Distributional Consumer Price Indices*

Xavier Jaravel

LSE & CEPR

x.jaravel@lse.ac.uk

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Abstract

This paper develops a new public database to estimate inflation heterogeneity across socio-demographic groups in the United States in real time. These distributional CPIs (D-CPIs) are fully consistent with the methodology of the official CPI and are available from 2002 to the present day by household income, age, race and other characteristics. Using this database, I establish three results showing that D-CPIs have important implications for the measurement of long-run trends in inequality and poverty, as well as of real wage dynamics during crises. First, "real" inequality across household income quintiles increased about 45 % faster with D-CPIs between 2002 and 2019, compared to the official CPI. While the pre-tax income gap between the top and bottom household income quintiles increased by 15.7 % during this period according to the official CPI, it increased by 22.6 % with D-CPIs. Similarly large adjustments apply to consumption inequality and inequality in pre-tax and post-tax national incomes. Second, today 2.3 million people are below the "real" poverty line using D-CPIs but above the poverty threshold using the official CPI. Third, during the inflation burst following the Covid-19 pandemic, inflation was higher for the middle class, compared to low-income and high-income households. This pattern is driven by gas and vehicles and implies that the compression of "real" wages was about 28 % faster with D-CPIs than with the official CPI. Similar patterns of inflation heterogeneity hold in extensions allowing for geographic heterogeneity in inflation, non-homothetic price indices, and expanding the analysis back to 1983.

Keywords: Inflation; inequality; poverty; non-homotheticities.

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1 Introduction

This paper develops a new public database to estimate inflation heterogeneity in the United States in real time. While a growing literature documents that there have been persistent gaps in inflation rates across income groups in the United States, two challenges remain unaddressed: (i) the available evidence is typically based on proprietary data sets or new linked data sets that are not necessarily consistent with the official aggregate Consumer Price Index; (ii) inflation inequality estimates are not available in real time.[1] The main contribution of this paper is to develop a publicly-available database addressing these two challenges, and to then use the new data to shed light on the distributional effects of inflation over the past twenty years.

The database leverages high-frequency public data sources—including monthly price changes from the Consumer Price Index (CPI) and annual expenditure shares from the Consumer Expenditure Survey (CEX)— to obtain inflation statistics that can be distributed across socio-demographic groups while remaining consistent with the aggregate CPI. The methodology follows the exact same data construction steps as the CPI, which ensures that it is consistent with official inflation statistics; the only difference is that expenditure shares across product categories are computed by socio-demographic groups (e.g., income percentiles, age, race, gender, occupations, etc.). Because they are fully consistent with the official CPI but can be disaggregated, I call the price series "Distributional Consumer Price Indices" (D-CPIs). The distributional impacts of inflation can thus be tracked from 2002 to the present day. All estimates are updated with each monthly release of inflation data by the Bureau of Labor Statistics, within a few hours, and are made available on the D-CPI Project webpage.

The new database constitutes a useful complement to the "distributional national accounts" (Piketty et al. (2017), Blanchet et al. (2022)), which have focused on changes in nominal inequality. Distributional national accounts use publicly-available data to provide inequality estimates that are consistent with macroeconomic aggregates and national accounts, but they use a single price index for all households. The approach taken in this paper extends the logic of distributional national accounts to allow for heterogeneity in inflation rates. D-CPIs are of direct relevance for the measurement of inequality and real wage dynamics, as well as the indexation of transfers, tax brackets and the poverty line. They can also be an important input for various economic applications, such as optimal redistribution with heterogeneous price changes (e.g., Jaravel and Olivi (2024)), optimal monetary policy with heterogeneous price changes (e.g., Olivi et al. (2024)), or the estimation of heterogeneous price responses to economic shocks.

Using D-CPIs, I establish three main results. First, analyzing long-run trends in inequality before the Covid-19 pandemic, I find that "real" inequality increased about 45% faster with D-CPIs than with the official CPI. With the official CPI, the income gap between the top and bottom household income quintiles increased by 15.7% between 2002 and 2019. In contrast, with D-CPIs, the income gap increased significantly more, by 22.6%. I also document large adjustments for trends in consumption inequality and inequality in pre-tax and post-tax national incomes. Together, these results show that D-CPIs can have

[1]Recent work on inflation heterogeneity includes several contributions by academics (e.g., Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2021), Jaravel and Lashkari (2023), Cavallo and Kryvtsov (2024), Chen et al. (2024)), as well as by BLS researchers using confidential data from the Bureau of Labor Statistics (Klick and Stockburger (2021), Klick and Stockburger (2024)). The relationship between these papers and mine is discussed at the end of the introduction.

important implications for the measurement of inequality.

A straightforward decomposition of the price indices reveals the product categories driving the inflation gap between the highest and lowest income quintiles. The item causing inflation inequality either have higher inflation than average and higher expenditure shares from the poor – like rent, cigarettes, and electricity – or lower inflation and higher expenditure share from the rich – like new or used vehicles, airline fares, televisions, and computers. The three most important categories alone – rents, vehicles, and airlines fares – account for about half of the total inflation gap.

D-CPI also capture inflation heterogeneity across other socio-demographic groups, by age, race, urban or rural households, or gender. While the differences are generally smaller in magnitude than for income, they can be meaningful. In particular, inflation for the 65+ age group has been consistently higher than average: in 2025, there is a 5.8 percentage point gap between the price index for households above 65 and the official CPI. Indexing Social Security retirement benefits on the price index for the population above 65 would have large budgetary implications, with an implied increase in annual retirement benefits over $58bn.

Second, I use D-CPIs to adjust the poverty line. The official CPI fails to account for the fact that inflation is higher for individuals in poverty, i.e. the poverty line should be indexed at a higher rate. With D-CPIs, by the end of 2024 there are 2.3 million people who are below the "real" poverty line but above the standard threshold based on official CPI. This group should have access to poverty alleviation programs such as Medicaid, which illustrates that using D-CPIs can be of direct policy relevance.

Third, I focus on the period of high inflation that started during the Covid-19 pandemic and the ensuing period of economic recovery, from May 2020 to May 2022. During this period, the cumulative inflation rates are inverse U-shaped, increasing from 13% at the bottom of the income distribution to 14.7% for the middle class, and falling back to 13.5% at the top of the income distribution. These estimates can be used to make adjustments to the compression of wages documented by Autor et al. (2023). Between May 2020 and May 2022, according to the official CPI, wages increased by 2% at the 10th percentile of the income distribution, compared to a fall of 4% at the median, i.e. there was a compression of the income distribution of 6pp. Using D-CPIs, the compression of the real wage distribution at the bottom is amplified by about 1.7pp, i.e. 28% of the baseline measure.[2]

The difference in inflation rates across the income distribution after the pandemic is entirely driven by two product categories that experienced high inflation rates during this period: gas and new or used vehicles. Middle class households have on average higher expenditure shares on these categories, i.e. they were more exposed to these inflation shocks. Setting aside these categories, inflation rates are fairly homogeneous across the income distribution during the Covid period. These results illustrate that it can be fruitful to analyze D-CPIs in real time, as short-run patterns may differ from long-run trends.

Finally, I present three extensions of the main analysis, which all confirm the patterns described above. The first extension allows for geographic heterogeneity in inflation, which is absent from the main analysis due to data limitations. This analysis is carried out with the publicly available data provided by the BLS for a sub-sample of cities covering about 40 % of total national expenditures. I find that the inflation inequality series remain virtually unchanged. Consistent with these results, using different data Molloy

[2] Pallotti et al. (2024) study the heterogeneous effects of the inflation surge in the Euro area after the Covid-19 pandemic, highlighting the importance of the composition of households' financial portfolios: households with nominal long-term debt benefit from a higher price level.

(2024) documents that differences in housing inflation and location choices have not generated differences in inflation rates by income group.[3]

The second extension departs from the BLS methodology and introduces non-homothetic price indices, which provide a welfare interpretation of the inflation heterogeneity patterns. Using the non-parametric algorithm of Jaravel and Lashkari (2023), I find that the non-homotheticity correction is relatively similar across income groups. This result implies that the changes in real income inequality and the adjustment of the poverty line remain similar to the baseline results.

The third and final extension extends the analysis going back to 1983. Because of limitations with the publicly-available data, a fixed sales shares methodology prior to 2002. Running validation tests on the post-2002 data suggests this approach should perform well: the level of inflation inequality measured with fixed end-of-period sales shares is similar to the baseline analysis with shares updated as in the baseline CPI. I find that inflation inequality was also at play in earlier decades, although it became stronger from the mid 1990s. I then present the implications for the measurement of real income growth across the income distribution, consumption inequality, and trends in pre-tax and post-tax national income inequality. The results show that inflation inequality can be critical for the measurement of inequality at longer horizons. For instance, compared to the baseline with a common CPI, with D-CPIs the rate of increase in inequality across household income quintiles from 1983 to 2019 is about 45 % faster for pre-tax income ratios and 70 % faster for post-tax income ratios.

Before proceeding, it is worth highlighting the main limitations of the analysis. Since the goal of this paper is to stay as close as possible to the official CPI methodology, the analysis is naturally subject to any limitation affecting this index. The official CPI uses specific expenditure shares, described in Section 2 below, which may lead to substitution bias of potentially different magnitudes for different socio-demographic groups. I can however directly address this potential issue by using the Chained CPI, which yields somewhat stronger inflation inequality. A more fundamental limitation is that I cannot allow for inflation heterogeneity across socio-demographic groups *within* product category, because the BLS does not collect expenditures within categories. Heterogeneity in expenditure patterns and inflation rates can be large within product categories. Prior work has shown that, in the United States in recent decades, within-category inflation has been lower for the rich within consumer packaged goods (Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2021)) and within health care (Jaravel et al. (2024)). Recent work documents particularly strong inflation inequality within consumer packaged goods after the Covid-19 pandemic (Cavallo and Kryvtsov (2024), Chen et al. (2024)), in part due to the price pass-through of commodity cost shocks (Sangani (2023)). Instead, this paper focuses exclusively on estimating the "between category" component of inflation inequality – which can then be combined with "within category" inflation inequality estimates from other, complementary analyses. While prior work suggests that the "within" component may amplify inflation inequality, an important direction for future work is to collect granular data to measure inflation inequality in a larger number of product categories.[4]

[3]In contrast, Moretti (2013) documented that, between 1980 and 2000, college graduates concentrated in cities with rising cost of housing, suggesting that real income inequality was dampened relative to nominal income inequality.

[4]This step would by definition depart from the data and methods of the BLS, since the BLS does not collect expenditure data within product categories, and is therefore outside of the scope of this paper. It is however instructive to combine the existing estimates. For instance, Jaravel (2019) estimates an annual gap in inflation rates of 66 basis points across the income distribution within consumer packaged goods between 2004 and 2015. Since these goods account for about 15 % of total expenditures, they contribute about 10 basis point to overall inflation inequality, a meaningful contribution to add to

Related literature. This paper contributes to a growing academic literature on the measurement of inflation inequality. This literature documents that, over the past 20 years, on average annual inflation was lower for higher-income households. However, these papers build price indices that are not entirely consistent with the CPI methodology, making it difficult to use them to correct published statistics about income inequality or poverty rates.

First, several recent studies (Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2021), Chen et al. (2024)) estimate inflation inequality within consumer packaged goods using scanner data, which account for a modest share of total expenditure (below 15%) and differ from the sample frame of the BLS. Besides being able to estimate "within category" inflation inequality, studies of scanner data have the advantage of accounting for inflation inequality arising from changes in product variety: Jaravel (2019) documents that changes in product variety strengthens inflation inequality within this sample.

Second, Jaravel (2019) and Jaravel and Lashkari (2023) study the full consumption basket, combining BLS price series to consumption expenditures from the CEX. However, they use data construction steps and price index formulas that deviate from the official CPI. For instance, between 2002 and 2019, the price index of Jaravel and Lashkari (2023) exhibits an average annual inflation rate that is 31 basis points higher than the official CPI (Appendix Figure A1). This discrepancy is large relative to the magnitude of estimated inflation inequality itself, approximately 45 basis points per year between the top and bottom income quintiles, which precludes using the Jaravel and Lashkari (2023) estimates to adjust official series such as household income inequality, consumption inequality, or poverty rates. By contrast, the D-CPI series are fully consistent with the official CPI. This consistency allows me to go beyond prior work by constructing robust, D-CPI-adjusted series for inequality and poverty, and by providing decompositions that identify the product categories driving inflation inequality using the official BLS product hierarchy. In contrast with Jaravel (2019), I find that substantial inflation inequality can be identified even at relatively coarse levels of product aggregation, without the need to exploit the most finely disaggregated micro price data.

Third, two papers by BLS researchers compute inflation heterogeneity by income quintiles using confidential BLS data and the same price index formulas as the official CPI. Klick and Stockburger (2021) build price indices by quintiles from 2003 to 2018 and, in contemporaneous work, Klick and Stockburger (2024) do so from 2006 to 2023. By using confidential BLS data, these papers have the advantage of avoiding certain imputations I must rely on publicly-available data.[5] A limitation of these studies is that they examine only income quintiles over a shorter time horizon, and researchers without access to the micro data cannot replicate or extend the analyses to other socio-demographic groups or alternative price indices. My paper presents a wider range of facts on inflation heterogeneity by income percentiles, age, gender, race, the poverty line, occupations, expenditure percentiles, etc. It provides a publicly-available data set from 1983 to the present day, with monthly updates to the database going

the annual inflation gap of 44 basis points obtained with D-CPIs. Given the importance of housing, vehicles and airfare, which account for about half of the inflation inequality estimated with D-CPIs, a fruitful direction for future work would be to collect suitable micro-data to investigate inflation heterogeneity within these three categories. For housing, Section 4.1 analyzes heterogeneity in the user cost of housing for homeowners, finding limited heterogeneity between the bottom and top income quintiles.

[5] Klick and Stockburger (2021) and Klick and Stockburger (2024) have access to the full geographic granularity, while I only observe it for 40 % of expenditures. Other differences include the treatment of the CEX data, as Klick and Stockburger (2021) and Klick and Stockburger (2024) follow the internal production methods of the BLS (e.g., using smoothed expenditure weights), and the fact that I must impute missing price series in the publicly-available data in certain periods.

forward, which anyone can use to study distributional CPIs for any socio-demographic group observed in the consumer expenditure survey, with any price index formula (e.g., including the correction for non-homotheticities). My results by income quintiles are close to those of Klick and Stockburger (2021) and Klick and Stockburger (2024) for the periods for which our analyses overlap, which validates the reliability of the approach using publicly-available data.[6]

Outline. The remainder of this paper is organized as follows. Section 2 presents the data and methodology to compute D-CPIs. Section 3 presents the main results, discussing in turn the implications of D-CPIs for the measurement of inequality and poverty over the long run, and of real wage dynamics during the inflation burst in the wake of the Covid-19 pandemic. Finally, Section 4 presents the three extensions. Complementary results and methodological discussions are reported in the Online Appendix.

2 Data and D-CPI Methodology

This section present the main data set: Section 2.1 describes how to replicate CPI with the most disaggregated publicly-available statistics, and Section 2.2 presents the approach to build group-specific CPIs.

2.1 CPI Replication with Publicly-Available Statistics

The key goal is to use publicly-available statistics to build monthly price indices that are specific to particular socio-demographic groups and remain consistent with the official Consumer Price Index. The first step is therefore to replicate the official CPI with the most disaggregated publicly-available statistics.

This subsection first briefly presents the methodology of the BLS. It then describes the publicly available statistics used for replication, highlighting the main challenges stemming from data constraints.

A primer on the calculation of the Official CPI. The aggregate CPI is computed each month by the Bureau of Labor Statistics by combining two data sources: monthly price data and expenditure shares. The monthly price data are collected in the Commodities and Services Survey and the Housing Survey, while the expenditure shares use the Consumer Expenditure Survey (CEX).

The monthly price changes are measured by the BLS at the level of about 300 product categories called "entry-level items" (ELI).[7] These category-level price changes are themselves based on the aggregation of thousands of price quotes, as discussed in Appendix A. The expenditure data observed in the CEX use a more detailed product classification, using "universal categorization codes" (UCC), with approximately 600 UCCs corresponding to the ELIs used in the calculation of the CPI.[8]

To aggregate prices into the CPI, the BLS works with 243 "basic items", which are slightly more aggregated product categories than ELIs, and keeps track of price changes in 32 areas. For simplicity, from here on I will call "items" the $7,776$ basic item-area cells (given by the 243 items times 32 areas)

[6] Earlier work by BLS researchers on subgroup price indices includes Garner et al. (1996), Cage et al. (2002), and Martin (2022). See also Chakrabarti et al. (2023).

[7] Specifically, there are 294 ELIs after 2020, 296 ELIs between 2010 and 2020, and 303 ELIs prior to 2010.

[8] The exact number of UCCs varies across years. For example, in 2022 there were 656 UCCs, of which 608 were relevant for the CPI.

which constitute the level of observation at which the BLS applies the expenditure shares measured in the CEX.

To compute the item-level expenditure shares to be used for the aggregate CPI, the BLS takes two main steps. First, in December of every other year, the BLS uses a crosswalk from UCCs to ELIs to assign expenditure shares to each item, using CEX data from prior years. Specifically, prior to 2023, BLS assigned these expenditure shares biennially in December of odd-numbered years using CEX data from the most recent two years prior to the update year. For example, BLS computed a new set of expenditure shares in December 2017 using CEX data from 2015 and 2016.[9] Starting from 2023, in an attempt to improve index accuracy and reduce the lag between the incidence and usage of spending data, BLS changed the update schedule of baseline expenditure weights to occur at an annual frequency, using expenditure data from a single calendar year to reflect the spending pattern from two years prior. For example, the CEX micro-data in 2021 are aggregated and used as baseline weights for January to December of 2023.[10] Let us denote these baseline December expenditure weights by $\omega_{i0(t)}$, where the notation "$0(t)$" refers to the most recent pivot December month prior to the month t when baseline expenditure weights are updated.

Second, for the period between the biennial or annual December updates, BLS computes the official CPI by taking the following weighted average with expenditure weights $\omega_{i0(t)}$:

$$\frac{P_t}{P_{0(t)}} \equiv \sum_k \left(\frac{p_{it}}{p_{i0(t)}} \cdot \omega_{i0(t)} \right), \tag{1}$$

where P_t denotes the overall price index in month t and i indexes the item. In words, the cumulative official CPI is a simple weighted average of cumulative price changes $\frac{p_{it}}{p_{i0(t)}}$ for each item i, using the baseline December expenditure shares $\omega_{i0(t)}$ as weights. This is a Laspeyres index, which is known to be exact for a Leontief utility function.

It is instructive to note that equation (1) is equivalent to the following monthly price index:

$$\frac{P_{t+1}}{P_t} = \sum_i \left(\frac{p_{i(t+1)}}{p_{it}} \cdot \omega_{it} \right), \tag{2}$$

with the monthly expenditure weights given by

$$\omega_{it} \equiv \frac{\frac{p_{it}}{p_{i0(t)}} \cdot \omega_{i0(t)}}{\sum_k \left(\frac{p_{kt}}{p_{k0(t)}} \cdot \omega_{k0(t)} \right)} = \frac{p_{it}/P_t}{p_{i0(t)}/P_{0(t)}} \cdot \omega_{i0(t)}.$$

Thus, the official CPI formula uses monthly price changes to infer the way the expenditure shares should evolve across product categories every month. In words, for every item, to calculate the updated monthly expenditure weights ω_{it}, BLS takes the ratio between the item price index in the current month, p_{it}, and in the most recent baseline update month, $p_{i0(t)}$, and multiplies this ratio by the baseline expenditure weights $\omega_{i0(t)}$. The resulting monthly relative importance weights are then re-normalized such that they

[9] For update year 2021, BLS decided to maintain the normal baseline weight updating practice and use CEX data from 2019 and 2020, after considering potential interventions to mitigate the impact on spending behavior due to Covid-19.

[10] For more information regarding BLS's decision to change the update schedule of baseline spending weights, see https://www.bls.gov/cpi/tables/relative-importance/weight-update-information-2022.htm. Appendix B.1 provides more information about the calculation of the expenditure shares in December of every other year, addressing certain simplifications made here in the main text to facilitate reading.

sum up to 1 in the current month.

This formula can be rationalized with a CES price index with elasticity of substitution $\eta = 0$, i.e. a Leontief utility function: product categories and areas with rising relative prices will be assigned larger imputed expenditure shares over time. The purpose of this procedure is to provide updated expenditure shares in real time, obviating the need to use actual expenditures each month.

The BLS also computes the Chained CPI, using actual monthly expenditure shares observed in the CEX for each product category, which may more accurately reflect consumers' substitution behaviors across items. But this index can only be produced with a lag, because the CEX data is released with a one-year lag. I further discuss the Chained CPI below.

Publicly-available data and five associated challenges. The analysis requires being able to replicate the CPI calculation using public data only, which raises five challenges.

The first and main challenge pertains to the crosswalk between UCCs and ELIs. BLS only publishes the most recent UCC-to-ELI crosswalk. However, UCCs change frequently over time. While more stable, the set of ELIs used in the CPI calculation also changes from time to time. By contacting the BLS, I could obtain additional crosswalks for 2023, 2022, 2020 and 2010. To create the crosswalks for the remaining years, I used a concordance published by the BLS which tracks how UCCs change over time. These changes happen at the quarterly level, i.e. I created quarterly crosswalks, starting from the ELIs present in the 2023 and mapping the corresponding UCCs to every quarter in the past using the UCC changes concordance.[11] The crosswalk goes back to 1999, making it possible to compute inflation rates from year 2002.

Second, the BLS does not publish any raw price information at the level of ELIs. The most granular, complete, and mutually exclusive breakdown of CPI items for which price index data is publicly available at the national level consists of 211 categories called "item strata", out of which 209 are commodities and services, plus 2 strata for housing. Furthermore, the BLS only publishes price indices for item strata at the national level; the local-level price indices used in the construction of the official index are publicly available only for a sub-sample of 23 cities, covering about 40 % of national expenditures. In the main analysis, I work with national-level price indices for item strata, and I return to geographic heterogeneity in Section 4. There is a simple crosswalk between ELIs and item strata: the first four characters in the ELI code corresponds to the third to sixth characters in the CPI item code. Therefore, I convert the UCC-ELI concordance into a UCC-item strata concordance and conduct the analysis at the level of item strata in everything that follows. Specifically, expenditure shares ω_{it} are computed as described above, except that i now indexes item strata rather than ELIs.

Third, only 181 item strata have published price series; the remaining 30 item strata require proxy price information. There are 26 "unsampled item strata", and 4 strata covered by "Health insurance" (item code *SEME*) for which no price series are available at the individual item level.[12] Unsampled item

[11]The mapping between UCCs and ELIs is many-to-many. Most of the time, if one UCC maps to many ELIs I distribute the UCC spending equally among the ELIs. However, in some cases I add specific weights obtained through correspondence with the BLS.

[12]BLS tracks the price change of Health insuranceusing an indirect approach called the retained earnings method, instead of directly collecting information on premiums, because premium changes should not be compared across insurance plans of varying quality. This method utilizes industry data to determine the percentage of premiums that health insurance companies keep as retained earnings as opposed to payments for medical goods and services to providers. The four item strata covered

strata corresponds one-to-one with "unsampled ELIs", a situation occurring when the underlying product or service has reported expenditures in the Consumer Expenditure Survey and is in the scope of CPI, but it is infeasible or impractical to collect price information.[13] I use the price series of the most immediate overarching category for each of the 30 item strata without original price information. For example, I use the price series of *Men's apparel (SEAA)* as proxy for that of item stratum *Unsampled men's apparel (SEAA09)*. Four unsampled item strata do not have a published expenditure weight and are dropped from the analysis. Moreover, the four item strata covered by health insurance map to the same price series. The final data set thus has 204 unique price series covering the full consumption basket.

Fourth, in some cases price changes are missing in a price series for specific months. Indeed, when the price index of any item fails to meet the publication quality threshold, it will be left out of any BLS publication. While these data points are not publicly available, they are still used by BLS internally in the official CPI calculation. This limitation can be addressed by imputing the missing price changes, which I do with a spline interpolation.

Fifth, the CEX expenditure data require various cleaning steps. First, to be consistent with the CEX published summary tables, prior to 2004 the CEX data is restricted to households who reported all of their income. After 2004, the BLS started imputing missing income and this restriction becomes unnecessary. Second, while the analysis requires computing monthly expenditures, for many items the CEX survey respondents only report expenditures over the prior three months. For every respondent, I create a three-month panel, and distribute their expenditures evenly across each month. I use the survey weights so that, when aggregating these monthly expenditures to the yearly level, I match the published CEX summary tables. Note that aggregating expenditures at the monthly level in this way is very different from the methods described in the CEX documentation and sample code, which are only relevant for yearly aggregation. Finally, I use the "Owned Living Quarters and Other Owned Real Estate" module of the CEX micro-data to obtain expenditures on "Owners' equivalent rent of primary residences" and "Owners' equivalent rent of secondary residences", which are not part of the CEX summary tables but which make up a large share of spending for the items relevant for the CPI. Instead of using owners' equivalent rents, the CEX tracks the costs of home ownership through spending on categories such as mortgage interest payments, insurance and property taxes, all of which are absent from the CPI.

To ensure that I handle the CEX data in a manner consistent with the BLS' practice, it is useful to implement several checks. First, I leverage the fact that the BLS publishes the set of weights $\omega_{i0(t)}$ used in pivot months. I use these weights directly when calculating the aggregate CPI to ensure that there is no source of error from the CEX; thus, in the main analysis I use the CEX data only to distribute aggregate spending across socio-demographic groups. I will also check below that I obtain very similar results when I compute the shares directly from the CEX data. Finally, I compare the patterns in the cleaned data set to the official CEX summary tables published by the BLS, as discussed in Section 2.2.

by Health insurance correspond to different operating mechanisms of health plans (e.g., health maintenance (HMO) plans and Medicare) and the individual price indexes for these item strata are not available, likely due to the proprietary data used for construction. For more details, see the CPI Factsheet on medical care: `https://www.bls.gov/cpi/factsheets/medical-care.htm#A2`.

[13] For example, purchases of private jets might appear in the CEX expenditure data. BLS does not sample the price of private jets, but instead group it into "unsampled new and used motor vehicles."

Chained CPI. As mentioned above, the official CPI uses a Laspeyres formula with little room for substitution when prices change. To better account for potential substitution patterns, the BLS also publishes a different price index, the Chained CPI. This index uses a combination of a Törnqvist Index and a CES index. The Törnqvist Index uses actual spending shares from the current and previous periods and thus accounts for the observed changes in spending patterns. The Törnqvist Index is calculated as follows:

$$P_t = P_{t-1} \prod_{i \in I} \left(\frac{p_{it}}{p_{i(t-1)}} \right)^{\frac{w_{i,t}+w_{i,t-1}}{2}}, \tag{3}$$

where $w_{i,t}$ are the actual monthly expenditure shares taken from the CEX data, with i indexing items.

These expenditure shares are only available with a lag, due to processing time with the CEX data, i.e. the Törnqvist Index cannot be calculated in real time. To get around this limitation, the BLS calculates an interim version of the Chained CPI using a CES price index, setting a constant elasticity of substitution above zero. Using expenditure and price data from 2003 to 2014, the BLS calculates an elasticity of substitution $\sigma \approx 0.6$ for most years in a regression of the Törnqvist index on the CES price index with free parameter σ. Thus, to update the weights from the most recent baseline period $0(t)$, one can use the CES update formula:

$$w_{i,t} = \left(\frac{p_{i,t}}{p_{i,o(t)}} \right)^{1-\sigma} w_{i,0(t)} \cdot \frac{1}{\sum_{j \in \mathcal{I}} \left(\frac{p_{i,t}}{p_{i,0(t)}} \right)^{1-\sigma} \cdot w_{j,0(t)}}.$$

The final CES price index is then calculated as:

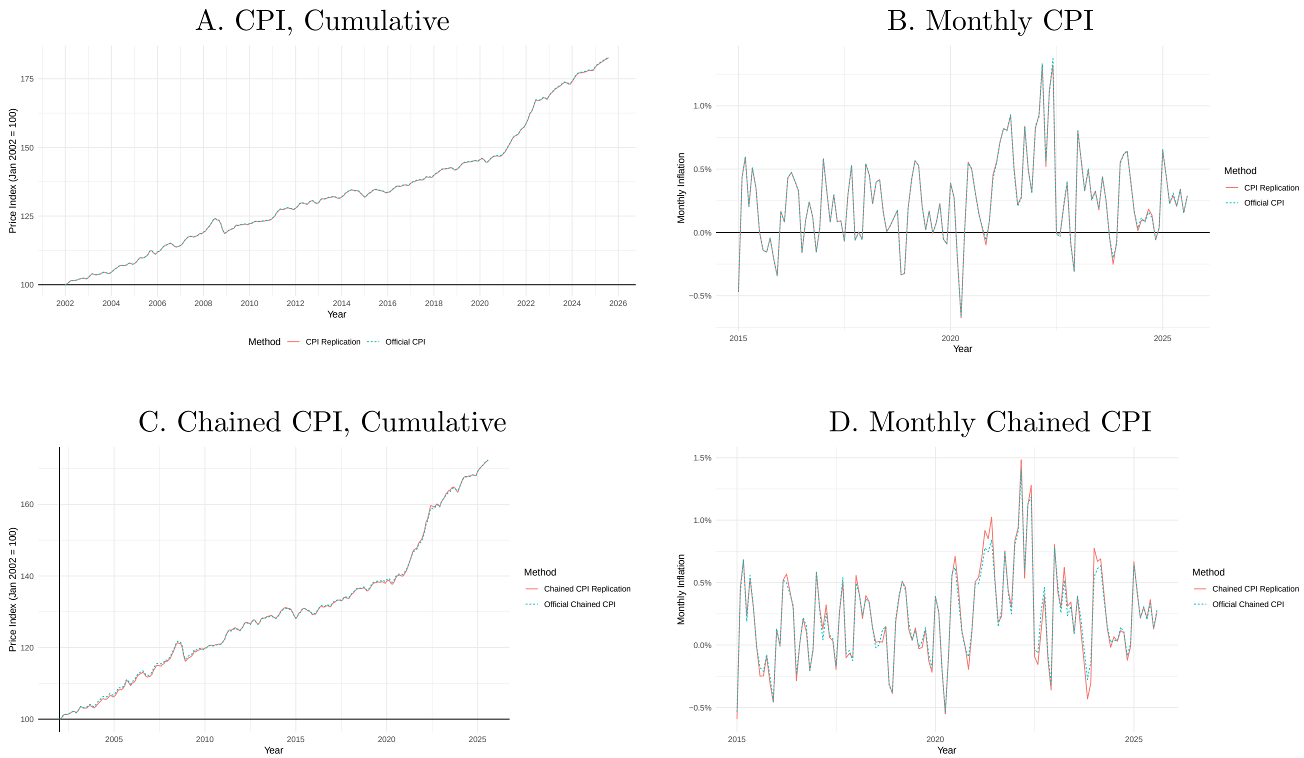
$$P_{i,t} = P_{i,t-1} \left(\sum_{i \in I} w_{i,t-t} \left(\frac{p_{i,t}}{p_{i,t-1}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

The Chained CPI uses the Törnqvist Index for all months where actual monthly spending weights are available, creates an interim price index using the CES index afterwards, and then creates a revised final index after the new set of monthly weights become available. I follow the exact same procedure, except that in the baseline analysis I work with national-level price indices at the level of item strata – rather than at the item level as in the official Chained CPI, which features the geographic variation unavailable in public data.

Validation Tests. To sum up, replicating the official using publicly-available statistics can be challenging because of data construction steps – notably the ELI-UCC crosswalk and the data cleaning steps in the CEX survey – and the fact that prices series are only available at the item strata level of aggregation, rather than at the item level, with missing data points in some cases requiring imputation. To assess how well CPI can be replicated, Figure 1 plots the results obtained with the publicly-available data against the official statistics released by BLS, from 2002 to 2025.

