Working Papers

FEDERAL RESERVE BANK OF BOSTON

No. 26-6

# The Price-change Statistics We've Weighted For

**Christopher D. Cotton and Vaishali Garga**

**Abstract:**
The real effects of monetary policy depend on price stickiness. Existing studies that measure aggregate stickiness using US consumer price index microdata hold the consumption basket fixed. This yields a lower level of stickiness in 2024 compared with 1978. We show instead that stickiness is unchanged. Although individual products now change prices more frequently, the effect is largely offset by shifts in consumer spending, notably toward services with stickier prices. These consumption-basket shifts reduce the estimated decline in monetary non-neutrality by 25 percentage points, suggesting that monetary policy remains far more effective than methods used in existing studies imply.

**JEL Classifications:** E31, E52, E58

**Keywords:** Frequency of price changes, size of price changes, price stickiness, distributions of price changes, monetary non-neutrality, expenditure weights, consumer price index

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The authors thank Anna Durall, Ben Grzyb, Kelly Jackson, and John O'Shea for excellent research assistance. They thank Bradley Akin and Ryan Ogden for support at the US Bureau of Labor Statistics, and Delia Sawhney for support at the Boston Fed. They thank Neil Mehrotra, Jacob Orchard, Jenny Tang, and seminar participants at the Boston Fed, BSE Summer Forum, Federal Reserve System Committee on Macroeconomics, and Bentley University for helpful comments.



**This version: April 2026** **https://doi.org/10.29412/res.wp.2026.06**

# 1 Introduction

How effectively can central banks stabilize the economy? The answer hinges critically on the degree of price stickiness. In New Keynesian models, stickier prices imply greater monetary non-neutrality, that is, a larger pass-through of nominal demand shocks to real output. The degree of price stickiness depends on the distribution of price changes at the microeconomic level, making it crucial to accurately measure price-change distributions.

To date, the most comprehensive measures of price-change distributions have been computed using microdata on products underlying the US consumer price index (CPI). When measuring the distributions over time, notable papers keep the consumption basket fixed (that is, they hold the expenditure weight of each product to its value in one year) and consider time variation only in product-level price-change statistics (Nakamura et al., 2018; Montag and Villar, 2025). We show that ignoring consumption-basket shifts over the last five decades leads to a considerable overstatement of the decline in price stickiness. When these shifts are properly incorporated, the aggregate frequency of price changes is similar to what it was five decades earlier. While individual products do change prices more frequently in 2024 than in 1978, the composition of consumer spending has shifted markedly toward services and other categories with low frequencies of price changes. Failing to account for these composition shifts exaggerates the decline in monetary non-neutrality by about 25 percentage points.

Our measurement of price-change distributions proceeds in three steps. First, we use restricted CPI microdata to construct monthly time series of price-change statistics and expenditure weights from 1978 to 2024 at the most granular level of products underlying the CPI.[1] Our expenditure weights correspond directly to those employed by the Bureau of Labor Statistics (BLS) in constructing the official CPI. This represents the first continuous time series of granular expenditure weights spanning nearly five decades.[2]

Second, we measure the monthly distributions of price changes in the United States from 1978 to 2024 allowing for time variation in both price-change statistics and expenditure weights at a granular level. We find that the aggregate frequency of price changes increases only mildly over the sample period and moves broadly in line with inflation—peaking in

[1] The US Bureau of Labor Statistics (BLS) indefinitely suspended external-researcher access to CPI microdata in 2024.

[2] The BLS has made these unpublished weights available to researchers on a one-off basis. For example, Nakamura and Steinsson (2008) obtained year-2000 weights from the BLS, and Klenow and Kryvtsov (2008) obtained weights for each year from 1988 through 1995 and 1999 through 2004. The expenditure weights released publicly by the BLS are instead at a higher aggregation level.

the late 1970s to early 1980s and then again during the COVID-19 pandemic. The aggregate absolute size of price changes remains largely unchanged relative to the beginning of the sample and generally shows less variation over time. Conversely, when the weights are held fixed (at their 2000 levels), the increase in the aggregate frequency of price changes over the sample becomes much larger, while the aggregate absolute size of price changes remains relatively unaffected.

Third, we decompose changes in price-change distributions into four components: a "within" effect capturing changes in product-level price-change statistics, a "between" effect capturing shifts in expenditure weights across products, a "cross" effect capturing covariance of the two, and an "entry/exit" effect. This decomposition, adapted from Foster, Haltiwanger, and Krizan (2001), allows us to quantify how much of the change in the distributions stems from changes in firm pricing behavior versus changes in consumer purchases.

For the frequency distribution, the between effect is large and negative, reducing the mean by 4.7 percentage points from 1978 to 2024. This nearly offsets the within effect, which raises the mean frequency by 5.6 percentage points. Similar patterns emerge when we exclude gas and used cars (which exhibit unusually high price-change frequencies and volatile weights), or when we examine proxies for the median. For the absolute-size distribution, the between effect is negative but counterbalanced by a positive cross effect, resulting in a relatively muted net impact of weights on the distribution.

Which consumption-basket shifts matter most? We show that services (excluding travel) is the most important sector driving the between effect throughout our sample period. Service products have low price-change frequencies, and their share in the consumption basket rises during our sample, as Galesi and Rachedi (2019) also discuss. However, other consumption-basket changes have had pronounced effects in the short term. For example, the decline and increase in relative expenditure on gas in the late 1980s and early 2000s drove a decline and rise, respectively, in the mean frequency. The subsequent decline in the mean frequency after the Great Recession resulted partly from lower relative expenditure on lodging away from home. We also document transitory effects from expenditure shifts induced by the COVID-19 pandemic.

Finally, we show that the consumption-basket effect is not just a technical correction, but rather it changes our understanding of monetary transmission. Using two complementary approaches, we show that fixed-basket measures substantially overstate the decline in monetary non-neutrality. First, following Alvarez, Le Bihan, and Lippi (2016), we compute sufficient statistics for monetary non-neutrality based on the kurtosis and frequency of price changes. We find that fixing the expenditure weights overstates the decline in monetary non-neutrality from 1978 to 2024 by 25 percentage points in our baseline measure and by a similar magnitude in several robustness checks. Second, we compute Phillips curve slopes using multisector sticky-price models (Calvo and menu cost) calibrated to match the empirical price-change distributions. We again find that the fixed-basket calibrations overstate the decline in monetary non-neutrality to a degree similar to the baseline. When correctly measured, the effectiveness of monetary policy remains far greater than existing estimates imply.

Methodologically, our primary contribution is the construction of a comprehensive data set of monthly expenditure weights and price-change statistics at the at the most granular level of products underlying the CPI from 1978 to 2024. These statistics include the frequency of price changes and the absolute size of price changes, both of which are the focus of this paper, as well as the frequency of price increases, the frequency of price decreases, the size of price increases, the size of price decreases, and the frequency of price changes including sales. Beyond its function in this paper, our data set can be used to calibrate multisector sticky-price models employed in various research and policy analyses.[3] We intend to release the annual data set for use by fellow researchers.

## Related Literature

Our work relates to many studies that use microdata on the nonshelter component of the CPI to examine the cross-sectional distributions of price changes. This literature begins with Bils and Klenow (2004), who show that for the United States during the 1995–1997 period, the median monthly frequency of price changes was 21 percent, which implies that the average duration of prices was about 4.3 months. Focusing on the 1998–2005 period, Nakamura and Steinsson (2008) document the importance of sales and product substitutions in measuring this statistic; when sales are excluded, the median monthly frequency of regular price changes is 9 to 12 percent, implying a duration of prices of about 8 to 11 months. Klenow and Kryvtsov (2008) find a duration of four to seven months during the 1988–2004 period.

A more recent strand of this literature documents the evolution of the distributions of price changes. For the United States, a subset of papers measures the evolution of the distributions, keeping the product weights fixed. This includes Nakamura et al. (2018), who measure the distributions of price changes from 1988 to 2014 and 1978 to 2014, respectively, holding product weights fixed to their 2000 expenditure shares, and Montag and Villar

[3]For example, the data could be used to discipline models in the recent literature examining nonlinearities in the slope of the Phillips curve (Blanco et al., 2024; Karadi et al., 2024).

(2025), who measure the distributions from 2018 to 2024, holding product weights fixed to their 2018 expenditure shares. In a related paper, Vavra (2014) measures changes in the aggregate frequency of price changes during recessions. Another subset of papers measures the evolution of the distributions, keeping the product price-change frequencies fixed. These papers isolate the role of factors affecting product shares in driving the distributions of price changes over time. These factors include changes in the intermediate share of industries (Pasten, Schoenle, and Weber, 2020), changes in production networks (Rubbo, 2023), changes in industrial composition (Galesi and Rachedi, 2019; Cotton and Garga, 2026)[4], and changes in demographics (Clayton, Jaravel, and Schaab, 2018; Mangiante, 2022). We contribute to the literature by measuring the evolution of the distributions, accounting comprehensively for changes in both product weights and product price-change statistics over time.

In the international context, microdata underlying consumer price indexes have been used to analyze price-adjustment behavior in Norway (Wulfsberg, 2016), Switzerland (Rudolf and Seiler, 2022), Sweden (Klein, Skeppås, and Tysklind, 2024), and the eurozone (Gautier et al., 2024). While some of these papers allow for time-varying product weights, as we do, they analyze a shorter time period, and none of them quantifies the impact of weights. Furthermore, these microdata have been used to study price-adjustment behavior in high-inflation versus low-inflation environments for Argentina (Alvarez et al., 2019) and Mexico (Gagnon, 2009).

The rest of the paper proceeds as follows. Section 2 describes the microdata and our construction of granular price-change statistics and expenditure weights at a monthly frequency. Section 3 presents the time series of moments of the frequency and size distributions of price changes. Section 4 uses a decomposition to show the quantitative importance of consumption-basket changes. Section 5 identifies which consumption-basket changes have had the greatest effect on the distributions. Section 6 shows the quantitative importance of consumption-basket changes in measuring monetary non-neutrality. Section 7 concludes.

[4]The earlier paper analyzes only how economic composition shifts—measured primarily using industry value-added shares—affected the distributions of price changes, while holding fixed the product-level price-change statistics (to their 1998–2005 averages, obtained from Nakamura and Steinsson (2008)). By contrast, this paper considers variation in both dimensions, allowing for simultaneous changes in product-level price-change statistics and expenditure weights when measuring the distributions of price changes from 1978 to 2024. The monthly price-change statistics are measured using restricted CPI microdata, and the expenditure weights correspond to those employed by the BLS in official CPI construction.

## 2 Data

We measure the distributions of price-change statistics by combining prices from the detailed microdata underlying the CPI for All Urban Consumers with CPI expenditure weights that are ultimately derived from the Consumer Expenditure Survey (CEX). All data are sourced from the BLS. Our final data set spans the period from 1978 through 2024, which covers all the years for which microdata are available from the BLS.[5]

We construct monthly expenditure weights and price-change statistics at the entry level item (ELI) level, which is the lowest level of product disaggregation in the CPI. The CPI is separated into hierarchical categories; at the highest level are major groups, followed by expenditure classes, item strata, and ELIs. In 2024, there were eight major groups, 70 expenditure classes, 211 item strata, and 335 ELIs.[6]

**ELI price-change statistics** To calculate monthly ELI price-change statistics, we aggregate item-level price changes in the BLS microdata to the ELI level. An item in the microdata is defined as a good or service sold at or offered by a particular business in a particular location. For example, a 12-ounce can of Diet Coke sold at the Target in Central Square in Cambridge, Massachusetts, would be an item. We first measure a price-change statistic for each item on a monthly basis.[7] We then aggregate that statistic to the ELI level by taking an unweighted mean of the statistic across all available items within the ELI by month. The monthly frequency of price changes for an ELI is the percentage of its prices in a given month that change relative to the prior month. To verify our ELI-level frequency computation, we compare our ELI frequencies averaged over the 1998–2005 period with the frequencies computed by Nakamura and Steinsson (2008) and find a correlation of 0.994 (see Figure A.1). When measuring the absolute size of price changes for an item, we measure the absolute log

[5]Data for 1987 and a handful of additional months in other years are not available in the BLS microdata. The missing months are November and December 1986, December 1989, March 1990, July 1991, August 1992, February 1994, December 1995, July 1996, and May 1997. For 2024, we have data through July.

[6]See `https://www.bls.gov/cpi/additional-resources/cpi-item-aggregation.htm`. At the beginning of the sample, there were seven major groups, 68 expenditure classes, 265 item strata, and 382 ELIs. For an illustration of the hierarchical structure, consider the major group Food and Beverages (code F). This group contains the expenditure class Beverage Materials Including Coffee and Tea (code FP). This expenditure class in turn contains two item strata: Coffee (FP01) and Other Beverage Materials Including Tea (FP02). The coffee item stratum contains a single ELI: coffee (FP011). The Other Beverage Materials Including Tea item stratum consists of two ELIs: Tea (FP021) and Other Beverage Materials (FP022).

[7]Note that the BLS assesses prices of all items on a monthly basis for only Chicago, New York, and Los Angeles after 1998 and for those three cities plus Philadelphia and San Francisco prior to 1998. Prices of some items (notably in food and energy) are collected monthly in all other cities as well. Prices of other items are collected on a bimonthly basis and are therefore not included in our sample. Other papers in this literature use a similar approach to measure price-change statistics.

change in the price from one month to the next, conditional on a nonzero price change. We drop extreme price changes, following Nakamura et al. (2018).[8]

We also compute annual ELI price-change statistics for the decomposition exercise. To compute the annual statistics, we calculate the weighted mean of the monthly price-change statistic for each ELI by year. We weight by the number of observations available in each month.[9]

Following Nakamura and Steinsson (2008), our baseline analysis focuses on regular price changes, that is, price changes excluding sales, on the basis that if a price returns to its prior level after a sale, it is less relevant in measuring monetary non-neutrality. The BLS flags sale prices, that is, prices that are discounted. We measure regular price changes by excluding any prices flagged as "on sale" in either the current or preceding month.

The BLS has recently begun using alternative sources for the CPI microdata. For instance, in March 2019, it started using prices provided directly by a single department store (Konny, Williams, and Friedman, 2022). Consequently, the processing of these alternative data produces large jumps in our measured price-change statistics for apparel and household-goods ELIs beginning in March 2019. We adjust for these "bad" statistics starting in March 2019 to smooth the fluctuations. We first determine the average percentile for a price-change statistic of the apparel or household-goods ELI in the distribution from 2010 through 2018. Then, for March 2019 and every month after, we replace the price-change statistic for that apparel or household-goods ELI with that percentile of the monthly distribution excluding apparel and household-goods ELIs. We make similar adjustments for the prescription-drugs ELI beginning in March 2015, when the BLS began receiving bimonthly price data from a single pharmaceutical retailer (Bieler et al., 2023) and for wage-related ELIs from 1978 through 1986, which show unusually large volatility. These adjustments to apparel, household goods, prescription drugs, and wages affect only 1.36 percent of the overall data set by weight. For more details on this adjustment, see Appendix A.2.

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[8] We drop any price quotes that are less than $0.4$ cents. For nonzero price changes, we drop absolute log price changes that are less than $10^{-6}$ or greater than the 99th percentile of the distribution of the absolute log price changes by year.

[9] We compute the annual statistic only when there are at least six months of statistics available for an ELI to prevent a small number of months from having an outsized impact. Note that for 2024, we have data only through July; therefore, we consider the months from August 2023 through July 2024 when measuring the 2024 annual statistics. We also compute seasonally adjusted versions of the price-change statistics to reduce the possibility that the absence of specific months in the microdata affects the measurement of statistics at an annual level. The results are similar to the baseline.

**ELI concordance** The BLS has made periodic adjustments to the ELIs included in its CPI surveys. The two largest adjustments were implemented in 1988 and 1998.[10] In these two years, the BLS also reclassified the codes used to identify ELIs, with about 30 percent of codes changing in 1988 and all codes changing in 1998. As a result of these reclassifications, ELIs in the 1978–1987 sample do not map one-to-one to ELIs in the 1988–1997 sample, which in turn do not map one-to-one to the ELIs in the post-1998 sample.

Other papers studying the evolution of the price-change distributions typically use a concordance between ELIs over time and then fix the ELI weights to a specific year. Due to reclassifications, however, if the weights are fixed to a specific year, ELIs that do not appear in the microdata in that year will drop out of the entire sample. To overcome this, Nakamura et al. (2018) construct an ELI concordance that maps every ELI code from the 1978–1987 period to a code from the 1988–1997 period, and every code from the 1988–1997 period to a code from 1998 onward.

Since we allow for weights to vary by year, we do not, in principle, need to implement such a concordance. Yet, so that our results are comparable to the related literature, we choose to use this concordance.[11] Using the concordance allows us to capture the entry and exit of ELIs in the same manner as previous studies.

**ELI expenditure weights** We first compute weights at the item-stratum level, which, as a reminder, is one level of aggregation higher than an ELI. CPI item-strata weights correspond to the share of consumer spending on that item stratum. The BLS periodically updates CPI item-strata weights using the CEX, which surveys households about their spending across many categories of goods and services (excluding housing). The BLS implemented CEX-based updates to the CPI item-strata weights in January 1978, January 1988, January 1998, January of each even year from 2002 through 2020, and January of every year from 2022 onward. In the months between CEX updates, the BLS reweights the item strata using item-strata price indexes, assuming no substitution effects. The idea is to fix the consumption basket so that if the price of one item stratum rises more than another, its expenditure weight increases correspondingly.

[10]For example, in 1997, there was one expenditure class for beverages, Non-Alcoholic Beverages (17), which comprised three item strata: Carbonated Drinks (1701), Coffee (1703), and Other Non-Carbonated Drinks (1705). From 1998 onward, there were instead two expenditure classes for beverages: Juices and Non-Alcoholic Drinks (FN) and Beverage Materials Including Coffee and Tea (FP), each broken down further, as described earlier.

[11]A handful of medical codes were changed in 2010. We map the pre-2010 codes to the post-2010 codes. We account for overlap of some codes in 1997. Some medical-services ELIs (57011, 57021, and 57031) also drop out of the microdata in 1997; we set the price-change statistics for these ELIs to be the same as they were in 1996.

The BLS publicly releases its CPI item-strata weights every one or two years. We use the same adjustment procedure as the BLS to convert these to monthly item-strata weights.[12] CPI weights for the 1978–1980 period are available at the expenditure-class level rather than the item-strata level. To obtain weights at the item-strata level for 1978 through 1980, we compute the fraction of each expenditure class's weight that comprised an item stratum in 1981 and apply these fractions to the expenditure-class weights for that period. Haver Analytics also releases monthly item-strata weights but only for item strata that are currently in the CPI. For this subset, we verify that our weights closely match; the mean absolute difference is only 0.29 percent.

We convert the monthly item-strata weights to ELI weights using the "ELI factor" in the microdata. The ELI factor represents the weight assigned to each item, which, given the narrow definition of an item in the microdata, can vary across geographies and stores. Therefore, to obtain the monthly share of an ELI within an item stratum, we compute the sum of the ELI factor across all items in an ELI by month and divide that by the sum of the ELI factor for items across all the ELIs in that item stratum in that month. This variable is available in the microdata from only 1988 onward; to cover the earlier period, we backfill the ELI factor variable. To verify our ELI-weights computation, we compare our ELI weights for the year 2000 with the weights that Nakamura et al. (2018) obtained from the BLS and find a correlation of 0.9996 (see Figure A.2).

Our data offer comprehensive coverage of the nonrent component of the CPI. Figure A.3 shows the proportion of the CPI for which we construct price-change statistics for each month of our sample. The BLS microdata do not include rents; therefore, we cannot measure price-change statistics for primary residence rent or owner's equivalent rent. However, we have near-total coverage of the rest of the CPI.[13]

Our baseline analysis uses the CPI weights because we want to closely match the process used by the BLS in constructing the official price indexes. However, we later consider two robustness checks: ELI expenditure weights measured directly from the CEX and ELI

[12] The BLS does not publicly release the price indexes for certain item strata that we need to follow the BLS procedure between CEX updates. In this case, we use index changes at the higher expenditure class and major group levels to fill the missing item-strata price changes, which aligns with BLS methodology.

[13] Rent in the CPI is constructed using the CPI Housing Survey, which is discussed in more detail in Gallin et al. (2024). In 1983, the BLS switched from measuring housing costs for homeowners using the cost of buying a home to a hypothetical cost of renting, hence the jump in the coverage of the CPI including rent in that year. The small fraction of nonrent CPI that we do not cover includes (1) unsampled items in the CPI, that is, items for which the BLS constructs a price index using other similar items; (2) certain health-care items—for example, health insurance paid directly by consumers—that are measured outside the main survey; and (3) certain items that are missing from a limited number of months in our sample, such as college tuition and postage.

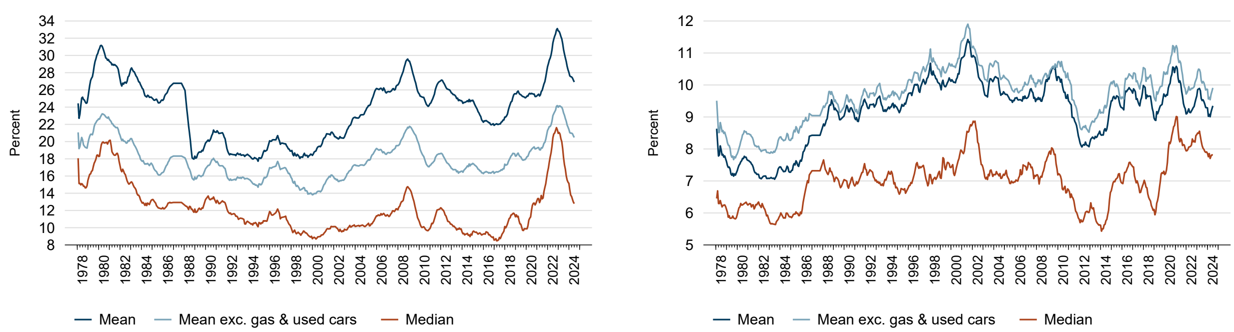
expenditure weights derived from the personal consumption expenditures (PCE) weights.[14]

## 3 Distributions of Price Changes

In this section, we introduce the moments of the price-change distributions that we consider throughout the rest of the paper. We first focus on the frequency and absolute size of price changes, as they are the most common price-change statistics used in calibrating modern New Keynesian models. As discussed previously, we are the first researchers to allow for variation in both ELI-level price-change statistics and weights when measuring these distributions.

Figure 1: Price-change Statistics, 1978–2024

(a) Frequency (b) Absolute size




*Notes*: To construct the frequency and size series, we compute the mean frequency of price changes and the mean absolute size of price changes, respectively, for each ELI in each month. We then compute the weighted mean across all ELIs, the weighted mean across all ELIs excluding gas and used cars, and the weighted median across all ELIs using the monthly expenditure weights. Finally, for each month, we calculate the 12-month moving average over the previous 12 months.
*Sources*: BLS, authors' calculations.

The first moment we consider is the weighted mean. Starting with the frequency distribution, Figure 1a shows the evolution of the weighted mean during the 1978–2024 period (navy blue line). After reaching a peak of 33 percent in early 1980, the weighted mean frequency showed a large decline in 1988 and then held steady for the next decade until the early 2000s. It then rose over the next eight years, reaching a peak of 29 percent during the Great Recession in 2008, and subsequently declined over the next eight years until 2016. From

[14]For the pre-1999 period, it is challenging to map the items in the CEX to those in the CPI, as highlighted by Jaravel (2024) and as we discuss later.

2016 to 2022, the weighted mean frequency rose again, with an especially sharp increase during the post–COVID-19 inflation surge, and peaked at 34 percent in the third quarter of 2022—even surpassing its peak during the Great Inflation era of the late 1970s. Starting in 2023, it declined again, moving back to about the same level as the beginning of the sample.

One issue is that outliers have an outsized effect on the weighted mean. The weighted mean frequency ranges from 20 percent to 30 percent over the sample. Therefore, ELIs with very high frequencies of price changes (close to 100 percent) are effectively outliers that will have this outsized effect. The two largest sets of ELIs with very high price-change frequencies are gas and used cars. Additionally, their weights show significant volatility over time.[15] To reduce the influence of these outliers, we consider two other moments: the weighted mean excluding gas and used cars and the weighted median.

The weighted mean frequency excluding gas and used cars (the light blue line in Figure 1a) shows increases and decreases similar to those of the weighted mean frequency but differs in levels. From 1986 to 1988, a period that saw a pronounced drop in the weight of used cars, there was a large decline in the weighted mean, but the weighted mean excluding gas and used cars showed a smaller decline. From the late 1990s to 2008, the weighted mean grew by much more than the weighted mean excluding gas and used cars. That is, the weighted mean grew by 10.8 percentage points (from 19.1 percent to 29.9 percent) from 1997 to 2008, while the weighted mean excluding gas and used cars grew by only 5.6 percentage points (from 15.9 percent to 21.5 percent).

The final moment we consider is the weighted median. The dynamics of the weighted median frequency (the red line in Figure 1a) are broadly similar to those of the weighted mean frequency excluding gas and used cars except that the weighted median rose less in the early 2000s and then rose and fell more during the post–COVID-19 inflation surge.

We then consider the same three moments for the distribution of the absolute size of price changes in Figure 1b. The size distribution generally shows smaller variation over time. The weighted mean (navy blue line) decreased moderately in the early 1980s, followed by a gradual rise until the early 2000s. It then fell again until 2012, after which it rose moderately until 2024. At the end of the sample, the weighted mean absolute size of price changes was at

[15]The monthly time series of weights of gas and used cars are shown in Appendix B.1. The total weight of gas rose from 4 percent to 6 percent in the early 1980s before falling back to about 3 percent in the 1980s. It then rose during the late 1990s and early 2000s, peaking above 7 percent in 2008, then fluctuated around 5 percent in the early 2010s and around 3.5 percent in the most recent decade. The weight of used cars rose from 3 percent in 1978 to 4.2 percent in 1986 before falling back to 1.2 percent in 1988, following a BLS reclassification. The weight then returned to about 2 percent for most of the rest of the sample except following the onset of the COVID-19 pandemic, when it briefly touched 4 percent. Other ELIs show large variation in weights over the full sample but much less variation within shorter time frames.

about the same level as it was at the beginning of the sample. The weighted mean excluding gas and used cars behaves very similarly to the weighted mean because gas and used cars are not outliers in the absolute-size distribution. The weighted median is also similar but showed a more muted rise in the middle period of the sample. We consider a similar analysis for the other price-change statistics and report their weighted mean, weighted mean excluding gas and used cars, and weighted median in Figure B.3 in Appendix B.2.

As noted earlier, our main contribution to the literature is our use of time-varying expenditure weights. In Figure 2, we overlay with dashed gray lines the evolution of the three moments of the frequency and size distributions measured under fixed year-2000 expenditure weights.[16] At first glance, we find that while there are similarities in the peaks and troughs, there are clear differences in levels, and these differences vary over time and are especially large at the beginning of the sample. By design, the solid and dashed gray lines in each subfigure overlap in the year 2000. We also see divergences in the later parts of the sample—typically the further away we are from 2000. These divergences are larger for the frequency distribution than for the size distribution. When we allow the weights to vary over time, the increase in the weighted mean frequency over the sample is smaller, suggesting that shifts in expenditure weights lower the weighted mean frequency. The same is true for the weighted mean excluding gas and used cars and the weighted median. In the next section, we formally quantify the impact of the time-varying expenditure weights on moments of the frequency and size distributions.

# 4 Quantifying the Impact of Weights on the Distributions

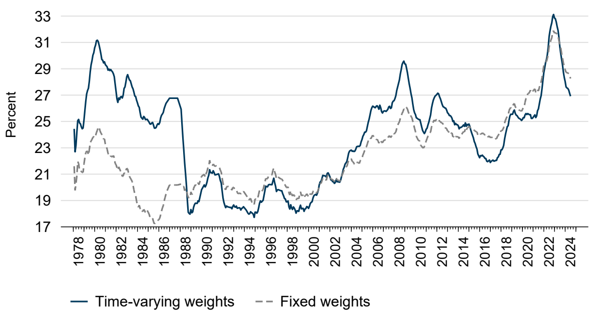
We start by decomposing changes in the moments of the frequency distribution using the methodology developed by Foster, Haltiwanger, and Krizan (2001) and then apply the same approach to decompose changes in the moments of the size distribution. Our goal is to decompose the total change in a moment into the contributions of frequencies (or size) of price changes and expenditure weights. To illustrate the methodology, let $F_t$ denote the weighted mean frequency of price changes:

$$F_t = \Sigma_i f_{i,t} w_{i,t}, \tag{1}$$

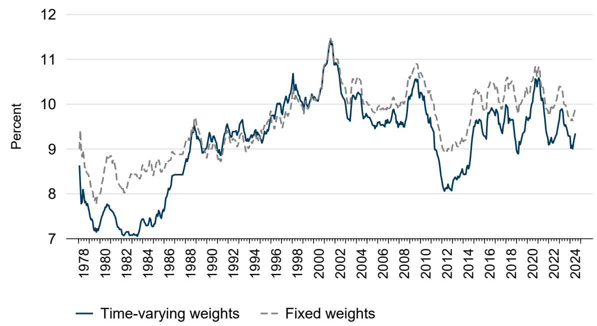
[16] The weighted median when using weights fixed to the year 2000 (the gray line in Figure 2e) corresponds to the figures in Nakamura et al. (2018). Over the sample considered in their paper (that is, 1978 through 2014), the median frequency of price changes fell, while the median absolute size of price changes remained unchanged, which is similar to what they find.

