Was the Post-Lockdown Inflation Surge Mainly Supply Driven?*

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Abstract

This paper studies PCE price and quantity changes at the disaggregate level using a generalization of Shapiro's (2024) inflation decomposition method, adapted to account for inflation dynamics. We apply the decomposition to analyze drivers of high inflation in PCE core goods and services between late 2020 and 2022. We benchmark the technique using a classic supply disruption, the 1973 oil embargo and find that 75 percent of non-trend inflation immediately following the embargo was supply-push. In contrast, 33 percent of non-trend inflation was supply-push following the pandemic lockdown. Restricting attention to categories with market-based prices, this falls to 26 percent.

1 Introduction

In October 1973, Saudi Arabia placed a total embargo on oil shipments to the U.S., with many other Arab oil producing countries following suit. By January 1974, the nominal price of oil had more than doubled; it continued to increase for years. Following the embargo, the US experienced stagflation: The price level of aggregate consumption excluding food and energy rose 16.5 percent over the next two years, while real quantities grew only 2.7 percent (see Table 1). These facts have led many macro textbooks to describe the event as

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the archetypal negative supply shock – a shift in the aggregate supply curve that raised costs and pushed prices up.[1]

In contrast to the consensus about post-oil shock inflation, the jury is still out regarding the causes of inflation after the pandemic lockdown. While some read the data as a positive aggregate demand shock, often citing the large fiscal stimuli that preceded the inflation, others have made the case for negative supply shocks. Describing then ongoing elevated price growth, Attinasi et al. (2021) wrote that "idiosyncratic supply chain disruptions (owing to the waves of the pandemic and adverse weather events, for instance) have also played a role, capping activity and trade growth and ultimately pushing up prices." In an article entitled "COVID-19 Inflation Was a Supply Shock," Brooks et al. (2024) wrote "the vast majority of the COVID-19 inflation surge is accounted for by supply-linked factors" and largely focus their analysis on supply-chain disruptions and longer delivery lags during the period.[2] As of 2025, many continue to describe post-lockdown price growth as supply driven. For example, in an ASSA 2025 panel discussion, Ben Bernanke stated "inflation was caused pretty much by the supply side," citing auto production as one example: ". . . The biggest quarter of price spikes of autos were accompanied by a sharp decline in the production of autos suggesting there was at least some supply side to that. My conclusion from that is that it was mostly a supply shock." (Bernanke et al., 2025, 4:12)

Should both experiences be taught as adverse supply shocks? The aggregate data suggest otherwise. While inflation was high in both cases, consumption growth was anemic for the former and robust for the latter (see Table 1).[3] *Prima faciea*, the more recent episode was not due to a negative supply shock.

In this paper, we generalize the supply-demand inflation decomposition introduced by Shapiro (2024), using it to conduct a detailed, disaggregate measurement of price and quantity co-movements at the consumption category level after both the oil shock and lockdown, which we then reconcile with the aggregate data. The exercise confirms the supply-push inflation pattern for the oil shock episode while disfavoring the supply-push explanation post-lockdown. 75 percent of the oil shock inflation was driven by supply-push inflation

[1] See for example Abel et al. (2010, Chapter 9), Hubbard and O'Brien (2018, Chapter 13), and Mankiw (2025, Chapter 20).

[2] In the conclusion, the authors do qualify their analysis: "A further complication stems from the fact that stretched delivery times and elevated margins inevitably have a demand component."

[3] We focus specifically on 2021 through 2022. Late 2020 ushered in the post-lockdown phase because, by this time, most schools had returned to in-person learning and various mobility indices (e.g., Her et al. (2022) and the Dallas Federal Reserve Bank's mobility index) had largely recovered from earlier lows; moreover, inflation did not ramp up early in the pandemic.

categories.[4] By contrast, we find only 33 percent of core post-lockdown inflation was driven by categories with negatively co-moving quantity and price growth VAR innovations (i.e., supply-push inflation categories). At the same time, the decomposition supports anecdotal evidence for negative supply shocks concentrated in a subset of categories, including autos and auto-related goods and services. We find that supply shocks *did* push prices up within these sectors. At the aggregate level, however, inflationary supply shocks were overshadowed by changes within categories that experienced two other types of price-quantity correlations: (i) elevated inflation in high-growth categories (i.e., demand-pull); (ii) high quantity growth *and* low price growth (i.e., deflationary supply-push). Summing across categories, on net inflation was mainly demand-pull. Moreover, restricting the consumption basket to exclude non-market categories (those for which prices are imputed) increase the share of inflation driven by demand to 75 percent; outside of sectors like autos, supply-driven inflation originated disproportionately from imputed prices.

According to Shapiro's method, if a category's consumption growth and inflation forecast errors share the same sign, then that category's inflation is assigned to demand. Otherwise it is assigned to supply. His tool is powerful for two reasons. First, it is simple and elegant. While requiring few assumptions, the method both tracks price and quantity comovement at the disaggregate level and summarizes that comovement into an aggregate measure. Second, the comovement it tracks is highly relevant given the prevalence of the supply-demand concept in economics. Shapiro's approach has been applied by other researchers to European countries and Australia,[5] and made its way into several central bankers' published remarks.[6] The generalization in this paper, developed by Max Dvorkin, augments Shapiro (2024) by assigning part of the decomposition of inflation to trend and decomposing innovations into their current and expected future effects on inflation. We motivate the generalization in the following section and present a detailed comparison between this paper's and Shapiro's approach in 4.

The outline of the paper follows. Section 2 describes the method. Section 3 applies the decomposition to the two episodes, and then interprets the behavior of key consumption categories during the post-lockdown period. Section 4 compares our results to those based on the Shapiro's decomposition. Section 5 concludes.

[4] Note that our supply-driven inflation finding applies to the first two years after the oil shock. Examining inflation and its causes in the remainder of that decade is beyond the scope of this paper.

[5] See Beckers et.al. (2022), Eickmeier and Hoffman (2022), Goncalves and Koester (2022) and Hoffman et.al. (2022)

[6] See, for example, Federal Reserve officials Brainard (2022), Collins (2023), Daly (2024), Kugler (2024), Waller (2022) and Lane (2023).

2 Parsing Categories by P & Q Comovement

Let $p_{i,t}$ and $q_{i,t}$ denote the log price level and log real quantity for consumption category i in month t respectively. Next, define $Y_{i,t} = [\Delta p_{i,t}, \Delta q_{i,t}]'$.

We estimate a K-order vector autoregression (VAR):

$$Y_{i,t} = C_i + \sum_{j=1}^{K} \Phi^i_j Y_{i,t-j} + W_{i,t} \tag{1}$$

The first and second elements of $W_{i,t}$ are denoted $\varepsilon^i_{p,t}$ and $\varepsilon^i_{q,t}$ respectively.

For each i, the algorithm proceeds in three steps.

1. Estimate (1) to recover $\hat{W}_{i,t}$ and calculate the implied moving average coefficients $\hat{\Psi}^i_j$ for all j.[7]

2. Classify each (i,t) pair into one of two types: demand-pull or supply-push. Category i at time t is a supply-push category if $\hat{\varepsilon}^i_{p,t}\hat{\varepsilon}^i_{q,t} < 0$. We denote this $\mathcal{S}_{i,t} = 1$. Otherwise, classify the (i,t) pair as demand-pull and let $\mathcal{S}_{i,t} = 0$.

