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Essays in Applied Economics: Inequality and Voting Decision in Brazil

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BERNARDO DANTAS PEREIRA COELHO

"ESSAYS IN APPLIED ECONOMICS: INEQUALITY AND VOTING DECISION IN BRAZIL"

Tese apresentada ao Curso de Doutorado em Economia da Escola de Pós-Graduação em Economia para obtenção do grau de Doutora em Economia.

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Resumo

Essa tese contém três capítulos. O primeiro capítulo estuda a relação entre o programa brasileiro de transferência condicional de renda Bolsa Família e os resultados das eleições de 2010. Nós procuramos estimar esse efeito utilizando uma abordagem estrutural, identificando características individuais que afetam o impacto eleitoral do programa. Fazemos isso utilizando um modelo mixed logit, um modelo de escolha discreta que considera tanto a distribuição paramétrica de variáveis não observadas quanto a distribuição não-paramétrica de variáveis conhecidas. Resultados indicam que o caráter redistributivo do programa possui um impacto eleitoral nos eleitores maior do que os ganhos individuais de renda dos beneficiários. O efeito marginal de ser um beneficiário do programa na decisão de voto é equivalente a um aumento de 81 reais na renda mensal do trabalho, menos do que o valor médio recebido por beneficiário que é de 90 reais. Nosso exercício contrafactual aponta que, sem o programa Bolsa Família, a incumbente, Sra. Rousseff, perderia 5,6% do total de votos, deixando o resultado da eleição inconclusivo.

O segundo capítulo estuda a participação feminina na política, que aumentou na última década tanto em países ricos como em desenvolvimento. Não é claro, no entanto, se isso é parte de uma tendência ou apenas um crescimento reversível. A literatura apresenta argumentos teóricos tanto para um efeito de reforço quanto para um negativo da exposição a uma liderança negativa na probabilidade de apoio futuro a uma candidata mulher. Usando dados eleitorais e do Censo para o Brasil, testamos se o efeito da presença de uma prefeita mulher numa cidade impacta o apoio futuro a candidatas mulheres para Deputada Federal e não encontramos evidência de efeito significativo. Além disso, mostramos que apenas o uso de estatísticas agregadas, como médias demográficas, levaria a concluir equivocadamente que eleitores expostos ao governo de uma prefeita mulher teriam uma menor probabilidade de votar numa candidata mulher.

O último capítulo investiga os determinantes para a queda de desigualdade de renda entre municípios brasileiros entre 2000 e 2010. Usando dados censitários, mostramos que a desigualdade caiu mais rápido em municípios com um maior nível de desigualdade em 2000 – sugerindo β-convergência. Nós então, utilizamos a decomposição dinâmica (Shorrocks, 1982) para identificar a contribuição de mudanças nas condições do mercado de trabalho, como aumento do salário mínimo, formalização e melhoria na educação na convergência de desigualdade regional. Encontramos que a queda na desigualdade de renda no emprego

formal foi o principal contribuinte para a redução de desigualdade de renda entre municípios no período.

Abstract

This thesis contains three chapters. The first chapter studies the relationship between the Brazilian CCT program *Bolsa Família* and the outcome of the 2010 elections. We seek to estimate this effect using a structural approach, identifying individual characteristics that affect the electoral impact of the program. We do so by using a mixed logit model, a discrete choice model that considers both a parametrical distribution of unobserved variables and a non-parametrical distribution of known variables. Results indicate that the redistributive character of the program has a larger electoral impact on voters than the individual income gains of the beneficiaries. The marginal effect of being a beneficiary of the program on voting decision is equivalent to 81 Reais increase in monthly labor income, less than the average value received by a beneficiary, which is 90 reais. Our counterfactual exercise points that, without *Bolsa Família*, the incumbent, Mrs. Rousseff, would have lost 5.6% of the votes, making the election results unclear.

The second chapter studies female participation in politics has increased in the last decade in both rich and developing countries. It is not clear, however, if this is part of a trend or just a reversible growth. Literature presents theoretical arguments for both a reinforcing force and a negative effect of the exposure to a female leadership on the probability of supporting a future female candidate. Using electoral and Census data for Brazil, we test the effect that the presence of a female mayor in a municipality has on future the support for a female candidate for Federal Deputy and find no evidence of a significant effect. Furthermore, we show that the use of aggregate statistics alone, as demographic averages, would mislead us to conclude that voters exposed to a female mayor have a smaller probability to support a female candidate.

The last chapter investigates the determinants of the decline of income inequality across municipalities in Brazil between 2000 and 2010. Using censuses data, we show that inequality fell faster in municipalities with higher inequality levels in 2000 – suggesting β-convergence. We, then, employ a dynamic decomposition (Shorrocks, 1982) to assess the contribution of changes in private labor market conditions as the increase in minimum wage, formalization and increase in education levels on the regional inequality convergence. We find that the fall in wage inequality in the private formal sector was the main driver of the reduction in income inequality across municipalities in the period.

Sumário

Capítulo 1

Electoral impact of Conditional Cash Transfers programs: The Bolsa Família experience

1. Introduction

Conditional Cash Transfer (CCT) programs expanded during the late 90's and 2000's as an attempt to decrease poverty and inequality.[1] Due to the direct cash transfer to particular groups, such programs have been questioned about their potential electoral motivation. This article's objective is to answer three questions: What is the size of the impact of a CCT program on the election outcome? Which individual characteristics relates to CCT electoral impact? How this impact compares with other political determinants?

In order to accomplish this objective, we analyze the Brazilian CCT program, *Bolsa Família*, which is often described as the largest in the world in number of beneficiaries (Loureiro, 2012). We study the case of 2010 Brazilian presidential election, which presented a geographical division correlated[2] with the size of the *Bolsa Família* program in the county, as shown by Figure 1, which depicts Mrs. Rousseff support on the runoff of 2010 elections and Bolsa Família coverage by Brazilian county. Political scientists (Zucco, 2008; Rennó and Peixoto, 2011; Hunter and Power, 2007) offer many explanations for this division, among them is the influence of *Bolsa Família*. This study attempts to further understand this division by analyzing not only the municipal coverage of the program, but the individual characteristics of the electors in each Brazilian county.

[1] Examples of programs are: Female Secondary School Assistance Project, established in 1994 in Bangladesh; Chile Solidario in 2002; Oportunidades/Progresa, in Mexico 2002; Program Minhet El-Osra, Egypt 2009; Şartlı Nakit Transferi (ŞNT) in Turkey 2003 and Bolsa Família in Brazil, 2003.
[2] Correlation between the two variables is of 0.72.

Figure 1 **- Election results and Bolsa Família coverage by municipality**

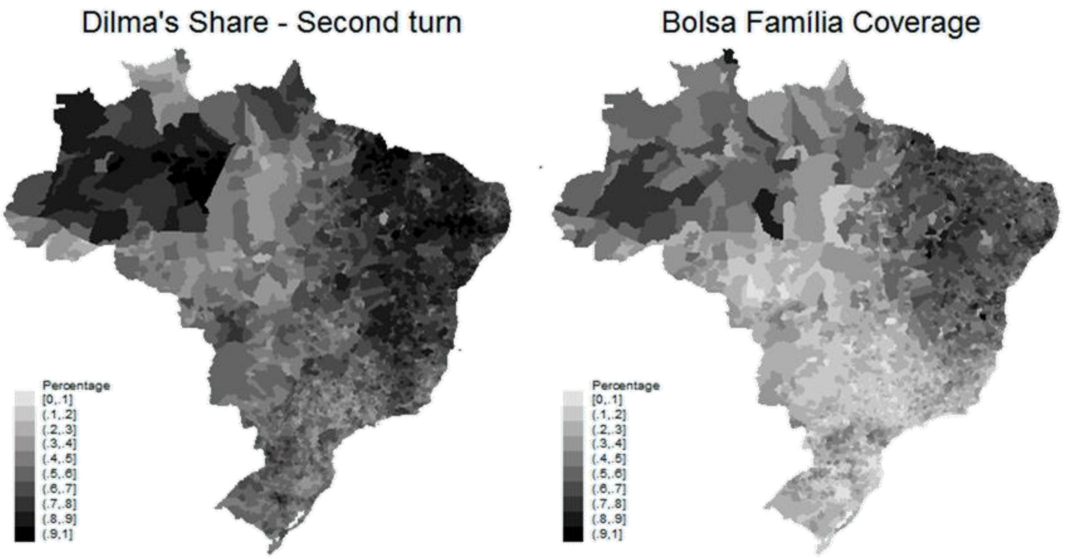

Figure presents the correlation between the electoral support of the incumbent candidate in the runoff of the 2010 elections and the coverage of the *Bolsa Família* program. North and Northeast regions, which are poorer and have larger *Bolsa Família* coverage, supported the government candidate, Mrs. Dilma Rousseff. Southern parts of Brazil, which are richer, majorly supported the opposition candidate - A pattern already observed in the 2006 elections.

While trying to measure the electoral impact of the Bolsa Família program we take part in a literature that seeks to identify the electoral impact of CCT programs. There is a vast discussion on the mechanism in which this impact would happen. Part of the literature argues that a welfare program that reduces inequality offers opportunity for incumbent propaganda (Pierson, 1996; Hunter and Power, 2007). Another fraction has a different vision and believe that such programs perpetuate a clientelism linkage and that voters may even vote against their preferences due to fear of ending of the program (Cornelius, 2004; Schedler, 2000). Another strand argues that the incumbent benefits from a mobilizing effect, which swings support from voters who have preferences for redistribution (De la O, 2010; Peixoto and Rennó, 2011). Analysis of worldwide experiences of CCT programs include, for example, Mexico (De la O, 2013; Cornelius, 2004; Schedler, 2000), Uruguay (Manacorda et al., 2011), Philippines (Labonne, 2013), Colombia (Nupia, 2011), and Turkey (Aytac, 2014).

The Brazilian experience with the *Bolsa Família* program has been previously studied with different approaches. When analyzing electoral literature, the first problem that arises is the natural absence of individual data. Votes are secret and because of that we can only have access to aggregate voting counts, which is one way to deal with the absence of individual observations. The other approach literature uses to solve this limitation is the use of individual data through surveys, as in Zucco (2013, 2015) and Zucco et al. (2016). Using both survey and aggregate data, the author finds evidence supporting the electoral influence of CCT programs, but more in the short than in the long run (Zucco, 2013). However, the use

of survey data can lead to estimation impacts much different from the models using aggregate data (Zucco, 2015), which can either be due to some restriction in survey data or to individual characteristics not captured by models that only use aggregate data.

One important advantage the use of survey data has over aggregate information is the possibility to test the mechanism of the electoral impact of CCT programs. For example, Zucco et al. (2016) identifies that, unlike assumed by the literature (Fiszbein et al., 2009; Lavinas et al., 2014), conditionality is not necessarily linked to the program acceptance by non-beneficiaries, although the authors find this link to be true for better-off individuals. The use of survey data, however, has some issues well known in literature (Selb and Munzert, 2013). One major problem with survey data is the possibility of untruthful answers, especially in cases when supporting one candidate is not broadly accepted, as was the case of Trump supporters in the 2016 U.S. election (Klar et al., 2016). Another concern is about the surveys' representativeness as surveys are, in general, applied in a restrictive region. In this paper we use data from Brazilian Census, which has the advantage of covering all Brazilian counties.

Working with aggregate data, however, does not solve all issues. Canêdo-Pinheiro (2015) observed two common methodological problems. Linear models are, in general, misused in this literature – both when using surveys and aggregate data – because the dependent variable of econometric models usually is the percentage of votes a candidate has in a region. Hence the range of the values is [0,1] while most linear models assume that the dependent variable is not limited, it may assume values in the range (-∞, ∞). The second problem is the aggregation bias, which can be defined as the inference error of individual choices from aggregate statistics. This error arises from individual heterogeneity, not contemplated by aggregate variables and may generate biased results. This problem is well documented by Stoker (1993) and Lourenço (2009). Pinho Neto and Machado (2017) mitigate the aggregation bias by analyzing data as disaggregated as possible, in the polling booth level. The authors use information on the percentage of Bolsa Família beneficiaries per booth and compare the results of different sessions in the same polling place, using fixed effects control for polling place.

In this paper we propose to solve the aggregation problem with the use of a structural econometric model. We estimate a mixed logit model by adapting BLP framework to consumer demand (Berry, Levinsohn and Pakes, 1995), in which consumer (voters) chose between products (candidates) from different firms (parties) in different markets (electoral districts). The Mixed logit model has the advantage to allow heterogeneous parameters, as

voters have individual preferences for observed and unobserved candidate characteristics and for abstention. Individual preferences are linked to aggregate votes and demographic variables, so that estimating the model allow for recovering the voters' indirect utility. At the same time, the use of the logit form solves the misuse of linear models, while incorporating individual data mitigates aggregation bias. Although we are not the first article to use a mixed logit model in the electoral context (Lourenço, 2009; Glasgow, 2001), we are, to the best of our knowledge, the first to incorporate individual data, and thus the cross effect, on the estimation of CCT electoral impact.

By incorporating the cross effect of individual variables on municipal characteristics, we are able to estimate how individual characteristics relate to the expansion of the *Bolsa Família* across municipalities. For example, we are interested in testing how individuals' labor income affect the probability of rewarding electorally the incumbent due to an increase in the *Bolsa Família* municipal coverage and, by doing so, identify if this effect is different between richer and poorer individuals.

Using the estimates, we are able to compare the marginal impact of characteristics such as labor income and being a Bolsa Família beneficiary on the probability of supporting the incumbent candidate. Individual parameters estimates also allow for counterfactual exercises in which we estimate incumbent voting shares in a scenario without *Bolsa Família*.

In our estimations, to avoid the possibility of endogeneity due to being a beneficiary of the program being correlated with the error term, we instrumentalize the Bolsa Família coverage using two different instruments based on the percentage of families eligible for the program.

The reason we study the 2010 elections is due to availability of data. Brazilian Superior Electoral Court provides voting shares of each candidate for very small levels of geographical aggregation. *Bolsa Família* coverage and individual characteristics, on the other hand, are available only at the municipal level, using the Brazilian Census (*Censo*) database. Being an expensive research, the *Censo* is only realized every ten years.[3] 2010 is, therefore, a year in which both presidential election and Census data are available.

Our estimations using the mixed logit model for the second ballot of the 2010 elections show that the coverage of *Bolsa Família* at the municipal level is positively associated

[3] The last five times the Census was researched was in 1970, 1980, 1991, 2000 and 2010. Due to lack of resources the Census expected to be realized in 1990 was postponed to the following year.

with voting shares of Mrs. Rousseff. Furthermore, the cross effect between Bolsa Família coverage and labor income suggests that the impact of the program is decreasing with individual income. This result indicates that aggregate models, limited to the use of average income, underestimate the electoral impact of the *Bolsa Família* program.

The counterfactual exercise of estimating the electoral shares of Mrs. Rousseff in a scenario without *Bolsa Família* indicates a reduction of 6.3% of total votes. In absolute numbers, this represents 6.2 million votes. In this scenario, President Rousseff would have 49.8 percent of the total valid votes on the runoff voting,[4] making the final election outcome unclear. The counterfactual results sheds light on the importance of incorporating individual information, as the same exercise applied on linear models using only aggregate data suggest a reduction of up to 2.45 percentage points.

Another form of measuring the electoral impact of the program is to analyze the marginal impact of both the *Bolsa Família* coverage and the individual receiving benefit from the program. *Bolsa Família* coverage marginal impact indicates the increase in probability of voting for Mrs. Rousseff as a result of the increase in 1% of the average coverage in all counties. The latter, regarding individual receiving cash transfers from the *Bolsa Família*,-indicates the changes on the probability of supporting Mrs. Rousseff if the individual has a beneficiary in the family. Our results indicate that, on average, an increase in 1% of *Bolsa Família* coverage among all counties increase support for Mrs. Rousseff by 0.14%. Furthermore, by comparing the marginal effect of being a beneficiary with the marginal impact of individual wages, we find that the value of the additional labor income required to have the same electoral impact of being a beneficiary of the program is 81 reais, less than the average *Bolsa Família* transfer of 90 reais.[5]

The main contribution of the paper is to incorporate individual data, and thus individual heterogeneity, into the literature that measures the electoral impact of CCT programs.

After this introduction, chapters 2 and 3 describes, respectively, the data and methodology used in this article. The analysis of our estimations' results are presented on the fourth chapter. Finally, chapter 5 presents our final remarks.

[4] The votes in the opposition and the null votes would represent the remaining 50.2 percent.
[5] Source: MDS (*Ministério do Desenvolvimento Social*) Brazilian Ministry of Social Development and Fight against Hunger.

2. Data

Bolsa Família is a conditional cash transfer program, founded by president Luiz Inácio Lula da Silva, from the Labor Party (PT), in 2003. The program started by combining five existing programs that provided different aid varying from education support like *Bolsa Escola* program to gas subsidies like *Auxílio Gas*. These existing programs – created by the previous president Fernando Henrique Cardoso, from the Brazilian Social Democracy Party (PSDB) – were relabeled, largely expanded through the following years and became one of the main propaganda of president Lula's government.

The program is considered to be one of the most successful conditional cash transfers programs in the world due to the large number of families covered. When created, it provided financial aid to 3.6 million families. This number rose to 11 million by 2006, reached 12.8 in 2010. By 2013 it reached its peak at 14.1 million families and since them fell to 13.8 million in 2015.[6]

Due to the relevance of the program, the number of families affected and the large propaganda from the Labor Party, the *Bolsa Família* political impact is debated since the 2006 elections. The data used in this article will come from two databases, as one of the main characteristics of the methodology used is to use distribution of individual data to estimate aggregate electoral shares, hence we use a database with municipality characteristics (electoral database) and one with individual information (demographic database).

Table 1, presents summary information for both datasets. The first five variables present information of each of the 5,564 municipalities in the electoral database. For the Census database, the first variable is the percentage of families eligible for the Bolsa Família program, a municipal information. While the last seven variables summarize the sample of 20,635,472 observations from the demographic database. Electoral and demographic databased were summarized using, respectively, weights of the municipality share in the election and individual weight in the Census database.

This paper decision of focusing on the 2010 elections is given by the combination of a presidential election year with the availability of data from the Brazilian Census database, the *Censo Demográfico* (here after, *Censo).* The main advantage of using this database is the possibility of identifying the municipality in which the individual lives, unlike *PNAD*,[7] the

[6] Source: MDS (*Ministério do Desenvolvimento Social*) Brazilian Ministry of Social Development and Fight against Hunger.
[7] *Pesquisa Nacional por Amostra de Domicílios*, Brazilian National Household Sample Survey.

second largest Brazilian household survey, in which only the state is observable. This is important for it allows us to estimate candidate' shares using the distribution of individual data of 5564 municipalities and not just the 27 Brazilian states. From this database we construct the demographic database by extracting, for simplicity, a sample of 1000 observations per municipality, extracted considering the weight of each observation in the *Census* database per municipality.

The first characteristic extracted is a dummy constructed to represent if the individual's family was eligible to receive *Bolsa Família*, despite if it actually received or not. This variable was constructed following Souza et al. (2013). There are basically two criterions for a family to be eligible: to be very poor (total household income per capita less than 70 reais[8] per month) or to be poor (total household income per capita less than 140 reais per month) and have children (up to 17 years old) enrolled in a school.[9] With this information we construct a variable representing the percentage of families eligible for the program in each municipality.

The remaining variables are individual characteristics. The first and more obvious is a dummy if the family of the individual is a beneficiary of the *Bolsa Família* program. *Censo* doesn't have a question about the amount received, only if the individual is a beneficiary of the program[10] and, as only one person per family receives the aid, we construct a dummy if someone in the family does. Table 1 shows that 22% of the individuals in our sample belong to a family in which a member receives income from the *Bolsa Família* program. The second and third variables analyzed are the Napierian logarithm of labor income[11] and a dummy if the individual lives in an urban area. The idea for both these variables is to capture, respectively, economic and geographical bias. The logarithm used in the labor income makes difficult for the value to be analyzed, but the fact that the standard deviation is larger than the income mean indicates how large is income inequality. Table 1 also shows that 84% of the individuals live in an urban area. The last variables depicted in the demographic database are dummies for the characteristics of the individuals, such as gender, race and ability to read. Table 1 shows that, in 2010, 83% of the population was alphabetized and 48% was white.

[8]According to Brazilian Central Bank, by the end of 2010, one real was worth around 0.60 dollar.

[9] See Souza et al. (2013) for further information.

[10] Question V0657 from the Census database asks if the individual has income from the Bolsa Família program or from the PETI (*Programa de erradicação do trabalho infantil*) Eradication of child labor program

[11] We use the logarithm in order to avoid problems with very large incomes. As $\ln(0) \rightarrow -\infty$, we add 1 real to each individual labor income. A small value that is not enough to generate any distortion, but sets the ln of labor income to zero for individuals without labor income.

