UNIVERSIDADE FEDERAL DO RIO DE JANEIRO
INSTITUTO DE ECONOMIA
MONOGRAFIA DE BACHARELADO

Structural Household Income Inequality Dynamics in Brazil
A Convergence and Mobility Decomposition Analysis (2012-2019)

Ana Luiza da Costa Pessanha de Mendonça
Matrícula nº: 116047469

Orientadora: Valéria Lúcia Pero

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ABSTRACT

This paper makes a longitudinal analysis of income inequality dynamics in Brazilian households among three periods: pre-economic crisis (2012-2014), recession (2014-2016) and recovery (2016-2019). Using a concept of structural income rather than observed income, I decompose Gini increases and decreases between Convergence (poorest having higher earnings growth rates) and Leapfrogging (poorest becoming richer than others). Structural income allows the analysis for the three periods of study, which is limited when considering observed income. Results show that, from 2012 to 2015, inequality decreased due to an increase in the income growth of the poorest, which was stronger than the leapfrogging effect. During the economic crises, inequality increased, with an increase of the reranking component, overtaking the convergence component. In the first year of economic recovery, income convergence decrease while leapfrogging continued to increase, maintaining the Gini index trend of growth. From 2018 to 2019, reranking effect decreased while the income growth of the poorest increased, contributing to the maintenance of structural income inequality. I also perform a separated analysis of the evolution of β-Convergence with a linear regression and inter quintilic mobility with transition matrices, both confirming previous results. Finally, I compare these results with an analysis of observed household income from 2015 to 2019 and show that the economic crisis had opposite effects on the dynamics of inequality between structural and observed household income.

Keywords: Gini Change Decomposition, Inequality, Structural income, Brazil, Convergence, Mobility

RESUMO

Este artigo faz uma análise longitudinal da dinâmica da desigualdade de renda nos domicílios brasileiros em três períodos diferentes: pré-crise econômica (2012-2014), recessão (2014-2016) e recuperação (2016-2018). Utilizando um conceito de renda estrutural, decomponho as variações do Índice de Gini entre os efeitos de convergência (maior taxa de crescimento da renda para os mais pobres em relação aos mais ricos) e de leapfrogging (os mais pobres se tornando mais ricos que outros). A renda estrutural permite a análise para os três períodos de estudo, o que é limitado quando se considera a renda observada. Os resultados mostram que, entre 2012 e 2015, a desigualdade diminuiu devido a uma aumento do crescimento da renda dos mais pobres, que superou o efeito da reordenação dos domicílios ao longo da distribuição. Durante a recessão, a desigualdade aumentou, com um aumento do efeito de reordenação, que ultrapassou o componente de convergência. Nos primeiros anos de recuperação econômica, a convergência de renda diminuiu enquanto o efeito reordenação continuou a aumentar, mantendo a tendência de crescimento do índice Gini. De 2018 a 2019, o efeito de reordenação diminuiu enquanto crescimento da renda dos mais pobres aumentou, contribuindo para a manutenção da desigualdade estrutural de renda. Também realizo uma análise separada da evolução da convergência e mobilidade inter quintilica por matrizes de transição, ambos confirmando resultados anteriores. Por fim, estes resultados são comparados com uma análise da renda domiciliar observada entre 2015 e 2019, o que mostra que a crise econômica gerou efeitos opostos na dinâmica da desigualdade de renda estrutural e desigualdade da renda domiciliar observada.

Palavras Chave: Desigualdade, Convergência, Brasil, Decomposição do Gini, Renda estrutural, Mobilidade

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1 Introduction

Income inequality in Brazil is one of the highest in the world, even considering the decrease in the 2000s. Inequality reduction was achieved mainly due to a period of economic growth and income and social inclusion policies, such as minimum wage increases and targeted social programs. The most commonly used inequality measure – the Gini coefficient (the closer to 1, the more unequal) – declined from 0.60 in 1990 to 0.51 in 2014. Neri (2013) point out that 55% of the reduction in Gini between 2002 and 2012 was due to labor income. On the other hand, Barros and Foguel (2007) highlights the contribution of education to the reduction of income inequality, due to the reduction of inequality in the education levels of the population and the salary premium for additional years of study. Poverty indicators also showed significant improvement in the same period, with the proportion of poor people declining from 34% in 1992 to around 8% in 2014 (Neri (2018)). With regard to the measure of poverty intensity (the distance between per capita household income and the poverty line), there was a reduction of about 10 pp between 2002 and 2013, in which 34% of this reduction attributed to the minimum wage (Scalioni Brito and Lessa Kerstenetzky (2019)).

However, the political instability and economic crisis change this performance. The average labor income decreased by about 10% among heads of household and by 11% among people with incomplete high school.The increase in unemployment, associated with double-digit inflation in 2015, were the main contributors to the drop in real income from work. From mid-2017, disinflation contributed to a small recovery in real income. However, unemployment had a small decreased, delaying the recovery of households' purchasing power. Consequently, the recession had a greater impact among the poorest, as average income declined 7% while the income of the poorest 5% declined 14% (Neri (2018)).

To sum up, the 2014-2016 recession was the worst and slowest Brazilian recession since the 1980s, with an accumulated decrease in GDP of 6.7% in the 2015-2016 biennium. In addition, the recovery from 2017 (around 1% per year) was not enough to reduce unemployment rates that remained at around 11%. Notoriously, the performance of the Brazilian economy and social indicators interact with each other, which may increase or reduce the well-being of the population. After the significant reduction in the 2000s, the proportion of poor people increased by about 3 pp during the recession and decreased by only 2% between 2017 and 2018. Regarding the performance of inequality in the post-recession period, the Gini Index of average real monthly household income per capita increased from 0.537 in 2016 to 0.545 in 2018. In addition, there was an increase in the proportion of households that declared they had no labor income considering the entire 2013-2018 period as well as the 2016 post-recession biennium (Lameiras and Corseuil (2019)).

The objective of this study is to analyse the dynamics of inequality in these periods considering the structural income defined as the part of the observed income that is derived from holding productive assets, that is, that can generate income, such as physical assets, schooling years and occupational sector (Mckay and Lawson (2002); Sandoval (2019)).The literature on inequality trends and socioeconomic mobility is quite extensive, especially in countries historically recognized as unequal. In the developed world, we have seminal studies on the evolution of inequality (Piketty (2003); Piketty and Saez (2003)) and their respective implications for intergenerational income mobility (Chetty et al. (2014), Chetty et al. (2017)). When we look at the Brazilian case, we also have several studies that analyze the evolution of inequality in different historical periods, using not only sample data (Barros and Foguel (2007);Neri (2013)) but also the work of (Medeiros and Souza (2018)) with income tax data. In addition, there is also a range of empirical papers that study income mobility (Pero and Szerman (2008)) and papers that discuss the relationship between poverty and inequality, showing a decomposition of the variation in poverty between pro-poor economic growth and the reduction of inequality (Barros and Mendonça (2001); Datt and Ravallion (1992)).

The works cited above use observed income from individuals, households or countries, which is usual within the field of studies on inequality as a whole. However, a part of the literature on the persistence of poverty that uses an estimated measure of structural income to understand the dynamics of the process in which income generation is insufficient for a household/individual to leave the situation of poverty permanently (Carter and Barrett (2006)). In this respect, using structural income can be considered more advantageous, since it allows for an analysis less tied to income shocks and dependence on government assistance transfers. However, studies that jointly discuss the three aspects of income distribution - inequality trends, existence (or absence) of pro-poor income growth and income mobility - for Brazil are still scarce. More specifically, there is no study (to my knowledge) that analysis this dynamic of inequality using some structural income estimation instead of observed income. In that sense, this work aims to fill this gap in Brazilian literature, introducing the concept of structural income in the debate on inequality.

Using Jenkins and Van Kerm (2006) methodology, I provide a Gini decomposition approach, which distinguish changes in income inequality between income growth rates across the distribution (β-convergence effect) and changes in ranking along the income scale (leapfrogging effect). Instead of using per capita household income, I follow the methodology of Sandoval (2019) to estimate an inter-annual data panel of structural income for Brazilian households between 2012 and 2018. Dividing the analysis of results between three periods - pre-economic crises (2012-2013), recession period (2014-2016) and recovery (2017-2019) - I show that inter-annual inequality of structural income in Brazil increased during and after the economic crisis, with both less increasing income of the poorest and less mobility - but the second outpacing the first since the recession period. In the recovery period, there was a small improvement in the pro-poor growth component, although still accompanied by the downward trend in mobility. Then, I perform a separated analysis of β-Convergence by a linear regression and inter quintilic mobility by transition matrices, both confirming previous results. Finally, I compare this results with the evidence from observed income and show that the economic crisis had opposite effects on the dynamics of inequality between structural and observed household income.

The remainder of this paper is organized as follows: Section 2 presents a literature review of the concept of structural income, Section 3 shows the Gini decomposition between R-component and P-component, Section 4 describes the Brazilian data and methodology used, Section 5 presents the results of inequality dynamics and Section 6 compares the previous results with the dynamics of observed household income. Finally, Section 7 discuss the main conclusions and research agenda.

2 Structural Income

The concept of structural income is derived from the literature on poverty trap. In this framework, the analysis of poverty requires an understanding of its multidimensionality and the distinction between its static and dynamic conception (Ravallion (2011)). In particular, it is necessary to distinguish theoretically and empirically individuals who experience transient poverty from those suffering from chronic poverty. In the first case, individuals transit this state of poverty temporarily, either because of stochastic factors or changes in asset accumulation and/or their respective returns. With regard to chronic poverty, the individual below a certain poverty line remains in this state repeatedly throughout his or her life cycle, due to structural rather than stochastic conditions (Carter and Barrett (2006)). Among the characteristics that may be associated with chronic poverty are the scarcity of physical assets and human capital, demographic composition, household location and low labor income (Mckay and Lawson (2002)). Thus, the study of chronic poverty concerns the understanding of poverty as a dynamic process in which poor individuals have low or no social mobility. In that sense, the concept of structural income can be an important theoretical apparatus for analyzing not only the poverty process but also the inequality dynamics within a country.

Regarding the historical evolution of the poverty trap estimation models, the models that include structural income belong to the third generation (Carter and Barrett (2006)). The first generation would correspond to the Foster-Greer-Thorbecke (FGT) measures, which calculate the proportion of poor individuals from the difference between the monetary poverty line and per capita household consumption or income at a given point in time. Thus, both the incidence of poverty (FGT (0)) and the intensity of poverty (FGT (1)) could be obtained. This type of method is widely used to track the evolution of a country's poverty through the provision of cross-sectional data. However, such analysis reveals only portraits of poverty at different points in time, so that it would be impossible to identify which percentage of the population that were poor at any period remained poor in the next one. Thus, "unfortunate" individuals could fall into the poor population in different samples and yet it would not be possible to identify whether there is a chronic poverty process or whether, through transient income shocks, individuals experienced transient poverty at different points in time of the analyzed period. Therefore, repeated observations of a certain proportion of poverty could, in reality, mean only a reordering of individuals in this state.

