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Elasticity of population (mis)reporting in Brazilian municipalities: A census tale

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Contents

Keywords
population reporting, census, Brazilian municipalities

JEL Codes
H70, H80, H83

Abstract · **Resumo**

This paper investigated population misreporting in Brazil from 1991 to 2010. We have firstly documented that there is a discontinuity in the population distribution, but only for census years. Secondly, we estimated the elasticity of population (mis)reporting regarding intergovernmental grant that ranges from 0.3 to 2.5. Lastly, we have found that not only political variables operate to help those municipalities to obtain more federal funds, but also fiscal autonomy and the proximity to local population office bureau.

1. Introduction

The primary instrument for distributing federal government resources to municipalities in Brazil is the Municipal Participation Fund (FPM, in Portuguese), which considers municipalities with less than 142,633 residents as the only criterion for the distribution of resources. These unconditional transfers allow for autonomy of local government to decide upon the size of public expenditure. Moreover, transferred resources can easily be captured by vested interests in locations with more vulnerable minorities and poor populations (Bardhan & Mookherjee, 2000). These unconditional transfers aim to correct horizontal inequalities across local governments, and local population is used to determine the quantity of granted

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resources. This may induce municipalities to pursue strategies that affect the size of their population in order to benefit from such transfers.

The objective of this paper was threefold. First, we aimed to investigate whether there is a distortion of population information in Brazil from 1991 to 2010. Using such a long period of time in our analysis, we were able to differentiate the possibility of population manipulation in census years from those off censuses. This is different from Litschig (2012), who argued that grants allocated through a population-based formula in Brazil would not be effectively shielded from special-interest politics in the 1980s Census. Our paper explores manipulation in not only in the Census data from 1991, which was the first census after the adoption of the Constitution of 1988, but also from 2000 and 2010.Second, we estimated the magnitude of the effect of grant generosity on population overreporting. In Brazil, the per capita grants to municipalities show a rise at population thresholds. More specifically, the grant per inhabitant changes discontinuously at 17 population thresholds (10,188; 13,584; 16,980; 23,772; 30,564; 37,356; 44,148; 50,940; 61,128; 71,316; 81,504; 91,692; 101,880; 115,464; 129,048; 142,632; 156,216), and per capita grants increase discontinuously at those thresholds. This might create incentives for municipalities to sort into the right side of the nearest threshold.[1] Although all municipalities might be tempted to misreport population figures, the incentives to misreport are stronger for municipalities near those population thresholds. Moreover, the exogenous increase in grants at each population threshold provides exogenous variation in the marginal effect of an additional resident. This allows us to identify the effect of grant generosity on population misreporting in elasticity terms.

Our last contribution is to document whether those municipalities estimated at the bunching present some observable characteristics that could potentially influence such anomalous population sizes. In particular, we test for two concurrent explanations. First, we follow Litschig (2012) to test for the influence of political variables on municipalities bunching. Second, we compute the distance between the location of the offices that count the population's administrative data (named as IBGE local offices) and that of municipalities to investigate if that distance could capture an iceberg cost in terms of political influence on publicizing the population of a municipality.

Monasterio (2014) has addressed the possible evidence of population manipulation for all the censuses from 1991, 2000 and 2010 and for 2007 (sample counting adjustment). The author observes that municipalities with less than 50,000 inhabitants display greater gains regarding the range change of MPF. Their results

[1] It is important to point out one important caveat. The municipalities in Brazil are not responsible for population report; however, the Brazilian Institute of Geography and Statistics (IBGE) is. Therefore, whenever we consider municipalities trying to misreport their population number, this must be understood as them trying to exert pressure on IBGE so that such institution misreports population counts.

show that the thresholds of the MPF exert a strong influence on the population data of these municipalities for the 2010 census. Mattos and Santos (2018) also found evidence for manipulation in the 2010 and 2000 census data, as well as for population count data in 2007. The authors aimed to demonstrate that even if those municipalities with anomalous population sizes were excluded, on average, the distribution of transferred resources would not change, which reinforces the use of the population as a running variable in discontinuous regression models.

More similar to our paper, De Witte and Geys (2015) studied the incentives introduced by a similar grant in Belgium, but they did not find any evidence of overreporting. The authors did, however, provide evidence of housing construction growth for those municipalities close to the population threshold, which they interpret as evidence that municipalities use real policies to try to reach the threshold. Brollo, Nannicini, Perotti, and Tabellini (2013) verified the relationship between the greater availability of revenues for municipalities and corruption using the variations of the federal transfers around the same thresholds in Brazil.

Policies that create rises in governments' choice sets are referred to as notches and kinks (Slemrod, 2010). Kinks have been used to study the effects of taxes on the behavior of individuals and firms (Saez, 2010; Chetty, Friedman, Olsen, & Pistaferri, 2011). On the other hand, analysis using notches were introduced in Kleven and Waseem (2013). Kleven (2016, p.2) highlighted: "although kinks are commonly observed in income redistribution policies (such as graduated income tax systems), notches are ubiquitous across a wide range of other tax and nontax settings."

We follow Foremny, Jofre-Monseny, and Solé-Ollé (2017) as our closest reference and used notches to study the response of local governments to the incentives introduced by intergovernmental grants in Brazil. We made use of these notches to estimate the effect of grant transfer on population reporting. Specifically, we estimated the excess in population density above the notch thresholds. This method allows us to estimate the response-elasticity of population reporting to grant transfers. However, we push forward the analysis to investigate the possible channels through which an eventual response of population reporting might be occurring.

Three aspects of the relationship between different levels of government in Brazil render it distinct from other federations. The first aspect concerns the composition of municipal revenues. The municipal tax revenues represent only 21 % of the total revenue, while more than 60 % of transfers come from the federal government.[2] The second aspect concerns the composition of grants for municipalities. General- (unconditional) and specific-purpose (conditional) grants are equally important in

[2]The opposite figure has been observed in other federations, where the own revenues of municipalities are the major source of local government financing. For instance, this situation differs from that of Australia, wherein transfers from the Commonwealth to the states are more important than transfers to municipalities, and of Canada or Argentina, wherein federal transfers to municipalities have historically been small and have decreased over the years.

the Brazilian local government, as the former represents nearly 60 % of the transfers received by the municipalities and the latter represents 40 %. Thirdly, according to the 1988 Brazilian Constitution, municipal governments have great autonomy for defining and allocating their budgets. Both the executive and the legislative branches are elected every four years by a compulsory vote, so Brazil provides an appropriate environment to test the effects of fiscal decentralization (see also Eggers, Freier, Grembi, & Nannicini, 2017).

The optimal allocation of grants has been extensively discussed (Oates, 1972, 1999; Wildasin, 1986; Bird & Smart, 2002 for surveys). Researchers have concluded that unconditional block grants are the optimal transfer type, which would lead to undistorted local spending and taxation decisions. Furthermore, grants should be formula-based to avoid any political bias in their allocation (Dixit & Londregan, 1995; Persson & Tabellini, 2002). However, these formulae are vulnerable to manipulation by recipients because the information needed to apply the allocation criteria is distributed asymmetrically between the government levels (Bordignon, Manasse, & Tabellini, 2001; Huber & Runkel, 2006). Recent literature on the role of intergovernmental grants in local public finance emphasizes the importance of robust empirical strategies for determining causal relationships between specific types of transfers, local public expenditures, and taxes (Dahlberg, Mörk, Rattsø, & Ågren, 2008; Litschig & Morrison, 2013; Lundqvist, 2013; Lundqvist, Dahlberg, & Mörk, 2013).

Significant reactions in the responsiveness of municipalities to grants were found. For the first cutoff, more than 100 municipalities were to the right of the cutoff when they should be on the left in the censuses of 2000 and 2010 (i.e. 25 and 42 % of the municipalities, respectively). This implies that the elasticity of population overreporting to grants is about 0.25 for the most responsive municipalities, while the average response is around 0.02. For the second threshold, 38, 27 and 20 municipalities are detected at the bunching for the years 2010, 2000 and 1991, respectively. This influenced 19.3, 12.4 and 19.6 % of the municipalities in the neighborhood to the left of the second threshold. The population over-reported was estimated as 82, 80 and 62 individuals, respectively. For the third threshold, the number of municipalities at the bunching was 35, 17 and 24 (28.4, 23 and 23.9 % of the municipalities), and finally, the average population overreported was 241, 109 and 74. In addition, the extent of overreporting is higher in the most recent census, but it is also prevalent in 1991 with respect to the second and third thresholds. Surprisingly, we have not found bunching for non-census years. Lastly, both political variables and distance from administrative offices can partially explain our estimated bunching phenomena regarding the population of municipalities. Political variables can impact the probability to be at the bunching by 0.18 % for the year 2010 and 0.39 % for the year 2010. However, the larger the distance from administrative population counting offices smaller the probability to find a municipality at the bunching by 0.22 % for the year 2010.

Section 2 provides the institutional background; sections 3 and 4 describe the data and our methodology; sections 5, 6 and 7 present our results, and section 8 has the conclusion.

2. Institutional background

In Brazil, the federative structure is composed of three entities: federal, state, and municipal. In 2010, the municipal revenue was equivalent to 1.8 % of the gross domestic product (GDP); however, municipal organizations were responsible for an expense equivalent to 5.3 % of the GDP. The difference between what is collected and expenses can be explained by the transfer mechanisms adopted in the Brazilian fiscal federalism. Regarding the municipalities, the main received transfer is the MPF, which represented 16.30 % of total municipality revenue in 2010. It is even more relevant for small municipalities. In the same year, for municipalities with less than 50,000 inhabitants, the MPF represented 31.12 % of the total revenue.

The MPF is an unconditional transfer that aims at a vertical equalization among Brazilian municipalities. The fund is comprised of 23.5 % of the federal income tax and income tax receipts. The MPF distribution criteria divide municipalities into three categories: municipalities in the capitals (10 % of the MPF); "reserve class" (*classe-reserva*), for those with more than 142,633 inhabitants (receive 3.6 % of the total); and the "inner class" (*classe-interior*), which account for 86.4 % of the MPF.