Figure 2: Comparison between Distributions under Time-varying and Fixed Weights, 1978–2024

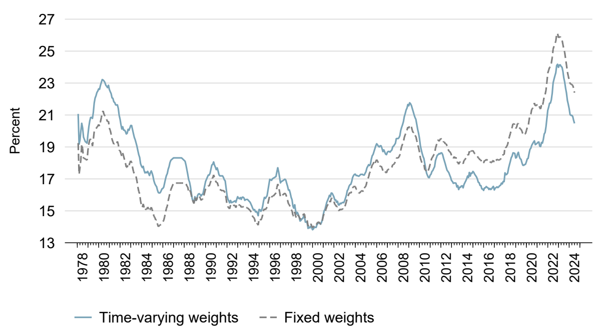
(a) Freq.: Weighted mean



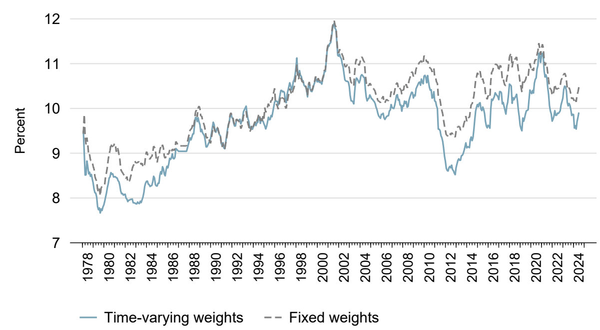

(b) Abs. size: Weighted mean



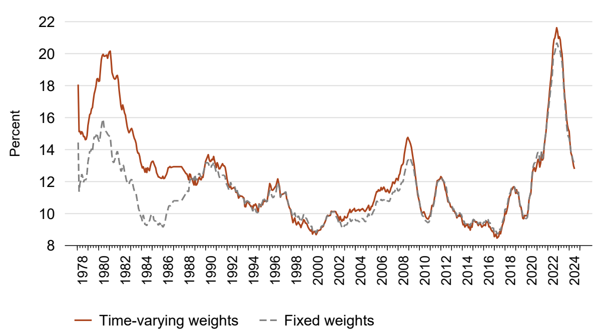

(c) Freq.: Weighted mean exc. gas & used cars



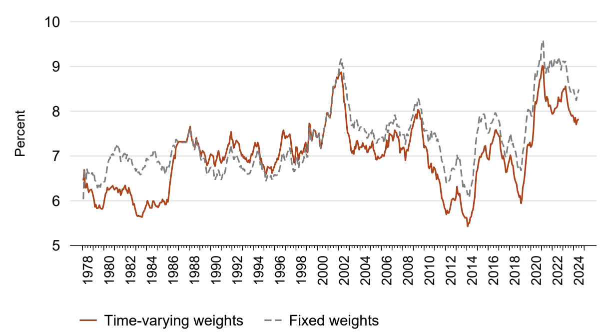

(d) Abs. size: Weighted mean exc. gas & used cars




(e) Freq.: Weighted median




(f) Abs. size: Weighted median




*Notes*: To construct the frequency (freq.) and size (abs. size) series, we compute the mean frequency of price changes and the mean absolute size of price changes, respectively, for each ELI in each month. We then compute the weighted mean across all ELIs, the weighted mean across all ELIs excluding gas and used cars, and the weighted median across all ELIs using the monthly expenditure weights. For the series under fixed weights, we use the ELI expenditure weights from 2000. Finally, for each month, we take the 12-month moving average over the previous 12 months.
*Sources*: BLS, authors' calculations.

where $f_{i,t}$ denotes the frequency of price changes of ELI $i$ at date $t$, and $w_{i,t}$ denotes the expenditure weight of ELI $i$ at date $t$. We rewrite equation (1) as:

$$\Delta F_t = \underbrace{\sum_{i \in C}(w_{i,t} - w_{i,t-1})(f_{i,t-1} - F_{t-1})}_{\text{between effect}} + \underbrace{\sum_{i \in C}(f_{i,t} - f_{i,t-1})w_{i,t-1}}_{\text{within effect}} + \underbrace{\sum_{i \in C}(w_{i,t} - w_{i,t-1})(f_{i,t} - f_{i,t-1})}_{\text{cross effect}}$$
$$+ \underbrace{\sum_{i \in N} w_{i,t}(f_{i,t} - F_{t-1}) - \sum_{i \in X} w_{i,t-1}(f_{i,t-1} - F_{t-1})}_{\text{entry/exit effect}}, \tag{2}$$

where $C$ is the set of continuing ELIs between the two periods, $N$ is the set of ELIs that entered the sample, and $X$ is the set of ELIs that exited the sample.[17]

Equation (2) decomposes the total change in the weighted mean into four parts: a between effect that captures the extensive margin impact due to reallocation of weights among the continuing ELIs, holding fixed their price-change frequencies; a within effect that captures the intensive margin impact due to changes in the price-change frequencies of continuing ELIs, holding fixed their weights; a cross effect that captures the correlation between the changes in price-change frequencies and changes in weights of continuing ELIs[18]; and an entry/exit effect that captures the changes in the consumption basket due to ELI entry and exit.[19]

Under the assumption of fixed weights, $w_{i,t} = \bar{w}_i$. As a result, the between and cross effects are zero. Additionally, the entry/exit and within effects are computed under the expenditure weights of the fixed year. Evaluating Equation (2) under fixed weights and subtracting it from the evaluation under varying weights, we obtain the following:

[17] Entry and exit is nonzero, despite our use of the ELI concordance. Examples of ELI entry include personal computers in 1998 and cellular telephones in 1998. Examples of ELI exit include interstate telephone services in 2009 and encyclopedias in 2016.

[18] For example, if the price-change frequency increases for those ELIs that also see a rise in their weights, then that would have a net positive effect on the weighted mean through the cross effect.

[19] We apply the decomposition to annual, rather than monthly, price-change statistics to bypass the need to correct for the seasonality inherent in the monthly statistics (Nakamura and Steinsson, 2008) and to reduce measurement error. If we do not have enough observations to construct the price-change statistics for an ELI in a given year and if that ELI has not permanently exited the sample, we carry forward the prior year's value for that statistic for that ELI. This ensures that we do not misattribute the annual change to the entry/exit effect.

Table 1: Decomposition of the Frequency and Size Distributions, 1978–2024

| Price-Change Statistic (%) | 1978 | 2024 | Change | Between | Within | Cross | Entry/Exit |
|---|---|---|---|---|---|---|---|
| *A. Frequency of Price Changes* | | | | | | | |
| A1. Weighted mean | 24.7 | 26.9 | 2.2 | -4.7 | 5.6 | 1.6 | -0.3 |
| A2. Weighted mean exc. gas & used cars | 19.4 | 20.3 | 0.9 | -3.1 | 3.5 | 1.0 | -0.5 |
| *B. Absolute Size of Price Changes* | | | | | | | |
| B1. Weighted mean | 7.7 | 9.2 | 1.5 | -0.6 | 1.1 | 0.8 | 0.2 |
| B2. Weighted mean exc. gas & used cars | 8.4 | 9.7 | 1.3 | -0.4 | 1.0 | 0.5 | 0.3 |

*Notes*: Each panel shows the change in two moments of the distribution of the frequency and absolute size of price changes from 1978 to 2024. The last four columns decompose changes from 1978 to 2024 into between, within, cross, and entry/exit effects.
*Sources*: BLS, authors' calculations.

$$\Delta F_t - \Delta F_t^{\text{fixed-weight}} = \underbrace{\sum_{i \in C} (w_{i,t} - w_{i,t-1})(f_{i,t-1} - F_{t-1})}_{\text{between effect}} + \underbrace{\sum_{i \in C} (w_{i,t} - w_{i,t-1})(f_{i,t} - f_{i,t-1})}_{\text{cross effect}}$$
$$+ \underbrace{\sum_{i \in C} (f_{i,t} - f_{i,t-1})(w_{i,t-1} - \bar{w}_i)}_{\text{scaled within effect}} + \underbrace{\sum_{i \in N} (w_{i,t} - \bar{w}_i)(f_{i,t} - F_{t-1}) - \sum_{i \in X} (w_{i,t-1} - \bar{w}_i)(f_{i,t-1} - F_{t-1})}_{\text{scaled entry/exit effect}} . \tag{3}$$

The two main sources of difference are the between and cross effects. There is also a difference due to the scaling effects, but these effects are quite small empirically.

Table 1 summarizes the decomposition of the changes in the frequency and size distributions from 1978 to 2024. Row A1 shows the results for the weighted mean frequency of price changes. From 1978 to 2024, the weighted mean increased by 2.2 percentage points, from 24.7 percent to 26.9 percent. This change can be decomposed into a –4.7 percentage point between effect, a 5.6 percentage point within effect, a 1.6 percentage point cross effect, and a –0.3 percentage point entry/exit effect, using equation (2). The negative between effect implies that the expenditure weights shifted toward ELIs with relatively lower price-change frequencies. The positive within effect implies that prices of individual ELIs changed more frequently in 2024 than they did in 1978. There is also a small positive cross effect, which suggests that changes in ELI weights correlate positively with changes in ELI frequencies. The negative between effect is nearly as large as the positive within effect, and the positive cross effect is small. Overall, this implies that changes in the consumer basket largely counteract the effect of higher ELI frequencies on the weighted mean frequency of price changes.

Row A2 shows the corresponding decomposition of the weighted mean frequency excluding gas and used cars. This weighted mean increased by a small amount—0.9 percentage point from 1978 to 2024. Once again, we see a strongly positive within effect of 3.5 percentage points, implying that individual ELIs, even excluding gas and used cars, changed their prices more frequently in 2024 than they did in 1978. However, this is counterbalanced by a strongly negative between effect of –3.1 percentage points, implying that the consumption basket, even excluding gas and used cars, shifted toward ELIs with relatively lower frequencies of price changes.

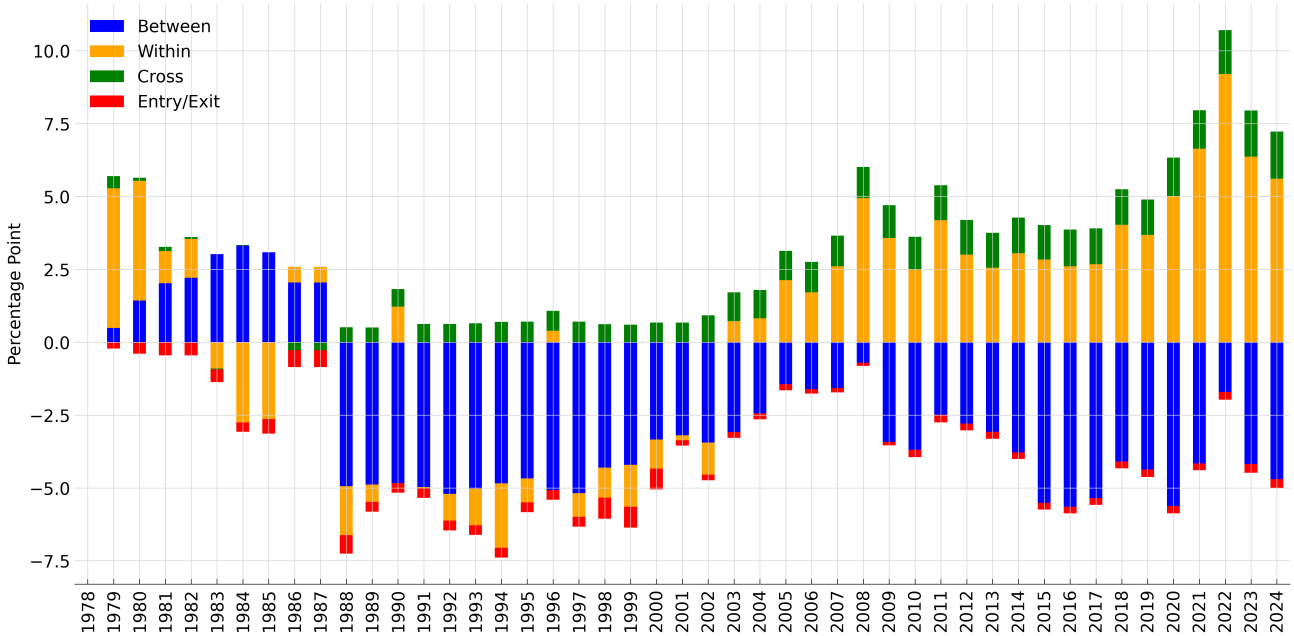
Panel B of Table 1 reports the decomposition of the corresponding moments of the size distribution. The weighted mean absolute size of price changes increased by 1.5 percentage points, from 7.7 in 1978 to 9.2 percent in 2024. The dominant source of the increase is a positive within effect, suggesting that at the ELI level, firms adjust their prices by larger absolute amounts on average. The cross effect is also sizable and positive, implying that changes in the weights of ELIs correlate positively with changes in the sizes of their price changes. The between effect is negative, indicating that the weight of ELIs with relatively smaller price changes increased, but this effect is small. Indeed, for the size distribution, the positive cross effect is slightly larger than the negative between effect, so the net impact of weights on the size distribution is relatively muted. The results for the weighted mean excluding gas and used cars are similar.

A potential concern is that the changes in the between effect from 1978 to 2024 might be due to changes during the reclassification years of 1988 and 1998. To study this, we consider how the decomposition has evolved. Figure 3 presents the evolution for the weighted mean and the weighted mean excluding used cars and gas, respectively. Each bar represents a year (as denoted on the x-axis), and its height captures the change in the frequency of price changes from 1978 to the corresponding year. Within each bar, the blue depicts the between effect, while the orange, green, and red illustrate the within, cross, and entry/exit effects, respectively. The bar for 2024 corresponds directly to the results in Panel A of Table 1.

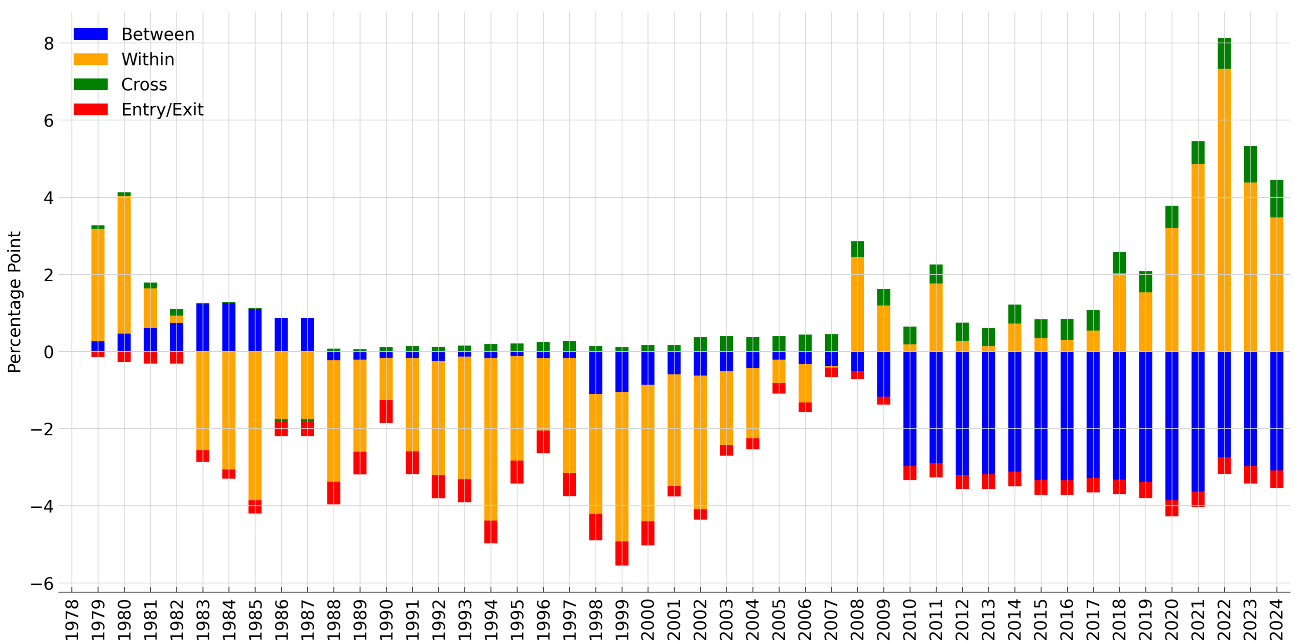
Considering first the between effect (the blue bars), we observe in Figure 3 that the between effect for the weighted mean declines notably (becoming more negative) during the 1988 reclassification. However, the changes in weights mattered throughout the sample, with notable increases in the between effect in the late 1990s and early 2000s and a decrease after the Great Recession. More recently, following the COVID-19 pandemic, there was a short-lived rise followed by a fall in the between effect. When gas and used cars are excluded in Figure 3b, the decline around the 1988 reclassification is much smaller; instead, the largest decline in the between effect occurs in 2010, after the Great Recession. In Section 5, we analyze in more detail which sectors drive these movements.

Figure 3: Annual Decomposition of the Change in Moments of the Frequency Distribution

(a) Weighted mean




(b) Weighted mean exc. gas & used cars




*Notes*: Each bar shows the contributions of the between, within, cross, and entry/exit effects to the change in the weighted moment between the year on the x-axis and 1978. The weighted mean and weighted mean excluding gas and used cars frequencies in 1978 were 24.7 percent and 19.4 percent, respectively.
*Sources*: BLS, authors' calculations.

Turning to the other effects, we observe that the within effect moves broadly with the level of inflation, which is consistent with Nakamura et al. (2018). As inflation fell in the late 1980s and 1990s, the ELI frequencies declined, leading to a decline in the within effect (that is, it became less positive). However, after inflation rose following the COVID-19 pandemic, there was a large increase in the within effect, which fell back somewhat as inflation declined in 2023 and 2024. That said, we also observe that the within effect exhibits an overall positive trend. It was higher in the mid-2010s than in 1978 for both the weighted mean excluding gas and used cars and especially for the weighted mean, even though inflation was lower in the mid-2010s. We also observe that the cross effect shows smaller variation over time, while the net entry/exit effect has little impact throughout the sample.

In Figure 4, we show a similar decomposition over time for the absolute size of price changes. For the weighted mean, the between effect was negative in the earlier part of the sample, then showed a large increase (becoming less negative) and turned positive following the 1988 reclassification. It then declined gradually from 1997 through 2011, turning negative again in the early 2000s. The between effect remained fairly stable over the next decade and then fluctuated slightly in the 2020s, always remaining negative. In the beginning of the sample, the between effect was larger than the cross effect. From 1998 onward, however, the cross effect roughly counterbalanced the between effect. As a result, the net impact of weights on the distribution of the absolute size of price changes is small, except in the beginning of the sample. Instead, the largest driver of the distribution is the within effect, which increases in the first half of the sample, declines following the Great Recession, and then rises again in the last part of the sample. The entry/exit effect is also small but, overall, increases over the sample. The results for the weighted mean excluding gas and used cars are similar.

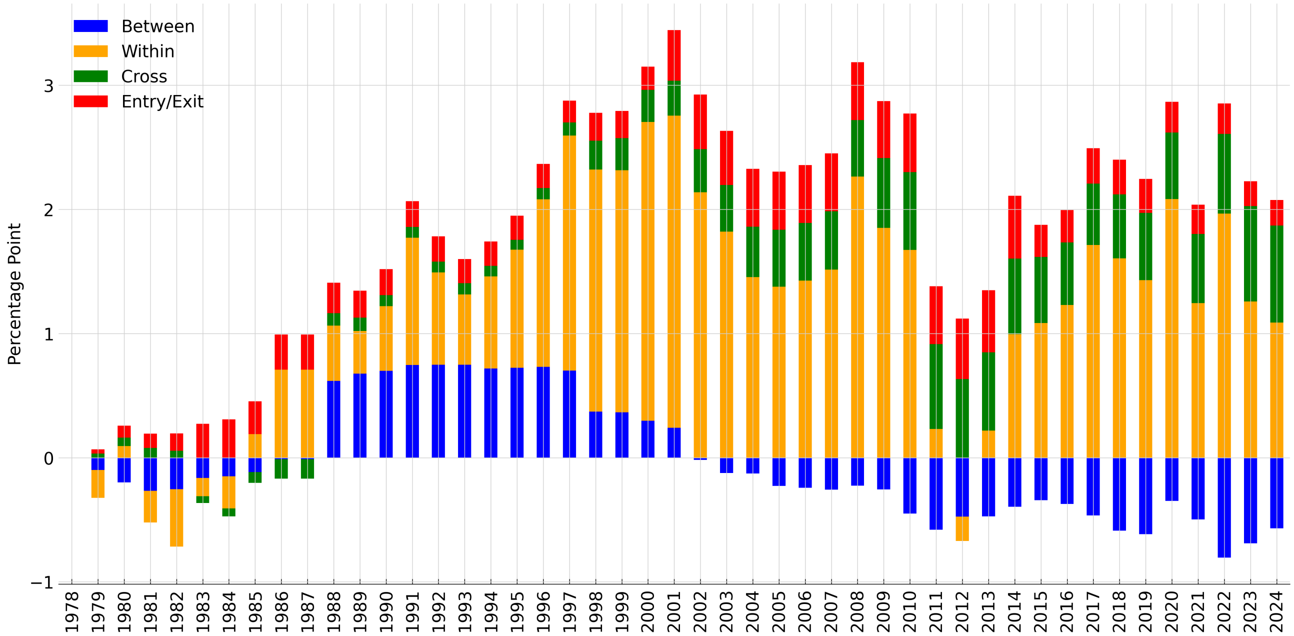
We cannot use equation (2) to decompose change in the weighted median, as the formula requires breaking down weighted sums. We consider two alternatives: weighted mean percentile and weighted mean duration. The weighted mean percentile captures changes in the distribution in a more balanced manner, similarly to the weighted median. We consider the weighted mean percentiles of the frequency and size distributions in Appendix C.2.1. We first show that this moment has a high correlation with the weighted median. We then present results of the decomposition for the weighted mean percentile. We find that the between effect is an important component of the change in this moment as well.

We then consider the weighted mean duration of price changes and decompose its change over time in Appendix C.2.2.[20] We again find that the expenditure weights are an important

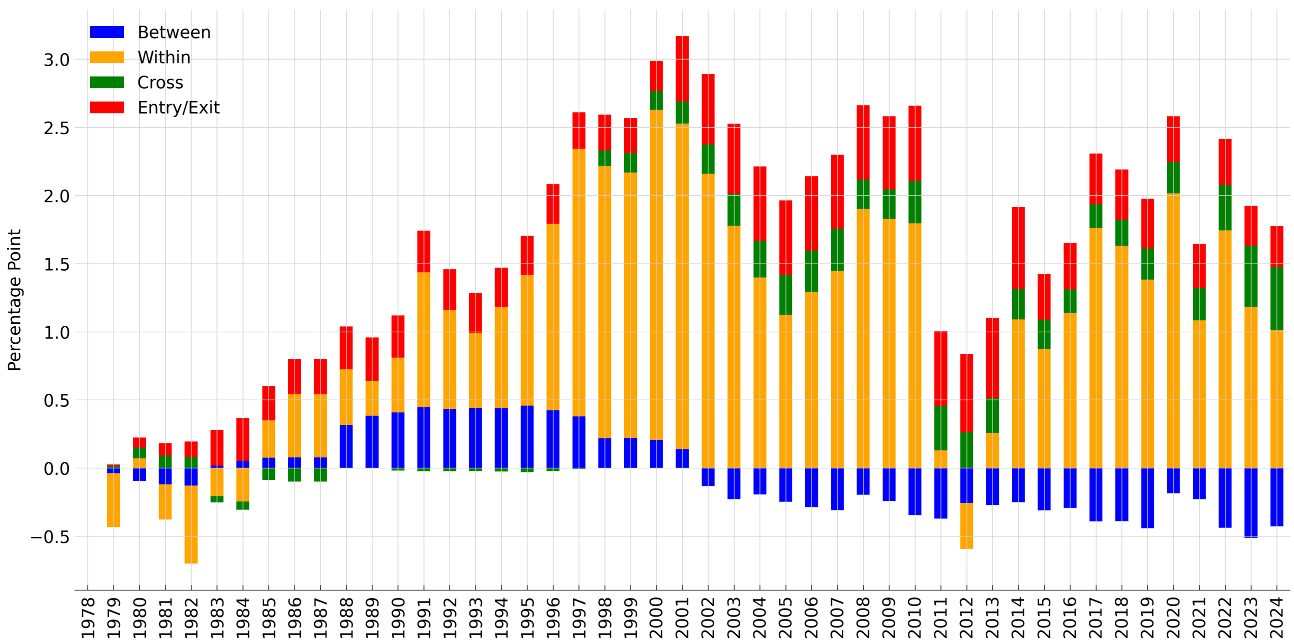
[20]Given a frequency of price changes $f_{it}$, the duration of price changes is computed as $\frac{-1}{\ln(1-f_{it})}$, that

Figure 4: Annual Decomposition of the Change in Moments of the Size Distribution

(a) Weighted mean




(b) Weighted mean exc. gas & used cars




*Notes*: Each bar shows the contributions of the between, within, cross, and entry/exit effects to the change in the weighted moment from 1978 to the year on the x-axis. The weighted mean and weighted mean excluding gas and used cars absolute size of price changes in 1978 were 7.7 percent and 8.4 percent, respectively.
*Sources*: BLS, authors' calculations.

driver of the change in the average duration of price changes, increasing it substantially every year since 1988 relative to 1978. By 2024, the impact of the changes in expenditure weights outweighs the impact of the changes in ELI frequencies.

## 4.1 Robustness Checks

We verify that our finding—that variation in expenditure weights represents an important driver of the frequency distribution—is robust to using alternative expenditure weights and alternative measures of price-change frequencies.

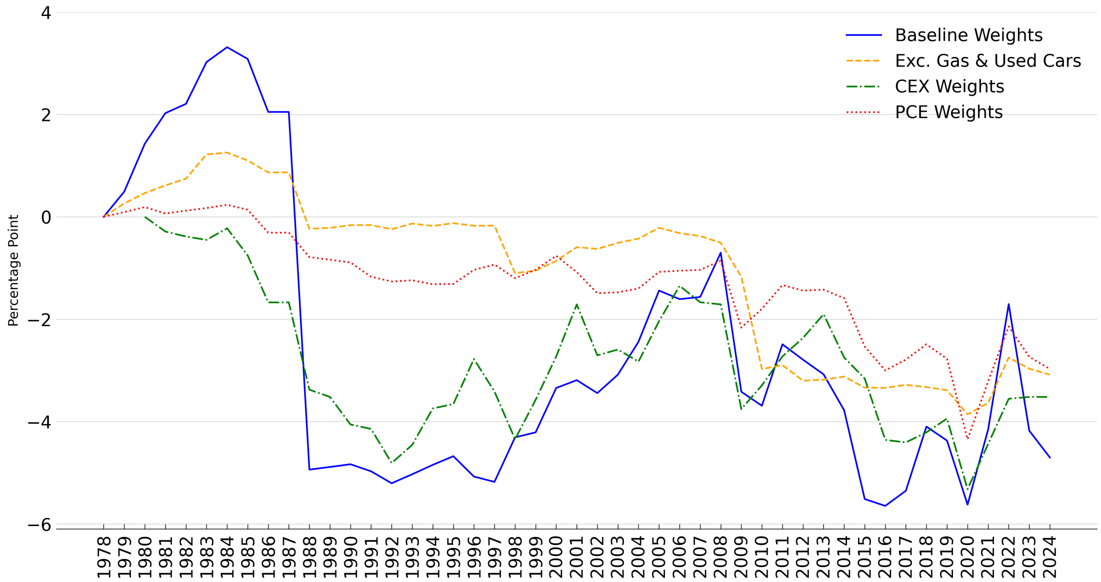
**Alternative Expenditure Weights** We assess the robustness of our results to using two alternative constructions of expenditure weights. Our baseline analysis uses CPI expenditure weights, which are derived from the CEX but are infrequently updated by the BLS, particularly before the late 1990s. Between updates, the BLS effectively holds the consumption basket fixed, so that expenditure share changes reflect changes only in relative prices. If substitution effects are quantitatively important, this feature of CPI weights could affect our decomposition results.

As a first alternative, we recompute expenditure weights directly from CEX microdata, which are available starting in 1980. CEX-based expenditure weights reflect contemporaneous expenditure shares, thereby allowing for substitution across item strata over time. We construct these weights at an annual frequency, following the approach of Jaravel (2024), who constructs item-strata weights from 1999 onward using these data. This exercise requires a crosswalk between expenditure categories in the CEX microdata (universal classification codes, or UCCs) and BLS microdata (item strata). Jaravel (2024) uses official BLS concordances to develop this crosswalk beginning in 1999. We use the same approach and extend the crosswalk back to 1980, as we describe in detail in Appendix A.3. Due to the absence of official BLS concordances, there could be greater measurement error in the pre-1999 period, which is why we do not use CEX weights in our primary approach.

Figure 3a compares the between effect of the decomposition of the weighted mean when using CPI weights (baseline, blue line) and CEX weights (green line). Note that the blue line corresponds to the heights of the blue bars in Figure 3a. The two series track each other closely after the late 1980s, indicating that our findings are generally not sensitive to whether expenditure weights are infrequently updated using CPI procedures or constructed

is, approximately the inverse of the frequency of price changes. As such, the weighted mean duration overweights ELIs with relatively lower frequencies of price changes.

