Pass-Through in Levels and the Unequal Incidence of Commodity Shocks

Kunal Sangani
Northwestern University*

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Abstract

We document a new source of fluctuations in inflation inequality. When the cost of upstream inputs rises, varieties within a product category tend to have similar absolute price increases. However, the same absolute price increase constitutes a larger percentage change for low-price products, resulting in excess inflation at the low end ("cheapflation"). Since low-income households tend to buy lower-priced varieties, the inflation rates they face are disproportionately sensitive to upstream costs. Using data on food-at-home purchases, we show that this mechanism generates cycles in inflation inequality and excessive volatility in inflation for low-income households relative to high-income households. This channel parsimoniously accounts for observed fluctuations in inflation inequality over time, including surges in cheapflation and inflation inequality during both the Great Recession and the 2021–2023 post-pandemic inflation. Official statistics mask these within-category differences in inflation and thus understate the differences in inflation experienced by low- and high-income households by 70–90 percent. We provide evidence that this mechanism applies to a range of consumption categories beyond food at home.

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1 Introduction

Inflation can differ markedly across households due to differences in the composition of households' expenditures. A large body of research has documented heterogeneity in the inflation rates faced by households across the income distribution due to differences in spending shares across product categories. For example, low-income households devote a greater share of their budgets to necessities like food and energy, which leads to differences in the inflation experienced by low- and high-income households when the relative prices of food and energy fluctuate (e.g., Hobijn and Lagakos 2005; Orchard 2022; Jaravel 2024).

In this paper, we document a new and quantitatively important source of inflation inequality that operates *within* product categories. We show that when firms pass through upstream cost shocks in levels, an increase in costs leads to systematically higher inflation rates for lower-priced varieties within narrow product categories. Since low-income households tend to buy lower-priced varieties, this pricing behavior leads to predictable and cyclical swings in inflation inequality.

The central empirical fact we document is that upstream cost shocks tend to induce similar absolute price changes across product varieties within narrow categories. For example, when the commodity price of coffee beans rises, both premium and budget coffee brands raise prices by similar amounts in cents-per-ounce. However, these identical dollar increases constitute larger percentage price changes for cheaper products. We show that this phenomenon—which we term *pass-through in levels*—emerges across a wide range of product categories. It implies that low-priced varieties systematically exhibit higher inflation rates than high-priced varieties when input costs rise.

Because low-income households disproportionately purchase low-priced varieties, pass-through in levels generates differences in inflation across the income distribution even holding households' spending shares across product categories fixed. Moreover, the extent of inflation inequality fluctuates over time with upstream cost conditions. When the price of commodity inputs rises relative to the overall price level, inflation rates faced by low-income households increase more than those faced by high-income households; when commodity prices fall, the reverse occurs.

Using scanner data for food-at-home purchases, we show that this channel can explain the bulk of variation in inflation inequality over the eighteen year period from 2006 to 2023. Differences in inflation within narrowly disaggregated product categories due to pass-through in levels account for nearly 60 percent of the variation in the gap between the first and fifth income quintiles' inflation rates over time. Further accounting for differences in households' expenditure shares across product categories increases the share of variation explained to 70 percent. Pass-through in levels also parsimoniously accounts for the extent to which inflation inequality was elevated during specific subperiods, such as during the Great Recession (2008–2011) or the post-pandemic inflation (2021–2023). The extent and causes of the 2021–2023 rise in inflation inequality in particular have been hotly debated, with commentators attributing the excessive inflation of low-priced varieties during this period—a phenomenon termed "cheapflation" by Cavallo and Kryvtsov (2024)—to the distribution of fiscal stimulus or to price-gouging by retailers. In contrast, we find that pass-through in levels and differences in household spending shares across categories account for the entirety of cheapflation and inflation inequality during this period, leaving little need for other channels.

An important feature of the mechanism we document is that it operates within narrowly defined product categories. As a result, it is largely obscured in official inflation statistics, which even at their most disaggregated level report inflation rates pooled across varieties within a product category. To take an example, one of the 273 entry-level items (ELIs) tracked by the Bureau of Labor Statistics (BLS) is "roasted and instant coffee." Despite the narrow category definition, scanner data reveals large fluctuations in the inflation gap between low- and high-income households within roasted coffee alone: the gap reached 8 percentage points when coffee commodity prices spiked in 2011 and fell to −3 percent when coffee commodity prices fell in 2013. These fluctuations occur entirely within a single ELI and are therefore invisible in the official data.

We find that even the most disaggregated official price indices substantially understate fluctuations in inflation inequality that we observe in product-level household purchase data. Using scanner data, we find that the pass-through of upstream food manufacturing costs to food-at-home prices for the lowest-income quintile is 10 percent higher than that of the highest income quintile. Analogous calculations using the most granular BLS data available understate this differential by 88 percent. Likewise, the variance of food-at-home inflation rates for the lowest-income quintile in scanner data is 21 percent higher than that of the highest income quintile; parallel calculations with BLS data understate the gap in inflation volatility by 70 percent. The omission of within-category inflation differences is especially severe when estimating whether the costs of specific inflationary episodes, such as the post-pandemic inflation, were equally borne across income groups. From 2021–2023, aggregation to the BLS's entry-level items understates the differential growth in food prices for the lowest-income quintile relative to the highest-income quintile by a factor of seven.[1]

[1]Our findings echo concerns raised by UK anti-poverty advocate Jack Monroe, who argued that the UK's national inflation index "grossly underestimates the real cost of inflation" for low-income households, citing large price increases for several low-price grocery products. Her campaign prompted the UK Office

Our main results use Laspeyres price indices, which most closely resemble the methodology used by the BLS to construct inflation rates. However, we show that these results are robust to using alternative price indices that account for households' abilities to substitute across goods and for nonhomothetic preferences. Accounting for substitution with Törnqvist price indices tends to reduce the estimated level and volatility of inflation, and does so roughly proportionately across income groups. In contrast, accounting for nonhomotheticities using the algorithm developed by Jaravel and Lashkari (2024) tends to *increase* the volatility of inflation. This is because when food-at-home prices rise faster than income, households tend to trade down to lower-priced varieties (Jaimovich, Rebelo, and Wong 2019; Argente and Lee 2021), which are exactly those varieties that experience the highest inflation rates when food-at-home input costs rise. When both substitution and nonhomotheticities are jointly accounted for, our estimates of the differences in inflation between low- and high-income households remain largely unchanged.

In the final section of the paper, we provide suggestive evidence that our channel extends to other categories of consumption beyond food at home. The lack of disaggregated, product-level inflation and household purchase data has typically made it challenging to generalize findings from scanner data on fast-moving consumer goods to other product categories. We address this challenge using two complementary strategies. First, we use data on prices of goods and services from across U.S. cities to detect similar patterns in cheapflation and inflation inequality. Second, we explore the automobile market, where detailed data on household purchases and model-level prices are also available. We find evidence of systematic fluctuations in cheapflation and inflation inequality in both cases, suggesting that our conclusions on cycles in inflation inequality—and the degree to which official statistics may understate the true differences in inflation experiences across income groups—generalize to the broader consumption bundle.

Although our focus is on differences in inflation across households, the same mechanism applies to inflation rates across any units with different expenditure patterns. For example, pass-through in levels implies that cities that consume more expensive varieties or that have larger distribution margins should experience muted responses to input cost shocks. Similarly, countries that import relatively high-priced varieties will see less import price inflation when global input costs rise. The mechanism thus predicts systematic cross-sectional variation in exposure to common input price changes.

for National Statistics to launch a study of inflation for low-price grocery items. However, due to limited product coverage, the study was unable to detect elevated inflation for low-price items.

Related literature. This paper relates to a literature that explores differences in inflation across households, surveyed by Jaravel (2021). The vast majority of this literature considers inflation differences that arise due to differences in household spending shares across product categories.[2] We show that aggregation to product categories masks considerable fluctuations in inflation experienced across the income distribution, due to differences in the varieties that income groups purchase within categories and how pass-through in levels creates differences in inflation across varieties in response to input cost shocks.

Our focus on cost-driven fluctuations in inflation inequality also differs from Broda and Romalis (2009), Kaplan and Schulhofer-Wohl (2017), and Jaravel (2019), who use scanner data to measure *secular* differences in inflation rates across income groups. We document that differences in the varieties that households buy within product categories, combined with pass-through in levels, lead to *fluctuations* in inflation inequality in response to input cost shocks. Given the lack of prior evidence, previous work has typically assumed that the differences in varieties purchased by households do not lead to fluctuations in inflation inequality. For example, Del Canto et al. (2025) note, "Prior work has found that households at different income levels experience different trend inflation in consumption prices, and that this difference is driven by differences within fine product groups. [.... However], there is no a priori reason to think inflation rates of finer product categories should be differentially responsive to short-run shocks." In contrast, we show that input cost shocks lead to systematic and substantial fluctuations in inflation inequality within narrowly defined product categories.

Our finding that pass-through in levels can parsimoniously account for fluctuations in inflation inequality over time relates to prior work that studies cheapflation and inflation inequality during specific periods, such as the Great Recession (Li 2019; Argente and Lee 2021; Becker 2024), the Covid-19 pandemic in 2020 (Jaravel and O'Connell 2020; Weber, Gorodnichenko, and Coibion 2023), and the period of inflation from 2021–2023 (Cavallo and Kryvtsov 2024; Chen, Levell, and O'Connell 2024).[3] Pass-through in levels likewise

[2]See, e.g., Michael (1979), Hagemann (1982), Garner, Johnson, and Kokoski (1996), Hobijn and Lagakos (2005), Hobijn, Mayer, Stennis, and Topa (2009), Cravino, Lan, and Levchenko (2020), Hottman and Monarch (2020), Klick and Stockburger (2021, 2024), Orchard (2022), Hochmuth, Pettersson, and Christoffer (2022), Chakrabarti, Garcia, and Pinkovskiy (2023), Ferreira, Leiva, Nuño, Ortiz, Rodrigo, and Vazquez (2023), Pallotti, Paz-Pardo, Slacalek, Tristani, and Violante (2023), Cavallo (2024), Jaravel (2024), Lan, Li, and Li (2024), Olivi, Sterk, and Xhani (2024), Del Canto, Grigsby, Qian, and Walsh (2025) and Lokshin, Sajaia, and Torre (2025). Each of these papers consider differences in inflation across households due to heterogeneous spending shares across BLS entry-level items (ELIs) or more aggregated product categories.

[3]An earlier draft of this paper used evidence of pass-through in levels from 2006 to 2020 to forecast a surge in cheapflation and inflation inequality during the period from 2021–2023. Those predictions were confirmed by analyses of online food prices by Cavallo and Kryvtsov (2024) and UK scanner data by Chen et al. (2024). The present paper shows that pass-through in levels in fact accounts for the extent of cheapflation and inflation inequality in U.S. retail scanner data over this period.

offers an explanation for the disproportionate effects of large aggregate cost shocks, such as currency devaluations, on low-income households that purchase lower-priced varieties (see e.g., Cravino and Levchenko 2017; Gouvea 2017).

Finally, we argue that fluctuations in cheapflation and inflation inequality arise due to pass-through in levels of upstream costs, relating to a large literature on the theoretical and empirical determinants of pass-through (see e.g., Bulow and Pfleiderer 1983; Campa and Goldberg 2005; Burstein, Eichenbaum, and Rebelo 2006; Nakamura and Zerom 2010; Weyl and Fabinger 2013; Burstein and Gopinath 2014; Mrázová and Neary 2017; Amiti, Itskhoki, and Konings 2019; and Miravete, Seim, and Thurk 2023, 2025). Our companion paper (Sangani 2025) surveys previous estimates of pass-through in levels and logs and derives conditions on demand that lead to pass-through in levels. That paper does not explore its implications for cheapflation and inflation inequality, as we do in this paper.

Layout. Section 2 describes the data sources we use in the paper. In Section 3, we use coffee as a laboratory to study the pass-through of input costs and its effect on cheapflation and inflation inequality. Section 4 broadens the analysis to the entire food-at-home basket. Section 5 provides evidence of similar dynamics in consumption categories beyond food at home. Section 6 discusses how the same mechanism can lead to heterogeneity in import price inflation across countries and inflation across cities, and Section 7 concludes.

2 Data Sources and Sample Construction

Our main analysis uses two datasets: NielsenIQ Retail Scanner data, which we use to construct inflation rates and explore how pass-through varies across the price distribution, and NielsenIQ Household Panelist data, which we use to construct inflation rates faced by different income groups.

2.1 Retail Scanner Data

The NielsenIQ Retail Scanner dataset records weekly sales and quantities sold of individual products (referred to hereafter as universal product codes, or UPCs) at over 30,000 retail stores across the United States. The data cover food-at-home products and other nondurables such as personal care products, household cleaning supplies, and general merchandise. We use data from 2006 to 2023, which covers over $5.4 trillion in cumulative sales. An advantage of the Retail Scanner dataset is that it includes all sales of tracked products in participating retail chains, allowing us to measure product-level inflation rates with much less sampling error than would be possible in panelist data.

For each universal product code i in each retail chain r, we calculate the average price in quarter t as $p_{irt} = \text{Sales}_{irt}/\text{Units}_{irt}$. Our choice to aggregate at the level of UPC by retail chain follows from DellaVigna and Gentzkow (2019), who show that stores within a retail chain tend to exhibit little variation in posted prices for a UPC at each point in time. We use these quarterly prices to construct year-over-year inflation rates for each UPC i in each retail chain r, starting in each quarter t:

$$\pi_{irt} = \frac{p_{irt+4}}{p_{irt}} - 1.$$

We primarily use these year-over-year inflation rates to avoid seasonality effects that may bias inflation measured over shorter horizons.

Appendix Table A1 reports that products with available inflation rates account for 91 percent of sales in the Retail Scanner data in each year. The remaining 9 percent of sales for which inflation rates are missing include products that are discontinued or whose attributes—such as package size or branding—have changed over the year.[4]

Construction of unit price groups. To analyze inflation dynamics across the price distribution, we stratify products within narrowly defined categories by unit price. Products in the NielsenIQ data are classified into about 1,200 highly disaggregated "product modules," such as refrigerated yogurt, bar soap, olive oil, paper towels, and antacids. For each of these product categories, we use product package sizes provided by NielsenIQ to calculate unit prices for products in the category (e.g., dollars per ounce of coffee). In each quarter, we calculate the average unit price for each UPC i at each retail chain r using sales and quantities sold over the prior four quarters, to ensure that these unit prices reflect persistent price differences. Then, we order products in each quarter by unit price and split products into N bins with equal sales. The first bin corresponds to UPC-retailer pairs in each product module with the lowest unit prices, while the Nth bin contains the products with the highest unit prices. For our analyses, we primarily use unit prices deciles (i.e., $N = 10$), though for some figures and analyses we use more aggregated terciles or quintiles ($N = 3$ or 5).

To calculate inflation rates for each unit price group, we aggregate product-level inflation rates using initial sales shares, $\pi_{gt} = \sum_{ir \in g} \lambda_{irt} \pi_{irt}$, where λ_{irt} is the sales of UPC i at

[4]NielsenIQ uses UPC versions to delineate such attribute changes. We are careful to treat different UPC versions as distinct products to avoid conflating quality changes with inflation for continuing varieties.

retailer r in quarter t as a share of the sales of all continuing varieties in group g. Likewise, we construct the change in price level for unit price group g as $\Delta p_{gt} = \sum_{ir \in g} \tilde{\lambda}_{irt} \Delta p_{irt}$, where $\Delta p_{irt} = p_{irt+4} - p_{irt}$ and $\tilde{\lambda}_{irt}$ is the quantity share (e.g., in ounces) of UPC i at retailer r in group g in quarter t.

2.2 Household Panelist Data

To analyze differences in inflation across income groups, we supplement the Retail Scanner data with data on purchases by a nationally representative panel of households. The NielsenIQ Homescan Consumer Panel includes around 60,000 participating households in each year. Households record the date and location of shopping trips, scan all purchased items in NielsenIQ-tracked categories, and report promotions and discounts. NielsenIQ offers participating households a variety of incentives to accurately report data and drops households from the program that do not meet minimum reporting standards.

Construction of income quintiles. To analyze inflation across the income distribution, we group households each year into income quintiles. We order households by reported income using the sixteen income bins provided by NielsenIQ and further sort households within each income bin by total expenditures divided by the square-root of household size.[5] We then split households into five equally-sized groups using projection weights provided by NielsenIQ. For robustness, we repeat our analyses splitting households into income deciles.

We construct inflation rates for each income group by calculating each group's expenditures on each UPC in each quarter and merging in UPC-level inflation rates from the Retail Scanner dataset. Our baseline analysis on inflation rates by income quintile aggregates at the level of UPC rather than UPC-retail chain, because matching by UPC allows us to cover a larger share of household expenditures. Appendix Table A2 reports that over 60 percent of expenditures reported in the Homescan data can be matched by UPC to the Retail Scanner data, compared to 25 percent when matching by both UPC and retail chain. This difference owes to the fact that not all retail chains that households purchase from participate in the NielsenIQ Retail Scanner program. We trim the top and bottom 0.5 percent of inflation observations to ensure that our results are not driven by extreme outliers.

[5]Using the square-root of household size to equivalize incomes and expenditures across households is a common practice in the income inequality literature. See e.g., the BLS's methodology for calculating the distributional of personal consumption expenditures (`https://www.bls.gov/cex/pce-ce-distributions.htm`) and Handbury (2021) and Klick and Stockburger (2024) for applications to price indices across income groups.

Our baseline measures of inflation for each income group are inflation rates measured using a Laspeyres index, $\pi_{gt} = \sum_i \omega_{igt}\pi_{it}$, where ω_{it} is the expenditure share of income group g on product i in quarter t and π_{it} is the year-over-year inflation in the quantity-weighted average price of UPC i. This Laspeyres price index most closely resembles the way the Bureau of Labor Statistics (BLS) constructs its consumer price index for urban consumers (CPI-U). Of course, the Laspeyres price index does not account for substitution across products in response to price changes or how nonhomotheticities cause households' baskets to change endogenously with real income. Section 4.4 explores how inflation across income groups compares under alternative price indices that account for these forces.

3 Coffee: A Case Study

We begin by using coffee products as a laboratory to explore how pass-through in levels generates heterogeneity in inflation rates across products and households. Coffee provides an ideal empirical setting for this analysis. The primary input in producing coffee—green Arabica coffee beans—is traded on global commodity markets, and its price exhibits large swings due to weather shocks in coffee-growing regions and exchange rate movements. These input cost shocks offer ample variation for identifying the pass-through of cost changes to retail prices.

The retail coffee market also exhibits substantial cross-sectional variation in prices, with premium brands like Starbucks and Peet's charging much higher unit prices than brands like Folgers and Maxwell House. This variation allows us to examine how a common cost shock translates into different inflation rates across the price distribution. Our analysis builds on Nakamura and Zerom (2010), who estimate the aggregate pass-through of commodity costs to coffee retail prices from 2000–2005. We extend their analysis by considering how the pass-through of input cost shocks varies across the price distribution and its implications for cheapflation and inflation inequality.

3.1 Pass-Through in Levels and Cheapflation

We pair NielsenIQ data on retail prices for coffee products with commodity price data from the International Coffee Organization (ICO). Specifically, we use the ICO's price of mild Arabicas at the dock in New York as our measure of commodity input prices. Following Nakamura and Zerom (2010), we adjust the commodity price to account for the fact that green coffee beans lose 19 percent of their weight during the roasting process.

Figure 1 plots inflation in coffee commodity prices alongside inflation for retail coffee products, split into three unit price groups. Coffee commodity prices exhibit large swings over our sample period from 2006 to 2023. In three instances—in 2011, 2014, and 2021—coffee commodity prices rose by over 60 percent within the span of one year. These swings in commodity prices appear to be incorporated into retail prices with a lag of about two quarters, as shown by the solid lines indicating inflation for retail coffee products.

The top panel of Figure 1 shows substantial heterogeneity in the response of retail prices to commodity prices across unit price groups. In each of the three episodes of rising commodity prices, inflation was substantially higher for products with lower unit prices. For example, in 2011, retail prices for products in the lowest tercile of unit prices rose by 40 percent, compared to 12 percent for products in the top tercile.

These differences across unit price groups disappear in the bottom panel of Figure 1, which instead shows price changes in levels (i.e., cents per ounce). For the largest commodity price increases in 2011 and 2021, unit prices rise by almost exactly the same amount across unit price terciles. The identical increases in price levels across products appear as larger inflation rates for products with lower unit prices, because the same price increase represents a larger percentage change for low-priced products.

