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Four decades of consumption inequality in Brazil (1987-2018)

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Although Brazil is a major developing economy and one of the most unequal countries in the world, there are notably few estimates of consumption inequality for that country. In this paper, we present the most comprehensive time series of consumption inequality ever built for Brazil, covering over four decades (1987-2018). We also innovate compared to previous analysis by estimating demand systems and using the estimated Engel income elasticities to correct for several forms of measurement error. This is especially important since older rounds of the Brazilian consumption survey are plagued with mismeasurement, biasing previous estimates. We find that when considering the ratio of the top 10\% to the bottom 40\% of income, consumption inequality remained constant until the mid-1990s, and has since decreased sharply to about 60\% of its initial levels.

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January, 2026

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Although Brazil is a major developing economy and one of the most unequal countries in the world, there are notably few estimates of consumption inequality for that country. In this paper, we present the most comprehensive time series of consumption inequality ever built for Brazil, covering over four decades (1987-2018). We also innovate compared to previous analysis by estimating demand systems and using the estimated Engel income elasticities to correct for several forms of measurement error. This is especially important since older rounds of the Brazilian consumption survey are plagued with mismeasurement, biasing previous estimates. We find that when considering the ratio of the top 10% to the bottom 40% of income, consumption inequality remained constant until the mid-1990s, and has since decreased sharply to about 60% of its initial levels.

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1 Introduction

Brazil is a paradigmatic example of high inequality worldwide. Recent work has shown that, at least since the early 20th century, income has been severely concentrated in the hands of the top 10 and top 1% of the income distribution, showing a small decrease only in the last few decades. In fact, in the 1970s, almost two-thirds of income was concentrated in the top 10%, and it has decreased only about ten percentage points since (Souza 2018).

Although income inequality is an important concept, as it is the closest measure of an individual's purchasing power and their ability to command labor from others in society, another important concept worth investigating is consumption inequality, as consumption is the economic concept closest to individual utility. Therefore, investigating trends in consumption inequality can inform us about how (economic) utility varies among people in a society.

From a conceptual perspective, income is an imperfect proxy for individual welfare. Consumption reflects realized living standards more directly, as it incorporates households' ability to smooth income fluctuations, self-insure against shocks, and reallocate resources over the life cycle. Since individuals tend to smooth consumption over time, consumption inequality better captures inequality in life-cycle income, rather than "income snapshots" that do not reflect how rich each person is over their lifetime. As a result, income and consumption inequality need not evolve in parallel, even in the absence of changes in preferences or technology. In contexts where income volatility, informality, and credit constraints are salient, such as in developing economies, exclusive reliance on income inequality may therefore provide a misleading picture of underlying welfare dynamics.

Historically, however, much greater emphasis has been placed on measuring income inequality. This is due to the fact that individual and household consumption are much harder to observe than income, depending on large-scale consumption surveys that only became available in the second half of the past century, and because these surveys are often riddled with measurement error. Indeed, all previous attempts to measure consumption inequality in Brazil found that results varied widely depending on the categories used or the assumptions made, indicating severe measurement errors (Barros, Cury, and Ulyssea 2007; Diniz et al. 2007; Silveira and Palomo 2023).

Our paper is the first to measure Brazilian consumption inequality across four decades, considering all five waves of the Brazilian household budget survey *Pesquisa de Orçamentos Familiares* (POF): 1986/87, 1995/96, 2002/03, 2008/09 and 2017/18. As mentioned above, especially older rounds of the survey were riddled with measurement errors. Comparing these disparate surveys is only possible because we employ a method of estimating consumption inequality by verifying how high-income and

low-income households allocate their expenses between luxuries and necessities (Aguiar and Bils 2015). This method does not require overall consumption to be well measured, and we see that results are surprisingly stable regardless of the categories used or the regression specification, unlike previous attempts in the literature.

By providing a consistent long-run perspective on consumption inequality, this paper contributes to the broader literature on inequality measurement and welfare analysis. Our results show that consumption inequality can exhibit dynamics that differ markedly from those of income inequality, and that measurement choices play a central role in shaping conclusions about long-run inequality trends. In this sense, Brazil serves as an informative case for understanding how data limitations and survey design can affect the assessment of welfare inequality in both developing and developed economies.

To see how survey mismeasurement might be a problem, consider a case where old surveys did not ask about consumption goods that are disproportionately consumed more by richer households (luxuries). Then consumption inequality would be downward-biased in these older surveys. Even worse, if this measurement error decreased over time as the quality of the survey improved, we would observe in the estimates an increase in consumption inequality due purely to measurement error bias. Therefore, and especially since we use old Brazilian surveys in this analysis, it is essential to employ a method robust to measurement error to estimate inequality in the consumption survey data.

The idea of our method, following Aguiar and Bils 2015, is to estimate Engel curve (income) elasticities of consumption for different categories of goods (a demand system). Then, by tracking how consumption across these categories varies over time across different quantiles of the income distribution, we can determine whether their overall consumption increased or decreased, even if total consumption is measured with error. Intuitively, if low-income households are consuming more relative to high-income households (consumption inequality is decreasing), we should observe a shift in their consumption basket towards luxuries at a higher rate than high-income households. As we demonstrate in detail in the paper, this method is robust to both household-income-specific and good-category-specific measurement errors.

We depict the main measures of economic inequality available from raw survey data in Figure 1. The triangle lines present the top 10% to bottom 40% income ratio as measured in the 1990 Brazilian Census and the *Pesquisa Nacional por Amostra de Domicílios* (PNAD), and its later design, *PNAD Contínua*. The red series denote income inequality measures considering the top 1%, and in blue inequality considering the top 10% without the top 1%, to be better comparable with our analysis (in which we do the same).[1] Then we have the circle lines, which present income inequality after

1. As we explain below, in the entire analysis we trim the upper 1% of the distribution, as outliers

taxes and transfers, using the BRASMOD microssimulation model for Brazilian tax and transfers system (Bottega et al. 2024). We also present, for comparison, a World Inequality Database series for income inequality in Brazil, shaped as saltire (World Inequality Database 2024). Finally, the squares depict income (blue) and consumption (green) inequality as measured in the POF, the data we use for our main analysis.[2]

Figure 1 shows that income inequality in Brazil is extreme, with the top 10% receiving at the beginning of our sample more than 30 times the average income of the poorest 40%, and nowadays still more than 20 times more. While our different measures vary somewhat, they all agree that there has been a steady and significant decrease in income inequality in this period, at least until 2015. On the other hand, consumption inequality as measured in the surveys is substantially smaller than income inequality. While in 2018 the top 10-1% earned 16 times as much income than the bottom 40% in Brazil, and after taxes and transfers still had an income 11 times larger, they consumed only 4.5 times as much. Interestingly, inequality after taxes and transfers seems to follow closely market income inequality for most of the period, implying that the difference we observe is not due to government intervention.[3]

Before moving on, we note that by analyzing using the raw data Brazilian consumption inequality, it might seem that Brazil has experienced a large and consistent decline in consumption inequality throughout our sample. In reality, this is due to measurement error, as our estimates show that consumption inequality only began to decrease after 1996, falling significantly (by 27.5%) during 1997-2008, and then less sharply (20%) in the decade after that.[4]

Our paper proceeds as follows. In Section 2 we review available estimates of income and consumption inequality in Brazil. In Section 3 we explain our data and data-cleaning process (a longer explanation is available in the Online Appendix), in Section 4 we explain our empirical methodology and in Section 5 we present and discuss our results. Finally, we conclude.

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could increase the variance of our estimator. The discussion here should be understood as measuring the inequality between the bottom 40% and the top 10-1%, excluding the richest 1%. This is not a feature of our investigation alone: inequality at the top is well known to be hard to measure using population surveys.

2. It is clear from Figure 1 that income in the 1996 wave of POF is measured with significant error. On that, we note that POF income data is not used in our main analysis.

3. It is a well-discussed stylized fact that even with the social assistance programs of Brazilian government, since the tax system has very limited progressivity, government in Brazil has overall a small effect in reducing inequality.

4. We make a more detailed comparison between the raw data consumption inequality and our estimated inequality trends in Section 5.3, especially Figure 8.

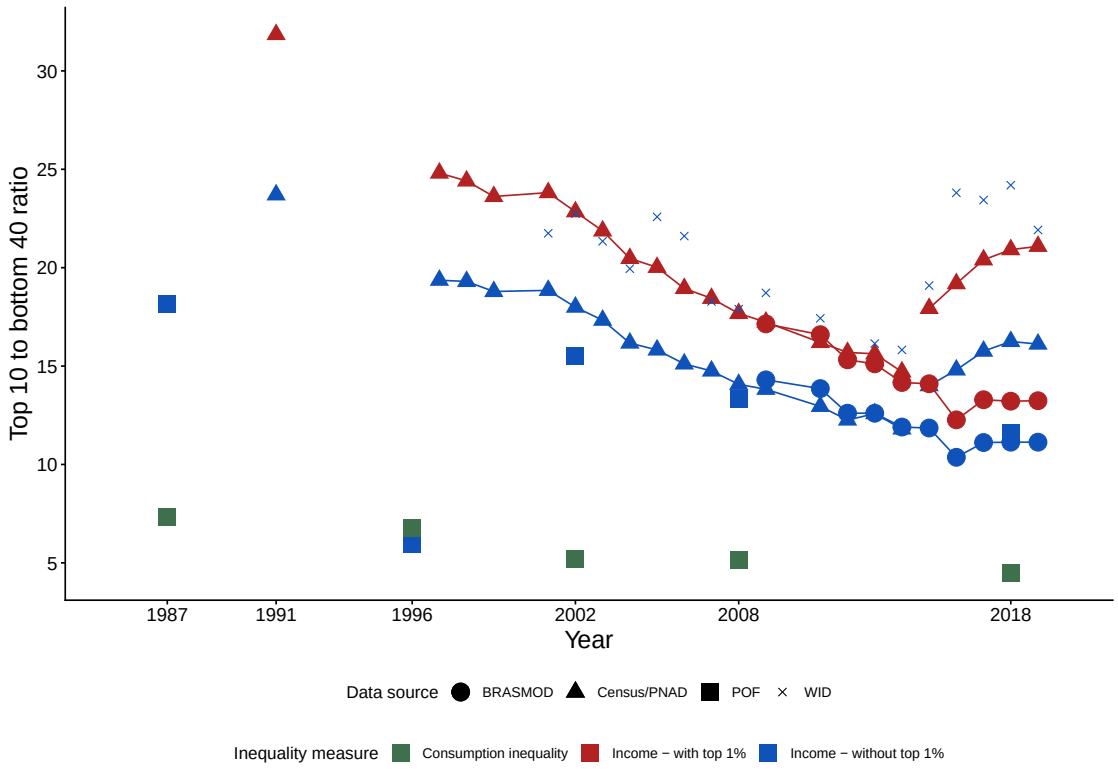


Figure 1: Trends in income and consumption inequality

Note: In the vertical axis we present the top 10% to bottom 40% ratio measures of inequality for different years and data sets. The red triangle line uses Census data for 1991, PNAD data from 1997 until 2015 and PNADc data from 2016 to 2019. The blue triangle line presents the results for the same surveys, but removing the top 1% for comparability with our methods. Squares use POF data, the blue points represent income inequality measured in POF, and green points the consumption inequality from the POF raw data. Circle lines present income inequality after tax and transfers calculated using BRASMOD. The rotated crosses are from My World in Data, for comparison.

