A Distributional Cost-of-Living Index From Aggregate Data*

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Abstract

This paper proposes a method to measure individual and aggregate changes in the cost of living when consumer behavior is nonhomothetic and microdata on consumption expenditures are not available. Aggregate prices and expenditure shares together with a single cross-sectional expenditure distribution are sufficient to create a distribution of nonhomothetic cost-of-living indices. The cost-of-living indices nest the homothetic Törnqvist price index as a limit case and only contain one unknown parameter, which is identified from macro data without aggregation bias. Using US Personal Consumption Expenditure (PCE) data, we construct nonhomothetic PCE price indices covering 71 product groups for the period 1959 to 2023. These indices reveal a 0.41 percentage point gap in annual inflation rates between the poorest and richest ten percent since 1959 and a 1.3 percentage point gap throughout 2022, thus suggesting that poorer households are hit harder both in the long run and in the recent inflation surge.

Keywords: cost of living, inflation inequality, nonhomotheticity, Personal Consumption Expenditures.

JEL Codes: C43, D12, D3, E01, E31.

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1 Introduction

Over 160 years of research since the early work of Engel (1857) suggests that consumption patterns vary systematically with income. It is therefore acknowledged that price movements create disparities in the cost of living between rich and poor, and a large body of evidence from consumer survey data points to considerable inflation inequality to the detriment of low-income groups. Yet, despite a growing interest in distributional questions related to national income and monetary policy, most national accounts-based deflators and inflation measures still rely on aggregate cost-of-living indices that are assumed to apply to everyone. The reason is mainly practical, since detailed household-level expenditure data consistent with the national accounts are rarely available. How the inflation inequality observed in consumer surveys translates into the national accounts, and its implications for real consumption estimates, consequently remains an open question. This paper constructs a first-ever distributional Personal Consumption Expenditures (PCE) price index to shed light on this issue.

The approach considered here is a generalization of the Törnqvist (1936) cost-of-living index that (i) allows consumer behavior to differ with the consumption expenditure level, (ii) can be implemented using publicly available macroeconomic data on prices and expenditure shares only, and (iii) nests the standard Törnqvist index as a limit case. While all other commonly used cost-of-living indices also satisfy (ii), they do so under the assumption of homothetic preferences, in which consumer behavior is independent of the expenditure level. These indices therefore only describe cost-of-living changes for an average household. By contrast, in the framework considered here a single cross-sectional distribution of household consumption expenditures is sufficient to generate a full distribution of cost-of-living indices at the household level in addition to the aggregate-level index.

Like the closely related paper by Hochmuth, Pettersson and Weissert (2024), the cost-of-living index relies on a theoretical foundation with utility-maximizing households whose preferences are of the "price independent generalized linearity" (PIGL) form originally defined by Muellbauer (1975, 1976).[1] These preferences are nonhomothetic, meaning that rich consumers allocate a larger budget share to luxuries than poor consumers, but nevertheless maintain tractable aggregation properties that allow us to consistently estimate any preference parameters from aggregate expenditure data. As shown by Hochmuth, Pettersson and Weissert, PIGL preferences generalize all common homothetic cost-of-living indices, including the Törnqvist index, and allow straightforward decompositions to identify the commodities that drive the overall changes in the cost of living.

The implementation of the PIGL cost-of-living index rests on a separable preference structure in which commodities are bundled into three intermediate baskets: necessities, luxuries, and homothetic goods. In doing so, the cost-of-living index of any individual person or group of people becomes a function of four components: (i) their total expenditure share allocated to necessities in some chosen base period; (ii) the aggregate expenditure share allocated to the homothetic bundle in every period; (iii) the prices of each basket; and (iv) a preference parameter that governs the elasticity of demand for necessities. Behavior within each intermediate basket is homothetic, so the prices of these are captured by standard Törnqvist indices that can be computed from aggregate time series. Thus, given an observed base-period distribution of household expenditures and aggregate time series on prices and expenditure shares, this approach requires the estimation of only one parameter, thereby keeping econometric concerns to a minimum.

[1] These preferences have become popular in the structural change literature; see Boppart (2014), Alder, Boppart and Müller (2022), Cravino, Levchenko and Rojas (2022), and Fan, Peters and Zilibotti (2023).

The empirical analysis focuses on US PCE data, which we use to construct nonhomothetic PCE price indices covering 71 separate commodity groups over the 65-year period between January 1959 and December 2023. The official PCE price index is the consumption deflator in the US national accounts and the main inflation measure for US monetary policy. Yet, the PCE data only cover aggregate consumption expenditures, so distributional inflation analyses with these data have not been possible before. We overcome this limitation through attempts initiated by Garner *et al.* (2022) to distribute PCEs across US households for recent years. Since the proposed approach here only needs a single cross-sectional distribution of household expenditures, these estimates are sufficient to characterize a full distribution of PCE inflation rates.

Our empirical results suggest that consumption-poor households face considerably higher PCE inflation than consumption-rich households both in the long run and in the recent episode of high inflation. When we consider the full 65-year sample from 1959 to 2023, the gap in annual inflation rates between the top and bottom deciles of the 2019 expenditure distribution amounts to 0.41 percentage points on average. This difference adds up to a cumulative 30 percent larger increase in the cost of living for the bottom decile over the same period. These long-run findings broadly corroborate the results of Jaravel and Lashkari (2024) for the 1955–2019 period. A key distinction, however, is that Jaravel and Lashkari rely on Consumer Expenditure Survey data and therefore have to interpolate and extrapolate across several decades to construct their pre-1980s estimates—an approach that may introduce measurement error or bias. Our method, by contrast, can consistently use aggregate PCE data throughout, which likely yields more reliable historical estimates.

Another advantage of our approach is that, since it only requires cross-sectional data for a single base period, it allows for timely estimates of inflation inequality even when cross-sectional microdata become available only with a time lag—a feature of particular value for policymakers.[2] In this spirit, we apply our nonhomothetic PCE index to the recent inflation surge, and find even more pronounced differences between the top and bottom of the expenditure distribution during this period. In 2022, the bottom decile faced an annual inflation rate that was on average 1.3 percentage points higher than that of the top decile, peaking at 2.3 percentage points in June of the same year. A decomposition of this gap identifies price increases for food consumed at home, energy, and motor vehicles as major drivers of the higher inflation of poor households. These are partially offset by increasing costs for restaurant meals and accommodations, transportation services, and financial services, which are consumed proportionately more by the rich.

Our findings contrast with those of Hochmuth, Pettersson and Weissert (2024), a paper which suggests that differences between the top and bottom of the expenditure distribution occur in the short run but finds no significant long-run divergence in the cost of living. Using Consumer Expenditure Survey data, Hochmuth, Pettersson and Weissert consider a coarse set of 21 nondurable consumption categories, and to shed light on these diverging conclusions we also bring our paper closer to their setting. Excluding durable goods lowers the inflation rate gap between the top and bottom deciles of the distribution from 0.41 to 0.25 percentage points overall and from 0.50 to 0.14 percentage points over the same years as in Hochmuth, Pettersson and Weissert. Calculating PCE indices at a higher level of aggregation with only 15 consumption categories lowers the inflation gap by a similar amount, thus reiterating Jaravel's (2019, 2021) concerns about aggregation bias when measuring inflation inequality. These two changes combined explain almost all of the difference to Hochmuth, Pettersson and Weissert's results.

[2] In this sense, our index is similar to the (homothetic) Lloyd-Moulton index, which the US Bureau of Labor Statistics uses to extrapolate their chained CPI with for periods in which Consumer Expenditure Survey data are not yet available.

Overall, the contribution of this paper is threefold. First, the cost-of-living index presented here extends Hochmuth, Pettersson and Weissert's (2024) nonhomothetic generalization of the Törnqvist price index, allowing commodities to be not only luxuries or necessities but also homothetic. The paper thereby adds to the literature on the economic approach to price index theory following, among many others, Konüs (1939), Samuelson and Swamy (1974), Diewert (1976, 1978), Feenstra (1994), Feenstra and Reinsdorf (2000), Barnett and Choi (2008), Redding and Weinstein (2020), and Darougheh *et al.* (2025).

Second, to the best of our knowledge this paper obtains the first-ever distribution of PCE inflation rates across households with different levels of consumption expenditures. This adds to the growing efforts by for instance Fixler *et al.* (2017), Piketty, Saez and Zucman (2018), Fixler, Gindelsky and Johnson (2020), and Garner *et al.* (2022) to construct distributional measures of income, consumption, and wealth in the national accounts. Up until now, the primary focus has been on nominal variables, with the deflators of real variables receiving limited attention. The recent contributions by Baqaee, Burstein and Koike-Mori (2024), and Jaravel and Lashkari (2024) provide partial remedies by proposing nonparametric algorithms to construct nonhomothetic real-consumption deflators. However, these methods require granular cross-sectional consumption data for every period of consideration and are thus not applicable to the PCE data.

Two other closely related papers in this regard are Oulton (2008, 2012), which recover cost-of-living indices for the Quadratic Almost Ideal Demand System (QAIDS) of Banks, Blundell and Lewbel (1997). Oulton's insight is that the QAIDS price elasticities are irrelevant for price index purposes and can therefore be collapsed into a small number of principal components, which makes estimation with aggregate data possible. The cost-of-living index is then inferred from the estimated model. Online Appendix A provides an in-depth comparison between his approach and ours. While Oulton (2008, 2012) focuses on aggregate inflation, we show that his method also permits inflation inequality analyses akin to ours.[3] Consequently, Oulton's method may constitute an attractive alternative. However, applying his approach to the PCE data yields results that are highly sensitive to the number of components chosen, even when they capture nearly all of the variation in prices. Moreover, the quadratic form of QAIDS leads to implausible predictions at high expenditure levels, with 20–30 percent of product categories receiving zero weight in the top decile. Our method, which uses PIGL preferences and relies more on standard price index methods than structural estimation, avoids these issues altogether.

Lastly, by showing that consumption-poor households in the United States face significantly higher inflation rates than the consumption-rich, both during the current inflation surge and in the long run, this paper contributes to the ever-growing literature on the measurement of inflation inequality that was recently surveyed by Jaravel (2021). Previous studies primarily use detailed microdata such as the Consumer Expenditure Survey or the Kilts-Nielsen Consumer Panel to construct separate homothetic price indices for different consumer groups.[4] By contrast, this paper uses a theoretically consistent framework and is the first to consider PCE data.

[3] We were initially unaware that Oulton's (2008, 2012) method was applicable in our setting. We thank an anonymous referee for pointing us in this direction.

[4] Examples include Hobijn and Lagakos (2005), McGranahan and Paulson (2005), Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2021), Klick and Stockburger (2021), Orchard (2022), Lauper and Mangiante (2024).

2 PIGL-Törnqvist Model

This section outlines the theoretical model of nonhomothetic consumer demand and derives the corresponding cost-of-living index. The material draws closely on Hochmuth, Pettersson and Weissert (2024), who consider a framework in which goods must be either necessities or luxuries. Our innovation here is to extend that framework to also include homothetic goods, which allows us to deal with product categories that cannot clearly be classified as necessities or luxuries in the data.

2.1 Preferences

Following Boppart (2014), suppose a household with consumption expenditure e who is faced with a price vector $\boldsymbol{p}$ has an indirect utility function of Muellbauer's (1975, 1976) PIGL form:

$$V(e,\boldsymbol{p}) = \frac{1}{\varepsilon}\left[\left(\frac{e}{F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)}\right)^{\varepsilon} - 1\right] - \frac{\nu}{\varepsilon}\left[\left(\frac{D(\boldsymbol{p})}{B(\boldsymbol{p})}\right)^{\varepsilon} - 1\right], \tag{1}$$

where $\varepsilon \in (0,1]$ governs the expenditure elasticity of demand for necessity goods and $\nu > 0$ is a scale parameter. The functions $B(\boldsymbol{p})$, $D(\boldsymbol{p})$, and $H(\boldsymbol{p})$ are linearly homogeneous and are treated throughout as unit cost functions of some intermediate homothetic consumption bundles (which are similarly referred to as the B, D, and H baskets). The function F is a CES composite of $H(\boldsymbol{p})$ and $B(\boldsymbol{p})$:

$$F\Big(H(\boldsymbol{p}),B(\boldsymbol{p})\Big) = \Big[\theta H(\boldsymbol{p})^{1-\sigma} + (1-\theta)B(\boldsymbol{p})^{1-\sigma}\Big]^{\frac{1}{1-\sigma}}, \tag{2}$$

where $\sigma > 0$ denotes the asymptotic elasticity of substitution between the B and H baskets as $e \longrightarrow \infty$, and $\theta \in (0,1)$ is a taste parameter for the H basket.

To add some structure that makes the demand system empirically tractable, a key separability restriction is imposed on preferences:

Assumption 1. Preferences are quasi-separable between $B(\boldsymbol{p})$, $D(\boldsymbol{p})$, and $H(\boldsymbol{p})$.[5] ◃

Under Assumption 1, the price of an individual commodity occurs in one and only one of the three price functions B, D, and H. This permits two-stage budgeting in which households first allocate expenditures between the three bundles, and subsequently make within-basket decisions conditional on the first-stage allocation. The expenditure share of bundle $C \in \{B,D,H\}$, defined as $w_C \equiv \sum_{j\in J_C} p_j q_j \,/\, e$ with J_C denoting the set of goods in C and p_j and q_j denoting the price and quantity of commodity j, is given by Roy's identity as

$$w_D = \nu\left(\frac{F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)}{e}\cdot\frac{D(\boldsymbol{p})}{B(\boldsymbol{p})}\right)^{\varepsilon}, \tag{3}$$

$$w_H = \theta\left(\frac{H(\boldsymbol{p})}{F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)}\right)^{1-\sigma}, \tag{4}$$

[5] Following Gorman's (1996) definition, quasi-separability groups *prices* of goods in the *expenditure function*, in contrast to direct separability which groups *quantities* of goods in the *utility function*.

$$w_B = (1-\theta)\left(\frac{B(\boldsymbol{p})}{F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)}\right)^{1-\sigma} - \nu\left(\frac{F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)}{e}\cdot\frac{D(\boldsymbol{p})}{B(\boldsymbol{p})}\right)^{\varepsilon}. \tag{5}$$

Since ε is positive, Equations (3) to (5) highlight that as the expenditure level increases, the budget share for D declines, the share for H remains unchanged, and the share for B increases. Since within-basket behavior is homothetic, it follows that D is a bundle of *necessities*, H is a bundle of *homothetic goods*, and B is a bundle of *luxuries*.

Our demand system closely follows the preferences used by Boppart (2014), but differs in two respects. First, the inclusion of homothetic goods in Equation (2) generalizes the Boppart specification, which only considers luxuries and necessities (the special case where $F(H(\boldsymbol{p}),B(\boldsymbol{p})) = B(\boldsymbol{p})$). Second, we consider a single elasticity parameter (ε) for both isoelastic terms on the right-hand side of Equation (1). Boppart specifies separate parameters for these terms to allow for both relative price effects and income effects on consumption patterns, and to separate the elasticity of substitution between B and D from the expenditure elasticity of demand for D (which are otherwise equal). Here, the presence of the homothetic basket generates similar properties: Equations (3) and (5) include both expenditure and relative price changes while the Allen-Uzawa elasticity of substitution between B and D and the expenditure elasticity of demand for D are, respectively, $1 - \frac{1-w_D}{w_B}\varepsilon$ and $1-\varepsilon$. Our simplification of the parameter set is therefore not a restriction in this regard.[6]

2.2 Cost-of-Living Index

To briefly review known results, let the minimum consumption expenditure needed to reach some utility level u when faced by a price vector $\boldsymbol{p}$ be given by the expenditure function $e = c(u,\boldsymbol{p})$. Konüs (1939) defines a cost-of-living index to be the change in minimum expenditures needed to maintain a fixed utility level as prices change from some base-period price vector $\boldsymbol{p}_s$ to a period-t price vector $\boldsymbol{p}_t$:

$$P(u,\boldsymbol{p}_t,\boldsymbol{p}_s) \equiv \frac{c(u,\boldsymbol{p}_t)}{c(u,\boldsymbol{p}_s)}. \tag{6}$$

The Konüs index (6) is independent of the reference utility level if and only if preferences are homothetic, in which case the index becomes a ratio of unit cost functions.[7] The prices of the three intermediate bundles are therefore simply

$$P_{Bt} = \frac{B(\boldsymbol{p}_t)}{B(\boldsymbol{p}_s)}, \qquad P_{Dt} = \frac{D(\boldsymbol{p}_t)}{D(\boldsymbol{p}_s)}, \qquad \text{and} \qquad P_{Ht} = \frac{H(\boldsymbol{p}_t)}{H(\boldsymbol{p}_s)}, \tag{7}$$

where the function arguments on the left-hand sides are left implicit to simplify notation. Moreover, $F\big(H(\boldsymbol{p}),B(\boldsymbol{p})\big)$ is a CES composite. Following Sato (1976) and Vartia (1976), its value in period t relative to any other period k can be written as a function of the expenditure share on H in these periods and the

[6] A separate elasticity parameter for $\frac{D(\boldsymbol{p})}{B(\boldsymbol{p})}$ is also somewhat difficult to pin down empirically. Alder, Boppart and Müller (2022), for instance, estimate a similar demand system on aggregate data for the US, the UK, Canada, and Australia and fails to find estimates in the interior of their theoretically imposed bounds. In our empirical implementation, we obtained similar results when we tried to estimate this parameter.