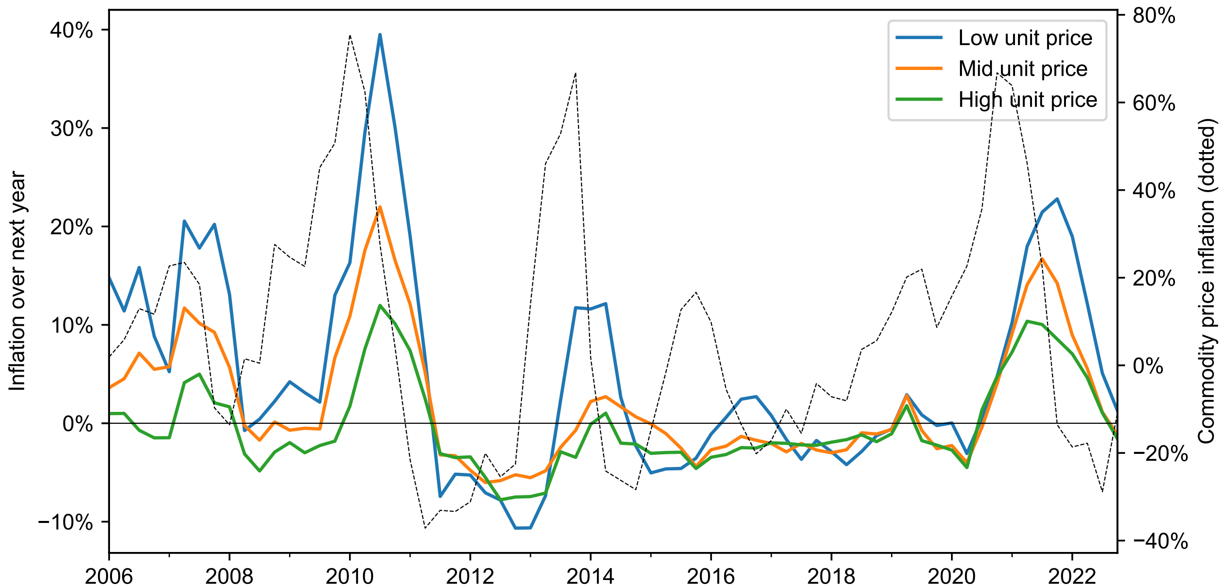
In their study of online food prices from 2021–2023, Cavallo and Kryvtsov (2024) term the pattern of higher inflation for lower-priced varieties "cheapflation." Figure 1 shows that cheapflation is not specific to the post-pandemic period: indeed, we find systematic appearances of cheapflation each time green coffee bean prices rise. Moreover, Figure 1 suggests a simple candidate explanation for these cheapflation cycles. If firms raise their prices by the same absolute amount in response to commodity cost increases, these identical absolute price changes generate larger percentage price increases for lower-priced varieties, and thus cheapflation.

To formalize this intuition, we estimate the pass-through of commodity cost changes to retail prices using the distributed lag specification,

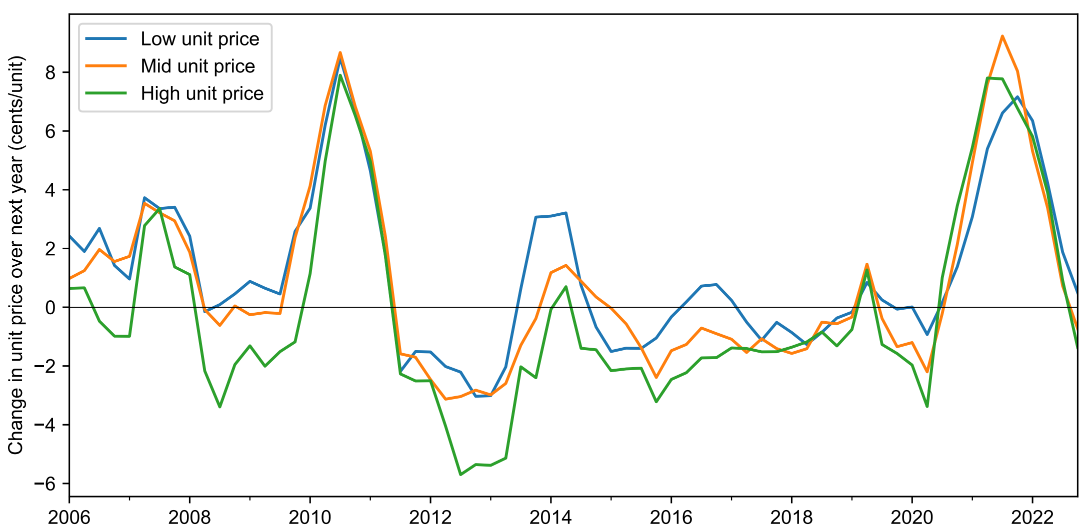
$$\Delta p_{irt} = a_{ir} + \sum_{k=0}^{K} b_k \Delta c_{t-k} + \sum_{k=1}^{4} d_k q_t + \varepsilon_{irt}. \tag{1}$$

where Δp_{irt} is the change in the price of UPC i at retailer r from quarter $t-1$ to t, Δc_t is the change in the commodity price, α_{ir} are fixed effects that absorb product-retailer trends, and q_t are quarter-of-year dummies that absorb seasonal variation in prices. The coefficients b_k capture the change in retail prices associated with a change in commodity input costs k quarters ago. Accordingly, the long-run pass-through is given by the sum of

Figure 1: Coffee price changes in percentages and levels, by unit price tercile.



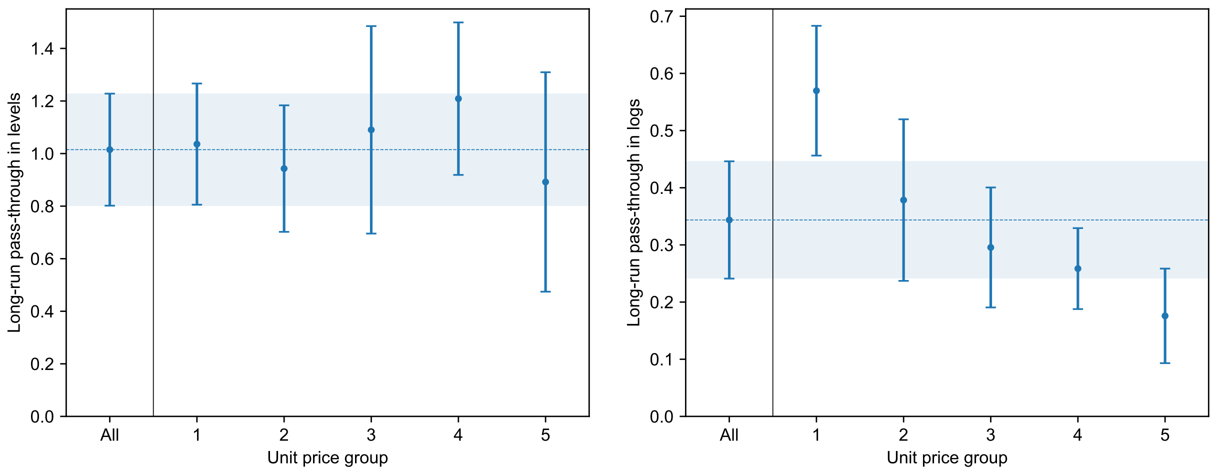
(a) Price changes in percentages (inflation).



(b) Price changes in levels.

Note: Panel (a) plots inflation over the next year for three unit price groups of coffee products, constructed using the procedure described in Section 2.1. The dotted line in panel (a) plots inflation in coffee bean commodity prices over the next year. Panel (b) plots the quantity-weighted average change in unit prices over the next year for coffee products in each unit price group, as described in Section 2.1.

Figure 2: Pass-through of coffee commodity costs to retail prices by unit price group.



(a) Pass-through in levels. **(b)** Pass-through in logs.

Note: Panels (a) and (b) show estimates of the long-run pass-through in levels $\sum_{k=1}^{K} b_k$ and logs $\sum_{k=1}^{K} \beta_k$, estimated with specifications (1) and (2) respectively. Error bars indicate 95 percent confidence intervals constructed using the delta method, with standard errors two-way clustered by brand and quarter. The dotted line and shaded region indicates the point estimate and 95 percent confidence interval for pass-through estimated in the full sample.

the coefficients, $\sum_{k=0}^{K} b_k$.

This specification is standard in the literature on incomplete pass-through, though the canonical specification uses price and cost changes measured in logs rather than in levels (see e.g., Campa and Goldberg 2005; Nakamura and Zerom 2010). For our baseline results, we choose a horizon of $K = 6$ quarters following Nakamura and Zerom (2010).

The left panel of Figure 2 plots the long-run pass-through in levels, estimated for the full sample of coffee products as well as separately for each unit price quintile. The pass-through in levels for the entire sample is 1.01 (standard error 0.11). In other words, increases in green coffee bean prices are eventually passed through cent-for-cent to retail prices. Furthermore, pass-through in levels appears largely uniform across unit price groups, and we cannot reject complete pass-through in levels for any unit price group.[6]

The right panel of Figure 2 plots the long-run pass-through in logs, estimated with the

[6]While Nakamura and Zerom (2010) document that the aggregate pass-through in levels of commodity prices to wholesale and retail coffee prices is close to one, they do not show that pass-through in levels emerges uniformly across the price distribution. In fact, their model instead predicts that pass-through in levels varies systematically with unit price (see Appendix Figure C1).

analogous specification,

$$\Delta \log p_{irt} = \alpha_{ir} + \sum_{k=0}^{K} \beta_k \Delta \log c_{t-k} + \sum_{k=1}^{4} \delta_k q_t + \varepsilon_{irt}. \tag{2}$$

Since pass-through is complete in levels, pass-through when measured in logs is mechanically incomplete: the log pass-through for the entire sample is 0.34 (standard error: 0.05). Complete pass-through in levels generates heterogeneous sensitivity in inflation rates to commodity inflation across unit price groups. For the lowest unit price quintile of products, the log pass-through of commodity inflation to retail prices is 0.57, compared to 0.18 for the highest unit price quintile.

Thus, we find that coffee products across unit price groups exhibit complete pass-through in levels of changes in commodity input costs. Complete pass-through in levels implies that the inflation rates of low-priced varieties are more sensitive to input cost inflation, because the same absolute price increase (or decrease) represents a larger proportional change in price for lower-priced varieties. Pass-through in levels thus systematically leads to cheapflation when input costs rise.

Robustness. One may be concerned that our estimates of the pass-through of commodity costs to prices are biased by reverse causality, for example due to demand shocks that feed back from retail prices to commodity prices, or may wonder whether changes to the specifications in (1) and (2) alter our results. We evaluate the robustness of these concerns in Table 1, which reports differences in pass-through in levels and logs across unit price quintiles. We continue to find uniform pass-through in levels across unit price groups and declining log pass-through with unit price when we use exchange rates for Brazil and Colombia and weather shocks to coffee-growing areas in Brazil and Colombia to isolate exogenous changes in commodity prices. Absorbing product-specific seasonality effects or changing the horizon over which we measure the long-run pass-through also does not meaningfully alter our results.

Explaining pass-through in levels. Why do coffee products across the unit price distribution exhibit pass-through in levels of upstream cost shocks? One candidate explanation is perfect competition: if products' prices exactly reflect marginal costs of production and production is Leontief in the commodity input, then changes in commodity costs will translate one-for-one into changes in products' prices. (The decline in log pass-through across unit price groups then reflects differences in the commodity cost share across groups.) In this vein, Cravino and Levchenko (2017) explain differences in inflation

Table 1: Robustness: Difference in pass-through across coffee unit price groups.

Unit price quintile	*Panel A. Pass-through in levels*					
	Baseline	Exchange rates IV	Weather shocks IV	Product-quarter fixed effects	Horizon $K = 4$	Horizon $K = 8$
1	0.13	0.10	0.25	0.22	0.23	−0.38
2	−0.44	−0.42	−0.17	−0.64	−0.40	0.18
3	0.33	0.52	0.24	−0.02	−0.15	0.06
4	1.06	0.85	−0.32	1.42	1.13	1.30
5	−0.51	−0.36	−0.30	−0.36	−0.52	−0.18
Unit price quintile	***Panel B. Pass-through in logs***					
	Baseline	**Exchange rates IV**	**Weather shocks IV**	**Product-quarter fixed effects**	**Horizon $K = 4$**	**Horizon $K = 8$**
1	2.90**	2.21**	1.70*	2.81**	2.57**	2.30**
2	0.39	0.35	0.13	0.25	0.14	1.05
3	−0.64	−0.35	−0.53	−0.88	−0.88	−0.76
4	−1.34	−1.14	−2.04**	−1.02	−0.76	−0.89
5	−2.50**	−2.33**	−2.05**	−2.28**	−2.22**	−2.32**

Note: Each cell reports $(\rho_i - \rho_{\text{all}})/(\sigma_i^2 + \sigma_{\text{all}}^2)^{1/2}$, where ρ_i is the estimated long-run pass-through of commodity costs to retail prices for unit price group i, ρ_{all} is the estimated pass-through for the entire sample, and σ_i and σ_{all} are the standard errors of the respective pass-through estimates. The column "Exchange rates IV" uses current and lagged Brazil and Colombia exchange rates (FRED series `CCUSMA02BRM618N` and `COLCCUSMA02STM`) to instrument for commodity cost changes. The column "Weather shocks IV" uses current and lagged minimum and maximum temperatures in coffee-growing regions in Brazil (21.55°S, 45.34°W) and Colombia (4.81°N, 75.70°W) to instrument for commodity cost changes. * (**) indicates that the absolute value of the statistic is greater than 1.65 (1.96).

across households following the 1994 Mexican peso devaluation by assuming perfectly competitive retailers that combine physical goods and distribution services in different proportions.

However, perfect competition is at odds with other features of the data. There is variation in prices of identical UPCs across retail chains and within store outlets over time that is unlikely to reflect changes in costs. Moreover, the response of quantities to these price changes imply modest demand elasticities that contrast with the perfectly elastic demand curves that would prevail under perfect competition.

Under imperfect competition, pass-through depends on how firms' markups adjust to cost changes, and there is no guarantee that firms should exhibit unitary pass-through in levels as we find in Figure 2. In fact, in many standard models of imperfect competition in macroeconomics and trade, such as the Dixit and Stiglitz (1977) CES demand model, firms retain fixed percentage markups in response to common cost shocks, implying that the pass-through in levels of cost changes is equal to firms' gross markups and is strictly greater than one.

In a companion paper (Sangani 2025), we show that one can reconcile imperfect competition with evidence of complete pass-through in levels using demand systems that satisfy a property called *shift invariance.* These demand systems allow for downward-sloping residual demand curves and positive markups while predicting that common cost shocks, such as shocks to commodity input prices, are passed through one-for-one in levels to firms' prices.[7] That paper also documents that the responses of prices and quantities to cost shocks across several markets conform with shift-invariant demand.

3.2 Within-Category Cycles in Inflation Inequality

If households across the income distribution purchase different varieties, differences in the sensitivity of varieties' inflation rates to commodity price inflation will lead to differences in inflation experienced across the income distribution. We estimate how the average unit price of varieties purchased by each income group differ using the specification,

$$\text{LogUnitPrice}_{gt} = \sum_{q=1}^{5} \beta_q 1\{g = q\} + \phi_t + \varepsilon_{gt}, \tag{3}$$

where LogUnitPrice_{gt} is the log of the average unit price of coffee products purchased by households in group g in quarter t and ϕ_t are time fixed effects that absorb changes in unit prices over time. We omit the dummy for the first quintile, so that the coefficients β_q estimate the difference in log unit prices paid by each income quintile relative to the lowest income group.

Panel A of Table 2 shows that high-income households purchase higher-priced varieties: households in the highest income quintile buy coffee products that are on average 24 percent more expensive than those purchased by households in the lowest income quintile. These patterns are consistent with previous work that documents differences in the relative prices of products purchased by income groups within narrow product categories (e.g., Handbury 2021; Sangani 2022).

These differences in the price of varieties purchased by income groups, combined with

[7] Examples of shift-invariant demand systems include the class of linear random utility models (McFadden 1981), "address" models with inelastic demand defined by Anderson, de Palma, and Thisse (1992), and mixed logit demand (e.g., Berry, Levinsohn, and Pakes 1995; Nevo 2001) without an outside option.

Table 2: From cheapflation to inflation inequality in coffee.

Panel A. Prices paid		*Panel B. Inflation sensitivity*		
	Log unit price (1)		*Coffee inflation for income group* (OLS)	(IV)
Income quintile 2	0.036**	Coffee inflation × Income quintile 2	−0.039**	−0.055**
	(0.000)		(0.002)	(0.018)
Income quintile 3	0.093**	Coffee inflation × Income quintile 3	−0.096**	−0.119**
	(0.001)		(0.004)	(0.030)
Income quintile 4	0.157**	Coffee inflation × Income quintile 4	−0.155**	−0.201**
	(0.005)		(0.008)	(0.050)
Income quintile 5	0.236**	Coffee inflation × Income quintile 5	−0.270**	−0.322**
	(0.006)		(0.017)	(0.024)
Time FEs	Yes	Time FEs	Yes	Yes
N	360	N	340	340
R^2	0.99	R^2	1.00	0.99
Within R^2	0.93	Within R^2	0.80	0.19

Note: Panel A reports results from specification (3) and Panel B reports results from specification (4). For ease of display, Panel B does not display the estimated group fixed effects α_g. The IV column in Panel B uses contemporaneous coffee bean commodity inflation rates and two lags to instrument for coffee inflation rates. Regressions weighted by consumer expenditures. Standard errors two-way clustered by year and income quintile.

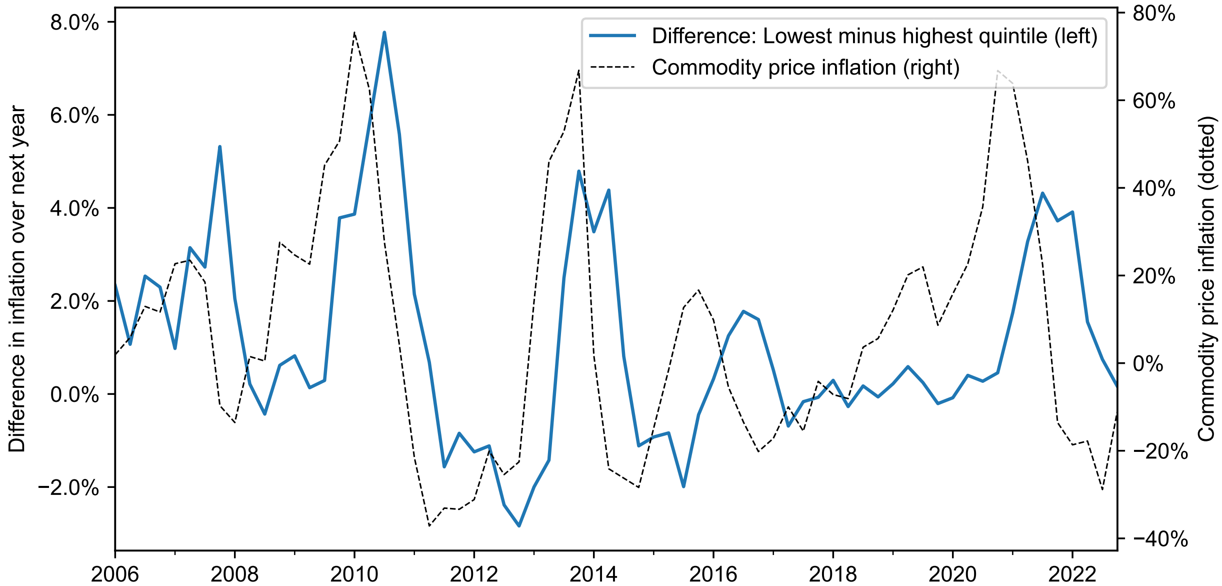
pass-through in levels, generate differences in the sensitivity of inflation rates faced by each income group to input cost fluctuations. We estimate these differences in inflation sensitivity using the specification,

$$\text{CoffeeInflation}_{gt} = \sum_{q=1}^{5} \beta_q \left(\text{AvgCoffeeInflation}_t \times 1\{g = q\} \right) + \alpha_g + \phi_t + \varepsilon_{gt}. \tag{4}$$

Here, $\text{CoffeeInflation}_{gt}$ is the year-over-year coffee inflation rate for income quintile g (measured as the inflation rate on a Laspeyres price index, as defined in Section 2.2) starting in quarter t, and $\text{AvgCoffeeInflation}_t$ is the overall inflation rate for coffee products in the Retail Scanner data starting in quarter t. The income group fixed effects α_g absorb differences in trend inflation across income quintiles, and the time fixed effects ϕ_t absorb coffee inflation over time. We again omit dummies for the first income quintile, so that β_q measures differences in the sensitivity of inflation rates for each income quintile to overall coffee inflation relative to the lowest income group.