3. Having classified each (i,t) pair and estimated the corresponding moving average coefficients, we write down the following representation:

$$Y_{i,t} = \underbrace{\hat{\mu}_{i,t}}_{\text{trend}} + \underbrace{\mathcal{S}_{i,t}\hat{W}_{i,t}}_{\text{current supply}} + \underbrace{(1-\mathcal{S}_{i,t})\,\hat{W}_{i,t}}_{\text{current demand}} + \underbrace{\sum_{j=1}^{T} \mathcal{S}_{i,t-j}\hat{\Psi}^i_j \hat{W}_{i,t-j}}_{\text{past supply}} + \underbrace{\sum_{j=1}^{T} (1-\mathcal{S}_{i,t-j})\,\hat{\Psi}^i_j \hat{W}_{i,t-j}}_{\text{past demand}} \tag{2}$$

   While the true moving-average representation may be infinite order, we truncate the number of lags considered at T in the above formula.[8]

We separately estimate the decomposition's underlying VAR separately for the oil shock and post-lockdown episodes, using data from 1960 through 1976 and 1990 through 2023 respectively and setting $K = 12$ in each case.[9] Note that the results from the decomposition will depend upon details of the VAR specification, such as the chosen lag length, the level of disaggregation of categories chosen, and the sample off of which the VAR is estimated.

[7] See Hamilton (1994, Chapter 11) for a description of this mapping.

[8] We provide the formula for $\hat{\mu}_{i,t}$ and $\hat{\Psi}^i_j$ in the appendix.

[9] For a discussion of the effect including the pandemic period has on the VAR estimation, see Appendix B.

We will sometimes refer to the components of (2) as shocks. Under this terminology, a category is subject to a positive (negative) *current demand shock* in period t when the innovations to both price growth and quantity growth are positive (negative) in that period. On the other hand, a positive (negative) *current supply shock* means that the price growth innovation was negative (positive) and the quantity growth innovation was positive (negative). In each case, the shock's size is equal to the corresponding price growth innovation. Next, the estimated dynamics will imply a period $t+j$ expected impact of an inflation innovation that happens at t. The past shock contribution at time t is the sum of these implied expected inflation movements based on the current demand (supply) shocks that happened at $t-1$, $t-2$, ... This appears as past demand (supply) in (2).

We define aggregate shocks by taking weighted sums of category level shocks. For a given month and category, we define a category's weight as the geometric mean of its nominal expenditure share in that month and the previous month. Letting $N_{i,t}$ be nominal spending on category i during month t, the weight is:

$$\omega_{i,t} = \sqrt{\frac{N_{i,t} N_{i,t-1}}{\sum_j N_{j,t} \sum_j N_{j,t-1}}}$$

We use these weights to sum across category-level price changes, yielding month over month log changes in the aggregate price (quantity) level.[10] The contribution towards overall consumption inflation of current supply, current demand, past supply, and past demand are in turn:

$$\sum_i \omega_{i,t} \mathcal{S}_{i,t} \hat{\epsilon}^p_{i,t}$$

$$\sum_i \omega_{i,t} \left(1 - \mathcal{S}_{i,t}\right) \hat{\epsilon}^p_{i,t}$$

$$\sum_{j=1}^{T} \omega_{i,t} \mathcal{S}_{i,t-j} \hat{\Psi}^i_j \hat{W}_{i,t-j}$$

$$\sum_{j=1}^{T} \omega_{i,t} \left(1 - \mathcal{S}_{i,t-j}\right) \hat{\Psi}^i_j \hat{W}_{i,t-j}$$

[10]In doing so, we attempt to recreate the BEA's weights: The BEA does not use a fixed basket of goods to weight price growth across categories when aggregating to the PCE. Instead, a category's weight for the price change between t_0 and t_1 is equal to the geometric mean of its share of total nominal personal consumption expenditures for t_0 and t_1. This weighting method, called the Fisher index, tries to account for consumers' substitution between categories by including information from multiple time periods (NIPA Handbook Chapter 5).

To calculate aggregate changes over longer horizons, we sum aggregate month-over-month changes for the relevant period.

The decomposition *measures* the unforecastable components of price and quantity movements and then *classifies* each category-time observation based upon their joint directions of movement. However, this exercise is distinct from statistical identification. From a known explanatory mechanism (model), with a set of potential underlying parameters, identifiability means it is theoretically possible to uncover the true parameter values after obtaining an infinite number of observations from it.[11] We neither specify a model and model parameters; as such, they do not constitute identification.[12]

The delineation of supply and demand shocks should be interpreted with caution. The method provides a definition, or naming convention, for a particular comovement pattern in the data. Along those lines, we envision situations in which the naming convention might accord poorly with the fundamental drivers of inflation, particularly for categories within PCE, like nonprofits and certain financial services, for which price indices are imputed rather than directly reflecting market prices.[13]

3 Empirical Results

3.1 Methodology

Figure 1 plots the decomposition for two 11-year periods, each of which contains one of the episodes. The green area corresponds to the year-over-year price growth contribution from trend. Note that because we let weights change over time and calculate all inflation (growth) components—including trend—at the category level before summing them for the aggregate decompositions, the aggregate trend can change over time. Changes in the aggregate trend therefore reflect the redistribution of consumption across categories, rather than changes in categories' trends themselves.

Dark red represents the weighted sum of the VAR innovations to inflation coming from demand-pull categories during the current period (both inflationary and disinflationary). Next, categories typically exhibit serial correlation. As such, past innovations have an expected impact on the current outcome variable through the autoregressive structure of the

[11] Here, we refer to point rather than set identification.

[12] For examples of papers that use the supply-demand concept for identification (either set or point) applied to the pandemic period, see Brinca et al. (2021) and Giannone and Primiceri (2024).

[13] For a discussion of how results change when we focus only on market consumption, see section 3.3.

time series. For example, a positive inflation innovation forecasts additional inflation in near future months for some categories. As such, we also track this impact as "past demand" in light red. Past demand represents the estimated dynamic impact from "current period" demand-pull inflation during previous periods. Similarly, dark blue and light blue indicate current and past inflation associated with supply-push categories.

Both panels exhibit dramatic inflation increases above trend on the rightward side of their respective charts. Between late 1973 through 1975, the non-trend contribution of inflation is primarily supply (light and dark blue), consistent with textbook interpretations of the 1973 oil shock. For the post-lockdown period, while supply-push inflation categories contribute to inflation starting in 2021, the majority of non-trend contribution of inflation is demand-pull (light and dark red). As a robustness exercise, we also decompose post-lockdown inflation using a VAR that excludes 2020-2022; under this alternative specification, an even larger share of inflation above trend appears demand driven (see Appendix Section B).

Figure 2 plots the cumulative change in the price level rather than the inflation rate during each of the episodes. In addition, we transform the data by subtracting trend price growth to highlight the contributions of supply and demand contributions.

During the oil shock period, nearly three-quarters of non-trend inflation stems from supply-push categories (panel (a)), and approximately a quarter from demand-pull. Reassuringly, applying the method to the disaggregate data tells the same story as the aggregate data described in Table 1. Panel (b) contains the analogous plot for the post-lockdown episode. The patterns across the two experiences are very different. In this case, most inflation was on net demand-pull. This also aligns with the aggregate data described in the introduction.

3.2 Market vs. Non-Market Categories

The BEA bases price and quantity changes on observed market prices for many categories. For some categories (which we term non-market), however, prices are imputed. Decomposing inflation from price and quantity in non-market categories might introduce spurious results, since the decomposition is motivated by the market supply/demand model.