Considering this gap, the second generation focused on a longitudinal analysis, in which the same sample of individuals is followed over time. The panel data would thus allow the distinction of individuals into persistently poor, transiently poor and persistently not poor (Carter and Barrett (2006)). Some empirical studies used this framework to estimate the dynamics of poverty. Fernández-Ramos et al. (2016), for example, found that 36% of Mexico's poverty is chronic and 64% is transitory, while Alia et al. (2016), following the same multinomial logistic regression strategy, found large and rapid turnover of Benin's households into and out of poverty, which means that they are vulnerable to income shocks. The shortcoming of this approach, however, lies in the fact that it brings together distinct processes of experiencing poverty in the same category. Individuals transitioning from poor to non-poor may have experienced a structural change in asset accumulation and return, or may have initially experienced a transient income shock that diverted them from their expected level of well-being to that stock of assets. Similarly, the transition from non-poverty to poverty can indicate both luck and the deterioration of assets and their returns, caused by a range of factors such as disease, natural disasters or unemployment (Carter and Barrett (2006)).

To overcome such obstacles, the third generation of measures is proposed by Carter and May (2001), based on the formulation of a poverty line based on the estimation of a structural income - or asset index - that is generated by the existence of productive assets. According to this framework, production technologies combine the stock of assets (land, human capital, social capital) with input flows, such as labor, to generate the income stream (Baulch and Hoddinott (2000)). Thus, household income would be decomposed into structural income and transient income, following Friedman (1957) hypothesis in which the level of consumption depends not on current income but on permanent income, which in turn depends on the stock of productive assets (Sandoval (2019)). The existence of transient income, determined by temporary shocks, is the main motivation for asset accumulation in developing countries, and may occur in the form of financial savings, accumulation of durable goods and investment in human capital. Therefore, according to the third generation of poverty studies, the poverty situation would exist when accumulated assets produce a level of well-being equal to or less than a predetermined absolute or relative poverty line. Considering a stable welfare function over time, a household suffers from stochastic or transient poverty if the stock of assets generates a higher structural income than the poverty line, even though its effective income is below that line, due to negative income shocks. Similarly, chronic poverty will be present if the stock of assets generates an income below the poverty line as well as its observed income (Carter and Barrett (2006)).

Based on this third generation, I estimate a structural household income using a model similar to Sandoval (2019). The main contribution of his paper regarding the purpose of this work is that he account for the fact that members of urban households typically work on different sectors of the economy, which means that we can not assume that they have the same income generating function as farmer workers. In this sense, he compares the results of structural income when using different aggregation variables such as assets of the head of the household, average possession of assets among workers and total assets among workers and finds out that those different aggregations do not change the substance of the results.

Nevertheless, I used this estimated household structural income to analyze the dynamics of Brazilian inequality, measured by the Gini Index and decomposed between its mobility and pro-poor growth components (see 3). This method allow us to study the evolution of structural economic mobility in Brazil, which is a novel analysis with Brazilian data. More specifically, I will divide this analysis into three periods: pre-economic crisis (2012-2013), recession (2014-2016) and recovery (2017-2018), which permit us to compare how the economic recession hit the poorest relative to the richest.

3 Dynamics of inequality

3.1 β-Convergence

The convergence theory is based on the neoclassical income growth model developed by Solow (1956), in which the higher income growth rate of poor countries relative to the rich countries would lead to the decrease of income gap, characterizing a process called the catching up effect. This could occur because poor countries have lower levels of capital accumulation, which combined with a technological progress function with diminishing returns can lead to higher income growth rate.

Considering the empirical estimation of convergence, a pioneering methodology that has the ability to identify a deterministic trend was developed by Sala-i Martin (1996), who coined the term β-Convergence as a measure of poor economies (in our case household's income) having greater GDP growth rates relative to the rich ones. However, he also suggests that β-convergence studies the mobility of income within the same distribution, which will be discussed in the section 3.2. In that sense, a framework for this measure is to perform the following regression:

$$\ln\left(Y_{i,t}/Y_{i,t-1}\right) = \beta_0 + \beta_1 \ln Y_{i,t-1} + \epsilon_{i,t} \tag{1}$$

Where $\ln Y_{i,t}$ and $\ln Y_{i,t-1}$ are the log income of a household in a period t and t-1. In this equation, β_1, if negative, means that the poorest had, from t-1 to t, an higher increase in average than the richest.

3.2 Gini changes decomposition

This section provides a theoretical and empirical framework in which the change in income inequality between two time periods for a same set of observations can be expressed in terms of two components. One is the income growth rates across the distribution and the other is the changes in ranking along the income scale (leapfrogging effect). The advantage of using this Gini decomposition approach is that it allows a non-parametric framework that identifies the key components of the convergence process. Hence, this framework do not require the underlying growth process to be constant across households, linear in income or monotonic as required when β-convergence is estimated in a linear regression framework (Jenkins and Van Kerm (2006); O'Neill and Van Kerm (2008)).

Take X as the per capita household income and $G(X_t)$ as the Gini coefficient of a distribution in any period t. Then, we can decompose the variation of the Gini coefficient between two time periods following the equation below:

$$\Delta G = G(X_t) - G(X_{t-1}) = R - P \tag{2}$$

Where R is a measure of reranking, defined by the equation:

$$R = G(X_t) - C(X_{t-1}, X_t) \tag{3}$$

Where $C(X_{t-1}, X_t)$ is the Concentration coefficient of income, determined by a weighted average of period t mean-normalized incomes, where the weights are determined by relative ranks of the baseline period (t-1) (O'Neill and Van Kerm (2008)). P, on the other hand, is defined by the equation:

$$P = G(X_{t-1}) - C(X_{t-1}, X_t) \tag{4}$$

According to Jenkins and Van Kerm (2006), P can be interpreted as an indicator of how much growth has benefited disproportionately to individuals towards the bottom of the distribution in the initial time period. In other words, is a weighted average of (mean-normalized) income growth for each household where the weights are given by the households' ranks in the initial distribution of incomes. Therefore, P-component equals zero if income growth rates are equal for all households. If it is positive, income growth tends to be higher for poorer households and inequality falls. In contrast, negative P-component means that income growth tends to be higher among richer households, which leads to an increase in inequality.In order to embody criticism of Sala-i Martin (1996) methodology regarding non-linearity in the growth process, O'Neill and Van Kerm (2008) interprets P-Component, as a non-linear measure of β-Convergence.

On the other hand, R-component captures how much a progressive income growth has lead to reranking between individuals, so that the net reduction in inequality is the difference between P and R. Friedman (1992) argued that the P component would not be a sufficient condition for convergence to occur, since it is possible to observe poor regions growing at higher rates compared to the richest regions and still diverging. In this case, the initially poorer countries leapfrog the richer countries, so that the rankings of countries change. Hence, for a distribution to exhibit β-Convergence, without reducing inequality, it must be the case that countries are changing ranks. Similarly, it is possible to present β-Convergence without any positional mobility or rank mobility (O'Neill and Van Kerm (2008)). Following Yitzhaki and Wodon (2005), R-component may be interpreted as a measure of mobility (in the form of reranking) in its own right. This interpretation follows the Pigou–Dalton principle, as stated by Dalton (1920), according to which a higher income growth for the poor brings more equality, as long as it does not make the richer to a poorer situation than the poor and, in this sense, incorporates the criticisms expressed by Friedman (1992).

Therefore, equation 2 states that inequality is reduced by progressive income growth unless more than offset by concomitant income mobility. The results of Jenkins and Van Kerm (2006) shows that both in United States and Germany the reranking effect more than offset the diminishing effect forced by the income growth pro-poor. The former effect was larger in USA than in Germany and inequality rose faster in the former compared to the latter.

3.3 Transition matrices

Additionally, I illustrate the evolution of a mobility process using a quintile transition matrix approach. Therefore, I calculated the probability of change of income quintile to which the household belongs one year later. The transition probability is calculated by the following formula:

$$p_{l,k}^{t} = P(Q_{12,t+1} = k | Q_{1,t} = l) = \frac{\sum_{j=1}^{11} \#(Q_{k,j,t} \rightarrow Q_{l,j+1,t+1})}{\sum_{j=1}^{11} \#(Q_{k,j,t})} \tag{5}$$

in which the first subscript (k or l) indicates the quintile the individual belongs to - from the richest 1º to the poorest 5º. The numerator gives the sum of the number (#) of individuals who migrated from quintile k to a given quintile (k and l can be equal, which in this case would be the total of individuals that remained in the same condition), one year later. The denominator gives the sum of the number (#) of individuals in quintile k in the first period. Thus, I obtain the probability of transition from category l to category k over one year. By definition, the transition matrix is necessarily stochastic. For example, the probability of transition from quintile 1 to 2 between 2012 and 2013 is the ratio of the sum of all households that migrated between these quintiles over the sum of all households that were in quintile 1 in 2012.

For the purpose of this paper of only highlighting possible patterns of mobility between income quintiles, this framework is appropriate. However, mobility analyses based on fractile matrices have disadvantages, as summarised by Fields and Ok (1999). First, a fractile matrix do not take into account income variations that takes place within subgroups. Second, it does not consider the empirically observed positive-skewness of the income distributions, which can lead to differences in the absolute income changes that are needed to move between classes. At last, a fractile matrix may fail to reflect the effect of income growth on the mobility pattern of the society, that is, one can not conclude changes in intertemporal equality of a mobility process.

4 Data and Descriptive statistics

This study uses two databases (annual and quarterly) from the National Continuous Household Sample Survey (PNADC), which is performed by Brazilian Institute for Geography and Statistics (IBGE). Both bases have followed the same household for five quarters, collecting information from households regarding labour market, education and demographic conditions. However, the main difference between annual and quarterly microdata is that the first one contains information about various income sources, while the quarterly data basically contains work related income. In addition, the annual database with the fifth interview only exists from 2016, while the annual database with the first interview exists since 2012. This is important for my analysis because the lack of information from other sources of income (besides the earnings income) in the fifth interview prevents me from comparing the estimated structural income with the observed household income for the period of 2012 to 2016.

In this sense, I estimate the structural household income in two steps. First, I use the annual database with the first interview from 2012 to 2019 to perform a OLS regression, using the survey weights, of the observed per capita household income on a set of variables that are considered relevant in the income generation for urban households, according to the definition of structural income presented in section 2. Therefore, I include the following variables: Age of the head of household, which can be a proxy for experience in labor market, number of schooling years and occupational group of the head of household (including a self-employed dummy), which represents measures of productive assets and a variety of demographic variables that can influence the household income, such as number of kids (do not contribute to the generation of household income) and number elderly people (can contribute to pension income and/or retirement). In addition, I also control for number of individuals within the household and a gender dummy for the head of the household.

Thus, we have the following equation for estimating structural income:

$$\begin{aligned}\ln Y_{hpc} = \beta_0 + \beta_1 N_ind + \beta_2 Age_{head} + \beta_3 Education_{head} + \beta_4 Ocupation_{head} + \beta_5 Number\_Employee \\ +\beta_6 Number\_Kids + \beta_7 Number\_Elderly + \beta_8 Region + \beta_9 Self\_employed + \beta_1 0 Gender_{head} + \epsilon\end{aligned} \quad (6)$$

Where $\ln Y_{hpc}$ is the observed log per capita income of a household in the first interview. N_ind is the number of individuals within the household, Age_{head} is the age of the head of the household, $Education_{head}$ is the schooling years of the head of the household, $Ocupation_{head}$ is a vector containing ten employee occupation dummies, following the database classification itself (baseline = "Other occupational group"), $Number\_Employee$ is the number of employees within the household, $Number\_Kids$ is a vector of the number of kids within the household grouped by age range (0-5 years, 6-14 years, 15-17 years and 18 years or more), $Number\_Elderly$ is the number of elderly people within the household, $Self\_employed$ is the number of self employed people within the household, $Region$ is a vector containing four region dummies (North, Midwest, Southeast and South), $Gender_{head}$ is a dummy which is equal to 1 if the household's head is female and ϵ is the term error.