I first present the comparison with the official CPI using the Laspeyres formula, in cumulative terms in panel A and by month in panel B. I use the official weights ω_{it} published by the BLS in the construction of the index, such that the potential discrepancies with the official index stem from the fact that I use slightly

Figure 1 Database Validation Tests



Notes: This figure compares the price indices published by the BLS to price indices built using publicly-available data from January 2002 to August 2025. Panel A and B use the official CPI, reporting a cumulative and monthly index respectively. Panels C and D report the results for the chained CPI.

different price series (at the item strata level rather than for ELIs, with imputation when needed). I find that my index is almost indistinguishable from the official index. The correlation between the monthly official CPI inflation rate and my reconstructed CPI is 0.9994.

Next, I report the comparison to chained CPI in panels C (cumulative) and D (monthly). I now use the CEX data directly to compute the expenditure shares every month. The indices are again almost indistinguishable, with a correlation of 0.9895 between the official monthly Chained CPI inflation rate and my reconstructed series. This result indicates that my treatment of the CEX data is consistent with BLS' practice.

2.2 Computing D-CPIs

Having established in the previous section that official indices can be replicated very well in real time (i.e., every month) using publicly-available data, the next step of the analysis is to distribute the aggregate expenditure shares across socio-demographic groups to obtain group-specific CPIs. This approach can be applied to any socio-demographic group – by income, age, race, gender, occupations, etc.

To obtain group-specific expenditure shares that remain consistent with macro aggregates, I start from the official set of weights $\omega_{i0(t)}$ used in pivot months and published by BLS. I then distribute these expenditures across socio-demographic groups using the CEX survey, and update the shares in the following months with price data, following the same methodology as the BLS. Specifically, I proceed in four steps:

First, I obtain the official set of weights ω_{i0} published by BLS.

Second, using the crosswalk from UCCs to item strata, for each item stratum i I compute the share of sales to each socio-demographic group g, denoted $\tilde{s}_{gi0}$.[14]

Third, using the shares $\tilde{s}_{gi0}$, I distribute the official expenditure weight of the item strata (used in the calculation of the official CPI) across groups indexed by g. For example, say that we observe that 25% of sales for the item strata for car purchases are accounted for by households in the top 5% of the income distribution. I then attribute 25% of the aggregate expenditure weight for cars to this household group. This step thus generates expenditure patterns for each household group g across all item strata. Normalizing by the sum of expenditures for each group, I obtain the group-specific expenditure shares $s_{i0(t)g} \equiv \frac{\tilde{s}_{gi0} \cdot \omega_{i0}}{\sum_k \tilde{s}_{gk0} \cdot \omega_{k0}}$, which are fully consistent with the calculation of the official CPI.

The last step is to use the same formula as the BLS to compute the price index for each group, using group-specific expenditure shares $s_{i0(t)g}$ in lieu of $\omega_{i0(t)}$ in formula (1) to obtain the cumulative CPI for each group. Likewise, the monthly CPI is obtained by applying formula (2), with group-specific expenditure shares updated each month, defined as $s_{itg} \equiv \frac{p_{it}/P_{tg}}{p_{i0(t)}/P_{0(t)g}} \cdot s_{i0(t)g}$. I thus obtain price indices by socio-demographic groups each month, using a method consistent with the calculation of the official CPI.

Finally, in robustness analyses I will use a Chained CPI index specific to each socio-demographic group. Indeed, the price index in equation (3) can be computed using monthly expenditure shares for each group, which are directly measured in the CEX survey.

Expenditure shares by income groups. Table I summarizes the expenditure patterns by income groups, focusing on December 2013 for illustration. Panel A reports the patterns at the level of eight broad product categories covering the full consumption baskets. At this level of aggregation, there is relatively little heterogeneity in expenditure shares across income groups. Panel B presents the shares for the 10 largest most detailed categories (item strata), depicting much larger spending share heterogeneity across the income distribution. Together, these ten categories account for 51.72 % of total spending in CPI.

Additional results are reported in the Online Appendix. Appendix Table A1 provides a full description of the expenditure patterns across all items strata, by income groups. Appendix Table A2 compares the expenditure weights in the CPI and CEX data for eight broad categories.

Data accessibility and replication. To facilitate future work on the distributional effects of inflation, data tables with price indices by socio-demographic groups as well as the underlying data can be downloaded from the D-CPI Project webpage. The webpage provides monthly price index series by income, age, race, gender, and occupations. In addition, the underlying data and crosswalks can be downloaded along with replication code to build alternative price indices, using any socio-demographic characteristic observed in the Consumer Expenditure Survey.

[14] I use the official CEX summary tables published by the CEX to check that I obtain the correct group-specific expenditures for each product. The BLS publishes a set of yearly expenditure summary tables by income quintile that I use to validate that the micro-data is processed correctly. I implement this check with the expenditures for the twelve most aggregated categories, which only require minor standardization over time.

Table I Expenditure Shares by Income Quintile, December 2013

Panel A: Broad Item Categories

Item Name	CPI Weight	Bottom 5%	1	2	3	4	5	Top 5%
Housing	41.21	42.63	44.19	42.01	40.32	38.92	38.81	39.71
Transportation	16.67	13.53	13.53	16.94	18.61	19.50	18.47	17.84
Food and beverages	15.18	17.79	16.67	15.35	15.35	15.61	14.64	14.20
Medical care	7.21	5.98	7.17	8.47	7.95	7.63	6.35	6.02
Education and communication	6.78	8.13	6.82	5.25	5.49	6.00	8.25	8.50
Recreation	5.95	4.56	4.44	4.94	5.17	5.71	6.61	6.68
Apparel	3.62	3.40	3.30	3.38	3.57	3.34	3.83	3.95
Other goods and services	3.38	3.97	3.89	3.65	3.55	3.30	3.04	3.10

Panel B: Ten Largest Item Strata

Item Name	CPI Weight	Bottom 5%	1	2	3	4	5	Top 5%
Owners' equivalent rent of primary residence	22.78	16.19	18.41	19.94	21.42	22.71	24.22	24.97
Rent of primary residence	6.61	16.42	14.62	10.80	8.08	5.24	2.46	1.89
Gasoline (all types)	5.11	6.20	5.83	6.65	7.03	6.78	5.36	4.69
New vehicles	3.15	0.47	0.66	1.88	2.97	3.42	4.27	4.36
Electricity	2.89	3.53	3.70	3.46	3.06	2.69	2.08	2.02
Full service meals and snacks	2.72	1.90	1.90	2.18	2.50	2.90	3.12	3.26
Motor vehicle insurance	2.53	1.57	2.28	3.12	2.77	3.02	2.16	1.92
Limited service meals and snacks	2.30	2.78	2.33	2.20	2.43	2.52	2.09	1.86
Used cars and trucks	1.86	2.08	1.71	1.95	2.07	2.17	1.80	1.82
College tuition and fees	1.77	3.67	2.39	0.92	1.09	1.19	2.97	3.30

Notes: This table reports expenditure shares for various products across the income distribution. Panel A focuses on eight broad categories covering the full consumption basket. Panel B reports the patterns for the ten largest item strata, which account for 51.72% of total spending.

3 Main Results

This section present the main results, first describing patterns of inflation inequality over the long run, going back to 2002, and then focusing on the recent inflation burst, in the wake of the Covid-19 pandemic.

3.1 Long-Run Inflation Inequality

I examine in turn the extent of inflation heterogeneity by income group and for other socio-demographic group (age, race, urban vs. rural). The results show that D-CPIs have important implications for the measurement of inequality and the indexation of the poverty line.

3.1.1 Long-run inflation inequality by income percentile

Figure 2 reports inflation across income percentiles from January 2002 to August 2025: inflation rates have been consistently higher for lower-income groups. Panel A shows that the gap opens up gradually over time, plotting the full time series for selected income percentiles. Panel B reports the cumulative inflation rates across the income distribution as of August 2025, which ranges from about 95% at the bottom of the income distribution to about 76 % at the top. Thus, the rate of increase in prices is about 25 % higher for the least affluent households, compared to the most affluent. At an annual frequency, during this period the annual inflation rate was 2.87 % at the bottom of the income distribution, compared to 2.43 % at the top, an annual inflation gap of 44 basis points.

How important are these trends for inequality? To address this question, it is useful to plots household income growth across the income distribution using the official CPI index and the indices accounting for inflation inequality. I use the official statistics of the U.S. Census Bureau to get household income growth by income quintile and for the top 5 %.[15] I focus on the period from 2002 to 2019, stopping the analysis before the onset of the Covid-19 pandemic, before turning to the pandemic period in the next subsection.

Figure 3 shows that, according to the official CPI, household real income growth between 2002 and 2019 was higher at the top of the income distribution, ranging from 7.7 % for the bottom income quintile to 24.6 % in the top income quintile, and up to 26.4 % for the top 5 % of households. This gradient becomes considerably steeper with the income-group-specific price indices. After accounting for inflation inequality, household real income growth is only 2.4 % at the bottom of the distribution, i.e. earnings are almost stagnating, while income growth at the top is even faster, at 25.5 % for the top quintile and 27.8 % for the top 5 %.

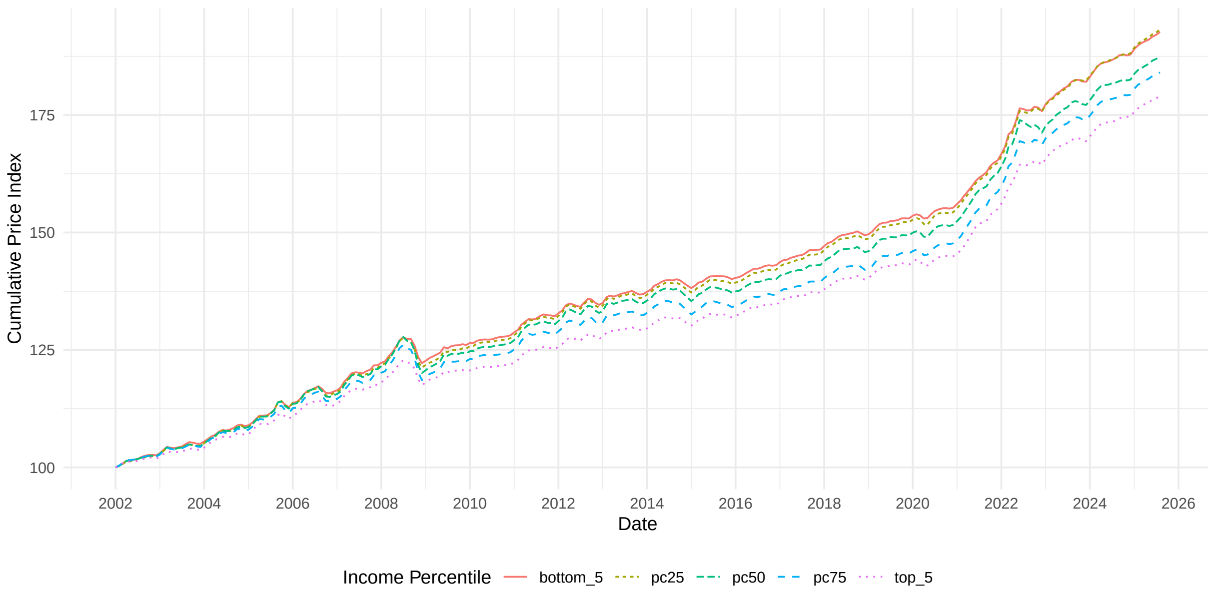
Thus, according to the official metric, the income gap between the top and bottom quintiles increased by 15.7 % between 2002 and 2019 (= 1.246/1.077). When accounting for inflation inequality, the income gap increases significantly more, by 22.6 % (= 1.255/1.024): the rate of increase in real income inequality is about 44 % faster than with the official CPI.

In the Online Appendix, I show that the results are qualitatively similar – and somewhat stronger quantitatively – with the Chained CPI formula, which keeps track of consumer demand substitution using

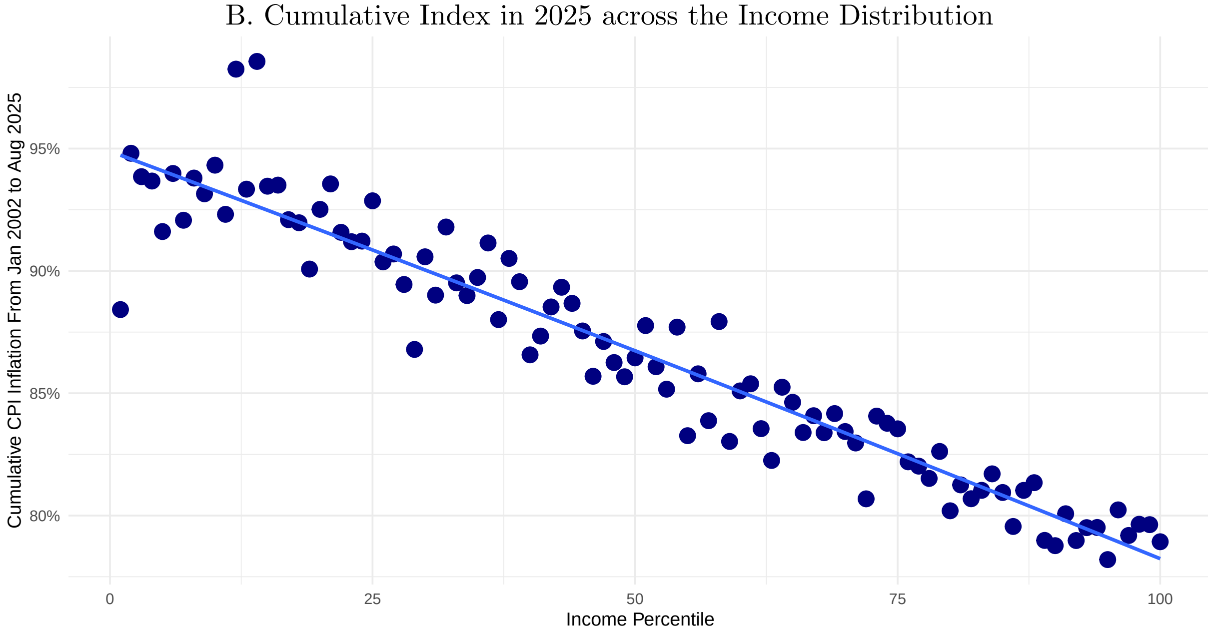
[15] The Census estimates are based on CPS data. Virtually identical results are obtained when working with the CPS micro data directly. As a given household's position in the income distribution is not fixed over time, the results should be interpreted as a depicting how the shape of the (real) income distribution changes over time, rather than as describing the income growth experience of specific households.

Figure 2 Long-Run Inflation Inequality by Income Percentile

A. Cumulative Index from 2002 to 2025 for Selected Income Percentiles

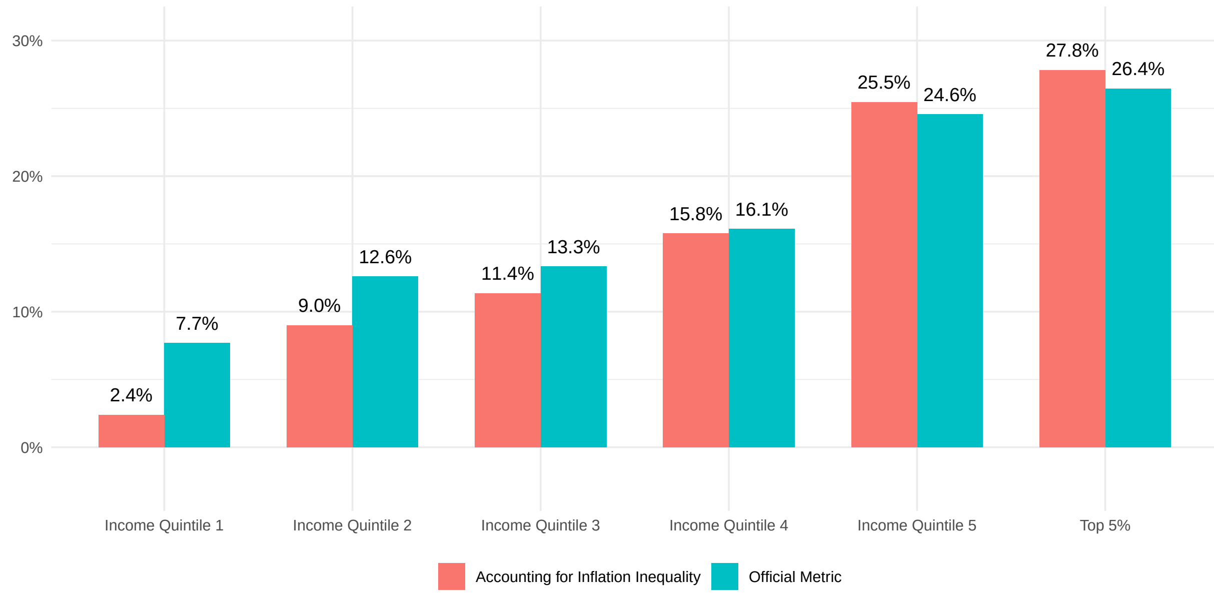


B. Cumulative Index in 2025 across the Income Distribution



Notes: This figure reports inflation rates by income percentile. Panel A show the monthly time series of the cumulative price index from January 2002 to August 2025 for selected income percentiles (bottom 5%, 25th, 50th, 75th, and top 5%). Panel B reports the cumulative CPI in August 2025 for all income percentiles, along with the OLS best-fit line.

Figure 3 Implications for Household Real Income Growth, 2002 to 2019



Notes: This figure reports cumulative real income growth from 2002 to 2019 by quintiles of the household income distribution, as well as for the top 5%. Two series are shown, with the official CPI and with the D-CPIs specific to each income group.

monthly CEX data. Specifically, Appendix Figure A2 documents that inflation heterogeneity across the income distribution is amplified with the chained CPI formula. The cumulative inflation rates across the income distribution in August 2025 ranges from about 87 % at the bottom of the income distribution to about 66 % at the top (compared to 95 %—76 % with the baseline CPI formula). Figure A3 shows that, with Chained CPI, the income gap between the top and bottom quintile increased by 15.7 % between 2002 and 2019, while with Chained D-CPIs it increases by 24.8 %. Thus, the rate of increase in real income inequality is about 58 % faster with Chained D-CPIs than with the official Chained CPI. The amplification of inflation inequality is even stronger with Chained D-CPIs than with the baseline D-CPIs because the bias from consumer demand substitution turns out to be slightly stronger at the bottom than at the top of the income distribution – consistent with the idea that it may be more challenging for households to reallocate expenditures away from necessities products, such as food, when their relative prices increase.

Next, Table II examines the implications of D-CPIs for consumption inequality. Consumption expenditures by household income quintile are obtained directly from the official CEX annual summary tables published by the BLS. The table reports the ratio of total consumption expenditures for households in the top and bottom income quintiles over time. With the official CPI, there is only a slight 2 % increase in this ratio between 2002 and 2019. With D-CPIs, there is a meaningful increase of about 8 %, four times as large as the baseline measure with the official CPI. While prior work has examined how measurement issues in surveys may bias estimates of consumption inequality (Krueger and Perri (2006), Aguiar and Bils (2015)), I find that heterogeneity in price indices is also an important factor for accurate measurement of consumption inequality.

Finally, Table III computes the pre-tax and after-tax national income ratios between the top and

Table II Trends in Consumption Inequality: Ratio of Top to Bottom Income Quintiles, 2002 to 2019

	Consumption ratios, top to bottom quintiles		% Change in consumption inequality
	2002 (1)	2019 (2)	2002 to 2019 (3)
With common price index	4.15	4.24	+ 2.05 %
With D-CPIs	4.15	4.49	+ 8.09 %

Notes: Columns (1) and (2) of this table report the ratios of consumption expenditures of households in the top and bottom income quintiles. Consumption expenditures are obtained from the CEX annual summary tables. The first row uses the official CPI to deflate consumption expenditures in 2019, while the second row uses quintile-specific CPIs. Column (3) reports the percentages change in the consumption ratios from 2002 to 2019.

Table III Trends in Pre-tax and After-tax National Income: Ratio of Top to Bottom Income Quintiles, 2002 to 2019

	Pre-tax income ratios			Post-tax income ratios		
	2002 (1)	2019 (2)	Δ 2002–2019 (3)	2002 (4)	2019 (5)	Δ 2002–2019 (6)
With common price index	15.11	17.70	17.20 %	5.21	5.10	- 2.01 %
With D-CPIs	15.11	18.75	24.14%	5.21	5.41	+ 3.79 %

Notes: Columns (1) and (2) of this table report the ratios of pre-tax national income for households in the top and bottom quintiles, as defined by Auten and Splinter (2024). The first row is obtained from Auten and Splinter (2024) (Figure 5), while the second row uses quintile-specific CPIs to correct the ratios. Column (3) reports the percentages change in the ratios from 2002 to 2019. Columns (4) to (6) repeat the analysis for post-tax national income ratios.

bottom income quintiles, using the data series of Auten and Splinter (2024). Here as well, the D-CPIs make a meaningful difference in the measurement of trends in inequality. Between 2002 and 2019, the pre-tax national income ratio between the top and bottom quintiles increased by 17.2% with the conventional measure but by 24.1 % with D-CPIs. During this period, the post-tax income ratios fell by 2 % with the traditional measure but increased by 3.8 % with D-CPIs, which again illustrates the importance of inflation heterogeneity for the measurement of inequality.

Decompositions Because it is a geometric average, the Chained CPI lends itself to convenient, exact additive decompositions that can shed light on the drivers of inflation inequality over time.

First, it is instructive to assess whether broad or detailed categories drive inflation inequality. Using the BLS' official product hierarchy, the 204 items strata can be grouped into 79 product categories ("Level 3"), which can themselves be grouped in 24 categories ("Level 2"), themselves sorted across 8 broad product categories ("Level 1"). For any categorization of products into a set of categories indexed by I, the difference in cumulative inflation rates can be decomposed into "between" and "within" components; Appendix C provides the derivation. Specifically, denoting by $\log(P_T^Q/P_0^Q)$ the cumulative price index for household quintile Q, the inflation difference between the top and bottom household income quintiles

Table IV Hierarchical Decomposition of the Cumulative Inflation Difference Between the Bottom and Top Income Quintiles, Jan. 2002 to Dec. 2019

Level of Aggregation	Between Percentage
Level 1, 8 product categories	29.30 %
Level 2, 24 product categories	31.02 %
Level 3, 79 product categories	85.41 %
Level 4, 204 item strata	100 %

Notes: This table reports the within-between decomposition of the log difference in cumulative inflation rates between the fifth and first household income quintiles, using equation (4) and the Chained CPI. The "between" component is mechanically 100% for Level 4, which is the most detailed level of observation, with no within variation.

can be written as:

$$\Delta\pi_{0,T}^{Q1,Q5} \equiv \log(P_T^{Q5}/P_0^{Q5}) - \log(P_T^{Q1}/P_0^{Q1}) = \underbrace{\sum_{t=0}^{T}\sum_{I}\left(\bar{s}_{i,t}^{Q1,Q5}\Delta\pi_{i,t}^{Q1,Q5}\right)}_{\text{Within}} + \underbrace{\sum_{t=0}^{T}\sum_{I}\left(\bar{\pi}_{i,t}^{Q1,Q5}\Delta s_{i,t}^{Q1,Q5}\right)}_{\text{Between}}, \quad (4)$$

where $\bar{s}_{I,t}^{Q1,Q5} = .5(s_{I,t}^{Q1} + s_{I,t}^{Q5})$ is the average expenditure share of the two household income groups on products in category I; $\Delta s_{i,t}^{Q1,Q5} = s_{I,t}^{Q1} - s_{I,t}^{Q5}$ is the difference in the expenditure shares of the two quintiles for category I; $\Delta\pi_{i,t}^{Q1,Q5} = \pi_{I,t}^{Q5} - \pi_{I,t}^{Q1}$ is the difference in the inflation rates experienced by the two quintiles within category I; and $\bar{\pi}_{i,t}^{Q1,Q5} = .5(\pi_{I,t}^{Q1} + \pi_{I,t}^{Q5})$ is the average inflation rate experienced by both groups within category I.

Table IV reports the results of the decomposition, studying cumulative inflation between January 2002 and December 2019. The first level of aggregation, with only 8 broad product categories (listed in Panel A of Table I), already captures a third of overall inflation inequality. The "between" contribution does not increase when considering 24 categories rather than the 8 broadest categories. The third level of aggregation, with 79 categories, explains 85.41 % of overall inflation inequality, i.e. in the CPI sample inflation inequality can be measured quite accurately with relatively aggregate data.[16]

To understand which products drive inflation inequality, it is useful to implement an item-level decomposition. The formula for Chained CPI in equation (3) implies an exact additive decomposition of the cumulative inflation gap between the top and bottom income quintiles:

$$\Delta\pi_{0,T}^{Q1,Q5} = \sum_{i}\left(\sum_{t=0}^{T}\Delta s_{i,t}^{Q1,Q5}\left(\log\left(\frac{p_{it}}{p_{i(t-1)}}\right) - \log\left(\frac{P_t}{P_{t-1}}\right)\right)\right). \quad (5)$$

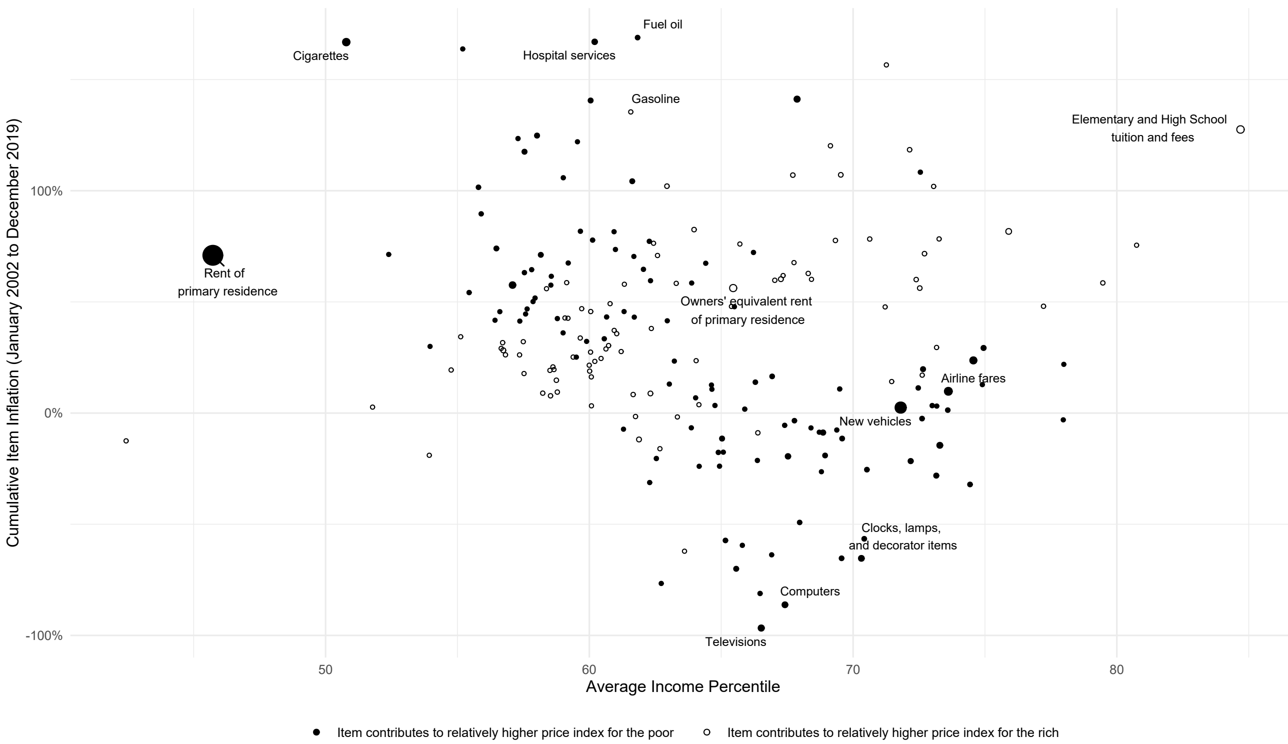
[16] These results show that it is valuable to build price series based on re-weighting of upper-level expenditure categories. This observation stands in contrast with some of the recommendations of a recent report on the modernization of the CPI by the National Academies of Sciences, Engineering, and Medicine (Sichel (2022)). Based on the academic work using scanner data to measure inflation inequality within detailed product categories, the report recommends that BLS should prioritize collecting new data to study expenditure patterns at the granular levels needed to more fully measure differences in inflation by income group (recommendation 6.3). The report explicitly recommends against a more aggregate approach, stating: "valuable CPI program resources should not be devoted to developing additional subgroup price indexes that simply entail a re-weighting of upper-level expenditure categories" (recommendation 6.2). The results obtained with D-CPIs show that, in fact, it appears valuable to combine both approaches. It is necessary both to keep track of inflation inequality arising across the product categories measured by the BLS – using D-CPIs consistent with the official CPI – and to collect more granular data to better measure within-category inflation heterogeneity – entailing a departure from standard BLS methods.

Table V Item Decomposition of the Cumulative Inflation Difference b/w the Bottom and Top Income Quintiles, Jan. 2002 to Dec. 2019

Item Name	Share of Inflation Inequality	CPI Weight	ΔExpenditure Shares, Q1 - Q5 (pp)	Annual Inflation
Rent (Rent of primary residence + Owners' equivalent rent of primary residence)	25.77 %	29.44 %	6.48	2.63 %
Vehicles (New vehicles + Used cars and trucks + Sports vehicles including bicycles + Leased cars and trucks)	17.74 %	8.23 %	-4.4	-0.25 %
Airline fares	7.37 %	0.75 %	-0.74	0.52 %
Elementary and high school tuition and fees	-6.6 %	0.34 %	-0.61	4.7 %
Cigarettes	6.47 %	0.64 %	0.81	5.63 %
Other lodging away from home including hotels and motels	5.82 %	0.77 %	-0.82	1.19 %
Electricity	4.78 %	2.85 %	1.72	2.57 %
Televisions	3.88 %	0.23 %	-0.08	-17.31 %
College tuition and fees	3.76 %	1.45 %	-0.12	5.04 %
Computers, peripherals, and smart home assistants	3.22 %	0.37 %	-0.12	-10.47 %

Notes: This table reports the within-between decomposition of the log difference in cumulative inflation rates between the fifth and first household income quintiles, using equation (5), for the period 2002-2019. The average annual inflation rate during this period was 1.81 %. The table reports the contributions of the top ten items, which collectively account for 72.21 % of the overall inflation gap between the top and bottom income quintiles and for 45.07 % of aggregate expenditures.

Figure 4 Item Inflation Rates and Customer Income, 2002 to 2019



Notes: This figure plots the average income percentile of households buying an item (using sales weights to compute the average) against the cumulative inflation rate for this item from 2002 to 2019. The size of each dot is proportional to the contribution of the item to inflation inequality between the bottom and top income quintiles between 2002 and 2019.

Intuitively, item i contributes to inflation inequality if it has a higher (lower) inflation rate than average and a higher spending share from the poor (rich).

Table V reports the results for the top ten item categories. Together, these products account for 72.21 % of the overall inflation gap between the top and bottom income quintiles from January 2002 to December 2019, and for 45.07 % of aggregate spending.

The first row pulls together rents of primary residence (for renters) and imputed rents (for homeowners),[17] which account for about a fourth of the inflation gap. This stems from two reasons: first, lower-income groups devote a higher share of spending to this aggregated rent categories (+ 6.48pp), which has higher inflation than the rest of the basket (at 2.63 %, compared to 1.81 % for the full basket); second, inflation is higher for actual rents (at 3.04 %, with higher spending shares from lower-income households) than for imputed rents (at 2.52 %, with higher spending shares from higher-income groups).

