Was Inflation Higher in Regions that Benefited Most from the Emergency Aid Program?

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Abstract

This research seeks to study the effects of the *Auxílio Emergencial* (Emergency Aid) program on the prices of goods, especially food. The main objective is to determine if the regions that benefited most from the program had higher price increases in their markets. This analysis will be done through estimations using two-way fixed effects with panel data of geolocalized prices in the municipality of São Paulo and the place of residence of the beneficiaries of the program, considering the deficiencies in the database. The estimates indicate that the incidence of the *Auxílio Emergencial* program in a region has significant effects on the price of *coxão mole* (topside), a food with high income elasticity, more responsive to changes in disposable income. However, when analyzing the food basket, there is no evidence of this same effect.

Keywords: Public policy evaluation, Cash Transfer Program, Emergency Aid, Inflation, Income Redistribution

1 Introduction

The *Auxílio Emergencial* (AE), Emergency Aid in English, was developed as a response to the health and economic crisis caused by the Covid-19 pandemic. Starting in April 2020, the program reached 67.7 million Brazilians at its peak and cost the federal government R$ 292.9 billion in 2020 and R$ 62.6 billion in 2021.[1] In the economic sphere, discussions were made about the effectiveness of this direct cash transfer program, with praise for its breadth and relief of poverty, but criticism over its potential indirect effects and targeting. The values of AE are shown in Table 1. This benefit was approved in April for three months and had a value of R$ 600 (which could reach R$ 1800, depending on the family structure), and was extended for two more months. From September to December, the basic value became R$ 300. In April 2021, a new round of aid was granted, with values between R$ 150 and R$ 375, lasting for four months, which was later extended until October. In November, the program was discontinued, being replaced by the program *Auxílio Brasil*.

Table 1: AE Value per Family over Various Months

Months	AE value per family
April/2020 - August/2020	R$600,00 - R$1800,00
September/2020 - December/2020	R$300,00 - R$900,00
January/2021 - March/2021	No AE
April/2021 - October/2021	R$150,00 - R$375,00

Source: Elaborated by the author with information from Dall'Agnol (2021)

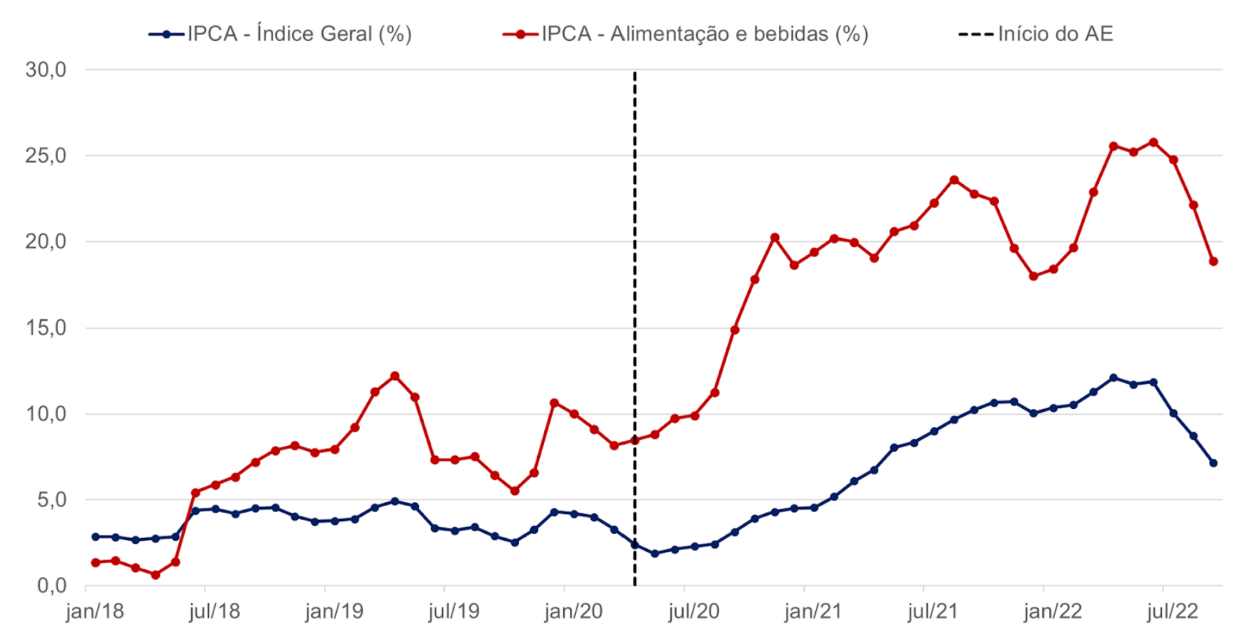
To be eligible for the 2020 AE, it was necessary to be over 18 years old, have declared less than R$28,559.70 in the previous year, have a monthly family income below R$3,135.00 and be in one of the following situations: employed without a signed contract, unemployed, self-employed, individual micro-entrepreneur (MEI), or a Social Security contributor (UOL, 2020). In 2021, the restriction of only one beneficiary per family was added, and people with assets over 300,000 reais, medical residents, multi-professionals, scholarship recipients, interns, or recipients of Social Security, welfare, or labor benefits were excluded (Valor Investe, 2021).

At the same time, the National Consumer Price Index calculated by the Brazilian Institute of Geography and Statistics (IPCA-IBGE) ended 2020 at 4.52%, above the center of the target set by the Central Bank, even with the economic crisis caused by the pandemic. Looking at the data, we can notice a drop in inflation during the first three months of the pandemic (March,

[1]The amount committed in 2020 and 2021 was, respectively, R$ 321,840,886,209 and R$62,607,725,000, but the amount actually paid was R$ 292,945,434,082.62 and R$ 60,210,304,846.84 (calculated through tables available at: https://www.tesourotransparente.gov.br/ckan/dataset/despesas-e-transferencias-totais/resource/96744fdd-91c6-46e0-a1c4-253fae51936c?inner_span=True)

April, and May), when it reached 1.88% in the accumulated 12 months, the lowest value since 1999. From June, inflation started to rise almost uninterruptedly, reaching 12.13% in April 2022, the highest value since October 2003. Furthermore, observing Figure 1, which shows the accumulated variation in 12 months of the IPCA, we can see the clear divergence between the general index and the Food and Beverages group of the IPCA - precisely the inflation group that affects the poorest the most - from April 2020, simultaneously to the beginning of the pandemic and the Emergency Aid.

Figure 1: Accumulated variation in 12 months of IPCA (%)



Source: Elaborated by the author with data from IBGE.

Given the correlation between the fiscal stimulus generated by the AE and the increase in inflation, this study seeks to investigate whether there is causality between these facts. This analysis is important because inflation reduces purchasing power and, as a result, the effectiveness of the AE itself. At the same time, it affects the poorer inhabitants more, who, due to flaws in the design of the program, did not have access to this benefit.[2]

This research seeks to contribute to the literature on evaluating income transfer policies, particularly in the little studied aspect of price level. This contribution is relevant currently due to the debates about the *Auxílio Brasil* - a program in the mold of AE, on a permanent basis - which, being a very recent policy, still lacks studies on its impact on the economy. It should

[2]Gonzalez and Araujo (2021) analyze data from the 2nd edition of the ICT Covid-19 (July to August 2020) and show that 20% of respondents from classes D and E could not access AE because they did not have a cell phone.

also be noted that inflation is a sensitive issue for Brazilians, with prominence in economic discussion and political-electoral effects, reinforcing the value of its study.