[7] See for instance the *Homogeneity Price Theorem* in Samuelson and Swamy (1974).

price changes of B and H: using Equations (3) to (5) it can be shown that

$$\frac{P_{Ft}}{P_{Fk}} = \frac{F\big(H(\boldsymbol{p}_t), B(\boldsymbol{p}_t)\big)}{F\big(H(\boldsymbol{p}_k), B(\boldsymbol{p}_k)\big)} = \left(\frac{P_{Bt}}{P_{Bk}}\right)^{1-\rho_{t,k}} \left(\frac{P_{Ht}}{P_{Hk}}\right)^{\rho_{t,k}}, \tag{8a}$$

where the weight on the H basket is given by

$$\rho_{t,k} = \frac{L\big(w_{Ht}, w_{Hk}\big)}{L\big(w_{Ht}, w_{Hk}\big) + L\big(1 - w_{Ht}, 1 - w_{Hk}\big)}. \tag{8b}$$

In (8b), $L(\cdot, \cdot)$ denotes the logarithmic mean, defined for positive values x and y as

$$L(x, y) = \begin{cases} \dfrac{x - y}{\ln x - \ln y} & \text{if } x \neq y, \\ x & \text{if } x = y. \end{cases} \tag{9}$$

Equation (8) is convenient because it implies that we do not need to know the two parameters σ and θ in empirical applications as long as we directly observe the expenditure shares for the H bundle.[8]

Having established the necessary foundations, we now turn to the cost-of-living index that corresponds to the indirect utility function (1). First, inverting the indirect utility function yields an expenditure function of the form

$$c(u, \boldsymbol{p}) = \Big[\big(1 - \nu + \varepsilon u\big)B(\boldsymbol{p})^{\varepsilon} + \nu D(\boldsymbol{p})^{\varepsilon}\Big]^{\frac{1}{\varepsilon}} \frac{F\big(H(\boldsymbol{p}), B(\boldsymbol{p})\big)}{B(\boldsymbol{p})}.$$

As shown by Hochmuth, Pettersson and Weissert (2024, Proposition 1), it is possible to pin down the reference utility level u in the expenditure function with the base-period expenditure share on necessities, w_{Ds}. Specifically, take the indirect utility function (1) in the base period s, substitute for u in any period-t expenditure function, and apply Equation (3). Together with the Konüs definition (6) and the price indices (7) and (8), we then obtain the PIGL cost-of-living index

$$P(u, \boldsymbol{p}_t, \boldsymbol{p}_s) = \Big[\big(1 - w_{Ds}\big)P_{Bt}^{\varepsilon} + w_{Ds}P_{Dt}^{\varepsilon}\Big]^{\frac{1}{\varepsilon}} \left(\frac{P_{Ht}}{P_{Bt}}\right)^{\rho_{t,s}}. \tag{10}$$

The cost-of-living index (10) is what is taken to the data and, to reiterate the introduction, it is a function of four components:

(i) the expenditure share w_D allocated to necessities in the *base period* s;
(ii) the expenditure share w_H allocated to homothetic goods in *both periods* s and t;
(iii) the prices of each basket; and
(iv) the single preference parameter ε.

Heterogeneity in the cost of living occurs because the expenditure share for necessities varies with the expenditure level, so richer individuals allocate a lower weight to price changes of necessities, as captured

[8] A quick derivation starts from the identity $0 = w_{Ht} - w_{Hk} + [(1 - w_{Ht}) - (1 - w_{Hk})] = L(w_{Ht}, w_{Hk}) \ln\left(\frac{w_{Ht}}{w_{Hk}}\right) + L(1 - w_{Ht}, 1 - w_{Hk}) \ln\left(\frac{1-w_{Ht}}{1-w_{Hk}}\right)$. Since Equations (3) to (5) imply that $w_H = \theta\left(\frac{H(\boldsymbol{p})}{F(H(\boldsymbol{p}),B(\boldsymbol{p}))}\right)^{1-\sigma}$ and $1 - w_H = (1-\theta)\left(\frac{B(\boldsymbol{p})}{F(H(\boldsymbol{p}),B(\boldsymbol{p}))}\right)^{1-\sigma}$, we can plug these into the logarithms and solve for $F\big(H(\boldsymbol{p}_t), B(\boldsymbol{p}_t)\big) \,/\, F\big(H(\boldsymbol{p}_k), B(\boldsymbol{p}_k)\big)$ to get Equation (8).

by P_{Dt}. Yet, this nonhomotheticity only shows up explicitly in the price index formula through the base-period allocation. Consequently, knowledge about the expenditure distribution for periods other than the base period is not needed. Expenditure shares for the H bundle are required for all periods considered, but these shares are homothetic and thus identical for everyone. They can therefore be obtained from aggregate time series in the data. This makes the PIGL cost-of-living index ideal for the present analysis. Moreover, while Equation (10) is derived for an individual household, an identical formula also holds for any group of households, in which P_{Dt} is weighted by the group's aggregate expenditure share on necessities.

The cost-of-living index (10) gives the total change in the cost of living, but it is also possible to decompose this change into individual contributions of each basket. Following Hochmuth, Pettersson and Weissert (2024, Lemma 1), the period-to-period change in the cost of living for someone with a base-period allocation w_{Ds} can be written as

$$\frac{P(u, \boldsymbol{p}_t, \boldsymbol{p}_s)}{P(u, \boldsymbol{p}_{t-1}, \boldsymbol{p}_s)} = \left(\frac{P_{Dt}}{P_{Dt-1}}\right)^{\phi_{t,t-1}(u)} \left(\frac{P_{Bt}}{P_{Bt-1}}\right)^{1-\phi_{t,t-1}(u)-\rho_{t,t-1}} \left(\frac{P_{Ht}}{P_{Ht-1}}\right)^{\rho_{t,t-1}}, \tag{11}$$

where the weight $\phi_{t,t-1}(u)$ on necessities, which varies across households, is defined as

$$\phi_{t,t-1}(u) = \frac{L\left(w^h_{Dt}, w^h_{Dt-1}\right)}{L\left(w^h_{Dt}, w^h_{Dt-1}\right) + L\left(1 - w^h_{Dt}, 1 - w^h_{Dt-1}\right)}. \tag{12}$$

In Equation (12), $L(\cdot,\cdot)$ is again the logarithmic mean (9) while w^h_{Dt} and w^h_{Dt-1} are *Hicksian* expenditure shares. That is, w^h_{Dt} and w^h_{Dt-1} are the necessity expenditure shares that prevail under period-t and period-$t-1$ prices along the indifference curve associated with the observed base-period allocation w_{Ds}. Though not directly observable, Hicksian expenditure shares are straightforward to construct for decomposition purposes: apply Shephard's lemma on the expenditure function in period $k \in \{t, t-1\}$ and use Equations (3) and (10) to get

$$w^h_{Dk} = \frac{w_{Ds} P^{\varepsilon}_{Dk}}{(1 - w_{Ds}) P^{\varepsilon}_{Bk} + w_{Ds} P^{\varepsilon}_{Dk}}. \tag{13}$$

2.3 A Nonhomothetic Törnqvist Index

It remains to parametrize the price indices for the three intermediate baskets. To that end, let $B(\boldsymbol{p})$, $D(\boldsymbol{p})$, and $H(\boldsymbol{p})$ be homogeneous translog expenditure functions. As shown by Diewert (1976), this implies that the corresponding price indices are of the Törnqvist (1936) form. That is, for each bundle $C \in \{B, D, H\}$, we have

$$\frac{P_{Ct}}{P_{Ct-1}} = \prod_{j \in J_C} \left(\frac{p_{jt}}{p_{jt-1}}\right)^{\delta^C_{j,t,t-1}}, \qquad \delta^C_{j,t,t-1} = \frac{w^C_{jt} + w^C_{jt-1}}{2}, \tag{14}$$

where $w^C_j \equiv p_j q_j \,/\, \sum_{j \in J_C} p_j q_j$ is the within-basket expenditure share. Since within-basket behavior is homothetic, these within-shares are identical across agents. The Törnqvist weights can therefore be constructed from aggregate data, just like the weight on the H basket in Equation (10).

With Equation (14) and Assumption 1, the overall price index becomes a two-stage index with a Törnqvist form at the bottom and a Sato-Vartia form at the top. Both index forms belong to the class of superlative price indices (Diewert, 1976; Barnett and Choi, 2008), which are known to exhibit the property of "approximate consistency in aggregation" (Diewert, 1978).[9] We should therefore expect the cost-of-living index to behave approximately as if quasi-separability was not imposed, thus highlighting that Assumption 1 is arguably not a strong restriction. Quasi-separable structures are also common in official statistics. The PCE price index, for instance, first combines "Electricity" and "Natural gas" into a price index for "Electricity and gas", and "Water supply and sewage maintenance" and "Garbage and trash collection" into a price index for "Water supply and sanitation". "Electicity and gas" and "Water supply and sanitation" are then combined into an index for "Household utilities", and so on.

The geometric-mean representation of Equations (11) and (14) also makes it straightforward to decompose the overall change in the cost of living into contributions of individual commodities, which is useful in applications. While the same is true for any other homothetic geometric-mean parametrization of P_{Ct}/P_{Ct-1}, the Törnqvist index is particularly neat because Equations (11) and (14) then nest the standard Törnqvist index as a homothetic limit case. We finish the section by stating this as a formal result, since it generalizes Proposition 4 in Hochmuth, Pettersson and Weissert (2024) to include the homothetic bundle H.

Proposition 1. *Let $B(\boldsymbol{p})$, $D(\boldsymbol{p})$, and $H(\boldsymbol{p})$ be homogeneous translog expenditure functions. If $\varepsilon \to 0$ and $\sigma \to 1$, then the PIGL cost-of-living index (11) becomes the standard Törnqvist index:*

$$\frac{P(u,\boldsymbol{p}_t,\boldsymbol{p}_s)}{P(u,\boldsymbol{p}_{t-1},\boldsymbol{p}_s)} = \prod_{j\in J}\left(\frac{p_{jt}}{p_{jt-1}}\right)^{\delta_{j,t,t-1}}, \qquad \delta_{j,t,t-1} = \frac{w_{jt}+w_{jt-1}}{2},$$

where $J = J_D \cup J_B \cup J_H$ is the full set of commodities available and $w_j = p_j q_j \,/\, e$ is the total expenditure share of commodity j.

Proof. If $\varepsilon \to 0$ and $\sigma \to 1$, the indirect utility function (1) becomes Cobb-Douglas: $V(e,\boldsymbol{p}) = \ln e - \ln\left[D(\boldsymbol{p})^{\nu}B(\boldsymbol{p})^{1-\theta-\nu}H(\boldsymbol{p})^{\theta}\right]$. The cost-of-living index between periods t and $t-1$ is then given by $\left(P_{Dt}/P_{Dt-1}\right)^{\nu}\left(P_{Bt}/P_{Bt-1}\right)^{1-\theta-\nu}\left(P_{Ht}/P_{Ht-1}\right)^{\theta}$, where the weights are homothetic, time-invariant expenditure shares: $\nu = w_D$, $1-\theta-\nu = w_B$, and $\theta = w_H$. Substituting in (14), the weight on good j in bundle C becomes $w_C\,\delta^C_{j,t,t-1} = (w_{jt}+w_{jt-1})/2$, since $w_j = w_C\,w^C_j$ holds by definition under Assumption 1. □

3 Data and Empirical Implementation

This section applies the theory above to aggregate US data on consumption expenditures and prices. The goal is to construct a nonhomothetic version of the PCE price index, which is the consumption deflator in the US national accounts and the main inflation measure for US monetary policy. All in all, the analysis requires no more than six publicly available tables from the US Bureau of Economic Analysis (BEA), three

[9] A price index can be calculated either by first computing indices for subsets of product categories and subsequently aggregating the resulting index numbers into an overall price index—like our index does here—or by directly combining all elementary categories in one go. If these approaches produce the same index number, the index is said to be consistent in aggregation (see Balk, 2008, ch. 3.7).

from the National Income and Product Accounts (NIPA) and another three from the Regional Economic Accounts (REA), which we combine with distributional PCE estimates of Garner *et al.* (2022).

The implementation strategy exploits the separability structure of the theoretical model, in which a good belongs to one and only one of the three commodity bundles. Under such separability, the overall basket expenditure shares (w_C) and the individual within-basket expenditure shares (w_j^C) can be inferred directly from the observed expenditure shares on individual goods (w_j) once we know the sets of goods that belong to each basket. These sets of goods can be identified via the fact that one basket is a bundle of necessities, one is a bundle of luxuries, and one is a bundle of homothetic goods: simply investigate the Engel curves of individual goods and classify them as necessity, luxury, or homothetic based on the slopes of the Engel curves. Following Hochmuth, Pettersson and Weissert (2024), the empirical procedure can then be summarized by the following steps:

(i) classify each individual good considered as “necessity”, “luxury”, or “homothetic”;
(ii) construct the Törnqvist price index (14) for each of the three baskets using within-basket expenditure shares for the sets of commodities identified in (i);
(iii) estimate ε using the expenditure share equation (3); and
(iv) for a given base-period expenditure distribution, construct the corresponding PIGL cost-of-living indices using (ii) and (iii).

The subsections below cover these steps in turn and provide additional detail on the data used in this regard.

3.1 Data on US Personal Consumption Expenditures and Prices

The classification of goods and the parameter estimation relies on annual PCE data by US state, which are available from 1997 onward in REA Table SAPCE3 and include details on over 70 separate consumption categories at the lowest level of product aggregation. These classification exercises also make adjustments for price differences across states with the regional price parities (RPPs) reported in REA Table SARPP, which are available at an annual frequency starting in 2008 for four broad expenditure groups (goods, housing, utilities, and other services). Rather than limiting us to this subsample starting in 2008, we manually extend the RPPs back in time using city-, region-, and category-specific CPI series matched to each state.[10] For example, we use the commodities CPI series for Seattle-Tacoma-Bellevue, WA, to extrapolate Washington's RPP for goods, and so on; whenever a state has no matching CPI city, we use the corresponding region's CPI series. This RPP extension adds another 11 years of data, thus allowing us to fully exploit all PCE data from 1997.[11]

Additionally, we construct the cost-of-living indices themselves over a 65-year period from January 1959 to December 2023 using monthly time series on aggregate US expenditures and prices for each consumption category. These data are provided in the BEA's underlying detail tables, NIPA Tables 2.4.4U and 2.4.5U. All expenditures in these sources and in the paragraph above are converted into per-capita terms using the population estimates reported in REA Table SAINC1 and NIPA Table 2.6.

[10] RPPs are relative prices of a state compared to the US average: $RPP_{i,t} = P_{i,t} \,/\, P_{US,t}$. It is thus possible to back out the RPP in some period given knowledge of inflation rates and an RPP benchmark level in some other period, say 2008, via $RPP_{i,t} = \frac{P_{i,t} \,/\, P_{i,2008}}{P_{US,t} \,/\, P_{US,2008}} RPP_{i,2008}$.

[11] Using only the 2008-onward sample with official RPPs, our main results remain substantively unchanged, confirming that our RPP extensions do not materially affect our conclusions.