The division rule for the municipalities of the inner-class sets participation coefficients for the states and for the municipalities according to population size. Table 1 presents the population intervals, the participation coefficients associated with each of them, and the percentage variation of the coefficients.

The variations in the coefficients create incentives for the municipalities that are to the left of the notch. Figure 1 presents the dispersion between the MPF received by municipalities in 2010 and population size, and we can observe the changes in levels of transfers for the six initial population bands.

In order to estimate the increase in transfers due to having population level at the right of the population threshold, we consider a 5 % window on both sides of each population threshold and compute the average per capita value of the transfers received by cities that are to the left and to the right of those notches. For instance, in 2010, there seems to be a discontinuous change in per capita earnings up to the fifth notch. Moving from the first to the second threshold, the distribution coefficient raises the per capita transfer by approximately BRL 25. We still find gains up to the seventh coefficient (sixth notch), BRL 34, BRL 16, BRL 2 and BRL 19, respectively. However, after the sixth notch, we do not observe any per capita gains. This seems to

Table 1. Coefficient of inner-class municipalities

Population bracket	Coefficient	Δ%
Up to 10.188	0.6	–
From 10.189 to 13.584	0.8	33%
From 13.585 to 16.980	1.0	25%
From 16.981 to 23.772	1.2	20%
From 23.773 to 30.564	1.4	17%
From 30.565 to 37.356	1.6	14%
From 37.357 to 44.148	1.8	13%
From 44.149 to 50.940	2.0	11%
From 50.941 to 61.128	2.2	10%
From 61.129 to 71.316	2.4	9%
From 71.317 to 81.504	2.6	8%
From 81.505 to 91.692	2.8	8%
From 91.693 to 101.880	3.0	7%
From 101.881 to 115.464	3.2	7%
From 115.465 to 129.048	3.4	6%
From 129.049 to 142.632	3.6	6%
From 142.633 to 156.216	3.8	6%
Over 156.216	4.0	5%

Source: Decree Law No. 1,881/1981 apud STN (2012).

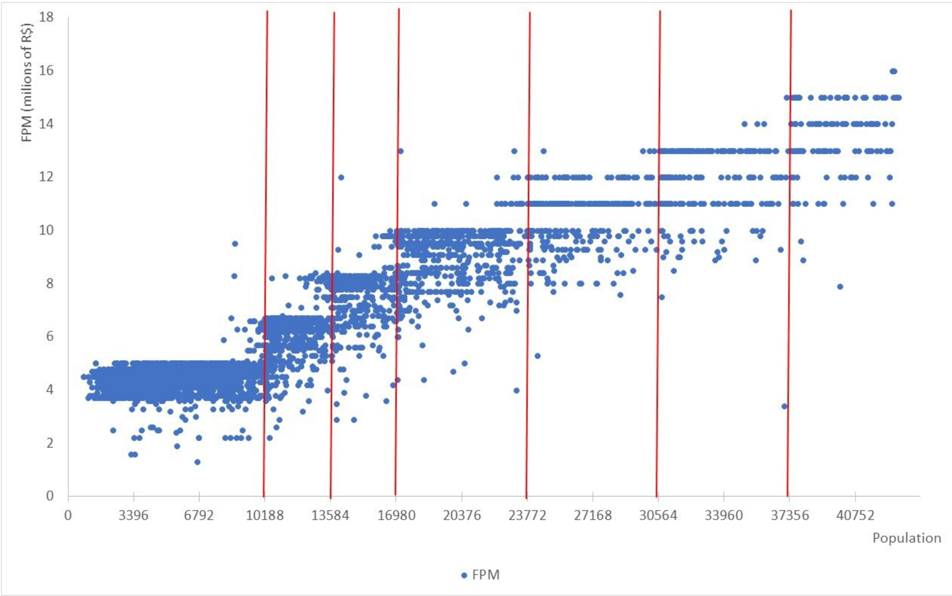


Figure 1. Distribution of grants in Brazilian municipalities, 2010

support that municipalities with less than 50,000 inhabitants have great incentives to change their populations.

The IBGE has carried out the Brazilian population census since 1940 with decennial frequency. However, since 1960, the institution adopts a probabilistic sample model with two questionnaires: sample and basic (non-sample) (IBGE 2012). For instance, the 2010 Census sample had five different fractions used according to the total population of the municipality. In municipalities with up to 2,500 inhabitants, the sample fraction was 50 %, that is, the sample questionnaire was applied in half of the total households. Municipalities with more than 2,500 to 8,000 inhabitants had a sample fraction of 33 %, whereas in those with more than 8,000 to 20,000 inhabitants, it was 20 %. In those with more than 20,000 to 500,000 inhabitants, the fraction was 10 %. And, finally, in municipalities with a population greater than 500 thousand, it was 5 %. The selection of households for the sample, which meant defining the type of questionnaire to be applied in a given household, was prepared automatically and randomly, in such a way that it is geographically spread over the entire extension of the census sector.

Finally, as also stated in Monasterio (2014), the IBGE offers municipalities the opportunity to request revisions to the preliminary numbers obtained in the census that might lead municipalities to present populations close to the MPF threshold to request population adjustments.[3] Only after eventual adjustments, the IBGE publicizes population census, which can subsidize public policies. Previous literature (Litschig, 2012; Monasterio, 2014; and Mattos & Santos, 2018) has already highlighted that there is some degree of manipulation in the population information of Brazilian municipalities. However, this does not mean that the IBGE has been doing a poor job in terms of population counting. On the contrary, Mattos and Santos (2018) show that only a small fraction of the municipalities can manage to have their population at the upper bracket of the MPF and, more importantly, without a change in the distribution of MPF in general. Our paper also reinforces that only a small fraction of municipalities have their population misreported.

3. Data

We applied population data from the censuses conducted by the IBGE for the years 1991, 2000 and 2010. Data on the MPF were collected in the Brazilian Local Public Finance (FINBRA, acronym in Portuguese) database provided by the Department of the Treasury (STN, acronym in Portuguese). The analysis is also conducted for the non-census years (1992, 1993, 1994, 1995, 1997, 1998, 1999, 2001, 2002, 2003, 2004, 2005, 2006, 2008 and 2009) and population counting years (1996 and 2007). For the non-census years, the IBGE publishes an estimate of the population based

[3]Monasterio (2014) considers only the first data in 2010, prior to any population adjustment.

on information from previous censuses.[4] Population analysis for non-census years works as our counterfactual exercise for census years.

Table 2 presents the descriptive statistics for the data of censuses years. We deflated MPF transfers for the year 2000 and presented real values for 2010. Nevertheless, as we had to collect the original figures for 1991 and for that period the Brazilian economy had suffered many periods of hyperinflation, we preferred to use the original dataset available at the STN.[5]

Figure 2 presents our first piece of evidence for the first three thresholds of the intergovernmental transfer system.[6] The graphs show the empirical distribution of the number of municipalities around each threshold. The data refer to years 1991, 2000 and 2010. The vertical axis provides the number of occurrences, and each point in the line represents the average value of the bin. The horizontal axis shows the population where each threshold used to redistribute MPF, which is identified by a red vertical line.

After the three thresholds, there seems to be a large number of municipalities, creating bunching just to the right of each threshold. This behavior seems to be followed by a concomitant reduction in the number of municipalities just to the left

Table 2. Descriptive statistics

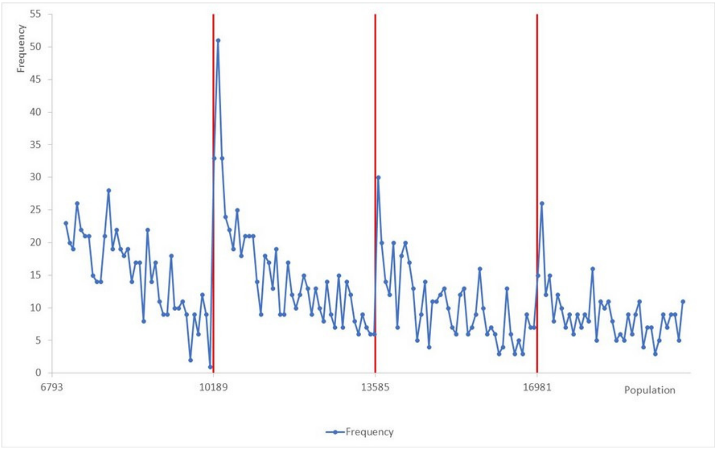
	Mean	Standard deviation	Minimum	Maximum	Observations
2010					
Population	34,253	200,793	805	11,000,000	5,564
MPF	9,544,209	16,900,000	1,280,942	549,000,000	5,487
MPF per capita	705	506	11	5,622	5,487
2000					
Population	30,762	182,563	795	10,000,000	5,507
MPF	3,071,330	6,443,012	26	263,000,000	5,298
MPF per capita	252	654	0	45,919	5,298
1991					
Population	32,688	187,341	751	9,600,000	4,491
MPF	321,165	707,141	711	41,600,000	4,005
MPF per capita	23	19	0	313	4,005

Source: IBGE and STN.

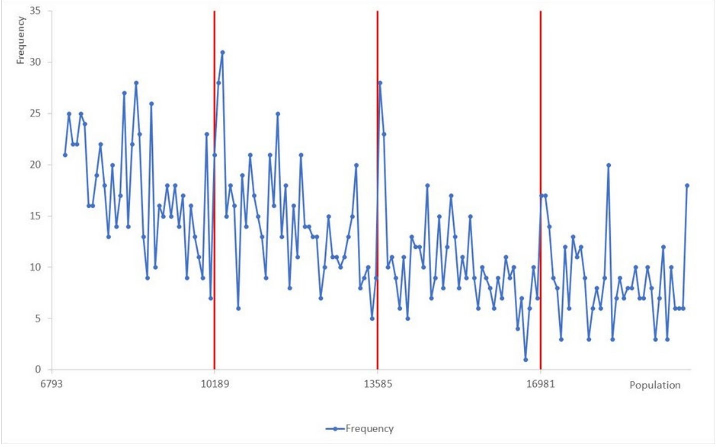
[4] Methodology available at https://www.ibge.gov.br/estatisticas/sociais/populacao/9103-estimativas-de-populacao.html?=&t=conceitos-e-metodos

[5] It is unclear whether the data have already been corrected for the new currency created in 1994 after the Real Plan or if they are listed in cruzeiros (the previous currency).