The observed per capita household income was deflated by income ranges, using an indicator created by the Applied Economic Research Institute (IPEA) (Ipea et al. (2019)). Then, I assume that the coefficients estimates are stable, that is, the returns do not changed in that year and estimate the per capita structural household income for the first and last interviews of that same household. That is, I gathered all the quarterly data of the initial year and subset for those households that were doing the first interview and the same for the following year, for those households that were doing the fifth interview. After that, I merge this two datasets by each household identification, creating a panel data. By following this procedure, I remove possible quarterly seasonal effects. This approach is necessary because of the lack of a data panel of the first and fifth interviews with all sources of income for the period of 2012 to 2018.

After estimating this regression for the income observed in the first interview, I input these coefficients in the data from the fifth interview. In that sense, the predicted income can be considered the structural income, as it is the part of the observed income that can be explained by productive assets such as schooling years, occupational groups and other demographic variables that can influence a household's income generation.

4.1 Annual microdata

Table 1 below shows the evolution of data observations of the yearly microdata used to estimate the structural household income coefficients. The sample from 2012 has almost 446,445 individuals that, when weighted, represents almost 200 million individuals from the total population. 2019 sample, on the other hand, has 443,790 individuals that, when weighted, represents little more than 209 million from the total population. However, our data observations are households and not individuals. Since all members of the household have the same values for the same variables, generating the number of single households in the sample. Hence, there are about 124,000 households in the panel data of 2012-2013, about 132,000 in 2013-2014 and almost 140,000 households for the following years.

Table 1: Number of individuals in PNADC

Year	Individuals	Weighted individuals
2012	446,445	197,720,534
2013	461,033	199,402,499
2014	465,038	201,108,347
2015	459,273	202,858,853
2016	459,718	204,532,351
2017	457,992	206,172,340
2018	452,654	207,853,293
2019	443,790	209,496,493

Source: PNADC from 2012 to 2019

Some descriptive statistics about the most relevant variables associated with structural income, that is, observed per capital household income, years of schooling and employee ocuppation of the head of the household are shown in the tables below. The statistics of all the other variables in the model can be found in the appendix section (8). From Table 2, we observe small changes in per capita household income (PCHI) statistics. I established that the minimum income is always equal to one because some households report zero income and this would prevent the log-transformation.

Table 2: Descriptive statistics of observed per capita household income (PCHI)

Year	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
2012	446,445	1,171.390	1,871.157	1.000	389.043	1,262.138	90,979.760
2013	461,033	1,194.238	1,826.776	1.000	410.185	1,296.787	82,180.530
2014	465,038	1,234.492	1,819.605	1.000	433.118	1,350.651	106,469.400
2015	459,273	1,195.463	1,782.119	1.000	416.074	1,316.851	89,739.790
2016	459,718	1,159.581	1,764.492	1.000	389.114	1,282.276	110,452.100
2017	457,992	1,189.682	1,897.078	1.000	393.977	1,307.519	159,786.200
2018	452,654	1,235.340	2,015.875	1.000	396.557	1,348.695	214,877.200
2019	443,790	1,248.000	2,049.431	1.000	400.900	1,372.500	154,502.700

Source: PNADC from 2012 to 2019

Table 3 shows the percentage of households for each year of the head of household's schooling, along with the mean and median for the period 2012-2019. We can observe that about 1/5 of the households have a head of household with 12 years of schooling. The second highest frequency is that of households whose head has 5 years of schooling, followed by households whose head has zero years of schooling. From 2017, this relationship

Table 3: Years of schooling of the head of household

	2012	2013	2014	2015	2016	2017	2018	2019
0	11.507	11.118	10.875	10.639	10.803	10.044	9.319	8.2
1	4.681	4.579	4.314	3.978	4.291	3.36	2.812	2.7
2	2.639	2.722	2.736	2.662	2.618	2.518	2.716	2.7
3	4.116	4.097	4.079	4.089	3.921	3.831	3.735	3.6
4	5.278	5.188	4.955	4.881	4.619	4.782	4.589	4.5
5	13.388	13.148	12.955	12.58	11.851	11.575	11.76	11
6	6.393	6.414	6.12	6.222	6.122	6.357	6.109	6.3
7	3.003	2.962	3.02	3.024	3.453	3.658	3.617	3.8
8	3.014	3.072	2.937	3.058	3.085	3.327	3.399	3.7
9	9.999	10.113	10.308	9.863	8.926	8.415	8.072	8.3
10	1.794	1.896	1.834	1.908	1.986	2.309	2.336	2.6
11	1.857	1.883	1.87	1.98	2.022	2.192	2.163	2.5
12	20.36	20.545	21.002	21.345	21.737	21.919	22.42	23.9
13	1.122	1.144	1.116	1.32	1.754	1.982	2.048	1.9
14	1.098	1.141	1.185	1.288	1.341	1.364	1.459	1.4
15	1.226	1.256	1.279	1.343	1.288	1.319	1.477	1.4
16	8.526	8.722	9.415	9.818	10.183	11.049	11.97	11.5
Mean	7.513	7.591	7.726	7.852	7.917	8.146	8.353	8.499
Median	7	7	8	8	8	9	9	9

Source: PNADC from 2012 to 2019

is reversed and the third highest frequency is that of households whose head has 16 years of schooling. This movement is a reflection of the increase of three percentage points in the percentage of households whose head has completed higher education and a reduction of two percentage points in the percentage of households whose head has zero and five years of study.

Table 4: Number of employed within the household

	2012	2013	2014	2015	2016	2017	2018	2019
0	33.344	33.677	34.517	35.499	38.13	39.689	40.547	40.1
1	27.93	28.175	28.002	27.928	27.431	26.251	25.825	20.33
2	28.091	28.146	27.806	27.469	26.269	26.03	25.842	28.02
3	7.793	7.338	7.154	6.776	6.081	5.985	5.846	8.04
4	2.221	2.127	2.004	1.859	1.673	1.648	1.569	2.66
5	0.476	0.415	0.411	0.373	0.327	0.317	0.299	0.63
6	0.115	0.097	0.084	0.07	0.066	0.055	0.055	0.15
7	0.024	0.018	0.017	0.017	0.013	0.016	0.011	0.04
8	0.005	0.005	0.003	0.006	0.007	0.006	0.004	0.02
9	0.002	0.001	0.001	0.001	0.001	0.002	0.001	0
10	-	0.001	0.001	0.001	0.003	-	0.001	-
11	-	-	-	-	-	0.001		-
Mean	1.197	1.178	1.158	1.131	1.071	1.05	1.033	1.156
Median	1	1	1	1	1	1	1	1

Source: PNADC from 2012 to 2019

In turn, the distribution of households by number of employed members is shown in the table 4 above. Although the median remained stable in one employed member of the household, there was an increase of about 7 percentage points in the percentage of households with zero employed members, throughout the sample period.

The descriptive statistics of the estimated structural income are are presented in Table 5. Comparing the first and fifth interview, we observed that there was an increase in mean income in 2013, 2014 and 2015, a decrease in 2016 and 2017, an increase in 2018 and a decrease in 2019, relative to the respective previous years. The income evolution pattern was similar for the first and fourth quartiles, except in 2018 and 2019, where the poorest and the richest quartiles showed opposite changes.

Table 5: Structural per capita household income

First Interview							
	2012	2013	2014	2015	2016	2017	2018
Min.	15	18	25	24	17	24	24
1st Qu.	506	524	559	573	519	475	502
Median	825	847	891	953	897	821	839
Mean	1062	1085	1127	1160	1116	1032	1113
3rd Qu.	1307	1331	1378	1525	1472	1357	1362
Max.	12323	13073	16293	11151	12655	10451	35202
Fifth Interview							
	2013	2014	2015	2016	2017	2018	2019
Min.	20	15	28	15	23	23	15
1st Qu.	537	563	582	524	474	500	482
Median	863	891	968	907	822	834	818
Mean	1094	1115	1169	1119	1032	1098	1093
3rd Qu.	1341	1368	1534	1466	1355	1342	1365
Max.	12709	14241	11071	13392	14296	20503	19414

Source: PNADC from 2012 to 2019

Finally, the structural and observed income mean per quintile are shown in table 6. In 2015 and 2016, the average of structural income is higher than the average of observed income for all quintiles except the richest (fifth quintile). In 2017, the average of structural income is smaller than the average of observed income for all quintiles except the poorest. In the last year, the average of structural income is smaller than the average of observed income for all quintiles except the first and second. Part of this difference can be attributed to the fact that some households report zero income as well as the construction of structural income itself.

Table 6: Income mean per quintile - First interview

Structural income					
Year	1º quintile	2º quintile	3º quintile	4º quintile	5ºquintile
2012	301	566	829	1196	2420
2013	316	586	850	1219	2449
2014	342	622	895	1265	2511
2015	342	645	959	1394	2461
2016	305	590	902	1341	2442
2017	282	539	826	1233	2281
2018	294	565	843	1240	2625
Observed income					
Year	1º quintile	2º quintile	3º quintile	4º quintile	5ºquintile
2015	276	575	910	1388	4019
2016	256	549	889	1330	3875
2017	250	553	912	1362	4036
2018	249	561	925	1400	4165

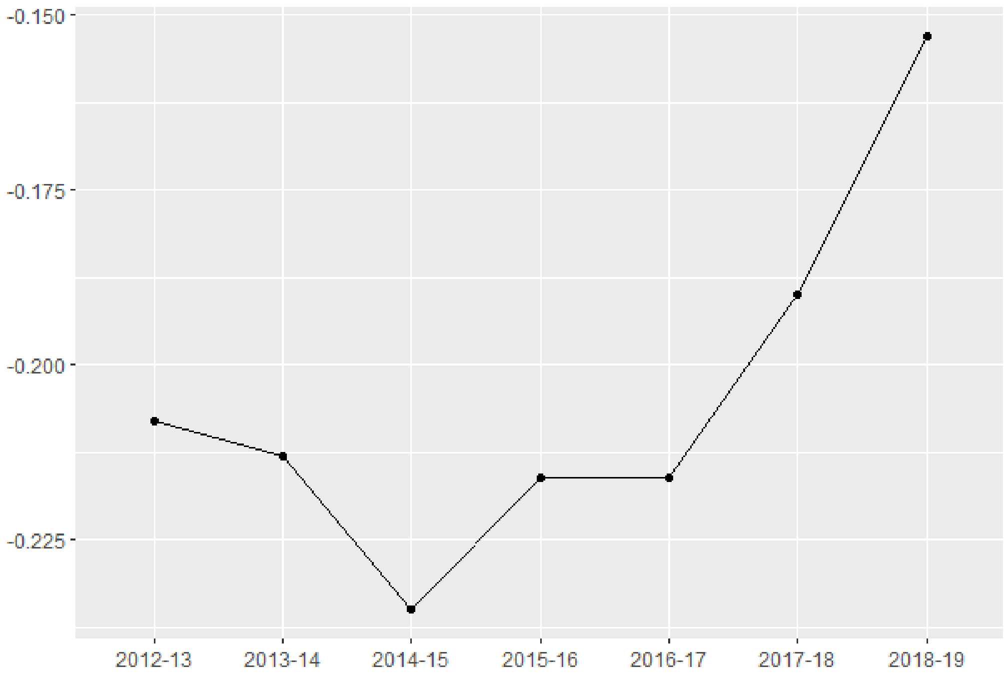
The remaining descriptive statistics can be found in the annex section 8. Table A1 presents the frequency of household in each region dummy, Table A2 shows the frequency of households in each occupational group and Table A3 shows the mean of the other explanatory variables. Tables A4-A7 presents the regression results and finally, Figures B1 to B8 show the scatter plots of the structural income and observed income between 2015 and 2019 (only years for which such analysis is possible).