As such, we repeat the decomposition, but exclude categories which the BEA leaves out of market consumption: nonprofit consumption, financial services and insurance, expenditures by nonresidents and remittances, spending on foreign travel and spending abroad, gambling, and group and farm housing.[14]

[14]Though the price of owner-occupied housing is imputed, we leave it in to better match the BEA's market

Table 2 reproduces Table 1 for market core rather than core inflation. Figure 3 shows the decompositions over the same period as Figure 1, but for market core rather than core inflation. Restricting the decomposition to only market core goods and services yields results consistent with the decomposition of core, but implies that a larger share of non-trend inflation post-lockdown was demand-pull driven. That is, a disproportionate share of the supply-push inflation we observe in core prices post-lockdown occurs in categories for which prices and real quantities are at least partially imputed. When we focus on directly observed prices and real quantities, inflation post-lockdown was 73 percent demand-pull. On the other hand, the share of inflation that was supply-push post-oil shock is the same (75 percent) whether we use market core or core.

3.3 The Distribution of Supply-Push and Demand-Pull Inflation

Next we compare the distribution of supply and demand driven inflation during the oil shock and post-lockdown episodes relative to the years that preceded them.

Figure 4 contains histograms of the month-over-month inflation rate during 1960-1976 (left column) and 1990-2023 (right column) for demand (red), supply (blue) and their sum (inflation net of trend, black). For each month, we calculate demand (supply) driven components as the sum of current and past demand (supply). Overlaying each histogram, we plot transparent (with black outline) histograms showing the distribution for the subset of observations occurring after the oil shock and after lockdown. For example, the red histogram in panel (a) shows the distribution of *all* observations of demand-driven inflation between 1960 and 1976, and a transparent histogram, the distribution for demand-driven inflation *only* during the post-oil shock episode.

First, note that during high inflation periods in general, both supply and demand driven inflation tend to be higher, independent of whether an episode is predominantly demand or supply driven. Figure 4 is consistent with this fact, i.e., both demand and supply inflation following the oil shock and lockdown were high relative to previous years.

Next, consider the distributions of demand and supply driven inflation post-oil shock (panels (a) and (c)). In panel (a), the transparent histogram is shifted to the right of the red of the red histogram, indicating that demand-driven inflation was higher post-oil shock than had been the norm. However, most of the transparent histogram continues to overlap with

basket. We approximate the BEA's official market consumption basket, but do not replicate it because the disaggregate data required to so exactly is not publicly available. In Appendix Section F we compare total price changes for the official market index against our own.

the center of the red histogram: While demand-driven inflation was elevated, it was not, for the most part, anomalous during this period. By contrast, in panel (c), the transparent histogram is centered about 20 basis points higher than its blue counterpart and accounts for all of the positive outliers. This indicates that supply-driven inflation following the oil shock were almost exclusively inflationary and tended to be large in magnitude, unlike the supply driven inflation observed during the preceding years.

Post-lockdown, the pattern is reversed. In panel (b), the transparent histogram is shifted significantly to the right of the red histogram. Compared to demand-driven inflation observed in previous years, demand inflation post-lockdown was generally much higher relative to the preceding two decades. On the other hand, in panel (d), the transparent histogram is centered only slightly to the right of its blue (1990-2023) counterpart.

Panels (e) and (f), which show the distributions of total inflation (net of trend) for the two periods in black, help to contextualize the patterns we observe in panels (a) through (d). In each case, the transparent histograms are shifted significantly to the right of the black ones, reflecting the fact that both oil shock and post-lockdown periods experienced relatively higher inflation. Given how much higher total inflation was during the oil shock period, demand driven inflation looks fairly low. Similarly, given how much higher total inflation was following lockdown, supply driven inflation is less dramatic. On the other hand, both supply (for the oil shock case) and demand (following lockdown) driven inflation look high relative to their values in previous years even after accounting for the high inflation environment overall.

3.4 Category Level Contributions

Figure 5 breaks cumulative changes in the price level after lockdown down into the category-level contributions from demand-pull and supply-push inflation. Blue and red bars show changes attributed to supply-push and demand-pull inflation, respectively. Black lines underneath bars correspond to their sum (inflation net of trend). Categories are ordered by magnitude of supply-push contributions to inflation.

The categories which contributed most to inflation above trend are all those for which prices are either fully or partially imputed: financial services, owner-occupied housing, and nonprofit consumption. Excess inflation within these is split between supply and demand. Because changes in these category primarily reflect non-market activity (nonprofits) and are imputed rather than directly measured (financial services and owner-occupied housing), the methods used to classify them into supply and demand may be less reliable.[15]

Home goods, car-related categories, and lockdown impacted service sectors like flights and restaurants also contribute significantly to growth in core prices post-lockdown. Among these categories, new and used autos stand out as especially supply driven, while price growth within restaurants and home goods are both entirely demand driven.

We observe offsetting supply and demand driven inflation in healthcare-related categories like hospital, nursing home, and outpatient medical services. In each case, supply-driven disinflation and demand-driven inflation lead, on net, to small price changes overall.

Supply-push factors explain a large share of inflation stemming from a subset of consumption categories but cannot explain the majority of *total* price growth, because they are offset in aggregate by supply-push disinflation of similar magnitude. On the other hand, we do not observe large negative demand driven contributions from any category; most categories' demand-pull contributions are positive or zero.

Autos and auto-related services and goods are often cited as prime examples of supply driven inflation post-lockdown. Although the decomposition finds the majority of core inflation stems from demand-pull factors, rather than supply-push, significant supply driven inflation within auto-related categories occurred, consistent with anecdotal evidence. To further study inflation within the auto sector, we sum across changes auto-related categories (new and used car sales; recreational vehicles; and car services, rentals, and parts), weighting by consumption share as for core and headline. Within this grouping, prices rose almost 20 percent between 2021 and 2022 - four times more than trend - while quantities consumed fell by almost 7.5 percent. About two-thirds of the price increase above trend was supply driven, particularly within used car sales. Repair services and parts were both slightly more demand-driven, consistent with consumers substituting towards existing vehicle maintenance in response to supply disruptions in markets for new and used vehicles.

[15] Nonprofit quantities within the PCE measure nonprofit gross output less any receipts of sale. As a result, quantities can increase sharply if receipts of sale decrease *more* than gross output, as was the case early in the pandemic. During the post-lockdown period we focus on, as receipts of sale began to recover and nonprofit quantities fall closer to their baseline, the change in nonprofit output is large and negative; the method treats this as a supply shock and contemporaneous price growth above historical trends as supply driven. Later in 2022, as quantity growth rebounds to levels above trend, the method classifies additional price growth above trend as demand driven.

4 Comparison with the Existing Approach

This paper's approach modifies the Shapiro (2024) decomposition along two dimensions. Relative to Shapiro, we: (i) remove the trend inflation before applying the decomposition[16] and (ii) account for the dynamic effects of the VAR innovation and parse current from expected future impacts of the innovation.

We discuss our rationale for each in turn, but first present the formula for the existing approach to compare with our equation (2):

$$Y_{i,t} = \underbrace{\mathcal{S}_{i,t} Y_{i,t}}_{supply} + \underbrace{(1 - \mathcal{S}_{i,t})\, Y_{i,t}}_{demand} \tag{3}$$

where $\mathcal{S}_{i,t}$ is defined as in Section 2.[17]

First, because average inflation is not zero for any reasonable length sample for the post-WWII US, not removing trend (average) inflation before executing the decomposition allows small differences in VAR innovations switch the sign of an innovation move all of the average inflation from supply to demand (or vice versa). Subtracting trend inflation prior to classifying shocks constrains the impacts of small changes in the sign of an innovation, thus reducing the fluctuations in the decomposition.

Second, we account for inflation and quantity dynamics as part of the decomposition. We follow Shapiro in estimating a VAR to construct reduced form shocks to consumption growth and inflation in each category. If a subset of VAR coefficients is not zero, then a residual this period anticipates a future effect on inflation. Our approach accounts for this dynamic effect whereas Shapiro's decomposition does not, allowing us to distinguish between past and current demand-pull and supply-push inflation types.