Next, purchases of new or used vehicles, as well as leasing, represent 17.74 % of overall inflation inequality. Indeed, these categories have lower inflation than average, with a slight deflation of 0.25 % per year, and higher spending shares from the rich (+ 4.4pp). The same patterns operate for airline fares, which account for 7.37 % of inflation inequality. Together, the top three product categories – rent, vehicles and airline fares – already account for about half of the overall inflation gap.

The next category in Table V, elementary and high school tuition and fees, contributes negatively, leading to relatively higher inflation for the rich. Indeed, the rich spend relatively more on this category (+ 0.61pp), which has substantially higher inflation than average, at 4.7 %.

Cigarettes are also an important source of inflation inequality, at 6.47 %: expenditure shares from the poor are higher (+ 0.81pp) and the inflation rate for cigarettes is much higher than average, at 5.63 %, due to rising taxes.[18] Similarly, electricity has higher expenditure shares from the low-income and higher inflation than average, contributing another 4.78 %.

Finally, it is worth highlighting the role of televisions and computers. While expenditure shares of the rich on these two item categories are only slightly higher than for the poor (+ 0.20pp), the deflation rates are large – at -17.31 % a year for televisions and -10.47 % for computers –, such that the impact on inflation inequality is meaningful. Televisions account for 3.88 % of the inflation gaps, compared to 3.22 % for computers.

While these ten categories account for the bulk of inflation inequality, there is large heterogeneity in relative price changes and customer income across items. To visualize this heterogeneity, Figure 4 plots the heterogeneous contribution of all 204 item strata to inflation inequality. The size of each dot on the figure reflects the size of the contribution to inflation inequality. Black dots correspond to items that increase inflation disproportionately for the poor, while hollow circles yield relatively higher inflation for the rich. The figure depicts the large heterogeneity in relative prices arising across product categories over time. Between 2002 and 2019, many items have a cumulative inflation rates over 100 %, while many other experience a cumulative deflation of over -50 %. On average, categories that sell more to the rich have lower inflation, but there are many exceptions, such as tuition fees for elementary school or high school.

[17] It is useful to report the results by pooling these two item categories as they have strong, opposite relationships with expenditure shares by income group, as reported in Panel B of Table I.

[18] In a behavioral model with internalities, rising prices for cigarettes may improve the welfare of the poor (e.g., Allcott et al. (2019)). While this is an important caveat to keep in mind, I proceed with the methodology of the BLS in computing a cost-of-living index.

Despite this wide heterogeneity at the product category level, the price indices across income percentiles have a clear linear pattern in Figure 2.

3.1.2 The indexation of the poverty line

Besides the measurement of inequality, the higher rates of inflation for lower-income groups might matter for the indexation of the poverty line and the number of people in poverty. Figure 5 analyzes this question. CPS micro data are used to identify people considered to be in poverty according to the official CPI, comparing an individual's family income to the official poverty threshold.[19]

How to compute the price index relevant for the indexation of the poverty line? The official CPI fails to account for the fact that inflation is higher for individuals in poverty, i.e. the poverty line should be indexed at a higher rate. Instead, D-CPIs can be used to keep track of the inflation rate experienced by individuals at the poverty line. Specifically, in each year I calculate the change in the price index for households at the 90th percentile of the household income distribution conditional on being below the poverty threshold.[20] I implement this calculation iteratively: starting in 2002, I compute a poverty-specific price index which is then used to index the poverty threshold in the following year, iterating this process year after year.

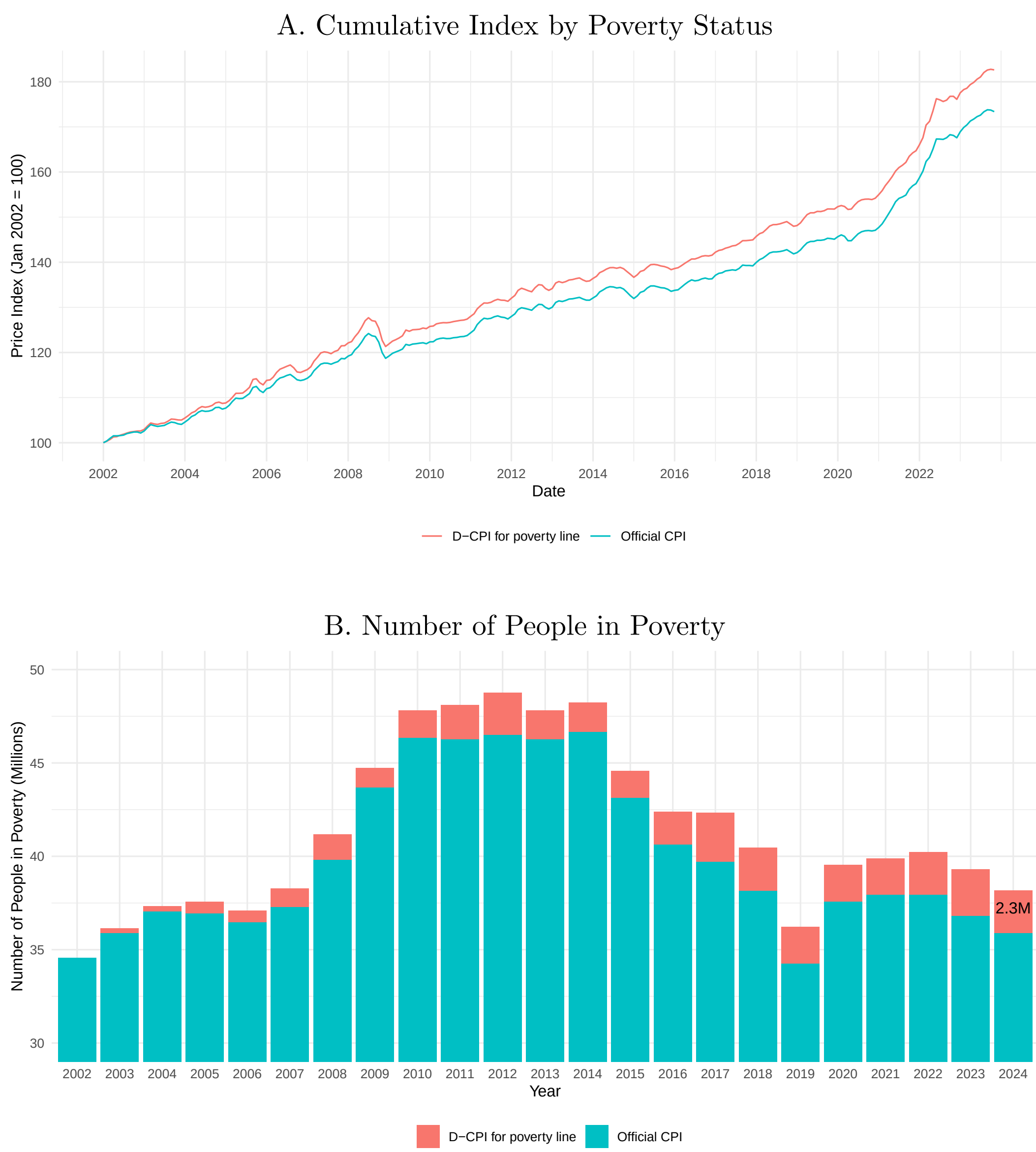
Panel A of Figure 5 plots the price index for the poverty line, compared to the official CPI. A gap emerges gradually and becomes substantial by the end of the period. Panel B computes the number of people in poverty with the standard threshold and the revised threshold using the price index relevant for the population in poverty. The figure shows that over time there is a substantial number of people who are misclassified – i.e., who are considered to be above the poverty line while they are really below due to heterogeneous inflation dynamics. By the end of 2024, there are 2.3 million people who are below the "real" poverty line but above the standard threshold based on official CPI. This group should have access to poverty alleviation programs such as Medicaid. Using D-CPIs is thus of direct policy relevance.

Of course, this adjustment of the official poverty line with D-CPIs only considers one specific source of bias, stemming from heterogeneous inflation rates across the income distribution – other important sources of bias affecting the poverty rate are analyzed in, e.g., Meyer and Sullivan (2012) and Han et al. (2022). But it is worth highlighting a distinctive feature of the heterogeneous inflation bias: since it is cumulative over time, it can become particularly important over long horizons, as long as there is a sustained pattern of higher inflation for lower-income groups, as is the case in the data for the United States.

[19] As an alternative to the official poverty measure (OPM), one could use the supplemental poverty measure (SPM), which accounts for non-cash government benefits and living expenses in determining who is in poverty. Because the SPM is only available from 2011 onward and is close to the OPM since then, I focus my analysis on the OPM.

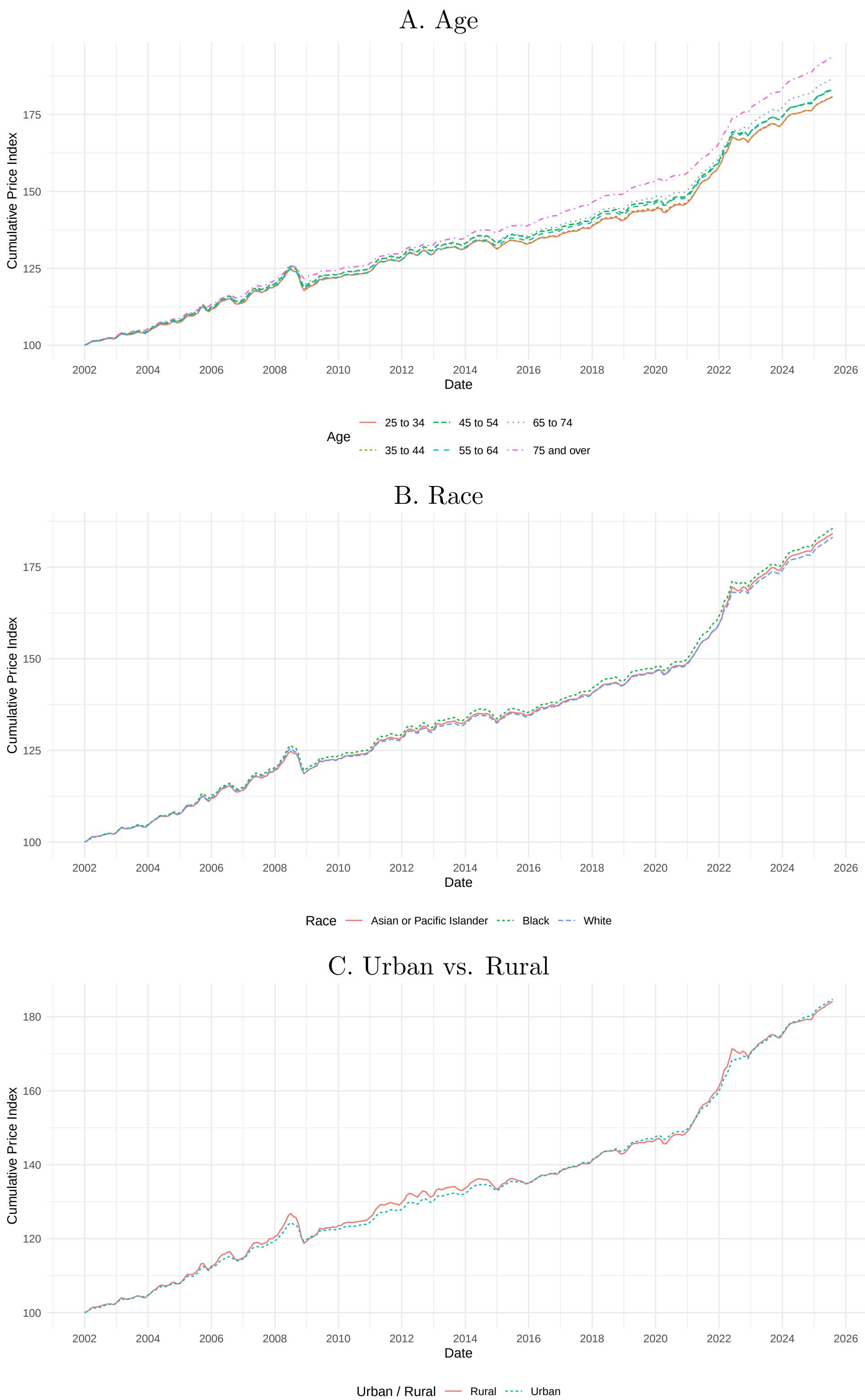
[20] I use the 90th percentile since, in the CPS micro data, among households below the poverty threshold there is a small tail of households with a large income after the correction for household size. This occurs since I correct for household income by dividing by the square root of the household size, whereas the official poverty line is based on a more precise correction based on the number of adults and children in the household. This specific choice does not materially affect the results: the findings are similar when computing the average inflation rate for all individuals below the poverty line, rather than focusing on households at the 90th percentile.

Figure 5 Implication for the Poverty Line



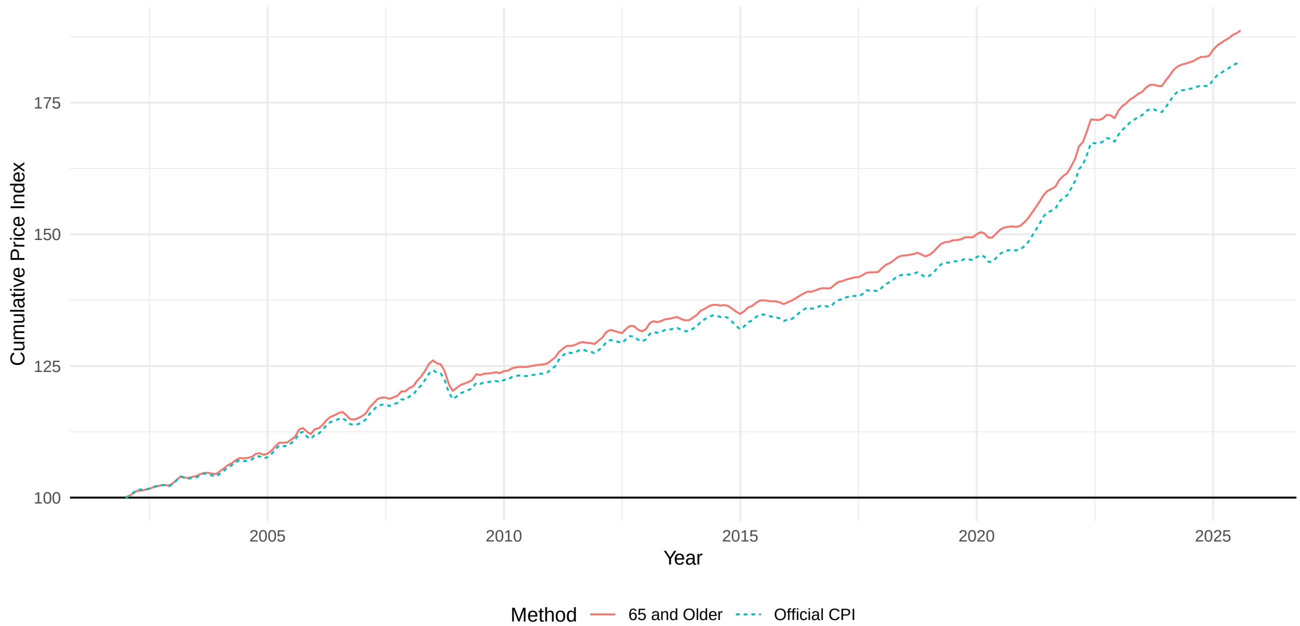
Notes: Panel A compares the cumulative price index from January 2002 to December 2024 for households in poverty to the official CPI. In panel B, the price index for households in poverty is used to index the poverty line over time and report the additional number of people who are under the poverty line (in red), compared to the official poverty line using CPI (in light green).

Figure 6 Long-Run Inflation Inequality across Other Socio-demographic Groups



Notes: This figure reports cumulative price indices from January 2002 to August 2025 for various household groups, by age (panel A), race (panel B), and urban vs. rural households (panel C).

Figure 7 65+ D-CPI and Official CPI



Notes: This figure reports cumulative price indices from January 2002 to August 2025 for various households with a household head above the age of 65, compared to the official CPI.

3.1.3 Long-run inflation inequality across other socio-demographic groups

Figure 6 reports inflation heterogeneity by age, race, and for urban versus rural households. The price indices are built using the age and race of the reference person, or "household head"; alternative methods are discussed in Section 3.3, yielding similar results.

Panel A shows that, from 2002 to 2025, inflation rates were higher for older households. The cumulative price index in August 2025 is about thirteen percentage point higher for households above the age of 75, compared to those between 25 and 34.

Panel B reports the patterns by race. A gap gradually emerges over time, with higher inflation for African-American households. Whites have the lowest inflation rate, while Asian households experienced a slightly larger inflation rate compared to Whites. These differences are however relatively modest compared to those observed across income groups.

Finally, Panel C documents the difference in inflation rates between urban and rural households.[21] The figure shows little difference. While gaps open in specific periods – for example right after the Covid-19 pandemic, which is investigated further below –, the differences appear to be short-lived.

For the indexation of government transfers, it is particularly instructive to compute a price index for households above the age of 65, who are eligible to receive Social Security Retirement benefits. Figure 7 shows the results, documenting that the population above 65 experiences higher inflation rates between 2002 and 2025. In August 2025, there is a 5.8 percentage point gap between the price index for households above 65 and the official CPI.[22] Indexing Social Security Retirement benefits on this alternative price series

[21] A limitation of the analysis of inflation differences across urban and rural households is that the CPI sample only collects prices in urban areas, which account for 93 % of total expenditures.

[22] These results are similar to those obtained with the BLS' research price index for Americans 62 years of age and older,

would have large budgetary implications. With a total cost of annual Social Security Retirement benefits of about $1 trillion in 2023, using an age-specific index would increase the total cost of pension benefits by about $58bn. When using the Chained CPI instead of the official CPI formula, the inflation gap increases further, to 6.3 percentage points, as reported in Appendix Figure A4.

Appendix Table A3 decomposes the inflation gap between households above or below the age of 65, using the Chained CPI and the decomposition in equation (5) applied to age rather than income groups. Five product categories explain about 56.7% of the inflation gap. First, older households spend less on vehicles, which have lower inflation rates: this category explains about one quarter of of the inflation gap between those above and below 65. Relatedly, older households also buy less gasoline, which features higher inflation rates; taken together, vehicle and gasoline purchases explain about 8% of the inflation gap. Second, older households incur higher expenditures for hospital services and prescription drugs, categories characterized by high inflation and which explain 19.09% of the inflation gap across age groups. Next, older households are less exposed to information technologies: telephone hardware and wireless phone services experienced deflation and account for 18.34% of the inflation gap. Finally, older households are more exposed to rents – considering both imputed rents and actual rents –, which explains another 11.28% of the inflation gap between those above or below 65. For completeness, Appendix Figure A5 plots the heterogeneous contribution of all 204 item strata to inflation gaps across age groups.

3.2 Inflation Inequality after the Covid-19 Pandemic

Having documented long-run trends in inflation inequality, I now focus on inflation heterogeneity across groups right after the Covid-19 pandemic, from May 2020 to May 2022. Inflation rates were particularly high during this period, notably because of two product categories, gas and new or used vehicles, as shown in Appendix Figure A6.

Figure 8 plots the results by income percentile. Panel A, considering all products, shows an inverted U-shaped pattern: inflation was a bit higher for the middle class during the inflation burst. While cumulative inflation between May 2020 and May 2022 was 13% at the bottom of the income distribution, it was about 14.7% at the 50th percentile, and 13.5% at the top.[23]

These estimates can be used to compare the compression of "real" wages during this period to the compression of nominal wages documented by Autor et al. (2023). Between May 2020 and May 2022, according to the official CPI, wages increased by 2% at the 10th percentile of the income distribution, compared to a fall of 4% at the median, i.e. there was a 6pp compression of the bottom half of the income distribution. From Panel A of Figure 8, this compression is amplified by about 1.7pp with D-CPIs. Thus, the compression of the real wage distribution at the bottom is amplified by about 28%.

Panel B of Figure 8 shows that the inverted U-shaped pattern of inflation heterogeneity in the wake of the Covid-19 pandemic is entirely driven by two product categories. When excluding gas and new/used vehicles, there is no difference in inflation rates across the income distribution during this period. Indeed,

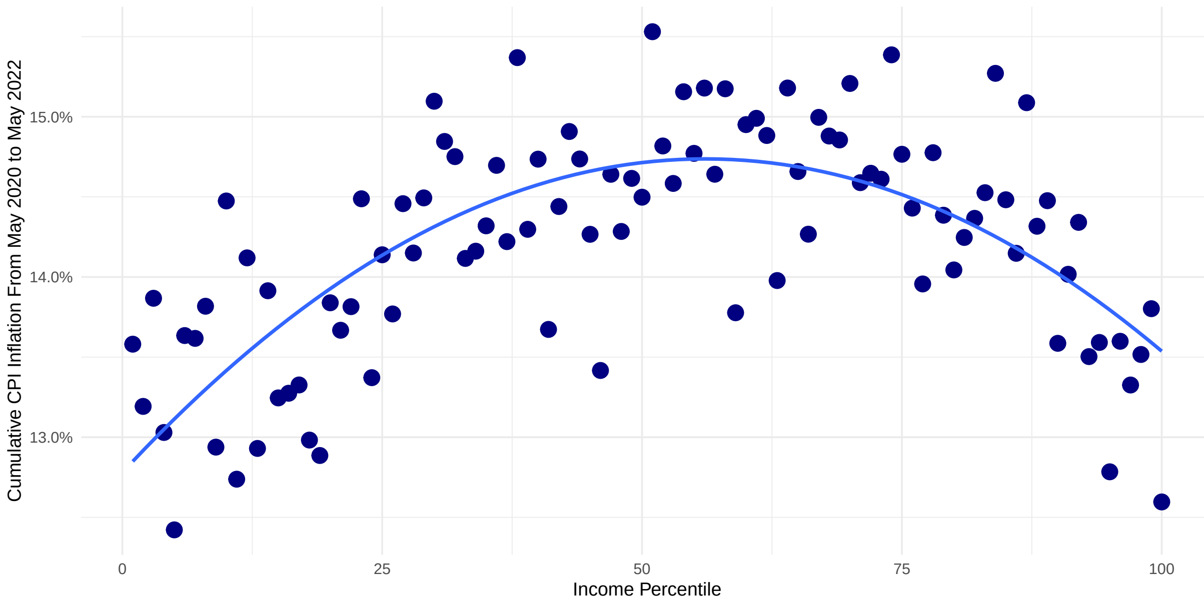
R-CPI-E (see, e.g., Stewart (2008)).

[23]As previously mentioned, I focus exclusively on patterns of inflation heterogeneity arising *across* product categories. The inverted U-shaped pattern could be affected by inflation heterogeneity *within* product categories. Indeed, recent work analyzing consumer packaged goods with scanner data documents higher inflation rates at the bottom of the income distribution due to a phenomenon of "cheapflation" during the Covid-19 pandemic, driven by the price pass-through of commodity cost shocks (Sangani (2023), Cavallo and Kryvtsov (2024), Chen et al. (2024)). For a discussion of the challenges in measure category-level expenditure shares during the Covid-19 pandemic, see Reinsdorf (2020) and Cavallo (2024).

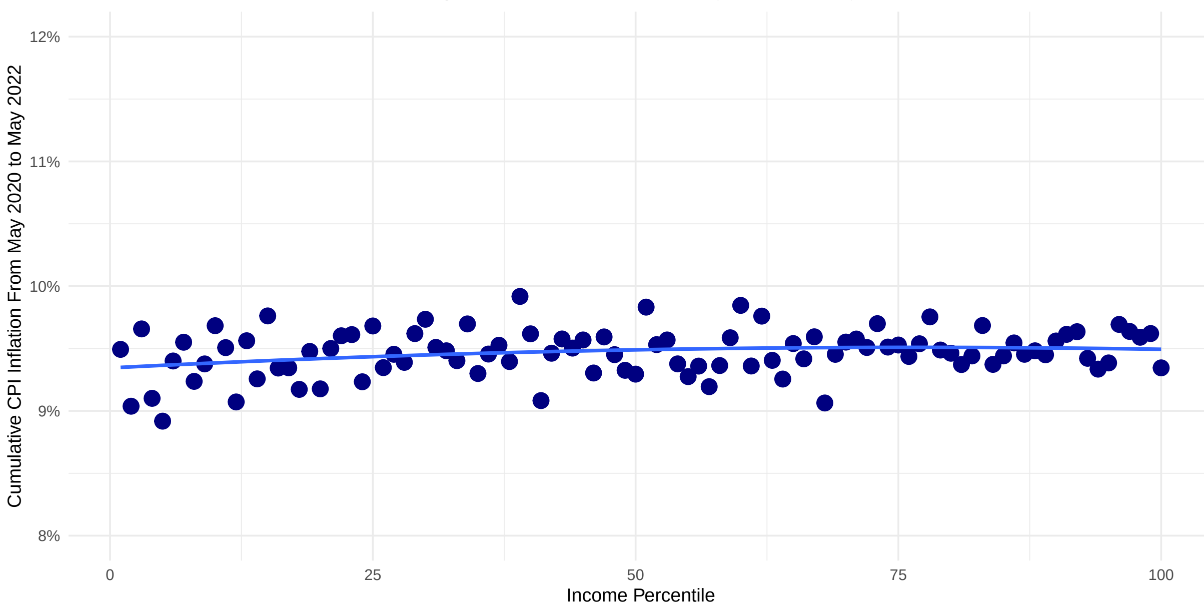
people who drive were particularly hit by the increase in gas prices and by high inflation rates for cars – caused by the semi-conductor crisis in 2021-2022.[24]

Figure 8 Short-Run Inflation Inequality by Income Percentile

A. All products, May 2020-May 2022



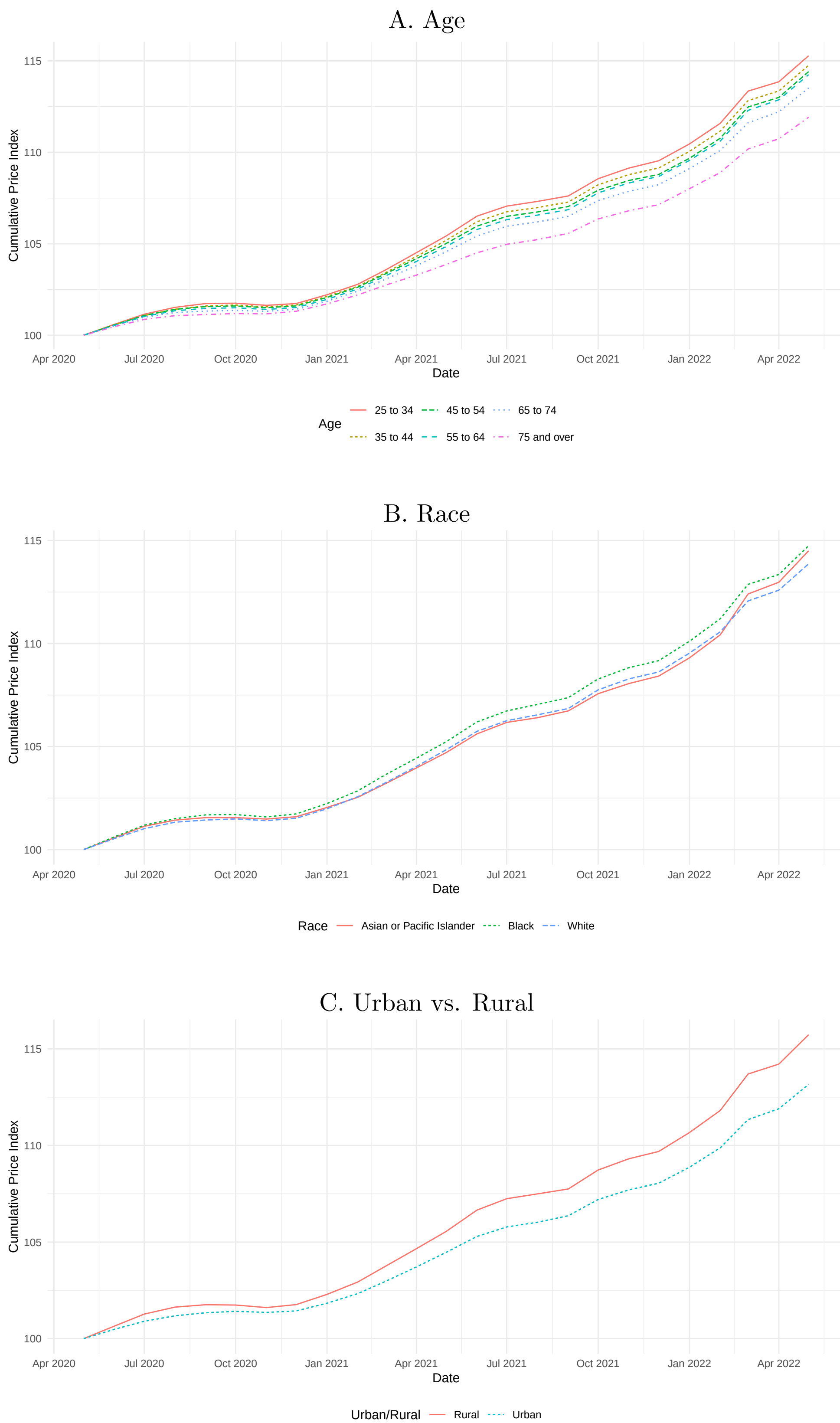
B. Excluding Gas & Vehicles, May 2020-May 2022



Notes: This figure plots the cumulative price index by income percentile from May 2020 to May 2022. While panel A includes all products, panel B excludes gas and vehicles.

[24]This pattern is relatively short-lived. Appendix Figure A7 shows that the U-shaped pattern becomes considerably less pronounced when extending the time window until May 2024.

Figure 9 Short-Run Inflation Inequality by Socio-demographic Groups, May 2020 – May 2022



Notes: This figure reports cumulative price indices from May 2020 to May 2022 for various household groups, by age (panel A), race (panel B), and urban vs. rural households (panel C).

Next, Figure 9 repeats the analysis by age, race, and for urban versus rural households. Panel A shows that younger households experienced significantly higher inflation between May 2020 and May 2022. Panel B documents that White households faced somewhat lower inflation during this period, with a cumulative inflation rate that was about 1pp higher for African-Americans or Asian as of May 2022. Finally, panel C document substantial differences between urban and rural households. As expected, rural households – who more frequently need to drive – experienced higher inflation rates. Their cumulative inflation rate was 2.6pp higher than that of urban households as of May 2022.

Overall, these results show that the patterns of inflation heterogeneity can vary across periods and are not always in line with the long-run trends documented in Section 3.1. While the poor experience higher inflation in the long run, during the pandemic the middle class was hit more strongly. While older households face higher inflation rates in the long run, they were less exposed to the inflation burst after the pandemic. This illustrates the usefulness of computing D-CPIs at a monthly frequency to keep track of the potentially changing patterns of inflation heterogeneity.

3.3 Robustness and Additional Results

This section discusses robustness and additional results, which are reported in the Online Appendix. First, Figure A8 presents cumulative inflation rates across the income distribution, as in Figure 2, using a bootstrap procedure to account for sampling uncertainty. The figure shows that the linear relationship between inflation and income percentiles over the long run is precisely estimated even when accounting for sampling uncertainty.

Second, it is instructive to analyze inflation heterogeneity with alternative measures of income, age, and race. Figure A9 reports the results by equivalized income percentiles, i.e., dividing household income by the square root of household size; the results are similar to those reported above with raw household income. As a proxy for permanent income, Figure A10 repeats the analysis by ranking households by consumption expenditures.[25] Similar to the results by income percentiles, cumulative inflation from January 2002 to August 2025 declines monotonically from about 97 % at the bottom of the expenditure distribution to about 84 % at the top. Next, Panel A of Figure A11 turns to the patterns across age groups, measuring household age the average age of all adult household members, rather than taking the age of the reference person alone as in the main text. The results are similar to the baseline patterns by age presented above. Similarly, Panel B of Figure A11 considers heterogeneity by race, focusing on the subset of households where all adult household members are of the same race, rather than focusing on the race of the reference person alone as in the main text; the results are also similar, with slightly lower inflation for Whites.

