Real-Time Estimates of Differences in Real Expenditure Growth and Inflation across Households

Masataka Mori and Juan M. Sánchez

Abstract

This article presents a framework to monitor differences in real expenditure growth and inflation in real time, focusing on variations across the expenditure distribution. High-frequency tracking of heterogeneity in real expenditure growth and inflation holds particular value for policymakers. The newly constructed time series reveals three key findings. First, households with lower expenditure levels have faced higher inflation since 2000 than those with higher expenditure levels, with significant disparities in the range of 0.57 and 1.23 percentage-point differences between 2005–2008 and 2011, respectively. Second, volatility in real expenditure growth is higher for lower-expenditure households than for higher-expenditure ones. Third, there was significant heterogeneity in the recovery of real expenditure in the two years following the outbreak of COVID-19.

JEL codes: D12, D30, E21, E31

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1. INTRODUCTION

Tracking real-time differences in real expenditure growth and inflation across households at a high frequency is valuable for understanding current economic situations and informing the policymaking process. The Bureau of Economic Analysis (BEA) releases the personal consumption expenditures (PCE) price index as a monthly measure of inflation and consumer spending on goods and services by U.S. households. However, these published figures lack details about which groups of households experience different rates of real expenditure growth.

This article presents a framework for estimating real expenditure growth and inflation across households along the expenditure distribution. The idea behind this methodology is to use an estimate of the by-category expenditure share for each household group (split by the level of expenditures). With the shares, the framework estimates the total expenditure of each household group every month at the PCE release, which provides total expenditure by category every month. Thus, this approach relies on two key facts: (i) Households at different

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expenditure levels buy distinct baskets of goods and services, and (ii) these baskets remain relatively stable over time.

Using the Consumer Expenditure Survey (CE), Garner et al. (2024) divide households into five expenditure-based quintiles and identify their spending shares across 16 categories that align with the PCE classification. Expenditures and income are highly correlated, suggesting that fluctuations in consumption by expenditure quintiles likely provide a reliable approximation for consumption patterns by income quintiles, as argued in Appendix 1. Estimating each quintile's share within PCE categories enables the computation of cross-household differences in expenditure growth based on PCE data.

A key challenge persists: The PCE shares in Garner et al. (2024) update even less frequently than the CE data. To bridge this gap, we develop a forecasting model that incorporates the latest expenditure data from the CE to predict PCE shares. For example, Garner et al. (2024) provide PCE share data through 2023, while the most recent CE microdata (PUMD) cover the first quarter of 2024, as of November 2025. Using the most recent CE data allows us to project PCE shares until 2024. After 2024, we assume that the PCE shares remain constant.

The analysis reveals three key findings. First, since 2000, households with lower expenditure levels have faced higher accumulated inflation than those with higher expenditure levels, though inflation disparities remain modest overall. Exceptions appeared during 2005–2008 and in 2011, when inflation was notably higher for lower-expenditure households. Second, real expenditure growth patterns generally align across all expenditure levels, yet lower-expenditure households experience more pronounced fluctuations. Therefore, having these five groups of households is enough to capture significant differences in real expenditure dynamics. Third, there was a significant difference in the recovery of real expenditures after the outbreak of COVID-19. In the early recovery years, households with higher expenditure levels experienced much faster real expenditure growth.

Several economic studies use the CE to explore household spending behavior. The CE provides household-level data on goods and services purchased, making it one of the most comprehensive tools for analyzing consumption. However, there is a significant lag in data release, limiting its usefulness for policymakers who need timely insights for decisionmaking.

The CE has been used to examine the relationship between consumption inequality and income inequality by numerous studies, including works by Krueger and Perri (2006), Aguiar and Bils (2015), and Meyer and Sullivan (2023). These studies have primarily focused on consumption levels per capita as an indicator of inequality, revealing how household spending can mirror disparities in income. However, the primary objective in this article is to track consumption growth to understand fluctuations in economic activity across different household groups.

The pivotal paper in real-time inequality is Blanchet, Saez, and Zucman (2022), which constructs monthly distributions of national income, wealth, and labor income for the United States. Chylak, Feler, and Hoke (2024) also present real-time data on spending patterns across groups of households (sorted by income). The analysis shows that in the post-pandemic period, retail demand growth has been primarily driven by middle- and high-income households, whereas spending among low-income households has remained stable.

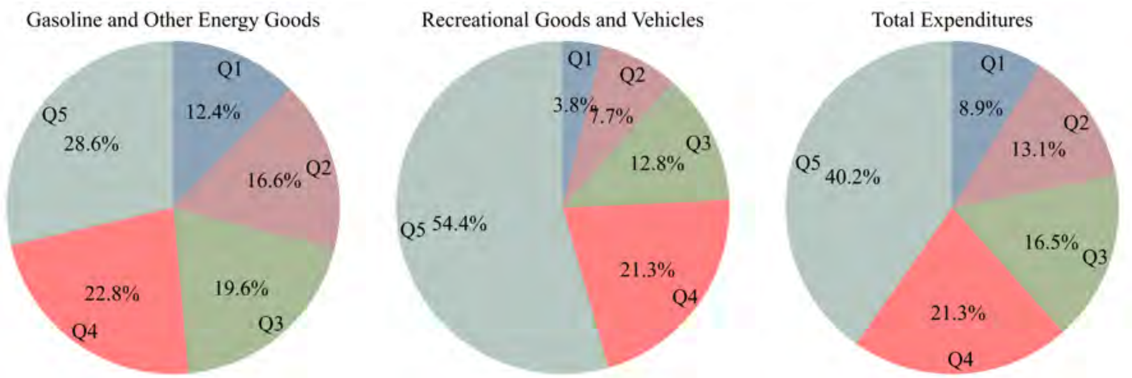
Coibion et al. (2017) investigate how monetary policy shocks influence consumption distribution, highlighting that contractionary monetary policy tends to increase inequality. Our findings contribute to this literature by examining consumption growth disparities in response to different economic environments.

A related literature studies inequality in inflation, including the work of Jaimovich, Rebelo, and Wong (2019), Kaplan and Schulhofer-Wohl (2017), Argente and Lee (2021), Jaravel (2021), and Argente, Hsieh, and Lee (2023). These studies explore how inflation affects different households based on their consumption patterns and economic characteristics, revealing disparities in the cost of living across the expenditure distribution.

Our findings on the evolution of consumption also contribute to the expanding literature in macroeconomics that employs heterogeneous agent models to address policy-relevant questions (Krueger, Mitman, and Perri, 2016; Kaplan, Moll, and Violante, 2018; Mustre-del-Río et al., 2024). These models emphasize the heterogeneity among households in understanding aggregate economic outcomes and have proven valuable in exploring monetary and fiscal policy effects, wealth inequality, consumer credit, and consumption responses to shocks.

The remainder of the article proceeds as follows. Section 2 outlines the methodology for constructing nominal expenditure growth, inflation, and real (inflation-adjusted) expenditure growth by groups of households, aligning with the BEA's methodology. Section 3 presents a forecasting framework for tracking cross-household differences in real expenditure growth and inflation in recent periods. Section 4 highlights our main findings, and Section 5 provides an example of the analysis that can be provided at a monthly frequency with this framework. Section 6 concludes the analysis.

Figure 1
Expenditure Shares by Expenditure Quintiles: Average of 2000–2023



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

2. METHODOLOGY

2.1 Expenditure Growth and Spending Shares

In an ideal setting, with price data $P_{t,n}$ for year t and category n, and consumption (purchased quantities) data $C_{t,n}$ for year t and category n, the nominal expenditure growth (NEG) for quintile i in year t would be calculated as

$$NEG_t^i = \frac{\sum_{n=1}^{N} P_{t,n}\, C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n}\, C_{t-1,n}^i} - 1.$$

This formula provides the growth in nominal expenditures by comparing total expenditures across all goods between two consecutive years.

While data on purchased quantities by quintile are unavailable, the PCE provides total nominal expenditure data, $P_{t,n}C_{t,n}$, by category at monthly frequency. We use the PCE shares from Garner et al. (2024) to allocate total nominal expenditures across quintiles of spending levels. In particular, Garner et al. (2024) compute the spending shares across 16 categories that align with PCE classifications using the microdata of the CE to describe the distribution of the PCE across U.S. households.[1] The key contribution is their matching method: In addition to matching comparable categories across statistical series, the authors adjust less-comparable CE categories of expenditures so that they better match PCE definitions, deleting expenditure items that are out of scope for the PCE and imputing expenditures for items that are out of scope for the CE.

Once a set of comparable and augmented CE data is collected, the authors rank households based on their levels of total expenditures per equivalent adult, assign households into five groups (quintiles) with equal population size, and compute expenditure shares by household groups for different goods and services in categories consistent with the PCE. They calculate expenditure levels per equivalent adult by dividing total expenditure levels by the square root of the number of family members.

Figure 1 shows the distribution of expenditures across expenditure quintiles for three categories. The three pie charts display the average expenditure shares from 2000 to 2023, derived from Garner et al. (2024). Some categories have more even expenditure distribution than other categories. For example, the average expenditure shares of the first and fifth quintiles are 12.4 percent and 28.6 percent in *Gasoline and Other Energy Goods*, while the expenditure shares of the first and fifth quintiles are 3.8 percent and 54.4 percent for *Recreational Goods and Vehicles*, respectively. These differences are key for our methodology. Aggregating the 16 categories that align with the PCE classification for each quintile provides the distribution of total expenditure across expenditure quintiles.

