Decomposing Supply and Demand Driven Inflation

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Abstract

The extent to which either supply or demand factors drive inflation has important implications for economic policy. I propose a framework to decompose inflation into supply- and demand-driven components. I generate two new data series, the supply- and demand-driven contributions to personal consumption expenditures (PCE) inflation, which quantify the degree to which either demand or supply is driving inflation in a current month. The series show expected time-series patterns. The demand-driven contribution tends to decline during recessions, while the supply-driven contribution tends to follow food and energy prices. Monetary policy tightening acts to reduce the demand-driven contribution of inflation. Oil-supply shocks act to increase the supply-driven contribution, but decrease the demand-driven contribution of inflation. The decompositions can be used to test theory or by policymakers and practitioners to track inflation drivers in real time.

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1 Introduction

At the heart of New Keynesian theory lies the Phillips curve which posits that inflation deviates from its expected path due to aggregate demand and supply factors. Indeed, oil-related supply factors and monetary-policy related demand factors were shown to play a large role in explaining the high inflation of the 1970s (Blinder and Rudd (2013)) and Primiceri (2006)). More recently, researchers are pointing to both supply and demand factors as being responsible for the recent post-COVID inflation surge.[1] More generally, the extent to which either supply or demand factors drive inflation may have important implications for economic policy, particularly monetary policy. Jerome Powell, Chair of the Federal Reserve, stated this directly, “What [the Fed] can control is demand, we can’t really affect supply with our policies…so the question whether we can execute a soft landing or not, it may actually depend on factors that we don’t control.”[2]

I propose a framework to decompose overall inflation into supply-driven and demand-driven components. I generate two new data series, the supply- and demand-driven contributions to personal consumption expenditures (PCE) inflation. These series quantify the degree to which either demand or supply is driving inflation in a current month. Since inflation is constructed as the weighted sum of category-level inflation rates, it is straightforward to divide inflation by category, or groups of categories. I separate categories each month into those where prices moved due to a surprise change in demand from those where prices moved due to a surprise change in supply.

The methodology is based on standard theory about the slopes of the supply and demand curves. Shifts in demand move both prices and quantities in the same direction along the upward-sloping supply curve, while shifts in supply move prices and quantities in opposite directions along the downward-sloping demand curve. Implementing this concept empirically entails the use of a sign-restrictions (Faust (1998) and Uhlig (2005)). The sign restriction implemented in this study—restricting the sign of the slopes of the supply and demand curves—is appealing because it is theoretically intuitive and therefore likely not controversial. While this restriction indicates whether a demand or supply shock occurred at any point in time (i.e., a binary variable), it does not pin down the extent to which supply or de-

[1] Jordà, Liu, Nechio, Rivera-Reyes, et al. (2022), Ball, Leigh, and Mishra (2022)

[2] Taken from Powell’s May 2022 interview on NPR’s Marketplace

mand is impacting inflation. One needs to make additional identifying restrictions, beyond sign restrictions, in order to quantify the magnitudes of the structural shocks. Including additional identifying restrictions, however, defeats the originally intended parsimonious appeal of sign-restrictions (Fry and Pagan (2011)). The advantage of using the category-level data is that one can obtain a continuous measure of the extent to which supply and demand factors are impacting inflation without having to impose additional non-sign restrictions. Specifically, category-level data allow one to track the share of (expenditure-weighted) PCE categories that are experiencing *at least* a supply shock or *at least* a demand shock.

Separate price and quantity regressions are run on each of the more than 100 goods and services categories that make up the PCE price index, and the residuals are collected.[3] The categories are then labeled as supply-driven or demand-driven based on the signs of residuals in the price and quantity reduced-form regressions. As shown in Jump and Kohler (2022), the signs of the residuals can be used to identify the signs of the structural shocks. Categories with residuals of the same sign experienced *at least* a demand shock and are labeled as demand-driven in that month. Categories with residuals of opposite signs experienced *at least* a supply shock, and are labeled as supply driven in that month. The demand-driven (supply-driven) contribution to inflation in a given month is then constructed as the expenditure-weighted average of the inflation rates of those categories labeled as demand-driven (supply-driven) in that month—the same weights used by the Bureau of Economic Analysis (BEA) in constructing aggregate PCE inflation from category-level inflation rates.

The supply- and demand-driven contributions track the share of PCE inflation that experienced at least a supply shock or at least a demand shock. Thus, they do not measure changes over time in the absolute size or the relative size of structural supply and demand shocks. For instance, under some parameterizations of supply and demand elasticities, a relatively large supply shock and small demand shock can cause both prices and quantities to rise for a specific category. One way to help validate that the methodology is in fact tracking demand- and supply-related factor is to assess how the series co-vary with economic

[3] The empirical analysis therefore relies on the fact that price dynamics are best explained at the category level. There is ample evidence in the literature that this holds. For example, the health care services sector is sensitive to prices administered by the government (that is, Medicare and Medicaid) as shown in Clemens and Gottlieb (2017), Clemens, Gottlieb, and Shapiro (2014), and Clemens, Gottlieb, and Shapiro (2016). Certain products, such as airline services Gerardi and Shapiro (2009) and technology goods (Aizcorbe (2006) and Copeland and Shapiro (2016)), tend to strongly move with technological progress and sector-specific competitive pressures.

events that are well known to be either demand- or supply-driven. Indeed, the contribution of demand-driven inflation falls during recessions and rises during economic booms. Specific key events also impact the series, for instance, the collapse in airline travel after September 11, 2001 reduced demand-driven inflation while the sharp energy price declines in 2014 and 2015 reduced supply-driven inflation. The decomposition also reveals information about the post-COVID surge in inflation. After a precipitous decline in 2020, demand-driven inflation began to surge in the Spring of 2021, coinciding with the re-opening of the economy and the implementation of the American Rescue Plan. Supply-driven inflation surged in early 2022 likely due to the economic disruptions associated with the Russian invasion of Ukraine. These patterns over the COVID-19 pandemic are roughly consistent with those found in Baqaee and Farhi (2022), Ferrante, Graves, and Iacoviello (2023) and Di Giovanni, Kalemli-Özcan, Silva, and Yildirim (2023) that take more structural approaches. These patterns are robust along several dimensions: using longer horizon impulse response instead of the one-period ahead residual, ignoring labels that are possibly labeled imprecisely, relaxing the assumption of binary labeling, and using alternative number of lags in the VAR.

As further demonstration of "proof of concept," I examine how the supply- and demand-driven contributions respond to aggregate supply and demand shocks constructed by external researchers. Specifically, I run local projections using high-frequency identified (HFI) monetary policy shocks (Gürkaynak, Sack, and Swanson (2005) and externally identified oil supply shocks (Baumeister and Hamilton (2019)). A monetary policy tightening, as measured by a 100 basis point surprise increase in the slope of yield curve around FOMC announcements, reduces the demand-drive contribution of inflation by a cumulative 1.5 percentage points over two years. This result is line with standard macro models, for example, (Smets and Wouters (2003), whereby monetary tightening reduces inflation through a dampening of demand. A negative oil supply shock has a small positive impact on the supply-driven contribution to core inflation, thus showing the well-known pass-through effect of oil prices on core prices.[4] Specifically, a 10 percent increase in oil prices translates into about a 15 basis point increase in the supply-driven contribution to core PCE inflation over 24 months. The results also show a small negative effect on demand-driven inflation, which is consistent

[4]There has been some debate in the literature on the degree to which energy prices pass through to non-core prices (see, for example, Hooker (2002), Blanchard and Gali (2007), Bachmeier and Cha (2011), Conflitti and Luciani (2019))

with the well-known finding that oil supply shocks reduce aggregate demand (Lee and Ni (2002), Hamilton (2008), Edelstein and Kilian (2009)). The same 10 percent increase in oil prices causes approximately the same size decrease in the demand-driven contribution. Thus, although the oil supply shock has no net effect on overall core inflation, the decomposition reveals off-setting supply and demand effects.

The supply and demand contributions can be used by researchers to help test and better understand existing macroeconomic theories. They can also be used to test how economic policy works in practice, such as examining whether monetary or fiscal policy has differential effects when inflation is driven by supply as opposed to demand (Boissay, Collard, Galí, and Manea (2021) and Ghassibe and Zanetti (2022)). As the series can be easily updated each month, they also provide an additional economic indicator for policymakers and market participants to track inflation in real time. The study is organized as follows. In section 2, I describe the methodology and provide a brief overview of the BEA data. In section 3, I provide an overview of the decomposition and review robustness tests. In section 4, I describe the local projection method and examine the impact of HFI monetary policy shocks and oil supply shocks on the inflation decompositions. I conclude in section 5.

2 Methodology and Data

2.1 Methodology

The framework stems from the assumption of an upward sloping supply curve and a downward sloping demand curve applied to each sector i:

$$\text{Supply curve:} \quad q_i = \sigma^i p_i + \alpha^i \tag{1}$$

$$\text{Demand curve:} \quad p_i = -\delta^i q_i + \beta^i \tag{2}$$

where q_i represents quantity (or real consumption), p_i represents the price level, σ^i is the slope of the supply curve, δ^i is the slope of the demand curve, and α^i and β^i are the intercepts. It is standard to refer to a shift in the intercept of (1) as a “supply shock” and a shift in the intercept of (2) as a “demand shock.” It follows that shifts (or shocks) to the supply and demand curve for each sector i can be represented as:

$$\text{Supply shock:} \quad \varepsilon_i^s = (q_{i,t} - \sigma^i p_{i,t}) - (q_{i,t-1} - \sigma^i p_{i,t-1}) \tag{3}$$

$$\text{Demand shock:} \quad \varepsilon_i^d = (\delta^i q_{i,t} + p_{i,t}) - (\delta^i q_{i,t-1} + p_{i,t-1}) \tag{4}$$

where $\varepsilon_i^s = \Delta\alpha^i$ and $\varepsilon_i^d = \Delta\beta^i$. This model can be estimated using time-series data by translating it into a structural VAR:

$$A^i z_{i,t} = \sum_{j=1}^{N} A_j^i z_{i,t-j} + \varepsilon_{i,t} \tag{5}$$

where $z_i = \begin{bmatrix} q_i \\ p_i \end{bmatrix}$, $A^i = \begin{bmatrix} 1 & -\sigma^i \\ \delta^i & 1 \end{bmatrix}$, and it follows that $\varepsilon_i = \begin{bmatrix} \varepsilon_i^s \\ \varepsilon_i^d \end{bmatrix}$ represent the structural supply and demand shocks in period t. Specifically, $\varepsilon_{i,t}$ represent the surprise shifts in the supply or demand curves in period t, where surprise is defined as new information relative to that observed prior to time t. Recovering the structural shocks entails running a reduced-form estimation of price and quantity (z_i) and collecting the reduced-form residuals, $\nu_{i,t}^q$ and $\nu_{i,t}^p$:

$$z_{i,t} = [A^i]^{-1} \sum_{j=1}^{N} A_j^i z_{i,t-j} + \nu_{i,t} \tag{6}$$

where $\nu_i = \begin{bmatrix} \nu_i^q \\ \nu_i^p \end{bmatrix}$. Specifically, the structural shocks can be recovered via a transformation of the reduced-form residuals:

$$\varepsilon_{i,t} = A^i \nu_{i,t}. \tag{7}$$

As shown in Jump and Kohler (2022), the restrictions on the slopes of the supply and demand curves (represented by A^i) imply restrictions on the signs of the structural shocks ($\varepsilon_{i,t}$) and hence, restrictions on the reduced-form residuals $\nu_{i,t}$. Specifically, it is straightforward to show that (7) implies that the signs of the reduced-form residuals reveal information about the signs of the structural shocks:

$$+\text{ Demand Shock}: \quad \nu_{i,t}^{p} > 0, \nu_{i,t}^{q} > 0 \rightarrow \varepsilon_{i,t}^{d} > 0 \tag{8}$$

$$-\text{ Demand Shock}: \quad \nu_{i,t}^{p} < 0, \nu_{i,t}^{q} < 0 \rightarrow \varepsilon_{i,t}^{d} < 0 \tag{9}$$