Third, Figure A12 examines inflation heterogeneity by gender. The inflation differences by gender are small, with a slightly higher inflation rate for men, whether the data is split based on the gender of the reference person in the household or whether the analysis is restricted to a sub-sample of households where all adult household members are of the same gender.

Finally, Figure A13 shows substantial heterogeneity in inflation rates across occupations, consistent

[25] Expenditures on new or used vehicles are excluded from the expenditure measure used for this ranking, due to the infrequent and lumpy nature of household spending on these products.

with the previous results by income groups.[26]

4 Extensions

This section present a series of extensions, first allowing for geographic heterogeneity in inflation, then introducing a non-homothetic price index, and finally extending the analysis further back in time. All extensions confirm the patterns presented in the main analysis, with systematically lower inflation for higher income groups.

4.1 Allowing for Geographic Heterogeneity

Figure 10 Inflation Heterogeneity Across Selected Cities

Notes: This figure reports cumulative inflation rates in a selected set of cities from January 2002 to August 2025.

I now examine whether the results change when price dynamics are allowed to vary across cities. This analysis can be conducted for a sub-sample of the data covering 23 cities accounting for 40% of total national expenditures, for which the BLS makes the local price series publicly available. In particular, the local price series cover both actual rents and owners' equivalent rents of primary residence, which may vary significantly across places and which explain over a quarter of inflation inequality in the baseline analysis (Table V).

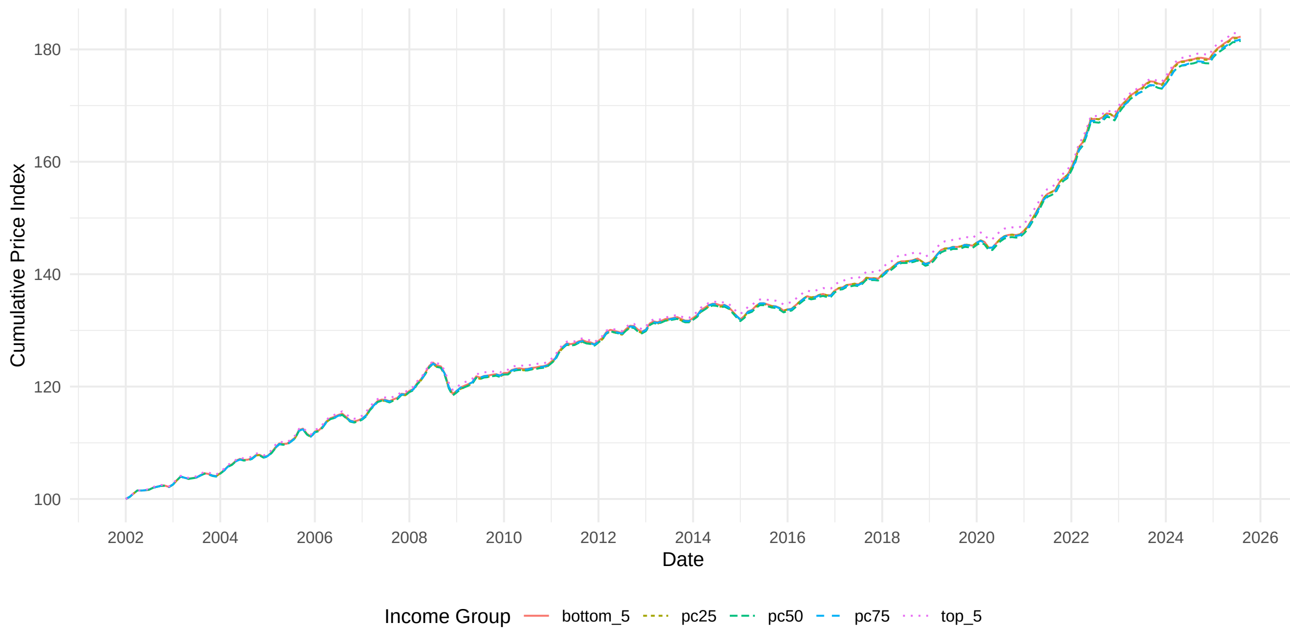
Figure 10 plots the price series for major cities between 2002 and 2025. Seattle has the highest inflation rate, while Chicago has the lowest during this period.[27]

[26]The steps used to obtain group-specific CPIs in Section 2.2 can be applied to produce price indices at the household level, with g indexing a single household rather than a group. In unreported results, I find that this approach yields large heterogeneity in inflation rates across households even within income or other socio-demographic groups, which is consistent with the results obtained by Kaplan and Schulhofer-Wohl (2017) and Jaravel and O'Connell (2020) for consumer packaged goods. However, durable goods make it challenging to use standard static (rather than dynamic) price indices at the household level, as households can have very large expenditures on certain durable goods such as vehicles. Analyzing group-level expenditures bypasses this issue by smoothing the timing of purchases of durables across many households.

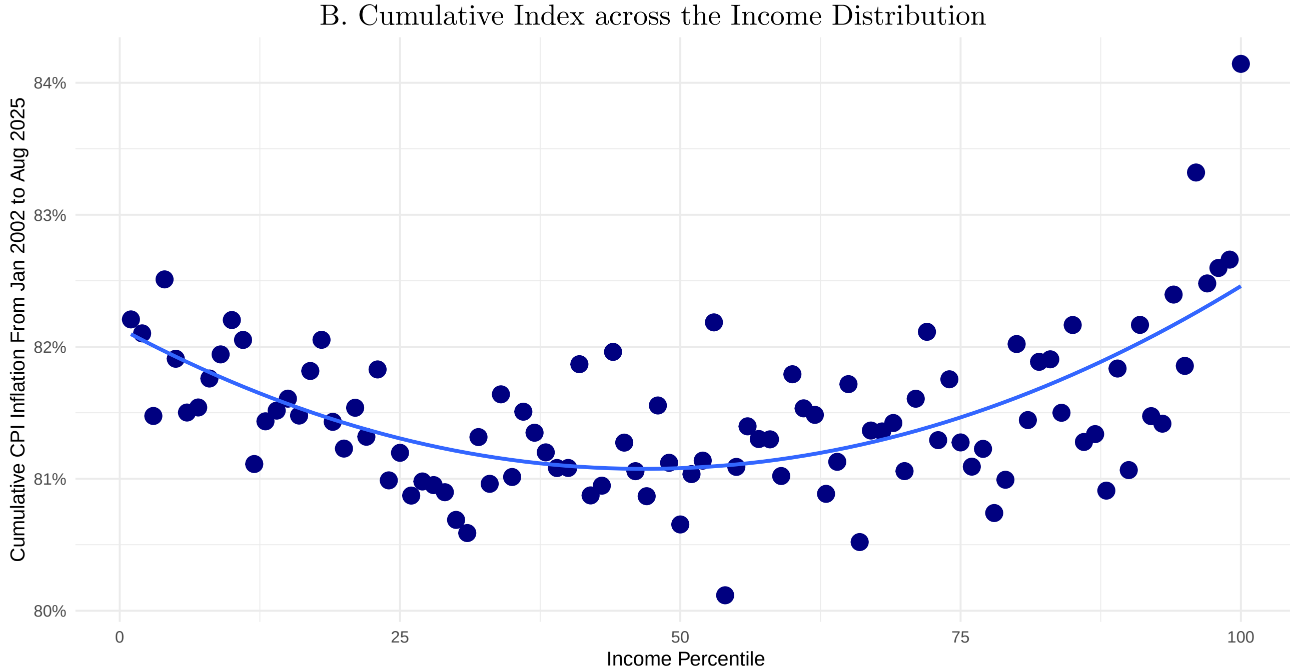
[27]Appendix Figure A14 reports heterogeneous inflation rates across quantiles of the income distribution within selected

Figure 11 Inflation Inequality from Geographic Heterogeneity Alone

A. Cumulative Index for Selected Income Percentiles



B. Cumulative Index across the Income Distribution

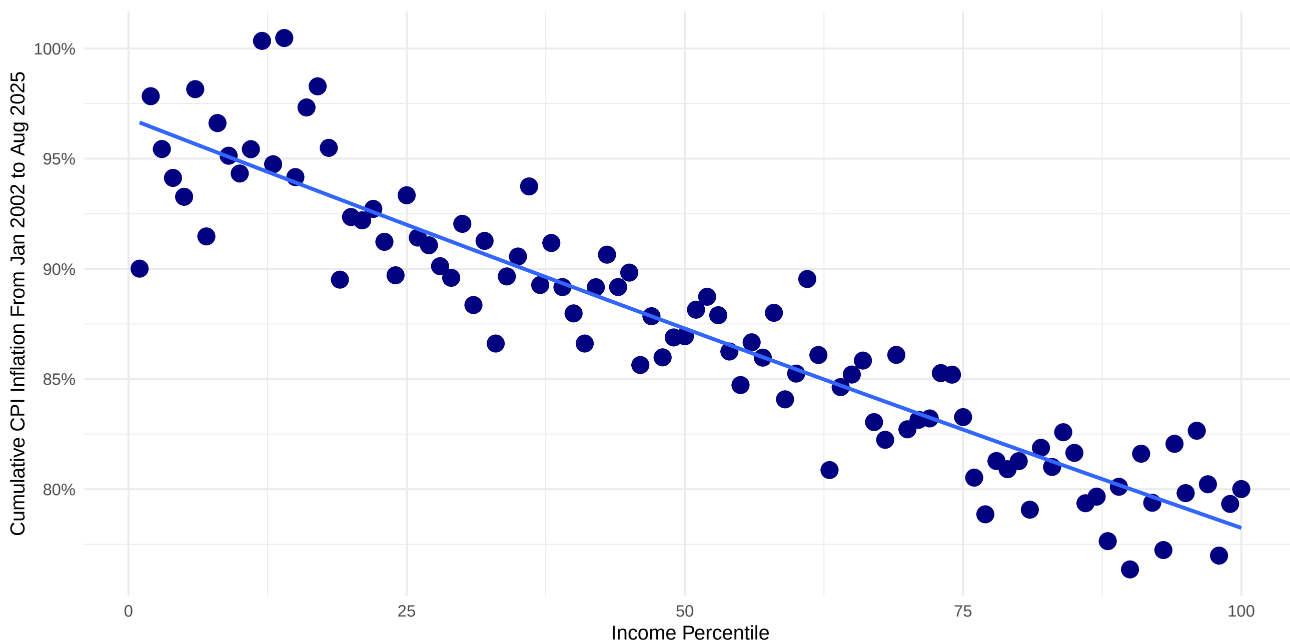


Notes: This figure reports inflation rates by income percentile. Panel A show the monthly time series of the cumulative price index from January 2002 to August 2025 for selected income percentiles (bottom 5%, 25th, 50th, 75th, and top 5%). Panel B reports the cumulative CPI in August 2025 for all income percentiles, along with the OLS best-fit line. In both panels, only the heterogeneity in inflation rates arising *across* 23 cities is taken into account.

Using this data, I implement the same methodology as described in Section 2, except that i now indexes

cities.

Figure 12 Inflation Inequality including Geographic Heterogeneity



Notes: This figure reports inflation rates by income percentile, inclusive of geographic heterogeneity, from January 2002 to August 2025.

items in a specific city. Appendix B.2 describes data availability and the data construction steps to allow for geographic heterogeneity. The analysis thus takes into account that inflation rates may be different across space, generating potential differences in inflation across income groups, who are heterogeneously sorted across cities.

To assess the importance of geographic heterogeneity, I start by computing the level of inflation inequality that arises only *between* cities, i.e. I compute price indices where all income groups are assumed to experience the same inflation rates *within* cities but have unequal expenditure shares *across* cities, as measured in the CEX data. Figure 11 reports the results. Panel A plots the cumulative index over time for selected income percentiles, which all experience very similar inflation rates throughout the period. Panel B reports the cumulative inflation rate from 2002 to 2025 by household income percentile, showing a flat pattern. Thus, geographic heterogeneity does *not* affect inflation inequality during this period. Figure 12 confirms this result, computing overall inflation inequality inclusive of geographic heterogeneity. The results are essentially unchanged compared to the baseline results without inflation heterogeneity (Figure 2).

In prior work, Moretti (2013) built city-specific CPIs and documented that, between 1980 and 2000, college graduates concentrated in cities with high cost of housing, suggesting that inequality in purchasing power is lower than commonly thought based on nominal wage differences. I instead study a different period, focusing on income groups. Consistent with my results, Molloy (2024) finds that different housing and location choices have not generated materially different shelter components of inflation across the income distribution.[28]

[28]While Molloy (2024) calculates changes in rents in the American Housing Survey, I use official BLS data, including imputed rents. Focusing on the period from 1980 to 2000 as Moretti (2013), Diamond (2016) uses a structural approach

Short-run dynamics with geographic heterogeneity. Online Appendix Figure A15 reports that geographic heterogeneity also leaves unchanged the short-run inflation heterogeneity dynamics documented in Section 3.2. There is an inverted U-shaped relationship between inflation and household income between May 2020 and May 2022, which becomes less pronounced when lengthening the time horizon to May 2024. This figure also shows that the patterns are similar with equivalized incomes.

The user cost of housing. Given the central role of housing inflation in driving inflation inequality (Table V), it is informative to assess whether alternative measures of housing inflation allowing for geographic heterogeneity affect the results. The preceding analysis follows the official methodology of the Bureau of Labor Statistics for homeowner shelter inflation, relying on imputed rents and the owners' equivalent rent (OER) price series. An alternative approach is to measure housing inflation for homeowners using the one-period user cost. The one-period user cost aims to capture the costs actually incurred by homeowners in a given period by combining maintenance expenses, mortgage interest costs, the opportunity cost of financial capital, and expected house price appreciation (Steiner (1961); Poterba (1984)). Unlike the official CPI measure, user-cost-based housing inflation is sensitive to changes in mortgage interest rates and house prices.

Appendix D computes the one-period user cost of homeownership using CEX data by income quintile; the resulting series are reported in Appendix Figure A16. This analysis yields two main findings. First, over most of the sample period, user-cost-based housing inflation rises more slowly than owners' equivalent rent and even exhibits deflation prior to 2020. During this phase, rapid house price appreciation lowers the user cost and more than offsets maintenance and mortgage interest costs. Following the Covid-19 pandemic, user costs catch up with rental inflation, reflecting the sharp increase in mortgage rates and the resulting rise in the financial cost of homeownership.

Second, user cost dynamics are similar for households in the bottom and top income quintiles. This similarity implies that using the user cost rather than imputed rents affects inflation inequality primarily through differences in homeownership rates across the income distribution, rather than through heterogeneity in the user cost of homeownership across the income distribution conditional on owning.

Taken together, these findings suggest that relying on the user cost rather than imputed rents would tend to amplify measured inflation inequality prior to the onset of the Covid-19 pandemic. During this period, a larger share of high-income households are homeowners and are therefore partially insulated from housing inflation; in fact, they benefit from rapid house price appreciation. Over the full sample, however, the difference relative to the baseline is more limited, as user costs eventually catch up with rents following the sharp rise in mortgage rates after 2020.

These patterns should nevertheless be interpreted with caution. Homeownership is an inherently dynamic decision shaped by transaction costs, long-term contracts, and adjustment frictions, implying that the one-period user cost does not correspond to the true economic cost of owning over the lifecycle (for instance, owners face moving costs and transaction fees such as realtor commissions). To address these issues, Chodorow-Reich et al. (2025) develop a quantitative general-equilibrium life-cycle model with transaction costs and long-term contracts, allowing them to evaluate welfare and price indices separately

to estimates that endogenous changes in amenities more than offset the changes in rents across cities during this period, concluding that inequality between high school and college graduates is higher than based on nominal wage differences.

for homeowners and renters. This structural, dynamic approach departs fundamentally from the static price-index methodology employed by the Bureau of Labor Statistics, which is the focus of the present paper.

4.2 Non-homothetic Price Indices

The analysis so far uses homothetic price indices, in line with BLS methods. Even though price indices were computed by income group, the maintained assumption was that each income group had homothetic preferences. This can be relaxed by implementing the algorithm of Jaravel and Lashkari (2023), which delivers a non-parametric non-homotheticity correction. Appendix E describes the algorithm and the data used for implementation.

The non-homotheticity correction ensures that measured inflation inequality translates into differences in real consumption, i.e. welfare, in contrast with the uncorrected measure.[29] As discussed in Jaravel and Lashkari (2023), the correction for non-homotheticities implies a systematic dependence of the measures of real consumption growth on the base vector of prices chosen to express them. Using 2002 prices as base, the non-homotheticity correction implies that real income growth is higher than with the conventional homothetic index. Indeed, since luxuries have lower inflation rates during the study period, as people get richer their preferences shift toward goods who relative prices are falling. Conversely, using 2019 prices as base, real income growth is lower with the non-homothetic index – because people in the past, who are poorer, benefit from relatively less expensive necessities. Regardless of the choice of the base period, if the correction is similar for all income groups, then the baseline estimates of inflation inequality may not change substantially.

Figure 13 reports the results. Panel A focuses on real income growth across the income distribution, from 2002 to 2019. As previewed, the sign of the non-homotheticity correction depends on the choice of the year used as base. The panel shows that the non-homotheticity correction is relatively similar across income groups, implying that the increase in real income inequality remains similar to the baseline results with homothetic indices. Indeed, with the non-homotheticity correction, the income gap between the bottom and top income quintiles increases by 21.7% (= 1.259/1.034) with 2002 prices as base, and by 23.2% (= 1.251/1.015) with 2019 prices – close to the rate of 22.6% obtained with the D-CPIs without the non-homotheticity correction.

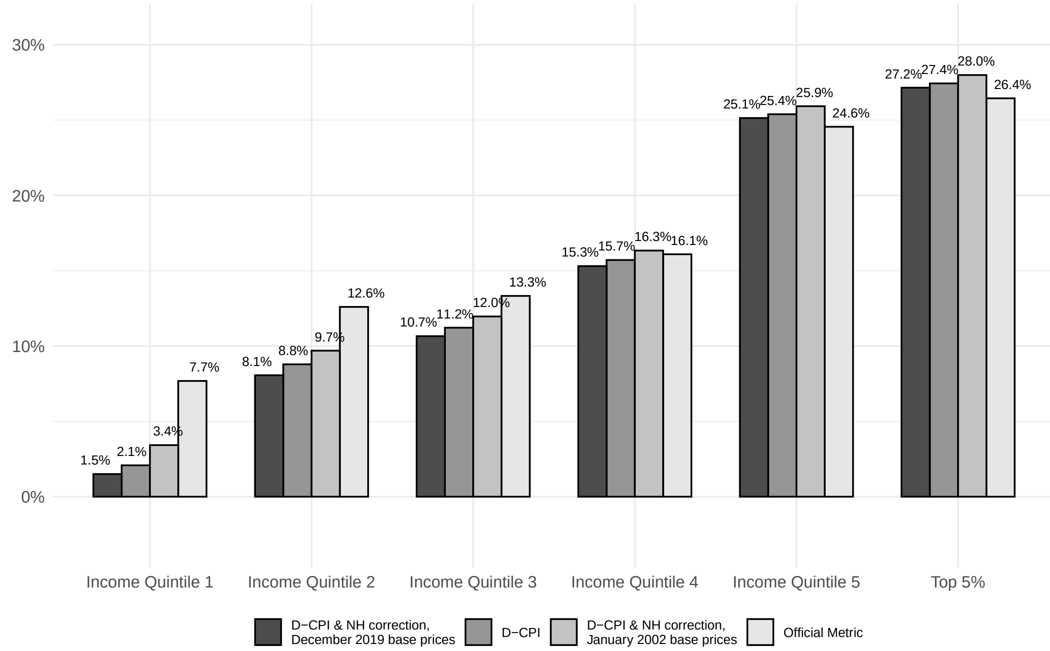
Next, panel B presents the inflation rate at the poverty line, with and without the non-homotheticity correction. The methodology to find the household at the poverty line in each period is the same as in Section 3.1.2, now computing the D-CPI using the non-homotheticity correction with 2002 prices as base, from January 2002 to December 2021.[30] As previously, the inflation rate with the non-homotheticity correction is slightly lower than with the baseline D-CPI. However, the inflation rate for the D-CPI with the non-homotheticity correction remains higher than for the official CPI. Accordingly, with the

[29] Oberfield (2023) describes this problem in a model of growth with inflation inequality.

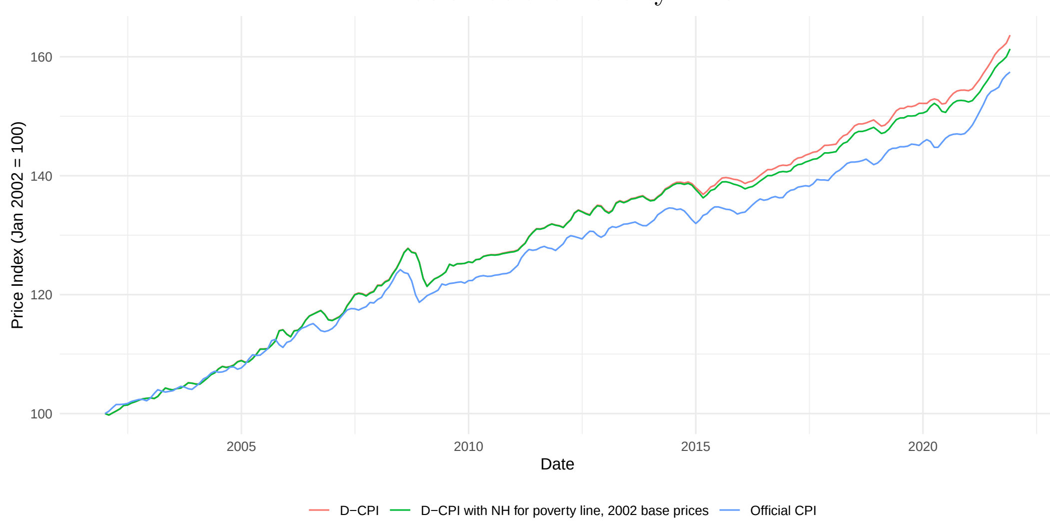
[30] Due to data constraints, December 2021 is the latest possible date when the algorithm in Appendix E can be implemented. Since the poverty line was defined several decades ago, it is most instructive to compute the non-homotheticity correction by using as base the prices in the first year of the study period, 2002. Indeed, the inflation rate using the D-CPI with the non-homotheticity correction under 2002 prices can be used over time to keep track of the nominal income level necessary for households to reach the same level of real consumption as households who were the poverty line in 2002. In principle, this analysis can be extended back to 1969, when the poverty line started being indexed on the CPI, setting 1969 prices as base.

Figure 13 Results with Nonhomothetic Price Indices

A. Household Real Income Growth, 2002 to 2019



B. Inflation at the Poverty Line



Notes: This figure accounts for non-homotheticities in the computation of inflation, using the algorithm of Jaravel and Lashkari (2023). Panel A reports real income growth across the income distribution under the official CPI (white), with D-CPIs without the non-homotheticity correction (grey), and with D-CPIs including the non-homotheticity correction using 2002 prices as base (light grey) or 2019 prices as base (dark grey). Panel B reports three cumulative price indices between January 2002 and December 2021: the official CPI (blue), the inflation rate at the poverty line with the homothetic D-CPI (red), and the inflation rate at the poverty line with the D-CPI and the non-homotheticity correction using 2002 prices as base (green).

D-CPI adjusted for non-homotheticicities, there are 1.4 million more people below the poverty line than according to the official CPI in December 2021 (Appendix Figure A17). The corresponding number with the homothetic D-CPI is 1.9 million. Thus, the non-homotheticity correction makes a difference, reducing the extra number of people classified below the poverty line by about 25% (= 1.4/1.9).

Overall, these analyses show that it is straightforward to account for non-homotheticities, with modest effects on the measurement of inequality and poverty in this period.

4.3 Going Further Back in Time

This subsection extends the analysis going back to 1983. The main analysis stops in 2002 because of additional challenges in building crosswalks between the expenditure and price data sets before that date. However, it is straightforward to keep each item's sales shares to each socio-demographic group fixed in 2002 and build the price index in prior years using these shares, going back to 1983.[31]

Specifically, as in Section 2.2, I start from the official set of weights ω_{i0} published by BLS for each item stratum, which are available going back to 1983. Panel A of Appendix Figure A18 shows that I replicate almost perfectly the official CPI using these weights and the publicly-available price data. Next, as in Section 2.2 I compute the share of sales to each socio-demographic group g in each item stratum to distribute the official expenditure weight across household groups. The only difference is that the sales shares, $\tilde{s}_{gi}$, are now fixed in 2002, while they were time-varying in Section 2.2. Thus, aggregate weights ω_{i0} vary from 1983 to 2002 as previously but the allocation of sales across household groups within for each item stratum is fixed to the allocation observed in the last period.

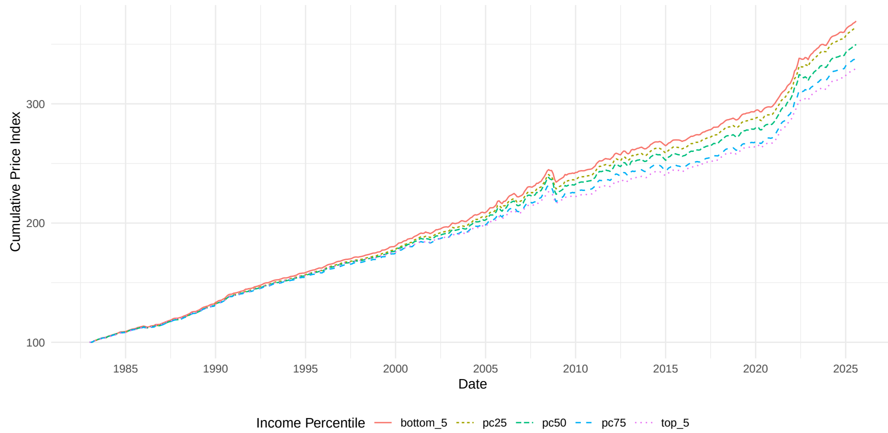
As a validation test of this approach, I compute inflation inequality from 2002 to 2025 with fixed sales shares in 2025 and compare the results to the full series using updated shares. Panel B of Appendix Figure A18 shows that the level of inflation inequality measured with fixed end-of-period sales shares is similar to the baseline analysis with updated shares (Figure 2). These results suggest that using fixed sales shares in 2002 may offer a good approximation to measure the patterns of inflation inequality prior to that date.

Figure 14 present the results, documenting inflation inequality from 1983 onward. In Panel A, the price series after 2002 are identical to the earlier results reported in Figure 2. The figure shows that the trend of inflation inequality started before 2002. Panel B show the cumulative inflation patterns by income percentile from 1983 to 2025, while Panel C focuses on the period from 1983 to 2001. While the relationship between household income percentiles and inflation was close to linear after 2002 (Panel B of Figure 2), Panel C of Figure 14 shows that prior to 2002 the relationship was non-linear. Inflation inequality before 2002 primarily affected households below the median of the income distribution. In the 1990s, a team of BLS researchers, Garner et al. (1996), studied inflation inequality from 1984 to 1994 using confidential BLS data and concluded there was no meaningful inflation heterogeneity. Studying the same period as them with my data set, I similarly find that inflation inequality was weak during this period, as reported in Appendix Figure A19 – which serves as another validation of the approach using public data. Thus, inflation inequality was sustained over several decades but existed primarily from the mid-1990s.

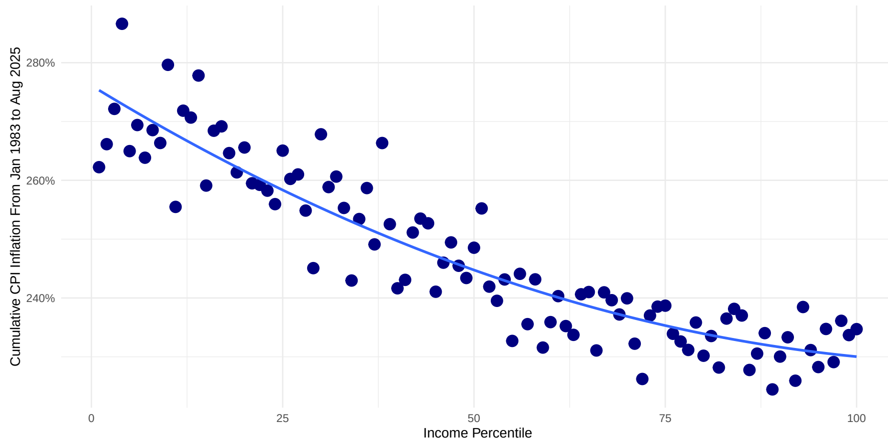
[31] The methodology of the BLS changed substantially before that date, in particular regarding the treatment of housing, therefore I do not extend the analysis to earlier dates.

Figure 14 Inflation Inequality by Income Percentile from 1983 to 2025

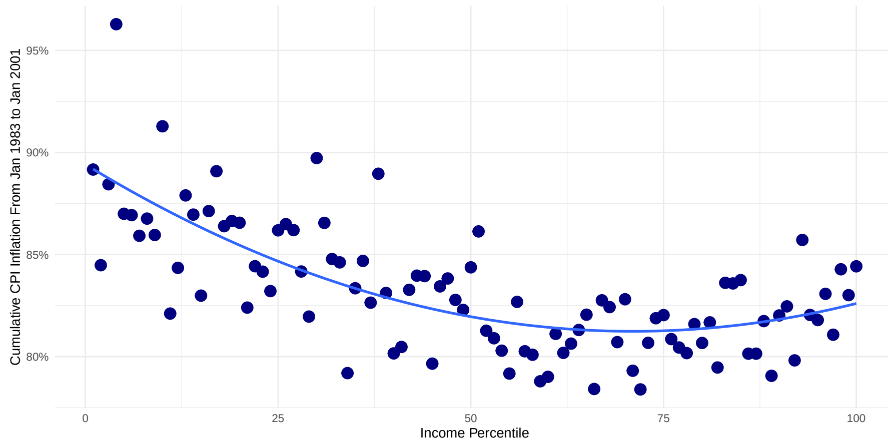
A. Cumulative Index from 1983 to 2025 for Selected Income Percentiles



B. Cumulative Index from 1983 to 2025 across the Income Distribution

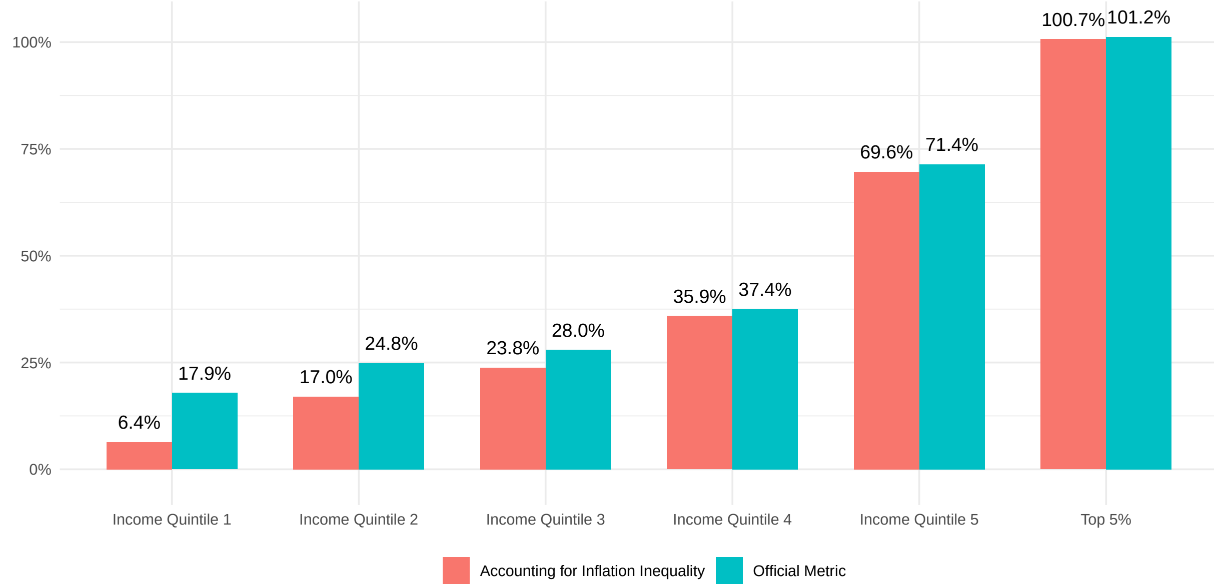


C. Cumulative Index from 1983 to 2001 across the Income Distribution



Notes: This figure reports inflation rates by income percentile. Panel A show the monthly time series of the cumulative price index from January 2002 to August 2025 for selected income percentiles (bottom 5%, 25th, 50th, 75th, and top 5%). Panel B reports the cumulative CPI in August 2025 for all income percentiles, along with the OLS best-fit line. Panel C repeats the analysis from 1983 to 2001.