The electoral information comes from Zucco database[12] which contain, among its variables, voting shares for each candidate and municipality in the second round of the 2006 and 2010 elections.[13] The 2010 voting shares are the dependent variable of our estimation and we use the shares of Mr. Lula in the 2006 election to control for a political bias of the municipality, as both elections were disputed between candidates of PT and PSDB.[14] The average of the variables, depicted in Table 1 are the election results, in which Mrs. Rousseff and Mr. Lula won with 56% and 61% of the votes in the runoff voting. Zucco's base also presents data on municipality GDP growth in the period 2008-2010, provided by IBGE,[15] which is important as individuals in municipalities that grow more might have higher probability to support incumbent candidates. On average, the GDP growth of the municipalities is virtually zero, which shows that on average Brazilian municipalities didn't present a harsh recession scenario in the period of the 2009 crisis. The last two characteristics needed in the database are the percentage of families in each municipality that receives *Bolsa Família* and the target of the program,[16] which was defined in 2004 and determined, for each municipality, the percentage of families that should receive *Bolsa Família*, according to the rule of the program. While individual information on being beneficiary of the program indicates the direct impact on household income, the municipality percentage of beneficiary families captures the redistributive impact on society.

[12] See Zucco (2013).
[13] Primary source is the TSE (*Tribunal Superior Eleitoral*), Brazilian Superior Electoral Court. In both 2006 and 2010 elections, the first round ended without majority and a second one was needed. In the second round, only the two candidates with the most votes in the first round dispute the election.
[14] Lula (PT) x Alckmin (PSDB) in the 2006 elections and Dilma (PT) x Serra (PSDB) in the 2010 ones.
[15] IBGE (*Instituto Brasileiro de Geografia e Estatística*), Brazilian Institute of Geography and Statistics.
[16] Primary source is MDS (*Ministério do Desenvolvimento Social*) Brazilian Ministry of Social Development and Fight against Hunger.

***Table 1* - Summary of data**

Database	Variable	Observations	Mean	Std. Dev.	Min	Max
Zucco	Rousseff's share on second ballot of 2010 elections	5,564	0.56	0.15	0.20	0.97
	Target % of families receiving *Bolsa Família*	5,564	0.21	0.16	0.03	1.00
	Share of families receiving *Bolsa Família*	5,564	0.23	0.19	0.00	1.00
	Mr. Lula share on second ballot of 2006 elections	5,564	0.61	0.16	0.15	0.97
	Municipal GDP growth in the period 2008-2010	5,564	0.01	0.07	-0.43	3.43
Census 2010	Dummy for Elegibility	20,635,472	0.17	0.38	0.00	1.00
	Estimated % of families eligible for *Bolsa Família*	5,564	0.16	0.14	0.00	0.79
	Dummy for Beneficiary in the family	20,635,472	0.22	0.41	0.00	1.00
	Ln of labor income	20,635,472	2.83	3.36	0.00	13.76
	Dummy for Urban	20,635,472	0.84	0.36	0.00	1.00
	Dummy for Literate	20,635,472	0.83	0.38	0.00	1.00
	Dummy for Man	20,635,472	0.49	0.50	0.00	1.00
	Dummy for White	20,635,472	0.48	0.50	0.00	1.00

This table displays descriptive statistics of the data used in this article. The variables are divided by database and include information on 5564 Brazilian municipalities and individual information available at Census. Source: 2010 Brazilian Census, IBGE, MDS and TSE.

3. Methodology

This session is divided in three parts. The first one describes the methodology of the mixed logit model; the second one presents the linear models counterparts of the mixed logit and the last one describes the instruments used in both the Instrumental Variables (IV) and mixed logit models.

3.1. Mixed Logit

The Mixed logit is a random-parameters logit demand model from product market shares, first presented by Berry, Levinsohn and Pakes (1995) – henceforth BLP. Unlike in traditional Industrial Organization applications, in which both the supply and the demand of a product are analyzed, in this electoral framework the supply (candidates) are given and the study the demand of the voters. Mixed logit belongs to the category of models based on the assumption that a voter's preference for a candidate or party can be described by a utility function, which depends on characteristics of the individual and the alternative of candidates. When voting, individual select the candidate that yields the highest utility.

The Mixed logit framework is particularly useful in the electoral analysis as it addresses one central challenge, which is the inference of individual behavior from aggregate data. We describe this method following Nevo (2000) and define the indirect utility of the elector i when voting for Mrs. Rousseff while living in the municipality t by:

$$u_{it} = B_t\alpha_i + w_t\beta_i + \xi_t + \varepsilon_{it}, \qquad \varepsilon_{it} \sim P_\varepsilon(\varepsilon) \tag{1}$$

where B_t stands for the *Bolsa Família*'s coverage in the municipality, w_t and ξ_t are, respectively, vectors of observable and non-observable characteristics of the municipality, and ε_{it} is the error term.

Let $w_{jt} = [x_{jt}\ 1]$, which is equivalent of w_{jt} plus a constant, it is possible to rewrite (1) as:

$$u_{ijt} = B_t\alpha_i + x_{jt}\gamma_i + \phi_i + \xi_{jt} + \varepsilon_{ijt} \tag{1'}$$

Furthermore, we define the vector of parameters to be estimated as:

$$\begin{pmatrix}\alpha_i\\ \gamma_i\\ \phi_i\end{pmatrix} = \begin{pmatrix}\alpha\\ \gamma\\ \phi\end{pmatrix} + \overbrace{\begin{pmatrix}\Pi_\alpha\\ \Pi_\gamma\\ \Pi_\phi\end{pmatrix}}^{\Pi} D_i + \overbrace{\begin{pmatrix}\Sigma_\alpha\\ \Sigma_\gamma\\ \Sigma_\phi\end{pmatrix}}^{\Sigma} \upsilon_i, \qquad \upsilon_i \sim P_\upsilon^*(\upsilon), D_i \sim \widehat{P}_D^*(D) \tag{2}$$

where D_i and υ_i represent, respectively, vectors of observable and non-observable individual characteristics. Π and Σ stands for the matrix of parameters that represent how individual preferences vary with observable and non-observable individual characteristics. $P_\upsilon^*(\upsilon)$ is the parametric distribution of υ, while $D_i \sim \widehat{P}_D^*(D)$ is the known, non-parametric distribution of the microdata.

Without generality loss, the model is completed by defining the indirect utility of voting on another candidate or voting null as containing only the error term, which has zero mean ($u_{i0t} = \varepsilon_{it}$). Let $D_i = [B_i\ \widetilde{D}_i]'$ be a vector that includes a binary variable that indicates whether the individual receives *Bolsa Família* (B_i) and the other observable characteristics of the voters ($\widetilde{D}_i$). Furthermore, we define the individual characteristics (both observable and non-observable) by $\tau_i = [D_i\ \upsilon_i]$.

The probability of the individual *i*, living in the municipality *t*, to vote for Mrs. Rousseff is given by:

$$Prob_{it} = Prob(U_{it} > 0) \tag{3}$$

Let A_t be the group of characteristics of the elector *i*, living in the municipality *t*, that makes him vote for Mrs. Rousseff. Hence:

$$A_t(w_t, B_t, \xi_t, \Pi, \Sigma) = \{(D_i, \upsilon_i, \varepsilon_{it}) | u_{it} \geq 0\} \tag{4}$$

where w_t and ξ_t are vectors of observable and non-observable individual characteristics. The share of votes of Mrs. Rousseff in the municipality *t* is:

$$s_t(w_t, B_t, \xi_t, \Pi, \Sigma) \ = \int_{A_i} dP^*(D, \upsilon, \varepsilon) \tag{5}$$

By applying the Bayes Rule, and then considering the independence of the individuals, we can rewrite 5 as follows:

$$s_t(w_t, B_t, \xi_t, \Pi, \Sigma) = \int_{A_i} dP_\varepsilon^*(\varepsilon)\, dP_\upsilon^*(\upsilon) d\hat{P}_D^*(D) \tag{5'}$$

where P^* represents the populations' distribution function.

From (2), we have:

$$\phi_i = \phi + \Pi_\phi D_i + \Sigma_\phi \upsilon_i \tag{6}$$

We can replace ϕ_i from equation (6) into equation (1') and as a result:

$$u_{it} = \phi + B_t \alpha_i(\tau_i) + x_t \gamma_i(\tau_i) + \Pi_\phi D_i + \Sigma_\phi \upsilon_i + \xi_t + \varepsilon_{it}$$

$$u_{it} = \phi + B_t \alpha_i(\tau_i) + x_t \gamma_i(\tau_i) + [\pi\ \widetilde{\Pi}_\phi][B_i\ \ \widetilde{D}_i]' + \Sigma_\phi \upsilon_i + \xi_t + \varepsilon_{it} \tag{7}$$

Note that (7) allows that not only being beneficiary of the *Bolsa Família* to affect voting decision, but also that non-beneficiaries also have their decision impacted by the program. Furthermore, municipalities characteristics, which are aggregate variables, affect voting decision differently depending on the individual's characteristics. Finally, both observable and non-observable individual characteristics affect voting decision.

From (5') we have that the shares of votes for Mrs. Rousseff on municipality *t* can be written as $s_t = \int_{A_i} dP_\varepsilon^*(\varepsilon)\, dP_\upsilon^*(\upsilon) d\hat{P}_D^*(D)$, which means that is not possible to estimate the share of votes of a candidate in a certain municipality without considering the distribution of individual characteristics. Also, it is only possible to write s_t as a function only of aggregate variables if $\alpha_i = \alpha$, $\gamma_i = \gamma$, $\Pi_\phi = 0$ e $\Sigma_\phi = 0$. In particular, if ε_{it} is identical and independently distributed following the extreme value distribution of type I:

$$s_t = \frac{\exp\,(\phi + B_t\alpha + x_t\gamma + \xi_t)}{1 + \exp\,(\phi + B_t\alpha + x_t\gamma + \xi_t)} \tag{8}$$

3.2. Linear Models

By defining a candidate's vote share in a given municipality by (8), we can easily modify the municipality or the demographic information to obtain counterfactual shares.

For instance, by setting *Bolsa Família* municipality coverage and individual benefits to zero, we estimate the candidate's share in a scenario without the program.

As described, the main advantage of using the mixed logit methodology is the possibility of using individual data distribution in the estimations. To analyze this impact in the estimation results, we will compare the mixed logit results with those of the aggregate data using ordinary least squares (OLS) and instrumental variables (IV) estimations. In these, instead of using the individual data sample distribution, we use municipality averages of the full database in the estimations.

Furthermore, in order to better compare the OLS and IV regressions with the mixed logit results, we estimate the candidate's share in both its linear and logit form. In particular, the logit version will assume the form:

$$\ln\left(\frac{s_t}{1-s_t}\right) = \phi + B_t\alpha + x_{jt}\gamma + \varepsilon_{jt} \tag{9}$$

As each municipality has a different number of observations and votes, the error variance will be $Var(\varepsilon_{jt}) = \frac{1}{N_t\mu_t(1-\mu_t)}$ as in Maddala (1983). To estimate (9) using OLS and IV each municipality observation should be weighted by $\omega_t = N_t s_t(1-s_t)$.[17]

3.3. Instruments

Before the analysis of the estimations results, we must consider the possibility of being a beneficiary to be correlated with the error, i.e. for the estimation to present endogeneity problem. To avoid this possible estimation deficiency, we instrumentalize the Bolsa Família coverage – B_t on equations 8 and 9 – with two different instruments, in both the BLP and IV estimations.

The first is the target of *Bolsa Família* program, defined in 2004 by the MDS, Brazilian Ministry of Social and Agrarian Development, in which the percentage of beneficiary families in each municipality was estimated. The second instrument also focus on the eligibility criteria of the program but was constructed using the demographic database. Following the eligibility criteria of the program – described in the second session of this article – we construct a dummy for individual eligibility and then aggregate to obtain the percentage of individuals in each municipality whose families are eligible for the *Bolsa Família* program, on the Census database. Hereafter these two instruments will be simply denominated as target and eligibility.

[17] See Canêdo-Pinheiro (2015) for further discussion.

The idea of using instrument is to find a variable that is both correlated with the Bolsa Família coverage and uncorrelated with the errors. The correlation between the coverage and the percentage of eligible families (both in the target and in the Census database) is straightforward. The remaining question is if these instruments are uncorrelated with the error. Zucco (2013, 2015) presents several characteristics of the program design which support both the target of the program and the eligibility as politically unbiased and thus uncorrelated with any omitted information. Among the characteristics listed are the technical definition of eligibility, preventing individual favoring; the direct transfer through bank system, preventing local politicians to make propaganda at the moment of payment and the audition by the comptroller general's randomized auditing of federal transfers to municipalities.

To better evaluate if the choice of the instruments is appropriate, we run a few tests, usual in the literature. Table 2 presents the first stage of the IV regression, in which the instrument and the other variables are used to estimate the variable we want to instrumentalize, the *Bolsa Família* Coverage. Table 3 presents, for our two instruments – in both linear and logit form – overidentification, underidentifications and weak instruments tests. The first stage of the IV regression and the tests use the specification BLP-3, described in the next session.

Table 2 presents the first stage regression estimations for eight equations, depending on three pairs: instrument used (target or eligibility), regression form (linear or logit) and instrumented variable (*Bolsa Família* coverage or its iteration with average labor income). The statistical significance of the instruments' β coefficient, presented in Table 2, indicates that the use of the instrument is necessary and the OLS estimations might be biased due to endogeneity problems.

Table 2 **- First stage regression of Bolsa Família Coverage**

	Target - Linear		Target - Logit		Eligibility - Linear		Eligibility - Logit	
	BF Coverage	BF Coverage * Labor Income	BF Coverage	BF Coverage * Labor Income	BF Coverage	BF Coverage * Labor Income	BF Coverage	BF Coverage * Labor Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Target	0.131***	-1.703***	0.108***	-2.120***				
	(0.01)	(0.04)	(0.02)	(0.12)				
Target * Labor Income	-0.021***	0.949***	0.002	1.050***				
	(0.01)	(0.01)	(0.01)	(0.04)				
Eligibility					0.109***	-2.048***	0.052*	-2.752***
					(0.02)	(0.05)	(0.03)	(0.17)
Eligibility * Labor Income					0.006	1.095***	0.001	1.045***
					(0.01)	(0.02)	(0.02)	(0.1)
GDP growth	-0.009	-0.145**	-0.005	0.035	0.016	-0.187***	0.013	-0.203**
	(0.03)	(0.06)	(0.03)	(0.09)	(0.03)	(0.06)	(0.03)	(0.1)
Lula's share 2006	0.051***	0.124***	0.046***	0.142***	0.054***	0.105***	0.050***	0.161***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)	(0.01)	(0.06)
Labor Income	-0.019*	-0.064***	-0.007	0.014	-0.008	-0.046**	-0.001	-0.065
	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)	(0.05)
Urban	0.015***	0.076***	0.021***	0.089***	0.016***	0.022**	0.019***	0.004
	(0)	(0.01)	(0.01)	(0.02)	(0)	(0.01)	(0.01)	(0.02)
GDP growth * Labor Income	0.003	0.057**	-0.003	-0.025	-0.005	0.074***	-0.008	0.060*
	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)	(0.04)
Bolsa Família beneficiary	0.890***	1.814***	0.934***	2.155***	0.904***	1.898***	0.991***	2.498***
	(0.01)	(0.03)	(0.02)	(0.09)	(0.01)	(0.04)	(0.03)	(0.16)
Constant	0.039	0.076	0.000	-0.156	-0.003	0.111*	-0.020	0.187
	(0.03)	(0.06)	(0.04)	(0.1)	(0.03)	(0.06)	(0.04)	(0.14)

This table presents the estimated coefficients for the first stage regression of the regression. Eight estimations are presented based on the instrument, regression form and instrumented variable. The instruments used are the target of the Bolsa Família program for columns (1) to (4) and the estimated share of families eligible for the program for columns (5) to (8). The estimation form can be linear or logit. If column is indicated as linear, regression comes from equation (8) and if it is logit, equation (9). The instrumented variable can be either the *Bolsa Família* coverage – columns (1), (3), (5) and (7) - or its iteration with average labor income – columns (2), (4), (6) and (8). The first value is the β and bellow, in parenthesis, the robust standard errors. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The first test analyzed in Table 3 is the Sargan-Hansen which is a test for overidentifying restrictions. The joint null hypothesis is that the instruments are valid instruments – uncorrelated with the error term – and that the excluded instruments are correctly excluded from the estimated equation. Under the null hypothesis, the test statistic is distributed as chi-squared in the number of (L-K) overidentifying restrictions, where L is the number of instruments and K of regressors, therefore L-K is the number of overidentifying restrictions.

The underidentification test is an LM test to see if the equation is identified – the excluded instruments are correlated with the endogenous regressors. Under the null hypothesis that the equation is underindentified, we test the rank of the matrix of reduced

form coefficients on the L1 excluded instruments, which has rank=K1-1 where K1 is the number of endogenous regressors. Under the null hypothesis, the statistic is distributed as chi-squared with L1-K1+1 degrees of freedom. If we reject the null hypothesis, then the matrix is full column rank and is identified.

We say the instrument has the problem of weak identification when the excluded instruments are correlated with the endogenous regressors, but only weakly. In this case, IV estimates are biased in same direction as OLS, and weak IV estimates may not be consistent (Chao and Swanson, 2005). We use the Kleibergen-Paap Wald version for this test. The Cragg-Donald Wald test demands errors to assume i.i.d. form, while the Kleibergen-Paap Wald test is better suited when estimations drop the i.i.d. assumption and are robust to heteroskedastic, which will be the case of our specifications.

Table 3 presents the results for the three tests described. The overidentification test is indicated by the Hansen J statistic, in which we reject, for very small significance levels, p-value <0.001, the null hypothesis of overindentification. For the specifications using the target coverage as instrument, and for the linear specification using percentage of eligible individuals as instrument, Underidentification test presented p-value close to zero, which allows us to reject the null hypothesis of underidentification and allowing the conclusion that these specifications are correctly identified. The last specification, using logit variable and eligibility as instrument, however, we cannot reject the null. This indicates that the instrument is irrelevant, as it is not correlated with the endogenous regressor. Finally, the weak identification test presents large F-statistic in the Kleibergen-Paap Wald test, for the specifications that were correctly identified using Stock-Yogo (2005) critical values. This allows us to reject the null hypothesis of weak identification and conclude that both instruments are well suited for both the linear form and target for the logit one of the equation 8 – for the BLP model – and 9 for the IV model.[18]

The redundancy of the instrument is naturally tested by the difference in the results between the OLS and IV coefficients. If the results are very similar, it indicates that the instrumentalized variable is uncorrelated with the errors, indicating that using an instrument is unnecessary. In the next session we show that in the linear models, for example, the coefficient for *Bolsa Família* Coverage loses statistical significance when an instrument is used.

[18] Equation 8 represents the Linear BLP specification and equation 9 the logit IV model.

***Table 3* - Instrument tests results**

	Target linear	Target logit	Eligibility linear	Eligibility logit
Underidentification test				
LM test – Chi-square	74.22	51.79	58.10	1.04
P-value	0.00	0.00	0.00	0.31
Weak identification test				
Kleibergen-Paap Wald rank F-statistic	41.198	28.5	28.565	0.385
Overidentification test				
Hansen J statistic	0.00	0.00	0.00	0.00

This table present the underidentification, weak identification and overidentification instruments test, based on the equations presented in Table 2. For the weak identification test, Stock-Yogo (2005) critical values are: 10% maximal IV size 7.03; 15% maximal IV size 4.58; 20% maximal IV size 3.95; 25% maximal IV size 3.63.

4. Results

In this chapter, we analyze the electoral impact of *Bolsa Família* program using the Mixed Logit models described in the previous chapter. In the first session of the chapter we analyze the coefficients of the regressions and compare them with the aggregate models; the second session does a counterfactual exercise and estimates Mrs. Rousseff's share in 2010 elections in a scenario without *Bolsa Família*; the last section analyzes the marginal effects and compare the program impact with labor income and economic growth of the municipalities.

4.1. Regressions coefficients

This section describes the coefficient results for both the mixed logit methodology and its linear counterparts. Table 4 presents the coefficients for different specifications of the mixed logit (BLP) estimation, and Table 5 depicts the OLS and IV regressions. Due to the logit form, the interpretation of the coefficient's value is not straightforward, as the β's are the means of the distribution of marginal utilities. Nevertheless, the signal of the coefficients and its statistical significance indicate the direction of variable's impact on electoral decision.

In our specifications, the dependent variable is Mrs. Rousseff's share in the runoff voting of 2010 elections (s_t), with the exception of logit OLS and IV regressions that are estimated using the direct counterpart of the mixed logit form and the dependent variable is $\ln\left(\frac{s_t}{1-s_t}\right)$. For each specification, Table 4 and 5 present the β and the standard deviation of the estimators. On Table 4, the total impact of a municipal variable, such as *Bolsa Família* Coverage is given by the sum of direct impact, depicted by its β, and the cross impact of the demographic variables and the municipal ones. For example, in specification BLP-3, the average impact of the distribution of labor income of individuals in the demographic database on the municipal *Bolsa Família* Coverage is estimated to be -0.98, with a standard

deviation of 0.29. The overall mean impact of a demographic variable on an individual probability to vote on Mrs. Rousseff is the coefficient of the interaction of the variable with the constant, plus the product of each coefficient of a municipal interaction with the municipal variable value for that individual.

