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Essays on Labor Economics

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I dedicate this work to my wife who sacrificed so much time to take care of our children and me while elaborating this work. Without her help it would not be finished. I also dedicate it to my mother for always encouraging me to study and for everything she sacrificed to help me complete my studies and to my Aunt Eliane, who was always willing to help during the entire doctorate.

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Nevertheless they did fast and pray oft, and did wax stronger and stronger in their humility,and firmer and firmer in the faith of Christ, unto the filling their souls with joy and consolation, yea, even to the purifying and the sanctification of their hearts, which sanctification cometh because of their yielding their hearts unto God." (THE BOOK OF MORMON, 2013)

ABSTRACT

This thesis consists of papers that analyzes different aspects of the labor Market in Brazil, using distinct methods. In the first paper we estimate gender and racial discrimination using data from the 2010 Brazilian Census and the reweighing and recentered influence function regressions proposed by Firpo, Fortin and Lemieux (2009). This method overcomes several limitations of the traditional Oaxaca-Blinder decomposition and improves upon the ones proposed by Machado and Mata (2005) and Melly (2005). For comparison purposes, we also perform the counterfactual analysis proposed by Chernozhukov, Fernández-Val and Melly (2013). The second paper is about migration, a topic that is debated by policymakers in many countries. McKenzie, Gibson and Stillman (2010) estimated the income gains from immigration using data from a random selection of immigrants in New Zealand. They also found evidences that the difference-in-differences (DID) and the bias-adjusted matching estimators perform best among the alternatives to instrumental variables. The DID estimator requires the assumption that the average outcomes for treated and controls follow parallel paths over time to produce reliable results. In this paper we identify the effects of migration on wages of immigrants, using a semi-parametric DID estimator proposed by Athey and Imbens (2006), which allows a systematic variation in the effects of time and treatment across individuals. Finally, Litschig and Morrison (2013) found evidence that intergovernmental transfers cause a reduction in poverty and an increase in per capita schooling and literacy rate. Thus, it is expected that improved educational and social conditions will lead to an increase in migration to municipalities receiving more transfers. The third article analyzes the impact of intergovernmental transfers on immigration in Brazil, using a corrected bias regressor discontinuity design (RKD), proposed by Calonico, Cattaneo and Titiunik (2014), and RAIS/MIGRA immigration data. We find evidence that transfers cause an increase in immigration.

Keywords: Labor Economics. Discrimination. Immigration.

RESUMO

Esta tese consiste em artigos que analisam diferentes aspectos do mercado de trabalho no Brasil, utilizando métodos distintos. No primeiro artigo estimamos a discriminação racial e de gênero utilizando dados do Censo de 2010 do Brasil e regressões da função de influência ponderada e recentrada proposta por Firpo, Fortin e Lemieux (2009). Este método supera várias limitações da decomposição tradicional de Oaxaca-Blinder e é uma melhoria da proposta por Machado and Mata (2005) e Melly (2005). Para fins de comparação, nós também realizamos a análise contrafactual proposta por Chernozhukov, Fernández-Val e Melly (2013). O segundo artigo é sobre migração, um tópico que é debatido pelos formuladores de políticas em muitos países. McKenzie, Gibson e Stillman (2010) estimaram os ganhos de renda da imigração usando dados de uma seleção aleatória de imigrantes na Nova Zelândia. Eles também encontraram evidências de que os estimadores de diferença-em-diferenças (DID) e o de bias-ajusted maching são as melhores alternativas para as variáveis instrumentais.O estimador DID requer o pressuposto de que os outcomes médios para tratados e controles sigam caminhos paralelos ao longo do tempo, para produzir resultados confiáveis. Neste artigo, identificamos os efeitos da migração sobre os salários dos imigrantes, utilizando um estimador semi-paramétrico DID proposto por Athey e Imbens (2006), que permite uma variação sistemática nos efeitos do tempo e do tratamento entre os indivíduos. Por fim, Litschig e Morrison (2013) encontraram evidências de que as transferências intergovernamentais causam uma redução da pobreza e um aumento da escolaridade *per capita* e da taxa de alfabetização. Assim, espera-se que a melhoria das condições educacionais e sociais provoquem um aumento na imigração para os municípios que recebem mais transferências. O terceiro artigo analisa o impacto das transferências intergovernamentais sobre a imigração no Brasil, utilizando um estimador de sharp regression discontinuity design (RKD) com viés corrigido, proposto por Calonico, Cattaneo e Titiunik (2014), e dados sobre imigração da RAIS/MIGRA. Encontramos evidências de que as transferências causam um aumento na imigração.

Palavras-chave: Economia do Trabalho. Discriminação. Imigração.

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1 INTRODUCTION

This work consists of three articles. The first presents estimates of discrimination in the labor Market in Brazil, and the other two study different topics about immigration of formal workers in Brazil. In this chapter I present the general introduction of this work. On each chapter, there is a more detailed introduction to each article.

In the first article I estimate the wage discrimination in the labor market. As pointed out by Fortin, Lemieux and Firpo (2010), although the literature on the decomposition methods that are used to estimate discrimination has evolved substantially in recent decades, several of these methodologies face limitations that may induce misleading results. Firpo, Fortin and Lemieux (2009) developed the re-weighting and recentered influence function regressions (RIF regressions), improving upon the decompositions proposed by Machado and Mata (2005) and Melly (2005).

More recently, Chernozhukov, Fernández-Val and Melly (2013) developed estimation and inference procedures for the counterfactual distribution of an outcome variable of interest Y, and its quantile function, based on regression methods. This approach, the counterfactual analysis, is an alternative to re-weighting, in the spirit of Horvitz and Thompson (1952) and DiNardo, Fortin and Lemieux (1996). Chernozhukov, Fernández-Val and Melly (2013) argue that both approaches are equally valid, under correct specification. The counterfactual analysis estimators are consistent and asymptotically Gaussian for the quantiles of the counterfactual marginal distributions of the outcome.

The main objective of the first paper is, therefore, to present detailed results of the decomposition of the wage gap between whites and non-whites, and males and females using data for Brazil and the reweighing and recentered influence function regressions proposed by Firpo, Fortin and Lemieux (2009). We use this method to break down the explained and unexplained differences in earnings between these groups into the contribution of each explanatory variable using a generalized Oaxaca-Blinder method, which does not require linearity assumptions. We also aim at decomposing the wage gap using the method proposed by Chernozhukov, Fernández-Val and Melly (2013).

Salardi (2013) is the first work that used RIF regressions to estimate wage discrimination in Brazil and she also presents results of many other decompositions. Besides the standard Oaxaca-Blinder decomposition, she also performs the decompositions developed by Brown, Moon and Zoloth (1980), Machado and Mata (2005), and Melly (2005). The results of the decompositions are very similar. One limitation of Salardi (2013) is that it does not address the problem of sensitivity to the choice of omitted baseline category (see Oaxaca and Ransom (1999)). To avoid perfect multicollinearity, one of the dummy variables is omitted in the regression equation. This variable represents the baseline category, and the coefficients of the remaining dummy variables are interpreted as deviations from this variable. The results of the RIF regressions and Oaxaca-Blinder decompositions are sensitive to the researcher's choice of the omitted baseline category.

In the second paper, we study about immigration, which is a topic that is central to political elections results in many countries. It generates divergent opinions, for some people see the immigrants as a contribution to the society while others see them as a threat. Many natives view the immigrants as their substitutes in the labor market, so the concern that immigrants may cause wage reductions and unemployment motivated many studies on the effects of immigration on the labor market.

The studies reviewed by Kerr and Kerr (2011) focus on the effects of immigration on the wages of immigrants. They conclude that immigrants experience lower wages and employment than natives at entry. The differences are likely to diminish over the time, but recent cohorts are expected to experience less success in the labor market than natives. In Brazil, Freguglia (2007) analyzes the effects of the immigration on the income of immigrants, using a fixed effects estimator and panel data of formal workers who moved to the state of São Paulo. He estimates that immigrants with middle school or lower educational level earn on average 6% less than non-migrants, while undergraduates earn on average 7% more than natives with similar characteristics.

McKenzie, Gibson and Stillman (2010) found unbiased estimates of the gains from migration by studying data from New Zealand which allows a quota of Tongans to immigrate with a random ballot. The random selection of immigrants is the perfect condition for using the instrumental variables estimator, since the instrument is strongly correlated with the endogenous regressor. In general, a strong instrument that generates unbiased estimates is difficult to find. Bound, Jaeger and Baker (1995) found that even the use of large data sets does not necessary insulate researchers from large finite-sample biases. McKenzie, Gibson and Stillman (2010) found evidences that the difference-in-differences and bias-adjusted matching estimators perform best among the alternatives to instrumental variables.

In this paper we identify the short- and long-run causal effects of immigration on wages of immigrants using the semiparametric DID estimator proposed by Athey and Imbens (2006) and data from RAIS for the years 2002 to 2007. We analyze the impact of migration on wages of migrants who were working in the state of Pernambuco, which ranked the 13Th position in terms of income *per capita* out of 27 states in Brazil, thus being an average income state. The *per capita* gross domestic product of Pernambuco grew on average 4% per year in 2000 decade, but in 2003 it fell 0.6%. There was also an increase in the unemployment rate in 2003. These conditions led to a increase in emigration in 2004, and the per cent growth in the number of immigrants is greater in 2004 than in the following years. We use data of workers of Recife and eleven metropolitan regions of Brazil to estimate the impact of immigration on the wages of the immigrants.

We analyze the wages of workers who were working in Pernambuco 2002, dividing them in 3 groups. The first is formed by individuals who never immigrated in the period 2002-2007 (control group). The second comprises immigrants who were working outside Pernambuco in 2004, thus we use their data to estimate the short-run effect of immigration. Finally, the third group comprises immigrants who were working outside this state in 2007, so that we use the data of this group to estimate the long-run effect of immigration.

Since the average effect of immigration on wages depends upon the state of destine, we estimate the impact of the migration on each of the five regions of Brazil. We take into account the difference in living costs when we estimate the impact of immigration on wages, therefore we adjust wages according to the living costs of 11 metropolitan cities of Brazil.

The third paper also analyzes the immigration. In Brazil, the federal government transfers part of its revenue to the cities. These transfers are called “fundo de participação dos municípios” (hereafter FPM). The volume of transfers depends only on population size, for municipalities with less than $156,216$ inhabitants. This rule was set exogenously and creates incentives for some municipalities to attract people so that they can increase the volume of transfers they receive. Thus it is expected that municipalities with smaller population and FPM transfers attract more immigrants. On the other hand, it is expected that municipalities with greater population and that receive a larger amount of transfers, end-up attracting more immigrants, since the extra revenue can be used to improve the public services, specially those related to health and education. Therefore, there is a controversy about the effects of the FPM on immigration. This paper aims to analyze the impact of FPM transfers on the number of people that migrates from one city to another, by exploring the discontinuities in the assignment of the FPM and using the regression kink design approach.

Mata (2014) studied the impacts of the increase in intergovernmental transfers on housing markets and on city growth, and found that the housing sector grows faster in municipalities that are less dependent on federal grants. He also studies the effects of FPM transfers on population growth, using it as an alternative measure of housing market and city growth. He finds a similar result in both analyses and concludes that locations with higher *per capita* FPM attract fewer people. In our analysis rather than using data on population growth we study the effects of FPM transfers on immigration using data from RAIS/MIGRA, which allowed us to calculate the number of immigrants in each municipality in Brazil for the years 2009 and 2010. In our data set, all immigrants were formal workers, then we could find the municipality where they were working in each year. The last Brazilian census was performed in 2010, which provide accurate data of the number of inhabitants in each municipality, thus we use population data for this year.

All municipalities are classified in three groups, according to the law nº 1.881/1981. Municipalities with more than $156,216$ inhabitants are classified as *municípios da reserva*, and receive on average more FPM transfers than the municipalities which are below this cutoff, which are called *municípios do interior*. The third group is formed by the state capitals, and is removed from our analysis, for all of them receive a very different amount of transfers.

Prior to estimating the regressions, we took two samples of our data. Sample I includes all municipalities with population size within the cutoffs created by the decree law nº 1.881/1981. We use sample I to estimate the effect of transfers on immigration in the first cutoffs as in Brollo et al. (2013). Sample II consists of municipalities with between $143,123$ and $168,511$ inhabitants, and we use it to verify the impact of FPM transfers on immigration around the $156,216$ cutoff. In sample II we designated the *municípios do interior* to the control group and the *municípios da reserva* to the treated group.

2 WAGE DISCRIMINATION IN BRAZIL: INFERENCES BASED ON RIF REGRESSIONS AND COUNTERFACTUAL DISTRIBUTIONS

2.1 Introduction

There are many evidences that racial and gender discrimination occurs in the labor market.[1] Bertrand and Mullainathan (2003), for example, performed a field experiment by responding to help-wanted ads in some U.S. newspapers with fictitious resumes. Each resume was assigned either a very African American sounding name or a very White sounding name. The fictitious people with White names received 50 percent more callbacks for interviews. Rouse and Goldin (2000) analyzed the effects of the use of "blind" auditions with a "screen" to conceal the identity of musicians from the jury. The screen increased by 50% the probability a woman would advance preliminary rounds, and greatly increased the probability that a female contestant would win the final round. In 1970 - prior to the change in the audition policy - less than 5% of the musicians in the top five orchestras in the United States were female, while in 1997 this share increased to 25%.

These authors succeeded in estimating discrimination in the hiring process. Nevertheless, it is difficult to estimate wage discrimination in the labor market. As pointed out by Fortin, Lemieux and Firpo (2010), although the literature on the decomposition methods that are used to estimate discrimination has evolved substantially in recent decades, several of these methodologies face limitations that may induce misleading results. For example, many studies focus in estimating the wage discrimination using the method proposed by Oaxaca (1973) and Blinder (1973). Although this method is widely popular, Barsky et al. (2002) showed that estimates based on the Oaxaca-Blinder decomposition may be biased when the true conditional expectation functions are nonlinear, for this method approximates the conditional expectations by the best linear predictors. More importantly, this method can be used only to decompose mean wage differentials.

A more recent method, proposed by Machado and Mata (2005), allows the decomposition of the wage gap to be performed on each quantile of the conditional wage distribution, an important advancement. Although this method gained certain popularity, Chernozhukov, Fernández-Val and Melly (2013) argue that the authors provide no econo-

[1] We thank Breno Sampaio for many important contributions to this paper.

metric theory for the quantile regression decomposition estimators. Also, the method is shown to be consistent only if the right functional form is used for the quantiles and is computationally demanding to estimate if the data set contains more than a few thousand observations.

Motivated by the basic ideas contained in Machado and Mata (2005), Melly (2005) proposed an estimator that is faster to compute. His model estimates the conditional distribution via parametric and nonparametric quantile regressions. The parametric quantile regression is an extension of the basic Oaxaca-Blinder mean decomposition to the full distribution. The nonparametric quantile regression is an efficient local-linear regression estimator for quantile treatment effects. This estimator performs well in Monte Carlo simulations, however it does not allow one to analyze the contribution of each explanatory variable after estimation of the composition (explained) and wage structure (unexplained) effects. Firpo, Fortin and Lemieux (2009) overcome this limitation by developing the reweighting and recentered influence function regressions (RIF regressions), improving upon the decompositions proposed by Machado and Mata (2005) and Melly (2005).

More recently, Chernozhukov, Fernández-Val and Melly (2013) developed estimation and inference procedures for the counterfactual distribution of an outcome variable of interest Y, and its quantile function [2] , based on regression methods. This approach, the counterfactual analysis, is an alternative to re-weighting, in the spirit of Horvitz and Thompson (1952) and DiNardo, Fortin and Lemieux (1996). Chernozhukov, Fernández-Val and Melly (2013) argue that both approaches are equally valid, under correct specification. The counterfactual analysis estimators are consistent and asymptotically Gaussian for the quantiles of the counterfactual marginal distributions of the outcome.

The main objective of this paper is, therefore, to present detailed results of the decomposition of the wage gap between whites and non-whites, and males and females using data for Brazil and the reweighing and recentered influence function regressions proposed by Firpo, Fortin and Lemieux (2009). We use this method to break down the explained and unexplained differences in earnings between these groups into the contribution of each explanatory variable using a generalized Oaxaca-Blinder method, which does not require linearity assumptions. We also aim at decomposing the wage gap using the method proposed by Chernozhukov, Fernández-Val and Melly (2013).

There are many studies analyzing wage discrimination in Brazil. Soares (2000) estimate the income differential between white men and the following groups: black men, white women and black women, using the Oaxaca-Blinder decomposition. His results indicate that the main cause of the wage differential between white men and black men is the difference in qualifications, although the black men and women also suffer from high

[2] Besides the quantile function, it is possible to analyze other functionals like distribution functions, quantile effects, distribution effects, Lorenz curves, and Gini coefficients.

wage discrimination.Bartalotti (2007) estimates the wage discrimination against black and female workers using the Machado and Mata (2005) decomposition, and compares four groups of workers: black males, white males, black females and white females. He finds evidences that the black female workers is the group most affected by the discrimination, followed by white females and black males. The discrimination against black males is lower among the poor, but it increases in the higher income groups. White females suffer discrimination along all quantiles of the wage distribution, and the most affected are the 15% richest females.

Souza, Salvato and França (2013) use the Machado and Mata decomposition to analyze discrimination in Brazil and its regions, using data for the years 2001 and 2011. Their main findings are: discrimination is what explains the gender wage gap; the difference in productive characteristics is the main cause of the racial wage gap; wage discrimination by gender in the Northeast is higher than in the South and Southeast; and the higher the income, the greater the discrimination. The authors found evidences that racial discrimination has increased in the northeast between the years 2001 and 2011.