Figure 15 Implications for Household Real Income Growth, 1983 to 2019



Notes: This figure reports cumulative real income growth from 1983 to 2019 by quintiles of the household income distribution, as well as for the top 5%. Two series are shown, with the official CPI and with D-CPIs accounting for inflation heterogeneity across income groups.

These results have several implications for the measurement of inequality. First, Figure 15 plots household real incomes across quintiles from 1983 to 2019. Real income for the bottom quintile increased by 17.9% according to the official CPI, but by only 6.4% with the D-CPI adjustment. For the top income quintile, the increase is 71.4 % with the official CPI and 69.6 % with the D-CPI. Thus, with D-CPIs real incomes between the top and bottom income quintiles diverged around 10 % faster than with the official CPI.[32] Second, Table VI reports the implications for consumption inequality. While consumption inequality between the top and bottom income quintiles increased by 6.74 % with the official CPI, the rate of increase is much faster, at 16.64 %, with D-CPIs. Third and finally, Table VII reports the results for pre-tax and post-tax national income ratios, applying the D-CPIs to the data of Auten and Splinter (2024). Here as well, the adjustments relative to the standard metric are substantial: compared to the baseline with a common CPI, the rate of increase in inequality with D-CPIs is about 46% faster for pre-tax income ratios and 68% faster for post-tax income ratios. Together, these results illustrate how important inflation inequality can be for the measurement of inequality at long horizons.

The Online Appendix reports additional results documenting inflation heterogeneity from 1983 to the present day for other socio-demographic groups. Figure A21 shows that inflation was higher for older households between 1983 and 2002, similar to the trend found after 2002. The figure also reports that, while there was no difference in inflation by race after 2002, from 1983 to 2001 African-American and Asian households experienced somewhat lower inflation rates compared to Whites. Furthermore, rural households experienced lower inflation than urban households on average between 1983 and 2001. Thus, depending on the period, long-run inflation heterogeneity patterns can differ meaningfully. Finally, Figure A22 reports no heterogeneity in inflation by gender, while Figure A23 reports sustained inflation

[32] Appendix Figure A20 reports the results from 1983 to 2002.

heterogeneity by occupation, consistent with the patterns by income.

Table VI Trends in Consumption Inequality: Ratio of Top to Bottom Income Quintiles, 1984 to 2019

	Consumption ratios, top to bottom quintiles		% Change in consumption inequality
	1984 (1)	2019 (2)	1984 to 2019 (3)
With official CPI	3.97	4.24	+ 6.74 %
Accounting for inflation inequality with D-CPIs	3.97	4.63	+ 16.64 %

Notes: Columns (1) and (2) of this table report the ratios of consumption expenditures of households in the top and bottom income quintiles. Consumption expenditures are obtained from the CEX annual summary tables. The first row uses the official CPI to deflate consumption expenditures in 2019, while the second row uses quintile-specific CPIs. Column (3) reports the percentage changes in the consumption ratios from 1984 to 2019.

Table VII Trends in Pre-tax and After-tax National Income: Ratio of Top to Bottom Income Quintiles, 1983 to 2019

	Pre-tax income ratios			Post-tax income ratios		
	1983 (1)	2019 (2)	Δ 1983–2019 (3)	1983 (4)	2019 (5)	Δ 1983–2019 (6)
With common price index	14.02	17.70	+ 26.32 %	4.38	5.10	+ 16.61 %
With D-CPIs	14.02	19.41	+ 38.49 %	4.38	5.60	+27.84%

Notes: Columns (1) and (2) of this table report the ratios of pre-tax national income for households in the top and bottom quintiles, as defined by Auten and Splinter (2024). The first row is obtained from Auten and Splinter (2024), while the second row uses quintile-specific CPIs to correct the ratios. Column (3) reports the percentages change in the ratios from 1983 to 2019. Columns (4) to (6) repeat the analysis for post-tax national income ratios.

5 Conclusion

This paper has built a public database, available from the D-CPI Project webpage, to measure inflation rates in real time (monthly) across socio-demographic groups in the United States, following data construction steps that are identical to the official CPI. D-CPIs can be used to improve measures of inequality and study the heterogeneous price effects of economic shocks – such as technology, trade, or immigration shocks.

The large literature on rising inequality in the United States has so far used common price indices. Several important "stylized facts" have emerged from this literature and sparked important measurement debates regarding the rising income share of the top 1% (e.g., Piketty and Saez (2003), Auten and Splinter (2024)), the growing impact of capital income (e.g., Karabarbounis and Neiman (2014), Piketty and Zucman (2014), Piketty et al. (2017), Smith et al. (2019)), rising top wealth inequality (e.g., Saez and Zucman (2016), Smith et al. (2023), Catherine et al. (2025)), the role of labor market polarization (e.g., Autor et al. (2008), Autor and Dorn (2013)), changes in consumption inequality (e.g, Krueger and Perri (2006), Aguiar and Bils (2015)), and trends in intergenerational mobility (e.g., Chetty et al. (2014), Chetty et al. (2017)). To date, inflation heterogeneity is not commonly viewed as an important factor for our understanding of inequality dynamics in the long run and the measurement of real incomes across household groups.

In this paper, I have shown with publicly-available D-CPIs that inflation heterogeneity is in fact of central importance for the measurement of long–run trends in income and consumption inequality. For instance, while the gap between the top and bottom household income quintiles increased by 15.7% between 2002 and 2019 according to the official CPI, it increased by 22.6% with D-CPIs. The amplification of inequality is even stronger with Chained D-CPIs. D-CPIs also meaningfully affect the measurement of consumption inequality and trends in pre- and post-tax national income inequality. The results are similar when D-CPIs are adjusted with a non-parametric non-homotheticity correction guaranteeing a welfare interpretation, when allowing for inflation heterogeneity across space, or when studying a longer period going back to 1983.

References

Aguiar, Mark and Mark Bils, "Has consumption inequality mirrored income inequality?," *American Economic Review*, 2015, *105* (9), 2725–2756. 3.1.1, 5

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky, "Regressive sin taxes, with an application to the optimal soda tax," *The Quarterly Journal of Economics*, 2019, *134* (3), 1557–1626. 18

Argente, David and Munseob Lee, "Cost of living inequality during the great recession," *Journal of the European Economic Association*, 2021, *19* (2), 913–952. 1

Auten, Gerald and David Splinter, "Income inequality in the United States: Using tax data to measure long-term trends," *Journal of Political Economy*, 2024, *132* (7), 000–000. III, 3.1.1, 4.3, VII, 5

Autor, David, Arindrajit Dube, and Annie McGrew, "The Unexpected Compression: Competition at Work in the Low Wage Labor Market," Working Paper 31010, National Bureau of Economic Research March 2023. 1, 3.2

Autor, David H and David Dorn, "The growth of low-skill service jobs and the polarization of the US labor market," *American economic review*, 2013, *103* (5), 1553–1597. 5

_ , Lawrence F Katz, and Melissa S Kearney, "Trends in US wage inequality: Revising the revisionists," *The Review of economics and statistics*, 2008, *90* (2), 300–323. 5

Blanchet, Thomas, Emmanuel Saez, and Gabriel Zucman, "Real-Time Inequality," Working Paper 30229, National Bureau of Economic Research July 2022. 1

Cage, Robert A, Thesia Isedora Garner, and Javier Ruiz Castillo, "Constructing household specific consumer price indexes: An analysis of different techniques and methods," *BLS Working Paper*, 2002. 6

Catherine, Sylvain, Max Miller, and Natasha Sarin, "Social Security and Trends in Wealth Inequality," *Journal of Finance*, 2025. 5

Cavallo, Alberto, "Inflation with Covid consumption baskets," *IMF Economic Review*, 2024, *72* (2), 902–917. 23

_ **and Oleksiy Kryvtsov**, "Price discounts and cheapflation during the post-pandemic inflation surge," *Journal of Monetary Economics*, 2024, *148*, 103644. 1, 23

Chakrabarti, Rajashri, Dan Garcia, and Maxim Pinkovskiy, "The EGIs: Analyzing the Economy Through an Equitable Growth Lens," *Liberty Street Economics*, 2023. 6

Chen, Tao, Peter Levell, and Martin O'Connell, "Cheapflation and the rise of inflation inequality," *CEPR Discussion Papers*, 2024. 1, 23

Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang, "The fading American dream: Trends in absolute income mobility since 1940," *Science*, 2017, *356* (6336), 398–406. 5

_ **, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner**, "Is the United States still a land of opportunity? Recent trends in intergenerational mobility," *American Economic Review*, 2014, *104* (5), 141–147. 5

Chodorow-Reich, Gabriel, Glaeser Edward, Xavier Jaravel, and Avi Lipton, "Homeownership and the Cost of Living," *Working paper*, 2025. 4.1, D

Diamond, Rebecca, "The determinants and welfare implications of US workers' diverging location choices by skill: 1980–2000," *American Economic Review*, 2016, *106* (3), 479–524. 28

Garner, Thesia I, David S Johnson, and Mary F Kokoski, "An experimental consumer price index for the poor," *Monthly Lab. Rev.*, 1996, *119*, 32. 6, 4.3, A19

Han, Jeehoon, Bruce D Meyer, and James X Sullivan, "Who is Poor, How Poverty has Changed, and Why it Matters: Poverty Measurement in the US and its Implications for Policy," 2022. 3.1.2

Jaravel, Xavier, "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector," *The Quarterly Journal of Economics*, 12 2019, *134* (2), 715–783. 1, 4

_ **and Alan Olivi**, "Prices, non-homotheticities, and optimal taxation," *Working Paper*, 2024. 1

_ **and Danial Lashkari**, "Measuring Growth in Consumer Welfare with Income-Dependent Preferences: Nonparametric Methods and Estimates for the United States," *The Quarterly Journal of Economics*, 09 2023, *139* (1), 477–532. 1, 4.2, 13, E, A1

_ **and Martin O'Connell**, "Real-time price indices: Inflation spike and falling product variety during the Great Lockdown," *Journal of Public Economics*, 2020, *191*, 104270. 26

_ **, Jonathan Kolstad, Kurt Lavetti, and Michael Nguyen-Mason**, "Health Inflation Inequality: Evidence from Utah," *Working Paper*, 2024. 1

Kaplan, Greg and Sam Schulhofer-Wohl, "Inflation at the household level," *Journal of Monetary Economics*, 2017, *91*, 19–38. The Swiss National Bank/Study Center Gerzensee Special Issue: âModern Macroeconomics: Study Center Gerzensee Conference in Honor of Robert G. King" Sponsored by the Swiss National Bank and the Study Center Gerzensee. 1, 26

Karabarbounis, Loukas and Brent Neiman, "The global decline of the labor share," *The Quarterly journal of economics*, 2014, *129* (1), 61–103. 5

Klick, Josh and Anya Stockburger, "Experimental CPI for lower and higher income households," *Working Paper*, 2021. 1, 5

_ and _ , "Examining U.S. inflation across households grouped by equivalized income," *Monthly Labor Review*, 2024. 1, 5

Krueger, Dirk and Fabrizio Perri, "Does income inequality lead to consumption inequality? Evidence and theory," *The Review of Economic Studies*, 2006, *73* (1), 163–193. 3.1.1, 5

Martin, Robert S, "Democratic Aggregation: Issues and Implications for Consumer Price Indexes," *Review of Income and Wealth*, 2022. 6

Meyer, Bruce D and James X Sullivan, "Winning the War: Poverty from the Great Society to the Great Recession," *Brookings Papers on Economic Activity*, 2012, *43* (2 (Fall)), 133–200. 3.1.2

Molloy, Raven, "JUE insight: Differences in rent growth by income from 1985 to 2021 and implications for inflation," *Journal of Urban Economics*, 2024, *142*, 103669. 1, 4.1, 28

Moretti, Enrico, "Real wage inequality," *American Economic Journal: Applied Economics*, 2013, *5* (1), 65–103. 3, 4.1, 28

Oberfield, Ezra, "Inequality and Measured Growth," *NBER Working Paper*, 2023. 29

Olivi, Alan, Vincent Sterk, and Dajana Xhani, "Optimal Monetary Policy during a Cost of Living Crisis," *Working Paper*, 2024. 1

Pallotti, Filippo, Gonzalo Paz-Pardo, Jiri Slacalek, Oreste Tristani, and Giovanni L Violante, "Who Bears the Costs of Inflation? Euro Area Households and the 2021–2023 Shock," *Journal of Monetary Economics*, 2024. 2

Piketty, Thomas and Emmanuel Saez, "Income inequality in the United States, 1913–1998," *The Quarterly journal of economics*, 2003, *118* (1), 1–41. 5

_ and Gabriel Zucman, "Capital is back: Wealth-income ratios in rich countries 1700–2010," *The Quarterly journal of economics*, 2014, *129* (3), 1255–1310. 5

_ , Emmanuel Saez, and Gabriel Zucman, "Distributional National Accounts: Methods and Estimates for the United States," *The Quarterly Journal of Economics*, 10 2017, *133* (2), 553–609. 1, 5

Poterba, James M, "Tax subsidies to owner-occupied housing: an asset-market approach," *The quarterly journal of economics*, 1984, *99* (4), 729–752. 4.1

Reinsdorf, Marshall, "COVID-19 and the CPI: is inflation underestimated?," 2020. 23

Saez, Emmanuel and Gabriel Zucman, "Wealth inequality in the United States since 1913: Evidence from capitalized income tax data," *The Quarterly Journal of Economics*, 2016, *131* (2), 519–578. 5

Sangani, Kunal, "Pass-Through in Levels and the Unequal Incidence of Commodity Shocks," *Available at SSRN 4574233*, 2023. 1, 23

Sichel, Daniel, "Modernizing the Consumer Price Index for the 21st Century," *Consensus Study Report of the National Academies of Sciences, Engineering, and Medicine. Washington, DC: The National Academies Press.*, 2022. 16

Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick, "Capitalists in the twenty-first century," *The Quarterly Journal of Economics*, 2019, *134* (4), 1675–1745. 5

_ , Owen Zidar, and Eric Zwick, "Top wealth in america: New estimates under heterogeneous returns," *The Quarterly Journal of Economics*, 2023, *138* (1), 515–573. 5

Steiner, Peter O, "Consumer Durables in an Index of Consumer Prices," in "The Price Statistics of the Federal Goverment," NBER, 1961, pp. 305–336. 4.1

Stewart, Kenneth J, "The experimental consumer price index for elderly Americans (CPI-E): 1982-2007," *Monthly Lab. Rev.*, 2008, *131*, 19. 22

For Online Publication

Appendix to "Distributional Consumer Price Indices"

Xavier Jaravel, *LSE & CEPR*

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A Data Appendix

This appendix presents background information on the CPI and CEX databases.

Consumer Price Index. The Consumer Price Index is a set of official price indices that capture price changes experienced by urban consumer in the US. BLS employs a multi-stage sampling design for the pricing surveys to select rotating samples of geographic areas, retail outlets, specific goods and services, and residential housing units. Each month, the surveys collect approximately 94,000 prices for commodities and services, and 8,000 rental housing unit quotes to compute rental price and owners' equivalent rent of residences. The CPI target population is all urban consumers, which covers 93% of the U.S. population.

BLS defines a specific scope of goods and services for CPI calculation that differs from other published consumption statistics such as the annual expenditure summary tables of the Consumer Expenditure Survey. At the most granular level of item classification, BLS defines 273 mutually exclusive and exhaustive entry-level items ("ELI") for which price information is sampled, plus 26 unsampled ELIs.[1]

After the collection of initial price data, BLS constructs basic price indices for each unique combination of 32 basic areas and 243 basic items ("basic-price-index items"), which follow a one-to-many mapping to the ELIs. These basic indices serve as the building blocks for any published CPI series, but are not available to the public. The most granular, complete, and mutually exclusive breakdown of CPI items for which price index data is publicly available at the national level consists of 211 "item strata".

BLS publishes multiple versions of the price series for each item stratum and each aggregate item group. Any series can be uniquely identified by its item code, geographic location, targeted population, seasonality adjustment, and base period. Not seasonally adjusted data are typically used for official purposes including monthly update of relative importance weights, and therefore chosen for all calculations in this paper.

BLS adheres to a regular publication schedule for the price series, which tends to be around the end of the second week of every month.[2] Other than the published price series, one can also find monthly summary information and relative importance weights in CPI News Release, which is made available concurrently with the newest CPI series. BLS also publishes many useful appendices to accompany the index data, one of which is the concordance table between UCC and ELI that allows users to identify the CPI-relevant UCCs and their associated expenditures in the CEX micro-data, and link the expenditure data to price series in a manner that is consistent with BLS' practice.

[1] Note that the total number of ELIs may change if BLS decides to update the item classification convention in future years. For a full list of sampled entry-level items and the content of each item under the current definition, see Appendix 2 of the CPI Handbook of Methods at https://www.bls.gov/cpi/additional-resources/entry-level-item-descriptions.htm.

[2] The schedule of release can be found at: https://www.bls.gov/schedule/news_release/cpi.htm.

Consumer Expenditure Survey. While BLS sources the raw price information from the Commodities & Services Survey and Housing Survey, it uses data from the Consumer Expenditure Survey to compute the weights that are used in index construction and aggregation. The expenditure shares obtained from the CEX are called "relative importance weights" by the BLS. These expenditure shares are published for pivot months, as discussed in the main text. The CEX expenditure micro-data is used to obtain the spending patterns of consumers in each socio-demographic group.

The CEX conducts two different surveys to analyze consumption patterns. The interview survey asks respondents to report spending over large consumption categories over the previous three months. The diary survey in contrast asks respondents to keep a detailed log of all purchases made over a week. Consumption is aggregated to a set of Universal Categorization Codes ("UCC"). Each survey also tracks a set of demographic and household information about the respondents. However, each respondent participates in only one survey. When calculating income percentiles, the percentiles within a given survey are used.

The BLS publishes a series of yearly expenditure tables that contain total expenditures by income quintile at various levels of aggregation. I use these tables to validate that I process the CEX micro-data correctly. However, the set of UCCs that are part of these CEX tables are not the same as the ones relevant for the CPI. The product scopes differ primarily for the category *owned dwelling*: for CPI this is captured in *owners' equivalent rent of residences* (OER), which is defined as the implicit rent that owner occupants would have to pay if they were renting their homes unfurnished; for the CEX expenditure summary this includes mortgage interests, property taxes and insurance, and expenses for repairs and maintenance.

B Price Index Calculations

This appendix presents additional information on the price indices and decompositions used in the paper.

B.1 Additional Information on the Calculation of Aggregate CPI

In Section A, the discussion of the calculation of item-level expenditure shares by the BLS omitted a step for simplicity, which is described here.

To illustrate the logic of this additional step, consider the computation of expenditure shares in December 2017. As discussed in Section A, BLS computes a new set of expenditure shares in December 2017 using CEX data from 2015 and 2016. In fact, the BLS also makes an adjustment for price changes between the years 2015-2016 and December 2017, inferring how expenditure shares should have changed given relative price changes between 2015-2016 and December 2017.

For consistency with the notation in the main text, let us denote the reference December period by $0(t)$, e.g. December 2017. $s_{ib(0(t))}$ denotes the expenditure share of item i in the base period $b(0(t))$ – e.g., with $0(t) =$ December 2017, $b(0(t))$ is 2015-2016. $s_{ib(0(t))}$ is computed directly in CEX data. Then the expenditure share assigned at $0(t)$ for category i is:

$$\omega_{i0(t)} \equiv \frac{\frac{p_{i0(t)}}{p_{ib(0(t))}} \cdot s_{ib(0(t))}}{\sum_k \left(\frac{p_{k0(t)}}{p_{kb(0(t))}} \cdot s_{kb(0(t))} \right)},$$

where $p_{ib(0(t))}$ denotes the average price index of the item over period $b(0(t))$, while $p_{i0(t)}$ is the price index in the focal December month.

B.2 Price Indices with Geography Heterogeneity

The BLS only publishes local price indices for a subset of items and a subset of locations. Consumption expenditures within these local areas represents roughly 40 % of total consumption. Furthermore, within each local area, consumption on items with a published prices series represents around 40-50 % of total consumption within that area. Specifically, local price series are available for the following categories: rent of primary residence, owners' equivalent rent of primary residence, electricity, utilities, gasoline, new vehicles, used vehicles, and childcare, tuition, and other school fees.

Let S be the set of all items and $I \subset S$ be the set of all items with a published local price series. Let C be the set of cities with published local prices. $p^c_{i,t}$ is the price of good i, in period t, in city c, P^c_t is the overall price index for city c, and $r_{i,t}$ is the published Relative Importance weight for item i in period t.

The first goal is to calculate the city-specific importance weights. As in the main text, $0(t)$ denotes the reference period and $b(t)$ is the base period for month t. For instance, for January 2018 to December 2019, $0(t)$ is December 2017 and $b(t)$ is January 2015 to December 2016. The BLS publishes the set of importance weights only for the reference period. These weights represent the consumption shares from the base period that have been updated to reflect any price changes that have occurred. The implied importance weights for the base period can be calculated by inverting the update formula:

$$r_{i,b(t)} = r_{i,0(t)} \frac{p_{i,b(t)}}{p_{i,0(t)}} / \frac{P_{b(t)}}{P_{0(t)}}$$

Using the microdata, one can calculate the fraction of spending on each item i that is from area c, which is denoted by $S^c_{i,t}$. Using the weight update formula applied to the city-specific prices yields:

$$\begin{aligned} r^c_{i,b(t)} &= r_{i,b(t)} S^c_{i,b(t)} \\ r^c_{i,0(t)} &= r^c_{i,b(t)} \frac{p^c_{i,0(t)}}{p^c_{i,b(t)}} / \frac{P_{0(t)}}{P_{b(t)}} \quad = r_{i,0(t)} \tfrac{p^c_{i,0(t)}}{p^c_{i,b(t)}} / \tfrac{p_{i,0(t)}}{p_{i,b(t)}} S^c_{i,b(t)} \end{aligned}$$

Local price indices available. When only a subset of the local goods are priced, one can calculate an implied local price index for these goods which is consistent with the overall price index for that area. Let $S^c_t = \sum_{i \in S} r^c_{i,t}$ be the share of total consumption going to area c. To measure all shares in the base period $b(t)$, one has to calculate $S^c_{0(t)}$using the share update formula:

$$S^c_{0(t)} = S^c_{b(t)} \frac{P^c_{0(t)}/P^c_{b(t)}}{P_{0(t)}/P_{b(t)}}.$$

One can then calculate changes in the local price index as

$$
\begin{aligned}
\frac{P^c_t}{P^c_{0(t)}} &= \sum_{i\in I} \frac{r^c_{i,0(t)}}{S^c_{0(t)}} \frac{p^c_{i,t}}{p^c_{i,0(t)}} + \sum_{i\in I^c} \frac{r^c_{i,0(t)}}{S^c_{0(t)}} \frac{p^c_{i,t}}{p^c_{i,0(t)}} \\
&\equiv w^c_{I,0(t)} \frac{P^c_{I,t}}{P^c_{I,0(t)}} + (1 - w^c_{I,0(t)}) \frac{P^c_{I^c,t}}{P^c_{I^c,0(t)}},
\end{aligned}
$$

where $P^c_{I,t}$ is the local price index for area c restricted to the set of goods I, and $w^c_{I,t} = \sum_{i\in I} \frac{r^c_{i,t}}{S^c_t}$ is the total share of consumption in area c that goes to the goods in set I. From this, one can calculate the change in the price index for the set of unpriced goods I^c:

$$
\frac{P^c_{I^c,t}}{P^c_{I^c,0(t)}} = (\frac{P^c_t}{P^c_{0(t)}} - w^c_{I,0(t)} \frac{P^c_{I,t}}{P^c_{I,0(t)}})/(1 - w^c_{I,0(t)}).
$$

For $i \in I^c$, the $r^c_{i,0(t)}$ are unknown. However, one can make the simplifying assumption that

$$
\frac{p^c_{i,0(t)}}{p^c_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} = \alpha^c_{0(t)},
$$

i.e. the ratio of the change in an item's local price to the change in the item's national price is constant across items. One can then solve for $\alpha^c_{0(t)}$:

$$
\begin{aligned}
(1 - w^c_{I,0(t)}) &= \sum_{i\in I^c} \frac{r^c_{i,0(t)}}{S^c_{0(t)}} \\
&= \sum_{i\in I^c} \frac{r_{i,0(t)} \frac{p^c_{i,0(t)}}{p^c_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} S^c_{i,b(t)}}{S^c_{0(t)}} \\
&= \sum_{i\in I^c} \frac{r_{i,0(t)} a^c_{0(t)} S^c_{i,b(t)}}{S^c_{0(t)}} \\
a^c_{0(t)} &= \frac{(1 - w^c_{I,0(t)}) S^c_{0(t)}}{\sum_{i\in I^c} r_{i,0(t)} S^c_{i,b(t)}}.
\end{aligned}
$$

Plugging back into the formula for the relative importance weights yields:

$$
\begin{aligned}
r^c_{i,0(t)} &= r_{i,0(t)} \frac{p^c_{i,0(t)}}{p^c_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} S^c_{i,b(t)} \\
&= (1 - w^c_{I,0(t)}) S^c_{0(t)} \frac{r_{i,0(t)} S^c_{i,b(t)}}{\sum_{i\in I^c} r_{i,0(t)} S^c_{i,b(t)}}.
\end{aligned}
$$

One can then use these implied relative importance weights to calculate local item prices that are consistent with the overall local price index of unpriced goods calculated above. One needs a similar simplifying assumption to the one above:

$$
\frac{p^c_{i,t}}{p^c_{i,0(t)}} / \frac{p_{i,t}}{p_{i,0(t)}} = \beta^c_t.
$$

Plugging into the definition of the local price index yields:

$$\begin{aligned}
\frac{P^c_{I^c,t}}{P^c_{I^c,0(t)}} &= \sum_{i\in I^c} \frac{r^c_{i,0(t)}}{S^c_{0(t)}} \frac{p^c_{i,t}}{p^c_{i,0(t)}} / (1 - w^c_{I,0(t)}) \\
&= \sum_{i\in I^c} \frac{r^c_{i,0(t)}}{S^c_{0(t)}} \frac{p_{i,t}}{p_{i,0(t)}} \beta_t / (1 - w^c_{I,0(t)}). \\
\beta_t &= \frac{\frac{P^c_{I^c,t}}{P^c_{I^c,0(t)}} (1 - w^c_{I,0(t)}) S^c_{0(t)}}{\sum_{i\in I^c} r^c_{i,0(t)} \frac{p_{i,t}}{p_{i,0(t)}}}.
\end{aligned}$$

Implied price index for location without local price series.

Around 60 % of spending occurs in areas with no local published prices. Denote by u the set of all areas that do not have local prices. One can calculate local prices within u so that the implied aggregate index for the whole US is consistent with the published index. Doing so follows almost the same steps as above. Let E be the set of all items. Then,

$$\begin{aligned}
\frac{P_t}{P_{0(t)}} &= \textstyle\sum_{c\in C} \sum_{i\in E} r^c_{i,0(t)} \frac{p^c_{i,t}}{p^c_{i,0(t)}} + \sum_{i\in E} r^u_{i,0(t)} \frac{p^u_{i,t}}{p^u_{i,0(t)}} \\
&\equiv w_{0(t)} \frac{P^C_t}{P^C_{0(t)}} + (1 - w_{0(t)}) \frac{P^u_t}{P^c_{0(t)}},
\end{aligned}$$

where $\frac{P^C_t}{P^C_{0(t)}}$ is the change in the price index for all goods across all areas where local prices are available, and $w_{0(t)} = \sum_{c\in C} \sum_{i\in E} r^c_{i,0(t)}$ is the share of total consumption that occurs in these areas. One can calculate the local price index as

$$\frac{P^C_t}{P^C_{0(t)}} = \sum_{c\in C} \sum_{i\in E} \frac{r^c_{i,0(t)}}{w_{0(t)}} \frac{p^c_{i,t}}{p^c_{i,0(t)}}.$$

From this formula, one can calculate the implied price index in areas with no local prices:

$$\frac{P^u_t}{P^u_{0(t)}} = \left(\frac{P_t}{P_{0(t)}} - w_{0(t)} \frac{P^C_t}{P^C_{0(t)}}\right) / (1 - w_{0(t)}).$$

The $r^u_{i,0(t)}$ are unknown. However, one can make the simplifying assumption that

$$\frac{p^u_{i,0(t)}}{p^u_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} = \gamma^u_{0(t)},$$

so that the ratio of the change in an item's local price to the change in the item's national price is constant across items. One can then solve for $\gamma^u_{0(t)}$

$$
\begin{aligned}
(1-w_{0(t)}) &= \sum_{i\in E} r^u_{i,0(t)} \\
&= \sum_{i\in E} r_{i,0(t)} \frac{p^u_{i,0(t)}}{p^u_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} S^u_{i,b(t)} \\
&= \sum_{i\in E} r_{i,0(t)} \gamma^u_{0(t)} S^c_{i,b(t)} \\
\gamma^u_{0(t)} &= \frac{(1-w_{0(t)})}{\sum_{i\in E} r_{i,0(t)} S^u_{i,b(t)}}.
\end{aligned}
$$

Plugging back into the formula for the relative importance weights yields:

$$
\begin{aligned}
r^u_{i,0(t)} &= r_{i,0(t)} \frac{p^u_{i,0(t)}}{p^u_{i,b(t)}} / \frac{p_{i,0(t)}}{p_{i,b(t)}} S^u_{i,b(t)} \\
&= (1-w_{0(t)}) \frac{r_{i,0(t)} S^u_{i,b(t)}}{\sum_{i\in E} r_{i,0(t)} S^u_{i,b(t)}}.
\end{aligned}
$$

One can then use these implied relative importance weights to calculate local item prices that are consistent with the overall local price index of unpriced goods we calculated above. One again needs a similar simplifying assumption to the one above:

$$
\frac{p^u_{i,t}}{p^u_{i,0(t)}} / \frac{p_{i,t}}{p_{i,0(t)}} = \delta^u_t.
$$

Plugging into the definition of the local price index yields:

$$
\begin{aligned}
\frac{P^u_t}{P^u_{0(t)}} &= \sum_{i\in E} r^u_{i,0(t)} \frac{p^u_{i,t}}{p^u_{i,0(t)}} / (1-w_{0(t)}) \\
&= \sum_{i\in E} r^u_{i,0(t)} \delta^u_t \frac{p_{i,t}}{p_{i,0(t)}} / (1-w_{0(t)}) \\
\delta^u_t &= \frac{\frac{P^u_t}{P^u_{0(t)}} (1-w_{0(t)})}{\sum_{i\in E} r^u_{i,0(t)} \frac{p_{i,t}}{p_{i,0(t)}}}
\end{aligned}
$$

C Price Index Decomposition

Consider a set of item categories $E = \cup I_1, \ldots, I_n$,where $I_i \cap I_j = \emptyset$ when $i \neq j$. We are interested in decomposing the inflation difference experienced between two household groups as the sum of the difference experienced *within* each of the sets I_i and the difference experienced *between* them.

