0.385	0.995
HeadEducation4	0.203	0.203	1.000	0.203	0.203	0.984
Siblings	1.025	1.025	0.999	1.025	1.025	0.998
Residents	4.177	4.177	0.992	4.177	4.177	0.992
OwnDwelling	0.847	0.847	0.994	0.847	0.847	0.994
IncomeLevel1	0.040	0.040	0.990	0.040	0.040	0.998
IncomeLevel2	0.178	0.178	1.000	0.178	0.178	0.994
IncomeLevel3	0.537	0.537	0.995	0.537	0.537	0.998
IncomeLevel4	0.244	0.244	0.998	0.244	0.244	0.997

Notes: This table reports the means of treatment and control groups and p-value for the mean difference for the entropy balancing analysis considering the sample for children aged between 18 and 30 years. Panel A reports the results before matching. Panels B, C and D reports the results after the entropy balancing procedure for the first moment, second and third moments, respectively. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A6 – Covariates balance for HTE for boys

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	1.000	1.000	.	1.000	1.000	1.000
Race	0.638	0.398	0.000	0.607	0.611	0.767
Age	9.156	9.234	0.466	9.270	9.173	0.462
Marriage	0.000	0.002	0.011	0.000	0.000	0.781
Migration	0.844	0.842	0.815	0.843	0.834	0.332
HeadGender	0.753	0.635	0.000	0.738	0.748	0.323
HeadRace	0.581	0.353	0.000	0.558	0.554	0.754
HeadAge	40.247	38.638	0.000	40.241	40.320	0.715
HeadMarriage	0.063	0.201	0.000	0.067	0.065	0.697
HeadMigration	0.490	0.535	0.000	0.484	0.469	0.227
HeadEducation1	0.175	0.456	0.000	0.172	0.174	0.893
HeadEducation2	0.141	0.193	0.000	0.148	0.136	0.159
HeadEducation3	0.465	0.297	0.000	0.460	0.468	0.516
HeadEducation4	0.219	0.055	0.000	0.220	0.223	0.777
Siblings	1.053	1.445	0.000	1.052	1.036	0.536

Residents	4.117	4.419	0.000	4.120	4.117	0.931
OwnDwelling	0.741	0.674	0.000	0.752	0.753	0.895
IncomeLevel1	0.091	0.530	0.000	0.094	0.094	0.969
IncomeLevel2	0.273	0.303	0.001	0.279	0.277	0.846
IncomeLevel3	0.478	0.150	0.000	0.467	0.476	0.478
IncomeLevel4	0.158	0.017	0.000	0.161	0.154	0.444
B. Sample children aged between 18 and 30 years						
Gender	1.000	1.000	.	1.000	1.000	1.000
Race	0.638	0.410	0.000	0.594	0.613	0.292
Age	22.492	22.730	0.023	22.473	22.513	0.756
Marriage	0.041	0.060	0.001	0.045	0.046	0.885
Migration	0.745	0.780	0.006	0.738	0.733	0.736
HeadGender	0.737	0.557	0.000	0.723	0.735	0.452
HeadRace	0.629	0.390	0.000	0.586	0.604	0.306
HeadAge	50.852	51.781	0.001	50.879	50.887	0.977
HeadMarriage	0.153	0.328	0.000	0.158	0.157	0.914
HeadMigration	0.427	0.463	0.014	0.408	0.399	0.584
HeadEducation1	0.578	0.284	0.000	0.265	0.275	0.538
HeadEducation2	0.166	0.144	0.046	0.162	0.152	0.450
HeadEducation3	0.372	0.218	0.000	0.395	0.375	0.258
HeadEducation4	0.178	0.061	0.000	0.177	0.197	0.157
Siblings	1.032	1.227	0.000	1.031	1.001	0.387
Residents	4.124	4.311	0.000	4.133	4.106	0.555
OwnDwelling	0.846	0.820	0.016	0.847	0.851	0.748
IncomeLevel1	0.037	0.274	0.000	0.041	0.040	0.901
IncomeLevel2	0.182	0.344	0.000	0.177	0.183	0.652
IncomeLevel3	0.538	0.342	0.000	0.534	0.535	0.960
IncomeLevel4	0.243	0.040	0.000	0.248	0.242	0.686

Notes: This table reports the means of the treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value of the mean difference test for the HTE analysis for boys. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A7 – Covariates balance for HTE for girls

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.000	0.000	.	0.000	0.000	.
Race	0.639	0.414	0.000	0.611	0.621	0.434
Age	9.027	9.164	0.200	9.076	9.024	0.696
Marriage	0.000	0.003	0.000	0.000	0.000	0.849
Migration	0.851	0.838	0.080	0.844	0.847	0.713
HeadGender	0.746	0.627	0.000	0.728	0.734	0.608
HeadRace	0.566	0.360	0.000	0.539	0.551	0.364

HeadAge	40.391	38.536	0.000	40.414	40.436	0.924
HeadMarriage	0.065	0.202	0.000	0.071	0.070	0.908
HeadMigration	0.499	0.533	0.001	0.486	0.483	0.820
HeadEducation1	0.177	0.449	0.000	0.171	0.171	0.955
HeadEducation2	0.155	0.194	0.000	0.157	0.149	0.375
HeadEducation3	0.443	0.299	0.000	0.446	0.447	0.926
HeadEducation4	0.226	0.057	0.000	0.225	0.233	0.483
Siblings	1.032	1.455	0.000	1.030	1.004	0.292
Residents	4.082	4.431	0.000	4.081	4.059	0.442
OwnDwelling	0.751	0.672	0.000	0.756	0.757	0.918
IncomeLevel1	0.097	0.525	0.000	0.103	0.107	0.655
IncomeLevel2	0.258	0.307	0.000	0.257	0.250	0.568
IncomeLevel3	0.471	0.150	0.000	0.460	0.467	0.599
IncomeLevel4	0.174	0.017	0.000	0.180	0.176	0.695
B. Sample children aged between 18 and 30 years						
Gender	0.000	0.000	.	0.000	0.000	.
Race	0.662	0.441	0.000	0.628	0.635	0.731
Age	22.390	22.627	0.039	22.477	22.411	0.642
Marriage	0.035	0.065	0.000	0.039	0.039	0.984
Migration	0.773	0.793	0.151	0.778	0.760	0.288
HeadGender	0.741	0.528	0.000	0.730	0.726	0.811
HeadRace	0.633	0.395	0.000	0.597	0.606	0.651
HeadAge	50.964	51.750	0.001	51.045	50.984	0.847
HeadMarriage	0.111	0.359	0.000	0.126	0.122	0.778
HeadMigration	0.428	0.459	0.063	0.409	0.412	0.911
HeadEducation1	0.227	0.537	0.000	0.224	0.223	0.958
HeadEducation2	0.142	0.153	0.361	0.143	0.136	0.594
HeadEducation3	0.400	0.241	0.000	0.412	0.408	0.857
HeadEducation4	0.230	0.069	0.000	0.221	0.233	0.482
Siblings	1.016	1.186	0.000	0.993	0.995	0.948
Residents	4.244	4.454	0.000	4.215	4.246	0.575
OwnDwelling	0.850	0.817	0.006	0.847	0.854	0.634
IncomeLevel1	0.044	0.309	0.000	0.052	0.058	0.536
IncomeLevel2	0.175	0.335	0.000	0.175	0.178	0.837
IncomeLevel3	0.543	0.316	0.000	0.531	0.533	0.916
IncomeLevel4	0.238	0.041	0.000	0.242	0.231	0.522

Notes: This table reports the means of the treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value of the mean difference test for the HTE analysis for girls. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A8 – Covariates balance for HTE when only the father is an entrepreneur

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.526	0.515	0.225	0.564	0.567	0.844
Race	0.635	0.413	0.000	0.617	0.627	0.570
Age	8.904	8.933	0.758	22.407	22.407	0.997
Marriage	0.000	0.002	0.000	0.043	0.045	0.781
Migration	0.849	0.841	0.188	0.752	0.749	0.833
HeadGender	0.825	0.773	0.000	0.856	0.852	0.792
HeadRace	0.566	0.362	0.000	0.596	0.608	0.495
HeadAge	40.206	38.729	0.000	51.036	50.985	0.851
HeadMarriage	0.027	0.023	0.148	0.060	0.059	0.879
HeadMigration	0.501	0.529	0.003	0.425	0.426	0.960
HeadEducation1	0.203	0.458	0.000	0.276	0.280	0.777
HeadEducation2	0.152	0.190	0.000	0.164	0.157	0.551
HeadEducation3	0.439	0.294	0.000	0.371	0.361	0.544
HeadEducation4	0.207	0.057	0.000	0.188	0.202	0.332
Siblings	1.071	1.436	0.000	1.016	1.015	0.956
Residents	4.174	4.559	0.000	4.248	4.264	0.712
OwnDwelling	0.737	0.688	0.000	0.836	0.839	0.802
IncomeLevel1	0.107	0.504	0.000	0.046	0.046	0.998
IncomeLevel2	0.292	0.314	0.011	0.188	0.201	0.379
IncomeLevel3	0.464	0.163	0.000	0.529	0.522	0.660
IncomeLevel4	0.137	0.019	0.000	0.236	0.231	0.761
B. Sample children aged between 18 and 30 years						
Gender	0.564	0.579	0.300	0.533	0.529	0.737
Race	0.654	0.437	0.000	0.608	0.611	0.796
Age	22.401	22.480	0.432	8.948	8.953	0.967
Marriage	0.041	0.055	0.009	0.000	0.000	0.812
Migration	0.760	0.791	0.012	0.847	0.840	0.446
HeadGender	0.859	0.781	0.000	0.810	0.818	0.410
HeadRace	0.636	0.399	0.000	0.544	0.543	0.933
HeadAge	50.974	52.022	0.000	40.176	40.272	0.636
HeadMarriage	0.058	0.057	0.797	0.027	0.027	0.906
HeadMigration	0.447	0.464	0.233	0.488	0.486	0.846
HeadEducation1	0.285	0.573	0.000	0.198	0.197	0.953
HeadEducation2	0.163	0.143	0.051	0.158	0.147	0.157
HeadEducation3	0.362	0.223	0.000	0.438	0.452	0.243
HeadEducation4	0.190	0.060	0.000	0.206	0.205	0.905
Siblings	1.030	1.257	0.000	1.064	1.057	0.748
Residents	4.260	4.635	0.000	4.175	4.172	0.910
OwnDwelling	0.840	0.844	0.695	0.747	0.746	0.964
IncomeLevel1	0.041	0.270	0.000	0.110	0.114	0.534
IncomeLevel2	0.195	0.343	0.000	0.292	0.286	0.555
IncomeLevel3	0.535	0.346	0.000	0.456	0.468	0.288
IncomeLevel4	0.229	0.041	0.000	0.142	0.132	0.182