In Section 3, we showed that using our decomposition the post-lockdown inflation was atypically driven by demand when compared to inflation from 1990 through 2023. When we compare these results with Shapiro's, we find they are broadly similar. Shapiro also finds high demand-driven initially falls during the pandemic lockdown, then rises post-lockdown

[16] We categorize a significant share of inflation as trend. During the post-oil shock period, trend inflation accounts for about 56% of core price growth; during the post-lockdown period, it accounts for about 35%.

[17] The Shapiro (2024) decompositon differs from the method applied here in several other ways. In particular, Shapiro (2024) estimates VAR coefficients using log levels. In addition, the coefficients used to categorize shocks for a given date correspond to estimation from backwards-looking ten year rolling samples. Shapiro (2024) also uses categories at the finest level of aggregation available. By comparison, we estimate VAR coefficients using two separate fixed sample periods and log changes for a smaller set of categories at a higher level of aggregation.

(circa 2021). Relative to our methodology, which finds that past demand continued to drive most excess inflation even into 2022, Shapiro's decomposition attributes a larger share of inflation during 2022 as supply-driven. During 2022, he associates an increase in supply-driven inflation with the war in Ukraine. Like us, Shapiro finds that the majority of inflation during the 1970s oil shock period was due to supply shocks (see Figure 3 of that paper).

In addition, Shapiro reports the categories that were most demand- and supply- driven during 2021-2022, which he defines by the share of months for which a category was coded having demand or supply shocks (see Table A1 from that paper). Although differences in categories and shock scales limit direct comparison, our category level findings are mostly consistent with his. As under our methodology, Shapiro finds inflation stemming from new cars and housing relatively more supply driven, while restaurant meals and clothing were more demand driven. Unlike under our methodology, Shapiro's decomposition finds that inflation in the financial services sector was relatively more demand driven; we find that the majority of excess price growth in financial services was supply driven.

We do note that the Shapiro decomposition delivers somewhat atypically demand-driven inflation for the episode relative to the earlier years. Using decomposition data from the SF Fed website covering 1990 through 2022, we compute the two-year sum of monthly inflation attributable to each component.[18] Next, we compute the time series for the ratio of demand inflation to overall inflation. For the post-lockdown episode, 44% of inflation was demand-driven. This was in the top fourteenth percentile for share of demand-driven inflation for 1990-2022, implying the post-lockdown inflation episode was largely demand-driven relative to inflation over the preceding three decades.

5 Conclusion

The supply-demand concept and its implication for price and quantity comovements is a cornerstone of economics.

We generalized an existing approach to measure and classify those comovements in disaggregate consumption and price data and then successfully benchmarked the approach's usefulness using the 1973 oil shock episode, considered a canonical negative supply shock experience.

We then applied the method to the post-lockdown US and showed the inflation was

[18] Besides supply and demand, Shapiro includes a third component (ambiguous) which we use in our calculation.

mostly demand-pull driven. The disaggregate results accord with the aggregate data.

A deeper understanding of the episode would be more ambitious. What drove the demand-pull pattern described in our paper? Candidates include large government transfers and pent up spending power from lockdown. Econometric identification and inference could permit recovering structural parameters, potentially even slopes of aggregate supply and aggregate demand. To be most useful, these would map to an economic model with meaningful deep parameters as in Lucas (1976).

One possibility is that, while a shift in demand was a primary driver of inflation, economic conditions *steepened* supply curves in some industries relative to before the pandemic.[19] The structural approach may be useful in testing this hypothesis.

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[19]See for example Comin et al. (2023) and De Soyres et al. (2024)

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A Figures and Tables

Table 1: Core PCE quantity and nominal price data, aggregate and disaggregate statistics: 1973 oil shock and post-lockdown episodes

	1973Q4-1975Q3	2021Q1-2022Q4
Aggregate		
Inflation (Cum. %)	16.53	10.15
Quantity Growth (Cum. %)	2.74	8.46
Disaggregate		
Supply Contribution (Share)	0.75	0.33
Demand Contribution (Share)	0.25	0.67

Notes: Supply contribution = supply / (supply + demand). Demand contribution = demand / (supply + demand). Data are not annualized.

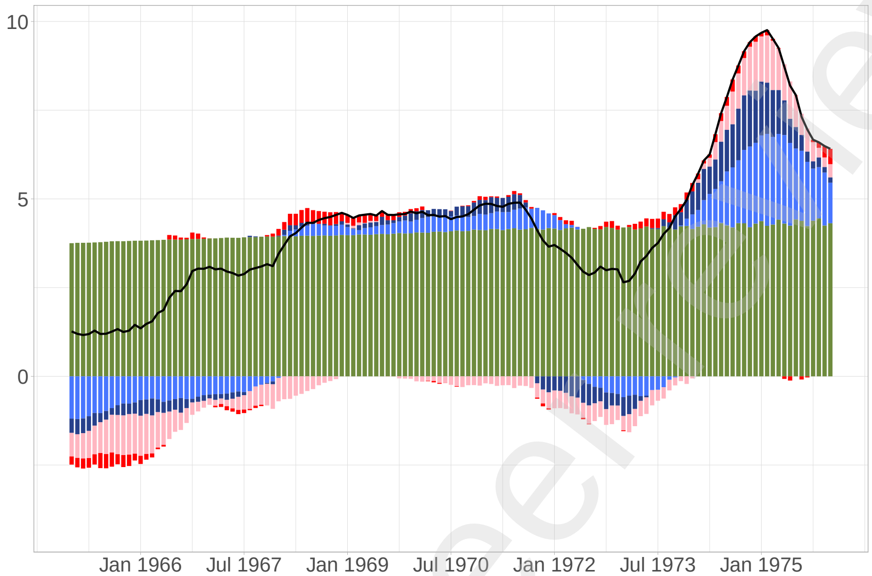
Table 2: Market Core PCE quantity and nominal price data, aggregate and disaggregate statistics: 1973 oil shock and post-lockdown episodes

	1973Q4-1975Q3	2021Q1-2022Q4
Aggregate		
Inflation (Cum. %)	16.42	9.48
Quantity Growth (Cum. %)	2.32	8.86
Disaggregate		
Supply Contribution (Share)	0.75	0.27
Demand Contribution (Share)	0.25	0.73

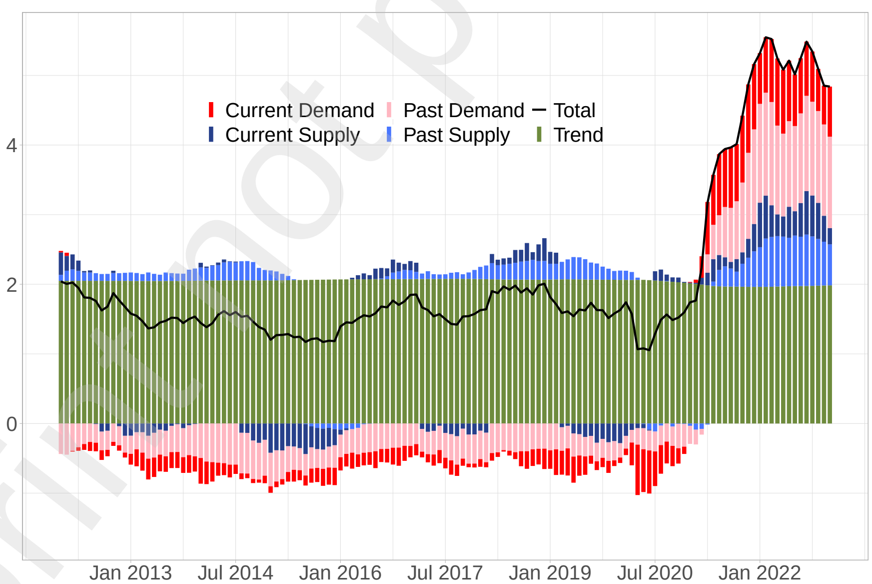
Notes: Supply contribution = supply / (supply + demand). Demand contribution = demand / (supply + demand). Data are not annualized.