This decomposition is straightforward using the Törnqvist Index, i.e. the Chained CPI, where the price index for group g can be written as $P^g_T/P^g_0 = \prod_{t=0}^{T} \prod_{i\in E} (p_{i,t}/p_{i,t-1})^{s^g_{i,t}}$, where $s^g_{i,t} = .5(r^g_{i,t} + r^g_{i,t-1})$

is the average expenditure share for group g, on item i between period t and $t-1$.[3] We define $p_{i,-1} = p_{i,0}$ to normalize the price index to 1 at $t = 0$.

Letting $\pi_{i,t} = \log(p_{i,t}/p_{i,t-1})$ and $s^g_{I,t} = \sum_{i \in I} s^g_{i,t}$, one can define the one period inflation experienced by group g at time t within set I as $\pi^g_{I,t} = \sum_{i \in I} \frac{s^g_{i,t}}{\sum_{j \in I} s^g_{j,t}} \pi_{i,t} = \sum_{i \in I} \frac{s^g_{i,t}}{S^g_{I,t}} \pi_{i,t}$. With this notation, one can decompose $\log(P^g_T/P^g_0) - \log(P^q_T/P^g_0)$ for any two groups g and q:

$$
\begin{aligned}
&\log(P^g_T/P^g_0) - \log(P^q_T/P^q_0) \\
&= \sum_{t=0}^{T} \sum_{i \in E} s^g_{i,t} \pi_{i,t} - \sum_{t=0}^{T} \sum_{i \in E} s^q_{i,t} \pi_{i,t} \\
&= \sum_{t=0}^{T} \sum_{I} \sum_{i \in I} \left(s^g_{i,t} \pi_{i,t} - s^q_{i,t} \pi_{i,t} \right) \\
&= \sum_{t=0}^{T} \sum_{I} \left(s^g_{I,t} \pi^g_{I,t} - s^q_{I,t} \pi^q_{I,t} \right) \\
&= \sum_{t=0}^{T} \sum_{I} \left(.5 s^g_{I,t} \pi^g_{I,t} + .5 s^q_{I,t} \pi^g_{I,t} - .5 s^g_{I,t} \pi^q_{I,t} - .5 s^q_{I,t} \pi^q_{I,t} + .5 s^g_{I,t} \pi^g_{I,t} - .5 s^q_{I,t} \pi^g_{I,t} + .5 s^g_{I,t} \pi^q_{I,t} - .5 s^q_{I,t} \pi^q_{I,t} \right) \\
&= \sum_{t=0}^{T} \sum_{I} \left(.5(s^g_{I,t} + s^q_{I,t})(\pi^g_{I,t} - \pi^q_{I,t}) + .5(\pi^q_{I,t} + \pi^g_{I,t})(s^g_{I,t} - s^q_{I,t} \right) \\
&= \underbrace{\sum_{t=0}^{T} \sum_{I} \left(\bar{s}^{g,q}_{i,t} \Delta \pi^{g,q}_{i,t} \right)}_{\text{Within}} + \underbrace{\sum_{t=0}^{T} \sum_{I} \left(\bar{\pi}^{g,q}_{i,t} \Delta s^{g,q}_{i,t} \right)}_{\text{Between}},
\end{aligned}
$$

where $\bar{s}^{g,q}_{I,t} = .5(s^g_{I,t} + s^q_{I,t})$ is the average value of $s_{I,t}$ for groups g and q, and $\Delta s^{g,q}_{i,t} = s^g_{I,t} - s^q_{I,t}$ is the difference.

D The User Cost of Housing

This section presents the calculation of the user cost, following the data cleaning steps of Chodorow-Reich et al. (2025) and conducting the analysis by household income quintiles. The user cost has five components: the cost of the mortgage, after interest deduction; the opportunity cost of investing the downpayment in financial markets; out of pockets costs; property taxes; and expected capital gains on housing. The formula is User Cost of Housing$_t = \rho_t P^{\text{Housing}}_t$, with

$$
\begin{aligned}
\rho_t = {} & i^{\text{Mortgage}}_t (1 - \tau^{\text{Federal}}_t)(1 - M_t) + i^{\text{Opportunity}}_t M_t (1 - \tau^{\text{Capital}}_t) \\
& + \tau^{\text{Property}}_t (1 - \tau^{\text{Federal}}_t) + \gamma_t - E_t \left[\pi^{\text{Housing}}_t \right],
\end{aligned}
$$

where we omit the household subscripts for brevity. P^{Housing}_t denotes the property value, i^{Mortgage}_t is the 30-year fixed mortgage rate, and $i^{\text{Opportunity}}_t$ denotes the opportunity cost of investing the down payment,

[3] $r^g_{i,t}$ denotes the expenditure share for each household group on item i in month t, as measured in the CEX data cross-walked to item strata.

which we set equal to the 10-year Treasury bond plus 5% (where 5% is the average equity premium from 1980 to 2015). τ_t^{Federal} denotes the marginal federal income tax rate, taken from Tax Foundation data and matched by income and family type to CEX respondents. The marginal income tax applies to the entire property value, without differentiating between equity and debt financing. The rationale is that mortgage interest is deductible for debt costs, whereas for equity, investors only receive after-tax interest earnings. M_t is the downpayment ratio. τ_t^{Capital} denotes tax rates on capital gains, set at 15%. γ_t captures out-of-pocket costs, i.e. depreciation, maintenance and repair, and real estate insurance, set at 1% of the property value. τ_t^{Property} denotes the property tax. Finally, $E_t\left[\pi_t^{\text{Housing}}\right]$ denotes expected housing inflation, which we set alternatively as the average realized inflation over the period or as the expectations measured in the New York Fed Survey of Consumer Expectations. Results are reported in Appendix Figure A16.

E Non-homotheticity Correction

This appendix presents the price index formula, algorithm, and data used to obtain the non-homotheticity correction.

Price index formulas and algorithm. Denoting the vector of prices by$\boldsymbol{p}_t$, nominal expenditure by y_t, expenditure shares by $\boldsymbol{s}_t$ and the expenditure function $E\left(u;\boldsymbol{p}\right)$, let us define a money metric $M_b\left(\cdot\right)$ for welfare under prices $\boldsymbol{p}_b$ (with $0 \leq b \leq T$):

$$c^b = M_b\left(u\right) \equiv E\left(u;\boldsymbol{p}_b\right).$$

The expenditure function under prices $\boldsymbol{p}$ can be expressed in terms of real consumption:

$$\widetilde{E}^b\left(c^b;\boldsymbol{p}\right) \equiv E\left(M_b^{-1}\left(c^b\right);\boldsymbol{p}\right).$$

The true cost-of-living index for real consumption c^b between periods t_0 and t (under base b) is then:

$$\mathcal{P}_{t_0,t}^b\left(c^b\right) \equiv \frac{\widetilde{E}^b\left(c^b;\boldsymbol{p}_t\right)}{\widetilde{E}^b\left(c^b;\boldsymbol{p}_{t_0}\right)}.$$

Jaravel and Lashkari (2023) show that real consumption growth can be obtained with a correction to deflated nominal expenditure growth:

$$\frac{d\ln c_t^b}{dt} = \frac{1}{1+\Lambda_t^b\left(c_t^b\right)}\left(\frac{d\ln y_t}{dt} - \sum_i s_{it}\frac{d\ln p_{it}}{dt}\right),$$

where the non-homotheticity correction is the elasticity of true index (from base b to t) with respect to real consumption c^b:

$$\Lambda_t^b\left(c^b\right) = \frac{\partial\ln\mathcal{P}_{b,t}^b\left(c^b\right)}{\partial\ln c^b}.$$

Under homothetic preferences, $\mathcal{P}_{t_0,t}^b\left(c^b\right) \equiv \overline{\mathcal{P}}_{t_0,t}$ for all c^b, so $\Lambda_t^b\left(c^b\right) \equiv 0$, i.e. there is no correction.

The purpose of the algorithm is to recover the correction $\Lambda_t^b\left(c^b\right) \equiv 0$ using data from a collection of households $n \in \{1, \cdots, N\}$ with identical preferences. Approximations must be used since c^b and $\mathcal{P}^b_{t_0,t}\left(c^b\right)$ are not directly observed in data. The algorithm uses the following steps:

First, in the base period $t = b$, by definition $c^n_b \equiv y^n_b$, so $\mathcal{P}_{b,b+1}\left(c^n_b\right) \approx \pi^n_{G,b}$, i.e. $\widehat{\mathcal{P}}_{b,b+1}\left(\cdot\right)$ can be directly estimated non-parametrically in the observed data, using a polynomial fit. One can then approximate the non-homotheticity correction $\widehat{\Lambda}_{b+1}\left(c\right) \equiv \frac{\partial \ln \widehat{\mathcal{P}}_{b,b+1}(c)}{\partial \ln c}$ and compute real consumption in the next period:

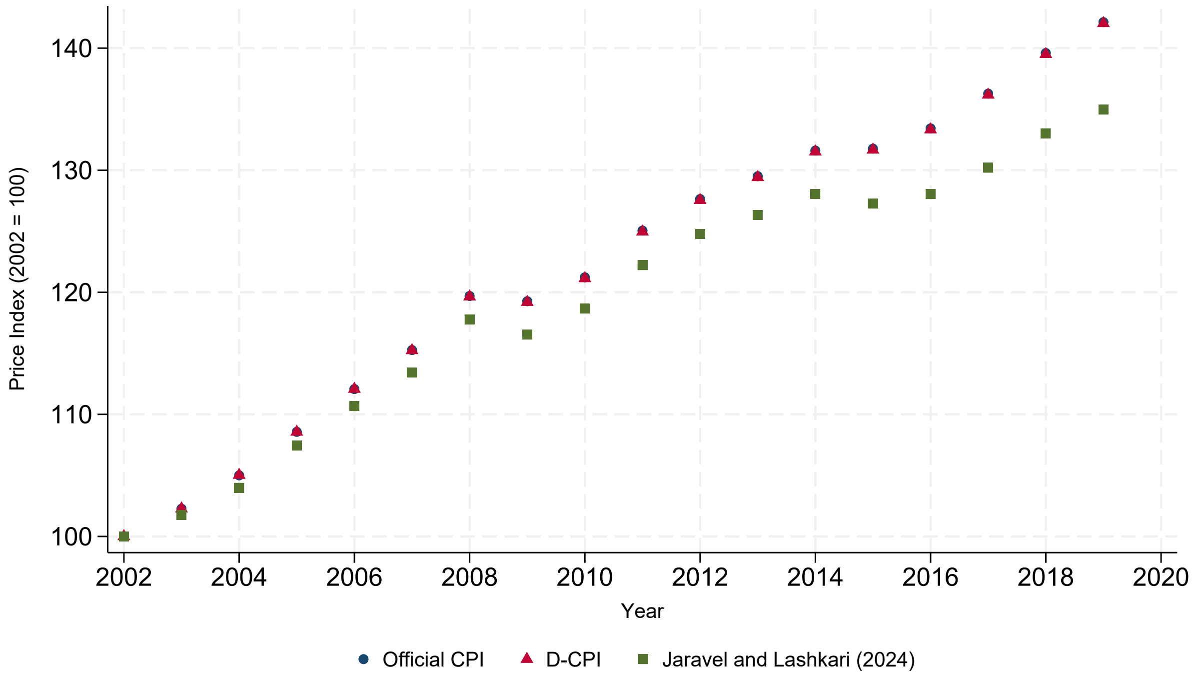
$$\ln \widehat{c}^n_{b+1} = \ln c^n_b + \frac{1}{1 + \widehat{\Lambda}_{b+1}\left(c^n_b\right)}\left(\Delta \ln y^n_b - \ln \pi^n_{G,b}\right).$$

The algorithm iterates the above steps for $t > b$, using $\ln \widehat{\mathcal{P}}_{b,t}\left(c\right) = \sum_{\tau=b}^{t-1} \ln \widehat{\mathcal{P}}_{\tau,\tau+1}\left(c\right)$.

Data. The data required to implement the algorithm above is the same as for the computation of D-CPIs. Since the magnitude of the bias from the non-homotheticity correction depends on consumption growth over time, and since household expenditure surveys are known to miss some expenditures, I apply a reweighting step to the expenditure data series from the CEX so that aggregates match the official aggregate personal consumption expenditures provided by the Bureau of Economic Analysis (BEA). Specifically, I apply a year-specific scaling factor to the household consumption data so that I match the BEA's personal consumption expenditures per household in each year. Using a rescaling factor applied to each income quintile, I also ensure that the the distribution of expenditures across quintiles matches the official CEX summary tables published by the BLS on aggregate expenditures by income quintiles.

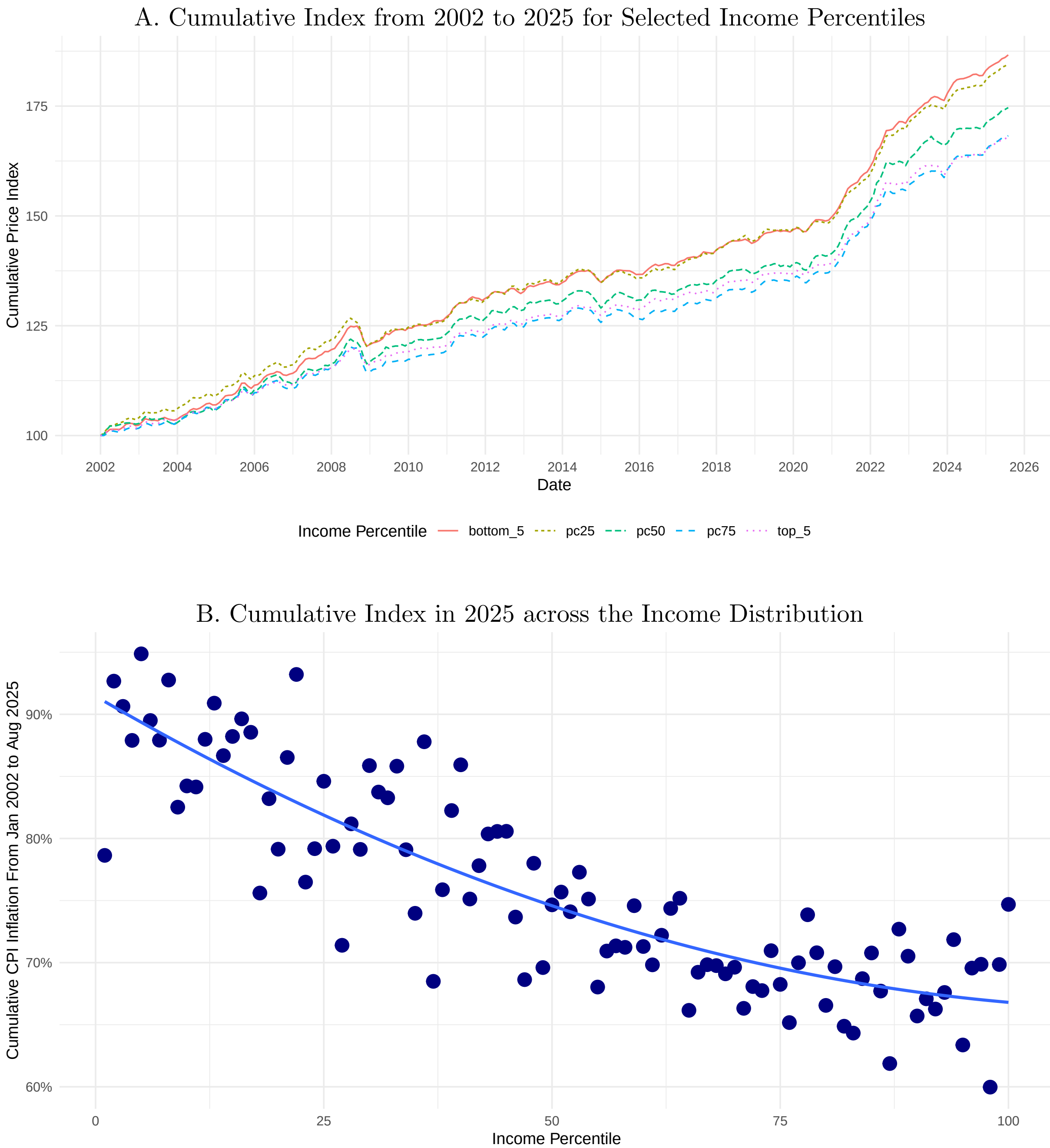
F Additional Figures and Tables

Figure A1 Comparison between Official CPI, the Jaravel and Lashkari (2023) price index, and D-CPIs



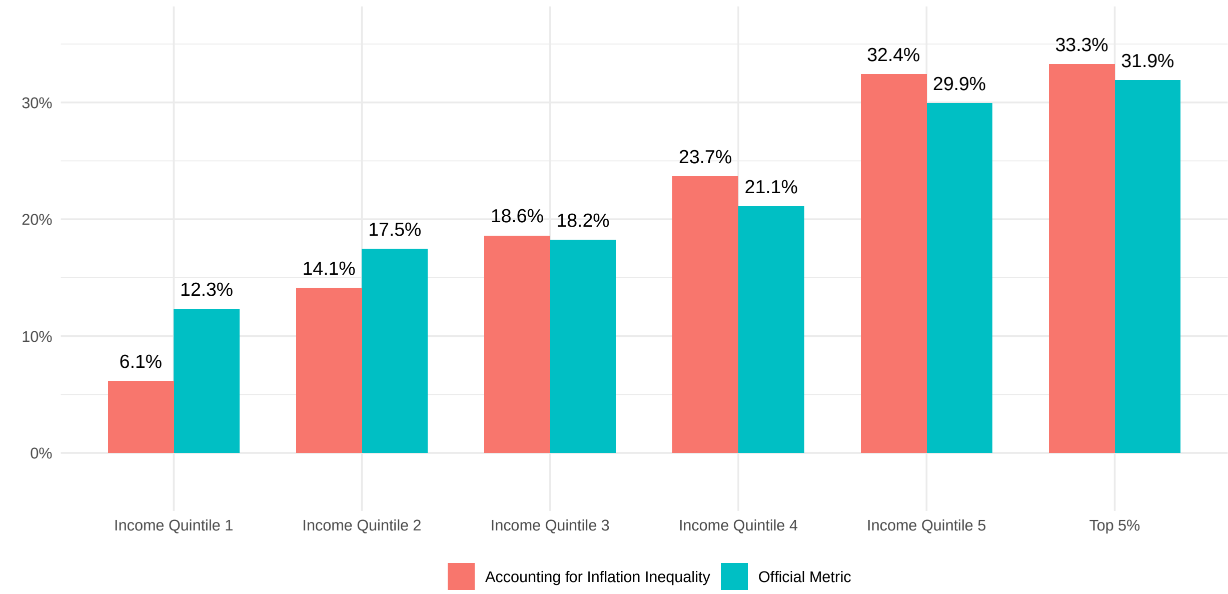
Notes: This figure reports aggregate inflation rates form 2002 to 2019 for the official CPI, the distributional CPI, and the price index of Jaravel and Lashkari (2023).

Figure A2 Long-Run Inflation Inequality by Income Percentile with Chained CPI



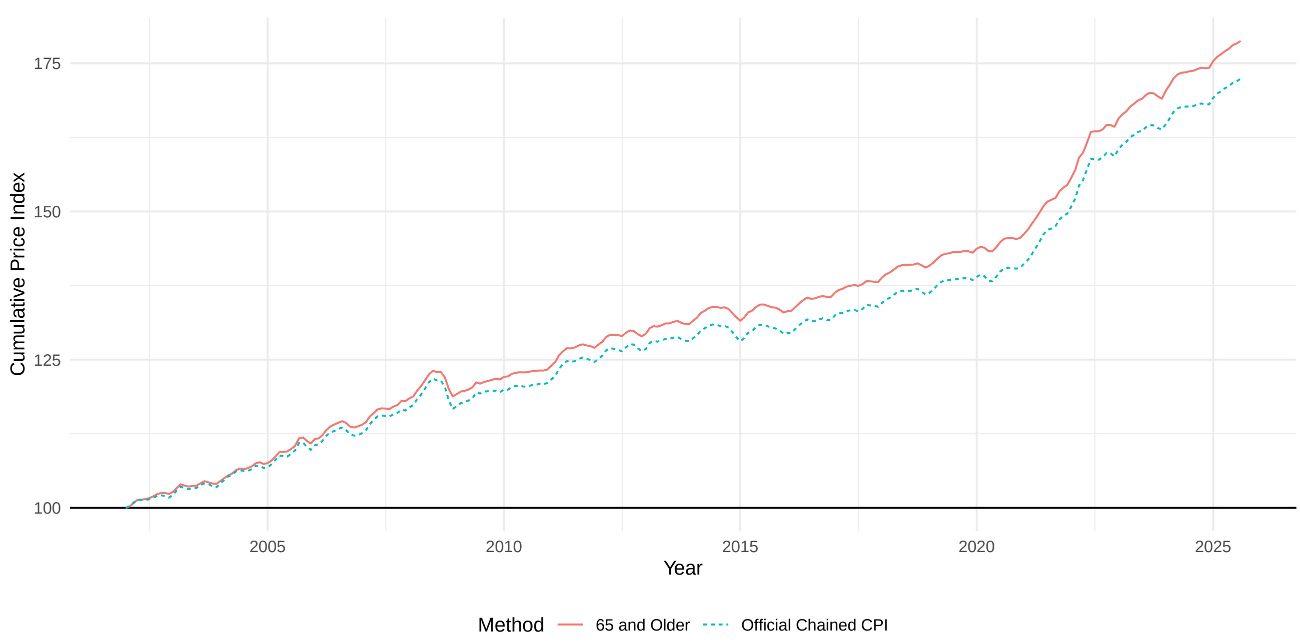
Notes: This figure reports inflation rates by income percentile using the Chained CPI. Panel A show the monthly time series of the cumulative price index from January 2002 to August 2025 for selected income percentiles (bottom 5%, 25th, 50th, 75th, and top 5%). Panel B reports the cumulative CPI in August 2025 for all income percentiles, along with the OLS best-fit line.

Figure A3 Implications for Household Real Income Growth, Chained CPI, 2002 to 2019



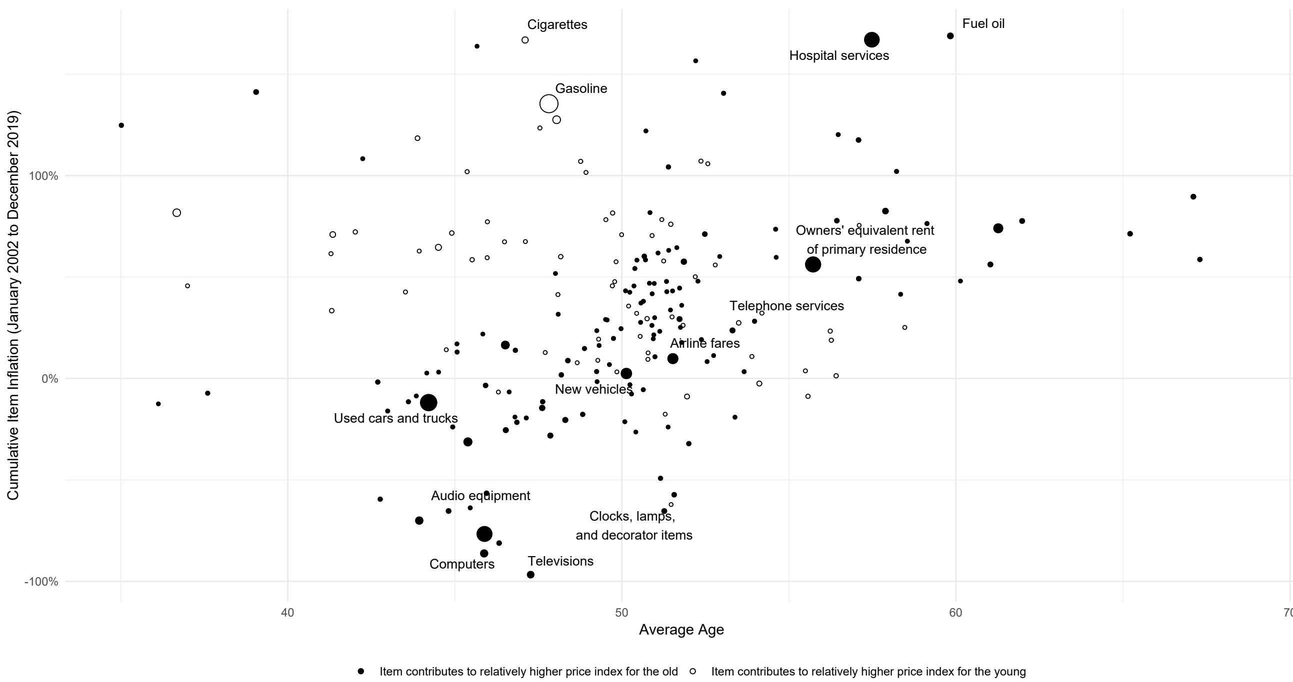
Notes: This figure reports cumulative real income growth from 2002 to 2019 by quintiles of the household income distribution, as well as for the top 5%. Two series are shown, with the official Chained CPI and with the Chained D-CPIs specific to each income group.

Figure A4 65+ D-CPI and Official CPI



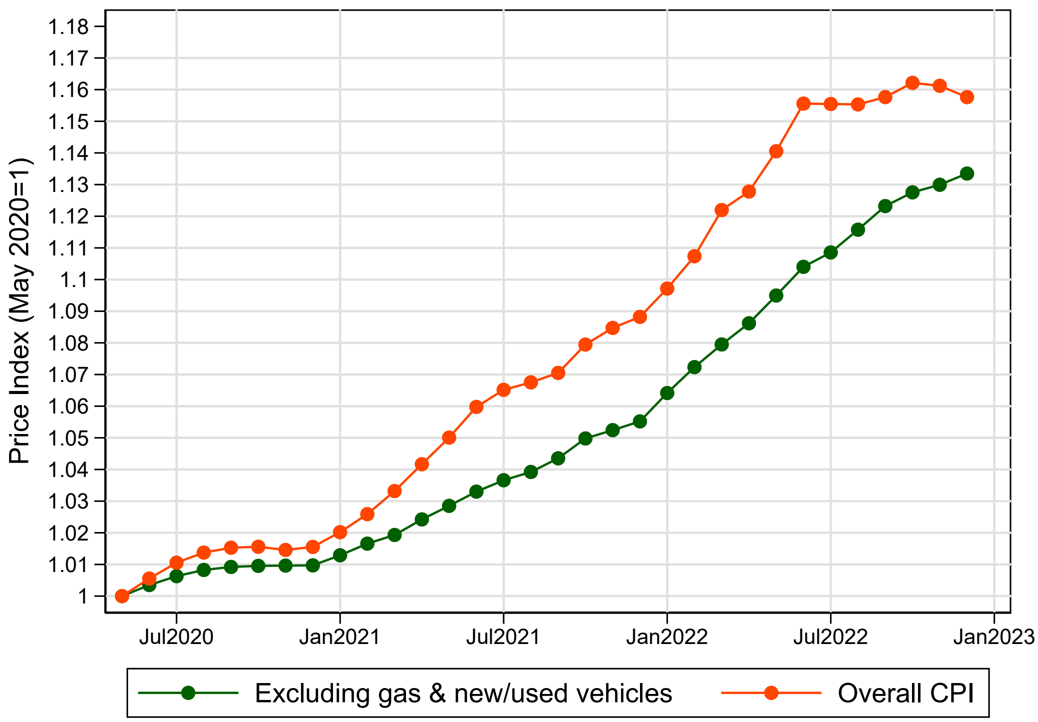
Notes: This figure reports cumulative price indices from January 2002 to August 2025 for various households with a household head above the age of 65, compared to the chained CPI.

Figure A5 Item Inflation Rates and Customer Age, 2002 to 2019



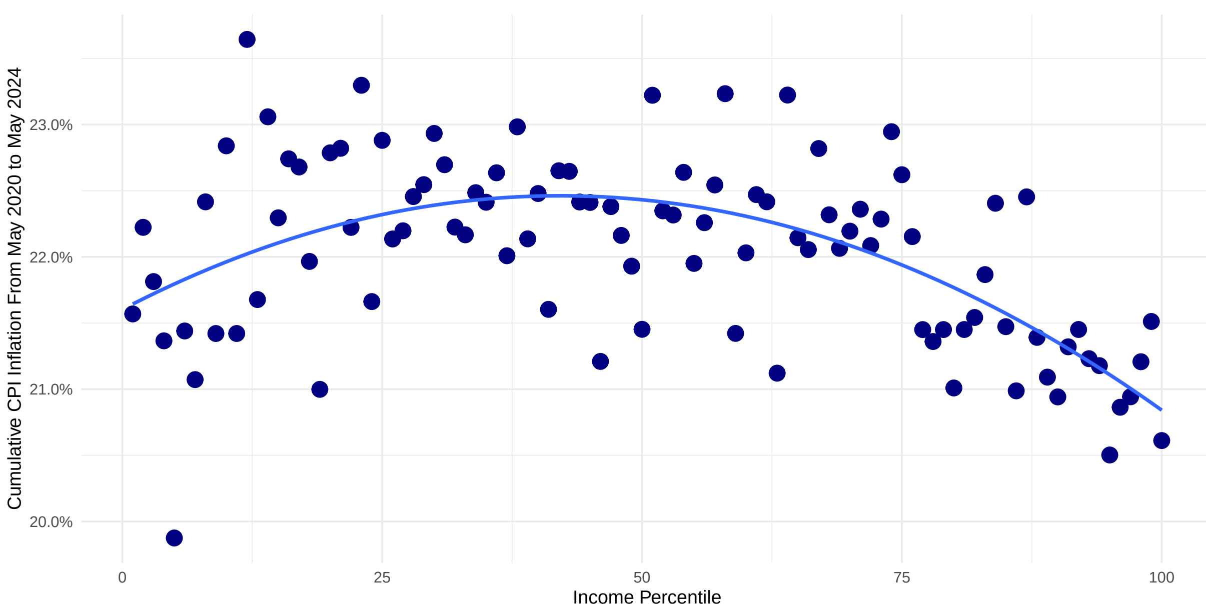
Notes: This figure plots the average age of households buying an item (using sales weights to compute the average) against the cumulative inflation rate for this item from 2002 to 2019. The size of each dot is proportional to the contribution of the item to inflation gap between households above and below the age of 65.

Figure A6 Inflation in the Wake of the Covid-19 Pandemic



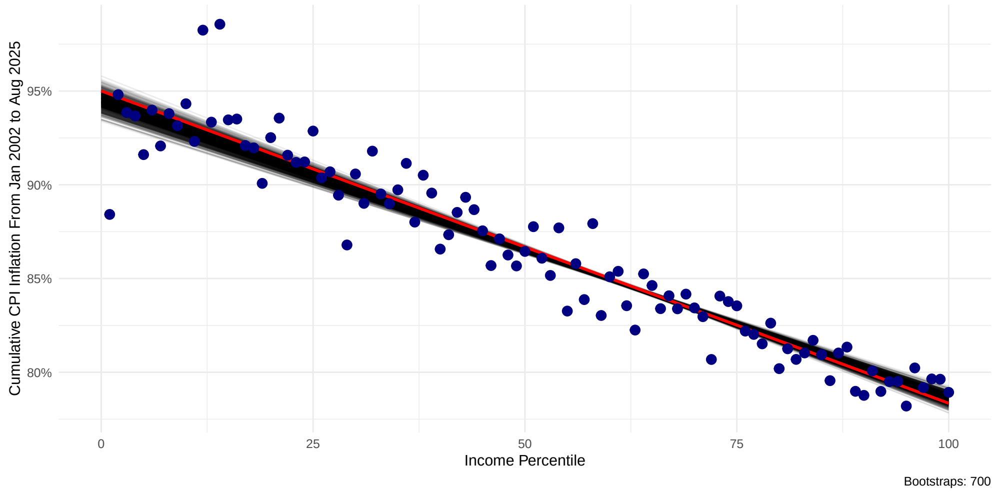
Notes: This figures plots the official CPI, as well as the CPI excluding gas and new/used vehicles, from May 2020 to December 2022.