The combination of these two datasets provides a natural measure of nominal expenditure growth for year t and quintile i:

$$\tilde{NEG}_t^i = \frac{\sum_{n=1}^{N} (P_{t,n}C_{t,n}) \cdot s_{t,n}^i}{\sum_{n=1}^{N} (P_{t-1,n}C_{t-1,n}) \cdot s_{t-1,n}^i} - 1. \quad (1)$$

1. See Figure 5 for the time series of expenditure shares in 2004–2022 by category. The evolution of expenditure shares reveals varying degrees of fluctuation among categories.

This approach captures the differences in nominal expenditure growth across households with different expenditure levels. However, it remains unclear how much of this growth resulted from increased real expenditure growth versus inflation. It would be ideal to examine real expenditure growth after removing the effects of price changes and capturing changes in the quantity of consumption.

A traditional approach to defining real expenditure growth involves summing expenditures across disaggregated categories with prices fixed at a base year. Thus, real expenditure growth for each quintile i can be computed as

$$REG_t^{i,FW} = \frac{\sum_{n=1}^{N} P_{b,n} C_{t,n}^i}{\sum_{n=1}^{N} P_{b,n} C_{t-1,n}^i} - 1,$$

where $P_{b,n}$ is the price data in the base year b for category n, and $C_{t,n}^i$ represents the level of real expenditure data in year t for category n. The resulting series is interpreted as the value of year t's output had all prices remained at the level of the base year. This is often referred to as a "fixed-weight" measure of real expenditure in levels. While the fixed-weight methodology offers simplicity and ease of interpretation, it also has several drawbacks. Most notably, the growth rate of a fixed-weight measure of real expenditures depends on the choice of base year due to the substitution bias associated with fixed-weight indices.[2]

To address these issues, the BEA introduced Fisher's chain index formula in 1996, which calculates the gross growth rate of real aggregate expenditure at time t as the geometric average of the gross growth rates of two fixed-weight indices: the Paasche index, which uses year t prices as weights, and the Laspeyres index, which uses year $t-1$ prices as weights.

Let price indices $P_{t,n}$ and quantities of consumption $C_{t,n}$ be given for each year and category. The Paasche index for each quintile and year is given as

$$PI_t^i = \frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t,n} \cdot C_{t-1,n}^i},$$

and the Laspeyres index for each quintile and year is given as

$$LI_t^i = \frac{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t-1,n}^i}.$$

Fisher's chain index formula then provides the period-over-period growth rate as the geometric mean of the Paasche and Laspeyres indices:

$$REG_t^i = \sqrt{PI_t^i \cdot LI_t^i} - 1. \tag{2}$$

The great advantage of this formula is that the growth rate does not depend on the choice of the base year, as it incorporates weights only from two adjacent periods. Unless there is a sudden economic shock, it is unlikely that households' consumption patterns change drastically between two adjacent periods. Hence, this approach helps reduce the extent of substitution bias.

This approach also allows the estimation of inflation heterogeneity attributed to the differences in consumption baskets across household groups. The period-over-period inflation is similarly calculated using the Fisher chain index formula:

$$\pi_t^i = \sqrt{\frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t,n}^i} \cdot \frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t-1,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t-1,n}^i}} - 1. \tag{3}$$

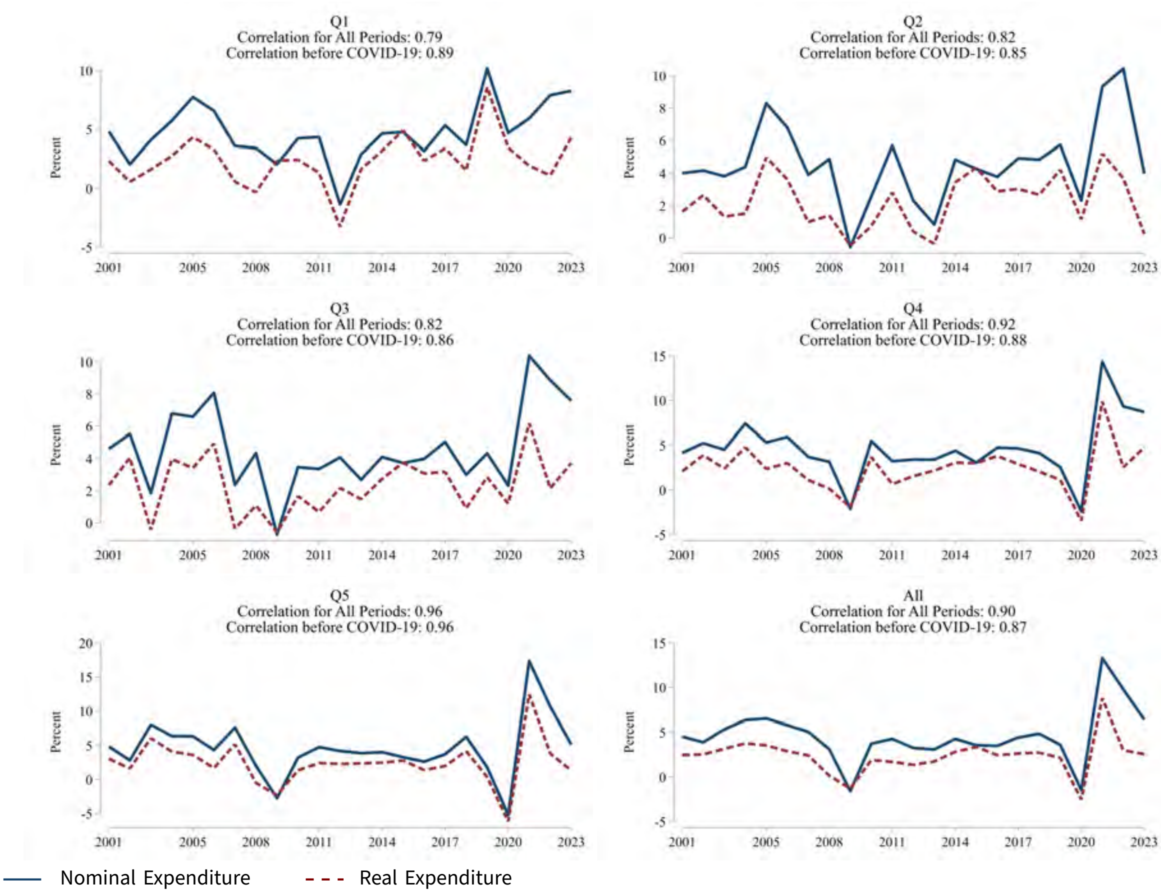
Additionally, the product of real expenditure growth and inflation equals nominal expenditure growth:

$$\begin{aligned}\left(1 + REG_t^i\right) \cdot \left(1 + \pi_t^i\right) &= \sqrt{\frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t,n} \cdot C_{t-1,n}^i} \cdot \frac{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t-1,n}^i}} \cdot \sqrt{\frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t,n}^i} \cdot \frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t-1,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t-1,n}^i}} \\ &= \frac{\sum_{n=1}^{N} P_{t,n} \cdot C_{t,n}^i}{\sum_{n=1}^{N} P_{t-1,n} \cdot C_{t-1,n}^i} = 1 + NEG_t^i. \end{aligned} \tag{4}$$

2. Whelan (2000) extensively discusses the motivation behind the switch to chain aggregation and the key implications of Fisher's chain index formula.

Figure 2

Nominal vs. Real: Percent Change in Annual Expenditures in 2001–2023



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

Combining the expenditure data by category from the PCE with the expenditure shares for each category for each household group from Garner et al. (2024), we can estimate the real expenditure growth and inflation rate for each household group:

(5)
$$R\tilde{E}G_t^i = \sqrt{\frac{\sum_{n=1}^{N}(P_{t,n}C_{t,n}) \cdot s_{t,n}^i}{\sum_{n=1}^{N}(P_{t,n}C_{t-1,n}) \cdot s_{t-1,n}^i} \cdot \frac{\sum_{n=1}^{N}(P_{t-1,n}C_{t,n}) \cdot s_{t,n}^i}{\sum_{n=1}^{N}(P_{t-1,n}C_{t-1,n}) \cdot s_{t-1,n}^i}} - 1,$$

and

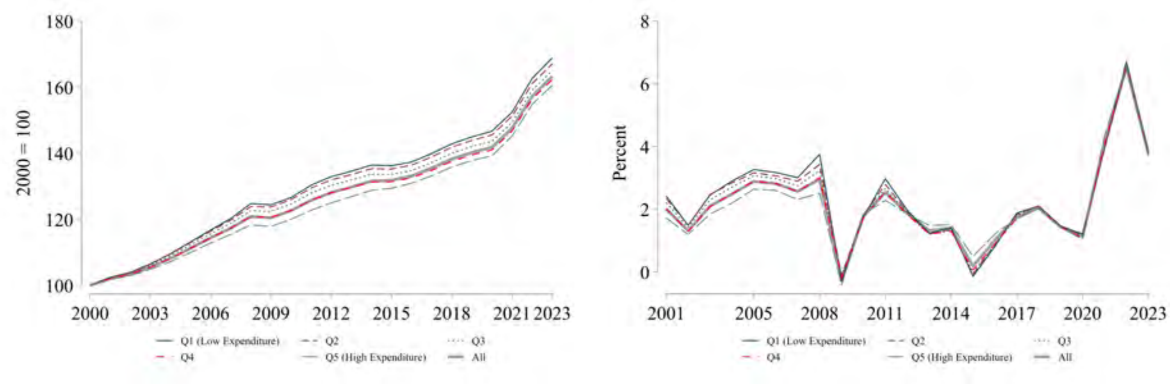
(6)
$$\tilde{\pi}_t^i = \sqrt{\frac{\sum_{n=1}^{N}(P_{t,n}C_{t,n}) \cdot s_{t,n}^i}{\sum_{n=1}^{N}(P_{t-1,n}C_{t,n}) \cdot s_{t,n}^i} \cdot \frac{\sum_{n=1}^{N}(P_{t,n}C_{t-1,n}) \cdot s_{t-1,n}^i}{\sum_{n=1}^{N}(P_{t-1,n}C_{t-1,n}) \cdot s_{t-1,n}^i}} - 1.$$