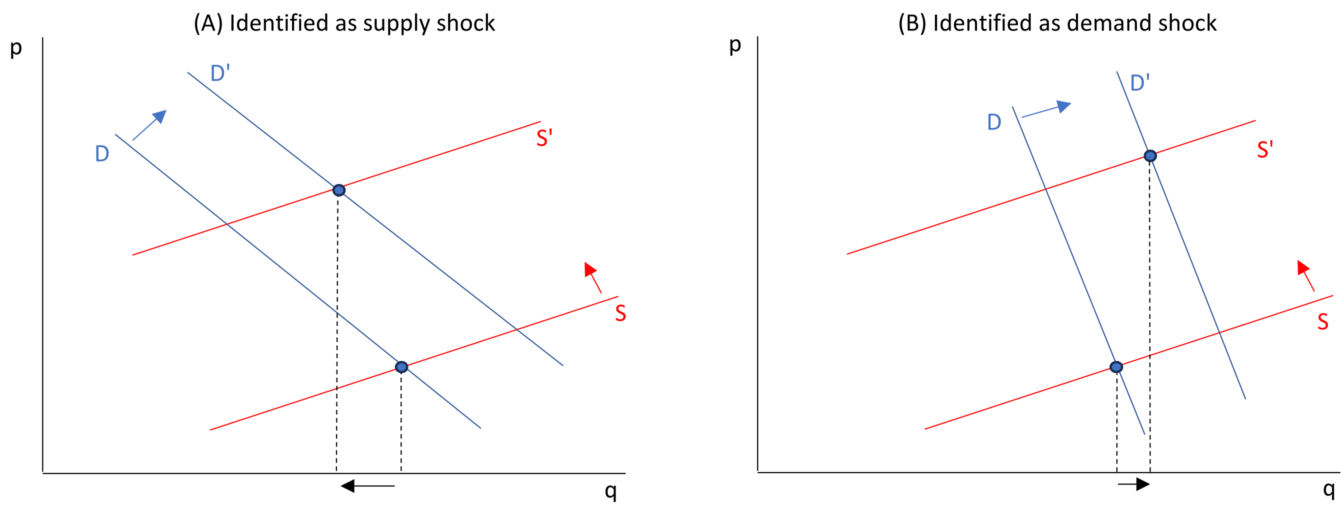
$$+\text{ Supply Shock}: \quad \nu_{i,t}^{p} < 0, \nu_{i,t}^{q} > 0 \rightarrow \varepsilon_{i,t}^{s} > 0 \tag{10}$$

$$-\text{ Supply Shock}: \quad \nu_{i,t}^{p} > 0, \nu_{i,t}^{q} < 0 \rightarrow \varepsilon_{i,t}^{s} < 0. \tag{11}$$

If the price and quantity residuals are of the same sign, it indicates a demand shock occurred. That is, a positive (negative) reduced-form residual obtained from both the price and quantity regressions in time t imply a positive (negative) demand shock occurred at time t, with an unknown sign of the supply shock. Residuals of opposite signs indicates a supply shock occurred. That is, a positive (negative) reduced-form residual obtained from the price regression and a negative (positive) reduced-form residual from the quantity regressions in time t imply a negative (positive) supply shock occurred at time t, with an unknown sign of the demand shock.

The use of sign restrictions comes with some caveats that should be emphasized. First, the structural shocks are only set identified and their size cannot be determined without further identification restrictions. Thus, changes over time in the supply- and demand-driven contributions do not measure changes over time in the size of the structural supply and demand shocks (i.e., ε_i^s and ε_i^d). Rather, the measures constructed in this study will track the share of (expenditure-weighted) categories that are experiencing *at least* a supply shock or *at least* a demand shock. This is shown in equations (8) through (11). Second, and relatedly, sign restrictions do not uncover the relative size of structural shocks when shocks occur simultaneously. That is, equations (8) through (11) do not reveal whether the demand shock or the supply shock is larger if the shocks occur simultaneously. The signs of the residuals only reveal whether a supply shock or demand shock occurred or not. Figure 1 shows an example with a simultaneous negative supply shock and positive demand shock. When the demand elasticity is relatively high, the simultaneous shock is attributed to a supply shock (panel A), while when the demand elasticity is relatively low the simultaneous shock is attributed to a demand shock (panel B). This example highlights the fact that further restrictions on the size of the underlying parameters σ and δ would be necessary to

Figure 1: Simultaneous Supply and Demand Shocks



pin down the relative size of the structural shocks.[5]

2.2 Data and estimation

I employ the monthly price, quantity, and expenditure data from the more than 100 goods and services categories in the publicly available personal consumption expenditure (PCE) data and from the Bureau of Economic Analysis (BEA). The data on the underlying detail of quantity, price, and expenditures of the PCE index are available in Tables 2.4.3U, 2.4.4U and 2.4.5U in the "Underlying Detail" page of the BEA's website. The BEA constructs different levels of aggregation depending on the category of product. I use the fourth level of disaggregation, for example, (1) services → (2) transportation services → (3) public transportation → (4) air transportation. Such an aggregation leaves 129 categories in the PCE price index and 117 categories in the core PCE index that go back to 1959.[6]

I run 10-year rolling price and quantity regressions for each of the 129 categories, i, in

[5]Suppose that $\nu^p > 0, \nu^q > 0$ such that the category was labeled as demand driven. Sign restrictions reveal that a demand shock must have occurred. However, for $\varepsilon^d > \varepsilon^s$ to also hold, it must be the case that $\frac{\nu^p}{\nu^q} > \frac{\delta-1}{\sigma+1}$. In this case, the additional restriction that demand is elastic (i.e $\delta < 1$) would ensure that $\nu^p > 0, \nu^q > 0 \rightarrow \varepsilon^d > \varepsilon^s$.

[6]Data are available for 136 total categories that go back to 1988.

the PCE index:

$$q_{i,t} = \sum_{j=1}^{12} \gamma_j^{qp} p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{qq} q_{i,t-j} + c + \nu_{i,t}^{q} \tag{12}$$

$$p_{i,t} = \sum_{j=1}^{12} \gamma_j^{pp} p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{pq} q_{i,t-j} + c + \nu_{i,t}^{p} \tag{13}$$

where $q_{i,t}$ is the log quantity index and $p_{i,t}$ is the log price index of category i, and c is a constant. My main specification uses 12 lags of price and quantity as controls—the results are robust to alternative numbers of lags, and running the specification in log first differences (i.e., $\Delta q_{i,t}$ and $\Delta p_{i,t}$ in place of $q_{i,t}$ and $p_{i,t}$).[7] These controls are meant to control for existing trends, which are not likely to represent a shift in demand or supply, but instead lower-frequency factors such as technology improvements, cost-of-living adjustments, or demographic changes.[8] Rolling-window regressions allow for the coefficients—γ_j^{qq},γ_j^{qp}, γ_j^{pp}, γ_j^{pq}—to vary over time. The first window begins in January 1959 and ends in December 1969. This generates residuals beginning in January 1969. I then roll the data window forward one month and repeat the process. I iterate this process for each month until I reach the last window of data. The reduced-form residuals, $\nu_{i,t}^{q}$ and $\nu_{i,t}^{p}$, collected for the final period of each window are used to label (or sign) each category i in each month t using the restrictions defined in equations (8) to (11):

$$\mathbb{1}_{i \in sup(+),t} = \begin{cases} 1 & \text{if } \nu_{i,t}^{p} < 0, \nu_{i,t}^{q} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i \in sup(-),t} = \begin{cases} 1 & \text{if } \nu_{i,t}^{p} > 0, \nu_{i,t}^{q} < 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i \in dem(+),t} = \begin{cases} 1 & \text{if } \nu_{i,t}^{p} > 0, \nu_{i,t}^{q} > 0 \\ 0 & \text{otherwise} \end{cases}$$

[7] Online appendix figure A5 and table 1 show that the main results in this study are robust using 3 lags and 24 lags, including a deterministic time trend, and replace log levels with log first differences. Running the specification in first-differences is a less flexible parameterization.

[8] An alternative specification would be to run reduced-form regressions in first differences—for instance, inflation rates. This residual, however, would represent a surprise to the acceleration (or deceleration) of prices and quantities in industry i (not the surprise increase or decrease in prices and quantities).

$$\mathbb{1}_{i\in dem(-),t} = \begin{cases} 1 & \text{if } \nu^p_{i,t} < 0, \nu^q_{i,t} < 0 \\ 0 & \text{otherwise} \end{cases}$$

It follows that the share of total consumption personal expenditures (PCE) experiencing each type of shock (s) in month t is:

$$\gamma_{s,t} = \sum_i \mathbb{1}_{i\in s,t}\omega_{i,t} \tag{14}$$

where $s \in \{dem(+), dem(-), sup(+), sup(-)\}$. and $\omega_{i,t}$ is the expenditure weight of category i in the PCE consumption basket. Thus, one can create a continuous measure of the degree to which supply and demand shocks are impacting PCE by aggregating over the binary indicator functions. For instance, $\gamma_{s,t} = 1$ indicates that the entire PCE basket is experiencing shock type s in month t, while $\gamma_{s,t} = 0.1$ indicates that 10 percent of the PCE basket is experiencing shock type s in month t.

Figure 2 shows a plot of these shares. Supply-shocks make up a larger fraction of the consumption expenditures than demand shocks over the 1969 to 2023 sample period—roughly 60 percent of the PCE is labeled with a supply shock. During recessions, negative-demand shocks are more prevalent while positive demand shock are less prevalent. Negative supply shocks were prevalent during the Great Inflation period, especially during the 1973-75 and 1980 recessions, and then again during the 1990-1991 Gulf War. Positive supply shocks became more apparent in the late 1990's stemming from an increases in the supply of new vehicles, financial services, energy, and telecommunication services. Spikes in positive supply shocks in 2004 and 2019 appear due to food consumed at home. Categories that experience relatively more negative demand shocks during recessions include information processing equipment, women's clothing, hotels, and air travel. More recently, the 2021-2022 post-COVID surge in inflation appears to be driven by a sharp increase in the number of categories labeled with positive demand shocks and negative supply shocks. Categories that experienced frequent positive demand shocks during the post-COVID period include hotels, gasoline, restaurants, and clothing. Categories that experienced frequent negative supply shocks in this period include new vehicles, housing, and nursing homes.[9]

[9] See online appendix table A1 for a list of the categories with the highest frequency of positive demand shocks and negative supply shocks during the 2021-2022 period, and the relative frequency of negative demand shocks during recessions.