As predicted by pass-through in levels, the sensitivity of coffee inflation rates for each

Figure 3: Within-category inflation inequality in coffee.



Note: The solid line plots the difference in coffee inflation rates over the next year for the first and fifth income quintiles, constructed using the procedure described in Section 2.2. The dotted line plots inflation in coffee bean commodity prices over the next year.

income quintile to overall coffee inflation declines systematically with income. Inflation rates for the highest income quintile are 27 percent less sensitive to overall fluctuations in coffee prices than for the lowest income quintile. We find similar results when we isolate input cost-driven fluctuations in coffee prices, using current and lagged inflation rates for coffee bean commodity prices to instrument for overall coffee inflation.

These results imply fluctuations in "inflation inequality"—i.e., the gap in inflation experienced by low- and high-income households—as commodity costs move around. Figure 3 plots the gap between the coffee inflation rate for households in the lowest income quintile and the highest income quintile. Indeed, there are large swings in the extent of the within-category inflation inequality, with spikes in 2011, 2014, and 2022 following increases in coffee commodity costs. The inflation gap is positive on average, consistent with the secular drivers of inflation inequality documented by Jaravel (2019, 2021), but also features cyclical variation predicted by complete pass-through in levels—even becoming negative in periods of commodity price deflation, such as in 2012–2013.

Comparison to BLS data. The within-category fluctuations in inflation inequality shown in Figure 3 are masked in official statistics due to aggregation. To organize price collection, the Bureau of Labor Statistics (BLS) classifies goods and services into 273 entry-level items (ELIs), which are grouped into 243 basic items and further aggregated into 211 item strata. The most disaggregated CPI data released publicly is at the item stratum level (typically reported across 32 geographic areas). A large literature studies differences in inflation across the income distribution by matching inflation rates on item strata to household expenditure shares across items (see e.g., the list in Footnote 2).

Such datasets built on ELI- or stratum-level prices can miss substantial fluctuations in inflation inequality that stem from differences in purchasing patterns within narrowly defined categories like coffee. Coffee, for instance, is assigned to item stratum SEFP01, which includes a single ELI (FP011) that covers both roasted and instant coffee. Over our sample period, the maximum year-over-year inflation rate in SEFP01 was 21 percent (in 2011), and the minimum was −8 percent (in 2014). In the disaggregated data, however, the inflation gap between the first and fifth income quintiles *within* roasted coffee was 8pp in 2011 and −3pp in 2014. In other words, assuming category-level inflation rates apply to households in each income group understates the degree of inflation inequality when costs rise and overstates the degree of inflation inequality when costs fall.

4 Cheapflation & Inflation Inequality Across Food at Home

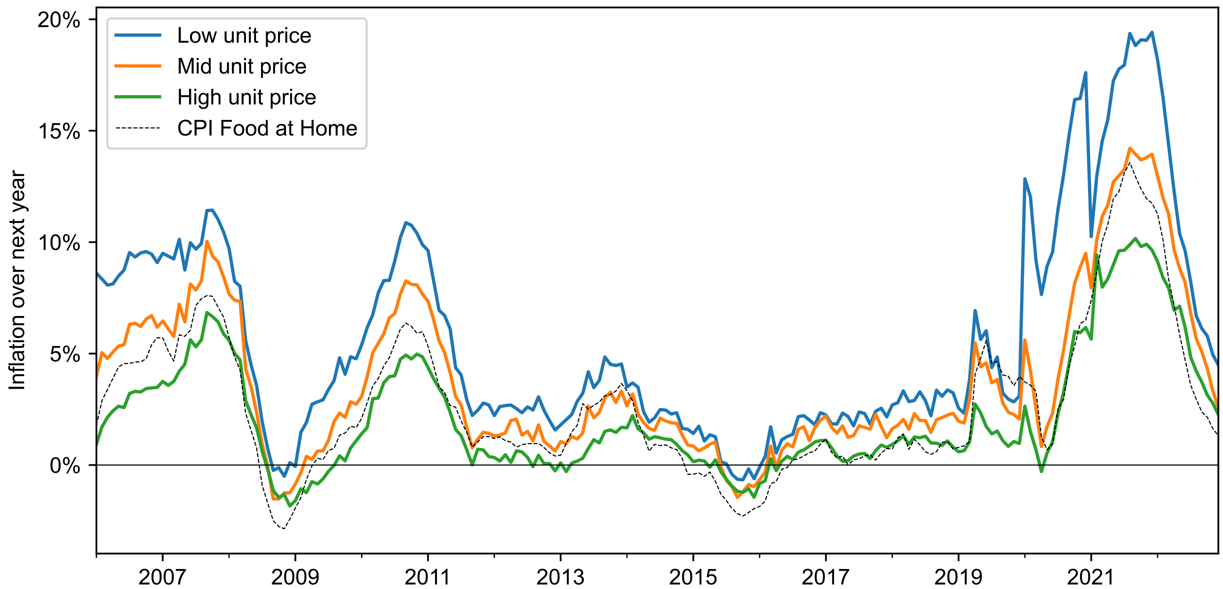
We now consider fluctuations in cheapflation and inflation inequality across the entire food-at-home basket. The same patterns that we documented in coffee extend to food-at-home products: pass-through in levels generates systematic fluctuations in cheapflation and inflation inequality in response to changes in the relative price of upstream inputs.

4.1 Pass-Through in Levels and Cheapflation

We use the Retail Scanner data to construct a food-at-home price index, using products in six departments: dry grocery, frozen foods, dairy, deli, packaged meat, and fresh produce. Kaplan and Schulhofer-Wohl (2017) and Beraja, Hurst, and Ospina (2019) show that price indices constructed from NielsenIQ scanner data track BLS statistics closely, and Appendix Figure A2 confirms that this is the case for our food-at-home price index: inflation rates for our food-at-home price index have a correlation with the BLS's food-at-home consumer price index of 0.96.

The advantage of the Retail Scanner data is that we can then disaggregate inflation in the overall food-at-home price index by unit price group to study how inflation varies across the price distribution. Figure 4 plots inflation rates from 2006 to 2023 for three

Figure 4: Cheapflation: Food-at-home inflation by unit price tercile from 2006–2023.



Note: The figure shows inflation over the next year for three unit price groups of food-at-home products, constructed using the procedure described in Section 2.1.

unit price groups. Recall that varieties in each product module are split into groups with equal sales, ensuring that each unit price group has an identical distribution of sales across product modules. Thus, differences in inflation across unit price groups reflect differences in inflation rates for low- and high-priced products in each product module, rather than differences in composition across modules.

Figure 4 reveals substantial differences in inflation rates for low-priced food-at-home products compared to high-priced food-at-home products. Low-priced varieties have higher inflation rates than high-priced varieties over the whole sample, consistent with the secular trends in inflation inequality documented by Jaravel (2019). But the gap in inflation rates also widens during periods when overall food-at-home inflation is high—such as during the food commodity price booms of 2008, 2011, and 2021—and narrows during periods when aggregate food-at-home inflation rates are low. Viewed in context of the entire time series, the "cheapflation" during the 2021–2023 period is not an isolated incident, but rather is part of a systematic pattern of widening inflation rates between low- and high-priced varieties during times of high food-at-home inflation.

To test whether these differences in inflation by unit price group reflect differential sensitivity to upstream costs, we estimate the pass-through of two upstream producer price indices (PPI) for Food Manufacturing and Farm Products to food-at-home price indices for each unit price group. These two producer price indices reflect changes in input costs of processed and raw food, respectively: Appendix Figure A1 shows that inflation in these price indices tends to lead food-at-home consumer inflation. We estimate log pass-through of these PPI to food-at-home price indices using a distributed lag specification analogous to the one that we used to measure pass-through in coffee,

$$\Delta \log p_t^g = \alpha^g + \sum_{k=0}^{K} \beta_k^g \Delta \log \mathrm{PPI}_{t-k} + \sum_{k=1}^{4} \delta_k^g q_t + \varepsilon_{it}. \tag{5}$$

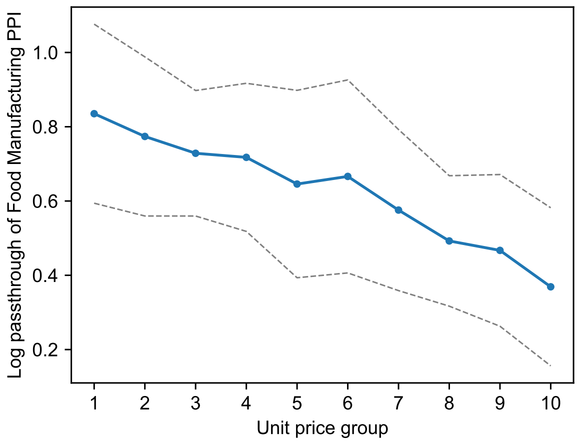
Here, $\Delta \log p_t^g$ is the change in the food-at-home price index for unit price decile g from quarter $t-1$ to t and $\Delta \log \mathrm{PPI}_t$ is the change in the producer price index over the same period. The intercepts α^g absorb secular differences in inflation rates across unit price groups, and quarter-of-year dummies q_t absorb seasonal effects. We choose a horizon of $K = 6$ quarters, matching our specification for coffee products. For our baseline results, we estimate these pass-through regressions over the period 2006–2020 to avoid the influence of the post-pandemic inflation, where changes in upstream producer price indices are correlated with changes in the aggregate price level.[8]

Figure 5 shows estimated long-run log pass-through, $\sum_{k=0}^{K} \beta_k^g$, of PPI changes to food-at-home prices by unit price decile. For both upstream cost indices, log pass-through systematically declines with unit price. For Food Manufacturing, log pass-through declines from 0.84 for the lowest price decile to 0.37 for the highest price decile, while for Farm Products, pass-through falls from 0.28 for the lowest decile to 0.13 for the highest price decile. In both cases, the estimated pass-through of upstream cost movements to prices for food-at-home products in the highest unit price decile are less than half that of the lowest decile. The decline by unit price is consistent with our hypothesis that pass-through in levels of cost shocks leads to larger percentage changes for lower-priced varieties.

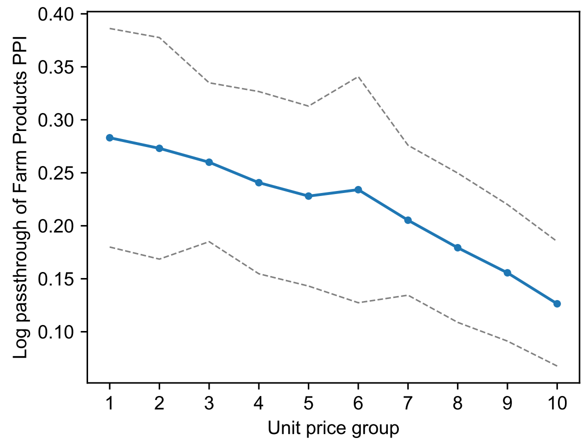
A simple formula for inflation differences under pass-through in levels. While the decline in log pass-through across unit price groups is consistent with pass-through in levels, it does not tell us whether pass-through in levels quantitatively accounts for the extent of pass-through differences across unit price groups. We can test for whether

[8] Appendix Figure A3 shows that estimating pass-through over the period from 2021–2023 results in higher estimates of PPI pass-through due to the fact that increases in PPI over that period were accompanied by inflation in aggregate price level. Increases in the aggregate price level affect other costs facing retailers, such as distribution costs. We can control for concomitant changes in the aggregate price level by augmenting (5) to include the pass-through of wage rate changes. Appendix Figure A3 shows that doing so yields similar estimates of PPI pass-through whether or not we include the period from 2021–2023.

Figure 5: Lower-price varieties have higher log pass-through of upstream price indices.



(a) Food Manufacturing PPI.



(b) Farm Products PPI.

Note: Estimates of long-run pass-through of upstream producer price indices by unit price decile from specification (5), estimated over the period 2006–2020. Dotted lines indicate 95 percent confidence intervals, constructed using the delta method with Newey-West standard errors.

pass-through in levels quantitatively accounts for differences in inflation across unit price groups by deriving an expression that relates price differences to predicted inflation differences under pass-through in levels.

To do so, we assume a simple pricing equation for each variety that yields pass-through in levels of input cost changes. Suppose there is a continuum of varieties indexed by $i \in [0, 1]$, and that the unit price of variety i is

$$p_i = m + \beta_i w, \tag{6}$$

where m denotes a common material input cost, w is the wage rate, and β_i are variety-specific weights on labor. Note that this pricing equation assumes that a unit of each variety contains the same quantity of the common material input (e.g., each ounce of roasted ground coffee across brands contains the same amount of coffee beans).

This pricing function obtains when each variety is produced by a single firm with marginal cost m, and the quantity demanded of each variety is given by the generalized logit demand system,

$$q_i = \frac{\exp(\delta_i - \beta_i p_i / w)}{\int_0^1 \exp(\delta_k - \beta_k p_k / w)\, dk},$$

where δ_i are taste shifters and β_i are price sensitivity parameters that each vary across varieties.[9] It also obtains if each variety is produced by a continuum of perfectly competitive firms, and each variety i is produced with a Leontief production function in the material input and labor with varying production weights β_i on labor. Under either microfoundation, (6) has the desirable properties that material cost changes are passed through to prices completely in levels (i.e., holding w fixed, $\Delta p_i = \Delta m$) while prices are neutral to changes in the aggregate price level (i.e., scaling material costs m and wages w by a common factor leads to proportional changes in each price p_i).

Given (6), we can characterize how a perturbation to materials and labor prices, denoted $\pi^m = d\log m$ and $\pi^w = d\log w$, shape inflation rates across groups of varieties. Let λ_i denote the initial sales share of variety i, and let $p = (\int_0^1 \lambda_i/p_i di)^{-1}$ denote the (unit-weighted) average unit price across varieties.

Proposition 1 (Differential inflation under pass-through in levels)**.** *Consider a group g of varieties defined by variety expenditure shares λ_i^g. Let p^g denote the initial (unit-weighted) average unit price of varieties in group g and $\pi^g = \int_0^1 \lambda_i^g \pi_i di$ denote the inflation rate on a Laspeyres price index for group g. Under* (6)*, the inflation rate π^g to a first order is*

$$\pi^g \approx \pi^{all} + \left(\frac{p}{p^g} - 1\right)\left(\pi^{all} - \pi^w\right),$$

where $\pi^{all} = \int_0^1 \lambda_i \pi_i di$ is the inflation rate on a Laspeyres price index that includes all varieties.

Proof. See Appendix B. □

Proposition 1 shows that the difference between the inflation rate for a group of varieties g and the aggregate inflation rate across all varieties depends on the average unit price of varieties in group g relative to all varieties, p/p^g, and the gap between the aggregate inflation rate and the wage inflation rate. Intuitively, when $\pi^{\text{all}} > \pi^w$, the price of materials is increasing faster than the wage. Pass-through in levels then implies that lower-priced varieties will have larger percentage price increases, leading to higher inflation rates $\pi^g > \pi^{\text{all}}$ for groups of varieties where the average unit price $p^g < p$.

Thus, if prices follow the pricing equation in (6), differences in inflation across subgroups of varieties can be predicted using three sufficient statistics: the ratio of the average unit price of products in the subgroup to all varieties p^g/p, the inflation rate for all varieties π^{all}, and the wage inflation rate π^w. Likewise, the extent of cheapflation—i.e., the gap in inflation between a group of low-priced products L and high-priced products H—to a first

[9] This generalized logit demand system is a special case of a broader class of "shift invariant" demand systems that yield complete pass-through in levels of common cost shocks.

order can be estimated using

$$\pi^L - \pi^H \approx \underbrace{\left(p/p^L - p/p^H\right)}_{\text{"Price gap"}} \underbrace{\left(\pi^{\text{all}} - \pi^w\right)}_{\text{"Excess inflation"}} . \tag{7}$$

We term the first bracketed quantity the "price gap" between low-priced and high-priced products, because it captures the difference in relative prices between the two groups. The second bracketed quantity is the excess inflation of the product module relative to wages.

Are fluctuations in cheapflation due to pass-through in levels? We use (7) to evaluate whether the pass-through in levels can quantitatively account for the differences in pass-through that we see across low- and high-priced unit price groups. We estimate the specification,

$$\text{Cheapflation}_{mt} = \beta\left(\text{PriceGap}_{mt} \times \text{ExcessModuleInflation}_{mt}\right) + \delta\text{PriceGap}_{mt} + \varepsilon_{mt}, \tag{8}$$

where Cheapflation_{mt} is the difference between the inflation rate for the lowest unit price decile and highest unit price decile of varieties in product module m from quarter t to quarter $t+4$, PriceGap_{mt} is the quantity defined in (7) calculated using average unit prices in quarter t, and $\text{ExcessModuleInflation}_{mt}$ is the overall inflation rate of product module m in excess of wage inflation. We measure wage inflation as the log change in average hourly earnings of production and nonsupervisory employees. The first-order approximation in Equation (7) predicts that under pass-through in levels, $\beta \approx 1$. In addition to the interaction term, we include PriceGap_{mt} separately in the regression to allow for secular differences in inflation rates across high- and low-priced varieties in a module.

Column 1 of Table 3 reports the results from estimating (8). We find that the interaction of the price gap in each module with excess module inflation is positively associated with cheapflation, as predicted by Equation (7). Moreover, the magnitude of the coefficient is roughly in line with the prediction from our first-order approximation in (7): we estimate $\beta \approx 1.2$.[10]

In column 2, we report the results from estimating a specification where we split the excess inflation of each product module into the module inflation rate and the wage inflation rate:

$$\text{Cheapflation}_{mt} = \beta^{\text{module}}\left(\text{PriceGap}_{mt} \times \text{ModuleInflation}_{mt}\right)$$

[10] Appendix Table A3 shows that similar results obtain if we instead split products in each module into five unit price groups and measure cheapflation as the gap between the first and fifth unit price quintiles.

Table 3: Explaining cheapflation with pass-through in levels.

	Inflation of lowest-price decile − highest-price decile					
	(1)	(2)	(3)	(4)	(5)	(6)
Excess module inflation × Price gap	1.183**		1.188**		1.194**	
	(0.027)		(0.025)		(0.019)	
Module inflation × Price gap		1.186**		1.188**		1.194**
		(0.025)		(0.025)		(0.019)
Wage inflation × Price gap		-1.657**		-1.047**		-1.540**
		(0.335)		(0.299)		(0.453)
Post-2020			-0.067**	-0.073**		
			(0.018)	(0.024)		
Price gap	0.006	0.030**	0.014	0.008	0.077**	0.092**
	(0.012)	(0.012)	(0.011)	(0.007)	(0.013)	(0.022)
Time FEs					Yes	Yes
Product Module FEs					Yes	Yes
N	42137	42137	42137	42137	42137	42137
R^2	0.92	0.92	0.92	0.92	0.93	0.93

Note: The table reports results from specifications (8) and (9). We measure wage inflation as the year-over-year log change in the average hourly earnings of production and nonsupervisory employees. All inflation rates are measured over the next year from quarter t to quarter $t+4$. The price gap in quarter t is measured as defined in (7) and is winsorized at the 1 percent level. Post-2020 is a binary indicator for years after 2020. Regressions weighted by sales. Driscoll-Kraay standard errors with four lags. * indicates significance at 10%, ** at 5%.

$$+ \beta^{\text{wage}} \left(\text{PriceGap}_{mt} \times \text{WageInflation}_t \right) + \delta \text{PriceGap}_{mt} + \varepsilon_{mt}, \quad (9)$$

Equation (7) predicts that $\beta^{\text{module}} \approx 1$ and $\beta^{\text{wage}} \approx -1$: higher inflation rates for a module lead to more cheapflation, but higher wage inflation rates narrow the inflation differences between low- and high-priced varieties. These predictions are borne out in column 2: we find that the estimated coefficient $\beta^{\text{module}} \approx 1.2$, while $\beta^{\text{wage}} \approx -1.7$ and is not significantly different from -1.[11]

How much of the cheapflation during the 2021–2023 inflation surge can be accounted for by pass-through in levels? In columns 3 and 4, we include an indicator for the post-2020 period to evaluate whether there was disproportionate cheapflation during the post-pandemic inflation. In fact, we find the opposite—after accounting for pass-through in levels, the extent of cheapflation during the period from 2021 to 2023 was actually

[11] In each of columns 2, 4, and 6, we cannot reject the null hypothesis that $\beta^{\text{module}} = -\beta^{\text{wage}}$ (p-values are 0.16, 0.65, and 0.45, respectively). This supports our conjecture that cheapflation is a result of changes in input prices relative to the aggregate price level, rather than a consequence of generalized inflation.

slightly less than expected given the rise in input costs.