We exclude four consumption categories from the analysis and subtract these from the expenditure totals: net expenditures abroad by US residents, net foreign travel, internet access, and final consumption expenditures of nonprofit institutions serving households. The first two are dropped because their expenditures are not guaranteed to be positive and because the BEA does not provide any corresponding price indices to use. We remove internet access because it only exists in the BEA data from 1988 on. The last category is excluded from the distributional PCE estimates by Garner *et al.* (2022), and is consequently also dropped here. These restrictions result in a data set with 71 distinct product groups that cover between 96 and 98 percent of total US personal consumption expenditures during our sample period.

3.2 Classification of Goods and Basket Price Indices

The classification of a good is implemented by investigating the slope of budget-share Engel curves implied from the cross-sectional variation in consumption expenditures across US states. As in, for instance, Wachter and Yogo (2010), Orchard (2022), and Hochmuth, Pettersson and Weissert (2024), the classification relies on a simple allocation rule: a good is classified as a necessity if the slope of its estimated Engel curve is negative and statistically significant at the 5 percent level, as a luxury if the slope is positive and similarly significant, and otherwise considered a homothetic good.

The Engel curve of a product j is estimated across states g and years t by regressing the state-level aggregate expenditure share $\overline{w}_{jgt}$ on the corresponding per-capita consumption expenditure $\bar{e}_{gt}$, according to a reduced-form model

$$\overline{w}_{jgt} = \alpha_{jr} + \alpha_{jt} + \beta_{je} \ln \bar{e}_{gt} + \beta_{jp} \ln RPP_{jgt} + u_{jgt}. \tag{15}$$

In this regression, α_{jr} is a dummy for the BEA region in which a state is located, α_{jt} is a good-j time fixed effect, RPP_{jgt} is a price parity adjustment across states, and u_{jgt} is an error term. We also weigh states by population size in each year.

In Equation (15), the regional fixed effects control for permanent differences in consumption patterns across regions that are unrelated to nonhomotheticity. It would for instance be bold to claim that nonhomothetic preferences alone explain why a landlocked region such as the Rocky Mountain Region exhibits lower expenditure shares on water transportation than, say, the Great Lakes Region, and the regional dummies mitigate these concerns while still allowing us to exploit the cross-sectional variation in the state data. The time-fixed effects control for aggregate changes in relative prices between goods and for any other common macro shocks, while the regional price parities similarly control for differences in relative prices across states and their evolution over time. These controls are also important, because all else equal we expect the expenditure share of a good to vary across years and states for which its relative price is different, even in the absence of nonhomothetic behavior.

Table 1 reports the 71 expenditure categories that we consider and their corresponding Engel slope estimate and resulting classification. The table also includes the average expenditure share of each good at the aggregate US level for our 1997–2023 classification sample. In total, we obtain 31 necessities, 33 luxuries, and 7 homothetic goods, and most of these are highly intuitive.[12] Goods (especially nondurables) are generally classified as necessities while services are luxuries broadly speaking. This pattern is consistent

[12] Table B.4 in Online Appendix B shows that our classification is largely unchanged if we consider the smaller 2008–2023 state sample with only the BEA's official RPPs, or if we include additional demographic controls. The former only impacts "Rental value of farm dwellings" and "Physician services", leaving over 95 percent of expenditures unchanged, while the latter mainly increases standard errors and thus classifies more categories as homothetic.

Table 1. Engel curve classification from 1997–2023 state PCE data.

PCE category	PCE share (in percent)	Engel slope Coefficient	Engel slope Std. Error	Classification
Motor vehicles and parts				
New motor vehicles	2.38	−0.006***	(0.001)	Necessity
Net purchases of used motor vehicles	1.26	−0.010***	(0.001)	Necessity
Motor vehicle parts and accessories	0.62	−0.005***	(0.000)	Necessity
Furnishings and durable household equipment				
Furniture and furnishings	1.58	0.006***	(0.000)	Luxury
Household appliances	0.49	−0.001***	(0.000)	Necessity
Glassware, tableware, and household utensils	0.38	0.004***	(0.000)	Luxury
Tools and equipment for house and garden	0.28	−0.002***	(0.000)	Necessity
Recreational goods and vehicles				
Video, audio, photographic, and information processing equipment and media	1.90	0.029***	(0.001)	Luxury
Sporting equipment, supplies, guns, and ammunition	0.58	−0.004***	(0.001)	Necessity
Sports and recreational vehicles	0.52	0.000	(0.001)	Homothetic
Recreational books	0.22	0.000	(0.001)	Homothetic
Musical instruments	0.05	0.000***	(0.000)	Luxury
Other durable goods				
Jewelry and watches	0.61	0.005***	(0.000)	Luxury
Therapeutic appliances and equipment	0.50	−0.004***	(0.000)	Necessity
Educational books	0.08	0.001***	(0.000)	Luxury
Luggage and similar personal items	0.23	0.003***	(0.000)	Luxury
Telephone and related communication equipment	0.17	0.001**	(0.000)	Luxury
Food and beverages purchased for off-premises consumption				
Food and nonalcoholic beverages purchased for off-premises consumption	6.86	−0.033***	(0.002)	Necessity
Alcoholic beverages purchased for off-premises consumption	1.15	0.003***	(0.000)	Luxury
Food produced and consumed on farms	0.00	0.000***	(0.000)	Necessity
Clothing and footwear				
Women's and girls' clothing	1.52	−0.002	(0.001)	Homothetic
Men's and boys' clothing	0.91	−0.004***	(0.001)	Necessity
Children's and infants' clothing	0.17	−0.001***	(0.000)	Necessity
Other clothing materials and footwear	0.69	−0.003***	(0.000)	Necessity
Gasoline and other energy goods				
Motor vehicle fuels, lubricants, and fluids	2.73	−0.043***	(0.002)	Necessity
Fuel oil and other fuels	0.21	−0.003***	(0.000)	Necessity
Other nondurable goods				
Pharmaceutical and other medical products	3.24	−0.034***	(0.002)	Necessity
Recreational items	1.43	−0.009***	(0.000)	Necessity
Household supplies	1.10	−0.003***	(0.000)	Necessity
Personal care products	1.05	0.006***	(0.000)	Luxury
Tobacco	0.88	−0.008***	(0.001)	Necessity
Magazines, newspapers, and stationery	0.59	0.004***	(0.001)	Luxury
Housing and utilities				
Rental of tenant-occupied nonfarm housing	3.61	−0.039***	(0.004)	Necessity
Imputed rental of owner-occupied nonfarm housing	12.14	0.012	(0.008)	Homothetic
Rental value of farm dwellings	0.17	0.000	(0.000)	Homothetic
Group housing	0.02	0.001***	(0.000)	Luxury
Water supply and sanitation	0.76	−0.005***	(0.000)	Necessity
Electricity	1.47	−0.016***	(0.001)	Necessity
Natural gas	0.49	−0.009***	(0.001)	Necessity
Health care				
Physician services	4.03	−0.003*	(0.001)	Necessity

Continued on the next page

Table 1. Engel curve classification from 1997–2023 state PCE data. (Cont.)

PCE category	PCE share (in percent)	Engel slope Coefficient	Engel slope Std. Error	Classification
Dental services	0.99	−0.003***	(0.000)	Necessity
Paramedical services	2.62	0.004*	(0.002)	Luxury
Hospitals	7.47	−0.084***	(0.003)	Necessity
Nursing homes	1.40	−0.013***	(0.001)	Necessity
Transportation services				
Motor vehicle maintenance and repair	1.44	0.001	(0.001)	Homothetic
Other motor vehicle services	0.73	0.004***	(0.001)	Luxury
Ground transportation	0.38	0.004***	(0.001)	Luxury
Air transportation	0.75	0.017***	(0.001)	Luxury
Water transportation	0.03	0.000***	(0.000)	Necessity
Recreation services				
Membership clubs, sports centers, parks, theaters, and museums	1.45	0.015***	(0.001)	Luxury
Audio-video, photographic, and information processing equipment services	1.03	0.006***	(0.001)	Luxury
Gambling	1.07	0.005***	(0.001)	Luxury
Other recreational services	0.45	0.005***	(0.000)	Luxury
Food services and accommodations				
Purchased meals and beverages	5.53	0.006***	(0.001)	Luxury
Food furnished to employees (including military)	0.16	−0.001***	(0.000)	Necessity
Accommodations	0.98	0.010***	(0.001)	Luxury
Financial services and insurance				
Financial services furnished without payment	2.45	0.012***	(0.001)	Luxury
Financial service charges, fees, and commissions	2.56	0.019***	(0.001)	Luxury
Life insurance	0.77	0.005***	(0.000)	Luxury
Net household insurance	0.08	0.000***	(0.000)	Luxury
Net health insurance	1.52	0.006**	(0.002)	Luxury
Net motor vehicle and other transportation insurance	0.61	0.004***	(0.001)	Luxury
Other services				
Telecommunication services	1.41	0.008***	(0.001)	Luxury
Postal and delivery services	0.12	0.000*	(0.000)	Necessity
Higher education	1.34	−0.007***	(0.002)	Necessity
Nursery, elementary, and secondary schools	0.35	0.000	(0.000)	Homothetic
Commercial and vocational schools	0.39	0.006***	(0.000)	Luxury
Professional and other services	1.58	−0.007***	(0.001)	Necessity
Personal care and clothing services	1.16	0.018***	(0.001)	Luxury
Social services and religious activities	1.46	0.017***	(0.003)	Luxury
Household maintenance	0.66	0.006***	(0.000)	Luxury

Notes. The "PCE share" column shows the 1997–2023 average of each good's share of total US personal consumption expenditures on the 71 categories we include. The remaining columns report the slope coefficients from regressing state-level expenditure shares on the corresponding level of logarithmized personal consumption expenditures per capita (with state-by-year clustered standard errors in parentheses) and the resulting classification as necessity, luxury, or homothetic. Each estimation controls for year fixed effects, BEA region fixed effects, and interstate price differences through regional price parities. States are weighted by relative population size. *, **, and *** denote statistical significance at the 5 percent, 1 percent, and 0.1 percent levels.

with the macro evidence on structural transformation.[13] For comparable individual categories, Table 1 aligns with classifications in similar analyses such as Wachter and Yogo (2010) and Orchard (2022) as well. Overall, these observations suggest that our approach works well on the state PCE data.

In using these Engel curve classifications in our cost-of-living index calculations, we implicitly assume that the cross-state variation identifying the slope in Equation (15) also identifies its household-level counterpart. This need of course not be the case: Getzen (2000), for instance, highlights that healthcare often appears to be a luxury in aggregate data (driven by between-group variation) but a necessity in microdata (driven by within-group variation). For this particular expenditure group then, it is reassuring that we find most healthcare categories to indeed be classified as necessities. In general, however, we cannot rule out such aggregation bias. As a sensitivity check, we therefore consider the Consumer Expenditure Survey data and product categories from Hochmuth, Pettersson and Weissert (2024) and estimate (15) on aggregated expenditures per capita across states and years. The resulting necessity-luxury split closely matches what they obtain directly from the microdata (see Table B.2 in Online Appendix B), thus suggesting that aggregation bias is likely of limited concern in this context.

Moreover, since we estimate Engel curves using 1997–2023 data but apply the resulting classifications over a much longer period of time, a natural concern is whether these classifications remain valid throughout this extended period. Engel slopes may flatten, steepen, or even change sign as incomes rise over time, as argued, for instance, by Moneta and Chai (2014). However, let us reiterate here that our cost-of-living index does not rely on the exact slope estimates reported in Table 1; we only use their signs to label goods as necessities, luxuries, or homothetic. It therefore does not matter whether Engel curves flatten or steepen over time.[14] This stands in contrast to approaches such as Oulton's (2008, 2012), where the estimated elasticities directly enter the cost-of-living index calculations and are thus more vulnerable to this issue.

Changes in the signs of slopes are potentially a more serious concern, since that would alter our classifications. While assessing this issue with PCE state data alone is difficult given the limited historical coverage of such data, other sources offer some insight. In particular, Aguiar and Bils (2011, 2015) provide IV estimates of a demand system covering 20 goods based on Consumer Expenditure Survey data for four separate periods: 1972–1973, 1980–1982, 1994–1996, and 2008–2010. The reported expenditure elasticities remain highly consistent over time: the correlation between their 1994–1996 benchmark elasticities and the other periods are, respectively, 0.90, 0.90, and 0.96. These findings clearly point to stable Engel curves in the United States across these years.

The classification in Table 1 yields basket expenditure shares at the aggregate US level that are shown in Figure 1a. As expected under sustained economic growth, the expenditure share on homothetic goods remains stable while the necessity share trends downwards. Over the full sample period, the necessity share declines by around 10 percentage points. Dividing individual expenditure shares by these basket shares generates the within-basket shares needed to compute the Törnqvist index (14) for each bundle. The resulting price indices are shown in Figure 1b together with the official PCE price index for reference.

[13] See for instance Boppart (2014), Herrendorf, Rogerson and Valentinyi (2014), Comin, Lashkari and Mestieri (2021), and Alder, Boppart and Müller (2022).

[14] In relation to the specific findings in Moneta and Chai (2014), it is furthermore unclear how their results relate to our classification: (i) they examine Engel curves in levels, which do not necessarily translate to similar conclusions for budget-share Engel curves; and (ii) they analyze UK data for 12 broad product categories, while we use US data at a more disaggregated product level.

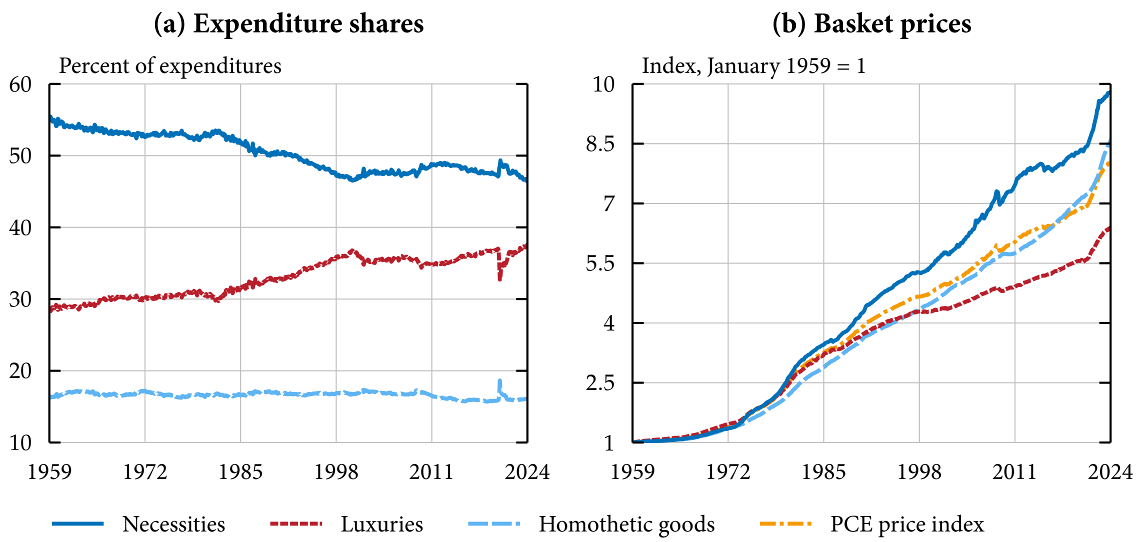

Figure 1. Constructed US time series, Jan 1959 to Dec 2023.

These indices reveal that the price of necessities relative to luxuries has increased by about 50 percent since 1959, which likely explains the flat trend in both necessity and luxury shares since the late 1990s.