For each interaction between the municipality variables and the demographic ones, the BLP estimations present the unobserved demographics' effect, labeled as standard deviation (SD), as the unobserved characteristics are captured by the econometric error term.[19] In all variables of every specification, the unobserved demographic effect on electoral decision is statistically insignificant.

In the mixed logit specifications, depicted by Table 4, *Bolsa Família* Coverage effect on the probability an individual voted on Mrs. Rousseff in the second ballot of the 2010 election is positive and statistically different from zero in every specification. This result indicates that, on average, municipalities that had a larger share of beneficiaries had a bigger probability of voting for the incumbent candidate.

On the other hand, municipality GDP growth in the period 2008-2010 appears to have no significant effect on electoral decision, as the only specification in which this variable's coefficient is statistically significant is the BLP-1, where no instrument was used and *Bolsa Família* Coverage was not included. Which suggests that local economic performance doesn't affect national electoral decision.[20] President Lula's share, however, is the only variable that has a positive impact for every estimation in which we use an instrument, even for very small significance level (less than 1%). Indicating that if an individual lives in a municipality where Mr. Lula had a better performance (hence has a bigger probability of having supported Mr. Lula in 2006), then he has a larger probability of supporting Mrs. Rousseff in 2010, indicating a political persistence.[21] There can be at least two non-excluding reasons for this persistence. Voters may prefer not to change the party they support; there might be persistent factors that result on voters supporting Mr. Lula in 2006 and Mrs. Rousseff in 2010.

The possibility of incorporating the distribution of demographic variables on the aggregate municipal information is the reason we used the Mixed Logit model. The first

[19] See Nevo (2000) for further explanation.
[20] (ln) of municipalities' GDP was also used as an economic variable, but the impact was also not statistically significant. The idea of using this variable is to measure the level of the local economy, instead of its growth.
[21] Governor Coalition – a dummy if the incumbent governor belongs to Mrs. Rousseff's coalition – was also included in some of the estimations, but their impact was not statistically significant.

impact we analyze is how labor income affects the electoral impact an individual has on the *Bolsa Família* Coverage. The negative sign of labor income coefficient on *Bolsa Família* Coverage indicates that although larger shares of beneficiary families in the program increase probability of voting for candidate Rousseff (as shown by the positive sign of the direct coverage coefficient), this increase in probability decreases with labor income and might even become negative for high labor income values. This result indicates, as could be expected, that *Bolsa Família* program has a larger political effect on individuals with lower income.

A positive (negative) coefficient sign of labor income impact on economic variables would indicate that individuals with higher wages would let their political decisions be more (less) affected by municipality economic growth. The statistical insignificance of the interaction, however, indicates that even individuals with higher labor income doesn't consider the status of municipal economy on national electoral decisions. This doesn't mean labor income has no impact on electoral decision. The direct impact of the demographic variables on the dependent variable – Mrs. Rousseff's share – is displayed as the interaction between the demographic variable and the constant. The positive value of labor income coefficient on the specifications where the value is statistically significant, indicates that, on average, individuals with higher labor income are more likely to vote on Mrs. Rousseff. This result is rather unexpected considering Figure 1, which shows that president Rousseff's performance was better on poorer regions, but indicates that, when controlled for other demographic variables, individual labor income has a positive impact on Mrs. Rousseff's share. A possible interpretation for this result is to understand individual labor income as a proxy for individual economic satisfaction, which would lead to a better evaluation of the incumbent president.

Even more surprising is the statistical insignificance of the dummy that indicates if the individual household is a beneficiary of the *Bolsa Família* program. In none of the BLP specifications, receiving *Bolsa Família* impacts directly the probability of an individual voting for Mrs. Rousseff, although the municipality coverage does affect, as shown. One possible explanation could be that the municipal variable, *Bolsa Família* Coverage, is capturing the individual effect due to correlation of both variables. However, the inclusion of the specification BLP-1, where the municipal coverage was not included was specifically to show that this is not the case. As said before, *Bolsa Família* program has two mechanism thought which it could affect electoral decisions, the approval of the redistributive program of the government and the direct income effect. What can be inferred is that the redistributive characteristic of the *Bolsa Família* program is correlated by the municipal coverage, while

having a beneficiary in the family is correlated with the income gains. The statistical insignificance of the later and the significance of the municipal coverage suggests that the redistributive effect of the program is more correlated with the decision of voting for Mrs. Rousseff than the direct income effect.

The last four demographic variables included in the specifications are control dummies for urban, literacy, gender and race. Only the dummy for living in an urban area is statistically significant in any specification, but while it has a negative sign in BLP-3, it has a positive sign in the specification where neither instruments nor *Bolsa Família* Coverage were used – BLP-1. The statistical insignificance of the gender dummy indicates that, although Mrs. Rousseff was the first female candidate to reach the second round in the history of Brazilian presidential elections, her endorsement from female electors was not higher than her endorsement from male electors. This goes in line with surveys from Ibope and Datafolha, the two majors' political surveys in Brazil that showed that, in the last survey before the elections, Mrs. Rousseff's share was even higher among male voters than among the female electorate.[22] The statistical insignificance of the coefficients of literacy and race indicates that the probability of voting for Mrs. Rousseff in the second round of 2010 elections is not influenced by neither race nor ability to read.

For the next exercises – comparison with linear models, counterfactual exercises, and marginal effects analysis – we pick a single specification to make comparison simper. We selected specification BLP-3 as it outstands in three desirable criterions: number of statistical significant variables, inclusion of *Bolsa Família* Coverage and the use of the coverage target as an instrument.

[22] Source: Ibope public opinion research of 30/10/2010 and Datafolha public opinion research of 30/10/2010, the day before the election.

***Table 4* - Coefficients estimated – Mixed Logit**

		BLP (1)	BLP (2)	BLP (3)	BLP (4)	BLP (5)	BLP (6)	BLP (7)	BLP (8)	BLP (9)
	Instrument used:			Target	Eligibility	Target	Target	Target	Target	Eligibility
	Bolsa Família Coverage		3.68***	3.25***	4.60*	2.64*	3.15*	3.01	3.96	4.80
			(0.46)	(0.92)	(2.39)	(1.46)	(1.62)	(2.16)	(8.84)	(13.12)
	GDP growth - 2 years	0.47**	-0.98	0.11	-0.08	0.15	0.79	0.70	0.05	-0.12
		(0.2)	(0.7)	(0.51)	(0.95)	(0.61)	(1.4)	(1.78)	(1.27)	(4.82)
	Lula's share 2006	5.25***	-0.08	3.52***	3.91***	3.71***	4.44***	4.38***	3.77***	3.85**
		(0.22)	(0.33)	(0.69)	(1.22)	(0.5)	(0.5)	(0.76)	(1.27)	(1.58)
	Constant	-3.16	-1.29***	-4.26***	-4.94	-3.79**	-5.39**	-4.94	-4.93	-5.20
		(0.29)	(0.44)	(1)	(3.29)	(1.72)	(2.72)	(3.31)	(13.87)	(15.44)
Bolsa Família Coverage	Labor income (ln)		21.35	-0.98***	-1.54*	-0.83**	-1.10**	-1.09*	-1.25	-1.52
			(26.95)	(0.29)	(0.82)	(0.36)	(0.47)	(0.62)	(2.03)	(2.76)
	Standard Deviation		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
			(31.7)	(53.77)	(27.01)	(76.65)	(67.77)	(101.66)	(120.75)	(156.37)
GDP growth - 2 years	Labor income (ln)	-0.14*	0.15	0.04	0.12	0.01	-0.19	-0.16	0.06	0.14
		(0.08)	(0.16)	(0.22)	(0.32)	(0.26)	(0.38)	(0.54)	(0.51)	(1.54)
	Standard Deviation	0.00	0.01	0.02	0.02	0.01	0.00	0.00	0.00	0.01
		(10.84)	(36.61)	(14.08)	(21.84)	(23.89)	(12.92)	(20.23)	(50.65)	(112.05)
Lula's share 2006	Standard Deviation	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00
		(9.99)	(24.61)	(47.17)	(31.61)	(68.98)	(19.63)	(30.33)	(67.41)	(80.17)
Constant	Labor income (ln)	0.51***	-10.72	0.45	0.52	0.42	0.78*	0.79	0.51	0.45
		(0.07)	(12.18)	(0.3)	(0.55)	(0.29)	(0.41)	(0.54)	(0.41)	(1.73)
	Bolsa Família beneficiary	0.79	-0.22	0.72	2.15	0.35	3.95	3.45	1.63	1.81
		(0.65)	(0.2)	(1.98)	(2.69)	(1.31)	(5.69)	(5.57)	(2)	(4.95)
	Urban	-1.59***	0.24	0.85**	1.13				1.16	1.19
		(0.18)	(0.68)	(0.41)	(1.18)				(1.17)	(1.95)
	Literate					0.36			0.03	0.08
						(1.73)			(14.72)	(20.89)
	Man						0.35		0.29	0.33
							(7.42)		(11.29)	(12.55)
	White							-0.32	-0.06	0.23
								(1.15)	(0.63)	(1.45)
	Standard Deviation	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
		(13.88)	(30.14)	(22.32)	(25.66)	(18.97)	(35.32)	(39.18)	(79.68)	(79.03)

This table presents the coefficients estimated with the Mixed logit model. Standard Deviation indicates the unobservable demographic impact. Bellow the constant are depicted the demographic variable's impact on the indicated municipal variable, which represents the cross effect of individual characteristics on municipal data. The first value is the β and bellow the standard error. * p-value<0.05, ** p-value <0.01, *** p-value <0.001.

Table 5 shows the equivalent regressions of specification BLP-3 using OLS and IV regressions. The demographic characteristics impact on municipal variables highlights the difference between the mixed logit methodology and the OLS and IV estimations. While the coefficients in the BLP specifications were estimated using the distribution of the demographic variable in each municipality, in the OLS and IV estimations the municipality

average was used and the interaction is simply the product of the variables. Therefore the effect of labor income on *Bolsa Família* Coverage' election impact is simply the product of these two variables.

The direct impact of municipalities' variables is similar to the results using mixed logit model. *Bolsa Família* Coverage and president Lula's 2006 share have a positive impact on the probability of voting for Mrs. Rousseff, while GDP municipal growth is statistically insignificant.

The most important difference between the aggregate models and mixed logits' coefficients is the statistical significance of the Bolsa Família beneficiary dummy in two of the specifications – OLS and IV in the linear forms, with the IV estimation using percentage of eligible families as an instrument. In both of this specifications the coefficient is positive, indicating that individuals who belong to a family that receives financial aid from the *Bolsa Família* program are more likely to vote on Mrs. Rousseff.

The remaining variables' estimation present similar results as the regressions using mixed logit models. The positive effect of *Bolsa Família* Coverage is decreasing with labor income, as indicated by the negative coefficients in every specification. The effect of labor income on the probability of supporting Mrs. Rousseff is positive in the specifications in which it is significant – the specifications with linear dependent variable – and has no statistical significant impact through GDP growth. The dummy for living in an urban area is negative significant in the aggregate models estimations. This result goes in line with Figure 1, which shows Mrs. Rousseff had more votes in northern regions of Brazil that predominantly rural.

Table 5 **- Coefficients Estimated - Aggregate Models**

		OLS - Linear (1)	OLS - Logit (2)	IV - Linear (3)	IV - Logit (4)	IV - Linear (5)	IV - Logit (6)
	Instrument used			Target 2006		Elibility	
	Bolsa Família Coverage	0.19***	1.11***	0.15	1.01	0.04	1.04
		(0.03)	(0.29)	(0.12)	(1)	(0.07)	(1.05)
	GDP growth - 2 years	0.06*	0.20	0.07	0.21	0.09*	0.21
		(0.04)	(0.31)	(0.04)	(0.35)	(0.04)	(0.37)
	Lula's share 2006	0.8***	3.39***	0.8***	3.39***	0.8***	3.39***
		(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.09)
	Constant	-0.05	-2.06***	-0.05	-2.07***	-0.05	-2.07***
		(0.04)	(0.39)	(0.04)	(0.39)	(0.04)	(0.4)
Bolsa Família Coverage	Labor income (ln)	-0.07***	-0.48***	-0.07***	-0.47**	-0.05***	-0.47**
		(0.01)	(0.1)	(0.02)	(0.17)	(0.01)	(0.19)
GDP growth - 2 years	Labor income (ln)	-0.01	0.05	-0.01	0.04	-0.02	0.04
		(0.01)	(0.12)	(0.02)	(0.14)	(0.01)	(0.14)
Constant	Labor income (ln)	0.06***	0.09	0.05***	0.09	0.05***	0.09
		(0.01)	(0.14)	(0.01)	(0.14)	(0.01)	(0.14)
	Bolsa Família beneficiary	0.08**	0.11	0.11	0.19	0.18**	0.17
		(0.03)	(0.22)	(0.08)	(0.72)	(0.05)	(0.72)
	Urban	-0.11***	-0.41***	-0.11***	-0.41***	-0.11***	-0.41***
		(0.01)	(0.05)	(0.01)	(0.05)	(0.01)	(0.05)

This table presents the coefficients estimated with the aggregate models. Bellow the constant are depicted the cross effect of municipal and individual characteristics. Unlike the mixed logit model, the individual characteristics in the aggregate model are given by municipal averages of Census observations. Dependent variable is s for linear models – columns (1), (3) and (5) – and $\frac{s}{(1-s)}$ for logit models – columns (2), (4) and (6). The first value is the β and bellow the robust standard error. * p-value<0.05, ** p-value <0.01, *** p-value <0.001.

4.2. Counterfactual

Due to the limitation of the analysis of the coefficients in the BLP estimations, the electoral effect of the *Bolsa Família* program is best understood by the counterfactual exercise in which we estimate the voting shares in a scenario without *Bolsa Família.* To do so, we simply apply the coefficients of the complete estimation on equation 8 and set both the municipal *Bolsa Família* coverage (B_t) and the individual dummy for being a beneficiary of the program (vector of D_t) to zero. All the estimations use the specification BLP-3. It is important to remember that the mixed logit model allows for individuals who are not beneficiary of the *Bolsa Família* to have their electoral preferences affected by the program. Thus, the shut down of the program does not affect only the beneficiaries, but all voters.

Table 6 presents the voting shares Mrs. Rousseff had on the runoff voting of the 2010 elections and the counterfactual estimated shares for each Brazilian region and for the

whole country.[23] The exercise shows that the impact of the Bolsa Família program is equivalent of 6.30% of the total valid votes. More important, the estimation of Mrs. Rousseff' share indicates she could lose the election by a very small margin. Naturally, the error margins of the estimations and the result so close to 50% don't allow us to conclude whether she would win the election or not, but the possibility already indicates a significant electoral impact.

The results depicted also indicate a clear heterogeneity of the impact among Brazilian regions. In the Northeast region, the poorest and where the *Bolsa Família* coverage is larger.[24] The decrease is so significant that would lead the region in which Mrs. Rousseff had over 70% of the valid votes to be even behind the Brazilian average. In the South and Central-West regions, removing counterfactually the *Bolsa Família* program would lead to an increase in votes for Mrs. Rousseff. This is due to the small number of beneficiaries in these regions – individuals to whom removing Bolsa Família decreases probability to vote on Mrs. Rousseff –and the fact that these regions have higher average labor income[25] – hence removing the program has a positive effect.

Table 6 **- Counterfactual Shares by Brazilian region –** ***Bolsa Família*** **effect**

	Observed Share (1)	Counterfactual Share (2)	Difference (1) - (2)
North	57.47%	45.42%	12.05%
Northeast	70.58%	49.15%	21.43%
Southeast	51.88%	51.53%	0.35%
South	46.11%	47.94%	-1.84%
Central-West	49.09%	49.63%	-0.55%
Brazil	56.07%	49.77%	6.30%

This table presents the counterfactual exercise in which we estimate, using the coefficients of regression BLP-3, the incumbent electoral share in a scenario without Bolsa Família program. Which means both Bolsa Família coverage and dummy for having a beneficiary in the family set to zero.

This positive impact of removing the program in richer regions is in line with Corrêa (2015) and Corrêa and Cheibub (2016), who find evidence supporting that the positive electoral effect conditional cash transfer programs is partially counter balanced by a negative impact of voters who don't approve the program, leading to an inconclusive impact.

In the Bolsa Família, specifically, Corrêa (2015) concludes that the overall impact in the 2006 Lula election is null and the program only reallocates the electorate. Our results, on the other hand, indicate that the positive effect is much larger than the negative one.

[23] Table 9, in the annex, presents the counterfactual estimations by Brazilian state.
[24] As shown in Figure 1.
[25] As shown in Table 10, in the annex.

Although our results are for the 2010 elections, the expansion of the program was small between 2006 and 2010 – going from 11 million families to 12.8 million – suggesting such different results could be due to differences only in the methodology, not in period analyzed.

Table 7 depicts the actual share and the counterfactual results per Brazilian region for each of the aggregate estimations, using the aggregate counterpart for the same specification. With exception of the logit model using eligibility as instrument, which is not correctly specificated,[26] the counterfactual exercise estimates similar shares to the real ones. This indicates that using only municipal averages, as Corrêa (2015), strongly underestimates the *Bolsa Família* impact on elections.

Table 7 **- Counterfactual Shares by Brazilian region – Aggregate Models**

	Share (1)	OLS linear (2)	OLS logit (3)	IV target linear (4)	IV target logit (5)	IV elibility linear (6)	IV elibility logit (7)
North	57.5%	56.9%	58.0%	58.8%	55.7%	54.7%	48.3%
Northeast	70.6%	67.5%	68.6%	70.0%	65.8%	64.6%	56.5%
Southeast	51.9%	51.5%	52.8%	52.0%	52.0%	50.8%	49.6%
South	46.1%	46.2%	47.0%	46.6%	46.3%	45.6%	44.1%
Central-West	49.1%	47.9%	48.8%	48.6%	47.7%	47.1%	44.6%
Brazil	56.1%	55.0%	56.1%	56.1%	54.7%	53.6%	50.1%

This table presents the counterfactual exercise in which we estimate, using the coefficients of regression from aggregate models, the incumbent electoral share in a scenario without Bolsa Família program. Which means both Bolsa Família coverage and dummy for having a beneficiary in the family set to zero.

4.3. Marginal effects

The last exercise describes the marginal effects of having a *Bolsa Família* beneficiary in the family on the probability of voting for the incumbent and compares it to the one of labor income, which indicates the increase in probability of voting for Mrs. Rousseff if labor income increases by 1 real. We once again use specification BLP-3, in which we define the utility of individual *i*, living on municipality *t*, of voting for Mrs. Rousseff on the run-off of 2010 election as:

$$u_{it} = \phi + BF\_Coverage_t * \beta_1 + GDP\_2Y_t * \beta_2 + Lula\_2006_t * \beta_3 + BF\_Coverage_t * \ Labor\_Income_i * \beta_4 + GDP\_2Y_t * \ Labor\_Income_i * \beta_5 + Labor\_Income_i * \beta_6 + BF\_beneficiary_i * \beta_7 + Urban_i * \beta_8 + SD_t * BF\_Cov_t * \beta_9 + SD_t * GDP\_2Y_t * \beta_{10} + SD_t * Lula\_2006_t * \beta_{11} + \varepsilon_{it} \quad (10)$$

where *BF_Coverage*, *GDP_2Y* and *Lula_2006* represents, respectively, the municipality variables of the Bolsa Família Coverage, the local GDP growth of the period 2008-2010 and the electoral share of president Lula on the run-off of the 2006 elections in the municipality.

[26] As seen on session 3.3 – Instruments.

Labor_Income, BF_beneficiary and *Urban* stand for individual ln of labor income, dummy for having a beneficiary of the Bolsa Família program in the family and dummy for living in an urban area, respectively. Finally, Standard Deviation represents the unobserved effect, while ϕ is the constant.

Applying this specification on the individual probability described by equation (9) and differentiating with respect to each variable, we find its marginal effect for each individual. Equations (11) to (15) describe the marginal effect for five selected variables.

$$ME\_BF\_Coverage_{it} = s_{it}(1 - s_{it})(\beta_1 + Wage_i * \beta_4) \quad (11)$$

$$ME\_Labor\_Income_{it} = s_{it}(1 - s_{it})(BF\_Cov_t * \beta_4 + GDP\_2Y_t * \beta_5 + \beta_6) \quad (12)$$

$$ME\_BF\_beneficiary_{it} = s_{it}(1 - s_{it})(\beta_7) \quad (13)$$

$$ME\_GDP\_2Y_{it} = s_{it}(1 - s_{it})(\beta_2 + Wage_i * \beta_5) \quad (14)$$

$$ME\_Lula\_2006_{it} = s_{it}(1 - s_{it})(\beta_3) \quad (15)$$

Table 8 summarizes the mean marginal effect for the variables described. Besides the overall average, it depicts the values by groups of: beneficiaries (having a beneficiary in the family) and non-beneficiaries, as well as urban and non-urban.