Figure 2 compares the nominal and real expenditure growth in annual expenditures by expenditure quintile from 2001 to 2023. These two time series show a high correlation for total expenditures and all expenditure quintiles. Nominal expenditure growth generally exceeds real expenditure growth in most years, suggesting positive inflation in all expenditure quintiles, as indicated by equation (4).

Figure 3 shows the price index and inflation rate over time by expenditure quintile. Panel (a) displays time series of the price index relative to the 2000 price level, with the 2000 price set to 100. The graph suggests that households with low expenditures have faced greater increases in the cost of living over the past two decades than those with higher expenditures. Panel (b) indicates that households across all expenditure quintiles experienced positive inflation over time except for notable declines in 2009 and 2015. This panel also suggests that

Figure 3
Inflation by Expenditure Quintile

(a) Price index **(b) Inflation rate**



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

households in different expenditure quintiles face uneven growth in the cost of living. Section 4.1 highlights more details on this comparison.

Notably, while low-expenditure households have generally experienced larger price increases over the long term, middle- or high-expenditure households have faced the worst inflation in specific years, such as 2013 to 2016. Additionally, this view reinforces the observation that inflation dispersion across households with different expenditure levels attributed to the differences in consumption baskets has generally been small. Most households experience broadly similar inflation most of the time, with higher inflation for low-expenditure households accumulating gradually over many years at slightly above-average rates.[3]

2.2 Monthly Expenditure Growth with Seasonal Adjustment

In a perfect setting, given the price data P and the level of real expenditure C, the month-over-month growth in real expenditures for each quintile i in month m of year y can be computed as

$$MREG^i_{y,m} = \sqrt{\frac{\sum_{n=1}^{N} P_{y,m,n} \cdot C^i_{y,m,n}}{\sum_{n=1}^{N} P_{y,m,n} \cdot C^i_{y,m-1,n}} \cdot \frac{\sum_{n=1}^{N} P_{y,m-1,n} \cdot C^i_{y,m,n}}{\sum_{n=1}^{N} P_{y,m-1,n} \cdot C^i_{y,m-1,n}}} - 1. \tag{7}$$

While the PCE provides expenditure data at monthly frequencies that are seasonally adjusted, Garner et al. (2024) only provides annual expenditure shares across quintiles for each category. We use a simple algorithm to compute month-over-month growth in real expenditures from the annual expenditure shares. The most basic approach would assign the yearly expenditure shares to each month of the year. However, this method introduces a large discontinuity in expenditure shares between December and January each year, leading to substantial discontinuities in monthly expenditure shares and growth.

To resolve this issue, we use an alternative method that produces smooth monthly time series. Monthly expenditure shares are estimated to match the annual average for each year while minimizing monthly variation. Specifically, the following optimization is solved for each category n and quintile i:

$$\begin{aligned} &\min \sum_{y,m} (\tilde{s}^i_{y,m,n} - \tilde{s}^i_{y,m-1,n})^2 \\ &\text{s.t.} \quad \frac{1}{12} \sum_{m=1}^{12} \tilde{s}^i_{y,m,n} = s^i_{y,i}, \end{aligned} \tag{8}$$

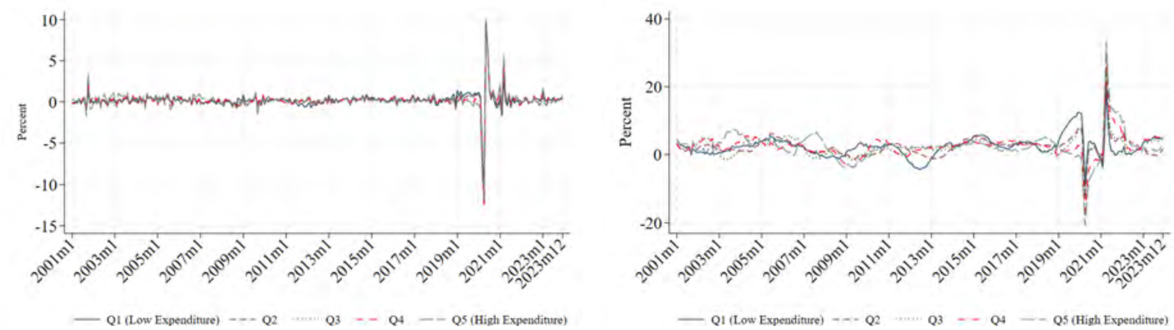
where m stands for a month and y stands for a year.

Appendix 2 compares the smoothed monthly time series produced by the minimization algorithm with the yearly time series, using the clothing and footwear category as an example. The results of this minimization,

3. Horwich (2024) uses the consumer price index by quintiles defined by income per equivalent adult (R-CPI-I) and reports similar findings regarding expenditures across the income distribution. The author observes that households facing the highest inflation vary, and inflation dispersion has typically been modest.

Figure 4
Growth in Monthly Real Expenditure by Expenditure Quintile in 2001–2023

(a) Month-over-month growth **(b) Year-over-year growth**



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

$\tilde{s}^i_{y,m,n}$ no longer exhibit large discontinuities between certain months, resulting in a smoother time series that is likely more realistic. After smoothing the shares to a monthly frequency, the shares of the five quintiles are summed, and a multiplier is applied to adjust each quintile's share proportionally. This adjustment ensures that the expenditure shares sum to 1 across quintiles for every month and year and that the total expenditures across the five quintiles equal the total expenditures for each category.

Combining the seasonally adjusted price and expenditure data by category from the PCE with the smoothed expenditure share for month m in year y and category n for quintile i, the month-over-month growth in real expenditures can be estimated as

$$(9) \qquad M\tilde{REG}^i_{y,m} = \sqrt{\frac{\sum_{n=1}^{N}(P_{y,m,n}C_{y,m,n}) \cdot \tilde{s}^i_{y,m,n}}{\sum_{n=1}^{N}(P_{y,m,n}C_{y,m-1,n}) \cdot \tilde{s}^i_{y,m-1,n}} \cdot \frac{\sum_{n=1}^{N}(P_{y,m-1,n}C_{y,m,n}) \cdot \tilde{s}^i_{y,m,n}}{\sum_{n=1}^{N}(P_{y,m-1,n}C_{y,m-1,n}) \cdot \tilde{s}^i_{y,m-1,n}}} - 1.$$

Figure 4 shows the time series of real expenditure growth by expenditure quintile from January 2001 to December 2023. Panel (a) displays the month-over-month percent change, corresponding to $M\tilde{REG}^i_{y,m}$ in equation (9), while panel (b) represents the year-over-year percent change. Notably, in the year-over-year growth, expenditure growth for households with lower expenditure levels fluctuated more than for those with higher expenditure levels, especially in 2009–2020. Section 4.2 highlights more details on this comparison. This monthly real expenditure growth aligns with the annual real expenditure growth but offers higher-frequency data, enabling real-time tracking of heterogeneity every month. Since PCE monthly expenditures are released at the end of each month for the prior month's data, this framework is highly valuable for policymaking.

A significant remaining challenge is the lag in updates to expenditure shares across the expenditure distribution. As of November 2025, Garner et al. (2024) provide estimates of expenditure distribution by expenditure quintile up to 2023. This lag between the latest available dataset and the current date limits the timeliness of heterogeneity estimates in real expenditure growth. Additionally, the exact replication of their expenditure share estimates is not possible, as Garner et al. (2024) use data to impute expenditures in certain sectors, such as health care. In the next section, we propose a simple framework to estimate more recent expenditure shares across households.

3. REAL-TIME ESTIMATION

3.1 Shares of Each Quintile for All Categories Using CE Data

In this section, we propose a simple framework to incorporate more recent spending data into estimates of expenditure shares. As described at the end of Section 2.2, there is a substantial lag between the latest year in Garner et al. (2024) and the current date. Exact replication of their estimates is not feasible, as their estimations require confidential information to impute expenditures in certain sectors. However, the publicly available microdata (PUMD) from the CE is available up to the first quarter of 2024 as of November 2025. Thus, with recent data on expenditures, a measure of expenditure shares can be constructed by combining the results of Garner et al. (2024) with estimates derived from the PUMD.