Figure 5: Between Effect for the Weighted Mean Frequency of Price Changes: Alternative Expenditure Weights




*Notes*: The blue, green, and red lines show the between effect measured using expenditure weights from the CPI, CEX, and PCE, respectively. The orange line shows the between effect measured using expenditure weights from the CPI excluding gas and used cars. The CEX line begins in 1980 because this is the first year for which CEX microdata are available.
*Sources*: BEA, BLS, authors' calculations.

directly from CEX microdata. Larger discrepancies appear from 1980 to 1987, when there were no consumption basket updates within the CPI. During this period, this non-updating appears to have especially affected gas and used cars, as each shows large variation in prices. Excluding these two categories (orange line) closes much of the gap in the between effect between the CPI weights and CEX-based weights (green line).[21] Despite these early-sample differences, the overall quantitative effect of expenditure weights is similar under baseline weights and CEX weights, indicating that our results are not artifacts of the specific updating mechanism used by the BLS. Quantitatively, variation in expenditure weights remains an important driver of the long-term changes in the weighted mean frequency of price changes.

As a second alternative, we repeat the analysis using expenditure weights derived from the PCE data. Unlike CPI weights, which are based on out-of-pocket household expenditures, PCE weights are constructed from national accounts and incorporate a broader concept of consumption, including expenditures on behalf of households by third parties. As a result, PCE and CPI weights differ both in levels and in their evolution. We map PCE

[21]We further show in the appendix that much of the remaining discrepancy is due to electricity and fuel oil prices. Figure C.1 shows that once we exclude gas, used cars, electricity, and fuel oil, the CPI weights (red line) closely follow the CEX-based weights (green line).

expenditure categories to CPI ELIs and construct monthly PCE-based expenditure shares that are comparable to the weights used in our baseline analysis.[22]

Using PCE weights (red line) yields results that are qualitatively similar to those obtained using the baseline CPI weights (blue line) and CEX weights (green line). In particular, variation in expenditure weights continues to play an important role in shaping the evolution of the weighted mean frequency of price changes. Differences in magnitude relative to the baseline reflect the broader consumption concept embedded in the PCE. For example, the reason the between effect does not show a more pronounced decline in 1988 and a smaller subsequent increase is because the PCE places a lower weight on gas and used cars relative to the baseline CPI weights, so large changes in their weights during this period have a less prominent effect.

Overall, the robustness of our findings across CPI, CEX, and PCE weights indicates that our conclusions are not sensitive to the specific source of expenditure data.

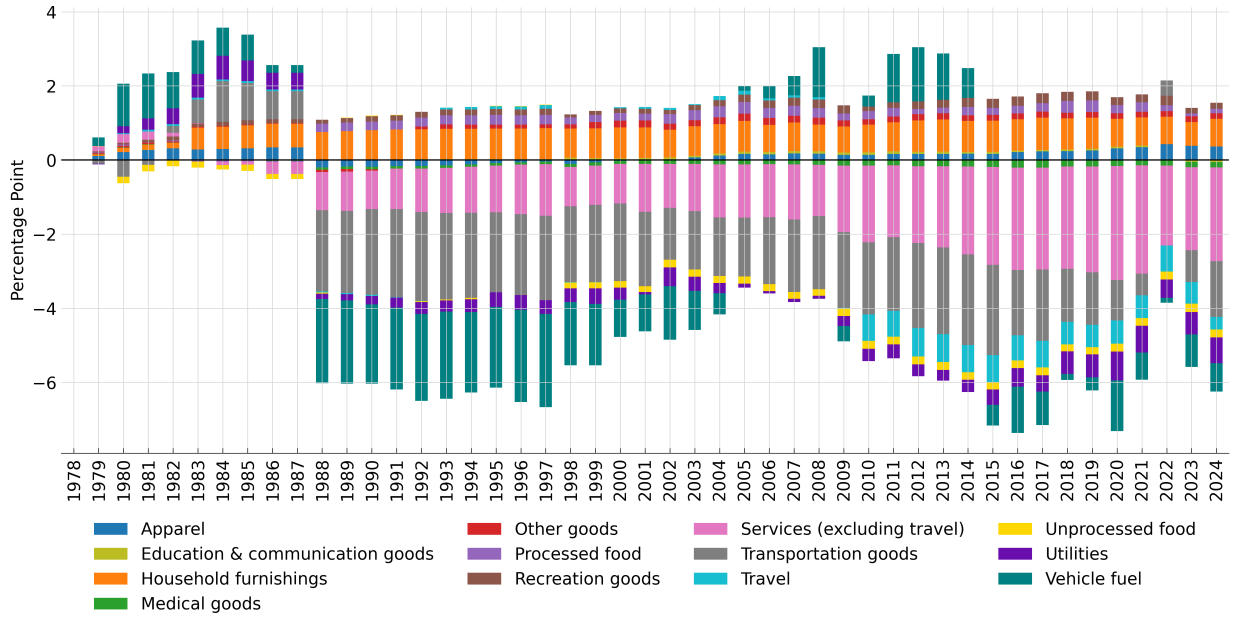
**Alternative Measures of Price-Change Frequencies** In Table C.2, we further verify that our finding is robust to considering alternative measures of price-change statistics. Panel A reproduces our baseline results. In Panel B, we seasonally adjust the price-change statistics data before applying the decomposition. In Panel C, we repeat the analysis excluding the ELIs for which we make the adjustments described in Section 2. Panel D presents the decomposition for the case in which sale prices are included in the measurement of the price-change statistics. We find large negative between effects across all four checks.

# 5 Identifying the Consequential Consumption-basket Changes

Having shown the importance of weights in driving the frequency distribution over time, we now examine which ELIs have predominantly driven these changes. For inference, we first aggregate the ELIs into 13 broad sectors (or spending groups), following Nakamura and

[22] We do this using the mapping available at `https://www.bls.gov/cpi/additional-resources/pce-cpi-code-mapping.pdf`, which covers all ELIs. Some PCE categories map to multiple ELIs. In such cases, we divide the weight of the PCE category equally among the ELIs to which it maps. Also, some ELIs map to multiple PCE categories. In these cases, we set the ELI weight to be the sum of the weights of those PCE categories.

Figure 6: Decomposition of the Between Effect for the Weighted Mean Frequency of Price Changes, By Sector




*Notes*: Each bar shows the contributions of each spending group to the annual between effect for the frequency of price changes between 1978 and the year on the x-axis.
*Sources*: BLS, authors' calculations.

Steinsson (2008).[23,24] We break down the between effect of the change in the weighted mean frequency of price changes into the contributions of these different sectors in Figure 6.

The last bar shows the between effect for the change in the weighted mean frequency from 1978 to 2024, corresponding to the blue component of the last bar in Figure 3a. The largest contributor to this negative between effect was services (excluding travel). Service ELIs generally have low frequencies of price changes, and their weight gradually increases over the sample. Among them, the ELI with the largest negative between effect was hospital services: Its average frequency of price changes is 8.1 percent, and its (rescaled) expenditure weight grew from 0.47 to 3.08 percent from 1978 to 2024. Other service ELIs with large contributions to the negative between effect were cellular telephones, college tuition, other

[23] According to the sector definitions used by Nakamura and Steinsson (2008), Travel contains services relating to travel, such as short-term accommodation, airfare, and other forms of long-distance transportation. Services (excluding travel) contains all other services. All the other sectors, except Utilities, contain only goods. Utilities contains electricity and gas for home use, which are considered services, and other fuels, which are considered goods. We make two changes to their definitions. First, we separate Other Goods into three sectors: Education and Communication Goods, Medical Goods, and Other Goods, depending on the major group of the ELI in the official CPI aggregation scheme. Second, we place the internet services ELI (EE031) in Services (excluding travel) instead of Other Goods.

[24] We show the time series of the moments of the price-change distributions along with the expenditure weights of these sectors in Appendix D.1 and Appendix D.2, respectively.

information services (including broadband), general medical practice, and motor vehicle insurance.[25]

While the rising share of low-frequency services predominantly drives the between effect in the long term, other sectors drive the effect in different years over the sample. The rise in the between effect before 1988 came from increases in the weights of vehicle fuel and used car ELIs, which have very high frequencies of price changes. The large negative between effect from 1987 to 1988 was primarily due to a drop in the weights of the same ELIs in the 1988 BLS reclassification of the CPI survey. There was a rise in the between effect from the late 1990s to the late 2010s, which was driven by an increase in the weight of vehicle fuel as gas prices increased. The large decline in the between effect from 2008 to 2012 was partly due to a significant decline in the weight of the lodging away from home ELI, which has a high frequency of price changes. There was then a temporary rise in the between effect from 2021 to 2022, which reflects the effects of the COVID-19 pandemic on household consumption.[26] We observe a shift away from low-frequency services—such as restaurants, day care centers, and beauty parlors—toward high-frequency residential utilities, such as electricity and gas, presumably as more people stayed at home.[27]

# 6 Implications for Monetary Non-Neutrality

Our results demonstrate that accounting for time-varying weights makes a meaningful difference in measuring price-change statistics. We now show that accounting for time-varying weights also makes an economically meaningful difference in measuring monetary non-neutrality. We use multiple approaches to measure monetary non-neutrality: a sufficient statistic, a multisector Calvo model, and a multisector menu cost model.

**Sufficient Statistics** We first measure monetary non-neutrality using the sufficient statistic formula for the real effects of monetary policy shocks derived by Alvarez, Le Bihan, and Lippi (2016). These authors show that in a large class of sticky-price models, the total cumulative output response (COR) of a small unexpected monetary shock depends on the ratio between two statistics: the kurtosis of the size distribution of price changes $Kur(\Delta p_i)$

[25]In Appendix D.3, we further detail the top 15 ELIs that made the largest contributions to changes in the frequency and absolute size distributions through positive and negative between and cross effects.

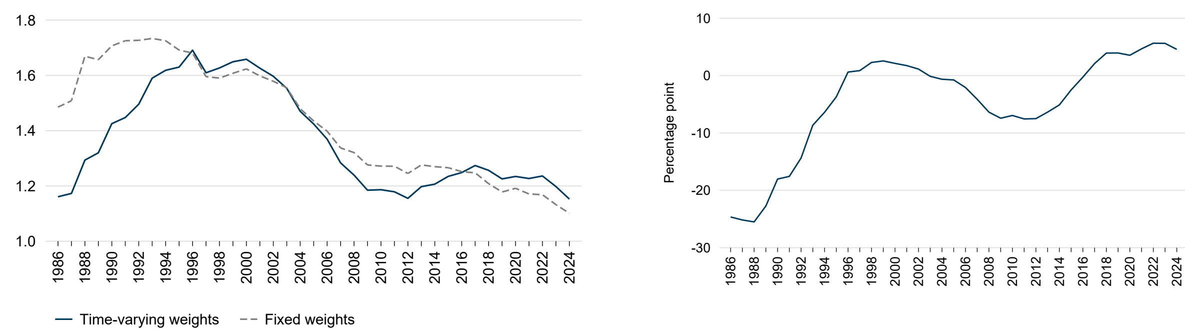
[26]Note that there is a two-year lag because the BLS updated its CPI weights in 2022 based on the 2020 CEX survey.

[27]We also decompose by sector the cross effect for the frequency and the between and cross effects for the absolute size in Appendix D.4.

and the average number of price changes per year $N(\Delta p_i)$. Intuitively, the average number of price changes captures the average effect—how frequently prices are changed—while kurtosis captures the selection effect—how often large and small price changes occur relative to the intermediate values of price changes. We compute these two statistics—kurtosis and the number of price changes—for the distributions measured using time-varying and fixed year-2000 expenditure weights over 10-year rolling windows (see Appendix E.1 for details). The resulting ratios under time-varying weights (navy blue line) and fixed weights (light blue line) are presented in Figure 7 Panel (a).[28] The difference between the sufficient statistic under the two approaches is presented in Panel (b).

Figure 7: Sufficient Statistic for Monetary Non-Neutrality, 1978–2024

(a) Level (scaled) (b) Difference: Varying minus fixed weight




*Notes*: The sufficient statistics are computed as the ratio of the kurtosis of the size distribution of standardized price changes to the average number of price changes in 10-year rolling windows ending with the year denoted on the x-axis. The underlying distributions are measured using concurrent ELI weights under the time-varying-weights approach and year-2000 ELI weights in the fixed-weights approach.
*Sources*: BLS, authors' calculations.

When using time-varying expenditure weights, we find a large rise and then a large fall in the degree of monetary non-neutrality. The rise is substantial—about a 50 percent increase from the 1980s to the late 1990s. However, monetary non-neutrality then declines back to its baseline level.

Measuring monetary non-neutrality with fixed expenditure weights only imperfectly captures these changes; there is only a small rise in monetary non-neutrality at the start of the sample and a more gradual decline later in the sample. Using fixed weights overestimates monetary non-neutrality at the start of the sample, underestimates it toward the end of the

[28]The full sufficient statistic in Alvarez, Le Bihan, and Lippi (2016) incorporates additional parameters representing the labor supply elasticity and the size of the monetary policy shock. Adding these parameters to the formula would scale both lines in Panel (a) by the same constant.

sample, and presents an overall misleading picture of a large decline in monetary non-neutrality over the sample. In particular, it overestimates the decline in monetary non-neutrality by 25 percentage points.

When we examine the source of the differences—kurtosis of the size distribution or the average number of price changes—we find that the difference is largely due to the average number of price changes (see Figure E.1). This is consistent with our earlier findings that accounting for time-varying weights is more important for the accurate measurement of the frequency distribution and less so for the size distribution, even when higher-order moments such as kurtosis are considered.

We perform a series of robustness checks to verify these results, as shown in Panel A of Table 2. The second column presents the percentage change in the sufficient statistic from the 1978–1987 period to the 2015–2024 period under time-varying weights. The third column presents the corresponding percentage change under fixed weights. The fourth column presents the percentage point difference between the second and third columns to capture the degree of misrepresentation of the monetary non-neutrality evolution under the fixed-weights approach. In row A1, we report the baseline results for reference. In row A2, we consider the sufficient statistics based on distributions excluding gas and used cars, since the role of time-varying expenditure weights in the frequency distribution is magnified due to these two ELIs. In rows A3 and A4, we compute the sufficient statistic in shorter rolling windows of five and two years, respectively. In rows A5 through A8, we compute the sufficient statistic using the expenditure weights fixed to years that are different from those in the baseline: 1978, 1988, 2008, and 2020, respectively. In rows A9 and A10, we use the alternative expenditure weights from the PCE and CEX, respectively, instead of CPI weights.[29] We find qualitatively similar results across all rows, with the magnitude of the difference ranging from 13 to 33 percentage points. Therefore, the finding that the fixed-weights approach overestimates the decline in monetary non-neutrality over the sample is robust. For each robustness check, we provide the annual time series of the difference between time-varying minus fixed weights in Appendix E.1.1.

**Phillips Curve Slopes from Multisector Models** We also measure monetary non-neutrality through multisector Calvo and multisector menu cost models. We calibrate these models to match the empirical frequency and size distributions across the 13 sectors (described in Section 5), each measured under time-varying and fixed weights for the 1978–1987 and 2015–2024 periods. The multisector Calvo model is described in Appendix E.2 and is similar to the

[29] As discussed earlier, the CEX weights did not become available until 1980, so we backfill the 1980 weights to 1977 through 1979.

Table 2: Change in Monetary Non-Neutrality, 1978–2024

| | Time-varying weights (%) | Fixed weights (%) | Difference (p.p.) |
|---|---|---|---|
| *Panel A: Sufficient Statistic: Cumulative Output Response* | | | |
| A1. Baseline | -1.74 | -27.01 | 25.27 |
| A2. Excluding gas and used cars | -0.47 | -20.16 | 19.69 |
| A3. 5-year rolling window | 0.18 | -26.46 | 26.64 |
| A4. 2-year rolling window | -15.58 | -34.27 | 18.69 |
| A5. Fixed 1978 weights | -1.74* | -14.76 | 13.02 |
| A6. Fixed 1988 weights | -1.74* | -28.10 | 26.36 |
| A7. Fixed 2008 weights | -1.74* | -34.64 | 32.90 |
| A8. Fixed 2020 weights | -1.74* | -19.19 | 17.44 |
| A9. PCE weights | -9.45 | -27.93 | 18.47 |
| A10. CEX weights | -13.70 | -27.35 | 13.65 |
| *Panel B: Model-based: Phillips Curve Slope* | | | |
| B1. Multisector Calvo | -5.69 | 16.63 | -22.32 |
| B2. Multisector menu cost | -14.07 | 1.89 | -15.97 |
| B3. Multisector menu cost (2% annual trend inflation) | 0.19 | -17.84 | -17.65 |

*Notes*: In Panel A, the second column reports the percentage change in the sufficient statistic from the 1978–1987 period to the 2015–2024 period, computed under time-varying weights. The third column reports the same percentage change but is computed under fixed weights (with the weights fixed to year 2000 except in rows A5 through A8). The fourth column reports the percentage point difference between the second and third columns and quantifies the degree of relative overestimation of the decline in monetary non-neutrality under the fixed-weights approach. Note that the * values are the same as those under the baseline (row A1) because fixing weights to different years does not impact the varying-weight computations. In Panel B, the second column reports the percentage change in the absolute value of the Phillips curve slope from the 1978–1987 period to the 2015–2024 period, computed under time-varying weights. The third column reports the same percentage change but is computed under weights fixed to the year 2000. The fourth column reports the percentage point difference between the second and third columns and quantifies the degree of relative overestimation of the rise in Phillips curve slope under the fixed-weights approach.
*Sources*: BLS, authors' calculations.

model in Carvalho (2006). The menu cost model builds on the framework of Nakamura and Steinsson (2010) (see details in Appendix E.3.1). For a given decade and a given choice of expenditure weights (time-varying or fixed), the sectoral frequencies of price changes in the Calvo model are set to be equal to their empirical counterparts. For the menu cost model, the sectoral menu costs and standard deviations of idiosyncratic productivity shocks of firms are estimated to target the empirical sectoral frequencies and absolute sizes of price changes (more details about the calibration procedure are provided in Appendix E.3.2). The sectoral weights and the trend inflation rate in each model are set to be equal to their empirical counterparts.[30] The match between the targeted moments in the model and the data, along with the set of estimated parameters for each of the four decade $\times$ weight combinations for the menu cost model, is shown in Appendix E.3.3.

We assess monetary non-neutrality using the slope of the Phillips curve. To derive the Phillips curve from the model solution, we simulate the responses of inflation and output to aggregate nominal demand shocks, implied by each of these calibrated models. We measure the slope by regressing the annual change in the 12-month moving average of the inflation rate on the 12-month moving average of the output gap. This measure of slope is consistent with the empirical estimates of the slope of the Phillips curve in Stock and Watson (2020). We evaluate how the absolute value of the slope changed from the 1978–1987 period to the 2015–2024 period under the time-varying and fixed-weight calibrations. We then compute the difference in the change under the two approaches, as we did with the sufficient-statistics approach.

Panel B of Table 2 shows the results. The fixed-weight calibrations of the multisector Calvo and menu costs models imply a steepening of the Phillips curve compared with a flattening under the time-varying-weights calibrations. The steepening of the Phillips curve is overstated by 22 and 16 percentage points in the Calvo and menu cost models, respectively. Because a steeper Phillips curve corresponds to lower monetary non-neutrality, this implies that, similarly to the sufficient-statistics approach, the fixed-weight calibrations of the multisector models relatively overestimate the decline in monetary non-neutrality.

In terms of the magnitude of the change in monetary non-neutrality, the relatively large decline in the slope of the Phillips curve under the time-varying-weights calibration and a mild increase under the fixed-weights calibration in the menu cost model (row B2) may be surprising, given the evolution implied by the sufficient statistic (row A1). The difference is

[30] Orchard (2025) presents a model of non-homothetic demand that endogenizes shifts in consumption baskets over the business cycle. In our model, we take as given both the consumption basket and price-change statistics over time. However, a framework that simultaneously endogenizes shifts in both these margins over the business cycle could be a fruitful topic for future research.

explained by the model's allowance of different trend inflation rates in the two decades—close to a 6 percent annual rate from 1978 to 1987 and 3 percent from 2015 to 2024. A larger trend inflation rate implies that matching a given frequency of price changes in the calibration requires relatively higher menu costs, as higher trend inflation provides an additional incentive to adjust prices. If instead we solve the calibrated models assuming 2 percent annual trend inflation in both decades, we find a much smaller slope of the Phillips curve from 1978 to 1987 under both calibrations.[31] These changes imply that the Phillips curve slope under the time-varying-weights calibration barely changes, while the fixed-weights calibration implies a large steepening of the Phillips curve (row B3)—more in line with the changes under the sufficient-statistic approach and the Calvo model.

# 7 Conclusion

Price stickiness is a key determinant of monetary non-neutrality. When using price-change distributions to measure the evolution of price stickiness in the US economy, the literature assumes that expenditure weights underlying the distributions are fixed. At the same time, however, several papers document that price stickiness is likely affected by expenditure-weight changes due to, for example, industrial composition or demographic shifts. This paper is the first to consider the long-term evolution of price-change distributions while allowing for simultaneous variation in both product price-change statistics and product weights. We compute these comprehensive new measures of price-change statistics for every month from 1978 through 2024.

We show that time-varying weights are quantitatively important for measuring price-change distributions, especially the frequency of price changes. Changes in the weights reduced the aggregate frequency of price changes through the between effect by 4.7 percentage points from 1978 to 2024, counteracting the rise in the aggregate frequency due to the within effect. We show that the largest driver of this long-term shift is the increase in the share of the services (excluding travel) sector, which has a low frequency of price changes. Shifts in the consumption of vehicle fuel, used cars, and lodging away from home also play a role in the intervening years over the sample.

Finally, we show that time-varying weights are also important for measuring monetary non-neutrality. Failing to account for shifts in expenditure weights relatively overstates

[31] The slopes are –0.41 instead of –0.49 under time-varying weights and –0.34 instead of –0.42 under fixed weights. The estimated slopes for the 2015–2024 period are also mildly lower under the 2 percent solution: –0.41 instead of –0.42 under time-varying weights and –0.40 instead of –0.42 under fixed weights.

the decline in monetary non-neutrality from 1978 to 2024 by 25 percentage points using the sufficient-statistics approach and by about 20 percentage points using the multisector sticky-price models.

We intend to make our underlying annual price-change statistics and accompanying expenditure weights data at a disaggregated ELI level available for use by other researchers. This data set will provide detailed statistics through which New Keynesian models can be calibrated and should prove particularly useful in the developing literature that examines how changes in trend inflation can affect price-setting behavior and the slope of the Phillips curve. We view this data set as especially relevant now given that the BLS has indefinitely suspended access to CPI microdata for researchers.

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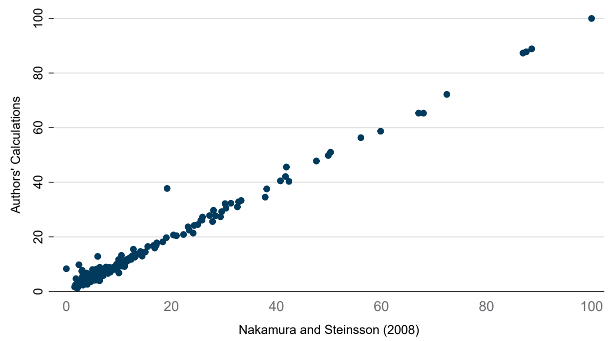
# Appendices

**Contents**

# A Section 2 (Data) Appendix

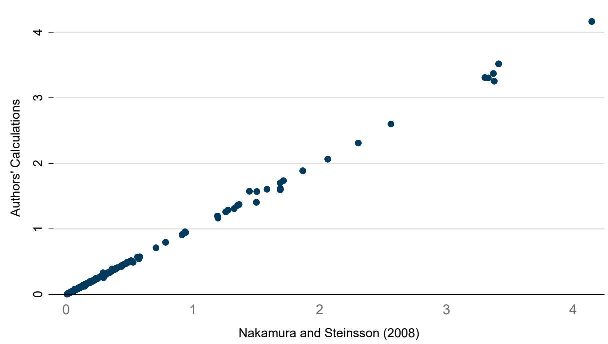
## A.1 Additional Exhibits

Figure A.1: Comparison of ELI Frequencies of Price Changes



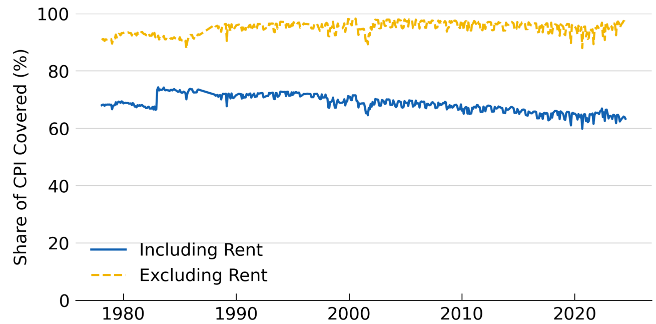

*Notes*: The plot compares the ELI frequencies obtained from Nakamura and Steinsson (2008), which they computed for the 1998–2005 period, with our ELI frequencies averaged over the same time frame. The correlation between these variables is 0.994. The most prominent outlier is ELI "Stoves and Ovens Excluding Microwaves."
*Sources*: BLS, authors' calculations.

Figure A.2: Comparison of ELI Weights




*Notes*: The plot compares the ELI weights obtained from Nakamura and Steinsson (2008), which correspond to the year-2000 weights they obtained from the BLS, with our ELI weights measured for the year 2000. The correlation between these variables is 0.9996.
*Sources*: BLS, authors' calculations.

Figure A.3: Share of the CPI Covered




*Notes*: The blue line (including rent) is calculated as the sum of the expenditure weights of ELIs for which we have price-change statistics divided by the sum of the expenditure weights of all ELIs, multiplied by 100, for each month in the sample. The orange line (excluding rent) excludes primary rent and owner's equivalent rent when computing the denominator. For the 1978–1982 period, the orange line also excludes costs relating to property ownership, which is how the BLS previously measured the costs of homeownership.
*Sources*: BLS, authors' calculations.

## A.2 Handling of Adjustments to ELIs

We adjust the frequency of price changes of apparel, household goods, prescription drugs, and wage-related ELIs to account for the spurious influences of changes in BLS's measurement of prices for items within these ELIs. These adjustments cumulatively affect only 1.36 percent of the full data set by weight.

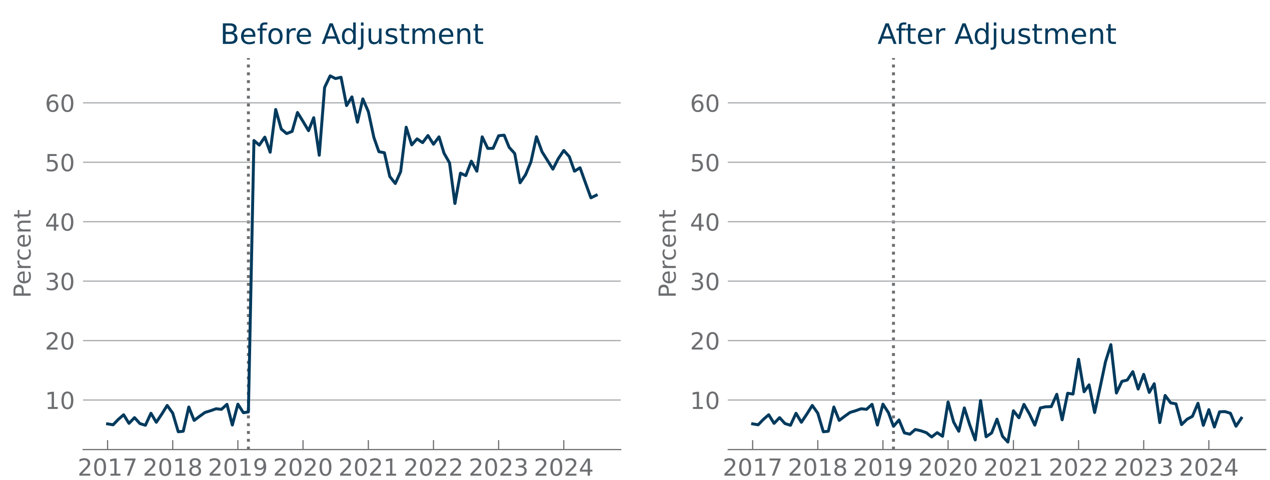
### A.2.1 Apparel and Household Goods

In March 2019, the BLS began using prices that were directly provided by one department store (Konny, Williams, and Friedman, 2022). The data set from the department store does not allow for individual items to be tracked in the usual way, so the BLS processes these price quotes, including making hedonic adjustments to account for quality changes. These adjustments seem to imply that the frequency of price changes is considerably higher than it was when measured previously. This department store appears to have made up a large share of price quotes in the apparel major group, as well as price quotes for household goods like luggage, curtains, and bedspreads. As a result, there was a sizable jump in the frequency of price changes in March 2019. This is shown in the left-hand panel of Figure A.4.

We adjust apparel and household goods after March 2019 so that they follow a pattern similar to the one before the department store data were used. Separately, for each price-change statistic, we first calculate each apparel and household goods ELI's average percentile in the distribution of that price-change statistic from 2010 to 2018. We then replace the price-change statistic for each of these ELIs for every month starting in March 2019 with the corresponding percentile in that month's distribution, excluding apparel and household goods. To illustrate this with an example, the monthly frequency of price changes for the ELI "Men's suits" (AA011) in January 2020 was 51 percent, which is likely artificially high due to the department store data. On average, from 2010 to 2018, men's suits were at the 39th percentile of the distribution of frequency of price changes (considering all ELIs). In January 2020, the 39th percentile frequency of price changes across all ELIs excluding apparel and household goods was 8 percent. We therefore replace the 51 percent value with 8 percent. The right-hand panel of Figure A.4 shows the impact of this adjustment on the average frequency of price changes within the apparel and household goods sectors. We apply a similar adjustment to the distributions of other price-change statistics as well.