Notes: This table reports the means of the treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value of the mean difference test for the HTE analysis when

only the father is an entrepreneur. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A9 – Covariates balance for HTE when only the mother is an entrepreneur

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.496	0.511	0.309	0.498	0.494	0.809
Race	0.595	0.407	0.000	0.566	0.564	0.924
Age	9.571	9.142	0.004	9.686	9.538	0.438
Marriage	0.000	0.002	0.004	0.001	0.001	0.897
Migration	0.834	0.841	0.537	0.828	0.831	0.880
HeadGender	0.624	0.533	0.000	0.515	0.524	0.625
HeadRace	0.548	0.357	0.000	0.520	0.516	0.834
HeadAge	40.066	38.429	0.000	40.092	40.071	0.945
HeadMarriage	0.206	0.187	0.101	0.219	0.202	0.257
HeadMigration	0.485	0.534	0.001	0.487	0.472	0.425
HeadEducation1	0.160	0.450	0.000	0.159	0.172	0.334
HeadEducation2	0.152	0.194	0.000	0.155	0.147	0.565
HeadEducation3	0.474	0.299	0.000	0.476	0.461	0.425
HeadEducation4	0.214	0.056	0.000	0.211	0.220	0.551
Siblings	0.999	1.457	0.000	1.009	1.001	0.826
Residents	3.906	4.447	0.000	3.910	3.922	0.770
OwnDwelling	0.732	0.672	0.000	0.737	0.737	0.984
IncomeLevel1	0.099	0.530	0.000	0.112	0.125	0.279
IncomeLevel2	0.288	0.304	0.208	0.288	0.284	0.819
IncomeLevel3	0.480	0.149	0.000	0.464	0.453	0.547
IncomeLevel4	0.132	0.017	0.000	0.136	0.138	0.875
B. Sample children aged between 18 and 30 years						
Gender	0.563	0.566	0.907	0.563	0.554	0.725
Race	0.618	0.423	0.000	0.568	0.581	0.594
Age	22.531	22.666	0.341	22.684	22.588	0.596
Marriage	0.035	0.061	0.000	0.042	0.039	0.802
Migration	0.760	0.786	0.127	0.764	0.760	0.879
HeadGender	0.435	0.526	0.000	0.419	0.434	0.555
HeadRace	0.594	0.392	0.000	0.556	0.558	0.928
HeadAge	50.634	51.593	0.001	50.722	50.712	0.980
HeadMarriage	0.377	0.315	0.001	0.386	0.372	0.554
HeadMigration	0.404	0.462	0.004	0.392	0.384	0.760
HeadEducation1	0.246	0.557	0.000	0.232	0.247	0.493
HeadEducation2	0.128	0.148	0.133	0.131	0.123	0.670
HeadEducation3	0.397	0.230	0.000	0.426	0.400	0.306
HeadEducation4	0.230	0.065	0.000	0.211	0.230	0.394
Siblings	1.003	1.223	0.000	1.0248	1.02	0.923

Residents	3.965	4.411	0.000	3.987	3.998	0.877
OwnDwelling	0.852	0.818	0.020	0.856	0.856	0.974
IncomeLevel1	0.050	0.291	0.000	0.060	0.068	0.538
IncomeLevel2	0.195	0.342	0.000	0.192	0.200	0.692
IncomeLevel3	0.542	0.327	0.000	0.542	0.523	0.453
IncomeLevel4	0.213	0.040	0.000	0.206	0.210	0.870

Notes: This table reports the means of the treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value of the mean difference test for the HTE analysis when only the mother is an entrepreneur. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

Table A10 – Covariates balance for HTE when both parents are entrepreneurs

Covariates	Before matching			After matching		
	Mean		P-value	Mean		P-value
	Treated	Control		Treated	Control	
A. Sample children aged under 18 years						
Gender	0.513	0.487	0.166	0.481	0.485	0.860
Race	0.724	0.415	0.000	0.687	0.695	0.734
Age	9.177	8.843	0.071	9.325	9.217	0.655
Marriage	0.000	0.000	.	0.000	0.000	.
Migration	0.861	0.841	0.105	0.854	0.854	0.974
HeadGender	0.769	0.767	0.898	0.766	0.764	0.906
HeadRace	0.647	0.364	0.000	0.619	0.629	0.653
HeadAge	41.224	38.524	0.000	41.370	41.688	0.425
HeadMarriage	0.000	0.000	.	0.000	0.000	.
HeadMigration	0.478	0.529	0.006	0.470	0.464	0.795
HeadEducation1	0.088	0.455	0.000	0.086	0.103	0.218
HeadEducation2	0.125	0.192	0.000	0.125	0.115	0.521
HeadEducation3	0.486	0.296	0.000	0.478	0.472	0.796
HeadEducation4	0.301	0.057	0.000	0.312	0.311	0.961
Siblings	1.000	1.443	0.000	1.007	1.001	0.902
Residents	4.101	4.586	0.000	4.111	4.111	0.985
OwnDwelling	0.804	0.687	0.000	0.811	0.809	0.921
IncomeLevel1	0.030	0.506	0.000	0.027	0.060	0.001
IncomeLevel2	0.119	0.313	0.000	0.135	0.105	0.052
IncomeLevel3	0.505	0.162	0.000	0.491	0.486	0.838
IncomeLevel4	0.346	0.018	0.000	0.347	0.349	0.950
B. Sample children aged between 18 and 30 years						
Gender	0.512	0.578	0.020	0.516	0.521	0.897
Race	0.688	0.439	0.000	0.671	0.661	0.766
Age	22.387	22.441	0.788	22.239	22.425	0.456
Marriage	0.035	0.053	0.059	0.039	0.037	0.882
Migration	0.740	0.792	0.034	0.753	0.721	0.327
HeadGender	0.802	0.768	0.137	0.811	0.790	0.480
HeadRace	0.680	0.400	0.000	0.645	0.647	0.951

HeadAge	50.981	51.793	0.038	50.939	51.118	0.743
HeadMarriage	0.000	0.000	.	0.000	0.000	.
HeadMigration	0.388	0.466	0.004	0.376	0.374	0.942
HeadEducation1	0.165	0.569	0.000	0.150	0.163	0.612
HeadEducation2	0.168	0.143	0.246	0.150	0.159	0.731
HeadEducation3	0.460	0.227	0.000	0.487	0.445	0.246
HeadEducation4	0.206	0.061	0.000	0.213	0.233	0.517
Siblings	0.989	1.276	0.000	0.982	0.978	0.961
Residents	4.220	4.702	0.000	4.208	4.230	0.787
OwnDwelling	0.868	0.845	0.231	0.874	0.856	0.471
IncomeLevel1	0.018	0.271	0.000	0.016	0.031	0.165
IncomeLevel2	0.078	0.345	0.000	0.087	0.077	0.631
IncomeLevel3	0.544	0.343	0.000	0.516	0.525	0.802
IncomeLevel4	0.361	0.041	0.000	0.382	0.367	0.675

Notes: This table reports the means of the treatment and control groups after matching for Propensity Score Method with a Biweight Kernel type and the p-value of the mean difference test for the HTE analysis when both parents are entrepreneurs. The first three columns reports the results before matching. The last three columns reports the results after matching. Panel A presents the covariates balance of the sample for children aged under 18 years. Panel B presents the covariates balance of the sample for children aged between 18 and 30 years. The samples before matching considers the sample weights. The variables of regions and federative units were omitted for space considerations.

3. Deforestation Policies in the Brazilian Legal Amazon: An analysis of the PPCDAm policy using the Triple Difference method

Abstract

This study evaluates the effects of PPCDAm implementation on the observed deforestation in the Brazilian Legal Amazon. The triple difference method is used to explore the relative differences between the group of non-metropolitan municipalities with indigenous lands and the group of other municipalities in the region. The results indicate a reduction in deforestation of approximately 16.1 km^2 per municipality between 2004 and 2007. This result represents a reduction of 10,293 km² in deforestation area and a stock of 498 million tons of CO_2 during the period. We verify the robustness of the results using placebo tests, analysis of heterogeneous effects, and analysis with the flexibility of the composition of the groups. Robustness tests corroborate the results. The results highlight the importance of remote monitoring policies to control deforestation in isolated regions and indigenous lands.

Keywords: Brazilian Legal Amazon, deforestation, environmental legislation, indigenous lands, triple difference.

JEL: C31, Q51, Q58.

Resumo

Este estudo avalia os efeitos da implementação do PPCDAm no desmatamento observado na Amazônia Legal brasileira. Utilizamos o método de tripla diferença para explorar as diferenças relativas entre o grupo dos municípios não metropolitanos com terras indígenas e grupo dos demais municípios da região. Os resultados indicam uma redução média no incremento do desmatamento de aproximadamente 16,1 km^2 por município entre 2004 e 2007. Esse resultado representa uma redução de 10.293 km^2 no desmatamento e ao estoque de 498 milhões de toneladas de CO_2 durante o período.Verificamos a robustez dos resultados realizando os testes de placebo, análise de efeitos heterogêneos e análise com flexibilização da composição dos grupos. Os testes de robustez corroboram os resultados. Os resultados destacam a importância de políticas de monitoramento remoto para o controle do desmatamento em regiões isoladas e em terras indígenas.

Palavras-chave: Amazônia Legal brasileira, desmatamento, legislação ambiental, terras indígenas, tripla diferença.

JEL: C31, Q51, Q58.