This study is divided into five sections, including this introduction. The second proposes a literature review and is followed by the section on hypotheses, data and methodology, which describes the initial hypotheses of the relationship of fiscal stimuli and inflation based on economic literature, details the sources of data used, and presents the process of treating these data and the econometric estimates. In section 4, tables with regressions and comments on the results are presented. Finally, section 5 interprets that there is evidence of causality between the percentage of the population benefiting from AE and the price of *coxão mole*, a food with high income elasticity, more responsive to changes in disposable income. However, when analyzing an aggregate of products (food basket), there is no evidence of a significant effect of AE on prices.

2 Literature Review

Cash transfer programs are already standard in developing countries. According to the World Bank (2017), 77% of these countries have some kind of program and the number of programs more than doubled from 2000 to 2017. There is a large literature on the impact of income transfer programs on inequality, consumption, employment, health, and education. However, the literature on the impact on prices is not as developed.

In a literature review by the Overseas Development Institute (Bastagli et al., 2016), with 165 articles on the subject, it shows that little focus has been given to the price level. Some newer studies seek to explore this aspect, but their results are not conclusive.

Filmer et al. (2018) study the price and nutrition effects resulting from a conditional cash transfer program in the Philippines through data from the randomized pilot phase of the Filipino national transfer program (Pantawid). The characteristics of this program are interesting because the value of the transfers represents approximately 23% of the per capita consumption of the beneficiary (for comparison, the Bolsa Família represents 12%). In addition, the country has a high level of growth delay among children and non-integrated local markets, which increases asymmetries between villages. Comparing the difference in data in villages affected and not affected by this pilot phase (and also between villages with different levels of eligible people), the authors are able to estimate the results of the program.

In what is most relevant to the present study, when analyzing prices, the authors observe a 16% increase in egg prices between villages with the minimum and maximum percentage of beneficiaries, which does not occur in more easily traded and non-perishable goods such as rice and sugar. Another source of data shows that egg prices can rise 7.7% in the provinces most affected. This increase generates a decrease in the real income of these families and less egg consumption by children. As a result, the percentage of non-beneficiary children with growth delay in control villages was 32% and in villages with a high percentage of beneficiaries was 43%. This negative externality has a greater magnitude than the positive effect on beneficiaries, which shows the great importance of beneficiary selection and the possible negative effects that a transfer program can have.

In another randomized trial analysis, the article Egger et al. (2019) analyzes the impact of a single (spread over two years) and significant monetary transfer (+ 15% of the region's GDP) in villages in Kenya. An interesting result is that the effect in one village is also influenced by the treatment of neighboring villages (there is spatial spillover), a fact included in the regression equations of the article and that will be the basis for this research - especially Equation 6, which models prices conditioned by the amount received by nearby regions and with fixed effects of time and region, using panel data.

The results show large impacts on the consumption of beneficiaries along with positive externalities for non-beneficiaries, with a large fiscal multiplier between 2.5 and 2.8 and without significant price increase (0.1% on average), even among non-tradable/perishable goods, a finding that contrasts with the article Filmer et al. (2018). There are few articles that analyze the inflation recorded from 2020 in Brazil as this phenomenon is still recent. The article Baccarin and de Oliveira (2021) seeks to compare the food inflation of the first half of 2020 with that between 2007 and 2019. It highlights the increase in demand for food that occurred in 2020, shown by the increase in supermarket sales. One of the hypotheses raised is that the elevation of income brought by the emergency aid may be one of the causes of this increase. However, there is no causal analysis in the article.

An important discussion about inflation is that the basket of goods used for calculating the inflation index in countries (in Brazil, calculated by IBGE's Family Budget Survey, POF) has become significantly outdated due to the pandemic - more spending on food, less on transportation, leisure, and restaurants. A working paper from July 2020 (Cavallo, 2020) calculated the difference between the official inflation index and the index according to proportional weights to the new consumption patterns during the pandemic. Among the 18 selected countries, Brazil had the largest disparity between the two indices, with a 0.88 percentage point difference in May 2020.

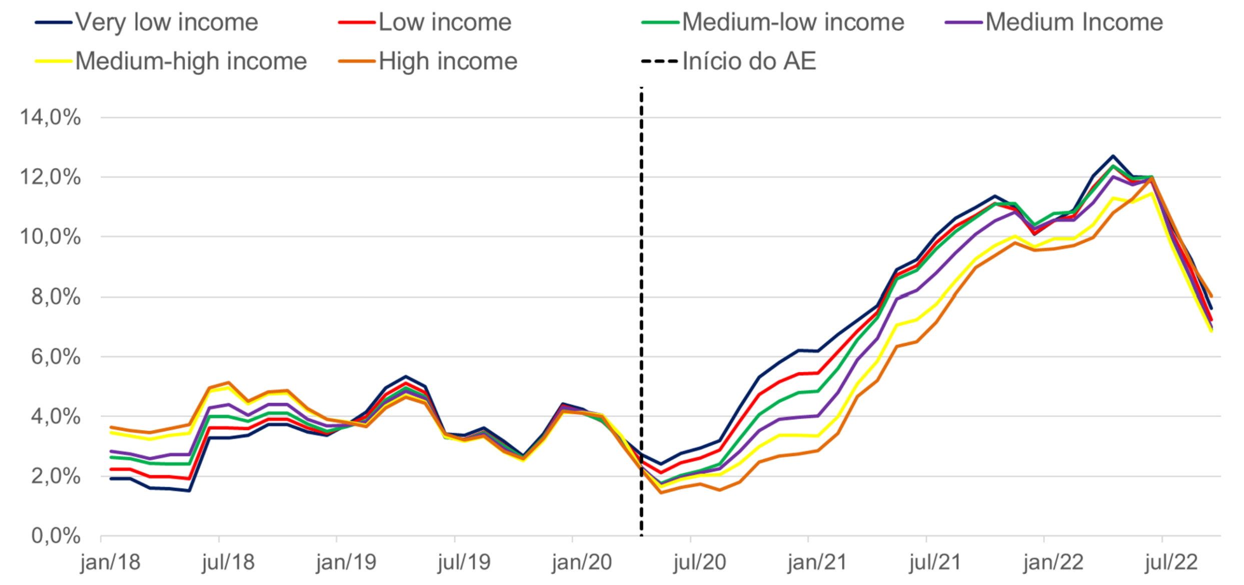
3 Hypothesis, data and methodology

3.1 Hypothesis

The central hypothesis of this study is that *Auxílio Emergencial* was one of the causes of the inflation observed in recent years. Through which mechanisms can AE have contributed to inflation? According to economic theory, an increase in population income would result in an increase in consumption according to its consumption propensity, and this propensity is higher precisely in poorer individuals. In the case of food, this relationship is known as Engel's Law, which describes the increase in spending on food as income increases and, at the same time, the decrease in the relative importance of this expenditure, as income becomes diversified in services, luxury goods, savings, etc. In economic terms, the income elasticity of demand for food is very high at low income levels and tends to decrease as income increases.

Therefore, if the Emergency Aid was greater than the income lost as a result of the pandemic, the demand of the beneficiaries for food should increase. The Conjunctural Letter of the Institute of Applied Economic Research (Ipea) of the 3rd quarter of 2020 (Carvalho, 2020) indicates this possibility: the income of low-income households was 103% of the usual in May 2020, despite the impact of the pandemic. The subsequent increase in demand could generate the observed increase in prices, assuming a constant supply. The Ipea itself calculates inflation by income ranges, based on the IPCA (Figure 2). Inflation for all ranges was close from 2019 until, in March 2020, there is a clear deviation: inflation for very low-income families grew far above inflation for high-income families.