CE expenditure shares are computed as follows: First, we use two main files from the most up-to-date quarterly CE interview surveys along with all quarterly surveys from past years: the Family-Level Interview File (FMLI), which reports household-level summary variables for demographics, income, and spending; and the Member-Level Interview File (MBTI), which reports more detailed household expenditure variables. We assume that each year is represented with the data from the four quarterly interview surveys. For years that do not have all four quarterly surveys, we regard the data from all available quarterly interview surveys as representative of the year. For example, since the first-quarter interview survey of 2024 is the most recent survey available, as of November 2025, it is assumed that the first-quarter interview surveys of 2024 represent 2024.

Second, we map the spending categories in the CE, known as Universal Classification Codes, to PCE categories following Bureau of Labor Statistics (2021), consistent with Garner et al. (2024). We also impose a lower bound of zero, which affects a small number of observations with negative expenditure totals at the major product level, ensuring adjustments for discrepancies between these two category systems.[4] Third, we calculate the sum of expenditures for each household, and they are ranked based on their total expenditures per equivalent adult, which are computed by dividing total household expenditures by the square root of family size. Based on the ranking of their total expenditures per equivalent adult, each household is assigned into one of five quintiles within each quarterly interview survey. In constructing this ranking, consumer units are weighted by their CE sampling weight (`finlwt21`). Lastly, for each category, we calculate the yearly sums of expenditures held by each quintile, weighted by the CE sampling weight, based on the four quarterly interview surveys. Then, we calculate CE expenditure shares as a ratio of the weighted sum held by each quintile relative to the total weighted sum of expenditures among the five quintiles.

Figure 5 contrasts the time series of expenditure shares by quintile from 2000 to 2023 between the estimates from Garner et al. (2024) (BLS data) and our estimates derived from the interview surveys in the first, second, third, and fourth quarters of the year (CE). In several sectors, such as *Recreation Goods and Vehicles*, the estimates obtained from these surveys align well with both the levels and trends indicated by the BLS data. Conversely, in sectors like *Housing and Utilities*, there are noticeable differences in the absolute levels, although the trends over time are effectively captured. This comparison highlights the importance of considering both absolute levels and differences when predicting future expenditure distributions, which can be achieved by accounting for the level of expenditure shares in the current and previous years. These findings highlight that recent changes in expenditure shares can offer valuable signals for forecasting purposes. Figure 6 further investigates the relationship between changes in the two estimated shares.

3.2 Forecasting the PCE Shares of Each Quintile for All Categories

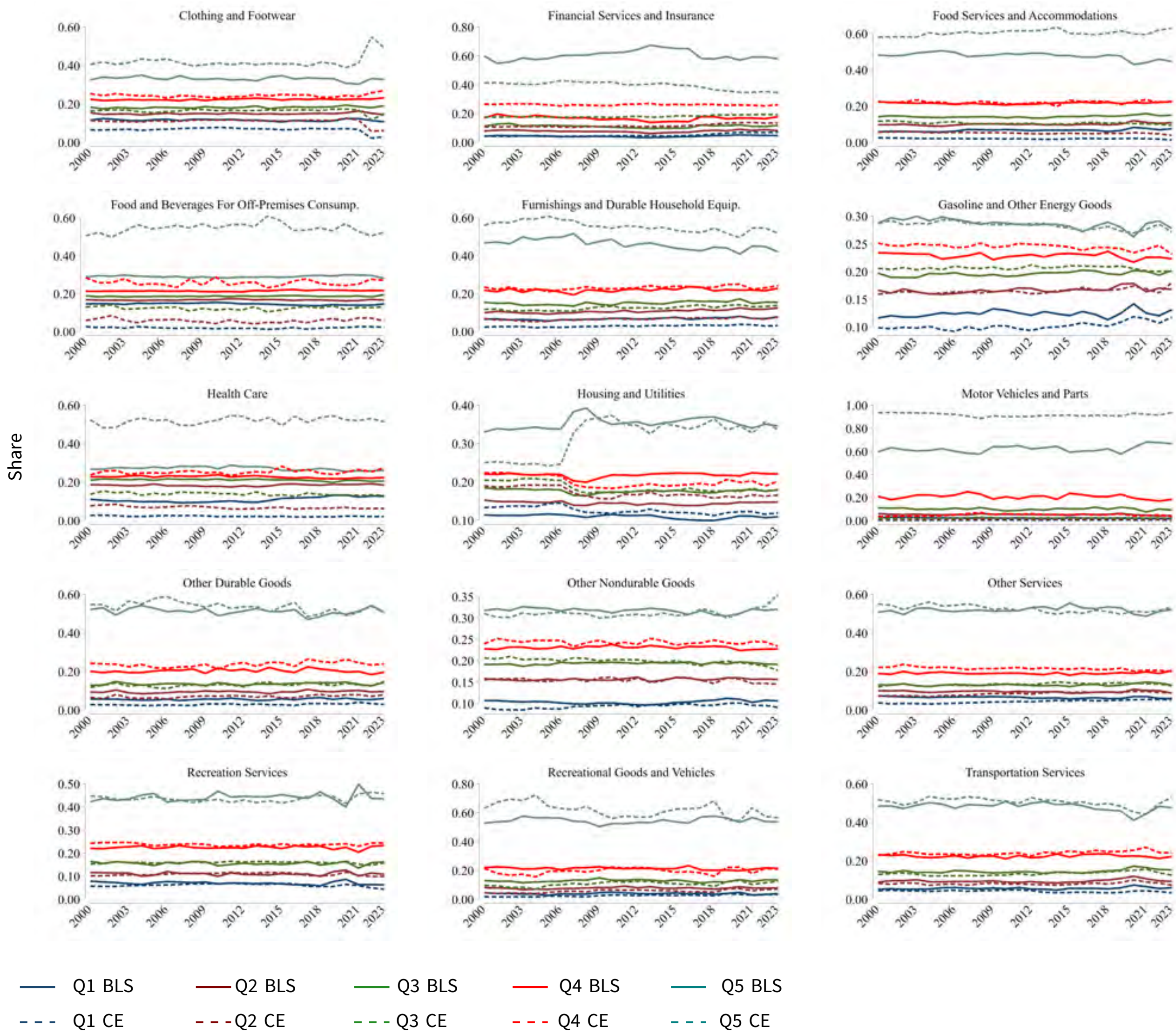
Using information from the CE shares, we construct an econometric model to forecast the PCE expenditure shares for 1 and 2 years. We consider two approaches of setting the PCE expenditure shares.

The first approach is to maintain the expenditure shares at a constant from the previous year. The second approach predicts the percentage-point changes in the PCE expenditure shares using the percentage-point changes in the CE expenditure shares. The previous section demonstrated that, although the CE shares do not precisely align with the PCE shares in Garner et al. (2024), the trends over time are effectively captured. This suggests that rather than directly adopting the CE shares, incorporating changes in the CE shares can predict shifts in the PCE shares. To forecast j years ahead, we compute the regression coefficients Φ_n that scale the percentage-point changes in the PCE and CE expenditure shares using the available datasets for each category n:

$$\Delta_{t+j,t} PCEExpShare_{i,n} = \Phi_n \cdot \Delta_{t+j,t} CEExpShare_{i,n} + \epsilon_{i,n,t},$$

4. This approach is consistent with Garner et al. (2024) and past studies using the CE, such as Coibion et al. (2017). Expenditures may be negative when households receive reimbursements for past purchases or return previously purchased items.

Figure 5
Garner et al. (2024) vs. Our CE estimates: Share of Expenditures by Category in 2000–2023



SOURCE: Bureau of Labor Statistics and Garner et al. (2024).
NOTE: Expenditure quintiles are defined based on individual respondents' spending levels per equivalent adult.

where $PCEExpShare_{i,n}$ represents the PCE expenditure share for quintile i in category n, $CEExpShare_{i,n}$ represents the CE expenditure share for quintile i in category n, and $\Delta_{t+j,t}$ represents the percentage-point changes in expenditure shares between year $t+j$ and year t. Then, using the estimated coefficients, the equation

$$\widehat{PCEExpShare}_{i,n,t+j} = PCEExpShare_{i,n,t} + \Phi_n \cdot \Delta_{t+j,t} CEExpShare_{i,n} \tag{10}$$