5 Results

5.1 Evolution of β Convergence Effect

Figure 1 shows the evolution of the coefficient associated with pro-poor growth. As mentioned in section 3, the more negative β is, higher in average was the income growth of those who were poorer in the first interview. As one can see, the pre-economic crisis period (2012-2014) was marked by a more negative coefficient, which means that the income growth rate of the poorest was higher, relative to the richest. In the recession (2014-2016), there was small reduction (in module) of the β coefficient, which means that the recession was stronger for the poorest compared to the richest. In the recovery period, there was a greater reduction (in module) of the β coefficient. This evidence suggests that the poorest households did not benefit from the recovery period of the economic recession.

Figure 1: β-Convergence from 2012-2013 to 2018-2019



Source: PNADC, IBGE - author's elaboration

5.2 Evolution of Gini Changes decomposition

After assigning the statistically significant coefficients of the tables A4, A5, A6 and A7 in the respective quarterly databases, we calculate the evolution of the Gini Index of structural household income. Table 7 bellow shows the average decomposition of annual Gini changes over the period. The results show that the Gini coefficient decrease between 2012 and 2015, increase between 2015 and 2016, remained stable in 2016-2017, increase in between 2017 and 2018 and remained stable in 2018-2019. Between 2012 and 2015, the pro-poor income growth (P-component) was greater than the leapfrogging effect (R-component), which led to a reduction in inequality. In 2016, the R-component increased and overtaked the P-component, which meant a positive variation in the Gini coefficient. In 2017, the R-component decreased, while the P-component remained stable, which led to a small variation of inequality. In 2018, the reranking effect more than offset the diminishing effect forced by the income growth pro-poor, which contributed to a big increase in inequality. Finally, in 2019, the R-component decrease while the P-component increase until they got closer in value, contributing to the maintenance of structural income inequality.

Table 7: Gini Dynamics Decomposition of the Structural Household Income Per Capita

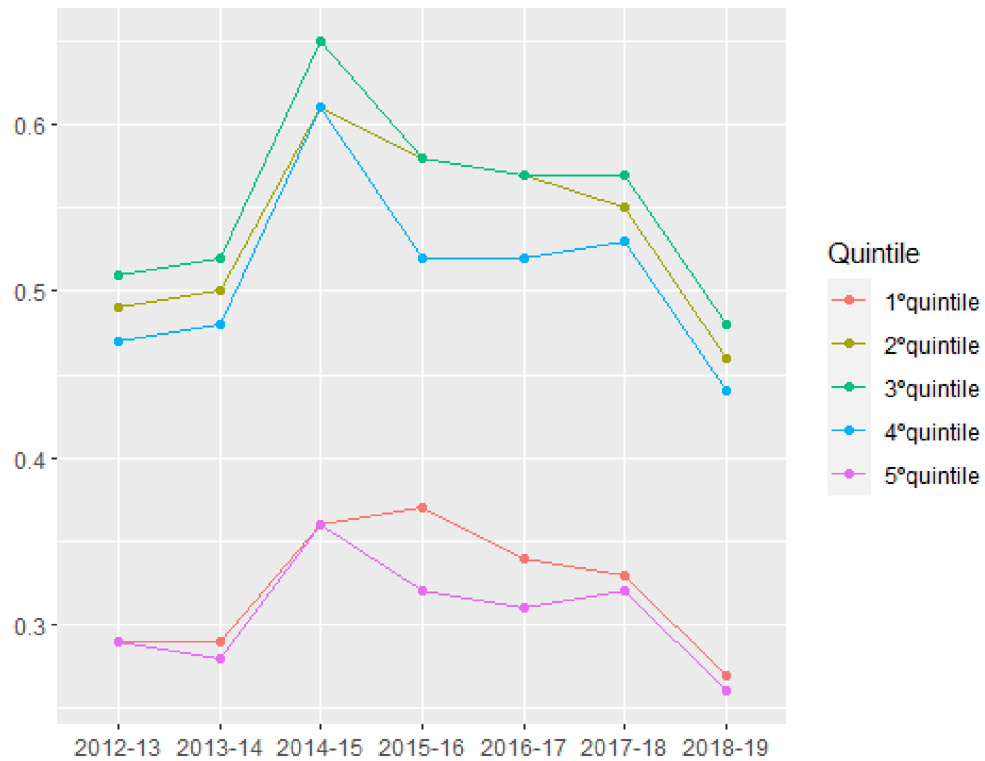
Decomposition	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19
G0	0.3939	0.3889	0.3803	0.366	0.3841	0.3881	0.4132
G1	0.3835	0.3748	0.3636	0.3818	0.3894	0.41	0.4147
delta	-0.0104	-0.0141	-0.0167	0.0157	0.0052	0.0218	0.0015
R-comp	0.0659	0.0643	0.0825	0.0923	0.0808	0.0811	0.0623
P-comp	0.0763	0.0784	0.0992	0.0765	0.0756	0.0593	0.0608

Source: Estimates from PNADC from 2012 to 2019,
based on Jenkins and Van Kerm (2006) methodology.

5.3 Evolution of Leapfrogging Effect

In this subsection, I show the evolution of two measures of mobility, using a quintile transition matrix. First, Figure 2 bellow shows the conditional probability of changing the structural income quintile to which the household belonged in the first interview. In the case of households belonging to the poorest quintile (1st quintile) in the first interview, we have the evolution of the probability that this household belongs to any other income quintile a year later, in the fifth interview. As one can see, the poorest and the richest showed similar patterns. The exceptions are in the economic crisis period, where the richest lost income mobility (that is, they have benefited, since they are at the top of the distribution and having mobility means being relatively poorer) and the poorest have gained mobility (that is, they also benefited, since having mobility means getting relatively richer) and in the first year of recovery, where the poorest lost mobility while the richest showed an increase. The quintiles of the middle of distribution also presented a similar pattern, with an increase in mobility in pre-crisis period, a decrease in the recession period, an increase in the first year of recovery and a downward trend in the following year.

Figure 2: Inter Annual Probability of Changing Structural Income Quintile from 2012-13 to 2018-2019

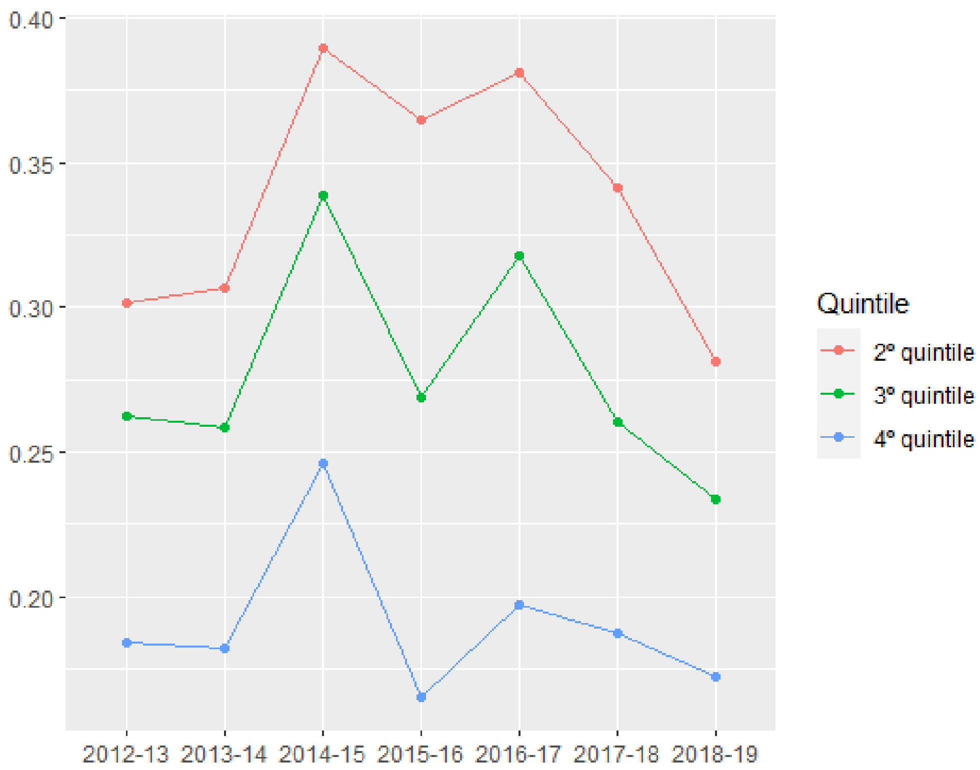


Source: PNADC, IBGE - author's elaboration

Comparing the changes in mobility between the pre-crisis and recovery periods for the extremes of the distribution I find that the richest quintile showed a 10% decrease in the probability of moving to a poorer quintile, while the poorest showed a 7% decrease in the probability of moving up in the distribution. This evidence suggests that the richest quintile benefited, in terms of mobility, with the economic crisis while the poorest were harmed.

Figure 3 shows us the probability of becoming richer for the middle quintiles. Results show that they presented similar patterns in the period, in which the 2nd and 3rd quintiles have considerably greater mobility than that of the 4th quintile. This evidence is counter-intuitive in relation to the structural income literature, since we would expect that the richest quintiles would be more likely to become richer, as they may face smaller barriers in the process of accumulating productive assets such as increased education, access to more stable formal jobs, inclusion in the credit market and access to social connections(Chantarat and Barrett (2012);Matsuyama (2004)).

Figure 3: Inter Annual Probability of rise from the 2nd, 3rd and 4th quintiles of structural income from 2012-13 to 2018-19



Source: PNADC, IBGE - author's elaboration

6 Observed and structural household income

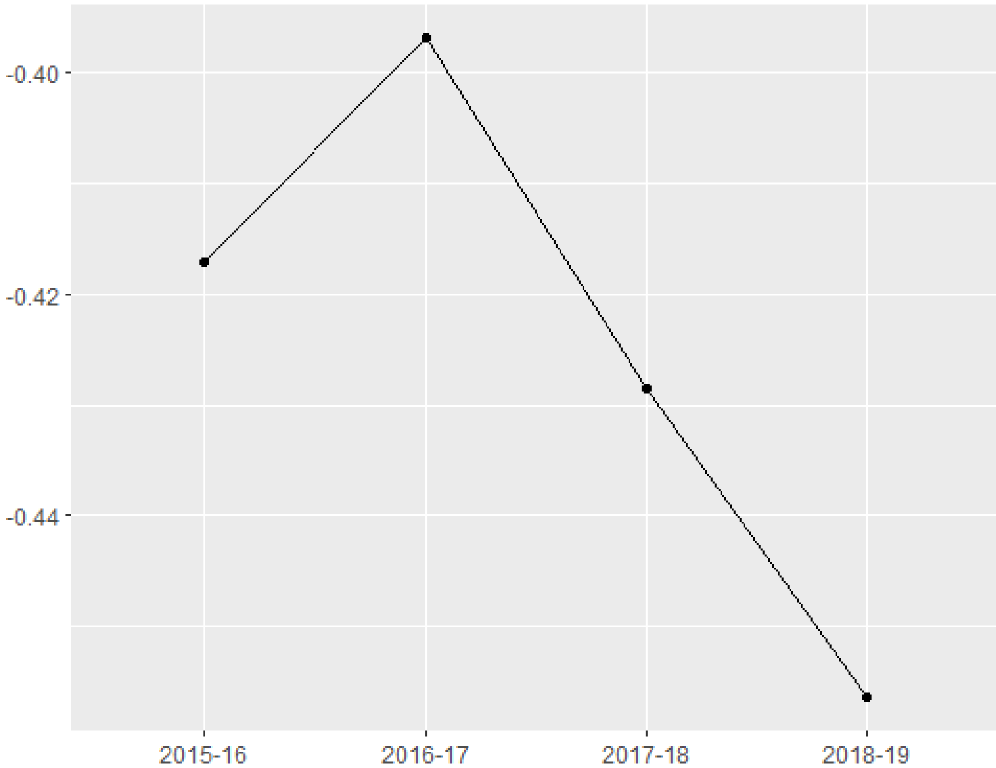
As mentioned in section 4, the absence of the fifth household interview in annual PNADC before 2016 do not allow the comparative analysis of the estimated structural income and observed income in the whole period (2012-2019). However, this section shows the decomposition of Gini changes and the evolution of β-Convergence and Leapfrogging effects using observed household income for the data we have (2016-2019), as a way of comparing with the results of structural income presented in section 5.