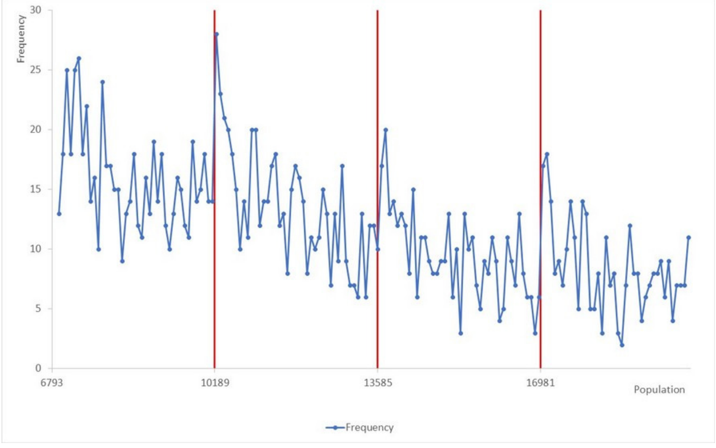
[6] The analyses were performed for the six thresholds and are available upon request.



(a) Census 2010



(b) Census 2000



(c) Census 1991

Figure 2. Distribution of municipalities around the first three thresholds

of that threshold. This seems to be a response to the transfer system. Additionally, the distribution shape decreases smoothly to the left side to the threshold and increases at the threshold and in its right-hand neighborhood. This is consistent with Kleven and Waseem (2013), who suggest that the missing area of mass is triangular. These descriptions are valid for all census years; however, the evidence is most prominent for 2010.

The McCrary test confirms that the distribution of municipalities seems to be manipulated at the population thresholds of the MPF transfer system. We have found a strong and statistically significant population discontinuity around the thresholds. The test has also been executed to placebo thresholds, and the results demonstrate that no manipulation occurs at the false threshold (Table 3).

4. Empirical strategy

The strategy of identifying bunching and mass missing follows Kleven and Waseem (2013) and Foremny et al. (2017). We used the pooled distribution for the census data (1991, 2000 and 2010) to illustrate the empirical strategy, as shown in Figure 3,

Table 3. McCrary Test summary

	Statistic McCrary			
	1991	2000	2010	All years
Population thresholds				
10,189	0.668	1.025	2.191	1.310
	(0.244)	(0.262)	(0.308)	(0.159)
13,585	0.663	1.508	1.661	1.308
	(0.240)	(0.325)	(0.341)	(0.191)
16,981	1.085	0.707	1.187	1.018
	(0.315)	(0.274)	(0.248)	(0.167)
Placebo threshold				
3,000	0.221	0.176	0.219	0.036
	(0.380)	(0.423)	(0.282)	(0.210)
5,000	0.270	0.511	0.275	0.106
15,000	0.153	0.199	0.167	0.192
	(0.289)	(0.216)	(0.271)	(0.146)
25,000	0.030	0.459	0.023	0.163
	(0.242)	(0.378)	(0.220)	(0.156)

Note: McCrary (2008) test in 1991, 2000, 2010 and pooled census information. Bandwidth and binwidth automatically determined. 40% window around the threshold. Standard errors in parentheses.

wherein $\hat{r}$ is the first threshold, r_U is the bunching limit and r_L is the beginning of the possible absence of data that precedes the threshold.

The bunching and the missing mass are measured by comparing the values of empirical and counterfactual density estimated by a polynomial, excluding the values between r_L and r_U. The counterfactual distribution is given by equation (1):

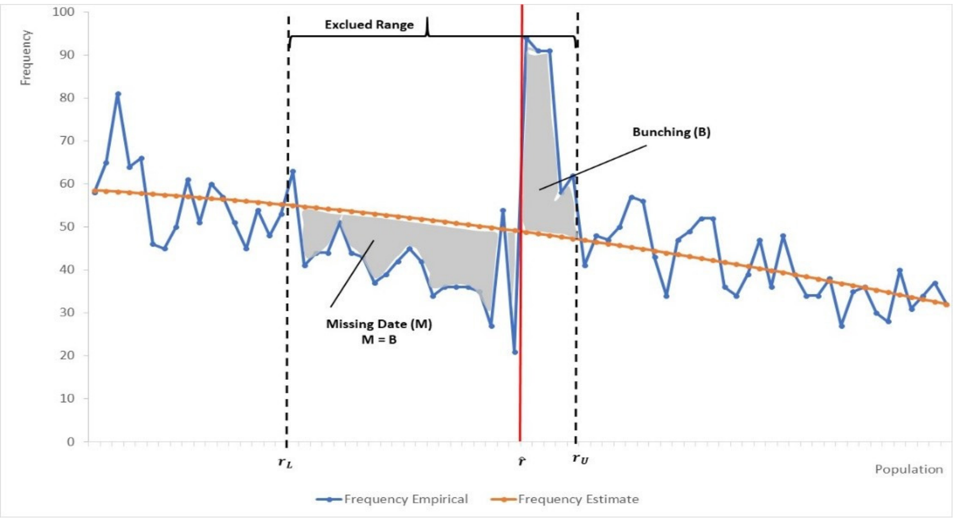
$$c_j = \sum_{p=0}^{p} \alpha_h (r_j)^p + \sum_{i=r_L}^{r_U} \gamma_i 1[r_j = i] + \varepsilon_j. \tag{1}$$

Here, c_j is the number of municipalities in the bin j; p is the polynomial order; and α_h are the parameters and γ are dummies for the values that are in the excluded range. The estimated distribution from equation (1), using the predicted values and omitting the contribution of the dummies, is as equation (2):

$$\hat{c}_j = \sum_{p=0}^{p} \hat{\alpha}_h (r_j)^p. \tag{2}$$

Figure 3 presents the counterfactual density and the areas of bunching and missing mass. Bunching and missing mass are measured by the difference between empirical and estimated densities. Thus, the number of municipalities (B) that form the bunching and the number of missing (M) are given by equations (3) and (4):

$$B = \sum_{j=\hat{r}}^{r_U} \hat{c}_j - cj \tag{3}$$



Note: Polled for 1991, 2000 and 2010. Bunching around the first threshold. Bin of 82 municipalities and 3,456 observations. Elaborated by the authors.

Figure 3. Representation of the empirical density and bunching estimation

$$M = \sum_{j=r_L}^{\hat{r}} c_j - \hat{c}_j \,. \tag{4}$$

In order to execute such strategy, the standard errors must be estimated by bootstrap. Given the characteristics of the empirical distribution, we expect the bunching to the right of the threshold to be sharp and to allow the visual identification of r_U without ambiguity. The definition of r_L is not visually simple, so we assume that the missing mass created in response to the bunching must be equal to the mass of the bunching, i.e. $B = M$.

4.1 Elasticity

Next, we detail how to estimate the population reporting elasticity for the Brazilian municipalities. We follow Foremny et al. (2017) to compute the population elasticity in relation to the change in transfers in each threshold, as follows:[7]

$$\epsilon_{r,h} = \left| \frac{\frac{\Delta r}{r}}{\frac{\Delta \tau}{\tau}} \right| \cong \left| \frac{\frac{(\hat{r}-r_L)}{r_L}}{\frac{\hat{r}}{(\hat{r}-r_L)} \frac{\beta}{\tau}} \right| = \left| \frac{(\hat{r}-r_L)^2}{r_L \hat{r}} \frac{\tau}{\beta} \right|, \tag{5}$$

where τ is the per capita transfer received by the municipalities; $\hat{r}$ is the designed threshold; β corresponds to the change in (mean) MPF per capita. More precisely, let

$$\overline{FPM}_{\text{pc}}^{\text{below}} = \frac{\sum_{i=r_L}^{\hat{r}} FPM_{\text{pci}}}{N_b}, \tag{6}$$

where N_b is the number of municipalites between $r_L \wedge \hat{r}$;

$$\overline{FPM}_{\text{pc}}^{\text{above}} = \frac{\sum_{i=\hat{r}}^{r_U} FPM_{\text{pci}}}{N_a}, \tag{7}$$

where N_a is the number of municipalites between $\hat{r} \wedge r_U$; and

$$\beta = \overline{FPM}_{\text{pc}}^{\text{above}} - \overline{FPM}_{\text{pc}}^{\text{below}}. \tag{8}$$

This allows us to estimate the population report elasticity properly on the part of Brazilian municipalities at each population threshold defined by the MPF rule of transfers.

[7]Note that the transfer is constant within a population bracket in Brazil, implying that per capita spending decreases from one notch to another. Therefore, equation (5) could underestimate this elasticity because grants are constant within a population bracket.

5. Results using census data

5.1 Estimation of bunching

Figures 4, 5 and 6 show the graphs with the bunching estimates for the analyzed thresholds. The dashed (green) lines define the R_L and R_U limits. The solid line (red) ideates the cutoff. The dashed line (blue) is the observed density distribution. The line with diamonds (orange) is the estimated density using equation (1).

Figure 4 presents the graphical analysis of the bunching estimation associated with the first MPF threshold including data from the census years. The bin set was 0.8 % of the threshold value. We follow Foremny et al. (2017) that used as benchmark (40/5,000). The population range was set between 30 % (above and below) of the threshold comparable to 40 % in Foremny et al. (2017). Last, we use a third-degree polynomial, which is the most used order in the literature and suggested in Saez (2010). The excess mass (bunching r_U) was defined by the visual inspection of the distribution, also following Foremny et al. (2017).[8] The counterpart calculated values for the r_U were 10,927, 10,599 and 10,681 for the years 2010, 2000 and 1991, respectively. The limit of missing data was 8,887 and 8,959, respectively, for the years 2010 and 2000. As observed in the year 1991 (4(c)), although there seems to have an excess mass in the neighborhood to the right of the threshold, we cannot find any missing data to the left of the threshold. Therefore, for 1991, we set the value of R_L to the notch ($\hat{r}$), so the analysis is restricted to measuring the bunching size.