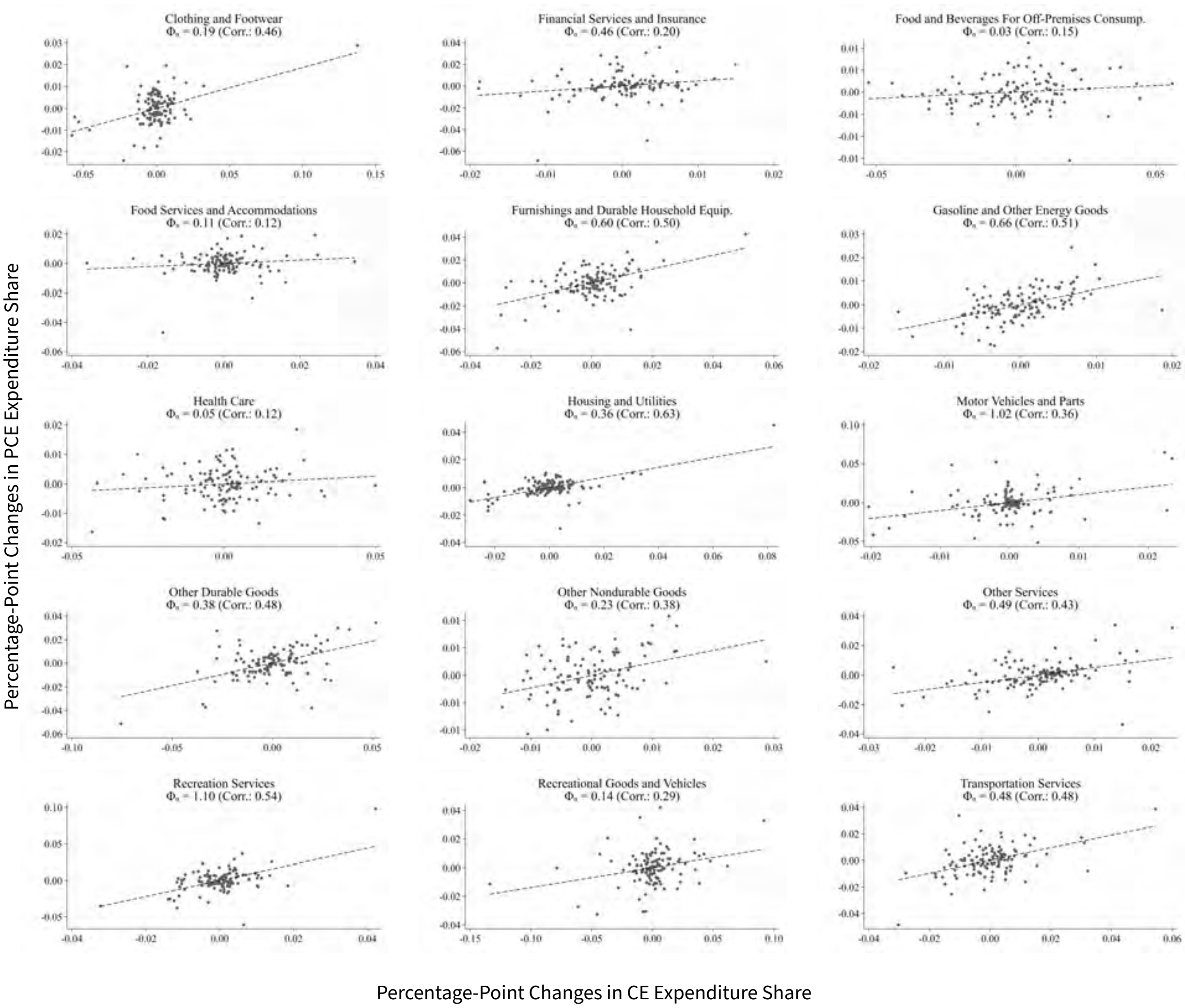
forecasts the expenditure shares for j years ahead. Note that the sum of expenditure shares across quintiles is equal to one by the definition. Hence, for each category n, the sum of percentage-point changes in expenditure shares across quintiles should be zero, which is

$$\sum_{i=1}^{5} \Delta_{t+j,t} PCEExpShare_{i,n} = \sum_{i=1}^{5} \Delta_{t+j,t} CEExpShare_{i,n} = 0.$$

This indicates that regardless of the size of the regression coefficients, Φ_n, the sum of the forecasted shares across quintiles is equal to one.

Figure 6

PCE vs. Our CE estimates: 1-Year Percentage-Point Changes in Share of Expenditures by Category in 2000–2023



SOURCE: Bureau of Labor Statistics and Garner et al. (2024).
NOTE: Expenditure quintiles are defined based on individual respondents' spending levels per equivalent adult.

Figure 6 illustrates the correlation of 1-year percentage-point changes between the PCE expenditure shares, estimated by Garner et al. (2024), and our CE estimates for each PCE category. The coefficient Φ_n and correlation coefficient are estimated from equation (10) using data from 2000 to 2023. The figure shows that some categories, such as *Gasoline and Other Energy Goods* and *Housing and Utilities*, demonstrate high fit with the econometric model, underscoring that our CE estimates can provide some information on the PCE shares before its data release.

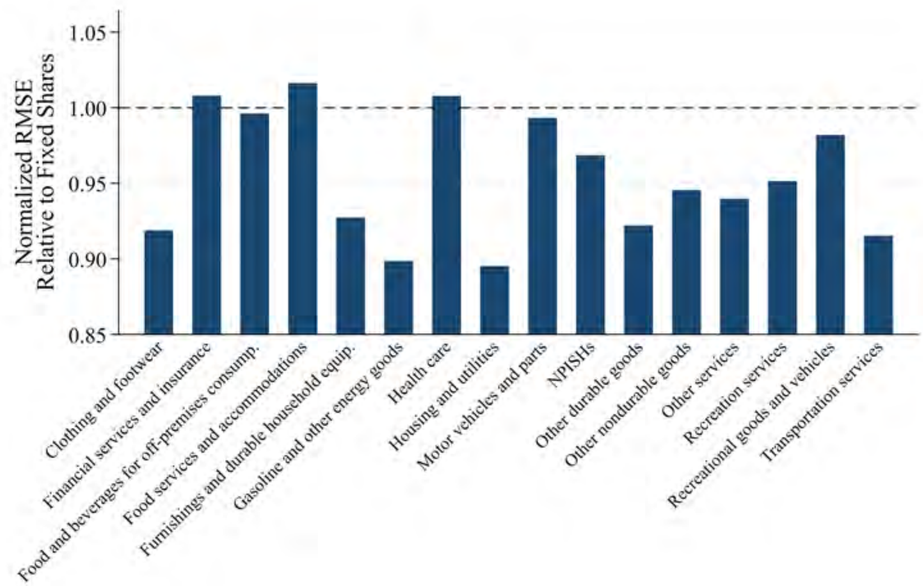
We examine the model's performance by observing the root mean squared errors computed from the leave-one-out cross-validation. For example, to project expenditure shares for 2015, we estimate regression coefficients for each category based on data from all years except 2015 and then apply these coefficients to forecast the expenditure shares for 2015. Similarly, we project expenditure shares for 2016 by computing regression coefficients for each category using the data in all years between 2000 and 2023 except 2016.[5]

Figure 7 shows the root mean squared errors of 1-year forecasted expenditure shares by category, normalized by the size of root mean squared errors when the expenditure shares are assumed to stay constant for 1

5. It is important to note that the CE includes data exclusively on household spending, thus excluding Nonprofit Institutions Serving Households (NPISHs). Consequently, we use expenditure shares in total expenditures, calculated from the CE, to predict PCE expenditure shares for NPISHs.

Figure 7

Root Mean Squared Errors of 1-Year Forecasted Expenditure Shares by Category

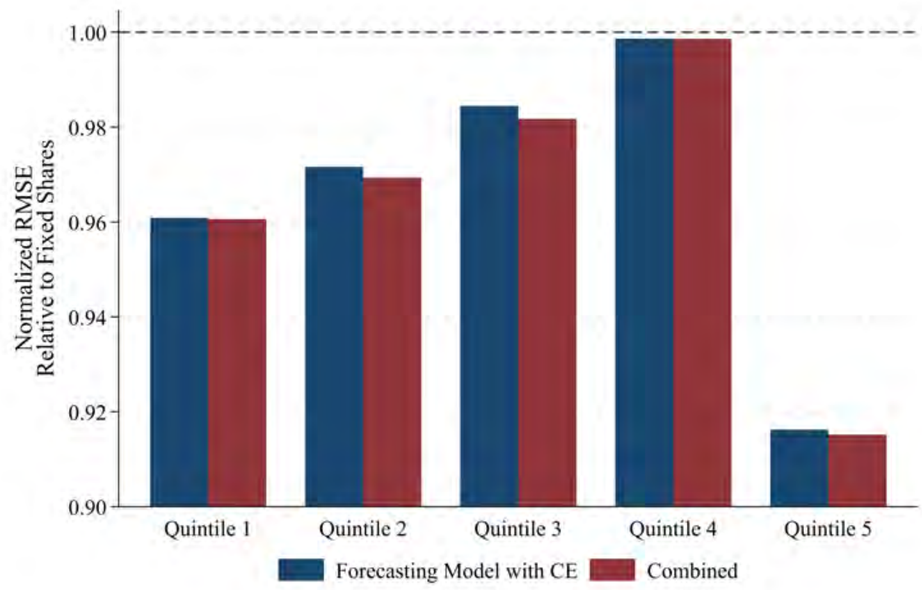


SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

year. Most categories perform better than in the case when the expenditure shares are fixed for a year. For example, *Gasoline and Other Energy Goods* and *Housing and Utilities* obtain root mean squared errors that are 10 percent smaller than under the fixed share approach. For each category, the forecasting model is used when it outperforms the case in which the shares are kept constant. Figure Appendix 3.1 presents the same plot for a 2-year-ahead forecast.