2 Inequality trends in Brazil

In this section, we document descriptive trends in inequality across income and consumption measures using Brazilian household and administrative data. The goal to provide a consistent empirical backdrop for the econometric analysis that follows.

2.1 Income inequality trends

Early empirical studies on income distribution in Brazil consistently documented extremely high levels of inequality, placing the country among the most unequal in the world throughout the 1980s and early 1990s. Using household survey data, this literature emphasized not only the magnitude but also the persistence of income concentration, with little evidence of convergence over time to the level of most advanced economies. At the same time, methodological work highlighted that

inequality measures based on household surveys are likely to understate true concentration—particularly at the top of the distribution—due to income under-reporting and the limited coverage of capital income (Hoffmann 1988). While such issues primarily affect the level of measured inequality, they underscored the possibility that true income disparities were even larger than those captured in survey data.

Despite substantial macroeconomic changes stemming from stabilization and trade liberalization during the 1990s, income inequality in Brazil remained both high and largely stable. Analyses relying on *Pesquisa Nacional de Amostra Domiciliar* (PNAD) household survey data found no clear downward trend through most of the decade. This reinforced the view that income concentration was structurally entrenched and unresponsive to short-run macroeconomic improvements (Barros, Henriques, and Mendonça 2001). By the decade's close, the prevailing assessment was clear: inflation control brought important welfare gains but failed to yield significant reductions in inequality. Thus, entering the 2000s, high inequality appeared to be a persistent feature of Brazil's economy.

This picture began to change in the early 2000s. A series of studies documented a statistically significant and sustained decline in income inequality starting in the mid-1990s and intensifying after 2001, as measured by the Gini coefficient and alternative distributional indicators derived from PNAD data (Barros, Foguel, and Ulyssea 2006; Hoffmann 2006; Soares and Osório 2006). Importantly, this decline was observed across a range of inequality measures and was robust to alternative welfare definitions and equivalence scales. Ferreira, Leite, and Litchfield (2008) further showed that the reduction reflected a combination of declining labor-income dispersion—associated with changes in educational attainment and returns—and the expansion of targeted transfer programs, thereby situating Brazil's experience within a broader comparative context.

Viewed together, the literature reveals a clear descriptive pattern in Brazil's survey-based income data: persistently high inequality throughout the 1980s and 1990s, followed by a marked decline in the 2000s.[5]

More recent work has revisited trends in income inequality in Brazil by exploiting administrative tax data. However, data coverage and integration differ importantly across studies. Early contributions primarily relied on personal income tax (PIT) tabulations to assess income concentration and the distributional effects of taxation. Through this approach, Gobetti and Orair (2017) and Fernandes, Campolina, and Silveira (2019) document high and persistent inequality at the top of the income distri-

5. Household survey–based income inequality measures may be affected by under-reporting, especially at the top (Hoffmann 1988). Nevertheless, PNAD's internal consistency and comparability over time have established it as the primary source for analyzing long-run trends (Barros, Foguel, and Ulyssea 2006; Soares and Osório 2006). While measurement issues may affect level estimates, they seem unlikely to explain the trends themselves.

bution. They also emphasize the role of capital income and the limited progressivity of direct taxes.

Building on this, subsequent work combined tax tabulations with household surveys to improve coverage of the full income distribution. Medeiros, Souza, and Castro (2015), together with Souza (2018), were among the first to integrate PIT tabulations with PNAD microdata to estimate inequality trends, showing that survey-based measures substantially understate income concentration at the top. While this hybrid approach represented an important advance, it relied on partial coverage of business income and did not fully allocate undistributed corporate profits to individuals.

More recent studies have further extended this framework by reconciling tax-based estimates with national accounts. For instance, De Rosa, Flores, and Morgan (2024) incorporate business income following standard assumptions from the distributional national accounts literature. As a result, researchers can make consistent cross-country comparisons of top income shares. The most recent generation of studies, meanwhile, takes a different tack by exploiting linked administrative microdata that combine personal and corporate tax records. With this approach, income sources and tax liabilities at the individual level become directly observable. For example, using such integrated administrative data, Palomo et al. (2025) provide comprehensive evidence on income concentration and tax progressivity in Brazil. By relying on integrated data, this method substantially reduces the imputation assumptions required in earlier work.

Taken together, this literature suggests a more nuanced view of recent inequality dynamics in Brazil. Survey-based measures document a decline in income inequality during the 2000s, followed by relative stability in the early 2010s. Yet, tax and administrative data point to persistently high income concentration at the top. Some estimates suggest that top income shares stabilize rather than decline after the 2000s, implying that reductions in inequality primarily reflect redistribution between income deciles below the upper tail of the distribution (Medeiros, Souza, and Castro 2015; De Rosa, Flores, and Morgan 2024; Palomo et al. 2025). Consequently, assessments of post-2010 inequality trends depend critically on data coverage and the treatment of capital and business income. Such differences underscore the importance of measurement choices for interpreting recent distributional dynamics.

While this literature has substantially advanced our understanding of income inequality dynamics in Brazil, considerably less is known about the evolution of consumption inequality over the same period. From a welfare perspective, consumption provides a complementary lens on inequality, yet existing evidence for Brazil remains limited and largely confined to repeated cross-sections of household expenditure surveys.

2.2 Consumption inequality

While income inequality has been the primary focus of the literature on distributional dynamics in Brazil, consumption inequality provides a complementary perspective on economic well-being. From a welfare perspective, consumption provides a complementary lens on inequality that differs conceptually from income. While income reflects the flow of resources available to households at a point in time, consumption captures realized living standards and incorporates households' ability to smooth income fluctuations over the life cycle through saving, borrowing, and informal insurance mechanisms. In standard life-cycle and permanent-income frameworks, consumption inequality is therefore expected to respond less strongly than income inequality to transitory shocks, particularly in the presence of credit access or effective risk-sharing arrangements (Attanasio and Pistaferri 2016). As a result, trends in consumption inequality need not mirror those observed for income, making consumption an informative object of study in its own right.

Early empirical evidence from the United States suggested a substantial decoupling between income and consumption inequality. Using household survey data, Krueger and Perri (2006) document that while income inequality rose sharply from the 1980s onward, consumption inequality increased much more modestly, which they interpret as evidence of improved consumption smoothing and expanded risk sharing. Subsequent work using improved consumption measures, however, qualified this conclusion. Exploiting a newly constructed consumption series from the Panel Study of Income Dynamics (PSID) in the US, Attanasio and Pistaferri (2014) show that consumption inequality increased more than previously documented, particularly over longer horizons, although still less than income inequality. Their results underscore the importance of data quality and consumption measurement for reassessing long-run inequality trends.

Evidence from the Great Recession further illustrates the distinct behavior of income and consumption inequality over the business cycle. Meyer and Sullivan (2013) show that income inequality rose sharply during the recession, while consumption inequality increased by substantially less, reflecting both consumption smoothing and the role of government transfers. At the same time, they emphasize that conclusions about the relative evolution of income and consumption inequality depend critically on how consumption is measured and on the treatment of housing and durable goods. More recent work by Meyer and Sullivan (2023) revisits long-run US consumption dynamics using enhanced expenditure measures, documenting substantial increases in consumption inequality over the past several decades and highlighting the sensitivity of these trends to measurement choices and definitions of consumption aggregates. More generally, concerns about mismeasurement have been formalized in subsequent

work. Aguiar and Bils (2015) argue that standard expenditure surveys systematically understate changes in consumption inequality and propose corrections based on Engel curve restrictions, finding that corrected consumption inequality tracks income inequality much more closely. Recent reassessments using alternative data sources and refined consumption definitions reach similar conclusions, while continuing to stress the sensitivity of estimates to measurement choices (Meyer and Sullivan 2023).

While the international literature has emphasized both the welfare relevance of consumption inequality and the sensitivity of its empirical measurement, evidence for Brazil remains comparatively limited in scope. Existing studies rely almost exclusively on cross-sections of POF and typically compute inequality measures using observed expenditure aggregates, often without a systematic treatment of measurement error or comparability across waves. Differences in survey design, consumption classification, and aggregation choices across waves imply that resulting estimates are often not directly comparable over time or across studies. As a result, the Brazilian literature has primarily documented levels of consumption inequality at specific points in time, with less consensus on long-run trends.

Studying consumption inequality in Brazil is possible due to POF, which provides detailed household-level information on expenditures and living conditions across five waves starting in 1986. Since the late 1980s, however, the POF has been conducted at irregular intervals, with changes in questionnaire design, item classification, and recall periods across waves. Most existing studies exploit individual POF cross-sections to compute standard inequality measures for aggregate consumption or selected expenditure categories, rather than constructing harmonized series across surveys.[6]

Early contributions using the 1987/88, 1995/96, and 2002/03 POF waves document high levels of consumption inequality in Brazil, comparable in magnitude to those observed for income. These studies emphasize that estimated inequality levels depend sensitively on how consumption is defined, particularly with respect to the inclusion of housing services and durable goods (Silveira 2004; Barros, Cury, and Ulyssea 2007; Diniz et al. 2007; Silva, Araújo, and Souza 2007). Across specifications, however, the dispersion of household consumption is found to be substantial, underscoring the extent of inequality in material living standards.

Evidence on the evolution of consumption inequality over time is more heterogeneous. Some studies report modest declines in inequality between the late 1990s and early 2000s, broadly in line with survey-based income trends, while others find relative stability or divergent patterns across consumption categories. These differences largely reflect variation in expenditure aggregation, equivalence scales, and the treat-

6. Appendix Table A2 summarizes the main studies estimating consumption inequality in Brazil using POF data, all of them discussed in this subsection.

ment of housing and non-durable consumption, which earlier work already showed to be central for interpreting income–consumption inequality gaps in Brazil (Hoffmann 2010; Souza 2015; Hoffmann and Vaz 2021). As a result, estimated trends are often specific to particular definitions and survey waves, limiting their comparability across studies.