Considering the annual data for the 1st and 5th interviews for 2016, 2017,2018 and 2019, I do not need to use the quarterly bases, as done in 4. Hence, the observed household income was calculated using only the PNAD Continuous annual database for the first and fifth interviews. Similarly to what was done in section 4, the annual bases of the first and fifth interviews were merged through an identifier for each person within the household, creating a panel data.

6.1 Evolution of β-Convergence Effect

Figure 4 bellow shows the evolution of the β-Convergence of the observed household income from period 2015-2016 to 2018-2019. As we can see, the coefficient decrease (in module) during the recession and increase (in module) during the recovery, which indicates an increase in the P-component, as shown in table 8. Comparing with the β-Convergence of structural income, this coefficient remained stable between 2016 and 2017 and decrease (in module) in the following years. This means that the period of economic recovery had opposite effects in the income growth rate of the poorest between observed income and the structural income.

Figure 4: β-Convergence from 2015-16 to 2018-19



Source: PNADC, IBGE - author's elaboration

6.2 Evolution of Gini Changes decomposition

The results of the table 8 bellow show us that inter-annual inequality of the observed income is higher than the Gini Index of the structural income. The observed income Gini decreased between 2015 and 2016, while the structural income Gini increased. In 2016-2017 both structural and observed income Gini remained relatively stable. In the following years, the observed income Gini remained stable, while the structural income Gini increased in the period 2017-2018 and remained constant in the last year of the sample. Between 2016 and 2017, the increase in income inequality observed was associated with a decrease in both components. In the following year, the pro-poor growth component increased and the mobility component decreased, with the first outpacing the second. In the last year, R-component increased more than the P-component, which contributed to the increase in inequality.

Table 8: Gini Dynamics Decomposition of the Observed Household Income Per Capita

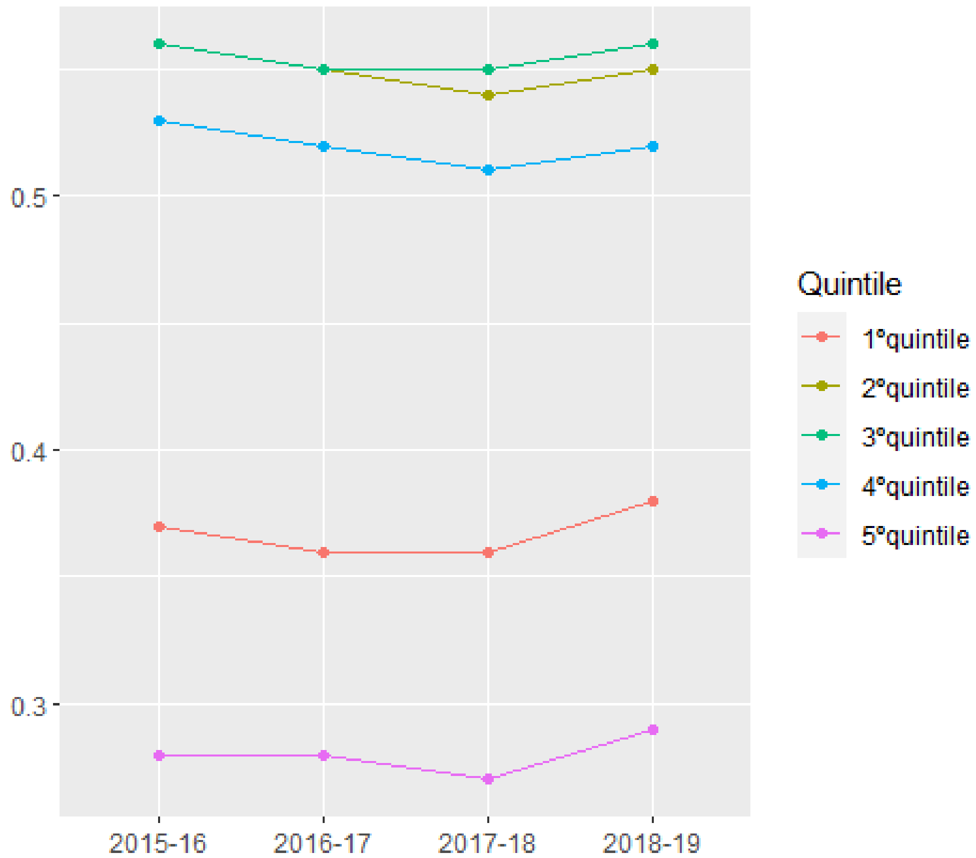
Decomposition	2015-16	2016-17	2017-18	2018-19
G0	0.5133	0.5156	0.5238	0.5286
G1	0.5086	0.5173	0.5204	0.5258
Gini Change	-0.0046	0.0017	-0.0035	-0.0027
Average R-component	0.0795	0.0787	0.0777	0.0913
Average P-component	0.0841	0.077	0.0812	0.0940

Source: Estimates from PNADC from 2016 to 2019,
based on Jenkins and Van Kerm (2006) methodology.

6.3 Evolution of Leapfrogging Effect

In this subsection, Figure 5 present the evolution of the leapfrogging effect from 2015-2016 to 2018-2019. The poorest and middle class presented similar patterns, with a decrease between 2016 and 2017, a stability between 2017 and 2018 and an increase in the last year. The second and fourth quintiles also showed a similar evolution, with a decrease in mobility in 2015-2018 and an increase between 2018 and 2019. The richest, however, showed a stability between 2016 and 2017, a decrease between 2017 and 2018, and an increase in the last year. Comparing with the structural income results, the two richest quintiles showed an increase in structural income mobility and a decrease in observed income mobility between 2017 and 2018. Moreover, in contrast to the increase in mobility observed with the observed income in the last year of the sample, structural income mobility decreased for all quintiles in that period.

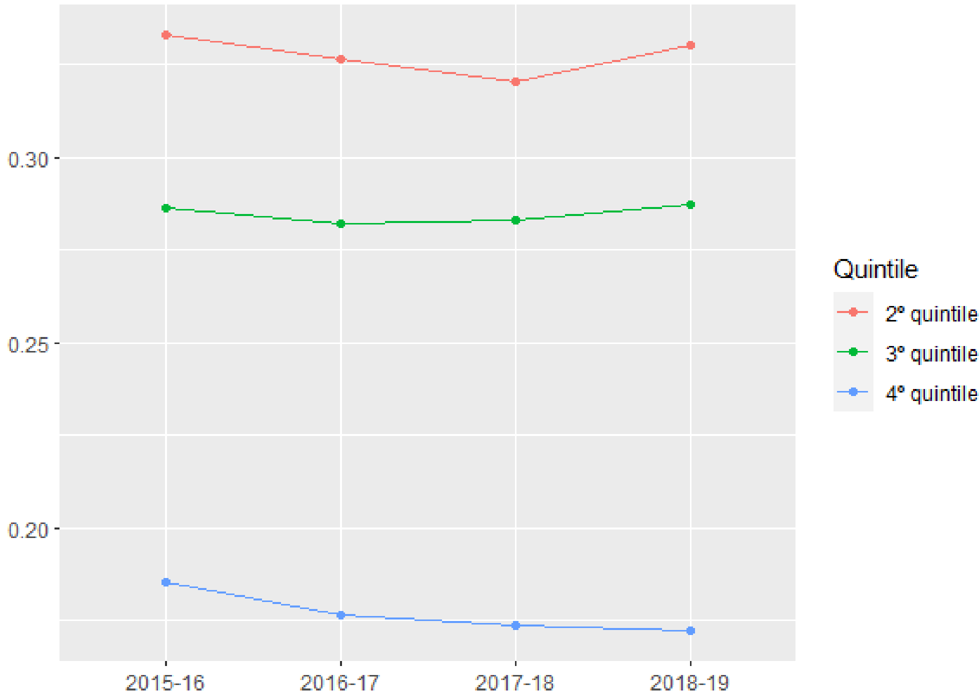
Figure 5: Inter Annual Probability of Changing Observed Per Capita Household Income Quintile from 2015-16 to 2018-19



Source: PNADC, IBGE - author's elaboration

Regarding the measure of ascension of the 2nd, 3rd and 4th quintiles, the results presented in figure 6 bellow shows that the probability of ascension of the 1st, 2nd and 3rd quintiles remained almost stable in the entire period, contrary to what was observed with structural income (increase for all quintiles between 2016 and 2017 and decreased in the following years).

Figure 6: Inter Annual Probability of rise from the 2nd, 3rd and 4th quintiles of observed income from 2015-16 to 2018-19



Source: PNADC, IBGE - author's elaboration

7 Conclusion

This paper showed that inter-annual inequality of structural income in Brazil increased after the economic crisis, with both less increasing income of the poorest and less mobility - but the second outpacing the first. Considering our longitudinal data on the same households for five quarters, I show that β-Convergence decreased by 26% (in module), from -0.20 to around -0.15. On the other hand, the pattern of the probability of a household to move from his structural household income quintile to another a year later was similar to the poorest and the richest. The exceptions are in the economic crisis period, where the richest lost income mobility (that is, they have benefited, since they are at the top of the distribution and having mobility means being relatively poorer) and the poorest have gained mobility (that is, they also benefited, since having mobility means getting relatively richer) and in the first year of recovery, where the poorest lost mobility while the richest showed an increase.

Comparing the whole period (2012-2019) for the extremes of the distribution I find that the richest quintile showed a 10% decrease in the probability of moving to a poorer quintile, while the poorest showed a 7% decrease in the probability of moving up in the distribution. This evidence suggests that the richest quintile benefited, in terms of mobility, with the economic crisis while the poorest were harmed. Regarding the middle class (3rdquintile), the loss of mobility between 2012 and 2019 was similar to that of the poorest quintile, with a decrease of about 6%. Moreover, the 2nd and 3rd quintiles have considerably greater mobility than that of the 4th quintile, which is counter-intuitive in relation to the structural income literature.