Figure 1: Decomposition of Core PCE inflation, 12 month percentage change

(a) 1965 through 1975



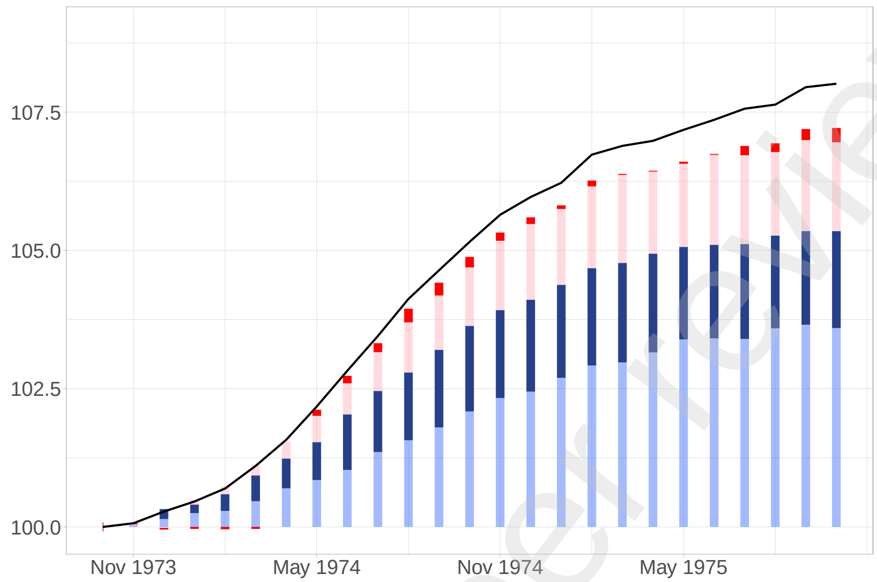
(b) 2012 through 2022



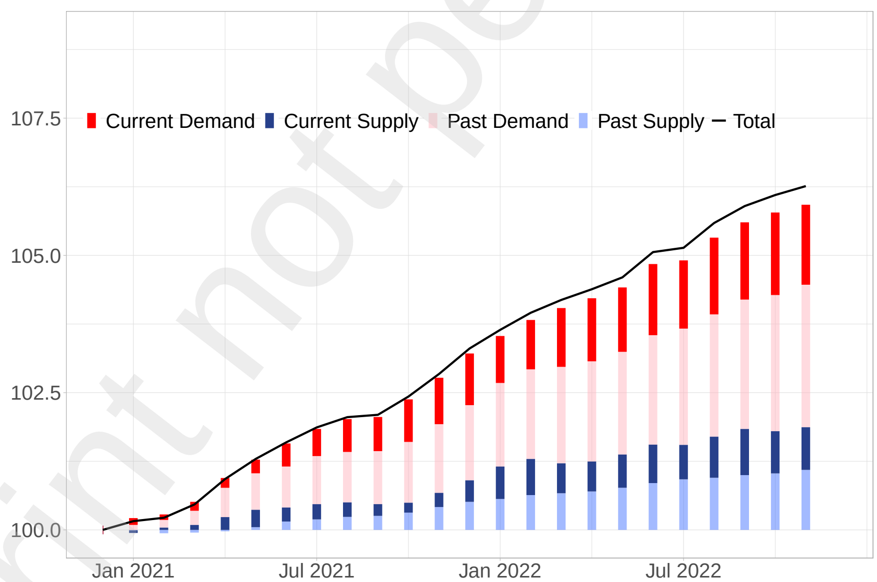
Notes: Both panels present inflation decompositions using a VAR(12) estimated on monthly data for 1960-1975 (panel (a)) and 1990-2023 (panel (b)). 12-month inflation rates are calculated using lagged moving sums of monthly rates.

Figure 2: Decomposition of Core PCE inflation: price level paths for two inflation episodes

(a) 1973Q4 through 1975Q3



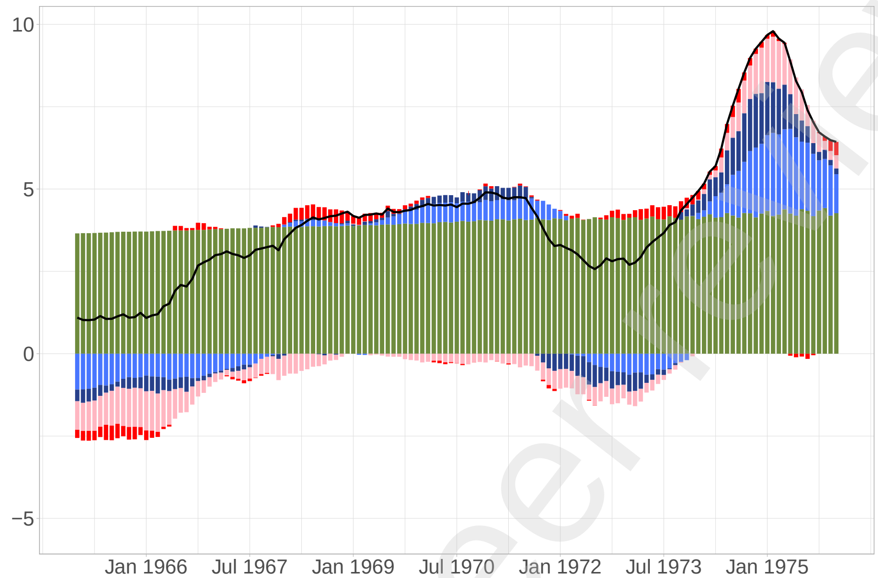
(b) 2021Q1 through 2022Q4



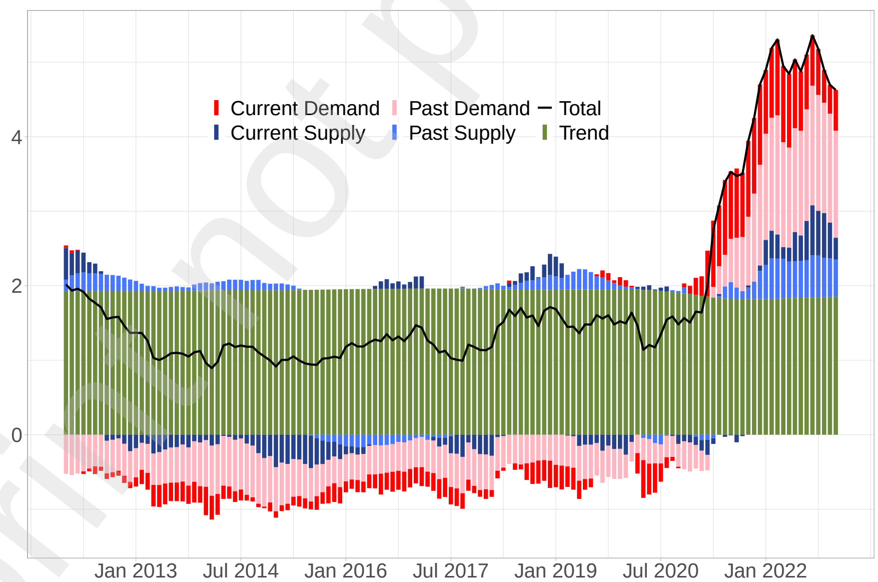
Notes: Black line = PCE price level (net of trend increase). Inflation in each time period is decomposed into contributions from inflation innovations (and their expected future impacts) based on classification of PCE categories into either supply or demand. Height of a stacked column does not equal the height of black line for each month because of higher order terms included in black line. See Appendix Section E for a longer discussion of the discrepancy.