Figure 2: Accumulated variation in 12 months of IPCA, separated by income range



Source: Elaborated by the author with data from Ipea.

From a macroeconomic point of view, AE represented a fiscal stimulus of 3.8% of GDP in 2020 (for comparison, *Bolsa Família* in 2019 represented only 0.4% of GDP). Even with this size, it did not prevent the 3.3% drop in GDP recorded in 2020, with the family consumption component falling by 4.5%, precisely the one that would be most affected by the Aid. So, from an aggregate point of view, AE was not enough to keep consumption at pre-pandemic levels.

When looking at it in a more disaggregated way, it is understood that AE had a heterogeneous impact on Brazilian regions. As part of the Macro Bulletin of FGV, Daniel Duque analyzes data from the Continuous Quarterly Household Sample Survey and concludes that the *Auxílio Brasil* (permanent program modeled after AE, but on a smaller scale) has a negative impact on the labor market participation rate, which, in September 2022, was 1.1% below the same month of 2019 (Fundação Getúlio Vargas, 2022). That is, income transfer is sufficient to remove people from the job search, contributing to the hypothesis that this type of aid is greater than the income that would be received in a job.

To analyze the relationship between the level of prices and AE, the great difficulty is to separate the roles of the pandemic and income transfer. To try to differentiate these effects, weighting areas [3] (*áreas de ponderação*) of the municipality of São Paulo that differ by the number of inhabitants who received AE will be compared. Due to the comparison being made

[3] A weighting area is the smallest geographic level of identification of the microdata sample of the 2010 Demographic Census (IBGE, 2010).

within the same city, there is less variation in the supply of products, the consumption pattern of the inhabitants and the impacts of the pandemic. The methodology will be detailed in more depth in section 3.3.

3.2 Data

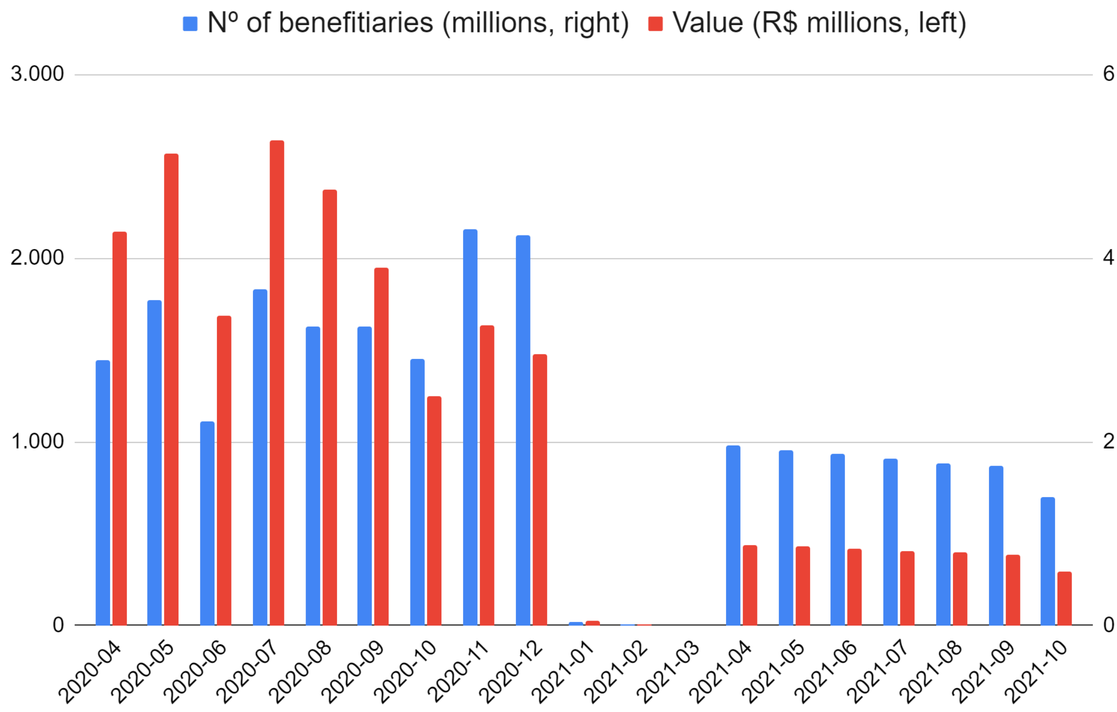
The data source for prices is the microdata of the Consumer Price Index of the Municipality of São Paulo collected by the Institute of Economic Research Foundation (IPC-Fipe) and provided by the institution for the preparation of this study. This data base contains the date of collection, the ZIP code of the market surveyed, and the name and price of the product. Data on food products from January 2018 to October 2021 were requested.

An alternative source of price data is the IPCA-IBGE, which conducts research in 16 capital cities and metropolitan regions. The choice of IPC-Fipe was made due to the ease of accessing its microdata, due to the institution's partnership with the University of São Paulo. Another positive characteristic is that the IPC analyzes a more homogeneous region (the city of São Paulo) than the IPCA, which reflects a lower variation in supply and consumer preferences among the regions analyzed.

Information on the Emergency Aid is available on the Transparency Portal of the General Comptroller of the Union (CGU), containing variables of name, Social Identification Number (NIS), municipality, classification (*ExtraCad*, *CadÚnico* or *Bolsa Família*) and the amount received by each beneficiary. The values from April 2020 to October 2021 will be used.

Figure 3 shows the value and number of beneficiaries of AE in the municipality of São Paulo, by month. It is possible to note the different phases of the program described in Table 1: in the first five months the highest values were distributed, while the highest number of beneficiaries was in November and December. In 2021, it is possible to note that there are data from January to March, even though the program does not exist in these months - for this study, these months will be disregarded. From April, a new round of AE begins, but with a much lower value and population coverage.

Figure 3: Emergency Aid: Number of Beneficiaries and Value Received in the Municipality Of São Paulo



Source: Elaborated by the author with data from Brazil's *Ministério da Cidadania*

In order to locate the beneficiaries of AE, the address data of the beneficiaries of the Single Registry (*CadÚnico*) was requested from the Ministry of Citizenship, through the Access to Information Law .[4] The database provided contains the NIS and the complete address of the people living in the city of São Paulo registered in the *CadÚnico*. Even with the address data of people registered in the *CadÚnico*, there is a problem: due to the emergency nature, it was not required to register each person in the *CadÚnico* for the receipt of AE. As a result, only a part of the beneficiaries can be located - those who were already registered in the *CadÚnico* due to *Bolsa Família* - as shown in Table 2. Of the 42 million observations of the AE base from April 2020 to October 2021 in the city of São Paulo, only 15,324,836 (35.7%) can be located, the majority being lines marked as "*Bolsa Família*" or "*CadÚnico*". Figure 4 shows that there is also variation between the months: in the first months, approximately 50% of observations have addresses, but this percentage decreases as the months pass. These problems will be addressed in the methodology section that follows.