Salardi (2013) is the first work that used RIF regressions to estimate wage discrimination in Brazil and she also presents results of many other decompositions. Besides the standard Oaxaca-Blinder decomposition, she also performs the decompositions developed by Brown, Moon and Zoloth (1980), Machado and Mata (2005), and Melly (2005). The results of the decompositions are very similar. One limitation of Salardi (2013) is that it does not address the problem of sensitivity to the choice of omitted baseline category (see Oaxaca and Ransom (1999)). To avoid perfect multicollinearity, one of the dummy variables is omitted in the regression equation. This variable represents the baseline category, and the coefficients of the remaining dummy variables are interpreted as deviations from this variable. The results of the RIF regressions and Oaxaca-Blinder decompositions are sensitive to the researcher's choice of the omitted baseline category.

Using the PSID microdata over the 1980-2010, Blau and Kahn (2016) investigated the evolution of the gender wage gap in the U.S., and found evidences that it declined considerably over this period. They decompose the gender wage gap using three methods: the Oaxaca-Blinder, the Juhn, Murphy and Pierce (1991) and the Chernozhukov, Fernández-Val and Melly (2013). They also surveyed the literature to identify the impact of norms, psychological attributes and noncognitive skills, and the impact of policy (including both antidiscrimination policy and family leave policies) on the gender wage gap.

Besides showing a detailed decomposition of the wage discrimination, this paper deals with the problem of sensitivity to the choice of reference group using the method proposed by Yun (2005). To our knowledge, this is the first paper that performs the decomposition method developed by Chernozhukov, Fernández-Val and Melly (2013) to analyze wage discrimination using data from Brazil. Therefore, the main contributions of this paper are to present more robust results of the RIF decomposition than the previous papers and to present the results of the counterfactual analysis, permitting a better understanding of the major components of the wage discrimination in Brazil.

We show that the wage discrimination between males and females does not present sharp variations across the quantiles of the wage distribution. Our results suggest that gender discrimination is not generalized to all activities, since activity is the main component of the unexplained effects. The racial discrimination increases along the quantiles of the wage distribution. It is greater than gender discrimination, and its most important components are education, experience and region. The estimation of the racial discrimination for each of the five regions of Brazil shows that it is smaller in north and northeast than in other regions. This occurs because non-whites are minority in south, southeast and Midwest, therefore, it is more likely that the discrimination is greater in these regions than in north and northeast. We found that wage discrimination by gender in the Northeast is lower than in the South and Southeast. This result differs from the result found by Souza, Salvato and França (2013). We also show that the results of the counterfactual analysis are similar to the results of the RIF regressions, especially when we consider the racial wage gap, although the estimates for racial wage discrimination are higher in the counterfactual analysis.

After this introduction, the rest of the paper is organized as follows. The next section describes the method and data used in the paper. In the third section we present our results. Finally, conclusions are presented in section 4. In the appendix we describe specific results for each region of Brazil.

2.2 Methods

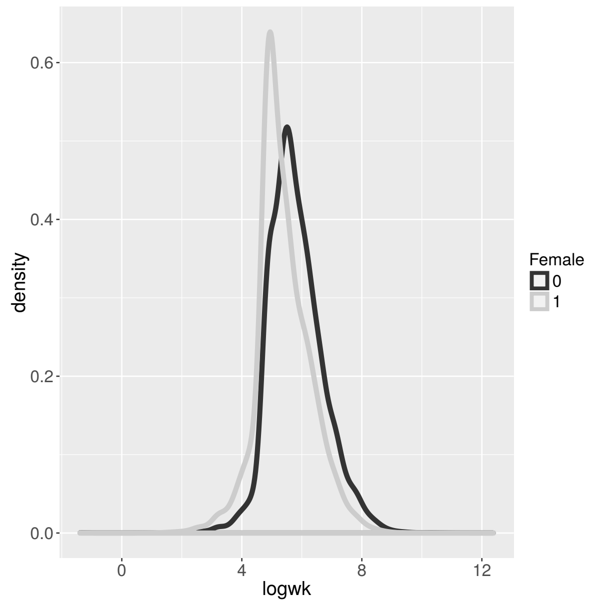
2.2.1 Data

The data we use throughout the paper was obtained from the Brazilian Census for the year 2010. The sample consists of 976,062 observations with detailed information for males and females between 40 and 49 years of age, with more than 8 years of schooling and positive income. These sample restrictions were made according to Angrist, Chernozhukov and Fernandez-Val (2006). Table 1 presents a description of the variables.

Panel (a) of figure 1 shows an estimate of the distribution of males and females according to the log of weekly wages. We can notice that the distribution of wages is more right skewed for females than for males, and this indicate the presence of gender discrimination. Analyzing the wage distribution of whites and non-whites, as shown in panel (b) of figure 1, we can also presume that there is racial discrimination.

Figure 1 – Densities of the log of weekly wage by group

(a) Density of the log of weekly wages of males and females



(b) Density of the log of weekly wages of whites and non-whites (black=1)

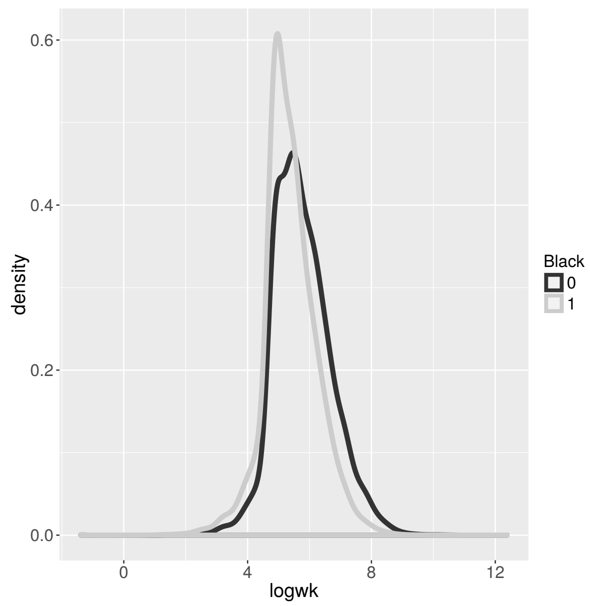


Table 1 – Description of the variables

Variable	Description
perw	Individual sampling weights
logw	Average log weekly wage, calculated as the log of Reported monthly income from work divided by weeks worked
educ	Years of schooling
black	Indicator variable for race that assumes the value 1 for blacks, browns and native Americans, and 0 for whites and yellows.
female	Indicator variable for gender that assumes the value 1 for females and 0 for males.
reg	Indicator variable for region that assumes the value 1 for north and north-east, and 0 for other regions.
sit	Indicator variable for home location that assumes value 1 for rural location.
age	Age in years
exper	Potential experience, calculated as $age - educ - 6$
exper^2	Square of exper
actv1 ... actv20	Dummies for sector of the economy, aggregated in 20 sector according to the Classificação Nacional de Atividades Econômicas Domiciliar 2.0 - CNAE-Domiciliar 2.0: agriculture, extractive industry, transformation Industry, electricity and gas, water and waste, construction, vehicle commerce and maintenance, transport, food, communication, finance, real state, professional and scientific, administration and other services, public administration, education, health and social services, arts and sports, other services, and domestic services.

In order to carry out a better analysis of the data, we calculate the mean of some variables and test the null hypothesis that the difference between the means of the variables associated to the groups (males, females, whites and non-whites) is equal to zero. We perform the t-test, assuming that the variables follow a normal distribution. Based on the results of the test for each variable, we reject the null hypothesis in all of them, except for the variable *age* between the groups of males and females. Therefore, we find evidences that the difference between the means of the variables related to the groups is different from zero, except for variable *age*.

Table 2 presents the means of the variables, the difference of the means of the variables between groups and the level of significance of the t-test. This table shows that on average, males earn more than females, and whites earn more than non-whites. The table also shows that on average, females are more educated than males, and that non-white have more experience than whites. These simple analysis of the data shows evidences that there is wage discrimination in Brazil.

It is not likely that the variables *educ* and *logw* follow a normal distribution, for their distributions are right skewed (see the density of the log of weekly wages in panel (a) of figure 1) . Therefore, we also perform the Kolmogorov–Smirnov and the Mann-

Whitney-Wilcoxon tests, which are non-parametric and do not require the assumption of normality. The null hypothesis of Mann-Whitney-Wilcoxon test is that the difference of the medians between groups is equal to zero. The results of these tests are similar to the results of the t-test and show evidences that only the difference of the medians of the variable *age* between the groups of males and females is equal to zero.

Table 2 – Descriptive Statistics

Variable	Mean		Difference	Mean		Difference
	(1) Males	(2) Females	(1)-(2)	(3) White	(4) Non-white	(3)-(4)
logw	5.91	5.49	0.41***	5.88	5.46	0.42***
educ	11.67	12.09	-0.42***	12.37	11.15	1.22***
age	44.12	44.13	-0.01	44.23	43.98	0.25***
exper	26.45	26.04	0.41***	25.86	26.83	-0.97***
$exper^2$	716.47	697.80	18.67***	687.55	736.85	-49.30***

Note: *** The null hypothesis of the t-test (the difference in means equals zero) is rejected with a confidence level of 5%.

In order to estimate and decompose the discrimination, we regress the log of weekly wage on education, experience, square of experience, female (or race) dummy, region, location and activity dummies, following the methodology described in the next section. We also estimate the discrimination in each region, to identify where the discrimination is located, and present the results in the appendix.

2.2.2 Reweighing and Recentered Influence Function Regressions

Let $T = 0, 1$ be two groups of workers. The wage depends on some observed variables X_i and on some unobserved variables $\varepsilon_i \in \mathbb{R}^m$ and is determined by wage structure functions $Y_{it} = g_t(X_i, \varepsilon_i)$, for $T = 0, 1$.

We can identify by nonparametric methods the distributions of $Y_1|T = 1 \sim^d F_1$ and of $Y_0|T = 0 \sim^d F_0$, from observed data on (Y, T, X). But we need more assumptions to identify the counterfactual distribution of $Y_0|T = 1 \sim^d F_C$. The counterfactual distribution F_C is the one that would have prevailed under the wage structure of group 0, but with the distribution of observed and unobserved characteristics of group 1. Consider these three distributions conditional on X: $Y_1|X, T = 1 \sim^d F_{1|X}$, $Y_0|X, T = 0 \sim^d F_{0|X}$ and $Y_0|X, T = 1 \sim^d F_{C|X}$.

Let ν_1,ν_0 and ν_C be a functional (variance, median, quantile, Gini, etc.) of the conditional joint distribution of $(Y_1, Y_0)|T$, and $F\nu$ is a class of distribution functions such that $F \in F\nu$ if $||\nu(F)|| < +\infty$. The difference in the ν's between the two groups is the difference in wages measured in terms of the distributional statistic ν, and is called the ν-overall wage gap.

$$\Delta_O^\nu = \nu(F_1) - \nu(F_0) = \nu_1 - \nu_0 \tag{2.1}$$

We can decompose equation (2.1) in two parts, using the fact that X can be unevenly distributed across groups, then

$$\Delta_O^\nu = (\nu_1 - \nu_c) + (\nu_c - \nu_0) = \Delta_S^\nu + \Delta_X^\nu \tag{2.2}$$

Where the first term Δ_S^ν corresponds to the effect on ν of a change from $g_1(\cdot,\cdot)$ to $g_0(\cdot,\cdot)$ keeping the distribution of $(X,\varepsilon)|T=1$ constant. This is called the wage structure effect or the unexplained difference effect. With no other restrictions, the second term Δ_X^ν corresponds to the effect of changes in distribution from the one of $(X,\varepsilon)|T=1$ to that of $(X,\varepsilon)|T=0$, keeping the "wage structure" $g_0(\cdot,\cdots)$ constant. This is called the composition effect or the explained difference effect.

We do not need any assumption about the format of $g_1(\cdot,\cdot)$ and $g_0(\cdot,\cdot)$. In the Oaxaca-Blinder decomposition it is assumed that $g_1(X,\varepsilon) = X^T\beta_1 + \epsilon_1$, $g_0(X,\varepsilon_0) = X^T\beta_0 + \epsilon_0$, and that

$$E[\epsilon_t|X,T=t] = 0 \tag{2.3}$$

. The assumption that the functions $g_1(\cdot,\cdot)$ and $g_0(\cdot,\cdot)$ are linear can be plausible in many cases, but the assumption of exogeneity described by equation (2.3), is more difficult to be accepted, since if any variable that affects wages (like ability) is missing in the model, we cannot affirm that this assumption is valid.

We can identify the parameters of interest under the common assumptions of Ignorability (sometimes called unconfoundedness) and Overlapping Support (or Common Support). The Ignorability assumption should be analyzed in each specific case, as it is more plausible in some cases than in others. In our specific case, it states that the distribution of the unobserved explanatory factors in the wage determination is the same across groups 1 and 0, once we condition on a vector of observed components. Formally, the Ignorability assumption is: Let (L,X,ε) have a joint distribution. For all x in $\mathcal{X}$, ε is independent of T given $X=x$.

The Overlapping Support assumption requires that there be an overlap in observable characteristics across groups, in the sense that there no value of x in X such that it is only observed among individuals in group $T=1$ or $T=0$. In gender wage gap decompositions where some of the detailed occupations are only held by men or by women, this assumption is not valid, but in our case the we consider only 20 sectors (or types of occupation), therefore the Overlapping Support assumption is plausible. Formally, the Overlapping Support assumption is: For all x in $\mathcal{X}$, $p(x) = Pr[T=1|X=x] < 1$. Furthermore, $Pr[T=1] > 0$.

2.2.2.1 Step 1: Decomposing the wage gap by reweighing

Assuming ignorability and overlapping support, Firpo, Fortin and Lemieux (2007) show that the distributions F_0,F_1 and F_C can be estimated by nonparametric methods using the weights:

$$\omega_1(T) \equiv \frac{T}{p}, \quad \omega_0(T) \equiv \frac{1-T}{1-p} \quad \text{, and} \quad \omega_C(T,X) \equiv \left(\frac{p(X)}{1-p(X)}\right) \cdot \left(\frac{1-T}{p}\right)$$

, where $p(X) = Pr[T=1|X=x]$ is the proportion of people in the combined population of two groups that is in group 1, given that those people have $X = x$, and p is the unconditional probability. $\omega_1(T)$ and $\omega_0(T)$ transform features of the marginal distribution of Y into features of the conditional distribution of Y_1 given $T = 1$, and of Y_0 given $T = 0$, respectively. $\omega_C(T)$ transforms features of the marginal distribution of Y into features of the counterfactual distribution of Y_0 given $T = 1$.

By identifying F_C we can identify the functional $\nu(F_C)$ (variance, median, quantile, Gini, etc.), and from equations (2.1) and (2.2) we can identify and Δ_S^ν and Δ_X^ν. Next, we explain how to estimate the weighting functions. The distributional statistics ν_1, ν_0 and ν_C can be computed directly from the appropriately reweighted samples. The three weighting functions we are interested in are $\omega_1(T)$, $\omega_0(T)$, and $\omega_C(T,X)$. The first two weights are are estimated by:

$$\hat{\omega}_1(T) = \frac{T}{\hat{p}}, \qquad \hat{\omega}_0(T) = \frac{1-T}{1-\hat{p}} \qquad \text{, and} \qquad \hat{\omega}_C(T,X) = \frac{1-T}{\hat{p}} \cdot \left(\frac{\hat{p}(X)}{1-\hat{p}(X)}\right)$$

, where $\hat{p}(\cdot)$ is an estimator of the true probability of being in group 1 given X and $\hat{p} = N^{-1}\sum_{i=1}^{N} T_i$. For details of the parametric and the non-parametric approaches to estimate this probability, see Firpo, Fortin and Lemieux (2007). We use a normalization to have weights summing up to one and represent them by $\hat{\omega_0}^*(T)$, $\hat{\omega_1}^*(T)$ and $\hat{\omega_C}^*(T,X)$.

We estimate ν_1, ν_0 and ν_C by replacing the CDF by the empirical distribution function: $\hat{\nu}_t = \nu(\hat{F}_t)$, $t = 0,1$ and $\hat{\nu}_C = \nu(\hat{F}_C)$, where

$$\hat{F}_t(y) = \sum_{i=1}^{N} \hat{\omega}_t{}^*(T_i) \cdot \mathbb{1}\{Y_i \leq y\}, t = 0.1$$

$$\hat{F}_C(y) = \sum_{i=1}^{N} \hat{\omega_C}^*(T_i, X_i) \cdot \mathbb{1}\{Y_i \leq y\}$$

.

In this paper we use quantiles as distributional measures for the decomposition of wage distributions. In decompositions of the gender wage gap, they are used to differentiate the effects of the discrimination in the middle of the distribution from its impact in the tails. To carry out the decomposition of the median, we first estimate me_t, $t = 0,1$ and me_C by reweighting as $\hat{me}_t = argmin_q \sum_{i=1}^{N} \hat{\omega}_t(T_i) \cdot |Y_i - q|$, $t = 0,1$ and $\hat{me}_C = argmin_q \sum_{i=1}^{N} \hat{\omega}_C(T_i) \cdot |Y_i - q|$. The estimators for the wage gaps are computed as: $\hat{\Delta}_O^{me} = \hat{me}_1 - \hat{me}_0$, $\hat{\Delta}_S^{me} = \hat{me}_1 - \hat{me}_C$ and $\hat{\Delta}_X^{me} = \hat{me}_C - \hat{me}_0$.