3.1. Introduction

The environment has been consolidated as a public, governmental and international topic of interest. The planet's tropical forests are mostly found in emerging countries (Saatchi *et al.*, 2011). The deforestation in these countries is mainly related to land use and conflicts of interest due to the production of primary goods (Assunção, Gandour and Rocha, 2015; Hargrave and Kis-Katos, 2013). In this sense, Brazil is important in discussing such a theme, where 70% of the Amazon Forest is found in the country, covering 7% of the planet's surface (Castro *et al.*, 2019). Furthermore, it is home to various indigenous ethnicities in its domains (BenYishay *et al.*, 2017; Soares-Filho *et al.*, 2010; Walker *et al.*, 2014). The Brazillian Amazon deforestation has once again brought global concern due to the growth in deforestation rates observed in Brazil in recent years (Azevedo *et al.*, 2021) and legal changes that have taken place in the last decade (Azevedo *et al.*, 2021; Soares-Filho *et al.*, 2014). The deforestation in Brazil was around 13,853 km^2 in 2020, and more than 80% occurred in the Brazilian Legal Amazon territory (Azevedo *et al.*, 2021).

However, the annual deforestation rate in Brazil presented a drastic reduction over the 2000s, moving from a record rate of 29,059 km^2 in 1995 to a level of 4,571 km^2 in 2012 (Arima *et al.*, 2014). The studies of Arima *et al.* (2014), Assunção, Gandour and Rocha (2013), Hargrave and Kis-Katos (2013) and Rosa, Souza and Ewers (2012) show that the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon - PPCDAm (Brasil, 2003) was effective in reducing deforestation observed between 2004 and 2012 in the Brazilian Legal Amazon. The PPCDAm promoted institutional changes coordinated between different ministries, the private sector, and civil society entities, aiming to combat deforestation in the Brazilian Legal Amazon. In this sense, this study analyzes the effectiveness of the PPCDAm in reducing deforestation. The PPCDAm was implemented in Brazil in 2004, aiming to monitor environmentally vulnerable areas, restrain the high rates of deforestation registered in the region, and promote territorial and land planning. The plan was executed in four parts from 2004 to 2020. One of the central policies of the PPCDAm in its first phase was implementing the Real-Time System for the Detection of Deforestation – DETER in 2004. DETER allowed the monitoring of the Brazilian Amazon region via satellite in near real-time, facilitating the identification and punishment of environmental infractions

in the Brazilian Legal Amazon. In addition to DETER, several other measures such as Presidential Decrees No. 6,321/2007 and No. 6,514/2008 and Resolution of the National Monetary Council – CMN No. 3,545/2008 presented institutional changes, demonstrating a favorable governmental environment for combating deforestation (PPCDAm, 2009).

To identify the causal effect of the first phase of the PPCDAm on deforestation in the Brazilian Legal Amazon, we propose using the Triple Difference method. We defined as a result variable the increase in annual deforestation made available by the Project for Monitoring Deforestation in the Legal Amazon (PRODES) of the National Institute for Space Research (INPE). The Triple Difference method makes it possible to assess the impact of the first phase of the policy on deforestation by exploring different variabilities between the characteristics of municipalities. Several data sources provide geographic and demographic characteristics, agricultural commodities prices, and the municipality's indigenous land proportion. The analysis period is from 2002 to 2007, and the data are arranged at the municipal level, comprising 756 municipalities in the Brazilian Legal Amazon region. As robustness analysis, we propose the application of placebo tests for the treatment and the outcome variable, the heterogeneous effect analysis, and the flexibility of the composition of the groups.

The results demonstrate that the first phase of the PPCDAm policy provided an average annual reduction of up to 16.1 km^2 per municipality on the increase in deforestation. This result represents a total reduction in deforestation of 10,293 km^2 during the period from 2004 to 2007. This reduction represented an additional stock of 498 million tons of carbon dioxide (CO_2), equivalent to approximately US$ 2.5 billion in 2012. The results remain strong after performing the robustness analyses. These results complement the studies of Assunção, Gandour and Rocha (2013, 2015), Hargrave and Kis-Katos (2013), Mello and Artaxo (2017) and Walker, Hamilton and Groth (2014), as they indicate that the PPCDAm was effective in containing deforestation in the Brazilian Legal Amazon in the 2000s.

This work contributes to the literature in several ways. First, the article innovates by being the first work in the literature to identify the causal effect of the first phase of the PPCDAm for the pre-2008 period. Second, it innovates in methodological terms by applying the triple difference method to identify the impact of the PPCDAm on deforestation. Third, the article explores several sources of variation in the increase in deforestation in the region,

including the presence, number, and proportion of indigenous lands in the municipalities. Fourth, the article provides new evidence on the importance of monitoring and enforcement policies for the protection of indigenous peoples in Brazil and highlights the importance of these mechanisms for the effectiveness of protected areas in containing environmental degradation. Finally, the article provides a cost-benefit analysis of the program for the pre-2008 period.

In addition to this introduction, the article reviews the literature on the topic in its second section. In section three, we present the identification strategy. Section four presents the database used and the construction of the variables for the estimations. Section five presents the results. Section six presents the robustness analysis and its results. Section seven presents the political considerations. Finally, section eight presents the final considerations.

3.2. Literature review

3.2.1. Brazilian Legal Amazon and environmental legislation

Brazil is essential for discussing environmental issues as it contains 70% of the Amazon Forest, corresponding to 28% of the South American subcontinent (Castro et al., 2019). The Brazilian Amazon represents 58.9% of the country's total territory and contains the Amazon biomes and part of the Cerrado and Pantanal biomes. The Brazilian Legal Amazon was made official in 1953 by the Brazilian federal government (Brasil, 1953) through Law nº 1.806/1953[10], which also established the Superintendence of the Economic Valorization Plan for the Amazon (SPVEA) to develop the region economically through agricultural, mineral and industrial production. The Brazilian Legal Amazon began to comprehend in 1977 the regions that currently correspond to the states of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, and Roraima, and part of the state of Maranhão (west region of the 44° meridian)[11]. However, the objective of the Brazilian federal government to develop the Amazon region economically with the SPVEA did not promote

[10] The law can be accessed at https://www.planalto.gov.br/ccivil_03/leis/1950-1969/l1806.htm

[11] This event occurred after the dismemberment of the state of Mato Grosso from Complementary Law nº 31/1977. The law can be accessed at http://www .planalto.gov.br/ccivil_03/leis/lcp/lcp31.htm

harmonious development between social, environmental, political, and economic aspects (Mello and Artaxo, 2017).

The Brazilian Institute for the Environment and Renewable Natural Resources (IBAMA) was created in 1989 by Federal Law nº 7,735/1989 to promote harmony between institutions in favor of environmental management and natural resources in Brazil. IBAMA is a federal agency linked to the Ministry of the Environment (MMA) with jurisdiction throughout the Brazilian territory and is part of the National Environment System (SISNAMA). The environmental management in Brazil was dissonant among the institutions responsible for its management until then: the Special Secretariat for the Environment – Sema (responsible for environmental conservation and rational use of natural resources) was linked to the Ministry of the Interior[12], the Brazilian Institute for Forestry Development – IBDF (responsible for forest management), and the Fisheries Superintendence - Sudepe (responsible for fisheries management) were linked to the Ministry of Agriculture, and the Rubber Superintendence - SUDHEVEA (responsible for the development of rubber production) was linked to the Ministry of Industry and Commerce. IBAMA was founded from the merger of these four bodies and had the purpose of (i) exercising the power of the federal environmental police force; (ii) operating the environmental licensing; (iii) inspecting, monitoring, and executing environmental control; (iv) authorizing the use of natural resources, and (v) execute supplementary federal actions and policies of the MMA regarding environmental standards.

The migratory expansion and disorderly land occupation led to the deforestation of approximately 18 million hectares in the Amazon region between the late 1980s and the 1990s (Laurance *et al.*, 2001; Malhi *et al.*, 2008; Mello and Artaxo, 2017), reaching its peak between 1994 and 1995 with the mark of 2.9 million deforested hectares (Fundo Amazônia, 2012). In 1998 Law No. 9,605/1998[13] was implemented in response to the escalation of deforestation in Brazil at the time, entitled the "Environmental Crimes Law" - LCA (Brazil, 1998). IBAMA lacked legal tools for prosecuting crimes committed against the environment

[12] Although SEMA aimed at sustainable management, the Ministry of the Interior had among its objectives the management of regional development, territorial occupation (colonization), and the national housing program. It is possible to access the decree-law with the areas of competence of the Ministry of the Interior through the address http://www.planalto.gov.br/ccivil_03/decreto-lei/del0200.htm

[13] The law can be accessed at http://www.planalto.gov.br/ccivil_03/leis/l9605.htm

before the LCA, in addition to existing discrepancies regarding punishments for different crimes committed against the same legal object. The LCA started to centralize and standardize the legal norms related to the subject, providing criminal and administrative sanctions for activities and conducts harmful to the environment. It also typified crimes against flora and fauna, environmental pollution, and administrative infractions for any actions or omissions that violate the norms of use, protection, promotion, and recovery of the environment (regardless of the occurrence of environmental damage). The application of the penalty for environmental crimes began considering the severity of the infraction (reasons and consequences), the offender's background of environmental crimes, and the offender's economic situation (in the case of fines). The Law also began to hold legal persons responsible for crimes against the environment administratively, civilly, and criminally, and, in a non-exclusive way, the legal representative or those responsible for the administration of infringing companies.