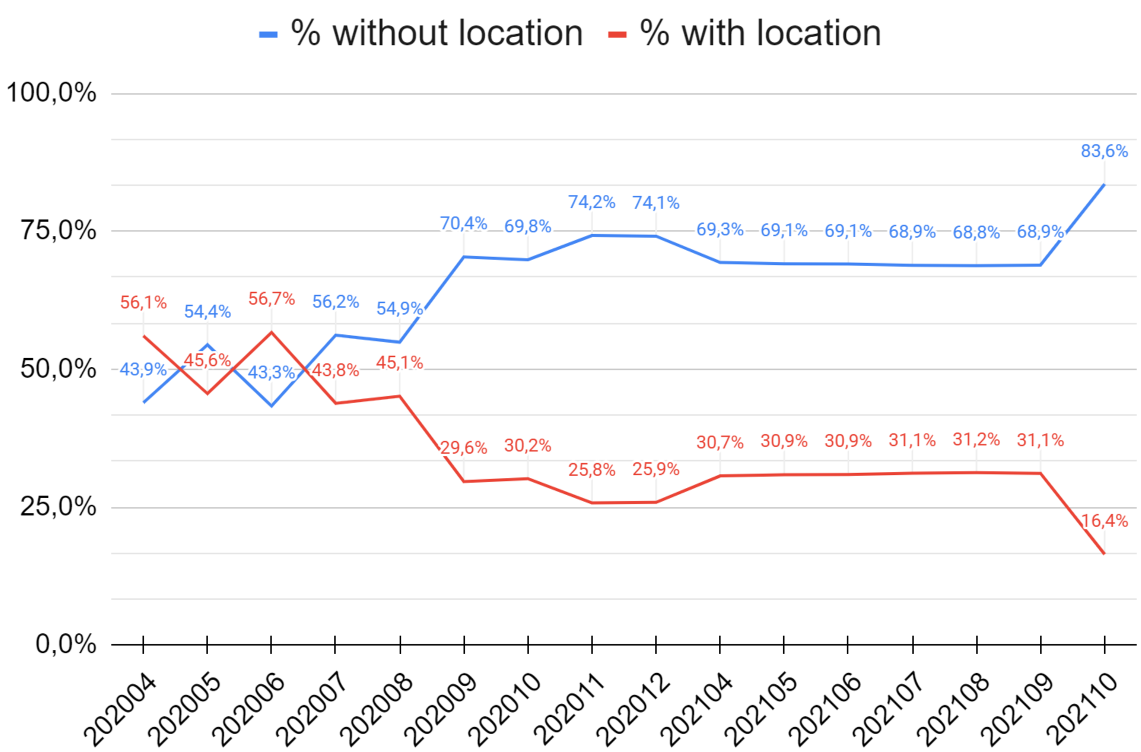
[4]Solicitation guide available at: https://www.gov.br/pt-br/servicos/solicitar-cessao-de-dados-identificados-do-cadastro-unico

Table 2: Number and Percentage of Observations with Location, by Classification

Framing	Number of lines	With location?	
		Yes	No
ExtraCad	26.904.203 (62,7%)	92.661 (0%)	26.811.542 (100%)
CadÚnico	6.698.947 (15,6%)	6.012.275 (90%)	686.672 (10%)
Bolsa Família	9.314.919 (21,7%)	9.219.900 (99%)	95.019 (1%)
Total	42.918.069 (100%)	15.324.836 (35,7%)	27.593.233 (64,3%)

Source: Elaborated by the author with data from Brazil's Ministério da Cidadania and CadÚnico

Figure 4: Percentage of Observations with Location, per Month



Source: Elaborated by the author with data from Brazil's *Ministério da Cidadania* and *CadÚnico*

In order to access information on average income, population, workers by National Classification of Economic Activities (CNAE) and level of education of people in the areas of weighting and in municipalities, we will use data from the 2010 Demographic Census. For the maps, territorial meshes available on the IBGE website will be used. Finally, additional data on municipalities and weighting areas in São Paulo will be obtained from the Social Vulnerability Index (IVS) of the Ipea and the Paulista Social Vulnerability Index (IPVS) calculated by the State Data Analysis System (SEADE).

3.3 Methodology

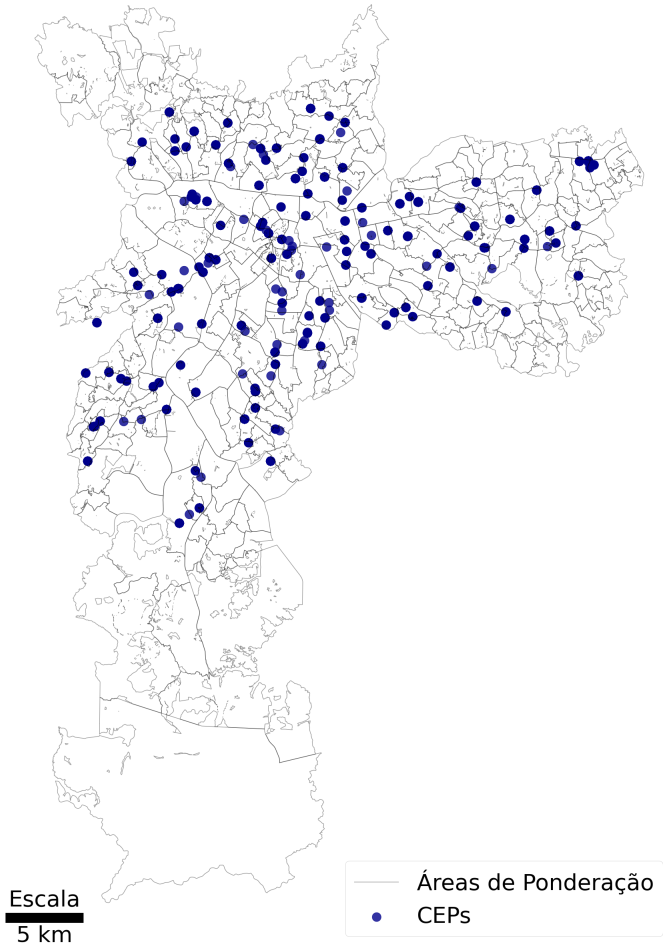
3.3.1 Methodology for geolocate ZIP codes

Since there is no table that relates CEPs with names and street numbers (let alone with geographical coordinates), a web scraping was done using the Selenium[5] library of Python, the Correios' website and Google Maps. In the case of IPC-Fipe data, in which we only have the CEP, we first used a script that searches for each CEP on the Correios[6] website and extracts the complete address from the page. The second script consists of concatenating the address data into one single string, placing it in the search bar of Google Maps and requesting the search. Once completed, the website's URL will contain the geographical coordinates, which are then saved for each CEP. This procedure is done for both the IPC-Fipe markets and the *CadÚnico* beneficiaries. From the process described above, a map is obtained with the markets surveyed by IPC-Fipe (Figure 5) and the people registered in *CadÚnico* (Figure 6).