More recent work extends the analysis to later POF waves and revisits consumption inequality using updated classifications. Silveira and Palomo (2023), for instance, document that inequality levels and trends continue to vary markedly depending on whether total consumption or narrower aggregates are considered, reinforcing earlier findings on the sensitivity of results to methodological choices. Taken together, this literature suggests that while consumption inequality in Brazil is persistently high, its evolution over time is less firmly established than that of income inequality, largely due to heterogeneity in consumption definitions and measurement approaches.

Overall, the study of consumption inequality in Brazil has been hampered by the lack of a coherent approach to dealing with measurement error in household expenditure surveys. As a result, existing estimates vary substantially with the choice of consumption categories (particularly the treatment of durables *versus* non-durables) and the methodology applied, raising concerns about bias and comparability over time. In this study, we address these limitations by correcting for measurement error and show that our estimates are notably invariant to empirical specifications and consumption definitions.

3 Data

In this section, we briefly describe our dataset and the expenditure categorization that we applied to harmonize and analyze the different waves of the Brazilian consumption survey. A more detailed description of our data preprocessing as well as differences accros each POF wave can be found in the Online Appendix B.

The data are drawn from the *Pesquisa de Orçamentos Familiares* (POF), a household survey conducted by the Brazilian Institute of Geography and Statistics (IBGE). Its main objectives are measuring the consumption structures of households and creating tools that make it possible to outline a profile of the population's living conditions based on their household budgets. The first wave of POF was first carried out between 1987 and 1988, and then repeated at irregular intervals over the next four decades (1995-1996, 2002-2003, 2008-2009, and 2017-2018), constituting overall five waves of the survey.

In its first two editions, POF's geographic coverage included the metropolitan areas of the state capitals Belém, Fortaleza, Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo, Curitiba, and Porto Alegre, as well as the Federal District and

the municipality of Goiânia. Beginning in 2002–2003, the survey was expanded to a national scope, thereby covering a sample of the entire urban and rural territory of Brazil.[7]

All POF waves are reported from a 12-month period basis. Except for POF 1987/88 wave (which was conducted when the Brazilian currency was the Cruzado, during a period of hyper-inflation in Brazil), all other editions were elaborated in Reais. Indeed, the 1987/88 wave was actually conducted through 18 months, because its first 6 months were considered unfit for use, since they coincided with an atypically high inflation period. This anecdote emphasizes the possibility of consumption mismeasurement to be widespread in the earlier surveys.[8]

The basic unit of analysis for both income and expenses in the POF and in this paper is the "consumption unit" (CU), which for the purposes of our study will be equivalent to family and our basic unit of analysis. Given the presence of outliers and their potential impact on our intertemporal assessment of consumption inequality, we trim the bottom and top 1 percent of the per capita family income distribution. Although this procedure does not fully eliminate outliers, a more aggressive trimming would be detrimental to the analysis, as a substantial share of income inequality in Brazil is concentrated in the top 10 and top 5 percent of the income distribution.

Additionally, we exclude families whose household head is younger than 18, as well as households reporting zero expenditure on food consumed at home, food consumed away from home, and housing combined. The latter exclusion is motivated by the fact that it is not feasible for a household to incur zero expenditure in all three categories over the entire survey period, which suggests a reporting error.

To document differences across income levels, households are grouped into seven income bins based on before-tax income[9], corresponding to the 1st–10th, 10th–20th, 20th–40th, 40th–60th, 60th–80th, 80th–90th, and 90th–99th percentiles. For each income group and survey wave, expenditure and income measures are expressed as per capita averages, obtained by dividing total household values by the number of household members. Our primary measure of inequality is the ratio of the mean income of the top group to the mean income of the bottom 40 percent of the distribution.

Turning to specific expenditures, the treatment of imputed rent for owner-occupied housing, as well as the treatment of durable goods, warrants further discussion.

7. At this point, our methodology departs from that of Aguiar and Bils 2015. While the authors restrict their analysis to urban households throughout the entire period of 1980 and 2010 — given that the CE survey waves from 1981 through 1983 include only urban households — we rely on the full sample available in each survey wave.We do so because limiting the analysis to the municipalities and metropolitan areas covered by the earliest POF waves could bias our estimates, as a substantial share of these samples consists of state capitals, which are among the wealthiest areas in Brazil.

8. When reporting monetary measures, we adjusted nominal values for January 2024 Reais. To this end, we use inflation as measured by the INPC.

9. Beginning with the 2002/03 POF, non-monetary purchases are also included.

According to the POF methodology, respondents are asked to estimate the rent they would pay if the dwelling they occupy were not owner-occupied, and this imputed value is recorded as part of household expenditure. It is worth noting that this information was not collected in the 1995/96 POF; therefore, rental values for that wave were estimated using a random forest model. As for durables, POF computes its whole ammount in the period they are acquired.

Finally, we made adjustments to the IBGE classification of goods and excluded certain expenses, in order to ensure goods are appropriately grouped into well-defined and comparable categories and the analysis is based on consumption rather than total household expenditure.[10] Expenditure categories are summed in Table 1.

4 Econometric approach

As already discussed, it is reasonable to expect that the Brazilian consumption survey measures total household consumption with error, especially in older survey waves. This is a problem because if mismeasurement varies with household income (poor households report their consumption with error), consumption category (goods consumed by poorer households have more measurement error), and time (more mismeasurement in earlier surveys), this would bias our consumption inequality estimates. For example, if consumption by poorer households is under-reported in earlier surveys relative to newer ones, this would overstate the reduction in inequality across time in Brazil.

In order to correct for this measurement bias in our inequality measures, we employ a two-stage econometric estimation procedure. Our strategy, based on Aguiar and Bils 2015, is to identify differential changes in consumption across income groups in Brazil by exploiting systematic differences in how consumption of certain categories responds to household resources. Rather than relying on levels of total expenditure, which are measured with noise and not fully comparable across POF waves, we use changes in the composition of household spending to infer changes in relative consumption between richer and poorer households over time.

The identification strategy exploits cross-category variation in income elasticities combined with cross-group differences in expenditure growth. Categories with higher income elasticities expand disproportionately as total consumption rises, while low-elasticity categories respond more weakly. Consequently, differences in how spending reallocates across categories with different elasticities provide information about changes in total consumption. Comparing these reallocations across income groups

10. Within the POF framework, expenditures associated with asset accumulation or depreciation, such as savings formation or loan stallments, are treated as consumption.These expenditures were excluded, as they do not represent consumption for the purposes of this analysis.

allows us to recover changes in relative consumption growth and, in turn, changes in consumption inequality. All identifying variation comes from relative comparisons: across categories within income groups, across income groups within categories, and across time.

Figure 2 offers a concrete illustration of this mechanism by focusing on the ratio of education expenditures to food consumed at home, for the top 10% in income and the bottom 40% of the distribution.[11] Education is a luxury category in Brazil, with high Engel elasticity of consumption (1.99 in our main specification), while food consumed at home is a necessity, with low income elasticity (0.33).[12] An increase over time in this ratio for lower-income households relative to higher-income households, therefore, reflects a reallocation toward more income-elastic goods, consistent with relatively faster growth in total consumption for lower-income groups (and therefore a reduction in consumption inequality) after 1996.

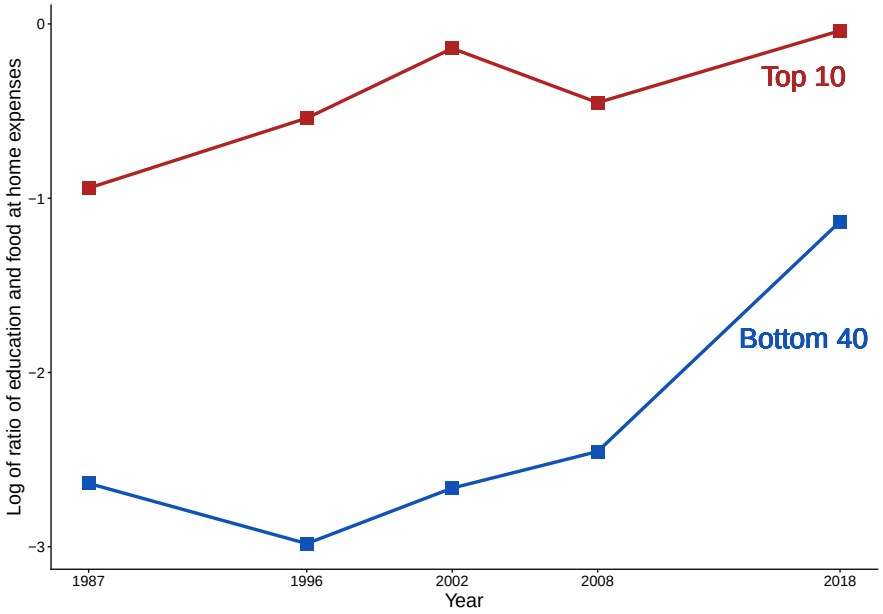


Figure 2: Growth of education over food at home expenses, by income group

Note: In the vertical axis we present the logarithm of the ratio of education expenses to the consumption of food at home. (Since households spend more in food at home, the logarithm is negative.) The horizontal axis is year. In blue we present the log of this average ratio for the bottom four deciles, in red for the top 10% in income.

This approach is robust to several sources of systematic measurement error in expenditure data. Category-level shocks common to all households in a given wave, such as price changes, item reclassification, or survey design differences, are absorbed by flexible category-by-year controls. Income-group–specific reporting differences

11. The figure plots the logarithm of this ratio to accentuate the larger proportional increase for a group with smaller baseline values.

12. The provision of universal (and free) public basic education in Brazil makes private expenditures in this category highly concentrated among the rich.

that affect all categories proportionally are eliminated by comparing relative spending patterns within each group (due to income group-wave dummies). Identification, therefore, does not require accurate measurement of total expenditure for any single household or survey wave.

The interpretation of the estimates relies on persistent differences in income sensitivity across consumption categories, which allow relative expenditure reallocations to be mapped into relative changes in total consumption. We also flexibly control for household demographics and region with category-specific coefficients to account for compositional change.

Within this framework, the empirical strategy recovers changes in relative consumption levels rather than absolute consumption levels for any single group. The next two subsections describe how elasticities are estimated in the first stage using a reference POF wave and how expenditure reallocation is used to recover changes in consumption inequality in a second-stage regression.