The average overall marginal effect of *Bolsa Família* Coverage indicates that an increase in 1% of the coverage, among all municipalities, would increase the average probability of an individual voting for Mrs. Rousseff on the run-off of 2010 elections by 0.14%. This effect would be four times larger, on average, among beneficiaries of the program in comparison to individuals that do not have a beneficiary of the program in the family. The effect is also 2.5 times larger on individuals that do not live in an urban area.

For the individual dummy of having a beneficiary in the family, the marginal effect is the increase in probability resulted by changing the dummy's value from 0 to 1 (from not having a beneficiary in the family to having one). The electoral overall marginal impact of having a beneficiary in the family represents, on average, an increase in the probability of supporting Mrs. Rousseff by 12.25%. For the group of beneficiaries, the value of 12.03% is better understood as the magnitude of the decrease of probability of supporting Mrs. Rousseff if the variable changes from 1 to 0, i.e. if the benefit is removed.

An increase in 1% of the average of labor income has an electoral impact of 2.78%, on average. This increase is larger for individuals that do not have a beneficiary in the family and for individuals who live in an urban area.

The electoral marginal effect of local GDP growth in the period 2008-2010 is of 0.04%, indicating that economic growth of municipalities has little impact on the probability of voting for Mrs. Rousseff, a result that is present among beneficiaries, non-beneficiaries and individuals that live in both zones. A hypothetical marginal increase on the share of votes president Lula had on 2006 elections, on the other hand, would have a significant impact on average probability of voting for Mrs. Rousseff on the following election. Estimations shows that roughly 60% of the increase on Mr. Lula support reflects on Mrs. Rousseff's support on the 2010 elections.

***Table 8* - Marginal Effects for selected variables**

	Overall	Beneficiaries	Non-Beneficiaries	Urban	Non-Urban
1% BF Coverage	0.14%	0.29%	0.07%	0.10%	0.24%
1% Labor Income	2.78%	0.80%	3.72%	3.44%	1.38%
100% BF Beneficiary	12.25%	12.03%	12.36%	12.29%	12.17%
1% GDP 2 years	0.04%	0.03%	0.04%	0.04%	0.03%
1% Lula 2006	0.60%	0.59%	0.61%	0.60%	0.60%

Values represent the average impact on the probability of voting for president Dilma Rousseff on the 2010 run-off, due to a marginal increase of the variables. For the dummy of having a Bolsa Família beneficiary in the family, the increase is the dummy from 0 to 1. For the remain variables, the increase is of 1%.

Our final analysis, Table 8, allows is to compare the marginal effects of having a beneficiary in the family with the one of Labor Income and identify electoral the trade-off between them. This relation indicates if, in terms of electoral results, is better to establish a policy to improve labor income or to aid in the form of conditional cash transfer. As labor income is presented in the natural log form, the trade-off is represented by the exponential of the ratio between the marginal effect of the dummy and the labor income, the result is 81.61 reais. As a comparison, the average *Bolsa Família* aid received by family in 2010 was of 87.24 reais.[27] This suggests that, although the program has a large electoral impact, it is still smaller than the impact of labor income.

5. Conclusion

In this paper, we investigate the effects of Bolsa Família, the world's largest conditional cash transfer program, on the 2010 Brazilian elections. The incumbent candidate,

[27] Source: MDS (*Ministério do Desenvolvimento Social*) Brazilian Ministry of Social Development and Fight against Hunger.

Mrs. Dilma Rousseff, was elected mainly due to the support received in the northern regions, which are poorer and thus is where most of the municipalities with high coverage of the program are located. We estimate voting shares using a mixed logit model, a discrete choice model that uses both parametrical distribution of unobserved variables and non-parametrical distribution of known variables. For the latter, we use data from the Brazilian demographic cense of 2010.

We find evidence supporting a positive electoral impact of the *Bolsa Família* program, as individuals that live in municipalities with higher coverage of the program have a bigger probability of voting for Mrs. Rousseff. This impact is decreasing with labor income and, for individuals with sufficiently large wages, the larger coverage of Bolsa Família in the municipality has a negative electoral impact. In terms of marginal effect, being a beneficiary of the program has the same election decision impact as an increase in 81 reais on monthly labor income. The counterfactual exercise, in which we estimate the voting share of Mrs. Rousseff in a scenario without *Bolsa Família*, estimates a decrease of 6.3% of the total votes. We estimated the aggregate counterpart of the mixed logit models and in these the electoral impact is smaller, indicating that the analysis of municipal averages underestimates the electoral influence of the *Bolsa Família* program, supporting the importance of using the full distribution of the variables.

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Annex

***Table 9* - Counterfactual Shares by Brazilian state – Bolsa Família effect**

Region	State	Observed Share (1)	Counterfactual Share (2)	Difference (1) - (2)
North	RO	47.37%	45.32%	2.05%
	AC	30.32%	37.18%	-6.86%
	AM	80.57%	57.39%	23.18%
	RR	33.44%	35.66%	-2.22%
	PA	53.27%	40.43%	12.83%
	AP	62.66%	51.11%	11.55%
	TO	58.88%	49.56%	9.32%
Northeast	MA	79.09%	48.83%	30.26%
	PI	69.95%	45.81%	24.13%
	CE	77.35%	52.05%	25.31%
	RN	59.54%	46.84%	12.70%
	PB	61.55%	47.80%	13.75%
	PE	75.65%	52.33%	23.32%
	AL	53.63%	38.22%	15.41%
	SE	53.56%	41.55%	12.01%
	BA	70.85%	50.49%	20.36%
Southeast	MG	58.45%	53.15%	5.30%
	ES	49.17%	53.30%	-4.14%
	RJ	60.48%	56.88%	3.60%
	SP	45.95%	48.71%	-2.76%
South	PR	44.56%	48.34%	-3.78%
	SC	43.39%	49.36%	-5.96%
	RS	49.06%	46.79%	2.27%
Central-West	MS	44.89%	45.58%	-0.69%
	MT	48.89%	46.48%	2.41%
	GO	49.25%	50.65%	-1.41%
	DF	52.81%	54.63%	-1.82%

***Table 10* - Counterfactual Shares by Brazilian state – Bolsa Família effect**

Region	State	Average household income per capita	Average household labor income per capita
North	RO	645.38	537.84
	AC	496.12	391.33
	AM	507.21	401.70
	RR	576.23	486.35
	PA	429.46	331.47
	AP	575.17	485.20
	TO	570.79	460.73
Northeast	MA	349.15	250.77
	PI	408.78	280.80
	CE	445.66	313.81
	RN	530.73	371.91
	PB	461.88	312.58
	PE	508.17	348.59
	AL	419.89	289.54
	SE	507.21	358.17
	BA	480.95	342.72
Southeast	MG	731.89	535.26
	ES	793.02	595.58
	RJ	990.72	691.65
	SP	1,031.35	783.72
South	PR	868.50	671.72
	SC	965.57	739.29
	RS	933.69	665.55
Central-West	MS	780.92	625.94
	MT	733.83	609.67
	GO	783.27	627.17
	DF	1,641.19	1,254.91

Capítulo 2

Tightening the gap – determinants of female political participation and the influence of quotas

1. Introduction

Over last decade, women made important progress in increasing its political participation, with the rise of female presidents and prime ministers both in developed countries, such as England and Germany, and in developing countries, like Brazil, Costa Rica, and Jamaica. The gender gap in terms of female participation in politics, however, remains large, with a world average share of 23.4% on the Lower Houses and 22.9% on the Upper Houses.[28]

The article address this subject and attempts to answer one question: what political and individual characteristics explain the electoral gender gap? Literature on women in politics has suggested political factors (Morgan and Buice, 2013; Bhalotra et al., 2013; Alexander, 2012) and individual characteristics (Lawless and Fox, 2010; Fraile and Gomez, 2015; Iversen e Rosenbluth, 2006) may contribute to underrepresentation of woman in politics, which leads to fewer policy choices in their favor (Bhalotra et al., 2013).

This paper proposes the use of two econometric models: fractional and mixed logit to estimate the probability of supporting a female candidate and present new evidence on the question presented. Fractional logit (Papke and Wooldrige, 1996) is a model commonly used to estimate shares.[29] The second model we use is the mixed logit (Berry et al., 1995). Its biggest advantage is the possibility of combining the distribution of individual data to aggregate data. While Fractional logit has the advantage of correctly estimating the dependent variable, mixed logit has the advantage of using not only municipalities' averages, but also the whole distribution of individual characteristics to estimate female candidates' electoral shares. By using this methodology, we are able to estimate how individual characteristics relates with the individual probability of voting for a female candidate for the Congress.

[28] Source: Inter-Parliamentary Union (IPU).

[29] Fractional logit method has the advantage of using quasi-likelihood, which does not require that the distribution of the observations to be known, only the average and the variance, as is the case of electoral data.

The literature has demonstrated the importance of political and institutional factors to explain gender gaps in political representation. Morgan and Buice (2013) describes three theoretical arguments that present different visions on how the political institutions' context shapes attitudes on female leadership: socialization, status discontent, and elite cues. These arguments differ from each other both in terms of the expected progress of female participation and in term of the mechanisms that affect the decision to support a female candidate, as we describe in Section 2.

Individual characteristics play a role as relevant as the context in which the voters are inserted. Age, labor income, civil state, education, are all determinants to shape not only electors perception on the female capacity to lead (Iversen e Rosenbluth, 2006), but also how the female candidates perceive their own capacity (Lawless and Fox, 2010). For example, the gap percentage between the share of men and women that have considered running for an office is the same as the gap in the share of self-assessment qualification to run for it: 16% (Lawless and Fox, 2012).

Alongside the literature investigating the causes of electoral gender gap, there are studies on policies aimed at increasing female participation in politics, the most common of which are gender quotas. In Section 2.3, we review the literature on this policy and discuss the Brazilian case. Brazil is one of the countries with the lowest female participation in the world, being in 154th place in a 193 countries ranking that measures the share of women in the Congress[30]. By 2006, women represented 12.7% of the candidates for the Lower House and 8.8% of the elected deputies. In 2009, a law was stablished that attempted to reduce the gender gap in the election outcome by increasing the percentage of female candidates through a quota policy which requires that 30% of the candidates in each party to be women.[31] After the implementation of the quota, the percentage of female candidates increased 50% and represented 19.1% of the total candidates for the Lower House in the 2010 election. The percentage of elected female candidates, which is the desired outcome, however, remained at 8.8%. Therefore, there may exist other factors holding women from actually being elected.

In this article, we analyze how female participation in Brazilian politics is affected by three aspects: local political factors, individual characteristics and gender quotas. For the analysis, we use data from the 2010 election for the Lower House of the Congress, as well as

[30] Source: Inter-Parliamentary Union (IPU).
[31] The quota is applied to Senators, Federal Deputies, State Deputies and members of Municipal Councilman

individual characteristics from the Census database of the same year to identify the individual characteristics that affect the probability an individual has to vote for a female candidate. We implement two econometric models to identify the determinants – political factors and individual characteristics – of the gender gap in political participation. We also test the influence the exposure to a female leader has by combining the individual information with a dummy for living in a municipality that elected a female mayor in the 2008 elections

The methodology we propose does not allow us to estimate the influence of elite cues, but it does test the socialization and state discontent arguments. The Fractional Logit models results suggested that individuals that live in a county with a female mayor have a smaller probability of supporting a female candidate for the Congress, a result that goes in line with Bhalotra et al. (2013) and Alexander (2012). However, further analysis using the demographic variables distribution using the Mixed Logit model show no evidence that the exposure to female mayor affects the probability to support female candidates. This result suggests that, in our data, models that only use demographic statistics might present aggregation bias, which is the inference error of individual choices from aggregate statistics.

Our findings that aggregation bias was relevant in the case of Brazilian 2010 elections do not allow us to infer that every analysis in the literature that uses aggregate information is biased. However, our results shed light on the importance of testing if aggregate statistics are representative of individual' behavior before estimating the influence of a demographic variable in the individual voters' choice. Since we find no evidence of a socialization effect on the Brazilian case, it is clear that to achieve a more gender egalitarian distribution of politicians, active policies are required, as we find no evidence supporting a natural growing process.

The main contribution of this article is to bring two new econometric models that, to the extent of our knowledge, have never been applied to this literature: Fractional Logit and Mixed Logit. We find evidence of aggregation bias in the analysis of the 2010 Brazilian elections for the Lower House, which indicates the importance of using individual data. Furthermore, we find no evidence of socialization effect when we use the distribution of individual characteristics in the Mixed Logit model. The limitation of both models proposed is that we cannot make causal claims neither investigate the channel through which the political and individual characteristics influence the electoral decision of supporting a female candidate. Nevertheless, understanding how female support correlates with individual

characteristics can indicate the direction that future studies and policies should focus in order to reduce electoral gender gap.

We present a brief literature review on the political factors and the individual characteristics that help explaining gender gap as well as an overview on the gender quotas policy in Section 2. In Section 3 we discuss the Brazilian case. Sections 4 and 5 detail the data and methods used, respectively. Section 6 presents the parameter estimates. Finally, Chapter 7 presents our final remarks.

2. Literature Review

In this chapter we present a brief review on the main topics on gender electoral inequality. Session 2.1 presents the three theoretical visions on the political explanations for women's low participation in politics. Session 2.2 focus on the individual characteristics that determine the support for a female candidate. Finally, Session 2.3 presents a discussion on the effects of quota policies implemented.

2.1. Political Explanations for Women's Political Representation

Female participation in politics has increased worldwide over the past decade. It is not clear, however, if this increase is permanent or an ephemeral phenomenon. In other terms, it is not clear the effect that recent progress has on future outcome. Although the literature on this subject is not extensive, different lines of theorizing have been presented, each with different predictions. Morgan and Buice (2013) categorize these theoretical analyses in three arguments: socialization, status discontent, and elite cues.

Socialization is defined by the authors as a self-reinforcing force. As women gain opportunities and increase influence on society decisions, social structures become more gender egalitarian, making women's gains self-reinforcing.

Several articles with different analysis present results supporting the socialization argument. Inglehart and Norris (2003) explores deeply the cultural changes that allowed the "rising tides" as the authors describe the female progress. They present data for developed countries since the 1970's and show evidence of a closing gap between male and female votes.

Bhalotra et al. (2013) use data on India's states election in the period 1980-2007 and regression discontinuity to test the effect of the election of a woman on the probability of a subsequent candidate. They find evidence supporting a significant increase in the fraction of

female candidates after a woman has been elected. There is no significant change in the gender pattern of voting turnout, the main driver for the raise is the increase in the probability to run for reelection, which is not so common in India. Moreover, there is no evidence of spillover effect, neither to the candidacy of nearby constituencies nor persistence of the effect to future elections after the first one.

Alexander (2012) defends that the increase in the percentage of women in parliament contributes to an increase in women's beliefs in their ability to govern. To support this hypothesis, the author used data from the World Values Survey, which includes for over 25 countries information about individuals' belief of the following statement: "On the whole men make better political leaders than women do." Banaszak and Plutzer (1993b) follow a similar line of argument as they suggest female empowerment in politics as dispelling "myths about women's inabilities to participate".

On the other hand, there are articles supporting the idea that female progress may provoke a backlash from those who see female conquests as a threat, in ways that can undermine the progress toward egalitarianism. This type of argument is named by Morgan and Buice (2013) as status discontent.

Sundström and Wängnerud (2016) analyses regional data from 18 European countries and identifies a negative correlation between corruption and female participation in politics. This results goes in line with the thought that both gender equality and government accountability are results of a developed liberal democracy (Sung, 2003). The idea is that in order to facilitate corruption 'shadowy arrangements' that benefit the incumbent's groups are made, thus undermining female participation. In this scenario, entrance of outside groups in politics is understood as endangering the corruption systems.

Although Banaszak and Plutzer (1993b) shows evidence that the female progress could increase belief on the women's capacity to lead, they also alert for the risk of men defending traditional norms to avoid competition of prosperous women. This conclusion comes from the analysis of survey data from the 1983 Euro-barometer, through which the authors identified that the areas in which female participation in labor force was larger, individuals adopted the most conservative values, suggesting that the status discontent may be pronounced in men left behind female progress.

The last classification, elite cues, suggests that the continuity of progress for women may be contingent, because it depends on the opinion leaders and the messages transmitted.

Bullock (2011) explores the idea that the elites can influence public opinion and presents experiments which support the idea that those with weak prior views are much more susceptible to the messages communicated via elite behavior.

The impact of this influence on political gender gap is explored in Klein (1982). By exploring polls of the 1972, 1976 and 1980 US elections, she found evidence suggesting women's opinions are likely to be deeply internalized and less affected by leader's influence. Men's position on gender issues, on the other hand, are more linked to liberal ideologies, and thus likely to be weakly held.

Perhaps the most solid analysis of individuals' perception on women in politics comes from the natural experiment and survey data analyzed by Beaman et al. (2009). Since 1998, in the Indian state of West Bengal, one third of the village council leader position are randomly reserved to women. Once a council has been reserved, only women can run for the position. In villages that have never been reserved, electors, especially men, are against the idea of a female leader. The mandated exposure to female leadership weakens the stereotype that men are associated with leadership activities, while women to domestic ones. The exposure also changes the perception of female leader effectiveness among men, but not women. Furthermore, female leaders are worse evaluated, on average, in villages that have never been exposed to a female leadership, but this difference in ratings disappears when the council position is reserved for the second time. These results indicate that, even though gender preferences and social norms are difficult to be changed, the institution of gender equalizing programs can improve the perception of a female leader effectiveness, which, with persistence, leads to a more gender egalitarian elections in non-reserved councils.

Morgan and Buice (2013) not only define these three classifications but also test each hypothesis through the analysis of survey data from 19 Latin American and Caribbean countries from the 2008 Americas Barometer. The results suggest the recent trend of equalitarian progress are potentially reversible, thus not supporting the socialization argument of self-perpetuating process of gender equality in the region politics. Instead, in countries where professional positions have a more gender balanced distribution, male support for female equality is lower. Indicating men may perceive opportunities for women as a threat for their own success. Furthermore, the authors show evidence indicating that male opinions on gender equality can be influenced by elite cues. In countries in which women are regularly nominated as ministers, men see women as more capable of leading.

Support for female leaders can also be a consequence of distrust of traditional political institutions, as female candidates are seen as outsiders of the system. This perception has the possibility of increasing support for women in a context of political frustration. However, as female representation in high executive levels increases, women lose the outside status and this contingent support is reversed.

2.2. Individual Factors and Female Support in Politics

In this subsection, we analyze the individual characteristics that could help understand the gender gap in political representation. Naturally, the differences in the political context of each country lead to different variables being correlated to the probability of supporting a female candidate. Nevertheless, some characteristics stand out as important explanations to the inequality in political representation.

Early studies, such as Almond and Verba (1963), suggested that women were more conservative, less interested in politics and thus participated less in the politics. This explanation is known as the "traditional gender gap". Since then, this vision was challenged and new studies pointed that female interest in politics rose as female participation on labor force rose.

One study that supports the modern female interest in politics is Iversen e Rosenbluth (2006), which shows that female interest in politics correlated, among other things, to labor inclusion and civil state. Single, employed women, for example, have a tendency to support left-winged parties. This effect is even stronger in countries with higher divorce rates and for women with high quality occupations. The cultural and economic context that helped define modern women in politics is deeply discussed in Inglehart and Norris (2003), which analyzes how transformation from agrarian to industrial and then to modern postindustrial society changed the lives of men and women. This is important to understand the relative difference of the gender egalitarian movement between developed and developing countries.

Lawless and Fox (2010) uses a unique survey database, the United States' Citizen Political Ambition Panel Study which present individual information for eligible candidates in 2001 and 2008 to analyze the gender influence on political ambition. Their results support the idea that women consider themselves less qualified to run for office than men do. Due to that, they express less will to run for office, which creates a gender gap in candidates that reflects in a gender gap in political representation. The results also indicate that this gender gap in political ambition is persistent over time.

A similar explanation for the gender gap in the candidates is a difference in political knowledge. Fraile and Gomez (2015) test, for Latin American and Caribbean countries, the variables that influence the gap in political knowledge. They present evidence showing the gap is smaller among educated individuals, in rural areas, where political knowledge is small but evenly distributed and in large cities. The comparison between countries also indicates that the larger the gender income inequality, the larger is the political knowledge gap. These results suggest that as the countries develop, the increase in education is expected to decrease the difference in political knowledge, and thus the difference in political representation, especially if this development is aligned with labor income to progress to be more gender egalitarian.

Another factor that could reduce the knowledge gender gap, tested by Wolf (2011), is if the presence of female candidates could improve the interest of female electors. The author tests this hypothesis by analyzing the correlation of the presence of a female candidate to the 2008 US senate on the registration and turnout of male and female electors. In the US, as voting is not mandatory, electors must register to be able to vote. The results showed no evidence that a state with a female candidate would have proportionally more female electors registering to vote, or in the turnout on election day. This result is important as it indicates that the gender gap cannot be reduced simply by introducing a female candidate.