We extend this logic to evaluate whether other time period- or product category-specific factors are important to explain patterns of cheapflation in columns 5–6. Studies of specific episodes such as the Great Recession or the post-pandemic inflation often attribute relative price changes across low- and high-priced varieties to how business cycle conditions or the distribution of fiscal stimulus affect price sensitivity for different income groups (e.g., Li 2019; Mongey and Waugh 2023; Becker 2024). Columns 5 and 6 provide one way of testing for these competing explanations, by including quarter and product module fixed effects to capture the effect of any period-specific economic conditions on the extent of inflation differences across low- and high-priced varieties. The resulting estimates of the coefficients on the interaction terms do not change substantially, suggesting that these estimates are not largely driven by one period or one product category. Moreover, the share of variation in cheapflation explained by the independent variables rises marginally from 0.92 to 0.93, suggesting that there is limited variation in cheapflation due to differences across product categories or time periods that is not explained by pass-through in levels.

4.2 Cycles in Inflation Inequality

As we saw for coffee products, fluctuations in cheapflation due to the pass-through of upstream costs lead to fluctuations in inflation inequality if income groups purchase different sets of varieties. Table 4 panel A shows that high-income households indeed tend to purchase more expensive varieties within each product module across the food-at-home basket: varieties purchased by the highest income quintile have 8.2 percent higher unit prices than those purchased by the lowest income quintile on average.

We test for whether these differences in the prices of varieties purchased lead to differences in inflation sensitivity across income groups using the specification,

$$\text{ModuleInflation}_{gmt} = \sum_{q=1}^{5} \beta_q \left(\text{AvgModuleInflation}_{mt} \times 1\{g = q\}\right) + \alpha_g + \phi_{mt} + \varepsilon_{gt}, \qquad (10)$$

where $\text{ModuleInflation}_{gmt}$ is the year-over-year inflation rate for product module m for income quintile g starting in quarter t, $\text{AvgModuleInflation}_{mt}$ is the overall inflation rate for product module m in the Retail Scanner data, and α_g and ϕ_{mt} are income quintile and module-quarter fixed effects. This specification is analogous to the specification (4) that we used to measure differences in inflation sensitivity for coffee products, extended to estimating differences in inflation sensitivity across all food-at-home product modules.

Table 4 panel B shows that the sensitivity of inflation rates experienced by each income

Table 4: From cheapflation to inflation inequality in food at home.

Panel A. Prices paid		*Panel B. Inflation sensitivity*	
	Log unit price (1)		*Module inflation for income group* (2)
Income quintile 2	0.012**	Avg. module inflation × Income quintile 2	0.000
	(0.003)		(0.003)
Income quintile 3	0.027**	Avg. module inflation × Income quintile 3	−0.008*
	(0.004)		(0.004)
Income quintile 4	0.049**	Avg. module inflation × Income quintile 4	−0.025**
	(0.006)		(0.006)
Income quintile 5	0.082**	Avg. module inflation × Income quintile 5	−0.052**
	(0.008)		(0.010)
Module-Time FEs	Yes	Module-Time FEs	Yes
N	213971	N	201667
R^2	1.00	R^2	0.99
Within R^2	0.19	Within R^2	0.08

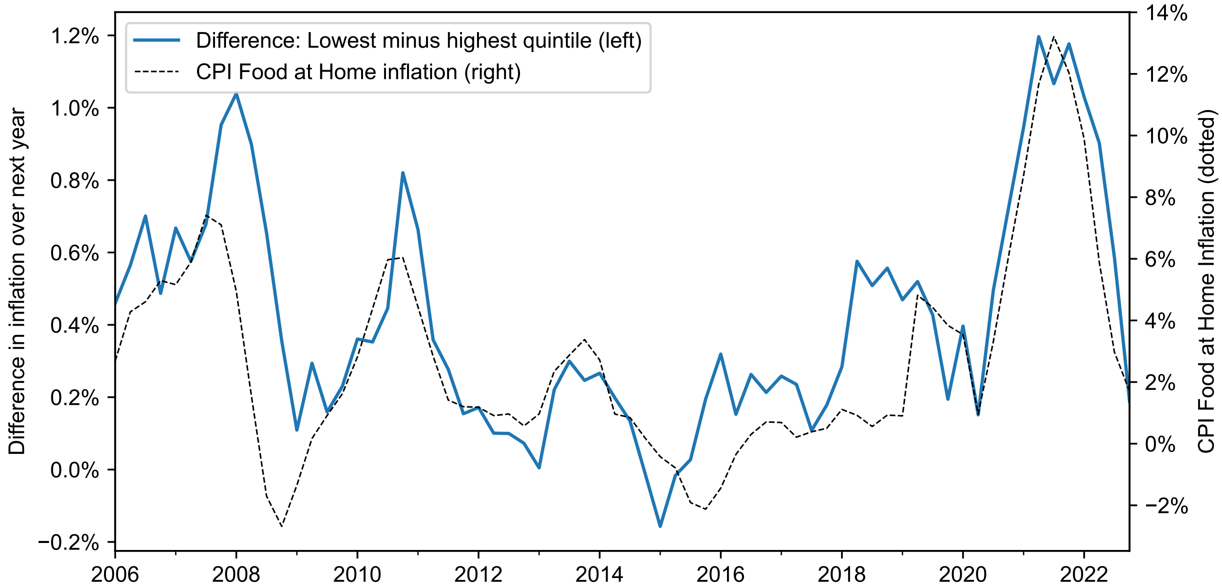
Note: Panel A reports results a regression of log unit prices on income quintile dummies and product module-time fixed effects. Panel B reports results from specification (10). For ease of display, Panel B does not display the estimated group fixed effects α_g. Avg. module inflation rates are winsorized at the 1 percent level. Regressions weighted by consumer expenditures. Standard errors two-way clustered by year and product module.

quintile to overall product inflation rates declines with income. Given a 10 percent rise in prices for a product module, inflation for the highest income quintile rises by 0.5 percentage points less than inflation for the lowest income quintile on average.

These differences in inflation sensitivity lead to meaningful fluctuations in the level of food-at-home inflation inequality over time. Figure 6 plots the difference in food-at-home inflation rates experienced by low- and high-income households in our data from 2006 to 2023. The gap is positive on average, but also varies with the overall rate of food-at-home inflation, widening when food-at-home inflation is high in 2008, 2011, and 2021, and narrowing when food-at-home inflation is low in 2009 and 2015. Falling food prices in 2015 even lead the gap to become negative, with the highest income quintile facing food-at-home inflation rates 0.2pp higher than the lowest-income quintile over 2015.

Predicted *vs.* actual inflation inequality. How much of the observed variation in food-at-home inflation inequality over time can be explained by pass-through in levels? We construct a measure of the predicted gap in inflation rates between the first and fifth

Figure 6: Gap in food-at-home inflation rates between lowest and highest income quintile.



Note: The solid line plots the difference in food-at-home inflation rates over the next year for the first and fifth income quintiles, constructed using the procedure described in Section 2.2. The dotted line plots inflation in the BLS's consumer price index for food at home.

income quintile from quarter t to quarter $t+4$ using

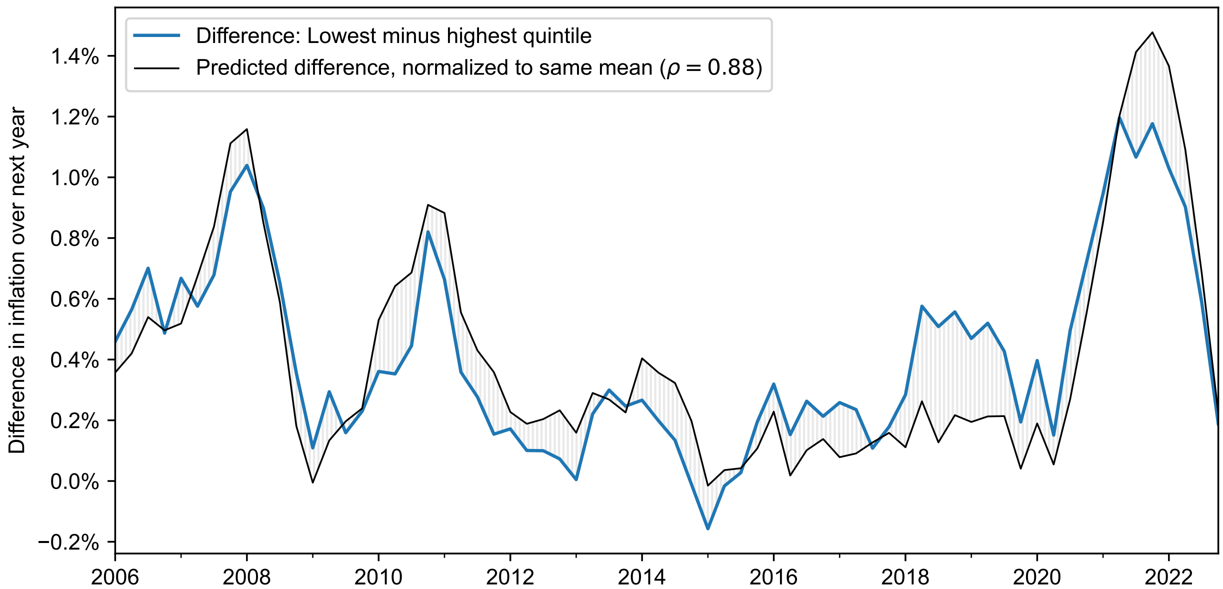
$$\text{PredictedInflationGap}_t = \underbrace{\sum_m \left(\omega_{mt}^1 - \omega_{mt}^5\right)\pi_{mt}^1}_{\substack{\text{Due to differences}\\ \text{in spending shares}}} + \underbrace{\sum_m \omega_{mt}^5 \widehat{\Delta\pi_{mt}},}_{\substack{\text{Due to pass-}\\ \text{through in levels}}} \tag{11}$$

where ω_{mt}^1 and ω_{mt}^5 are the first and fifth income quintiles' expenditure shares on product module m in quarter t, π_{mt}^1 is the inflation rate for module m from quarter t to quarter $t+4$ for the first income quintile, and the predicted gap in inflation rates within each product module m, $\widehat{\Delta\pi_{mt}}$, is

$$\widehat{\Delta\pi_{mt}} \equiv \left(p_{mt}/p_{mt}^1 - p_{mt}/p_{mt}^5\right)\left(\pi_{mt}^{\text{all}} - \pi_t^{\text{w}}\right).$$

This expression for the within-module gap in inflation rates across income quintiles uses the expression derived in (7). Note that our predictions for the inflation gap within each module, $\widehat{\Delta\pi_{mt}}$, and the overall inflation gap, $\text{PredictedInflationGap}_t$, use only information about differences in income groups' spending shares and unit prices in quarter t—alongside the inflation rates π_{mt}^{all}, π_{mt}^1, and π_t^{w}—to predict gaps in inflation rates over the next year. Figure 7 plots the predicted inflation gap from (11) alongside the actual

Figure 7: Predicted gap in food-at-home inflation rates between lowest and highest income quintile, alongside observed inflation gap.



Note: The figure plots the gap in food-at-home inflation rates for the lowest and highest income quintile as shown in Figure 6 against the predicted inflation gap from Equation (11). The predicted inflation gap is shifted upward to account for secular differences in inflation over time, so that both the predicted and observed inflation gaps have the same mean over the sample.

inflation gap over the sample; the correlation between the two is 0.88.[12]

The first column of Table 5 quantifies how much of the variation in inflation inequality over time can be accounted for by these predictions. Over the full sample from 2006 to 2023, the variance of the gap in food-at-home inflation rates between the bottom and top quintiles is 0.100 squared percentage points. The variance of the inflation gap after accounting for differences in within-module inflation rates due to pass-through in levels—i.e., the second term in (11)—is 0.043. In other words, 57 percent of the variance in inflation inequality over time is accounted for by differences in within-module inflation rates generated by pass-through in levels. Once we further account for differences in expenditure shares across product modules, the residual gap in inflation rates across the first and fifth income quintiles has a variance of 0.030 squared percentage points. That is, the predicted inflation gap in (11) accounts for 70 percent of the variance in inflation inequality over the sample.[13]

[12] We can also decompose the predicted inflation gap using the first quintile's expenditures as the base, i.e., $\text{PredictedInflationGap}_t = \sum_m (\omega^1_{mt} - \omega^5_{mt})\pi^5_{mt} + \sum_m \omega^1_{mt} \widehat{\Delta\pi_{mt}}$. This decomposition yields similar results.

[13] As we found for cheapflation, business cycle variables have limited explanatory power for fluctuations

Table 5: Explaining variation in inflation inequality over time.

	Variance of inflation gap (pp^2)	*Excess inflation inequality relative to full sample average* (percentage points)	
	All Years	2008–2011	2021–2023
Actual	0.100	0.122	0.323
After accounting for pass-through in levels	0.043	0.002	0.117
After accounting for pass-through in levels and module expenditure shares	0.030	−0.041	−0.043

Note: The inflation gap is the difference between food-at-home inflation rates for the first and fifth income quintile, as plotted in Figure 6. The "Excess inflation inequality" columns report the average inflation gap over the prior year for all years in the reported range, inclusive of the start and end year. "Accounting for pass-through in levels" reports statistics after subtracting the second term in (11), and "Accounting for pass-through in levels and module expenditure shares" reports statistics after subtracting the predicted inflation gap from (11).

The predicted inflation gap can also account for heightened inflation inequality during specific periods, such as the Great Recession and the post-pandemic inflation. Argente and Lee (2021) and Becker (2024) document larger gaps in inflation rates across income groups during the Great Recession. The second column of Table 5 shows that the gap in inflation rates during the recession period from 2008–2011 is indeed 0.122 basis points higher than the average over the whole sample. However, the gap disappears (and in fact becomes negative) after accounting for pass-through in levels and differences in expenditure shares across income groups. Indeed, Figure 7 suggests that the elevated inflation inequality from 2008–2011 was largely the result of two surges in food commodity prices in 2008 and 2011.

Pass-through in levels and differences in module expenditure shares likewise account for the entirety of the surge in inflation inequality during the post-pandemic inflation from 2021–2023, as shown in the third column of Table 5. If anything, inflation inequality was slightly lower than expected, echoing our results on lower-than-expected cheapflation post-2020 in Table 3.

in inflation inequality after accounting for pass-through in levels. A regression of the inflation gap on the predicted inflation gap from (11) has an R^2 of 0.78. Further including business cycle variables—the unemployment gap and the GDP gap—marginally increases the R^2 to 0.82.

4.3 How Much Do Official Statistics Miss?

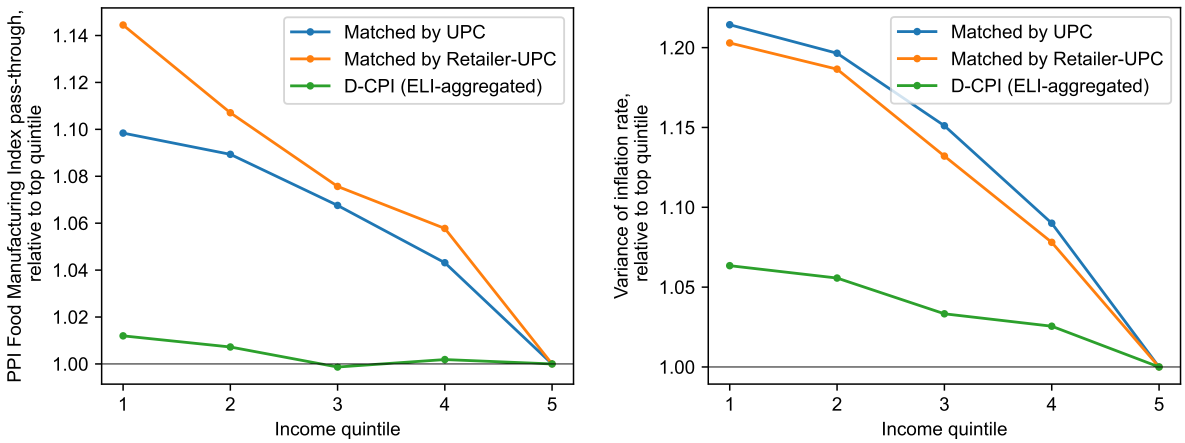
Official statistics on consumer price inflation published by the Bureau of Labor Statistics are built up from inflation measured at the level of 273 product categories referred to as entry-level items (ELIs). Thus, aggregation to these categories masks the cyclical differences in inflation rates across varieties within these categories.

To evaluate how this aggregation affects the measurement of inflation inequality, we compare the food-at-home price indices across income quintiles constructed using our product-level disaggregated data to food-at-home inflation indices created with publicly available BLS data. Our measures of income quintile-specific food-at-home inflation indices are built on the distributional consumer price indices (D-CPIs) developed by Jaravel (2024). Jaravel (2024) creates these distributional consumer price indices by matching BLS price index data to income group expenditure shares from the Consumer Expenditure Survey at the finest level of disaggregation available in public data. We adapt his code to produce distributional consumer price indices for food-at-home products across income quintiles, which we can compare on equal footing to the food-at-home inflation indices that we construct in the scanner data.

We first compare differences in food-at-home inflation across income groups, constructed using either our UPC-level disaggregated data or the ELI-aggregated price data, over the period from 2006–2020. We then compare differences in food-at-home price index growth across income groups over the period 2021–2023. In both cases, we find that the aggregation of within-category inflation differences in publicly available statistics substantially understates the degree to which food-at-home inflation experiences differ across income groups.

Pass-through of upstream costs and inflation volatility over 2006–2020. The left panel of Figure 8 plots differences in the log pass-through of the upstream costs to food-at-home price levels across income groups. We estimate the long-run pass-through of the Food Manufacturing PPI to price indices using the same specification (5) that we used to measure pass-through across unit price groups and report differences relative to the top income quintile. The pass-through of upstream costs to prices is 9.8 percent higher for the lowest-income quintile than the highest income quintile. The higher pass-through of upstream costs to prices for low-income households is primarily due to differences in the varieties that households buy within narrow product categories: Figure 8 shows that the pass-through of the Food Manufacturing PPI to food-at-home indices constructed with ELI-aggregated price data differ across income groups by only 1.2 percent. In other words, aggregation to ELIs masks nearly 90 percent of the disproportionate sensitivity of

Figure 8: Food-at-home inflation for lower income quintiles is more sensitive to upstream costs and more volatile.



(a) Pass-through of Food Manufacturing PPI.

(b) Variance of inflation rates.

Note: Panel (a) reports the long-run log pass-through of the Food Manufacturing producer price index to the food-at-home price index for each income group, estimated using (5) for the period 2006–2020. Panel (b) reports the variance of year-over-year inflation rates for each income group for 2006–2020. In both panels, estimates for each income group are normalized by the estimate for the top income quintile. The "matched by UPC" and "matched by retailer-UPC" estimates use food-at-home price indices constructed with the Retail Scanner data, disaggregating household purchases and product-level inflation at the UPC and retailer-UPC level respectively. The "D-CPI" estimates use food-at-home distributional price indices constructed from BLS price data by Jaravel (2024).