2.2.2.2 *Step 2: Application of the UQR methodology to obtain a detailed (variable-by-variable) decomposition*

Let $\nu = \nu(F)$ be a general functional. The influence function, introduced as a measure of robustness of ν to outlier data, is

$$IF(y;\nu,F) = lim_{\epsilon\to 0}\frac{\nu((1-\epsilon)F+\epsilon\delta_y)-\nu(F)}{\epsilon}$$

, where F is a cumulative distribution function, $0 \leq \epsilon \leq 1$, and where δ_y is a distribution that only puts mass at the value y. It can be shown that the expectation of the influence function is equal to zero. Intuitively, the influence function (IF) represents to "contribution" of a given observation to the statistic (means, quantile, etc.) of interest. We use a recentered influence function: $RIF(y;\nu,F) = \nu(F)+IF(y;\nu,F)$ whose expectation is the original ν:

$$\int_{-\infty}^{\infty} RIF(y;\nu,F)dF(y) = \int_{-\infty}^{\infty}(\nu(F)+IF(y;\nu,F))dF(y) = \nu(F)$$

. We use the quantile function as our distributional statistics ($\nu(F) = q_\tau$) to find how a marginal quantile of y can be modified by a small change in the distribution of the covariates. The rescaled influence function of the τ-th quantile of the distribution F is

$$RIF(y;q_\tau) = q_\tau + IF(y;q_\tau) = q_\tau + \frac{\tau - \mathbb{1}\{y \leq q_\tau\}}{f_y(q_\tau)}$$

. The rescaled influence function of the median is

$$RIF(y;me) = me + \frac{\frac{1}{2} - \mathbb{1}\{y \leq me\}}{f_y(me)}$$

. In order to estimate the linear RIF-regressions, we compute the rescaled influence function for each observation by plugging the sample estimate of the median, $\hat{me}$, and estimating the density at the sample median, $\hat{f}(\hat{me})$. For the median of $Y_1|T=1$, we would use

$$\widehat{RIF}(y;me_1) = \hat{me}_1 + \left(\hat{f}_1(\hat{me}_1)\right)^{-1}\cdot(\frac{1}{2} - \mathbb{1}\{y \leq \hat{me}_1\})$$

where $\hat{f}_1(\cdot)$ is a consistent estimator for the density of $Y_1|T=1$, $f_1(\cdot)$. Kernel methods can be used to estimate the density. We use the Gaussian kernel function with half-width of kernel equals to 0.06. The RIF-regressions are then estimated by replacing the usual dependent variable, Y , by the estimated value of $RIF(y;me_1)$.

Let $\hat{\gamma}^\tau$ be the parameter obtained by regressing the RIF on covariates, $E[RIF(Y;\tau)|X] = X'\hat{\gamma}^\tau$. The change in the marginal quantile q_τ is going to be explained by a change in the distribution of the covariates. Then in the case where the conditional expectation is linear, the detailed (variable-by-variable) decomposition is given by:

$$\Delta_S^{me} = \mathbb{E}[X,T=1]^T\cdot(\hat{\gamma}_1^{me} - \hat{\gamma}_C^{me})$$

,

$$\Delta_X^{me} = (\mathbb{E}[X|T=1] - \mathbb{E}[X|T=0])^T \cdot \hat{\gamma}_0^{me} + \hat{R}^{me}$$

, where $\hat{R}^{me} = \mathbb{E}[X|T=1]^T \cdot (\hat{\gamma}_C^{me} - \hat{\gamma}_0^{me})$.

2.2.2.3 *Step 3: Solving the sensitivity to the choice of reference group problem*

Table 1 shows that there are some dummy variables in our data set. There is no easy way to determine which category should be chosen as the reference group, and the results of the detailed decomposition are sensitive to this choice. To solve this problem, we apply the Yun (2005) method, which is very simple. Given that we have many choices for the reference group, the method consists of using the average of the contribution of individual variables to the wage differentials with varying reference groups.

2.2.3 Counterfactual Distributions

Finally, we describe the method developed by Chernozhukov, Fernández-Val and Melly (2013). Suppose we would like to analyze the wage differences between men ($T = 0$), and women ($T = 1$). Y_T denotes wages and X_T the characteristics affecting wages for these populations. The conditional distribution functions $F_{Y_0|X_0}(y|x)$ describe the stochastic assignment of wages to men and $F_{Y_1|X_1}(y|x)$ describe the stochastic assignment of wages to women, with characteristics x. Let $F_{Y\langle 0|0\rangle}$ and $F_{Y\langle 1|1\rangle}$ be the observed distribution function of wages for men and women and $F_{Y\langle 0|1\rangle}$ the counterfactual distribution function of wages that would have prevailed for women if they had not faced wage discrimination: $F_{Y\langle 0|1\rangle}(y) := \int_{\mathcal{X}_1} F_{Y_0|X_0}(y|x)dF_{X_1}(x)$. This distribution is constructed by integrating the conditional distribution of wages for men with respect to the distribution of characteristics for women, and it is well defined if the support of characteristics of men ($\mathcal{X}_0$) includes the support of characteristics of women ($\mathcal{X}_1$), or more formally $\mathcal{X}_1 \subseteq \mathcal{X}_0$. The 95% simultaneous confidence bands are obtained by empirical bootstrap. The estimation of the counterfactual distribution function $F_{Y\langle 0|1\rangle}$ is computationally demanding, then when we computed the standard errors and the 95% confidence intervals, we reduced the sample size to 70,000 observations, prior to use the empirical bootstrap with 100 repetitions.

To decompose the differences between the unconditional wage distribution of men and women, we use an approach similar to Oaxaca (1973) and Blinder (1973), as follows:

$$F_{Y\langle 1|1\rangle} - F_{Y\langle 0|0\rangle} = [F_{Y\langle 1|1\rangle} - F_{Y\langle 0|1\rangle}] + [F_{Y\langle 0|1\rangle} - F_{Y\langle 0|0\rangle}]$$

, where the first term in the right hand side is due to differences in the wage structure or unexplained effects, and the second term is due to differences in the characteristics or explained effects.

2.3 Results

In this section we show the decomposition of the wage gap between males and females, and between whites and non-whites using data from Brazil. We decompose the wage differentials in explained and unexplained effects. The later give an estimate of the discrimination. The graphs show the decomposition of the wage differentials from the 10th until the 90th quantile of the wage distribution, and the estimates are made for each ten quantiles in this range.

We first present the estimate of the total wage differential between males and females and estimates of the explained and unexplained effects obtained by using the method develop by Firpo, Fortin and Lemieux (2009). Panel *a* of figure 2 shows that the wage discrimination between males and females does not present sharp variations across the quantiles of the wage distribution. It is higher in the 90th quantile and lower in the 50th quantile. Table 3 shows the results of the decompositions for selected quantiles of the wage distribution. All values are in log of weekly wages. As we can see in this table, the gender discrimination varies around its mean value of 0.06 across the quantiles.

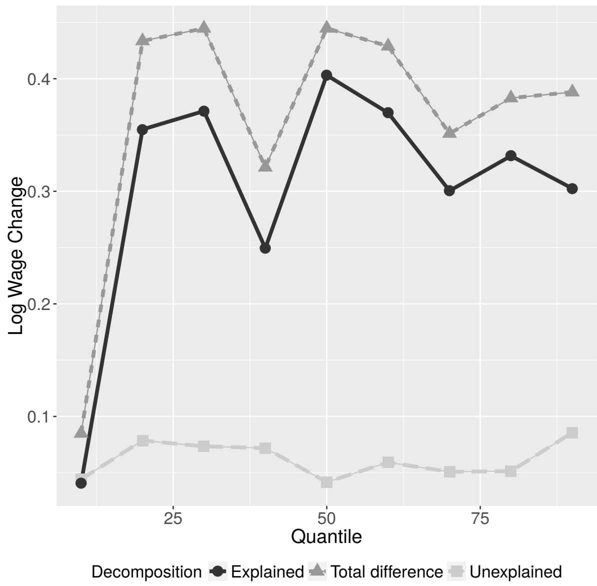
Panel *b* of figure 2 displays the decomposition of the unexplained effects, and shows that activity is the greater component of the unexplained differences. This means that there are activities in which women receive smaller wages than men. These results suggest that the gender discrimination is not generalized to all activities, for if it were true, activity would not be an important component of the unexplained effects. If, for example, education were the main component of the discrimination, then we would conclude that in general women with the same educational level than men would receive a smaller wage.

These results differ from Salardi (2013), who used the RIF-OLS technique developed by Firpo, Fortin and Lemieux (2009) and found evidences that education is the primary contributor to differences in endowments, and that experience is an important contributor to the unexplained wage gap between male and female and white and non-white workers. Bartalotti (2007), using the Machado-Mata decomposition, found evidences that the gender discrimination in Brazil increases smoothly from the lower quantiles until the 85th and then increases sharply thereafter. Our results suggest that gender discrimination in Brazil is greater on the 90th quantile, does not present sharp variations in the lower quantiles, and decreases between the 50th and 80th quantiles.

Figure 3 is similar to figure 2 and presents estimates of the racial discrimination. Panel *b* of figure 3 shows that racial discrimination increases along the quantiles of the wage distribution and it is greater than gender discrimination. The total wage gap is also greater between whites and non-whites than between males and females. This is more evident in the upper quantiles. Table 3 shows that the total wage gap is -0.058 in the 10th quantile and increases to 0.215 in the 90th quantile.

Figure 2 – Gender Discrimination and Decomposition of Unexplained Effects based on methods in Firpo, Fortin and Lemieux (2009)

(a) Wage Gap Decomposition



(b) Decomposition of Unexplained Effects

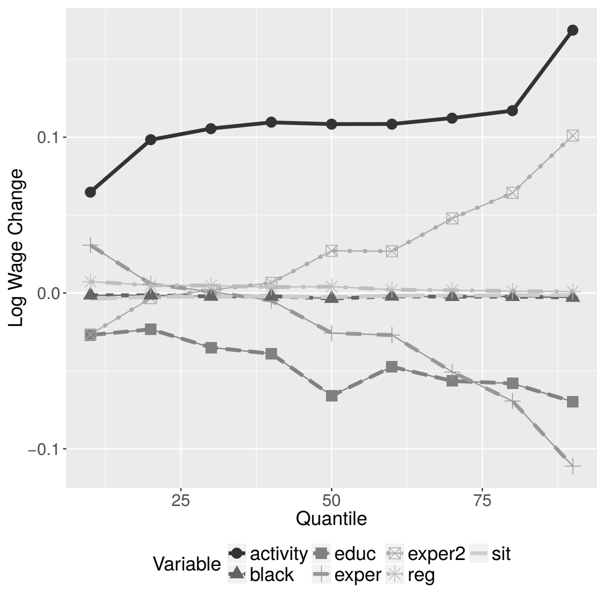
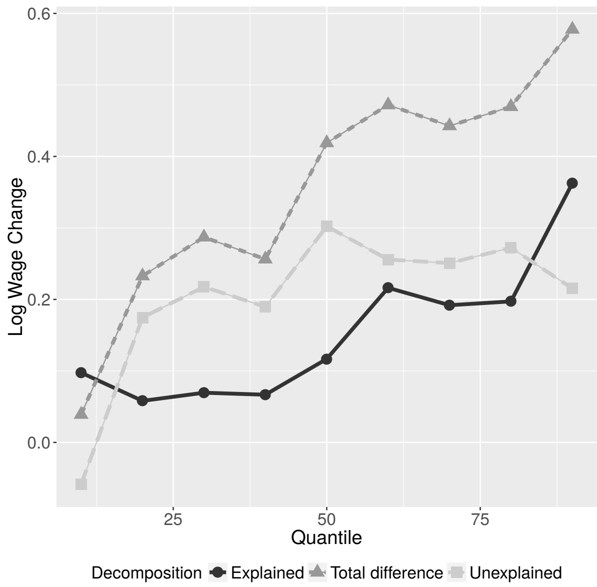
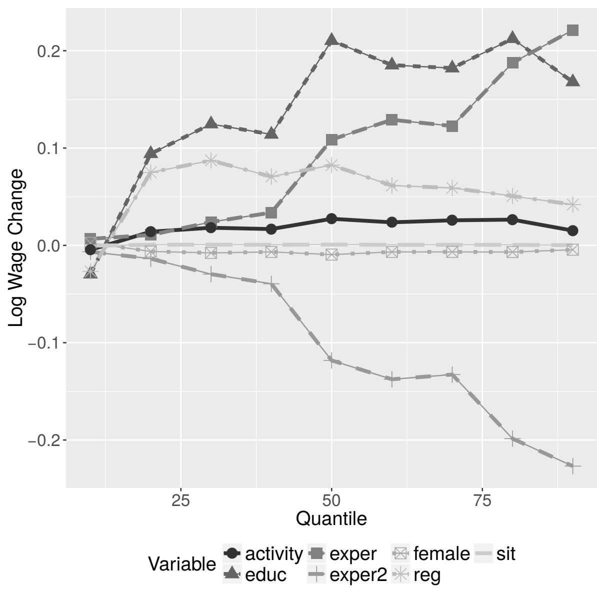


Figure 3 – Racial Discrimination and Decomposition of Unexplained Effects based on methods in Firpo, Fortin and Lemieux (2009)

(a) Wage Gap Decomposition



(b) Decomposition of Unexplained Effects



Our results are similar to those found by Álvarez (2013), who analyzed the racial wage gap in Brazil using the Melly (2005) decomposition, and data from the PNAD for the years 2001 and 2011. The graphs of the racial wage gap and discrimination have a U-shape (specially in 2011), with the minimum point located at the 20th quantile, but the discrimination increases in the upper quantiles. He found that the explained and unexplained effects were roughly equal. Therefore, approximately half of the wage gap occurs because of racial discrimination.

The decomposition of the unexplained effects is displayed in panel *b* of figure 3. Education, experience and region are the most important components of the racial discrimination. In the upper quantiles, education and experience become more important, while region becomes less important. Table 3 shows that in the 10th quantile the components of the discrimination are very similar, but above the 50th quantile education, experience, and region stand out.

These results imply that non-whites who receive higher wages have a smaller return to education than whites. Region is an important component of the discrimination; this means that in some regions the discrimination is greater than in others. Region is a dummy variable that assumes the value 1 for north and northeast and 0 for other regions, and these two regions have a greater portion of non-whites than the others. Thus it is likely that discrimination be smaller in north and northeast than in other regions, where non-whites are minority. To verify this, we estimate gender and racial discrimination for each of the five regions of Brazil. The results are shown in figures 5 and 6 in the appendix. Figure 5 shows that gender discrimination is very small in north and northeast regions, and it is greater in the other regions. Figure 6 shows that racial discrimination is smaller in north and northeast than in other regions, but it is greater than gender discrimination in this two regions.

Next we present the results of the Chernozhukov, Fernández-Val and Melly (2013) decomposition. Panel *a* of figure 4 shows that the gender wage discrimination increases in the upper quantiles of the distribution. It is higher in the 90th quantile, analogous to the results of the Firpo, Fortin and Lemieux (2009) decomposition. The mean value of the discrimination is 0.062, which is close to the value found in the RIF-OLS method (0.06).

Panel *b* of figure 4 displays the decomposition of the racial wage gap. The racial discrimination increases with the quantiles and is greater than the gender discrimination, a result that is similar that obtained by the unconditional quantile regression method. Table 4 shows that the unexplained effect is 0.055 in the 10th quantile and increases to 0.27 in the 90th quantile. On average, the Firpo, Fortin and Lemieux (2009) decomposition produces an estimated unexplained effect that is slightly higher than the Chernozhukov, Fernández-Val and Melly (2013) decomposition, and these averages are 0.20 and 0.16, respectively.

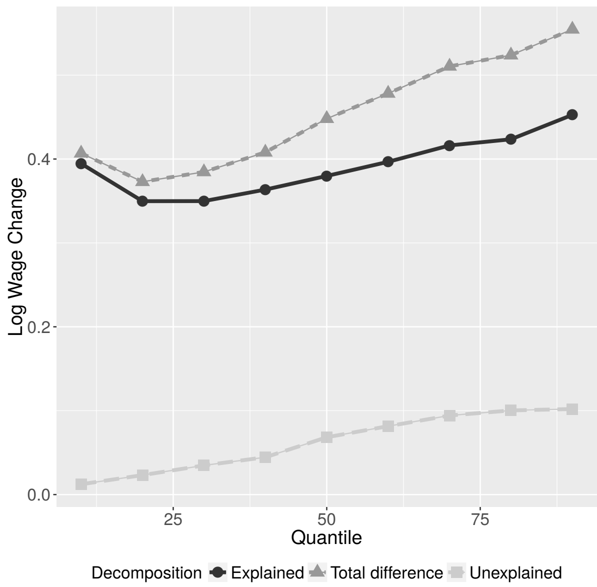
Table 3 – Decomposition Results

	Males and Females			Whites and non-whites		
Decomposition of The Wage Gap						
Quantile	**10**	**50**	**90**	**10**	**50**	**90**
Total Wage Gap	0.085	0.445	0.388	0.039	0.419	0.578
	(0.004)	(0.003)	(0.004)	(0.001)	(0.003)	(0.003)
Unexplained	0.044	0.042	0.086	-0.058	0.302	0.215
	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)
Explained	0.041	0.403	0.302	0.098	0.117	0.363
	(0.003)	(0.002)	(0.004)	(0.001)	(0.002)	(0.003)
Decomposition of Unexplained Effects						
educ	-0.027	-0.066	-0.070	-0.030	0.210	0.168
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
exper	0.031	-0.026	-0.111	0.007	0.109	0.221
	(0.003)	(0.002)	(0.007)	(0.002)	(0.006)	(0.010)
exper2	-0.027	0.027	0.101	-0.007	-0.118	-0.227
	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.004)
black	-0.001	-0.004	-0.003			
	(0.000)	(0.000)	(0.000)			
female				0.003	-0.009	-0.004
				(0.000)	(0.001)	(0.000)
reg	0.007	0.004	0.001	-0.027	0.083	0.042
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
sit	-0.004	-0.003	-0.001	0.000	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
actv	0.065	0.108	0.169	-0.005	0.027	0.015
	(0.006)	(0.014)	(0.007)	(0.001)	(0.002)	(0.002)

Notes: This decomposition of log of weekly wages is based on methods in Firpo, Fortin and Lemieux (2009).Standard errors are in parenthesis. The unexplained effects corresponds to discrimination.