Differences in political interest not always directly result in a difference in engagement, as Morgan et al. (2008) shows. The authors analyze data from the Dominican Republic in the period 1994-2004 and suggest that, although the gender differences in engagement narrowed, the traditional gap in interest remained. They also show evidence supporting a difference in the effects of age and education among men and women. Men develop an interest in politics when their age is in the 40's at the same time their support for female in politics becomes more positive. On the other hand, women's interest and view is more evenly distributed among age groups. The education influence, however, is much stronger at boosting women's interest in politics than men's.

Morgan et al. (2008) findings are important as they contradict a common view that as younger generations replace the older ones, the population support to feminism increases. They indicate that to achieve that, education is a key element, a result that goes in line with Banaszak and Plutzer (1993a) which got to similar results while studying data from western European countries, suggesting that the educational effect on women interest in politics stands even in developed countries, with higher educational levels.

2.3. Quotas and Female Participation

The most common policy instrument proposed to reduce the gender gap in political representation is gender quotas, adopted in over 100 countries (O'Brien and Ricke, 2014)). Consequently, the literature on women in politics has a large session dedicated to the analysis of gender electoral quotas in the many forms it has been implemented. In this chapter we briefly discuss the different impacts documented in the literature. Most authors agree that gender quotas increase female participation in politics, but there are several points in which there is still much debate, both in terms of the impact of the quotas and the design of the law in order of it to be efficient.

Paxton et al (2010) use data of 110 countries from 1975 to 2000 and focus on the different growth rates of female participation, instead of a comparison between the level in each country. By doing so, they are able to identify the influence of the establishment of gender quotas[32] in different countries. Their results suggest that gender quotas affect female political presence, but at lower levels than defined by the law. On average, a 1% increase in the threshold of a quota only increases the female participation in 0.1% of its overall trajectory of growth, as estimated using a latent growth model. Moreover, they present the case of two countries, Egypt and Pakistan. Both countries had a female participation in the congress of less than 5% before the establishment of a quota policy. When implemented, the share of women increased to 8%, as enforced by the quota. Finally, after the quota was removed, both countries presented a reversal of the female participation to less than 5% share. In the Pakistani's case, the final level of participation was even lower than before the seats reserve to women.

In a similar analysis, Schwindt-Bayer (2009) seeks to identify the characteristics that lead to an effective quota policy. The analysis uses data comparison between 26 countries and an OLS model to estimate the share of congress seats held by women. The conclusion is that the number of elected women represents only one third of the defined by gender quotas in the number of candidates, when there is no enforcement mechanism and the placement is not mandatory. When the quota stipulates both mechanisms, the percentage reaches the values defined by the quota law, but does not grow much further than the threshold value.

[32] The authors analyze both quotas that require a minimum percentage of women on parties list and placement mandates quotas.

Albeit most authors agree that gender electoral quotas increase female participation, there are who argument that quotas usually frustrates advocates as the increase is not as large as expected (Matland, 2006). The authors suggest that two conditions are necessary for the increase in the female participation, namely: proportional representation electoral system and a system that produces high party magnitude. The later can be defined as the number of seats a party wins in a specific electoral district.

There are, however, successful cases in which the number of women elected reached or even exceeded the requirement defined by the quota, as is the case of Niger analyzed by Kang (2013). The reasons appointed for the success at reaching the 25% female minimum candidates and 10% minimum elected women are the combination of three factors. The design of the law, the institutional context, and the fact that quota implementation is monitored by groups of women's activists. The design includes not only the threshold of minimum candidates and reserved seats, but also the establishment of an enforcement mechanism and the institution, the Constitutional Court, had the *de jure et de facto* power to invalidate party lists that did not comply the law.

Although most authors only explore the correlation between quotas and female participation, there are studies that seek a causal relation. O'Brien and Rickne (2016) exploit a quasi-experiment of a zipper quota[33] in Swedish Social Democratic national party on municipal party groups and find that gender quotas have a positive impact on women's election but not on reelection. Furthermore, a close look on the pool of candidates show that the increase in the number of female candidates does not change the distribution of age, education and income of the candidates.

A natural conclusion after this review is that, without proper enforcement, political parties do not respect gender quotas. The design of the law and the mechanisms of enforcement are crucial for the effectiveness of the gender quotas.

3. The Quota for Women in Lower House Elections in Brazil

In this chapter we discuss the case of female participation in politics in Brazil, which is currently one of the countries with the lowest female participation.[34] Since 1995, Brazil has experienced quota policies. At first only at municipal level, but in 1997 a new law implemented the quota system for every representative election. However, these laws had

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[33] Zipper is the name used to describe a rule in a closed list system in which the names in a party list must alternate between men and women.
[34] Source: Inter-Parliamentary Union (IPU).

very little enforcement due to two reasons: the percentage of reserved female candidates was implemented with an increase in the total allowed candidates, which guaranteed that none of the traditional male candidates would lose their candidacy; no political party was ever punished for not achieving the minimum required percentage of female candidates. This scenario lasted until the 2010 election, when an enforcement of the law was implemented. Since then, Brazil has experimented a minimum requirement of 30% female candidates per party.[35]

Brazil has elections every 2 years, alternating between national and local elections. In the former, the President, Senators, Governor, Federal Deputies and State Deputies[36] are elected. In the latter, the Mayors and members of Municipal Councilman are elected. With the exception of Senators, who have a mandate of 8 years, all others have a 4 years' mandate.

Of the 513 total deputies elected in 2014 for the Brazilian Lower House, only 51 (9.9%) are women. The Senate has slightly higher participation of women with 12 elected female Senators among the 81 (14.8%) in the House.[37] The low representation is a phenomenon observed in all political spheres, in all regions and has not improved In the last years.

Table 11 presents the percentage of women among the candidates and elected politicians of the last four national elections. The share of women running for each political office increased between 2002 and 2014. The same cannot be said about the share of women elected. With the exception of the Governor, for all the other offices the female participation increased by over 50% between 2002 and 2014. The two offices that had the smaller increase in the number of female candidacies were, not coincidently, the two in which the parties are not required to comply the gender quota, as offices in which each party has one (Governor) or just a few (Senators) candidates.

The participation on the elected, however, decreased in the same period, with the exception of the share of women elected as Federal deputies. This decrease indicates that despite the increase in the number of female candidates might be due to the quota for the

[35] A bill already approved in the Upper House and waiting to be voted on the Lower House of the congress intends to enhance the existing law and not only require a percentage of female candidates but also reserving seats on majority elections for each gender. If approved, the number of seats reserved will increase for the three elections following the approval. In the first election, the number reserved is of 10% of the total, increasing to 12% and finally 16% of the seats.

[36] Technically, Brasilia does not have state deputies, but districtal deputies. Here we consider both as the same.

[37] Brazilian senators have a mandate of 8 years. Of the total of 81 senators currently in exercise, 54 were elected in 2010 and 27 in 2014. In the former 7 were women (13.0%) and in the latter 5 were women (18.5%)

female candidates, this policy was not able to achieve its goal, which is to increase the percentage of elected women.

Table 11 **- Female Participation - Federal and state elections**

	Federal deputy		State deputy		Governor		Senator	
Year	Candidates	Elected	Candidates	Elected	Candidates	Elected	Candidates	Elected
2002	11.5%	8.2%	14.8%	12.8%	9.8%	7.4%	11.9%	14.8%
2006	12.7%	8.8%	14.3%	11.6%	12.8%	11.1%	15.8%	14.8%
2010	19.1%	8.8%	21.4%	13.3%	10.7%	7.4%	13.0%	13.0%
2014	19.1%	9.9%	29.1%	11.2%	12.1%	3.7%	20.6%	13.6%

Source: TSE

On the elections for Municipal Councilman and Mayors, where the candidacy is considerably cheaper, the situation is not much better. In 2016 elections, 68% of Brazilian municipalities did not have a single female candidate.

Table 12 shows the percentage of candidates and elected women. The analysis in this case can be split in two parts. The first takes into account the increase in the female participation in the period 2000-2012. The second, its stagnation and even decrease in the 2016 elections.

The period 2000-2012 shows a constant increase in the number of candidacies of women for both offices and in the share of elected Mayors. For the office in the Municipal Chambers, the increase is much smaller, but exists. The elections of 2016, however, show a decrease in the share of elected women for Mayor.

Table 12 **- Female participation - Municipal elections**

	Municipal Councilman		Mayor	
Year	Candidates	Elected	Candidates	Elected
2000	19.5%	12.5%	8.5%	6.9%
2004	22.0%	13.3%	10.5%	9.7%
2008	21.9%	12.5%	11.0%	9.1%
2012	32.65	13.3%	13.18	11.8%
2016	33.1%	13.5%	13.0%	11.6%

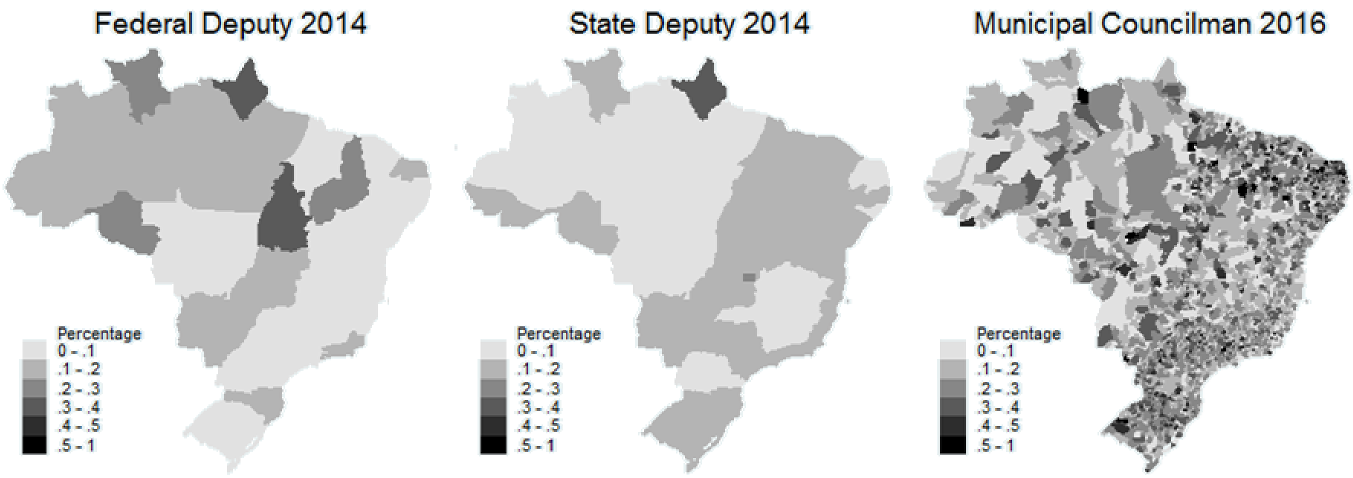
Source: TSE

Brazil is a country of continental proportions, with a history of deep inequalities that culminates in a nation in which few things can be assumed to be true for the whole country. Low female participation on politics, however, is one of them. Figure 2 shows, for the offices of Federal Deputy, State Deputy and Municipal Councilman, the percentage of women

among the elected on each Brazilian state (Federal and State Deputy, 2014 election) and municipality (Municipal Councilman, 2016 election).

For the office of Federal Deputy, the North region of Brazil appears outstand as the one with the most elected women, but when we analyze the distribution of State Deputies elected, the opposite can be said. Finally, from the map of elected Councilwomen, we do not observe a region in which the female participation is clearly larger.

Figure 2 **- Women elected in Brazil**



This map describes the percentage of female elected in per Brazilian State for Federal and State Deputy in the 2014 elections and Municipal Councilman elected per county in 2016. Source: TSE

4. Data

In this chapter we look for individual factors that can help explain the gender gap in political participation. In particular, we do so analyzing the percentage of votes in female candidates for Federal Deputy in 2010. The reason for choosing the Federal Deputy in our analysis is that it is the most important office for which we have data. Many states did not have a single female candidate for Governor in 2010. We could have used Municipal Councilman data, but Federal Deputy has the advantage that the candidates are the same for all counties in a state, which allows us to use fixed effects for the state, as we discuss in the methodology in Chapter 5.

Our focus on the 2010 elections is given by the combination of a federal election year with the availability of data from the Brazilian Demographic Census (hereafter, *Census)*. The main advantage of using this database is representativeness and the possibility of identifying the municipality in which the individual lives. This allows us to estimate the

support to female candidates in the population using the distribution of individual data of 5564 municipalities.

Electoral data comes from Brazilian Superior Electoral Court (*Tribunal Superior Eleitoral*). From this database we extract information in order to construct two variables. The first is the percentage of votes each candidate has in each county. Using this variable we are able to aggregate and generate the desired variable which is the voting share of female candidates per county. The second one is the dummy for having elected a female mayor in 2008, which we extract from the electoral results from the 2008 elections.

From the Census database we construct the demographic database by extracting, for simplicity, a sample of 1000 observations per municipality. The sample was extracted considering the weight of each observation in the *Census* database per municipality.

Table 13 presents summary statistics of the data from both the electoral and the demographic databases, using the full sample of the Census. Our variable of interest is the percentage of votes for female candidates for the Lower House of the Congress. We observe that 7% of the votes were casted for female candidates. In order to test the effect of having a female leader in the municipality on the probability of supporting a female candidate, we use a dummy for female mayor in 2008, year in which 9% of the municipalities elected a woman as mayor.

Next we present the statistics for the variables extracted from the *Census* 2010. The first variable is the gender dummy, which assumes value 1 to male individuals. The age shows that Brazilian population is still young, with an average of 31.58 years. The third and fourth variables analyzed are the Napierian logarithm of labor income[38] and a dummy if the individual lives in an urban area. The idea for both these variables is to capture, respectively, economic and geographical bias. The logarithm used in the labor income turn difficult for the value to be analyzed, but the fact that the standard deviation is larger than the income mean indicates how large is income inequality. Table 13 also shows that 84% of the individuals live in an urban area. The last variables depicted in the demographic database are dummies for the characteristics of the individuals, such as gender, race and ability to read. Table 13 shows that, in 2010, 83% of the population was alphabetized and 48% was white.

[38] We use the logarithm in order to avoid problems with very large incomes. As $\ln(0) \rightarrow -\infty$, we add 1 real to each individual labor income. A small value that is not enough to generate any distortion, but sets the ln of labor income to zero for individuals without labor income.

***Table 13* - Summary Statistics**

Source	Variable	Observations	Mean	Std. Dev.	Min	Max
TSE	% votes in female candidates	5,564	0.07	0.11	0.00	0.87
	Dummy for female mayor	5,564	0.09	0.29	0	1
Census 2010	Dummy for Man	20,635,472	0.49	0.50	0	1
	Age	20,635,472	31.58	20.40	0	139
	(Ln of) Labor Income	20,635,472	2.83	3.36	0.00	13.76
	Dummy for Urban	20,635,472	0.84	0.36	0	1
	Dummy for Literate	20,635,472	0.83	0.38	0	1
	Dummy for White	20,635,472	0.48	0.50	0	1

This table displays descriptive statistics of the data used in this article. The variables are divided by database and include information on 5564 Brazilian municipalities and individual information available at Census. Source: 2010 Brazilian Census and TSE.

5. Methodology

We want to estimate which factors influence the probability that an individual votes for a women. Our variable of interest is the percentage of female votes in each municipality in the 2010 election for Federal Deputies. Therefore, we do not estimate the probability an individual has to support one particular candidate, but any female candidate. Since our interest variable is a pool of candidates, we cannot use individual candidate characteristics, such as the party, campaign costs, *et cetera*, as control variables.

Estimating without controlling for candidates' characteristics could lead to biased estimators as these variables, which are correlated with the dependent variable, would be included in the error term. To solve this problem, we control our estimations using fixed effects per Brazilian state. The candidates for the Congress are the same in all municipalities in the same state, therefore these fixed effects absorb any common features of the candidate pool or state level politics. We exploit variation in electoral outcomes in different municipalities within each state.

As our interest variable is a fraction in the interval [0,1], the use of OLS (Ordinary Least Squares) models is not recommended, as the dependent variable is not limited, it may assume values in the range $(-\infty, \infty)$, which can lead to biased results. Even models OLS regression with Gaussian distributional assumption, which are a common choice to model fractional outcomes, has severe problems in the range [0,1], as it fails to assume Gaussian distribution (Liu, 2014). Among the problems, one characteristic of fractional outcome is that the average and variance are not independent. For example, the variance shrinks as the mean approaches boundary points of [0, 1], which indicates heteroscedasticity.

In our analysis, we use two models to estimate the average probability an individual has to vote for a female candidate. The first is the fractional logit, which is a model commonly used to estimate variables in which the dependent variable is a share. This model estimates average female support per county. The second model we use is the mixed logit. Its most important advantage is the possibility of combining individual and aggregate data. Instead of using municipalities averages to estimate female electoral shares, this estimation uses the whole distribution of the population. By using this methodology, we are able to estimate how individual characteristics affect the individual probability of voting for a female candidate for the Congress. Differently from the Fractional Logit model, in the Mixed Logit the estimated values are the individual probability of supporting a female candidate, which are then aggregated by county.

As described in the previous chapter, we will use information of gender, age, labor income, literacy, race and if the individual lives in an urban area as the individual characteristics implemented in the model.

One particular characteristic we want to test is if for individuals that live in a municipality with a female mayor, the probability of supporting a female candidate is bigger. This would indicate a socialization effect, in line with Bhalotra et al (2013), Inglehart and Norris (2003) and others. Furthermore, by combining the presence of a female mayor with gender dummy and labor income variables, we are able to capture heterogeneous preferences for a female leadership and test if on average it increases or not the support for female candidates. This test allows to identify for the presence of a status discontent effect, as described by Banaszak and Plutzer (1993b).

The limitation of both Fractional and Mixed Logit models is that we cannot make causal claims neither investigate the channel through which the political and individual characteristics influence the electoral decision of supporting a female candidate.

5.1. Fractional logit

The fractional logit model[39] (Papke and Wooldrige 1996) carries out a quasi-likelihood estimation of a model with dependent variable in the interval (0,1) as described by Wedderburn (1974). The difference between likelihood and quasi-likelihood is that for the former the estimation must specify the form of the distribution of observations, while the latter needs only to specify a relation between the mean and variance of the observations.

[39] The version of the model used is the one implemented on STATA by Powers (2013).

This is important in our case since the distribution of the votes is unobserved, as the votes are secret, but the mean and variance are known.

Following Papke and Wooldrige (1996), we define the fractional logit as:

$$E(y_i|x_i) = G(x_i\beta) \tag{2}$$

where $0 \leq y_i \leq 1$ and $\mathrm{i} = 1, \ldots, \mathrm{N}$. $G(\cdot)$ is a known function in which $0 < G(z) < 1$ for all $z \in \mathbb{R}$. In our analysis, using the logit form, $G(z) \equiv \exp(z)/[1 + \exp(z)]$. This functional form requires the sequence of observations (x_i, y_i) to be independent, but not necessarily identically distributed. To assume that votes are independent is a weak assumption and thus we can assume the model is correctly specified.

The model is estimated using the quasi-likelihood method using a Bernoulli log-likelihood function, given by:

$$l_i(b) \equiv y_i \log[G(x_i b)] + (1 - y_i) \log[1 - G(x_i b)] \tag{3}$$

As (3) is a member of linear exponential family (LEF), the quase-maximum likelihood estimator (QMLE) of β can be obtained from the maximization problem

$$\max_b \sum_{i=1}^{N} l_i(b) \tag{4}$$

5.2. Mixed logit

The Mixed logit is a random-parameters logit demand model from product market shares, first presented by Berry et al. (1995) – henceforth BLP. We describe this method following Nevo (2000) and define the indirect utility of the elector *i* when voting for the pool of female candidates while living in the municipality *t* by:

$$u_{it} = F_t\alpha_i + w_t\beta_i + \xi_t + \varepsilon_{it}, \qquad \varepsilon_{it} \sim P_\varepsilon(\varepsilon) \tag{5}$$

where $\mathrm{F_t}$ stands for the percentage of votes in female candidates in the municipality, $\mathrm{w_t}$ and ξ_t are, respectively, vectors of observable and non-observable characteristics of the municipality, and $\varepsilon_{\mathrm{it}}$ is the error term.