Figure A7 Inflation across the Income Distribution from May 2020 to May 2024



Notes: This figure reports cumulative inflation rates from May 2020 to May 2024 across the income distribution.

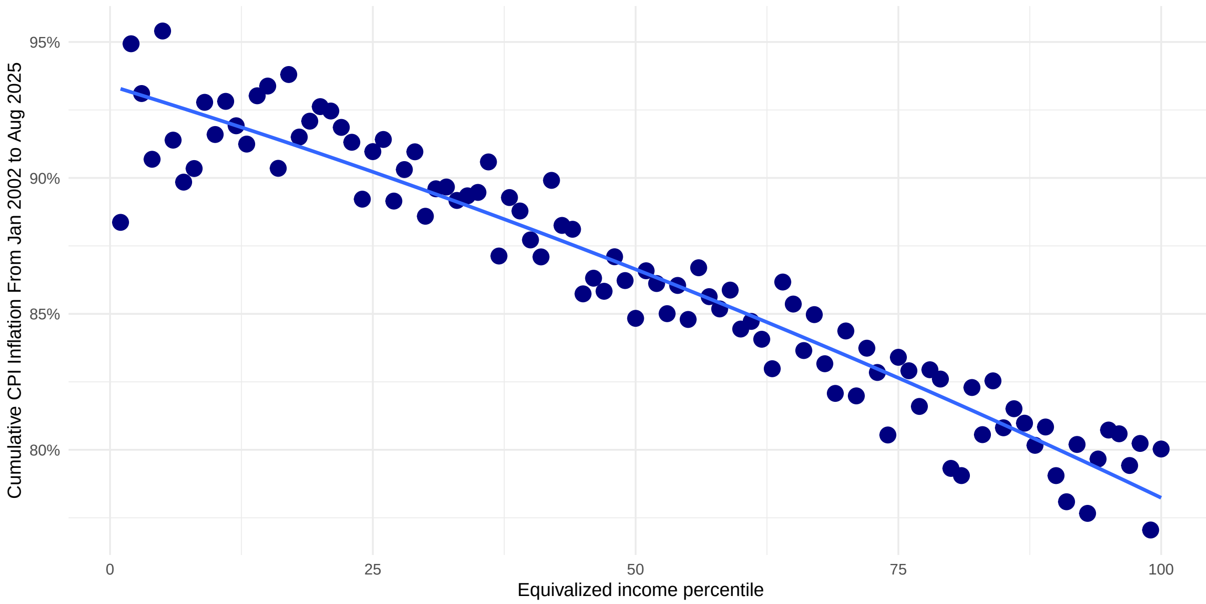
Figure A8 Bootstrapped Estimates of Long-Term Inflation Inequality



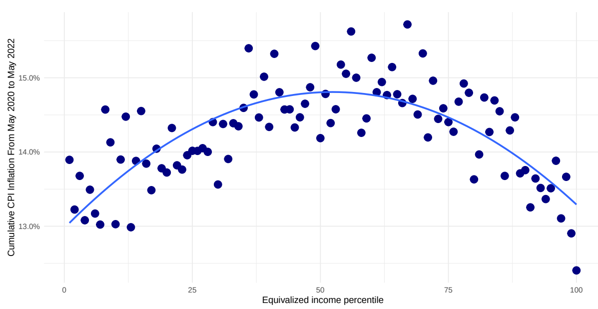
Notes: This figure reports inflation rates by income percentile, using the bootstrap to account for sampling uncertainty. The cumulative CPI is reported for all income percentiles in the full sample, along with the OLS best-fit lines obtained in 700 bootstrap samples; the red line is the OLS best-fit line in the full sample. The figure thus shows that sampling uncertainty is small.

Figure A9 Inflation Inequality by Equivalized Income Percentile

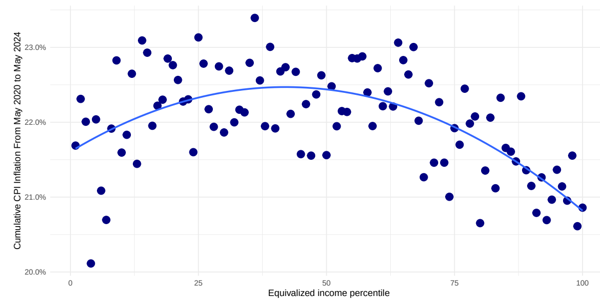
Panel A: Long-Run Dynamics, 2002-2024



Panel B: Short-Run Dynamics, 2002-2004



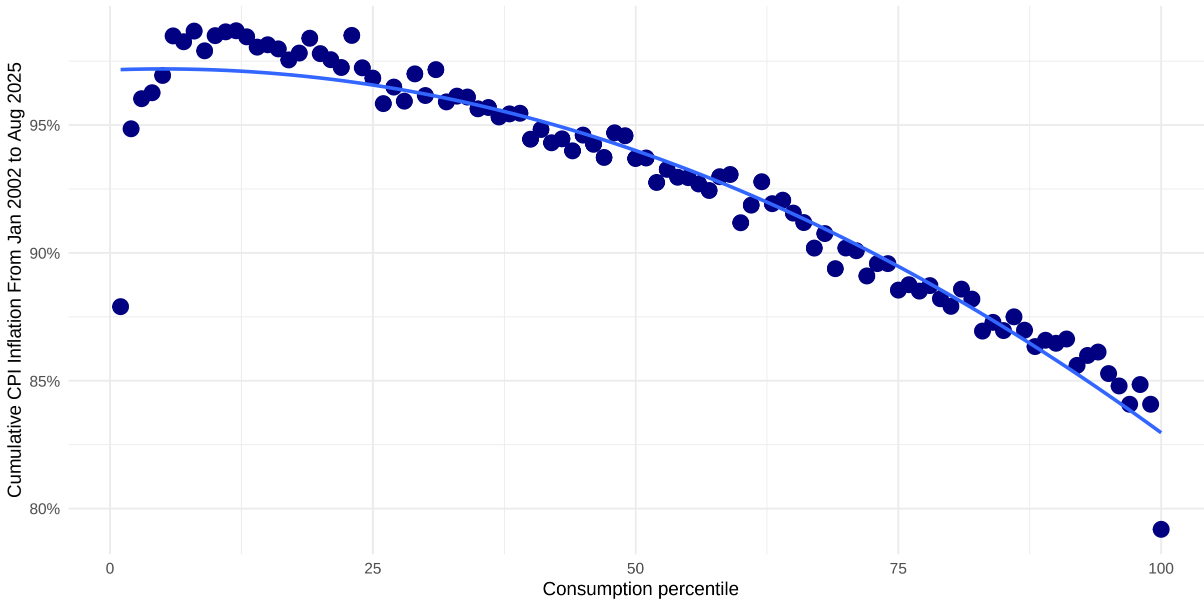
(i) May 2020-May 2022



(ii) May 2020-May 2024

Notes: This figure reports cumulative inflation rates across equivalized income percentiles. Equivalized income are obtained by dividing household income by the square root of household size.

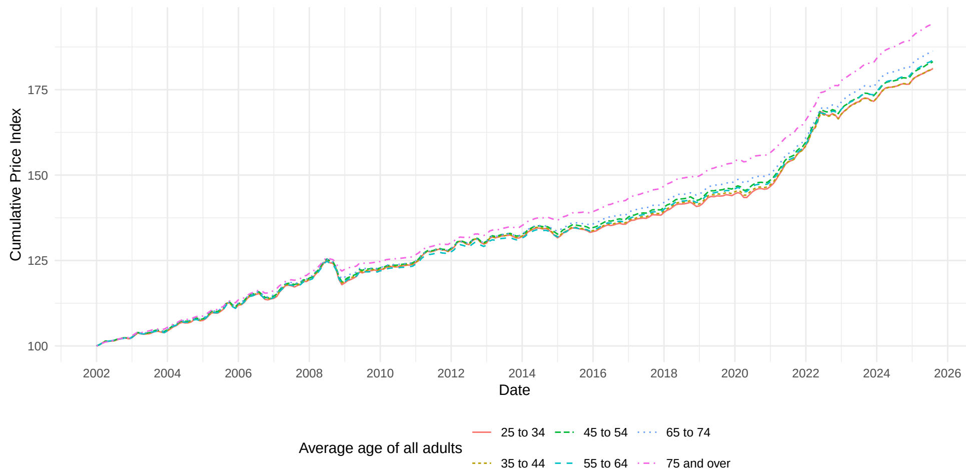
Figure A10 Long-Run Inflation Inequality by Expenditure Percentile



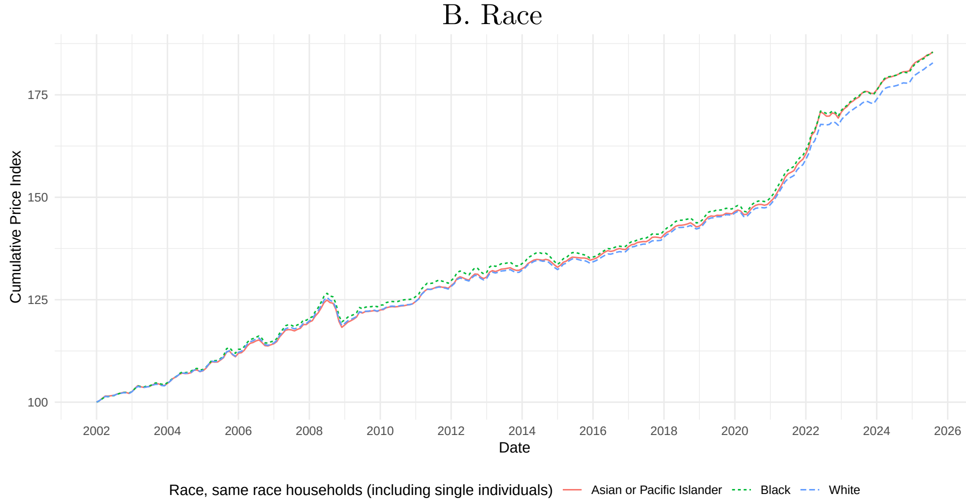
Notes: This figure reports inflation rates by consumption percentile percentile. Households are ranked separately within the interview and diary surveys in each year, excluding new and used vehicles from the interview survey. The figure reports the cumulative CPI from January 2002 to August 2025 for all expenditure percentiles, along with the OLS best-fit line.

Figure A11 Long-Run Inflation Inequality by Age and Race, Robustness

A. Age



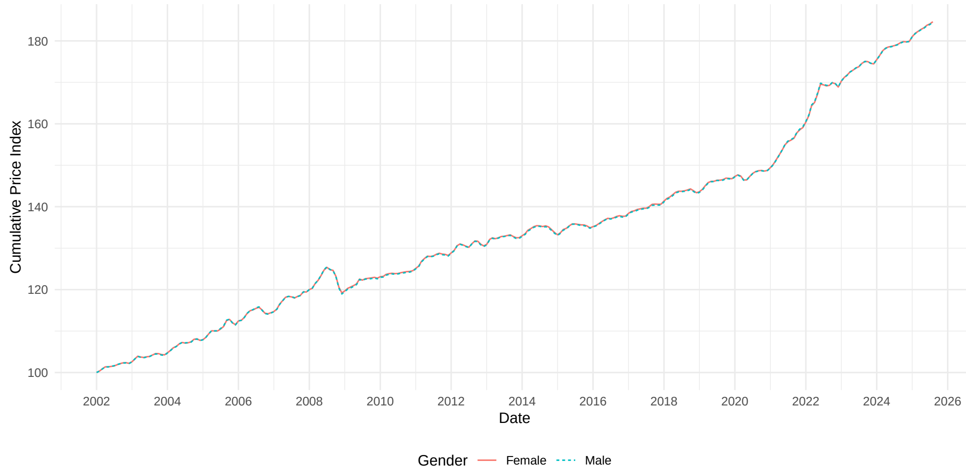
B. Race



Notes: This figure reports cumulative price indices from January 2002 to August 2025 for various household groups. Panel A considers age groups, above and below 65, by computing household age as the average age of all adult household members, rather than taking the age of the reference person alone as in the main text. Panel B considers heterogeneity by race, focusing on the subset of households where all adult household members are of the same race, rather than focusing on the race of the reference person alone as in the main text.

Figure A12 Long-Run Inflation Inequality by Gender

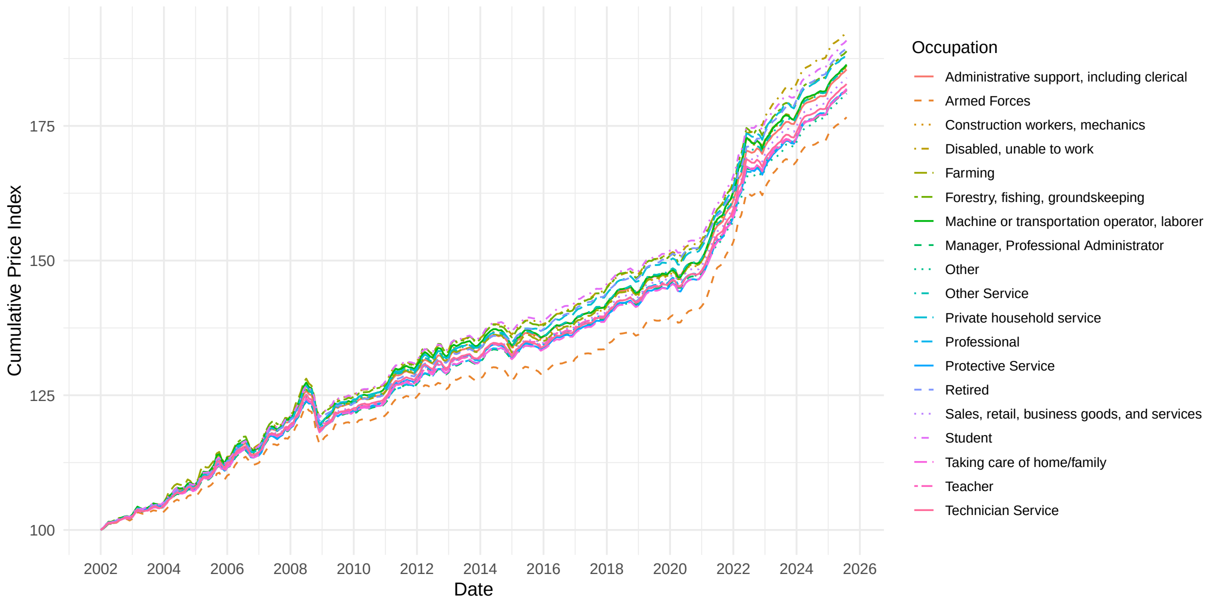
A. By Gender of Household Head



B. All Adult Household Members of the Same Gender

Notes: This figure reports cumulative price indices from January 2002 to August 2025 by gender. Panel A splits the data based on the gender of the reference person, or "household head". Panel B focuses on a sub-sample of households where all adult household members are of the same gender.

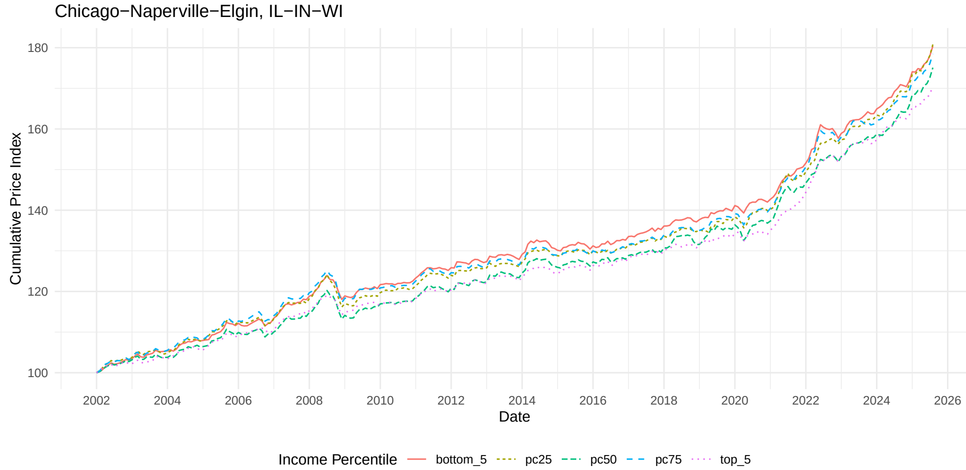
Figure A13 Long-Run Inflation Inequality across Occupations



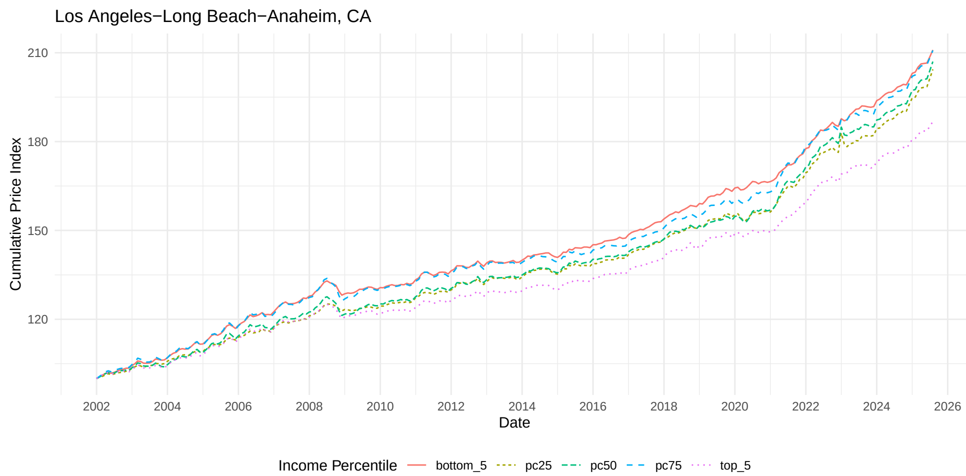
Notes: This figure reports cumulative price indices from January 2002 to August 2025 for various occupations.

Figure A14 Inflation Inequality within Selected Cities

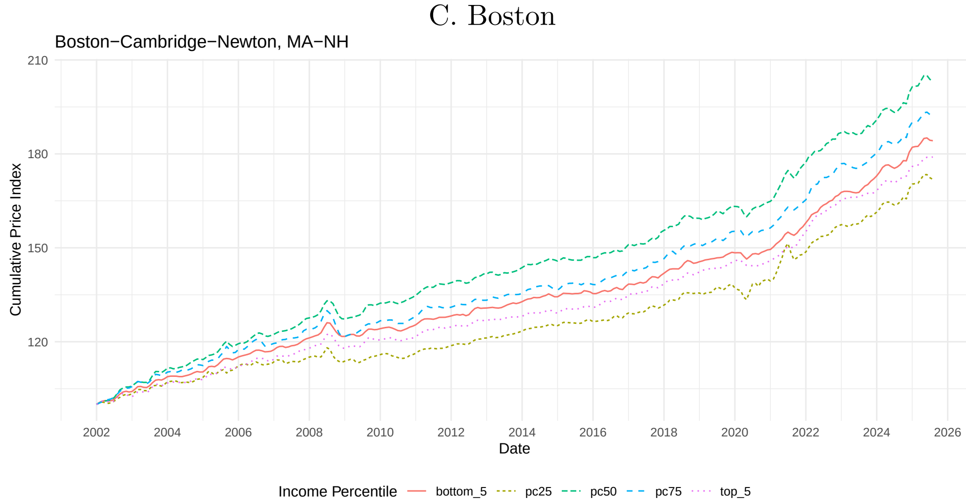
A. Chicago



B. Los Angeles



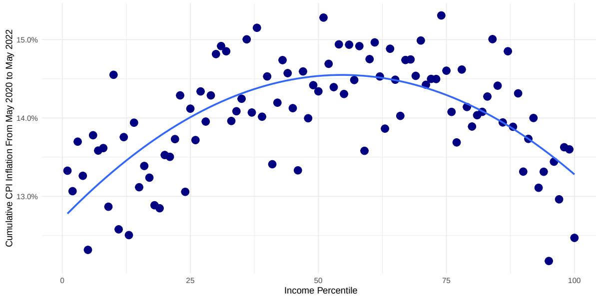
C. Boston



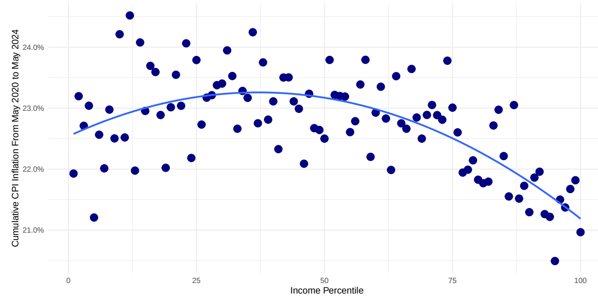
Notes: This figure reports inflation rates by income percentile for three cities from January 2002 to August 2025.

Figure A15 Short-Run Inflation Dynamics with Geographic Heterogeneity

Panel A: Income Percentiles

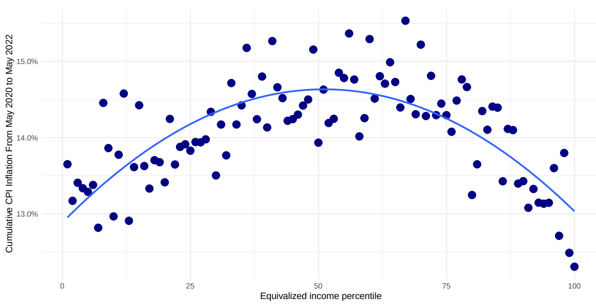


(i) May 2020-May 2022

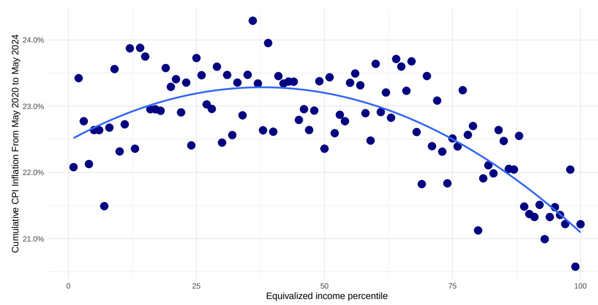


(ii) May 2020-May 2024

Panel B: Equivalized Income Percentiles



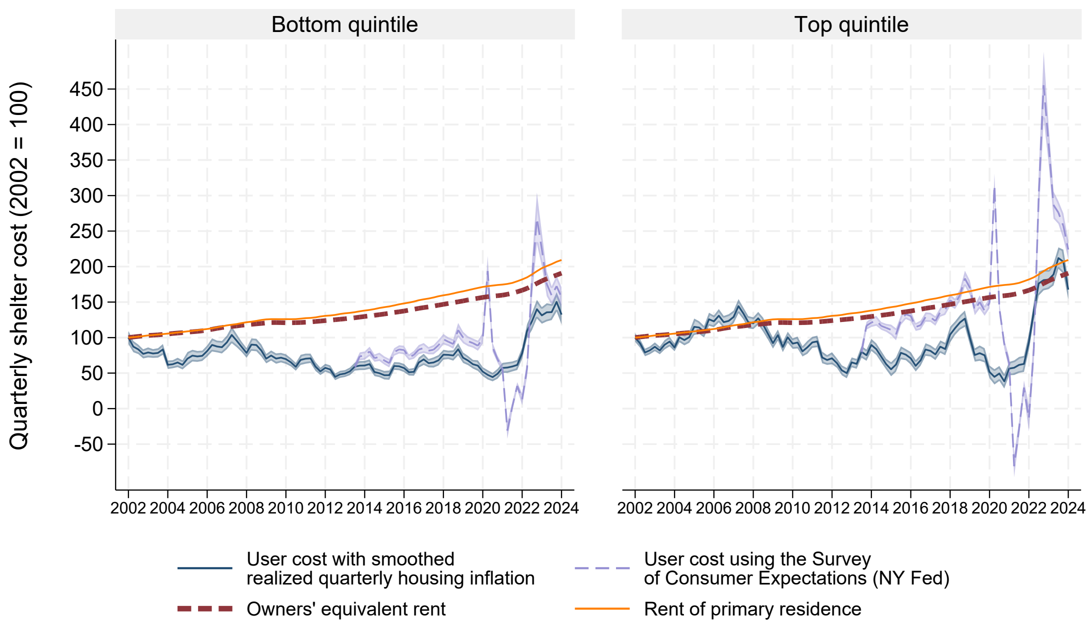
(i) May 2020-May 2022



(ii) May 2020-May 2024

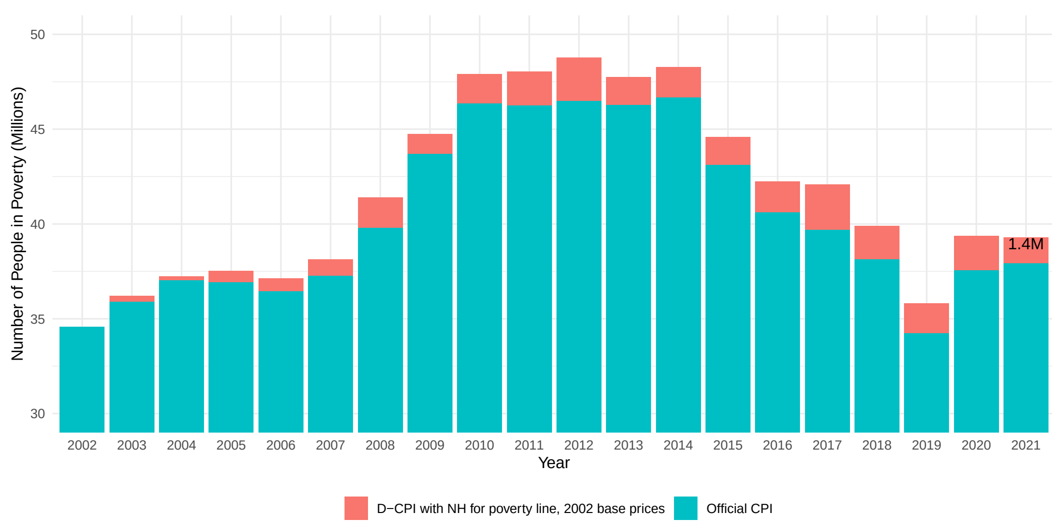
Notes: This figure reports cumulative inflation rates across equivalized income percentiles. Equivalized income are obtained by dividing household income by the square root of household size.

Figure A16 User Cost of Homeownership by Income Quintiles



Notes: This figure reports shelter costs for the bottom (left panel) and top (right panel) income quintiles. Each panel reports the evolution of rents of primary residence, owners' equivalent rent, and two user cost series using alternatively the average realizing house price growth over the period or housing inflation expectations measured in the New York Fed Survey of Consumer Finances. All series are normalized to 100 in the first period. Appendix D describes the data construction steps for the user cost series.

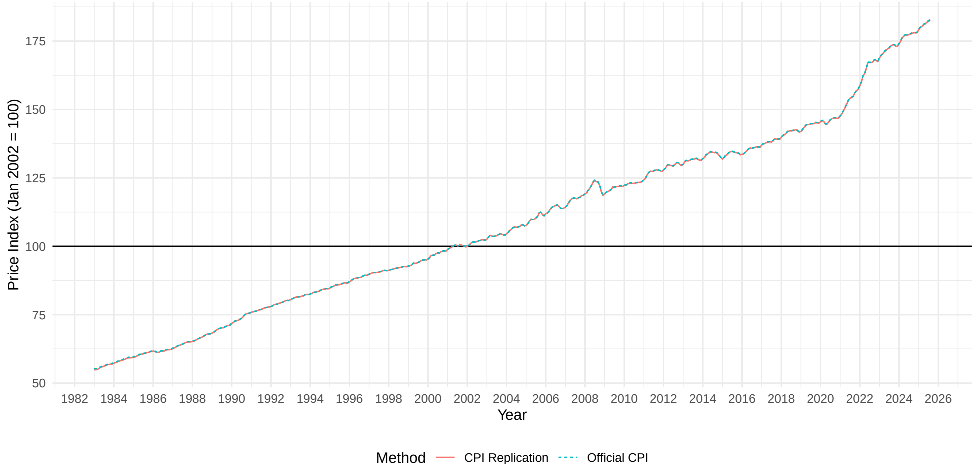
Figure A17 Number of People in Poverty with Non-homotheticity Correction



Notes: In this figure, the price index for households in poverty – using the D-CPI with the non-homotheticity correction setting 2002 prices as base – is used to index the poverty line over time and report the additional number of people who are under the poverty line (in red), compared to the official poverty line using CPI (in light green).

Figure A18 Validation Tests for Analysis with Fixed Expenditure Shares

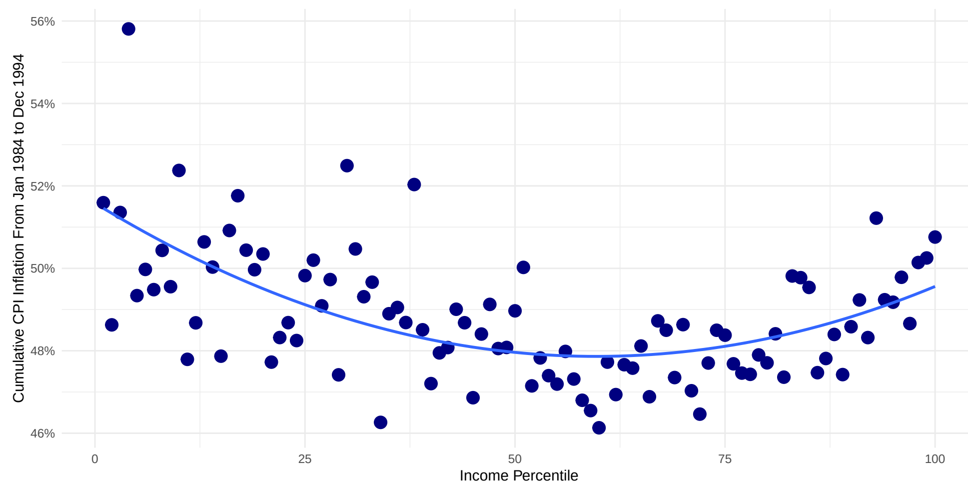
A. Comparison to Official CPI, using Fixed Expenditure Shares prior to 2002



B. Inflation Inequality between 2002 and 2025, with 2025 Sales Shares

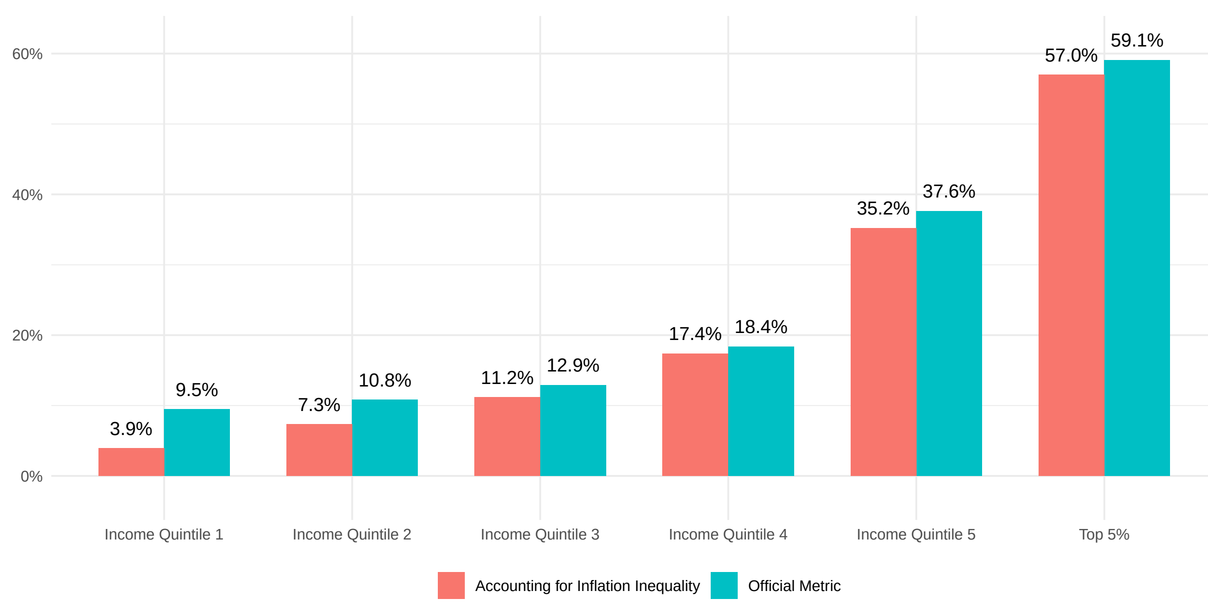
Notes: This figure reports two tests of the reliability of price indices built with fixed shares. Panel A compares the official CPI to my reconstructed CPI, using the official relative importance weights in all years prior; for year after 2002, the figure is identical to Figure 1. Panel B reports the cumulative inflation rates from 2002 to 2025 using the approach described in Section 4.3, i.e. fixing the allocation of sales across income groups within each item stratum to the allocation observed in August 2025. The gap between the top and bottom of the income distribution is around 13 percentage points, which is similar to the difference observed in the baseline analysis updating shares every year (see Figure 2, where the inflation difference is about 15 percentage points).