The results for the Gini coefficient showed that structural income inequality decrease between 2012 and 2015, increase between 2015 and 2016, remained stable in 2016-2017, increase between 2017 and 2018 and remained stable in 2018-2019. Decomposing the inter-annual Gini changes, we can see that both reranking effect and pro-poor income growth component decreased throughout the whole period. Between 2012 and 2015, the pro-poor income growth (P-component) was greater than the leapfrogging effect (R-component), which led to a reduction in inequality. In 2016, the R-component increased and overtaked the P-component, which meant a positive variation in the Gini coefficient. In 2017, the reranking effect decreased, while the P-component remained stable, which led to a small variation of inequality. In 2018, the reranking effect more than offset the diminishing effect forced by the income growth pro-poor, which contributed to a big increase in inequality. Finally, in 2019, the R-component decrease while the P-component increase, which kept the structural income inequality stable.

I also present the same analyzes using observed household income between 2015 and 2019, which are the years we have income data from all sources for both the first and fifth interviews. To sum up the compared results, the evolution of β-Convergence was different between structural and observed income. More specifically, the coefficient decrease (in module) during the recession and increase (in module) during the recovery, which indicates an increase in the P-component. Comparing with the β-Convergence of structural income, this coefficient remained stable between 2016 and 2017 and decrease (in module) in the following years.This evidence suggests that the period of economic recovery had opposite effects in the income growth rate of the poorest between observed income and the structural income.

Analyzing the evolution of observed income inequality, the recession period was characterized by a reduction in observed income inequality and an increase in structural income Gini. In 2016-2017 both structural and observed income Gini remained relatively stable. In the following years, the observed income Gini remained stable, while the structural income Gini increased in the period 2017-2018 and remained constant in the last year of the sample. Regarding the quintile transition matrices, the poorest and middle class presented similar patterns, with a decrease between 2016 and 2017 and an increase in the last year. The richest, however, showed a stability between 2016 and 2017, followed by a decrease in 2017-2018 and an increase in the last year of the sample.

There are some limitations of analysis derived from data restriction and methodology. First, the OLS estimation of the structural income do not allow for omitted variable issues,such as physical assets. Second, in this article, I do not consider the possibility of a positive relationship between income and marginal return on the productive assets included in the model. (Carter and Barrett (2006)).

Nevertheless, this study brings a novel longitudinal analysis for the period in Brazil and introduces the concept of structural income to the debate on poverty, inequality and socioeconomic mobility. Not only the structural income Gini is considerably smaller than the observed income Gini but the results suggest that the change in structural income inequality is greater than the change in income inequality observed. The analysis of structural income is relevant to the public policy debate as it introduces the concept of households' ability to generate income. This is important when considering development projects for a country, in which the poorest families are expected to suffer more from the instability and low income generation capacity.

Because of the absence of similar studies for Brazil to serve as a comparison, further research on structural income with more extensive panel data is needed to generate increasingly robust evidence about three facets of the structural income generation process: the persistence of poverty, the low income mobility in Brazil and the trend difference between structural and observed income. With this evidence, policy makers have a greater basis for building more effective and efficient policies to combat poverty and structural inequality.

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8 Annex

Table A1: Frequency of dummy regions - Annual PNADC

	2012	2013	2014	2015	2016	2017	2018	2019
North	17.67	18.2	18.43	18.2	18.57	18.46	18.12	20.97
South	26.7	26.3	26.08	26.33	26.18	26.11	26.12	24.90
Midwest	15.11	15.14	14.88	14.86	15.03	15.05	14.97	14.79
Southeast	40.53	40.36	40.61	40.61	40.22	40.38	40.8	39.32

Source: PNADC from 2012 to 2019

Table A2: Frequency of occupational groups - Annual PNADC

	2012	2013	2014	2015	2016	2017	2018	2019
Directors and managers	5.69	5.67	5.23	5.17	4.76	4.73	4.23	4.17
Science and intellectual professionals	7.44	7.41	7.77	7.84	8.15	8.48	9.36	9.48
Administrative support workers	4.49	4.57	4.54	4.49	4.36	4.56	5.03	4.91
Mid-level technicians and professionals	6.78	6.83	7.01	7.09	6.61	6.45	6.57	6.39
Skilled agricultural workers	12.76	12.35	12.4	13.15	14.01	13.41	13.61	13.60
Service and trade workers	15.61	16.19	16.89	17.44	18.66	20.1	20.44	21.32
Operators of installations and machines	15.21	14.9	14.72	14.96	14.72	14.01	13.52	13.18
Mechanical workers and construction craftsmen	10.15	9.76	9.48	9.24	8.82	8.65	8.73	8.33
Elementary occupations	21.26	21.62	21.04	19.58	18.88	18.58	17.46	17.66
Police and military firefighters	0.61	0.69	0.92	1.02	1.02	1.04	1.06	0.91

Source: PNADC from 2012 to 2019

Table A3: Mean of explanatory variables and per capita household income - Annual PNADC

Variables	2012	2013	2014	2015	2016	2017	2018	2019
Urban household	0.744	0.734	0.734	0.735	0.733	0.735	0.734	0.727
Female head of household	0.351	0.358	0.364	0.374	0.398	0.419	0.434	0.456
Number of kids under 5 years	0.275	0.269	0.252	0.243	0.236	0.233	0.226	0.338
Number of kids between 6 and 14 years	0.492	0.473	0.451	0.427	0.405	0.395	0.382	0.574
Number of kids between 15 and 17 years	0.173	0.166	0.161	0.157	0.153	0.146	0.136	0.198
Number of kids with 18+ years	0.518	0.501	0.498	0.492	0.49	0.49	0.481	0.682
Number of elderly within the household	3.237	3.178	3.12	3.074	3.039	3.02	2.978	2.426
Number of individuals within the household	3.237	3.178	3.12	3.074	3.039	3.02	2.978	3.694
Number of self-employed within the household	0.314	0.313	0.312	0.318	0.308	0.301	0.295	0.332
Age of the head of household	48	48	49	49	49	49	50	48
Years in current job of the head of household	2.366	2.344	2.335	2.307	2.221	2.139	2.106	2.11
Years of schooling of the head of household	7.513	7.591	7.726	7.852	7.917	8.146	8.353	8.499

Source: PNADC from 2012 to 2019

Table A4: Regression Results 2012-2013

	Dependent variable:	
	Log per capita household observed income	
	2012	2013
	(1)	(2)
(Intercept)	4.961***	5.152***
	(0.031)	(0.029)
Number of household members	-0.057***	-0.088***
	(0.006)	(0.005)
Age of head of the household	0.012***	0.012***
	(0.001)	(0.001)
Age of head of the household squared	0.00***	0.129***
	(0.000)	(0.000)
Urban household	0.135***	0.129***
	(0.009)	(0.008)
Years of education of head of the household	0.064***	0.063***
	(0.001)	(0.001)
One year in the current job	0.654***	0.497***
	(0.065)	(0.067)
Two years in the current job	0.745***	0.609***
	(0.063)	(0.065)
Three years in the current job	0.747***	0.616***
	(0.063)	(0.065)
Four years in the current job	0.781***	0.656***
	(0.062)	(0.008)
Number of kids up to 5 years	-0.204***	-0.165***
	(0.008)	(0.008)

	Dependent variable:	
	Log per capita household observed income	
	2012	2013
	(1)	(2)
Number of kids between 6 and 14 years	-0.175***	-0.137***
	(0.007)	(0.007)
Number of kids between 15 and 17 years	-0.191***	-0.156***
	(0.008)	(0.009)
Number of kids with 18+ years	-0.008	0.02**
	(0.006)	(0.006)
Number of employed household members	0.151***	0.166***
	(0.005)	(0.005)
Number of eldery members (60+ years)	0.155***	0.152***
	(0.007)	(0.006)
North region	0.115***	0.074***
	(0.012)	(0.011)
Midwest region	0.351***	0.343***
	(0.011)	(0.011)
South region	0.386***	0.373***
	(0.009)	(0.009)
Southeast region	0.286***	0.262***
	(0.007)	(0.007)
Directors and managers	0.205**	0.276***
	(0.063)	(0.065)
Science and intellectual professionals	0.201**	0.298***
	(0.062)	(0.065)
Mid-level technicians and professionals	-0.1	-0.043

	Dependent variable:	
	Log per capita household observed income	
	2012	2013
	(1)	(2)
	(0.062)	(0.065)
Administrative support workers	-0.307***	-0.259***
	(0.063)	(0.065)
Service and trade workers	-0.359***	-0.294***
	(0.062)	(0.064)
Skilled agricultural workers	-0.408***	-0.416***
	(0.063)	(0.065)
Operators of installations and machines	-0.315***	-0.249***
	(0.062)	(0.065)
Mechanical workers and construction craftsmen	-0.303***	-0.268***
	(0.062)	(0.064)
Elementary occupations	-0.550***	-0.504***
	(0.062)	(0.064)
Police and military firefighters	0.215**	0.211**
	(0.074)	(0.074)
Number of self-employed household members	-0.084***	-0.082***
	(0.006)	(0.006)
Female head of the household	0.047***	0.008
	(0.006)	(0.006)
Observations	137,938	145,074
R^2	0.343	0.346
Adjusted R^2	0.343	0.346
Residual Std. Error	21.416 (df 137906)	20.654 (df = 145042)

	Dependent variable:	
	Log per capita household observed income	
	2012	2013
	(1)	(2)
Note:	*p<0.05; **p<0.01; ***p<0.001	

Table A5: Regression Results 2014-2016

	Dependent variable:		
	Log per capita household observed income		
	2014	2015	2016
	(1)	(2)	(3)
(Intercept)	5.178***	5.119***	5.063***
	(0.029)	(0.029)	(0.03)
Number of household members	-0.057***	-0.067***	-0.059***
	(0.005)	(0.005)	(0.005)
Age of head of the household	0.01***	0.011***	0.006***
	(0.001)	(0.001)	(0.001)
Age of head of the household squared	0.00***	0.00***	0.00***
	(0.000)	(0.000)	(0.000)
Urban household	0.093***	0.103***	0.087***
	(0.008)	(0.008)	(0.009)
Years of education of head of the household	0.064***	0.061***	0.063***
	(0.001)	(0.001)	(0.001)
One year in the current job	0.41***	0.585	0.546*
	(0.066)	(0.409)	(0.255)
Two years in the current job	0.492***	0.654	0.693**
	(0.064)	(0.409)	(0.254)

	Dependent variable:		
	Log per capita household observed income		
	2014	2015	2016
	(1)	(2)	(3)
Three years in the current job	0.499***	0.663	0.723**
	(0.064)	(0.409)	(0.255)
Four years in the current job	0.542***	0.704	0.763**
	(0.063)	(0.409)	(0.254)
Number of kids up to 5 years	-0.193***	-0.195***	-0.19***
	(0.008)	(0.008)	(0.008)
Number of kids between 6 and 14 years	-0.178***	-0.17***	-0.165***
	(0.007)	(0.007)	(0.007)
Number of kids between 15 and 17 years	-0.193***	-0.19***	-0.209***
	(0.008)	(0.009)	(0.009)
Number of kids with 18+ years	-0.02**	-0.015*	-0.032***
	(0.006)	(0.006)	(0.006)
Number of employed household members	0.169***	0.164***	0.187***
	(0.005)	(0.005)	(0.005)
Number of eldery members (60+ years)	0.146***	0.145***	0.181***
	(0.006)	(0.006)	(0.006)
North region	0.073***	0.06***	0.061***