Let $w_{jt} = [x_{jt}\ 1]$, which is equivalent of w_{jt} plus a constant, it is possible to rewrite (5) as:

$$u_{ijt} = B_t\alpha_i + x_{jt}\gamma_i + \phi_i + \xi_{jt} + \varepsilon_{ijt} \tag{5'}$$

Furthermore, we define the vector of parameters to be estimated as:

$$\begin{pmatrix}\alpha_i\\ \gamma_i\\ \phi_i\end{pmatrix} = \begin{pmatrix}\alpha\\ \gamma\\ \phi\end{pmatrix} + \overbrace{\begin{pmatrix}\Pi_\alpha\\ \Pi_\gamma\\ \Pi_\phi\end{pmatrix}}^{\Pi} D_i + \overbrace{\begin{pmatrix}\Sigma_\alpha\\ \Sigma_\gamma\\ \Sigma_\phi\end{pmatrix}}^{\Sigma} \upsilon_i, \qquad \upsilon_i \sim P_\upsilon^*(\upsilon), D_i \sim \hat{P}_D^*(D) \tag{6}$$

where D_i and υ_i represent, respectively, vectors of observable and non-observable individual characteristics. Π and Σ stands for the matrix of parameters that represent how individual preferences vary with observable and non-observable individual characteristics. $P_\upsilon^*(\upsilon)$ is the parametric distribution of υ, while $D_i \sim \hat{P}_D^*(D)$ is the known distribution of the microdata.

Without loss of generality, the model is completed by defining the indirect utility of voting null or for a male candidate as containing only the error term, which has zero mean ($u_{it} = \varepsilon_{it}$). Furthermore, we define the individual characteristics (both observable and non-observable) by $\tau_i = [D_i\ \upsilon_i]$.

The probability of the individual *i*, living in the municipality *t*, to vote for a female candidate is given by:

$$Prob_{it} = Prob(U_{it} > 0) \tag{7}$$

Let A_t be the group of characteristics of the elector *i*, living in the municipality *t*, that makes him vote for a female candidate. Hence:

$$A_t(w_t, F_t, \xi_t, \Pi, \Sigma) = \{(D_i, \upsilon_i, \varepsilon_{it}) | u_{it} \geq 0\} \tag{8}$$

where w_t and ξ_t are vectors of observable and non-observable individual characteristics. The share of votes of female candidates in the municipality *t* is:

$$s_t(w_t, F_t, \xi_t, \Pi, \Sigma) = \int_{A_i} dP^*(D, \upsilon, \varepsilon) \tag{9}$$

By applying the Bayes Rule, and then considering the independence of the individuals, we can rewrite 9 as follows:

$$s_t(w_t, F_t, \xi_t, \Pi, \Sigma) = \int_{A_i} dP_\varepsilon^*(\varepsilon)\, dP_\upsilon^*(\upsilon) d\hat{P}_D^*(D) \tag{9'}$$

where P^* represents the populations' distribution function.

From (6), we have:

$$\phi_i = \phi + \Pi_\phi D_i + \Sigma_\phi v_i \tag{10}$$

We can replace ϕ_i from equation (10) into equation (5) and as a result:

$$u_{it} = \phi + F_t\alpha_i(\tau_i) + x_t\gamma_i(\tau_i) + \Pi_\phi D_i + \Sigma_\phi v_i + \xi_t + \varepsilon_{it}$$

$$u_{it} = \phi + F_t\alpha_i(\tau_i) + x_t\gamma_i(\tau_i) + [\widetilde{\Pi}_\phi][\mathrm{D}_i]' + \Sigma_\phi v_i + \xi_t + \varepsilon_{it} \tag{11}$$

Note that (11) allows that the effect of a female mayor to be different depending on individual characteristics. This allow us to identify the average effect of being exposed to a female mayor in a group consisted of male with low labor income, for example. Furthermore, municipalities and candidates characteristics, which are aggregate variables, affect voting decision differently depending on the individual's characteristics. Finally, both observable and non-observable individual characteristics affect voting decision.

From (9') we have that the shares of votes female candidate has on municipality *t* can be written as $s_t = \int_{A_i} dP_\varepsilon^*(\varepsilon)\, dP_v^*(v) d\hat{P}_D^*(D)$, which means that is not possible to estimate the share of votes of a candidate in a certain municipality without considering the distribution of individual characteristics. Also, it is only possible to write s_t as a function of aggregate variables if $\alpha_i = \alpha$, $\gamma_i = \gamma$, $\Pi_\phi = 0$ e $\Sigma_\phi = 0$. In particular, if ε_{it} is identical and independently distributed following the extreme value distribution of type I:

$$s_t = \frac{\exp\,(\phi + B_t\alpha + x_t\gamma + \xi_t)}{1 + \exp\,(\phi + B_t\alpha + x_t\gamma + \xi_t)} \tag{12}$$

6. Results

In this session, we present the estimation results using both methodologies. Table 14 presents the coefficients estimated using the Fractional logit model and the ones estimated using the OLS as well, to allow for a better comparison. Table 15 will then present the elasticity of the variables. Due to the logit form of the Fractional model, the interpretation of the coefficient's value is not straightforward, as the β's are the means of the distribution of marginal utilities. Nevertheless, the signal of the coefficients and its statistical significance indicate the direction of variable's influence on electoral decision of supporting a female candidate.

In both OLS and Fractional logit models, the variables used in the estimation are municipal averages. The dependent variable is the percentage of votes to female candidates in the municipality in the 2010 elections. For independent variables, we use a dummy for having a female mayor (elected in 2008) and the averages of individual characteristics (dummy for gender, age, urban, literacy and labor income). The average of a dummy can be interpreted as the percentage of individuals in the municipality that belong to the group described.

As Table 14 shows, OLS models fail to identify determinants for the support to female candidates, since the only variable that is both statistically and economically significant is the percentage of individuals living in urban areas, which is positive correlated to the female voting shares. The difference between the specifications that use the Fractional logit model is that FL(1) does not include fixed effects for Brazilian states, FL(2) does not include the combined effect of individual characteristics and dummy for female mayor, while FL(3) include both elements.

The negative value of the coefficient for the Female mayor dummy in FL(2) and FL(3) suggest that municipalities in which the 2008 elected mayor was a women, had statistically less votes to women, when we control for the state fixed effects (which includes the candidates characteristics). This negative correlation provide evidence suggesting a backlash effect that can undermine female political progress, although no causal relation can be inferred. However, unlike Banaszak and Plutzer (1993b), in which this negative was particularly strong for men with lower labor income, the negative sign of the coefficient for (Female mayor * Men * labor income) suggest that the female share is even lower in counties with a female mayor and higher labor income.

The direct effect of counties' average of individual characteristics goes in line with the Iversen e Rosenbluth (2006) and Fraile and Gomez (2015), which also identify that urban areas, younger population and higher labor income, all increase the probability an individual has to support a female candidate. Higher levels of education have a positive correlation with female support in the FL models that include State fixed effects.

Table 14 **- Coefficients estimated – OLS and Fractional Logit**

	OLS (1)	OLS (2)	FL (1)	FL (2)	FL (3)
Female mayor	0.19	-0.09	2.90	-0.18*	-1.56
	(0.48)	(0.21)	(6.57)	(0.09)	(2.22)
Men	0.13	0.18	1.66	2.73	2.36
	(0.25)	(0.21)	(2.98)	(2.64)	(2.77)
Age	0.005***	0.00	-0.06***	-0.03	-0.03
	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)
Urban	0.08***	0.09***	1.15***	1.13***	1.13***
	(0.02)	(0.02)	(0.26)	(0.25)	(0.25)
Literacy	-0.12	0.08	-1.69	1.15	1.16
	(0.10)	(0.09)	(1.25)	(1.13)	(1.13)
Ln of labor income	0.05*	0.03	0.57*	0.34	0.34
	(0.03)	(0.02)	(0.32)	(0.26)	(0.26)
Men * Ln of labor income	-0.05	-0.06*	-0.56	-0.77*	-0.74*
	(0.04)	(0.03)	(0.47)	(0.41)	(0.4)
Female mayor * Men	-0.31	0.19	-4.86		3.11
	(0.96)	(0.41)	(13.1)		(4.38)
Female mayor * Men * labor income	-0.04	-0.01	-0.47		-0.09
	(0.02)	(0.01)	(0.31)		(0.18)
Constant	0.16	0.11	-1.56	-3.06*	-2.89
	(0.14)	(0.14)	(1.68)	(1.73)	(1.79)
State fixed effects	No	Yes	No	Yes	Yes

This table presents the coefficients estimated with the aggregate models: Ordinary Least Squares (OLS) and Fractional Logit (FL). Unlike the mixed logit model, the individual characteristics in the aggregate model are given by municipal averages of Census observations. The first value is the β and bellow the robust standard error. Source: TSE and 2010 Brazilian Census * p-value<0.05, ** p-value <0.01, *** p-value <0.001.

The signal and significance of the estimated β only allows us to infer the direction of the correlation. In order to analyze its magnitude, we check the elasticity of the variables – how the share of votes of female candidates change in response to a 1% increase in the variable. Table 15 presents the average elasticity and semi-elasticity estimated. For the variable Ln of labor income and the variables in which the Ln of labor income interacts with other variables, the changes in response to an 1% increase is given by the semi-elasticity, as the variable is already in the ln form.

For these aggregate models, individual characteristics are represented by the municipal averages. Therefore, the interpretation of the elasticity of these variables is straightforward. Average elasticity indicates how the proportion of female votes varies with a 1% increase in the individual characteristic. The Fractional logit model FL(3) estimates that a 1% increase on average proportion of individuals living in urban areas increases the support for female candidates by 0.86%. The estimated value of -1.59 for the variable age in the FL(1) model indicates the ratio at which female voting shares would decrease, should the average

age of individuals increase by 1%. The interaction between the proportion of men in a municipality and the average ln of labor income, an expansion of 1% on this variable decreases the mean voting share of female candidates by 0.67%, according to FL(3) model.

Table 15 **- Estimated elasticity and semi-elasticity – Fractional logit and OLS**

	OLS (1)	OLS (2)	FL (1)	FL (2)	FL (3)
Female mayor	0.25	-0.26	0.24	-0.02*	-0.13
	(0.71)	(25.4)	(0.55)	(0.01)	(0.19)
Men	0.73	1.42	0.73	1.21	1.04
	(1.65)	(81.4)	(1.32)	(1.16)	(1.22)
Age	-1.72	-1.09	-1.59***	-0.86	-0.87
	(1.73)	(62.8)	(0.54)	(0.62)	(0.62)
Urban	0.73**	1.06	0.88***	0.87***	0.86***
	(0.33)	(25.9)	(0.2)	(0.19)	(0.19)
Literacy	-1.20	1.01	-1.28	0.87	0.88
	(1.71)	(55.4)	(0.95)	(0.86)	(0.85)
Ln of labor income	0.56	0.42	0.51*	0.31	0.30
	(0.70)	(23.9)	(0.29)	(0.23)	(0.23)
Men * Ln of labor income	-0.55	-0.95	-0.51	-0.70*	-0.67*
	(0.77)	(53.6)	(0.42)	(0.37)	(0.37)
Female mayor * Men	-0.20	0.26	-0.20		0.13
	(0.69)	(25.4)	(0.53)		(0.18)
Female mayor * Men * labor income	-0.41	-0.13	-0.42		-0.08
	(0.42)	(7.49)	(0.28)		(0.16)
State fixed effects	No	Yes	No	Yes	Yes

Note: This table presents the estimated marginal effect (dy/dx) and semi-elasticity (dy/dx)*(x) and the standard error between parentheses. The marginal effect is presented for the variables: Female Mayor; Ln of labor income; Men * Ln of labor income; Female mayor * Men and Female mayor * Men * labor income. For the remaining: Men, Age, Urban and Literacy, we present the semi-elasticity. Source: TSE and 2010 Brazilian Census. * p-value<0.05, ** p-value <0.01, *** p-value <0.001.

Up to this point, results depicted are based on models that use only aggregate statistics. Table 16 presents the coefficients estimated using a Mixed Logit (ML) model. The most important difference between this model and the ones presented before is that we use the distribution of demographic variables, instead of counties averages. Thus, to estimate the female voting shares for the 5,564 counties, we use the dummy for female mayor in 2008 and, for the demographic variables, a sample of 1000 individuals per county. The direct correlation between demographic variables and the probability of supporting a female candidate is given by the interaction between the demographic variable and the constant.

For each interaction between the county variables – constant and dummy for female mayor in 2008 – and the demographic ones, the Mixed Logit estimations present the

unobserved demographics' effect, labeled as standard deviation (SD), since the unobserved characteristics are captured by the econometric error term (Nevo, 2000).

When demographic distribution is taken into account, the models' ability to explain female voting share vanishes, as Table 16 suggests. The statistical insignificance of all variables in both ML(1) – when state fixed effects are not included in the model – and ML(2) – when it does – suggests that none of the demographic variables distribution are correlated with female support.

The statistical insignificance of the dummy for female mayor shows no evidence supporting nor socialization nor status discontent theories, as it indicates that individuals who habit a county with a female mayor do not have a different probability of supporting a female candidate than electors who don't.

Unobserved characteristics, captured by the standard deviation variables are also statistically insignificant, indicating that the incapacity of the model to explain female support is not due to non-observable variables.

In cases in which the distribution has a "fat tail" – distributions that exhibit large skewness or kurtosis – the average often does not represent well the behavior of the variable. This is a simple possible explanation for why demographics average are correlated with female support but its distribution is not.

Our result suggest that models that intend to explain female support in election that are based on demographic aggregate statistics, such as the average of the distribution, might have a biased result, as is the case for Brazilian 2010 elections. The use of aggregate data, as in the Fractional logit model would lead us to conclude that a status discontent behavior exists. That is, the presence of a female mayor in the county reduces the probability of support to female candidates for Federal Deputy in the following election. While further analysis, including the whole distribution shows no such evidence of this behavior.

***Table 16* - Coefficients estimated - Mixed Logit**

	ML (1)	ML (2)
Female mayor - 2008	0.17	-3.77
	(50.06)	(14.15)
Men	10.12	0.10
	(12.21)	(41.66)
Age	-0.03	-0.03
	(0.07)	(0.34)
Urban	-0.90	4.57
	(0.55)	(6.11)
Literacy	-0.13	0.54
	(11.55)	(13.89)
Ln of labor income	1.68	-0.19
	(3.00)	(3.01)
Men * Ln of labor income	-1.80	-1.03
	(2.54)	(13.34)
Female mayor - 2008 * Men	-0.19	-10.81
	(43.4)	(42.82)
Female mayor * Men * labor income	0.02	3.67
	(15.65)	(14.84)
Female Mayor - SD	0.07	0.28
	(85.21)	(38.66)
Constant - SD	0.00	0.02
	(19.33)	(67.4)
Constant	-11.96	-5.28
	(8.42)	(36.37)
State fixed effects	No	Yes

This table presents the coefficients estimated with the Mixed logit model. SD stands for standard deviation, indicates the unobservable demographic impact. Bellow the constant are depicted the demographic variable's impact on the indicated municipal variable, which represents the cross effect of individual characteristics on municipal data. The first value is the β and the standard error between parentheses. Source: TSE and 2010 Brazilian Census. * p-value<0.05, ** p-value <0.01, *** p-value <0.001

7. Conclusion

In this paper, we investigate the political factors and individual characteristics that determine the support to a female candidate. By doing so, we are interested in identifying if the recent progress in the participation of women in politics is a natural process or a consequence of the increasingly implemented policies, such as gender quotas.

This question has been debated in a growing literature that has demonstrated the significance of political and institutional factors. Morgan and Buice (2013) categorizes three theoretical arguments — socialization, status discontent, and elite cues— that present different visions on how the context shapes attitudes on female leadership. We propose the

use of Fractional logit and Mixed logit models to test the existence of socialization and status discontent effects.

Our initial results, using aggregate data and Fractional logit model, show evidence supporting status discontent arguments, indicating that the process of growing female participation can be undermined by contrary movements, specially of men that have lower education and don't live in urban areas. However, further analysis using a Mixed logit model which includes information of the whole distribution of data and not only its averages, indicate that demographic variables are not correlated with female support, and show no evidence of neither socialization nor status discontent effects.

Our results indicate that in order to achieve a more gender egalitarian distribution of politicians, active policies are required. Since we find no evidence that exposure to female leadership affects the voters' probability to support a female candidate, we cannot expect that the recent female electoral progress to be self-reinforcing.

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Capítulo 3

Determinants of the decline in regional income inequality in Brazil

1. Introduction

There has been a recent surge in interest on the dynamics of income inequality. The interest is justified not only because extreme inequality is a social issue on itself (Sen, 1973) but also because it is often linked to different other social problems (Wilkinson and Pickett, 2009). Part of the debate focus on the rise in inequality at the very top of the income distribution in developed economies (Piketty, 2013). However, global inequality, although still large, has dropped 2 Gini points between 1988 and 2008 (Lakner and Milanovic, 2015). Brazil is one of these cases of remarkable inequality reduction, with the national Gini Index falling from 0.59 in 2002 to 0.53 in 2012 (Neri and Souza, 2013).

Standard growth models (Solow, 1956) predict that average income per capita in different economies should converge in the steady state. The dispersion of income levels should get smaller over time. More recent models pose that income distribution in different local economies should also converge over time. Barro and Sala-i-Martin (1995) and Ravallion (2001, 2003) show that inequality tends to fall faster on countries with high baseline inequality than in those with low inequality. The convergence of income inequality across different economies is often named β-convergence. Close to this paper, Bénabou (1996) studies the factors that drive more unequal economies to catch up with less unequal ones. The author uses a model with market imperfections and endogenous redistributions to empirically investigate β-convergence across countries. Using a sample of 69 countries between 1970 and 1990, he finds evidence of β-convergence in the first decade analyzed, but not in the second. Facundo and Gasparini (2013), in an extensive review on inequality in developing economies, show evidence supporting β-convergence among these countries.

In the last few years, some papers started investigating the convergence of inequality in regions within a country. Evidence has been mixed, while Ho (2014) do not find evidence supporting β-convergence for the US states between 1916 and 2012, Lin and Huang (2011) finds convergence between American states in a similar period (1916–2005). Gomes (2014)

tested for β-convergence across Brazilian municipalities for the period 1991-2000. His findings lead to the conclusion that regional inequality is converging, but towards a higher level of inequality. This is a period of rising inequality in Brazil, so Gomes shows that, although the inequality gap between municipalities declined, the average inequality rose in the period.

This paper asks whether income inequality across Brazilian municipalities converged in the 2000-2010 period. If so, which changes in Brazilian economy explain this convergence? To answer these questions we perform two exercise. First, we test if the gap between municipalities' income inequality declined in Brazil between 2000 and 2010 – β-convergence. Second, we follow Shorrocks (1982) and Souza (2012) and decompose individual income by its sources to identify the economic factors underlying the β-convergence. To this goal we use a version of β-convergence tests as proposed by Barro and Sala-i-Martin (1992) – and later revisited by Ravaillon (2001, 2003) among others – and Brazilian Census microdata from 2000 to 2010. The main contribution of the paper is to combine both methodologies to analyze a case of unprecedented decline in inequality. To the best of our knowledge, this is the first paper to put both methodologies together to study inequality.

We find evidence of β-convergence across municipalities' inequality between 2000 and 2010. Inequality difference between municipalities fell on average 50% between 2000 and 2010. Note that a smaller gap does not imply lower overall inequality. The difference between municipalities' inequality can reduce in two ways: either to a faster increase of inequality of municipalities where inequality was lower or to a faster decrease of inequality in municipalities where inequality was higher. We find evidence supporting the latter, meaning that not only the gap between municipalities inequality declined in the period, but municipalities also became less unequal.

We seek to identify the determinants of the inequality convergence by factor decomposing inequality index, as proposed by Shorrocks (1982), who showed that it is possible to decompose the Gini Index into factor components. We apply this decomposition both in the inequality level and its β-convergence. By decomposing the underlying drivers of this fall, we find that a reduction on labor income inequality is the main driver of the decline in both inequality levels within and across municipalities. The reduction in income inequality in formal jobs accounts for 37.2% of total reduction in the difference between municipalities' household income inequality, being the factor that explains the most. Minimum wage, formalization and education contributed to the observed reduction in

inequality levels, but explained little the convergence across municipalities. Our analysis indicates that inequality convergence exists between municipalities, and although these drivers help us explain the reduction in inequality levels, income convergence is widely spread between economic factors, not being caused by only one.

Weisbrot et al. (2014) describes the main changes in Brazil in the last two decades and shows evidence supporting poverty and inequality reduction.[40] Decrease in unemployment and informality, increase in minimum wage and expansion of conditional cash-transfer programs with the introduction of *Bolsa Família* are some of the causes for the poverty and inequality reduction. Lower unemployment and informality are a result of a decade of constant growth of Brazilian economy. Real GDP per capita rose, on average, 2.5% per year between 2003 and 2014, three times faster than in the previous government (0.8% per year, on average, in the period 1995-2002).