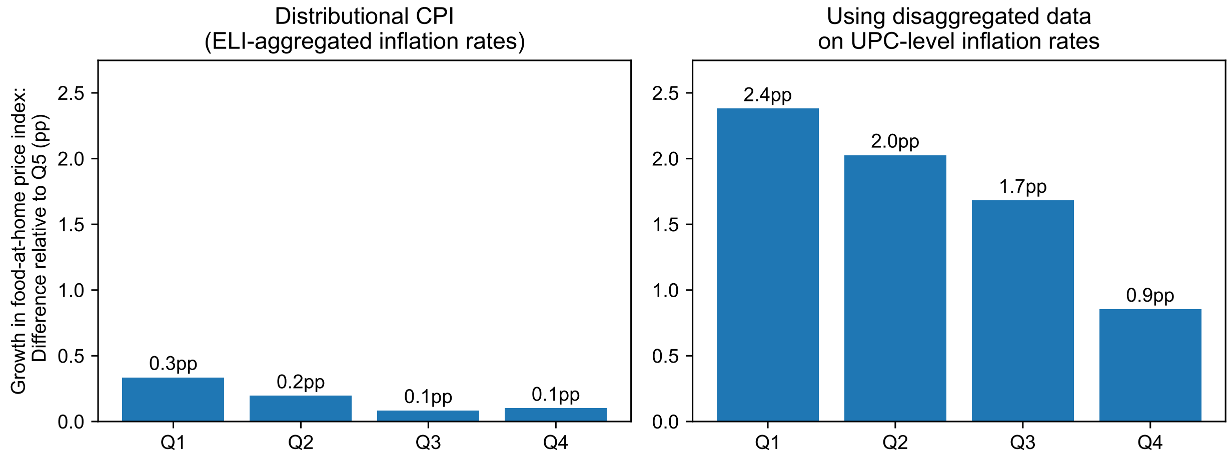
food-at-home inflation rates for low-income households to upstream costs.[14]

Similar results obtain for the pass-through of the Farm Products PPI to income groups' food-at-home prices (not pictured). The pass-through of Farm Products PPI to prices for the lowest-income quintile is 5.8 percent higher than for the highest-income quintile. In comparison, the differential pass-through of Farm Products PPI to ELI-aggregated food-at-home prices across income groups is only 1.6 percent.

These differences in the pass-through of upstream costs to prices across income groups translate into differences in inflation volatility. The right panel of Figure 8 plots differences in the variance of year-over-year food-at-home inflation rates experienced by each income quintile relative to the highest-income group. The variance of food-at-home inflation rates

[14]Disaggregating household purchases further by retail chain and UPC increases the difference in pass-through across income groups to 14.2 percent. (Likewise, for the pass-through of Farm Products PPI to food-at-home prices, disaggregating to the retailer-UPC level increases the difference in pass-through across income groups to 8.0 percent, compared to 5.8 percent using the UPC-disaggregated data.) However, as we discuss in Section 2, matching consumer expenditures to retail scanner data at the retailer-UPC level data captures a smaller share of panelists' spending (25 percent *vs.* over 60 percent).

Figure 9: Differences in food-at-home price growth by income quintile, 2020Q4 to 2023Q4.



Note: Each subfigure plots the difference between the growth of the food-at-home price index for the income quintile from 2020Q4 to 2023Q4 and the growth of the food-at-home price index for the highest income quintile over the same period. The left panel uses food-at-home distributional price indices constructed from BLS price data by Jaravel (2024), and the right panel uses food-at-home price indices constructed with the Retail Scanner data.

for the lowest-income quintile is 21.4 percent higher than that of the income quintile, a difference that can largely be accounted for by the differences in pass-through of upstream costs across quintiles. In contrast, food-at-home inflation rates constructed using ELI-aggregated price data are only 6.3 percent more volatile for the lowest income quintile than the highest income quintile. Appendix Figure A4 shows that these results on elevated pass-through of upstream costs and inflation volatility for low-income households are robust to instead splitting households into income deciles.

Price growth over 2021–2023. Aggregation at the ELI-level also masks differences in inflation experienced by low- and high-income households over the post-pandemic inflation from 2021 to 2023. Figure 9 plots the growth in food-at-home price indices across income quintiles, measured as the difference in price growth relative to the top income quintile. The price indices constructed with ELI-aggregated price data show small differences across income groups, with prices for the lowest income quintile increasing 0.3 percentage points more than the highest income quintile.

Differences in price growth measured using the disaggregated data are an order of magnitude larger, with low-income households experiencing 2.4 percentage points higher growth in food-at-home prices than high-income households. Relative to the overall growth in the food-at-home consumer price index over this period, this difference repre-

Table 6: Aggregation and inflation inequality: How much do official statistics miss?

	Difference between lowest and highest income quintile		
Measure	Disaggregated UPC-level data	BLS-based data	Understatement in BLS-based data
Pass-through of Food Manufacturing PPI to food-at-home inflation, 2006–2020	9.8%	1.2%	88%
Pass-through of Farm Products PPI to food-at-home inflation, 2006–2020	5.8%	1.6%	72%
Variance of food-at-home inflation rates, 2006–2020	21.4%	6.3%	70%
Growth in food-at-home price index, 2006Q4–2020Q4	5.9pp	−0.1pp	101%
Growth in food-at-home price index, 2020Q4–2023Q4	2.4pp	0.3pp	86%

Note: Disaggregated UPC-level data refers to food-at-home price indices we construct in the Retail Scanner data, and BLS-based data refer to food-at-home distributional consumer price indices constructed from BLS price data by Jaravel (2024).

sents a 10 percent larger increase in prices for low-income households than high-income households.

The differences in Figure 9 suggest an explanation for varying conclusions about the extent of inflation inequality over the post-pandemic period. Studies that use ELI-aggregated data to estimate changes in inflation inequality from 2021–2023 overlook differences in inflation experienced across income groups within narrow product categories, even when using the finest level of disaggregation available in official statistics. This aggregation understates the extent of inflation differences across income groups when pass-through in levels leads to disproportionate inflation for the low-priced products bought by low-income households. The period from 2021–2023 saw especially large increases in materials costs relative to other prices, with the producer price indices for Food Manufacturing and Farm Products rising by 26 percent and 35 percent relative to 16 percent for core CPI (see Appendix Figure A5). Pass-through in levels of these material cost increases results in especially severe differences in inflation across products purchased by low- and high-income households.

Thus, both for the business-as-usual period from 2006–2020 and for the inflationary period from 2021–2023, the aggregation of product-level inflation rates in official statistics understates the differences in food-at-home inflation experienced across income groups. Table 6 summarizes the extent of this bias across several measures we have considered, including pass-through of upstream costs, inflation volatility, and price growth during these subperiods. In each case, ELI-aggregated data understates the differences in experiences across income groups by 70 percent or more.

4.4 Accounting for Substitution and Nonhomotheticity

Our baseline measures of inflation across income groups use Laspeyres price indices, which weight product-level inflation rates by households' initial expenditure shares. As noted by Boskin, Dulberger, Gordon, Griliches, and Jorgenson (1998), Laspeyres measures of inflation can overstate the true increase in the cost of living because they do not account for substitution across varieties and across product categories in response to relative price changes. They also do not account for how nonhomotheticities—i.e., changes to households' preferred consumption basket in response to real income changes—affect the change in household utility that results from price changes.

We explore how accounting for substitution and nonhomothetic preferences affects our results on the differences in inflation experienced by households across the income distribution. To account for the effect of substitution on cost of living changes, we construct the inflation rate on a Törnqvist price index for each income group, given by

$$\pi_{gt}^{\text{Törnqvist}} = \prod_{i} (1 + \pi_{it})^{\frac{1}{2}(\omega_{igt} + \omega_{igt+4})} - 1, \tag{12}$$

where (using the same notation as Section 2) π_{it} is the year-over-year inflation rate for UPC i starting in quarter t and ω_{igt} is the expenditure share of income group g on UPC i in quarter t. This Törnqvist measure incorporates the effects of substitution on cost of living, because it weights product-level inflation rates using an average of current and future expenditure shares. As noted by Diewert (1976), the Törnqvist price index is a superlative index, providing a second-order approximation to the true cost-of-living index for any twice differentiable, homothetic expenditure function.

To further account for nonhomotheticities, we use the second-order algorithm developed by Jaravel and Lashkari (2024) to estimate changes in real consumption and price indices for each income group in each period. This algorithm uses cross-sectional variation in inflation rates across households with different real consumption levels to estimate the elasticity of real consumption to total expenditure.[15]

[15]In particular, we use the algorithm from Jaravel and Lashkari (2024) Appendix A.2.1, which estimates

Table 7: Price indices accounting for substitution and nonhomotheticity.

	Panel A. Growth in food-at-home price index from 2020Q4–2023Q4 (pp)			*Panel B. Variance of food-at-home inflation rates from 2006–2020 (pp^2)*		
Income quintile	Homothetic Laspeyres (1)	Homothetic Törnqvist (2)	Nonhomothetic (Base=2020Q4) (3)	Homothetic Laspeyres (4)	Homothetic Törnqvist (5)	Nonhomothetic (Base=2006Q1) (6)
1	27.27	25.43	27.01	4.69	4.67	4.89
2	26.92	24.90	26.41	4.62	4.59	4.92
3	26.57	24.52	25.99	4.45	4.43	4.78
4	25.74	23.87	25.27	4.21	4.23	4.55
5	24.89	23.13	24.45	3.86	3.90	4.15
Q1/Q5	1.10	1.10	1.10	1.21	1.20	1.18

Note: Columns 1 and 4 are our baseline measures of inflation using Laspeyres price indices. Columns 2 and 5 account for substitution using the Törnqvist inflation measure from (12). Columns 3 and 6 use the second-order nonhomothetic adjustment from Jaravel and Lashkari (2024). For both panels, the base period is chosen to be the first quarter of the sample and is listed in the column heading.

Table 7 shows how inflation experiences across income groups change under these alternative price indices, as compared to our baseline Laspeyres measures. Panel A shows the growth in the food-at-home price index across income quintiles over 2021–2023. For the lowest (highest) income quintile, accounting for substitution changes the growth in the food-at-home price index by −1.84pp (−1.76pp), and further accounting for nonhomotheticities increases the food-at-home price index by +1.58pp (+1.32pp). The two forces roughly net out, and under each measure the inflation experienced by the lowest-income quintile is about 10 percent higher than the highest quintile.

Why do nonhomotheticities increase the estimated rise in the cost of living? During 2021–2023, food-at-home prices grew faster than income. Declining real consumption leads households to trade down to lower-priced varieties (Jaimovich et al. 2019; Argente and Lee 2021), which are exactly those products that experienced the highest inflation rates from pass-through in levels. Since income effects tilted households' consumption baskets toward products whose prices were rising the fastest, they amplified the rise in households' costs of living.

This effect of nonhomotheticities on cost of living extend to other cycles in food-at-home inflation rates over the sample. Panel B of Table 7 shows that the volatility of

changes in real consumption growth to a second order. We use a fourth-order polynomial (i.e., $K_N = 4$) to fit the relationship between inflation and real consumption in each period. For expenditures of households in each income quintile, we use average income by quintile by year from Census TableA-4b.

inflation rates experienced by each income quintile from 2006–2020 rise by 5–7 percent after accounting for substitution and nonhomothetic preferences. Pass-through in levels leads to higher inflation rates for precisely those products that households trade down toward in periods where real food-at-home consumption is falling, and less deflation for products that households trade up toward in periods where real food-at-home consumption is rising. While accounting for substitution and nonhomotheticities alter the level of inflation volatility, they do not change the conclusion that low-income households face greater inflation volatility than high-income households.

5 Beyond Food at Home

The analyses so far suggest that aggregation even to narrow product categories masks variation in inflation rates across individual products and across income groups. Do these cycles in cheapflation and inflation inequality generalize beyond food-at-home products? While detailed scanner and panelist data for food at home and other fast-moving consumer goods facilitates disaggregating inflation to the product level in these categories, the lack of comparable data for other categories of consumption has made it difficult to assess whether patterns that appear in these categories extend to other parts of the consumption bundle.[16]

In this section, we provide suggestive evidence of fluctuations in cheapflation and inflation inequality across other consumption categories. First, using data on inflation across U.S. cities from the C2E2 Cost of Living Index (COLI) and from the BLS's metropolitan area price indices, we find evidence of both higher inflation sensitivity for lower-priced varieties and for higher-income cities in categories beyond food at home. Second, we use microdata on household vehicle purchases from the Consumer Expenditure Survey to document similar fluctuations in cheapflation and inflation inequality in automobile prices.

[16]Theoretically, pass-through in levels should lead to similar fluctuations in inflation inequality in other categories if (1) firms have input costs besides labor, (2) firms pass through these input costs to prices in levels, and (3) consumer purchase differently-priced varieties. Both (1) and (2) are likely to hold in other categories. For (1), the 2017 BEA input-output tables suggest most industries use a substantial share of intermediate inputs: even for services-producing industries, the average ratio of intermediate inputs to total industry output is 39 percent. For (2), Sangani (2025) suggests that pass-through in levels describes pricing dynamics across a range of markets, including industries that span the U.S. manufacturing sector.

5.1 Evidence on Cheapflation from COLI

We use microdata underlying the C2ER Cost of Living Index (COLI). The data record quarterly prices of sixty-three goods and services from about 300 urban areas across the U.S. from 1990 to 2010. In addition to grocery products, the data include prices of apparel products (e.g., the price of a pair of boy's denim jeans), of other goods (e.g., the price of generic medicines such as Aspirin, the price of a monthly newspaper subscription, and the price of a can of tennis balls), and services (e.g., the price of a man's barbershop haircut, or the minimum labor charge for a washing machine repair call). The full list of products is included in Appendix Table A4.

Unlike the NielsenIQ Homescan data, which capture differences in consumption patterns across households with different income levels, products in the COLI data are chosen to be as standardized as possible across cities, and thus do not necessarily reflect differences in varieties purchased across cities. Hence, we cannot use these data to infer how much inflation rates differ across cities with different income levels due to the differences in product varieties purchased by households of different income levels.

We can, however, use these data to explore whether heightened product inflation leads to disproportionate inflation for cheaper products (i.e., cities where the product tracked by C2ER is initially less expensive), and see whether these differences in inflation sensitivity extend to goods and services beyond food-at-home products in the NielsenIQ data. We estimate the specification,

$$\text{Inflation}_{ict} = \beta\left(\text{AvgProductInflation}_{it} \times \text{RelativePrice}_{ict}\right) + \alpha_{it} + \delta_{ic} + \kappa_{ct} + \varepsilon_{ict}, \qquad (13)$$

where $\text{Inflation}_{ict} = \log p_{ict+4} - \log p_{ict}$ is the year-over-year change in the price of product i in city c starting in quarter t, $\text{AvgProductInflation}_{it}$ is the average inflation of product i starting in quarter t across all cities in the data, and $\text{RelativePrice}_{ict} = \log p_{ict} - \log \bar{p}_{it}$ is the log deviation in city c's initial price for product i from the average price of the product across all cities. Product-quarter, product-city, and city-quarter fixed effects α_{it}, δ_{ic}, and κ_{ct} absorb the average inflation of product i at time t as well as systematic differences in inflation across cities in each quarter and secular product-city-specific inflation trends.

When input costs rise for a product, if cities with relatively low prices for the product see excessive inflation, we should find that the coefficient on the interaction term $\beta < 0$. Table 8 column 1 shows that this is indeed the case for the full sample of products in the COLI dataset: a higher average inflation rate for a product is associated with disproportionate inflation in cities with lower relative prices and less inflation in cities with higher relative prices. Columns 2–6 split the sample into grocery products, apparel

Table 8: Fluctuations in cheapflation beyond food at home: Evidence from COLI data.

		Product Inflation in City				
	All	Grocery	Apparel	Other Goods	Services	Housing & Utilities
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Product Infl. × Relative Price	−1.565**	−1.496**	−2.440**	−1.343**	−5.181**	−0.586*
	(0.250)	(0.329)	(0.522)	(0.366)	(1.996)	(0.274)
Product-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Product-City FEs	Yes	Yes	Yes	Yes	Yes	Yes
City-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	1 164 952	516 770	55 111	183 189	262 382	147 500
R^2	0.35	0.38	0.55	0.55	0.27	0.55

Note: The table reports the results from specification (13). Inflation$_{ict}$ and RelativePrice$_{ict}$ are winsorized at the one percent level. Standard errors two-way clustered by year and product. * indicates significance at 10%, ** at 5%.

products, other goods, services, and housing and utilities. Beyond grocery products, we find that the pattern of cheapflation when average product inflation is high extends to apparel, other goods, and even to services and housing and utilities.

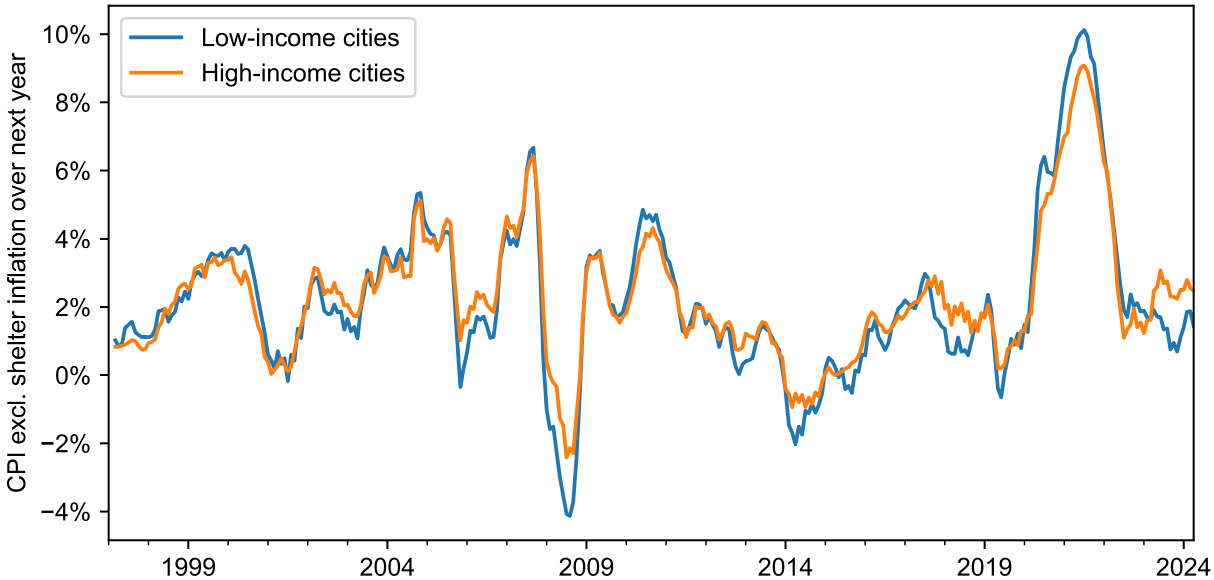
5.2 Evidence on Inflation Inequality from BLS Area Price Indices

While the BLS aggregates price data for products at the entry-level item (ELI) level, it does so across 32 geographic areas using prices collected in each area. Differences in inflation across geographic areas can thus indicate differences due to the composition of varieties consumed by households across areas with different income levels. If households in cities with higher incomes purchase higher priced varieties, pass-through in levels predicts that inflation in higher income cities will be less sensitive to overall inflation.

We merge the BLS's most recent release on price indices by metropolitan area—which includes price indices for 27 metropolitan areas from January 1997 to April 2025[17]—with annual measures of per-capita income by metropolitan area from the Bureau of Economic Analysis (CAINC1 series). Figure 10 plots the average inflation in consumer prices excluding shelter across cities in the top and bottom quartile of per-capita income

[17] The BLS does not make data available for all 32 geographic areas it uses internally, and the publicly available data for different cities are also available at different frequencies (e.g., monthly, bi-monthly, or semi-annual). We include only cities with either monthly or bi-monthly price series observations. Appendix Table A5 reports the list of metropolitan areas grouped into income quartiles. The list is split for before/after 2018, since the geographic areas used by the BLS were revised in 2018 (see `https://www.bls.gov/cpi/additional-resources/geographic-revision-2018.htm`).

Figure 10: Inflation in consumer prices excluding shelter for low- vs. high-income cities.



Note: High- and low-income cities are cities in the top and bottom quartile of per-capita income. The list of cities changes with the BLS's revision of geographic areas in 2018; see Appendix Table A5 for the list of cities in each quartile. The plotted lines are three-month moving averages of year-over-year inflation in the consumer price index excluding shelter (`SA0L2`), averaged across cities in each group.

over the sample period. Inflation in high-income cities indeed appears to be less volatile, for example reaching a peak of 9.5 percent in 2021 compared to 10.4 percent for low-income cities.

To formally test for differences in inflation sensitivity across metropolitan areas with different income levels, we use the specification,

$$\text{Inflation}_{ct} = \beta\left(\text{USInflation}_t \times \text{LogIncome}_{ct}\right) + \gamma\text{LogIncome}_{ct} + \alpha_c + \delta_t + \varepsilon_{ct}, \tag{14}$$

where Inflation_{ct} is the year-over-year inflation rate for metropolitan area c starting in month t, USInflation_t is the analogous inflation rate for all urban consumers in a U.S. city average, and LogIncome_{ct} is the log of per-capita income in metropolitan area c in the year of month t. Metropolitan area and time fixed effects α_c and δ_t absorb secular differences in inflation across cities and across time periods. Under pass-through in levels, we predict that consumer price inflation for households in higher income areas is less sensitive to national fluctuations in inflation, i.e., $\beta < 0$.