Figure 2: Share of PCE by shock type

Notes: Plotted is the expenditure-weighted share of PCE that is labeled as supply or demand driven in a given month, centered five-month moving average. Panel A shows the share of PCE labeled demand driven, and then further decomposed into negative and positive shocks. Panel B shows the analogous series for supply driven labels. All four series above sum to one for any given month. Unweighted shares are shown in online appendix figure A1

3 Decomposing PCE Inflation

3.1 Constructing demand- and supply-driven contributions to inflation

In the same fashion as constructing the share of total consumption expenditures experiencing either a supply or demand shock, one can also construct the share of inflation that is experiencing either a supply or demand shock. I use the labels defined in equations (8) to (11) on the estimated residuals from equations (12)-(13) to decompose PCE inflation into two separate components—supply driven inflation and demand-driven inflation. Specifically, I define two indicator functions that determine whether category i experienced a supply shock or demand shock in period t:

$$\mathbb{1}_{i \in sup,t} = \begin{cases} 1 & \text{if } \nu^p_{i,t} > 0, \nu^q_{i,t} < 0 \text{ or } \nu^p_{i,t} < 0, \nu^q_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i \in dem,t} = \begin{cases} 1 & \text{if } \nu^p_{i,t} > 0, \nu^q_{i,t} > 0 \text{ or } \nu^p_{i,t} < 0, \nu^q_{i,t} < 0 \\ 0 & \text{otherwise} \end{cases}$$

It follows that monthly PCE inflation can be divided into two distinct components, the supply- and demand-driven contributions:

$$\pi_{t,t-1} = \underbrace{\sum_i \mathbb{1}_{i \in sup,t} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{supply-driven } (\pi^{sup}_{t,t-1})} + \underbrace{\sum_i \mathbb{1}_{i \in dem,t} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{demand-driven } (\pi^{dem}_{t,t-1})} \tag{15}$$

where $\omega_{i,t-1}$ is the expenditure weight of category i in the PCE consumption basket where the expenditure weight is a Laspyeyres weight, and is calculated a the share of consumption expenditures in period $t-1$. The variable $\pi_{i,t,t-1}$ is the monthly percent change in the price index of category i between $t-1$ and t. The supply-driven component, $\pi^{sup}_{t,t-1}$, is the contribution to overall inflation from those categories labeled as having experienced a supply shock in time t, and the demand-driven component, $\pi^{dem}_{t,t-1}$, is the contribution from categories labeled as having experienced a demand-shock at time t. It follows that the share of inflation that is experiencing a supply (demand) shock is the ratio of the supply (demand) driven contribution divided by the inflation rate.

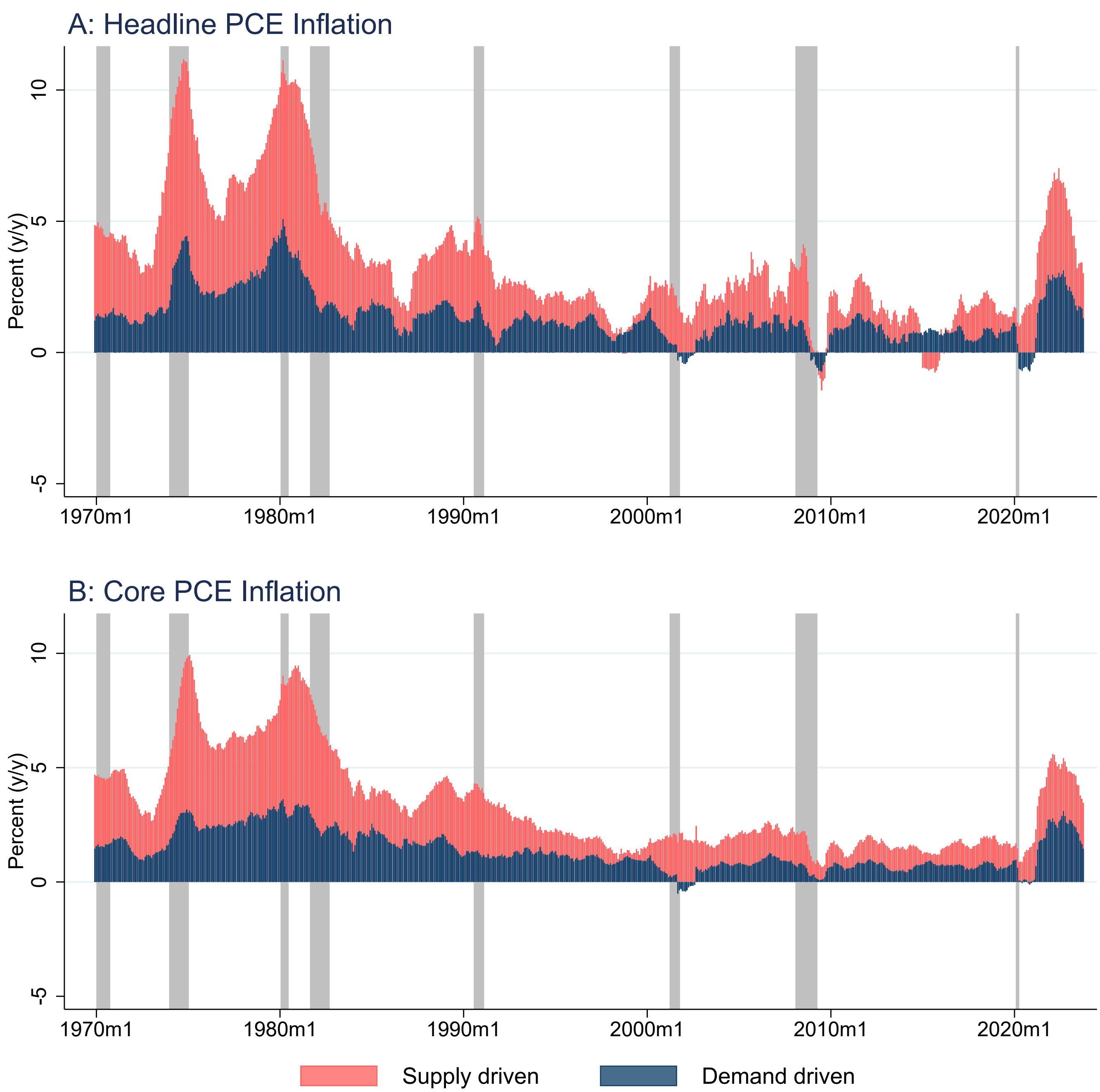
Figure 3 shows the supply- and demand-driven contributions to year-over-year headline (panel A) and core (panel B) PCE inflation. The supply- and demand-driven contributions to year-over-year inflation are constructed as the running product of the current and past 11 monthly supply- and demand-driven contributions: $\pi^{sup}_{t,t-12} = \prod_{k=0}^{11}(1 + \pi^{sup}_{t-k,t-k-1}) - 1$ and $\pi^{dem}_{t,t-12} = \prod_{k=0}^{11}(1 + \pi^{dem}_{t-k,t-k-1}) - 1$. The Great Inflation era saw a relatively larger share of supply-driven inflation. The collapse in airline travel immediately after September 11, 2001 reduced demand-driven inflation, while the sharp energy price declines in 2014 and 2015 reduced supply-driven inflation. More recently, over the COVID period, the decomposition shows that demand-driven inflation fell precipitously at the onset of the pandemic, contributing a negative amount in the late Spring of 2020. Demand-driven inflation then quickly reversed course causing the well-known upswing in inflation throughout 2021. Supply-driven peaked in the Spring of 2022 likely attributable to food and energy supply disruptions, including those associated with the invasion of Ukraine. Demand-driven inflation stayed strong into 2023.

The contribution of demand-driven inflation generally declines at the tail end of recessions, however, this phenomenon is more apparent in the period after the Great Inflation. Figure 4 shows the dynamics of the cumulative supply and demand contributions to PCE inflation for the 26 months following the peak of a recession, where peak is defined as the onset of the recession by the NBER. This specification includes 12 lags of the supply and demand contributions as well as 12 lags and intervening periods of the peak recession dummies. As shown in panels A and B, demand-driven inflation declines on average following the peak of the recession, while supply-driven inflation increases. Headline inflation shows a more immediate supply-driven effect, while core inflation shows a more immediate demand-driven effect. Panels C and D show that the dynamics changed considerably between the pre and post Great Inflation era. Inflation dynamics during recessions in the 1970s and 1980s were dominated by large upswings in supply-driven inflation. By contrast, inflation dynamics during recessions since then have been dominated by declines in demand-driven inflation.

3.2 Robustness

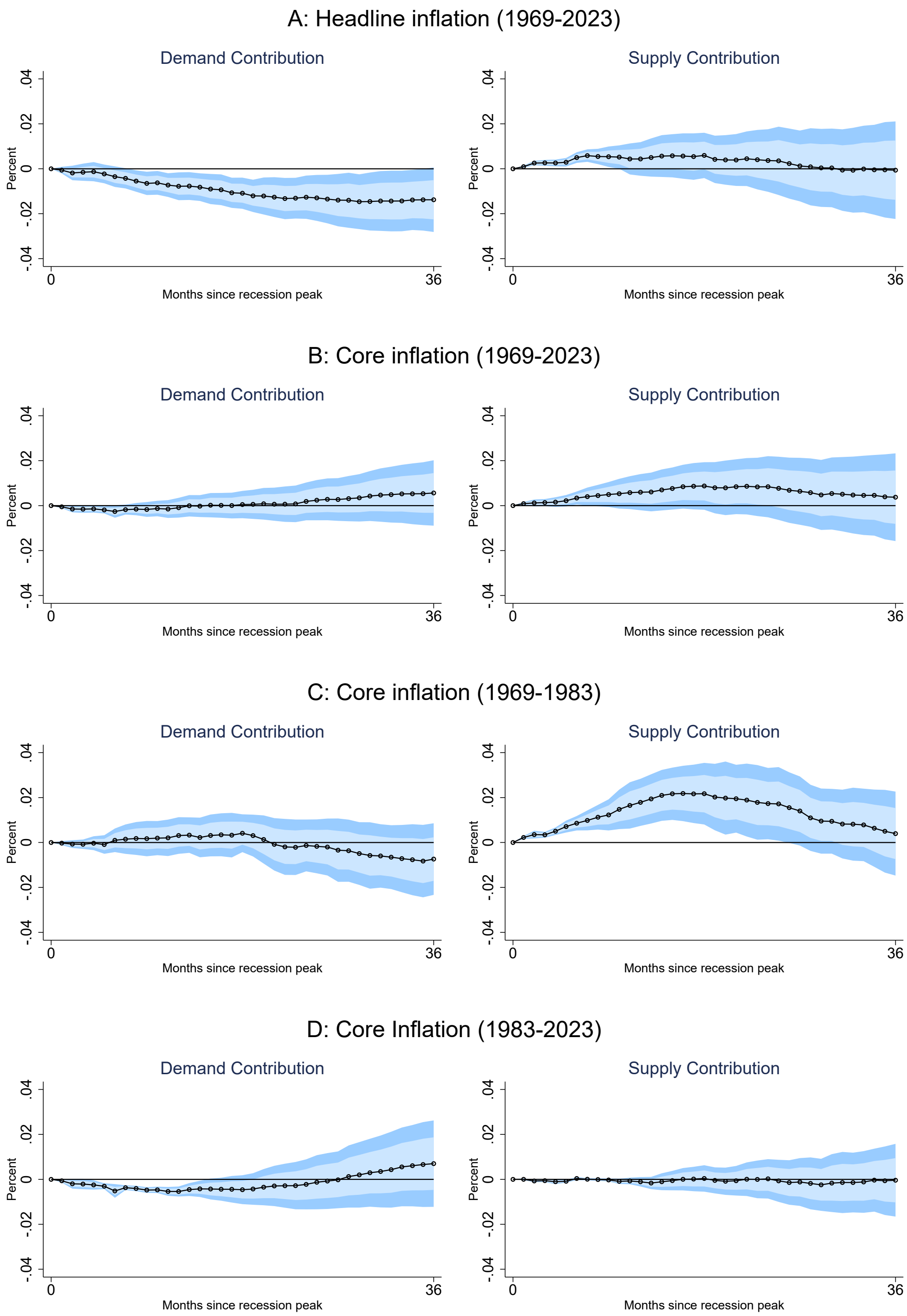
To test the robustness of the results of the methodology I go through a series of alternative estimation specifications. The residuals, $\nu^p_{i,t}$ and $\nu^p_{i,t}$, used to determine whether a category

Figure 3: Supply- and demand-driven PCE Inflation



Notes: Panel A the contributions to the 12-month change in headline PCE inflation and panel B shows the contributions to the 12-month change in core PCE inflation. Both series are divided intro contributions determined as supply-driven (red) and demand-driven (blue).