Note that we currently do not have access to the BLS microdata. If and when we regain access, we will check whether it is possible to recompute the price-change statistics for apparel and household goods ELIs excluding price quotes associated with this specific department store.

Figure A.4: Apparel and Household Goods: Frequency of Price Changes

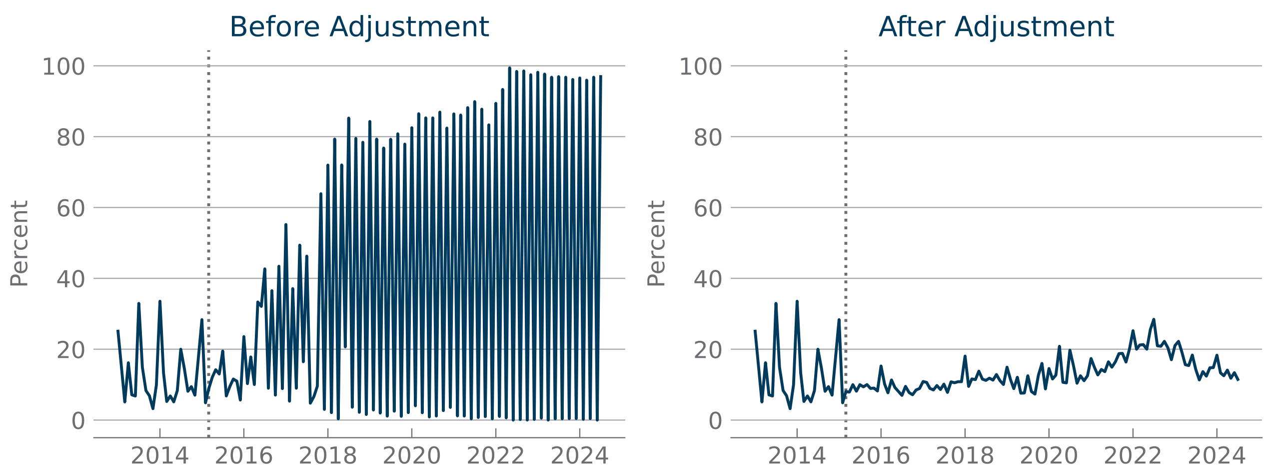



*Notes*: The figure shows the weighted mean frequency of price changes among the ELIs within apparel and households goods. The dotted vertical line marks the date after which the adjustment is implemented.
*Sources*: BLS, authors' calculations.

### A.2.2 Prescription Drugs

In March 2015, the BLS began receiving a bimonthly data set from a pharmaceutical retailer consisting of average prices from a sample of the company's in-store prescription drug transactions (Bieler et al., 2023). This change has led to a bimonthly pattern of very low and very high frequencies of price changes for prescription drugs, as shown in the left-hand panel of figure A.5. We adjust the values of the frequency of price changes and the size distribution of price changes in a way similar to our adjustment for apparel and household goods, using its average percentile from 2005 to 2014. For example, on average, from 2005 to 2014, prescription drugs were at the 52nd percentile of the distribution of the frequency of all price changes. Starting in March 2019, we replace the value of prescription drugs in each month with the value at the 52nd percentile of the distribution in that month. The resulting series is shown in the right-hand panel of figure A.5.

Figure A.5: Prescription Drugs: Frequency of Price Changes

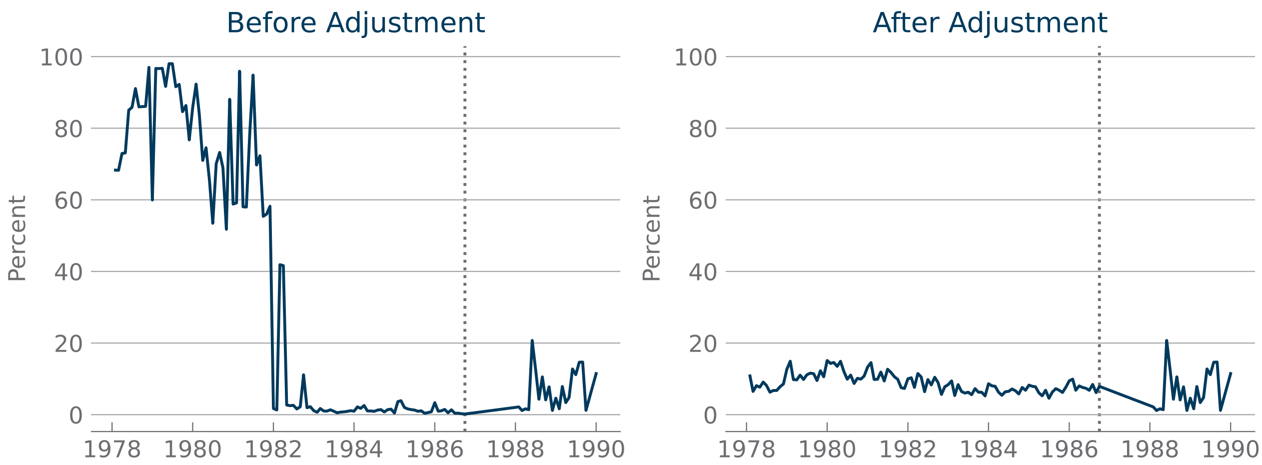



*Notes*: The figure shows the frequency of price changes of the ELI prescription drugs. The dotted vertical line marks the date after which the adjustment is implemented.
*Sources*: BLS, authors' calculations.

### A.2.3 Wage-related ELIs

Finally, we adjust similarly for wage-related ELIs that all displayed a pattern of very high to very low frequencies of price change during the 1978–1986 period. We adjust these ELIs using their average percentiles from 1988 to 1997. Figure A.6 shows the average frequency of price changes before and after the adjustment.

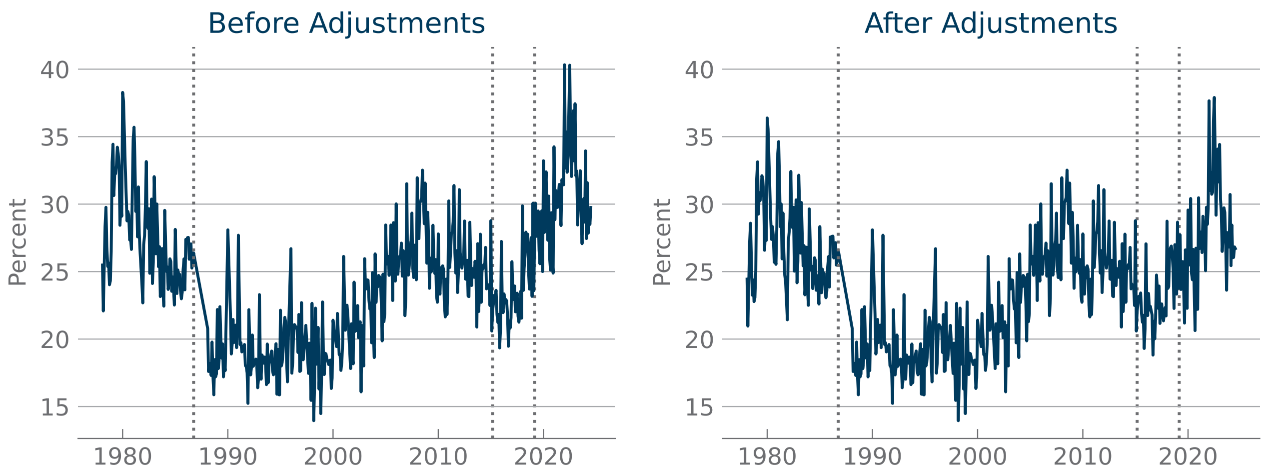
Figure A.6: Wage-related ELIs: Frequency of Price Changes




*Notes*: The figure shows the weighted mean frequency of price changes of the wage-related ELIs. These ELIs include college tuition, elementary/high school tuition, babysitting (later, day care and nursery school), minimum wage rates priced in Washington (later, domestic services), and gardening or lawn-care services. The dotted vertical line marks the date after which the adjustment is implemented.
*Sources*: BLS, authors' calculations.

Finally, Figure A.7 shows the effect on the aggregate average frequency of price changes in the raw data and after all the adjustments have been implemented. We find that the series move together closely, and in a later robustness check, we verify that these adjustments do not impact our main findings regarding the importance of weights on the distributions of price changes.

Figure A.7: Frequency of Price Changes




*Notes*: The figure shows the weighted mean frequency of price changes across all ELIs. The three dotted vertical lines mark the dates when the adjustment is implemented for wage-related ELIs, prescription drugs, and apparel, respectively.
*Sources*: BLS, authors' calculations.

## A.3 CEX-based Annual Expenditure Weights

The CPI expenditure weights used in our baseline analysis are ultimately derived from the Consumer Expenditure Survey (CEX). However, during much of our sample—especially prior to the late 1990s—the Bureau of Labor Statistics (BLS) updated CPI item-strata expenditure weights infrequently. In the intervening periods between updates, expenditure shares were effectively held fixed up to relative-price adjustments, assuming implicitly no substitution across item strata. As a robustness check, we therefore construct annual expenditure weights directly from CEX microdata and assess the sensitivity of our results to using these alternative weights.

We use public use microdata (PUMD) from the CEX Interview and Diary Surveys to construct annual expenditure shares at the item-stratum level. The microdata are primarily obtained from the BLS; for the years 1982 through 1989, which are not available directly from the BLS, we use archived PUMD from the ICPSR.

Our methodology closely follows Jaravel (2024), but we do not utilize data on rent and housing, and we do not disaggregate expenditures by income or demographic groups. For the interview surveys, we obtain monthly consumer unit (CU) expenditures by UCC from the "mtbi" files. Every CU is asked to report their UCC-expenditure over the last three months. For the diary surveys, we obtain daily consumer unit (CU) expenditures by UCC from the "expd" files. Every CU is asked to record their UCC-expenditure on the day of the survey, which we then convert to a monthly expenditure by assuming that they would incur the same expense on the corresponding day of every week for the rest of the month.[32] Finally, we obtain consumer unit (CU) sample weights from the "fmli" and "fmld" files for the interview and diary surveys, respectively.

Following Jaravel (2024), we make adjustments for instances in the interview surveys, where a CU reports expenditures for months that fall outside their 3-month recall period. At the end of the adjustment process, we have consistent 3-month panels for each CU and we assign the same CU sample weight to each of the three months. We compute the monthly UCC expenditure as the weighted average of the CU expenditures on that UCC. [33]

Next, we map UCCs to CPI item strata to obtain monthly item-stratum expenditures. For 1999 onward, we use the combined concordance constructed by Jaravel (2024). For the pre-1999 period, when no such concordance is available, we construct our own using the CEX data dictionary. In some instances, this procedure involves a coarser correspondence between UCCs and item strata than in the post-1999 periods.[34]

Once we have the monthly item-stratum expenditures, we take the weighted average of the expenditure across the months within a year (using the sum of CU weights within a month as weights) to obtain the annual item-stratum expenditures. Finally, we convert these to item-stratum expenditure shares by dividing the annual expenditure of the item stratum by the total annual expenditure across all item strata for that year.

Using this approach, we obtain annual CEX-based item-strata expenditure weights from 1980 through 2023. We verify that our post-1999 weights closely track those reported by Jaravel (2024)—the correlation between the weights for every year ranges from 0.98–0.99 (see Figure A.8). In the final step, we apply the ELI factor from the BLS microdata to convert

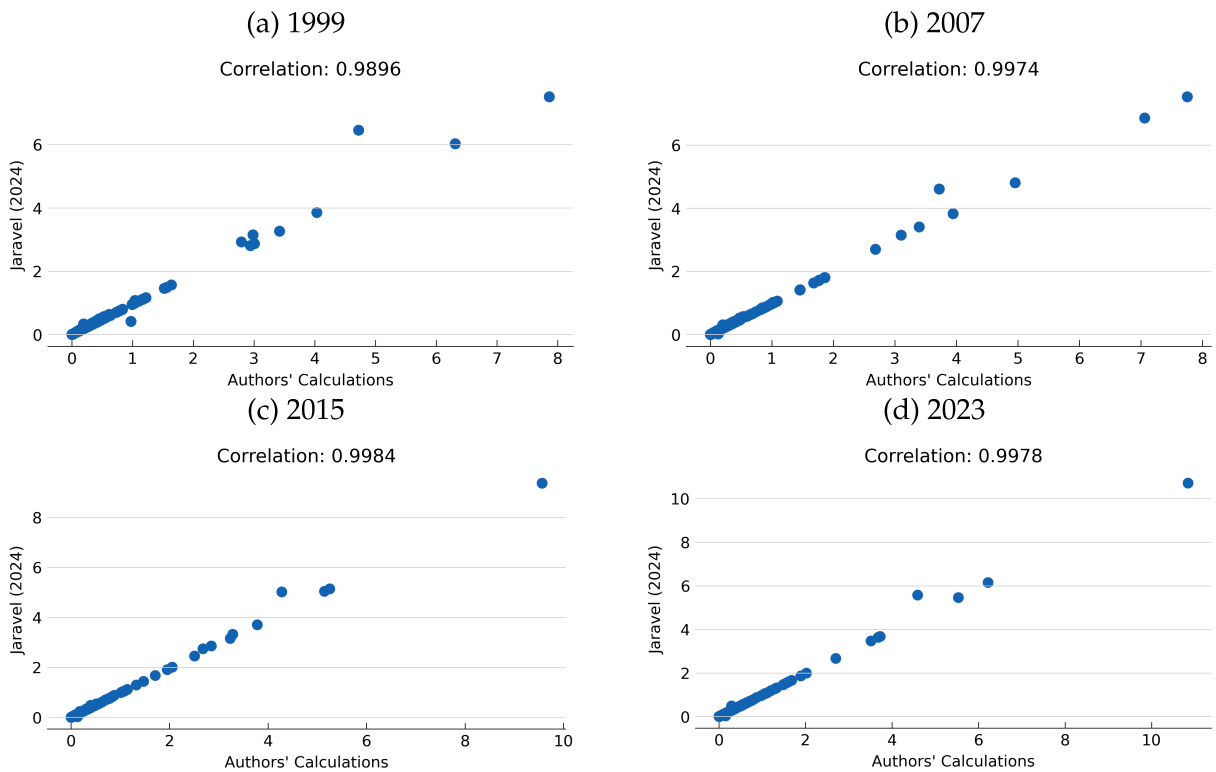
[32]Specifically, we compute: monthly UCC-expenditure = (daily UCC-expenditure x number of days in the month)/7.

[33]Following Jaravel (2024), prior to 2004, we restrict the sample to households reporting all sources of income. Post-1999, we only keeping expenditures that were used in public reports; however, earlier in the sample we include all expenditures, since excluding the nonpublic expenditures leads to the omission of certain item strata. However, we do not leverage distinctions in primary sampling units, as these data are not publicly available before 2006. We also do not conduct Jaravel (2024)'s additional steps of mapping CEX weights to the year in which they are used by the BLS in constructing the CPI or of applying the CPI inflation adjustment.

[34]For example, item strata for Food Away from Home are divided by vendors (such as, full service restaurants, vending machines, cafeterias, etc.). UCCs in the post-1999 period are stratified by vendor and meal (breakfast, lunch, dinner, or snacks). However, pre-1999, the UCCs are only separated by meal. As such, all UCCs corresponding to Food Away from Home are spread evenly across all item strata corresponding to Food Away from Home in the pre-1999 mapping.

the item-strata expenditure weights to monthly ELI expenditure weights, as we did for the baseline weights (see section 2).

Figure A.8: Comparison of Item-Stratum Expenditure Weights



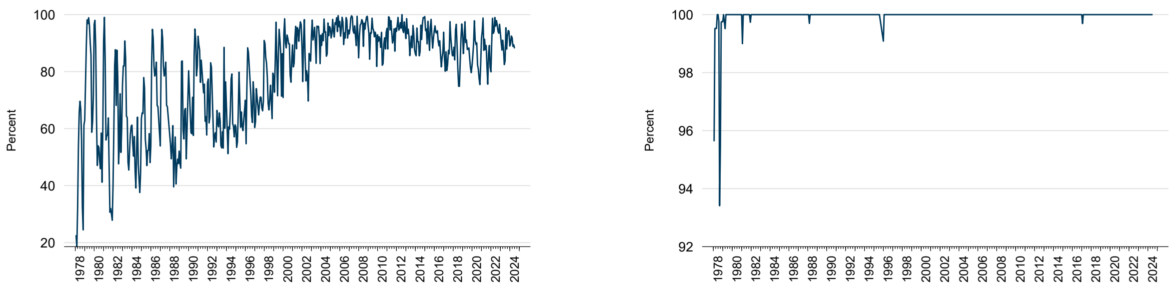

*Notes*: The weights are computed as the ratio of average monthly expenditures on each item strata over the sum of average monthly expenditures over they calendar year. The most prominent outlier in each panel is the item stratum "Used Cars and Trucks."
*Sources*: BLS, ICPSR, Jaravel (2024), authors' calculations.

# B Section 3 (Distributions of Price Changes) Appendix

## B.1 Gas and Used Cars

Figure B.1: Frequency of Price Changes, 1978–2024

(a) Gas (b) Used cars




*Notes*: The price-change frequency for each category is computed as the weighted mean of the frequencies across the ELIs within that category for each month.
*Sources*: BLS, authors' calculations.

Figure B.2: Expenditure Weights, 1978–2024

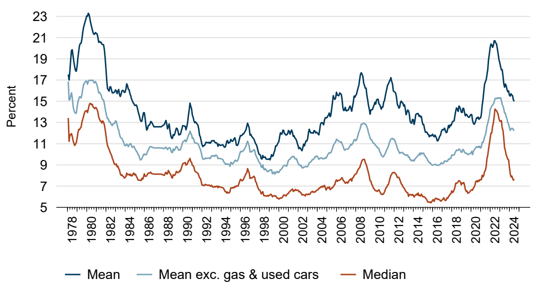
(a) Gas (b) Used cars


*Notes*: The weight for each category is computed as the sum of the weights across the ELIs within that category for each month.
*Sources*: BLS, authors' calculations.

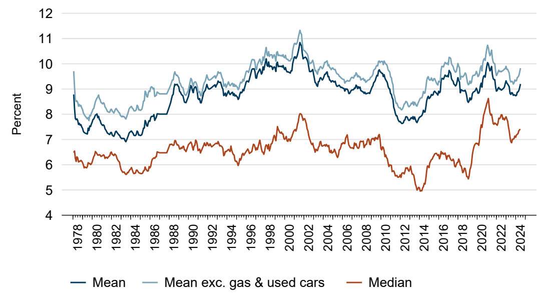
## B.2 Other Price-change Statistics

Figure B.3: Other Price-change Statistics, 1978–2024

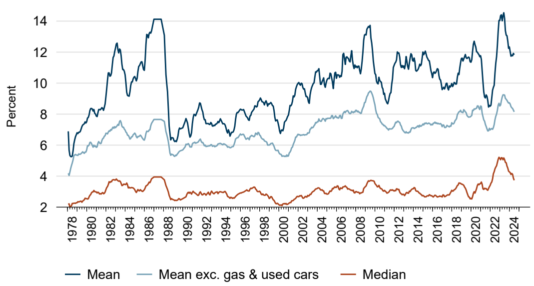
(a) Frequency of price increases



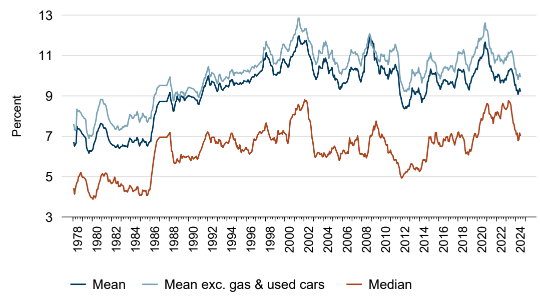

(b) Size of price increases



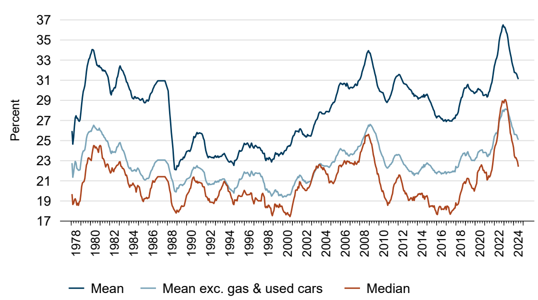

(c) Frequency of price decreases




(d) Absolute size of price decreases

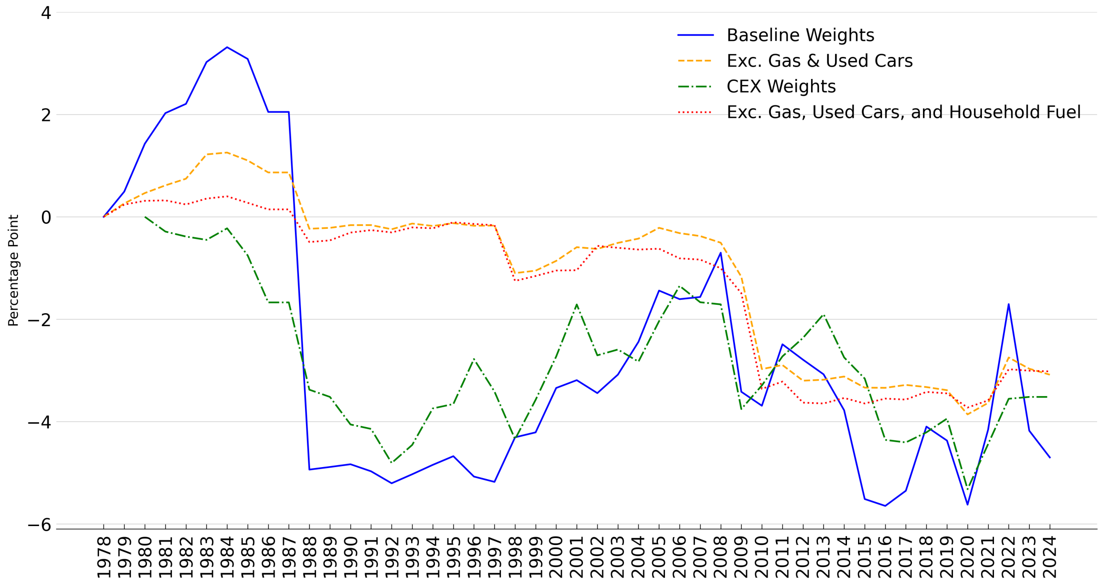



(e) Frequency of price changes including sales




*Notes*: Each statistic is constructed by calculating the mean of the statistic across items within an ELI and then computing the weighted mean, weighted mean excluding gas and used cars, and weighted median across all ELIs by month. For each month, we then compute the 12-month moving average over the previous 12 months.
*Sources*: BLS, authors' calculations.

Figure C.1: Between Effect for the Weighted Mean Frequency of Price Changes: Alternative Expenditure Weights, Additional Series




*Notes*: The blue and green lines show the between effect measured using expenditure weights from CPI and CEX, respectively. The orange line shows the between effect measured using expenditure weights from CPI excluding gas and used cars. The red line further excludes household fuel (fuel oil and electricity). The CEX line begins in 1980 because this is the first year for which CEX microdata are available.
*Sources*: BEA, BLS, authors' calculations.

# C Section 4 (Quantifying the Impact of Weights on the Distributions) Appendix

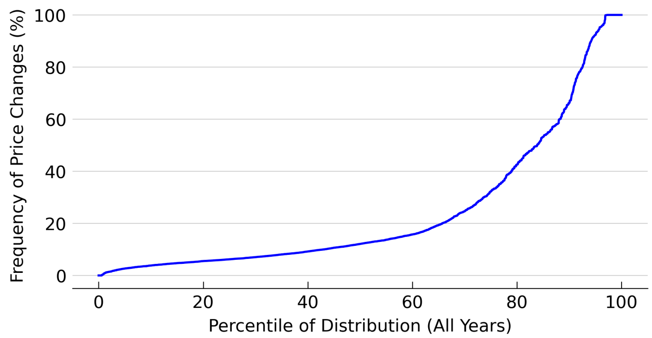
## C.1 Additional Exhibits

## C.2 Decomposition of a Proxy for the Weighted Median Frequency of Price Changes

### C.2.1 Weighted Mean Percentile of the Frequency of Price Changes

We cannot apply Foster, Haltiwanger, and Krizan (2001)'s decomposition equation directly to the weighted median, as it is not a weighted sum. We instead use the weighted mean percentile as a proxy for the weighted median. To do this, we first convert each price-change frequency to its "percentile" in the weighted distribution of price-change frequencies across all ELIs across all months from 1978 through 2024. Figure C.2 shows this mapping.[35]

Figure C.2: Cumulative Distribution of Frequencies across All Years




*Notes*: The cumulative distribution of all the frequencies of price changes of ELIs from 1978 through 2024.
*Sources*: BLS, authors' calculations.

We then compute the weighted mean of the percentile over time, which we plot with the teal line on the secondary y-axis in Figure C.3. We find that the "percentile" distribution closely tracks the median distribution, which is shown as the burnt orange line. This makes sense because changes in weights at low and high frequencies of price changes have a balanced impact on the percentile distribution, similarly to the weighted median.[36]

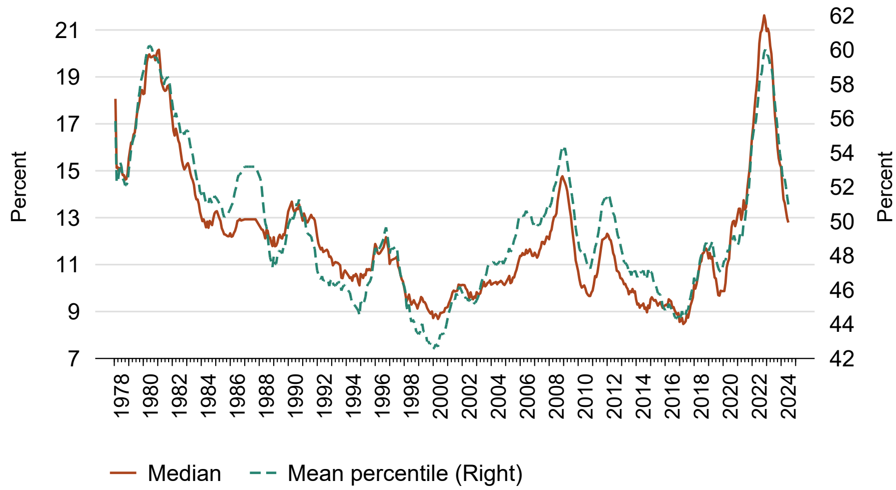
We show the correlation of each of the moments we focus on in Table C.1. We also include the 10th, 25th, 75th, and 90th percentiles of the distribution. The weighted mean frequency of price changes (in column 1) has a higher correlation with the weighted upper percentiles (75th and 90th) rather than the weighted lower percentiles (10th, 25th, and the median) of the distribution. The weighted mean excluding gas and used cars suggests a more symmetrical distribution, since its correlation is highest with the weighted median compared with other weighted percentiles of the distribution, although it remains strongly correlated with the weighted mean as well. As expected, the weighted median correlates most closely with the weighted mean percentile (0.92) compared with a correlation of 0.85 with the weighted mean excluding gas and used cars and 0.73 with the weighted mean.

Figure C.4 and Figure C.5 show the impact of applying the same decomposition as in Section 4 to the weighted mean percentile of frequency and absolute size of price changes,

[35]We convert from the frequency of price changes on the y-axis to the percentile on the x-axis.

[36]For example, if the 1st percentile of the distribution in 1987 changes from 0.01 to 0.02 (that is, from the 1st percentile to the 2nd percentile in the overall distribution), this raises the weighted mean percentile by 0.0001, whereas if the 99th percentile of the distribution in 1987 changes from 0.99 to 0.98 (that is, from the 99th percentile to the 98th percentile in the overall distribution), this lowers the weighted mean percentile by 0.0001.

Figure C.3: Weighted Median and Weighted Mean Percentile of the Frequency Distribution, 1978–2024




*Notes*: To construct the weighted median frequency of price changes, we compute the mean frequency of price change for each ELI in each month. We then compute the weighted median across all ELIs using the monthly expenditure weights. To construct the weighted mean percentile series, we first convert the frequency distribution into a percentile distribution at the ELI level. We then compute the weighted mean across all ELIs using the monthly expenditure weights. Finally, for each month, we calculate the 12-month moving average over the previous 12 months.
*Sources*: BLS, authors' calculations.