Table 9 reports the results from estimating (14) for consumer price inflation overall and for several aggregates that capture various parts of consumer expenditures. Column 1 finds that a 10 percent increase in per-capita income is associated with 9.7 percent lower sensitivity of consumer price inflation in a city to nationwide consumer price inflation. Column 2 excludes shelter, since we think the forces that dictate differences in shelter inflation across cities are likely to differ from our mechanism of pass-through in levels. Narrowing in on inflation in consumer prices excluding shelter, we find that a 10 percent increase in per-capita income is associated with a 4.5 percent lower sensitivity of inflation to nationwide inflation rates.

Similar results obtain for specific categories of consumption. Columns 3, 5, and 6 split the consumer price index excluding shelter into three mutually exclusive categories: food, other goods excluding food, and services excluding shelter. Column 4 also splits out food away from home to explore whether the inflation inequality results we document in food-at-home extend to other food consumption. In each case, we find that higher-income cities exhibit less sensitivity of inflation rates to nationwide inflation, consistent with the mechanisms that we document for food-at-home products extending to other consumption categories.

For more aggregated consumer price indices, such as overall consumer price inflation (column 1) and inflation in consumer prices excluding shelter (column 2), differences in inflation sensitivity across cities may be due in part to differences in expenditure shares across categories rather than differences in within-category inflation rates arising from pass-through in levels. For example, households in higher income cities may spend a lower share of total expenditures on volatile consumption categories such as food and gasoline. To get a sense of how much of the reduced sensitivity of inflation rates in high-income cities is due to differences in expenditure shares, we combine the BLS's published expenditure weights by metropolitan area with national inflation rates to construct counterfactual city-level inflation rates that would result if all cities faced identical inflation rates within each category and only differed in terms of the composition of expenditures. Appendix Table A6 finds that the estimated difference in the sensitivity of city-level inflation rates to national inflation is half as large when using these counterfactual inflation rates. In other words, heterogeneity in inflation rates across cities *within* BLS categories appear to account for half of the differences in inflation sensitivity to nationwide inflation across cities.[18]

[18]One may be concerned that our findings on different inflation sensitivity across cities are driven by the 2021–2023 period. Appendix Table A7 finds that this is not the case: if anything, the post-pandemic inflation saw smaller differences in the sensitivity of city-level inflation rates to nationwide inflation rates across cities with different incomes.

Table 9: Fluctuations in inflation inequality beyond food at home: Evidence from BLS metropolitan area price indices.

			Inflation in Metropolitan Area			
		CPI Ex.	All	Food Away	Goods	Services
Series	CPI	Shelter	Food	from Home	Ex. Food	Ex. Shelter
BLS Code	`SA0`	`SA0L2`	`SAF1`	`SEFV`	`SACL1`	`SASL2RS`
	(1)	(2)	(3)	(4)	(5)	(6)
U.S. Avg. Inflation × Log Income	−0.970**	−0.452**	−0.258**	−0.589**	−0.227**	−0.271*
	(0.085)	(0.066)	(0.084)	(0.242)	(0.041)	(0.161)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Metropolitan Area FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	3540	3534	3528	3515	3534	3534
R^2	0.85	0.89	0.75	0.42	0.92	0.57

Note: The table reports the results from specification (14). Driscoll–Kraay standard errors with twelve lags in parentheses. * indicates significance at 10%, ** at 5%.

5.3 Cheapflation and Inflation Inequality in Automobiles

Finally, we use microdata on household vehicle purchases to evaluate whether the same patterns of cheapflation and inflation inequality apply to vehicle purchases. Net outlays on vehicle purchases represent nearly as large a share of consumption expenditures as food at home, constituting 6.8 percent of consumer expenditures from 2021–2023 compared to 7.8 percent for food at home.

We use data on the prices and characteristics of vehicle makes and models from Ward's Automotive. We combine these data with the average income of a vehicle make's buyers, which we construct from data on household vehicle purchases from the Consumer Expenditure Survey. Appendix D describes the procedures we use to clean the the data and reports summary statistics for the merged dataset, which spans the period 2006–2018.

We find evidence of differential inflation sensitivity for lower-priced car models and for vehicles with lower-income buyers (see Appendix Table D2). Within a vehicle make, the year-over-year growth in manufacturer-suggested retail prices (MSRPs) for a model with a 10 percent lower initial price is 3.9–7.0 percent more sensitive to average price growth. That is, when overall vehicle prices increase, price growth is disproportionately high for cheaper models within a brand (or make). These results are robust to controlling for secular differences in price growth across models and for changes in models' characteristics across years. Likewise, across all vehicles, models with a 10 percent lower-income customer base have inflation rates that are 8.6–9.1 percent more sensitive to overall vehicle inflation.

Aggregation in official statistics masks this heterogeneity in inflation rates across vehicle makes and models. The BLS constructs two price indices for new cars and trucks (ELI code TA011) and used car and trucks (ELI code TA021), but does not further disaggregate differences in inflation across vehicle makes and models. Thus, as in food at home, official statistics are likely to miss quantitatively important differences in inflation rates faced by households across the income distribution due to differences in households' purchasing patterns.

6 Unequal Incidence of Cost Shocks in Other Contexts

Our analysis thus far has focused on differences in the incidence of cost shocks across income groups. However, pass-through in levels also implies systematic cross-sectional heterogeneity in inflation across other units—such as cities and countries—in response to common cost shocks.

Inflation across cities. Appendix E.1 shows that pass-through in levels leads to spatial variation in inflation in response to common cost shocks. Cities that consume lower-priced varieties—either because of lower distribution costs or differences in consumer preferences—are more exposed to national cost shocks, resulting in higher local inflation when adverse shocks occur. We document this mechanism using coffee products as a case study, showing that cities with lower-priced coffee varieties experience higher coffee inflation when commodity prices rise.

Import price inflation across countries. Appendix E.2 extends this logic to import price inflation across countries. Pass-through in levels implies that countries that import lower-priced varieties will experience larger increases in import price inflation following a global cost shock. Using trade data on coffee imports, we show that this prediction holds in the data: countries with lower average unit values for imported coffee have greater percentage increases in import prices when global coffee prices rise. Thus, differences in the relative price of imported varieties lead to systematic heterogeneity in countries' exposures to global commodity shocks.

7 Conclusion

Pass-through in levels generates systematic differences in inflation across product varieties in response to fluctuations in the relative price of inputs. This generates "cheapflation" when the relative price of inputs rise and leads to systematic fluctuations in inflation inequality. This mechanism can parsimoniously account for fluctuations in the extent of cheapflation and inflation inequality over time. In particular, we find that pass-through in levels, along with differences in expenditure shares across categories, can explain elevated inflation inequality during the Great Recession and the post-pandemic period without the need for other explanations such as price gouging by retailers or differential changes in households' price elasticities of demand.

The unequal incidence of cost shocks on prices for different income groups is largely hidden in official statistics, which aggregate inflation data at the level of product categories. For various measures of the different inflation experiences of low- and high-income households, we find that aggregating at this level understates the disparities across income groups by between 70 and 90 percent. This gap between official statistics and true differences in inflation across income groups is likely to extend to other categories of household consumption beyond food at home, given our evidence on price indices across U.S. cities and vehicle purchases. In all, these analyses suggest that available measures underreport the uneven burden of cost-driven inflation across the income distribution. The biases from using aggregated data are particularly severe when the relative price of inputs increases sharply, such as during the 2021–2023 period.

While this paper focuses on the unequal incidence of cost shocks across income groups, this mechanism also implies differences in exposure to common cost shocks across cities and countries. For example, cities with lower-priced varieties experience higher inflation in response to national cost shocks. Likewise, countries that import lower-priced varieties are more exposed to higher import price inflation following global cost shocks. Thus, pass-through in levels can be a source of systematic, cross-sectional variation in inflation in response to shocks.

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Online Appendix for *Pass-Through in Levels and the Unequal Incidence of Commodity Shocks*

(Not for publication)

Appendix A Additional Tables and Figures

Table A1: Share of quarterly sales matched to inflation rate in next year.

Unit price decile	UPC	Retailer-UPC
1	92.9	89.6
2	94.0	90.7
3	94.5	91.0
4	95.1	91.5
5	95.4	91.8
6	95.6	91.8
7	95.6	91.7
8	95.5	91.6
9	95.6	91.5
10	94.9	90.6
All	94.9	91.2

Note: The share of sales matched to inflation data excludes 2023, the last year of the sample.

Table A2: Share of panelist expenditures matched to Retail Scanner data by income group.

Income	Matched to UPC		Matched to retailer-UPC	
quintile	Total	With inflation	Total	With inflation
1	62.4	57.4	24.0	20.0
2	61.9	57.3	24.9	21.1
3	62.1	57.6	25.8	22.0
4	62.2	58.3	27.0	23.6
5	60.9	56.3	28.6	24.6

Note: The share of expenditures matched to inflation data excludes 2023, the last year of the sample.

Table A3: Cheapflation within product modules: Robustness using unit price quintiles.

	Inflation of lowest-price quintile − highest-price quintile					
	(1)	(2)	(3)	(4)	(5)	(6)
Excess module inflation × Price gap	1.176**		1.181**		1.188**	
	(0.027)		(0.025)		(0.019)	
Module inflation × Price gap		1.178**		1.181**		1.188**
		(0.025)		(0.025)		(0.019)
Wage inflation × Price gap		-1.561**		-0.926**		-1.261**
		(0.299)		(0.243)		(0.336)
Post-2020			-0.048**	-0.056**		
			(0.011)	(0.014)		
Price gap	0.004	0.023*	0.012	0.001	0.051**	0.054**
	(0.010)	(0.011)	(0.007)	(0.006)	(0.007)	(0.013)
Time FEs					Yes	Yes
Product Module FEs					Yes	Yes
N	42405	42405	42405	42405	42405	42405
R^2	0.92	0.92	0.93	0.93	0.94	0.94

Note: The table reports results from specifications (8) and (9). We measure wage inflation as the year-over-year log change in the average hourly earnings of production and nonsupervisory employees. All inflation rates are measured over the next year from quarter t to quarter $t + 4$. The price gap in quarter t is measured as defined in (7) and is winsorized at the 1 percent level. Post-2020 is an indicator equal to one if the observation year is strictly greater than 2020. Regressions weighted by sales. Driscoll-Kraay standard errors with four lags. * indicates significance at 10%, ** at 5%.

Table A4: Product categories in Cost of Living Index dataset.

Category	Products
Grocery	Baby food, Bacon, Bananas, Beer, Chunk light tuna, Coffee, Corn flakes, Eggs, Fresh orange juice, Fried chicken, Frozen corn, Frozen meal, Frozen orange juice, Ground beef, Lettuce, Liquor, Margarine, Parmesan cheese, Peaches, Potato chips, Potatoes, Sausage, Shortening, Soft drink, Sugar, Sweet peas, T-bone steak, Tomatoes, White bread, Whole milk, Wine
Apparel	Boys' jeans, Boys' underwear, Men's denim jeans, Men's dress shirt, Men's slacks, Women's slacks
Other Goods	Aspirin, Board game, Cigarettes, Detergent, Facial tissues, Gasoline, Ibuprofen, Lipitor, Newspaper, Polysporin, Shampoo, Tennis balls, Toothpaste
Services	Beauty salon, Bowling, Commuter fare, Dental visit, Doctor visit, Dry cleaning, Fried chicken (at fast food restaurant), Haircut, Hamburger (at fast food restaurant), Hospital room, Movie ticket, Optometrist visit, Pizza (at restaurant), Tire balancing, Veterinary services, Washer repair
Housing & Utilities	Apartment rent, Electricity (both for all-electric homes and for homes using other types of energy), Home price, Monthly payment, Mortgage rate, Other energy, Telephone bill, Total energy

Table A5: List of BLS metropolitan areas with bi-monthly or monthly data on consumer price index excluding shelter.

Quartile	Code	BLS Area Description	Frequency
Prior to 2018:			
1	A210	Cleveland-Akron, OH	Bi-monthly
1	A421	Los Angeles-Riverside-Orange County, CA	Monthly
1	S23B	Detroit-Warren-Dearborn, MI	Bi-monthly
1	S35C	Atlanta-Sandy Springs-Roswell, GA	Bi-monthly
2	S35B	Miami-Fort Lauderdale-West Palm Beach, FL	Bi-monthly
2	S37A	Dallas-Fort Worth-Arlington, TX	Bi-monthly
2	S37B	Houston-The Woodlands-Sugar Land, TX	Bi-monthly
2	S49A	Los Angeles-Long Beach-Anaheim, CA	Monthly
3	S12B	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Bi-monthly
3	S23A	Chicago-Naperville-Elgin, IL-IN-WI	Monthly
3	S35E	Baltimore-Columbia-Towson, MD	Bi-monthly
3	S49D	Seattle-Tacoma-Bellevue WA	Bi-monthly
4	A311	Washington-Baltimore, DC-MD-VA-WV	Bi-monthly
4	S11A	Boston-Cambridge-Newton, MA-NH	Bi-monthly
4	S12A	New York-Newark-Jersey City, NY-NJ-PA	Monthly
4	S35A	Washington-Arlington-Alexandria, DC-VA-MD-WV	Bi-monthly
4	S49B	San Francisco-Oakland-Hayward, CA	Bi-monthly
After 2018:			
1	S23B	Detroit-Warren-Dearborn, MI	Bi-monthly
1	S35C	Atlanta-Sandy Springs-Roswell, GA	Bi-monthly
1	S35D	Tampa-St. Petersburg-Clearwater, FL	Bi-monthly
1	S48A	Phoenix-Mesa-Scottsdale, AZ	Bi-monthly
1	S49C	Riverside-San Bernardino-Ontario, CA	Bi-monthly
1	S49F	Urban Hawaii	Bi-monthly
2	S24B	St. Louis, MO-IL	Bi-monthly
2	S35B	Miami-Fort Lauderdale-West Palm Beach, FL	Bi-monthly
2	S37A	Dallas-Fort Worth-Arlington, TX	Bi-monthly
2	S37B	Houston-The Woodlands-Sugar Land, TX	Bi-monthly
2	S49A	Los Angeles-Long Beach-Anaheim, CA	Monthly
2	S49G	Urban Alaska	Bi-monthly
3	S12B	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Bi-monthly
3	S23A	Chicago-Naperville-Elgin, IL-IN-WI	Monthly
3	S24A	Minneapolis-St.Paul-Bloomington, MN-WI	Bi-monthly
3	S35E	Baltimore-Columbia-Towson, MD	Bi-monthly
3	S48B	Denver-Aurora-Lakewood, CO	Bi-monthly
3	S49D	Seattle-Tacoma-Bellevue WA	Bi-monthly
3	S49E	San Diego-Carlsbad, CA	Bi-monthly
4	S11A	Boston-Cambridge-Newton, MA-NH	Bi-monthly
4	S12A	New York-Newark-Jersey City, NY-NJ-PA	Monthly
4	S35A	Washington-Arlington-Alexandria, DC-VA-MD-WV	Bi-monthly
4	S49B	San Francisco-Oakland-Hayward, CA	Bi-monthly

Table A6: Inflation inequality across U.S. metropolitan areas due to consumption weights.

	Inflation in Metropolitan Area			
	CPI Data		Constructed with Area Weights	
	CPI	CPI Ex. Shelter	CPI	CPI Ex. Shelter
	(1)	(2)	(3)	(4)
U.S. Avg. Inflation × Log Income	−0.970**	−0.452**	−0.208**	−0.224**
	(0.085)	(0.066)	(0.035)	(0.030)
Time FEs	Yes	Yes	Yes	Yes
Metropolitan Area FEs	Yes	Yes	Yes	Yes
N	3540	3534	7452	7452
R^2	0.85	0.89	0.99	0.99

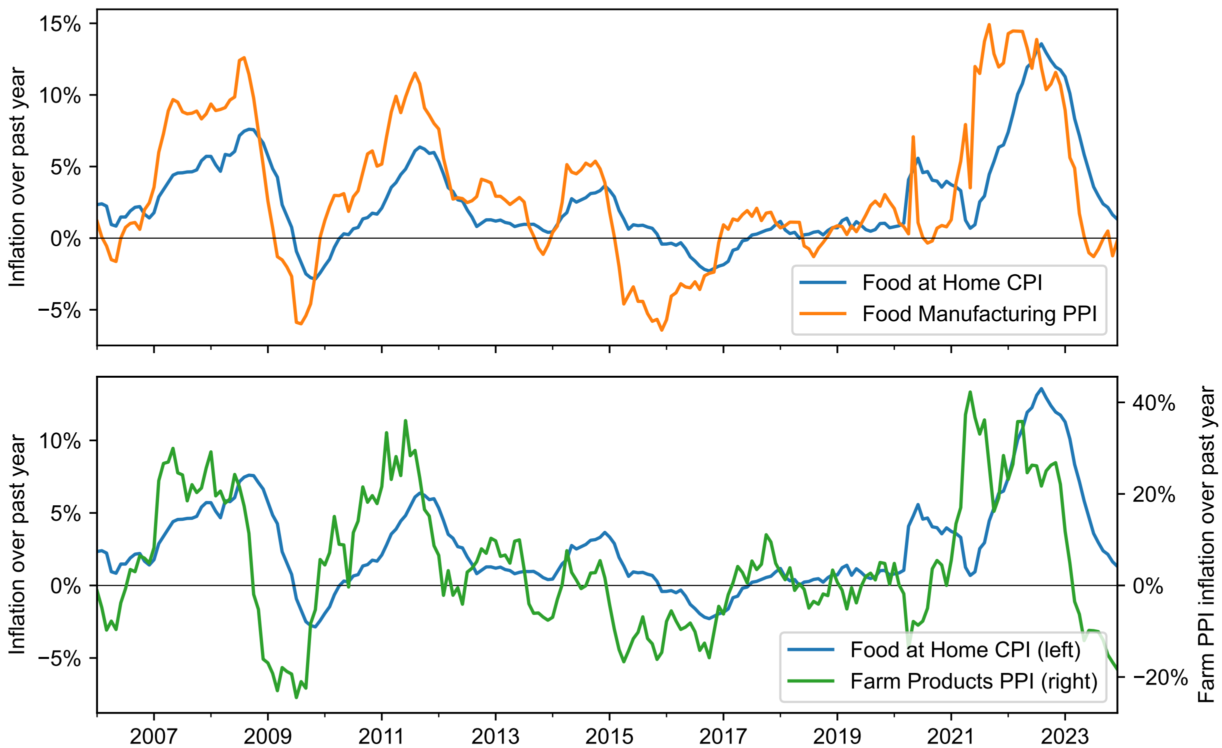
Note: The table reports the results from specification (14). Columns 1–2 use metropolitan area CPI data. Columns 3–4 use counterfactual inflation rates for each metropolitan area using the metropolitan area's relative importance weights across items but using the inflation rate for each item for the U.S. city average. Relative importance weights for each metropolitan area are from the BLS's December 2024 release, which was the most recent release at the time of writing (available at `https://www.bls.gov/cpi/tables/relative-importance`). Driscoll–Kraay standard errors with twelve lags in parentheses. * indicates significance at 10%, ** at 5%.

Table A7: Breaking out post-2020 period for inflation inequality across U.S. metropolitan areas.

	Inflation in Metropolitan Area	
	CPI	CPI Ex. Shelter
	(1)	(2)
U.S. Average Inflation × Log Income	−0.986**	−0.575**
	(0.151)	(0.066)
U.S. Average Inflation × Log Income × Post-2020	−0.046	0.202*
	(0.168)	(0.105)
Time FEs	Yes	Yes
Metropolitan Area FEs	Yes	Yes
N	3540	3534
R^2	0.85	0.89

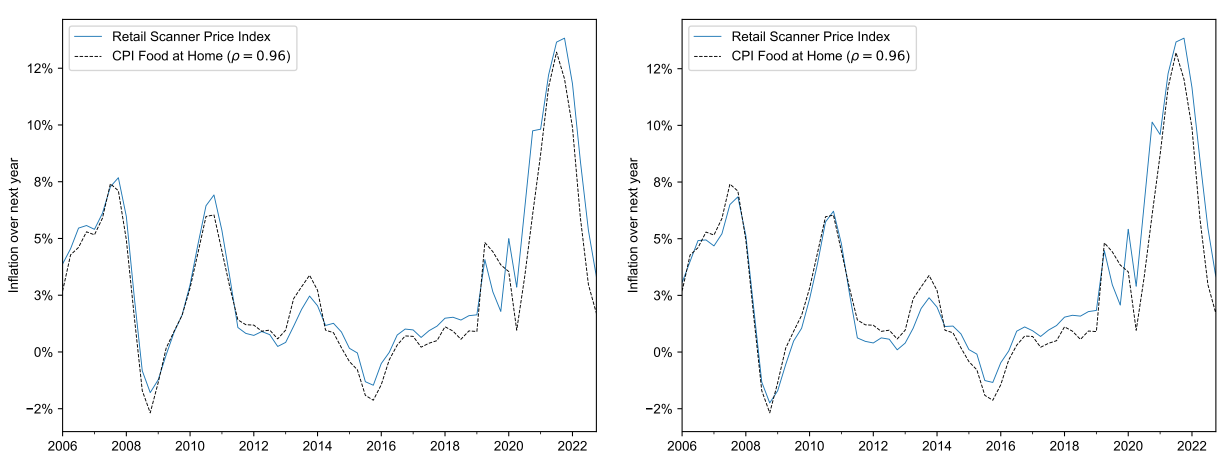
Note: The table reports the results from specification (14), augmented to include an additional interaction term for U.S. Average Inflation × Log Income × Post-2020. Driscoll–Kraay standard errors with twelve lags in parentheses. * indicates significance at 10%, ** at 5%.