Figure 4 – Decomposition of Gender and Racial Discrimination based on methods in Chernozhukov, Fernández-Val and Melly (2013)

(a) Decomposition of the Gender Wage Gap



(b) Decomposition of the Racial Wage Gap

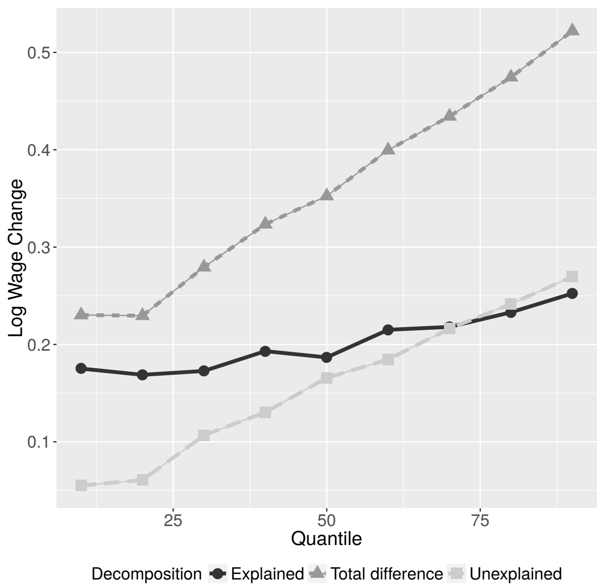


Table 4 – Decomposition of The Wage Gap

	Males and Females			Whites and non-whites		
Quantile	**10**	**50**	**90**	**10**	**50**	**90**
Total Wage Gap	0.407	0.448	0.555	0.230	0.352	0.522
	(0.011)	(0.007)	(0.015)	(0.012)	(0.007)	(0.014)
Unexplained	0.012	0.068	0.102	0.055	0.166	0.270
	(0.005)	(0.005)	(0.007)	(0.013)	(0.006)	(0.012)
Explained	0.395	0.380	0.453	0.175	0.187	0.252
	(0.011)	(0.006)	(0.015)	(0.006)	(0.005)	(0.008)

Notes: The decomposition of log of weekly wages is based on methods described in Chernozhukov, Fernández-Val and Melly (2013).Standard errors are in parenthesis. The unexplained effects corresponds to discrimination.

2.4 Conclusions

In this paper we decomposed the wage gap in Brazil between whites and non-whites, and males and females using the reweighing and recentered influence function regressions and the counterfactual analysis. The wage discrimination between males and females does not present sharp variations across the quantiles of the wage distribution. It is greater in the 90th quantile of the wage distribution. Our results suggest that gender discrimination is not generalized to all activities, since activity is the main component of the unexplained effects. We also found evidences that gender discrimination is very small in north and northeast regions, and it is greater in the other regions.

The racial discrimination increases along the quantiles of the wage distribution and it is greater than gender discrimination. The decomposition of the unexplained effects shows that education, experience and region are the most important components of the racial discrimination. This means that whites have a greater return to education and experience than non-whites and discrimination is greater in some regions than in others. The estimation of the racial discrimination for each of the five regions of Brazil shows that racial discrimination is smaller in north and northeast than in other regions. This occurs because non-whites are minority in south, southeast and Midwest, therefore it is more likely that the discrimination is greater in these regions than in north and northeast. One limitation of this paper is that it does not identify the activities where gender and racial discrimination occurs.

Brazil is one of the most unequal countries in the world. Racial and gender discrimination may be important factors contributing to this inequality. Although some policies are being created to reduce the inequality of opportunity - in 2004 the Universidade Federal de Brasília was the first public university to adopt a quota system to increase the number of non-whites students - there are many more actions to be implemented to reduce the discrimination and inequality that are present in every region of this country. Bertrand and Mullainathan (2003) argue that training alone may not be enough to alleviate the barriers raised by discrimination, since blacks living in the U.S. with the same qualification as whites, have a lesser probability of receiving callbacks for interviews, after responding to help-wanted ads. We hope that the insights on the subject provided by this paper may stir up the debate about discrimination, so that non-whites may have the same access to education, job interviews, and receive the same return to education and experience as whites, in a near future.

Appendix

Figure 5 – Decomposition of the regional wage gap: Males and Females

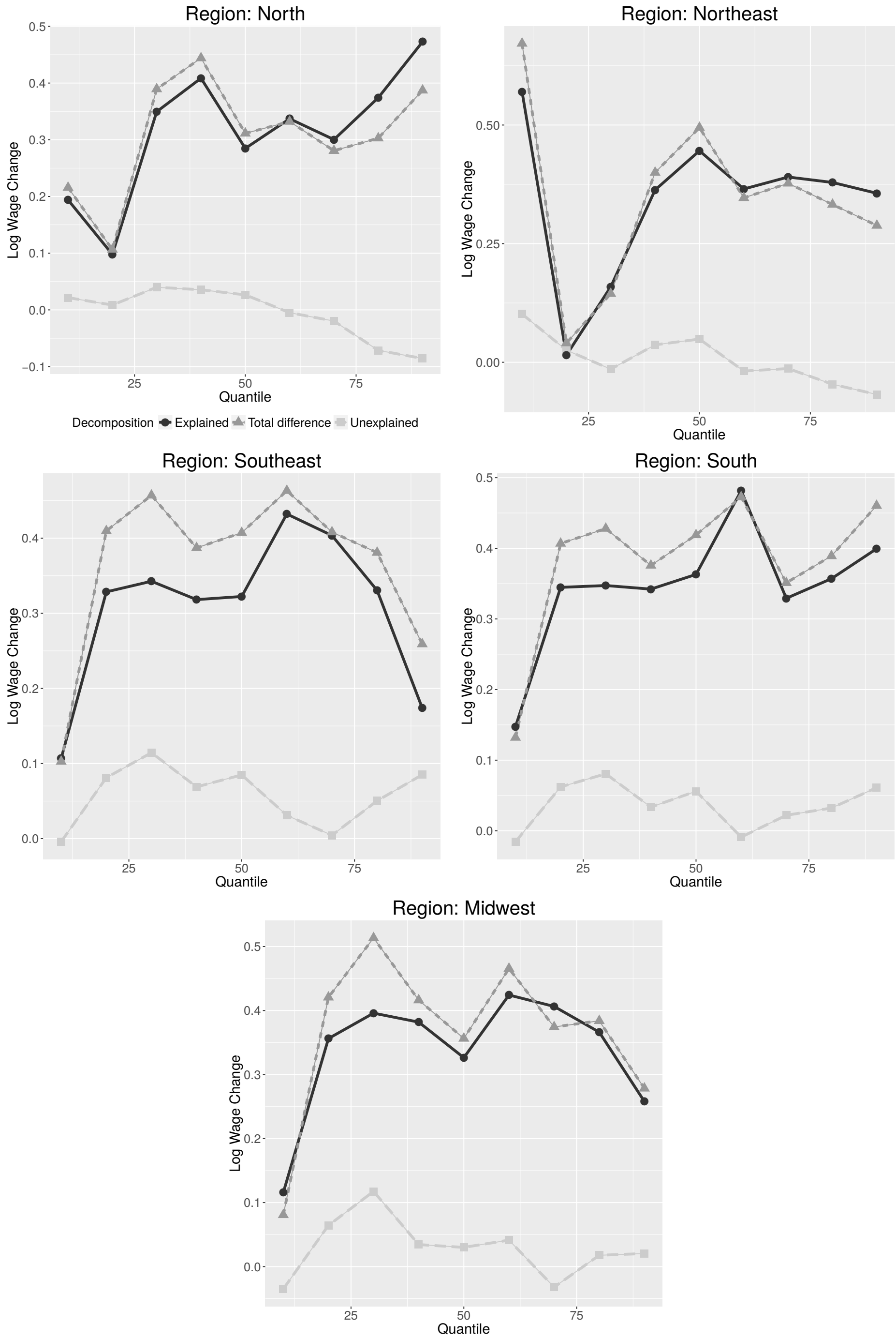
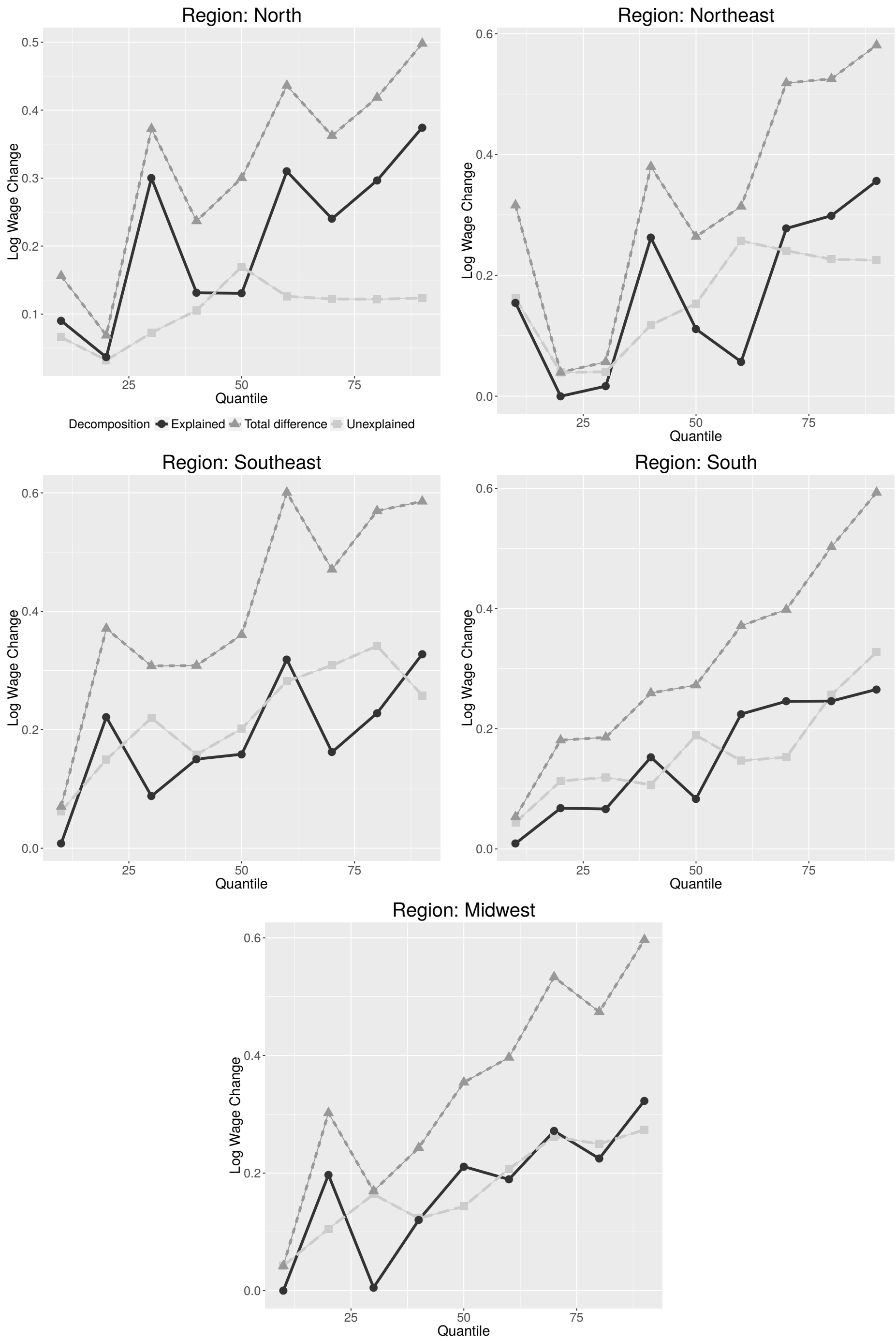


Figure 6 – Decomposition of the regional wage gap: Whites and Non-whites



3 THE IMPACT OF MIGRATION ON WAGES: EVIDENCES FROM BRAZILIAN WORKERS

3.1 Introduction

Migration is a topic that is central to political elections results in many countries. It generates divergent opinions, for some people see the immigrants as a contribution to the society while others see them as a threat. This topic was debated in the 2017 presidential election in France. Candidate Marine Le Pen vows to suspend immigration to 'protect France'. The Prime Minister of the United Kingdom Theresa May argues that a high and uncontrolled migration causes difficulties in the provision of public services and lowers wages of workers at the "lower end of the income scale". This topic was much debated during the 2016 US presidential campaign. There was a wide policy gap between the candidates, for Trump promised to reduce illegal immigration by building a wall and deporting immigrants living illegally in the country, while Clinton promised help integrate some undocumented immigrants into American society. According to a 2016 Gallup, 84 percent of respondents supported citizenship for undocumented immigrants if they meet certain requirements, and 74 percent considered that immigration is a "good thing" for the United States.

On the other hand, many natives view the immigrants as their substitutes in the labor market, so the concern that immigrants may cause wage reductions and unemployment motivated many studies on the effects of immigration on the labor market. This topic is much studied by economists. The papers of Migration Studies, an online journal, have been read over 100,000 times by readers of 130 countries, in the first four years of publication. Most of the recent studies on the economic effects of immigration show that immigrants are complementary to natives and produce positive effects in the economy. Basso and Peri (2015) argues that there are three mechanisms found in the literature that explain the positive effects of immigrants: first, immigrants and natives complement each other, for they supply different types of work. Second, they may improve the efficiency, specialization and technology adopted by firms. Third, they can bring new ideas and stimulate innovations, specially the highly educated immigrants. The studies reviewed by Kerr and Kerr (2011) find that there is only a minor effect on employment and wages even after large immigrant flows.

Other studies reviewed by Kerr and Kerr (2011) focus on the effects of immigration on the wages of immigrants. They conclude that immigrants experience lower wages and employment than natives at entry. The differences are likely to diminish over the time, but recent cohorts are expected to experience less success in the labor market than natives. In Brazil, Freguglia (2007) analyzes the effects of the immigration on the income of immigrants, using a fixed effects estimator and panel data of formal workers who moved to the state of São Paulo. He estimates that immigrants with middle school or lower educational level earn on average 6% less than non-migrants, while undergraduates earn on average 7% more than natives with similar characteristics.

McKenzie, Gibson and Stillman (2010) found unbiased estimates of the gains from migration by studying data from New Zealand which allows a quota of Tongans to immigrate with a random ballot. The random selection of immigrants is the perfect condition for using the instrumental variables estimator, since the instrument is strongly correlated with the endogenous regressor. In general, a strong instrument that generates unbiased estimates is difficult to find. Bound, Jaeger and Baker (1995) found that even the use of large data sets does not necessary insulate researchers from large finite-sample biases. McKenzie, Gibson and Stillman (2010) found evidences that the difference-in-differences and bias-adjusted matching estimators perform best among the alternatives to instrumental variables.

In this paper we identify the short- and long-run causal effects of immigration on wages of immigrants using the semiparametric DID estimator proposed by Athey and Imbens (2006) and data from RAIS for the years 2002 to 2007. We analyze the impact of migration on wages of migrants who were working in the state of Pernambuco, which ranked the 13Th position in terms of income *per capita* out of 27 states in Brazil, thus being an average income state. The *per capita* gross domestic product of Pernambuco grew on average 4% per year in 2000 decade, but in 2003 it fell 0.6%. There was also an increase in the unemployment rate in 2003. Panel (a) of figure 7 shows the *per capita* GDP growth rate in Pernambuco. We can easily see a sharp fall in the GDP growth rate in 2003. Panel (b) shows the monthly unemployment rate in Recife-PE (the state capital) and in Recife-PE metropolitan area . These conditions led to a increase in emigration in 2004, and the per cent growth in the number of immigrants is greater in 2004 than in the following years (see figure 8). We use data of workers of Recife and eleven metropolitan regions of Brazil to estimate the impact of immigration on the wages of the immigrants.

We analyze the wages of workers who were working in Pernambuco 2002, dividing them in 3 groups. The first is formed by individuals who never immigrated in the period 2002-2007 (control group). The second comprises immigrants who were working outside Pernambuco in 2004, thus we use their data to estimate the short-run effect of immigration. Finally, the third group comprises immigrants who were working outside this state in 2007, so that we use the data of this group to estimate the long-run effect of immigration.

Since the average effect of immigration on wages depends upon the state of destine, we estimate the impact of the migration on each of the five regions of Brazil. We take into account the difference in living costs when we estimate the impact of immigration on wages, therefore we adjust wages according to the living costs of 11 metropolitan cities of Brazil.

The method we use was inspired in Card (1990). He analyzed the impact of the massive immigration occurring after Castro's declaration in 1980 that Cubans were free to emigrate to the United States from the port of Mariel - as a result around 125,000 people immigrated in this year. This event constituted a natural experiment that closely corresponds to a exogenous increase in the quantity of immigrants of a particular labor market and allows the study of the effect of immigration on the wages and labor market opportunities of natives. This study overcame the limitations of previous studies which consisted in analyzing the correlation between wages and immigrant densities across cities. In our study we identified an event - the 2003 economic crisis in Pernambuco - that triggered an exogenous increase in immigration.

Card (1990) estimated the effects of immigration on wages and employment of natives, using the DID estimator, which requires the assumption that the average outcomes for treated and controls follow parallel paths over time to produce reliable results. Athey and Imbens (2006) proposed a semi-parametric DID estimator which differs from the standard DID approach, for it allows a systematic variation in the effects of time and treatment across individuals. This variation occurs because the response of each individual to the treatment depends on many factors, for example, the effects of immigration on wages are different on high skilled and low skilled immigrants and the effects of a new health treatment are different on each patient, depending on the the extent and severity of the disease. The standard DID method depends on the assumption that the effect of the policy is constant across individuals to estimate correctly the effect of a policy intervention in the counterfactual event that it were applied to the control. The non-linear DID estimator also allows a change over time on the distribution of unobservables, so that the results are not affected by a possible change in the mean, the variance or in the distribution of outcomes, in the absence of the policy intervention. Another disadvantage of the standard DID models is that it does not allow the possibility that the treatment group adopted the policy, and our case, immigration, "because they expected greater benefits than the control group" (ATHEY; IMBENS, 2006).

In our study, the assignment of control and treatment groups, was not aleatory. Also in Card (1990) the immigrants did not make an aleatory choice to immigrate to Miami. Therefore, this city was not randomly assigned to receive immigrants and become the treatment unit. Similarly the other cities were not randomly selected to become the control group. Miami was chosen by the immigrants because it has more Latin Americans and possibly they had relatives living there.