Table C.1: Pairwise Correlation between Moments of the Frequency Distribution

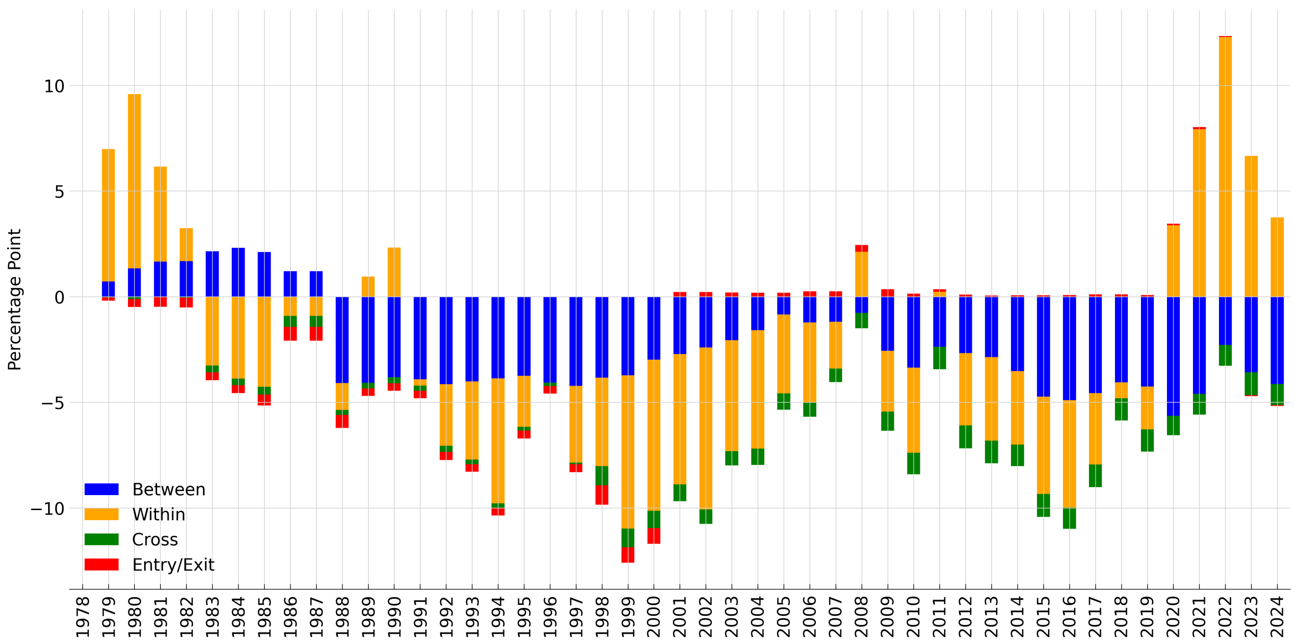
| | Mean | Mean exc. gas & used cars | Median | 10th pct. | 25th pct. | 75th pct. | 90th pct. | Mean percentile |
|---|---|---|---|---|---|---|---|---|
| Mean | 1 | | | | | | | |
| Mean exc. gas & used cars | 0.883*** | 1 | | | | | | |
| Median | 0.714*** | 0.821*** | 1 | | | | | |
| 10th pct. | 0.362*** | 0.478*** | 0.561*** | 1 | | | | |
| 25th pct. | 0.626*** | 0.727*** | 0.841*** | 0.648*** | 1 | | | |
| 75th pct. | 0.815*** | 0.720*** | 0.444*** | 0.206*** | 0.344*** | 1 | | |
| 90th pct. | 0.783*** | 0.533*** | 0.288*** | 0.0266 | 0.217*** | 0.635*** | 1 | |
| Mean percentile | 0.850*** | 0.894*** | 0.918*** | 0.636*** | 0.883*** | 0.607*** | 0.443*** | 1 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: The table presents pairwise correlations between the 12-month backward-looking moving averages of the different moments of the distribution of price-change frequency. To construct the frequency distribution, we first compute the mean frequency of price change for each ELI in each month. We then compute the weighted moment across all ELIs or ELIs excluding gas and used cars using the monthly expenditure weights. For the weighted mean percentile computation, we first convert the frequency to a corresponding percentile in the full distribution across all ELIs across all months and then compute the weighted mean of the percentiles across all ELIs using the monthly expenditure weights.
*Sources*: BLS, authors' calculations.

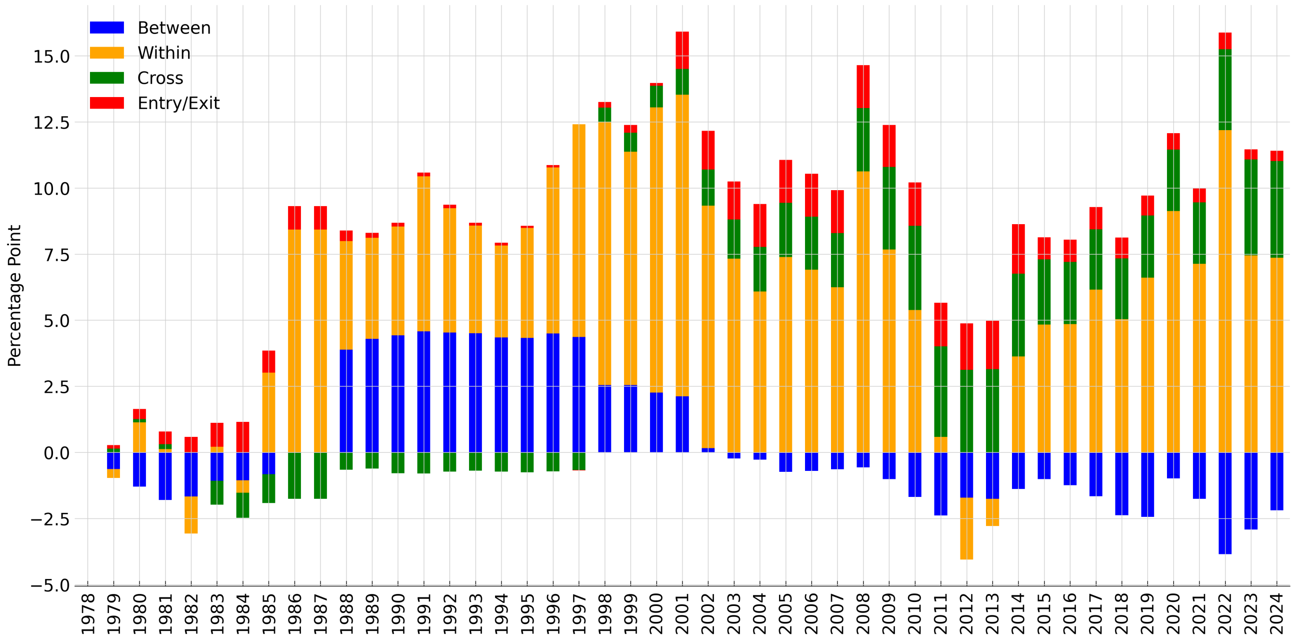
respectively.

Figure C.4: Annual Decomposition of the Change in the Weighted Mean Percentile for Frequency




*Notes*: Each bar shows the contributions of the between, within, cross, and entry/exit effects to the change in the weighted mean percentile from 1978 to the year on the x-axis.
*Sources*: BLS, authors' calculations.

Figure C.5: Annual Decomposition of the Change in the Weighted Mean Percentile for Absolute Size




*Notes*: Each bar shows the contributions of the between, within, cross, and entry/exit effects to the change in the weighted mean percentile from 1978 to the year on the x-axis.
*Sources*: BLS, authors' calculations.

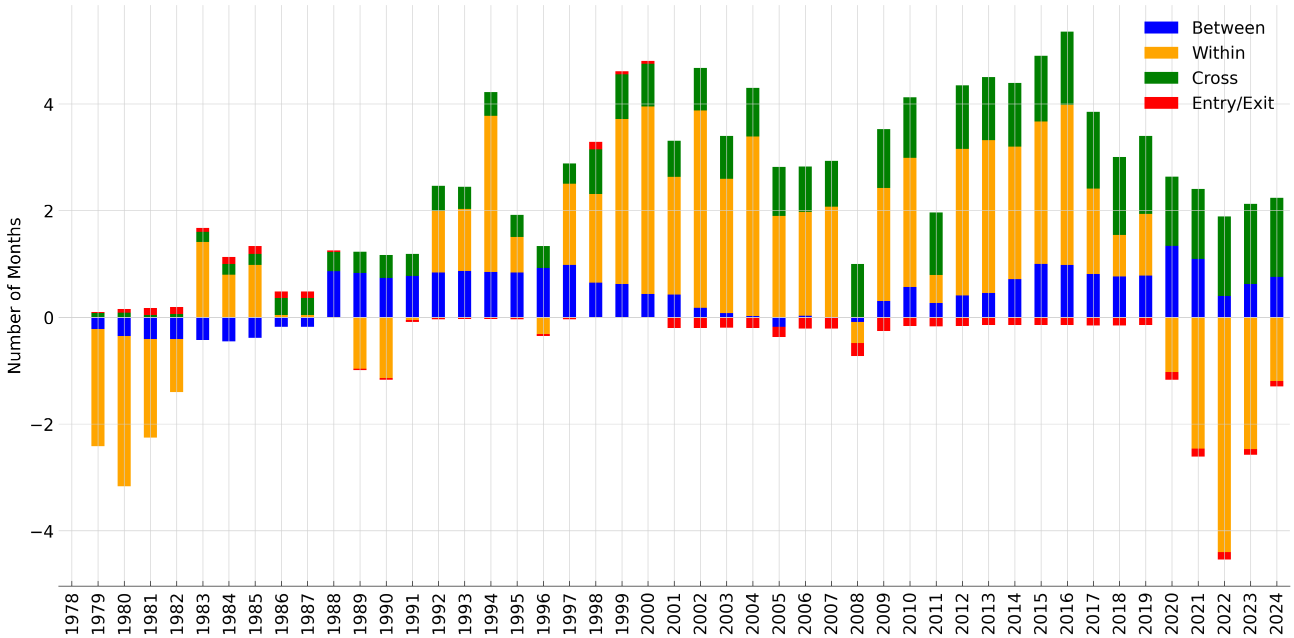
### C.2.2 Weighted Mean Duration of Price Changes

Another proxy for the weighted median frequency that we consider and are able to decompose is the weighted mean duration of price changes. For a given frequency of price changes $f_{it}$, we compute the duration of price changes as $\frac{-1}{\ln(1-f_{it})}$. If the frequency of price changes is exactly 100 percent, the denominator of this expression will be $-\infty$. Therefore, when the frequency is 100 percent, we set the duration of price changes to be zero months. Prices that last a long time can have an outsized effect on the weighted mean duration. Therefore, we top-code the maximum duration of prices to be 48 months.

Just as the weighted mean frequency overweights ELIs with relatively higher frequencies of price changes, the weighted mean duration overweights ELIs with relatively lower frequencies of price changes. We would generally expect frequency and duration of price changes to move in the opposite direction, and they do, as shown in Figure C.6.

We find that the impact of the expenditure weights from 1978 through 2024, given by the sum of the between (blue bar) and cross (green bar) components in the bar on the extreme right, increase the mean duration of price changes by 2.2 months. This is partly counteracted

Figure C.6: Annual Decomposition of the Change in the Weighted Mean Duration of Price Changes




*Notes*: Each bar shows the contributions of the between, within, cross, and entry/exit effects to the change in the weighted duration of price changes from 1978 to the year on the x-axis.
*Sources*: BLS, authors' calculations.

by the negative within and entry-exit effects, which together lower the mean duration by 1.3 months. However, overall, we observe that the net impact of consumption-basket shifts toward ELIs with higher price durations outweighs the impact of the fall in ELI-level price durations, resulting in a higher duration of prices in 2024 relative to 1978. In fact, the duration of price changes is higher in every year since the 1980s due to shifts in consumption baskets toward ELIs with relatively higher price durations.

## C.3 Robustness Table for the Decomposition Results

Table C.2: Alternative Measures of Price-change Frequencies

| Price-Change Frequency (%) | 1978 | 2024 | Change | Between | Within | Cross | Entry/Exit |
|---|---|---|---|---|---|---|---|
| *A. Baseline* | | | | | | | |
| A1. Weighted mean | 24.7 | 26.9 | 2.2 | -4.7 | 5.6 | 1.6 | -0.3 |
| A2. Weighted mean exc. gas & used cars | 19.4 | 20.3 | 0.9 | -3.1 | 3.5 | 1.0 | -0.5 |
| *B. Seasonally adjusted* | | | | | | | |
| B1. Weighted mean | 24.6 | 26.8 | 2.2 | -4.9 | 5.1 | 1.7 | 0.3 |
| B2. Weighted mean exc. gas & used cars | 19.4 | 20.6 | 1.1 | -3.1 | 3.1 | 1.1 | -0.0 |
| *C. Removing Adjusted Price-Change Stats* | | | | | | | |
| C1. Weighted mean | 25.0 | 28.1 | 3.2 | -4.7 | 5.8 | 1.8 | 0.3 |
| C2. Weighted mean exc. gas & used cars | 19.6 | 21.2 | 1.6 | -3.1 | 3.7 | 1.1 | -0.1 |
| *D. With Sales* | | | | | | | |
| D1. Weighted mean | 27.3 | 31.1 | 3.9 | -6.8 | 9.4 | 1.7 | -0.4 |
| D2. Weighted mean exc. gas & used cars | 22.3 | 24.9 | 2.7 | -5.5 | 7.7 | 1.0 | -0.5 |

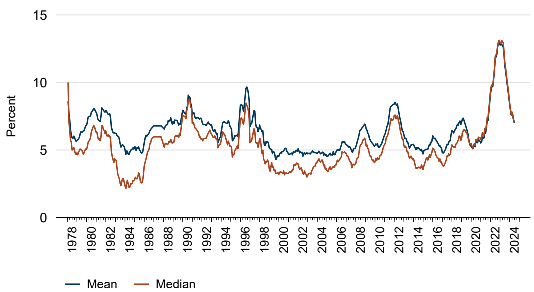
*Notes*: Each panel shows the results of the decomposition of the weighted mean and weighted mean excluding gas and used cars for the frequency of price changes into the between, within, cross, and entry/exit changes. The weighted moments are computed using alternative measures of price-change frequencies in each panel.
*Sources*: BLS, authors' calculations.

# D Section 5 (Identifying the Consequential Consumption-basket Changes) Appendix

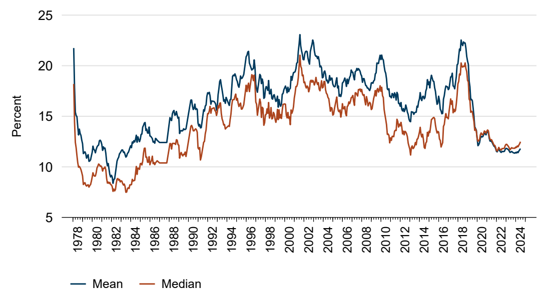
## D.1 Frequency and Absolute Size of Price Changes By Sector, 1978–2024

Figure D.1: Apparel

(a) Frequency of price changes



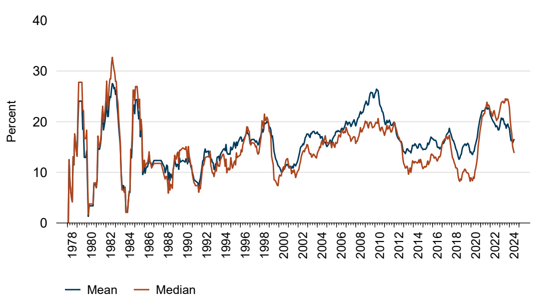

(b) Absolute size of price changes



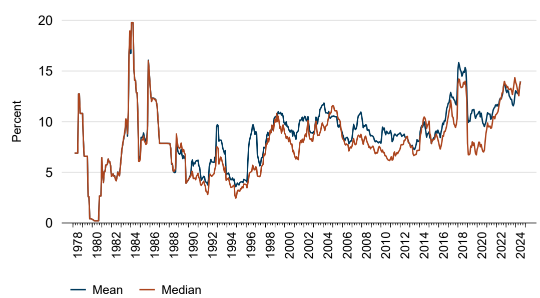

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we compute the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.2: Education and communication goods

(a) Frequency of price changes



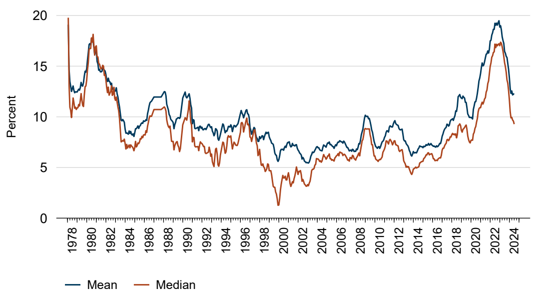

(b) Absolute size of price changes



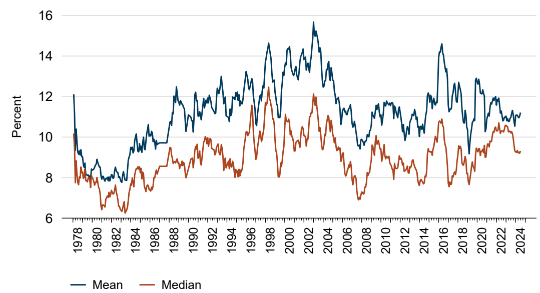

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we compute the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

## Figure D.3: Household furnishings

(a) Frequency of price changes



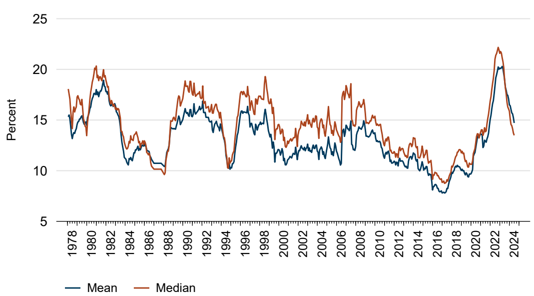

(b) Absolute size of price changes



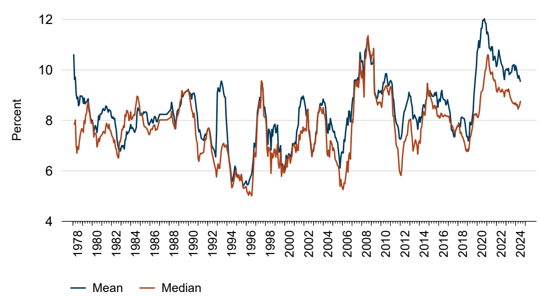

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

## Figure D.4: Medical goods

(a) Frequency of price changes



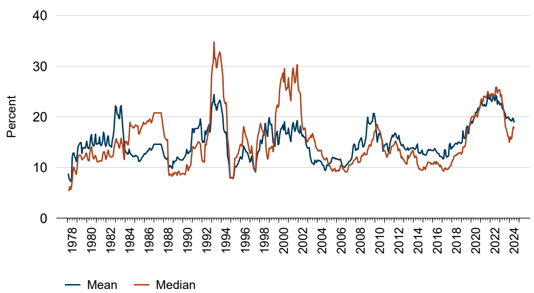

(b) Absolute size of price changes



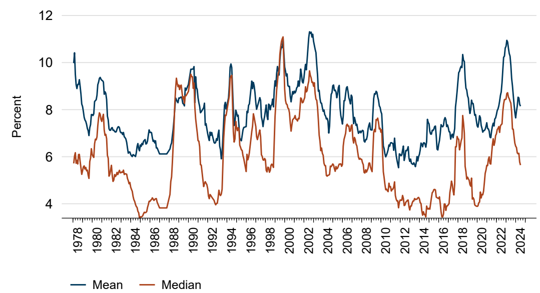

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we compute the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

## Figure D.5: Other goods

(a) Frequency of price changes



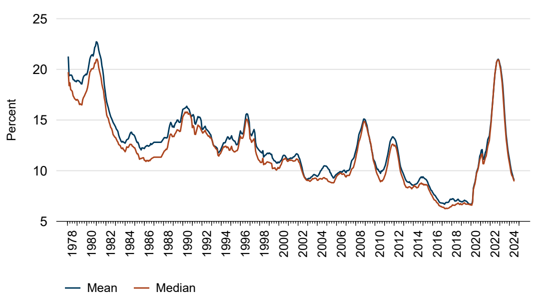

(b) Absolute size of price changes



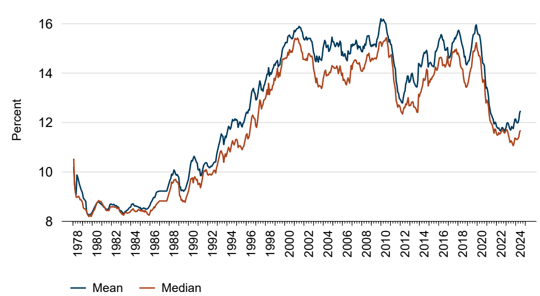

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

## Figure D.6: Processed food

(a) Frequency of price changes



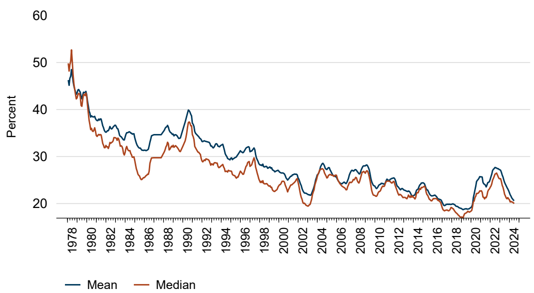

(b) Absolute size of price changes



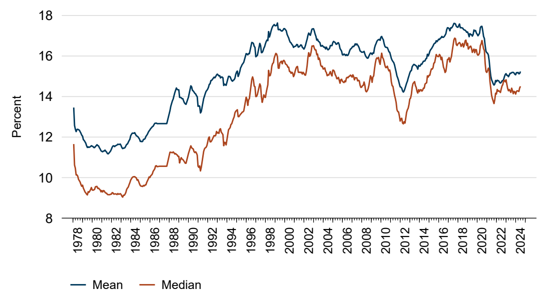

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.7: Unprocessed food

(a) Frequency of price changes



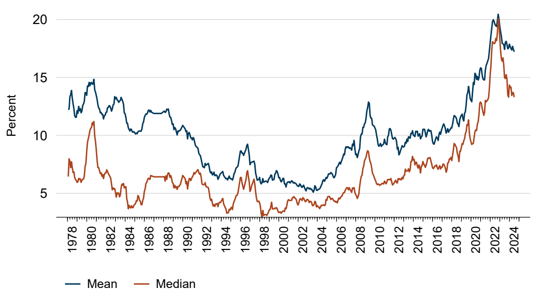

(b) Absolute size of price changes



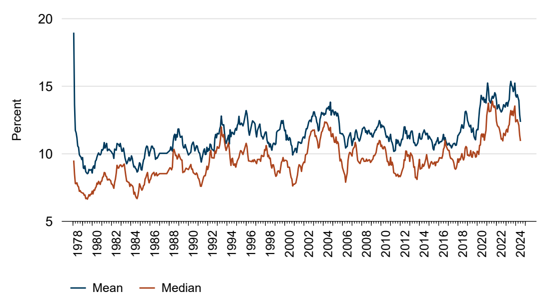

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.8: Recreation goods

(a) Frequency of price changes



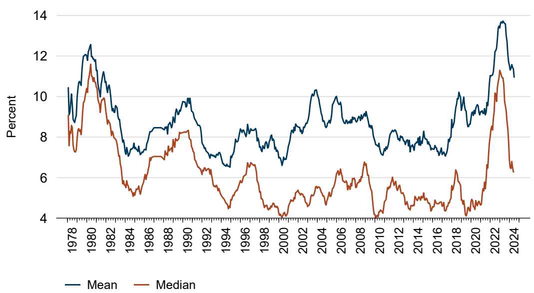

(b) Absolute size of price changes



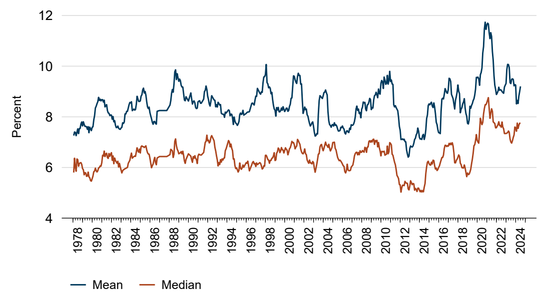

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.9: Services (excluding travel)

(a) Frequency of price changes



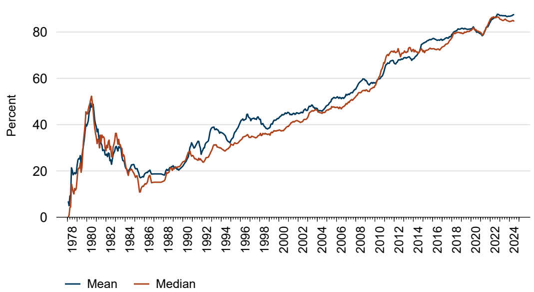

(b) Absolute size of price changes



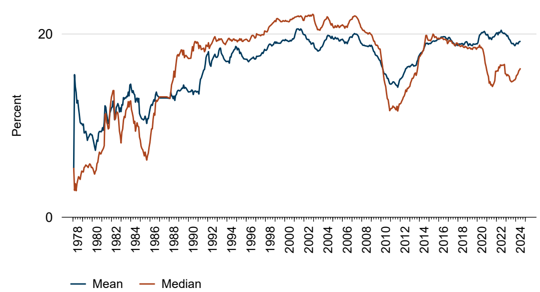

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.10: Travel

(a) Frequency of price changes



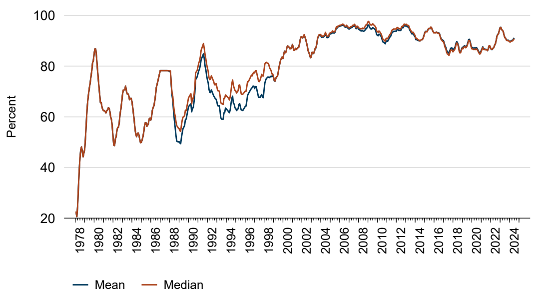

(b) Absolute size of price changes



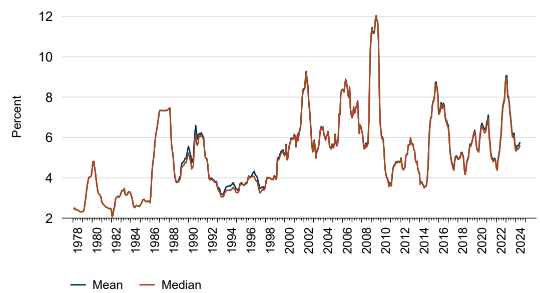

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.11: Vehicle fuel

(a) Frequency of price changes



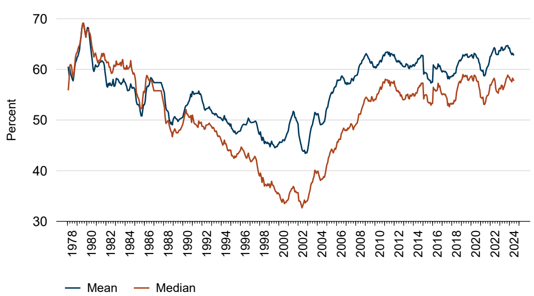

(b) Absolute size of price changes



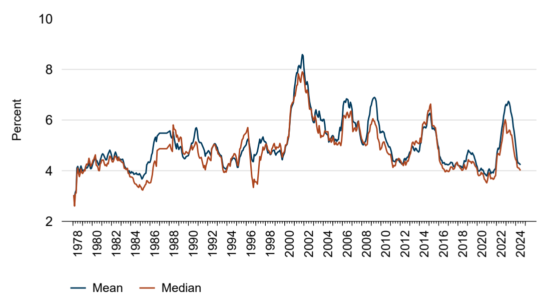

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.12: Utilities

(a) Frequency of price changes



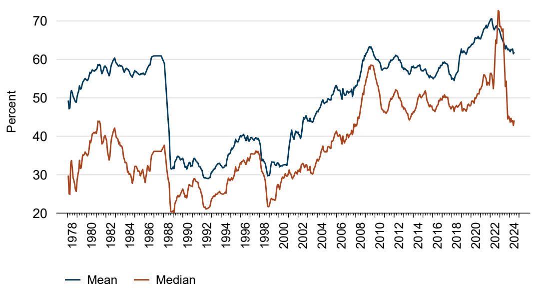

(b) Absolute size of price changes



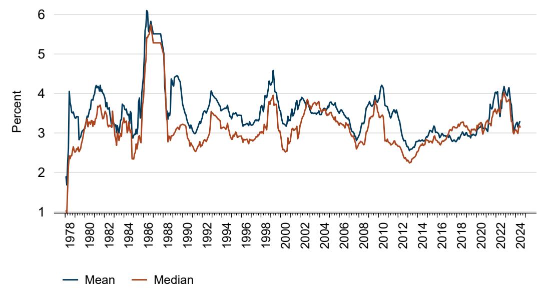

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

Figure D.13: Transportation goods

(a) Frequency of price changes



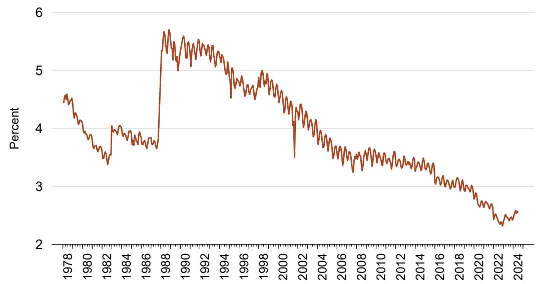

(b) Absolute size of price changes



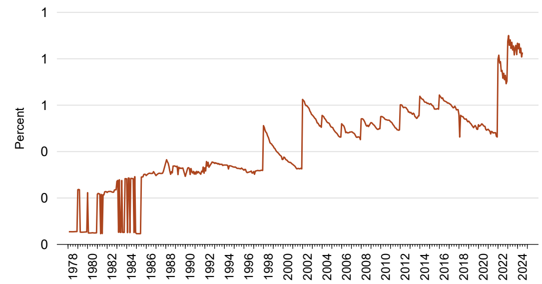

*Notes*: The price-change statistics are computed as the weighted mean or weighted median of the statistic across the ELIs within the sector for each date. Then, for each month, we calculate the 12-month moving average over the preceding 12 months.
*Sources*: BLS, authors' calculations.