Figure 4: Supply- and demand-driven PCE Inflation during recessions



Notes: Shown are the cumulative responses of the supply and demand contributions to PCE inflation since the peak of recession, defined as the onset of the recession by the NBER. Panels A and B show cumulative headline and core inflation over the full sample period 1969-2023. Panel C shows the responses during the great inflation era (pre-1984) and panel D shows the responses in the post great inflation era. Regressions include 12 lags of inflation and 12 lags and intervening recession peak dummies as controls. Shown are one-standard deviation and 90th percentile confidence bands.

is labeled as supply- or demand-driven may include measurement error, modeling error, or more broadly, may not be indicative of a clearly defined net demand or net supply shock. A poorly measured residual could cause a category to be mislabeled, clouding the underlying measures of supply- and demand-driven inflation.

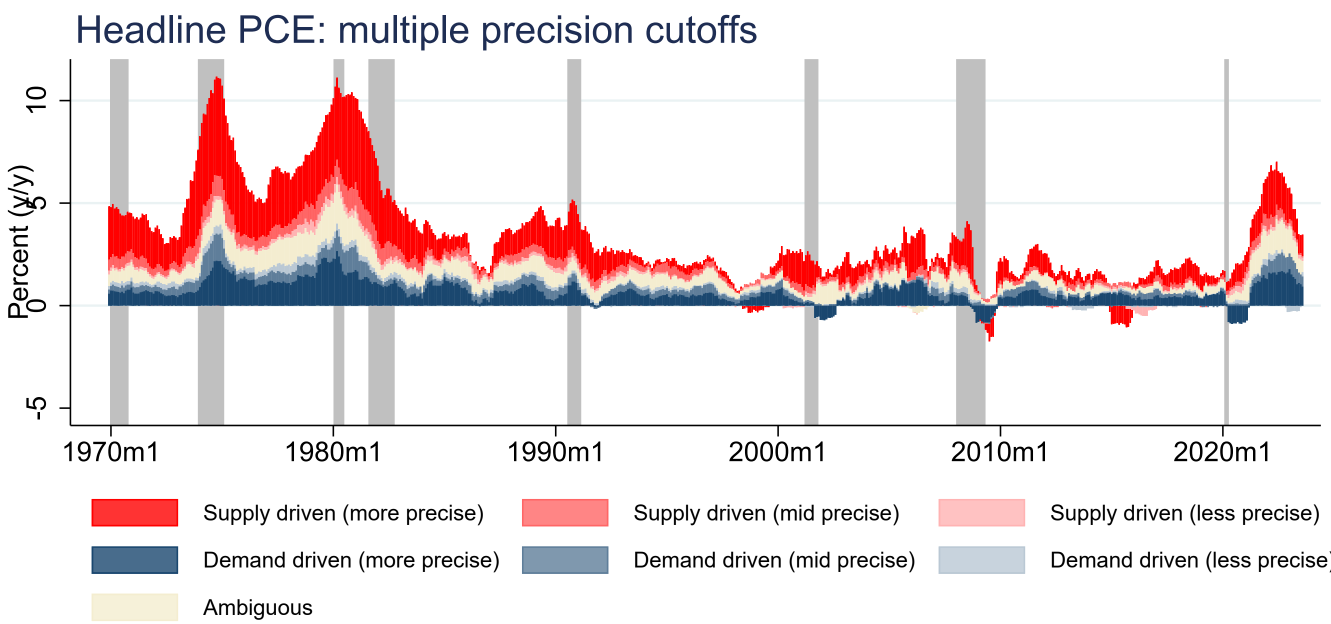
As a first exercise, I isolate those observations that are most likely to be incorrectly labeled, namely cases where $\nu^p_{i,t}$ or $\nu^p_{i,t}$ are "close to zero." Specifically, I relabel a category as "ambiguous" if either of the price or quantity residuals are relatively small. These are observations where supply and demand shocks may be occurring simultaneously or where there were only small structural shocks occurring.[10] In the column and row labeled "precision" in Table 1, I report the correlation of the supply and demand contributions using a cut-off equal to 0.1 standard deviations from zero. This threshold results in re-labeling 15 percent of category-month observations across the entire sample as "ambiguous," however, the results are robust to enlarging this cut-off. Figure 5 uses multiple precision cut-offs representing those category-months with a residuals up to 0.15 standard deviations and 0.30 standard deviations from zero. This exercise unmasks more interesting patterns in the data. For instance, the 50 percent of inflation during Great Inflation era is labeled as precisely supply driven (dark red bars) while 20 percent of inflation during this period is labeled as precisely demand driven (dark blue bars). Another example, is the period during September 11th, which shows a markedly strong increase in the "ambiguous" category, which was previously labeled supply-driven.

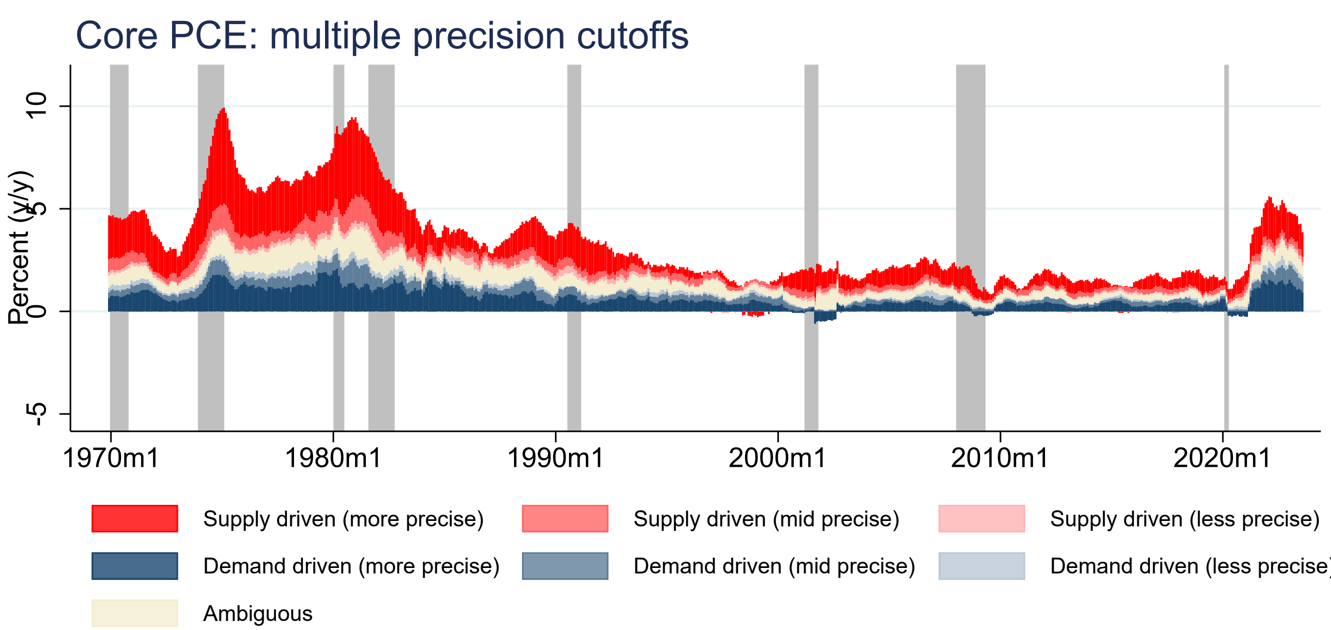
As a second exercise, I relax the assumption that the labeling is definitive (or binary). Instead I assume that the labeling is stochastic (or probability-based), which allows for the possibility that supply and demand shocks occur simultaneously. Specifically, one can replace equation (15) from that which is based on indicator functions to that which is based on probability weights:

$$\pi_{t,t-1} = \underbrace{\sum_i \phi^{sup}_{i,t} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{supply-driven } (\pi^{sup}_{t,t-1})} + \underbrace{\sum_i \phi^{dem}_{i,t} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{demand-driven } (\pi^{dem}_{t,t-1})} . \tag{16}$$

[10] Since supply and demand shocks move quantities in opposite directions for the same-direction price change, simultaneous supply and demand shocks will result in asymmetric price and quantity changes. That is, these will be observations with smaller changes in quantities than expected for a given price increase, and vice versa.

Figure 5: Precision Labeling





Notes: Panel A shows headline PCE (12-month change) divided into three components: supply driven, demand driven, and ambiguous. The ambiguous component include those categories where the residual from either the price or quantity index regression lied less than 0.1 category-specific standard deviations from zero. Panel B further divides the supply- and demand-drive contributions into three subcomponents: "more precise," "mid precise" and "less precise." "More precise" includes those categories where the residuals from both the price and quantity regression lied at least 0.25 standard deviations from zero. "Mid precise" and "less precise" reduces the threshold to 0.15 and 0.30 category-specific standard deviations.

Table 1: Cross-correlations, alternative measures of supply- and demand-driven contributions to PCE inflation

Variables	Baseline	IRF (2 mon.)	IRF (3 mon.)	AR-3	AR-24	Wt. (Norm.)	Wt. (Bayes)	Precision	Filter	First diff
					Supply-driven contribution					
Baseline	1.000									
IRF (2 mon.)	0.984	1.000								
IRF (3 mon.)	0.978	0.988	1.000							
AR-3	0.991	0.985	0.979	1.000						
AR-24	0.987	0.980	0.970	0.987	1.000					
Wt. (Norm.)	0.985	0.983	0.985	0.983	0.982	1.000				
Wt. (Bayes)	0.984	0.981	0.980	0.982	0.978	0.992	1.000			
Precision	0.993	0.983	0.975	0.986	0.982	0.977	0.977	1.000		
Filter	0.974	0.972	0.976	0.974	0.972	0.987	0.976	0.972	1.000	
First diff	0.990	0.983	0.979	0.986	0.985	0.987	0.986	0.985	0.976	1.000
					Demand-driven contribution					
Baseline	1.000									
IRF (2 mon.)	0.952	1.000								
IRF (3 mon.)	0.925	0.958	1.000							
AR-3	0.975	0.953	0.929	1.000						
AR-24	0.967	0.942	0.909	0.966	1.000					
Wt. (Norm.)	0.956	0.937	0.933	0.951	0.954	1.000				
Wt. (Bayes.)	0.958	0.940	0.926	0.949	0.947	0.974	1.000			
Precision	0.986	0.944	0.917	0.966	0.965	0.935	0.947	1.000		
Filter	0.933	0.914	0.914	0.931	0.935	0.971	0.936	0.910	1.000	
First diff	0.973	0.947	0.927	0.963	0.963	0.964	0.963	0.962	0.941	1.000