The main assumption of the non-parametric DID estimator is that the change in distribution of outcomes in the treated group would have been the same in absence of treatment. The method to find the effect of the treatment consists of three steps, the first is to estimate the counterfactual distribution of outcomes of the treated group, i.e. the distribution of outcomes there would have prevail in the treated group in the absence of the treatment. The second is to compare it with the actual second period distribution for the treated group. Finally, the third step is to estimate the distribution of outcomes of the control group, using the change over time - between the first and second periods - in the outcomes of the control group (ATHEY; IMBENS, 2006).

Our results shows that on average the immigration cause a wage loss of around 13%, and that immigrating to the metropolitan regions of Southeast and Midwest cause a wage loss especially because of higher living costs.

We check the robustness of our result by performing a placebo test. We select workers who emigrated only in 2004 and compare the wages of these immigrants in 2002 and 2003, prior to the immigration, to the wages of the non-immigrants (the control group) in these same years, to verify If there is some change on wages of the treated group in the absence of treatment. If the estimates of our placebo test are non zero, our results may be biased.

This paper gives some contributions to the study of immigration by: analyzing wages of workers living in Recife metropolitan area who immigrated to 11 Brazilian metropolitan regions and wages from non immigrants, using a non-parametric approach; comparing the effects of immigration on the 5 Brazilian regions; adding the two main wages prior to estimating the model. This is important to make sure that if workers had one job prior to immigration, immigrated to an area with many employment opportunities, and got two jobs that pay more than his previous employment, then the immigration had a positive effect on his wage, while the results would show a negative effect if only the wage of main position is considered. This is usually the case in previous studies. We also adjust the wages to consider the cost of living of each region, to produce more accurate comparisons of the wages prior and after the migration. Finally, one important contribution is the use of an estimator that one of the most efficient in estimating the change in wages after a migration (see McKenzie, Gibson and Stillman (2010)).

3.1.1 Related Literature

This paper is related to a large literature studying the effects of immigration on wages. Chiswick (1978) compares the wages of foreign-born and native born white men in the United States using data from the 1970 Census. His results suggest that immigrants earn on average 10 percent less than natives, 5 years after immigration. The earnings are approximately equal, after 13 years, and the immigrants earn 6 percent more than natives, after 20 years, holding observable variables constant (schooling, years of total labor-market experience, area of residence, and week worked). He explains that foreign born may have more innate ability, motivation or more likely to invest in human capital.

Borjas (1985) criticizes these results because the positive correlation between the relative wage of immigrants and years-since-migration, estimated using cross-section data, does not imply that the wages of immigrants are converging to those of natives. Borjas (1994) compares the progress of two groups of immigrants, the first arrived in the United States between 1965 and 1969, and the second arrived between 1975 and 1979. The wage differential between the immigrants of the first group and natives of similar characteristics changes from 12 percent to 5.9 percent from 1970 to 1980. The wage differential between the immigrants of the second group and natives of similar characteristics changes from 21.3 percent to 15.5 percent in the period from 1980 to 1990.

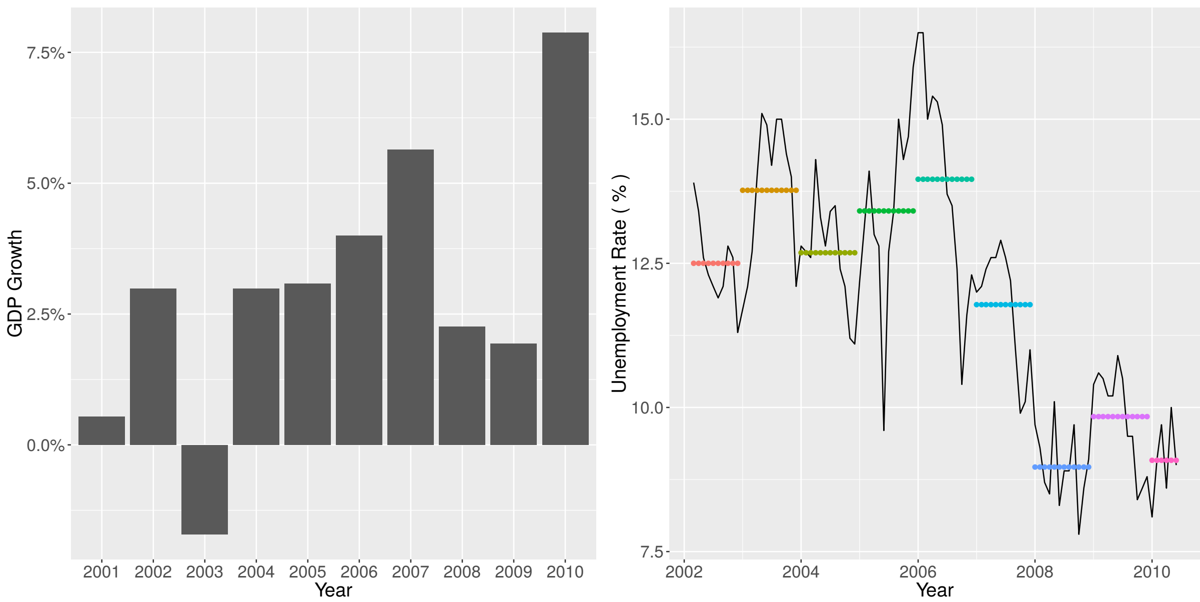
More recently, Tumen (2016) estimates the impact of immigration on consumer prices in Turkey, using a difference-in-differences strategy. He exploited the forced inflow of Syrian refugees as a natural experiment. Hanson and Slaughter (2016) compares the wages of immigrants in science, technology, engineering, and math (STEM) occupations in the United States, with the wages of native in these occupations. Across many occupations immigrants earns less than their native-born counterparts, but they found that immigrants working in STEM fields earned more than their native counterparts.

In Brazil, Santos (2006) analyzes the impact of interstate migration on income distribution, and finds evidences that migration increases state average income (except Rio de Janeiro and São Paulo), and the country average income. Freguglia and Procópio (2013) evaluate the wage differentials resulting from employment changes and interstate migration, for the shift in the wage of the workers can be due to the change of employment (firm effect) but not necessarily as a consequence of migration. The estimated effect of migration on wages was 3.5%.

Machado, Pero and Ponte (2013) analyzes the wage differentials between migrants and non-migrants born in the state and in the city of Rio de Janeiro, using panel data from RAIS-MIGRA/MTE and the fixed effects estimator. Results shows that the migrants from the state and city of Rio earned on average 6.1% and 8.4% less than the non-immigrants, respectively. Nevertheless, the immigrants who lived in the state of São Paulo between 2000 e 2008 earned more than non-migrants. The rest of this paper is organized as follows. The next three sections describes the data, the econometric model and the results. Section 5 concludes.

Figure 7 – *per capita* GDP Growth in Pernambuco and Monthly Unemployment Rate in Recife-PE Metropolitan Area.

(a) *per capita* GDP Growth (b) Monthly Unemployment Rate



Note: Dots show yearly averages of Unemployment Rates.

3.2 Data

We use data from RAIS-MIGRA/MTE from 2002 to 2007, removing retired, deceased and public sector workers, since public sector workers immigrate because they are transferred. They are usually high skilled workers and thus we argue that they differ substantially from the private sector workers. The cost of livings differs across regions, thus we adjust the wages for the cost of living estimated in 11 Brazilian metropolitan regions by Almeida and Azzoni (2016), before comparing the wages of immigrants with the wages of non-immigrants. We also use the index we created based on the estimated living costs to deflate the wages.

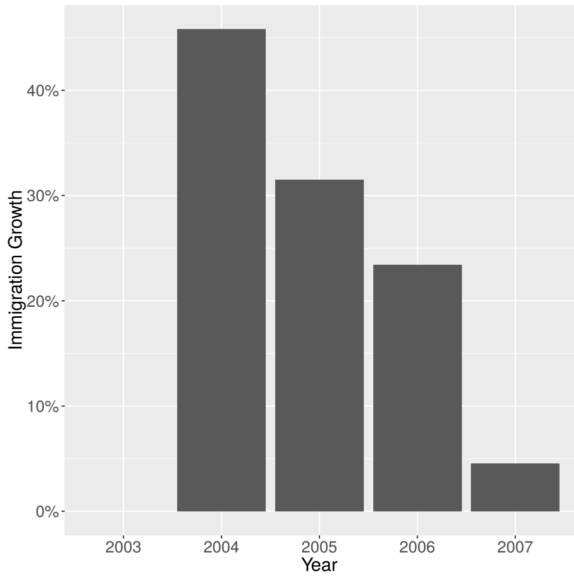
3.3 Methods

In the standard Difference-in-Differences there are two groups g of interest, the treated and the control, denoted by t and c. Their outcomes y are observed for two time periods, $p1$ and $p2$, and no groups receives treatment in t_0. The Difference-in-Differences estimator is given by:

$$\delta_{DD} = (y_{t,p2} - y_{c,p2}) - (y_{t,p1} - y_{c,p1}) \tag{3.1}$$

This equation implies that if the outcomes of the two groups were equal prior to the treatment, then the estimator is equal to the difference in the outcomes after

Figure 8 – Immigration Growth Rate: Growth of the number of people was working in Pernambuco in 2002 and immigrated in the following years.



Note: The growth rate was not calculated in 2003, because the number of immigrants in 2002 was not available.

the treatment, and the equation (3.1) becomes $\delta_{DD} = (y_{t,p2} - y_{c,p2})$. If the outcomes were different prior to the treatment, the estimator adjust itself by subtracting the term $y_{t,p1} - y_{c,p1}$ corresponding to the difference in outcomes in the two groups prior to the treatment.

We can write the following model for the DID estimator:

$$Y_{g,t} = \hat{\alpha} + \hat{\beta} \cdot TREAT_g + \hat{\gamma} \cdot Post_{time} + \delta_{DD}(TREAT_g \cdot Post_{time}) + \epsilon_{g,t} \tag{3.2}$$

Where $Treat_g$ is a dummy variable that is 0 if the group is control and 1 if the group is the treated, $Post_{time}$ is a dummy variable that is 1 in the post-treatment periods and 0 before the treatment period.

To see how the δ_{DD} of equation (3.1) corresponds to the δ_{DD} of equation (3.2), we need to find the value of $(y_{t,p2} - y_{c,p2}) - (y_{t,p1} - y_{c,p1})$ implied by equation (3.2).

After substituting the possible values of the dummy variables in equation (see table 5), we find that

$$\begin{aligned}
(y_{t,p2} - y_{c,p2}) - (y_{t,p1} - y_{c,p1}) &= (\alpha + \beta + \gamma + \delta_{DD} + \epsilon_{g,t} - \alpha - \gamma - \epsilon_{g,t}) \\
&\quad - (\alpha + \beta + \epsilon_{g,t} - \alpha - \epsilon_{g,t}) && (3.3)\\
&= (\beta + \delta_{DD}) - \beta && (3.4)\\
&= \delta_{DD} && (3.5)
\end{aligned}$$

The model can be more robust if it includes another control, then the Difference-

Table 5 – Derivation of the DID estimator

$Treat_g$	$Post_{time}$	$Y_{g,t} = \hat{\alpha} + \hat{\beta} \cdot TREAT_g + \hat{\gamma} \cdot Post_{time} + \delta_{DD}(TREAT_g \cdot Post_{time}) + \epsilon_{g,t}$
1	1	$Y_{t,p2} = \alpha + \beta + \gamma + \delta_{DD} + \epsilon_{g,t}$
0	1	$Y_{c,p2} = \alpha + \gamma + \epsilon_{g,t}$
1	0	$Y_{t,p1} = \alpha + \beta + \epsilon_{g,t}$
0	0	$Y_{c,p1} = \alpha + \epsilon_{g,t}$

Note: See Angrist and Pischke (2014).

in-Difference-in-Differences is given by:

$$\delta_{DDD} = (y_{t,p2} - y_{t,p1}) - (y_{c1,p2} - y_{c1,p1}) - (y_{c2,p2} - y_{c2,p1}) \tag{3.6}$$

The expanded version of the model given by equation (3.2) is:

$$\begin{aligned} Y_{g,t} &= \hat{\alpha} + \hat{\beta}_1 \cdot TREAT_1 + \hat{\beta}_2 \cdot TREAT_2 + \hat{\beta}_3 \cdot TREAT_1 \cdot TREAT_2 \\ &= + \hat{\gamma}_1 \cdot Post_{time} + \hat{\gamma}_2 \cdot Post_{time} \cdot TREAT_1 + \hat{\gamma}_3 \cdot Post_{time} \cdot TREAT_2 \\ &= + \hat{\delta}_{DDD}(Post_{time} \cdot TREAT_1 \cdot TREAT_2) + \epsilon_{g,t} \end{aligned} \tag{3.7}$$

3.3.1 The non-parametric DID model

In the general DID model the individual i belongs to a group g, and is observed in time period $t \in \{p_1, p_2\}$. Athey and Imbens (2006) assume that the outcomes of the control group, denoted by Y_i^C ,satisfy:

$$Y_i^C = g^C(U_i, t_i) \tag{3.8}$$

The random variable U_i represents the unobserved characteristics of individual i. The function $g^C(U_i, t_i)$ is increasing in U_i and equation 3.8 incorporates the idea that the outcome of an individual with $U_1 = u$ will be the same in a given time period, regardless the group that the individual i belongs to.

The distribution of U_i can vary across groups, but do not change over time within groups, so that $U_i \perp t_i | g_i$. The standard DID model needs three more assumptions. The first two are given by the equations (3.9) and (3.10) and are called additivity and single index model, respectively.

$$U_i = \alpha_0 + \alpha_1 g_i + \epsilon_i \tag{3.9}$$

$$g(u, t) = \phi(u_\delta \cdot t) \tag{3.10}$$

The third assumption is that $\phi(\cdot)$ is equal to the identity function.

The model proposed by Athey and Imbens (2006) allows that the treatment group's distribution of unobservables be different from that of the control group, in arbitrary ways. It also allows that a particular individual has different U_i in each period. It is assumed that the outcomes of the treated group (after the intervention), denoted by Y_i^T ,satisfy:

$$Y_i^T = g^I(U_i, t_i) \tag{3.11}$$

The function $g^T(U_i, t_i)$ is also increasing in U_i. Intuitively, the effect of the intervention on an individual with $U_1 = u$ will be the same in a given time period, regardless the group that the individual i belongs to. It is not required any assumption about how the treatment affects outcomes, i.e. the functional form of $g^I(\cdot)$, then the effect of the intervention is equal to $g_I(u,1) - g^N(u,1)$ and can differ across individuals with $U_i = u$. The average effect of the treatment can vary across groups, since the distribution of u can also change in different groups.

3.3.1.1 *The changes-in-changes (CIC) model*

Let $Y_{gt}^C \sim F_{Y^N,gt}$ and $Y_{gt}^I \sim F_{Y^I,gt}$. If the above assumptions hold and if $\mathbb{U}_1 \subseteq \mathbb{U}_0$ (support), then the distribution of Y_{1p2}^N is identified and Athey and Imbens (2006) prove[1] that :

$$F_{Y^C,Tp2} = F_{Y,Tp1}(F_{Y,Cp1}^{-1}(F_{Y,Cp2}(y)))$$

Using the following transformation we can obtain the second-period outcome Y_{Tp2}^C for an individual with an unobserved component u, such that $g(u,p1) = y$.

$$K^{CIC} = F_{Y,Cp2}^{-1}(F_{Y,Cp1}(y)) \tag{3.12}$$

The distribution of $Y_{T,p2}^C$ is equal to the distribution of $K^{CIC}(Y_{Tp1}$. This transformation suggests that the average treatment effect can be written as:

$$\begin{aligned} \tau^{CIC} = \mathbb{E}[Y_{Tp2}^T - Y_{Tp2}^C] &= \mathbb{E}[Y_{Tp2}^T] - \mathbb{E}[K^{CIC}(Y_{Tp1})] \\ &= \mathbb{E}[Y_{Tp2}^T] - \mathbb{E}F_{Y,Cp2}^{-1}(F_{Y,Cp1}(y_{Tp1})) \end{aligned} \tag{3.13}$$

and is estimated using empirical distributions and sample averages.

3.4 **Results**

In table 6 we compare the data of immigrants and non-immigrants in the year 2002, when both are in the region of origin and in the year 2004, when immigrants are living in a new region and non-immigrants are still living in the region of origin. The

[1] $F_{Y,Cp1}^{-1}$ is the inverse of $F_{Y,Cp1}^{-1}$ and exists because is $g^(U_i, t_i)$ is invertible, in consequence of the assumption that the function $g^(U_i, t_i)$ is increasing in U_i

average wage of workers in 2002 who will immigrate is R$ 185,85 higher than the wage of those workers who will not immigrate, and they have attended school for two years more than the non-immigrants, on average. Chiswick (2000) argues that the migrants are favorably selected. He argues that migrants, on average, tend to be more "able, ambitious, aggressive, entrepreneurial" than other people who chose to stay at their place of origin. The immigrants also differ in other attributes from their counterparts. They are, on average, 4 years younger than non-immigrants and worked for a shorter period in the company prior to the immigration, for on average, they worked 32 months less than their counterparts.

Table 6 – Average Values of Variables - Non-immigrants and Immigrants in the Short-run

	Non-Immigrants		Immigrants		Differences		Difference in Differences
	2002	2004	2002	2004	(2)-(1)	(4)-(3)	(6)-(5)
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentage of Males	0.667	0.671	0.673	0.671	0.004	-0.002	-0.006
Months at Work in the Company	59.637	73.269	27.451	16.956	13.632	-10.495	-24.127
	(1.023)	(1.064)	(0.885)	(0.706)	(1.492)	(1.152)	(1.759)
Weekly Hours in Contract	42.115	42.485	42.016	42.653	0.369	0.637	0.268
	(0.095)	(0.082)	(0.103)	(0.069	(0.125	(0.121	(0.158
Age	34.396	36.278	30.951	32.699	1.882	1.748	-0.134
	(0.144)	(0.144)	(0.170)	(0.170)	(0.206)	(0.236)	(0.279)
Years of Schooling	9.840	10.057	11.563	11.938	0.217	0.375	0.158
	(0.059)	(0.059)	(0.066)	(0.064)	(0.083)	(0.092)	(0.110)
Real Wage	891.261	1077.119	1950.682	2087.703	185.859	137.021	-48.838
	(19.778)	(24.748)	(76.936)	(68.728)	(31.736)	(102.992)	(88.710)

Notes: Wages were adjusted to reflect living costs. Standard-errors in parenthesis.