## D.2 Expenditure Weights by Sector, 1978–2024

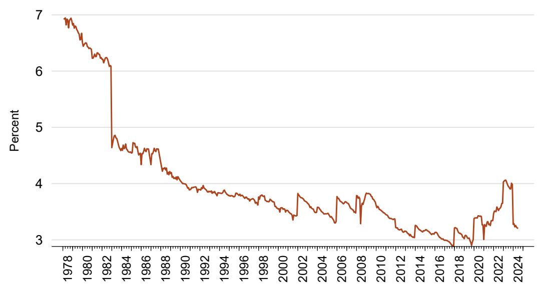
(a) Apparel



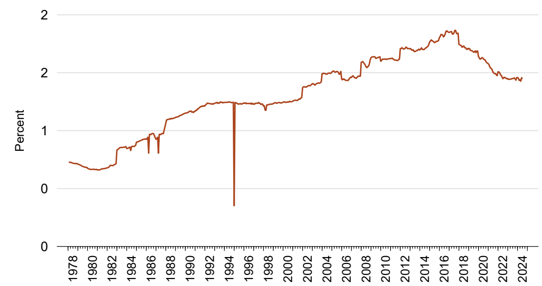

(b) Education and communication goods



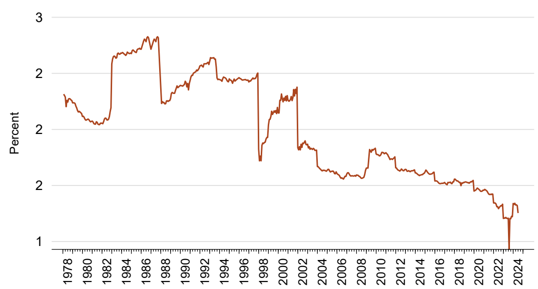

(c) Household furnishings



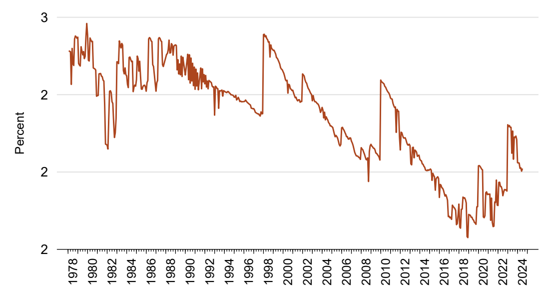

(d) Medical goods



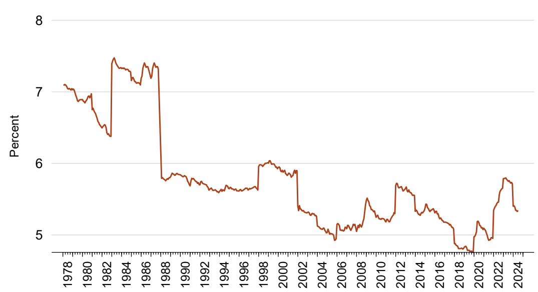

(e) Other goods



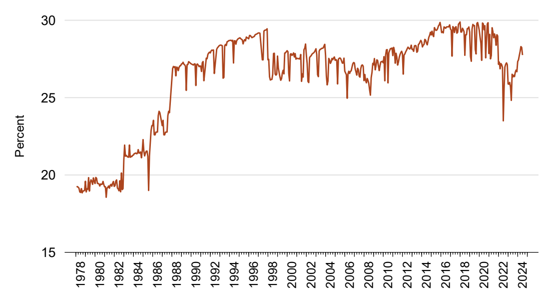

(f) Recreation goods



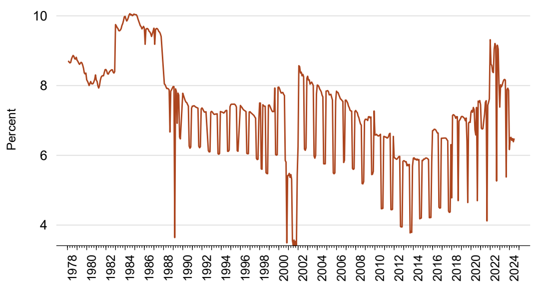

(g) Processed food



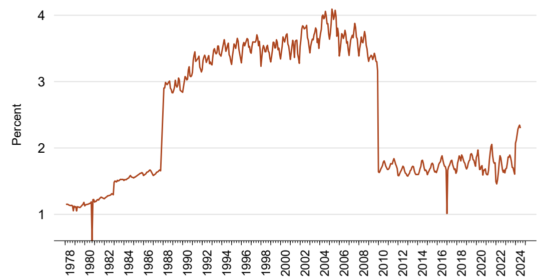

(h) Services (excluding travel)



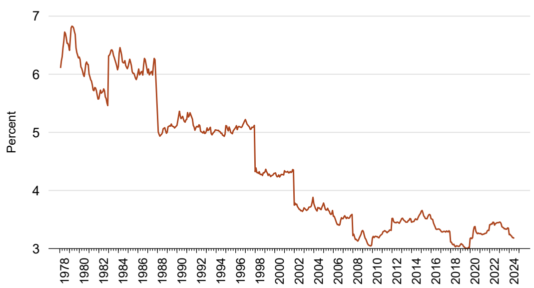
(i) Transportation goods



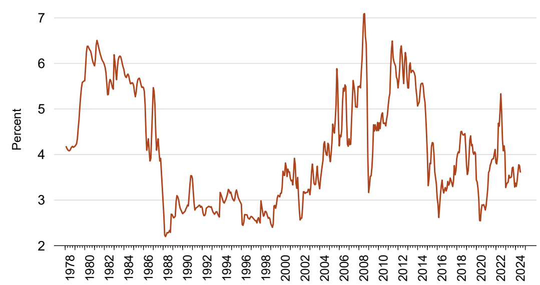

(j) Travel



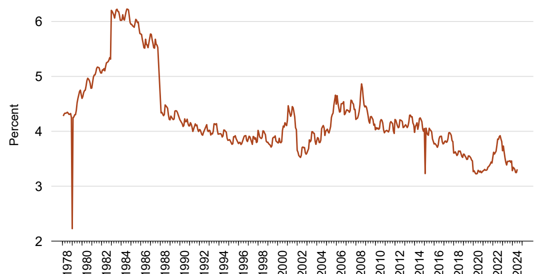

(k) Unprocessed food




(l) Vehicle fuel




(m) Utilities




*Notes*: The weight for each sector is computed as the sum of weights across all ELIs within that sector for each month.
*Sources*: BLS, authors' calculations.

## D.3 Contributions of Individual ELIs

We lay out the ELIs that made the largest contributions through changes in their weights to changes in the frequency and size distributions in Tables D.1–D.4 and Tables D.5–D.5, respectively. Three observations about these tables are worth noting. First, regarding gas (or vehicle fuel) ELIs, there are three gas ELIs in our sample: regular unleaded gasoline (TB011), midgrade unleaded gasoline (TB012), and premium unleaded gasoline (TB013). The first ELI appears in every year in the sample, while the latter two enter in 1988. That is why the first ELI contributes to a large negative between effect as the weight of gas declines over the full sample, while the other two have smaller positive between effects as their weight increases over the sample (from 1988 to 2024). The overall expenditure weight for the gas sector is shown in Figure B.2a. Second, the names of ELIs in these tables correspond to the names used in Nakamura and Steinsson (2008) relating to the early 2000s, For example, "Other Information Services" includes broadband, which is why it has grown substantially. Third, in the concordance we use, the 1998 ELI codes can map to multiple pre-1998 ELI codes, which can induce large weight changes over the sample. For example, several ELIs in the pre-1998 BLS classification map to the 1998 ELI code HH011—"room size rugs"—which is why the weight for room size rugs was large at the beginning of the sample.

A negative between effect for the weighted mean frequency (Table D.1) usually occurs in one of two cases. First, when an ELI has a high frequency of price changes and its weight declines from the beginning to the end of the sample, similarly to regular unleaded gasoline. Second, when an ELI has a low frequency of price changes and its weight rises from the beginning to the end of the sample, similarly to hospital services. However, there are exceptions, such as rental of lodging away from home (hotels), which has a high frequency of price changes and whose weight rises over the sample. This can occur if the rise in the weight of the ELI took place in a year when its frequency of price changes was low, even though the ELI has a high frequency of price changes on average.

Similarly, a positive cross effect for the weighted mean frequency (Table D.4) occurs when an ELI's frequency of price changes increases at the same time as its weight rises or an ELI's frequency decreases at the same time as its weight decreases. However, an ELI's frequency could increase at the same time as its weight and then its weight could decline while its frequency remains constant. In this case, there could be a positive cross effect even as the first-half frequency is lower compared with the last-half frequency, while the first weight is higher than the last weight (for example, regular unleaded gas or fuel oil).

Table D.1: Weighted Mean Frequency of Price Changes: Negative Between Effect

| Code | Description | Spending Group | Contrib | First Weight | Last Weight | Mean Freq |
|---|---|---|---|---|---|---|
| TB011 | Regular Unleaded Gasoline | Vehicle fuel | -1.91 | 6.08 | 1.79 | 82.3 |
| TA021 | Used Cars | Transportation goods | -0.67 | 4.63 | 3.39 | 100.0 |
| TA011 | Subcompact Cars | Transportation goods | -0.5 | 5.79 | 5.98 | 37.4 |
| HE011 | Fuel Oil | Utilities | -0.44 | 1.13 | 0.16 | 66.5 |
| MD011 | Hospital Services | Services (excluding travel) | -0.43 | 0.47 | 3.08 | 8.1 |
| ED031 | Cellular Telephones | Services (excluding travel) | -0.42 | 0.09 | 2.11 | 4.8 |
| HF021 | Utility Natural Gas Service | Utilities | -0.4 | 2.02 | 1.08 | 70.7 |
| HB021 | Rental Of Lodging Away From Home | Travel | -0.31 | 0.72 | 1.75 | 46.3 |
| EB011 | Full College Tuition and Fixed Fees | Services (excluding travel) | -0.25 | 0.92 | 1.9 | 9.0 |
| EE031 | Other Information Services | Services (excluding travel) | -0.24 | 0.03 | 1.53 | 9.1 |
| MC011 | General Medical Practice | Services (excluding travel) | -0.24 | 1.61 | 2.8 | 4.1 |
| FV021 | Limited Service Meals and Snacks | Services (excluding travel) | -0.23 | 2.64 | 3.75 | 8.1 |
| ED021 | Interstate Telephone Services | Services (excluding travel) | -0.23 | 1.0 | 0.75 | 20.8 |
| TA031 | Vehicle Leasing | Transportation goods | -0.21 | 1.4 | 0.94 | 37.8 |
| TE011 | Motor Vehicle Insurance | Services (excluding travel) | -0.19 | 2.57 | 4.43 | 12.7 |

*Notes*: The table shows the top 15 ELIs that drove the negative between effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean frequency of price changes through the between effect. First/last weight is the weight of the ELI in the first/last available year after rescaling for ELIs for which we do not have frequency data.
*Sources*: BLS, authors' calculations.

Table D.2: Weighted Mean Frequency of Price Changes: Positive Between Effect

| Code | Description | Spending Group | Contrib | First Weight | Last Weight | Mean Freq |
|---|---|---|---|---|---|---|
| TB013 | Premuim Unleaded Gasoline | Vehicle fuel | 0.66 | 0.64 | 1.79 | 85.3 |
| TB012 | Midgrade Unleaded Gasoline | Vehicle fuel | 0.66 | 0.66 | 1.79 | 86.5 |
| HH011 | Room Size Rugs | Household furnishings | 0.46 | 2.83 | 0.12 | 11.0 |
| HP043 | Inside Home Maintenance and Repair Services | Services (excluding travel) | 0.25 | 1.4 | 0.12 | 8.2 |
| GA011 | Cigarettes | Other goods | 0.21 | 1.56 | 0.68 | 23.7 |
| GD031 | Coin-Operated Apparel Laundry and Dry Cleaning | Services (excluding travel) | 0.18 | 1.18 | 0.23 | 4.3 |
| HF011 | Electricity | Utilities | 0.14 | 3.03 | 3.89 | 51.3 |
| FV041 | Candy/Gum/Crackers/Pastries/Chips/Similar Items | Services (excluding travel) | 0.14 | 0.89 | 0.06 | 4.2 |
| FV031 | Food At Employee Sites and Schools | Services (excluding travel) | 0.13 | 0.64 | 0.12 | 4.3 |
| GC011 | Beauty Parlor Services For Females | Services (excluding travel) | 0.12 | 1.4 | 0.96 | 3.5 |
| ED041 | Residential Telephone Services | Services (excluding travel) | 0.11 | 1.63 | 0.35 | 17.4 |
| HD011 | Tenants' Insurance | Services (excluding travel) | 0.1 | 0.74 | 0.61 | 8.5 |
| FN011 | Cola Drinks | Processed food | 0.1 | 1.33 | 0.5 | 13.8 |
| TG031 | Intracity Mass Transit | Services (excluding travel) | 0.09 | 0.54 | 0.17 | 3.3 |
| RG011 | Single Copy Newspapers and Magazines | Recreation goods | 0.08 | 0.48 | 0.02 | 3.8 |

*Notes*: The table shows the top 15 ELIs that drove the positive between effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean frequency of price changes through the between effect. First/last weight is the weight of the ELI in the first/last available year after rescaling for ELIs for which we do not have frequency data. Mean frequency is the average frequency of the ELI from 1978 to 2024.
*Sources*: BLS, authors' calculations.

## Table D.3: Weighted Mean Frequency of Price Changes: Negative Cross Effect

| Code | Description | Spending Group | Contrib | First Half Weight | Last Half Weight | First Half Freq | Last Half Freq |
|---|---|---|---|---|---|---|---|
| TA012 | New Motorcycles | Transportation goods | -0.2 | 0.72 | 0.13 | 13.7 | 12.4 |
| HB021 | Rental Of Lodging Away From Home | Travel | -0.09 | 1.97 | 2.2 | 27.2 | 64.7 |
| HD011 | Tenants' Insurance | Services (excluding travel) | -0.07 | 0.4 | 0.53 | 8.4 | 8.5 |
| FK041 | Other Fresh Fruits | Unprocessed food | -0.05 | 0.41 | 0.33 | 62.3 | 41.5 |
| GA011 | Cigarettes | Other goods | -0.05 | 1.63 | 1.02 | 21.7 | 25.7 |
| MC011 | General Medical Practice | Services (excluding travel) | -0.04 | 2.07 | 2.4 | 4.6 | 3.6 |
| ED031 | Cellular Telephones | Services (excluding travel) | -0.03 | 0.08 | 1.79 | 25.4 | 2.2 |
| TD021 | Shock Absorbers and Macpherson Struts | Services (excluding travel) | -0.03 | 0.85 | 0.78 | 9.6 | 11.2 |
| FV021 | Limited Service Meals and Snacks | Services (excluding travel) | -0.03 | 2.72 | 3.68 | 8.4 | 7.9 |
| FX011 | Beer, Ale, and Other Malt Beverages Away From Home | Services (excluding travel) | -0.03 | 0.6 | 0.58 | 6.4 | 4.7 |
| RA011 | Televisions | Recreation goods | -0.03 | 0.31 | 0.19 | 14.4 | 28.2 |
| RB011 | Dog Food | Recreation goods | -0.02 | 0.28 | 0.47 | 13.6 | 9.3 |
| EE011 | Personal Computers and Peripheral Equipment | Education & communication goods | -0.02 | 0.09 | 0.37 | 32.1 | 21.8 |
| FB011 | White Bread | Processed food | -0.02 | 0.54 | 0.33 | 13.2 | 10.3 |
| EB031 | Day Care and Nursery School | Services (excluding travel) | -0.02 | 0.64 | 1.13 | 7.2 | 6.7 |

*Notes*: The table shows the top 15 ELIs that drove the negative cross effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean frequency of price changes through the cross effect. First-half and last-half weight (freq) is the average weight (frequency of price changes) of the ELI in the 1978–2000 period and the 2001–2024 period, respectively, after rescaling for ELIs for which we do not have frequency data.
*Sources*: BLS, authors' calculations.

## Table D.4: Weighted Mean Frequency of Price Changes: Positive Cross Effect

| Code | Description | Spending Group | Contrib | First Half Weight | Last Half Weight | First Half Freq | Last Half Freq |
|---|---|---|---|---|---|---|---|
| TB011 | Regular Unleaded Gasoline | Vehicle fuel | 0.58 | 3.98 | 2.09 | 71.3 | 92.9 |
| HE011 | Fuel Oil | Utilities | 0.33 | 0.84 | 0.24 | 54.6 | 77.9 |
| TA031 | Vehicle Leasing | Transportation goods | 0.18 | 1.04 | 0.94 | 26.0 | 48.7 |
| TB012 | Midgrade Unleaded Gasoline | Vehicle fuel | 0.18 | 0.86 | 2.04 | 77.0 | 91.2 |
| TB013 | Premuim Unleaded Gasoline | Vehicle fuel | 0.18 | 0.85 | 2.05 | 74.4 | 91.3 |
| TB021 | Automotive Diesel Fuel | Vehicle fuel | 0.11 | 0.53 | 0.08 | 48.6 | 78.6 |
| ED021 | Interstate Telephone Services | Services (excluding travel) | 0.1 | 0.94 | 1.08 | 12.5 | 41.8 |
| HF021 | Utility Natural Gas Service | Utilities | 0.07 | 1.92 | 1.4 | 63.5 | 77.7 |
| TA011 | Subcompact Cars | Transportation goods | 0.06 | 5.64 | 5.73 | 29.5 | 45.0 |
| FP011 | Roasted Coffee | Processed food | 0.05 | 0.34 | 0.21 | 25.3 | 13.6 |
| TB022 | Alternative Automotive Fuels | Vehicle fuel | 0.05 | 0.68 | 0.07 | 55.5 | 52.8 |
| FR011 | Sugar and Artificial Sweeteners | Processed food | 0.05 | 0.16 | 0.08 | 16.3 | 14.0 |
| FL021 | Lettuce | Unprocessed food | 0.04 | 0.11 | 0.09 | 69.2 | 29.0 |
| FC011 | Uncooked Ground Beef | Unprocessed food | 0.04 | 0.53 | 0.32 | 29.4 | 26.2 |
| FH011 | Eggs In Shell | Unprocessed food | 0.04 | 0.24 | 0.16 | 64.7 | 42.1 |

*Notes*: The table shows the top 15 ELIs that drove the positive cross effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean frequency of price changes through the cross effect. First-half and last-half weight (freq) is the average weight (frequency of price changes) of the ELI in the 1978–2000 period and the 2001–2024 period, respectively, after rescaling for ELIs for which we do not have frequency data.
*Sources*: BLS, authors' calculations.

Table D.5: Weighted Mean Absolute Size of Price Changes: Negative Between Effect

| Code | Name | Spending Group | Contrib | First Weight | Last Weight | Mean Size |
|---|---|---|---|---|---|---|
| TA012 | New Motorcycles | Transportation goods | -0.27 | 0.29 | 0.17 | 5.2 |
| EB011 | Full College Tuition and Fixed Fees | Services (excluding travel) | -0.19 | 0.96 | 2.12 | 9.9 |
| TB013 | Premuim Unleaded Gasoline | Vehicle fuel | -0.14 | 0.66 | 2.0 | 5.2 |
| TB012 | Midgrade Unleaded Gasoline | Vehicle fuel | -0.14 | 0.68 | 2.0 | 5.5 |
| TE011 | Motor Vehicle Insurance | Services (excluding travel) | -0.09 | 2.75 | 4.95 | 5.7 |
| FV011 | Full Service Meals and Snacks | Services (excluding travel) | -0.08 | 3.14 | 4.16 | 6.7 |
| AC021 | Women's Dresses | Apparel | -0.07 | 0.55 | 0.2 | 19.3 |
| FV021 | Limited Service Meals and Snacks | Services (excluding travel) | -0.05 | 2.81 | 4.18 | 6.5 |
| FN011 | Cola Drinks | Processed food | -0.04 | 1.42 | 0.55 | 16.3 |
| TG031 | Intracity Mass Transit | Services (excluding travel) | -0.04 | 0.52 | 0.34 | 18.5 |
| FV041 | Candy/Gum/Crackers/Pastries/Chips/Similar Items | Services (excluding travel) | -0.03 | 0.95 | 0.13 | 16.1 |
| HF011 | Electricity | Utilities | -0.03 | 3.24 | 4.34 | 5.0 |
| AC032 | Women's Skirts | Apparel | -0.03 | 0.29 | 0.3 | 17.0 |
| AC033 | Women's Suits and Suit Components | Apparel | -0.03 | 0.19 | 0.02 | 16.3 |
| MC011 | General Medical Practice | Services (excluding travel) | -0.03 | 1.72 | 2.4 | 12.7 |

*Notes*: The table shows the top 15 ELIs that drove the negative between effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean absolute size of price changes through the between effect. First/last weight is the weight of the ELI in the first/last available year after rescaling for ELIs for which we do not have size data. Mean size is the average absolute size of price changes of the ELI from 1978 to 2024.
*Sources*: BLS, authors' calculations.

Table D.6: Weighted Mean Absolute Size of Price Changes: Positive Between Effect

| Code | Name | Spending Group | Contrib | First Weight | Last Weight | Mean Size |
|---|---|---|---|---|---|---|
| TA011 | Subcompact Cars | Transportation goods | 0.13 | 6.18 | 6.67 | 3.4 |
| ED031 | Cellular Telephones | Services (excluding travel) | 0.1 | 0.09 | 2.35 | 13.7 |
| TA021 | Used Cars | Transportation goods | 0.09 | 4.94 | 3.78 | 1.7 |
| RF021 | Admis. To Movies, Theaters, Concerts and Other Recurring Events | Services (excluding travel) | 0.07 | 0.23 | 0.66 | 15.9 |
| HB021 | Rental Of Lodging Away From Home | Travel | 0.06 | 0.77 | 1.95 | 18.3 |
| ED021 | Interstate Telephone Services | Services (excluding travel) | 0.05 | 1.06 | 0.77 | 5.4 |
| GA011 | Cigarettes | Other goods | 0.05 | 1.67 | 0.76 | 5.0 |
| HP043 | Inside Home Maintenance and Repair Services | Services (excluding travel) | 0.04 | 1.49 | 0.08 | 6.3 |
| HH011 | Room Size Rugs | Household furnishings | 0.04 | 3.02 | 0.14 | 6.7 |
| ED041 | Residential Telephone Services | Services (excluding travel) | 0.04 | 1.66 | 0.39 | 5.4 |
| AC031 | Women's Sweaters, and Sweater Vests | Apparel | 0.04 | 0.16 | 0.39 | 20.4 |
| MC021 | Prosthodontics and Implants | Services (excluding travel) | 0.04 | 1.16 | 1.32 | 10.3 |
| TB021 | Automotive Diesel Fuel | Vehicle fuel | 0.04 | 0.66 | 0.09 | 4.9 |
| FT062 | Spanish/Mexican Foods | Processed food | 0.03 | 0.23 | 0.67 | 14.5 |
| ED011 | Main Station Charges | Services (excluding travel) | 0.03 | 1.27 | 1.2 | 4.7 |

*Notes*: The table shows the top 15 ELIs that drove the positive between effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean absolute size of price changes through the between effect. First/last weight is the weight of the ELI in the first/last available year after rescaling for ELIs for which we do not have size data. Mean size is the average absolute size of price changes of the ELI from 1978 to 2024.
*Sources*: BLS, authors' calculations.

Table D.7: Weighted Mean Absolute Size of Price Changes: Negative Cross Effect

| Code | Name | Spending Group | Contrib | First Half Weight | Last Half Weight | First Half Size | Last Half Size |
|---|---|---|---|---|---|---|---|
| TA011 | Subcompact Cars | Transportation goods | -0.13 | 5.79 | 6.0 | 3.7 | 3.1 |
| HH011 | Room Size Rugs | Household furnishings | -0.08 | 0.77 | 0.08 | 6.9 | 6.5 |
| RG011 | Single Copy Newspapers and Magazines | Recreation goods | -0.06 | 0.45 | 0.06 | 15.1 | 21.4 |
| GD031 | Coin-Operated Apparel Laundry and Dry Cleaning | Services (excluding travel) | -0.04 | 0.92 | 0.4 | 11.2 | 8.7 |
| FV031 | Food At Employee Sites and Schools | Services (excluding travel) | -0.03 | 0.68 | 0.35 | 7.8 | 10.2 |
| RF021 | Admis. To Movies, Theaters, Concerts and Other Recurring Events | Services (excluding travel) | -0.03 | 0.47 | 0.8 | 18.9 | 13.1 |
| ED031 | Cellular Telephones | Services (excluding travel) | -0.02 | 0.08 | 1.9 | 5.1 | 14.8 |
| EB011 | Full College Tuition and Fixed Fees | Services (excluding travel) | -0.02 | 1.6 | 2.33 | 7.8 | 11.7 |
| HJ021 | Sofas Other Than Sofa Beds | Household furnishings | -0.02 | 0.32 | 0.34 | 8.3 | 9.9 |
| HD011 | Tenants' Insurance | Services (excluding travel) | -0.02 | 0.42 | 0.56 | 6.3 | 5.0 |
| FV041 | Candy/Gum/Crackers/Pastries/Chips/Similar Items | Services (excluding travel) | -0.02 | 0.81 | 0.17 | 13.4 | 19.8 |
| ED021 | Interstate Telephone Services | Services (excluding travel) | -0.02 | 0.97 | 1.1 | 6.2 | 3.2 |
| HP031 | Moving, Storage, Freight Express | Services (excluding travel) | -0.01 | 0.18 | 0.15 | 7.1 | 9.8 |
| HN011 | Soaps and Detergents | Household furnishings | -0.01 | 0.66 | 0.46 | 9.3 | 10.2 |
| EB021 | Elementary and High School Tuition and Fixed Fees | Services (excluding travel) | -0.01 | 0.48 | 0.58 | 4.8 | 5.1 |

*Notes*: The table shows the top 15 ELIs that drove the negative cross effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean absolute size of price changes through the cross effect. Weights are shown after rescaling for ELIs for which we do not have size data. First-half and last-half weight (size) is the average weight (absolute size of price changes) of the ELI in the 1978–2000 period and the 2001–2024 period, respectively, after rescaling for ELIs for which we do not have size data.
*Sources*: BLS, authors' calculations.

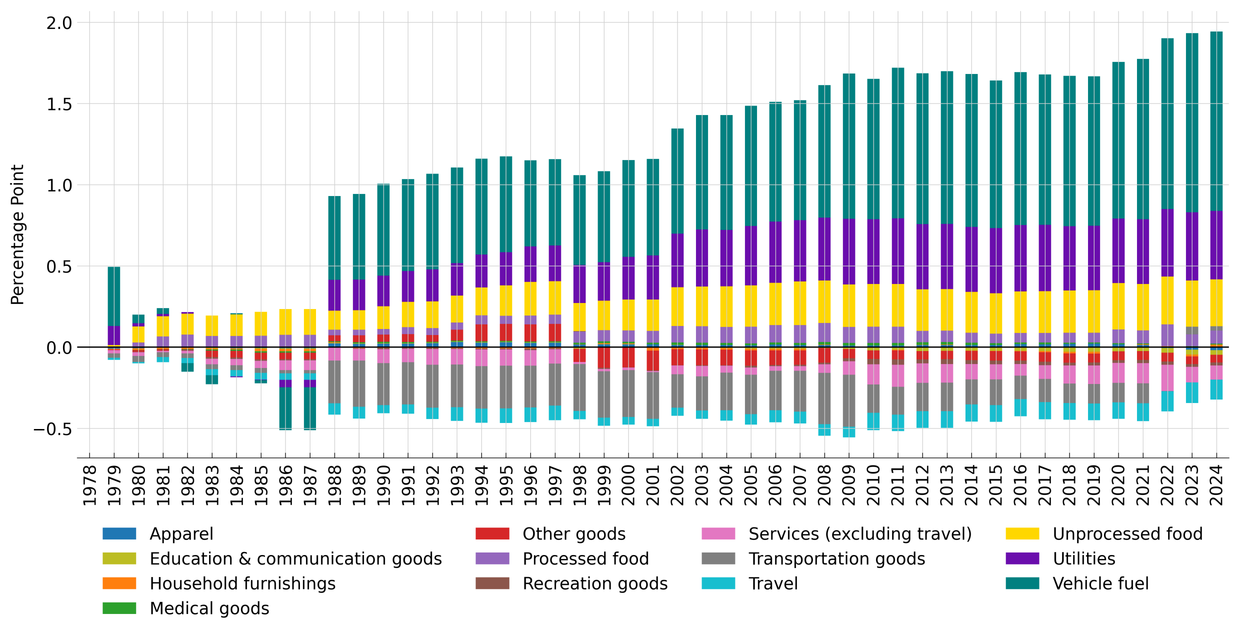
Table D.8: Weighted Mean Absolute Size of Price Changes: Positive Cross Effect

| Code | Name | Spending Group | Contrib | First Half Weight | Last Half Weight | First Half Size | Last Half Size |
|---|---|---|---|---|---|---|---|
| TB011 | Regular Unleaded Gasoline | Vehicle fuel | 0.15 | 4.1 | 2.18 | 4.3 | 6.6 |
| TA012 | New Motorcycles | Transportation goods | 0.14 | 0.73 | 0.13 | 5.6 | 4.3 |
| RF011 | Club Membership Dues | Services (excluding travel) | 0.1 | 0.88 | 0.95 | 15.6 | 13.9 |
| TE011 | Motor Vehicle Insurance | Services (excluding travel) | 0.08 | 3.17 | 3.62 | 6.5 | 5.0 |
| HB021 | Rental Of Lodging Away From Home | Travel | 0.07 | 2.02 | 2.28 | 17.6 | 18.9 |
| TB012 | Midgrade Unleaded Gasoline | Vehicle fuel | 0.06 | 0.88 | 2.13 | 4.2 | 6.2 |
| TB013 | Premuim Unleaded Gasoline | Vehicle fuel | 0.06 | 0.86 | 2.14 | 4.0 | 5.9 |
| FV011 | Full Service Meals and Snacks | Services (excluding travel) | 0.06 | 3.45 | 4.31 | 5.3 | 7.9 |
| HF021 | Utility Natural Gas Service | Utilities | 0.06 | 1.97 | 1.46 | 4.5 | 5.6 |
| AC032 | Women's Skirts | Apparel | 0.05 | 0.42 | 0.35 | 15.1 | 18.8 |
| HL012 | Paintings and Pictures | Household furnishings | 0.04 | 0.2 | 0.39 | 9.4 | 14.9 |
| HE011 | Fuel Oil | Utilities | 0.03 | 0.86 | 0.25 | 5.0 | 6.3 |
| AC031 | Women's Sweaters, and Sweater Vests | Apparel | 0.03 | 0.38 | 0.5 | 19.4 | 21.4 |
| AG021 | Jewelry | Apparel | 0.03 | 0.4 | 0.34 | 18.8 | 14.6 |
| TB022 | Alternative Automotive Fuels | Vehicle fuel | 0.03 | 0.7 | 0.08 | 4.5 | 8.4 |

*Notes*: The table shows the top 15 ELIs that drove the positive cross effect from 1978 to 2024. Contribution represents the percentage point effect of this ELI on the weighted mean absolute size of price changes through the cross effect. Weights are shown after rescaling for ELIs for which we do not have size data. First-half and last-half weight (size) is the average weight (absolute size of price changes) of the ELI in the 1978–2000 period and the 2001–2024 period, respectively, after rescaling for ELIs for which we do not have size data.
*Sources*: BLS, authors' calculations.