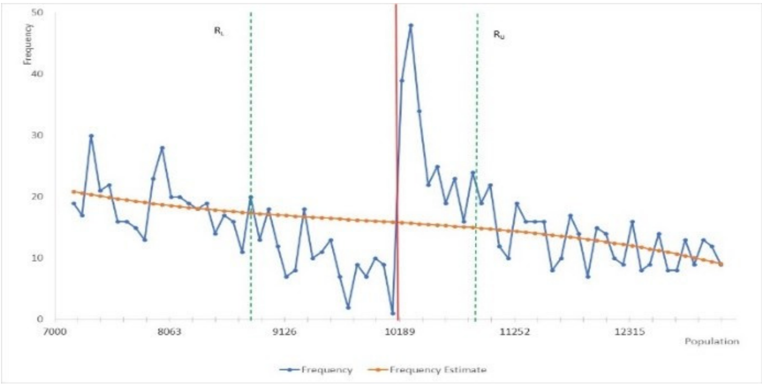
Figures 5 and 6 present our graphical analysis of the bunching estimation for the second and third thresholds, respectively. Our bin choice remains 0.08 % of the threshold value, and the density is estimated using a third-degree polynomial. The window size was 20 % for the second threshold and 16 % for the third. The reduction of the window relative size is due to the proximity of the fourth threshold much closer to the third one.[9]

Different from the first threshold, we have found a statistical bunching effect for 1991 census data, in which the observed empirical distribution behaves extremely similar across the three censuses years, with well-defined bunching and missing data. However, the bunching size seems smaller than those identified for the first threshold.

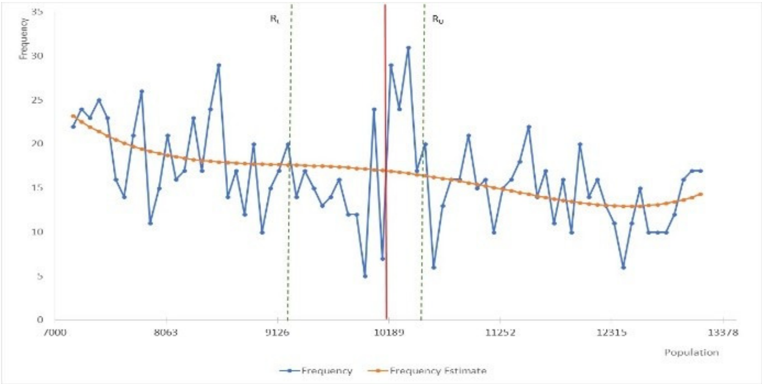
From the graphical inspection for the data of the 1991 census, Litschig (2012, p.1051) reported that it is clear "that these gaps (to the left) and spikes (to the right) of the thresholds do not reflect 1991 census population[s]." However, if one broadens the distribution around the thresholds, we observe that gaps and

[8]The results do not change qualitatively when altering such parameters. We consider the population range, by keeping a similar number of municipalities in both sides of each threshold. The size of the bin and degree polynomial follows Foremny et al. (2017) and Saez (2010). More results are in the Appendix.

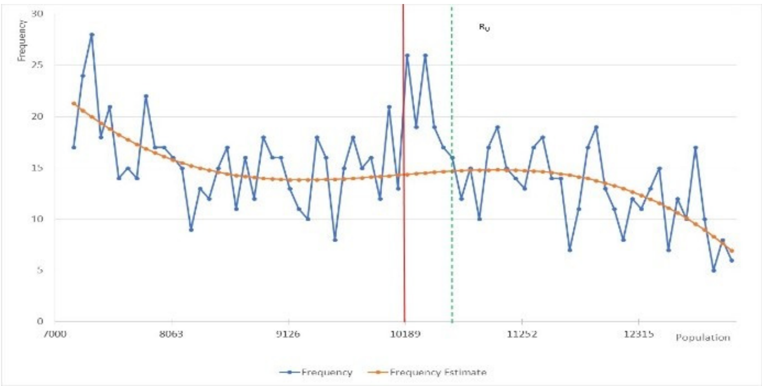
[9]See our Appendix for the 4th, 5th, and 6th cutoffs.



(a) 2010

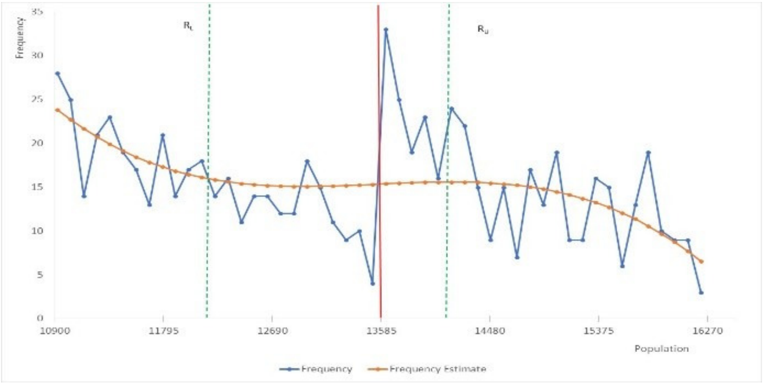


(b) 2000

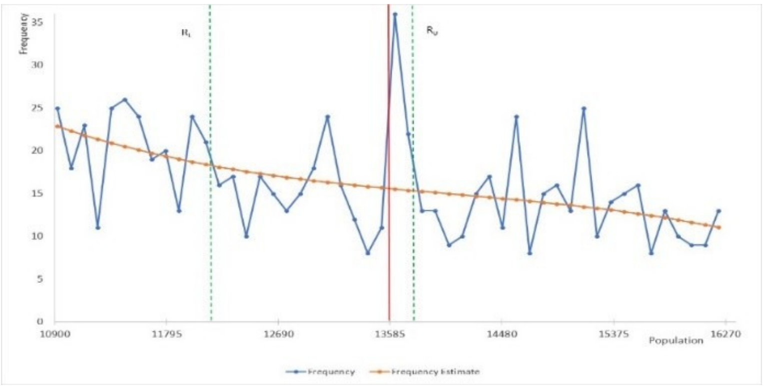


(c) 1991

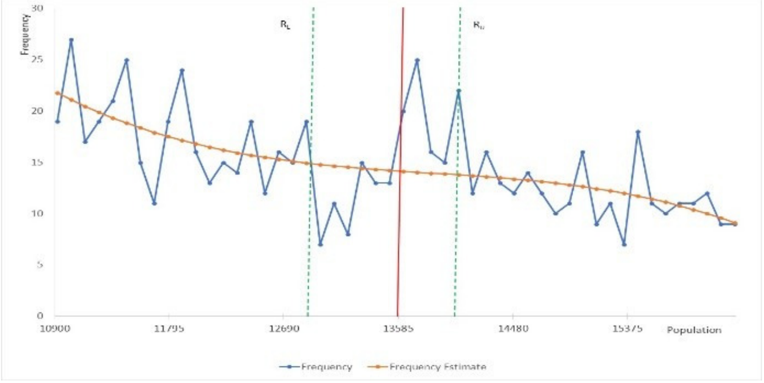
Figure 4. Bunching around the first threshold



(a) 2010

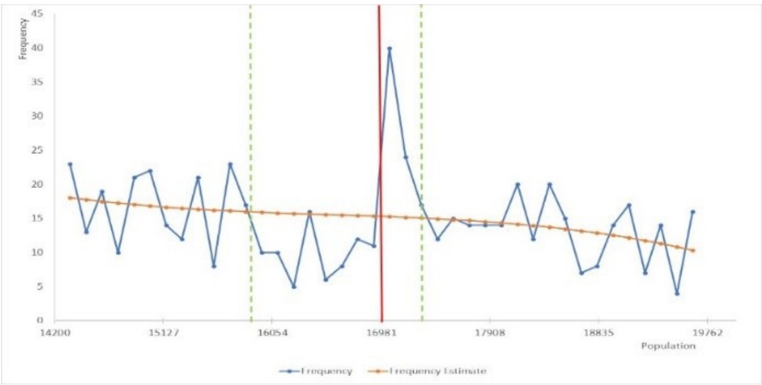


(b) 2000

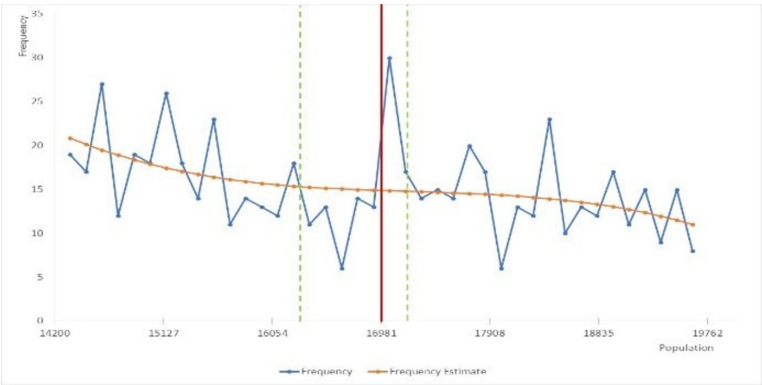


(c) 1991

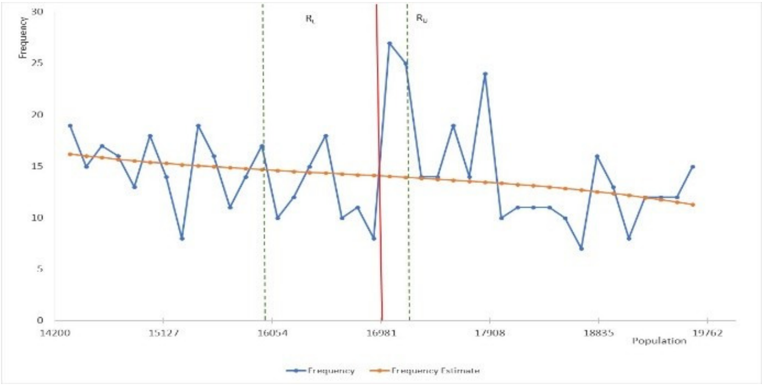
Figure 5. Bunching around the second threshold



(a) 2010



(b) 2000



(c) 1991

Figure 6. Bunching around the third threshold

spikes do seem to exist.[10] It is noteworthy that we measure bunching based on an estimated frequency distribution defined by population ranges (see section 4) with a predetermined window between R_L and R_U (see equation (1)). Litschig (2012), for the 1991 Census data, made only a visual observation of the frequency distribution of the municipalities. More importantly, the investigator did not test the possible manipulation of data in the 1991 census.