4.1 First stage: estimating Engel curve income elasticities

The first stage regression estimates category-specific Engel elasticities that summarize how household spending on different consumption categories respond to total expenditure. These elasticities provide the key source of identifying variation in the second stage and are treated as stable category characteristics over time.[13]

Let $g \in \{1, \ldots, G\}$ index the $G = 21$ consumption categories, t denote survey waves, and i index households. For each household i, let x_{igt} denote expenditure on category g in wave t, and let X_{it} denote total household expenditure. To accommodate zero expenditures and reduce sensitivity to extreme values, all expenditure variables are transformed using the inverse hyperbolic sine function, which behaves like the logarithm for large values while remaining well defined at zero.

We estimate Engel curves using the reference POF wave $t_0 = 2002/03$ to obtain a vector of category-specific elasticities $\{\beta_g\}_{g=1}^{21}$. Because earlier POF rounds do not consistently record zero expenditures for non-consumed categories, we construct a harmonized household-by-category dataset in which unreported category expenditures are treated as zeros. This ensures that extensive-margin variation is represented consistently across survey waves and that Engel elasticities are comparable over time.

Formally, for each household i, good category g, and survey wave t observation, we estimate:

$$\text{arsinh}(x_{igt}) = \beta_g \, \text{arsinh}(X_{it}) + \Gamma_g' Z_{it} + \alpha_{gt} + \delta_{jt} + \kappa_{gr} + \lambda_{jr} + u_{igt}, \tag{1}$$

13. We present evidence that corroborates this in what follows.

where x_{igt} denotes household i's expenditure on consumption category g at time t, X_{it} is total household expenditure, r indexes the household's region of residence, and j denotes the household's income group. The coefficient β_g captures the Engel income elasticity for consumption category g.[14] The vector Z_{it} includes demographic controls, specifically age and household size, with coefficients allowed to vary across consumption categories. The specification also includes category-by-wave fixed effects (α_{gt}), income-group-by-wave fixed effects (δ_{jt}), category-by-region fixed effects (κ_{gr}), and income-group-by-region fixed effects (λ_{jr}). The fixed-effects structure absorbs category-level intercepts and scale differences, so that each β_g is identified from within-category variation in expenditures across households in the same region and in the same income group. Standard errors are clustered at the household level to account for correlation in unobservables across categories within households.

A potential issue is that measurement error in category-level expenditure might be aggregated into a correlated error in total household expenditure. We therefore also estimate equation (1) using an instrumental variables strategy that instruments total expenditure with per-capita household income. Both the endogenous regressor and the instrument are interacted with category indicators, allowing the relationship between income and total expenditure to vary flexibly across consumption categories. Under the standard exclusion restriction—that income affects category expenditures only through its effect on total household resources—this strategy yields consistent estimates of category-specific Engel elasticities.

The resulting estimates $\widehat{\beta}_g$ rank consumption categories from necessities (low income elasticity) to luxuries (high income elasticity). These elasticities are not interpreted as structural preference parameters; rather, they summarize total relative demand sensitivity to income across categories. In order to not bias our two-stage procedure, in our main analysis we estimate the first stage using only 2002 data, and then remove the 2002 wave from the second-stage estimation, avoiding a "circular" regression.

4.2 Second stage: recovering relative consumption growth

In the second stage, we treat the estimated elasticities as fixed inputs and use cross-category differences in expenditure growth to recover changes in relative total expenditures across income groups and over time. Conceptually, this step inverts the Engel curve estimation in the first stage: rather than mapping total resources into category demands, we use observed category-level spending to back out, given already

14. Note that since $\text{arsinh}(x) = \ln\left(x + \sqrt{x^2+1}\right)$, for large values of x, $\text{arsinh}(x) \approx \ln(2x) = \ln(x) + \ln(2)$. Therefore, an arsinh-arsinh regression is approximately equivalent to a log-log regression with an appropriate adjustment of the intercept (namely, by $(\beta - 1)\ln 2$). For reference, for $x = 100$, the approximation error of using the inverse hyperbolic sine for estimating elasticity is about 0.00025%.

estimated income elasticities of demand, the changes in overall consumption. The key idea is that, once categories are ranked by their income sensitivity, differential growth across categories can be mapped back into relative growth in overall consumption.

Let j index income groups and t index survey waves, with the reference wave of 2002 denoted by t_0. For each category g, wave t, and income group j, we compute the average expenditure on category g for group j in wave t. To isolate changes in expenditure composition from shifts driven by demographics, we first residualize category expenditures with respect to age, household size, and region using category-specific coefficients in a series of leave-one-out regressions.[15] We then work with the logarithm of residualized mean expenditures (since these averages are always larger than zero).

The estimating equation in the second step relates changes in category-level expenditures to Engel elasticities:

$$\log \tilde{x}_{gjt} = \theta_{jt} \widehat{\beta}_g + \alpha_{gt} + \varepsilon_{gjt}, \tag{2}$$

where $\tilde{x}_{gjt}$ denotes the average residualized expenditure on category g for income group j in wave t, and $\widehat{\beta}_g$ is the Engel elasticity estimated in the first stage. The coefficient θ_{jt} captures the total average expenditure X_{jt} for income group j in wave t, relative to the baseline group-year. Category-by-wave fixed effects α_{gt} absorb category-specific shocks common to all income groups in a given wave, such as price changes or survey design differences.

Identification in equation (2) comes from cross-category variation in Engel elasticities. Intuitively, if an income group experiences faster growth in total consumption, its spending should expand relatively more in high-elasticity categories than in low-elasticity categories. The coefficient θ_{jt} summarizes this systematic reallocation and provides an estimate of relative consumption growth for group j at time t.

We estimate equation (2) by weighted least squares, where categories are weighted by their average expenditure shares. This weighting scheme places greater emphasis on categories that account for a larger fraction of household consumption and reduces sensitivity to noise in small or infrequently consumed categories. Inference accounts for the two-step nature of the estimation, adjusting standard errors to reflect sampling uncertainty in the first stage Engel elasticities with a Murphy-Topel correction and two-stage clustered bootstrap.

The estimated coefficients $\widehat{\theta}_{jt}$ trace the evolution of relative consumption across income groups and survey waves. Differences in $\widehat{\theta}_{jt}$ across groups and over time form the basis for our estimates of changes in consumption inequality.

15. Namely, for the 2008 mean consumptions $\bar{x}_{gj2008}$, for example, we compute the demographic coefficients using all waves except for 2008, and then use these coefficients to residualize the expenditures in 2008.

Figure 3 plots, for each consumption category, the Engel elasticity estimated in the reference 2002 wave on the horizontal axis and the difference in expenditure growth between high- and low-income groups over time on the vertical axis. Categories with low income elasticities, such as food consumed at home, tend to exhibit larger expenditure growth among higher-income households relative to low-income households. In contrast, categories with high income elasticities, such as private vehicles and personal services, exhibit relatively faster growth among lower-income households relative to the richer ones.

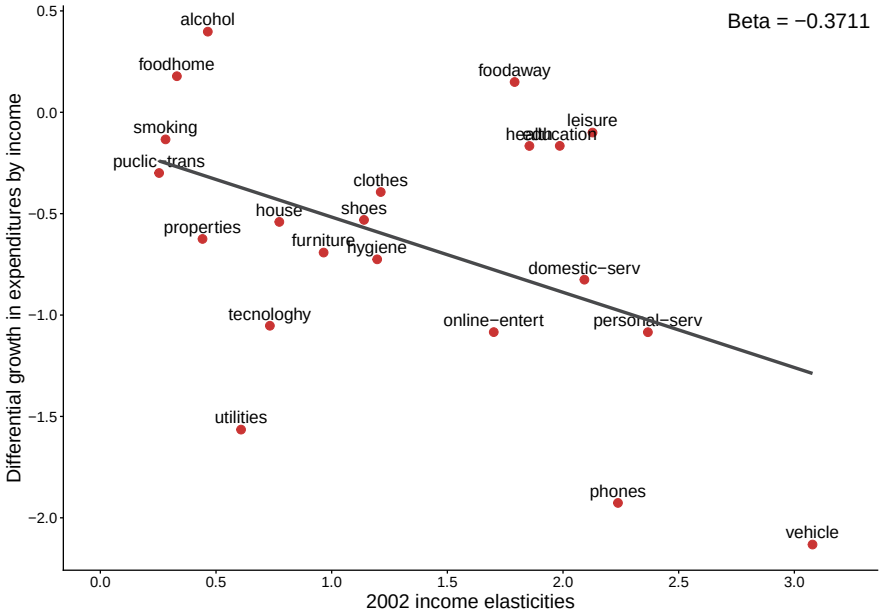


Figure 3: Relative consumption growth and Engel elasticities

Note: In the horizontal axis we have the 2002 Engel curve (income) elasticities, estimated in Table 1, column (3). In the vertical axis we present the relative (high income minus low income) difference in the log consumption between 1987 and 2018, net of demographics (age, household size and region with category-specific coefficients, category-year, income-year and income-region dummies).

This pattern provides the core source of identification in the second step. Because Engel elasticities summarize how category expenditures respond to changes in total consumption, a relative expansion of spending in high-elasticity categories indicates faster underlying consumption growth for that group. Conversely, disproportionate growth in low-elasticity categories signals slower growth in overall consumption. In fact, this simple unidimensional regression coefficient of -0.37 implies a reduction in inequality across these four decades of 31%, very similar to the 36.2% reduction that we encounter in the main specification of our econometric analysis.[16]

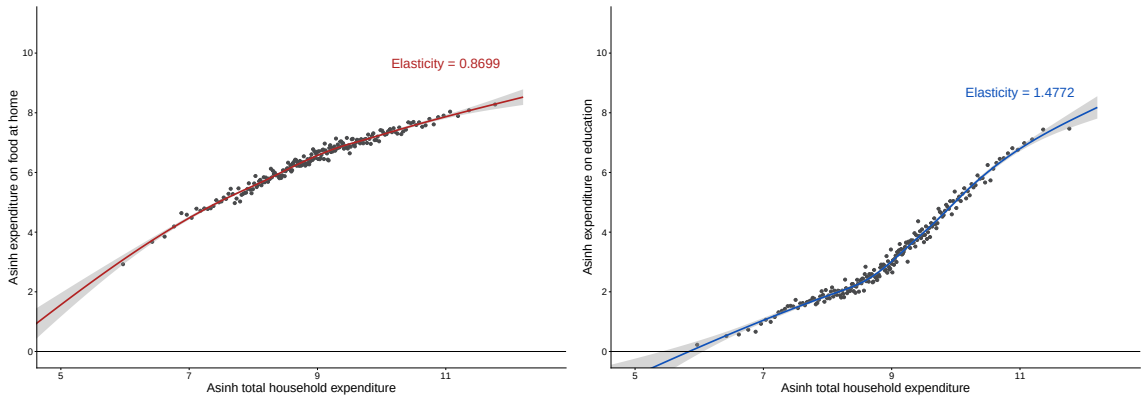
16. From Figure 3, $\ln(x_{g10,2018}/x_{g40,2018}) - \ln(x_{g10,1987}/x_{g40,1987}) = -0.377\ln(X_{2002}/X_{2002})$. Exponentiating both sides gives $(X_{10,2018}/X_{40,2018})/(X_{10,1987}/X_{40,1987}) \approx e^{-0.3711}$, which corresponds to a change of $e^{-0.3711} - 1 \approx -0.31$, or a 31% decline.