## D.4 Between and Cross Effects over Time: Decomposed by Sector

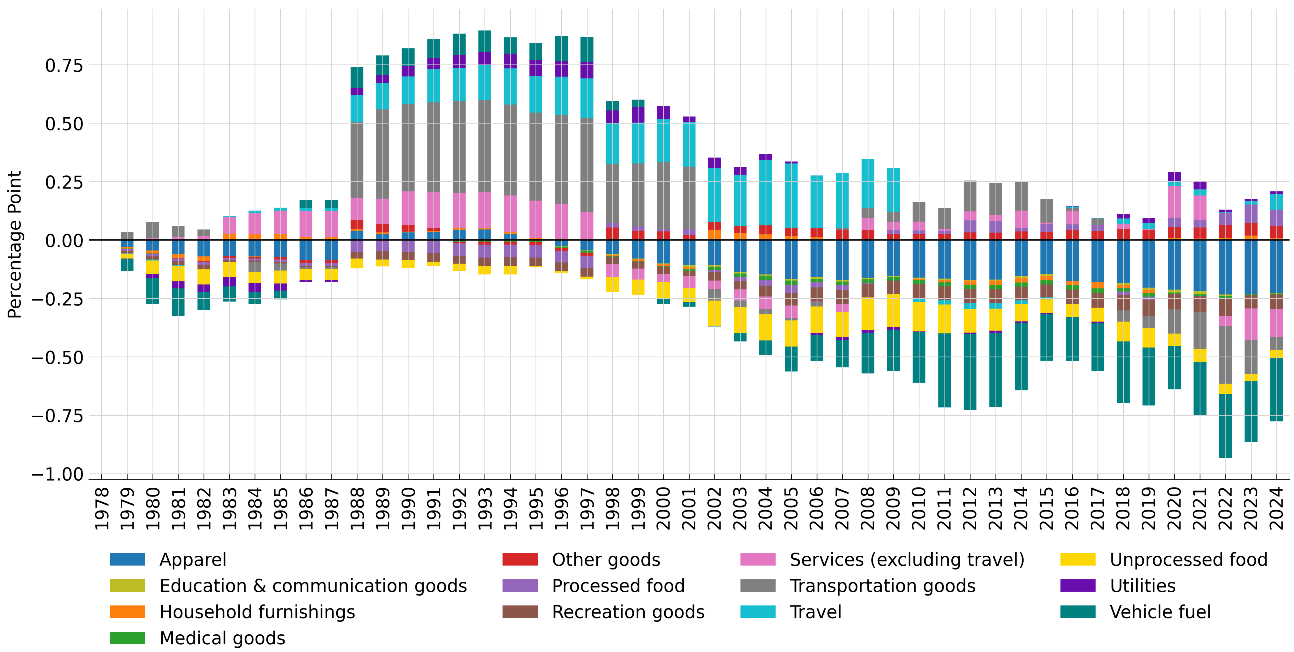
Figure D.15: Annual Decomposition of Cross Effect of the Weighted Mean Frequency of Price Changes by Sector



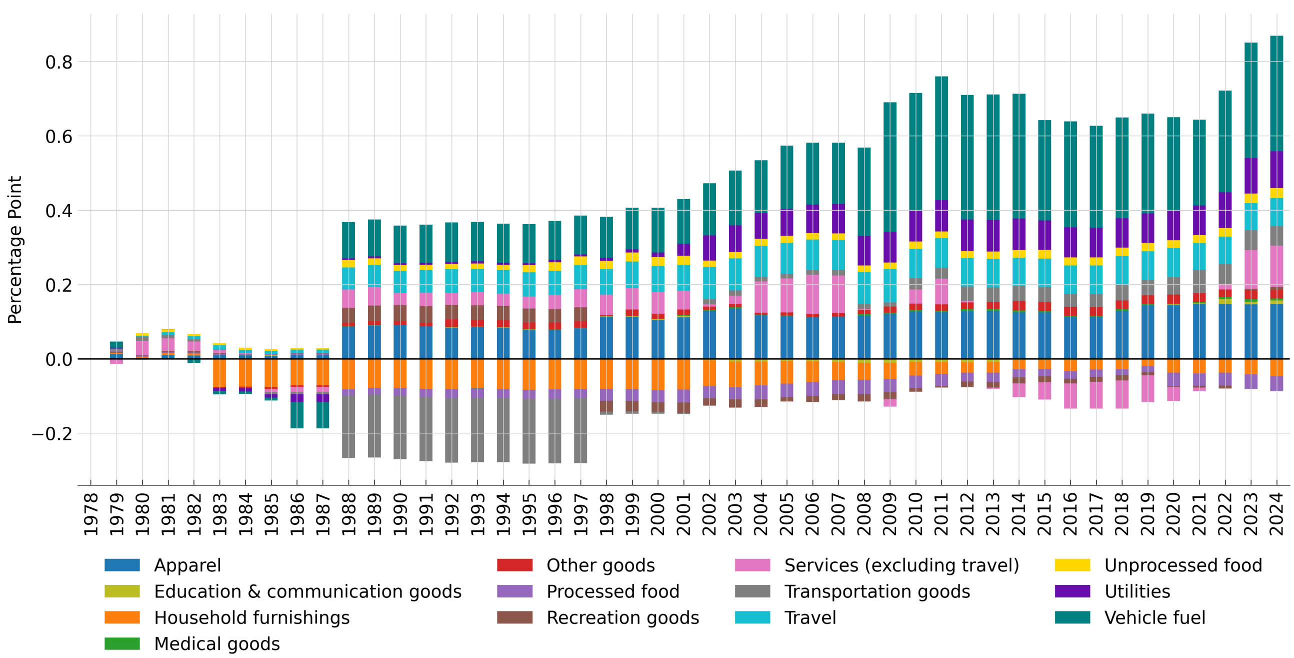

*Notes*: Each bar shows the contributions of each spending group to the cross effect for the weighted mean frequency of price changes between 1978 and the year on the x-axis.
*Sources*: BLS, authors' calculations.

Figure D.16: Annual Decomposition of the Between and Cross Effects of the Weighted Mean Absolute Size of Price Changes by Sector

(a) Between effect




(b) Cross effect




*Notes*: Each bar shows the contributions of each sector to the annual between (in Panel [a]) and cross (in Panel [b]) effects for the weighted mean absolute size of price changes between 1978 and the year on the x-axis.
*Sources*: BLS, authors' calculations.

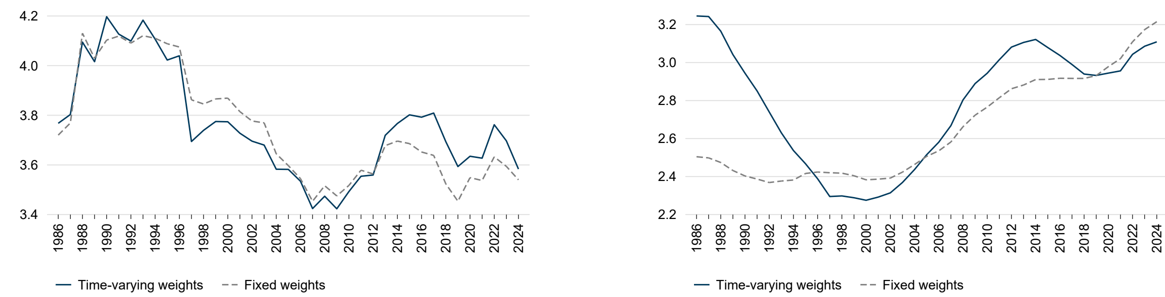
# E Section 6 (Implications for Monetary Non-Neutrality) Appendix

## E.1 Monetary Non-Neutrality: Time Series of the Sufficient Statistic

Following Alvarez, Le Bihan, and Lippi (2016), before computing the required moments for the sufficient statistic, we address the concern about heterogeneity in the size of price changes across ELIs by standardizing the size of price changes at the ELI level. To reduce potential measurement error, we then remove as "outliers" any observations with log-price changes larger in absolute value than the 99th percentile of absolute log price changes. We also drop any zero price changes.

Panels (a) and (b) of Figure E.1 show how the kurtosis of the size distribution of standardized price changes and the average number of price changes, respectively, evolve over rolling 10-year windows in our sample. The navy blue line depicts these moments based on distributions measured using time-varying expenditure weights, while the light blue line depicts them based on distributions measured using fixed weights. We find that the kurtosis under fixed weights is roughly similar to that under time-varying weights over the sample, with the difference being slightly more pronounced in the last 10 (rolling) years of the sample, when the fixed-weights approach attributes lower weights to ELIs that exhibit extreme price changes. The average number of price changes, on the other hand, is quite different under the two approaches: It is lower under fixed weights in the earlier part of the sample, from 1978 to 1996 and then again from 2006 to 2016; in the remainder of the sample it is higher under fixed weights than under time-varying weights.

Figure E.1: Evolution of the Moments Used in the Sufficient Statistic under Time-varying versus Fixed Weights, 1978–2024



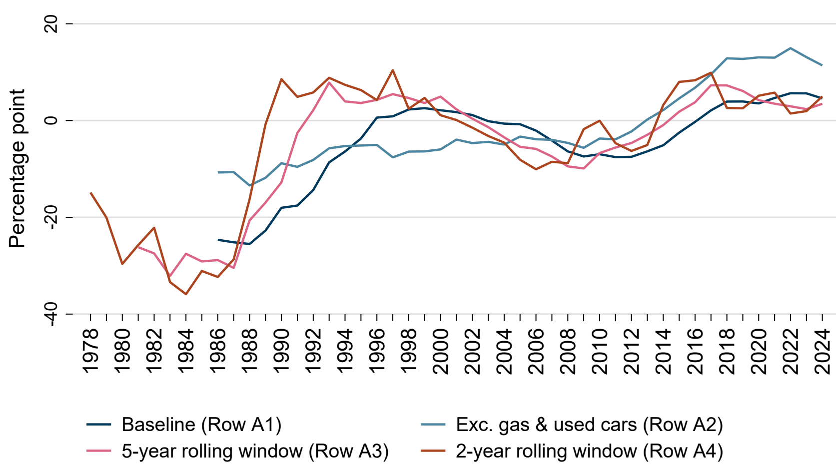

(a) Kurtosis of the size distribution of price changes

(b) Average number of price changes

*Notes*: The price-change statistics are computed as the weighted moments across all ELIs over rolling 10-year windows ending with the year denoted on the x-axis. For the kurtosis computation, we first standardize the price change by ELI. To compute the average number of price changes, we multiply the monthly frequency of price changes by 12. The underlying distributions are measured using concurrent ELI weights under the time-varying approach and year-2000 ELI weights in the fixed-weights approach.
*Sources*: BLS, authors' calculations.

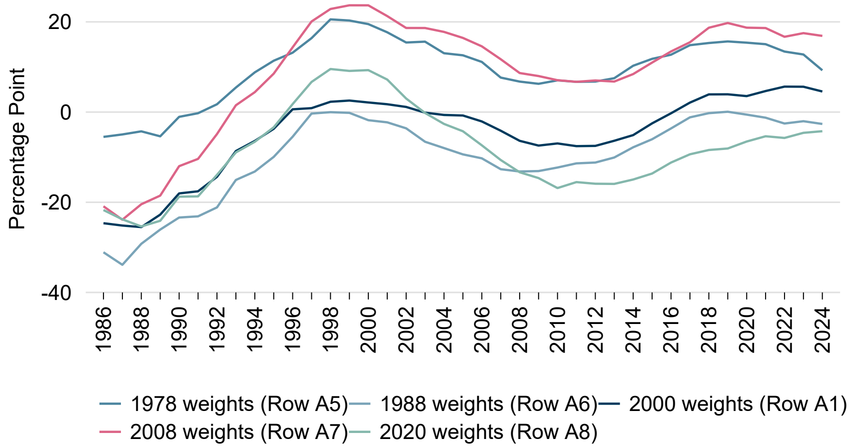
### E.1.1 Robustness Checks

Figure E.2: Sufficient Statistic under Time-varying versus Fixed Weights: Robustness Checks



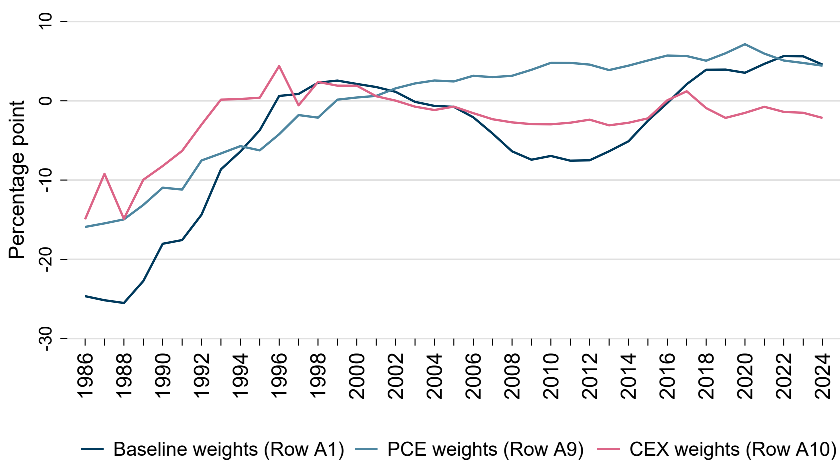

*Notes*: Each line shows the difference in the sufficient statistic computed under varying versus fixed weights, similarly to Figure 7b. The underlying sufficient statistics are computed as the ratio of the kurtosis of the size distribution of standardized price changes to the average number of price changes in 10-year rolling windows ending with the year denoted on the x-axis. The underlying distributions are measured using concurrent ELI weights under the time-varying approach and using the year-2000 ELI weights under the fixed-weights approach.
*Sources*: BLS, authors' calculations.

Figure E.3: Sufficient Statistic under Time-varying versus Fixed Weights: Weights Fixed to Different Years




*Notes*: Each line shows the difference in the sufficient statistic computed under varying versus fixed weights, similarly to Figure 7b. The underlying sufficient statistics are computed as the ratio of the kurtosis of the size distribution of standardized price changes to the average number of price changes in 10-year rolling windows ending with the year denoted on the x-axis. The underlying distributions are measured using concurrent ELI weights under the time-varying weights approach and ELI weights for the year specified in the legend under the fixed-weights approach.
*Sources*: BLS, authors' calculations.

Figure E.4: Sufficient Statistic under Time-varying versus Fixed Weights: Alternative Expenditure Weights




*Notes*: Each line shows the difference in the sufficient statistic computed under varying versus fixed weights, similarly to Figure 7b. The underlying sufficient statistics are computed as the ratio of the kurtosis of the size distribution of standardized price changes to the average number of price changes in 10-year rolling windows ending with the year denoted on the x-axis. The underlying distributions are measured using concurrent weights under the time-varying-weights approach and weights for the year 2000 under the fixed-weights approach.
*Sources*: BLS, authors' calculations.

## E.2 Multisector Calvo Model

### E.2.1 Model Setup

**Representative Household** The representative household has a relatively standard setup. At time $t+i$, they consume $C_{t+i}$ for price $P_{t+i}$, obtaining CRRA utility; they work $L_{t+i}$, yielding disutility for which they are paid a real wage, $W_{t+i}$. Households can invest in a nominal bond in time $t+i-1$ that pays a nominal interest rate of $I_{t+i}$ at time $t+i$. Their maximization problem is given by:

$$\max_{\{C_{t+i}, L_{t+i}, B_{t+i+1}\}_{i=0}^{\infty}} \mathbb{E}_t \left[ \sum_{i=0}^{\infty} \beta^i \left( \frac{C_{t+i}^{1-\gamma}}{1-\gamma} - \phi \frac{L_{t+i}^{1+\eta}}{1+\eta} \right) \right]$$

s.t.

$$P_{t+i} C_{t+i} + B_{t+i} I_{t+i-1} \leq P_{t+i} W_{t+i} L_{t+i} + B_{t+i+1}.$$

We can solve this to obtain standard Euler and consumption-leisure conditions:

$$C_t^{-\gamma} = \mathbb{E}_t \left[ \beta \frac{I_t}{\Pi_{t+1}} C_{t+1}^{-\gamma}) \right] \tag{E.1}$$

$$C_t^{-\gamma} W_t = \phi L_t^{\eta}, \tag{E.2}$$

where $\Pi$ is inflation, that is, $\Pi_{t+1} = \frac{P_{t+1}}{P_t}$.

**Final Goods Firms** There are $J$ sectors in the economy. Each sector $j$ has a continuum of monopolistic intermediate goods firms. The amount produced by a monopolistic firm $i$ in sector $j$ at time $t$ is denoted $Y_{i,j,t}$. The production of the monopolistic firms is aggregated to a final good for sector $j$, denoted $Y_{j,t}$ by a competitive final goods firm for that sector that has a CES production function:

$$Y_{j,t} = \left( \int_0^1 Y_{i,j,t}^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}. \tag{E.3}$$

Under standard CES computations, the monopolistic firms face the following demand:

$$Y_{i,j,t} = Y_{j,t} \left( \frac{P_{i,j,t}}{P_{j,t}} \right)^{-\sigma}, \tag{E.4}$$

where the price level $P_{j,t}$ is given by:

$$P_{j,t} = \left( \int_0^1 P_{i,j,t}^{1-\sigma} di \right)^{\frac{1}{1-\sigma}}. \tag{E.5}$$

Each sector has a weight $a_j$ in the overall economy, with the weights summing to one, that is, $\sum_{j=1}^{J} a_j = 1$. The amount produced in each sector $j$ at time $t$ is denoted $Y_{j,t}$. Another perfectly competitive firm aggregates the output from each sector. It has the following production function:

$$Y_t = \left( \sum_{j=1}^{J} a_j^{\frac{1}{\tau}} Y_{j,t}^{\frac{\tau-1}{\tau}} dj \right)^{\frac{\tau}{\tau-1}}. \tag{E.6}$$

Since this final goods firm has CES production, each sector faces the following demand:

$$Y_{j,t} = a_j Y_t \left( \frac{P_{j,t}}{P_t} \right)^{-\tau}. \tag{E.7}$$

Note that if $P_{j,t} = P_t$ then $Y_{j,t}$ equals $a_j Y_t$, in line with $a_j$ being the share of sector $j$ in the economy.

The aggregate price level is given by:

$$P_t = \left( \sum_{j=1}^{J} a_j P_{j,t}^{1-\tau} \right)^{\frac{1}{1-\tau}}. \tag{E.8}$$

This can be rewritten as:

$$1 = \sum_{j=1}^{J} a_j \left( \frac{P_{j,t}}{P_t} \right)^{1-\tau}. \tag{E.9}$$

**Monopolistic Firms Production** Firms have the following production function:

$$Y_{i,j,t} = L_{i,j,t}. \tag{E.10}$$

To aggregate this, we set the labor used in sector $j$ to be the integral of all labor used across the monopolistic firms, that is, $L_{j,t} = \int_0^1 L_{i,j,t} di$, and the labor used across the whole economy is just the labor used in each sector, that is, $L_t = \sum_{j=1}^{J} L_{j,t}$. We can then aggregate Equation (E.10) using Equation (E.4) to yield the sector-level production:

$$\int_0^1 Y_{i,j,t} di = \int_0^1 L_{i,j,t} di$$

$$\int_0^1 Y_{j,t} \left( \frac{P_{i,j,t}}{P_t} \right)^{-\sigma} di = L_{j,t}$$

$$Y_{j,t} \nu_{j,t} = L_{j,t}, \tag{E.11}$$

where we define sector-specific price dispersion as

$$\nu_{j,t} = \int_0^1 \left( \frac{P_{i,j,t}}{P_t} \right)^{-\sigma} di.$$

Inputting Equation (E.6) and then summing yields:

$$\sum_{j=1}^{J} a_j Y_t \left( \frac{P_{j,t}}{P_t} \right)^{-\tau} \nu_{j,t} = L_t.$$

This yields:

$$\nu_t Y_t = L_t, \tag{E.12}$$

where we define aggregate price dispersion as:

$$\nu_t = \sum_{j=1}^{J} a_j \left(\frac{P_{j,t}}{P_t}\right)^{-\tau} \nu_{j,t}. \tag{E.13}$$

We also observe that the marginal cost of the firm at time $t$, $MC_t$ is just the wage at time $t$:

$$MC_t = W_t. \tag{E.14}$$

**Monopolistic Firms' Pricing Problem** The monopolistic firms in sector $j$ only change their price with probability $\lambda_j$. We denote the price the monopolistic firms in sector $j$ that do get to change their price pick at time $t$ as $P^{\star}_{j,t}$. Monopolistic firms discount $k$ periods ahead by $M_{t,t+k}$. The monopolistic firm faces demand from the final goods firm in that sector given by Equation (E.4). The monopolistic firm in each sector therefore faces the following problem:

$$\max_{P^{\star}_{j,t}, Y_{i,j,t},\ldots} \mathbb{E}_t \left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k [\frac{P^{\star}_{j,t} Y_{i,j,t+k}}{P_{t+k}} - MC_{t+k} Y_{i,j,t+k}]\right]$$

s.t.

$$Y_{i,j,t+k} = Y_{j,t+k} \left(\frac{P^{\star}_{j,t}}{P_{j,t+k}}\right)^{-\sigma}.$$

We can input the constraint to obtain:

$$\max_{P^{\star}_{j,t}} \mathbb{E}_t \left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k Y_{j,t+k} P^{\sigma}_{j,t+k} [\frac{{P^{\star}_{j,t}}^{1-\sigma}}{P_{t+k}} - MC_{t+k} {P^{\star}_{j,t}}^{-\sigma}]\right].$$

Solving the maximization problem yields:

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k Y_{j,t+k} P^{\sigma}_{j,t+k} \left[(1-\sigma)\frac{{P^{\star}_{j,t}}^{-\sigma}}{P_{t+k}} + \sigma MC_{t+k} {P^{\star}_{j,t}}^{-\sigma-1}\right]\right] = 0.$$

Dividing by $(1-\sigma)P^{\star}_{j,t}{-\sigma-1}$, inputting $Y_{j,t+k}$ (Equation (E.7)), and dividing by $a_j P^{\sigma}_{j,t}$ yields:

$$\mathbb{E}_t\left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k Y_{t+k}\left(\frac{P_{j,t+k}}{P_{t+k}}\right)^{-\tau}\left(\frac{P_{j,t+k}}{P_{j,t}}\right)^{\sigma}\left[\frac{P^{\star}_{j,t}}{P_{t+k}}-\frac{\sigma}{\sigma-1}MC_{t+k}\right]\right]=0. \tag{E.15}$$

We define auxiliary variables to help rewrite the firm's problem in a more manageable form:

$$U_{j,t}=\mathbb{E}_t\left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k Y_{t+k}\left(\frac{P_{j,t+k}}{P_{t+k}}\right)^{-\tau}\left(\frac{P_{j,t+k}}{P_{j,t}}\right)^{\sigma}\left(\frac{P_{t+k}}{P_t}\right)^{-1}\right]$$

$$V_{j,t}=\mathbb{E}_t\left[\sum_{k=0}^{\infty} M_{t,t+k}(1-\lambda_j)^k Y_{t+k}\left(\frac{P_{j,t+k}}{P_{t+k}}\right)^{-\tau}\left(\frac{P_{j,t+k}}{P_{j,t}}\right)^{\sigma}\frac{\sigma}{\sigma-1}MC_{t+k}\right].$$

We observe that the following condition holds:

$$U_{j,t}\frac{P^{\star}_{j,t}}{P_{j,t}}\frac{P_{j,t}}{P_t}=V_{j,t}. \tag{E.16}$$

We can then rewrite $U_{j,t}, V_{j,t}$ recursively:

$$U_{j,t}=Y_t\left(\frac{P_{j,t}}{P_t}\right)^{-\tau}+\mathbb{E}_t[M_{t,t+1}(1-\lambda_j)\Pi^{\sigma}_{j,t+1}\Pi^{-1}_{t+1}U_{j,t+1}] \tag{E.17}$$

$$V_{j,t}=Y_t\left(\frac{P_{j,t}}{P_t}\right)^{-\tau}\frac{\sigma}{\sigma-1}MC_t+\mathbb{E}_t[M_{t,t+1}(1-\lambda_j)\Pi^{\sigma}_{j,t+1}V_{j,t+1}]. \tag{E.18}$$

We rewrite the price level definition for each sector $j$ as:

$$P^{1-\sigma}_{j,t}=\int_0^1 P^{1-\sigma}_{i,j,t}\,di$$

$$P^{1-\sigma}_{j,t}=\lambda_j P^{\star\,1-\sigma}_{j,t}+(1-\lambda_j)P^{1-\sigma}_{j,t-1}$$

$$1=\lambda_j\left(\frac{P^{\star}_{j,t}}{P_{j,t}}\right)^{1-\sigma}+(1-\lambda_j)\Pi^{\sigma-1}_{j,t}. \tag{E.19}$$

We can rewrite the price dispersion for sector $j$ as follows:

$$\nu_{j,t}=\int_0^1 P^{-\sigma}_{j,t}\,di$$

$$\nu_{j,t} = \lambda_j {P^{\star}_{j,t}}^{-\sigma} + (1-\lambda_j) \int_0^1 {P_{i,j,t-1}}^{-\sigma} di$$

$$\nu_{j,t} = \lambda_j \left(\frac{P^{\star}_{j,t}}{P_{j,t}}\right)^{-\sigma} + (1-\lambda_j) \int_0^1 \left(\frac{P_{i,j,t-1}}{P_{j,t}}\right)^{-\sigma} di$$

$$\nu_{j,t} = \lambda_j \left(\frac{P^{\star}_{j,t}}{P_{j,t}}\right)^{-\sigma} + (1-\lambda_j)\nu_{j,t-1}{\Pi_{j,t}}^{\sigma}. \tag{E.20}$$

We also note that sector-specific inflation is given by:

$$\frac{P_{j,t}}{P_{j,t-1}} = \frac{P_{j,t}}{P_t}\Pi_t \left(\frac{P_{j,t-1}}{P_{t-1}}\right)^{-1}. \tag{E.21}$$

We set the discounting by the monopolistic firm to be $M_{t,t+k} = \beta^k \frac{u'(C_{t+k})}{u'(C_t)}$, in line with the household's problem.

**Central Bank** We assume the central bank takes a similar form as in the multisector menu cost model. Therefore, the central bank sets nominal demand $S_t$:

$$S_t = P_t C_t.$$

Nominal demand evolves following a random walk:

$$\log(S_t) = \log(S_{t-1}) + \log(\bar{\Pi}) + \eta_t.$$

We rewrite both of these equations in difference form:

$$\frac{S_t}{S_{t-1}} = \Pi_t \frac{C_t}{C_{t-1}} \tag{E.22}$$

$$\log\left(\frac{S_t}{S_{t-1}}\right) = \log(\bar{\Pi}) + \eta_t. \tag{E.23}$$

**Resource Equation** The resource condition is:

$$Y_t = C_t y. \tag{E.24}$$

### E.2.2 DSGE Conditions

Thus, we obtain $8+6J$ equations (aggregate conditions equations (E.2), (E.9), (E.12) to (E.14) and (E.22) to (E.24) and a condition for each sector for equations (E.16) to (E.21)) over $8+6J$ unknowns ($L_t, \frac{S_t}{S_{t-1}}, C_t, W_t, \Pi_t, MC_t, Y_t, \nu_t$ and $6$ sector-specific variables $U_{j,t}, V_{j,t}, \frac{P_{j,t}}{P_t}, \frac{P^\star_{j,t}}{P_{j,t}}, \Pi_{j,t}, \nu_{j,t}$). Of these variables, $\frac{P_{j,t}}{P_t}, \nu_{j,t}, C_t$ are states for which we require the $t-1$ values, while the rest are controls.