Figure 8 displays the root mean squared errors of 1-year forecasted expenditure shares by quintile, normalized by the size of root mean squared errors when the expenditure shares stay constant over 1 year. The figure shows that, in all quintiles, our forecasting model outperforms the fixed share approach. In addition, the approach of using the econometric model for some categories while keeping the expenditure shares fixed for others—depending on the root mean squared errors—performs better than using one of the approaches for all categories. Figure Appendix 3.2 shows the same plot for a 2-year-ahead forecast and supports our approach, displaying that the combination of these two approaches performs better than applying one of them for all categories.

Figure 8
Root Mean Squared Errors of 1-Year Forecasted Expenditure Shares by Quintile



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

4. MAIN FINDINGS

This section highlights the main findings from our framework. Section 4.1 highlights that households with lower expenditure levels faced higher inflation than those with higher expenditures during the Global Financial Crisis. In Section 4.2, the volatility of real expenditures shows that real expenditure growth for lower-expenditure households has been more volatile than real expenditure growth for higher-expenditure households. Section 4.3 examines real expenditure growth in the post-pandemic period and suggests a significant heterogeneity in the recovery of real expenditure growth since the onset of COVID-19.

4.1 Disparities in Inflation around the Global Financial Crisis

Table 1 shows the inflation rate by quintiles of expenditure levels from 2004 to 2011, the period surrounding the Global Financial Crisis. During this time, the first quintile experienced an annualized rate of 2.5 percent, while the fifth quintile faced an annualized rate of 2.0 percent. This difference results in a 4.4 percentage-point difference in the cost of living after 7 years.

The year-over-year inflation rate gives us a more detailed picture of the rise in the cost of living. Households with lower expenditures consistently experienced higher inflation than those with higher expenditures over time. In particular, significant disparities in inflation are highlighted during 2005–2008 and 2011, where the percentage-point differences between the first and fifth quintiles range from 0.57 to 1.23 percentage points.

Argente and Lee (2021) construct income-specific price indexes from detailed scanner data collected at the household level and find that substantial differences across income groups arose during the Great Recession because rich households were more able to substitute toward lower-quality goods. Kaplan and Schulhofer-Wohl (2017) argue that most of the heterogeneity comes not from variation in broadly defined consumption bundles but from variation in prices paid for the same types of goods across income groups. It is also important to note that the coverage of scanner data is limited, and the distribution of spending across types of goods in the scanner data is different from the CE and PCE. Kaplan and Schulhofer-Wohl (2017) document that about 61 percent of spending in their dataset is on food and beverages, whereas the category has only a 15 percent weight in the published CPI, constructed from the CE. While our findings are obtained under the assumption that all households pay the same price for the same categories from the PCE, they are consistent with the findings from these two studies.

4.2 Larger Volatility of Real Expenditure Growth for Low-Expenditure Households

Table 2 shows standard deviations of the log of real expenditure levels from January 2000 to December 2023. This statistic captures the volatility of real expenditure growth. Low-expenditure households experienced

Table 1
Inflation around the Global Financial Crisis

	Annualized Rate	Inflation Rate						
	2004 to 2011	2005	2006	2007	2008	2009	2010	2011
Total	2.18	2.88	2.82	2.57	2.96	-0.28	1.79	2.53
Quintile 1	2.51	3.26	3.17	3.00	3.75	-0.29	1.75	2.97
Quintile 2	2.43	3.16	3.07	2.89	3.43	-0.10	1.81	2.79
Quintile 3	2.32	3.07	2.97	2.75	3.23	-0.13	1.77	2.66
Quintile 4	2.19	2.90	2.81	2.56	3.01	-0.20	1.72	2.55
Quintile 5	1.96	2.64	2.60	2.30	2.52	-0.43	1.84	2.28

SOURCE: Authors' calculations based on numbers from the Bureau of Labor Statistics and the Bureau of Economic Analysis.
NOTE: Quintiles of spending levels per equivalent adult.

Table 2
Volatility of Real Expenditure Growth between January 2000 and December 2023

	Standard Deviation, %
Total	14.8
Quintile 1	15.5
Quintile 2	15.2
Quintile 3	14.8
Quintile 4	14.8
Quintile 5	14.7

SOURCE: Authors' calculations based on numbers from the Bureau of Labor Statistics and the Bureau of Economic Analysis.
NOTE: Quintiles of spending levels per equivalent adult.

Table 3
Heterogeneity in Annual Real Expenditure Growth since January 2020

	% Change in Real Expenditure Growth, SAAR	
	January 2020 to January 2021	January 2021 to January 2023
Total	-0.1	4.4
Quintile 1	-1.7	2.0
Quintile 2	-0.8	3.2
Quintile 3	0.1	3.6
Quintile 4	0.3	5.0
Quintile 5	0.3	5.5

SOURCE: Authors' calculations based on numbers from the Bureau of Labor Statistics and the Bureau of Economic Analysis.
NOTE: Quintiles of spending levels per equivalent adult. SAAR stands for seasonally adjusted annual rate.

larger volatility of real expenditure growth over time than high-expenditure households, as the first quintile's volatility is 5 percent higher than that of the fifth quintile. This finding aligns with that of Mustre-del-Río et al. (2024), who argue that households in zip codes with a higher incidence of financial distress have larger swings of consumption during recessions because (i) their responses to shocks are larger and (ii) the shocks that they receive are also larger.

4.3 Uneven Recovery after the COVID-19 Recession

Table 3 shows estimates of annualized, seasonally adjusted real expenditure growth from January 2020 to January 2021 (left column) and from January 2021 to January 2023 (right column). The left column shows that by January 2021, national real expenditure levels had nearly returned to their January 2020 levels (–0.1 percent real growth). However, households in the highest quintile (those with the highest level of expenditure) recovered to pre-pandemic levels, with 0.3 percent growth. In contrast, the recovery in the quintile with the lowest household spending lagged significantly behind, with its real expenditure level declining by 1.7 percent. This period highlights sharp disparities in real expenditure growth across quintiles. The right column indicates that from January 2021 to January 2023, real expenditure levels increased across all quintiles, yet growth at the bottom of the distribution was notably slower. Households in the lowest expenditure quintile (quintile 1) saw a 2.0 percent increase, while the highest expenditure quintile (quintile 5) grew more than twice that rate, underscoring a persistent gap.

Our finding is consistent with that of Hoke, Feler, and Chylak (2024), who use retail spending data by household income and argue that middle- and high-income households have driven the strong demand for retail goods, while low-income households' spending has been stable in the post-pandemic period. Orhun and Palazzolo (2019) suggest households' liquidity constraints as a potential obstacle for recovering real expenditure levels because a lack of intertemporal savings hinders low-income households from taking advantage of "a good deal," such as bulk discounts and temporary sales.

5. REAL-TIME TRACKING OF DIFFERENCES IN REAL EXPENDITURE GROWTH AND INFLATION

This section provides an example, with the latest available data, of the monthly analysis that can be provided with the methodology explained above. The first part of the analysis describes cross-household differences in real expenditure growth, while the second part focuses on cross-household differences in inflation.

Figure 9 presents the month-over-month growth in real expenditure and price level in the most recent three months. The latest information corresponds to the release on September 26, 2025. These estimates use the expenditure shares forecasted by our model for 2024.[6] In addition, the expenditure shares in 2025 are held constant from 2024 and used in the algorithm that computes smoothed monthly time series. The analysis highlights that in the most recent month, real expenditure growth was stronger for households with high expenditure levels than those with low levels, and that month-over-month inflation was quite even across household groups.

6. As described in Section 3.1, due to lack of data for the full year in 2024, we assume that the first-quarter survey of 2024, which is the only quarterly interview survey available for 2024, represents 2024.

Figure 9
Example of Monthly Analysis

Recent Evolution of Differences in Real Expenditure Growth and Inflation across Households

Real Expenditures (PCE), 2025

	% Change from Previous Month, SA		
	Jun	Jul	Aug
Total	0.26	0.38	0.35
Quintile 1	0.31	0.21	0.29
Quintile 2	0.30	0.24	0.32
Quintile 3	0.29	0.29	0.35
Quintile 4	0.26	0.36	0.37
Quintile 5	0.22	0.53	0.36

Source: Authors' calculations based on numbers from the Bureau of Labor Statistics and the Bureau of Economic Analysis.
Note: Quintiles of spending levels per equivalent adult. SA stands for seasonal adjustment.

- In August, seasonally adjusted real expenditure grew by 0.35% relative to the previous month. Real expenditure growth was slightly stronger for high-expenditure households (HEHs) (0.36%) and low-expenditure households (LEHs) (0.29%).

Price Index (PCE), 2025

	% Change from Previous Month, SA		
	Jun	Jul	Aug
Total	0.29	0.16	0.27
Quintile 1	0.31	0.11	0.27
Quintile 2	0.31	0.13	0.25
Quintile 3	0.30	0.13	0.25
Quintile 4	0.29	0.15	0.25
Quintile 5	0.27	0.21	0.29

Source: Authors' calculations based on numbers from the Bureau of Labor Statistics and the Bureau of Economic Analysis.
Note: Quintiles of spending levels per equivalent adult. SA stands for seasonal adjustment.