Notes: Shown are the contemporaneous correlations of the contributions to 12-month headline PCE inflation. IRF uses the residual from either 2-months-ahead, or 3-months-ahead projection of the dependent variable (i.e, impulse response function). AR-3 uses a 3-lag VAR to compute the residuals. AR-24 uses a 24 lag VAR to compute the residuals.Wt. (Bayes) uses probability-based label weights constructed from the posterior distribution of Bayesian estimation of (12) and (13). Wt. (Param.) uses probability-based label weights constructed from an assumed parametric distribution of supply and demand residuals. Precision removes (i.e, re-labels as ambiguous) those categories where the residual from either the price or quantity index regression lied less than 0.1 category-specific standard deviations from zero. "Filter" performs a Hamilton (2018) filter on the log price and log quantity before main estimation, with the horizon set to 24 months. "First diff" substitutes log levels of price and quantity with the first differences of log price and log quantity in the VAR.

where $\phi_{i,t}^{sup}$ represents the probability that category i experienced a supply shock in period t and $\phi_{i,t}^{dem}$ represents the probability that category i experienced a demand shock in period t, such that $\phi_{i,t}^{sup} + \phi_{i,t}^{dem} = 1$. There are of course a large possibility of choices for modeling these probability weights. I choose two sets of constructions based on their tractability. The first set is constructed using an assumed parametric distribution of the residuals, similar to that used in the precision labeling exercise above. The parametric model assumes that the probability of simultaneous structural shocks occurring decreases with the absolute size of the product of the reduced-form residuals.[11] The other set of probabilities is constructed using the posterior distribution from Bayesian estimation of (12) and (13). Here the assumption is that the probability of simultaneous structural shocks occurring decreases with the precision of the structural shock labeling. Details are provided in the online appendix, section A.1. While these two methodologies are based on quite different modeling assumptions, they result in supply and demand contributions with similar time series patterns to the baseline. The cross-correlations shown in Table 1, labeled as "Wt. (Bayes.)" and "Wt. (Param),"[12] are both above 0.98 for supply-driven and above 0.95 for demand-driven.

As another exercise, I account for the possibility that current prices and quantities adjust to *previous* periods' shocks, as in a model with sticky prices. To do so, I run the main specifications (12) and (13) using the local projection, impulse response function (IRF), method of (Jorda (2005)) which is similar to the standard vector auto-regression (VAR) approach but less restrictive. For a given forecast horizon h, a regression can be run:

$$q_{i,t} - q_{i,t-h-1} = \sum_{j=1}^{12} \gamma_j^{qp,h} p_{i,t-j-h} + \sum_{j=1}^{12} \gamma_j^{qq,h} q_{i,t-j-h} + c + \nu_{i,t}^{q,h} \tag{17}$$

$$p_{i,t} - p_{i,t-h-1} = \sum_{j=1}^{12} \gamma_j^{pp,h} p_{i,t-j-h} + \sum_{j=1}^{12} \gamma_j^{pq,h} q_{i,t-j-h} + c + \nu_{i,t}^{p,h} \tag{18}$$

[11]Consider the case where σ and δ both equal one, such that $\nu^q = 0.5(\varepsilon^s + \varepsilon^d)$ and $\nu^p = 0.5(\varepsilon^s - \varepsilon^d)$. One single demand shock ($\varepsilon^s = 0$ and $\varepsilon^d = 2\alpha$) implies that $\nu^q = \alpha$ and $\nu^p = \alpha$, or $|\nu^p \nu^q| = \alpha^2$. Analogously, one single supply shock ($\varepsilon^s = 2\alpha$ and $\varepsilon^d = 0$) implies that $\nu^q = \nu^p = 2\alpha$ or $|\nu^p \nu^q| = \alpha^2$. Two equal sized supply and demand shocks ($\varepsilon^d = \varepsilon^s = \alpha$) implies that $\nu^q = \alpha$ and $\nu^p = 0$, and therefore $|\nu^p \nu^q| = 0$, while two equal and opposite sized supply and demand shocks ($\varepsilon^d = \alpha$ and $\varepsilon^s = -\alpha$) implies that $\nu^q = 0$ and $\nu^p = \alpha$, and therefore $|\nu^p \nu^q| = 0$.

[12]The series are shown graphically in the online appendix figure A6

where the residuals $\nu^{q,h}_{i,t}$ and $\nu^{p,h}_{i,t}$ include the accumulation of residuals between periods $t-h$ and t. In addition to accounting for residuals from previous periods, this methodology also accounts for potential noise by inherently taking the rolling sum of monthly residuals. The drawback here is that this method uses perhaps stale information to define the label in the current period. I test two different IRF specifications where $h = \{2, 3\}$. I report the cross-correlations of the implied 12-month supply- and demand-driven contributions to headline inflation in Table 1, labeled as "IRF (2 months)," "IRF (3 months)."[13] The correlations are all quite high with the baseline specification, ranging from 0.95 to 0.98. Another method to control for sticky prices or measurement error is to estimate the methodology on quarterly data, which shows similar results to using monthly data.[14]

Another concern is model misspecification, which could result in biased estimates of the residuals $\nu^{p}_{i,t}$ and $\nu^{p}_{i,t}$. One type of miss-specification bias is the number of lags included in equations (12) and (13), which is 12 in the baseline specification. I test two alternative lag specifications: $J = 3$ and $J = 24$ lags. The cross-correlations of the implied 12-month supply- and demand-driven contributions to headline inflation are shown in Table 1, labeled as "AR-3" and "AR-24."[15] Changing the lag-structure of the VAR has a minimal impact on the constructed demand and supply contributions. The correlations with the baseline specification range from 0.93 to 0.96. Another type of miss-specification could be attributable to deterministic trends, for instance technological improvements. For this reason, I test a specification which filters the price and quantity indexes using the Hamilton (2018) filter before running the main estimation 12 and 13.[16] The correlations with the baseline specification are 0.97 and 0.93 for the supply and demand contributions, respectively.

As a final exercise, I run a specification in first-differences of the log values of prices and quantities:

[13] The series are shown graphically in the online appendix figure A4.

[14] Results using quarterly data are shown in Appendix Figure A2.

[15] The series are shown graphically in the online appendix Figure A5.

[16] I run the filter with Hamilton's preferred 2-year horizon. That is, I run $p_{i,t} = \sum_{j=24}^{36} \gamma_j p_{i,t-j} + c + \varepsilon^p_{i,t}$ and $q_{i,t} = \sum_{j=24}^{36} \gamma_j q_{i,t-j} + c + \varepsilon^q_{i,t}$ for each category i. These residuals, $\varepsilon^p_{i,t}$ and $\varepsilon^q_{i,t}$, are substituted in as the main variables (p and q) in estimation of equations 12 and 13.

$$\Delta q_{i,t} = \sum_{j=1}^{12} \gamma_j^{qp} \Delta p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{qq} \Delta q_{i,t-j} + c + \nu_{i,t}^{q} \tag{19}$$

$$\Delta p_{i,t} = \sum_{j=1}^{12} \gamma_j^{pp} \Delta p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{pq} \Delta q_{i,t-j} + c + \nu_{i,t}^{p} \tag{20}$$

which is a more restrictive regression as it imposes the coefficient on the lagged dependent variable to equal one, but it plausibly better controls for nonstationarity. First-differencing also helps alleviate concerns about a mechanical correlation in the price and quantity levels—the BEA measures real quantities by deflating nominal expenditures by the price index, meaning upside measurement error on the BEA's price index would be correlated with downside measurement error in the BEA's measure of the quantity index. First-differencing will remove this bias as long as the measurement issue remains relatively constant between periods. If the measurement error is trending or is persistent, the bias would be alleviated by the inclusion of lagged dependent variables. If the measurement error is i.i.d., it becomes included in the residuals $\nu_{i,t}^{q}$ and $\nu_{i,t}^{p}$. In this case the issue becomes similar to the measurement error discussed above, and would be alleviated by using a smoothed function of the residuals, such as the local projection specifications (17) and (18). The correlations with the baseline specification are 0.99 and 0.97 for the supply and demand contributions, respectively.

4 Proof of concept

As a way to test whether the methodology is performing as intended I assess how externally identified aggregate shocks impact the constructed inflation decompositions. There is more assurance that the inflation measures are externally valid if externally-constructed shocks move the supply- and demand-driven contributions in anticipated directions. This is similar to a falsification test. Standard macroeconomic models (for example, Smets and Wouters (2003) and Christiano, Eichenbaum, and Evans (2005)) predict that monetary policy tightening reduces inflation via a reduction in aggregate demand. Analogously, declines in the supply of oil are known to be associated with declines in aggregate output and increases in inflation (Hamilton (1983), Rotemberg and Woodford (1996), and Blanchard and Gali

(2007)).

I measure how high-frequency identified (HFI) monetary policy shocks and externally-identified oil supply (OS) shocks drive the supply-driven and demand-driven contributions to inflation. I use the local projection method, such that for each forecast horizon h, a distinct regression is run for a given contribution measure ($\pi^{dem}_{t+h,t}$ or $\pi^{sup}_{t+h,t}$) on the HFI monetary policy and OS shocks, as well as controls:

$$\pi^{j}_{t+h,t-1} = \alpha^{h}_{j} HFI_t + \beta^{h}_{j} OS_t + \mathbf{A}^{h}_{j} \sum_{\tau=0}^{6} \mathbf{Y}_{t-\tau} + \zeta_{j,t+h}. \tag{21}$$

where $\pi^{j}_{t+h,t-1}$ is the cumulative growth in the contribution of $j \in \{dem, sup\}$ between $t-1$ and $t+h$. The HFI monetary policy shocks, developed in Kuttner (2001), were taken from Gürkaynak, Sack, and Swanson (2005) and are available from 1990 to 2016. These shocks are constructed from surprises in bond/futures prices around Federal Open Market Committee announcements. My main specification use surprises to the slope of the 10-year yield curve due to monetary policy tightenings.[17] Monetary policy shocks to the slope of the yield curve can be estimated over the zero-lower bound period and are known to cause monotonic and persistent increases in the unemployment rate (see Rudebusch and Wu (2008), Eberly, Stock, and Wright (2019), Barnichon and Mesters (2020) and Barnichon and Mesters (2022)).[18] The oil supply shocks (OS) are constructed by Baumeister and Hamilton (2019) and represent surprise decreases in the supply of oil.[19] Results using alternative oil supply shocks—oil supply news shocks by Känzig (2021)—produce qualitatively similar results.[20] Controls, $\mathbf{Y}_t$, include current and six lags of the monthly demand and supply contributions, unemployment rate, the excess bond premium, and credit spreads (Gilchrist and Zakrajšek (2012)).

Figure 6 shows the results on the contributions to core PCE inflation, along with one-standard deviation and 90th percentile confidence intervals.[21] A monetary policy tightening—

[17] Results were robust to using the surprise to the 5 minus the surprise to the federal funds rate, as well as assessing it over the 2008 to 2016 sample period used in Eberly, Stock, and Wright (2019). See online appendix figure A10.

[18] Online appendix figure A10 shows that a 1 percentage point surprise increase in the slope shock increases the unemployment rate by approximate 2 percentage points within 2 years. Figure A10 shows the impact of a 1 percentage point surprise increase in the level of the federal funds rate, estimated over the 1990 to 2007 sample period. The unemployment rate declines upon impact and then begins to by the end of the first year.