[5]Documentation available at: https://selenium-python.readthedocs.io/

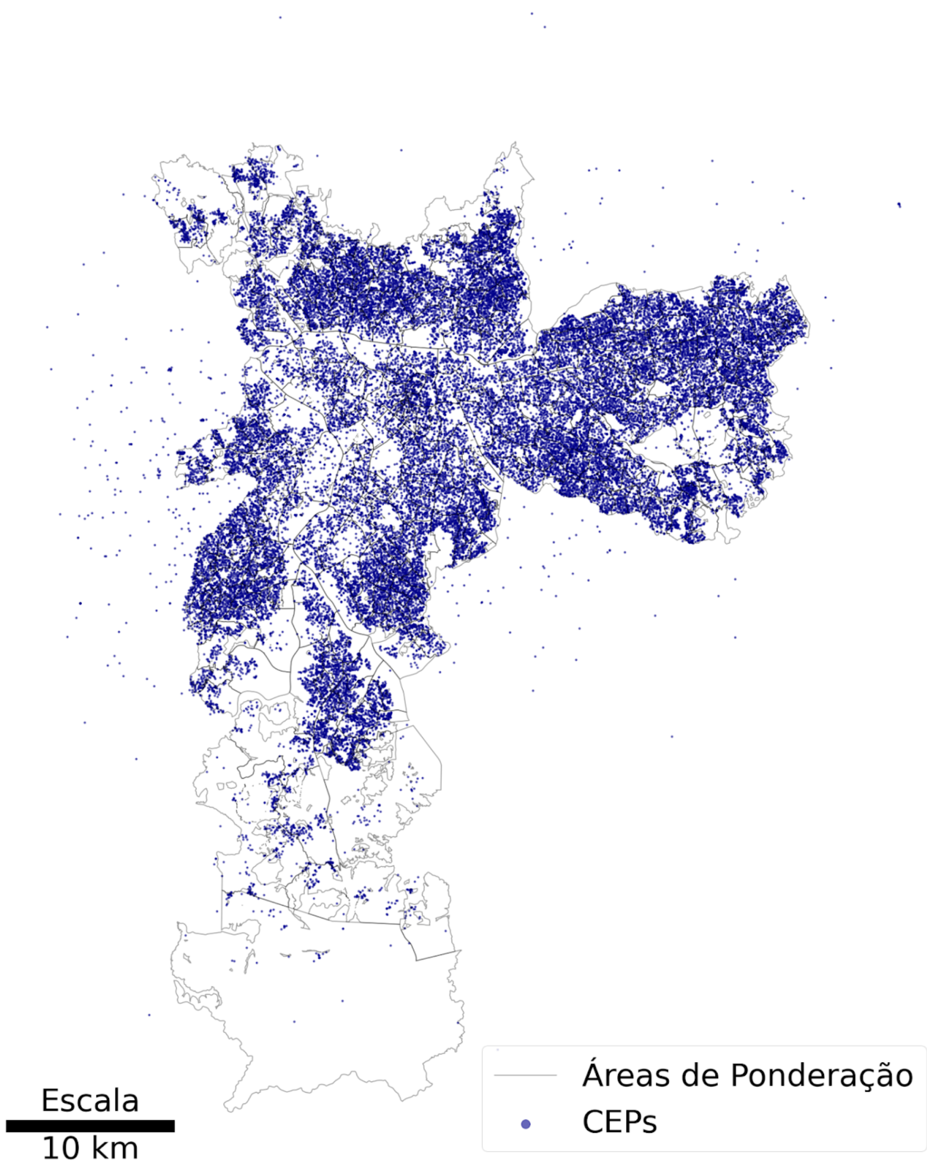
[6]Correios' website to search Zip codes: https://buscacepinter.correios.com.br/app/endereco/index.php

Figure 5: Markets Surveyed by IPC-Fipe between January 2018 and October 2021



Source: Elaborated by the author with data from IPC-Fipe and IBGE

Figure 6: People Registered in *CadÚnico* in the Municipality of São Paulo



Elaborated by the author with data from IPC-Fipe and IBGE

The Figure 6 shows that there are some addresses in the *Cadastro Único* database that are not located in the city of São Paulo, but in neighboring cities. Additionally, there is a clear lack of observations in the South, the extreme North, the edges of the Pinheiros and Tietê rivers, the Billings and Guarapiranga reservoirs, and the Carmo Park, which corresponds to reality, indicating that the method used is consistent.

3.3.2 Spatial Interpolation of prices

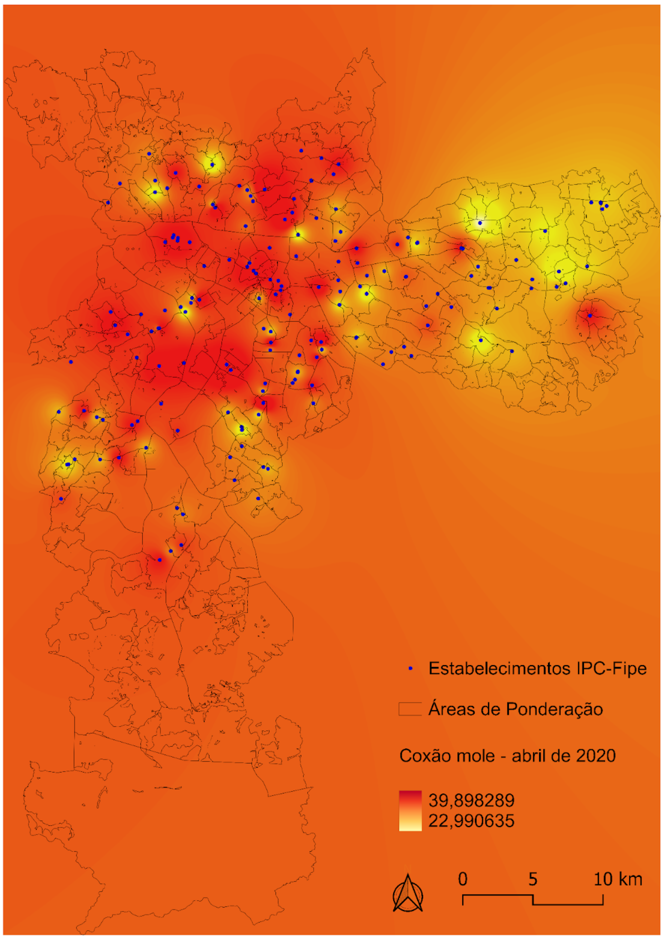
As shown on Map 1, in the IPC-Fipe database there are no markets in all the weighting areas. To circumvent this problem, spatial interpolation was done using the inverse distance weighting (IDW) method by Shepard (1968), aimed at projecting a price proxy in each weighting area based on the distance to each market - this process is done for each product, in each month. Equation 1 is the function to define prices in each point x in space, where the weight $w_i(x)$ is used based on the inverse of the distance squared in relation to each surveyed market *i*, as seen in Equation 2.

$$f(x) = \frac{\sum_{i=1}^{N} w_i(x) u_i}{\sum_{i=1}^{N} w_i(x)} \tag{1}$$

$$w(x) = \frac{1}{d(x, x_i)^2} \tag{2}$$

Figure 7 is an example of a surface (raster) generated by spatial interpolation, of the product "*coxão mole*", in the month of April 2020. It is possible to notice that, for example, markets with lower prices have a negative influence on the prices of the closest weighting areas.

Figure 7: Interpolated Surface of *Coxão Mole* Prices in April 2020



Source: Elaborated by the author with data from IPC-Fipe and IBGE

3.3.3 Value of the food basket in each weighting area

The aggregate chosen to represent the level of food prices is the food basket of the Interunion Department of Statistics and Socioeconomic Studies (DIEESE, 2009) - its composition is shown in Table 3. Using the interpolated prices in each area of weighting, as described in the above subsection, the price of the DIEESE basic basket is calculated in each area of weighting, each month.