- In August, the price index displayed a positive growth from the previous month (0.27%). The month-over-month inflation was quite even between HEHs and LEHs in August, with 0.27% for LEHs and 0.29% for HEHs.

6. CONCLUDING REMARKS

This article provides a methodology to estimate the differences in real expenditure growth and inflation across households with different levels of expenditure. Tracking real-time heterogeneity in real expenditure growth and inflation at a high frequency is especially valuable for informing the policymaking process.

First, the findings indicate that households with lower expenditure levels have faced higher inflation since 2000 than those with higher expenditure levels. Notably, in 2005–2008 and 2011, households with lower expenditures have faced higher inflation rates than those with higher expenditures. Second, real expenditure growth for lower-expenditure households has fluctuated significantly more than for higher-expenditure households. Third, recent data indicate uneven real expenditure recovery across households with varying expenditure levels in the first two years following the COVID-19 outbreak.

The monthly expenditure growth and inflation rates provided here may offer an opportunity for future research. For example, they may help validate the predictions of modern heterogeneous agent models used to study business cycle fluctuations.

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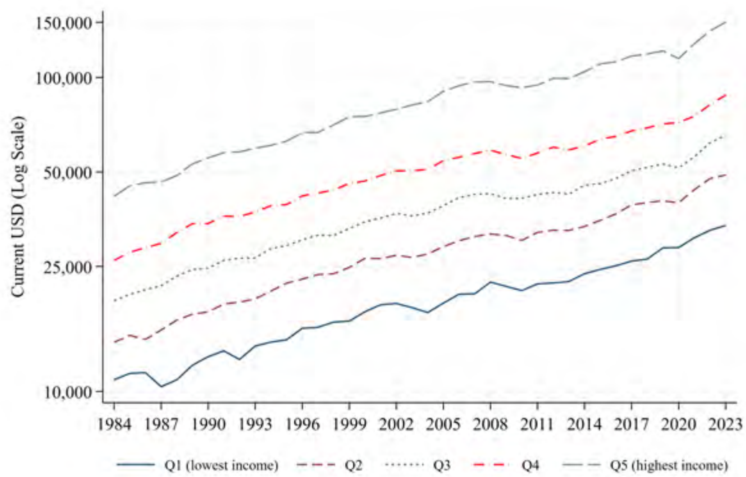
APPENDIX 1. INCOME AND EXPENDITURE

This article aims to estimate consumption growth across households with varying income levels. However, the PCE shares provided by Garner et al. (2024) are organized by expenditure quintiles rather than income. This appendix argues that expenditures and income are highly correlated, suggesting that fluctuations in consumption by expenditure quintiles likely provide a reliable approximation for consumption patterns by income quintiles.

Intuitively, higher-income households are expected to consume more than those with lower incomes. Figure Appendix 1.1 presents the log-scaled time series of average annual expenditures across income quintiles (before taxes), derived from the CE. The plot supports this hypothesis, showing a clear correlation between income levels and consumption patterns.

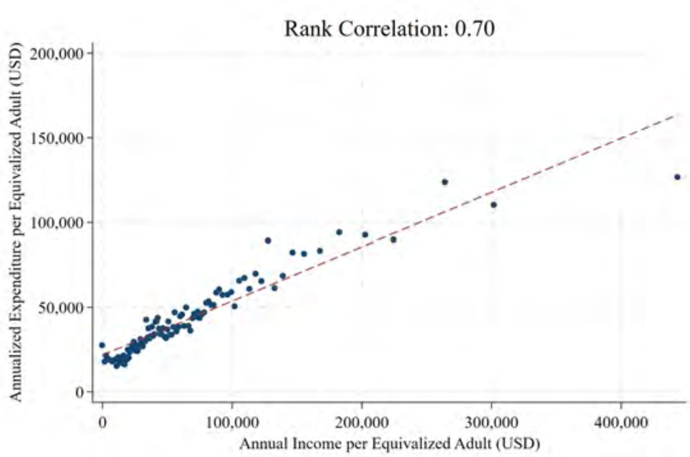
Figure Appendix 1.1
Average Annual Expenditures by Income Quintile from the CE



SOURCE: Bureau of Labor Statistics.

Figure Appendix 1.2 presents a scatterplot of annual income versus expenditure, based on data from the second quarter of 2023 in the CE. Income and expenditures are transformed to be per equivalent adult by dividing total household income and expenditure by the square root of the number of family members. The plot indicates a strong correlation between household rankings in income and consumption.

Figure Appendix 1.2
Income vs. Expenditure from the CE

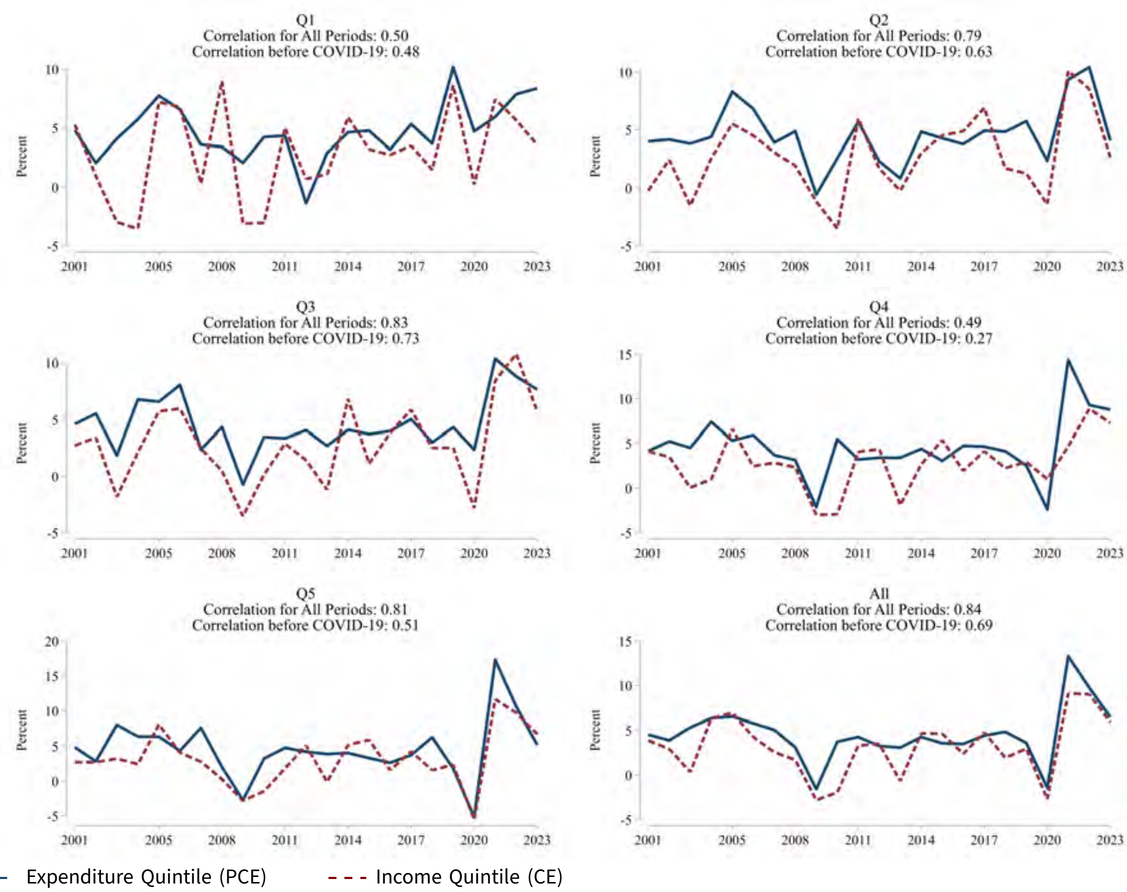


SOURCE: 2023 Consumer Expenditure Surveys.

Figure Appendix 1.3 compares the time series of nominal expenditure growth by expenditure quintile, $\tilde{NEG}$, with nominal expenditure growth by income quintile, representing the growth rates of the series in Figure Appendix 1.1. There are two differences between the two time series. The first difference is the definition of grouping: The former shows the nominal expenditure growth of households divided into five groups based on their expenditure per equivalent adult, while the latter shows the nominal expenditure growth of households split into five groups based on their income. The second difference is the source of datasets: The former is constructed using both the PCE and CE, while the latter relies solely on the CE. The plot shows that these two measures of nominal expenditure growth appear to comove over time. This result appears consistent across total expenditures and for all quintiles. More importantly, ensuring alignment between the numbers derived from PCE expenditures—using the expenditure shares from Garner et al. (2024)—and those computed directly from the CE is desirable because PCE will be used to deliver real-time insights into the differences in real expenditure growth and inflation across households.