	Dependent variable:		
	Log per capita household observed income		
	2014	2015	2016
	(1)	(2)	(3)
	(0.011)	(0.011)	(0.011)
Midwest region	0.315***	0.32***	0.329***
	(0.01)	(0.01)	(0.011)
South region	0.356***	0.361***	0.369***
	(0.008)	(0.008)	(0.009)
Southeast region	0.237***	0.236***	0.253***
	(0.006)	(0.007)	(0.007)
Directors and managers	0.367***	0.273	0.259
	(0.064)	(0.409)	(0.254)
Science and intellectual professionals	0.377***	0.257	0.29
	(0.063)	(0.409)	(0.254)
Administrative support workers	-0.138*	-0.261	-0.279
	(0.064)	(0.409)	(0.254)
Mid-level technicians and professionals	0.054	-0.064	-0.046
	(0.063)	(0.409)	(0.254)
Skilled agricultural workers	-0.334***	-0.455	-0.453
	(0.064)	(0.409)	(0.254)

	Dependent variable:		
	Log per capita household observed income		
	2014	2015	2016
	(1)	(2)	(3)
Service and trade workers	-0.196**	-0.34	-0.343
	(0.063)	(0.408)	(0.254)
Operators of installations and machines	-0.14*	-0.282	-0.311
	(0.063)	(0.408)	(0.254)
Mechanical workers and construction craftsmen	-0.157*	-0.272	-0.287
	(0.063)	(0.409)	(0.254)
Elementary occupations	-0.377***	-0.522	-0.538*
	(0.063)	(0.408)	(0.254)
Police and military firefighters	0.35***	0.291	0.301
	(0.07)	(0.41)	(0.256)
Number of self-employed household members	-0.07***	-0.089***	-0.103***
	(0.005)	(0.005)	(0.006)
Female head of the household	0.021***	0.025***	0.035***
	(0.006)	(0.006)	(0.006)
Observations	149,052	149,423	151,284
R^2	0.343	0.342	0.342
Adjusted R^2	0.343	0.342	0.342
Residual Std. Error	20.284 (df = 149020)	20.693 (df = 149391)	21.865 (df = 151252)

	Dependent variable:		
	Log per capita household observed income		
	2014	2015	2016
	(1)	(2)	(3)
Note:			$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table A6: Regression Results 2017-2018

	Dependent variable:	
	Log per capita household observed income	
	2017	2018
	(1)	(2)
(Intercept)	4.816***	4.787***
	(0.031)	(0.031)
Number of household members	-0.005	-0.003
	(0.006)	(0.006)
Age of head of the household	0.005***	0.003**
	(0.001)	(0.001)
Age of head of the household squared	0.00***	0.00***
	(0.00)	(0.00)
Urban household	0.093***	0.105***
	(0.009)	(0.009)
Years of education of head of the household	0.064***	0.067***
	(0.001)	(0.001)
One year in the current job	0.549	0.315
	(0.447)	(0.195)
Two years in the current job	0.658	0.477*
	(0.447)	(0.194)
Three years in the current job	0.699	0.497*
	(0.447)	(0.195)
Four years in the current job	0.739	0.545**
	(0.447)	(0.194)
Number of kids up to 5 years	-0.228***	-0.218***
	(0.009)	(0.008)

	Dependent variable:	
	Log per capita household observed income	
	2017	2018
	(1)	(2)
Number of kids between 6 and 14 years	-0.209***	-0.216***
	(0.007)	(0.007)
Number of kids between 15 and 17 years	-0.249***	-0.254***
	(0.01)	(0.01)
Number of kids with 18+ years	-0.073***	-0.088***
	(0.007)	(0.007)
Number of employed household members	0.169***	0.17***
	(0.005)	(0.005)
Number of eldery members (60+ years)	0.176***	0.168***
	(0.007)	(0.006)
North region	0.041***	0.048***
	(0.012)	(0.012)
Midwest region	0.358***	0.348***
	(0.011)	(0.011)
South region	0.41***	0.412***
	(0.009)	(0.009)
Southeast region	0.255***	0.285***
	(0.007)	(0.007)
Directors and managers	0.437	0.649***
	(0.447)	(0.195)
Science and intellectual professionals	0.447	0.578**
	(0.447)	(0.194)
Administrative support workers	-0.125	0.059
	(0.447)	(0.194)

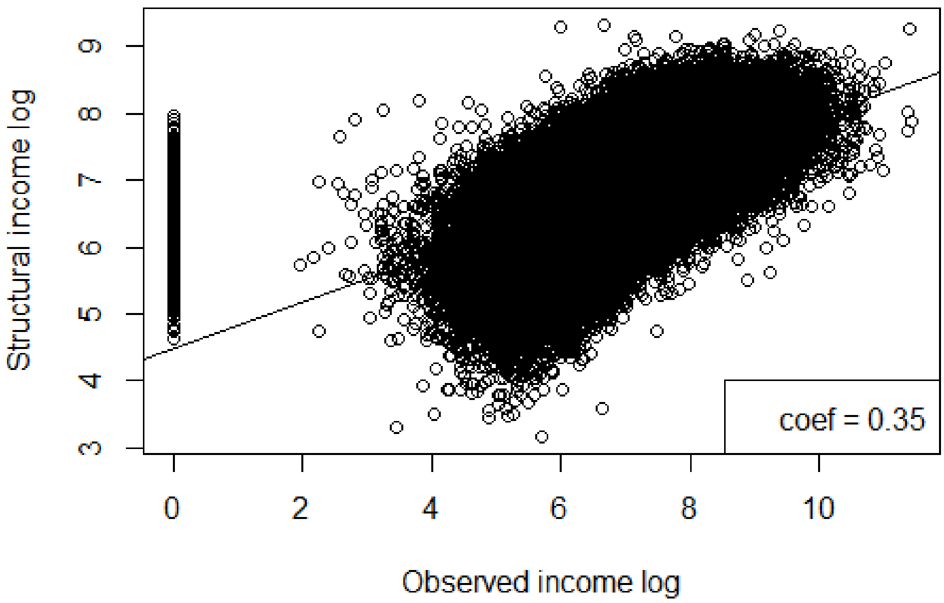
	Dependent variable:	
	Log per capita household observed income	
	2017	2018
	(1)	(2)
Mid-level technicians and professionals	0.07	0.273
	(0.447)	(0.194)
Skilled agricultural workers	-0.272	-0.069
	(0.447)	(0.194)
Service and trade workers	-0.215	-0.035
	(0.447)	(0.194)
Operators of installations and machines	-0.17	0.014
	(0.447)	(0.194)
Mechanical workers and construction craftsmen	-0.141	0.047
	(0.447)	(0.194)
Elementary occupations	-0.397	-0.226
	(0.447)	(0.194)
Police and military firefighters	0.532	0.721***
	(0.448)	(0.197)
Number of self-employed household members	-0.121***	-0.122***
	(0.006)	(0.006)
Female head of the household	0.063***	0.063***
	(0.006)	(0.006)
Observations	151,655	151,979
R^2	0.330	0.340
Adjusted R^2	0.329	0.340
Residual Std. Error	23.125 (df = 151623)	23.182 (df = 151947)
Note:		*p<0.05; **p<0.01; ***p<0.001

Table A7: Regression Results 2019

	Dependent variable: Log per capita household observed income
(Intercept)	4.8094***
	(0.0311)
Number of household members	0.0192***
	(0.0056)
Age of head of the household	0.0002
	(0.0011)
Age of head of the household squared	0.0002***
	(0.0000)
Urban household	0.109***
	(0.0008)
Years of education of head of the household	0.0701***
	(0.0008)
One year in the current job	0.7884**
	(0.2531)
Two years in the current job	0.9708***
	(0.2523)
Three years in the current job	1.0263***
	(0.2524)
Four years in the current job	1.0544***
	(0.2522)
Number of kids up to 5 years	-0.2392***
	(0.0086)
Number of kids between 6 and 14 years	-0.2385***
	(0.0074)
Number of kids between 15 and 17 years	-0.2803***
	(0.0066)
Number of kids with 18+ years	-0.0947***
	(0.0066)
Number of employed household members	0.1366***
	(0.0054)
Number of eldery members (60+ years)	0.1566***
	(0.0064)
North region	0.0364**
	(0.0115)
Midwest region	0.3607***
	(0.0115)
South region	0.44***

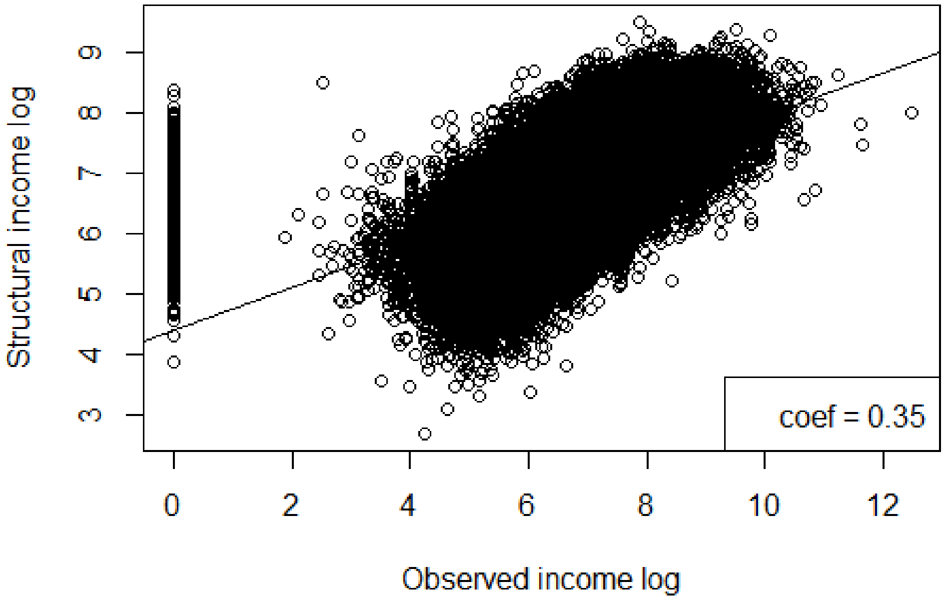
	Dependent variable: Log per capita household observed income
	(0.0091)
Southeast region	0.3289***
	(0.0071)
Directors and managers	0.1647
	(0.2524)
Science and intellectual professionals	0.0973
	(0.2522)
Mid-level technicians and professionals	-0.2331
	(0.2523)
Administrative support workers	-0.4358
	(0.2523)
Service and trade workers	-0.5161*
	(0.252)
Skilled agricultural workers	-0.554*
	(0.2524)
Operators of installations and machines	-0.437
	(0.2521)
Mechanical workers and construction craftsmen	-0.4858
	(0.2522)
Elementary occupations	-0.7079**
	(0.2521)
Police and military firefighters	0.2257
	(0.2546)
Number of self-employed household members	-0.1136***
	(0.006)
Female head of the household	0.0414***
	(0.0062)
Observations	150,667
R^2	0.339
Adjusted R^2	0.339
Residual Std. Error	23.542 (df = 150635)
F Statistic	2,491*** (df = 31; 150635)
Note:	*p<0.05; **p<0.01; ***p<0.001

Figure B1: Scatter plot of observed and structural household income from 1º interview of 2015