Table 3: Composition of DIEESE'S Food Basket

Product	**Quantity**
Meat	6 kg
Milk	15 l
Beans	4,5 kg
Rice	3 kg
Flour	1,5 kg
Potato	6 kg
Vegetables (Tomato)	9 kg
Bread	6 kg
Coffee (powder)	600 g
Fruits (Banana)	90 units
Sugar	3 kg
Cooking Oil	1,5 kg
Butter	900 g

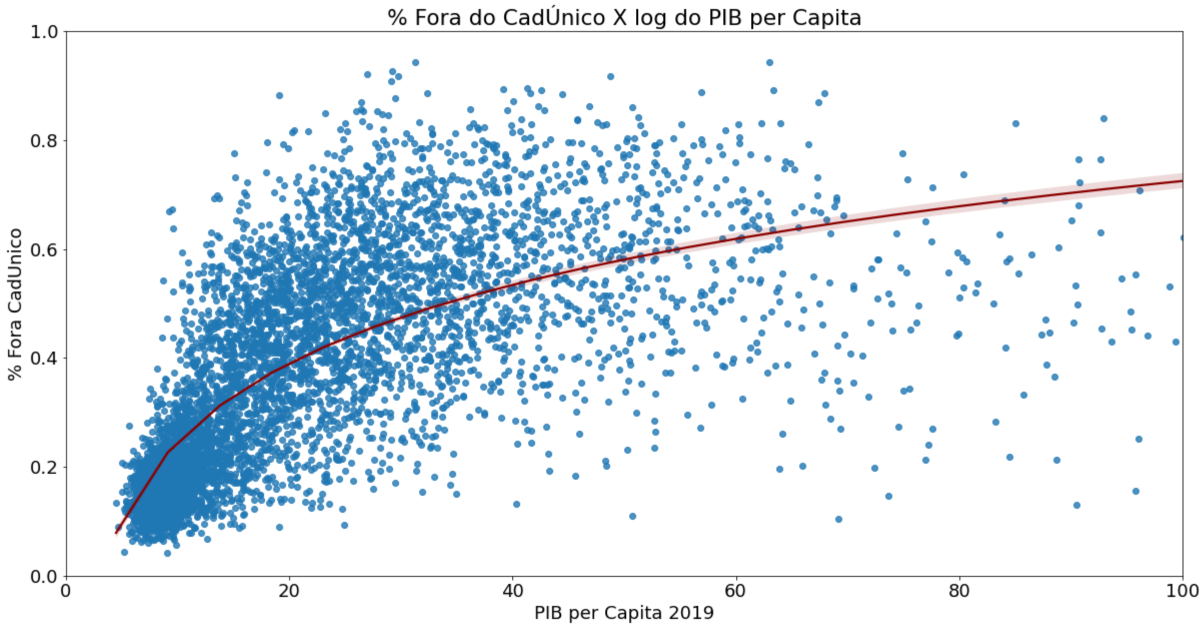
Source: DIEESE

3.3.4 Estimating beneficiaries outside of *CadÚnico*

As mentioned in section 3.2, only 35.7% of AE beneficiaries were able to be located with the data provided by the Ministry of Citizenship. This problem can create bias in the estimation, since it is likely that the beneficiaries with an address are different from those without - for example, they are more poor, since many of them previously received *Bolsa Família*.

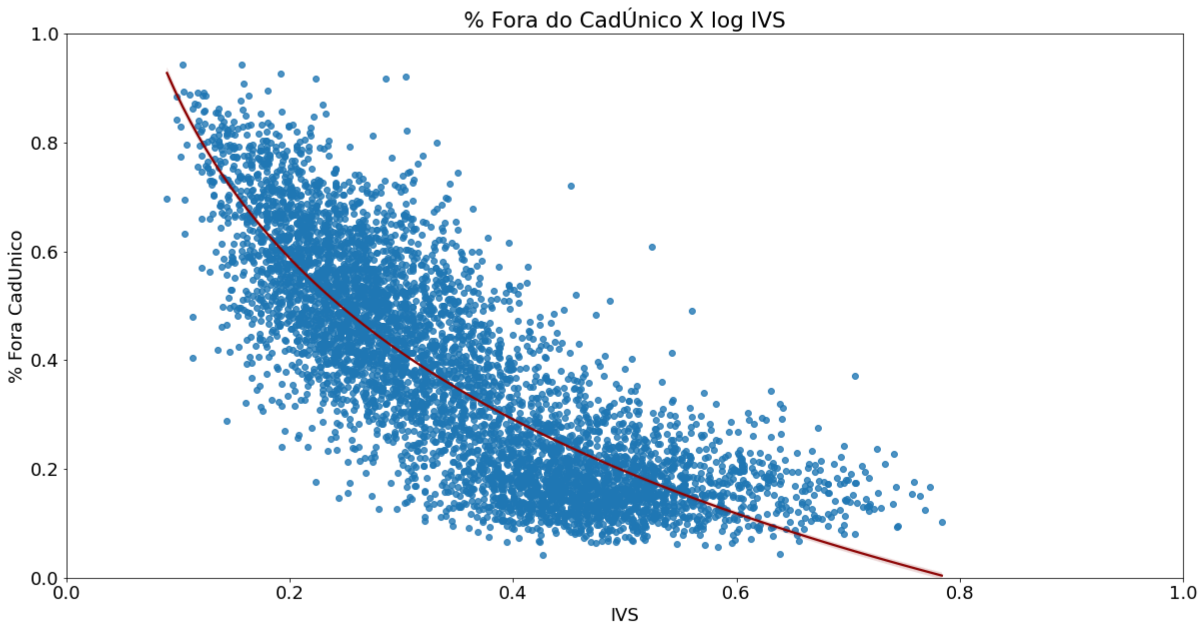
In order to analyze whether there is a difference or not between these two groups, we regressed the percentage of beneficiaries outside of *CadÚnico* for each municipality in Brazil against the natural log of GDP per capita in the municipality in 2019 and against the natural log of the Social Vulnerability Index (IVS) of Ipea. The scatter plot and the regression line are represented in Figure 8 and 9, respectively.

Figure 8: Regression Line Between Percentage Outside of *CadÚnico* and Log of GDP per Capita for each Municipality



Source: Elaborated by the author with data from *Ministério da Cidadania* and IBGE

Figure 9: Regression Line Between Percentage Outside of *CadÚnico* and Log of IVS of each Municipality



Source: Elaborated by the author with data from *Ministério da Cidadania* and Ipea

As expected, the higher the income of the municipality and the lower the IVS, the lower the percentage of beneficiaries outside of *CadÚnico* will be, that is, if the analysis is only done with

AE beneficiaries registered in *CadÚnico*, there will be bias in the estimates. For this reason, the variable $\text{Perc\_Benef}_{r,t}$, which represents the percentage of the population of area of weighting r in month t that receives Emergency Aid, should be broken down into two parts, as shown in Equation 3:

$$\text{Perc\_Benef}_{r,t} = \text{Aux\_Cad}_{r,t} + \text{Aux\_Fora\_Cad}_{r,t} \tag{3}$$

Where $\text{Aux\_Cad}_{r,t}$ is the percentage of AE beneficiaries registered in *CadÚnico* over the population of r in t and $\text{Aux\_Fora\_Cad}_{r,t}$ is the percentage of AE beneficiaries outside of *CadÚnico* over the population of r in t. The first variable is calculated with the geolocated AE data and the population of each area of weighting according to the 2010 Census. The second variable will be calculated using Equation 4:

$$\begin{aligned} Aux\_Fora\_Cad_{m,t} = {} & \gamma_1 \ln(\text{Rend\_Médio})_m + \gamma_2 \ln(\text{Rend\_Médio})^2_m + \gamma_3 \text{Acima\_EM}_m \\ & + \sum_t \gamma_1 \ln(\text{Rend\_Médio})^2_m \cdot \text{Mês}_t + \sum_t \gamma_2 \text{Acima\_EM}_m \cdot \text{Mês}_t \\ & + \phi_t + \epsilon_{m,t} \end{aligned} \tag{4}$$

Where $Aux\_Fora\_Cad_{m,t}$ is the percentage of AE beneficiaries marked in the base as "ExtraCad" over the population of municipality m, $\ln(\text{Rend\_Médio})_m$ is the natural log of the average income for people over 10 years of age in m in the Demographic Census 2010, Acima_EM_m is the percentage of the population over 25 years old with a level of education of High School or higher in m, ϕ_t is the fixed effect of month, and $\varepsilon_{m,t}$ is the error. The interactions of the variables with the month dummies are added, to control for different effects in each month. The results of the first coefficients of the regression, which represent the interaction of the variables with the base month (April 2020), are described in Table 4.