The results presented in figures 4, 5 and 6 are detailed in Table 4,[11] which is divided into three blocks (a, b and c) with the results for the years 2010, 2000 and 1991, respectively. Columns 2–4 include the results found for the first three thresholds.

Considering column 2 (first threshold, 10,189 inhabitants) for 2010, we have 111 municipalities arbitrarily in the neighborhood to the right of the threshold. That is, 111 municipalities that were supposed to be on the left of the threshold were able to manage to position themselves to the right of the threshold. This number corresponds to 42 % of the municipalities that should be between the limit (r_L) and the threshold. On average, the municipalities in the bunching have their population overreported by 231 inhabitants.

Using the same column 2, for 2000, 44 municipalities are arbitrarily above the threshold, and this number corresponds to 17 % of the number of municipalities that should be between the limit R_L and the threshold. On average, the municipalities in the bunching region have their population overreported by 80 inhabitants. The difference between the two periods (2010 and 2000) is consistent with the behavior of the distribution observed in Figure 1.

For the year 1991, the estimated bunching corresponded to 36 municipalities. This result is statistically significant. In the interval between the threshold and R_u, we have 125 municipalities. Thus, the percentage of municipalities overclassified in the bunching is 29 %. This number is much lower than the general result of 48 % found by Litschig (2012).

Column 3 includes the results for the second threshold. The estimated results show that 38, 25 and 20 municipalities are detected to be at the bunching for the years 2010, 2000 and 1991, respectively. This bunching might have influenced 19.3, 12.4 and 19.6 % of the municipalities in the neighborhood to the left of the threshold. We estimate population overreporting as 92, 81 and 62 inhabitants, respectively. For the third threshold (column 4), similarly, the number of municipalities was 35, 17 and 24; the influence was of 28.4, 23 and 23.9 %; and finally, on average, population overreported is estimated as 241, 109 and 74 inhabitants.

[10] Perhaps these are not as evident as in the data on the population distribution estimated in Litschig (2012).

[11] In the Appendix we present the results with different polynomial orders. We also allow for different size of bins and limits (r_L and r_U). We also combine different sizes of bins with varied polynomial orders and different limits. In all extensions, we have found that the results remain consistent.

Table 4. Results – Bunching for Census years (1991, 2000 and 2010)

	Thresholds		
a) 2010	**First** (Notch at 10189)	**Second** (Notch at 13585)	**Third** (Notch at 16981)
Polynomial order (q)	3	3	3
Bin size	82	108	136
Range $[R_L, R_U]$	[8,887; 10,927]	[12,181; 14,125]	[15,893; 17,389]
# Municipalities (B)	111***	38***	35***
s.e. (B)	12.36	10.06	7.21
% of respondents	42%	19.34%	28.40%
Average dr	231	92	241
b) 2000	**First**	**Second**	**Third**
Polynomial order (q)	3	3	3
Bin size	82	108	136
Range $[R_L, R_U]$	[8,959; 10,599]	[12,181; 13,801]	[16,301; 17,253]
# Municipalities (B)	44***	27***	17***
s.e. (B)	8.91	5.57	5.49
% of respondents	17%	12.40%	23.04%
Average dr	80	81	109
c) 1991	**First**	**Second**	**Third**
Polynomial order (q)	3	3	3
Bin size	82	108	136
Range $[R_L, R_U]$	[Notch; 1,681]	[12,829; 14,017]	[16,029; 17,253]
# Municipalities (B)	36***	20***	24***
s.e. (B)	8.610	6.94	4.43
% of respondents	–	19.60%	23.90%
Average dr	–	62	74

Note: ***1% significance.

These results confirm the descriptive evidence that municipalities around the MPF notches have overreported their population information. In addition, the bunching size and the number of inhabitants overreported grows at the three thresholds for each new census. The second step here is to understand the sensitivity of this overreported marginal variations of MPF.

5.2 Elasticities[12]

Table 5 shows the population reporting elasticities for the municipalities at each threshold of the MPF. We present the additional gain in transfer per capita (β), the average and the maximum estimated elasticity. The estimated elasticity at the bunching represents a mean response of population reporting on MPF thresholds for the grouping (Kleven, 2016).[13] For 2010, β corresponds to be BRL 40 and the estimated average elasticity is 2.5 %. For 2000, that β is BRL 15 and the estimated average elasticity is 0.77 %. Our results are not different from those in Foremny et al. (2017), in which a mean elasticity of 1.3 % was estimated for the first notch in Spanish municipalities. We also show the maximum point elasticity within each bin.

Table 5. Results – Elasticities for census years (1991, 2000 and 2010)

	Thresholds		
a) 2010	**First** (Notch at 10189)	**Second** (Notch at 13585)	**Third** (Notch at 16981)
β (Δ MPF per capita)	40	23	27
Elasticity (maximum)	25.74 %	27.92 %	8.63 %
Elasticity (average)	2.5 %	1.03 %	1.19 %
b) 2000	**First**	**Second**	**Third**
β (Δ MPF per capita)	15	−6	5
Elasticity (maximum)	18.21 %	36.67 %	6.40 %
Elasticity (average)	0.77 %	1.53 %	0.62 %
c) 1991	**First**	**Second**	**Third**
β (Δ MPF per capita)	–	1	0.40
Elasticity (maximum)	–	17.81 %	5.71 %
Elasticity (average)	–	0.80 %	0.30 %

Note: We did not observe the missing data. Thus, we could not calculate the β to estimate the elasticity.

[12] For the Brazilian case, this might underestimate the elasticity, once transfers are not per capita, different from Foremny et al. (2017).

[13] Best, Cloyne, Ilzetzki, and Kleven (2018) shows that the potential bias of such statistics due to aggregation of elasticities is in general small and cannot *a priori* invalidate the estimations.

For instance, it corresponds to 25.74 *versus* 18.21 % for the first bin in 2010 and 2000, respectively. The distance between the maximum and mean elasticities reflects the heterogeneity in the responses of the agents to the transfers. According to Foremny et al. (2017, p.59), "an average elasticity is the figure that can be considered most representative of the global effects of population overreporting."

Figure 7 shows the estimated (average) elasticity curve for both years 2010 and 2000 at each population size right before the first MPF threshold (10,189). Our results show a slight increase in population response to MPF change across two censuses years for that threshold.

An interesting difference between our paper and Foremny et al. (2017) regards the fact that data considered in the analysis in Spain are different in Brazil. In Spain, the authors study the intra-census population, which is self-reported by the local administration. Therefore, the local administration can suffer punishment due to that eventual population misreporting, which is the sample used in Foremny et al. (2017) to estimate the population manipulation. In the Brazilian case, the information used in the paper corresponds to the census data reported by the IBGE. Thus, the friction costs associated with generating information is local and decentralized in the Spanish case, while any potential misreporting can be associated with a central jurisdiction, at least partially, in our case.

Regarding the difference in the estimated (average) elasticity between 2000 and 2010, we understand this is the case for two reasons. First, the economic environment might have affected the structure of incentives. The total MPF was BRL 13 billion in 2000, whereas it corresponded to BRL 43 billion in 2010, i.e. there was a real MPF growth of approximately 192 %. This seems to have created a more attractive benefit for being on the right side of the notch in 2010 compared to that in 2000. Second

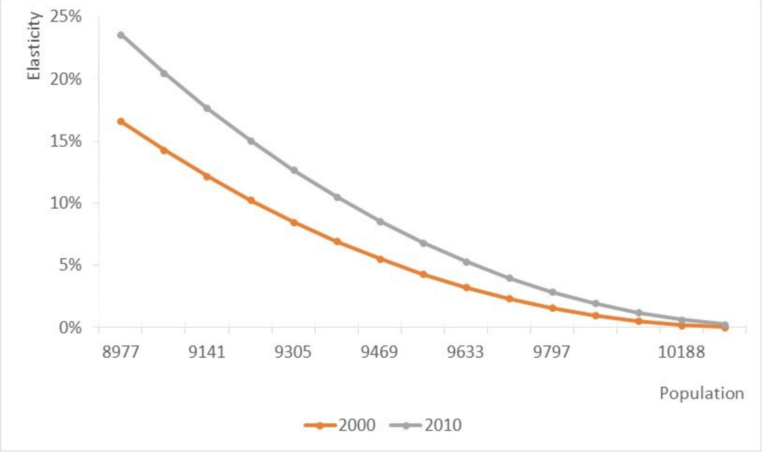


Figure 7. Population elasticity as to the Municipality Population Fund per capita around the first threshold (2010 and 1991)

and mostly important, one could have experienced a moral hazard effect. The fact that no municipality has been punished for reporting a larger population or one to the right of MPF thresholds in 2000 might have influenced a similar decision for other municipalities in 2010.

Columns 3 and 4 show the elasticity for the second and third thresholds. The values of β were 23 and 27 for the year 2010; −6 and 5 for 2005;[14] 1 and 0.40 for 1991. The heterogeneity with respect to the transference response remains in the other thresholds. Furthermore, the results for 1991 are quite below the results found for the other years. This reinforces the argument that the lack of punishment can generate incentives to overreported population.

6. Counterfactual analysis (non-census years)

Our counterfactual analysis used data from the population estimates and count made by the IBGE in the period between censuses.[15] We consider pooling by non-censuses years the population estimates (1992, 1993, 1994, 1995, 1996, 1998, 1999, 2001, 2002, 2003, 2004, 2005, 2006, 2008, 2009) and pooling of population count (1996 and 1997). Figure 8 presents the frequency distribution of the number of municipalities from the first three thresholds for aggregated data population estimates (orange line and frequency on the secondary axis) and population count (blue line).