Figure Appendix 1.3

PCE vs. CE: Percent Change in Annual Nominal Expenditures in 2001-2023



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

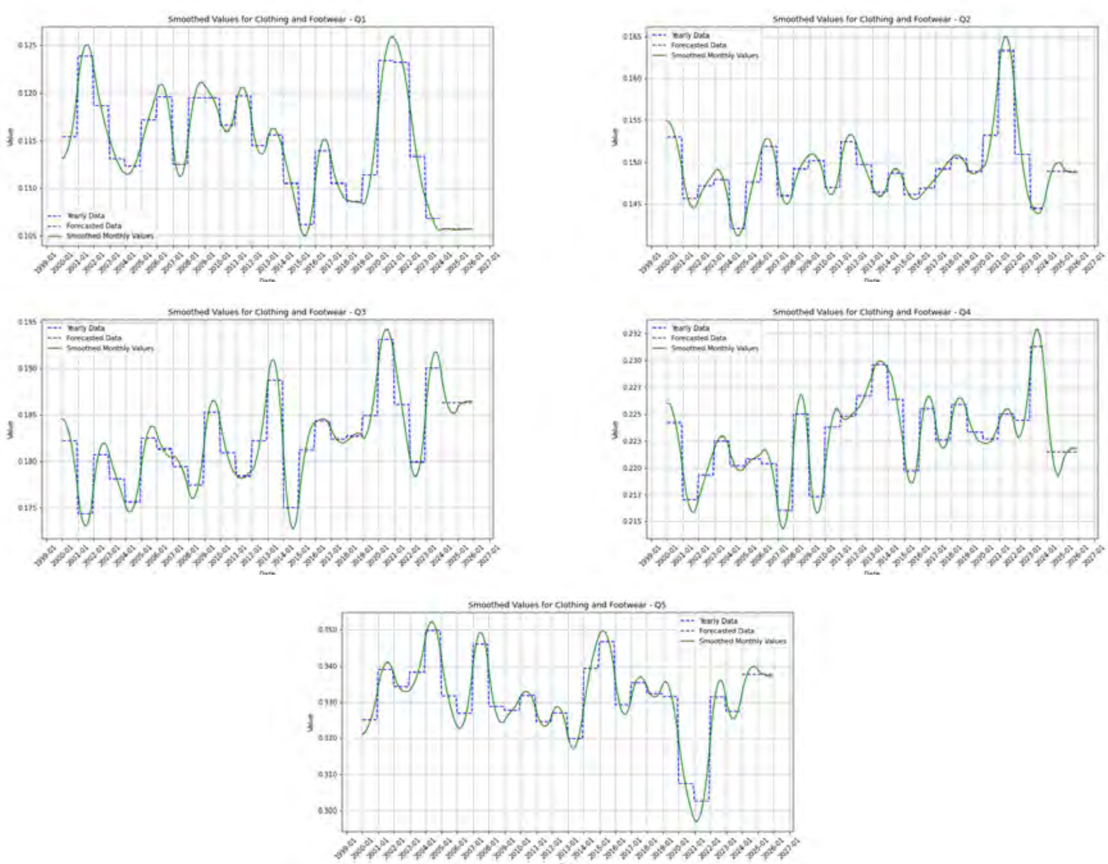
While this article primarily examines differences in consumption growth using expenditure quintiles per equivalent adult, this result suggests that tracking differences in expenditure growth and inflation across households with different expenditure levels can also inform our understanding of heterogeneity in these variables across the income distribution.

APPENDIX 2. SMOOTHING MONTHLY EXPENDITURE SHARES

Figure Appendix 2.1 illustrates the monthly expenditure share series, displaying both the yearly average across all months of each year and a smoothed monthly series achieved through a minimization algorithm. The *Clothing and Footwear* category is used as an example to showcase the methodology. The smoothed monthly series preserves the overall yearly averages while minimizing short-term fluctuations to maintain continuity across months. The same smoothing algorithm is applied to all 16 PCE categories and all expenditure groups. This approach aims to provide a more interpretable time series by reducing noise while retaining the long-term trends observed in the yearly data, thereby making it suitable for subsequent economic analysis and forecasting.

Figure Appendix 2.1

Smoothed Monthly Expenditure Shares for Clothing and Footwear

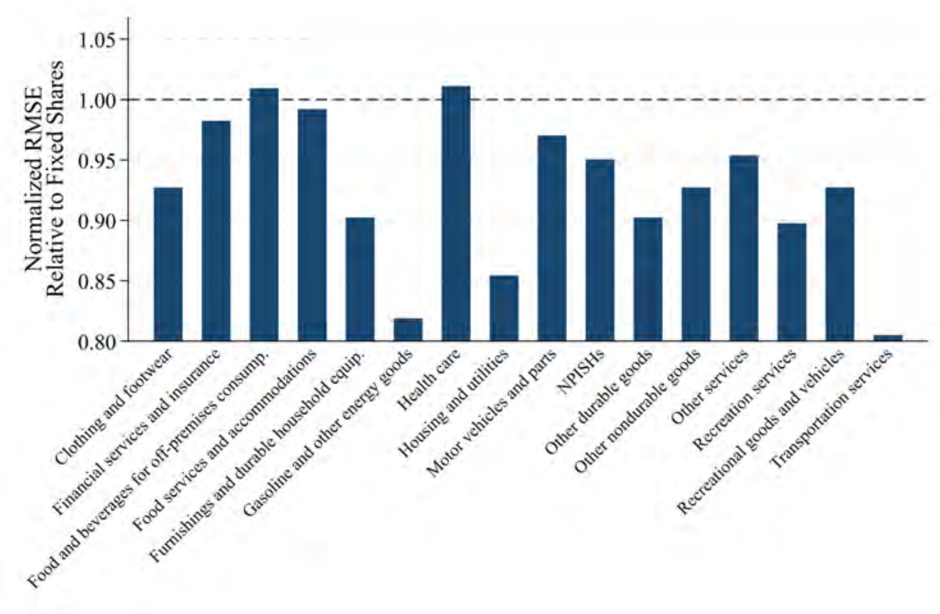


APPENDIX 3. FORECASTING TWO-YEAR-AHEAD EXPENDITURE SHARES

This section describes the method that forecasts 2-year-ahead PCE expenditures shares. This model follows the methodology described in Section 3.2. In other words, first, this method runs the econometric model for the 2-year-ahead forecast, described in equation (10). Second, it evaluates whether the econometric model performs better than the constant shares and chooses one of these approaches for each category based on their performances in the LOOCV. Then, the 2-year-ahead expenditure shares are predicted using regressions with all observations available from Garner et al. (2024). To implement this method, we assume that the PCE expenditure share is available up to two previous periods and the CE expenditure share is available up to the contemporaneous period.

Figure Appendix 3.1 shows the root mean squared errors of 2-year forecasted expenditure shares by category, normalized by the size of root mean squared errors when the expenditure shares are assumed to stay constant over 2 years. For each category, we select model that obtains lower root mean squared errors to forecast 2-year-ahead PCE expenditure shares.

Figure Appendix 3.1
Root Mean Squared Errors of 2-Year Forecasted Expenditure Shares by Category

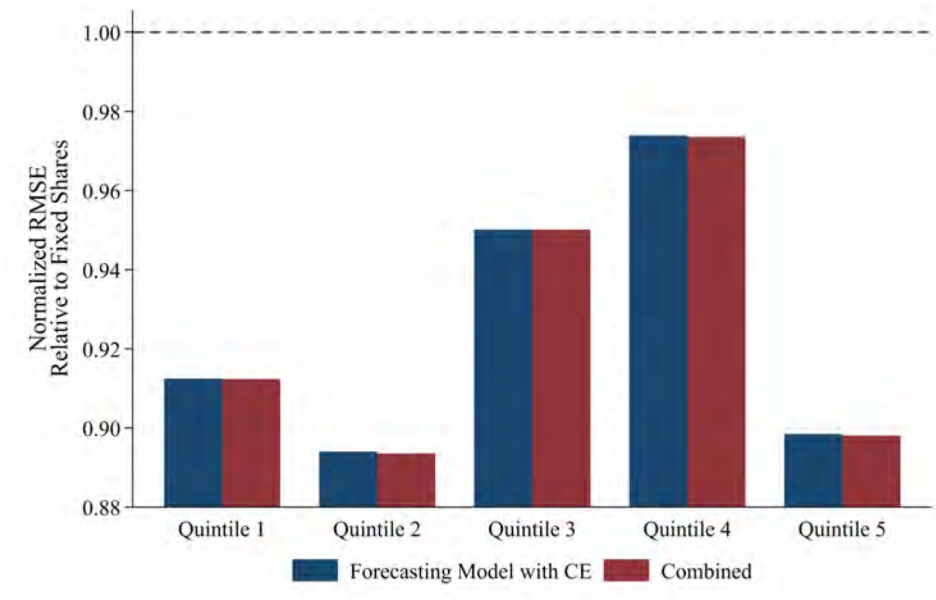


SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).

Figure Appendix 3.2 displays the root mean squared errors of 2-year forecasted expenditure shares, normalized by the root mean squared errors when the expenditure shares are assumed to stay constant over two years. The figure shows that in all quintiles, our forecasting model performs better than when using the fixed shares. In addition, the approach of using the econometric model for some categories while keeping the expenditure shares constant for others, depending on the root mean squared errors, performs better than using one of the approaches for all categories. This result is analogous to Figure 8, which showed that our method performs the best with 1-year-ahead forecasts for all quintiles.

Figure Appendix 3.2

Root Mean Squared Errors of 2-Year Forecasted Expenditure Shares by Quintile



SOURCE: Bureau of Economic Analysis, Bureau of Labor Statistics, and Garner et al. (2024).