This paper relates to studies that investigate the recent fall in income inequality in Brazil. Caperoz et al. (2016) analyze the period 1977-2013, and argue that Brazilian macroeconomic instability, which lasted until 1994, helped to produce a regime of low income shares at the bottom of the distribution. The authors argues that since the stabilization of the economy, minimum wage and social programs are the main reasons for improve in income distribution, especially since 2002. Ferreira et al (2017) show evidence of the importance of reductions in the gender, race, informality and urban-rural wage gaps, conditional on human capital and institutional variables, to the decline in income inequality in the period 1995-2012. Alvarez et al (2015) explore the decline in earnings inequality in the period 1996-2012 by using an administrative linked employer-employee data. The idea of the authors is to use firms fixed effects in a model with overlapping sub periods in order to identify the drivers of the decline. The authors show evidence supporting that changes in pay policies (minimum wage and formalization), rather than changes in firm fundamentals, indicating a weak link between firm's productivity and wages. Souza (2012) decomposed, for the period 2001-2009, the inequality reduction and suggested that the main drivers are minimum wage, conditional cash transfer (CCT) programs and education. Barros et al. (2010) decompose the inequality reduction in the period 2001-2007 and finds three factors that explain it, namely government transfers, decline in wage differentials by education level and the improvement in spatial and sectoral integration of labor markets, in particular among

[40] Between 2003, when the Workers' Party Government begun, poverty reduced from 35.8 percent of the population to 15.9 percent in 2012 and the amount of income received by the top 10 percent fell from more them half to about one-third in the same period.

metropolitan and non-metropolitan areas. Furthermore, the authors show that this is the first experience in which poverty decreased at the same time of inequality. In the two previous poverty reduction experiences, during the economic boom in the 70's and after the 'Real plan' in 1994, which ended the hyperinflation, the inequality reduction was minimal. Freguglia and Menezes-Filho (2012) use a database that allows them to follow the same workers in the period 1995-2002 focusing on the effect of inter-regional migration, which was large in the period. By controlling using fixed effects of the workers characteristics, they are able to conclude that the overall wage variability across Brazilian States fell to almost one third of its initial level. We contribute to this literature by also highlighting the key role of labor market dynamics not only on inequality reduction, but also on inequality convergence and by studying regional inequality. We also corroborate these studies by showing evidence of the importance of minimum wage, formalization and education to the decrease in inequality.

The rest of the paper is organized as follows: Section 2 describes the data and provides summary statistics; Section 3 explain empirical methodology used; Section 4 presents the results and Section 5 concludes.

2. Data

Our main source of data is Brazilian Demographic Census conducted by IBGE, Brazil's main statistic center. The *Censo* is a household survey covering all municipalities and we use the three last available periods: 1991, 2000 and 2010.

As of today, Brazil has 5570 municipalities, but many of these were founded after 1991. To allow comparison over time, we limit our analysis to the minimum comparable areas between the 1991 and 2010 Census, resulting in 4267 municipalities.[41] The Census presents data that allows us to identify for each individual, his income, labor earnings, education and whether or not he works and the type of occupation (formal or informal contract).

The inequality index used is the Gini Index, which is the most common measure of dispersion used on inequality literature. It's mathematically defined as half of the relative mean absolute difference:

[41] See Reis et al. (2007)

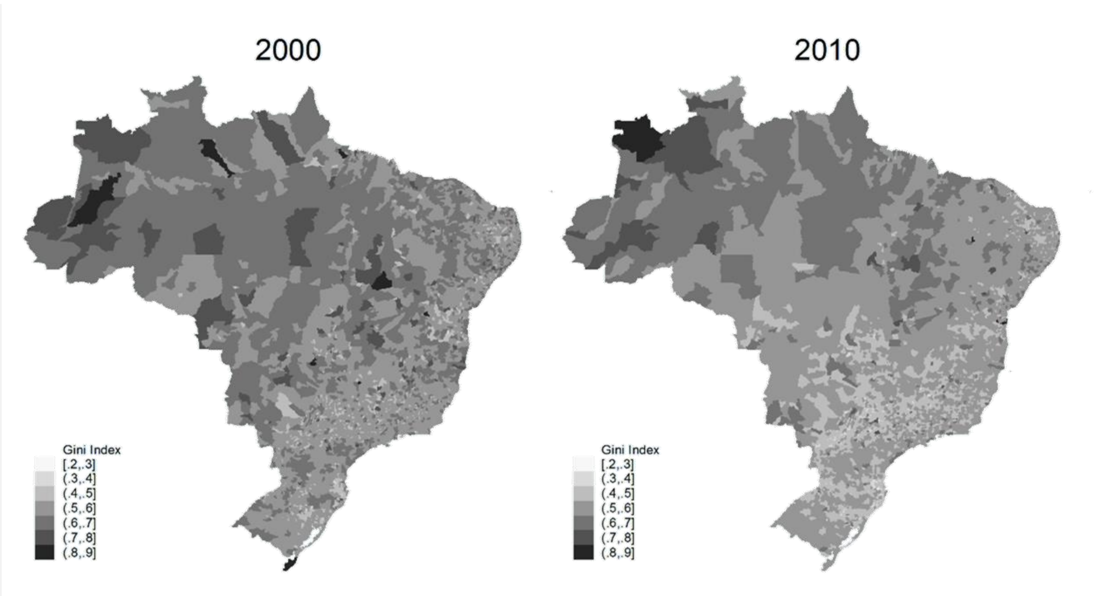
$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2\sum_{i=1}^{n}\sum_{j=1}^{n}x_j} \tag{1}$$

where n is the total population, x_i is the income of individual *i* and G is the Gini Index. One of the reasons this index is so common is its simplicity: it assumes values between 0 and 1, and the higher the value the more unequal is the economy.

Inequality reduction only imply β-convergence if the decrease is larger on municipalities with higher initial inequality. This paper studies if this is the case: if the difference between municipalities inequality is reducing as overall inequality falls and then analyze the factors that may explain this.

To motivate the discussion, Figure 1 bellow presents a map of Brazilians municipalities Gini Index for 2000 and 2010. The index is calculated for household income per capita. A brief comparison allows us to identify two points: the map becomes slightly lighter between 2000 and 2010, showing the overall decrease in inequality; and northern municipalities seem to be more unequal.

Figure 1- **Brazilian income per capita inequality per municipality - Gini Index**



Source: Census, 2000 and 2010.

Summary statistics of the main variables used in this paper are presented in Table 1. Mean Gini Index decreases by 0.05 points, supporting overall inequality reduction depicted by Figure 1. As a result of economic growth, total household income increased by 44% in the period 2000-2010, an increase of 3.7% per year on average. This income can be split in two: Labor Income and Other Income, which includes pensions, social security benefits and direct transfers (such as *Bolsa Família*), among others. Labor Income increased, on average,

2.7% per year, while Other Income increased 6.2% per year. Formal[42] occupations accounted for almost 45% of total jobs in 2000 and increased to over 52% in 2010, corresponding to over 15 millions new formal jobs. This formalization is one of the main reasons for Labor Income increase, as formal workers have, in general, higher income than those who work without legal documentation.[43]

Increase in social spending in the period 2000-2010 included an increase in education investment, which represented 4.7% of GDP in 2000 and rose to 5.8% of GDP in 2010.[44] This total includes spending from state governments, public enterprises and development banks, as well as the central government. The percentage of the population with higher education rose in the three top levels, and only decreased in the bottom one. Although the biggest increase was in the percentage of individuals with 11 to 14 years of schooling, corresponding to individuals with complete high school and incomplete undergrad, the number of individuals with 15+ years of schooling – complete undergrad – more than doubled.

Given the same household income, a couple will have a better living condition than a household composed by a couple and four children. This is the reason why the average number of individuals per household is important, especially due to the fact that this number is usually higher in poorer areas. During the decade depicted in Table 1, the average number of individuals per household reduced significantly, by over half person per household.

***Table 17* - Summary Statistics**

Average per municipality	2000	2010	Δ
Gini Index	0.56	0.51	-0.05
% Formal Occupations	44.98	52.65	7.67
% Informal Occupations	55.02	47.35	-7.67
% Education 0-7	78.30	63.24	-15.06
% Education 8-10	10.84	15.50	4.67
% Education 11-14	9.01	16.95	7.94
% Education 15+	1.86	4.31	2.45
Household Income – Labor Income	287.17	374.80	87.63
Household Income – Other Income	102.13	185.80	83.67
Household Income – Total Income	389.30	560.47	171.17
Individuals per Household	3.89	3.36	-0.54

Source: Census, 2000 and 2010. Household income in reais of 2010.

[42] The definition of occupation position follows Brazilian National Account definition, where formal occupations include: registered employees, servicemen, public servants, signed domestic worker and employers. Informal jobs include: unsigned employees, unpaid workers, unsigned domestic worker, self-employed workers and worker for own consumption production.
[43] See Maloney (2004) for a deeper analysis of informality in Brazil and Latin America.
[44] See Weisbrot et al. (2014).

3. Methodology

In order to identify the existence of inequality convergence between Brazilian municipalities, we are going to put together the literature on dynamic decomposition of an inequality index and the convergence one. In this session, we describe both decomposition and β-convergence methodologies and how to connect them.

3.1. Decomposition

The dynamic decomposition of the Gini Index, as expressed in Shorrocks (1982), gives us the possibility to decompose the inequality changes by factor components. Furthermore, it allows us to identify the contribution of the inequality variations that occur within each component and the one that is due to the changes in the relative weight of the components. This methodology is commonly used in inequality literature because of the simplicity to interpret the results. However, dynamic decomposition arithmetic's becomes complicated for some measures. One of the measures that allow dynamic decomposition is the Gini Index, which we use in this paper.

The dynamic decomposition has elements of the static one. For clarity of exposition we present first the static, as described in Souza (2012). The static is the Gini index decomposition for any given point in time, as follows.

Let x_i represent household income per capita, i.e. the sum of each household's individual income from H different sources, divided by the number of individuals in the household. $x_i = \sum_{h=1}^{H} x_{hi}$, where x_{hi} is the household per capita income from source h
If we define $\emptyset_h$ - the relative income share - as the ratio between the source's mean income μ_h and the overall mean income (μ), then $\emptyset_h = \frac{\mu_h}{\mu}$. Finally, the static decomposition will be sum of each income source's coefficient of concentration weighted by its relative income share.

$$G = \sum_{h=1}^{H} \emptyset_h C_h \qquad (2)$$

where G is the Gini index, C_h is the coefficient of concentration, which measures the inequality within each income source h. Unlike the Gini Index, that assumes values in the range (0,1), the coefficient of concentration values goes from -1 to +1. The difference is because the covariance is calculated with data sorted by overall household income per capita, and not the income source of the concentration coefficient. The extreme case in which C_h would assume the value -1 is if the poorest household – considering total income per capita

– had the totality of the source's *h* income. Mathematically it is defined as the covariance between the position of the individual in the list sorted by income and the ratio between the individual income and the average of the source *h*:

$$C_h = \frac{2}{n} cov\left(i, \frac{x_{hi}}{\mu_h}\right) \tag{3}$$

Finally, the dynamic decomposition is defined using the coefficient of concentration, the average Gini Index and relative income share. For two given points in time, the change in the dynamic decomposition of the Gini Index is:

$$\Delta G = \sum_{h=1}^{H} \left((\overline{C_h} - \bar{G}) \Delta \emptyset_h + \Delta C_h \overline{\emptyset_h} \right) \tag{4}$$

The first term in the sum captures the Between Effect (BE), hereafter the between groups effect, which represents the change in the weight of income sources. The second term is the Within Effect (WE), which captures the changes in the income distribution within each income source. Hence, we can rewrite equation (4) as follows:

$$\Delta G = \sum_{h=1}^{H} (BE_h + WE_h) = BE + WE \tag{5}$$

3.2. Convergence

This decomposition is now incorporated into inequality β-convergence, as proposed by Benabou (1996), Ravaillon (2003, 2012), and others. β-convergence, as defined by the authors, exists and leads to a lower index level only if inequality reduces faster in the municipalities – or countries, etc. – that have higher initial inequality.

We perform a simple and standard test to investigate the existence of income inequality β-convergence in Brazil during the last decade. We follow Ravaillon (2003) and regress the variation in the Gini index in the municipality j (ΔG_j) on a constant (α) and the Gini Index in 2000 in the municipality (G_{j0}) and ε_j is the error term:

$$\Delta G_j = \alpha + \beta G_{j0} + \varepsilon_j \tag{6}$$

β captures the impact of initial inequality on inequality changes. A positive value means that municipalities with higher initial inequality will increase Gini Index more than municipalities with lower initial Gini. A negative β implies inequality will reduce more in municipalities with higher initial inequality. We say that β-convergence exists when β is negative and statistically

different from zero. From now on, when we mention convergence, it stands for β-convergence.

To interpret the value of the beta – the magnitude of convergence – let us rewrite equation 6 as follows:

$$G_{j1} = \alpha + (1+\beta)G_{j0} + \varepsilon_j \quad (7)$$

0 and 1 represent the initial and final periods, respectively. For two different municipalities, *j* and *k*, this means that the inequality difference between them at the final period is:

$$G_{j1} - G_{k1} = (1+\beta)\left(G_{j0} - G_{k0}\right) + \varepsilon_j - \varepsilon_k \quad (8)$$

Since the regression is a linear equation, we can substitute the left-hand side of the regression represented by equation (6), the delta Gini, by its dynamic decomposition, as previously shown by equation (4). This way, if we have *k* income sources, we have a within and a between term for each component leaving us with 2*k* regressions, as expressed by equation (9):

$$\Delta G = \sum_{h=1}^{H}\left((\overline{C_h} - \bar{G})\Delta\emptyset_h + \Delta C_h\overline{\emptyset_h}\right) = \sum_{h=1}^{k} BE_h + WE_h = \alpha + \beta G_0 + \varepsilon \quad (9)$$

The sum of the betas of the 2*k* regressions will be the beta of the original regression, as represented in (9). To show this, let N be the number of municipalities, and **X** be the matrix Nx2 with the regressors in (5). Define γ = [α β], as proposed by Wong (2002) and later by Canêdo-Pinheiro and Barbosa Filho (2011). The ordinary least square (OLS) estimator will be:

$$\hat{\gamma} = (X'X)^{-1}X'\Delta G \quad (10)$$

Combining (5) and (10), we have:

$$\hat{\gamma} = (X'X)^{-1}X'\sum_{h=1}^{H}(BE_h) + (X'X)^{-1}X'\sum_{h=1}^{H}(WE_h)$$

$$= \sum_{h=1}^{H}(\hat{\gamma}_h^{BE}) + \sum_{h=1}^{H}(\hat{\gamma}_h^{WE}) \quad (11)$$

By doing so we are able to decompose the estimator of the β-convergence test in two terms. The first represents the between groups effect on convergence, while the second will represent the impact of each group. In our case, it is the impact of each income source on inequality β-convergence of Brazilian municipalities.

As usual in the convergence literature, we can simply add control variables in the right-hand side of the equation. This methodology allows us to analyze both the decomposition in the inequality index and in the inequality β-convergence between municipalities.

4. Results

In this session we present the results of both inequality decomposition and inequality β-convergence between municipalities. We start by classifying income in two: labor income and other income. The latter component is a mix of different incomes, which includes pensions, direct transfers, capital remuneration, rent payments and others. The reason why these incomes are all put together is simply due to the fact that the Census database indicates whether a person receives each of those incomes, but not the amount. In order to use the dynamic decomposition, we must have the sum of the components income equal to the total income, hence we must have the value of each component share of total individual income.

In section 4.1.1 we dynamically decompose inequality using this classification for the periods 2000-2010 and 1991-2000. Then we present the results for β-convergence for the most recent period in section 4.1.2.

Section 4.2 analysis the impact of minimum wage by redoing the dynamic decomposition and β-convergence exercises taking into account the minimum wage component on income. Section 4.3 breaks labor income into two depending if labor is formal or not. Finally, section 4.4 identifies the impact of education on inequality by splitting income sources into finer categories depending on individual education.

4.1.1 – Dynamic Composition

The results of the dynamic decomposition – as described in equation (4) – for each of the 4267 municipalities are summarized in Table 2, which presents the mean values of the Gini Index variation. Each row presents an income source and the columns, the two effects decomposed (Between and Within). The values are municipalities' mean Gini variation due to that component, with the percentage of the total change in the Gini Index presented between bracers bellow. These variations can be summed in both line and column and the results are presented in the totals. Table 2 shows that, on average, municipalities' inequality decreased 0.048 Gini Index points between 2000 and 2010. From this value, 0.037 (77.6%) was due to reduction of Labor Income inequality. Another 17.5% are consequence of a better income distribution of the Other Income source, and only 4.9% are due to changes in the

relative weight from one income source to the other. These results indicate that labor market is the main driver of the inequality decrease, although direct transfers and other policies have an important contribution.

To understand better the Between Effect, $(\overline{C_h} - \bar{G})\Delta\emptyset_h$ in equation (9), we must know if its decrease is caused by a change in relative weight from labor to other income, or the other way around. This term will be negative – inequality decreases – if the relative weight of the income source increases and the mean concentration coefficient is smaller than the average Gini Index, or if relative weight drops in a source that has a higher mean concentration coefficient than the mean Gini index. In other words, the between effect helps the Gini Index to fall if the most unequal income source presents a weight decrease in total income.[45]

Table 18 – Dynamic Decomposition, Labour and Other Income, 2000-2010

	Between	Within	Total
Labor Income	0.000 [0.7%]	-0.037 [77.6%]	-0.037 [78.2%]
Other Income	-0.002 [4.3%]	-0.008 [17.5%]	-0.010 [21.8%]
Total	-0.002 [4.9%]	-0.045 [95.1%]	-0.048 [100.0%]

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

Next, we test if relative importance of labor income to explain inequality holds a different situation. We apply the same methodology over the period 1991-2000, when average inequality rose by 0.018 Gini point in Brazilian municipalities, in contrast to the fall of 0.048 Gini points over the following decade. Table 3 presents the results for the 1991 and 2000 period and shows that not only the increase in inequality within Labor Income is responsible to the overall increase, but also it corresponds to almost 98% of it. Furthermore, the Within Effect is responsible for the increase in the Gini index, as both Labor Income and Other Income presented a negative value in the between effect. Table 13, in the

[45] Table 12, in the Appendix, presents auxiliary results needed to determine the direction of the Between Effect. The first two columns, when multiplied, generate the Between Effect, and the last two the Within Effect. The data shows that the mean of Other Income is less unequal than the average Gini index and, from 2000 to 2010, the relative weight in total income rose 7 percentage points. In this case, the between effect was very small, but it is still important to fully understand it, as it has a larger contribution in some of the following exercises.

Appendix, shows that the concentration effect of both labor income and other income have the same increase, 0.02. The relative Within Effect of labor income is higher due to the higher relative importance in total income. These results suggest that, over the last two decades, changes in Labor Income inequality consisted the main driver of the observed changes in household income per capita inequality.

Table 19 – Dynamic Decomposition, Labour and Other Income, 1991-2000

	Between	Within	Total
Labor Income	0.000 [-1.7%]	0.018 [97.9%]	0.018 [96.2%]
Other Income	-0.004 [-22.7%]	0.005 [26.5%]	0.001 [3.8%]
Total	-0.004 [-24.5%]	0.023 [124.5%]	0.018 [100.0%]

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

4.1.2 – $\boldsymbol{\beta}$-convergence

These results suggest that Labor Income is able to explain most of changes in inequality over the past two decades. Now, we move towards the main goal of this article, which is to investigate whether there is a convergence of inequality between municipalities and what may explain it. To do so, we regress the decomposition described in equation (9). Naturally, our first attempt is to decompose between Labor Income and Other Income.

Table 4 presents, for the initial decomposition, the basic statistics from regression (9), which tests the effect of the initial Gini index on each income source (Labor and Other Income) and decomposition components (Between and Within). The statistics presented are the coefficients β's of the Gini in the initial period and its standard error. The decomposition allows for the income factors and the decomposition components to be summed, resulting in the total effect of the initial Gini index. Therefore, between bracers we present the percentage of the total effect that is due to each of the four components. To better understand the results depicted in Table 4 we go back to Equation (8), which describes the inequality gap between two municipalities in the final period as the initial gap multiplied by a constant (1+ β) plus the difference between the errors. As errors have zero mean, Gini Index reduction – the difference between the inequality gap in the final and the initial periods – is a function of β. The estimated total coefficient of -0.51 indicates, therefore, that the average gap between two municipalities in 2010 is 0.49 (1+ β) the average gap in 2000. This result indicates that inequality difference between two municipalities halved between 2000

and 2010, when no controls are used. This shows that convergence is not only statistically significant, but also economically relevant.

The analysis of the decomposition show that the Within Effect of the Labor Income is the major responsible for the municipalities' household income inequality β-convergence, as well as it is for pure inequality decomposition. This shows that, not only Labor Income was the main driver for the inequality reduction, but also this reduction was larger on municipalities that were more unequal in 2000.

The Within Effect, considering both Labor and Other Income, is responsible for over 90% of total Initial Gini impact on inequality changes. This means is that income inequality between municipalities fell in the period mostly because of a reduction in inequality within each income source, and not due to changes in the participation of different income sources in the household budget.