We observed differences in the behavior of the two data sets. The data distribution of the population estimates is smoother around the thresholds. McCrary tests (Table 6) reinforce the lack of statistical significance in the discontinuity of the distribution of municipalities for date intra-census (population estimate) and strong discontinuity in population counting data. Thus, aggregate data from the population estimates do not demonstrate a behavior similar to that observed in the census information and described in the previous section.[16] As aggregate data of the estimates do not present evidence of manipulation and Bunching formation, we can use them as counterfactual of the frequency distribution around the thresholds instead of the polynomial estimations. However, we have 15 years of information from population estimates and only three years of census need to weigh by 0.2 the frequencies in the data of population estimates.

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[14]We emphasize that for the year 2000, the negative value of the per capita variation of the MPF does not interfere on the elasticity that is given in absolute values.

[15]The population estimation is the population estimate contingents of the municipalities and is based on the relation of the population growth tendency of the municipality, which was observed between two consecutive demographic censuses. Population counts are carried out in a field with dimension and complexity lower than the census. Both are conducted and disseminated by the IBGE.

[16]The results are only valid for aggregate data. The tests show that in some years the population estimates also present bunching around the thresholds.

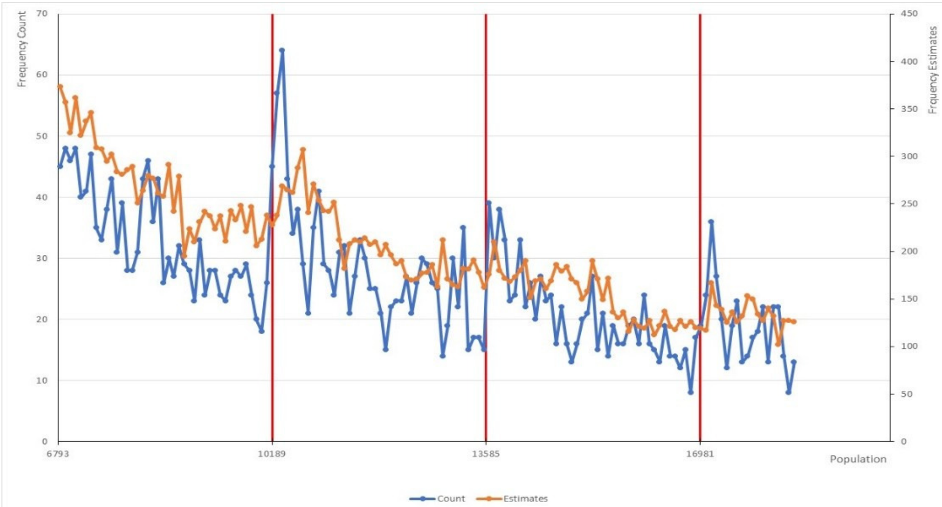


Figure 8. Distribution of municipalities around the first three thresholds (population estimate and population count)

Table 6. Summary of McCrary test (estimate population)

	Statistic McCrary	
	Estimate Population	Count Population
Population thresholds		
10,189	0.086	1.243
	(0.076)	(0.199)
13,585	0.056	1.012
	(0.057)	(0.214)
16,981	0.128	0.838
	(0.077)	(0.202)
False population threshold		
5,000	0.021	0.123
	(0.077)	(0.151)
15,000	0.020	0.255
	(0.062)	(0.224)

Note: McCrary (2008) test on pooled intra-census information. Bandwidth and binwidth automatically determined. 40% window around the threshold. Standard errors in parentheses.

Figure 9 shows bunching estimation in the first threshold for the aggregated data of the three censuses (1991, 2000 and 2010). Using the frequency distribution of the aggregate data of the population estimates as counterfactual. Note that the frequency distribution of census data is the same as that observed in Figure 3 (section 4). The factual distribution has a behavior much more like the census data. Despite the behavioral similarity of the series, the bunching region and the missing date area are still evident. We have found that the r_u of 10,599 matches is visually exactly what had already been defined before. The number of municipalities in bunching is 132 and this result is statistically significant at 1 %. The estimated bunching in the second and third thresholds was of 71 and 69 municipalities (both statistically significant at 1 %).

The results of the counterfactual show that data from the population estimates performed based on demographic parameters do not show signs of possible manipulations of the information around the thresholds. However, the methodology considers the census information of the previous years. Thus, it does not correct the population information generated in the census year, it only makes an allocation in the distribution that alters or selects the bunching.

Another issue to emphasize is that in the two population counts during the studied period, the existence of bunching around thresholds was also identified. This fact reinforces the idea, given by Litschig (2012), that there is some mechanism in place that can influence the overreported population. In the next section we will try to explore some possible mechanisms.

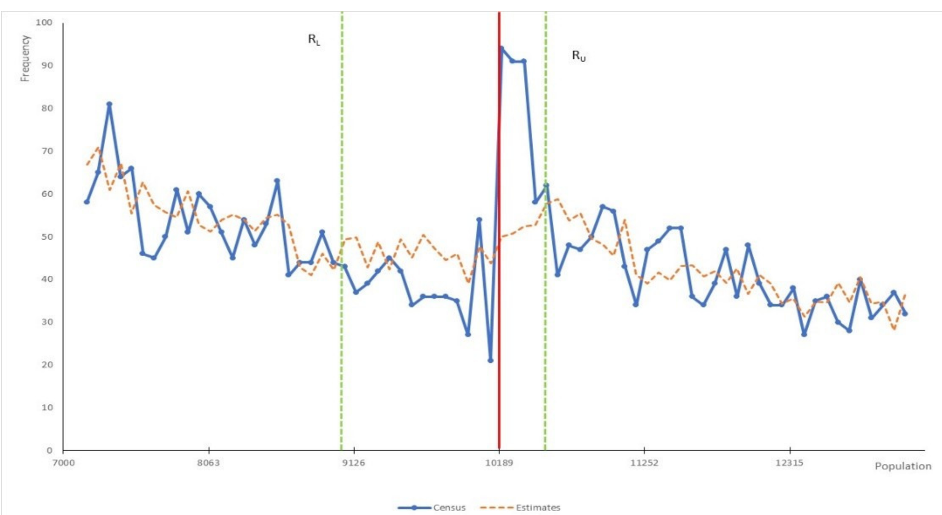


Figure 9. Bunching around the first threshold with contrafactual population estimates

7. Possible channels

The purpose of this section is to shed a light on what could explain, at least partially, the population evolution around the notches. Understanding some of these mechanisms can help to control and design future public policies determined by population thresholds. De Witte and Geys (2015) from Belgium suggest that municipalities can adopt policies that encourage migration, such as reducing local taxes and incentives for new construction. These policies favor population expansion, but do not constitute a "fraud" in population information. Foremny et al. (2017) describe two possible "fraudulent" mechanisms practiced in Spain: the municipalities have not reported the departure of immigrants and duplicates nor have they even created registers of "ghost" residents. Litschig (2012) suggests for Brazilian data in the nineties that political variables are determinants for a municipality to establish itself in the right-hand neighborhood of the population notch created by the MPF.

The main explanatory variable used in Litschig (2012) was the fraction of votes received by each municipality for the federal deputies that formed the basis of the Federal Government elected in the previous elections (Share). The political interference in the distribution of resources could be directly associated with a special interest group policy.

Like Litschig (2012), we have used Share as the main variable to explain the probability of a municipality to be at the right side of MPF threshold, at the bunching. We aggregated our data for the first three notches. Our dependent variable is called bunch, which is binary and assumes value equals to one if the municipality is at the bunching or zero if the municipality is in the missing data area.[17] Hence, we have for the first three notches:

$$Bunch = \begin{cases} 1, & \text{if } Notch < Population < R_U; \\ 0, & \text{if } R_L < Population < Notch. \end{cases}$$

Incorporating a vector (X) of control variables, we have the following estimation equation:

$$Bunch_i = \beta_1 Share_i + \beta_2 X_i + \varepsilon_i. \tag{9}$$

The control variables are Gini index, infant mortality rate, illiteracy rate, population above 65 years, per capita income, dependency ratio, unemployment rate, urban population, and economically active population. State fixed effects estimates were also incorporated. These variables aim to capture income, educational, demographic, fiscal and economic development differences across those municipalities.

Additionally, we introduce the following political variables: dummy for mayor aligned with federal government; dummy for governor aligned with the federal

[17]We note that Litschig (2012) proposes a dependent variable that assumes value one if the municipality is at the bunching and zero, otherwise, i.e. he compares "treated" with all other municipalities.

government and a dummy for municipalities where a candidate for federal deputy received more than 50 % of valid votes (dominant deputy). Last, we build the variable Share, as in Litschig (2012), to capture the proportion of non-ideological voters in each municipality. We build that as the municipality-level right(left)-wing vote share—defined as the electoral support for right-wing parties in the preceding elections to the the Federal Chamber of Deputies for 1991 and 2000 (2010) election years. The idea is that if the right(left)-wing vote share captures the ideological bias of the municipality, a positive relationship with population will indicate core-support targeting. For a non-linear concave relationship, we understand that as a swing-voter targeting (see figures 15 and 16 in Appendix).