5 Results

In this section, we present the results of our econometric analysis. In the first subsection, we show our estimates of the first-stage demand system in equation (1). Beyond their inherent interest, these constitute the first stage of our main regression (2), whose results we present in the latter subsection.

5.1 Engel curves

The first stage of our estimation procedure is to estimate Engel curves of demand for different good categories. An ilustration of the Engel curves estimated is in Figure 4, again for food at home (a necessity) and education (a luxury good in Brazil). We can see that while no household consumes zero food at home, a large share of them have no private expenditure in education.[17] On the other hand, although food at home consumption is everywhere increasing with income, education expenses increase faster, and very high-income households spend even more on education than on home food.



(a) Engel curve for food at home

(b) Engel curve for education

Figure 4: Engel curves for two example consumption categories

Note: Both panels plot the inverse hyperbolic sine of total expenditure on the horizontal axis, and the inverse hyperbolic sine of consumption of the given category on the vertical axis. Estimated elasticity is simply the slope of the best-fitting linear approximation to the curve, and thus differs (slightly) from the complete specification estimates in Table 1. The figure includes all survey waves.

This naive estimation of Engel elasticities, albeit relatively close to our empirical results, is potentially biased. Consider, for example, that people in the Southeast are culturally more willing to eat food at home, and that the Southeast region is also richer. Then the naive estimate of income elasticity of consumption would be biased upwards (as we observe when comparing it to the econometric estimates). For this

17. As already mentioned, the Brazilian government provides universal free basic education.

reason, as explained in Section 4, we employ a variety of demographic controls and group dummies in our estimation.

The results of our first stage estimation are presented in Table 1 below. In each row, we present one of the 21 categories we employ in our analysis, ranked by their share of the consumption basket calculated for 2002. As expected, housing, food at home, transportation, and utilities account for the largest share of Brazilian household expenses (slightly over half of the total basket). In columns (1) through (3), we then present different estimates of the income elasticity of consumption for these good categories, using equation (1).

Table 1 shows that, as expected, necessities like food at home, utilities, and public transportation have low income elasticities (in fact, public transportation is estimated as almost an inferior good), while luxuries like food away from home, leisure, and domestic services have very high estimated Engel curve elasticities.

The first column presents a simple OLS regression of inverse hyperbolic sine (arsinh) of category consumption on arsinh total household consumption and a range of fixed effects (see Section 4). It is well known that this simple regression presents problems because measurement errors in the category consumption are aggregated into the household total consumption, creating a correlation between regressor errors and the dependent variable. In column (2) then we follow the standard approach in the literature and estimate a instrumental variables regression, instrumenting total consumption by household *per capita* income, which has (assumedly) independent measurement errors. Results are not qualitatively different.

Finally, while in columns (1) and (2) we use the entire data to estimate these elasticities, and they are presented for comparison and general interest, column (3) presents the estimates from an IV regression using only the 2002 wave of the consumption survey, which are the estimates that will form the second-stage independent variables in our main analysis.

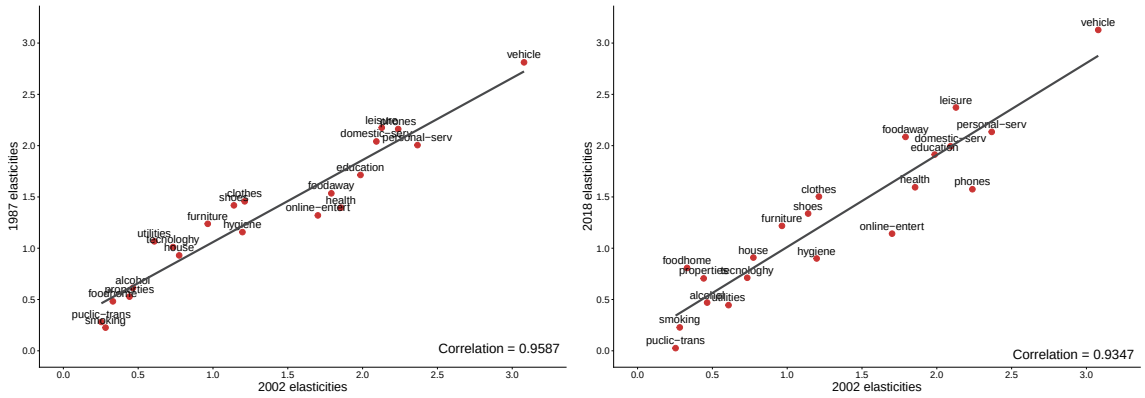
As explained in Section 4, we estimate the first stage regression using the 2002 wave, and then remove this wave from subsequent analysis so that errors in the first stage estimation procedure (that influence the elasticity estimates) do not generate an unobservable component in the second stage, which is, by construction, correlated with the dependent variable. We chose 2002 as our first-stage wave because it represents the middle point of our sample, and has the smallest interval between survey waves. Nonetheless, it is reasonable to ask how the elasticity estimates vary if we use other survey years as the baseline.

Table 1: Empirical estimates of the Engel curve (income) elasticities, by good category

Category	Share of total consumption	(1) OLS	(2) IV	(3) IV (2002)
Housing	0.241	0.756	0.894	0.774
		(0.006)	(0.013)	(0.039)
Food at home	0.154	0.614	0.553	0.331
		(0.011)	(0.017)	(0.051)
Private transportation and vehicles	0.076	2.564	3.028	3.079
		(0.015)	(0.022)	(0.061)
Utilities	0.074	0.598	0.834	0.608
		(0.007)	(0.014)	(0.040)
Food away from home	0.052	1.538	1.738	1.791
		(0.014)	(0.021)	(0.058)
Health expenditures	0.051	1.344	1.586	1.855
		(0.011)	(0.018)	(0.052)
Public and alternative transportation	0.045	0.100	0.108	0.254
		(0.017)	(0.023)	(0.069)
Furniture and fixtures	0.044	1.233	1.187	0.965
		(0.012)	(0.019)	(0.056)
Telecommunications, phones etc	0.042	1.644	2.028	2.238
		(0.011)	(0.018)	(0.054)
Clothing	0.039	1.218	1.437	1.212
		(0.012)	(0.019)	(0.051)
Personal care and hygiene	0.032	0.993	1.165	1.197
		(0.009)	(0.015)	(0.046)
Education and school supplies	0.030	1.594	1.842	1.986
		(0.014)	(0.021)	(0.058)
Non digital leisure	0.027	1.853	2.187	2.128
		(0.012)	(0.019)	(0.053)
Digital entertainment and associated	0.020	1.144	1.366	1.701
		(0.014)	(0.022)	(0.059)
Shoes and other apparel	0.018	1.099	1.304	1.140
		(0.012)	(0.019)	(0.052)
Domestic, child and animal services	0.013	1.725	2.082	2.092
		(0.014)	(0.021)	(0.058)
Appliances and associated services	0.013	0.715	0.868	0.733
		(0.014)	(0.021)	(0.059)
Personal, financial and other services	0.011	1.634	2.057	2.367
		(0.012)	(0.019)	(0.050)
Tabacco, other smoking and lottery	0.010	0.178	0.281	0.282
		(0.015)	(0.022)	(0.060)
Housing properties for occasional use	0.003	0.359	0.581	0.442
		(0.011)	(0.018)	(0.051)
Alcoholic beverages	0.003	0.358	0.518	0.465
		(0.011)	(0.018)	(0.052)
Number of Observations		992,145	992,145	992,145

Note: Dependent variable is the inverse hyperbolic sine of consumption of a given category, explanatory variable is log total consumption interacted with category group. All specifications include category-year, income group-year, age and household size with varying coefficients per category. Column (1) is an ordinary least squares estimation using all surveys. Column (2) presents an instrumental variables regression using emphper capita income as an instrument for total consumption. Column (3) presents IV results only using 2002 survey, and is the results that are used in the second-stage regression. Observations are clustered by household.

First, we can already note in Table 1 that columns (2) and (3) do not differ significantly for most categories, indicating that the 2002 wave must be mostly representative of the Engel elasticities for the entire sample. Second, we present further evidence in this direction in Figure 6 below. In the left panel, we compare income elasticities estimated from the 1986/87 survey with the 2002 survey. The figure shows that the order of elasticities remains mostly the same and are also quantitatively similar. In the right panel, we then compare the 2017/18 survey with our 2002 benchmark. In both cases, the Pearson correlation coefficient is above 0.9.



(a) Comparison between 2002 and 1987 (b) Comparison between 2002 and 2018

Figure 6: Comparison between Engel elasticities estimated using different POF surveys

Note: On the left panel we compare Engel elasticities estimated using surveys of 1987 (vertical) with 2002 (horizontal), our benchmark. On the right panel we once again compare our main analysis year of 2002 (in horizontal axis) with the Engel elasticities estimated using 2017 survey in the vertical axis.

5.2 Bias-free estimation of trends in consumption inequality

Having estimated the first-stage demand system, we now move on to estimating the second-stage equation (2). For each good category-survey wave-income group unit, we recover its estimated total consumption relative to a baseline by inverting the demand system from the first stage and using the estimated first-stage coefficients as regressors. As explained in Section 4, these results provide a measure of trends in consumption inequality that is robust to many forms of measurement error.

The results are presented in Table 2 below.[18] The first specification, and the main one, weights the second-stage regression by the share of each good category in the consumption basket, giving less weight to goods like alcohol or domestic services that constitute a small share of household expenses. These results are shown in levels in column (1) and in differences in column (4). Consistent with the cross-category patterns illustrated in Figure 3, the estimates indicate relatively faster consumption

18. In all specifications, the first-stage estimates are the ones in column (3) of Table 1.

growth among lower-income households, driven by disproportionate expansion in more income-elastic consumption categories.