***Table 20* - $\boldsymbol{\beta}$-Convergence dynamic decomposition – 2000-2010**

	Between	Within	Total
Labor Income	-0.0123*** (0.001) [2.4%]	-0.3532*** (0.016) [69.7%]	-0.3656*** (0.016) [72.2%]
Other Income	-0.0367*** (0.002) [7.2%]	-0.1042*** (0.008) [20.6%]	-0.1409*** (0.007) [27.8%]
Total	-0.0491*** (0.003) [9.7%]	-0.4574*** (0.016) [90.3%]	-0.5065*** (0.017) [100.0%]

This table presents, for each income source and decomposition components, the β coefficients, robust standard error (between parentheses) and p-value (between brackets) of the regression depicted by equation 9. These coefficients can be summed in both line and column and the results are presented in the totals. * p<0.05, ** p<0.01, *** p<0.001

Results presented in Table 4 were estimated in a model without controlling for covariates. In order to derive more confidence in our results, we add two controls for municipalities' characteristics: education distribution[46] and average number of habitants per household. We include the average number of habitants per household to control for changes in household composition. The population aged and the average number of children per house fell. Since our study object is the household income per capita, one of the reasons inequality fell among municipalities could be due to a faster decrease in average children per household in most unequal municipalities. Assuming that children have no income, this would rise the household income per capita.

[46] We create five variables with the percentage of habitants that belong to different education level group. Data allows us to identify the following education levels: 0-3 years of school; 4-7; 8-10; 11-14 and 15 or more.

Table 5 presents the results from the equation when we include controls for education and demographic of these municipalities in 2000. We find that the inclusion of these controls does not affect the main results of Table 3.

These first results indicate that the Within Effect of the Labor Income is the major responsible for both the inequality changes in the household income per capita, measured by the Gini index, and the β-Convergence of inequality across municipalities. However, we are not able to identify a change in income pattern that can explain the inequality convergence, as it is an effect that exists in both income components.

***Table 21* - β-Convergence dynamic decomposition with education controls – 2000-2010**

	Between	Within	Total
Labor Income	-0.0123*** (0.001) [2.1%]	-0.4234*** (0.015) [73.7%]	-0.4358*** (0.015) [75.8%]
Other Income	-0.0395*** (0.002) [6.9%]	-0.0994*** (0.008) [17.3%]	-0.1389*** (0.007) [24.2%]
Total	-0.0518*** (0.003) [9.0%]	-0.5228*** (0.016) [91.0%]	-0.5746*** (0.017) [100.0%]

This table presents, for each income source and decomposition components, the β coefficients, robust standard error (between parentheses) and p-value (between brackets) of the regression depicted by equation 9. These coefficients can be summed in both line and column and the results are presented in the totals. * p<0.05, ** p<0.01, *** p<0.001

The next step is to further investigate the Labor Income. We use these first results as a benchmark and, given that Labor Income seems to be the key to understand Brazilian inequality changes in the last decade, we analyze the most important changes in the labor market: minimum wages, formalization and education.

4.2. Minimum wage

During the period 2000-2010, the real minimum wage rose 76%.[47] The impact of minimum wage on income inequality is far from being consensus,[48] but it is clear that this raise affects the labor market. Thus, we begin our analysis of labor market effect on inequality convergence by including minimum wage on income decomposition.

Labor market is not the only component that is affected by the rise of minimum wage. Many pensions and other benefits are directly linked to it. BPC/LOAS, for instance, is a social security program that grants to all elderly or handicapped person a minimum wage

[47] Source: Institute for Applied Economic Research (IPEA).
[48] See Flinn (2010).

if household income is bellow a quarter of minimum income. For that reason, we separate our analysis in two: impact of minimum wage on labor income and impact on other income.

We follow Souza (2012) and split each of the two income components in another two. Total Labor Income is divided into Labor Income and Labor Minimum Wage. Total Other Income is decomposed similarly, into Other Income and Other Income Minimum Wage.

We define, for each household *i*, Labor Minimum Wage depending whether Total Labor Income is bigger or smaller than minimum wage, defined by $\overline{w}$, as follows:

$$Labor\ Minimum\ Wage_i = \begin{cases} \overline{w} & if\ Total\ Labor\ Income_i \geq \overline{w} \\ 0 & if\ Total\ Labor\ Income_i < \overline{w} \end{cases}$$

$$Labor\ Income_i = \begin{cases} \text{Total Labor Income}_i - \overline{w} & if\ Total\ Labor\ Income_i \geq \overline{w} \\ \text{Total Labor Income}_i & if\ Total\ Labor\ Income_i < \overline{w} \end{cases}$$

We define these variables at the individual level within each household and, then, we aggregate each income source component in per capita terms at the household level.

Table 6 describes the decomposition of inequality considering these four components. Labor Minimum Wage corresponds for almost half of total labor effect, while Other Income Minimum Wage is responsible for over half of other income percentage. But the most important result in this table is the increase in total Between Effect. Between Effect of labor minimum wage is alone responsible for almost 40% of total Gini Index decrease. Table 14 in the Appendix shows that labor minimum wage concentration coefficient is negative. Therefore, a negative Between Effect represents an increase in Labor Minimum Wage relative income. This result is not a surprise, as increase in real minimum wage, in general, increases the number of workers who receive a minimum wage.

This helps us understand the inequality decrease observed in the benchmark decomposition. In that first exercise we concluded that the decrease was presented both among Labor and Other Income components. Table 6 results show that over half of labor inequality decrease is caused by changes in Labor Minimum Wage income share.

Our results are consistent with Engbom and Moser (2015), which quantifies the effect of the rise in the minimum wage on Brazil's inequality evolution. The authors use a different methodology from ours and find that 70% of the observed decline in the variance of log earnings are due to the rise in the minimum wage.

***Table 22* – Minimum wage dynamic decomposition – 2000-2010**

	Between	Within	Total
Labor Income	-0.005 [9.7%]	-0.017 [35.8%]	-0.022 [45.6%]
Labor Minimum Wage	-0.019 [39.9%]	0.003 [-7.2%]	-0.016 [32.7%]
Other Income	0.003 [-5.6%]	-0.007 [14.7%]	-0.004 [9.1%]
Other Income Minimum Wage	-0.008 [17.6%]	0.002 [-4.9%]	-0.006 [12.7%]
Total	-0.029 [61.6%]	-0.018 [38.4%]	-0.048 [100.0%]

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

Minimum wage decomposition shows that this change in income source pattern helped explaining the inequality decrease. What we test next is if this also contributes to explain β-Convergence between municipalities inequality.

Table 7 presents the β-Convergence dynamic decomposition results, using the same methodology as Table 4 did for the benchmark decomposition. Labor Minimum Wage's Between Effect accounts for 40% of mean inequality decrease, but only explains 5.2% of convergence. Total Within Effect, that in the benchmark exercise is responsible for over 90% of total inequality convergence, now explains a little less than 80%, but is still the main responsible for municipalities convergence. Labor Income Within Effect represents over 60% of total, while Minimum Wage has almost no within impact.

The conclusion is that, despite minimum wage decomposition being able to explain part of inequality reduction in the labor market, its relevance is not equal to municipalities β-Convergence. In fact, adding the between and within components of both labor and other income minimum wage, we only have a little over 10% of total convergence coefficient.

Table 23 **- Minimum wage β-Convergence dynamic decomposition**

	Between	Within	Total
Labor Income	-0.0252*** (0.001) [5.0%]	-0.3110*** (0.014) [61.4%]	-0.3362*** (0.015) [66.4%]
Labor Minimum Wage	-0.0263*** (0.003) [5.2%]	-0.0028 (0.002) [0.6%]	-0.0292*** (0.003) [5.8%]
Other Income	-0.0243*** (0.002) [4.8%]	-0.0818*** (0.006) [16.2%]	-0.1061*** (0.007) [20.9%]
Other Income Minimum Wage	-0.0319*** (0.003) [6.3%]	-0.0032 (0.002) [0.6%]	-0.0350*** (0.003) [6.9%]
Total	-0.1077*** (0.006) [21.3%]	-0.3988*** (0.015) [78.7%]	-0.5065*** (0.017) [100.0%]

This table presents, for each income source and decomposition components, the β coefficients, robust standard error (between parentheses) and p-value (between brackets) of the regression depicted by equation 9. These coefficients can be summed in both line and column and the results are presented in the totals. * p<0.05, ** p<0.01, *** p<0.001

4.3. Formalization

The second change in labor market that we analyze is formalization. Between 2000 and 2010, formal occupations rose from 45% to 52.6%. This may not seem a huge change, but when we compare the number of workers on each occupation position the difference shows up. The number of informal workers rose 13.2%, from 36.1 million in 2000 to 40.8 million workers in 2010. The number of formal workers, on the other hand rose 54%, moving from the initial 29.5 to 45.4 million workers.

In this analysis, we split Labor Income in two. For each individual in a household, Labor Income is defined as Formal Income or Informal Income depending on the individual's job occupation.[49]

Table 8 presents, following the pattern of the previous analysis, the dynamic decomposition for the period 2000-2010 of the Formal and Informal Labor Income. The between component of both labor occupations is small, and when added to the Other Income between coefficient, sums to a zero value. The negative contribution of the informal income can be better understood by Table 15, in the Appendix. This income source has a more equal distribution than the overall Gini Index, as can be seen by the concentration

[49] The definition of occupation position follows Brazilian National Account definition, where formal occupations include: registered employees, servicemen, public servants, signed domestic worker and employers. Informal jobs include: unsigned employees, unpaid workers, unsigned domestic worker, self-employed workers and worker for own consumption production.

coefficient, which is smaller than the Gini Index. Hence, a decrease in relative weight – represented by a negative $\Delta ø$ – increases the inequality measured by the between component.

In this exercise, all of the total inequality decrease is due to the Within Effect. This means that, in this decomposition, changes in income pattern make no difference in inequality, and all its reduction is caused by decrease within income sources distributions.

It is important to notice that the small Between Effect of Formal Income is given by the almost zero change in its relative weight in total income. This means that, although the percentage of formal jobs rose, its income share did not. However, when we consider only Labor Income, its share do grow. What happens is that other income weight rose when compared to labor income. Formalization can be perceived in income source shares by a decrease in informal weight, and not by an increase in the formal one.

***Table 24* – Formalization dynamic decomposition – 2000-2010**

	Between	Within	**Total**
Formal Income	-0.001 [1.2%]	-0.032 [66.6%]	-0.032 [67.8%]
Informal Income	0.003 [-5.4%]	-0.008 [15.9%]	-0.005 [10.5%]
Other Income	-0.002 [4.3%]	-0.008 [17.5%]	-0.010 [21.7%]
Total	0.000 [0.0%]	-0.048 [100.0%]	-0.048 [100.0%]

Source: Census 2000 and 2010. This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

Formalization β-convergence dynamic decomposition, whose results are depicted in Table 9, presents no new insight to our benchmark analysis. As we only further decompose labor income, without changes in Other Income analysis, both its between and within components are very similar to those previous results. Labors Between Effect, adding both Formal and Informal effects, rose when compared to the benchmark, but only explains 8.2% of total convergence.

Finally, if in the dynamic decomposition the within coefficient of Formal Income is over four times bigger than the one of Informal Income, in the convergence analysis their contribution to overall convergence is very similar, with Informal Income β being slightly larger. This means that although the concentration coefficient of informal income does not drop as much as formals – it presents a decrease of 0.02, while formal falls 0.09 – these

variations were equally important to reduce the difference between municipalities household income inequality.

Table 25 **- Formalization β-Convergence dynamic decomposition**

	Between	Within	Total
Formal Income	-0.0267*** (0.003) [5.3%]	-0.1614*** (0.014) [31.9%]	-0.1881*** (0.014) [37.2%]
Informal Income	-0.0149*** (0.003) [2.9%]	-0.1623*** (0.01) [32.1%]	-0.1771*** (0.01) [35.0%]
Other Income	-0.0368*** (0.002) [7.3%]	-0.1041*** (0.008) [20.6%]	-0.1409*** (0.007) [27.8%]
Total	-0.0784*** (0.006) [15.5%]	-0.4278*** (0.015) [84.5%]	-0.5061*** (0.017) [100.0%]

This table presents, for each income source and decomposition components, the β coefficients, robust standard error (between parentheses) and p-value (between brackets) of the regression depicted by equation 9. These coefficients can be summed in both line and column and the results are presented in the totals. * p<0.05, ** p<0.01, *** p<0.001

4.4. Education

Our last attempt to understand the decrease in household income per capita inequality between municipalities, as described by the existence of β-Convergence, is using the decomposition of Labor Income by the worker's schooling level. Education is widely recognized as one of the most important factors to understand labor market and is also one of the main policies of government during most part of the period 2000-2010. The government focus was on the years of education, not the quality of it. Its intention was to increase the number of students and hence increase the average number of schooling years, which would ultimately decrease inequality. The preference for quantity over quality can be seen in some of Brazil's education results. The average years of schooling of Brazilian individuals is 5.5 in 1995, 6.4 in 2001 and 8.0 in 2013, a 2.1% increase *per* year on average.[50] On the other hand, according to World Economic Forum's Human Capital Report, Brazil is placed 78th on a ranking with 124 countries, with a human capital index lower than countries like Jordan.

In the Census database we do not have access to individual's years of schooling (henceforth YOS), only to the education level the individual belongs. Due to this restriction,

[50] Source: IPEA (*Instituto de Pesquisas Econômicas Aplicadas*, Institute for economic applied research)

we decompose labor income into 4 categories, depending on the individual's education. The categories are 0-7; 8-10; 11-14 and 15+ YOS.

Table 10 describes this last dynamic decomposition. The first thing that one might notice is that the Between Effect becomes relevant, but has a negative contribution to inequality decrease. This effect occurs among all education levels with exception of 8-10 YOS which presents zero effect. In order to understand this negative effect we must analyze the signal of $\overline{C_h} - G$, presented in Table 15, in the Appendix. The two lower education levels present a negative signal, which means they have a more equal income distribution than the overall Gini. Therefore, the increase in education levels, which decreased the income share of the 0-7 education level by 12%, results on a positive Between Effect for this education level. The 8-10 Between Effect is zero because of the zero change in its income weight. Finally, the 11-14 and 15+ income weights increased by 3% and the concentration effect is higher than the Gini Index, therefore the Between Effect is also positive.

The inequality decrease measured by the Gini Index is a result of the largely negative within effect, even though the Between Effect is positive. The concentration coefficient reduction, which results in a negative within effect, is observed in all education levels. Because of this, the decomposition of labor income into education levels does not present an explanation to the inequality reduction, as concentration coefficient reduction is present among every education level and the changes in its income relative weight have an opposite effect, and would even increase inequality.

***Table 26* – Education dynamic decomposition – 2000-2010**

	Between	Within	Total
Education 0-7	0.018 [-38.8%]	-0.019 [39.7%]	0.000 [0.9%]
Education 8-10	0.000 [0.6%]	-0.015 [32.3%]	-0.016 [32.8%]
Education 11-14	0.003 [-6.3%]	-0.027 [56.4%]	-0.024 [50.1%]
Education 15+	0.008 [-17.2%]	-0.006 [11.6%]	0.003 [-5.6%]
Other Income	-0.002 [4.3%]	-0.008 [17.4%]	-0.010 [21.7%]
Total	0.027 [-57.4%]	-0.075 [157.4%]	-0.048 [100.0%]

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

Table 11 presents the main statistical results of the education β-Convergence dynamic decomposition. The Between Effect of the education level, which presented a negative contribution to inequality decrease in the dynamic decomposition, here has a positive contribution to the inequality β-convergence among all level of education.

The lowest education level, which includes individuals with 0-7 years of schooling, is the component that contributed the most to inequality convergence. Even more, its contribution is bigger than the sum of all the others educations levels, considering both the Between and Within Effects. This indicates that the reduction in municipalities' inequality difference is directly linked to reduction in inequality among the poorest individuals. Table 10 shows that income distribution becomes more equal on every education level and the 11-14 education level is even more relevant to inequality decrease, but its importance in convergence is only half of the lowest education level.

Changes in income pattern as a result of changes in education levels – the aggregate education Between Effect – is responsible for a little more than 20% of the total convergence coefficient, while reduction in inequality within each education income distribution is responsible for over half of it. This shows that the majority of convergence still cannot be explained by changes in education levels.

Table 27 **- Education β-Convergence dynamic decomposition**

	Between	Within	Total
Education 0-7	-0.0438*** (0.004) [8.6%]	-0.1428*** (0.012) [28.2%]	-0.1866*** (0.011) [36.8%]
Education 8-10	-0.0076*** (0.001) [1.5%]	-0.0342*** (0.005) [6.8%]	-0.0418*** (0.005) [8.3%]
Education 11-14	-0.0334*** (0.003) [6.6%]	-0.0570*** (0.007) [11.3%]	-0.0904*** (0.009) [17.9%]
Education 15+	-0.0277*** (0.005) [5.5%]	-0.0189*** (0.003) [3.7%]	-0.0466*** (0.007) [9.2%]
Other Income	-0.0368*** (0.002) [7.3%]	-0.1043*** (0.008) [20.6%]	-0.1410*** (0.007) [27.8%]
Total	-0.1492*** (0.01) [29.5%]	-0.3572*** (0.015) [70.5%]	-0.5064*** (0.017) [100.0%]

This table presents, for each income source and decomposition components, the β coefficients, robust standard error (between parentheses) and p-value (between brackets) of the regression depicted by equation 9. These coefficients can be summed in both line and column and the results are presented in the totals. * p<0.05, ** p<0.01, *** p<0.001

5. Conclusion

Brazil has deep social problems linked directly to inequality. Although a general issue, both poverty and inequality are higher in northern Brazilian municipalities. For example, while in the South region of Brazil the Gini index of total income is 0.48, in the North and Northeast regions the value is of 0.52 and 0.53, respectively.[51] During the last two decades, overall inequality fell in Brazil. Moreover, the inequality gap between municipalities fell, indicating that inequality reduction was larger in municipalities where, initially, inequality was higher

This paper shows that the inequality gap between municipalities in Brazil between 2000 and 2010 declined, indicating β-convergence. The gap between municipalities inequality, measured by the Gini Index, almost halved on average. More important, this convergence is to a lower overall inequality level, meaning that not only the regional inequality gap reduced, but also municipalities become less unequal.

We then analyze the economic changes that could have influenced this regional convergence in income inequality. To identify the relevant economic changes that led to inequality decrease and β-convergence between municipalities, we decompose both the Gini Index and its decrease in the last decade. We find that labor income is the most important driver of the declined of both inequality levels and regional inequality -- β-convergence. The interpretation for these two results is that: the labor market has become less unequal on Brazilian municipalities as a whole in the period 2000-2010, hence the decline in inequality; municipalities in which the labor market was more unequal in 2000 were the ones that presented the largest decline.

Increase in minimum wage, formalization and higher education are determinants to the decrease in inequality levels, but explain little β-convergence. This is because although the reduction on labor income inequality is the main driver for total income convergence, this convergence cannot be fully explained by neither the increase in minimum wage, nor the formalization and nor the increase in education levels. It is a phenomenon widely spread between economic factors, not being caused by only one.

[51] Source: Census 2010.

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Appendix

***Table 28* - Decomposition components - Benchmark decomposition 2000-2010**

2000-2010	$\overline{C_h} - G$	$\Delta \varnothing_h$	ΔC_h	$\overline{\varnothing_h}$
Labour Income	0.00	-0.07	-0.05	0.67
Other Income	-0.02	0.07	-0.02	0.33

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

***Table 29* - Decomposition components - Benchmark decomposition 1991-2000**

1991-2000	$\overline{C_h} - G$	$\Delta \varnothing_h$	ΔC_h	$\overline{\varnothing_h}$
Labour Income	0.00	-0.12	0.02	0.76
Other Income	-0.03	0.12	0.02	0.24

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

***Table 30* - Decomposition components - Minimum wage decomposition 2000-2010**

2000-2010	$\overline{C_h} - G$	$\Delta \varnothing_h$	ΔC_h	$\overline{\varnothing_h}$
Labor Income	0.04	-0.12	-0.02	0.62
Labor Minimum Wage	-0.43	0.05	0.06	0.06
Other Income	0.09	0.03	-0.04	0.20
Other Income Minimum Wage	-0.29	0.03	0.03	0.13

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

***Table 31* - Decomposition components - Formalization decomposition 2000-2010**

2000-2010	$\overline{C_h} - G$	$\Delta \varnothing_h$	ΔC_h	$\overline{\varnothing_h}$
Formal	0.06	0.00	-0.09	0.34
Informal	-0.05	-0.07	-0.02	0.34
Other Income	-0.02	0.07	-0.02	0.33

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.

Table 32 **- Decomposition components - Education decomposition 2000-2010**

2000-2010	$\overline{C_h} - G$	$\Delta\emptyset_h$	ΔC_h	$\overline{\emptyset_h}$
Education 0-7	-0.17	-0.12	-0.06	0.30
Education 8-10	-0.05	0.00	-0.16	0.09
Education 11-14	0.11	0.03	-0.15	0.17
Education 15+	0.31	0.03	-0.04	0.10
Other Income	-0.02	0.07	-0.02	0.33

This table presents for each income source the municipalities' mean Gini variation due to each component, and the percentage of the total change in the Gini Index. These variations can be summed in both line and column and the results are presented in the totals. Estimates come from equation (5).
Source: Census 2000 and 2010.