However, the early 2000s presented high deforestation rates in the Amazon region (Malhi et al., 2008; Mello and Artaxo, 2017; Soares-Filho et al., 2006). The deforested area in the Brazilian Legal Amazon already corresponded to 837 thousand km² in 2001 (Soares-Filho et al., 2006). According to data from PRODES/INPE, the annual deforestation in the Amazon region grew from 17,383 km² in 1998 to 25,396 km² in 2003 (Fundo Amazônia, 2012). Faced with this scenario, the Presidential Decree of July 3, 2003, was signed, establishing a Permanent Interministerial Working Group (WG) to establish measures and coordinate actions to reduce deforestation rates in the Legal Amazon[14] (Brasil, 2003). In this sense, the Interministerial WG planned a set of actions by various public authorities to curb the deforestation of the Brazilian Amazon rainforest, resulting in the 2004 Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm). The PPCDAm was a strategic initiative of the Brazilian government that established guidelines and priorities under the Sustainable Development Plan for the Amazon – PAS. It coordinated partnerships between various ministries, the private sector, and civil society entities to reduce deforestation rates in the Brazilian Legal Amazon (Mello and Artaxo, 2017). The PPCDAm has three main axes: promoting sustainable practices, territorial and land use management, and intensifying deforestation control and containment. This way, specialized institutions

[14] The decree can be accessed at http://www.planalto.gov.br/ccivil_03/dnn/2003/dnn9922 .htm

such as the Federal Police, the Federal Highway Police, the Brazilian Army, and INPE work together to combat deforestation. So far, the plan has had four phases: phase I (2004-2008), phase II (2009-2011), phase III (2012-2015), and phase IV (2016-2020).

Some policies and institutional changes promoted during the execution of the PPCDAm were prominent. The first phase of PPCDAm (phase I) introduced DETER in 2004 to improve remote monitoring and control of the region. The system was designed by INPE and enabled faster and more effective monitoring of the forest cover of the Brazilian Legal Amazon via satellite through the georeferenced MODIS[15] (Moderate-Resolution Imaging Spectroradiometer) images generated every two weeks. DETER allowed the identification of shallow forest cuts, forest degradations in preparation for future deforestation, and scars of forest fires with a minimum size of 25 hectares (Azevedo *et al.*, 2021). The region's monitoring relied on voluntary reports indicating each area's condition within the Legal Amazon before the implementation of DETER, imposing limitations on IBAMA's prompt legal repression against environment infractors.

The National Monetary Council – CMN (Brasil, 2008) implemented Resolution No. 3,545/2008 in 2008 aiming to mitigate the effects of the expansion of agribusiness on deforestation in the region (Assunção, Gandour, Romero, *et al.*, 2013; Assunção, Gandour and Rocha, 2015; Hargrave and Kis-Katos, 2013). This institutional change imposed restrictions on rural credit in the Amazon by requiring proof of compliance with environmental legislation on the credit takers. The resolution began to demand the absence of embargoes and proof of ownership to borrowers, and rural credit would be subject to suspension and termination in the event of irregularities in the use of land. In the same year, the Ministry of the Environment – MMA established a list of priority municipalities in the fight against deforestation in the Brazilian Legal Amazon through MMA Ordinance nº 28/2008 (MMA, 2008).

Another important change induced by PPCDAm was the increase in protected areas, which are conservation units (comprised of integral protection and sustainable use units), permanent preservation areas (PPAs), legal reserves (LR), and indigenous lands. Regarding indigenous lands, several authors highlight the importance of their demarcations as a

[15] MODIS is a space instrument launched from Earth by NASA and started in 1999 and is part of the Earth Observing System (EOS). The program provides remote sensing data of high temporal and spectral resolution and moderate spatial resolution.

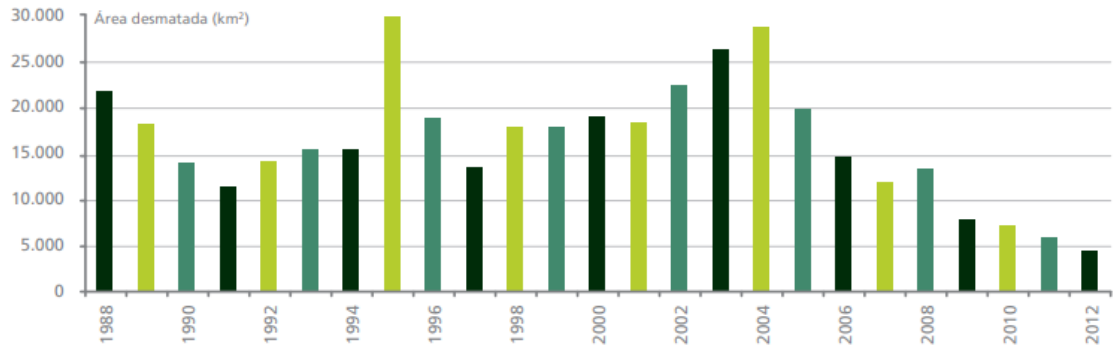
protective measure for the protection of the environment and biodiversity (BenYishay *et al.*, 2017; Nepstad *et al.*, 2006; Pfaff *et al.*, 2015; Ricketts *et al.*, 2010; Soares-Filho *et al.*, 2010). Conservation Units in the Brazilian Legal Amazon increased by more than 520 thousand km² n between 2004 and 2009, and about 43% of the Legal Amazon area was considered a protected area in 2010 (Assunção, Gandour and Rocha, 2015).

According to the 2012 Amazon Fund's Annual Activity Report, the pace of deforestation in the Legal Amazon decreased substantially from the second half of the 2000s onwards. This behavior can be seen in Figure 1. Several studies consider the introduction of the PPCDAm as the main reason for this change of course (Arima *et al.*, 2014; Assunção, Gandour and Rocha, 2013; Assunção and Rocha, 2019; Mello and Artaxo, 2017; Sills *et al.*, 2015). Thus, the empirical literature related to deforestation in the Amazon territory indicates that the policies to combat deforestation implemented by the PPCDAm helped contain deforestation and reduce environmental devastation in the region from the second half of the 2000s onwards. The introduction of the "New Forest Code" in 2012 through Federal Law nº 12.651/2012[16] in 2012 established changes in the requirements that characterize PPAs and LRs, providing conditions for amnesty for illegal deforestation committed by small rural properties[17] until July 2008. Soares-Filho *et al.* (2014) highlight that these changes qualified 90% of rural producers for amnesty, resulting in the forgiveness of 58% of Brazil's "environmental debt" at the time. According to the authors, leniency with environmental crimes provided by the 2012 Forest Code represented an institutional risk. Despite this, deforestation levels remained stable between 2013 and 2018 (Azevedo *et al.*, 2021). The 2020 Annual Report on Deforestation in Brazil (2021) indicates that from 2018 onwards, environmental degradation in the Amazon region increased again, with a 30% increase in the number of alerts issued by DETER in the Amazon region between 2018 and 2019. Deforestation rates rose again in 2020 compared to the previous year, reaching the mark of 13,853 km², consolidating the annual rate of deforestation in the Brazilian Amazon at a level three times higher than the 4,571 km² recorded in 2012 (Azevedo *et al.*, 2021).

[16] The law can be accessed at http://www.planalto.gov.br/ccivil_03/_ato2011-2014/2012/lei/l12651.htm

[17] The size of properties considered small varies between 20 hectares, for the Brazilian Southeast, up to 440 hectares, for the Brazilian Legal Amazon.

Figure 1 – Annual deforestation in the Brazilian Legal Amazon (km²)



Source: Amazon Fund's Annual Activity Report using data from PRODES/INPE (2012).

3.2.2. The First Phase of PPCDAm

The Presidential Decree of July 3, 2003, promoted the creation of the PPCDAm in 2004, intending to reduce deforestation rates in the Legal Amazon. The PPCDAm was conceived by integrating several ministries. The Ministry of the Civil House of the Presidency of the Republic was responsible for coordinating the Interministerial WG that formulated the plan. This group was composed of the following governmental agencies: Ministry of Agriculture, Cattle and Supplying (MAPA); Ministry of Science and Technology (MCT); Ministry of Defense (MD); Ministry of Agrarian Development (MDA); Ministry of Development, Industry and Foreign Trade (MDIC); Ministry of National Integration (MI); Ministry of Justice (MJ); Ministry of the Environment (MMA); Ministry of Mines and Energy (MME); Ministry of Transport (MT); and Ministry of Labor and Employment (MTE). Since the decree was signed on March 15, 2004, the Ministry of Planning, Budget and Management and the Ministry of Foreign Affairs joined the group[18].

The Interministerial WG on Deforestation in the Amazon supported the coordination between different spheres of the public sector and provided subsidies for establishing the four working subgroups responsible for elaborating strategic proposals in their respective areas of activity. The working subgroups were divided into (i) Territorial Land Ordinance, working on territorial planning instruments with a focus on land policy, conservation units, and

[18] PPCDAm. Action Plan for the Prevention and Control of Deforestation in the Legal Amazon. Phase I. Brasília, DF: Civil House, 2004.

sustainable development strategies; (ii) Monitoring and Control, acting in instruments for monitoring, licensing, and inspection of deforestation, burning and logging; (iii) Promotion of Sustainable activities, operating in rural credit and tax incentives, technical assistance, and rural extension, and scientific and technological research; and (iv) Infrastructure, working on infrastructure policies, focusing on the transport and energy sectors[19].

The instructions for deforestation containment strategies were based on the region's socioeconomic, environmental, and infrastructure context. In this sense, the PPCDAm followed a series of structuring policies in accordance with the following strategic guidelines: (i) promote the valorization and sustainable use of the forest for the purposes of biodiversity conservation and regional development; (ii) promote technological innovations as a way to increase productivity, reduce pressures on remaining forests and improve the recovery of degraded areas; (iii) attain land and territorial planning aimed at containing the predatory use of natural resources, creating conservation units and homologation of indigenous lands; (iv) improve the monitoring, licensing and inspection tools for deforestation; (v) encourage the strategic planning of infrastructure constructions according to cost-benefit, as well as socioeconomic and environmental impacts; (vi) strengthen cooperation between Federal Government institutions; (vii) execute public policies and environmental management in a decentralized manner involving the Union, states and municipalities; (viii) encourage the active participation of the different interested sectors of society in the management of policies related to the restriction and prevention of deforestation; (ix) encourage promising pilot experiences, providing opportunities for incorporation into public policies; and (x) establish a system for monitoring deforestation and public policies in the Amazon, aiming at a permanent process of learning and improvement in environmental preservation.[20] The Operational Plan for the first phase of the PPCDAm was established following the strategic guidelines and the working subgroups by their respective areas of activity. The subgroups are detailed as follows: (i) Monitoring and Control, (ii) Land Ordinance and Territorial, (iii) Promotion of Sustainable Activities, and (iv) Infrastructure.