[19] I take the negative value of the positive supply shocks constructed in the paper.

[20] See online appendix figure A9.

[21] Results for headline inflation show similar results and are shown in online appendix figure A8.

that induces a 100 basis point surprise increase in the slope—reduces the demand-driven contribution of inflation by a cumulative 1.5 percentage points over 24 months.[22] The same tightening induces no change to the supply-driven contribution to inflation. There appears to be little evidence of a cost-channel effect of monetary policy, whereby higher costs of capital are passed on to consumers (Barth and Ramey (2001) and Ravenna and Walsh (2006)).

The bottom two panels of figure 6 show the impact of the negative oil supply shock. The negative supply shock has a small, yet precisely estimated, positive impact on the supply-driven contribution to core inflation. The Baumeister and Hamilton (2019) shock, which corresponds to an immediate 3.5 percent increase in the price of crude oil, causes a 5 basis point increase in the supply-driven contribution to core PCE inflation over 24 months. This implies that a 10 percent increase in the price of oil translates into a 15 basis point increase inflation over two years—a small response. There also appears to be an equally small sized *negative* effect on demand-driven inflation, which is consistent with the idea that energy price increases also act as negative demand shocks (Lee and Ni (2002), Hamilton (2008), Edelstein and Kilian (2009)). Thus, the oil supply shock has no net effect on overall core inflation, but the decomposition reveals interesting underlying supply and demand effects.

Repeating the oil supply shock exercise on headline inflation, shown in figure 7, reveals more interesting dynamics. As expected, the oil supply shock has a larger impact on the supply-driven component of headline inflation than the supply-driven contribution to core inflation. Specifically, a 10 percent increase in the price of crude oil causes a 0.5 percentage point increase in the supply-driven contribution to headline inflation. The oil supply shock has a smaller, yet statistically significant, *positive* impact on the demand-driven contribution to headline inflation. A deeper examination into the components of non-core inflation reveal interesting cross-substitution dynamics between different types of energy products causing this effect. The bottom panel of figure 7 shows that the quantity and prices of fuel oil move in oppositive directions—corroborating the externally identified negative supply. However, the quantity and price of “other fuels” (i.e., propane, kerosene, and firewood) move in the same direction, indicative of a demand shock. Thus, the inflation decomposition reveals an increase in demand for oil substitutes stemming from the decline in oil supply. An important takeaway from this result is that shocks generally deemed as “aggregate demand” or “aggregate supply” can include endogenous supply and demand *reactions* within the

[22] Results showing the impact over 48 months are depicted in online appendix figure A10

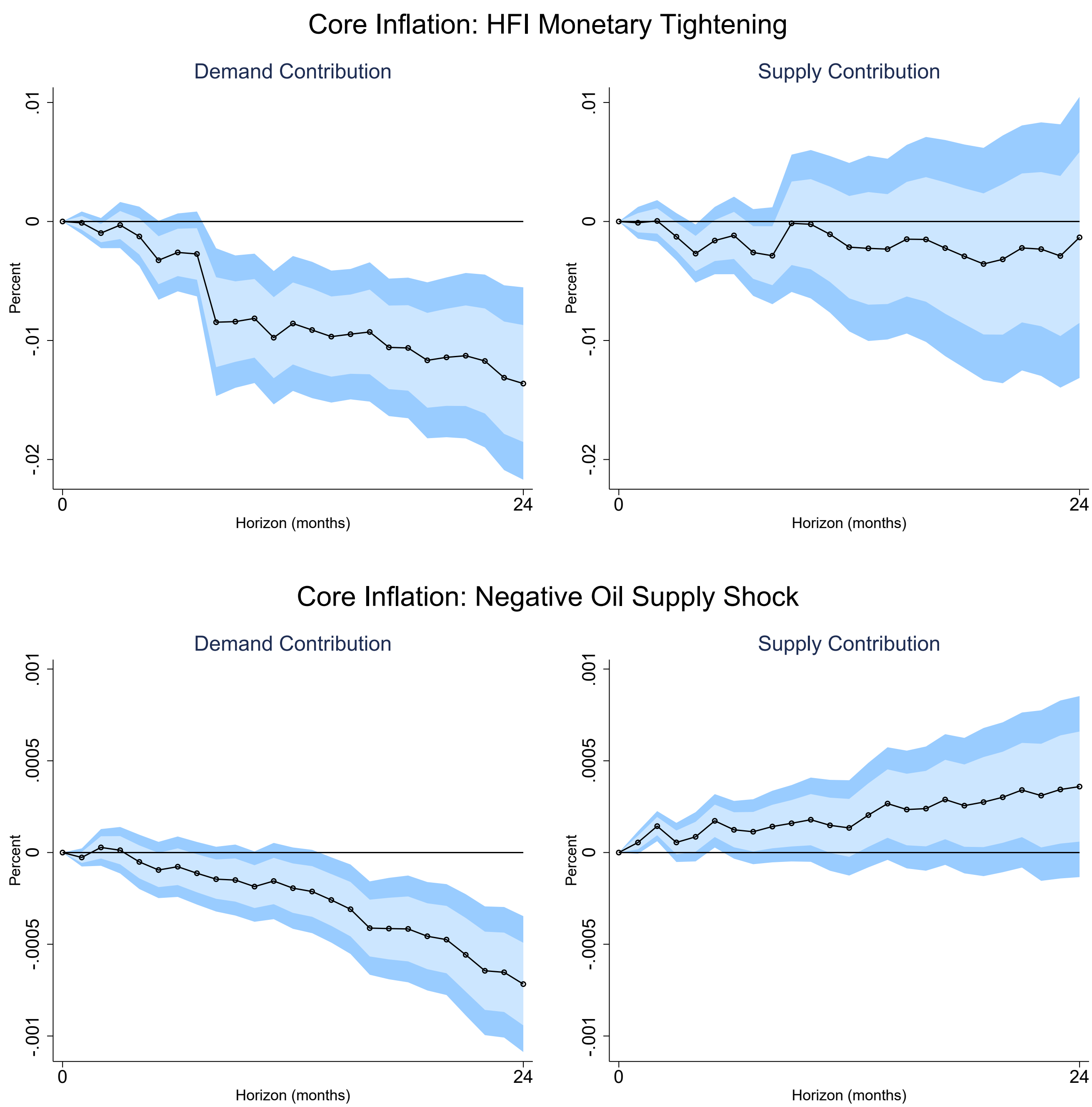
underlying inflation measure. Thus, this methodology takes into account the endogenous supply and demand reactions to aggregate supply and demand shocks. The labeling is therefore agnostic as to whether the root source of the shock in question is an aggregate demand or aggregate supply shock.

5 Conclusion

This study provides an overview of a simple framework to decompose PCE inflation into supply- and demand-driven components. The approach relies on the use of sign restrictions on categorical-level data. I label categories as either supply or demand driven based on the signs of the residuals in the reduced-form price and quantity regressions. The time-series patterns of the series show intuitive and sensible dynamics. The series also respond to externally identified supply and demand shocks in theoretically predicted ways.

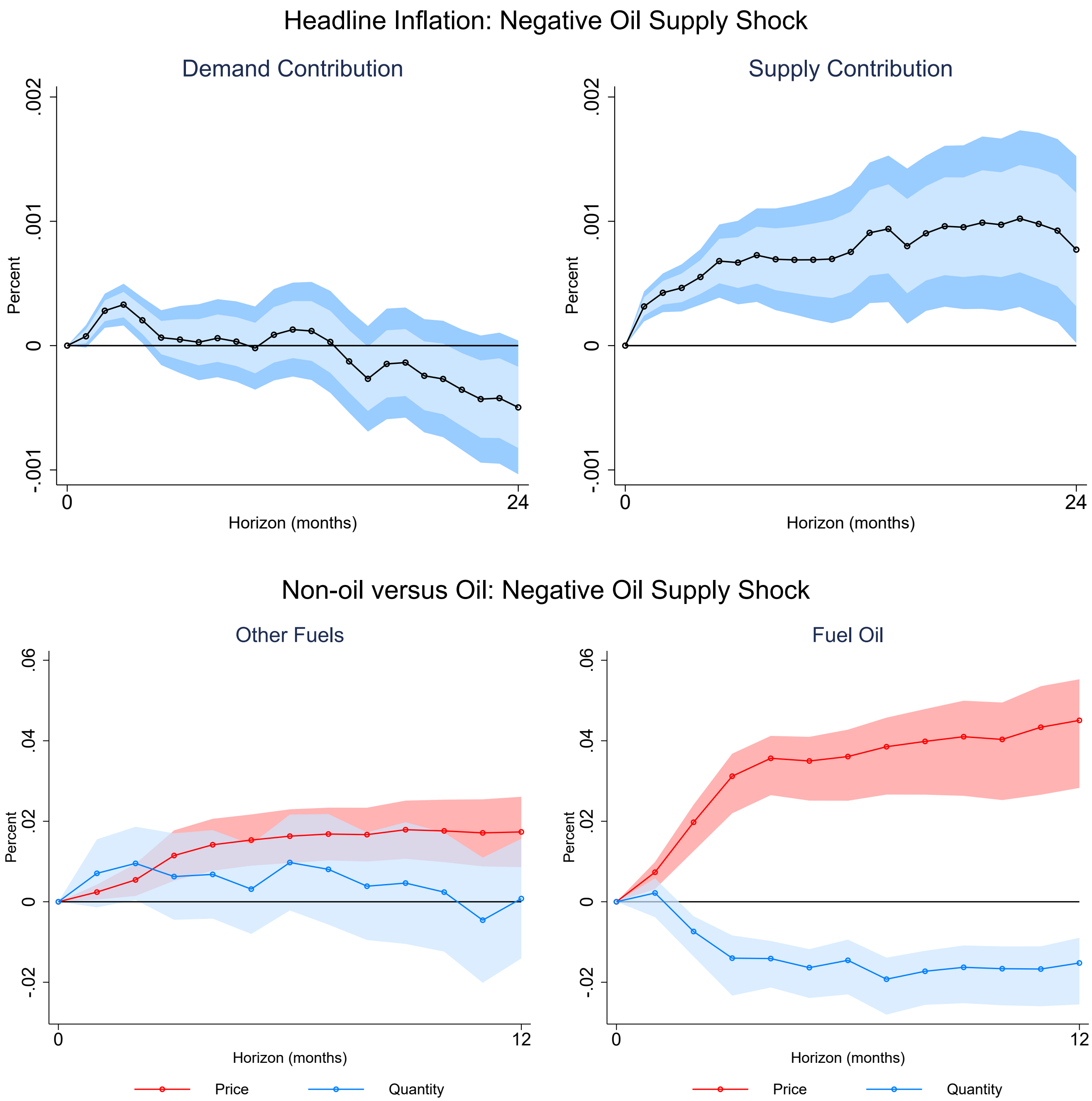
The supply- and demand-contributions can be updated and used by researchers to help answer a host of existing and future economic questions. For instance, one could test whether monetary or fiscal policy impacts the economy differently when inflation is high due to supply versus demand reasons. They can also be used to help tease out supply and demand effects on inflation from productivity or government spending shocks. Finally, the series can help track whether supply or demand factors are pushing on inflation in the current month, which can help policy makers in real time.