3.3 Estimation of Preference Parameters

We estimate the preference parameter ε using the same cross-state variation as for the classification. In doing so, we exploit that PIGL preferences consistently aggregate individual-level expenditure shares into market-level expenditure shares as functions of per-capita expenditures. Specifically, for any measure N of consumers (indexed by h below) facing the same prices, the corresponding aggregate necessity share $\overline{w}_D$ is defined as the expenditure-weighted average of individual-level expenditure shares. This definition together with Equations (3), (7) and (8) generates an aggregate expenditure share in some implicit time period of the form

$$\overline{w}_D \equiv \frac{1}{N}\int_0^N \frac{e_h}{\overline{e}}\, w_{Dh}\, dh = \widetilde{\nu}\kappa^{-\varepsilon}\left(\frac{P_F}{\overline{e}}\cdot\frac{P_D}{P_B}\right)^{\varepsilon}, \tag{16}$$

where $\overline{e}$ is the expenditure level per person within the group, $\widetilde{\nu} \equiv \nu\left[F\left(H(\boldsymbol{p}_s), B(\boldsymbol{p}_s)\right)D(\boldsymbol{p}_s)/B(\boldsymbol{p}_s)\right]^{\varepsilon}$ is a scale parameter, and the aggregation factor

$$\kappa = \left[\frac{1}{N}\int_0^N \left(\frac{e_h}{\overline{e}}\right)^{1-\varepsilon} dh\right]^{-\frac{1}{\varepsilon}} \tag{17}$$

is a scale-invariant inequality measure. It is therefore possible to estimate ε from macro data without aggregation bias.

Taking logs of Equation (16) consequently allows us to run a linear fixed-effects regression on state-level necessity shares, per-capita expenditures, and prices.[15] Assuming that the aggregation factors (17) are

[15] Obvious caveats here include a potential simultaneous equation bias between expenditure shares and prices, and potential measurement errors on expenditures and prices. Fully addressing these issues is beyond the scope of the paper, though the final part of the paper includes a sensitivity analysis on the value for ε.

Table 2. Preference parameters estimated from US state-level data.

	(1)	(2)	(3)	(4)
ε	0.647*** (0.020)	0.792*** (0.033)	0.657*** (0.021)	0.574*** (0.018)
Excluding durables[a]			✓	
Demographic controls				✓
Observations	1,377	816	1,377	1,377
Within R^2	0.574	0.608	0.570	0.609

Notes. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at the 5 percent, 1 percent, and 0.1 percent levels. Column (2) uses only the official regional price parities published by the BEA, column (3) excludes durables, and column (4) adds additional controls for the state age structure. States are weighted by relative population size. To construct basket prices and expenditure shares, column (3) uses the baseline classification in Table 1 whereas columns (2) and (4) use their own classifications corresponding to the cases in Table B.4 in Online Appendix B.

[a] Motor vehicles and parts, furnishings and durable household equipment, recreational goods and vehicles, and other durable goods.

uncorrelated with expenditures and prices beyond what is captured by any fixed effects,[16] we obtain the estimating equation

$$\ln \overline{w}_{Dgt} \;=\; \alpha_r + \alpha_t + \varepsilon \ln \left[\frac{P_{Fgt}}{\bar{e}_{gt}} \cdot \frac{P_{Dgt}}{P_{Bgt}} \right] + u_{gt}, \tag{18}$$

where α_r and α_t again denote region and time fixed effects, P_{Fgt}, P_{Dgt}, and P_{Bgt} are basket price indices for state g in year t, and u_{gt} is an error term. To construct the price indices, we first compute state and category-specific prices by adjusting the PCE price indices for all 71 product categories with the corresponding RPP adjustment factors and then apply the formulas in Section 2 on these prices together with the state-level expenditure shares.

Table 2 reports the results of estimating Equation (18) on state PCE data. The first column shows our preferred estimate of ε, which we use when constructing the nonhomothetic PCE price indices. The remaining columns report how this estimate changes under various adjustments: column (2) considers only years in which the official BEA RPPs are available to gauge how sensitive the estimation is to our own RPP extensions; column (3) excludes durable goods, which is a useful consideration as these categories include investment-good properties that may interfere with our notion of consumption; and column (4) includes additional controls for the population age composition in each state, as reported by the US Census Bureau. This last alternative is motivated by Cravino, Levchenko and Rojas (2022), who identify population aging as an important driver of aggregate US structural transformation from goods to services (and consequently, from necessities to luxuries).

We find an ε of 0.647 in our benchmark regression, with homothetic preferences ($\varepsilon = 0$) being clearly rejected. This estimate lies close to previous work: considering virtually identical PIGL demand systems, Alder, Boppart and Müller (2022) estimate ε to 0.71 using twentieth-century macro data for the United States, whereas Hochmuth, Pettersson and Weissert (2024) find a value of 0.677 with CEX microdata. As in Boppart (2014), excluding durables marginally increases ε. Zooming in on the 2008–2023 subsample could be an improvement due to higher-quality RPP estimates, or the opposite due to fewer observations;

[16] Figure B.4 in Online Appendix B plots estimates of $\kappa^{-\varepsilon}$ at the US state level using the same CEX data as in Hochmuth, Pettersson and Weissert (2024), and shows little variation across states, with $\kappa^{-\varepsilon}$ ranging between 0.96 and 1 with an average of 0.98.

we nevertheless find that it too increases ε, to 0.792. Consistent with Cravino, Levchenko and Rojas (2022), controlling for age lowers the degree of nonhomotheticity, thus suggesting that age-specific tastes explain some of the observed consumption patterns. The estimate for ε remains significantly different from zero though, and in a similar ballpark as our benchmark. Taken together, these econometric results point to a value for ε somewhere between 0.5 and 0.8, with our benchmark being close to the midpoint of this range.

3.4 Base-Period Distribution of US Personal Consumption Expenditures

The basket prices and the parameter value for ε allow us to compute the PIGL cost-of-living index for a given base-period expenditure share on necessities. This, in turn, is sufficient to analyze aggregate changes in the cost of living using the expenditure shares in Figure 1, or to answer questions about cost-of-living changes for hypothetical groups or individuals with some given expenditure levels. To obtain empirically relevant estimates of cost-of-living inequality, however, we need information about the distribution of base-period expenditures. Until recently, no such PCE data existed, but a recent paper by Garner *et al.* (2022) bridges this gap by distributing PCE spending in 2019 across US households, which we consequently use as base year here.[17] These estimates divide aggregate spending by decile in the expenditure distribution, both for total expenditures and for 15 broad commodity groups. The former also includes expenditure shares for the top 1 and 5 percent of the distribution.

Garner *et al.*'s (2022) breakdown into deciles and into 15 commodity groups is too coarse to directly infer household-level expenditure shares on the necessity basket identified in Table 1. Fortunately, the theoretical model predicts a direct link between expenditure shares at the household level, the corresponding aggregate expenditure share, and the overall distribution of consumption expenditures. Denote the Lorenz curve associated with the expenditure distribution by $\ell(x)$, where x is the expenditure rank, and its derivative with respect to the rank by $\ell'(x)$. Evaluated at the rank x_h of household h, this derivative satisfies $\ell'(x_h) = e_h \,/\, \bar{e}$. Using the individual expenditure share (3) and the aggregate expenditure share (16) then yields

$$w_{Dh} \;=\; \frac{w_{Dh}}{\overline{w}_D}\,\overline{w}_D \;=\; \left(\frac{e_h}{\bar{e}\kappa}\right)^{-\varepsilon}\overline{w}_D \;=\; \left(\frac{\ell'(x_h)}{\kappa}\right)^{-\varepsilon}\overline{w}_D. \tag{19}$$

Similarly, by Equation (17), the aggregation factor κ in (19) can be written

$$\kappa \;=\; \left[\int_0^1 \ell'(x)^{1-\varepsilon}\,dx\right]^{-\frac{1}{\varepsilon}}, \tag{20}$$

by change of integration variable. Thus, the Lorenz curve $\ell(x)$, an empirically observed aggregate expenditure share $\overline{w}_D$ and a parameter value for ε are sufficient to impute all base-period expenditure shares at the individual level.[18]

We therefore use the estimates by Garner *et al.* (2022) to construct a consumption Lorenz curve. To that end, we follow Sitthiyot and Holasut's (2021) suggestion and parameterize $\ell(x)$ as a weighted average

[17] Since our initial analysis, similar estimates have been constructed for additional years. These estimates can be downloaded from the webpage of the US Bureau of Labor Statistics.

[18] A similar prediction holds for a group, say a decile d, over a distribution interval $[x_{d0}, x_{d1}]$. Then $\Delta\ell_d \,/\, \Delta x_d = \bar{e}_d \,/\, \bar{e}$, where $\bar{e}_d$ is group-d average expenditures and $\Delta\ell_d = \ell(x_{d1}) - \ell(x_{d0})$, $\Delta x_d = x_{d1} - x_{do}$. The aggregate expenditure share of the group becomes $\overline{w}_d = \left(\frac{\Delta\ell_d/\Delta x_d}{\kappa/\kappa_d}\right)^{-\varepsilon}\overline{w}_D$, where κ_d is a group-specific aggregation factor given by $\kappa_d = \left[\frac{1}{\Delta x_d}\int_{x_{d0}}^{x_{d1}}\left(\frac{\ell'(x)}{\Delta\ell_d/\Delta x_d}\right)^{1-\varepsilon}dx\right]^{-1/\varepsilon}$.

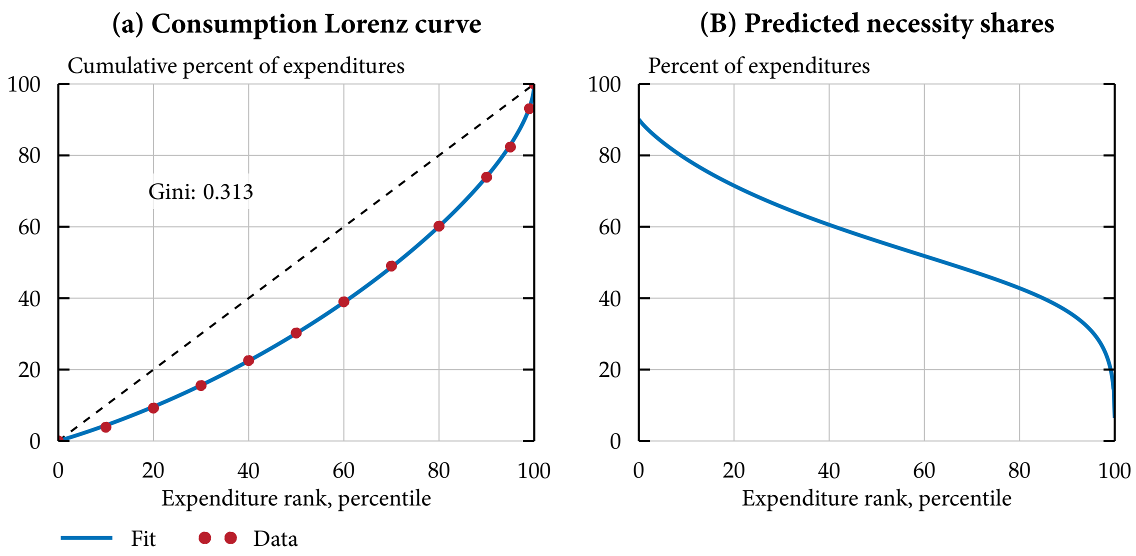

Figure 2. Estimated US consumption profiles for the base year 2019.

between an exponential function and the functional form implied by the Pareto distribution: $\ell(x) = (1-\omega)x^{\eta} + \omega\big(1-(1-x)^{1/\eta}\big)$, where ω and η are parameters to estimate. Fitting this function to the distributional PCE data yields the Lorenz curve that fits the data near perfectly, as shown in Figure 2a. Figure 2b shows the corresponding expenditure share predictions from Equations (19) and (20). Together with the basket prices in Figure 1b and the parameter value for ε, these shares yield the nonhomothetic PCE price indices that underlie the results in the next section.

4 PCE Inflation Across the Expenditure Distribution

Unlike most other approaches to measuring inflation inequality, a key benefit of the PIGL cost-of-living index is that it can be implemented without requiring detailed microdata for every period of consideration.[19] Once constructed, the nonhomothetic PCE price index therefore easily sheds light on the very latest inflation developments as well as on long-run changes. In this section, we discuss these two cases in turn.

4.1 Long-Run Inflation Inequality

Starting with the full sample period from 1959 to 2023, we find larger increases in the cost of living for consumption-poor households over the last 65 years. Figure 3 summarizes this empirical long-run result. Qualitatively, this comes as no surprise in light of the increasing relative price of necessities shown in Figure 1b, since poorer households attach higher weights to necessities than the rich do. Quantitatively, Figure 3b displays average annual inflation rates that decrease monotonically with the base-period expenditure level from 3.6 percent per year at the very bottom of the distribution to less than 3.1 percent per year at the very top. Heterogeneous changes in the cost of living therefore generate persistent inflation inequality across the entire expenditure distribution.

[19] The only other method we are aware of that is applicable in our setting is that of Oulton (2008, 2012). In Online Appendix A, we apply his approach to our PCE data. Although this method appears quantitatively sensitive to different implementation choices, it always generates the same qualitative conclusions as in this section.

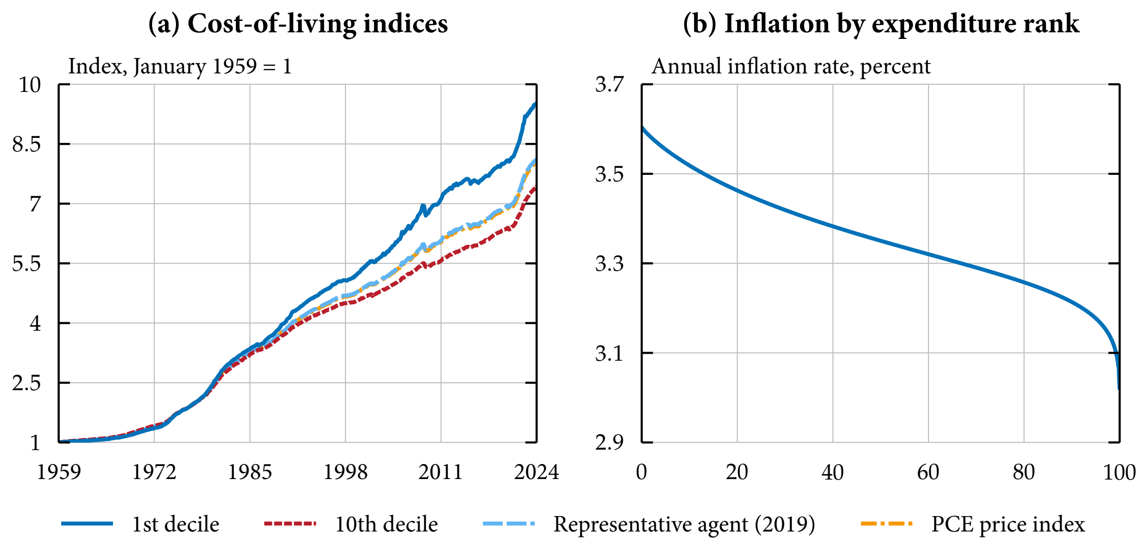

Figure 3. Long-run inflation inequality.

Notes. "Representative agent (2019)" refers to the cost-of-living index that uses the aggregate US expenditure share on necessities in 2019 as index weight.

Figure 3a illustrates the dynamics of the cost-of-living indices for selected expenditure groups. The figure shows cumulative increases in the cost of living of 850 percent for the bottom ten percent of the expenditure distribution and 639 percent for the top ten percent. The gap of 211 percentage points corresponds to a 0.41 percentage point difference in average annual inflation rates between these groups. These differences are consistent with Jaravel and Lashkari (2024), the one study we know of that focuses on long-run changes for the United States, who find near-identical inflation inequality between 1955 and 2019 using CEX data. Our analysis consequently reinforces these trends with PCE data.

How much should we care about these long-run developments? After all, a 0.41 percentage point inflation difference may not sound like much in a given year. But small annual differences have large impacts on real consumption measures in the long run. To illustrate, note that the ratio between the official PCE price index and the nonhomothetic PCE cost-of-living index for any individual or group is the percentage change in estimated real consumption growth for that individual or group when switching deflator from the former to the latter.[20] Figure 3a therefore reveals that real consumption growth between 1959 and 2019, measured in 1959 reference prices, is about 15 percent lower for the bottom decile and 8 percent higher for the top decile than what a common homothetic deflator suggests. Real consumption inequality, as measured by the 90/10 percentile ratio, consequently grows by 26 percent more over this period than it does if we ignore the inequality in cost-of-living changes.