[19] The bodies responsible for each work subgroup are: (i) Secretariat of Policies for Sustainable Development – SDS/MMA (coordinator), Secretariat for the Coordination of the Amazon – SCA/ MMA, MDA, MI, MDIC, MD, MJ/Funai; (ii) IBAMA/MMA (coordinator), SCA/MMA, MCT, MD, MJ, TEM, Amazon Protection System - Sipam/CasaCivil; (iii) Secretariat of Biodiversity and Forests – SBF/MMA (coordinator), SCA/MMA, MDIC, MAPA, MDA, MCT, MI, TEM, MF (guest); and (iv) SCA/MMA (coordinator), MT, MME, MAPA, MI, MDIC.

[20] PPCDAm, op. cit., 2004

DETER was the main instrument for improvement in the monitoring and deforestation control areas. The innovation of this system allowed near real-time monitoring and detection of deforestation events through satellite images. This georeferenced data provided the federal government and states with subsidies in identifying new deforestation occurrences and mapping critical areas to guide inspection actions and contain environmental crimes. These changes made it possible to overlay labor, environmental, fiscal, tax, and land ownership information to track activities linked to illegal The actions of the federal government in the land and territorial planning axis aimed at combating public land grabbing, the creation of new conservation units (sustainable use or integral protection) and the demarcation and approval of indigenous lands. It should be noted that this axis prioritized the regions of the *Arco do Deforestamento*[21], especially in the vicinity of the BR-163 (Santarém-Cuiabá Highway). The federal government acted with the state governments (Pará, Mato Grosso, Rondônia, and Acre) and civil society entities to execute the ecological-economic zoning (ZEE)[22] along the Deforestation Arch and the area of influence of BR-163. Further, the government encouraged the expansion of sustainable activities in deforested areas indicated by the ZEE (PPCDAm, 2004).

New guidelines and criteria were established for granting credit through the Constitutional Funds for Financing in the North (FNO) and Midwest (FCO)[23] to promote sustainable activities with natural resources in the Amazon. The Green Protocol[24] was improved with its implementation by public and private banks responsible for complying with environmental laws in their credit operations. Additionally, the federal government provided training for labor focused on intensive agriculture (in areas that have already been deforested) and forest management, acting in partnership with state governments, civil society, and the business sector (PPCDAm, 2004).

[21] The "Arc" comprised southeastern Maranhão, northern Tocantins, southern Pará, northern Mato Grosso, Rondônia, southern Amazonas and southeastern Acre. In the period 2000-2001, approximately 70% of deforestation in the Legal Amazon occurred in about 50 municipalities in the states of Mato Grosso, Pará and Rondônia, representing around 15.7% of the total area of the region (PPCDAM, 2004). (PPCDAm, 2004).

[22] Established by Decree No. 4,297/2002, the ZEE establishes measures and standards for environmental protection in order to ensure environmental quality, water resources and soil and the conservation of biodiversity, promoting sustainable development and improving living conditions.

[23] Regulated by Law No. 7,827/1989, the FNO and FCO aim to contribute to the economic and social development of the North and Midwest regions, through regional federal financial institutions, through the execution of financing programs productive sectors, in line with the respective regional development plans.

[24] The Green Protocol is a letter of principles signed in 1995 by Brazilian financial institutions in favor of measures in harmony with sustainable socio-environmental development.

The federal and state governments jointly coordinated the strategic planning of infrastructure works to promote infrastructure development in the Amazon region along with socio-environmental responsibility. This joint action mitigated the environmental degradation caused by the construction of highways as in previous decades. It fostered the planning and execution of preventive, mitigating, and compensatory measures to be carried out in the works (PPCDAm, 2004). However, the Infrastructure axis migrated to PAS in 2004, concentrating the PPCDAm's activities on activities directly related to illegal deforestation in the Amazon, with emphasis on productive activities linked to forest management, extractivism, recovery of degraded areas, and productive intensification of open areas (PPCDAm, 2009).

According to the PPCDAm report (2004), the total budget provisioned in 2004 for actions to combat illegal deforestation was R$ 394 million, of which R$ 244.3 million (62%) were allocated to land and territory, R$ 82.7 million (21%) to the monitoring and control axis, and R$ 67 million (17%) to the promotion of sustainable activities. Compared to the amount allocated to the monitoring and control axis, R$ 4.7 million (1.2%) was allocated to improving monitoring systems and financing the planning, development, and installation of DETER. Between 2004 and 2007, INPE, responsible for developing and using DETER, had its annual Budget with Costing and Capital (OCC) increase from R$ 41.8 million in 2004 to R$ 116.8 million in 2007 (INPE, 2008). Furthermore, the annual budget provisioned for IBAMA also increased, from R$570 million in 2004 to more than R$1.1 billion in 2007. Converting to dollars, the two institutes spent more than U$ 1.8 billion[25] in this period.

Several results in its axes of action were achieved during the first phase of the PPCDAm due to a governmental environment favorable to institutional changes committed to combating deforestation (PPCDAm, 2009). The edition of Ordinance MDA/INCRA nº 10 in December 2004 determined the re-registration of rural properties in municipalities in the Amazon whose declaration of legal status was characterized by possession[26] by simple occupation, and more than 60 thousand rural property titles were inhibited (PPCDAm, 2009).

[25] Value corrected according to the free exchange rate of the US Dollar (sale) as provided for at address: https://www3.bcb.gov.br/sgspub/consultarvalores/consultarValoresSeries.do?method=consultarValores

[26] Squatter without title document, promising buyer who holds possession and holder of possession arising from a concession of use provided by the Federal, State or Municipal Government.

Law 11,132 was sanctioned[27] in July 2005 as an amendment to the Law on the National System of Nature Conservation Units (SNUC). It established the instrument of "provisional administrative limitation" of areas to perform studies for the creation of UCs in conflict zones. More than 25 million hectares of conservation units strategically located near the Arch of Deforestation were created between 2004 and 2008. Additionally, more than 10 million hectares were created in Indigenous Lands, and 48 new Indigenous Lands were homologated (CIMI, 2009). In the same period, Deforestation in the Integral Protection Conservation Units reduced from 499 km² to 119 km², from 1277 km² to 435 km² in the Sustainable Use Conservation Units, and from 567 km² to 398 km² in Indigenous Land.

The monitoring and control axis promoted several technological and institutional advances. The DETER creation and the PRODES improvement provided subsidies for strategic actions to combat deforestation strategically and quickly. Decree 6,321 of December 2007 started to establish priority municipalities with high deforestation rates based on three criteria: (i) total deforested area; (ii) total deforested area in the last three years; and (iii) an increase in the deforestation rate in at least three of the last five years. Priority municipalities suffered indirect consequences, such as the refusal of slaughterhouses to purchase cattle from legally irregular farms, greater restrictions on obtaining rural credit, and the requirement for greater effort in more sustainable production. In addition, Decree 6,514 of July 2008 established more detailed and objective infractions and administrative sanctions related to environmental crimes, providing federal administrative processes to investigate such infractions and the appropriate measures. Thus, IBAMA started to adopt new inspection methodologies in the Brazilian Legal Amazon, working with the planning of operations in priority areas and jointly with the Army, the Federal Police, and the Federal Highway Police. It incurred greater effectiveness in the seizure of illegal wood, application of fines, and fight against corruption, resulting in the arrest of more than 600 public servants who committed crimes against the environment and public order (PPCDAm, 2009).

The promotion of sustainable activities during the first phase of the PPCDAm attained the institution of the Public Forest Management Law (Law 11,284/06)[28], promoting greater transparency in identifying public forests and facilitating the forest concession process. The

[27] The law can be accessed at https://www.planalto.gov.br/ccivil_03/_ato2004-2006/2005/lei/l11132.htm
[28] The law can be accessed at http://www.planalto.gov.br/ccivil_03/_ato2004-2006/2006/lei/l11284.htm

federal agency Serviço Florestal Brasileiro became responsible for managing public forests in Brazil and the National Forestry Development Fund – FNDF. It promoted the development of sustainable forest-based activities in Brazil and technological innovations in the sector. Law 11,284/06 resulted in the first public bidding for a forest concession in Flona Jamari (RO), and the Sustainable Forest District of BR-163 (PPCDAm, 2009) was created.

3.2.3. The importance of PPCDAm and evidence from the literature

The magnitude and difficulty of accessing the Brazilian Legal Amazon impose great challenges in the fight against illegal deforestation. In this sense, DETER offered an important monitoring instrument for isolated regions with little integration with the rest of society (Walker *et al.*, 2014), subsidizing greater inspection and potentially increasing the scrutiny of the rest of society regarding conflicts. They were related to illegal deforestation in such regions (Aldrich *et al.*, 2020). Indigenous people were in a vulnerable situation before the implementation of the PPCDAm due to the lack of prompt monitoring (Walker *et al.*, 2014) and the lack of regulation around indigenous lands (BenYishay *et al.*, 2017). Additionally, Börner, Marinho and Wunder (2015) highlight the importance of *enforcement* that guarantees Indigenous land ownership for indigenous peoples. The authors also reinforce that property vulnerability is associated with the deforestation of these lands and neighboring municipalities and that the isolation of indigenous peoples can make Indigenous Lands more susceptible to extractive threats. Ricketts *et al.* (2010) report that the probability of deforestation within indigenous lands or protected areas (TIAP) is between 7 and 11 times lower concerning areas around them and emphasize that the TIAPs established between 2003 and 2007 in the Amazon Brazilian law can prevent deforestation of up to 272 thousand km² by 2050, equivalent to one-third of CO_2 in the world.