We present two different asymptotically consistent inference methods in this table. Within parentheses are the second-stage standard errors with the Murphy-Topel two-step correction (Murphy and Topel 2002).[19] Below, the 95% confidence intervals are presented in brackets, estimated using a clustered bootstrap procedure. As shown in the table, both inference methods yield qualitatively similar results.

We see in column (4) that between 1986/077 and 1995/96 the point estimate of change in consumption inequality is positive, but statistically indiscernible from zero. From 1995/96 to 2008/09, however, we observe a significant drop in consumption inequality, with the top 10-to-bottom 40 ratio falling by 27.5% in slightly over 10 years. This trend slowed somewhat in the next decade (2008-2018), with a continued 20.2% decrease in the 10-40 ratio, with an overall decline of 40% in two decades.

For comparison, in columns (2) and (5) we present the unweighted (OLS) estimates of the second stage. While the level estimates are different, the estimated inequality trend is qualitatively similar, albeit much noisier. We again estimate a constant trend in the first decade, a substantial fall in inequality in the year 2000s, and a more discrete, but still statistically significant, fall in the later decade.

A standard concern in this literature is that consumption inequality estimates might be driven by particularly poorly measured consumption categories, such as durables (namely, appliances and associated services, digital entertainment and associated equipment, and housing). Durable consumption is especially problematic for consumption surveys, since they are purchased rarely and their periodic cost must be inputted. Another concern is that alcoholic beverages and tobacco, which are sin goods, might be underreported by some households.

In columns (3) and (6), we present levels and trends, respectively, for our estimates removing these consumption categories in a weighted regression, and the estimates are extremely similar to our benchmark. Although the fact that removing alcohol and tobacco does not affect our estimates is not surprising, since they represent a very small share of the consumption basket (0.3% and 1%, respectively), durables represent a significant share of household expenditure (27.4% across the 3 categories). The fact that removing it does not affect our estimates is a comforting indication that our estimates are robust, and not plagued by measurement bias as previous attempts.

19. Although we compute the correction, since the first-stage estimation has 3 orders of magnitude more observations than the second stage, its contribution to the total variance ends up being negligible.

Table 2: Consumption inequality estimates corrected for measurement error

	(1) WLS	(2) OLS	(3) Nondurables	(4) WLS	(5) OLS	(6) Nondurables
log(top 10) - log(bottom 40) — 1987	1.034	0.894	1.079	—	—	—
	(0.097)	(0.144)	(0.091)	—	—	—
	[0.954; 1.110]	[0.818; 0.966]	[1.007; 1.164]	—	—	—
log(top 10) - log(bottom 40) — 1996	1.132	0.873	1.112	0.098	-0.021	0.033
	(0.088)	(0.227)	(0.102)	(0.131)	(0.268)	(0.137)
	[1.002; 1.259]	[0.735; 1.006]	[0.983; 1.233]	[-0.053; 0.251]	[-0.186; 0.106]	[-0.115; 0.180]
log(top 10) - log(bottom 40) — 2008	0.810	0.633	0.830	-0.322	-0.240	-0.282
	(0.088)	(0.194)	(0.090)	(0.124)	(0.298)	(0.136)
	[0.743; 0.875]	[0.557; 0.704]	[0.753; 0.898]	[-0.466; -0.169]	[-0.396; -0.065]	[-0.435; -0.132]
log(top 10) - log(bottom 40) — 2018	0.584	0.523	0.594	-0.226	-0.110	-0.236
	(0.109)	(0.157)	(0.120)	(0.140)	(0.249)	(0.150)
	[0.548; 0.632]	[0.480; 0.589]	[0.550; 0.652]	[-0.292; -0.156]	[-0.192; -0.009]	[-0.305; -0.162]
Categories	All	All	No durables, alcohol, and tobacco	All	All	No durables, alcohol, and tobacco
Weighted	Yes	No	Yes	Yes	No	Yes
Second-stage N	420	420	320	420	420	320

Note: This table presents the results of the two-stage estimation of consumption inequality. Within parenthesis are the second-stage sandwich variance estimators with Murphy-Topel correction, while 95% confidence intervals (in brackets) are calculated using two-stage, clustered bootstrap. Columns (1) through (3) present estimated difference in log total consumption between top 10 richest and bottom 40 households. Column (1) weights categories by their share in total consumption, column (2) presents the unweighted regression, column (3) removes some exceptional categories such as tobacco, alcohol and durables. Columns (4) through (6) present for these 3 specifications the time lag in consumption inequality.

5.3 Brazilian overall consumption inequality

As explained in Section 4, our method identifies, regardless of good category-wave or income group-wave measurement errors in consumption, trends in its inequality. These results are already interesting as they inform us about how inequality has been trending, and possibly give clues about what policies might have led to these changes.

In the case of Brazil, in particular, that it is one of the most unequal countries in the world, we might be interested in whether the country is also considerably more unequal than other countries when measured by consumption inequality, as well as how consumption inequality relates to other measures of inequality, most notably inequality of income. If we want to do that, we need to know the *level* of Brazilian consumption inequality.

To move from identifying trends to making claims about the level of inequality, we need additional assumptions. Namely, we need to assume that for one of the years the consumption ratios are well measured, and then we can use the estimated changes to find the inequality measure for the other waves (there is a missing intercept problem). The most natural choice is to assume that survey quality has increased over time, and the estimates we have today are the correct ones. This is what we do in Figure 8 below, where we assume that inequality in 2018 is correctly measured, and then show what this implies for 2008, 1996 and 1987 consumption inequality.

As we see in Figure 8, consumption inequality computed from the raw consumption survey data presents large jumps across the years, and differs significantly on whether we consider only non-durables or the entire consumption, an evidence that mismeasurement might be relevant. However, when corrected by measurement bias by our method, we see that the trends are smoother and differ little on whether we consider all categories or remove non-durables, alcohol and tobacco.[20] Interestingly, although we nowhere make this restriction, our procedure leads to estimates of 1987 consumption inequality that are very similar to what we observe in the data.

6 Conclusion

In this paper, we processed, cleaned and harmonized all five waves of Brazilian consumption survey *Pesquisa de Orçamentos Familiares* to build the longest available time-series of consumption inequality for that country. Importantly, we also employ a two-stage demand estimation procedure to clear the inequality trends from mismeasurement issues that plague consumption surveys.

Especially in Brazil, that during the 1980s and beginning of the 1990s suffered

20. This similarity comes from both the fact that estimates for 2018 are robust to the inclusion or not of non-durables, as well as the results for trends in Table 2, columns (4) and (6), being very similar.

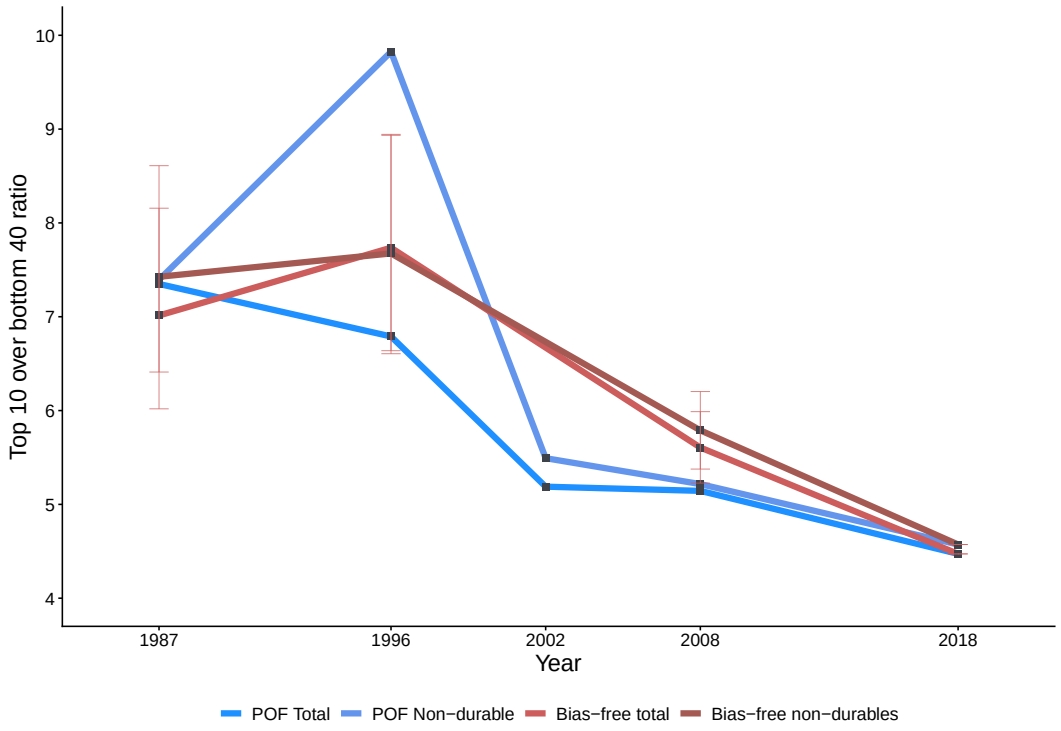


Figure 8: Consumption inequality corrected and uncorrected for mismeasurement

Notes: Figure depicts top decile over bottom 40% mean consumption from raw survey data, in blue, and when corrected for measurement bias by our empirical methodology, in red, for both total consumption (light color, Table 2, column 4) and only non-durables consumption (darker color, Table 2, column 6). Overall levels for bias-free consumption inequality assume that inequality observed in the raw data in 2018 (but not previous years) is unbiased.

through hyper-inflation, as well as many changes of currency during that period, it is to be expected that problems of mismeasurement are ubiquituous. Therefore, previous measures that did not correct for measurement bias are likely to be less trustworthy. Indeed, while previous estimates are very sensitive to the particular specification or which categories are analyzed, our estimates are robust to both factors.

The Brazilian society experienced political democratization during the 1980s, that eventually led to a large expansion of social assistance policies during the first decade of the 21st Century. It is an important question of public policy and inequality studies whether the change to more left-leaning governments in the last few decades in Brazil, and the associated increase in the size of government and social assistance policies, led to a marked decrease in consumption inequality.

In this paper we resolve that research question, by showing conclusively that this period was marked by a significant decrease in consumption inequality. Indeed, our inequality measure of the top 10% over bottom 40% ratio fell by 40% in the two decades since 1996, an amazing improvement.