4.2 Inflation Inequality in the Recent Inflation Surge

Amid concerns in the public debate that the recent cost-of-living crisis fell hardest on low-income households, we next ask whether the long-run inflation disparities carry over to the 2021–2023 inflation surge. To that end, Figure 4 reports annualized PCE inflation rates between January 2020 and December 2023 for the same groups considered in Figure 3a. While the inflation dynamics of the nonhomothetic PCE

[20] For a given change in nominal expenditures e_t/e_s between periods s and t, real growth measured in period-t prices is given by the quantity index $Q(u_t, u_s, \boldsymbol{p}_t) = (e_t/e_s)\,/\,P(u_s, \boldsymbol{p}_s, \boldsymbol{p}_t)$, where u_s and u_t are the utility levels corresponding to e_s and e_t. Abusing notation, denote the official PCE price index and its associated quantity index by $P^{PCE}_{s,t}$ and $Q^{PCE}_{s,t} = (e_t/e_s)\,/\,P^{PCE}_{s,t}$. The change in real expenditure growth from switching deflators is then $Q(u_t, u_s, \boldsymbol{p}_t)/Q^{PCE}_{s,t} = P^{PCE}_{s,t}/P(u_s, \boldsymbol{p}_s, \boldsymbol{p}_t)$.

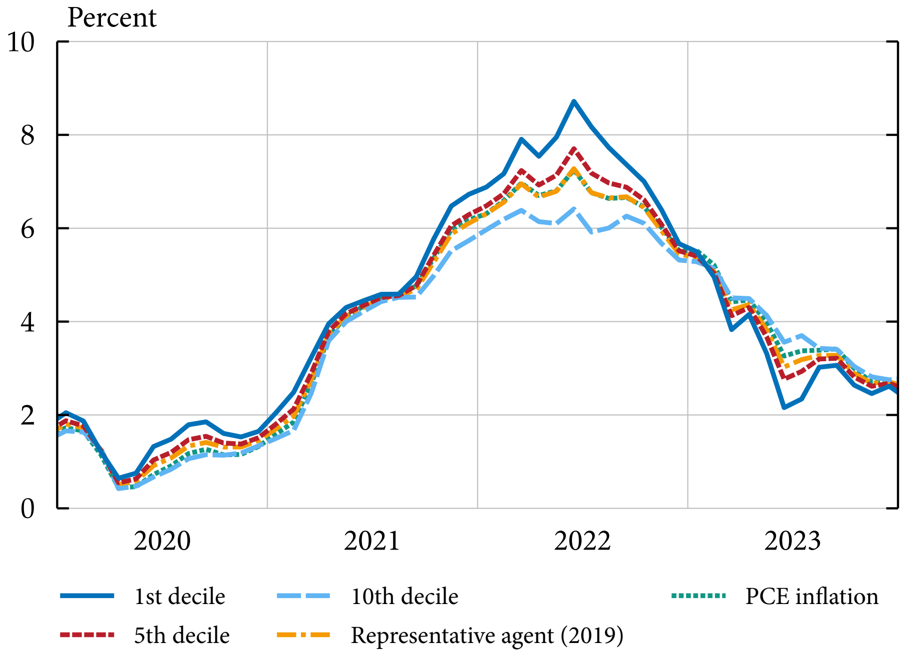

Figure 4. Annual PCE inflation rates during the inflation surge.

Notes. "Representative agent (2019)" refers to the inflation implied from the cost-of-living index that uses the aggregate expenditure share on necessities in 2019 as weight.

measures closely follow official PCE inflation, we find that as inflation takes off in 2021, then so does the gap between rich and poor. Throughout 2022, the bottom decile experiences inflation rates that exceed those of the top decile by on average 1.3 percentage points, ultimately peaking at 2.3 percentage points in June 2022 before contracting. This gap is roughly an order of magnitude larger than those found in comparable pre-2021 analyses, such as Jaravel (2019), Argente and Lee (2021), and Klick and Stockburger (2021), thus underscoring that concerns about the disproportionate impact on low-income households during the inflation surge are indeed legitimate.

To get an idea of what the entire cross-sectional distribution of inflation rates looks like, Figure 5 plots the density of inflation rates and the variation along the full expenditure distribution in June 2022. The distribution in Figure 5a exhibits a mean and standard deviation of 7.76 and 0.87 percent, which implies that around 70 percent of inflation rates fall within a narrow band of 6.9 to 8.6 percent.[21] This is also the month with the largest inflation disparities, for which Figure 5b shows an inflation rate gap of up to three percentage points between the very poorest and richest—in stark contrast to the 0.5–0.6 percentage point gap in Figure 3 for the entire sample period.

What are the underlying sources of these inflation disparities? The negative relationship between the inflation rate and the consumption expenditure level in Figure 4 again points to an increasing relative price of necessities, just as in the long-run case. We can provide a more exact breakdown than this, however, since the PIGL cost-of-living index features a complete decomposition of the contributions of individual products. Using this property, Figure 6 identifies the key drivers at work by decomposing the inflation rate gap between the top and bottom expenditure deciles. For ease of exposition, we aggregate goods into broader groups, with Figure 6 subsequently displaying the seven largest contributors.

[21] The distribution of inflation rates is narrower than those obtained by Kaplan and Schulhofer-Wohl (2017), but the large dispersion in that paper is primarily driven by differences in prices paid and by heterogeneous household characteristics and tastes, which this paper abstracts from.

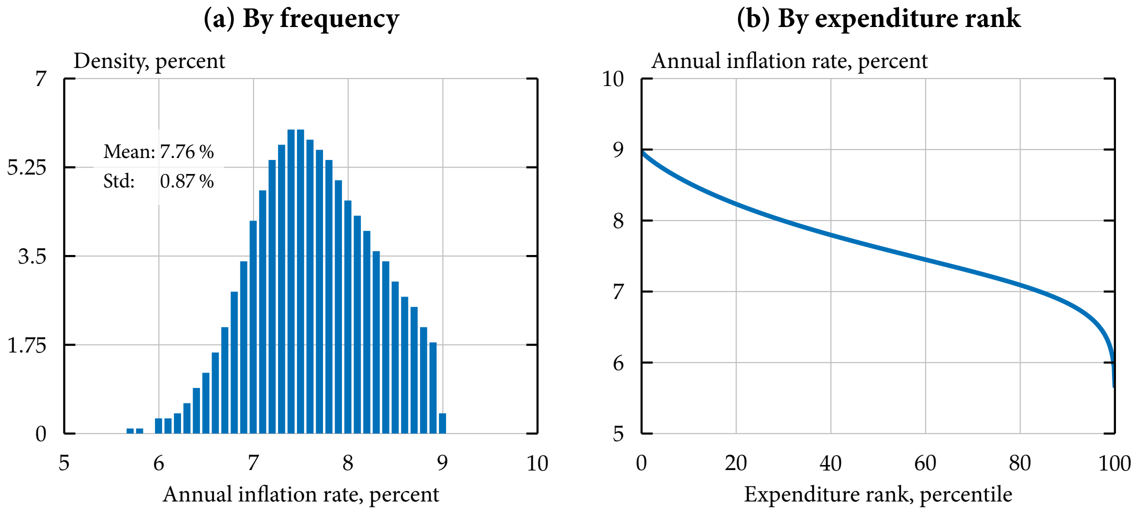

Figure 5. The cross-sectional distribution of PCE inflation rates, June 2022.

Notes. The histogram in Figure 5a is constructed with a bin width of 0.1 percentage points.

From mid-2021 through 2022, the period in which the largest inequality occurs, Figure 6 identifies increasing costs for food consumed at home, energy, and motor vehicles as the primary sources of the higher inflation faced by the poor. For instance, in June 2022, the peak month for inflation inequality, increasing prices for gasoline and other energy products raised the inflation rate for the bottom decile by 1.70 percentage points more than it did for the top decile. The corresponding numbers for food at home, housing and utilities, and motor vehicles are 0.93, 0.66, and 0.53 percentage points, respectively. Downside contributors are higher prices for food services and accommodations, transportation services, and financial services, which are consumed proportionately more by the rich. Especially the former two are somewhat expected considering the product groups that raise the inflation gap, since food and energy are vital inputs in these two industries.

In sum, this section shows that the short-run inflation inequality found in Consumer Expenditure Survey data and in US scanner data by for example Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), Argente and Lee (2021), and Klick and Stockburger (2021) also holds up in the PCE data. While corroborating the qualitative conclusions from these studies, the magnitudes found here during the recent inflation surge are considerably larger. The reason is much the same as the reason why inflation was high in general: prices of food and energy soared, and these products are consumed proportionately more by the poor.

5 Disentangling the Inflation Differences

While our main results are consistent with much of the recent literature on inflation inequality, they contrast with the work in Hochmuth, Pettersson and Weissert (2024). Using the same approach with CEX microdata, they find an inflation rate gap of 0.06 percentage points between the top and bottom deciles between 1995 and 2020. Several factors may explain this difference. For instance, Hochmuth, Pettersson and Weissert focus on consumption which is more limited in scope (durable goods are excluded, for example), use different parameter values, apply empirical rather than imputed expenditure shares in the price index formula, and consider a coarser level of product aggregation. Motivated by these differences, this section attempts to shed light on how these factors affect our baseline PCE results.

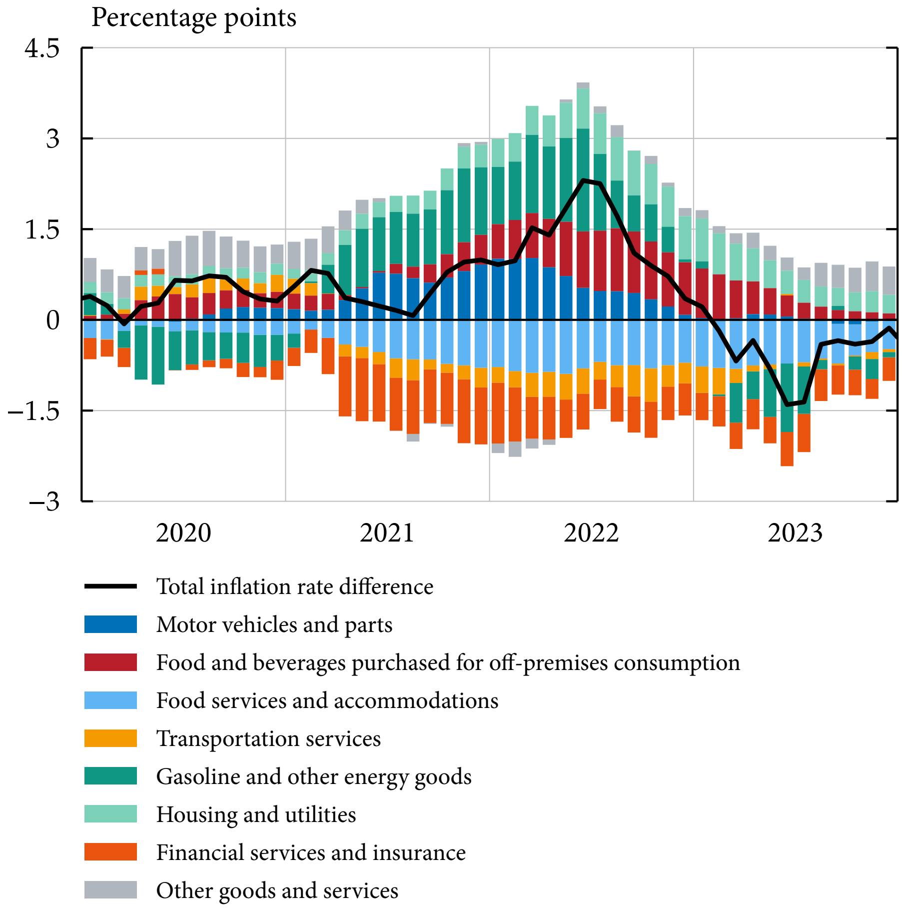

Figure 6. Inflation rate gap between the top and bottom expenditure deciles.

5.1 The Role of Durable Goods

We first consider the impact of durable goods. In the BEA data, the price of durable goods relative to the overall PCE price index steadily declines from 1950 on, thus implying that the presence of durables dampens the overall inflation level in our main estimates. More uncertainty surrounds the measured inflation inequality, however, where the impact can go in either direction. To investigate the importance of durable goods, we exclude these categories from the sample and redo the main analysis. That is, we subtract the first four major groups in Table 1 (motor vehicles and parts, furnishings and durable household equipment, recreational goods and vehicles, and other durable goods) from the expenditure totals, use the parameter estimate for ε from the no durables specification in Table 2, and compute all inflation measures again. Recalling that ε is virtually unchanged when we exclude durables, the drivers in this exercise are the changes that we obtain in the price indices of necessities, luxuries, and the homothetic basket.[22]

Figure 7 compares the no-durables case to our baseline results, which reveals that durable goods explain about half of the estimated inflation inequality. For instance, the annual inflation rate gap between the top and bottom deciles shrinks from 0.41 to 0.25 percentage points. Meanwhile (and as expected), the overall inflation level increases when we exclude durables, with the average annual inflation rate rising by 0.4 percentage points for the median consumer. The reduction in inflation inequality as measured by absolute differences is thus contrary rather than due to the change in the inflation level. For the 1995–2020 period considered by Hochmuth, Pettersson and Weissert (2024), we also find a decline in the inflation

[22] Figure B.1 in Online Appendix B contrasts the basket prices with and without durable goods.

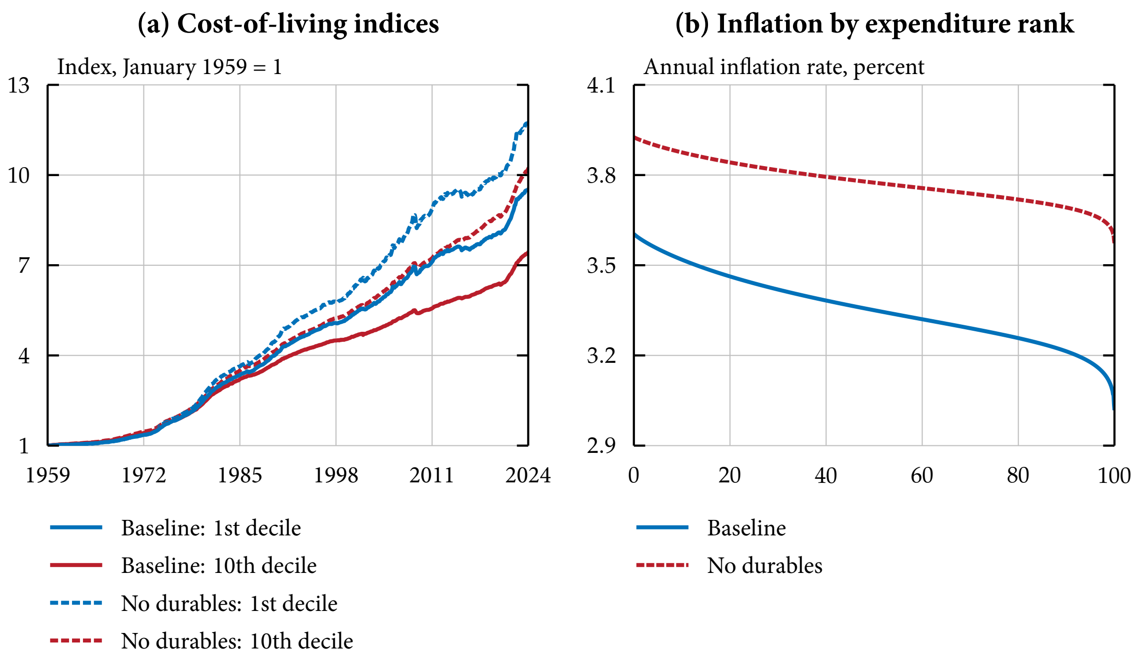

Figure 7. Cost-of-living indices and average inflation without durable goods.

Notes. The scenario without durable goods excludes the first 17 categories of Table 1. The classification into necessity, luxury and homothetic basket is unchanged to the baseline, but ε is re-estimated.

rate gap between the top and bottom deciles from 0.50 to 0.14 percentage points, thus suggesting that durables explain about two thirds of the difference to Hochmuth, Pettersson and Weissert's CEX-based estimates.

5.2 The Role of the Parameter Value for ε

The approach in this paper relies on a cost-of-living index that requires the estimation of one exogenous preference parameter. A key concern that this subsection investigates is whether the inflation inequality uncovered above is sensitive to the choice of value for this parameter.