To define these political variables, we consider party compositions assumed in the previous elections to the Censuses date. For the 2000 Census data, the 1996 and 1998 elections results are used and the parties considered as the government support are PSDB, PFL, PPB, PTB and PSD. For the year of 2010 we consider the elections of 2006 and 2008 and the support of the elected government are the following parties: PT, PRB, PCdoB, PSB, PP, PDT, PL and PMDB.[18]

7.1 Political variables

Figure 10 shows the mean values of the political variables and their confidence interval for the years 2000 and 2010. The diamonds and ball dots are the mean values of the variables for the years 2000 and 2010, respectively. The 54 % percentage of the

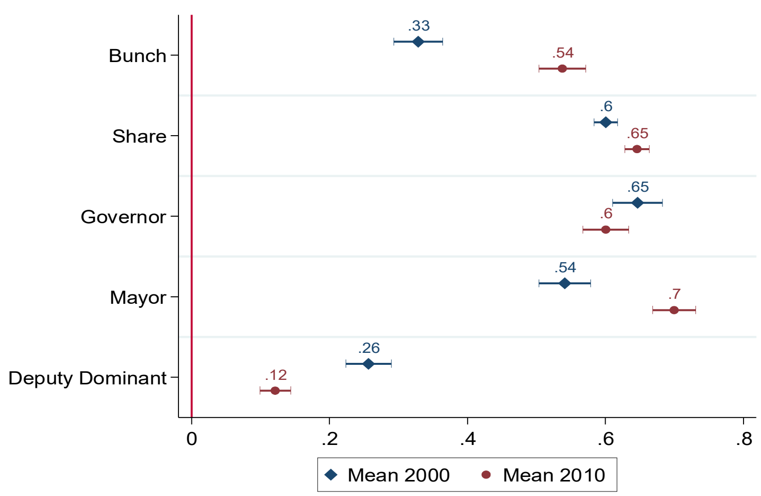


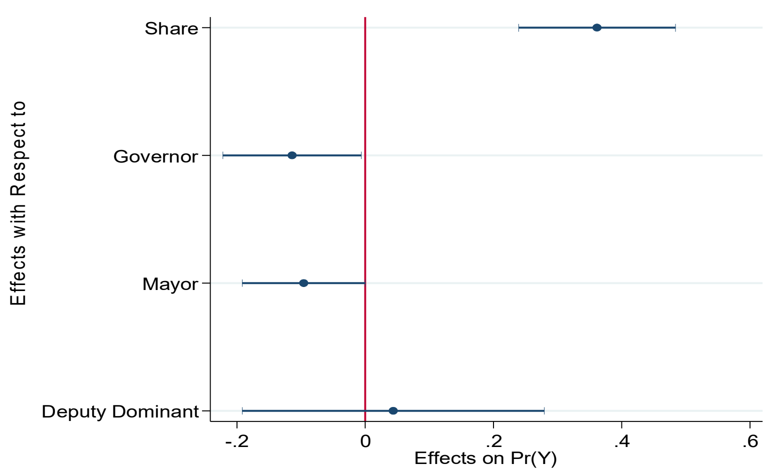
Figure 10. Mean values with 90% Cis (years 2000 and 2010)

[18]Our analysis comprises ideological alternation in the Federal Government. We can consider that the Federal Government was closer to the right in terms of ideological spectrum in 2000 and from 2010 the government has moved toward left.

municipalities in the bunching area in 2010 were much higher than the percentage of 33 % registered in the year 2000. Similarly, the percentage of municipalities with mayors aligned with the federal government in 2010 was 70 %, while only 54 % in 2000. The percentage of municipalities with deputy candidates that received more than 50 % of the votes in 2000 was twice as high as in 2010. The only variables that did not present great differences were Share and the percentage of governors of the federal government colligation.

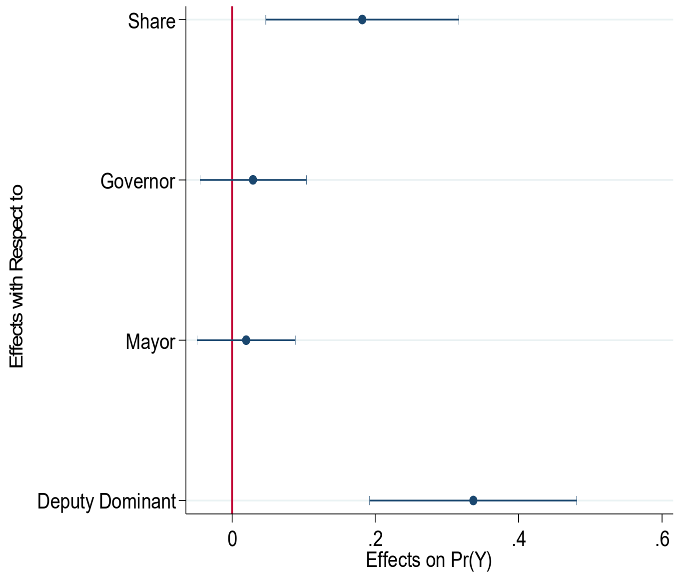
Figures 11 and 12 illustrate the results of the estimates incorporating other political controls. The results show that a marginal increase in share raises by 0.18 and 0.39 % the probability of the municipality being at the bunching area for the years of 2000 and 2010, respectively. For the year of 2010, besides this political variable (share), only the Governor variable was statistically significant, but with marginal negative effect, suggesting that the Governor's political alignment reduces the probability of the municipality being at the right side of the bunch. For 2000, the dominant deputy variable was also significant and showed a marginal positive effect.

In general, the results suggest that the local political environment can be used as a strategic mechanism in the process of generating population information for the municipality, in order to establish itself on the right side of the population. The intuition established here is that the reported population of the IBGE decentralized units seems to be influenced by the local political group, that is, politicians with great electoral power can exert pressures on the population census carried out in their geographical area.



Note: Estimation using Probit (standard adjusted for clusters id). The reported coefficients refer to the marginal effect. Number of observations: 839. Socioeconomic control variables and interaction between the political variables that are binary. See Appendix for full tables.

Figure 11. Average marginal effects with 90 % Cis (year 2010)



Note: Estimation using Probit (standard adjusted for clusters identification). The reported coefficients refer to the marginal effect. Number of observations: 682. Socioeconomic control variables and interaction between the political variables that are binary.

Figure 12. Average marginal effects with 90% Cis (year 2000)

7.2 Using geographic and fiscal variables[19]

Firstly, we describe the size of fiscal dependence for most of the Brazilian municipalities in relation to the federal transfers, in particular to MPF. This dependency automatically creates an incentive for the municipality to be to the right of the population threshold and obtain more per capital revenues. In other words, the lack of autonomy in terms of tax revenues might lead the municipality to misreport the population size. This is why we also control the fiscal autonomy in our regressions. Second, we argue that the political environment may exert pressures on population counting results.

These two findings make us think about what could reduce the overreported population size. We were able to reflect about two potential mechanisms. The first one is that fiscal dependence of the MPF is reduced if the municipality performance is greater in the tax collection, that is, a greater fiscal autonomy should reduce the incentives for overreporting the population of municipalities. Accordingly, we must expect that the political pressure on administrative units of the IBGE to overreport a population are lessened. The other potential mechanism is to exert a political pressure that is associated with some (monetary/political) costs. We claim

[19]In this section, we have used only the data for the year 2010. We do not have information about the location of the IBGE units for the year 2000.

that the most obvious one is captured as an iceberg type, i.e. the cost to get to the administrative units of the IBGE. Therefore, we must observe an inverse relationship in the distance between the municipality and the decentralized administrative unit of the IBGE versus the incentives to overreporting of the population.

In 2010, the IBGE presented administrative agencies in 543 municipalities spread across all five Brazilian regions. We defined the cost variable as the distance between the investigated municipality and the one with the closest local head office of the IBGE. Our fiscal autonomy variable was computed as the per capita tax revenue of the municipality. We have also created two dummies: for the municipality that has a tax revenue of more than 3.6 % of the budget and for the farther than 36 km away from IBGE headquarters. Both values chosen refer to the median of the variables, so we defined that the ones above these points have a greater fiscal autonomy and a higher iceberg cost.

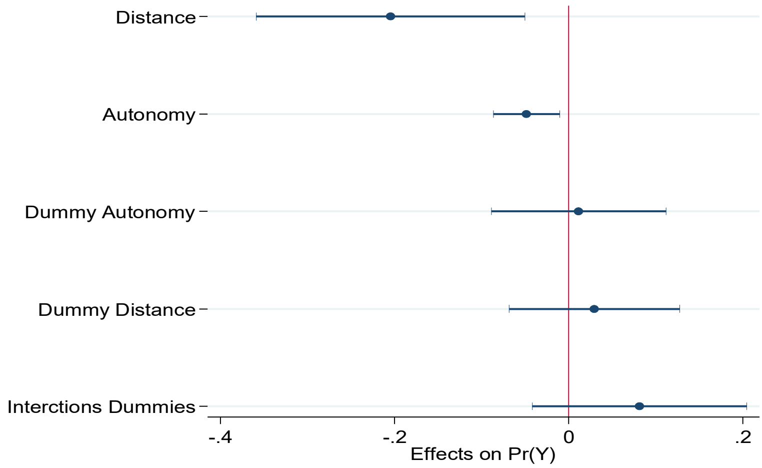
According do Table 7, the average distance observed is 46 km and 25 % of the municipalities are at a distance greater than 55 km. Among the 839 municipalities of the sample, only 11 have IBGE headquarters (distance equal to zero). Regarding fiscal autonomy, average tax revenue is BRL 71 per capita and only 10 % of municipalities have a tax revenue of more than 8.4 % of budget revenue. In addition, all municipalities have their own level of tax revenue.

Figure 13 shows the estimation result for equation (9), with the distance variables and autonomy substituting the political variables. In order to improve the visualization of the results, the distance and autonomy of variables were divided by 100. In this way, the interpretation of the marginal effects refers to a variation of 100 km and BRL 100 of per capita tax revenue. Using our previous sample of

Table 7. Descriptive statistics

Stats	Distance (in km)	Autonomy (in per capita tax revenue)	Autonomy (in % of the budget)
Mean	47	71	4.8 %
p50	36	43	3.6 %
Min	0	5	0.5 %
Max	393	1,291	47.5 %
p10	18	18	1.8 %
p25	25	28	2.5 %
p75	55	73	5.6 %
p90	88	129	8.4 %
Sd	38.44	105.00	0.04
N	839	750	750

Source: STN and IBGE.



Note: Estimation using Probit (standard adjusted for clusters identification). The reported coefficients refer to the marginal effect. Number of observations: 750. Socioeconomic control variables and the fixed effects for states. See Appendix for full tables.