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A Apendix A: Additional Tables

Table A1: Trends in inequality: Ratio of High-Income to Low-Income respondents

	1987	1996	2002	2008	2018	Diff. log 87–96	Diff. log 87–02	Diff. log 87–08	Diff. log 87–18
Income per capita	18.146	5.978	15.515	13.310	11.587	-1.110	-0.157	-0.310	-0.449
Expenditure	7.349	6.790	5.189	5.144	4.472	-0.079	-0.348	-0.357	-0.497
Non-durable Expenditures	7.394	9.824	5.492	5.216	4.572	0.351	-0.360	-0.432	-0.520

Table A2: Summary of studies estimating consumption inequality in Brazil using POF data

Author(s)	Year	POF wave(s)	Consumption definition	Inequality measure(s)	Main notes
Silveira	2004	1987/88, 1995/96	Total consumption	Gini	Early evidence on high consumption inequality; sensitivity to aggregation choices
Paes de Barros et al.	2007	1987/88, 1995/96, 2002/03	Total and non-durable	Gini, Theil	Comparison of income and consumption inequality using POF
Diniz et al.	2007	1987/88, 1995/96, 2002/03	Total and non-durable	Gini	Emphasizes heterogeneity across expenditure aggregates
Silva et al.	2007	2002/03	Cultural consumption	Gini	Focus on specific consumption categories
Souza	2015	2002/03, 2008/09	Total consumption	Gini	Highlights sensitivity to equivalence scales
Hoffmann	2010	2002/03, 2008/09	Total consumption	Gini, Theil	Documents lower consumption than income inequality
Hoffmann & Vaz	2021	2002/03, 2008/09, 2017/18	Total and non-durable	Gini	Comparative analysis of income and consumption inequality
Silveira & Palomo	2023	2008/09, 2017/18	Alternative aggregates	Gini	Updated classifications; strong sensitivity to definition

Notes: The table summarizes selected studies using POF data to estimate consumption inequality in Brazil. Differences in consumption definitions, aggregation choices, and survey waves limit comparability across estimates.

B Appendix B: Data features

B.1 Key aspects and differences across POF waves

The origins of the POF can be traced back to the National Household Expenditure Survey (Estudo Nacional de Despesas Familiares – ENDEF), conducted in the mid-1970s by IBGE. ENDEF stands out for its breadth and depth and remains a benchmark in Brazilian social research. In addition to collecting detailed information on household expenditures and income, the survey gathered anthropometric data (height and weight) and detailed food consumption information. Given the high costs associated with a national survey of such wide scope, subsequent data collection efforts were carried out through the POF, which, while narrower in scope than ENDEF, enabled the regular production of household-level data on income and consumption in Brazil.

As discussed in Section 3, the POF comprises five survey waves, conducted in 1987–1988, 1995–1996, 2002–2003, 2008–2009, and 2017–2018. In its first two editions, POF's geographic coverage was limited to the metropolitan areas of the state capitals Belém, Fortaleza, Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo, Curitiba, and Porto Alegre, as well as the Federal District and the municipality of Goiânia.[21] Beginning in 2002–2003, the survey was expanded to a national scope, thereby covering a sample of the entire urban and rural territory of Brazil.

The basic unit of analysis for both income and expenses in the POF and in this paper is the "consumption unit" (CU), which for the purposes of our study will be equivalent to family. A consumption unit consists of either an individual or a group of individuals who share the same food source and/or report common food expenditures. When neither food stocks are shared nor common food expenditures exist, the identification of a CU is carried out based on housing expenditures. A single may contain one or more consumption units. Table A3 reports CUs and the number of families they represent in each of the survey waves [22].

Table A3 reports CUs and the number of families they represent in each of the survey waves. [23]

Data collection relies on respondents' answers to a set of distinct questionnaires, which also varied throughout different waves of the survey. Five questionnaries constituted the survey: (1) dwelling characteristics; (2) individual income; (3) individual expenses[24]. Collective household expenditures are collected through two

21. In 1996, these areas comprised 29,85% of the brazilian population.

22. Each observation in the sample represents a given number of units in the population. Expansion factors are used by IBGE to weight the survey data and derive population estimates.

23. Each observation in the sample represents a given number of units in the population. Expansion factors are used by IBGE to weight the survey data and derive population estimates.

24. These expenses were recorded using a 7-day or 90 days reference periods, except for the purchaase of vehicles and family cerimonies which were recorded using a 6-month time frame.

Table A3: Sampling frame - POF

Year	CUs	Families	Individuals	Average family size
1987/88	13.707	11.014.088	44.776.242	4,07
1995/96	16.060	12.544.069	46.382.098	3,70
2002/03	48.568	48.534.638	175.845.964	3,64
2008/09	56.091	57.816.604	190.519.297	3,30
2017/18	58.039	69.017.704	207.103.790	3,01

Note: The table presents the number of consumption units (CUs) in each POF wave. Survey weights (or expansion factors) are assigned to each CU, calculated according to the sampling design and later recalibrated to ensure consistency with population estimates for each survey's reference period.

distinct instruments: (4) a collective expenditure diary and (5) a collective expenditure questionnaire. The diary records market and food-related expenditures for 14 consecutive days, whereas the questionnaire [25] covers less frequent but regular household expenses, such as utilities, including electricity, water, and other housing-related services as well as durables acquisition. For owner-occupied dwellings, imputed rental values were derived from respondents' self-reported estimates of the rental value of the property.

In 1995/96, the same five questionnaires were applied. Nevertheless, data collection presented differences, with the most the notable change being that imputed rental values were not collected in the latter survey.

In the 2002/03 wave, imputed rental values were reintroduced and subsequently collected in all later waves. The survey also added a new living conditions questionnaire, collecting self-assessments of housing conditions and food quality, as well as information on delayed payments for rent, utilities, and installments. The most relevant change, for the purposes of our paper, is that this edition was the first in which non monetary acquisitions were included.

Concerning 2008/09 edition of the POF, the collective expenditure diary recorded expenditures with food for 7 consecutive days. This is a factor that should be highlighted in our analysis. If a household made food purchases shortly before the survey period, even if substantial, these expenditures would not be recorded. As a result, food expenditures may be systematically underestimated in the data.A new questionnaire was also introduced to assess food individual consumption. Finally, no major changes were identified in the latest POF wave.

25. These expenses were recorded using reference periods of six months or 90 days.

B.2 A savings analysis based in the POF

For the calculation of savings values, we draw Silveira and Moreira 2014 and Komatsu, Menezes Filho, Gandra, et al. 2020, with some adaptations[26]. First, it is worth noting that the POF classifies as expenditures certain items traditionally regarded as forms of saving (such as contributions to private pension plans, which are recorded as current expenditures), while it reports as increases in household assets some acquisitions that do not represent savings, such as the purchase of club titles. For this reason, our metric does not follow the survey's classification of increases in assets and decreases in debts. Similarly, we do not consider an appropriate saving rate to be measured as the difference between household income and expenditures. The categories of savings analyzed are:

- **S1**: Net change in financial assets, such as private pension plans, capitalization bonds, investment funds, savings accounts, stocks, and other.
- **S2**: S1 plus the net change in real estate assets — purchases and sales of land or properties, whether fully paid off or not.

Savings, as a percentage of household income, are reported in Table A4. We can note that, unlike average family income, which exhibits an increasing trend across all periods, the savings analysis reveals a relatively increasing pattern from 2002/03 to 2008/09 and a decreasing trend between 2008/09 and 2017/18, which may de correlated with the Brazilian economic crisis from 2015.

Table A4: Average per capita household savings by percentiles, as a % of income

	2002/03		2008/09		2017/18	
Percentiles	S1	S2	S1	S2	S1	S2
1 – 10%	0.3	1.4	0.2	1.4	0.1	0.3
10 – 20%	0.3	1.1	0.5	1.4	-0.02	1.2
20 – 40%	0.4	1.2	0.7	1.8	0.4	0.8
40 – 60%	0.7	1.5	0.5	1.6	0.5	1.3
60 – 80%	0.9	1.9	1.0	2.3	0.6	1.4
80 – 90%	1.4	2.4	1.2	4.3	0.8	2.2
90 – 99%	2.3	3.7	2.4	6.1	1.9	3.4

Note: The table reports average per capita household savings for different income groups. Average savings were calculated by dividing per capita savings (S1 and S2) by the average incomen per capita of the percentile under analysis. The reported values were calculated considering the full sample of UCs interviewed in each analyzed POF wave.

26. Silveira and Moreira 2014 classifies savings into four different categories whereas we use only the first two for our analysis.Komatsu, Menezes Filho, Gandra, et al. 2020, on its turn, use monetary values to account for savings, instead of percentages as we do.

B.3 Measurement errors in the POF

As largely discussed over our paper, every survey which intends to investigate consumption and income as reported by each individual or household will, in some measure, be affected by measurement errors and the same is true for POF. Biased measurement errors or even errors that are directly correlated to a specific set of goods or income group may induce estimates to understate or overstate income inequality.

The POF is not immune to such errors, and corrections varied substantially during each POF wave. In the 1987/88 wave, no corrections or value imputations are reported (IBGE 1991).

In the 1995/96 wave, the same approach from the previous wave was adopted to assessing estimate precision. In addition, several data-correction and value-imputation procedures were reported, including a Hot Deck imputation method to address non-response and rejected observations (IBGE 1998).

In later survey waves, several more robust data-adjustment and imputation procedures were adopted. During the data-processing phase, missing or incomplete information—as well as observations deemed inconsistent— were imputed using similarity matrices constructed from variables that are highly correlated with the variable receiving the imputed value (IBGE 2019).

Despite these corrections and adjustments, some issues remain. One important limitation concerns food-at-home expenditures, which are recorded using a seven-day reference period. For low-income households, whose food purchases tend to be concentrated at specific points in the month—often around paydays—this short reporting window may fail to capture typical monthly consumption, leading to underreporting relative to monthly averages. For example, in the 2008/09 POF, 3,241 households report no food expenditures during the reference period. Among low-income households, such zero reports, driven by the short reference period, may lead to a downward bias in measured well-being.

Moreover, in recent POF waves, housing expenditures for families living in owner-occupied dwellings are based on self-reported estimates of the rental value of the property. This approach may lead to either overestimation or underestimation of housing costs due to limited information on the part of respondents or the presence of unintentional or systematic biases.

Rounding represents an additional concern in the data. Whether in the imputation of rental values, the reporting of expenditures in general, or even income, we observe a concentration of reported values at round numbers. This pattern may reflect a natural tendency of respondents to round figures when exact amounts are not readily available in memory or easily accessible for verification.