As estimated coefficients above are all significant at a 1% level of significance and have the expected sign: higher education and higher income generate a greater number of AE beneficiaries outside of *CadÚnico* (since only the poorest would be beneficiaries of *Bolsa Família* and therefore registered in *CadÚnico*), but higher income presents decreasing returns, as shown by the negative sign of the squared income. The coefficients of the interactions with the dummies do not vary much in sign or intensity.

These coefficients are then used to estimate the variable $Aux\_For\hat{a}\_Cad_{r,t}$ for each weight-

Table 4: Results of the Estimation of the Variable 'Aux_Fora_Cad' for the Municipalities - Equation 4

	Dependent variable:
	Aux_Fora_Cad
ln_Rend_Médio	0.284^{***}
	(0.028)
ln_Rend_Médio_quadr	-0.023^{***}
	(0.002)
Acima_EM	0.141^{***}
	(0.008)
Model	One-Way Fixed Effect (time)
Time Variable	Mês
Observations	89,040
R^2	0.390
Adjusted R^2	0.390
F Statistic	$1{,}185.309^{***}$ (df = 48; 88976)
Note:	*p<0.1; **p<0.05; ***p<0.01

Source: Elaborated by the author

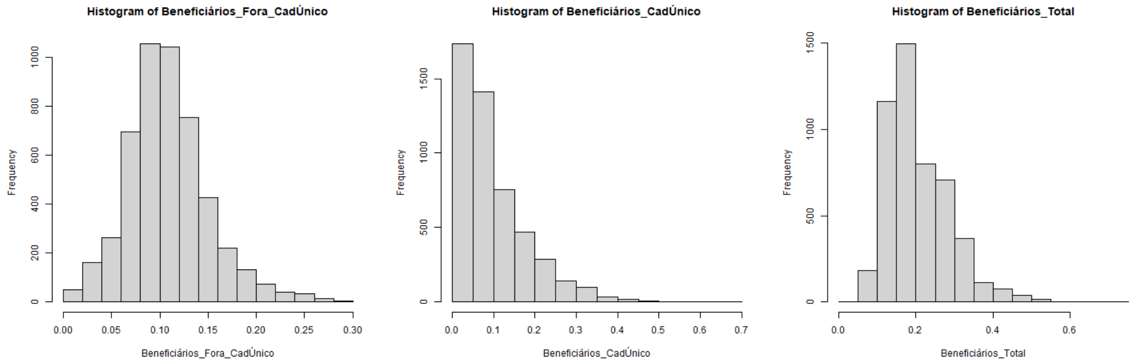
ing area[7], again using data from the 2010 Demographic Census in the explanatory variables, according to Equation 5:

$$\begin{aligned} \widehat{Aux\_Fora\_Cad}_{r,t} &= \hat{\gamma}_1 \ln(\text{Rend\_Médio})_r + \hat{\gamma}_2(\ln(\text{Rend\_Médio})_r)^2 + \hat{\gamma}_3\text{Acima\_EM}_r \\ &+ \sum_t \hat{\gamma}_1(\ln(\text{Rend\_Médio})_r)^2\text{Mês}_t + \sum_t \hat{\gamma}_2\text{Acima\_EM}_r\text{Mês}_t + \hat{\phi}_t + \hat{\varepsilon}_{r,t} \end{aligned} \tag{5}$$

The histograms of the estimated variable $\widehat{Aux\_Fora\_Cad}_{r,t}$, calculated by the above regression, and the variables $Aux\_Cad_{r,t}$ and $Perc\_Benef_{r,t}$, are described in Figure 10. Figure 11, in turn, shows the estimated percentage of beneficiaries ($Perc\_Benef$) in the city of São Paulo per month.

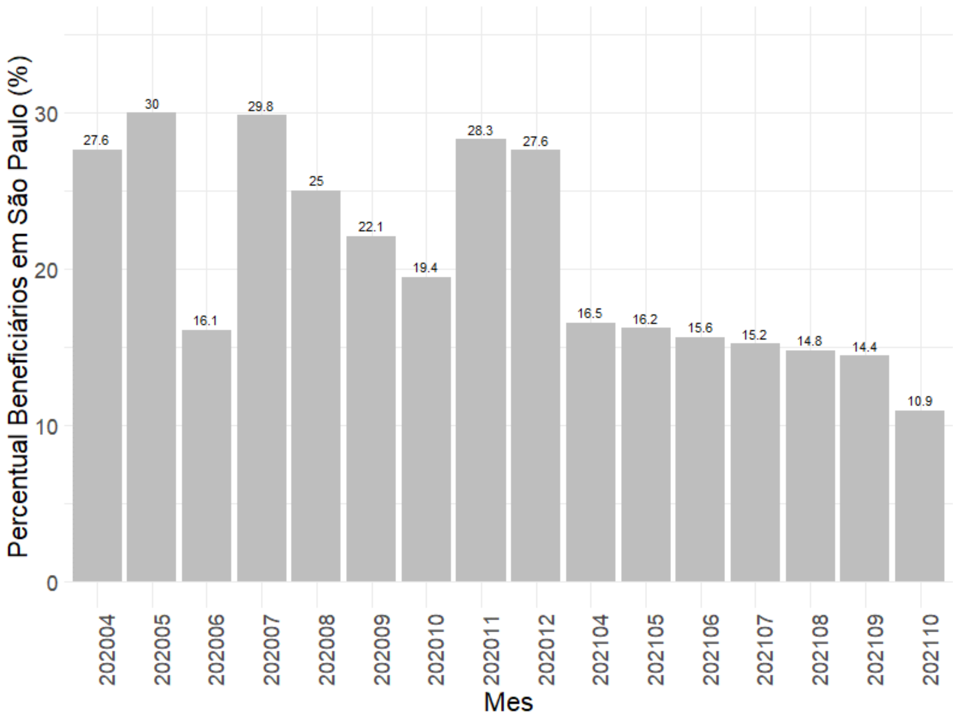
[7]If the projected variable is negative, it is replaced with 0. Only 31 out of 4960 projections (310 weighting areas and 16 months) are negative.

Figure 10: Histograms of Percentage of Beneficiaries Variables



Source: Elaborated by the author

Figure 11: Estimated Percentage of Beneficiaries in the City of São Paulo per Month



Source: Elaborated by the author

Finally, having possession of the $Perc\_Benef_{r,t}$ variable, it is possible to make the main estimates, described in the next section.