As a starting point, suppose we redo the whole exercise for some other feasible parameter choices. Consider, for instance, the following cases: homothetic Cobb-Douglas preferences, in which $\varepsilon \longrightarrow 0$; quasi-homothetic preferences, in which $\varepsilon = 1$; and an intermediate case $\varepsilon = 0.3$ with a lower degree of nonhomotheticity than in our baseline. Figure 8a compares the average annual inflation rates over the full sample period for these specifications against those of the baseline estimation. At first sight, it seems that the choice of parameter value matters a great deal: the inflation gap between the top and the bottom of the distribution ranges from almost 1 percentage point under quasi-homothetic preferences to the zero differences (naturally) obtained with homothetic preferences.

These disparities are driven by two possible channels. First, since we consider imputed necessity expenditure shares $w_{Dh} = \left(\ell'(x_h) \,/\, \kappa\right)^{-\varepsilon} \overline{w}_D$, the parameter choice affects the base-period allocation and thereby also the index weight on necessities. Second, ε also affects the predicted substitution behavior of households between the necessity and luxury baskets, as captured by the direct presence of this parameter

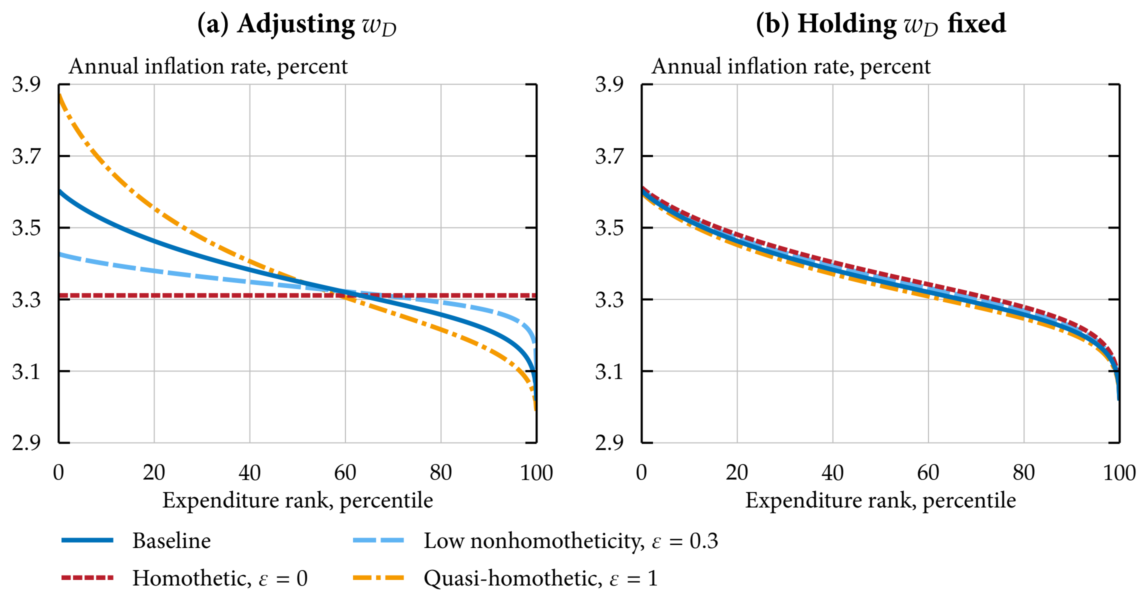

Figure 8. Long-run inflation inequality for different parameter values.

in the cost-of-living index formula (10).[23] For applications where base-period expenditure shares on the necessity basket can be directly observed in the data, it is the sensitivity with respect to the second channel that is of primary interest.

A perhaps more interesting analysis is therefore to consider how the results change if we vary the parameter values but keep the base-period consumption patterns fixed according to the baseline estimates. In this case, any differences to the baseline effectively highlight the role of substitution effects across the three different baskets. The results from this exercise, shown in Figure 8b, paint a completely different picture regarding the sensitivity of the results to different parameter choices. At any given point in the expenditure distribution, the range of inflation rates between the four cases is never more than 0.03 percentage points. Differences in inflation inequality are even smaller: the inflation rate gap between the top and bottom deciles is always 0.4 percentage points. This finding is also not limited to the specific cases in Figure 8: Table B.3 in Online Appendix B reveals that the gap remains stable over a full grid of parameter values. Thus, both inflation inequality and the general level of inflation are close to identical across the different parameter specifications.

The key takeaway from this exercise is therefore that ε matters only insofar as we need to impute expenditure shares from individual expenditure levels and aggregate expenditure shares. When individual expenditure shares can be inferred directly from the data for some base period, the choice of parameter value seems inconsequential for the inflation inequality measures obtained with the PIGL cost-of-living index. This distinction is important because for most other applications, the latter is arguably the more relevant case.

5.3 The Role of Imputed Expenditure Shares and Product Aggregation

The conclusions from Section 5.2 clearly do not apply to this paper since we *do* impute the necessity expenditure shares from the estimated ε. Because empirical counterparts for these imputed shares do

[23] Recall that the elasticity of substitution between the luxury bundle and the necessity bundle in our theoretical framework is given by $1 - \frac{1-w_D}{w_B}\varepsilon$.

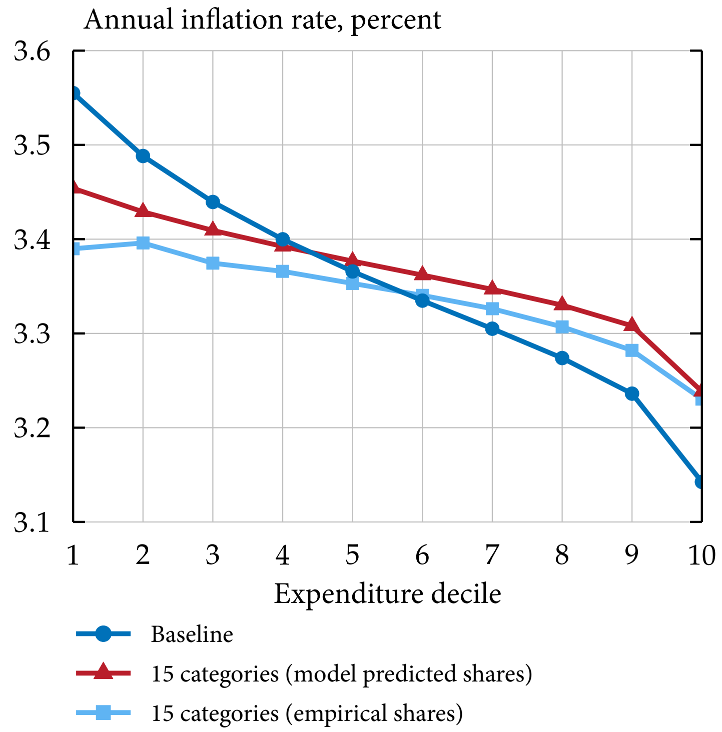

Figure 9. Average inflation rates between 1959 and 2023 for different levels of aggregation.

not yet exist at the product aggregation level that we consider, we cannot say for sure how sensitive our results are to this imputation. Some insight can be obtained from Garner *et al.*'s (2022) distributional PCE estimates, however, as these data include expenditure shares by consumption decile for 15 broad product groups.[24] Implementing our approach at this coarser level of product aggregation allows us to examine the difference between imputing expenditure shares and using the distributional PCE directly in the price index formula.

To implement the nonhomothetic PCE index for the product groups in Garner *et al.* (2022), there are now effectively two ways to classify goods into necessities, luxuries, and homothetic goods: either by applying our baseline approach with state PCE data, or by directly inferring expenditure elasticities from the cross-sectional slopes of expenditure shares in the distributional PCE data. Applying both approaches, we find identical classifications for over 95 percent of expenditures, with motor vehicles and parts being the only unmatched category.[25] This outcome provides additional support for our baseline classification approach with state PCE data. Proceeding with the classification based on the distributional PCE data, we estimate an ε of 0.273 (with a standard error of 0.017) across states, which suggests a lower degree of nonhomotheticity when product categories are more aggregated. We subsequently use this classification and parameter estimate to construct the relevant cost-of-living indices.

Considering both the level and dispersion of inflation rates, we find negligible differences between model-imputed and empirical necessity shares at the coarser level of product aggregation. Figure 9 plots the average annual inflation rates between 1959 and 2023 by expenditure decile, which illustrates a difference

[24] These groups include: motor vehicles and parts; furnishings and durable household equipment; recreational goods and vehicles; other durable goods; food and beverages purchased for off-premises consumption; clothing and footwear; gasoline and other energy goods; other nondurable goods; housing and utilities; health care; transportation services; recreation services; food services and accommodations; financial services and insurance; and other services.

[25] See Table B.1 in Online Appendix B for a comparison.

between the two cases which is never more than 0.06 percentage points for any given expenditure decile. The similarities are not by construction, since the necessity shares ultimately stem from separate sources: the model-predicted expenditure shares are imputed from the cross-sectional variation in state PCE data whereas Garner *et al.* (2022) construct the distributional PCE estimates primarily from CEX microdata. These findings therefore give us confidence that the imputation also works well in the baseline case with 71 product categories.

Figure 9 and the lower point estimate for ε also echo Jaravel's (2019, 2021) emphasis on using the most disaggregated product categories possible when measuring inflation inequality. Plotting the versions with 15 product categories against our baseline results reveals a reduction in the inflation gap by about one half when using the coarser set of products. The difference comes from changes at both ends of the expenditure distribution, narrowing the gap between the first and tenth deciles from 0.41 percentage points in the baseline to about 0.15 to 0.20 percentage points. Consequently, we close the paper by corroborating Jaravel's concern about aggregation bias, showing that it applies not only when working with microdata but also in applications using US PCE data.

6 Conclusion

This paper uses recent estimates of the cross-sectional distribution of US Personal Consumption Expenditures to construct a first-ever distribution of PCE inflation across US households. The underlying cost-of-living index originates from a theoretically sound nonhomothetic utility function, generalizes the Törnqvist price index, and only contains one unknown parameter. A central point in the paper is that the implementation of this index requires no more than a handful of publicly available tables from the BEA's national and regional accounts, provided that a single cross-sectional distribution of consumption expenditures exists.

The nonhomothetic PCE price indices reveal new facts about the distribution of PCE inflation. Using 2019 utility levels as base, the average annual inflation rate of the bottom expenditure decile is 0.41 percentage points higher than that of the top decile over the 65-year period starting in 1959, half of which is explained by a relative price decline of durable goods. A similar 1.3 percentage point difference holds throughout 2022, in the midst of the recent inflation surge. Inflation inequality is therefore a long-run as well as a short-run phenomenon in the United States.

On a broader level, our paper adds to several previous calls for improved distributional national accounts. The documented aggregation bias and the insensitivity of the price index parameter when expenditure shares can be inferred from the data suggest that statistical agencies should aim to construct distributional consumption data at increasingly detailed levels of product aggregation. Such data would allow practitioners to quickly and more accurately obtain nonhomothetic deflators and inflation measures by simply choosing some rough parameter value for the price index formula presented here and plugging in the empirical expenditure shares. While these efforts are already well under way among statistical agencies, much remains to be done.

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A Distributional Cost-of-Living Index From Aggregate Data
Online Supplement

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This supplement provides (a) an in-depth comparison between the method proposed in the main body of the paper to that of Oulton (2008, 2012), and (b) additional figures and tables.

Appendix A Comparison with Oulton (2008, 2012)

This appendix compares our results to those obtained with the method proposed by Oulton (2008, 2012). We first give a brief review of this method and then apply it to our setting and contrast the results to those with our approach.

A.1 Brief Review of Oulton's Method

Oulton (2008, 2012) starts from the Quadratic Almost Ideal Demand System (QAIDS) of Banks, Blundell and Lewbel (1997), for which the expenditure share of product j in period t reads

$$w_{jt} = \frac{\partial \ln A(\boldsymbol{p}_t)}{\partial \ln p_{jt}} + \beta_j \ln\left(\frac{e_t}{A(\boldsymbol{p}_t)}\right) + \frac{\lambda_j}{\prod_{i\in J} p_{it}^{\beta_i}}\left[\ln\left(\frac{e_t}{A(\boldsymbol{p}_t)}\right)\right]^2, \tag{A.1}$$

where $A(\boldsymbol{p}_t)$ is a linearly homogeneous function and where the parameters satisfy $\sum_{j\in J}\beta_j = \sum_{j\in J}\lambda_j = 0$. From here, Oulton imposes the normalization $\ln\bar{u} = 0$, where $\bar{u}$ is the reference utility level of the representative agent in a chosen base period s. With this normalization, the QAIDS cost-of-living index at this particular reference utility can be shown to satisfy

$$P(\bar{u}, \boldsymbol{p}_s, \boldsymbol{p}_t) = \frac{A(\boldsymbol{p}_t)}{A(\boldsymbol{p}_s)}, \tag{A.2}$$

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so that the aggregate expenditure share $\overline{w}_{jt}$ corresponding to representative agent expenditure level $\bar{e}_t$ can be written

$$\overline{w}_{jt} = \frac{\partial \ln A(\boldsymbol{p}_t)}{\partial \ln p_{jt}} + \beta_j \ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right) + \frac{\lambda_j}{\prod_{i \in J} p_{it}^{\beta_i}} \left[\ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right)\right]^2. \tag{A.3}$$

Oulton's idea for applying the demand system in (A.3) empirically is twofold. The first is that, while the curse of dimensionality associated with a growing number of product categories quickly makes the estimation of the partial derivatives $\frac{\partial \ln A(\boldsymbol{p}_t)}{\partial \ln p_{jt}}$ infeasible with aggregate data alone, the exact values of these individual price elasticities are irrelevant for price index purposes. It is therefore possible to circumvent this issue by collapsing $\frac{\partial \ln A(\boldsymbol{p}_t)}{\partial \ln p_{jt}}$ into a small number K of principal components defined over relative prices, such that Equation (A.3) becomes

$$\overline{w}_{jt} = \alpha_j + \sum_{k=1}^{K} \theta_{jk} PC_{kt} + \beta_j \ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right) + \frac{\lambda_j}{\prod_{i \in J} p_{it}^{\beta_i}} \left[\ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right)\right]^2, \tag{A.4}$$

where PC_{kt} is the k-th principal component and the parameters satisfy $\sum_{j \in J} \alpha_j = 1$ and $\sum_{j \in J} \theta_{jk} = 0$ for all $k \in \{1, \ldots, K\}$.

The second is to note that the true cost of living index behaves just like a Divisia index along a fixed indifference curve, but with weights given by Hicksian rather than Marshallian expenditure shares. It is thus possible to approximate the true cost-of-living index $P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)$ by a superlative price index formula such as the Törnqvist, but with Hicksian expenditure shares $\overline{w}_j^h$ that hold at utility $\overline{u}$ as weights:

$$\frac{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_{t-1})} = \prod_{j \in J} \left(\frac{p_{jt}}{p_{jt-1}}\right)^{\delta^h_{j,t,t-1}}, \qquad \delta^h_{j,t,t-1} = \frac{\overline{w}^h_{jt} + \overline{w}^h_{jt-1}}{2}. \tag{A.5}$$

By Equation (A.3) and the normalization $\ln \overline{u} = 0$, the Hicksian shares for the representative agent can, in turn, be written as a function of observed expenditure shares $\overline{w}_{jt}$ via

$$\overline{w}^h_{jt} = \overline{w}_{jt} - \beta_j \ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right) - \frac{\lambda_j}{\prod_{i \in J} p_{it}^{\beta_i}} \left[\ln\left(\frac{\bar{e}_t / \bar{e}_s}{P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)}\right)\right]^2. \tag{A.6}$$

Equations (A.4) to (A.6) form a fixed-point problem over the cost-of-living index that can be solved by iteration for a large number of product groups even with aggregate data:

(i) Guess the cost-of-living index $P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)$, using the homothetic Törnqvist index with Marshallian expenditure shares in the first iteration.
(ii) Estimate Equation (A.4) by regression from aggregate time series of prices, expenditures, and expenditure shares.
(iii) Predict Hicksian expenditure shares using Equation (A.6).
(iv) Compute a new guess for $P(\overline{u}, \boldsymbol{p}_s, \boldsymbol{p}_t)$ using the predicted Hicksian shares and Equation (A.5).
(v) Repeat until convergence on the cost-of-living index.