With respect to income reporting, there are different difficulties. Assouad, Chancel,

and Morgan 2018 document that, for Brazil, survey-reported income accounts for only about 60% of income measured in national accounts. A number explanations may account for this tendency. Wealthier individuals are more likely to refuse participation in household surveys and, when they do participate, are more likely to fail to respond to income-related questions. Moreover, even in cases in which such questions are answered, higher levels of underreporting are observed, whether due to difficulties in aggregating all sources of income, concerns about unreported income, lack of information regarding part of total income, or even discomfort in reporting very high income levels to an interviewer.

Additionaly, we identify a underreporting in low income households, especially the ones with recipients of Bolsa Família. Several factors may account for this underreporting, including social stigma associated with receiving government assistance benefits, fear of disclosure to the authorities among individuals who receive such benefits irregularly and lack of awareness regarding which program provides them this income. At the time of the 2008/09 POF wave, the number of beneficiary households reported on a monthly basis by the Ministry of Citizenship ranged between 10.5 and 11 million. In contrast, the POF data indicate approximately 7.83 million beneficiaries. Similarly, in 2017, the number of beneficiary households according to the Ministry of Citizenship fluctuated between 13.7 and 14 million, whereas the POF data once again reported a lower figure: approximately 10 million beneficiaries.

Finally, given its relevance for our estimates, we assess whether income underreporting is associated with consumption underreporting and find no evidence of such a relationship. From a conceptual standpoint, consumption is measured through multiple questionnaires, each with a specific reference period (7 days, 30 days, 90 days, and 12 months), which imposes a substantial cognitive burden on respondents when aggregating expenditures. Consistent with this interpretation, at least 25% of households in the most recent POF wave report total expenditures exceeding reported income.

B.4 Expenditure Categorization

For the purpose of this study, it was necessary to adjust the expenditure categorization developed by IBGE for the POF survey. At first, POF categorization was not consistent across subsequent survey waves and, therefore, not comparable. Moreover, it was necessary to disaggregate some larger expenditure groups while aggregating smaller ones. The aim of these adjustments was to avoid grouping expenditures that exhibit different consumption profiles and respond differently to income fluctuations, as well as to avoid classifications such as "other expenditures," which are not informative about the consumption patterns of households. The final outcome was the set

of 21 categories listed and explained in Tables A6 and A7.

Considering our objective of studying consumption inequality, the following expenditures were excluded from the analysis: public and private pensions, alimony payments, interest and loan repayments, contributions to capitalization bonds, loans to third parties, and contributions to professional associations and political parties, among others.

Furthermore, due to the potential bias that could be introduced by including expenditures on property acquisition—since the total value of such spending would be recorded in a single period—we chose to exclude property purchases. In contrast, vehicle purchases were retained, given their lower unit value. House renovations, which according to IBGE's classification are regarded as increases in assets, were included under Housing consumption because they reflect an increased household wellbeing.

Moreover, expenditures on health and education are considered consumption expenses. Although some authors argue that these expenditures constitute human capital investment and should therefore be excluded from consumption inequality analyses[27], we maintain that the most appropriate approach for a highly unequal country is to include them, as they represent a direct manifestation of household wealth.

We also choose to separate leisure from other expenditure categories, dividing it into digital and non-digital leisure. The main motivation for this approach comes from the findings of Aguiar and Bils 2015, who reports different income elasticities for "entertainment equipment and subscription television" versus "entertainment fees, admissions, and reading materials". The latter group exhibits a higher income elasticity than the former, indicating that non-digital leisure behaves as a luxury good, which is consistent with our findings. Moreover, Almeida, Lima, and Gatto 2020 documents unequal access to cultural goods between low- and high-income households. [28]

Finally, in order to ensure our categorization was apropriate, we studied the distribution of household total expenses among the categories we created and throughout diferent POF waves. We observe that expenditures on Housing, Food (both at home and away from home), and Utilities account for approximately 50% of total household spending in the three latest editions, with a slight decline between 2003 and 2018 - in line with what is expected for such expenses. Following Table A5, we report distribution of total expenditure by all categories. Although some categories had a small share in total consumption, their maintenance in our dataset aimed to ensure

27. This is adopted, for example, by Meyer and Sullivan 2023.

28. Evaluating POF 2008/09, the authors found that audiovisual expenditures at home accounted for over 40% of total cultural spending in low-income households, compared to less than 30% in high-income households.

that expenditures directly associated with high income (such as the acquisition of a second property), as well as the consumption of goods often regarded as inferior (such as tobacco and lotteries), were not excluded from the analysis.

Table A5: Distribution of Total Expenditure by Category

Categories		% of Total Expenditure	
Code	**Category**	**2003**	**2018**
1	Food at home	19.8%	13.0%
2	Food away from home	4.7%	4.8%
3	Shoes and other apparel	1.8%	1.3%
4	Alcoholic beverages	0.3%	0.3%
5	Education and school supplies	2.2%	3.1%
6	Appliances and associated services	1.4%	1.2%
7	Digital entertainment and associated	1.9%	1.0%
8	Tobacco, other smoking and lottery	1.3%	0.9%
9	Health expenditures	5.3%	7.3%
10	Housing	22.4%	24.3%
11	Non-digital leisure	2.5%	2.6%
12	Furniture and fixtures	4.9%	3.3%
13	Personal care and hygiene	3.0%	5.5%
14	Domestic, child and animal services	1.1%	2.1%
15	Personal, financial and other services	1.1%	1.5%
16	Telecommunications, phones, etc	3.2%	4.6%
17	Private transportation and vehicles	7.6%	10.7%
18	Public and alternative transportation	3.4%	1.8%
19	Utilities	8.1%	8.1%
20	Clothing	4.2%	2.3%
21	Housing properties for occasional use	0.2%	0.4%

Note: The table reports average household expenditure values, expressed as a percentage of total household expenditure, for each category of goods analyzed in this study for the years 2003 and 2018.

Table A6: Expenditure Categorization: 1 to 11

Code	Category	Description
1	Food at home	Includes all categories under “Food at home” in the IBGE classification, except for takeaway food and alcoholic beverages. Takeaway food is classified as food away from home, while alcoholic beverages are allocated in categorie 4.
2	Food away from home	Includes all categories under “Food away from home” proposed by IBGE, as well as takeaway food.
3	Shoes and other apparel	Follows the description “Footwear and accessories” from Level 4 of the IBGE classification.
4	Alcoholic beverages	Covers goods classified as “Beverages and infusions” (Level 4 of the IBGE classification within the “Food at home” category).
5	Education and school supplies	Includes school supplies (such as textbooks and stationery), tuition fees and enrollment fees, school uniforms and extracurricular activities for children in education (such as language courses and sports activities). This category follows IBGE Level 3: “Education.”
6	Appliances and associated services	Includes household appliances, tools (excluding TVs, wine coolers, and video game consoles), and repair services for these items. This category combines some codes classified by IBGE as “Household repairs and articles” and others under “Household appliances.”
7	Digital entertainment and associated	Includes TVs and devices used for leisure within the household (sound systems, Blu-ray players, DVDs, home theaters). It also includes videogames and streaming subscriptions, as well as computers, tablets, and laptops.
8	Tobacco, other smoking and lottery	Includes IBGE Level 3: "Tobacco", as well as Level 4: "Games and betting". These goods are grouped due to their association with addictive behavior and their well-documented declining consumption pattern with income.
9	Health expenditures	Includes medicines, medical supplies, medical and dental consultations, diagnostic tests, and health insurance payments. Corresponds to IBGE Level 3 “Health care.”
10	Housing	Encompasses expenditures on rent (both actual and imputed), property taxes, as well as construction and renovation expenses. Expenditures related to the purchase of housing units and mortgage payments for previously acquired properties are excluded.
11	Non digital leisure	Includes expenditures on leisure activities excluding those of a digital nature (such as video games, gaming, and television). This category includes travel expenses, magazines, books, tickets for concerts and events, as well as celebratory events (weddings, birthdays, and parties in general).

Note: The table presents the expenditure categorization (categories 1 to 11) adopted in this study and their correspondence with the expenditure categories defined by IBGE for recent POF waves, when applicable.

Table A7: Expenditure Categorization: 12 to 21

Code	Category	Description
12	Furniture and fixtures	Includes materials and labor for minor repairs, furniture (excluding household appliances), and home maintenance products such as cleaning supplies.
13	Personal care and hygiene	Covers soaps, perfumes, and other personal hygiene items, as well as services such as hairdressing, manicure, and pedicure. Includes all items under IBGE Level 3 “Personal Hygiene and Care” and selected citens from the "Personal Services" level.
14	Domestic, child and animal services	Includes domestic services (such as babysitters), furniture and utensils for children and babies, as well as children’s clothing. Also covers expenditures on pet food, treats, and other pet-related accessories.
15	Personal, financial, and other services	Captures expenditures on bank fees, other personal services (e.g., dry cleaning, laundry), professional services (lawyers, engineers, accountants, etc.), postal services, and insurance payments (excluding vehicle and property insurance).
16	Telecommunications, phones etc	Includes internet access packages, cable TV, and mobile data plans. Also includes expenditures on mobile phones and landline phones. Values for bundled TV, internet, and mobile data packages could not be disaggregated. Streaming subscription fees are excluded.
17	Private transportation and vehicles	Covers the acquisition of privately owned vehicles and related expenditures (fuel and maintenance), as well as vehicle taxes (IPVA), fees, and insurance. Also includes spending on ride-hailing apps, motorcycles, and bicycles.
18	Public and alternative transportation	Constructed based on the categories “Public Transportation” and “Other Alternative Transport” from IBGE’s quality-of-life index. Includes intramunicipal public transportation by land and water, as well as intermunicipal and interstate travel. School transport (under Education and school-related items) and air travel (private transport) are excluded.
19	Utilities	Covers expenditures on electricity, water and sewage, domestic fuels, and other forms of household lighting, as well as public lighting fees, waste collection, and similar services. Also includes condominium fees and electronic security services.
20	Clothing	Includes personal accessories such as glasses and watches, as well as jewelry and costume jewelry. From the General Expenditure Table, it includes all items under “Men’s clothing” and “Women’s clothing.” “Children’s clothing” is included under category 14.
21	Housing properties for occasional use	Includes IBGE Level 4 “Occasional-use properties” and all expenditures related to maintaining a second property, regardless of type. Expenditures for purchasing a second property are excluded.

Note: The table presents the expenditure categorization (categories 12 to 21) adopted in this study and its correspondence with the expenditure categories defined by IBGE for recent POF waves, when applicable.