### E.2.3 Log-linearized Conditions

These equations can be log-linearized.

For the eight aggregate equations:

$$-\gamma\hat{C}_t + \hat{W}_t = \eta\hat{L}_t$$

$$\hat{\nu}_t + \hat{Y}_t = \hat{L}_t$$

$$0 = \sum_{j=1}^{J}(1-\tau)a_j\overline{\left(\frac{P_j}{P}\right)}^{1-\tau}\widehat{\left(\frac{P_{j,t}}{P_t}\right)}$$

$$\widehat{MC}_t = \hat{W}_t$$

$$\bar{\nu}\hat{\nu}_t = -\sum_{j=1}^{J}\tau a_j\overline{\left(\frac{P_j}{P}\right)}^{-\tau}\bar{\nu}_j\left(\widehat{\left(\frac{P_{j,t}}{P_t}\right)} + \hat{\nu}_{j,t}\right)$$

$$\widehat{\frac{S_t}{S_{t-1}}} = \hat{\Pi}_t + \hat{C}_t - \hat{C}_{t-1}$$

$$\widehat{\frac{S_t}{S_{t-1}}} = \eta_t$$

$$\hat{Y}_t = \hat{C}_t.$$

For the six sector-level equations:

$$\hat{U}_{j,t} + \widehat{\left(\frac{P^\star_{j,t}}{P_{j,t}}\right)} + \widehat{\left(\frac{P_{j,t}}{P_t}\right)} = \hat{V}_{j,t}$$

$$\bar{U}_j\hat{U}_{j,t} = \left(\frac{\bar{P}_j}{\bar{P}}\right)^{-\tau}\bar{Y}\left(-\tau\widehat{\left(\frac{P_{j,t}}{P_t}\right)} + \hat{Y}_t\right) + \beta(1-\lambda_j)\bar{\Pi}^{\sigma-1}\bar{U}(\hat{M}_{t,t+1} + \sigma\hat{\Pi}_{j,t+1} - \hat{\Pi}_{t+1} + \hat{U}_{j,t+1})$$

$$\bar{V}_j\hat{V}_{j,t} = \left(\frac{\bar{P}_j}{\bar{P}}\right)^{-\tau}\bar{Y}\frac{\sigma}{\sigma-1}\bar{MC}\left(-\tau\widehat{\left(\frac{P_{j,t}}{P_t}\right)}+\hat{Y}_t+\hat{MC}_t+\hat{m}_t\right)+\beta(1-\lambda_j)\bar{\Pi}^{\sigma}\bar{V}_j(\hat{M}_{t,t+1}+\sigma\hat{\Pi}_{j,t+1}+\hat{V}_{j,t+1})$$

$$0 = (1-\sigma)\bar{\lambda}_j\left(\frac{P_j^\star}{P_j}\right)^{1-\sigma}\widehat{\left(\frac{P_{j,t}^\star}{P_{j,t}}\right)}+(\sigma-1)(1-\lambda_j)\bar{\Pi}^{\sigma-1}\hat{\Pi}_{j,t}$$

$$\hat{\Pi}_{j,t} = \widehat{\left(\frac{P_{j,t}}{P_t}\right)}+\hat{\Pi}_t-\widehat{\left(\frac{P_{j,t-1}}{P_{t-1}}\right)}$$

$$\bar{\nu}_j\hat{\nu}_{j,t} = -\sigma\lambda_j\left(\frac{P_j^\star}{P_j}\right)^{-\sigma}\widehat{\left(\frac{P_{j,t}^\star}{P_{j,t}}\right)}+(1-\lambda_j)\bar{\nu}_j\bar{\Pi}^{\sigma}(\hat{\nu}_{j,t-1}+\sigma\hat{\Pi}_{j,t}).$$

#### E.2.4 Steady State

We select the steady-state inflation level, $\bar{\Pi}$, which determines the growth in nominal demand through equation (E.22).

We can rewrite the price-updating equation (equation (E.19)) in steady state to calculate each sector's reset price in terms of inflation:

$$1 = \lambda_j\overline{\left(\frac{P_j^\star}{P_j}\right)}^{1-\sigma}+\frac{1-\lambda_j}{\Pi^{\star 1-\sigma}}$$

$$\overline{\left(\frac{P_j^\star}{P_j}\right)} = \left(\frac{1-\frac{1-\lambda_j}{\Pi^{\star 1-\sigma}}}{\lambda_j}\right)^{\frac{1}{1-\sigma}}. \tag{E.25}$$

The key step is then to back out the steady-state marginal cost. The firm's FOC condition (equation (E.15)) becomes, in steady state:

$$\sum_{k=0}^{\infty}(1-\lambda_j)^k\beta^k\Pi^{\star k\sigma}\left[\overline{\left(\frac{P_j^\star}{P}\right)}\frac{1}{\Pi^{\star k}}-\frac{\sigma}{\sigma-1}\bar{MC}\right]$$

$$\frac{1}{1-\frac{(1-\lambda_j)\beta\Pi^{\star\sigma}}{\Pi^\star}}\overline{\left(\frac{P_j^\star}{P}\right)} = \frac{1}{1-(1-\lambda_j)\beta\Pi^{\star\sigma}}\frac{\sigma}{\sigma-1}\bar{MC}$$

$$\bar{MC} = \frac{\sigma-1}{\sigma}\frac{1-(1-\lambda_j)\beta\Pi^{\star\sigma}}{1-(1-\lambda_j)\beta\Pi^{\star\sigma-1}}\overline{\left(\frac{P_j^\star}{P_j}\right)\left(\frac{P_j}{P}\right)}. \tag{E.26}$$

Note that we already know $\frac{P_j^\star}{P_j}$ from equation (E.25)).

Inversion yields:

$$\bar{MC}\left[\frac{\sigma}{\sigma-1}\frac{1-(1-\lambda_j)\beta\Pi^{\star\sigma-1}}{1-(1-\lambda_j)\beta\Pi^{\star\sigma}}\left(\frac{P_j^\star}{P_j}\right)^{-1}\right]=\overline{\left(\frac{P_j}{P}\right)}. \tag{E.27}$$

Next, we note that in steady state, the overall price equation (equation (E.9)) becomes:

$$\sum_{j=1}^{J}a_j\overline{\left(\frac{P_j}{P}\right)}^{1-\tau}=1. \tag{E.28}$$

Therefore, we can input equation (E.27) into equation (E.28) to yield:

$$\bar{MC}^{1-\tau}\sum_{j=1}^{J}\left(a_j\left[\frac{\sigma}{\sigma-1}\frac{1-(1-\lambda_j)\beta\Pi^{\star\sigma-1}}{1-(1-\lambda_j)\beta\Pi^{\star\sigma}}\left(\frac{P_j^\star}{P_j}\right)^{-1}\right]^{1-\tau}\right)=1.$$

This allows us to obtain $\bar{MC}$, which in turn allows us to determine $\frac{P_j}{P}$.

We can also compute the price dispersion steady state:

$$\bar{\nu}_j=(1-\lambda_j)\frac{\bar{\nu}_j}{\Pi^{\star-\sigma}}+\lambda_j\overline{\left(\frac{P_j^\star}{P_j}\right)}^{-\sigma}$$

$$(1-(1-\lambda_j)\Pi^{\star\sigma})\bar{\nu}_j=\lambda_j\overline{\left(\frac{P_j^\star}{P_j}\right)}^{-\sigma}.$$

This allows us to obtain $\bar{\nu}$ using equation (E.13).

The wage follows from equation (E.14):

$$\bar{W}=\overline{MC}.$$

$\phi$ is set such that $\bar{L}=1/3$. In this case, using equations (E.2), (E.12) and (E.24), we obtain:

$$\bar{Y}=\frac{\bar{L}}{\bar{\nu}}$$

$$\bar{C}=\bar{Y}$$

$$\phi=\bar{C}^{-\gamma}\bar{W}\bar{L}^{-\eta}.$$

### E.2.5 Calibration

We calibrate the model to closely match the multisector menu cost model. Therefore, we set $\gamma = 1, \eta = 0, \beta = 0.96^{\frac{1}{12}}, \sigma = 4, and \tau = 4$.We set the level of trend inflation to match what was observed in the economy during the decade under consideration.

The weights and price-change frequencies of the sectors $(a_j, \lambda_j)$ are set similarly to the multisector menu cost model. The frequencies are always set based on the decade under consideration. The weights are set based on that decade in the time-varying-weights case. The weights are set to be equal to their values in 2000 in the fixed-weights case.

We measure the cumulative output response as the sum of the deviation in output from its steady state in response to a one-time nominal demand shock.

## E.3 Multisector Menu Cost Model

### E.3.1 Model details

We construct a version of a multisector menu cost model as outlined in Nakamura and Steinsson (2010). The model includes three types of agents: a representative household, monopolistic firms operating across multiple sectors of production, and a central monetary authority. The model features both firm-specific idiosyncratic productivity shocks, drawn from a sector-specific distribution, and aggregate nominal demand shocks. The idiosyncratic productivity shocks are essential for realistically modeling firm-level pricing decisions that differ within each sector, while the aggregate shocks allow us to investigate the dynamics of the macroeconomic aggregates such as output and inflation and, crucially, the slope of the Phillips curve.

**A. Household**

A representative household maximizes expected discounted utility over an infinite horizon:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left[ \frac{1}{1-\gamma} C_{t+\tau}^{1-\gamma} - \frac{\omega}{\psi+1} L_{t+\tau}^{\psi+1} \right], \tag{E.29}$$

where $E_t$ denotes the mathematical expectation conditional on information available in period $t$, $\beta \in (0,1)$ is the discount factor, $L_t$ denotes the hours worked in period $t$, $\gamma$ is the coefficient of relative risk aversion, and $\omega$ and $\psi$ are the level and convexity parameters for labor disutility. $C_t$ is a Dixit–Stiglitz aggregate of consumption in period $t$ given by:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz\right]^{\frac{\theta}{\theta-1}}, \tag{E.30}$$

where $c_t(z)$ denotes the household consumption of good $z$ at time $t$, and $\theta > 1$ is the elasticity of substitution between the differentiated goods.

Expenditure minimization by the household implies that the demand for differentiated good $z$ in period $t$ is given by:

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t}\right)^{-\theta}, \tag{E.31}$$

where $p_t(z)$ is the price of differentiated good $z$ in period $t$, and $P_t$ is the aggregate price level in period $t$, given by:

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz\right]^{\frac{1}{1-\theta}}. \tag{E.32}$$

The budget constraint of the household is given by:

$$P_t C_t + E_t[D_{t,t+1} B_{t+1}] \leq B_t + W_t L_t + \int_0^1 \Pi_t(z) dz, \tag{E.33}$$

where $B_{t+1}$ is a random variable that denotes the state-contingent payoffs of the portfolio of financial assets purchased by the households in period $t$ and sold in period $t+1$, $D_{t,t+1}$ denotes the stochastic discount factor that prices these payoffs in period $t$, $W_t$ is the wage rate at time $t$, and $\Pi_t(z)$ denotes the profits of firm $z$ in period $t$.

The first-order conditions of the household's utility maximization subject to their budget constraint are:

$$D_{t,T} = \beta^{T-t} \left(\frac{C_T}{C_t}\right)^{-\gamma} \frac{P_t}{P_T}, \tag{E.34}$$

$$\frac{W_t}{P_t} = \omega L_t^{\psi} C_t^{\gamma}, \tag{E.35}$$

where equation (E.34) is the standard intertemporal Euler equation linking asset prices to the path of consumption, and equation (E.35) is the optimal labor supply condition.

**B. Firms**

The economy is divided into $J$ sectors. In each sector, there is a continuum of firms indexed by $z$. Each firm produces a differentiated good using intermediate products as well as labor. We follow Nakamura and Steinsson (2010) in incorporating intermediate products, but excluding them by setting $s_m = 0$ does not alter our results. The firm's production function is of the form:

$$y_t(z) = A_t(z)L_t(z)^{1-s_m}M_t(z)^{s_m}, \tag{E.36}$$

where $L_t(z)$ denotes the labor hours employed by firm $z$ in period $t$, $M_t(z)$ is a composite of intermediate inputs used by firm $z$ in period $t$, and $A_t(z)$ denotes firm $z$'s productivity in period $t$. The composite of intermediate inputs is given by:

$$M_t(z) = \left[\int_0^1 m_t(z,z')^{\frac{\theta-1}{\theta}} dz'\right]^{\frac{\theta}{\theta-1}}, \tag{E.37}$$

where $m(z, z')$ denotes the quantity of firm $z'$'s output used as an input by firm $z$.

Cost minimization by the firm implies that the demand for intermediate good $z'$ by firm $z$ in period $t$ is given by:

$$m_t(z,z') = M_t(z)\left(\frac{p_t(z')}{P_t}\right)^{-\theta}. \tag{E.38}$$

Adding consumer demand in equation (E.31) to intermediate demand in equation (E.38) yields the total demand for firm $z$'s output as a function of its relative price, given by:

$$y_t(z) = Y_t\left(\frac{p_t(z)}{P_t}\right)^{-\theta}, \tag{E.39}$$

where $Y_t = C_t + \int_0^1 M_t(z)dz$.

Finally, we assume that the firm's idiosyncratic productivity follows an AR(1) process in logs:

$$\log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t(z), \tag{E.40}$$

where $\epsilon_t \sim N(0, \sigma^2_{\epsilon,j})$ are independent, and the variance of the firm's idiosyncratic shocks is sector-specific.

Each firm $z$ maximizes the expected discounted value of its lifetime profit stream, given by:

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau}\Pi_{t+\tau}(z), \tag{E.41}$$

subject to its production function in equation (E.36) and demand for its product in equation (E.39).

Firm $z$'s profits in period $t$ are given by:

$$\Pi_t(z) = p_t(z)y_t(z) - W_t L_t(z) - P_t M_t(z) - \chi_j W_t I_t(z) - P_t U, \tag{E.42}$$

where $I_t(z)$ is an indicator variable equal to $1$ if the firm changes its price in period $t$ and $0$ otherwise. We introduce nominal rigidity into the model in the form of a menu cost $\chi_j$ by assuming that a firm in sector $j$ needs to hire an additional $\chi_j$ units of labor if it wants to change its price. $U$ is a fixed cost of production in terms of the real output—it does not affect the firm's optimal decision but is needed to reconcile the large estimated markups with the small profits observed in the national accounts data.

The presence of nominal rigidity makes the firm's optimization problem dynamic. We can write it in a recursive form as:

$$V\left(A_t(z), \frac{p_{t-1}(z)}{P_t}, \frac{S_t}{P_t}\right) = \max_{p_t(z)} \left\{\Pi_t^R(z) + E_t\left[D_{t,t+1}^R V\left(A_{t+1}(z), \frac{p_t(z)}{P_{t+1}}, \frac{S_{t+1}}{P_{t+1}}\right)\right]\right\}. \tag{E.43}$$

**C. Monetary Authority**

We assume that the monetary authority targets a path for the nominal aggregate demand, $S_t = P_t C_t$. Specifically, the log of the nominal aggregate demand follows a random walk with drift:

$$\log S_t = \mu + \log S_{t-1} + \eta_t, \tag{E.44}$$

where $\mu$ represents trend inflation, and $\eta_t \sim N(0, \sigma_\eta^2)$ are independent.

**D. Equilibrium**

The general equilibrium of the model consists of a sequence of stochastic price and quantity variables that satisfy the household's utility maximization problem, firms' profit maximization problems, and market clearing conditions, and are consistent with the given evolution of exogenous variables.

Solving for the equilibrium is an intractable problem, since the state space of the firm's problem includes the aggregate price level $P_t$, which is an infinite dimensional endogenous state variable, as per equation (E.32). To make the model tractable, we follow Nakamura and Steinsson (2010) by assuming that the firm's perceived evolution of the aggregate price level depends only on the nominal aggregate demand deflated by the preceding period's aggregate price level:

$$\frac{P_t}{P_{t-1}} = \Gamma\left(\frac{S_t}{P_{t-1}}\right). \tag{E.45}$$

This assumption makes the model tractable, as $P_{t-1}$, though endogenous, is in the firm's information set at time $t$, and $S_t$ follows an exogenous process. The general equilibrium solution is then obtained using value function iteration on a discretized state space. We refer readers interested in the details of the solution to the online appendix of Nakamura and Steinsson (2010).

### E.3.2 Sequential General-equilibrium Calibration Procedure

This appendix describes the calibration procedure used to discipline the sectoral menu cost and idiosyncratic productivity shock parameters in the multisector general-equilibrium model.

#### A. Targeted Moments and Parameters

The model features 13 production sectors. For each sector (i = 1,. . . ,13), we calibrate two parameters:

- $K_i$: the menu cost parameter governing the fixed cost of price adjustment, and
- $\sigma_{\varepsilon,i}$: the standard deviation of sector-specific idiosyncratic productivity shocks.

These parameters are chosen to match, at a monthly frequency, two empirical moments computed for each sector: 1) the mean frequency of price changes and 2) the mean absolute size of price changes.

The empirical targets correspond to sector-specific moments constructed for a particular decade (1978 through 1987 or 2015 through 2024) and a particular choice of weights (time-varying or fixed to a chosen year). The model is solved at a monthly frequency, with trend inflation set equal to the decade-specific annual CPI inflation rate converted to a monthly growth rate.

#### B. General-equilibrium Environment

For any given vector of sectoral parameters $\theta = \{K_i, \sigma_{\varepsilon,i}\}_{i=1}^{13}$, the model delivers a stationary general equilibrium characterized by an equilibrium mapping $G(\theta)$. This object governs the evolution of real prices through aggregate inflation and ensures consistency across firms' pricing decisions, the stationary distribution of states, and market clearing.

Importantly, the model-implied moments for any individual sector depend on the full parameter vector $\theta$ through general-equilibrium interactions. As a result, calibrating sectors independently in partial equilibrium would generally not deliver a joint general-equilibrium fit to the data.

### C. Sequential Block-coordinate Calibration Strategy

To avoid the computational burden of jointly optimizing over all 26 parameters while maintaining general-equilibrium consistency, we implement a sequential block-coordinate (Gauss–Seidel) calibration procedure.

The algorithm proceeds as follows.

*Step 0: Initialization*

We begin from a baseline parameter vector $\theta^{(0)}$, either taken from a prior calibration or set to common initial values across sectors. Given $\theta^{(0)}$, we solve the full general-equilibrium model to obtain a consistent equilibrium mapping $G^{(0)} = G(\theta^{(0)})$ and the associated sectoral moments.

*Step 1: Sector-by-Sector Updates within a Sweep*

For a given sweep (s = 1,2,. . . ) and for each sector (i = 1,. . . ,13), we perform the following steps:

1. Hold fixed all parameters $\{K_j, \sigma_{\varepsilon,j}\}_{j\neq i}$ at their current values.
2. Optimize over the two-dimensional parameter block $(K_i, \sigma_{\varepsilon,i})$ to reduce the discrepancy between the model-implied and empirical moments for sector $i$.

   During this optimization, candidate parameter values are evaluated using a **fast** general-equilibrium solver that:

   - is warm-started from the current equilibrium mapping $G$, and
   - performs only a limited number of fixed-point iterations on $G$.

   This step provides an accurate local approximation while substantially reducing computational cost.

3. Once the optimal $(K_i, \sigma_{\varepsilon,i})$ is selected for sector $i$, we re-solve the full general-equilibrium model, with tight convergence tolerances and warm-starting from the previous $G$, to obtain an updated equilibrium mapping consistent with the accepted parameters.

   After the full solve, the updated parameters and equilibrium mapping are carried forward to the next sector.

*Step 2: Iteration across Sweeps*

Completing steps (1) through (4) for all 13 sectors constitutes one sweep. Because general-equilibrium feedback implies that updating later sectors can affect the moments of earlier sectors, a single sweep is generally insufficient to achieve convergence.

We therefore repeat sweeps until both of the following criteria are satisfied: 1) The norm of the change in the full parameter vector across sweeps falls below a specified tolerance, and 2) the maximum absolute deviation between model-implied and empirical moments across all sectors falls below a specified tolerance.

### E.3.3 Calibration Results

Table E.1: Model Calibration: 1978–1987 Using Time-varying Weights

| | Sector 1 | Sector 2 | Sector 3 | Sector 4 | Sector 5 | Sector 6 | Sector 7 | Sector 8 | Sector 9 | Sector 10 | Sector 11 | Sector 12 | Sector 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data Freq | 0.062 | 0.092 | 0.121 | 0.122 | 0.139 | 0.141 | 0.144 | 0.157 | 0.263 | 0.367 | 0.572 | 0.590 | 0.646 |
| Model Freq | 0.062 | 0.092 | 0.121 | 0.122 | 0.139 | 0.141 | 0.144 | 0.157 | 0.262 | 0.366 | 0.572 | 0.590 | 0.646 |
| Data AbsSize | 0.117 | 0.081 | 0.091 | 0.099 | 0.081 | 0.093 | 0.072 | 0.087 | 0.115 | 0.119 | 0.040 | 0.045 | 0.039 |
| Model AbsSize | 0.117 | 0.081 | 0.091 | 0.099 | 0.081 | 0.093 | 0.072 | 0.087 | 0.095 | 0.085 | 0.040 | 0.045 | 0.039 |
| Data Weight | 0.055 | 0.301 | 0.078 | 0.038 | 0.011 | 0.003 | 0.034 | 0.099 | 0.019 | 0.086 | 0.127 | 0.075 | 0.074 |
| Model Weight | 0.055 | 0.301 | 0.078 | 0.038 | 0.011 | 0.003 | 0.034 | 0.099 | 0.019 | 0.086 | 0.127 | 0.075 | 0.074 |
| $K$ | 0.019 | 0.006 | 0.006 | 0.008 | 0.004 | 0.006 | 0.003 | 0.005 | 0.003 | 0.002 | 0.000 | 0.000 | 0.000 |
| $\sigma_\varepsilon$ | 0.054 | 0.035 | 0.043 | 0.048 | 0.039 | 0.046 | 0.034 | 0.043 | 0.054 | 0.054 | 0.030 | 0.035 | 0.031 |

*Notes*: Each panel shows the sectoral frequency of price changes, absolute size of price changes, and weight from the data and the calibrated model, along with the final calibrated parameters $\theta = \{K_i, \sigma_{\varepsilon,i}\}_{i=1}^{13}$.
*Sources*: BLS, authors' calculations.

Table E.2: Model Calibration: 2015–2024 Using Time-varying Weights

| | Sector 1 | Sector 2 | Sector 3 | Sector 4 | Sector 5 | Sector 6 | Sector 7 | Sector 8 | Sector 9 | Sector 10 | Sector 11 | Sector 12 | Sector 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data Freq | 0.072 | 0.095 | 0.102 | 0.123 | 0.126 | 0.143 | 0.172 | 0.178 | 0.220 | 0.618 | 0.648 | 0.820 | 0.895 |
| Model Freq | 0.072 | 0.095 | 0.102 | 0.123 | 0.126 | 0.143 | 0.172 | 0.178 | 0.220 | 0.618 | 0.648 | 0.812 | 0.895 |
| Data AbsSize | 0.149 | 0.087 | 0.137 | 0.117 | 0.095 | 0.127 | 0.120 | 0.082 | 0.162 | 0.046 | 0.032 | 0.194 | 0.062 |
| Model AbsSize | 0.149 | 0.087 | 0.137 | 0.117 | 0.095 | 0.127 | 0.120 | 0.082 | 0.162 | 0.046 | 0.031 | 0.102 | 0.062 |
| Data Weight | 0.043 | 0.441 | 0.080 | 0.051 | 0.025 | 0.030 | 0.010 | 0.022 | 0.050 | 0.055 | 0.111 | 0.027 | 0.056 |
| Model Weight | 0.043 | 0.441 | 0.080 | 0.051 | 0.025 | 0.030 | 0.010 | 0.022 | 0.050 | 0.055 | 0.111 | 0.027 | 0.056 |
| $K$ | 0.025 | 0.007 | 0.017 | 0.011 | 0.007 | 0.011 | 0.008 | 0.004 | 0.012 | 0.000 | 0.000 | 0.000 | 0.000 |
| $\sigma_\varepsilon$ | 0.071 | 0.042 | 0.067 | 0.058 | 0.047 | 0.064 | 0.062 | 0.042 | 0.089 | 0.037 | 0.025 | 0.099 | 0.064 |

*Notes*: Each panel shows the sectoral frequency of price changes, absolute size of price changes, and weight from the data and the calibrated model, along with the final calibrated parameters $\theta = \{K_i, \sigma_{\varepsilon,i}\}_{i=1}^{13}$.
*Sources*: BLS, authors' calculations.

## Table E.3: Model Calibration: 1978–1987 Using Fixed Weights

| | Sector 1 | Sector 2 | Sector 3 | Sector 4 | Sector 5 | Sector 6 | Sector 7 | Sector 8 | Sector 9 | Sector 10 | Sector 11 | Sector 12 | Sector 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data Freq | 0.064 | 0.090 | 0.119 | 0.132 | 0.140 | 0.146 | 0.151 | 0.154 | 0.246 | 0.402 | 0.468 | 0.596 | 0.646 |
| Model Freq | 0.065 | 0.090 | 0.120 | 0.132 | 0.139 | 0.146 | 0.155 | 0.153 | 0.242 | 0.399 | 0.468 | 0.596 | 0.646 |
| Data AbsSize | 0.118 | 0.084 | 0.095 | 0.098 | 0.080 | 0.093 | 0.067 | 0.086 | 0.131 | 0.132 | 0.045 | 0.047 | 0.039 |
| Model AbsSize | 0.118 | 0.084 | 0.098 | 0.053 | 0.083 | 0.097 | 0.069 | 0.087 | 0.098 | 0.084 | 0.044 | 0.047 | 0.039 |
| Data Weight | 0.065 | 0.389 | 0.050 | 0.036 | 0.017 | 0.005 | 0.032 | 0.082 | 0.051 | 0.059 | 0.109 | 0.053 | 0.051 |
| Model Weight | 0.065 | 0.389 | 0.050 | 0.036 | 0.017 | 0.005 | 0.032 | 0.082 | 0.051 | 0.059 | 0.109 | 0.053 | 0.051 |
| $K$ | 0.018 | 0.007 | 0.007 | 0.002 | 0.005 | 0.006 | 0.003 | 0.005 | 0.004 | 0.002 | 0.000 | 0.000 | 0.000 |
| $\sigma_\varepsilon$ | 0.055 | 0.037 | 0.047 | 0.022 | 0.040 | 0.048 | 0.033 | 0.043 | 0.055 | 0.055 | 0.030 | 0.036 | 0.031 |

*Notes*: Each panel shows the sectoral frequency of price changes, absolute size of price changes, and weight from the data and the calibrated model, along with the final calibrated parameters $\theta = \{K_i, \sigma_{\varepsilon,i}\}_{i=1}^{13}$.
*Sources*: BLS, authors' calculations.

## Table E.4: Model Calibration: 2015–2024 Using Fixed Weights

| | Sector 1 | Sector 2 | Sector 3 | Sector 4 | Sector 5 | Sector 6 | Sector 7 | Sector 8 | Sector 9 | Sector 10 | Sector 11 | Sector 12 | Sector 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data Freq | 0.073 | 0.094 | 0.103 | 0.121 | 0.123 | 0.148 | 0.207 | 0.210 | 0.221 | 0.638 | 0.638 | 0.820 | 0.897 |
| Model Freq | 0.073 | 0.094 | 0.103 | 0.121 | 0.123 | 0.148 | 0.207 | 0.210 | 0.221 | 0.638 | 0.639 | 0.814 | 0.954 |
| Data AbsSize | 0.147 | 0.083 | 0.136 | 0.116 | 0.095 | 0.143 | 0.134 | 0.064 | 0.153 | 0.035 | 0.047 | 0.188 | 0.062 |
| Model AbsSize | 0.147 | 0.083 | 0.136 | 0.116 | 0.095 | 0.143 | 0.134 | 0.064 | 0.153 | 0.034 | 0.041 | 0.139 | 0.058 |
| Data Weight | 0.065 | 0.389 | 0.082 | 0.050 | 0.017 | 0.036 | 0.005 | 0.032 | 0.059 | 0.109 | 0.053 | 0.051 | 0.051 |
| Model Weight | 0.065 | 0.389 | 0.082 | 0.050 | 0.017 | 0.036 | 0.005 | 0.032 | 0.059 | 0.109 | 0.053 | 0.051 | 0.051 |
| $K$ | 0.024 | 0.007 | 0.016 | 0.010 | 0.007 | 0.013 | 0.009 | 0.002 | 0.011 | 0.000 | 0.000 | 0.001 | 0.000 |
| $\sigma_\varepsilon$ | 0.070 | 0.039 | 0.067 | 0.057 | 0.046 | 0.073 | 0.072 | 0.033 | 0.084 | 0.026 | 0.033 | 0.135 | 0.064 |

*Notes*: Each panel shows the sectoral frequency of price changes, absolute size of price changes, and weight from the data and the calibrated model, along with the final calibrated parameters $\theta = \{K_i, \sigma_{\varepsilon,i}\}_{i=1}^{13}$.
*Sources*: BLS, authors' calculations.