3.3.5 Main equations

The Equation 6 is the base model for the analysis sought in this study (similar to that of Egger et al. (2019)). It represents a two-way fixed effects regression (TWFE) in which $\ln(\text{Preço}_{r,t})$ represents the natural log of the basic basket price for each weighting area r and month t -

built from the interpolation described in sub-section 3.3.2 - $\mathrm{Perc\_Benef}_{r,t}$ is the percentage of people who received the AE within the population of s in t, α_r and λ_t are the fixed effects of weighting area and month and $\varepsilon_{r,t}$ are the errors.

$$\ln(\mathrm{Preço}_{r,t}) = \beta_1 \mathrm{Perc\_Benef}_{r,t} + \alpha_r + \lambda_t + \varepsilon_{r,t} \tag{6}$$

Due to the significant change in the AE from 2020 to 2021, both in terms of coverage and values (Figure 3), we decided to estimate a regression with interaction with the Ano2021 dummy, which has a value of 1 if the year is 2021 and 0 otherwise, as illustrated in Equation 7.

$$\ln(\mathrm{Preço}_{r,t}) = \beta_1 \mathrm{Perc\_Benef}_{r,t} + \beta_2 \mathrm{Perc\_Benef}_{r,t} \times \mathrm{Ano2021} + \alpha_r + \lambda_t + \varepsilon_{r,t} \tag{7}$$

Another interesting control to analyze is the effect of the sectoral composition of workers on prices. The premise is that areas of weighting where workers are found in sectors more affected by the pandemic - such as services - would have a greater drop in income, making the AE insufficient to increase aggregate demand, not generating price increases (or generating a smaller increase). Equation 8 shows the base model enriched with the interaction of the variables $\mathrm{Agro\_pc}_r$, $\mathrm{Indust\_pc}_r$ and $\mathrm{Serv\_pc}_r$, representing the percentage of employees in the agricultural, industrial and service sectors, by area of weighting.

$$\begin{aligned}\ln(\mathrm{Preço}_{r,t}) = {} & \beta_1 \mathrm{Perc\_Benef}_{r,t} + \beta_2 \mathrm{Perc\_Benef}_{r,t} \times \mathrm{Agro\_pc}_r \\ & + \beta_3 \mathrm{Perc\_Benef}_{r,t} \times \mathrm{Indust\_pc}_r + \beta_4 \mathrm{Perc\_Benef}_{r,t} \times \mathrm{Serv\_pc}_r \\ & + \alpha_r + \lambda_t + \varepsilon_{r,t}\end{aligned} \tag{8}$$

The results of the estimations of the three equations above are demonstrated in section 4.

4 Results

4.1 Regressions with food basket prices

As shown in Table 5, only model 6 points to a positive and significant effect of the percentage of beneficiaries on the basic basket price, in models 7 and 8 the coefficient is still positive, but not significant. On the other hand, the coefficients of the interactions of the percentage of beneficiaries with the 2021 dummy are negative and significant, indicating that there is

Table 5: Table of Results from Equation 5, 6 and 7 with Food Basket Prices

	Dependent variable:		
	ln_Cesta		
	(1)	(2)	(3)
Perc_Benef	0.020**	0.009	0.027
	(0.008)	(0.008)	(0.040)
Perc_Benef:Ano2021		−0.117***	−0.109***
		(0.021)	(0.021)
Perc_Benef:Agro_pc			0.205
			(0.436)
Perc_Benef:Indust_pc			−0.600***
			(0.204)
Perc_Benef:Serv_pc			0.145**
			(0.068)
Model	Two-Way Fixed Effects	Two-Way Fixed Effects	Two-Way Fixed Effects
Time Variable	Mês	Mês	Mês
Individual Variable	Área de ponderação	Área de ponderação	Área de ponderação
Observations	4,960	4,960	4,960
R^2	0.001	0.008	0.016
Adjusted R^2	−0.069	−0.062	−0.054
F Statistic	6.403** (df = 1; 4634)	18.644*** (df = 2; 4633)	14.821*** (df = 5; 4630)
Note:			*p<0.1; **p<0.05; ***p<0.01

an opposite effect in 2021: being in this year brings a negative contribution to the impact of receiving AE (the net effect depends on the percentage of beneficiaries in each year). Remembering the decrease in the value of AE in 2021, illustrated in Figure 3 , it is possible to interpret that this lower value of AE is not sufficient to replace the income lost by residents of more beneficiary regions (and therefore, poorer). The interaction with the sectoral variables made in the third model presents a negative and significant result in Industry, indicating that regions with more industrial workers had their prices less affected by AE, a not very intuitive result, since this was not the sector most affected by unemployment during the pandemic. At the same time, the positive and significant coefficient of the interaction of the percentage of beneficiaries with the service sector per capita workers is also not expected, suggesting that regions with more workers in this sector had their prices more affected by AE.

4.2 Regressions with *coxão mole* prices

Analyzing the *coxão mole* - selected meat in the basic basket of DIEESE - is interesting because of the characteristic of meats to be products with high income elasticity (their consumption is highly sensitive to income). The rationale is that an increase in available income would generate a large increase in meat consumption, assuming constant supply in the short term, which would raise its prices. We estimate the same models 6, 7 and 8, but this time using the prices of *coxão mole* (Table 6).

Table 6: Table of Results from Equation 5, 6 and 7 with *coxão mole*

	Dependent variable:		
	ln_Coxão_mole		
	(1)	(2)	(3)
Perc_Benef	0.066***	0.070***	0.180***
	(0.012)	(0.013)	(0.062)
Perc_Benef:Ano2021		0.036	0.025
		(0.032)	(0.033)
Perc_Benef:Agro_pc			−0.852
			(0.676)
Perc_Benef:Indust_pc			−0.244
			(0.317)
Perc_Benef:Serv_pc			−0.263**
			(0.106)
Model	Two-Way Fixed Effects	Two-Way Fixed Effects	Two-Way Fixed Effects
Time Variable	Mês	Mês	Mês
Individual Variable	Área de ponderação	Área de ponderação	Área de ponderação
Observations	4,960	4,960	4,960
R^2	0.006	0.007	0.008
Adjusted R^2	−0.063	−0.063	−0.062
F Statistic	29.623*** (df = 1; 4634)	15.425*** (df = 2; 4633)	7.740*** (df = 5; 4630)
Note:			*p<0.1; **p<0.05; ***p<0.01

This time there is a positive and significant effect of the percentage of beneficiaries on the price in all models. However, there is no significant difference in this effect between years, indicating that even a lower benefit value contributed to price increases - consistent with the high income elasticity of the *coxão mole*. When observing the interaction with sectoral variables made in the third model, the result is different from that found in Table 5. This time, only the coefficient of services is significant. Its negative sign makes sense within what was expected: regions with more workers in the services sector had their prices less affected by the AE, as they were more affected by unemployment caused by the pandemic.

5 Conclusion

In this study, the relationship between the Emergency Aid and inflation, with emphasis on food, was studied. Microdata from IPC-Fipe were used along with publicly available Emergency Aid data and address information of people registered in *CadÚnico* made available through the Freedom of Information Act, as well as additional data from various sources. The deficiency of the database in not containing the location of all beneficiaries was taken into account by estimating the percentage of beneficiaries outside of *CadÚnico* using municipality data as a proxy. Spatial interpolation was also used to extrapolate the prices of surveyed markets to all weighting areas.

In summary, assuming that there are no omitted variables that are correlated with the percentage of beneficiaries and not captured in fixed effects, the results presented in Table 6 indicate a causality between the incidence of AE and the increase in prices of *coxão mole*, a food with high income elasticity, more responsive to changes in available income. However, when analyzing the basic basket, there is no evidence of a significant effect of the percentage of beneficiaries on the price of this aggregate basket of goods.

Despite this evidence, more studies are needed to answer this important question. One way to improve this methodology would be to obtain the addresses of all Emergency Aid beneficiaries. Better results can also be obtained by using the information from the 2022 Demographic Census (not available at the time of this research). Finally, it is possible to analyze the product supply side, but there is no supply data for such small regions as weighting areas in São Paulo. For this analysis, it would be necessary microdata from prices in several states, such as IPCA-IBGE, along with state-level production data, such as PIM-Regional from IBGE.

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