Column (7) of table 6 shows the estimate of the standard difference-in-differences estimator for each variable. The immigration reduced the months at work in the company, then we can assume that most workers are changing from one company to another, and only a few of them is working at the same company at another location. According to the DID estimator, in the short-run the immigration has no causal effect on wages in Brazil, since it causes a insignificant decrease in wages.

In table 7 we compare the data of immigrants and their counterparts in the year 2002 (before the immigration), and in the year 2007 (after the immigration). The characteristics of the workers are similar, but the immigrants in this group earn more then the control group, 5 years after the immigration. This result is similar to the results found in literature reviewed by Kerr and Kerr (2011), for the immigrants tend to earn more in the long-run.

Table 7 – Average Values of Variables - Non-immigrants and Immigrants in the Long-run

	Non-Immigrants		Immigrants		Differences		Difference in Differences
	2002	2007	2002	2007	(2)-(1)	(4)-(3)	(6)-(5)
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentage of Males	0.667	0.673	0.695	0.708	0.006	0.013	0.007
Months at Work in the Company	59.637	94.928	27.165	24.040	35.292	-3.125	-38.417
	(1.023)	(1.201)	(0.785)	(0.777)	(1.589)	(1.118)	(1.819)
Weekly Hours in Contract	42.115	42.412	42.375	42.673	0.297	0.298	0.002
	(0.095)	(0.084)	(0.102)	(0.075)	(0.125)	(0.123)	(0.160)
Age	34.396	39.293	30.498	35.861	4.897	5.362	0.466
	(0.144)	(0.145)	(0.164)	(0.164)	(0.207)	(0.231)	(0.272)
Years of Schooling	9.840	10.328	11.047	11.857	0.488	0.810	0.322
	(0.059)	(0.059)	(0.070)	(0.064)	(0.083)	(0.095)	(0.112)
Real Wage	891.261	1393.688	1610.995	2442.855	502.428	831.860	329.433
	(19.778)	(31.988)	(85.284)	(72.032)	(37.647)	(112.712)	(100.270)

Note: Wages were adjusted to reflect living costs. Standard-errors in parenthesis.

Next, we show the results obtained by the Changes-in-Changes model. We estimated the causal effect of migration on wages, in Brazil and its regions. We compare the wages of immigrants in each region to the wages of non-immigrants, to estimate these effects. Table 8 shows the short-run impact of immigration on wages. The dependent variable is the log of wage, since it is more robust to outliers than the variable wage. The results show that a worker who immigrates to the Southeast earns on average 19% less than non-immigrants, and the worker who immigrates to Midwest earns on average 22% less than the control group. A worker who immigrates to other regions does not receive significantly less than her counterpart. On average the wage of a immigrant is 13% lesser than of a non-immigrant.

Table 8 – Short-run Impact of Migration on wages

Region	Year: 2004
Brazil	-0.1341 (0,0423)
North	-0.0024 (0.1093)
Northeast	0.0490 (0.0412)
Midwest	-0.2285 (0.0795)
South	-0.0693 (0.0997)
Southeast	-0.1967 (0.0391)

Note: Standard errors in parenthesis. Dependent variable log wages.Estimates of the CIC model using data from the population immigrating in 2003 and data from non-immigrants.

In table 9, we display the results of the changes-in-changes model, which evaluates the long-run impact of immigration on wages. According to the results, the immigrant who works in Midwest receives on average a wage 31% lesser than her counterpart who did not immigrate, while the worker who lives in the Southeast region receives on average 17% less than the non-immigrant. The estimated long-run effect of immigration is on average very similar to the short-run effect. The long-run effect we obtained by the CIC estimator differs substantially from the results obtained by the differences-in-differences estimator.

Table 9 – Long-run Impact of Migration on wages

Region	Year: 2007
Brazil	-0.1324 (0.0451)
North	-0.0588 (0.1258)
Northeast	-0.0454 (0.0384)
Midwest	-0.3195 (0.0665)
South	-0.1140 (0.0903)
Southeast	-0.1701 (0.0433)

Note: Standard errors in parenthesis. Dependent variable log wages.Estimates of the CIC model using data from the population immigrating anywhere in the period 2003-2007 and data from non-immigrants.

3.4.1 Robustness Test

We test the robustness of the short-run effects of immigration on wages by applying the CIC model on data of workers for the year 2003, prior to their immigration. For example, we selected the individuals who immigrated in 2004, and we estimate the "effect" of the immigration in 2003, when she was working in the same region as the control group. If the effects were significant then we could infer that other factors were causing a change in the wage of the immigrants. Table 10 shows that the effects estimated were not significant, thus they support the validity of our estimates.

Table 10 – 2003 as a Placebo Year of Immigration

Region	2004 immigrants	2004-2007 immigrants
Brazil	-0.0385 (0.0458)	-0.0165 (0.0404)
Midwest	0.0795 (0.1493)	0.0588 (0.0799)
Southeast	-0.0532 (0.0559)	-0.0386 (0.0368)

Note: Standard errors in parenthesis. Dependent variable log wages.Estimates of the CIC model using data for the year 2003, and contains data of workers prior to their immigration.

3.5 Conclusions

We use data of the emigration of workers to estimate the impact of immigration on wages of immigrants. During 2003, there was a sharp fall in the GDP growth rate of Pernambuco, Brazil, and the unemployment rate was very high in Recife-PE (the state capital) and in the Recife-PE metropolitan area. These conditions led to a increase in emigration in 2004.

Using a semi-parametric DID estimator proposed by Athey and Imbens (2006), we found that immigration caused a reduction of 13% in the long-run and short-run wages of immigrants. The effects vary across the regions of Brazil, being greater in the Midwest and Southeast regions, and very small and insignificant in other regions.

Our paper made some contributions to the literature on immigration. We adjusted the wages by the different living costs of the regions, prior to analyzing the effects of the immigration of wages, using the living cost estimates of Almeida and Azzoni (2016) for eleven metropolitan regions of Brazil. We used one of the most efficient estimation strategies, for according to McKenzie, Gibson and Stillman (2010), the difference-in-differences and bias-adjusted matching estimators perform best among the alternatives to instrumental variables, which is the ideal method to achieve the objectives of this paper, but it is very difficult to find a situation in which occurred a random selection of immigrants in the Brazilian regions, similar to the random selection of immigrants that occurred in New Zealand.

The limitations of this paper are: we set placebo dates of immigration to test the robustness of our results, but we did not use alternative control groups, nor exploited carefully the variation in the time of immigration to see if the results change as a function of the duration (intensity) of the immigration. Our results show that when a worker immigrates to the Midwest, in the short-run his real wage, adjusted for the living cost, decreases 22%. If the immigration affects negatively his wage in the short-run, it is expected that this effect is even more negative in the long-run. Indeed, the impact of the immigration to the Midwest region in the long-run is -31%, then this results meet our expectations. Nevertheless, when we analyze the results for the Southeast region we notice that the impact of the immigration is lower in the long-run than in the short-run. This appears to be a puzzle to be solved by future research.

Another topic for future research is the relationship between the results of the standard DID estimator and the non-parametric DID estimator developed by Athey and Imbens (2006). We already explained that the latter is more general than the former, because it requires less assumptions to produce reliable results. We estimated the effects of the immigration using both estimators and found that their results are very different. Besides this paper, the comparison of the results of the two estimators was made by Athey and Imbens (2006) when they replicated the results of Meyer, B.D. Viscusi and Durbin (1995) using de CIC model and the standard DID model. Meyer, B.D. Viscusi and Durbin (1995) analyzed the effect of a increase in the disability benefits on the number of weeks a worker spent on disability. The distribution of injury duration is highly skewed. They found that their results changed substantially when the outcome is measure in number of week and when the natural logarithm of the number of weeks. Comparing the results of the DID-log and the CIC models, the conclusion was that they presented different, results, but depending on the quantile of the distribution, the results were comparable. One of the main differences between the models is that the CIC model does not require the assumption of heterogeneous treatment effects. It is reasonable that the effects of immigration on wages are heterogeneous, therefore it may be the cause of the difference in the results obtained by these models.

4 IMPACTS OF INTERGOVERNMENTAL TRANSFERS ON IMMIGRATION IN BRAZIL - EVIDENCE FROM A REGRESSION KINK DESIGN

4.1 Introduction

In Brazil, the federal government transfers part of its revenue to the cities. These transfers are called "fundo de participação dos municípios" (hereafter FPM). The volume of transfers depends only on population size, for municipalities with less than $156,216$ inhabitants. This rule was set exogenously and creates incentives for some municipalities to attract people so that they can increase the volume of transfers they receive. Thus it is expected that municipalities with smaller population and FPM transfers attract more immigrants. On the other hand, it is expected that municipalities with greater population and that receive a larger amount of transfers, end-up attracting more immigrants, since the extra revenue can be used to improve the public services, specially those related to health and education. Therefore, there is a controversy about the effects of the FPM on immigration. This paper aims to analyze the impact of FPM transfers on the number of people that migrates from one city to another, by exploring the discontinuities in the assignment of the FPM and using the regression kink design approach.

If one municipality has a greater population and receives more transfers than others, it can also attract corrupt politicians. Brollo et al. (2013) found a positve effect of FPM transfers on three corruption measures. The first, *broad corruption*, includes irregularities that could be defined as bad administration instead of corruption. The second, *narrow corruption*, includes severe irregularities. And finally, the third was called *narrow fraction of the amount* and is defined as the ratio between the total amount of funds involved in the detected violation and the total amount audited. They also found that the transfers caused a reduction in the quality of politicians, measured by the fraction of opponents with college degree and their average years of schooling. Thus, the increase in FPM transfers also causes an increase in political corruption. Therefore, greater revenues, may not necessarily be related to improved public services, like public health and education.

Transfers also help politicians to re-elect themselves. Litschig and Morrison (2012) uses discontinuities in the FPM transfers around the first three population cutoffs, over the period 1982-1985 to estimate the impact of transfers on re-election probability and per *capita* government spending using a sharp RDD estimator. They found evidences that extra fiscal transfers are linked to an increase in the re-election probability of local incumbent parties. Their results also showed that the transfers caused an increase of 20% in local government *per capita* spending.

Although the FPM transfers increase corruption, they have a positive impacts on development variables. Litschig and Morrison (2013) found that intergovernmental transfers cause an increase in schooling *per capita* and in literacy rates. Therefore, their analysis confirms that municipalities that receive greater transfers indeed tend to offer better public services.

On the other hand, Mata (2014) studied the impacts of the increase in intergovernmental transfers on housing markets and on city growth, and found that the housing sector grows faster in municipalities that are less dependent on federal grants. He also studies the effects of FPM transfers on population growth, using it as an alternative measure of housing market and city growth. He finds a similar result in both analyses and concludes that locations with higher *per capita* FPM attract fewer people. In our analysis rather than using data on population growth we study the effects of FPM transfers on immigration using data from RAIS/MIGRA, which allowed us to calculate the number of immigrants in each municipality in Brazil for the years 2009 and 2010. In our data set, all immigrants were formal workers, then we could find the municipality where they were working in each year. The last Brazilian census was performed in 2010, which provide accurate data of the number of inhabitants in each municipality, thus we use population data for this year.

Another difference between this study and others is that they focus the analysis on the first cutoffs, for they argue that the variation in FPM transfers in the other cutoffs is too small to impact municipal budgets (LITSCHIG; MORRISON, 2013). In this paper, we focus on the $156,216$ cutoff, for municipalities above this threshold receive the same value of FPM transfer within the state (if they have similar population size) plus an additional value that municipalities below this threshold do not receive. This additional value was on average R\$ $252,708.00$ in 2010 currency units. We argue that this value is not too small and it can have a great impact on the municipalities with more than $156,216$ inhabitants. Figure 11 shows that there is a sharp increase in FPM transfers around this cutoff.

All municipalities are classified in three groups, according to the law nº 1.881/1981. Municipalities with more than $156,216$ inhabitants are classified as *municípios da reserva*, and receive on average more FPM transfers than the municipalities which are below this cutoff, which are called *municípios do interior*. The third group is formed by the state capitals, and is removed from our analysis, for all of them receive a very different amount of transfers.

Prior to estimating the regressions, we took two samples of our data. Sample I includes all municipalities with population size within the cutoffs created by the decree law nº 1.881/1981. We use sample I to estimate the effect of transfers on immigration in the first cutoffs as in Brollo et al. (2013). Sample II consists of municipalities with between 143, 123 and 168, 511 inhabitants, and we use it to verify the impact of FPM transfers on immigration around the 156, 216 cutoff. In sample II we designated the *municípios do interior* to the control group and the *municípios da reserva* to the treated group.

Our results show that the effect of the increase in intergovernmental transfers causes a change in the slope of the line that relates population and immigration by 6.238, near the 156, 216 cutoff. The effect of FPM on immigration in the first cutoffs (sample I) is small, but statistically significant. We perform some robustness checks and test the validity of our identification assumptions. The main contribution of this paper is to show evidences that an increase in FPM transfers causes an increase in immigration in municipalities with population size near the cutoff.

To our knowledge this is the first paper to analyze the impact of transfers around the 156, 216 cutoff, which separates two very different groups of municipalities in terms of transfers - the *municípios do interior* and *municípios da reserva* - although this groups are very similar in population and other characteristics. We argue that there are two reasons for the similarity of these municipalities. First, the rule that determines the transfers (decree law nº 1.881/1981) was exogenous to the control of municipalities, thus they did not choose the amount of transfers they receive, for it was chosen by the Federal Government. Second, we compare only the municipalities with population size around this cutoff, so we compare them based on fact that they were assigned to either group by a very small difference in population size. Therefore, this rule set by the government created a quasi-experiment.

The rest of this paper is structured as follows. After this introduction, we present the data and methods in the next three sections. Section 5 shows our results and section 6 concludes.

4.2 Data

We use data of migration from RAIS/MIGRA for the years 2009 and 2010 to find the number of immigrants in 2010 in each municipality. Our data set contains only immigrants who were formal workers in this spell. We remove from our sample the public sector workers, since they tend to migrate because of work requirements - specially the military personnel, who are a large fraction of public workers - or they migrate to work in a public job and then return to their home municipality after applying and receiving a location transfer. In this paper we test if the municipalities that are receiving more transfers, tend to receive more immigrants, so these peculiar situations of public workers are not according to the assumptions we make. We also exclude the retired workers.

The population data used is from the 2010 Census. The first threshold is $10,188$, the second is $13,584$, so the difference is $3,396$. For the sake of symmetry, sample I is restricted to municipalities with more than 6796 inhabitants as in Brollo et al. (2013). We aim to achieve symmetry in the upper thresholds, but at the same time we want to avoid the sample size to be too small. The interval between the last threshold and the last but one threshold is $13,584$, we restricted sample I to municipalities with less than $183,373$ inhabitants. The difference between this limit and the last cutoff is $27,168$, thus we believe that this limit is balance a between the goals of achieving symmetry and getting a sample size that is not too small.

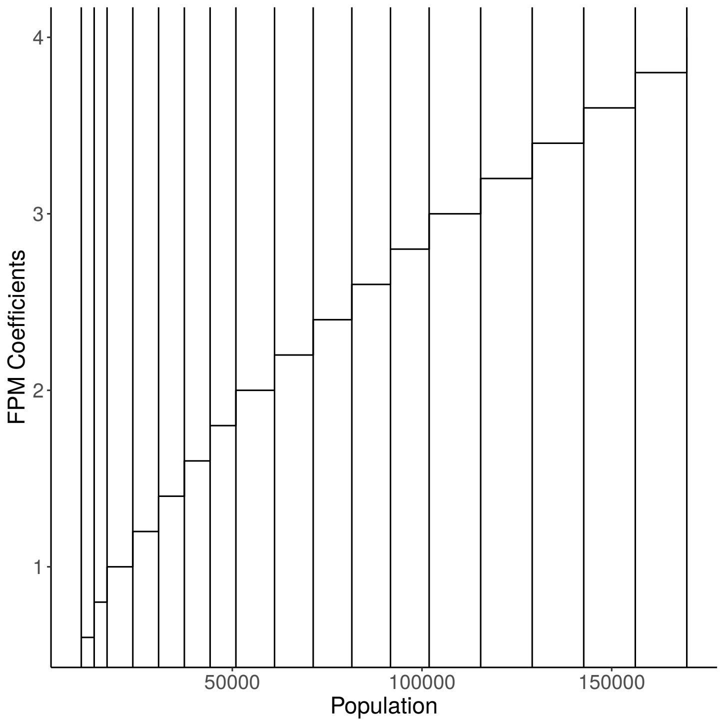
The top left graph in figure 10 shows that there are many municipalities with more than 156216 inhabitants receiving much more FPM transfers than the municipalities with less than 156216 inhabitants - the last threshold. Similarly, the top left panel of figure 11 shows that FPM increases substantially after the $156,216$ cutoff. This occurs because municipalities with more than $156,216$ inhabitants are called *municípios da reserva* and receive the FPM corresponding to coefficient 4 (the highest coefficient) plus an additional value based on *per capita* income and population size, relative to the state where it is located. Thus we restrict sample II to municipalities with between $143,123$ and $169,511$ inhabitants.

Table 11 shows the descriptive statistics of samples I and II. The average number of immigrants in sample II is much higher than in sample I, suggesting that the FPM transfers have a strong effect on immigration. The municipality with the highest number of immigrants among the two samples is Lauro de Freitas-BA, which had $163,449$ inhabitants in 2010, belongs to sample II, and is part of the *municípios de reserva* group. Carvalho et al. (2007) analyses immigration in Brazilian municipalities and find that Lauro de Freitas-BA is among the ten highest municipalities receiving immigrants among all Brazilian municipalities over one hundred thousand inhabitants in 2000.