Figure A1: Food at Home CPI, Food Manufacturing PPI, and Farm Products PPI.



Note: Data pulled from FRED: consumer price index for Food at Home (`CUSR0000SAF11`), producer price index for Food Manufacturing (`PCU311311`), and producer price index for Farm Products (`WPU01`).

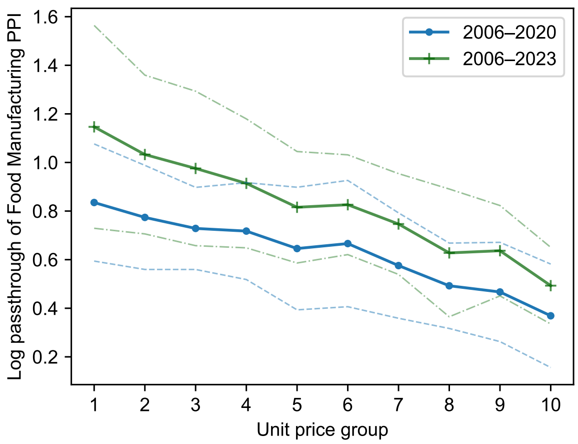
Figure A2: Comparing food-at-home inflation in Retail Scanner data to CPI.



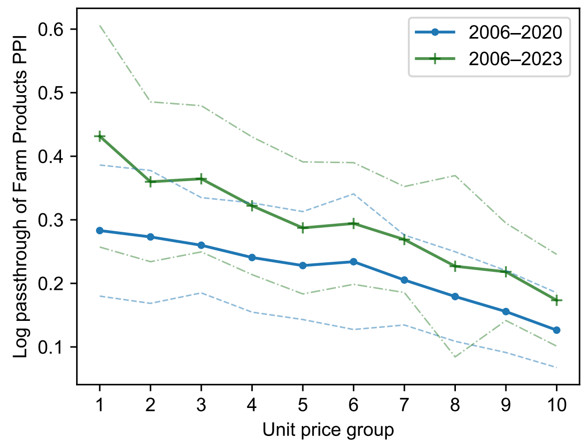
(a) Level of aggregation: Retailer-UPC

(b) Level of aggregation: UPC

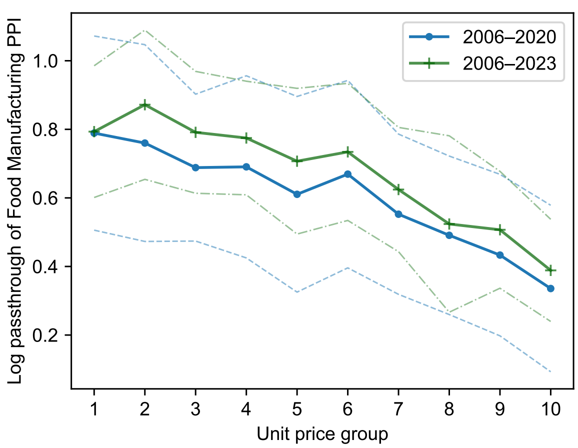
Figure A3: Log pass-through of upstream price indices by unit price group: Comparing estimates from 2006–2020 to estimates from 2006–2023.



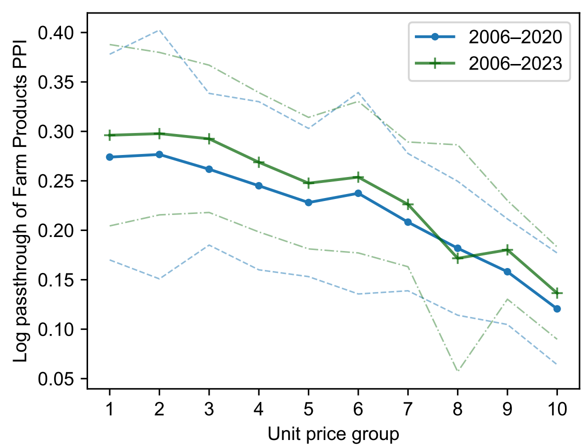
Food Manufacturing PPI:
(a) Baseline specification.



Farm Products PPI:
(b) Baseline specification.



Food Manufacturing PPI:
(c) Specification with wage pass-through.



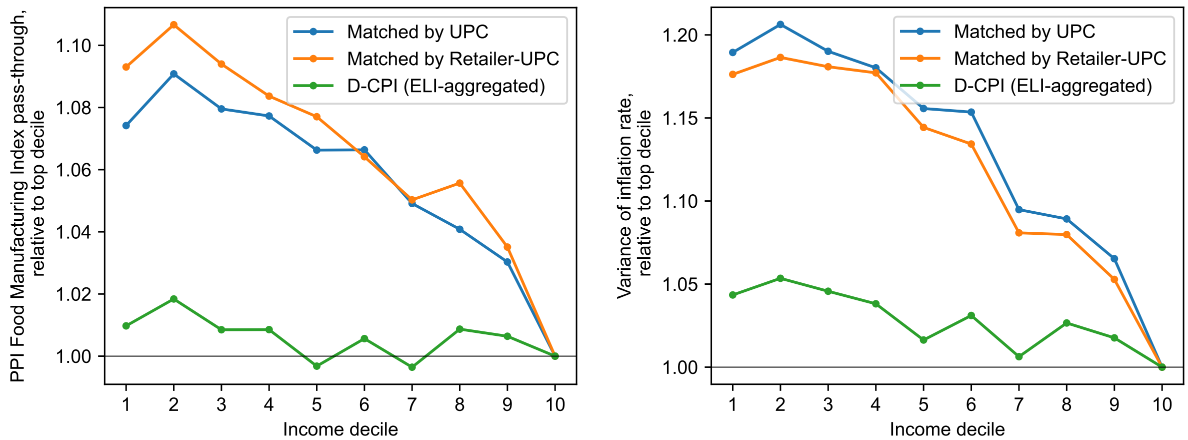
Farm Products PPI:
(d) Specification with wage pass-through.

Note: Panels (a) and (b) report estimates of long-run pass-through of upstream producer price indices by unit price decile using specification (5). Panels (c) and (d) report the long-run pass-through of upstream PPI using a specification augmented with wage pass-through,

$$\Delta \log p_t^g = \alpha^g + \sum_{k=0}^{K} \beta_k^g \Delta \log \mathrm{PPI}_{t-k} + \sum_{k=0}^{K} \gamma_k^g \Delta \log w_{t-k} + \sum_{k=1}^{4} \delta_k^g q_t + \varepsilon_{it},$$

where $\Delta \log w_t$ is the change in the log of average earnings of production and nonsupervisory employees from quarter $t-1$ to t. Dotted blue lines indicate 95 percent confidence intervals for pass-through estimates using 2006–2020, and dot-dashed green lines indicate 95 percent confidence intervals for pass-through estimates using 2006–2023. Both are constructed using the delta method with Newey-West standard errors.

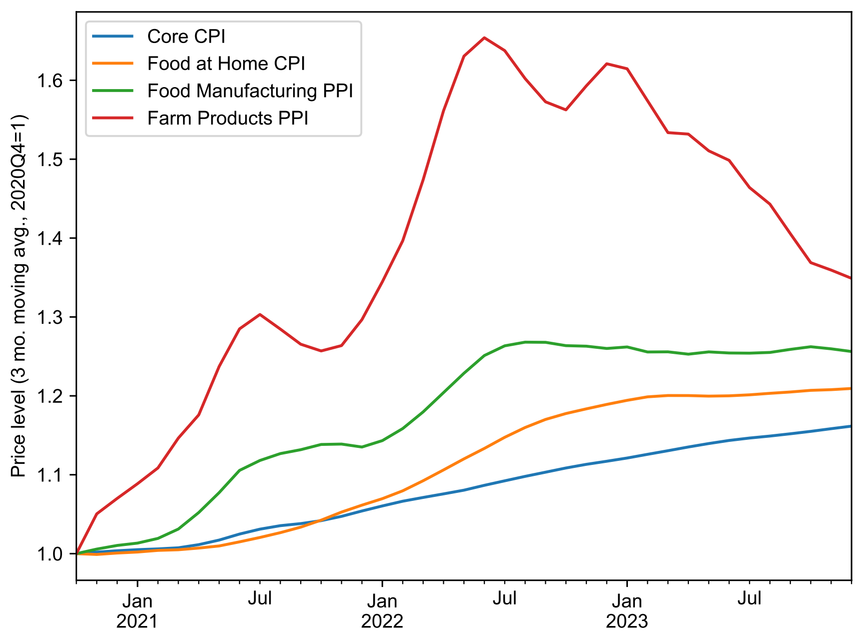
Figure A4: Differences by income decile: Sensitivity of food-at-home inflation to upstream PPI and variance of food-at-home inflation rates.



(a) Pass-through of Food Manufacturing PPI.

(b) Variance of inflation rates.

Figure A5: Price growth for Core CPI, Food at Home CPI, Farm Products PPI, and Farm Manufacturing PPI from 2020Q4 to 2023Q4.



Note: Data pulled from FRED: core consumer price index (`CPILFESL`), consumer price index for Food at Home (`CUSR0000SAF11`), producer price index for Food Manufacturing (`PCU311311`), and producer price index for Farm Products (`WPU01`). The figure plots a three-month moving average, with price indices normalized to one for October 2020.

Appendix B Proofs

Proof of Proposition 1. Given a perturbation to materials and labor prices, $d\log m$ and $d\log w$, the change in the price of variety i to a first order is

$$d\log p_i \approx \frac{m}{p_i} d\log m + \frac{\beta_i w}{p_i} d\log w.$$

Thus, the inflation rate on a Laspeyres index using initial expenditure shares on each variety λ_i^g is

$$\begin{aligned}\pi^g \equiv \int_0^1 \lambda_i^g d\log p_i di &\approx \int_0^1 \lambda_i^g \left(\frac{m}{p_i} d\log m + \frac{\beta_i w}{p_i} d\log w\right) di \\ &= m\left[\int_0^1 \frac{\lambda_i^g}{p_i} di\right] d\log m + \left(1 - m\left[\int_0^1 \frac{\lambda_i^g}{p_i} di\right]\right) d\log w.\end{aligned}$$

Let p^g be the λ_i^g-weighted harmonic average of p_i, i.e., $p^g = \left(\int_0^1 \lambda_i^g / p_i di\right)^{-1}$. Then,

$$\pi^g = \frac{m}{p^g} d\log m + \left(1 - \frac{m}{p^g}\right) d\log w. \tag{15}$$

Using π^{all} and p to denote the Laspeyres inflation rate and average unit price constructed with varieties' sales shares λ_i, we can rearrange (15) to express the change in the materials price $d\log m$ in terms of the category Laspeyres inflation rate and change in the wage,

$$d\log m = \frac{p}{m}\pi^{\text{all}} - \left(\frac{p}{m} - 1\right) d\log w.$$

Substituting into (15) yields

$$\pi^g = \frac{p}{p^g}\pi^{\text{all}} + \left(1 - \frac{p}{p^g}\right) d\log w,$$

which can be rearranged to yield the expression in Proposition 1. □

Appendix C Pass-Through Across the Price Distribution in Nakamura and Zerom (2010)

Consistent with our results on pass-through in levels in Section 3, Nakamura and Zerom (2010) estimate that changes in coffee bean commodity prices are passed through completely in levels to wholesale and retail coffee prices. However, they do not estimate pass-through across the price distribution. In this appendix, we show that the demand system estimated by Nakamura and Zerom (2010) predicts systematic variation in pass-through across products with different prices, at odds with our evidence of uniform pass-through in levels across the price distribution.

Simulating the Nakamura and Zerom (2010) demand system. Nakamura and Zerom (2010) assume that the utility to individual i from purchasing product j takes the form,

$$U_{ijmt} = \alpha_i^0 + \alpha_i^p (y_i - p_{jmt}) + \xi_{jmt} + \epsilon_{ijmt},$$

where y_i is the individual's income; p_{jmt} is the price of product j in market m at time t; ξ_{jmt} is an unobserved demand shifter that varies across products, markets, and time periods; ϵ_{ijmt} is a type-1 extreme value taste shock; and the parameters α_i^0 and α_i^p, which determine an individual's mean utility of purchasing coffee and her price sensitivity, are allowed to vary with income $\tilde{y}_i$ (normalized to have mean zero and variance of one across all markets),

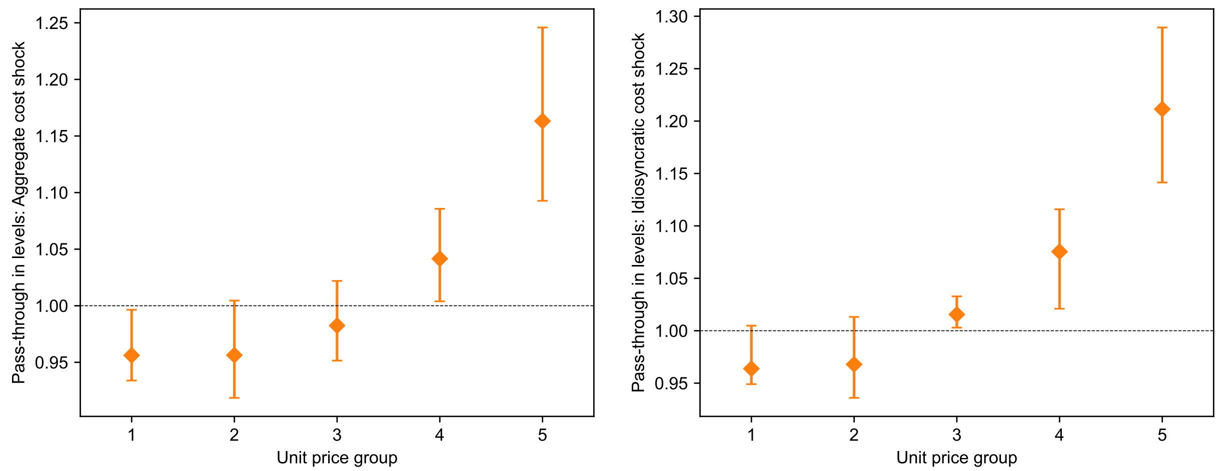
$$\alpha_i^0 = \alpha^0 + \Pi_{y0}\tilde{y}_i, \qquad \text{and} \qquad \alpha_i^p = \alpha^p + \Pi_{yp}\tilde{y}_i.$$

Nakamura and Zerom (2010) assume that each individual chooses the product j that maximizes her utility U_{ijmt}, or chooses to forego purchasing any product if $U_{ijmt} < 0$ for all j (i.e., the utility of the "outside option" is normalized to zero).

Nakamura and Zerom (2010) report estimates for the parameters α^0, α^p, Π_{y0}, and Π_{yp}. However, in order to estimate the pass-through of aggregate cost shocks, we also need data on products' prices p_{jmt} and the unobserved demand shifters ξ_{jmt}. A challenge is that the underlying market data used by Nakamura and Zerom (2010) are from 2000–2004 and are not available through current agreements with NielsenIQ.

To recover estimates of pass-through for coffee products, we thus use data on prices and sales shares of coffee products in NielsenIQ Retail Scanner data from 2006–2020 and assume that the demand parameters estimated by Nakamura and Zerom (2010) apply to this period. As we will show, their model implies meaningful differences in pass-through across the price distribution, and we can trace these differences in pass-through to the

Figure C1: Pass-through in levels across unit price groups in simulation of Nakamura and Zerom (2010) demand system.



(a) Aggregate cost shock.

(b) Idiosyncratic cost shock.

Note: Panels (a) and (b) show the pass-through of an aggregate cost shock (a) and idiosyncratic cost shock (b) across coffee products split by unit price. Scatter points indicate the average across all products, and error bars indicate the interquartile range. The dotted line indicates complete pass-through in levels.

underlying demand system.

Applying the demand system to data from 2006–2020 necessitates a few changes to the process used to assemble the data, which we now describe. We retain the set of products that Nakamura and Zerom (2010) include in their estimation, plus five additional brands that have substantial market shares in the later sample: Eight O' Clock, Millstone, Seattle's Best Coffee, Peets Coffee, New England, and Chase & Sanborn. All other products are grouped with the outside option. Ownership matrices are also updated to reflect subsequent acquisitions over 2006–2020. Rather than use demographic data from the CPS, we use demographic data from the Homescan consumer panel, aggregated using weights provided by NielsenIQ. Finally, we choose the relationship between the number of adults in a market and market size to match the median share of the outside option in Nakamura and Zerom (2010), which is 74%.

Given this demographic data and products' market shares and prices, along with the parameter estimates from Nakamura and Zerom (2010), we can invert the demand system in each market and each month to recover the unobserved demand shifters ξ_{jmt}. The model is then fully specified to simulate pass-through of idiosyncratic and aggregate cost shocks.

Pass-through along the price distribution. The left panel of Figure C1 plots the pass-through of an aggregate cost shock—defined as an infinitesimal increase in the marginal cost of producing all coffee products—across coffee products grouped by unit price in each month. While the pass-through of aggregate cost shocks on average is close to one, it systematically increases with unit price, averaging 0.96 for products in the lowest unit price quintile and 1.16 for products in the highest unit price quintile.

Why does the model imply pass-throughs of aggregate cost shocks different from one? Note that, when there is no outside option, mixed logit demand is shift-invariant with respect to products' prices, and firms exhibit complete pass-through in levels of aggregate cost shocks. However, the Nakamura and Zerom (2010) calibration includes an outside option that is not exposed to the aggregate cost shock. Thus, each product's pass-through of an aggregate cost shock depends on the curvature of its residual demand curve.

The influence of the firms' residual demand curves on the pass-through of aggregate cost shocks can be seen in the right panel of Figure C1, which shows that the model-implied pass-through of idiosyncratic cost shocks is also increasing in unit price. As we show below, the pass-through of idiosyncratic shocks is dictated by the shape of firms' residual demand curves. Figure C1 thus shows that while the pass-through of aggregate cost shocks is compressed toward one, it inherits its pattern from the pass-through of idiosyncratic shocks, since the presence of an outside option means that the shape of firms' residual demand curves also affect the pass-through of aggregate shocks.