Figure 6: Impulse responses of core PCE inflation to externally identified demand and supply shocks



Notes: Panels A and B show the cumulative impulse responses of the demand and supply contributions to core PCE inflation to a high frequency identified (HFI) monetary surprises. Surprises are measured as the change in the slope of the yield curve (the surprise to the 10-year on-the-run Treasury yield minus the surprise to the fed funds rate) around the FOMC announcements within a 30 minute window (Gürkaynak, Sack, and Swanson (2005)). Panels C and D show the impulse responses of the demand and supply contributions to core PCE inflation to an oil supply news shock (Baumeister and Hamilton (2019)). Shown are the 90th percentile and one-standard deviation confidence bands. Estimation sample is 1990-2016.

Figure 7: Impulse responses of headline PCE inflation and energy products to negative oil supply shock



Notes: The top two panels show the cumulative impulse response of the demand and supply contributions of headline PCE inflation to an oil supply shock (Baumeister and Hamilton (2019)). Shown are the 90th percentile and one-standard deviation confidence bands. The bottom two panels show the cumulative impulse responses of the log price index and log quantity index of “fuel oil” and “other fuels” to the same oil supply shock, along with one-standard deviation error bands. “Other fuels” consist of propane, kerosene, and firewood (see CPI-PCE Concordance).Estimation sample is 1990-2016.

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A Online Appendix

A.1 Probability Weighting

I construct two types of probability weights, $\phi_{i,t}^{sup}$ and $\phi_{i,t}^{dem}$ that are used in constructing the "weighted labels" version of the inflation decomposition:

$$\pi_{t,t-1} = \underbrace{\sum_i \phi_{i,t}^{sup} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{supply-driven } (\pi_{t,t-1}^{sup})} + \underbrace{\sum_i \phi_{i,t}^{dem} \omega_{i,t-1} \pi_{i,t,t-1}}_{\text{demand-driven } (\pi_{t,t-1}^{dem})} . \tag{22}$$

where $\phi_{i,t}^{sup}$ represents the probability that category i experienced a supply shock in period t and $\phi_{i,t}^{dem}$ represents the probability that category i experienced a demand shock in period t.

Bayesian weights: I fit equations (12) and (13) to a Bayesian VAR model, using the conjugate Minnesota prior with tightness parameter and lag decay parameter both equal to 1. The Markov chain Monte Carlo (MCMC) sample size is $S = 10,000$ with a burn-in period of 2,500. I collect the posterior estimates of the coefficients and construct expected values and residuals. This results in S estimates of residuals, and hence S estimates of indicator functions $\mathbb{1}_{i\in dem,t}^{s}$ and $\mathbb{1}_{i\in sup,t}^{s}$ for each category i and month t. It follows that the probability weights are then constructed from the distribution of posterior indicator functions:

$$\begin{aligned} \phi_{i,t}^{dem} &= (1/S) * (\sum_{s=1}^{S} \mathbb{1}_{i\in dem,t}^{s}) \\ \phi_{i,t}^{sup} &= 1 - \phi_{i,t}^{dem}, \end{aligned}$$

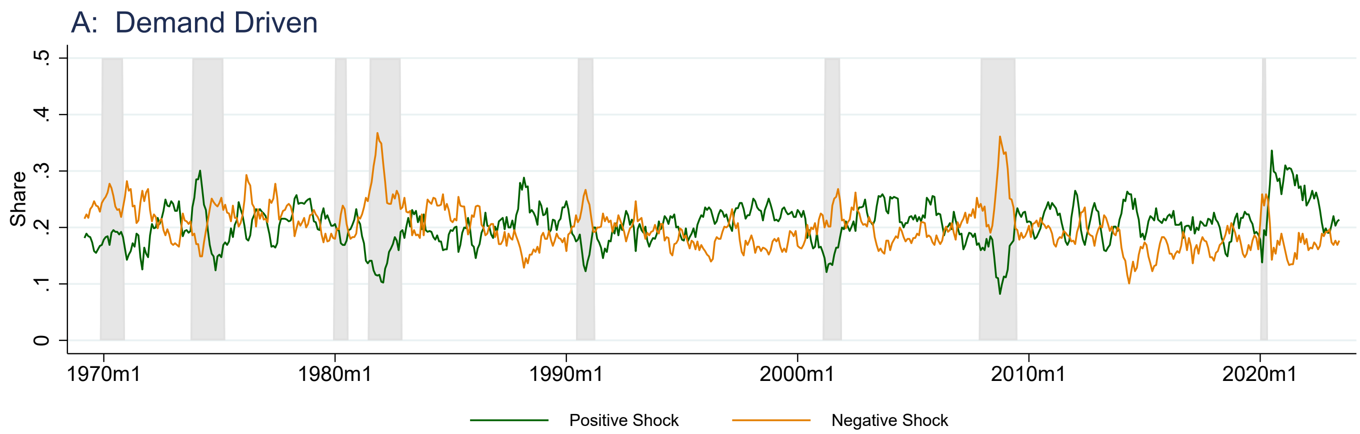
Parametric weights: For any given month t and category i, the parametric model assumes that the probability that category i experienced a supply (demand) shock increases the larger the values of $\nu_{i,t}^{p}$ and $\nu_{i,t}^{q}$, conditional on residuals being of the opposite (same) sign. The variable $\lambda_{i,t} = \nu_{i,t}^{p} \cdot \nu_{i,t}^{q}$ taken from a normal distribution has these characteristics. It follows that:

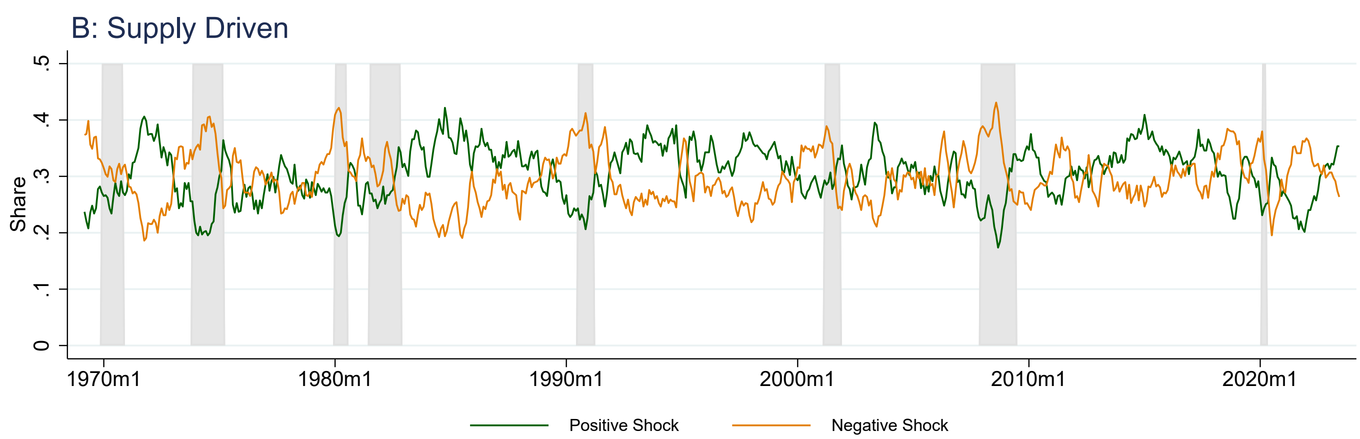
$$\begin{aligned} \phi_{i,t}^{dem} &= P[z(\lambda_{i,t})] \\ \phi_{i,t}^{sup} &= 1 - P[\mathbf{z}(\lambda_{i,t})], \end{aligned}$$

where $P(\cdot)$ is the cumulative normal distribution, and $\mathbf{z}(\lambda_{i,t})$ is the number of standard deviations $\lambda_{i,t}$ is from zero. If either $\nu^p_{i,t}$ and $\nu^q_{i,t}$ is close to zero, the algorithm assumes a roughly equal probability that the category experienced either a supply or demand shock.

A.2 Figures and Tables

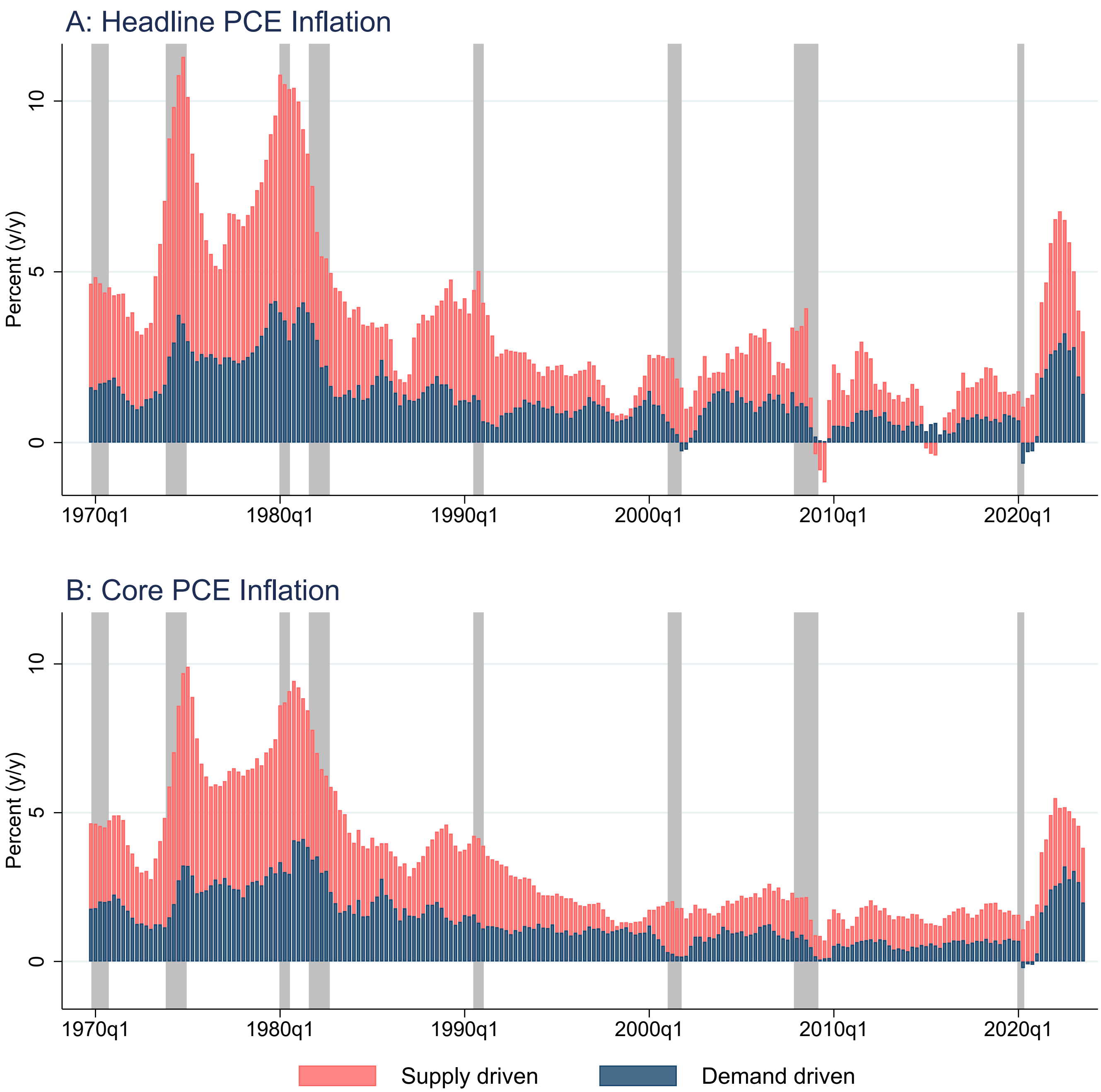
Figure A1: Unweighted share of categories by shock type