Figure 3: Decomposition of Market Core PCE inflation, 12 month percentage change

(a) 1965 through 1975

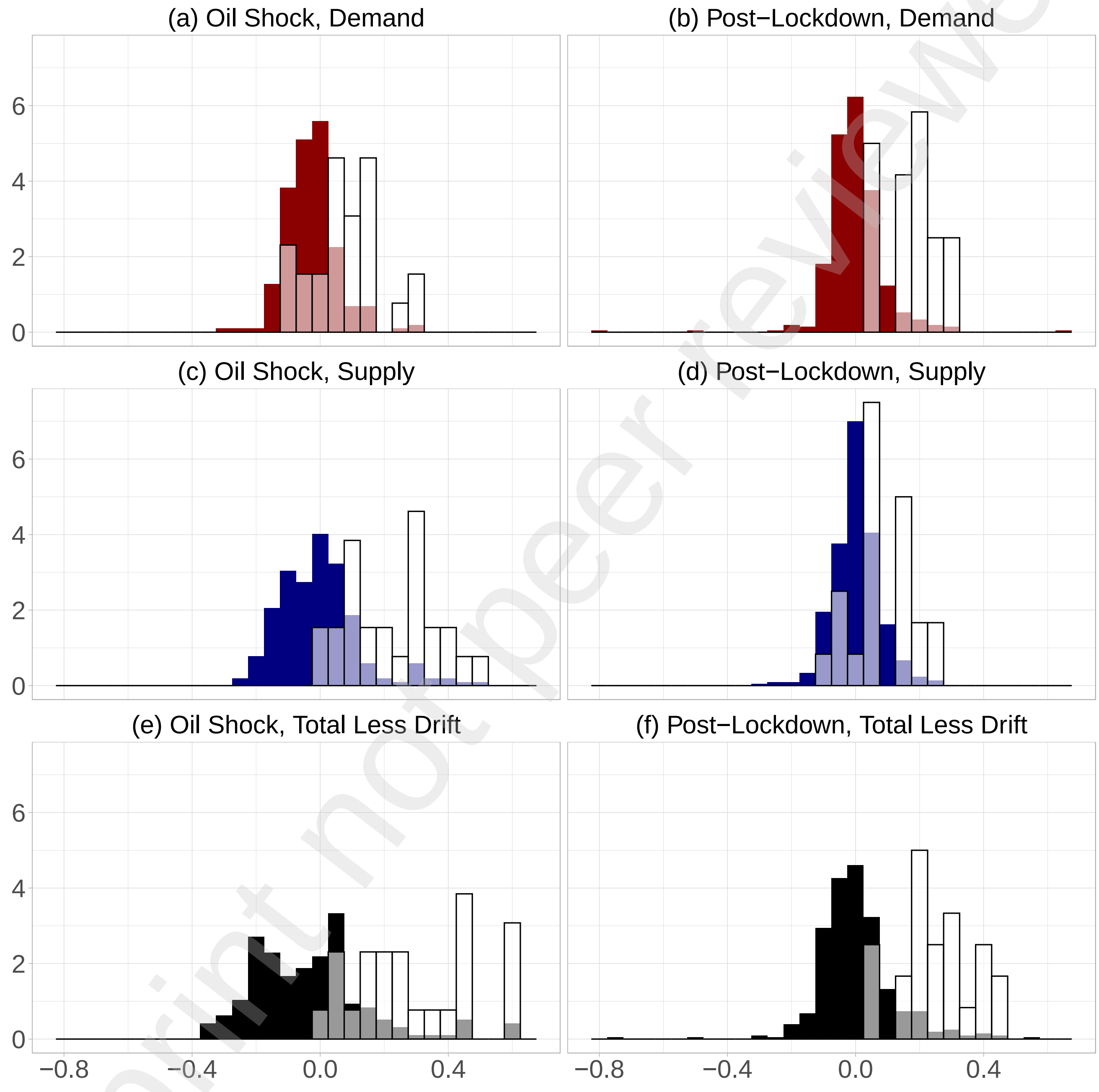


(b) 2012 through 2022



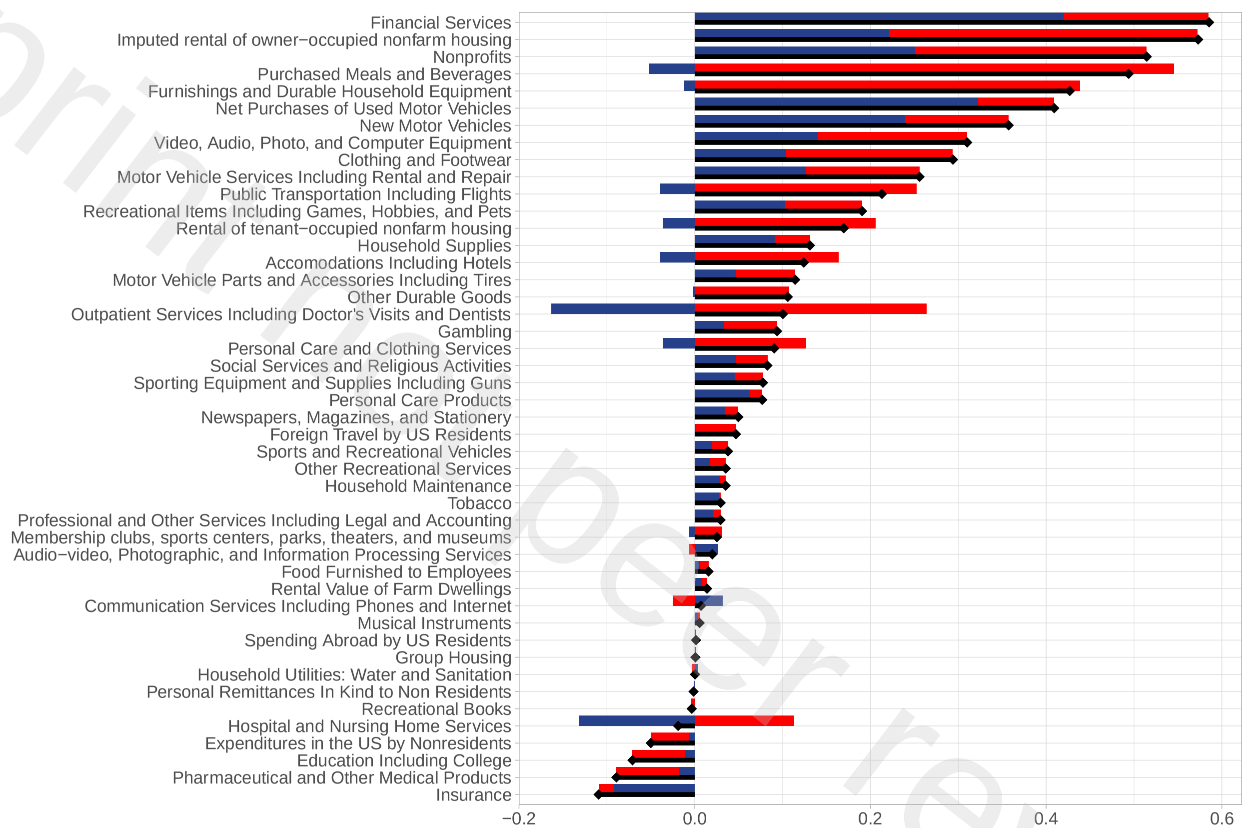
Notes: Both panels present inflation decompositions using a VAR(12) estimated on monthly data for 1960-1976 (panel (a)) and 1990-2023 (panel (b)). 12-month inflation rates are calculated using lagged moving sums of monthly rates.