To characterize the determinants of pass-through more systematically, let us define the elasticity and super-elasticity of the residual demand curve for product j in market m at time t as

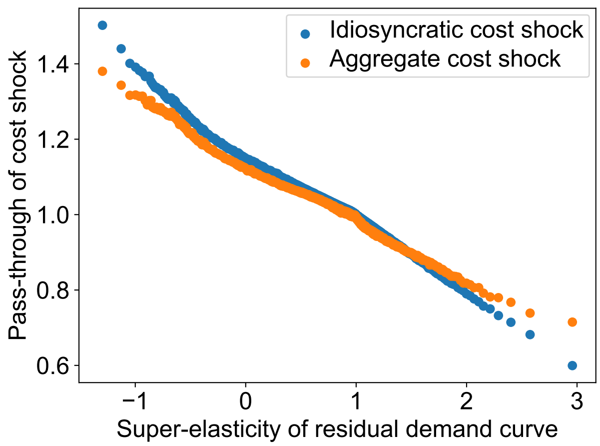
$$\sigma_{jmt} = -\frac{\partial \log q_{jmt}}{\partial \log p_{jmt}}, \qquad \text{and} \qquad \varepsilon_{jmt} = \frac{\partial \log \sigma_{jmt}}{\partial \log p_{jmt}}.$$

For single-product firms, profit-maximizing markups are given by the usual Lerner formula, $\sigma_{jmt}/(\sigma_{jmt} - 1)$. One can show that the pass-through of an idiosyncratic cost shock (in levels) is thus

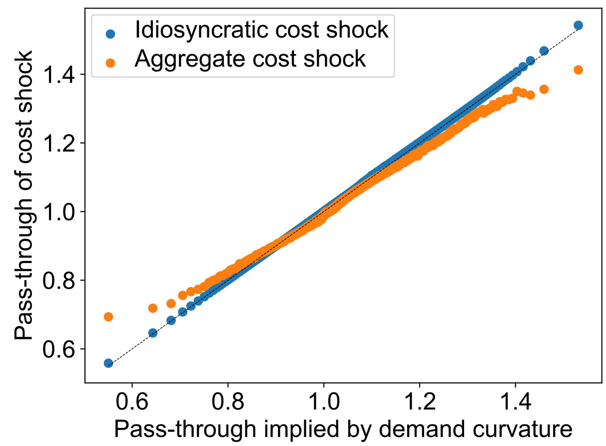
$$\rho_{jmt}^{\text{idiosyncratic}} = \frac{\sigma_{jmt}}{\sigma_{jmt} + \varepsilon_{jmt} - 1}. \tag{16}$$

Figure C2 plots the pass-through of idiosyncratic and aggregate cost shocks against products' super-elasticities of demand and the pass-through implied by (16). The pass-through of idiosyncratic shocks is well-approximated by (16) (the presence of multi-product firms in the data means that the pass-through of idiosyncratic shocks could in practice differ from (16)). While the pass-through of aggregate cost shocks is more condensed than the pass-through of idiosyncratic cost shocks, it nevertheless also varies considerably across products. The super-elasticity of a product's residual demand curve

Figure C2: Pass-through of aggregate and idiosyncratic cost shocks in simulations of Nakamura and Zerom (2010) demand system.



(a) Super-elasticity of demand.



(b) Pass-through implied by demand curvature.

Note: Each plot shows a binscatter with 1,000 bins. The pass-through of idiosyncratic shocks is calculated as the response (in levels) of firms' optimal prices for a product to an infinitesimal change in the product's cost. The pass-through of aggregate shocks is calculated as the response of firms' optimal prices to an infinitesimal change in all products' costs within the market, excluding the outside option. The pass-through implied by the demand curvature in panel (b) is given by (16).

and the pass-through implied by the product's residual demand curve are systematic predictors for the pass-through of aggregate cost shocks: products with a super-elasticity of demand below one tend to pass through both idiosyncratic and aggregate cost shocks more than one-for-one, while products with a super-elasticity above one tend to pass through both types of shocks less than one-for-one. In other words, the Nakamura and Zerom (2010) model predicts systematic variation in the pass-through in levels of aggregate cost shocks.

Table C1 further illustrates the variation in pass-through by regressing products' pass-throughs of aggregate cost shocks on various product characteristics. Doubling price per ounce of coffee is associated with a 0.14 increase in the pass-through of aggregate cost shocks, and increasing the market share of a brand or firm is associated with a decline in the predicted pass-through. Likewise, the curvature of products' residual demand curves directly affect the extent of pass-through. These predictions contrast with the uniform pass-through in levels that we document in Figure 2.

One may ask whether the variation in pass-through that we find is due to differences in the data that we use to simulate the model (i.e., the 2006–2020 data, compared to the 2000–2004 data used by Nakamura and Zerom 2010). Some ancillary statistics reported

Table C1: Determinants of pass-through of aggregate cost shocks in Nakamura and Zerom (2010) demand system.

	Pass-through in levels of aggregate cost shock				
	(1)	(2)	(3)	(4)	(5)
Log Unit Price	0.144**				
	(0.003)				
Log Brand Market Share		-0.033**			
		(0.001)			
Log Firm Market Share			-0.036**		
			(0.001)		
Super-elasticity				-0.153**	
				(0.001)	
Predicted pass-through eq. (16)					0.865**
					(0.009)
Intercept	1.154**	0.872**	0.876**	1.125**	0.115**
	(0.004)	(0.004)	(0.004)	(0.002)	(0.009)
N	374607	374607	374607	374607	374607
R^2	0.39	0.29	0.30	0.80	0.80

Note: Standard errors clustered by market. ** indicates significance at 5%.

by Nakamura and Zerom (2010) suggest that the degree of heterogeneity in pass-through is likely to be as large in their sample. First, Nakamura and Zerom (2010) report that the median super-elasticity of demand in their sample is 4.64. Figure C2a finds that products whose super-elasticities differ from one tend to have pass-throughs quite far from one. Second, Nakamura and Zerom (2010) describe the market in 2000–2004 as a near duopoly between Maxwell House and Folgers. In the NielsenIQ data in 2006, the market is less concentrated due to increased penetration by higher-end brands like Starbucks and Peets Coffee. As shown in column 2 of Table C1, variation in market share tends to be associated with significant variation in pass-through across products.

Appendix D Cheapflation and Inflation Inequality in Automobiles

In this appendix, we use microdata on vehicle prices and consumer vehicle purchases to show that the same fluctuations in cheapflation and inflation inequality that we observed in the main text appear in the market for automobile purchases.

D.1 Data

We combine datasets on vehicle prices and characteristics from Ward's Automotive with data on vehicle purchases by households from the Consumer Expenditure Survey.

Vehicle prices and characteristics. We use data on vehicles sales, manufacturer suggested retail prices (MSRPs), and characteristics from Ward's Automotive, as collected by Grieco, Murry, and Yurukoglu (2024). Vehicle brands—called "makes"—each produce several models, and models in turn are typically available in several different varieties, or "trims." Since sales are only available at the make-model level, the data are aggregated to the make-model level in each year, using the median for the MSRP and other product characteristics across trims.

Consumer purchases. The Consumer Expenditure Survey (CEX) includes detailed interview questions on households' vehicle purchases. We use these data to construct measures of the income of each make's buyers. We use data from 2006 to 2018, during which the makes of purchased vehicles are consistently coded (variable `MAKE`). We exclude vehicles that are purchased for business (i.e., `VEHBSNZ` $\neq 0$) and exclude vehicles that are purchased for someone outside the household or that are received as gifts (i.e., `VEHGFTC` $\neq 1$). For each vehicle make in each year, we calculate the average log before-tax income (`FINCBTAX`) and income quintile (calculated from `INC_RANK`) of households that purchase that vehicle make.

Summary statistics. Table D1 reports summary statistics for each vehicle make-model-year observation in our dataset covering 2006–2018. The first section of the table reports vehicle sales, prices (MSRPs), and characteristics such as horsepower and dimensions. The second section of the table reports changes in model prices and characteristics from one year to the next. The average change in each of these characteristics is small on average (less than 1 percent in all cases), and for each of the non-price characteristics, the median

Table D1: Summary statistics in vehicle make-model-year dataset, from 2006–2018.

Variable	*N*	Mean	Standard deviation	Min	Max
Sales	3986	49351.05	81315.60	10.00	844448.00
MSRP	3986	39.25	17.23	13.54	99.99
Miles per gallon	3986	21.32	7.85	10.00	50.00
Horsepower	3986	242.77	84.74	66.00	645.00
Height	3986	63.25	8.04	46.60	107.50
Width	3986	73.44	4.00	60.90	89.00
Length	3986	188.24	17.89	106.10	273.80
Curbweight	3986	3934.64	890.58	1808.00	7230.00
Δ Log MSRP ($\times$100)	3381	0.18	6.04	-59.74	57.26
Δ Log Miles per gallon ($\times$100)	3381	0.20	6.89	-117.12	65.23
Δ Log Horsepower ($\times$100)	3381	0.82	8.10	-69.31	58.94
Δ Log Height ($\times$100)	3381	0.01	1.02	-11.15	12.79
Δ Log Width ($\times$100)	3381	0.09	1.46	-18.37	19.62
Δ Log Length ($\times$100)	3381	0.12	1.22	-22.30	22.30
Δ Log Curbweight ($\times$100)	3381	0.28	2.99	-37.01	37.01
Average Log Income of Buyers	3957	10.89	0.32	9.89	12.47
Average Income Quintile of Buyers	3957	3.53	0.35	2.25	4.64

Note: Each observation is a make-model-year. Summary statistics are unweighted. MSRPs are in thousands of 2015 dollars, deflated using core CPI. Vehicle height, length, and width are in inches, and vehicle curbweight is in pounds.

change in model's characteristics is zero. When considering the year-over-year growth in prices (MSRPs) for a vehicle model, our robustness exercises will also control for other changes in vehicle characteristics. The final section of the table reports the average of log income for CEX buyers of the make to which a model belongs and the average income quintile of make buyers. Makes exhibit considerable variation in the average income of buyers; for a vehicle model one standard deviation above average, the average income of its buyers is 32 percent higher than average.

D.2 Cheapflation and Inflation Inequality

We begin by assessing whether vehicle prices exhibit cheapflation—i.e., the price of relatively inexpensive models are more sensitive to overall growth in prices for a make. To do so, we estimate the specification,

$$\begin{aligned}\text{MSRPGrowth}_{imt} = \beta \left(\text{AvgMSRPGrowth}_{mt} \times \text{LogMSRP}_{imt}\right) \\ + \gamma \text{LogMSRP}_{imt} + \delta' X_{imt} + \phi_{mt} + \varepsilon_{imt}, \quad (17)\end{aligned}$$

where MSRPGrowth_{imt} is the MSRP growth from year t to year $t+1$ for model i of make m, $\text{AvgMSRPGrowth}_{mt}$ is the (sales-weighted) average growth in prices for all models with make m, LogMSRP_{imt} is the log price of model i of make m in year t, X_{imt} is a vector of controls, and ϕ_{mt} are make-year fixed effects.

Columns 1–3 of Table D2 report the results from estimating (17). Each column includes successively more controls in X_{imt}: column 2 includes fixed effects for each model i, and column 3 includes both model FEs and controls for the changes in each vehicle characteristic (miles per gallon, horsepower, height, width, length, and curbweight). In each case, we find that $\beta < 0$: the growth in prices for relatively cheaper models is more sensitive to make inflation rates. In other words, the same systematic fluctuations in cheapflation appear in the vehicle context, with lower-priced varieties exhibiting more inflation (deflation) when prices on average are rising (falling).

Next, we test whether this leads to disproportionate sensitivity of inflation for low-income households. We do so by estimating an analogous specification that instead estimates how the sensitivity of price growth for each vehicle model to overall vehicle price changes varies with the average income of its make's buyers. We estimate the specification,

$$\begin{aligned}\text{MSRPGrowth}_{imt} = \beta\left(\text{AvgMSRPGrowth}_{t} \times \text{LogBuyerIncome}_{mt}\right)\\ + \gamma\text{LogBuyerIncome}_{mt} + \delta' X_{imt} + \phi_t + \varepsilon_{imt}, \quad (18)\end{aligned}$$

where MSRPGrowth_{imt} is the MSRP growth from year t to year $t+1$ for model i of make m, AvgMSRPGrowth_{t} is the (sales-weighted) average growth in prices for all vehicles starting in year t, $\text{LogBuyerIncome}_{mt}$ is the average of log income for all households purchasing make m in year t, and ϕ_t are year fixed effects. Note that, unlike specification (17), this specification exploits variation in buyer incomes across vehicle makes, since that is the finest level of disaggregation at which we observe buyer choices in the CEX.

Columns 4–6 of Table D2 report the results from (18). Regardless of the set of controls, we find that price growth for vehicles with a higher-income customer base is less sensitive to overall vehicle inflation rates. That is, the same systematic fluctuations in inflation inequality arise when considering vehicle purchases.

As in the cases discussed in the main text, the difference in inflation across vehicle makes purchased by low- and high-income households is masked in official statistics. The BLS differentiates between inflation rates for new car and truck purchases (ELI code TA011) and used cars and trucks (ELI code TA021), but does not capture further differences in product-level inflation within these categories.

Table D2: Cheapflation and inflation inequality for automobiles.

	MSRP Growth for Make					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. MSRP Growth for Make						
× Log MSRP	−0.699**	−0.531**	−0.392**			
	(0.192)	(0.175)	(0.163)			
Avg. MSRP Growth for All Vehicles						
× Log Buyer Income				−0.894**	−0.860**	−0.911**
				(0.270)	(0.255)	(0.243)
Make-Year FEs	Yes	Yes	Yes			
Year FEs				Yes	Yes	Yes
Model FEs		Yes	Yes		Yes	Yes
Controls for other attribute changes			Yes			Yes
N	3381	3381	3381	3358	3358	3358
R^2	0.32	0.54	0.59	0.15	0.21	0.31

Note: Columns 1–3 report results from (17), and columns 4–6 report results from (18). In columns 3 and 6, controls for attribute changes include the change in log horsepower, miles per gallon, height, length, width, and curbweight. Standard errors two-way clustered by year and model. * indicates significance at 10%, ** at 5%.

Appendix E Differential Inflation Across Other Units

While the main text focuses on how pass-through in levels generates different inflation rates across income groups, the same mechanism applies to inflation across other units with heterogeneous expenditure patterns across varieties. In this appendix, we provide empirical evidence that input cost shocks lead to systematic differences in inflation across cities and import price inflation across countries. In both cases, we use coffee products as an example to illustrate these effects.

E.1 Inflation Across Cities

Data. We use data on prices of coffee from the C2ER Cost of Living Index. These data report the price of a "11 to 11.5 ounce can of Maxwell House, Hills Brothers, or Folgers" across U.S. urban areas on a quarterly basis from 1990Q1 to 2010Q1. The set of urban areas for which coffee prices are collected varies slightly from year to year, ranging from 203 to 260 urban areas per observation period.

For each urban area c in each quarter t, we calculate the $\text{RelativePrice}_{ct}$ of coffee relative to other urban areas as the log difference between the price in c and the national average, and the inflation rate Inflation_{ct} as the log change in the coffee price of coffee in c from quarter t to quarter $t+4$,

$$\text{RelativePrice}_{ct} = \log\left(\frac{p_{ct}}{\sum_{c'} p_{c't}}\right), \qquad \text{and} \qquad \text{Inflation}_{ct} = \log\left(\frac{p_{ct+4}}{p_{ct}}\right).$$

We winsorize both relative prices and inflation rates at the 1 percent level. The national inflation rate, $\text{NationalInflation}_t$, is the average across urban areas in quarter t.

We supplement these data with estimates of income in each urban area using the Bureau of Economic Analysis (BEA) annual estimates of per capita income by metropolitan and micropolitan statistical area (CAINC1).

Specifications and results. Pass-through in levels predicts that cities with lower coffee prices will be more sensitive to fluctuations in input prices. We estimate the specification,

$$\text{Inflation}_{ct} = \beta\,(\text{NationalInflation}_t \times \text{RelativePrice}_{ct}) + \delta_c + \alpha_t + \epsilon_{ct}, \tag{19}$$

where δ_c are urban area fixed effects that absorb secular trends in coffee inflation across urban areas and α_t are quarter fixed effects that absorb the average inflation rate in each quarter as well as any other shifters in coffee inflation across time periods.

Table E1: Heterogeneous incidence of cost shocks on inflation across cities: Coffee.

	Coffee Inflation in City			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Average Coffee Inflation × Relative Price	−1.003**	−1.054**		
	(0.253)	(0.285)		
Average Coffee Inflation × Log Income			−0.129**	−0.119**
			(0.061)	(0.061)
City FEs	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
N	19 431	19 431	16 990	16 990
R^2	0.67	0.67	0.68	0.68

Note: Columns 1–2 report the estimated coefficient β from (19), and columns 3–4 report the estimated coefficient γ from (20). In columns 2 and 4, the average coffee inflation from quarter t to quarter $t+4$ is instrumented with the annual inflation in coffee commodity prices and two lags. Standard errors two-way clustered by city and date. * indicates significance at 10%, ** at 5%.

Column 1 of Table E2 reports that urban areas where coffee is relatively more expensive indeed have muted responses of inflation to national fluctuations in coffee inflation. Increasing the relative price of coffee by 10 percent reduces the sensitivity of local inflation to national coffee inflation by 10 percent. Column 2 finds similar results when we isolate fluctuations in coffee prices induced by input costs, using current and lagged inflation in green coffee bean commodity prices to instrument for national coffee inflation rates.

Prices of coffee may differ across cities because of variation in distribution margins or because of differences in consumer preferences over coffee varieties (though our data from the cost of living index largely minimizes the second component by focusing on the prices of roughly equivalent varieties like Maxwell House, Folgers, and Hills Brothers). An important determinant of both sources of variation is local income, which may be correlated with higher retail wages and thus higher costs of distribution services as well as with preferences for more expensive varieties.[19] To isolate how pass-through in levels implies different inflation sensitivity across urban areas with different incomes, we estimate the specification,

$$\text{Inflation}_{ct} = \beta\left(\text{NationalInflation}_t \times \text{LogIncome}_{ct}\right) + \delta_c + \alpha_t + \epsilon_{ct}. \tag{20}$$

Column 3 reports that coffee inflation in higher-income cities is likewise less sensitive to nationwide fluctuations in coffee inflation. A 10 percent increase in per capita income

[19] Sangani (2022) estimates that retail markups increase with income across cities with an elasticity of 0.11, consistent with the magnitude of the results in Table E2.

is associated with a 1.3 percent lower sensitivity of local coffee inflation to national inflation. We find similar results when instrumenting for national inflation with coffee bean commodity cost fluctuations in column 4.

E.2 Import Price Inflation Across Countries

Data. We use data on the value and quantity of coffee imports across countries from the World Integrated Trade Solution (WITS). We define coffee imports as imports under HS-6 code 090121 ("Roasted coffee, not decaffeinated"). These data report the total trade value in USD and the quantity of imports in kilograms for up to 172 countries over the period 1992–2023. For each country c in each year t, we calculate the unit value of coffee imports as the total trade value divided by the quantity of imports,

$$\text{UnitValue}_{ct} = \frac{\text{TradeValue}_{ct}}{\text{Quantity}_{ct}}.$$

We define WorldUnitValue_t analogously as the total trade value across all countries divided by the total quantity of imports across all countries. The relative price of imported coffee, $\text{RelativeImportPrice}_{ct}$, is defined as the log difference between import unit values for country c relative to the world,

$$\text{RelativeImportPrice}_{ct} = \log\left(\frac{\text{UnitValue}_{ct}}{\text{WorldUnitValue}_t}\right).$$

The import price inflation for country c in year t is the log growth in unit values from t to $t+1$,

$$\text{ImportPriceInflation}_{ct} = \log\left(\frac{\text{UnitValue}_{ct+1}}{\text{UnitValue}_{ct}}\right).$$

We winsorize import price inflation at the 5 percent level. The world import price inflation is defined analogously as the log growth in the world unit value from year t to $t+1$.

Specification and results. Pass-through in levels predicts that countries that import relatively more expensive coffee varieties will see greater import price inflation in response to global increases in coffee prices. We test this prediction using the specification,

$$\begin{aligned}\text{ImportPriceInflation}_{ct} = \beta\left(\text{WorldImportPriceInflation}_t \times \text{RelativeImportPrice}_{ct}\right)\\ + \gamma\,\text{WorldImportPriceInflation}_t + \delta_c + \epsilon_{ct}. \quad (21)\end{aligned}$$

Table E2: Heterogeneous incidence of global cost shocks on import price inflation: Coffee.

	Country Import Price Inflation			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
World Import Price Inflation × Relative Import Price	−0.221**	−0.285**	−0.225**	−0.167
	(0.075)	(0.101)	(0.093)	(0.106)
Country FEs	Yes	Yes	Yes	Yes
Year FEs			Yes	Yes
N	4480	4480	4480	4480
R^2	0.12	0.07	0.25	0.25

Note: The table reports the estimated coefficient β from (21). Columns 3–4 augment specification (21) with year fixed effects. In columns 2 and 4, the log change in the coffee commodity price from year t to year $t+1$ is used as an instrument for world import price inflation. Standard errors two-way clustered by country and year. * indicates significance at 10%, ** at 5%.

where δ_c are country fixed effects that absorb secular differences in import price inflation across countries.

Table E2 reports the results from estimating specification (21). Column 1 finds that fluctuations in world coffee prices are indeed associated with relatively less import price inflation for countries that have relatively more expensive coffee imports: a 10 percent increase in the import prices is associated with 2.2 percent lower sensitivity of import price inflation to world coffee prices. Isolating commodity cost-driven fluctuations in world coffee import prices using coffee bean commodity prices as an instrument produces similar results in column 2. Columns 3–4 also find similar quantitative results, though statistical significance is attenuated, when we augment specification (21) with time fixed effects that absorb any arbitrary variation in coffee import price inflation across time. Thus, these results suggest that countries that import more expensive varieties within a HS-6 code experience muted responses of import price inflation in response to global input cost shocks.