Figure A19 Inflation Inequality between 1984 and 1994



Notes: This figure reports cumulative D-CPIs across the income distribution from January 1984 to December 1994, the period studied by Garner et al. (1996) using confidential BLS data. Consistent with the results in Garner et al. (1996), this figure documents there was no meaningful inflation inequality during this period.

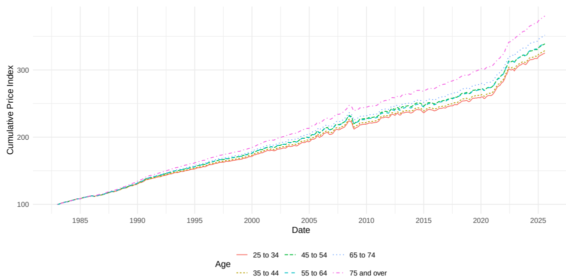
Figure A20 Implications for Household Real Income Growth, 1983 to 2002



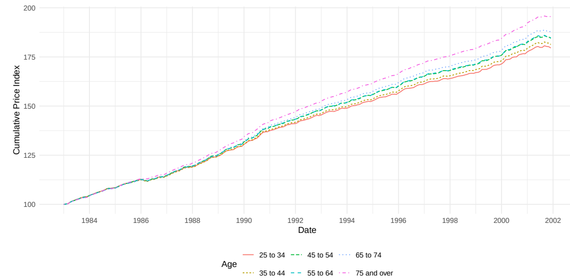
Notes: This figure reports cumulative real income growth from 1983 to 2002 by quintiles of the household income distribution, as well as for the top 5%. Two series are shown, with the official CPI and with the D-CPIs specific to each income group.

Figure A21 Inflation Inequality across Other Socio-demographic Groups from 1983 to 2025

A. Age

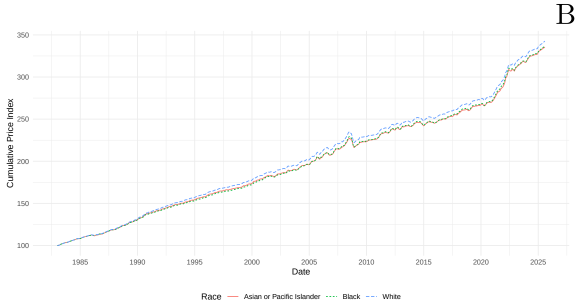


(i) 1983-2025

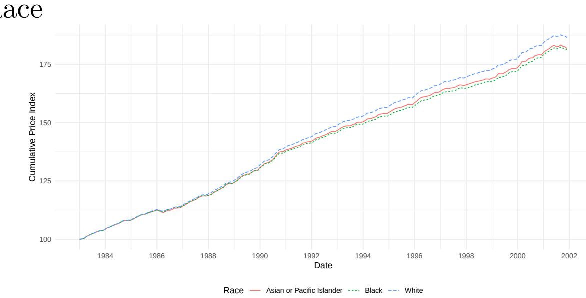


(ii) 1983-2001

B. Race

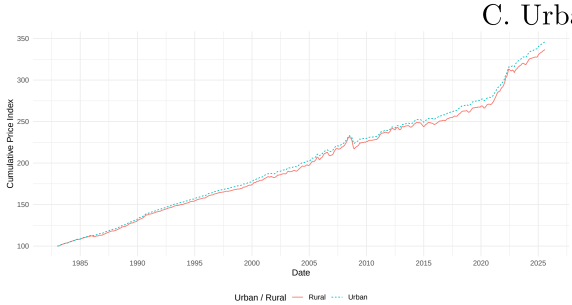


(i) 1983-2025

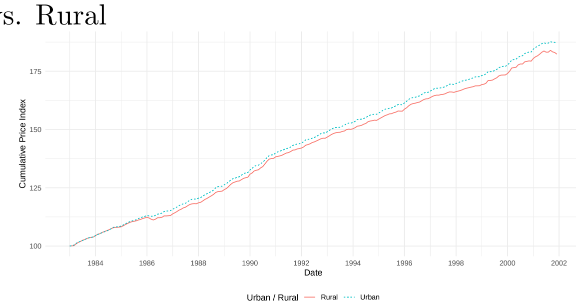


(ii) 1983-2001

C. Urban vs. Rural



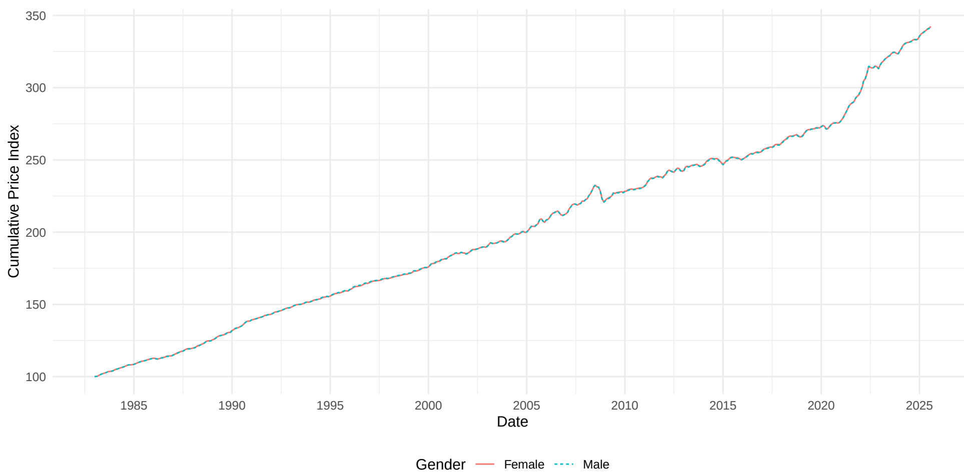
(i) 1983-2025



(ii) 1983-2001

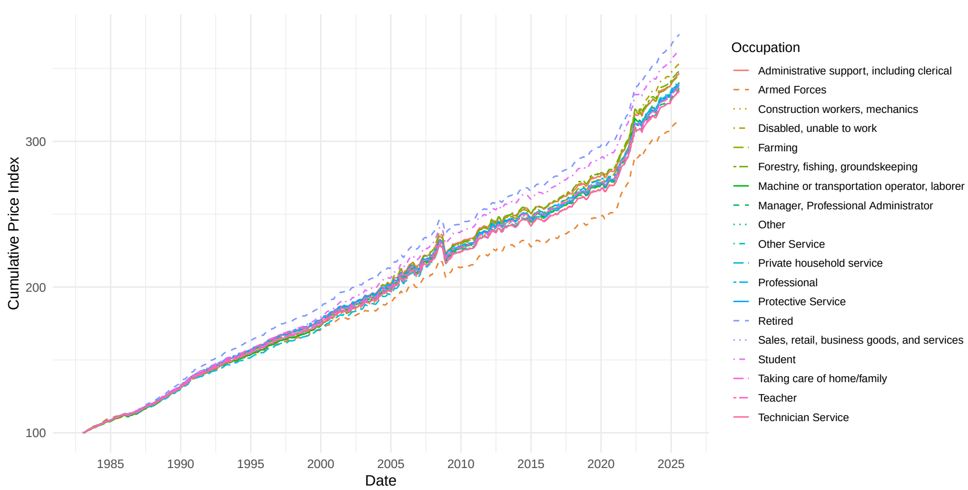
Notes: This figure reports cumulative price indices from January 1983 to August 2025, and the January 1983 to December 2001 sub-period, for various household groups, by age (panel A), race (panel B), and urban vs. rural households (panel C).

Figure A22 Long-Run Inflation Inequality by Gender



Notes: This figure reports cumulative price indices from January 1983 to August 2025 by gender. The figure splits the data based on the gender of the reference person, or "household head".

Figure A23 Long-Run Inflation Inequality across Occupations



Notes: This figure reports cumulative price indices from January 1983 to August 2025 for various occupations.

Table A1 Expenditure Shares by Income Quintile

Item Name	CPI Weight	Bottom 5%	1	2	3	4	5	Top 5%
Owners' equivalent rent of primary residence	22.78	16.19	18.41	19.94	21.42	22.71	24.22	24.97
Rent of primary residence	6.61	16.42	14.62	10.80	8.08	5.24	2.46	1.89
Gasoline (all types)	5.11	6.20	5.83	6.65	7.03	6.78	5.36	4.69
New vehicles	3.15	0.47	0.66	1.88	2.97	3.42	4.27	4.36
Electricity	2.89	3.53	3.70	3.46	3.06	2.69	2.08	2.02
Full service meals and snacks	2.72	1.90	1.90	2.18	2.50	2.90	3.12	3.26
Motor vehicle insurance	2.53	1.57	2.28	3.12	2.77	3.02	2.16	1.92
Limited service meals and snacks	2.30	2.78	2.33	2.20	2.43	2.52	2.09	1.86
Used cars and trucks	1.86	2.08	1.71	1.95	2.07	2.17	1.80	1.82
College tuition and fees	1.77	3.67	2.39	0.92	1.09	1.19	2.97	3.30
Physicians' services	1.62	1.24	1.54	1.85	1.77	1.72	1.42	1.31
Hospital services	1.60	1.44	1.65	1.95	1.89	1.82	1.47	1.34
Unsampled owners' equivalent rent of secondary residences	1.43	0.45	0.83	1.16	1.06	1.21	1.93	2.28
Cable and satellite television service	1.42	1.58	1.73	1.68	1.57	1.43	1.09	0.98
Wireless telephone services	1.40	1.20	1.18	1.37	1.43	1.40	1.06	0.95
Prescription drugs	1.33	1.20	1.64	1.84	1.55	1.34	1.00	0.94
Residential telephone services	0.96	1.17	1.36	1.20	1.04	0.89	0.71	0.68
Water and sewerage maintenance	0.93	1.03	1.10	1.14	1.06	1.03	0.84	0.77
Utility (piped) gas service	0.90	0.77	0.88	0.91	0.85	0.80	0.71	0.70
Airline fares	0.79	0.32	0.39	0.47	0.62	0.77	1.28	1.36
Day care and preschool	0.79	0.24	0.31	0.44	0.48	0.81	1.22	1.22
Dental services	0.78	0.69	0.59	0.84	0.85	0.82	0.74	0.79
Cigarettes	0.75	1.47	1.35	1.22	1.01	0.79	0.35	0.22
Pets and pet products	0.68	0.72	0.66	0.74	0.71	0.72	0.57	0.52
Health insurance	0.66	0.40	0.55	0.72	0.71	0.68	0.56	0.53
Admissions	0.64	0.44	0.32	0.36	0.47	0.59	0.89	0.97
Haircuts and other personal care services	0.63	0.45	0.48	0.53	0.57	0.61	0.71	0.72
Other miscellaneous foods	0.63	0.76	0.86	0.64	0.61	0.60	0.56	0.53
Motor vehicle repair	0.60	0.44	0.50	0.60	0.63	0.64	0.58	0.59
Other lodging away from home including hotels and motels	0.60	0.20	0.22	0.27	0.38	0.51	0.82	0.88

Women's suits and separates	0.59	0.54	0.54	0.50	0.49	0.52	0.62	0.61
Internet services and electronic information providers	0.57	0.50	0.46	0.54	0.61	0.61	0.48	0.41
Club membership for shopping clubs, fraternal, or other organizations, or participant sports fees	0.57	0.19	0.21	0.29	0.39	0.47	0.88	0.96
Motor vehicle maintenance and servicing	0.46	0.37	0.41	0.43	0.46	0.46	0.46	0.45
Pet services including veterinary	0.42	0.15	0.20	0.40	0.31	0.43	0.57	0.49
Women's underwear, nightwear, swimwear, and accessories	0.40	0.38	0.40	0.38	0.39	0.37	0.47	0.53
Nonfrozen noncarbonated juices and drinks	0.40	0.55	0.49	0.43	0.41	0.37	0.33	0.31
Elementary and high school tuition and fees	0.40	0.04	0.12	0.10	0.14	0.30	0.83	0.94
Alcoholic beverages away from home	0.38	0.35	0.24	0.30	0.37	0.40	0.46	0.49
Services by other medical professionals	0.38	0.23	0.29	0.36	0.36	0.42	0.38	0.36
Leased cars and trucks	0.37	0.21	0.16	0.18	0.25	0.32	0.48	0.57
Other food away from home	0.37	0.28	0.26	0.17	0.21	0.30	0.59	0.74
Tenants' and household insurance	0.36	0.35	0.35	0.35	0.35	0.36	0.35	0.36
Outdoor equipment and supplies	0.35	0.15	0.18	0.29	0.23	0.33	0.42	0.49
Household cleaning products	0.35	0.49	0.46	0.38	0.35	0.35	0.28	0.25
Hair, dental, shaving, and miscellaneous personal care products	0.34	0.29	0.33	0.32	0.30	0.31	0.32	0.31
Living room, kitchen, and dining room furniture	0.33	0.14	0.21	0.30	0.29	0.27	0.39	0.49
Women's footwear	0.33	0.28	0.34	0.33	0.32	0.29	0.29	0.28
State motor vehicle registration and license fees	0.32	0.64	0.45	0.40	0.36	0.32	0.25	0.23
Snacks	0.32	0.38	0.37	0.34	0.34	0.34	0.31	0.28
Unsampled recreation services	0.31	0.13	0.15	0.16	0.25	0.30	0.41	0.40
Nonprescription drugs	0.31	0.25	0.32	0.30	0.31	0.29	0.27	0.24
Toys	0.31	0.26	0.24	0.23	0.24	0.26	0.29	0.27

Legal services	0.30	0.14	0.20	0.35	0.25	0.28	0.36	0.45
Garbage and trash collection	0.30	0.29	0.32	0.31	0.32	0.30	0.27	0.25
Cosmetics, perfume, bath, nail preparations and implements	0.30	0.26	0.28	0.28	0.28	0.28	0.30	0.30
Milk	0.29	0.44	0.46	0.38	0.33	0.31	0.25	0.22
Frozen and freeze dried prepared foods	0.29	0.36	0.37	0.34	0.30	0.29	0.21	0.19
Breakfast cereal	0.29	0.39	0.39	0.36	0.28	0.28	0.24	0.21
Cheese and related products	0.28	0.37	0.34	0.29	0.30	0.30	0.27	0.26
Spices, seasonings, condiments, sauces	0.28	0.35	0.32	0.28	0.28	0.28	0.24	0.24
Miscellaneous household products	0.28	0.25	0.25	0.26	0.25	0.28	0.29	0.29
Chicken	0.28	0.37	0.41	0.32	0.30	0.26	0.22	0.21
Carbonated drinks	0.28	0.45	0.41	0.33	0.31	0.25	0.20	0.17
Tires	0.28	0.21	0.21	0.26	0.31	0.30	0.31	0.28
Beer, ale, and other malt beverages at home	0.27	0.42	0.29	0.26	0.30	0.29	0.24	0.19
Intracity transportation	0.27	0.31	0.36	0.29	0.22	0.22	0.30	0.34
Food at employee sites and schools	0.26	0.48	0.23	0.21	0.25	0.31	0.29	0.28
Other meats	0.26	0.33	0.36	0.30	0.29	0.28	0.23	0.22
Domestic services	0.25	0.11	0.17	0.13	0.13	0.13	0.44	0.52
Eyeglasses and eye care	0.25	0.18	0.21	0.25	0.24	0.25	0.24	0.22
Girls' apparel	0.24	0.26	0.22	0.27	0.25	0.25	0.26	0.24
Household paper products	0.24	0.31	0.33	0.27	0.27	0.23	0.20	0.18
Other fresh vegetables	0.24	0.28	0.28	0.26	0.23	0.24	0.23	0.22
Sports vehicles including bicycles	0.24	0.07	0.08	0.08	0.16	0.26	0.38	0.44
Laundry and dry cleaning services	0.24	0.29	0.35	0.26	0.20	0.18	0.25	0.31
Gardening and lawncare services	0.24	0.12	0.21	0.19	0.16	0.17	0.32	0.40
Other bakery products	0.23	0.32	0.28	0.25	0.24	0.23	0.20	0.19
Fees for lessons or instructions	0.23	0.06	0.07	0.06	0.12	0.19	0.41	0.46
Clocks, lamps, and decorator items	0.23	0.13	0.11	0.14	0.13	0.17	0.28	0.31
Other fresh fruits	0.23	0.24	0.25	0.24	0.21	0.22	0.24	0.23
Bedroom furniture	0.23	0.17	0.16	0.20	0.18	0.24	0.25	0.31
Jewelry	0.22	0.06	0.08	0.14	0.17	0.25	0.35	0.38

Bread	0.22	0.33	0.31	0.27	0.24	0.22	0.18	0.17
Wine at home	0.22	0.10	0.12	0.13	0.14	0.21	0.29	0.33
Computers, peripherals, and smart home assistants	0.22	0.20	0.15	0.13	0.14	0.18	0.21	0.21
Fuel oil	0.22	0.14	0.28	0.32	0.31	0.30	0.28	0.27
Uncooked ground beef	0.22	0.37	0.36	0.29	0.28	0.25	0.17	0.15
Men's shirts and sweaters	0.22	0.11	0.16	0.20	0.20	0.20	0.25	0.26
Educational books and supplies	0.22	0.76	0.43	0.17	0.17	0.19	0.25	0.26
Parking and other fees	0.22	0.16	0.13	0.14	0.16	0.21	0.31	0.32
Financial services	0.22	0.13	0.18	0.19	0.20	0.22	0.25	0.25
Men's footwear	0.21	0.35	0.28	0.24	0.25	0.16	0.19	0.22
Uncooked beef steaks	0.21	0.23	0.24	0.23	0.25	0.22	0.20	0.18
Sports equipment	0.20	0.12	0.09	0.18	0.13	0.19	0.20	0.21
Miscellaneous personal goods	0.20	0.14	0.17	0.16	0.18	0.18	0.21	0.19
Infants' and toddlers' apparel	0.19	0.23	0.23	0.23	0.21	0.19	0.16	0.17
Men's underwear, nightwear, swimwear and accessories	0.19	0.15	0.16	0.17	0.18	0.19	0.21	0.23
Boys' apparel	0.19	0.25	0.19	0.18	0.19	0.18	0.19	0.21
Cakes, cupcakes, and cookies	0.19	0.22	0.23	0.21	0.19	0.19	0.17	0.17
Other motor fuels	0.18	0.24	0.12	0.17	0.28	0.28	0.26	0.26
Candy and chewing gum	0.18	0.22	0.19	0.19	0.18	0.19	0.17	0.16
Other dairy and related products	0.18	0.22	0.21	0.19	0.17	0.18	0.17	0.16
Women's dresses	0.18	0.06	0.07	0.15	0.14	0.22	0.17	0.18
Tools, hardware and supplies	0.17	0.16	0.13	0.14	0.15	0.23	0.15	0.15
Fresh fish and seafood	0.16	0.18	0.21	0.18	0.16	0.15	0.18	0.20
Housing at school, excluding board	0.16	0.24	0.17	0.06	0.08	0.09	0.31	0.34
Funeral expenses	0.16	0.53	0.33	0.18	0.18	0.15	0.10	0.11
Boys' and girls' footwear	0.15	0.23	0.16	0.21	0.18	0.12	0.13	0.11
Major appliances	0.15	0.06	0.08	0.10	0.14	0.17	0.16	0.18
Men's pants and shorts	0.15	0.21	0.17	0.13	0.13	0.14	0.15	0.13
Processed fish and seafood	0.15	0.20	0.21	0.17	0.16	0.15	0.14	0.12
Canned fruits and vegetables	0.15	0.21	0.19	0.17	0.15	0.15	0.12	0.11
Other intercity transportation	0.15	0.04	0.06	0.07	0.07	0.12	0.25	0.25
Bacon, breakfast sausage, and related products	0.14	0.22	0.23	0.20	0.18	0.15	0.11	0.09
Postage	0.14	0.14	0.20	0.14	0.15	0.15	0.13	0.14
Other linens	0.14	0.12	0.12	0.09	0.13	0.13	0.15	0.15
Unsampled items	0.14	0.10	0.10	0.07	0.28	0.19	0.09	0.15

Unsampled tools, hardware, outdoor equipment and supplies	0.14	0.09	0.11	0.11	0.13	0.13	0.15	0.12
Vehicle accessories other than tires	0.14	0.15	0.15	0.19	0.19	0.14	0.10	0.09
Nursing homes and adult day services	0.14	0.05	0.13	0.16	0.15	0.15	0.13	0.16
Ice cream and related products	0.13	0.21	0.17	0.15	0.14	0.14	0.13	0.11
Newspapers and magazines	0.13	0.11	0.13	0.14	0.13	0.12	0.13	0.14
Coffee	0.13	0.16	0.18	0.16	0.14	0.15	0.13	0.11
Rice, pasta, cornmeal	0.13	0.20	0.17	0.15	0.13	0.13	0.11	0.11
Men's suits, sport coats, and outerwear	0.12	0.10	0.11	0.08	0.10	0.11	0.15	0.19
Televisions	0.12	0.07	0.06	0.07	0.08	0.08	0.08	0.10
Other furniture	0.12	0.07	0.08	0.07	0.08	0.10	0.15	0.16
Other fats and oils including peanut butter	0.12	0.18	0.18	0.15	0.13	0.11	0.10	0.09
Other appliances	0.11	0.09	0.09	0.09	0.13	0.11	0.09	0.11
Citrus fruits	0.11	0.12	0.13	0.12	0.11	0.10	0.09	0.09
Eggs	0.11	0.18	0.19	0.16	0.14	0.12	0.09	0.09
Fresh biscuits, rolls, muffins	0.11	0.14	0.12	0.13	0.11	0.12	0.11	0.10
Unsampled video and audio	0.11	0.08	0.09	0.15	0.12	0.10	0.08	0.10
Unsampled tuition, other school fees, and childcare	0.11	0.10	0.07	0.07	0.07	0.10	0.16	0.15
Women's outerwear	0.11	0.14	0.12	0.11	0.10	0.09	0.13	0.14
Propane, kerosene, and firewood	0.11	0.17	0.17	0.11	0.13	0.12	0.10	0.10
Video discs and other media, including rental of video	0.10	0.11	0.09	0.10	0.12	0.11	0.09	0.09
Indoor plants and flowers	0.10	0.05	0.08	0.06	0.07	0.09	0.13	0.13
Recreational books	0.10	0.06	0.06	0.07	0.07	0.09	0.11	0.12
Soups	0.09	0.14	0.12	0.10	0.09	0.09	0.07	0.07
Other beverage materials including tea	0.09	0.12	0.11	0.10	0.10	0.09	0.08	0.07
Watches	0.09	0.04	0.05	0.05	0.24	0.04	0.06	0.05
Moving, storage, freight expense	0.09	0.09	0.09	0.07	0.07	0.10	0.09	0.12
Frozen fruits and vegetables	0.09	0.12	0.11	0.10	0.10	0.09	0.08	0.07
Other pork including roasts, steaks, and ribs	0.09	0.12	0.11	0.11	0.11	0.09	0.08	0.07

Apples	0.09	0.10	0.10	0.09	0.08	0.09	0.08	0.08
Care of invalids and elderly at home	0.08	0.23	0.15	0.11	0.06	0.07	0.07	0.09
Uncooked beef roasts	0.08	0.09	0.10	0.10	0.10	0.09	0.09	0.08
Tomatoes	0.08	0.10	0.10	0.10	0.09	0.07	0.07	0.07
Food from vending machines and mobile vendors	0.08	0.16	0.10	0.11	0.10	0.09	0.06	0.04
Nonelectric cookware and tableware	0.08	0.09	0.10	0.06	0.06	0.07	0.09	0.08
Repair of household items	0.08	0.04	0.04	0.06	0.07	0.09	0.10	0.13
Ham	0.08	0.11	0.10	0.11	0.09	0.07	0.06	0.05
Bananas	0.08	0.10	0.10	0.09	0.07	0.07	0.06	0.06
Telephone hardware, calculators, and other consumer information items	0.08	0.06	0.06	0.07	0.08	0.08	0.06	0.05
Potatoes	0.08	0.10	0.10	0.09	0.08	0.08	0.06	0.06
Medical equipment and supplies	0.08	0.07	0.09	0.10	0.07	0.07	0.06	0.06
Other uncooked poultry including turkey	0.07	0.09	0.09	0.09	0.08	0.08	0.07	0.07
Unsampled household operations	0.07	0.05	0.06	0.06	0.06	0.07	0.09	0.10
Window coverings	0.07	0.01	0.03	0.03	0.06	0.05	0.11	0.12
Butter and margarine	0.07	0.14	0.11	0.09	0.09	0.08	0.07	0.06
Baby food	0.07	0.09	0.10	0.09	0.09	0.07	0.05	0.08
Distilled spirits at home	0.07	0.07	0.06	0.05	0.07	0.07	0.07	0.07
Unsampled new and used motor vehicles	0.07	0.03	0.01	0.03	0.05	0.15	0.06	0.07
Audio equipment	0.07	0.07	0.04	0.03	0.06	0.05	0.07	0.09
Car and truck rental	0.07	0.03	0.03	0.03	0.05	0.06	0.09	0.11
Lettuce	0.07	0.08	0.08	0.08	0.07	0.07	0.06	0.06
Salad dressing	0.06	0.08	0.08	0.07	0.07	0.07	0.06	0.06
Other sweets	0.06	0.08	0.08	0.07	0.06	0.06	0.05	0.05
Pork chops	0.06	0.10	0.11	0.08	0.07	0.06	0.04	0.03
Technical and business school tuition and fees	0.06	0.00	0.03	0.04	0.04	0.04	0.11	0.13
Sewing machines, fabric and supplies	0.06	0.04	0.04	0.06	0.06	0.07	0.06	0.06
Motor vehicle body work	0.06	0.05	0.04	0.04	0.07	0.05	0.07	0.07
Photographers and photo processing	0.06	0.03	0.03	0.02	0.05	0.08	0.07	0.10

Other processed fruits and vegetables including dried	0.05	0.08	0.08	0.06	0.06	0.05	0.04	0.04
Tobacco products other than cigarettes	0.05	0.09	0.08	0.06	0.06	0.06	0.05	0.03
Sugar and sugar substitutes	0.05	0.10	0.09	0.07	0.07	0.05	0.04	0.03
Uncooked other beef and veal	0.05	0.07	0.08	0.07	0.05	0.06	0.05	0.05
Flour and prepared flour mixes	0.05	0.07	0.06	0.05	0.06	0.05	0.04	0.03
Photographic equipment and supplies	0.05	0.08	0.03	0.03	0.03	0.04	0.06	0.06
Dishes and flatware	0.04	0.02	0.03	0.03	0.03	0.03	0.05	0.05
Recorded music and music subscriptions	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04
Computer software and accessories	0.04	0.04	0.03	0.03	0.03	0.04	0.04	0.04
Music instruments and accessories	0.04	0.09	0.03	0.04	0.03	0.03	0.05	0.03
Floor coverings	0.04	0.01	0.01	0.01	0.03	0.03	0.06	0.06
Unsampled service policies	0.04	0.01	0.01	0.03	0.04	0.04	0.04	0.02
Apparel services other than laundry and dry cleaning	0.03	0.02	0.02	0.02	0.02	0.03	0.05	0.05
Other video equipment	0.02	0.02	0.01	0.01	0.02	0.02	0.02	0.02
Unsampled motor vehicle fees	0.02	0.01	0.00	0.01	0.00	0.03	0.04	0.04
Unsampled recreation commodities	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.01
Unsampled women's apparel	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.02
Frozen noncarbonated juices and drinks	0.01	0.02	0.02	0.02	0.01	0.02	0.01	0.01
Unsampled information and information processing	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Delivery services	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Unsampled sporting goods	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01
Unsampled men's apparel	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01
Unsampled personal care products	0.01	0.02	0.01	0.01	0.01	0.00	0.00	0.00
Unsampled furniture	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.00
Unsampled tobacco and smoking products	0.01	0.03	0.01	0.01	0.01	0.01	0.00	0.00
Unsampled recreational reading materials	0.00	0.03	0.01	0.00	0.01	0.00	0.00	0.00

Unsampled public transportation	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Unsampled appliances	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Unsampled photography	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A2 Comparison of Expenditure Shares in CEX and CPI, December 2013

Item Name	CEX Weight*	CPI Weight
Housing	38.95	41.21
Transportation	19.99	16.67
Food and beverages	16.14	15.18
Medical care	7.94	7.21
Education and communication	2.61	6.78
Recreation	6.24	5.95
Apparel	4.02	3.62
Other goods and services	4.10	3.38

Notes: This table compares expenditure shares in the CEX micro data to the CPI expenditure weights, at the level of eight broad categories. Even at this level of aggregation, there is not a 1:1 mapping between CEX categories and CPI categories. For instance "Computer information services" is classified as "Housing" in the CEX data but gets mapped to "Education and communication" in the CPI categories. We map the following CEX categories to "Other Goods and Services": Miscellaneous, Personal care products and services, Tobacco products and services. We also map "Entertainment" and "Reading" to "Recreation".

Table A3 Item Decomposition of the Cumulative Inflation Difference Across Age Groups, Above vs. Below 65, Jan. 2002 to Dec. 2019

Item Name	Share of Inflation Inequality	CPI Weight	ΔExpenditure Shares, >65 - <65 (pp)	Annual Inflation
Vehicles (New vehicles + Used cars and trucks + Sports vehicles including bicycles + Leased cars and trucks)	24.91 %	8.23 %	-2.15	-0.25
Hospital services + Prescription drugs	19.08 %	3.22 %	2.24	4.44
Telephone hardware, calculators, and other consumer information items + Wireless telephone services	18.34 %	1.72 %	-0.66	-5.16
Gasoline	-16.91 %	4.47 %	-1.06	4.9
Rent (Rent of primary residence + Owners' equivalent rent of primary residence)	11.28 %	29.44 %	3.56	2.63

Notes: This table reports the within-between decomposition of the log difference in cumulative inflation rates between households with a household head above or below 65, using equation (5), for the five product categories with the largest contributions.