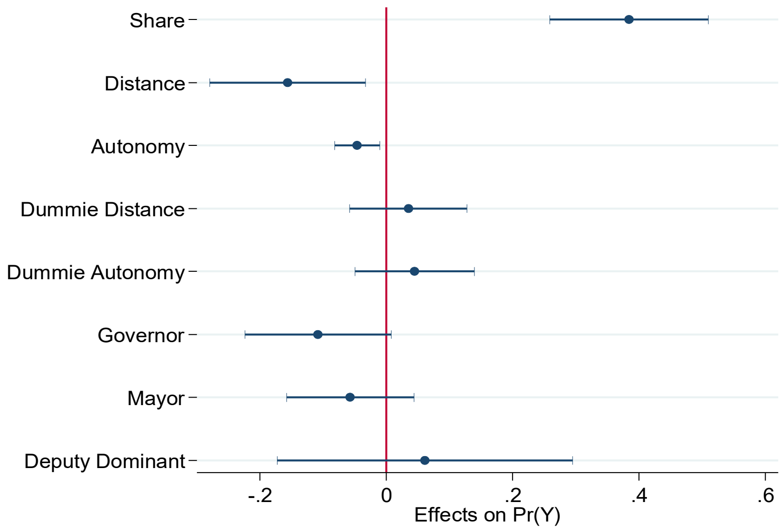
Figure 13. Average marginal effects with 90% Cis (year 2010)

municipalities, i.e. those close to the threshold, our estimated coefficients corroborate that an increase in distance and autonomy is associated with a reduction in the probability that the municipality is at the right side of the population threshold.

The results show that the increase of 100 km away from the IBGE headquarters reduces by 0.22 % the probability of being in the bunching piece. Similarly, an increase of BRL 100 in the municipality per capita tax revenue reduces the probability by 0.05 %. The dummies variables do not affect the probability of the municipality being in the bunch.

Finally, Figure 14 presents the estimation results with all the political, geographic, and fiscal variables. Despite minor changes in the magnitude of the coefficients, the interpretations remain the same. This shows that in addition to the political variables (as in Litschig, 2012), the iceberg costs and the fiscal capacity of the municipalities must be considered.

Assuming the validity of results we can consider that the incentives for the manipulation of population information can be reduced by policies that increase the municipal taxation capacity. A recent example of this type of policy is the municipalization of the tax on rural territories (ITR, acronym in Portuguese). Another way is to reduce the decentralization of IBGE activities. Placing administrative headquarters only in cities with more than 200,000 inhabitants could reduce to agencies in only 153 cities.



Note: Estimation using Probit (standard adjusted for clusters identification). The reported coefficients refer to the marginal effect. Number of observations: 750. Socioeconomic control variables and interaction between the political variables that are binary. See Appendix for full tables.

Figure 14. Average marginal effects with 90% Cis (year 2010)

8. Conclusion

In this study, we investigated the notches generated by a transfer system to local governments in Brazil. We have found significant evidence that the incentives from the grant schedule results in the overreporting of population figures. Distinct from the findings of Foremny et al. (2017), the inflation of population figures occurs only during census years.

Specifically, we found a missing mass of up to 40% of the municipalities to the left of the 10,188-inhabitant threshold for the 2010 census, but on average, that figure corresponds to 15–20%. In addition, our estimated elasticity (population responsiveness) is decreasing in the cutoffs, that is, the smaller the cutoff the larger the estimated elasticity. This occurs predominantly due to the largest expected gains in the first thresholds.

Our analysis using both census and off-census year's reveals that it is not a simple problem of information provision on the part of municipalities. The fact that we have found no bunching in off-census figures also suggests that municipalities may not respond to transfers by attracting more residents.

This paper contributes to the previous literature in Brazil, such as Monasterio (2014) and Mattos and Santos (2018). We argue that the population estimation by the IBGE may dilute the bunching observed in census years to non-census. Applying the formula for population growth to those municipalities moves them to the peaks to the right of the threshold. Thus, once the municipality can establish itself on the right side of bunching in the census year, it practically guarantees itself a permanent position on the highest range of the MPF for the next 10 years.

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Appendix.

Table 8. Different orders of polynomials and sizes of bins (first threshold)

a) 2010					
Polynomial order (q)	3	4	2	3	4
Bin size	82	82	82	92	52
Range $[R_L, R_U]$	[8,887; 10,927]	[8,887; 10,927]	[8,887; 10,927]	[8,809; 10,927]	[8,837; 10,969]
# Municipalities (B)	111***	96***	111***	110***	94***
s.e. (B)	12.36	16.64	12.34	10.8	12.38
% of respondents	42%	33%	40%	39%	36%
Average dr	231	260	248	226	215
Elasticity (max)	25.74%	25.74%	25.74%	28.79%	26.80%
Elasticity (average)	2.5%	2.8%	2.78%	2.5%	2.4%
b) 2000					
Polynomial order (q)	3	4	2	3	4
Bin size	82	82	82	92	52
Range $[R_L, R_U]$	[8,959; 10,599]	[8,959; 10,599]	[8,959; 10,599]	[8,959; 10,599]	[9,305; 10,501]
# Municipalities (B)	44***	38***	44***	36***	27***
s.e. (B)	8.91	10.13	9.03	9.9	8.45
% of respondents	17%	14%	17.4%	12.5%	15%
Average dr	80	106	90	85	76
Elasticity (max)	18.21%	18.21%	18.21%	23.3%	9%
Elasticity (average)	0.77%	0.99%	0.88%	0.80%	0.42%
1991					
Polynomial order (q)	3	4	2	3	4
Bin size	82	82	82	92	52
Range $[R_L, R_U]$	[Notch; 1,681]	[Notch; 1,681]	[Notch; 1,681]	[Notch; 10,741]	[Notch; 10,501]
# Municipalities (B)	36***	33***	39***	31***	33***
s.e. (B)	8.610	9.09	9.52	8.85	7.21
% of respondents	–	–	–	–	–
Average dr	–	–	–	–	–
Elasticity (max)	–	–	–	–	–
Elasticity (average)	–	–	–	–	–

Note: ***Significance at 1%.

Figures 15 and 16 present the estimation of values predict from the linear and quadratic relation of the variable Share with the variable Bunch. Clearly, we observed that Share is an important variable to explain the probability of the municipality being at the bunch. This result is in line with Litschig (2012) arguments. The quadratic fit for probability of the municipality to be at the bunch is not significant for the year 2000, suggesting a linear correlation that according to Litschig (2012, p.8) "under the assumption that the right-wing share vote captures the ideological bias of the municipality, a positive relationship with fictitious population would indicate core-support targeting". For the year 2010, the quadratic fit of the probability of being on the Bunch in relation to the share is confirmed suggesting a U-shape forecast for this variable. This means that municipalities with share equals to 0.40 present a probability of being at the right side of the bunching as 45 % (lower value) and if our variable share presents a value of 0.85 that probability moves to 65 %. This quadratic correlation suggests a more balanced relationship between larger and smaller Share municipalities. However, there are no statistically significant differences between linear and quadratic projections.

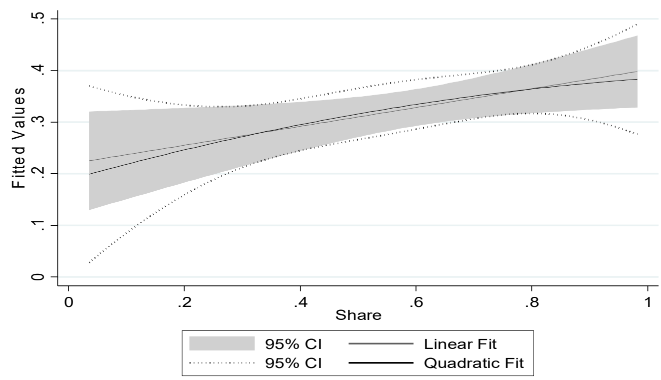

Figure 15. Predicted Values (year 2000)

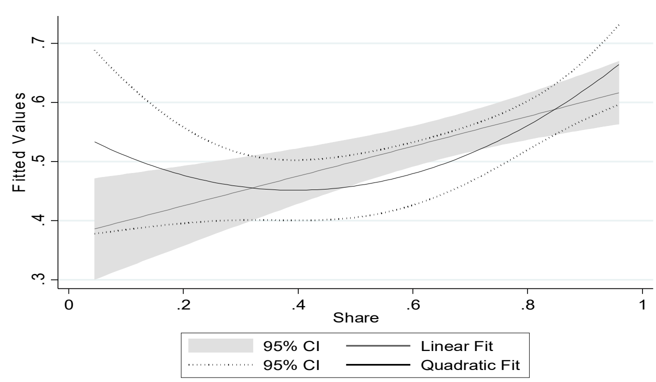

Figure 16. Predicted Values (year 2010)

Table 9. Full estimates

Variables	Coefficients – 2010			Coefficients – 2000
	dF/dx	dF/dx	dF/dx	dF/dx
Political Variables				
Share	0.380 ***	–	0.429 ***	0.189 **
Governor	−0.119 *	–	−0.123	0.082
Mayor	−0.100	–	−0.063	0.085
Deputy Dominant	0.045	–	0.069	0.400 ***
Interactions Variables				
Governor * Mayor	0.092	–	0.037	−0.096
Governor * Deputy Dominant	−0.002	–	−0.055	−0.283 ***
Mayor * Deputy Dominant	−0.128	–	−0.168	−0.328 ***
Governor * Mayor * Deputy Dominant	0.199	–	0.227	0.446 ***
Geographic and Fiscal Variables				
Distance	–	−0.218 **	−0.162 **	–
Autonomy	–	−0.051 **	−0.058 **	–
Dummy Distance	–	0.031	0.040	–
Dummy Autonomy	–	0.012	0.043	–
Interactions Dummies	–	0.085	0.078	–
Control Variables				
Gini Index	0.954 **	0.705	0.806 *	0.205
Infant Mortality Rate	0.004	0.005	0.005	0.004 *
Population above 65 years	0.0001 **	0.002 ***	0.001 **	−0.0001
Illiteracy Rate	−0.007 *	−0.007	0.008 **	−0.003
Per Capita Income	−0.0006 ***	−0.003	0.005 **	−0.0002
Unemployment Rate	−0.016 ***	−0.009	−0.003	0.009 **
Urban Population	−0.0008	−0.0001 *	−0.0005 **	0.0001
Economically Active Population	0.0001	0.0001	−0.0001	0.0001 ***
Dependency Ratio	−0.004	0.002	−0.0001	−0.002
Fixed Effects for States	No	Yes	No	No
Observations	839	750	750	682

Notes: Estimating using Probit (Std. Adjusted for clusters id). The coefficients reported refer to the marginal effect.
***, **, * significance at 1 %, 5 % and 10 %.