Hargrave and Kis-Katos (2013) addressed the relationship between the expected profitability of agricultural production, the environmental policies of the PPCDAm, and deforestation between 2002 and 2007. The authors assess how land use methods are affected by variations in beef, soy and wood prices, as well as by the actions of the environmental police (IBAMA) and by the flow of rural credit. It is identified that the greater availability of agricultural credit and the increase in soy and cattle prices are associated with higher

deforestation rates. On the other hand, the presence of environmental policing was effective in reducing deforestation. The study also presents an analysis using the GMM estimator on differences considering environmental fines and rural credit endogenously to the model. It identifies that the percentage increase in the intensity of fines resulted in a reduction of about 0.5% in deforestation. Vasconcelos *et al.* (2013) analyze the incidence of fires in the Amazon between 2004 and 2012 using a quasi-GLM Poisson model. The authors identify that 95% and 99% of fire outbreaks occur during high fire periods, presenting strong seasonality between August, September, and October and a strong negative correlation with rainfall. According to the authors, these results indicate that environmental degradation in the Brazilian Legal Amazon is associated with agricultural production, establishing a relationship between fire outbreaks and the management of deforested lands. Assunção, Gandour and Rocha (2013) article verify the impact of Resolution nº 3,545/2008 on rural credit. The authors employ the difference-in-differences strategy, controlling for fixed effects of seasonal months, agricultural commodity prices, and other relevant conservation policies. The results show that the institutional change caused a reduction in the granting of rural credit in the Amazon biome. Counterfactual simulations indicate that the deforestation of 2,700 km² between 2009 and 2011 was avoided.

Arima et al. (2014) study assess the impact of Ordinance MMA nº 28/2008 on deforestation in the Brazilian Legal Amazon using difference-in-differences and propensity score methods. It compares priority municipalities to municipalities outside the list. The results indicate that increased inspections in the list's municipalities resulted in a reduction in deforestation between 2,304 and 10,653 km^2 between 2009 and 2011, equivalent to a stock of 110 million to 528 million tons of carbon. Assunção and Rocha (2019) also checked the effectiveness of the MMA Ordinance nº 28/2008 with the difference-in-differences method, controlling for agricultural prices and the share of protected areas in each municipality. The study demonstrates that the deforestation of 11,396 km² in priority municipalities was avoided between 2008 and 2011. The main mechanisms that motivated this drop were advances in monitoring and the applicability of the Law.

The literature indicates that it is advantageous to interact institutional changes favorable to environmental conservation with other determinants, such as monitoring capacity and economic sanctions (Assunção *et al.*, 2013; Assunção, Gandour and Rocha,

2013; Pfaff *et al.*, 2015; Ricketts *et al.*, 2010). Thus, many studies for the Brazilian Legal Amazon focus on the synergy between policies to combat deforestation and institutional changes introduced in 2004 and 2008. Assunção, Gandour and Rocha (2015) report that the first phase of the PPCDAm contributed to a significant containment of deforestation, even controlling for the effects of prices of agricultural products. The advent of DETER in 2004, the Presidential Decrees nº 6,321 /2007 and nº 6,514/2008, and Resolution nº 3,545/2008 of the CMN contributed crucially to such reduction. According to the authors' estimate, deforestation would have been 56% higher between 2005 and 2009 in the absence of policies, equivalent to the deforestation of 73,000 km² during the period. In another study, Assunção, Gandour and Rocha (2013) assess the impact of the combination of increased monitoring of deforestation after 2004, resulting from the implementation of DETER, with the total number of fines for environmental infractions applied to result from the implementation of resolution nº 3.545/2008 of the CMN (Brasil, 2008). The study applies two-stage estimates (2SLS) for municipalities in the Amazon biome between 2007 and 2011. The study results demonstrate that the increase in the number of fines applied in a given year significantly reduces deforestation in the following year for the same municipality and that the application of fines prevented the deforestation of 122,700 km² of the Amazon biome, reducing the emission of 900 million tCO2 annually.

3.3. Identification strategy

The first phase of the PPCDAm implemented a system for almost real-time remote monitoring of deforestation in the Brazilian Legal Amazon, in addition to promoting advances in inspection, land ordinance, and delimitation of environmental protection areas and indigenous lands. The municipalities of the Legal Amazon present differences in socioeconomic, cultural, and infrastructure terms. Therefore, we can explore the variability of certain areas of the region, disaggregating these areas into two groups of municipalities. Those municipalities represent the first group with higher population density, higher income, better infrastructure, and close to better quality roads. The second group is municipalities with opposite characteristics, being more isolated and difficult to access regions. An additional source of variability is whether or not indigenous lands exist within the

municipalities of these groups. Indigenous lands in Brazil have specific rules regarding the severity of environmental crimes in their domains. Non-metropolitan municipalities and indigenous land areas are more sensitive to the innovations brought by DETER. We can assume that the ratio of characteristics between these groups is maintained over time. Thus, non-metropolitan municipalities with indigenous lands are relatively more affected by PPCDAm than metropolitan municipalities or municipalities without indigenous lands.

We propose to identify the causal effect of PPCDAm on deforestation from 2002 to 2007 between the non-metropolitan municipalities with indigenous lands and the group of other municipalities through the Triple Difference (DDD) method (Gruber, 1994). The main hypothesis of the DDD method is the existence of parallel trends in the outcome variable between the groups of municipalities compared to the pre-intervention period[29]. The method allows the addition of covariates, which can make estimating the causal effect more accurate. In terms of econometric specification, the relationship has the following form:

$$Y_{it} = \beta_0 + \beta_1 * NM_i + \beta_2 * IL_i + \beta_3(NM_i * IL_i) + \lambda_1 * d_t + \lambda_2(d_t * NM_i) + \lambda_3(d_t * IL_i) + \lambda_4(d_t * NM_i * IL_i) + \theta_{it} * X_{it} + \pi_{it} + \varepsilon_{it} \quad (1)$$

where Y_i represents the result variable "increase in the area of deforestation" for the municipality "i" of the Brazilian Legal Amazon. The variable NM_i represents a dummy variable identifying the non-metropolitan municipality. The variable IL_i represents a binary variable identifying if the municipality has indigenous lands (lands greater than 0 km²). The variable d_t identifies the period after the implementation of the environmental policy (2004 to 2007). The interaction between the environmental policy treatment variables captures the causal effect of the environmental policy change on the outcome variable. The vector X_i represents the covariates for the municipality. The parameter. The magnitudes of the effects are captured by the parameters β, λ, and θ. The parameters π_{it} and ε_{it} represent the time-fixed effects and error term, respectively.

We estimated four different models concerning the vector of covariates considered. The first model considers only municipal fixed effects and time fixed effects. The second

[29] The difference-in-differences method has already been adopted in other evaluations of policies to combat deforestation (Arima *et al.*, 2014; Assunção, Gandour, Romero, *et al.*, 2013; Assunção and Rocha, 2019).

model considers the geographic control covariates (*AreaKm2*, *NoForest*, *Hydrography*, *Population*, *UF*, *DistanceCapUF*, *DistanceCapUFSqrd*, *DistanceCapProx* and *DistanceCapProxSqrd*). The third model considers the geographic control covariates and the agricultural and livestock covariates of the municipalities (price indices of agricultural products and *TemporaryTilArea*). Finally, the fourth model considers all the previous covariates and adds the covariates referring to the characteristics of indigenous lands in the municipalities (*ILProportion* and *ILNumber*). All models consider cluster-robust standard errors by the municipality.

3.4. Data

We utilized seven municipal-level databases for the period from 2002 to 2007. The first database comes from PRODES/INPE and provides annual deforestation rates of municipalities in the Brazilian Legal Amazon. The second database is the Registry of Metropolitan Regions, Urban Agglomerations, and Integrated Development Regions for the year 2010 of the Brazilian Institute of Geography and Statistics (IBGE). The third database is related to the demarcation of indigenous territories and was prospected through the Terras Indígenas no Brasil website. The fourth database is IBGE's Population Estimates (EstimaPop), which provides annual data on population estimates for each municipality. The fifth database was collected from the Secretary of Agriculture and Supply of the State of Paraná (SEAB-PR) of the Department of Rural Economy (DERAL) and provides the prices of agricultural commodities. The sixth database used in the analysis is IBGE's Municipal Agricultural Production (PAM). Finally, the seventh database was extracted from INPE's TerraBrasilis portal, enabling the municipalities to generate geographic coordinates.

To measure the effect of the first phase of the PPCDAm on deforestation, we used the result variable of deforestation increment (*DeforestationIncrement*) from the PRODES/INPE database, which provides an estimate of the annual variation of deforestation[30] in km² for 760 municipalities in the Brazilian Legal Amazon. We considered the period from 2002 to 2007 to identify the effect of introducing the first phase of the PPCDAm from 2004 onwards. A

[30] These estimates are calculated by the analysis of images captured between August 1st and July 30th of the following year.

binary variable was created to identify the treatment, assuming a value of one for 2004 to 2007, and zero for the previous years. We estimated the effect of the intervention by the relative differences in *DeforestationIncrement* between non-metropolitan municipalities with Indigenous Lands and the other municipalities for the post-intervention period. For this purpose, we established the interaction between two binary variables. The first binary variable refers to the region of the municipality (*NMetropMunicipality*), assuming a value of one when the municipality is located in a non-metropolitan region and zero if the municipality is located in a metropolitan region. The criterion for identifying the metropolitan region was based on the Registry of Metropolitan Regions, Urban Agglomerations and Integrated Development Regions for 2010 of the Brazilian Institute of Geography and Statistics (IBGE). The second binary variable was collected through data from the *Terras Indígenas no Brasil* ("Indigenous Lands in Brazil") website. It captures the existence of indigenous lands in the municipality approved until 2007 (*ILMunicipality*), assuming a value of one when the municipality has a non-null area of Indigenous Lands (km²) in its domains and zero otherwise. From the interaction of these two variables, we identified non-metropolitan municipalities with Indigenous Lands (*NMetropMunicipalityWIL*), assuming value one when both variables *NMetropMunicipality and ILMunicipality* are equal to one and zero otherwise.