Table 11 – Descriptive Statistics

	Sample I		Sample II	
Statistic	**Population**	**Immigrants**	**Population**	**Immigrants**
Mean	27,508.05	339.3	155,653.2	2,558.6
St. Dev.	27,445.140	880.259	7,836.2	4,950.7
Min	6,798	1	143,123	33
Max	183,373	26,450	169,511	26,450
N	3433	3433	28	28

Figure 9 – FPM Coefficients and Population Cutoffs



Note: FPM Coefficients are used to compute the FPM received by each municipality (decree law nº 1.881/1981). Cutoffs are represented by the vertical lines.

4.3 **Methods**

In this paper, we use the regression kink design (RKD), which is similar to the regression discontinuity design (RDD). These methods can be used when a known assignment rule determines at least in part the policy variable of interest and they consist in estimating values near to the threshold value using local polynomial regressions. The main differences between them are: in the RDD there is a discontinuity in the assignment rule and it is estimated a shift in the intercept, while in the RKD the "policy rule is assumed to have a kink in the relationship between the policy variable and the underlying assignment variable"(CARD et al., 2017) and it is estimated a shift in the slope.

We use the kink in the relationship between the policy variable (fpm received in each municipality) and the underlying assignment variable (population), to estimate the causal effect of the fpm on migration to the municipalities, the outcome variable. The fpm received by the municipalities exhibit discrete jumps, and depends on the population.

4.3.1 Identification

Let FPM denote the *fundo de participação dos municípios* (the treatment variable of interest), V the population of the municipality (the assignment variable), U the error term and $Y = y(FPM, V, U)$ the number of migrants in the municipality (the outcome

Figure 10 – Scatterplots of 2010 FPM Transfers versus Population and Cutoffs (vertical lines)

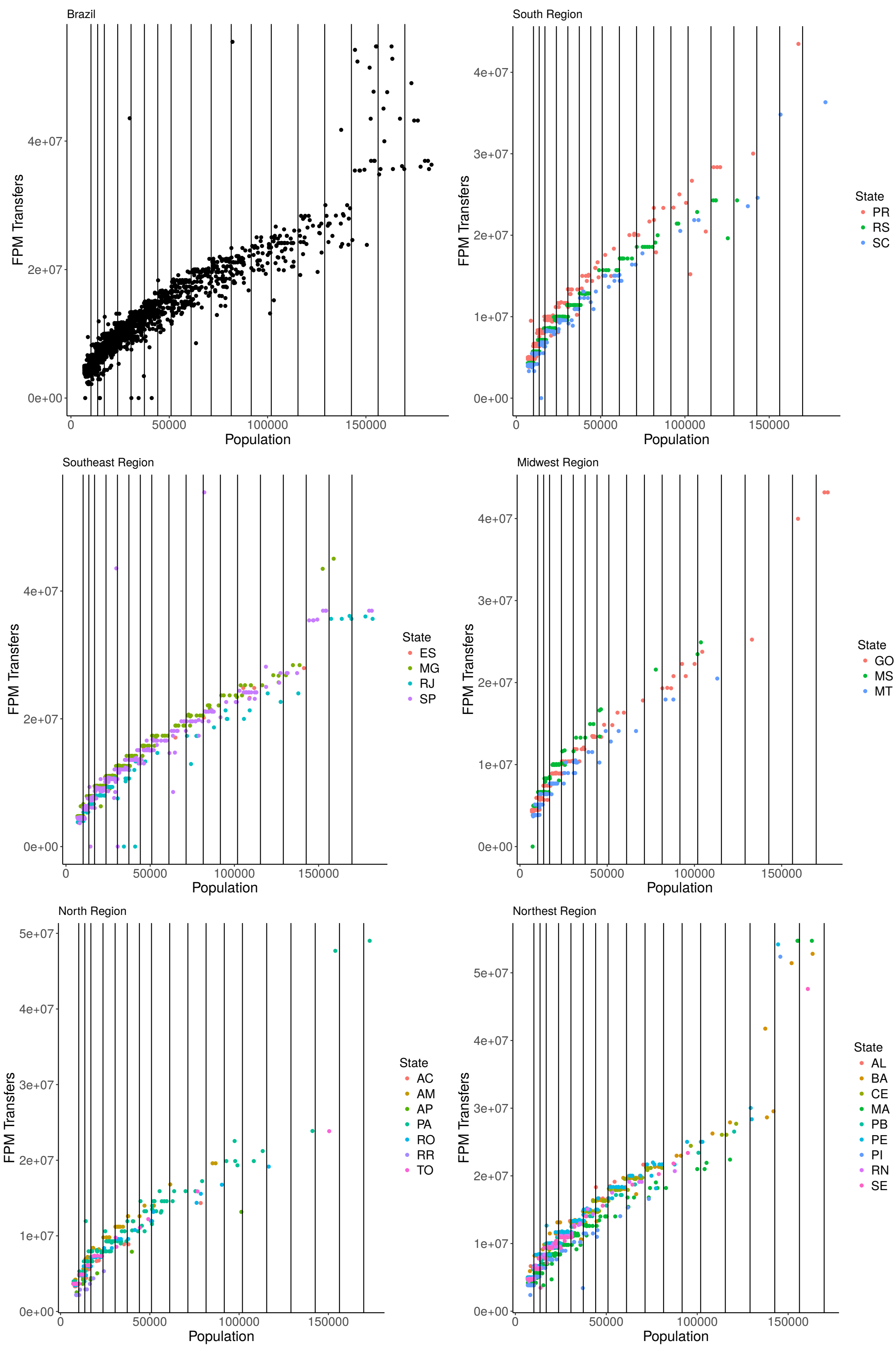
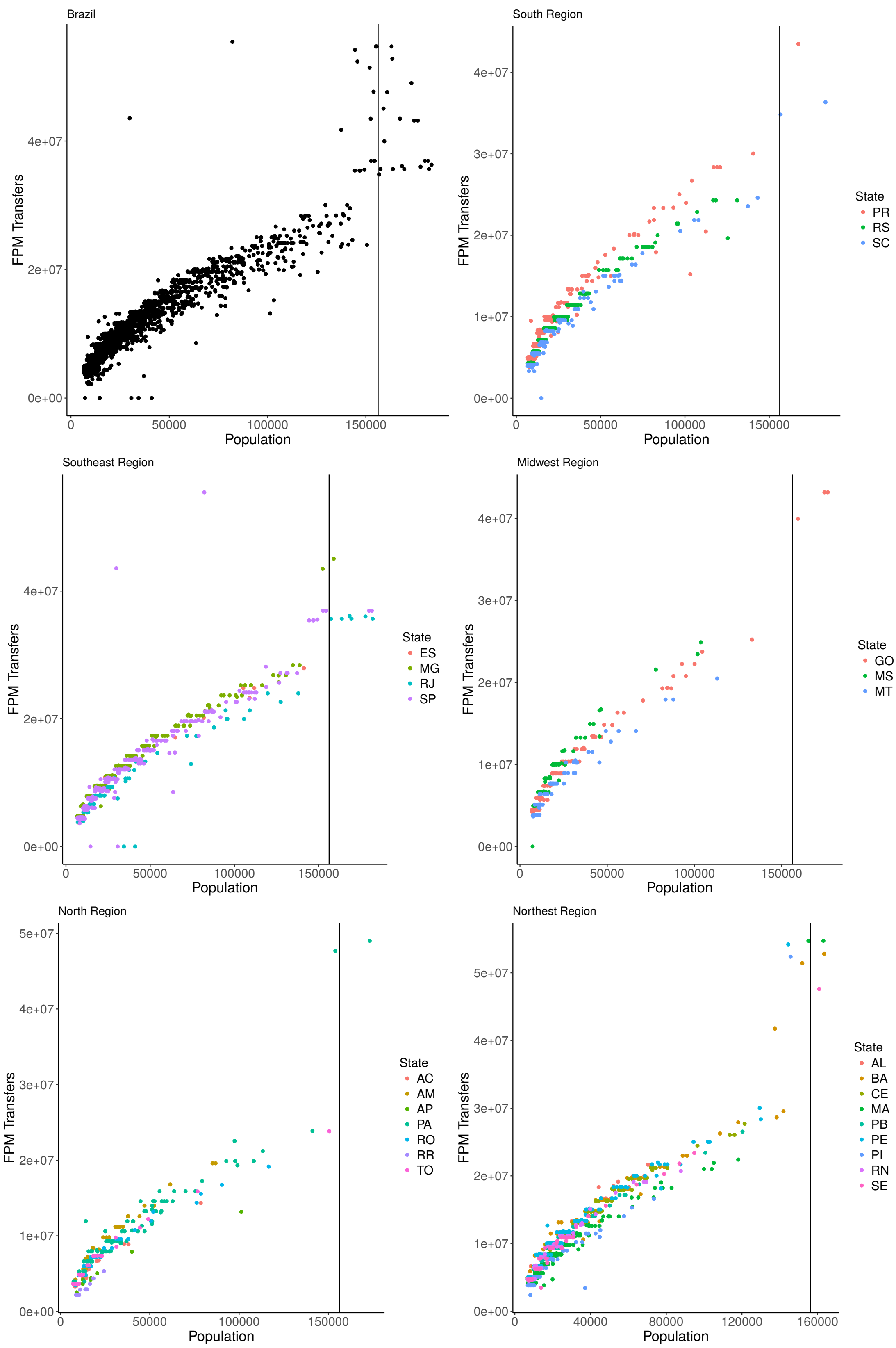


Figure 11 – Scatterplots of 2010 FPM Transfers versus Population and the 156,216 Population Cutoff (vertical line)



variable). We estimate the causal effect of an increase in FPM on Y. This effect corresponds to the partial derivative of y with respect to FPM, denoted by $y_{FPM}(FPM, V, U)$. FPM is a deterministic function of V, under the "sharp" regression kink design, i.e, $PPM = b(V)$ with a slope change (kink) at the cutoffs, shown in table 15 in tha appendix, which can be normalized to zero (CARD et al., 2017).

The main assumptions of the sharp RKD design are: first, the marginal effect of FPM must be a continuous function of the observables and the unobserved error U; second, V can affect Y, but only if its marginal effect is continuous; third, the researcher knows the function $b(V)$, and that there is a kink in the relationship between FPM and V at the threshold $V = 0$, and the density of V ís positive around the threshold for a nontrivial sub-population; and fourth, the conditional density $f_{P|U=u}(v)$ and its partial derivative with respect to v, $\frac{\partial f_{P|U=u}(v)}{\partial v}$, are continuous (CARD et al., 2015). If the kink threshold is normalized to zero, and the assumptions hold, we have:

$$\tau = \frac{\lim_{p_0 \to 0^+} \frac{dE[Y|V=v]}{dv}|_{v=v_0} - \lim_{v_0 \to 0^-} \frac{dE[Y|V=v]}{dv}|_{v=v_0}}{\lim_{v_0 \to 0^+} \frac{db(v)}{dv}|_{v=v_0} - \lim_{v_0 \to 0^-} \frac{db(v)}{dv}|_{v=v_0}} = E[y_{FPM}(b_0, 0, U)|V = 0] \quad (4.1)$$

, where $b_0 = b(0)$.

Equation 4.1 states that the average treatment effect is the slope change in the outcome variable, given by the numerator, scaled by the change in the first stage, given by the denominator(CARD et al., 2017). This treatment effect parameter is a "weighted average of the treatment effects across the population, where individuals receive higher weights for having a higher likelihood of being at the threshold (p = 0)"(CARD et al., 2017). Ando (2017) explains that the numerator of τ ís the change in the slope of the conditional expectation function $E(Y|V = v)$ at the kink point ($v = 0$) and the denominator is the change in the slope of the deterministic assignment function $b(V)$ at the kink.

Britto (2016) explained the kink relationship between the treatment and the assignment variable when it equals 50, using graphs. The left side of figure 12 shows a linear assignment rule in which individuals receive a linearly increasing level of treatment. The right side of figure 12 shows three possible effects of the treatment on the outcome variable. The line, the dashed line and the dotted line represent the cases where there is no effect, a positive effect and a negative effect of the treatment on the outcome variable, respectively, around the kink point. In summary, the effect of the treatment is captured by the change of slope in the relationship between the assignment and the outcome variables.

Figure 13 shows some features of an RKD estimator. The effect of B on Y is described as the ratio of change from the line CD (the tangent at $v \to 0^-$) to the line $C'D'$ (the tangent at $v \to 0^+$).

Figure 12 – Graphic Example RKD (Britto (2016))

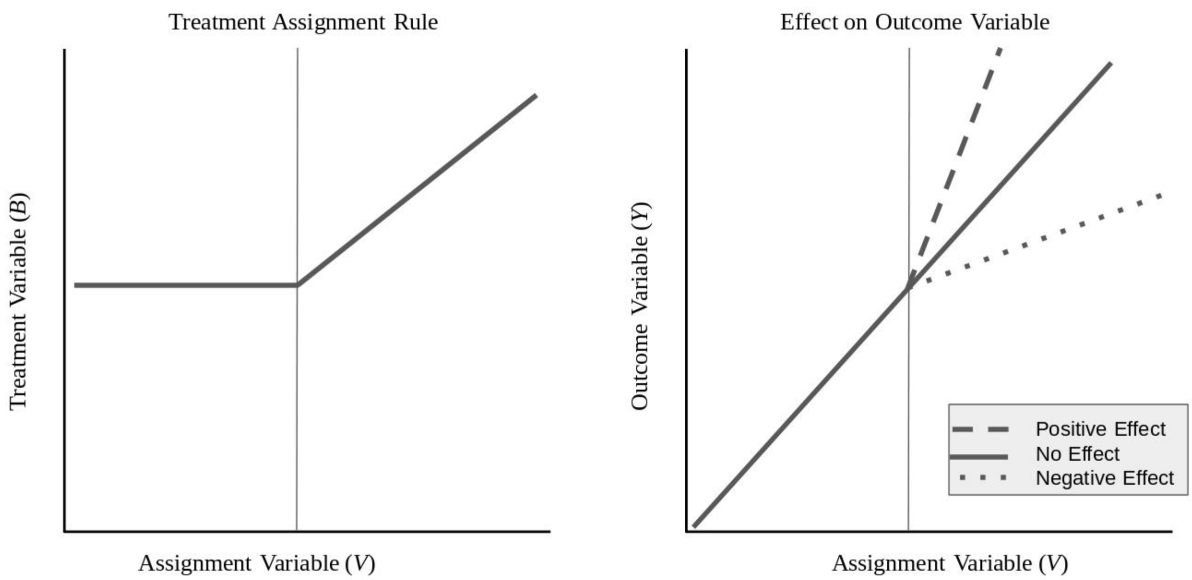
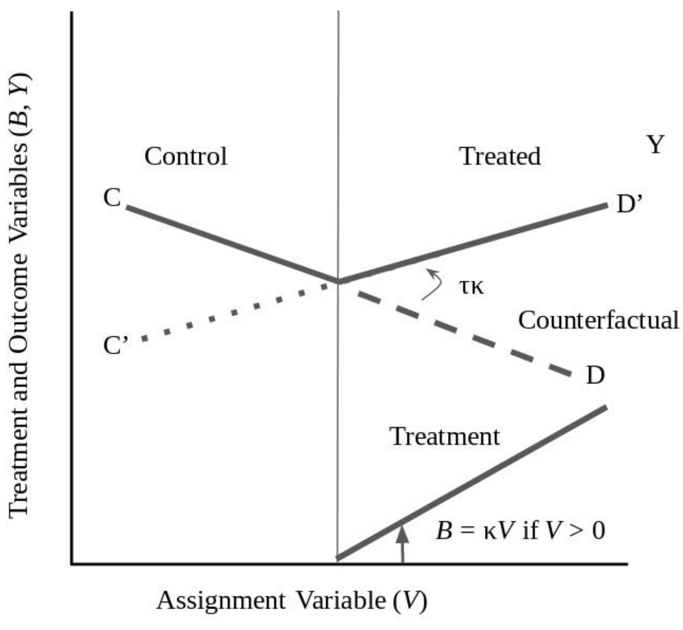


Figure 13 – Features of a the Regression Kink Design (Based on Ando (2017))



4.4 Estimation and Inference

We estimate local polynomial regressions of order p to left and the right of the kink point, with bandwidth h and kernel K, to measure kinks in the outcome and treatment variable (CARD et al., 2015). We use the triangular kernel for it is boundary optimal (CHENG; FAN; MARRON, 1997), and a direct plug-in to select the bandwidth based on a mean squared error (MSE) expansion of the sharp RD estimators to obtain a MSE-optimal bandwidth (CALONICO; CATTANEO; TITIUNIK, 2014), given by:

$$h_{MSE,p,\nu} = C_{MSE,p,\nu} n^{-\frac{1}{2p+3}}, C_{MSE,p,\nu} = \left(\frac{(1+2\nu)V_{\nu,p}}{2(p+1-\nu)B^2_{\nu,p}} \right)^{\frac{1}{2p+3}} \tag{4.2}$$

The fuzzy RKD estimator is defined as

$$\hat{\tau} = \frac{\hat{\beta}_1^+ - \hat{\beta}_1^-}{\hat{\kappa}_1^+ - \hat{\kappa}_1^-}, \tag{4.3}$$

where $\hat{\kappa}_1^+$ and $\hat{\kappa}_1^-$ are the first-stage slope estimators above and below the threshold. $\hat{\beta}_1^+$ and $\hat{\beta}_1^-$ denote the outcome slope estimators. The sharp RKD estimator is a special case in which $\hat{\kappa}_1^+$ and $\hat{\kappa}_1^-$ are equal to the known slopes in the first stage: $\hat{\kappa}_1^+ = \lim_{p\to 0^+}$ and $\hat{\kappa}_1^- = \lim_{p\to 0^-}$.