Figure 4: Histograms of core inflation, by component and by episode (month-over-month)



Notes: Transparent (with black outline) histograms correspond to month over month inflation rates during months of oil shock and post-lockdown episodes. Remaining histograms correspond to inflation rates during entire sub-period (1960-1976 for the oil shock) and (1990-2023 for post-lockdown). Light red, light blue, and gray regions indicate overlap between shock period and full period distributions. Supply inflation combines current and past, with demand inflation calculated analogously. Heights of the bars correspond to density.

Figure 5: Cumulative Contributions to Core Inflation, 2021-2022



Notes: Each bar shows the cumulative change in the core price level from Jan 2021-December 2022 attributable to supply-push (blue), demand-pull (red) and combined supply plus demand (green) by categories. Categories are sorted in descending order, with the largest supply-push categories (measured by combined current and past inflation contributions) ordered first.

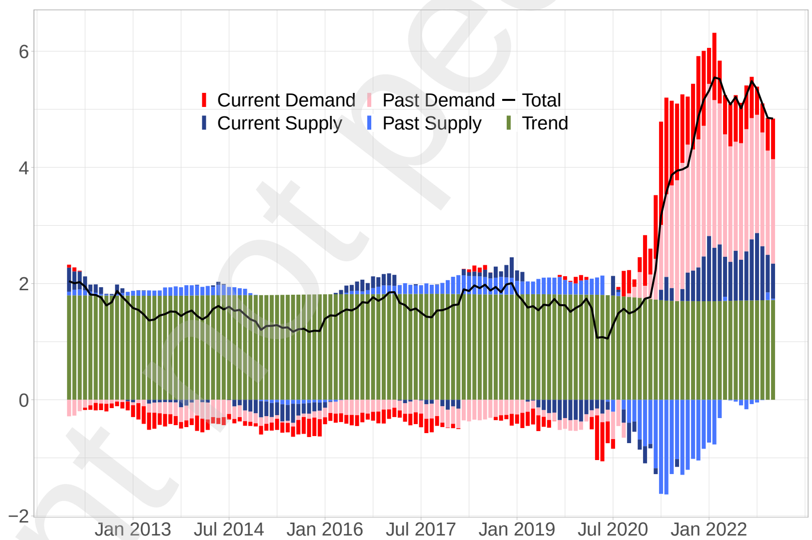
Supplemental Appendices (not for publication)

B Including the Pandemic Period in the VAR

Table 3: Core PCE quantity and nominal price data, aggregate and disaggregate statistics: 1973 oil shock and post-lockdown episodes

	1973-1975	2021-2022
Aggregate		
Inflation (Cum. %)	16.50	10.15
Quantity Growth (Cum. %)	2.71	8.46
Disaggregate		
Supply Contribution (Share)	0.74	0.15
Demand Contribution (Share)	0.25	0.84

Figure 6: 2012 through 2022



Notes: Figure 6 and Table 3 recreate Figure 3 and Table 1, respectively, using a VAR(12) estimated on monthly data from 1990-2023 but excluding 2020-2021. 12-month inflation rates are calculated using lagged moving sums of monthly rates.

As a robustness check, we also decompose inflation 1990-2024 using VAR coefficients estimated from data 1990-2019 and 2022-2023, excluding 2020-2021. Below, we contrast results between the two versions and explain why, in our preferred specification, we include data from 2020-2021 in sample when estimating reduced form VARs.

The decomposition estimated excluding 2020-2021 implies that an even larger share (84%) of above-trend core inflation was supply-push driven (see Table 3). However, excluding data during the pandemic lockdown means that we estimate the dynamic effects of large pandemic-related shocks out-of-sample, based on coefficients estimated using the dynamic effects of smaller and systematically different shocks historically. Doing so leads us to attribute a higher share of cumulative inflation to past supply and demand relative to current – because the pandemic's initial impact was a larger one-time shock than any included within the sample, the linear effects we estimate will tend to overstate the shock's dynamic effects. This can introduce bias into current shock estimates as well, since these are defined as the difference between the actual residual and the predicted residual, given past supply and demand innovations. If past innovations are large relative to the actual residual, they can spuriously inflate current period innovations, a phenomenon which in some cases becomes self-propagating. For example, observe the large and offsetting dark blue (current supply) and light blue (past supply) innovations in Figure 6 circa 2021, which do not appear in Figure 3. On the other hand, including the pandemic within our sample data tends to decrease the magnitude of past innovations relative to current period ones, while slightly increasing the trend.

C Data Construction

The BEA constructs monthly Personal Consumption Expenditures (PCE) price and quantity indices by aggregating across sub-categories of consumption. These categories are organized hierarchically; at the most disaggregate level, there are over 200 categories. For example, "Tires and New Domestic Trucks" are both categories within the "Motor Vehicles and Parts" category, which is itself housed within "Durable Goods." Choosing a category level from which to identify supply and demand driven shocks requires a tradeoff between observing trends more closely and introducing additional noise. The BEA terms categories at finer levels of disaggregation than its major product types "Underlying Detail" and omits them from most publications because "these detailed estimates are more likely to be based on judgmental trends or on less reliable source data" (pg. 7, NIPA Handbook Chapter 5).

In our partitioning of the categories, our panel uses third- and fourth-layer categories. While these categories are mostly under the "Underlying Detail" section, they avoid relying on the finest level of disaggregation. For example, we distinguish between "New Motor Vehicles" and "Net Sales of Used Vehicles", but do not identify shocks from more detailed categories. Previous authors have either used categories at the finest level of disaggregation (i.e. Shapiro) or identified structural shocks from aggregate data. Using broader categories allows us to extend the decomposition to earlier periods of inflation, including the mid-1970s.[20] We choose a disaggregation level such that all categories considered have continuous price and quantity indices beginning in 1959, although the composition of goods and services within those categories may have shifted over time. For example, Communication Services includes separate subcategories for both long distance landline telephone charges (available 1959-present) and internet access (available 1987-present). Because we study inflation during both pre- and post-1987 periods, we use indices for Communication Service (overall) across all estimation periods.

The PCE Price Index includes some types of non-household consumption expenditures in its basket of goods.[21] Namely, these are: final consumption expenditures of household-serving nonprofits (nonprofit gross output less receipts of sale), payments in kind (employer-employee compensation via benefits like health insurance and meals), net foreign travel (foreign travel by US residents less spending in the US by nonresidents), and net expenditures abroad (spending abroad by US residents less remittances in kind to nonresidents). The BEA includes these categories in the PCE for reconciliation with other national accounts. These categories pose a challenge for the decomposition because their prices and quantities are more likely to be affected by non-market and international factors. We include these categories in the decomposition to keep our aggregate inflation and consumption growth series consistent with the official series. Whenever possible, we include them at their highest available aggregation level. For example, we decompose changes in the final consumption of nonprofits as a whole, rather than tracking changes in subcategories like religious services. Net foreign travel (composed of the difference between foreign travel and nonresident spending in the US) does not have a single quantity index; rather, its subcategories have quantity indices, and some (i.e. nonresident spending in the US) are subtracted from totals when calculating overall inflation. In this case, we use the subcategories with consistently defined quantity indices.