Oulton (2008, 2012) focuses on the representative agent and aggregate changes in the cost of living, but his approach can be used in a manner similar to ours to study inflation inequality. Specifically, for any other base-period expenditure level e_s with reference utility level u, it is easy to show that the corresponding Hicksian expenditure shares and cost-of-living index can be written as a function of the representative agent's Hicksian shares, expenditures, and cost-of-living index via

$$w_{jt}^{h} = \overline{w}_{jt}^{h} + \beta_j \ln\left(\frac{P(u,\boldsymbol{p}_s,\boldsymbol{p}_t)}{P(\overline{u},\boldsymbol{p}_s,\boldsymbol{p}_t)}\cdot\frac{e_s}{\overline{e}_s}\right) + \frac{\lambda_j}{\prod_{i\in J} p_{it}^{\beta_i}}\left[\ln\left(\frac{P(u,\boldsymbol{p}_s,\boldsymbol{p}_t)}{P(\overline{u},\boldsymbol{p}_s,\boldsymbol{p}_t)}\cdot\frac{e_s}{\overline{e}_s}\right)\right]^2. \tag{A.7}$$

Again, this equation system forms a fixed-point problem over the price index $P(u,\boldsymbol{p}_s,\boldsymbol{p}_t)$ that can be solved by iteration. So, once the initial estimation is complete, it is possible to predict Hicksian expenditure shares and cost-of-living indices for any other expenditure/utility point in the base period, just like we do with our approach.

A.2 Comparison With Oulton's Method

Oulton's (2008, 2012) method is similar to ours in several respects: both (i) rely on specific functional form assumptions—Oulton on the QAIDS (an extension of PIGLOG) and we on a quasi-separable PIGL demand system; (ii) estimate Engel curve slopes that determine if goods are luxuries or necessities; (iii) use these estimates to predict Hicksian expenditure shares for the populations of interest; and (iv) construct the relevant price index weights from these predictions. However, several distinctions make our approach better suited to our research question and data setting.

First, Oulton's Engel curve estimates are directly used to predict the Hicksian shares and compute the cost-of-living index. By contrast, our method relies more on standard price index methods than on structural estimation. We use Engel slopes solely to classify goods as luxuries or necessities; the point estimates themselves do not enter the price index calculations. Estimation precision is therefore not as critical, which allows for a more parsimonious implementation based on cross-sectional state data. Oulton's method, on the other hand, requires a complete set of relative prices to determine the principal components, and such detailed PCE price data are not yet available at the US state level, thus restricting this approach to aggregate time series data in the PCE setting.

Second, while the QAIDS is known to match Engel curves well, it only does so locally. The regularity conditions for utility maximization do not hold globally and its quadratic nature makes it bound to eventually predict expenditure shares outside the permitted zero-to-one range. This problem already appears in Oulton's (2008) estimations at the representative-agent level. Using QAIDS estimated on aggregate time series to predict expenditure shares across the cross-sectional expenditure distribution is likely to exacerbate the issue, especially at high expenditure levels far outside the estimating sample. The PIGL demand system features better global properties. Being part of the "intertemporally aggregable" class of preference described by Alder, Boppart and Müller (2022), the PIGL system supports well-behaved expenditure shares even as expenditures grow without bound at a given set of prices.

Third, Oulton provides no guidance on how to pick the number of principal components to include in the estimation—a choice that may seriously affect the results. To illustrate this point, we implement his method for the same base year and the same product categories as in Table 1, using monthly aggregate PCE data between 1959 and 2023 (780 periods). We then apply Equation (A.7) to compute inflation inequality between the top and bottom expenditure deciles over these years. Whenever Equation (A.7) predicts

Table A.1. Comparing the baseline inflation inequality with Oulton's method.

	Price variation explained (%)	Average inflation rate (% per year)			Hicksian shares = 0 (% of categories)	
		1st decile	10th decile	Gap (pp)	1st decile	10th decile
Baseline results		3.56	3.14	0.41	0.0	0.0
Oulton's method						
1 PC	89.7	3.46	2.99	0.47	4.6	24.0
2 PCs	96.0	3.53	3.11	0.42	5.2	29.0
3 PCs	98.1	3.51	3.07	0.44	4.6	25.4
4 PCs	98.7	3.48	2.62	0.86	4.6	19.3
5 PCs	99.2	3.58	2.61	0.97	6.0	19.3
6 PCs	99.4	3.48	2.92	0.56	4.3	28.6
7 PCs	99.5	3.51	2.96	0.56	5.4	27.6
8 PCs	99.6	3.50	2.93	0.57	5.4	28.0
9 PCs	99.7	3.50	2.92	0.58	5.2	27.1
10 PCs	99.7	3.50	2.96	0.54	5.3	26.6
11 PCs	99.8	3.44	3.07	0.37	5.7	23.9
12 PCs	99.8	3.42	3.00	0.42	5.0	24.3
13 PCs	99.8	3.42	2.95	0.47	5.1	24.9
14 PCs	99.9	3.42	3.00	0.42	5.6	29.1
15 PCs	99.9	3.42	3.07	0.35	5.5	28.0

negative Hicksian shares, we follow Oulton (2008) and set these to zero, then rescale all other expenditure shares to sum to one. We repeat this procedure using successively 1 to 15 principal components and compare the results to our own in Table A.1.

Table A.1 reveals that, while Oulton's method repeatedly corroborates that lower-income groups faced higher inflation during this period, the magnitudes it generates are highly sensitive to the choice of principal components. The inflation rate gap between the top and bottom deciles ranges from around 0.4 percentage points per year with just a few components to almost a full percentage point with five, before reverting and seemingly stabilizing around 0.4 percentage points beyond ten components. A full percentage point gap is implausibly large compared to prior estimates in the literature, which consistently lie between 0.2 and 0.4 percentage points per year between top and bottom income groups in the United States.[1] Our approach cannot generate such a large gap even under the stark assumption of quasi-homothetic preferences shown in Figure 8a.

In a way then, it seems reassuring that the higher numbers of principal components produce inflation inequality within the range of reasonable values from this and previous work, since these choices capture virtually all of the variation in the price data. But five components alone already accounts for over 99.2 percent of the variation in the price data, so better coverage seems unlikely to explain these large swings. From this perspective, choosing between five and fifteen components appears rather arbitrary and left to the researcher to make without much further guidance. Our approach instead offers a systematic implementation that avoids this choice altogether.

While pinpointing the exact drivers of the differences in Table A.1 is beyond the scope of this paper, we show in the final columns of the table that negative expenditure share predictions indeed becomes a serious issue, especially at higher expenditures. In the top decile, between 20 and 30 percent of all product

[1] Besides this paper, see for example McGranahan and Paulson (2005), Jaravel (2019), Argente and Lee (2021), Klick and Stockburger (2021), and Jaravel and Lashkari (2024).

categories are given a Hicksian share of zero, regardless of how many principal components are used.[2] This is somewhat unsurprising, as PCE spending in the top decile reaches well over $100,000 per person in 2019, far outside the QAIDS estimation sample, which ranges from around $1,700 in 1959 to $53,700 in 2023. Oulton's method is thus unlikely to generate a good approximation of the behavior at the top of the distribution. With the PIGL demand system, however, we have no such issues, as shown in the top row of Table A.1.

[2] These categories account for a roughly proportional share of aggregate PCE spending.

Appendix B Additional Figures and Tables

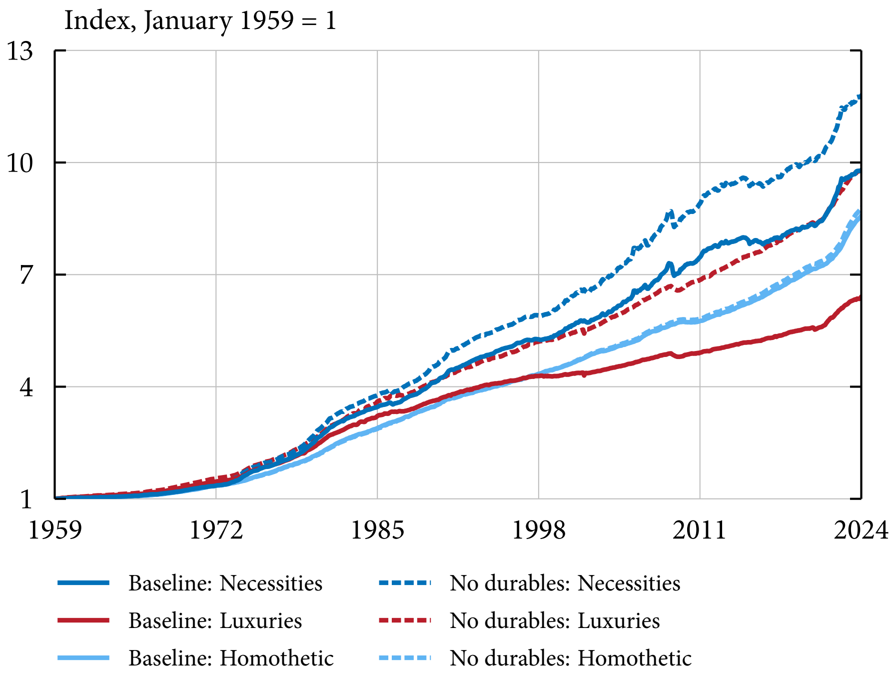

Figure B.1. Basket prices with and without durable goods.

Notes. The basket prices without durable goods is the equivalent Törnqvist index but excluding the first 17 categories that correspond to durable goods.

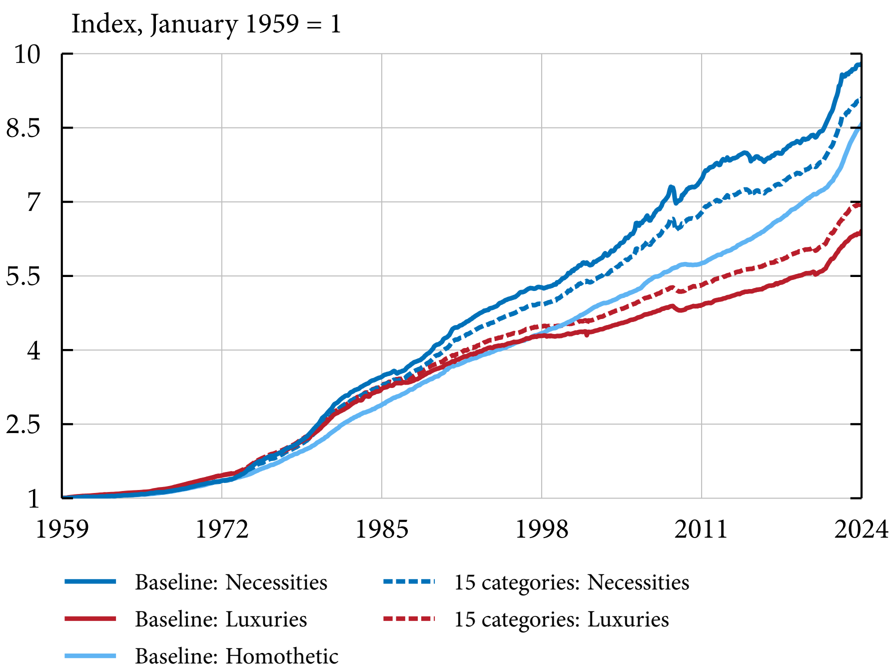

Figure B.2. Basket prices for different levels of aggregation.

Notes. No product category is classified as homothetic at the broader level of aggregation, and therefore the price index for the homothetic basket on that level of aggregation is not shown in the figure.

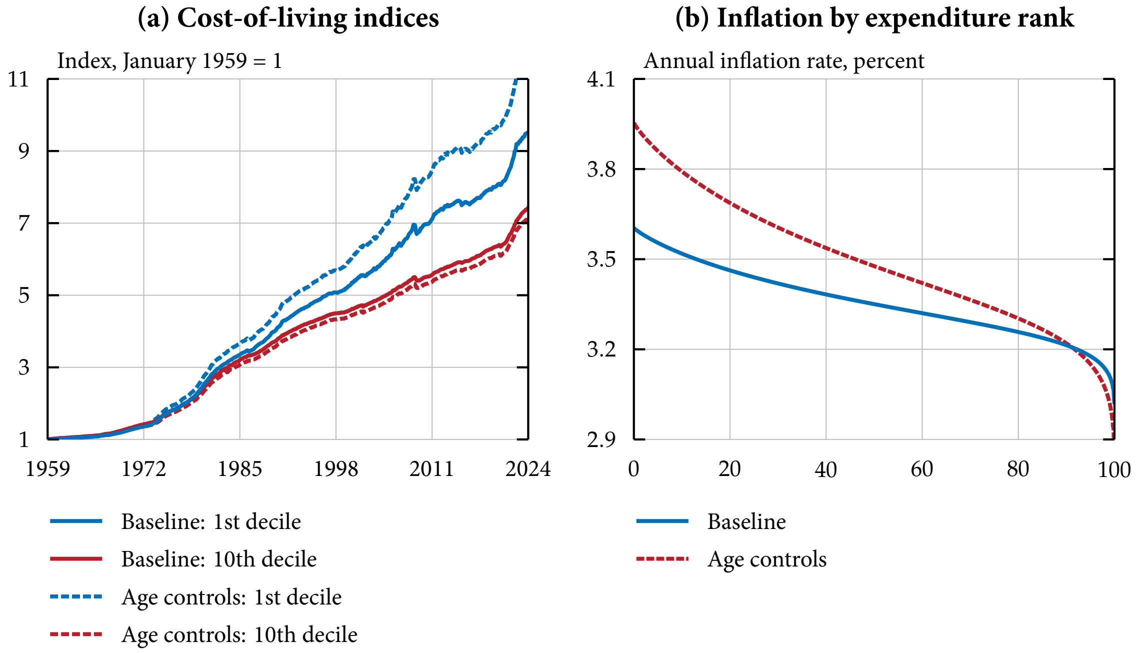

Figure B.3. Cost-of-living indices compared with the scenario including age controls.

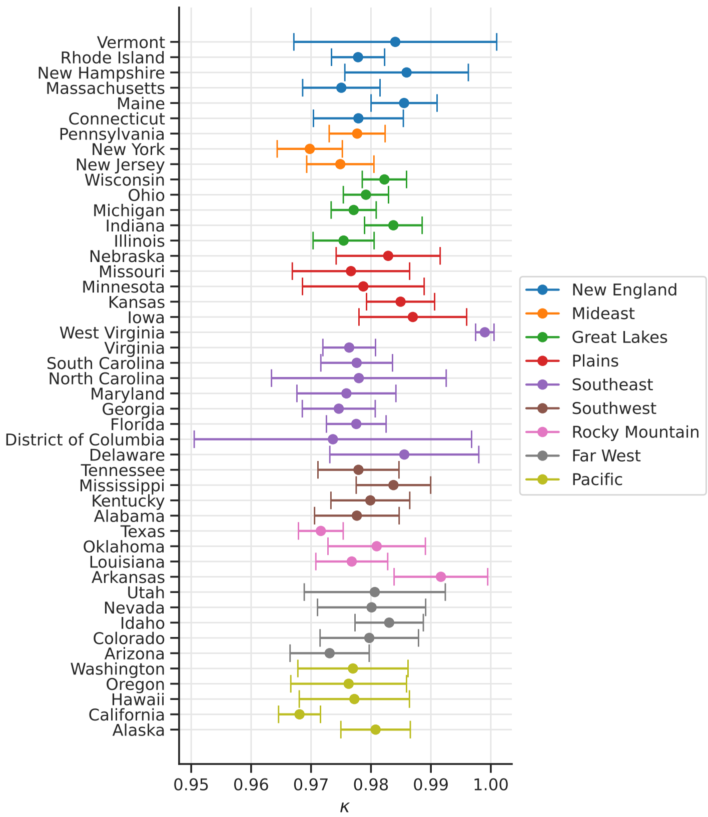

Figure B.4. Empirical measure of the aggregation factor, $\kappa_t^{-\varepsilon}$, by US states using microdata from the CEX.