The set of covariates considers geographic and population characteristics, prices of agricultural products, and the predominance of lands and indigenous peoples. These data enable controlling heterogeneous demography and location among the municipality's aspects in the sample. We constructed the municipal covariate's total area in km² (*AreaKm2*), the area of non-forest in the municipality in km² (*NoForest*), the hydrographic area in km² (*Hydrography*), and dummies of the federative units (*UF*) from the PRODES/INPE data. The covariate population (*Population*) indicates the size of the municipality's population in the year, which was obtained by the IBGE's Population Estimates (EstimaPop) database. The agricultural covariates used by Assunção *et al.* (2013) are represented by the price indices of agricultural products deflated for the year 2000. For this, we used the data from the Secretary of Agriculture and Supply of the State of Paraná (SEAB-PR) to create the covariates (i) real price index for rice (*RiceIndex2000*), (ii) real price index for sugarcane (*SugarcaneIndex2000*), (iii) real price index for live cattle (*CattleIndex2000*), (iv) price index

real price index for cassava (*CassavaIndex2000*), (v) real price index for corn (*CornIndex2000*), and (vi) real price index for soybeans (*SoybeanIndex2000*)[31]. We also create the covariates indicating the number of Indigenous Lands in the municipality (*NILNumber*) and the proportion of the sum of the Indigenous Lands area in the municipality in square kilometers (*ILProportion*). We prospected the geographic coordinates of the municipalities through the TerraBrasilis/INPE database to control the heterogeneity of distance of the municipalities to large urban centers. We established the centroid of each municipality and constructed the covariate of the linear distance between the centroid of the municipality and the centroid of the capital of its federative unit (*DistanceCapUF*) and its quadratic term (*DistanceCapUFSqrd*). Furthermore, we constructed the covariate of the linear distance between the municipality and the centroid of the closest capital independent of the state (*DistanceCapProx*) and its quadratic term (*DistanceCapProxSqrd*).

The descriptive statistics of the variables used in this study are shown in Table 9, containing their mean, standard deviation, minimum and maximum statistics.

Table 9 – Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Outcome Variable				
DeforestationIncrement	28.193	80.408	0	1,407.80
Municipalities Types				
NMetropMunicipalityWIL	0.212	0.409	0	1
NMetropMunicipalityWoIL	0.733	0.443	0	1
MetropMunicipality	0.056	0.229	0	1
Covariates				
Population	28,829.34	92,908.65	981	1,688,524
AreaKm2	6,684.467	13,892.57	64	159,540
NoFlorest	1,266.804	2,407.819	0	19,780.8
Hydrography	149.300	431.435	0	4,499.9
DistanceCapUF	324.976	238.172	0	1,485.384
DistanceCapUFSqrd	162,322.9	24,6075.7	0	2,206,364
DistanceCapProx	281.3542	165.651	0	902.557
DistanceCapProxSqrd	106,594.4	113,722	0	814,609.1
RiceIndex2000	216.950	49.782	151.681	296.464
SugarcaneIndex2000	172.397	30.241	123.964	219.615
CattleIndex2000	135.119	12.657	111.244	151.948
CassavaIndex2000	167.483	72.805	67.912	284.257

[31] Four municipalities that did not have agricultural data in the PAM database were excluded, resulting in a sample of 756 municipalities.

ÍndiceMilho2000	137.555	14.410	119.748	164.541
SoybeanIndex2000	182.313	25.918	151.652	220.662
ILNumber	0.522	1.457	0	14
ILProportion	0.049	0.140	0	0.999

Notes: Descriptive state statistics have been omitted for space considerations. The municipality types presented in this table are the group of non-metropolitan municipalities with indigenous lands (NMetropMunicipalityWIL), the group of non-metropolitan municipalities without indigenous lands (NMetropMunicipalityWoIL), and metropolitan municipalities (MetropMunicipality).

3.5. Results

The hypothesis of identification of the triple difference method assumes the existence of parallel trends between the analyzed groups. The results of the statistic test for this identification hypothesis demonstrate that we can accept the hypothesis that the groups show parallel trends in the period before the intervention, presenting an F statistic of 1.91 with a probability of approximately 20%[32]. We estimate four different triple difference models. Table 10 presents the results of the main analysis of the effects of the first phase of the PPCDAm from 2004 on the deforestation increment in the Brazilian Legal Amazon. The Columns 1 to 4 presents the results in the same order as described in section three.

Table 10- Effect of the first phase of PPCDAm 2002-2007

	(1)	(2)	(3)	(4)
DDD Effect	-15.324**	-16.083**	-16.083**	-16.069**
	(6.709)	(6.761)	(6.761)	(6.762)
Cov. Demographics	NO	YES	YES	YES
Cov. Agropecuary	NO	NO	YES	YES
Charact. Indig Lands	NO	NO	NO	YES
FE Municipalities	YES	YES	YES	YES
FE Time	YES	YES	YES	YES
N	4,536	4,536	4,536	4,536

Notes: This table presents the results for the triple difference regressions. The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. Column 1 presents the results for the model controlling for municipal and temporal fixed effects. Column 2 presents the results for the model controlling for fixed effects and demographic covariates. Column 3 presents the results for the model controlling for fixed effects, demographic covariates, and agropecuary covariates. Column 4 presents the results for the model controlling for fixed effects, demographic covariates, agropecuary covariates, and characteristics of indigenous

[32] The test was performed with cluster-robust standard errors by the federative unit.

lands covariates. The values in parentheses are standard deviations of the coefficient. Covariate coefficients were omitted for space considerations.

All models in Table 10 present effects with at least 5% confidence significance. Column 1 results indicate that the PPCDAm implied a reduction in the deforestation increment of 15.3 km² (p-value < 0.05) per municipality on average. After adding covariates, the results in Columns 2, 3, and 4 indicate a reduction in deforestation increment of approximately 16.1 km^2 (p-value < 0.05). This result represents an average annual reduction in deforestation between 2,452 and 2,573 km² in the Brazilian Legal Amazon per municipality. It corresponds to a total reduction between 9,807 and 10,293 km² from 2004 to 2007[33].

Assunção, Gandour and Rocha (2015) report a 56% reduction in deforestation in the Amazon between 2005 and 2009. Also, in line with these results, Soares-Filho *et al.* (2010) identify that the expansion of protected areas, especially indigenous lands, led to a decline in deforestation from 1997 to 2008. Arima *et al.* (2014) indicate that the increase in inspections in priority municipalities through the Ordinance MMA nº 28/2008 resulted in an average annual reduction in deforestation between 2,304 and 10,653 km^2 between 2009 and 2011. In another study, Assunção and Rocha (2019) identified that the MMA Ordinance nº 28/2008 avoided the deforestation of 11,396 km² in the priority municipalities between 2008 and 2011. In this sense, our results are within the range of those of Arima et al. (2014) and Assunção and Rocha (2019). They indicate that the first phase of the PPCDAm was successful in the environmental protection of municipalities with indigenous lands.

3.6. Robustness analyzes

3.6.1. Placebo tests

We conducted placebo tests to check the robustness of the results found. The placebo test checks whether the estimated treatment effect occurred by chance. Thus, the results of these tests should be statistically non-significant. This test allows checking whether the

[33] We consider the 160 non-metropolitan municipalities with indigenous lands in the sample.

results are related to the treatment effect or the time trajectory of the variable of interest. Thus, we performed the placebo test for the treatment period and the outcome variable.

Table 11 reports the results of the placebo tests. Columns 1 and 2 report the results of the placebo test on the variable identifying the treatment period for the first phase of the PPCDAm using the year 2003 as a placebo. There should be no effect for the previous period as the Law was implemented in 2004. Columns 3 and 4 show the results of the placebo test for the outcome variable. For that, the effect on the area of the permanent farming variable was analyzed instead of the deforestation increment. The objective is to test whether implementing policies to combat deforestation impacted other outcome variables unrelated to treatment. We expect no effects considering that this variable is not related to deforestation[34]. These tests verify that the effects found were not type I errors. The results of the placebo tests shown in Table 11 were not statistically significant, indicating that the effects identified in the main analysis (Table 10) did not occur by chance.

Table 11 - Placebo Tests

	(1)	(2)	(3)	(4)
Placebo DDD Effect	0.656 (11.936)	-0.096 (22.899)	0.346 (0.860)	0.020 (0.942)
Fixed Effects	YES	YES	YES	YES
Covariates	NO	YES	NO	YES
N	4,536	4,536	4,536	4,536

Notes: The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. Columns 1 and 2 presents the results of the placebo test on the variable identifying the treatment period for the first phase of the PPCDAm using the year 2003 as a placebo. Columns 3 and 4 presents the results of the placebo test using the municipality's permanent crop area as the result variable. Covariate coefficients were omitted for space considerations.

3.6.2. Heterogeneous analysis

We want to verify the heterogeneous effects of the policy each year after its application. Thus, we perform a heterogeneous analysis for the policy applied from 2004 onwards, identifying its effect for each year after its implementation. All estimated values

[34] According to Assunção, Gandour and Rocha (2015), rice, sugarcane, cassava, corn and soybean (temporary) harvests corresponded to approximately 70% of the harvest in the region between 2002 and 2009.

are within the 95% confidence interval, and we used cluster-robust standard errors[35]. Table 12 presents the significant heterogeneous temporal effects. Columns 1, 2, and 3 present 2005, 2006, and 2007, respectively. We identified a reduction of approximately 13.2 km² (p-value < 0.1) in 2005. In 2006 and 2007, more significant effects were identified (p-value < 0.01), resulting in reductions in the deforestation increment of 24.9 km² and 23.8 km², respectively. A possible explanation for the lack of effect in 2004 would be the agents' adaptation period for the assimilation of the policy due to the DETER's remote aspect.

Table 12 - Heterogeneous Effects Analysis

	(1)	(2)	(3)
DDD Effect	-13.159* (6.975)	- 24.926*** (8. 217)	-23.814*** (8.829)
Fixed Effects	YES	YES	YES
Covariates	YES	YES	YES
N	4,536	4,536	4,536

Notes: The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. Columns 1, 2, and 3 present the results for the analysis of heterogeneous effects for the years 2005, 2006, and 2007, respectively. Covariate coefficients were omitted for space considerations. No significant effect was identified for the year 2004.