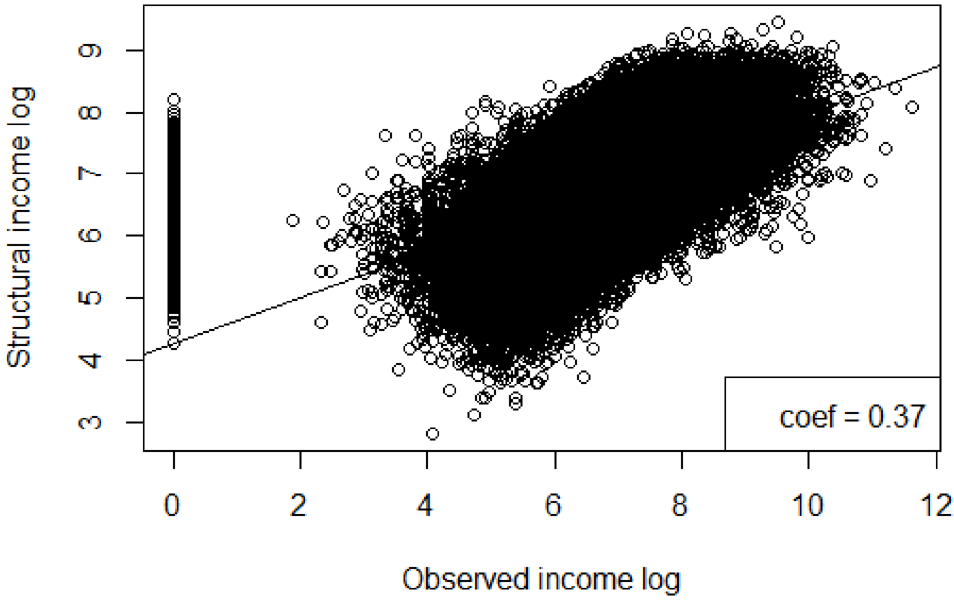
Source: PNADC, IBGE - author's elaboration

Figure B2: Scatter plot of observed and structural household income from 5º interview of 2016



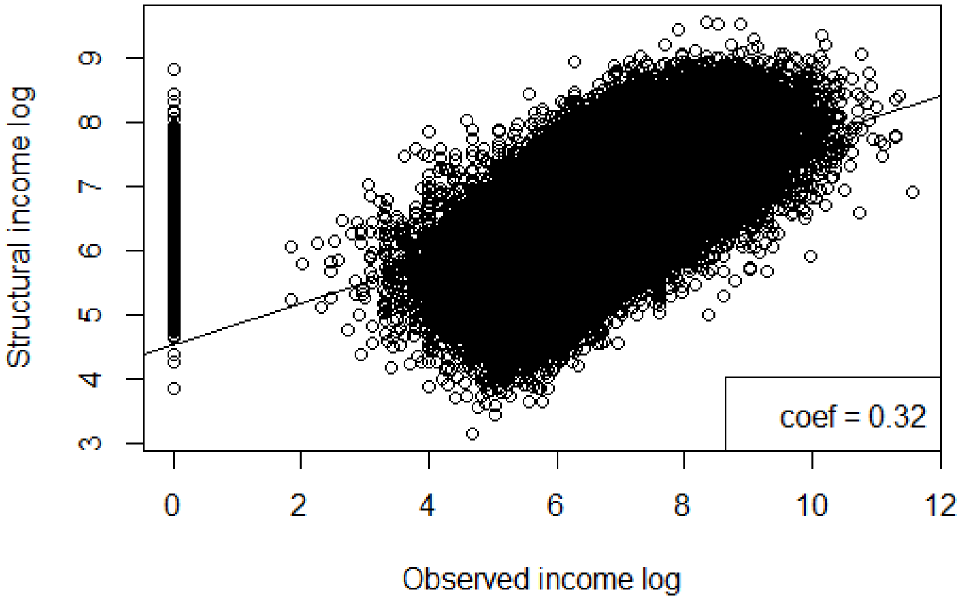
Source: PNADC, IBGE - author's elaboration

Figure B3: Scatter plot of observed and structural household income from 1º interview of 2016



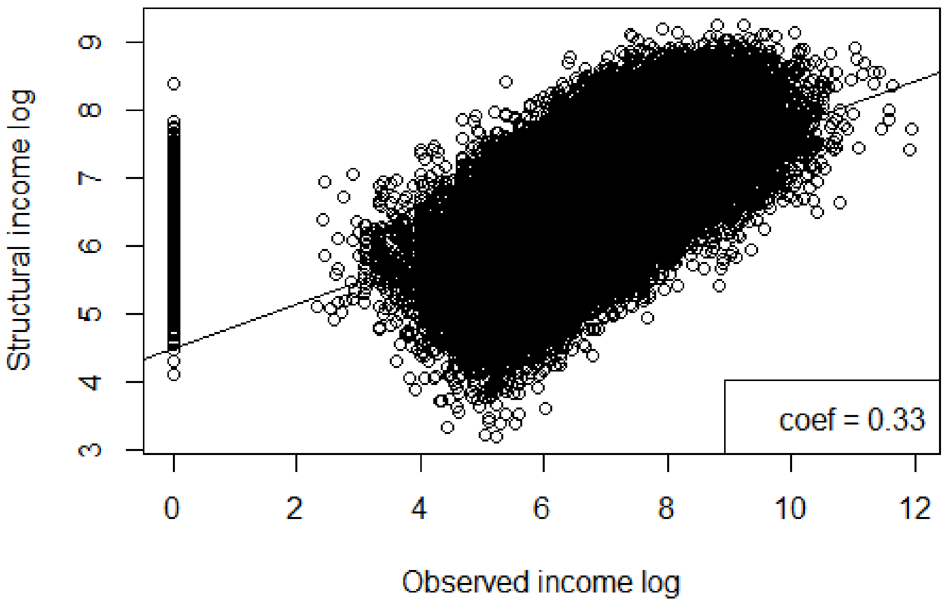
Source: PNADC, IBGE - author's elaboration

Figure B4: Scatter plot of observed and structural household income from 5º interview of 2017



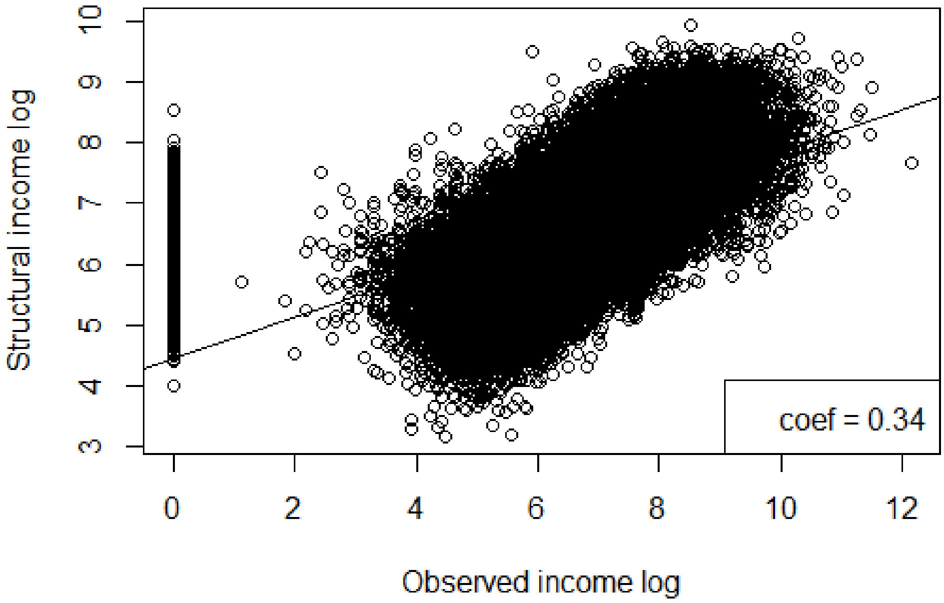
Source: PNADC, IBGE - author's elaboration

Figure B5: Scatter plot of observed and structural household income from 1º interview of 2017



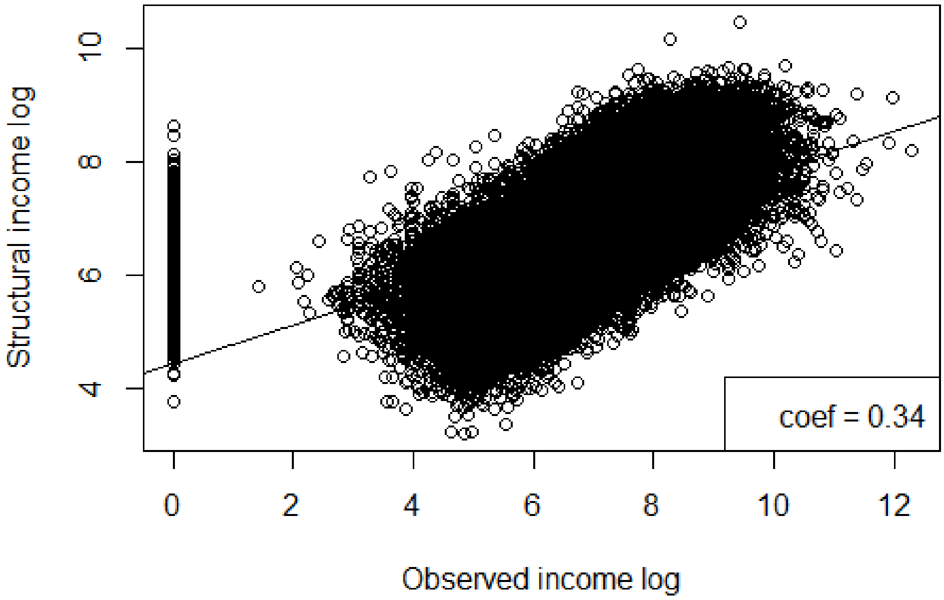
Source: PNADC, IBGE - author's elaboration

Figure B6: Scatter plot of observed and structural household income from 5º interview of 2018



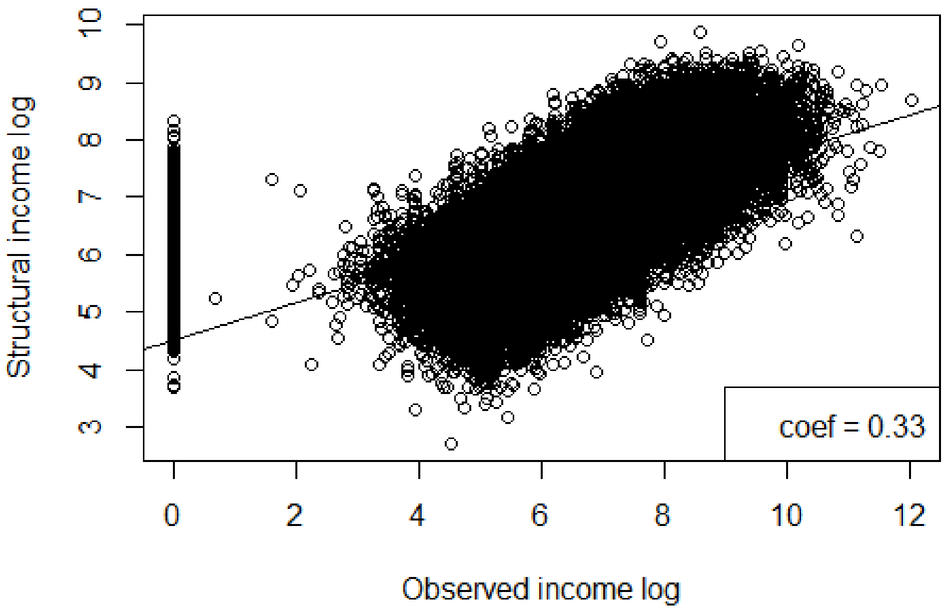
Source: PNADC, IBGE - author's elaboration

Figure B7: Scatter plot of observed and structural household income from 1º interview of 2018



Source: PNADC, IBGE - author's elaboration

Figure B8: Scatter plot of observed and structural household income from 5º interview of 2019



Source: PNADC, IBGE - author's elaboration