Notes. Data from the CEX with the same sample restrictions as in Hochmuth, Pettersson and Weissert (2024). The dots show the average and the error bars show the standard deviation of $\kappa_t^{-\varepsilon}$ over all years. Some US states are missing because the CEX sample we use does not contain any observations within these states.

Table B.1. Engel curve classification of major product groups.

PCE major product group	PCE share (in percent)	State PCE		Distributional PCE	
		Engel slope	Std. Error	Engel slope	Std. Error
Durable goods					
Motor vehicles and parts	4.27	-0.021^{***}	(0.002)	0.036^{***}	(0.001)
Furnishings and durable household equipment	2.71	0.006^{***}	(0.001)	0.007^{***}	(0.001)
Recreational goods and vehicles	3.27	0.027^{***}	(0.002)	0.020^{***}	(0.001)
Other durable goods	1.60	0.005^{***}	(0.001)	0.007^{***}	(0.001)
Nondurable goods					
Food and beverages purchased for off-premises consumption	8.01	-0.030^{***}	(0.002)	-0.047^{***}	(0.001)
Clothing and footwear	3.28	-0.010^{***}	(0.002)	-0.010^{***}	(0.001)
Gasoline and other energy goods	2.94	-0.046^{***}	(0.002)	-0.013^{***}	(0.001)
Other nondurable goods	8.29	-0.044^{***}	(0.002)	-0.020^{***}	(0.001)
Services					
Housing and utilities	18.66	-0.040^{***}	(0.006)	-0.043^{***}	(0.001)
Health care	16.51	-0.099^{***}	(0.005)	-0.059^{***}	(0.001)
Transportation services	3.32	0.025^{***}	(0.001)	0.012^{***}	(0.001)
Recreation services	4.00	0.030^{***}	(0.002)	0.008^{***}	(0.001)
Food services and accommodations	6.68	0.015^{***}	(0.002)	0.019^{***}	(0.001)
Financial services and insurance	7.98	0.047^{***}	(0.004)	0.051^{***}	(0.001)
Other services	8.47	0.042^{***}	(0.004)	0.031^{***}	(0.001)
Sample years		1997–2023		2000–2023	
Observations per good		1,377		240	

Notes. The "PCE share" column shows the 1997–2023 average of each good's share of total US personal consumption expenditures on the 71 categories we include. The subsequent column reports the slope coefficients from regressing state-level expenditure shares on the corresponding level of logarithmized personal consumption expenditures per capita (with state-by-year clustered standard errors in parentheses). Each estimation controls for year fixed effects, BEA region fixed effects, and interstate price differences through regional price parities. States are weighted by relative population size. The last columns report the same estimation over cross-sectional expenditure deciles, as reported in the March 2025 version of the distributional PCE. *, **, and *** denote statistical significance at the 5 percent, 1 percent, and 0.1 percent levels.

Table B.2. Classifying products as necessity, luxury, or homothetic in the CEX.

CEX category	CEX data aggregated to state averages			Directly from microdata
	Engel slope	Std. Error	Classification	
Food and beverages				
Food at home	−0.131***	(0.004)	Necessity	Necessity
Food away from home	0.006**	(0.002)	Luxury	Luxury
Alcoholic beverages	0.004***	(0.000)	Luxury	Luxury
Housing				
Owned dwellings	0.059***	(0.007)	Luxury	Luxury
Rented dwellings	−0.070***	(0.006)	Necessity	Necessity
Other lodging	0.024***	(0.002)	Luxury	Luxury
Natural gas; electricity; fuel oil and other fuels	−0.031***	(0.001)	Necessity	Necessity
Telephone services	−0.013***	(0.001)	Necessity	Necessity
Water and other public services	−0.007***	(0.001)	Necessity	Necessity
Household operations; household furnishings and equipment	0.080***	(0.009)	Luxury	Luxury
Other spending				
Apparel and services	0.005*	(0.002)	Luxury	Luxury
Gasoline, other fuels, and motor oil	−0.022***	(0.001)	Necessity	Necessity
Other vehicle expenses	−0.009**	(0.003)	Necessity	Luxury
Public and other transportation	0.009***	(0.002)	Luxury	Luxury
Healthcare	−0.001	(0.003)	Homothetic	Luxury
Entertainment	0.038***	(0.006)	Luxury	Luxury
Personal care products and services	0.001*	(0.000)	Luxury	Luxury
Reading	0.002***	(0.000)	Luxury	Luxury
Education	0.023***	(0.003)	Luxury	Luxury
Tobacco products and smoking supplies	−0.007***	(0.001)	Necessity	Necessity
Miscellaneous	0.007***	(0.001)	Luxury	Luxury

Notes. The estimation results show the slope coefficients from regressing state-level aggregate expenditure shares on the corresponding level of logarithmized consumption expenditures per capita. States are weighted by their relative population size. Standard errors in parentheses are clustered by year-by-state cells. The last column reports the classification obtained by Hochmuth, Pettersson and Weissert (2024) using CEX microdata directly. *, **, and *** denote statistical significance at the 5 percent, 1 percent, and 0.1 percent levels.

Table B.3. Long-run inflation rate gap for different parameter values with w_D fixed.

ε	γ										
	0.00	**0.10**	**0.20**	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	**0.80**	**0.90**	**1.00**
0.00	0.39	0.39	0.38	0.37	0.36	0.36	0.35	0.34	0.34	0.33	0.33
0.10	0.40	0.39	0.39	0.38	0.37	0.36	0.36	0.35	0.34	0.34	0.33
0.20	0.41	0.40	0.39	0.39	0.38	0.37	0.36	0.36	0.35	0.34	0.34
0.30	0.42	0.41	0.40	0.39	0.39	0.38	0.37	0.36	0.36	0.35	0.34
0.40	0.43	0.42	0.41	0.40	0.40	0.39	0.38	0.37	0.36	0.36	0.35
0.50	0.44	0.43	0.42	0.41	0.40	0.40	0.39	0.38	0.37	0.36	0.36
0.60	0.45	0.44	0.43	0.42	0.41	0.40	0.40	0.39	0.38	0.37	0.36
0.70	0.46	0.45	0.44	0.43	0.42	0.41	0.41	0.40	0.39	0.38	0.37
0.80	0.48	0.47	0.45	0.44	0.43	0.42	0.41	0.41	0.40	0.39	0.38
0.90	0.49	0.48	0.47	0.46	0.45	0.43	0.42	0.42	0.41	0.40	0.39
1.00	0.51	0.49	0.48	0.47	0.46	0.45	0.44	0.43	0.42	0.41	0.40

Notes. The table shows the percentage point difference in the average annual inflation rate between the top and bottom expenditure deciles over the period January 1959 to December 2023 when the base-period allocation is held fixed at the baseline estimates. The table considers the general model of Boppart (2014), in which $V(e, \boldsymbol{p}) = \frac{1}{\varepsilon}\left[\left(\frac{e}{F\left(H(\boldsymbol{p}),B(\boldsymbol{p})\right)}\right)^{\varepsilon} - 1\right] - \frac{\nu}{\gamma}\left[\left(\frac{D(\boldsymbol{p})}{B(\boldsymbol{p})}\right)^{\gamma} - 1\right]$ and $P(u, \boldsymbol{p}_s, \boldsymbol{p}_t) = \left[\left(1 - \frac{\varepsilon w_{Ds}}{\gamma}\right) P_{Bt}^{\gamma} + \frac{\varepsilon w_{Ds}}{\gamma} P_{Dt}^{\gamma}\right]^{\frac{1}{\varepsilon}} P_{Ft} P_{Bt}^{-\frac{\gamma}{\varepsilon}}$. See Hochmuth, Pettersson and Weissert (2024) for the price index derivation. The diagonal corresponds to the benchmark model in this paper.

Table B.4. Engel curve classification from state PCE data, robustness.

PCE category	(1)		(2)		(3)	
	Slope	Std. Error	Slope	Std. Error	Slope	Std. Error
Motor vehicles and parts						
New motor vehicles	−0.006***	(0.001)	−0.008***	(0.001)	0.007***	(0.002)
Net purchases of used motor vehicles	−0.010***	(0.001)	−0.013***	(0.001)	−0.010***	(0.001)
Motor vehicle parts and accessories	−0.005***	(0.000)	−0.005***	(0.000)	−0.003***	(0.000)
Furnishings and durable household equipment						
Furniture and furnishings	0.006***	(0.000)	0.006***	(0.001)	0.008***	(0.001)
Household appliances	−0.001***	(0.000)	−0.002***	(0.000)	−0.001***	(0.000)
Glassware, tableware, and household utensils	0.004***	(0.000)	0.003***	(0.000)	0.005***	(0.000)
Tools and equipment for house and garden	−0.002***	(0.000)	−0.003***	(0.000)	−0.003***	(0.000)
Recreational goods and vehicles						
Video, audio, photographic, and information processing equipment and media	0.029***	(0.001)	0.032***	(0.002)	0.033***	(0.002)
Sporting equipment, supplies, guns, and ammunition	−0.004***	(0.001)	−0.005***	(0.001)	0.005***	(0.001)
Sports and recreational vehicles	0.000	(0.001)	0.000	(0.002)	0.002***	(0.001)
Recreational books	0.000	(0.001)	0.001	(0.001)	−0.005***	(0.001)
Musical instruments	0.000***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Other durable goods						
Jewelry and watches	0.005***	(0.000)	0.006***	(0.001)	0.005***	(0.000)
Therapeutic appliances and equipment	−0.004***	(0.000)	−0.005***	(0.000)	−0.003***	(0.000)
Educational books	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Luggage and similar personal items	0.003***	(0.000)	0.003***	(0.000)	0.004***	(0.000)
Telephone and related communication equipment	0.001**	(0.000)	0.001**	(0.000)	0.001***	(0.000)
Food and beverages purchased for off-premises consumption						
Food and nonalcoholic beverages purchased for off-premises consumption	−0.033***	(0.002)	−0.035***	(0.002)	−0.024***	(0.003)
Alcoholic beverages purchased for off-premises consumption	0.003***	(0.000)	0.002***	(0.001)	0.003***	(0.001)
Food produced and consumed on farms	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Clothing and footwear						
Women's and girls' clothing	−0.002	(0.001)	−0.002	(0.001)	−0.002*	(0.001)
Men's and boys' clothing	−0.004***	(0.001)	−0.004***	(0.001)	−0.006***	(0.001)
Children's and infants' clothing	−0.001***	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)
Other clothing materials and footwear	−0.003***	(0.000)	−0.002***	(0.000)	−0.004***	(0.000)
Gasoline and other energy goods						
Motor vehicle fuels, lubricants, and fluids	−0.043***	(0.002)	−0.048***	(0.003)	−0.032***	(0.002)
Fuel oil and other fuels	−0.003***	(0.000)	−0.003***	(0.000)	−0.002**	(0.001)
Other nondurable goods						
Pharmaceutical and other medical products	−0.034***	(0.002)	−0.042***	(0.003)	−0.038***	(0.002)
Recreational items	−0.009***	(0.000)	−0.011***	(0.001)	−0.011***	(0.001)
Household supplies	−0.003***	(0.000)	−0.003***	(0.000)	−0.003***	(0.000)
Personal care products	0.006***	(0.000)	0.004***	(0.001)	0.002**	(0.001)
Tobacco	−0.008***	(0.001)	−0.009***	(0.001)	−0.010***	(0.001)
Magazines, newspapers, and stationery	0.004***	(0.001)	0.002*	(0.001)	−0.001	(0.001)
Housing and utilities						
Rental of tenant-occupied nonfarm housing	−0.039***	(0.004)	−0.032***	(0.005)	−0.057***	(0.004)
Imputed rental of owner-occupied nonfarm housing	0.012	(0.008)	−0.012	(0.010)	0.000	(0.007)
Rental value of farm dwellings	0.000	(0.000)	0.001*	(0.001)	−0.003***	(0.001)
Group housing	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Water supply and sanitation	−0.005***	(0.000)	−0.006***	(0.000)	−0.007***	(0.000)
Electricity	−0.016***	(0.001)	−0.018***	(0.001)	−0.014***	(0.001)
Natural gas	−0.009***	(0.001)	−0.009***	(0.001)	−0.010***	(0.001)

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Table B.4. Engel curve classification from state PCE data, robustness. (Cont.)

PCE category	(1)		(2)		(3)	
	Slope	Std. Error	Slope	Std. Error	Slope	Std. Error
Health care						
Physician services	−0.003*	(0.001)	0.000	(0.002)	−0.004*	(0.002)
Dental services	−0.003***	(0.000)	−0.003***	(0.001)	0.001	(0.001)
Paramedical services	0.004*	(0.002)	0.006***	(0.002)	−0.006**	(0.002)
Hospitals	−0.084***	(0.003)	−0.085***	(0.004)	−0.089***	(0.004)
Nursing homes	−0.013***	(0.001)	−0.012***	(0.001)	−0.025***	(0.001)
Transportation services						
Motor vehicle maintenance and repair	0.001	(0.001)	−0.002	(0.001)	0.007***	(0.001)
Other motor vehicle services	0.004***	(0.001)	0.005***	(0.001)	0.005***	(0.001)
Ground transportation	0.004***	(0.001)	0.004***	(0.001)	−0.001	(0.001)
Air transportation	0.017***	(0.001)	0.020***	(0.002)	0.016***	(0.001)
Water transportation	0.000***	(0.000)	0.000**	(0.000)	−0.001***	(0.000)
Recreation services						
Membership clubs, sports centers, parks, theaters, and museums	0.015***	(0.001)	0.016***	(0.002)	0.017***	(0.002)
Audio-video, photographic, and information processing equipment services	0.006***	(0.001)	0.008***	(0.001)	0.004***	(0.001)
Gambling	0.005***	(0.001)	0.004*	(0.002)	0.008***	(0.001)
Other recreational services	0.005***	(0.000)	0.005***	(0.001)	0.006***	(0.001)
Food services and accommodations						
Purchased meals and beverages	0.006***	(0.001)	0.010***	(0.002)	−0.009***	(0.002)
Food furnished to employees (including military)	−0.001***	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)
Accommodations	0.010***	(0.001)	0.012***	(0.002)	0.010***	(0.001)
Financial services and insurance						
Financial services furnished without payment	0.012***	(0.001)	0.012***	(0.001)	0.011***	(0.001)
Financial service charges, fees, and commissions	0.019***	(0.001)	0.027***	(0.002)	0.016***	(0.002)
Life insurance	0.005***	(0.000)	0.002**	(0.001)	0.006***	(0.001)
Net household insurance	0.000***	(0.000)	0.000**	(0.000)	0.000**	(0.000)
Net health insurance	0.006**	(0.002)	0.013***	(0.003)	0.016***	(0.004)
Net motor vehicle and other transportation insurance	0.004***	(0.001)	0.004**	(0.001)	0.005***	(0.001)
Other services						
Telecommunication services	0.008***	(0.001)	0.008***	(0.001)	0.011***	(0.002)
Postal and delivery services	0.000*	(0.000)	0.000**	(0.000)	0.000	(0.000)
Higher education	−0.007***	(0.002)	−0.010***	(0.002)	−0.002	(0.001)
Nursery, elementary, and secondary schools	0.000	(0.000)	−0.001	(0.000)	0.001**	(0.000)
Commercial and vocational schools	0.006***	(0.000)	0.007***	(0.000)	0.005***	(0.000)
Professional and other services	−0.007***	(0.001)	−0.003*	(0.002)	−0.009***	(0.001)
Personal care and clothing services	0.018***	(0.001)	0.022***	(0.002)	0.014***	(0.001)
Social services and religious activities	0.017***	(0.003)	0.020***	(0.004)	0.008**	(0.003)
Household maintenance	0.006***	(0.000)	0.004***	(0.000)	0.012***	(0.000)
Demographic controls					✓	
Sample years	1997–2023		2008–2023		1997–2023	
Observations per good	1,377		816		1,377	

Notes. Each specification shows the slope coefficients from regressing state-level aggregate expenditure shares on the corresponding level of logarithmized consumption expenditures per capita. (1) is the baseline classification, (2) uses a shorter state panel but with only official RPPs, and (3) adds controls for the state-level age composition. States are weighted by their relative population size. Standard errors in parentheses are clustered by year-by-state cells. *, **, and *** denote statistical significance at the 5 percent, 1 percent, and 0.1 percent levels.

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