[20] At the finest level of disaggregation, only some categories are available continuously from 1959 – present.

[21] In contrast, the Bureau of Labor Statistics' Consumer Price Index does not include non-household categories.

D Constructing the Moving Average Representation

For each category i, let

$$\hat{F}(i) = \begin{bmatrix} \hat{\Phi}_1^i & \hat{\Phi}_2^i & \cdots & \hat{\Phi}_K^i \\ I & 0 & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & I & 0 \end{bmatrix}$$

Then, $\hat{\Psi}_j^i = \hat{F}(i)_{11}^{(j)}$ where $\hat{F}(i)_{11}^{(j)}$ is the upper-left block of the matrix $\hat{F}(i)^{(j)}$. Moreover, $\hat{F}(i)^{(j)}$ is the matrix $\hat{F}(i)$ raised to the jth power.

Next,

$$\hat{\mu}_{i,t} = \begin{cases} \hat{C}_i \text{ for } t = 0 \\ \hat{C}_i \left(I + \hat{\Psi}_1^i + \cdots + \hat{\Psi}_t^i\right) \text{ for } 0 < t \leq T \\ \hat{C}_i \left(I + \hat{\Psi}_1^i + \cdots + \hat{\Psi}_T^i\right) \text{ for } t > T \end{cases}$$

E Explaining Differences in Cumulative Price Growth

For each plot showing cumulative price growth, there are discrepancies between total price growth and the sum of supply, demand, and trend growth individually. In this section we describe why this discrepancy occurs.

We directly observe cumulative total price level growth, because it is the difference between PCE price indices at times t = 0 and t = T, relative to the index's value at t = 0. Unlike total inflation, we do not directly observe cumulative supply or demand price level growth. Instead, we only observe supply and demand in terms of their monthly percentage changes. Cumulative supply (or demand) driven price level growth is a hypothetical object reflecting the cumulative amount by which the price level would have changed between t = 0 and t = T if only supply (demand) inflation had occurred throughout that period.

To calculate cumulative supply (demand) driven price level growth, we first divide the un-annualized monthly percent change attributable to supply (demand) by 100 and add 1. This gives us the current month's price level relative to the previous month. For every month after the shock begins, we calculate the cumulative product of current month's price levels relative to previous month's price levels. We standardize by setting the price level during the last month before our shock (t = 0) equal to 100 and multiply the cumulative product in every period afterwards by 100. This gives us the current month's price level relative to t = 0.

Total cumulative growth does not equal the sum of supply, demand, and trend growth; the discrepancy depends on the cross-correlation of shock types and grows larger during periods of prolonged high inflation. To understand why, it's useful to consider the two-period, two-shock type case. Letting s and d be supply (demand) driven inflation, P_t be the overall price level in period t, and P_t^s and P_t^d be the hypothetical price levels implied by supply (demand):

$$P_{t=2} = (1 + s_{t=1} + d_{t=1}) * (1 + s_{t=0} + d_{t=0}) * P_{t=0}$$

$$= (1 + s_{t=1} * s_{t=0} + d_{t=1} * d_{t=0} + s_{t=0} + d_{t=0} + s_{t=1} + d_{t=1}) + s_{t=1} * d_{t=0} + d_{t=1} * s_{t=0}$$

$$= (P^s_{t=2} + P^d_{t=2} - 1) + s_{t=1} * d_{t=0} + d_{t=1} * s_{t=0}$$

$$s_{t=1} * d_{t=0} + d_{t=1} * s_{t=0} \neq 0 \longrightarrow P_{t=2} \neq (P^s_{t=2} + P^d_{t=2} - 1)$$

If the cross-period products of supply and demand are small and/or offset each other in sign, then total cumulative price level change in period 2 will be approximately equal to the sum of cumulative price level change attributable to supply and demand (ignoring trend). On the other hand, if the cross-period products are large and/or not offsetting, then the total cumulative price level will differ from that implied by summing the cumulative changes attributable to each shock type individually. Usually, the difference is positive (i.e. the total cumulative price level growth is greater than the sum of its parts) but this is not necessarily the case.

F Comparing Constructed and Official Market Core

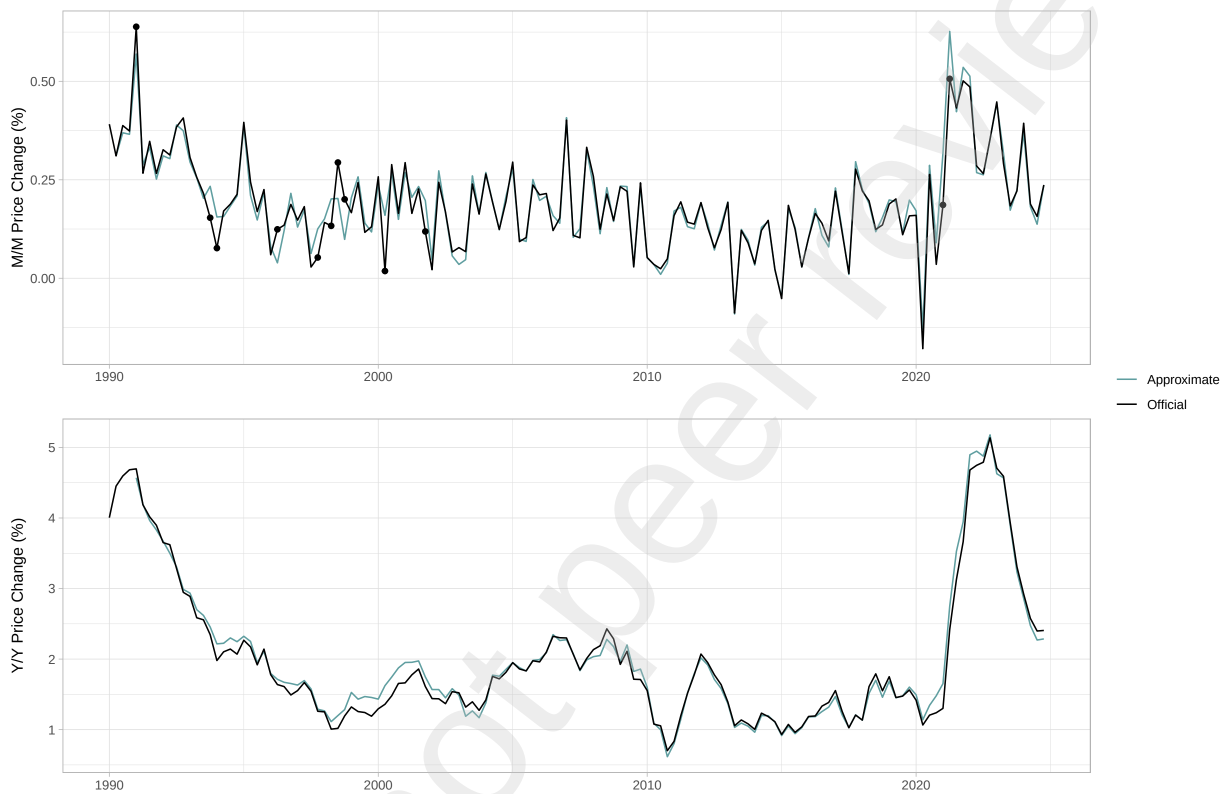


Figure 7

Notes: The top panel plots the month-over-month changes in Market PCE excluding food and energy for the official BEA aggregate (black) and our approximation using disaggregate categories (blue). We restrict the plot to dates during which both are available. Black dots indicate months during which the difference between official and approximate was larger than half of the official series's standard deviation. The bottom panel shows the same information for year-over-year changes.