4.5 Results

In this section we present the results of the estimation of the effect of FPM transfers on immigration in Brazilian municipalities. Another objective of this section is to test the validity of the estimates of these effects. We check the validity of the identifying assumptions, by performing the density test suggested by McCrary (2008). We check the robustness of the results by performing a placebo test, changing the true cutoffs given by the the Federal Decree 1,881/81 for fake ones created by using the midpoint between two nearest cutoffs.

4.5.1 Effect of FPM transfers on Immigration

The right side of table 12 shows the RKD estimates using data of sample I, which consists of municipalities with less than $183,373$ and more than $6,796$ inhabitants. We found positive effect of FPM transfers on Immigration, so near the cutoffs an increase in FPM transfers has a causal relationship of changing the slope of the line that relates population and immigration by 0.013 on average across all cuttoffs, according to the bias corrected RKD estimator. The causal effect is significant but small.

The left side of table 12 shows the estimates using data of sample II, which consists of municipalities with between $143,123$ and $168,511$ inhabitants. The effect of the increase in intergovernmental transfers a change in the slope of the line that relates population and immigration by 6.238.

Mata (2014) main result is that *per capita* FPM in 1982 has an negative impact on housing markets during the 1980 decade. The increase in *per capita* FPM transfers by R$ 100 is associated with a 2.2 percent decrease in housing growth. The results also show evidences of a similar impact of FPM *per capita* on population growth between 1980-1991.

Table 12 – RKD estimates of Immigration Responses to FPM Transfers in 2010

	Sample I		Sample II	
	Estimate	**Bandwidth**	**Estimate**	**Bandwidth**
τ_{standard}	0.007	6356.236	1.785	4109.311
	(0.002)		(1.292)	
$\tau_{\text{bias corrected}}$	0.013	5894.150	6.238	6042.689
	[0.0048]		[3.982]	
N	3433		28	

Note: Standard errors for the estimates are in parentheses and robust standard errors are reported between brackets. The dependent variable is number of immigrants during the period from 2009 to 2010. The running variable is population size. Sample I comprises municipalities with between 6792 and 183384 inhabitants, and with cutoffs given by table 15. Sample II comprises municipalities with between 142632 and 169800 inhabitants, and the cutoff is $156,216$ inhabitants.

The impact on immigration, measured by the population growth, is similar, because there is a great correlation between housing growth and population growth in Brazil.

Figure 14 shows the RKD evidence of the effect of FPM transfers on immigration. This figure shows the relationship between the number of immigrants arriving in a municipality during 2010 and its population in 2010 around the kink $156,216$. The sharp change in the slope of this relationship provides supportive evidence for the effect of FPM transfers on the number of immigrants arriving in a municipality.

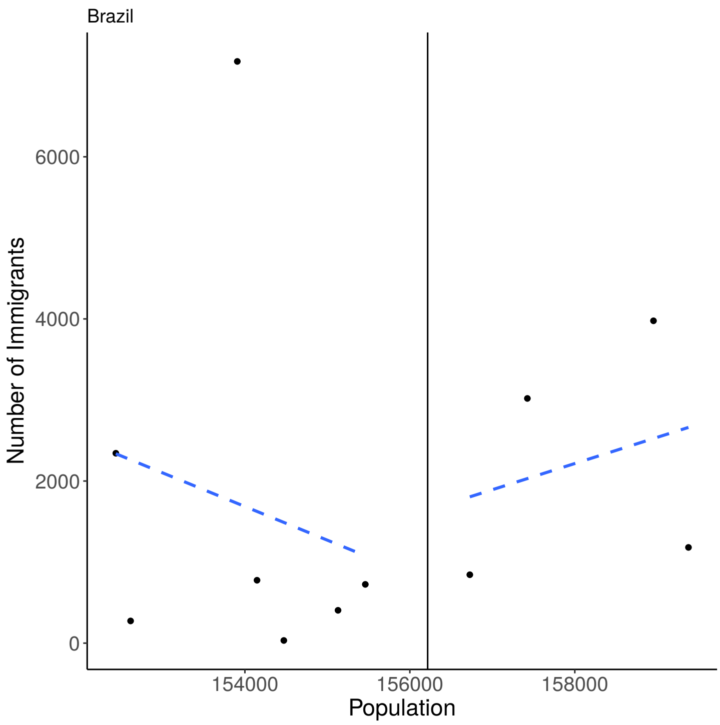
We noted that the sample II size is small, when compared to sample I. This is due to the fact that in Brazil most of municipalities have less than 100,000 inhabitants. The total number of cities in Brazil is above 5,000, but only a little more than 300 have a population above 100,000 inhabitants.

4.5.2 Robustness checks

When we apply fake population cutoffs (midpoints between real population cutoffs) into the RKD estimator in sample I, we find that the effect decreases from 0.013 to 0.0044. This result is significant but is very small (see table 13). Therefore we conclude that the estimates in sample I does not pass this robustness check, although the estimates are nearly zero.

Next we perform this robustness check on sample II, by choosing two fake cutoffs. The first one is the midpoint between the $142,632$ and the $156,216$ cutoffs. The second one is symmetric to the first and is $163,008$. The estimates were not significant, therefore we conclude that the estimates of the causal effect of FPM transfers on immigration are robust when we use data from sample II.

Figure 14 – RKD Evidence of the Effect of FPM Transfers on Immigration



Note: The graph shows evidence of a kink in the relationship between population size and number of immigrants (the outcome) at the threshold. The dashed lines show the predicted values of the linear regressions with a discontinuous shift.

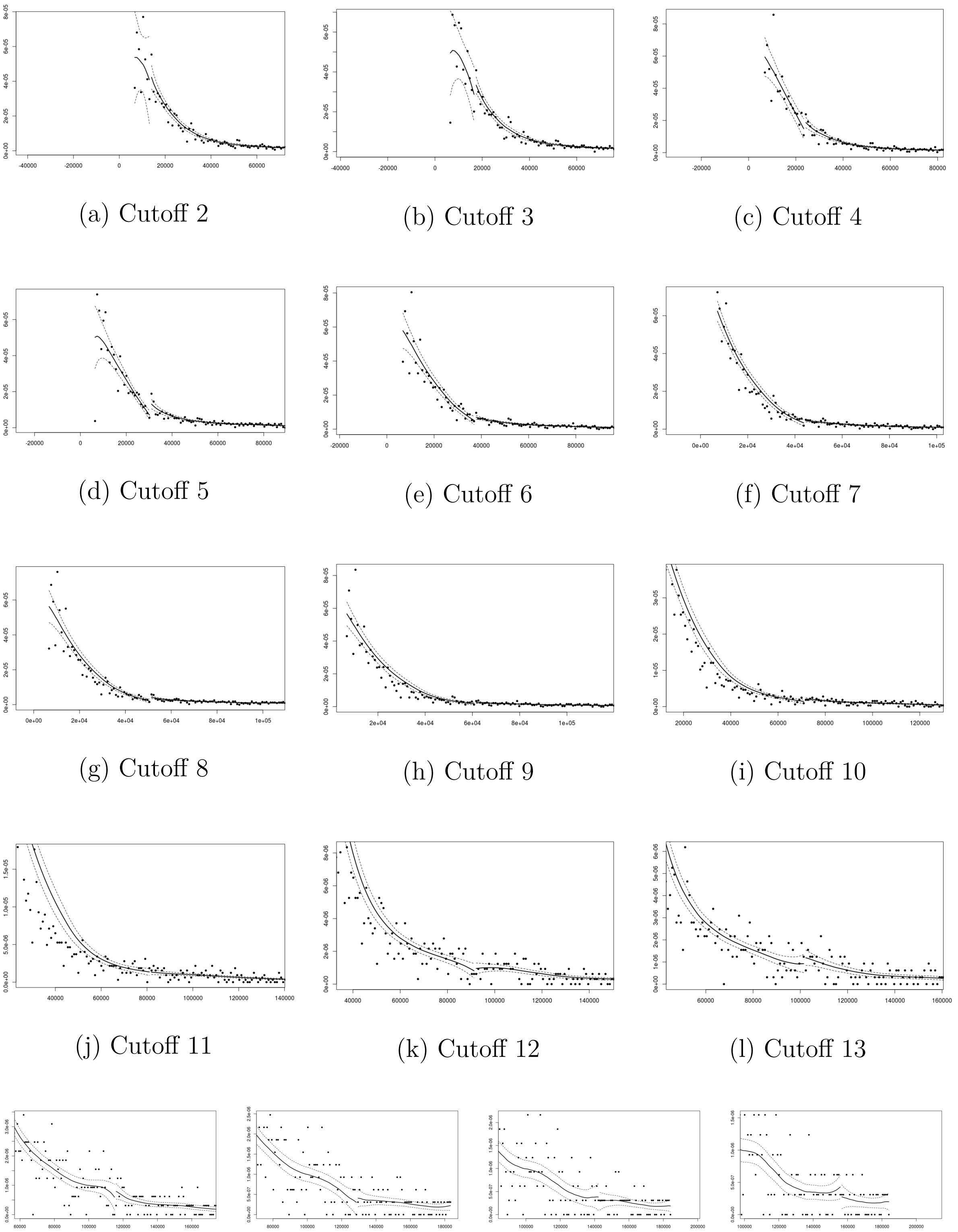
Table 13 – Placebo Test Effects of FPM Transfers on Immigration using Sample I

	Fake Thresholds			
	Estimate	**Bandwidth**	**CI Lower**	**CI Upper**
τ_{standard}	0.004290435	6024.789	0.0018	0.0067
	(0.001244155)			
$\tau_{\text{bias corrected}}$	0.004481519	7279.803	0.002	0.0069
	[0.002973216]			
N	3433			

Note: Standard errors for the estimates are in parentheses and robust standard errors are reported between brackets. The dependent variable is number of immigrants during the period from 2009 to 2010. The running variable is population size. True thresholds are given in table 15. Fake thresholds are the midpoint between the real population thresholds.

Finally, we perform the density test proposed by McCrary (2008) to verify potential discontinuities of the conditional expectation of counterfactual outcomes in the running variable. This test fails if agents are able to manipulate the running variable. In our case the agents are the municipalities. Figure 15, in the appendix, shows the density estimates for all 17 cutoffs, except cutoff 1 (see a more complete explanation in the figure note). In the figure there are no clear discontinuities.

Figure 15 – McCrary Density Tests



(a) Cutoff 2 (b) Cutoff 3 (c) Cutoff 4

(d) Cutoff 5 (e) Cutoff 6 (f) Cutoff 7

(g) Cutoff 8 (h) Cutoff 9 (i) Cutoff 10

(j) Cutoff 11 (k) Cutoff 12 (l) Cutoff 13

(m) Cutoff 14 (n) Cutoff 15 (o) Cutoff 16 (p) Cutoff 17

Notes: The density test is described in McCrary (2008). The data on population is from the 2010 Brazilian Census. The cuttofs are given by the FPM distribution rule - comprising 17 population cutoffs - described in the Federal Decree 1,881/81. The test could not be performed on the first cutoff, for it is too low with respect to the data.

Table 14 – Placebo Test Effects of FPM Transfers on Immigration using Sample II

	Fake Thresholds			
	Threshold I (149424)		Threshold II (163008)	
	Estimate	**Bandwidth**	**Estimate**	**Bandwidth**
τ_{standard}	-0.421	5105.861	-1.339	8303.681
	(1.106)		(1.584)	
$\tau_{\text{bias corrected}}$	-0.593	9536.976	-1.953	14236.777
	[1.848]		[2.451]	
N	28		28	

Note: Standard errors for the estimates are in parentheses and robust standard errors are reported between brackets. The dependent variable is number of immigrants during the period from 2009 to 2010. The running variable is population size. True threshold is 156216. Fake threshold I is the midpoint between $156,216$ and $142,632$, and fake threshold II is the midpoint between $156,216$ and $169,800$, the real population thresholds.

4.6 Conclusion

The municipalities with more than $156,216$ inhabitants receive more transfers than municipalities below this cutoff, and the difference is on average R\$ $252,708.00$ in 2010 currency units. We found that intergovernmental transfers to these municipalities cause an increase in the number of immigrants arriving in them. This result is consistent with the the findings of Litschig and Morrison (2013), for they concluded that intergovernmental transfers cause an increase in schooling *per capita* and in literacy rates. Thus these municipalities end-up attracting more people. We check the robustness of our results by performing several tests. Our results shows that when in focus on the first cutoffs, the effect of FPM on immigration is very small, but statistically significant.

Our results differ from those found by Mata (2014), for we use a very different data set. We use data on RAIS/MIGRA, while he uses data on population growth to calculate the number of immigrants in each municipality. He uses data from the municipalities of the state of *São Paulo*, while we use data from municipalities in all states of Brazil. Our data contains only immigrants who were formal workers in 2009 and 2010. We could find accurately the municipality where they were working in 2009, then we identified where they were working in 2010. With these data we could calculate how many immigrants each municipality received in 2010.

One limitation of this paper is that we use a sharp RKD estimator, while most authors use a fuzzy RDD estimator to study the causal effect of FPM transfers on the outcome variable. Litschig and Morrison (2012) uses discontinuities in the FPM transfers around the first three population cutoffs, over the period 1982-1985 to estimate the impact of transfers on re-election probability and per *capita* government spending using a sharp

RDD estimator. We decided to follow Litschig and Morrison (2012) because it is much simpler than to create a variable to measure theoretical transfers, compere between this measure and the actual transfer and decide which municipalities are not complying to the decree law, since the values transferred depend on state data, so it is very difficult to create reliable values for the theoretical transfers.

In this paper we used the robust regression kink design estimator proposed by Calonico, Cattaneo and Titiunik (2014). To our knowledge, this is the first paper to estimate the impact of FPM transfers on immigration using data from RAIS/MIGRA and the regression kink discontinuity design. We hope that in the near future, several other variables that have a causal relationship with FPM transfers can be identified.

Appendix

Table 15 – FPM Coefficients

Population	FPM Coefficient
10188	0.6
13584	0.8
16980	1
23772	1.2
30564	1.4
37356	1.6
44148	1.8
50940	2
61128	2.2
71316	2.4
81504	2.6
91692	2.8
101880	3
115464	3.2
129048	3.4
142632	3.6
156216	3.8

Note: FPM Coefficients are used to compute the FPM received by each municipality (decree law nº 1.881/1981)

5 CONCLUDING REMARKS

In the first paper we decomposed the wage gap in Brazil between whites and non-whites, and males and females using the reweighing and recentered influence function regressions and the counterfactual analysis. The wage discrimination between males and females does not present sharp variations across the quantiles of the wage distribution. It is greater in the 90th quantile of the wage distribution. Our results suggest that gender discrimination is not generalized to all activities, since activity is the main component of the unexplained effects. We also found evidences that gender discrimination is very small in north and northeast regions, and it is greater in the other regions.

Brazil is one of the most unequal countries in the world. Racial and gender discrimination may be important factors contributing to this inequality. Although some policies are being created to reduce the inequality of opportunity - in 2004 the Universidade Federal de Brasília was the first public university to adopt a quota system to increase the number of non-whites students - there are many more actions to be implemented to reduce the discrimination and inequality that are present in every region of this country. Bertrand and Mullainathan (2003) argue that training alone may not be enough to alleviate the barriers raised by discrimination, since blacks living in the U.S. with the same qualification as whites, have a lesser probability of receiving callbacks for interviews, after responding to help-wanted ads. We hope that the insights on the subject provided by the first paper may stir up the debate about discrimination, so that non-whites may have the same access to education, job interviews, and receive the same return to education and experience as whites, in a near future.

In the second paper we use data of the emigration of workers to estimate the impact of immigration on wages of immigrants. Using a semi-parametric DID estimator proposed by Athey and Imbens (2006), we found that immigration caused a reduction of 13% in the long-run and short-run wages of immigrants. The effects vary across the regions of Brazil, being greater in the Midwest and Southeast regions, and very small and insignificant in other regions.

Our paper made some contributions to the literature on immigration. We adjusted the wages by the different living costs of the regions, prior to analyzing the effects of the immigration of wages, using the living cost estimates of Almeida and Azzoni (2016) for eleven metropolitan regions of Brazil. We used one of the most efficient estimation strategies, for according to McKenzie, Gibson and Stillman (2010), the difference-in-differences and bias-adjusted matching estimators perform best among the alternatives to instrumental variables, which is the ideal method to achieve the objectives of this paper, but it is very difficult to find a situation in which occurred a random selection of immigrants in the Brazilian regions, similar to the random selection of immigrants that occurred in New Zealand.

In the third paper we explained that the municipalities with more than $156,216$ inhabitants receive more transfers than municipalities below this cutoff, and the difference is on average R\$ $252,708.00$ in 2010 currency units. We found that intergovernmental transfers to these municipalities cause an increase in the number of immigrants arriving in them. This result is consistent with the the findings of Litschig and Morrison (2013), for they concluded that intergovernmental transfers cause an increase in schooling *per capita* and in literacy rates. Thus these municipalities end-up attracting more people. We check the robustness of our results by performing several tests. Our results shows that when in focus on the first cutoffs, the effect of FPM on immigration is very small, but statistically significant.

One limitation of the third paper is that we use a sharp RKD estimator, while most authors use a fuzzy RDD estimator to study the causal effect of FPM transfers on the outcome variable. Litschig and Morrison (2012) uses discontinuities in the FPM transfers around the first three population cutoffs, over the period 1982-1985 to estimate the impact of transfers on re-election probability and per *capita* government spending using a sharp RDD estimator. We decided to follow Litschig and Morrison (2012) because it is much simpler than to create a variable to measure theoretical transfers, compere between this measure and the actual transfer and decide which municipalities are not complying to the decree law, since the values transferred depend on state data, so it is very difficult to create reliable values for the theoretical transfers.

In the third paper we used the robust regression kink design estimator proposed by Calonico, Cattaneo and Titiunik (2014). To our knowledge, this is the first paper to estimate the impact of FPM transfers on immigration using data from RAIS/MIGRA and the regression kink discontinuity design. We hope that in the near future, several other variables that have a causal relationship with FPM transfers can be identified.

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