3.6.3. Flexibility in the composition of groups

We want to test the robustness of the treatment variable municipalities for different proportions of indigenous lands in its territorial composition (*ILProportion*). Thus, we propose to limit the group of non-metropolitan municipalities with Indigenous Lands according to the percentile of the variable *ILProportion*. In addition to the original model (independent of *ILProportion*), three new DDD models were established considering non-metropolitan municipalities with Indigenous Lands with *ILProportion* (i) equal to or above 25%, (ii) equal to or above 50%, and (iii) equal to or above 75%. Additionally, we performed the Wald test to verify the null hypothesis of equality between the coefficients associated with the DDD effect of the four models.

[35] We cluster the subjects in the municipal level

The estimations are presented in Table 13. Column 1 presents the result for the model with the treatment variable independent of the *ILProportion* (main analysis estimates), Column 2 presents the result of the treatment variable considering the *ILProportion* equal to or above 25%, and Column 3 presents the result for the treatment variable considering the *ILProportion* equal to or above 50%. Column 4 presents the result for the treatment variable considering the *ILProportion* equal to or above 75%. Wald test indicates whether the treatment effect considering different compositions of *ILProportion* are equal. Columns 1 to 3 show effects with significance up to 5%, and Column 4 shows an effect with significance up to 10%. The Wald test presents a χ^2 statistic of 0.55 with 3 degrees of freedom. The p-value of 0.907 demonstrates the non-rejection of the null hypothesis and indicates statistical equality between the treatment effect coefficients of the four regressions.

Table 13 - Effect of PPCDAm conditioned to IL Proportion

	(1)	(2)	(3)	(4)
	ILProportion > 0%	ILProportion > 25%	ILProportion > 50%	ILProportion > 75%
DDD Effect	-16.069**	-19.211***	-20.398**	-15.900*
	(6.762)	(6.737)	(8.599)	(8.766)
Fixed Effects	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
N	4,536	4,536	4,536	4,536
Wald Test		0.55		
(p-value)		(0.907)		

Notes: The symbols *, ** and *** represent statistical significance of 10%, 5% and 1%, respectively. Columns 1 to 4 present the results for the analysis with the treatment variable considering non-metropolitan municipalities with indigenous lands with *ILProportion* above 0%, 25%, 50%, and 75%, respectively. The Wald test verifies the null hypothesis of equality between the coefficients of the four models. The Wald test statistic is distributed as χ^2. Covariate coefficients were omitted for space considerations.

3.7. Political Considerations

Quantifying the effect of the PPCDAm policy on deforestation is fundamental for understanding such policies' real impact, enabling future strategies' design and improvement. It is possible to identify the amount of deforestation avoided in the Brazilian Legal Amazon through the causal effect of the policy. From that, we can calculate the volume of carbon

stock in tons in carbon dioxide emissions per square kilometer ($tCO2/km^2$)[36]. The Amazon Fund (2012) began to estimate the CO_2 emissions in the Brazilian Legal Amazon, resulting from the difference between the historical average rate of deforestation and the deforestation rate in the year under evaluation multiplied by the amount of carbon present in biomass, measured in tons of carbon per hectare (tC/ha). Since 2012 the entity has adopted the reference value of 132.2 tC/ha of Amazon forest, equivalent to 48,473 tCO_2/km^2 [37].

According to the results identified in Table 9, we estimate that the conservation of approximately 10,293 km² caused by the introduction of the first phase of the PPCDAm in the course of 2004 to 2007 provided an additional stock of 498 million tCO_2 [38]. It represented a value of approximately U$ 2.5 billion[39]. We evaluate the PPCDAm annual cost two with two approaches. First, using the budget for actions to combat deforestation for 2004 (R$ 394 million)[40] as a reference, presenting an average annual cost of 0.97 U$/tCO2. Second, considering the main instruments to combat deforestation during the period, which belongs to the monitoring and control axis, is mostly represented by IBAMA's and DETER's budget. According to IBAMA's total annual budget and INPE's Cost and Capital Budget (OCC), the average annual cost could potentially be 3.54 U$/tCO2 from 2004 to 2007. We calculate that the PPCDAm generated a potential profit between U$ 737 million and U$ 2 billion.

3.8. Final considerations

The debate around climate change, the preservation of biodiversity, and the integrity of indigenous gained prominence again with the recent advance in the Brazilian Legal Amazon's deforestation rate. However, the Brazilian Amazon region experienced a drastic reduction in deforestation rates between 2004 and 2012. Therefore, understanding how

[36] The parameters presented by the IPCC 2006 Guidelines for National Greenhouse Gas Inventories (Eggleston *et al.*, 2006) are frequently used to estimate the loss of carbon stocks resulting from deforestation, using aspects such as the loss of forests, the ratio of belowground to aboveground biomass, the carbon fraction of dry matter and the conversion factors for the tree species.

[37] According to the 2012 Amazon Fund's Annual Activity Report, the value of 100 tC/ha is equivalent to 367 tCO_2/ha.

[38] We consider the conversion factor of 48,473 tCO_2/km^2.

[39] We consider the standard price of 5 U$/$tCO_2$ commonly used at the time (Assunção, Gandour and Rocha, 2013; Fundo Amazônia, 2012).

[40] We assume a budget growth for the following years in the same proportion as that observed in IBAMA's budget in the same period. The dollar amounts have been corrected according to the free exchange rate of the US Dollar (sale) for each year.

public policies have affected deforestation in the region is essential for preserving the Amazon rainforest.

This study aimed to analyze the effects of PPCDAm on deforestation in the Brazilian Legal Amazon. We explored the variability between the regional municipalities' characteristics through the triple difference method when comparing the annual increase in deforestation between non-metropolitan municipalities with indigenous lands and other municipalities in the Brazilian Amazon.

This article innovated the literature in several ways. First, the article innovates by identifying the causal effect of PPCDAm for the period between 2004 and 2007. Furthermore, it innovates methodologically by using the triple difference method to assess the effect of PPCDAm on deforestation. The article also presented new evidence on the effectiveness of initiating the PPCDAm in safeguarding the forest in municipalities with indigenous lands in the Amazon and explored sources of variation such as the number of indigenous lands and the proportion of indigenous land area in the municipalities.

The results showed a reduction of potentially 10,293 km² in deforestation of non-metropolitan municipalities with indigenous lands between 2004 and 2007. Additionally, the analysis of heterogeneous effects indicated that the policy became more effective after 2005. Our estimates regarding the effects on carbon emissions indicate the retention of 498 million tCO2 in the carbon stock resulting from forest preservation. Our cost-benefit analysis shows that the program had a profit of at least $737 million in the period, suggesting that the policy was also financially efficient.

We identify that the institutional changes promoted by the PPCDAm in favor of environmental crime monitoring in the Amazon, such as the improvement of remote monitoring of deforestation spots resulting from the introduction of DETER, were significant for reducing deforestation in municipalities isolated from large urban centers. Regarding the limitations of this study, the databases used do not allow classifying the types of environmental crimes that cause the levels of deforestation observed in the municipalities. Additionally, the population size of indigenous lands was not considered due to the lack of population data for several isolated peoples. We recommend the application of new methodologies for isolating the causal effect of PPCDAm on deforestation rates in Amazonian municipalities may be relevant, as well as new analysis

to verify the efficiency of different policies that reinforce the environmental surveillance and monitoring of indigenous lands and isolated municipalities.

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4. Final remarks

This dissertation aimed to contribute to the human capital and environment literature. We employed several microeconometric methods to verify effect relations in both essays. The first essay presents a series of matching procedures to verify the influence of parents' entrepreneurial attitude on children's human capital accumulation (Austin *et al.*, 2016; DuGoff *et al.*, 2014; King and Nielsen, 2019). In the second essay we identify the causal effect of the first phase of the PPCDAm on the reduction of the Brazilian Legal Amazon deforestation through the Triple Difference method (Gruber, 1994), in which we assess the heterogeneity between non-metropolitan municipalities with indigenous lands and other municipalities in the region.

The first essay discusses the impacts of the entrepreneurial attitude on the parents' decision regarding their children's education. We employed five PSM Kernel methods to analyze such impact using the micro data complex sample from the PNAD 2015. First, we verified the goodness of fit of several matching methods by Dehejia and Wahba's (2002) selection criteria. Second, we employed the sample weights according to the specifications proposed by Austin, Jembere and Chiu (2016) for the matching estimators selected. The results indicate that children of entrepreneurial parents are approximately 25% more likely to study at private (elementary and high school) and 17% more likely to attending higher education. We identified no effects on children's years of schooling, similar to the results found by Parikh & Sadoulet (2005). The robustness of the results were supported by the placebo test, PSW method, Entropy Balancing procedure, and the HTE analysis. Additionally, the HTE analysis results indicates an increase on the effect magnitude when both parents are entrepreneurs, and also presents heterogeneous effects conditioned to the gender of the children and parents. This study expands the discussion on entrepreneurship spillovers in the family dynamics beyond the effects directly associated with family businesses and career choice. Our findings can guide policymakers on the formulation of new policies oriented towards entrepreneurship activities and human capital development.

In the second essay we analyzed the impact of the first phase of the PPCDAm on curbing the Brazilian Legal Amazon deforestation between the years of 2004 and 2007. We used the longitudinal municipalities' deforestation data from PRODES, in addition to other

data sources on municipal characteristics. We applied the Triple Difference method to compare the effectiveness of the PPCDAm between non-metropolitan municipalities with indigenous lands to the other cities in the Brazilian Legal Amazon region. Our estimates present a reduction of potentially 10,293 km² in the Brazilian Legal Amazon deforestation during the 2004 and 2007. We estimated that the avoided deforestation provided an additional 498 milllion tCO2 carbon stock. The study also provided a cost-benefit analysis, indicating that the first phase of the PPCDAm was financially efficient and presented a profit of at least $737 million. The validity of these results was confirmed through placebo tests, the heterogeneous effect analysis, and the flexibility of the composition of the groups. Our findings are in line with the consensus of the environmental literature regarding the reduction of deforestation (Arima et al., 2014; Assunção, Gandour, and Rocha, 2013; Assunção, Gandour, and Rocha, 2015; Hargrave and Kis-Katos, 2013). The evidence presented highlights the importance of maintaining and expanding the monitoring to regions isolated from large urban centers. This study also demonstrates the importance of indigenous territories in containing deforestation, as well as the vulnerability of municipalities with indigenous territories in the absence of remote monitoring.