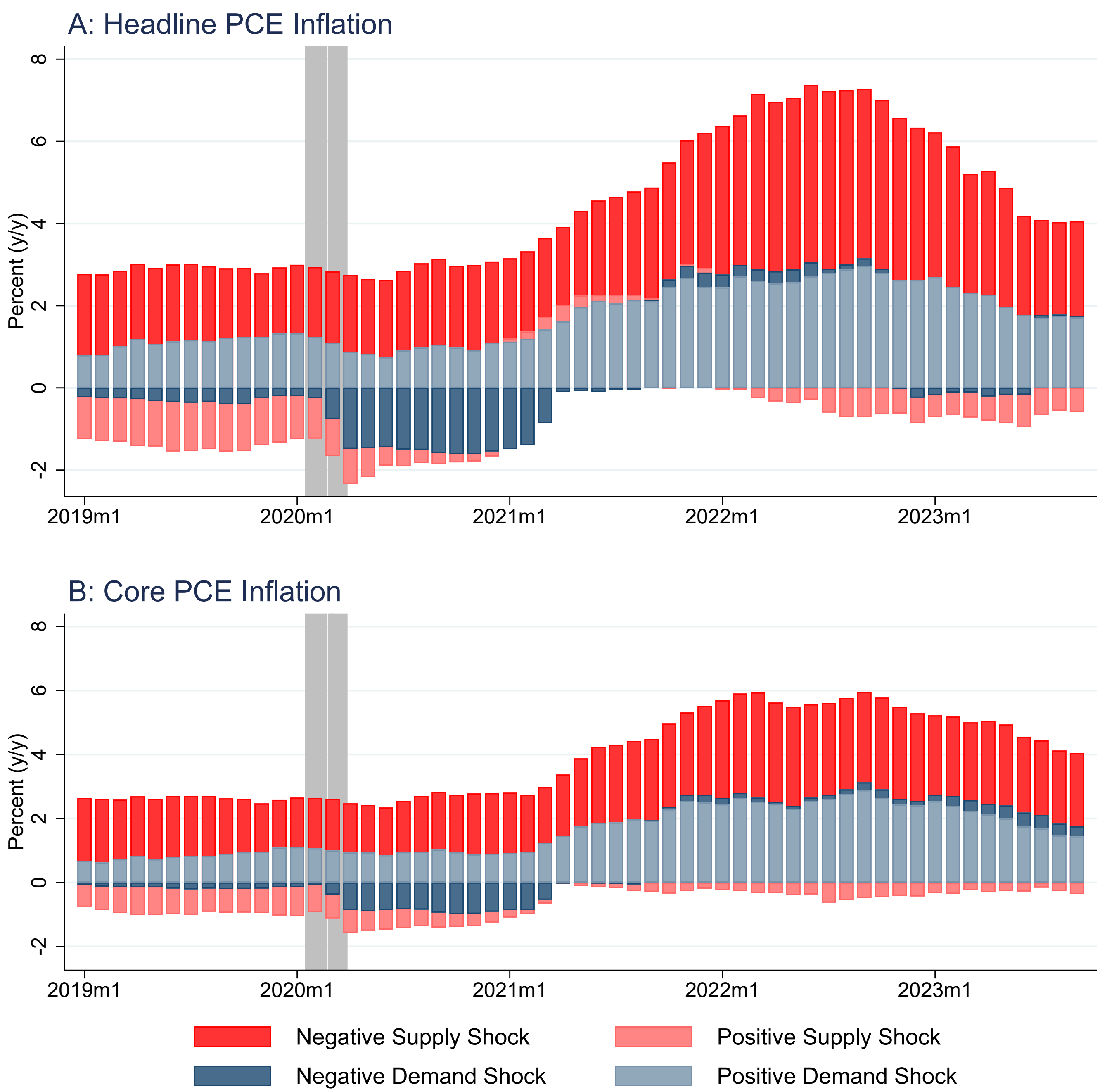
Notes: Plotted is the unweighted share of PCE categories that are labeled as supply or demand driven in a given month, centered five-month moving average. Panel A shows the share of categories that were labeled demand driven, and then further decomposed into whether the category experienced a negative or positive shock. Panel B shows the analogous series for categories that were labeled supply driven. All four series sum to one for any given month.

Figure A2: Supply- and demand-driven PCE Inflation (quarterly inflation)



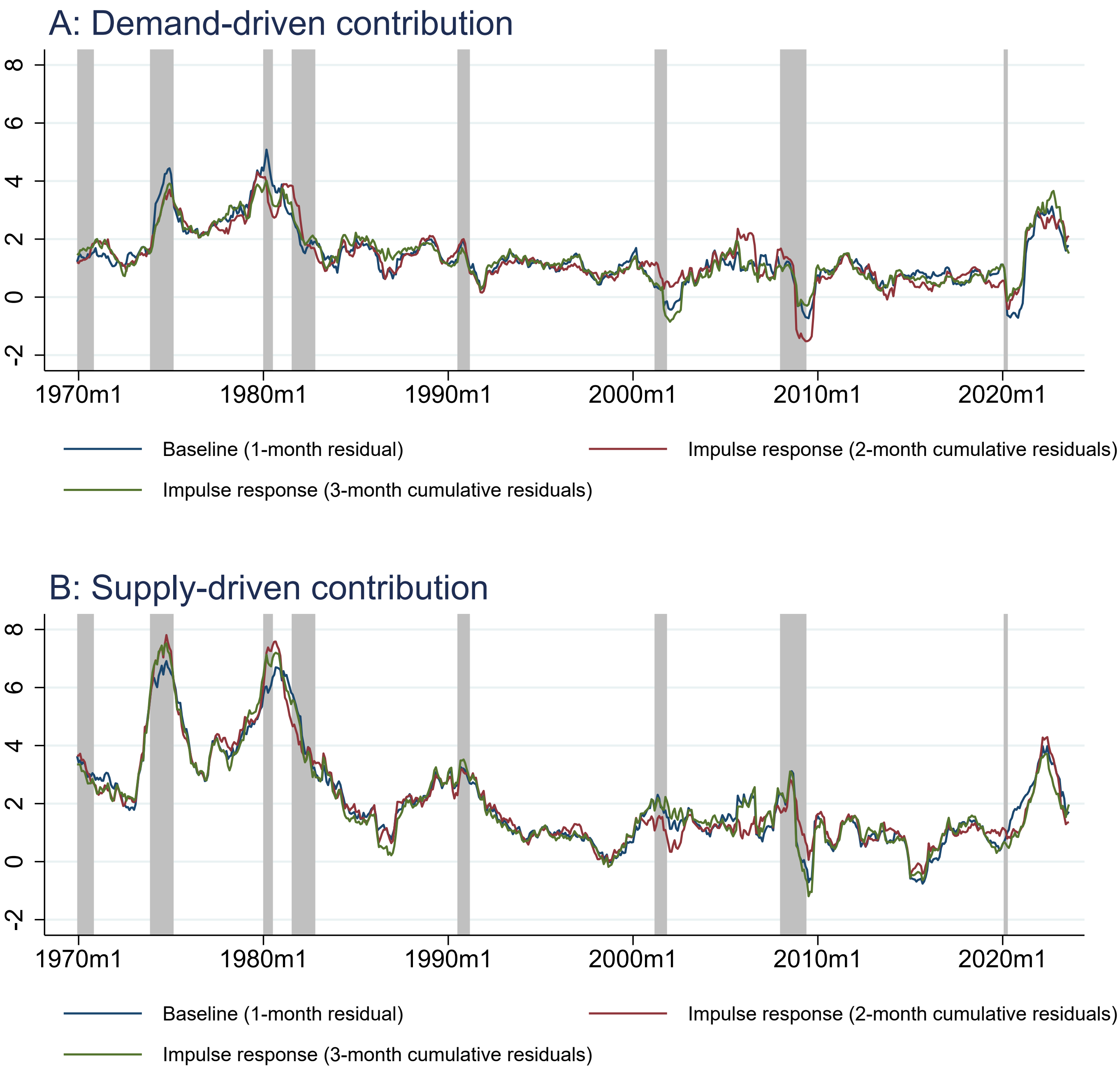
Notes: Panel A the contributions to the year-over-year change in quarterly headline PCE inflation and panel B shows the contributions to the year-over-year change in quarterly in core PCE inflation. Both series are divided intro contributions determined as supply-driven (red) and demand-driven (blue).

Figure A3: Supply- and demand-driven PCE Inflation (direction of shocks)



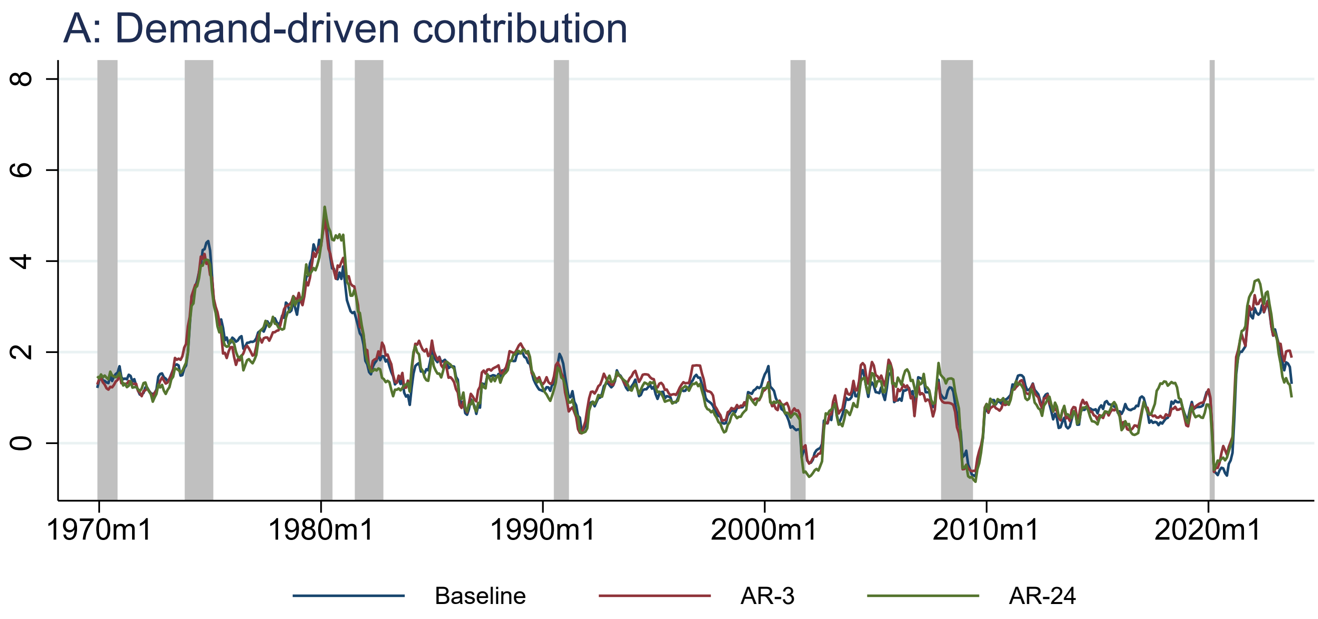
Notes: Panel A the contributions to the year-over-year change in headline PCE inflation and panel B shows the contributions to year-over-year core PCE inflation. Both series are divided intro contributions determined as negative supply-driven, positive supply-driven, and negative demand-driven and positive demand-driven.

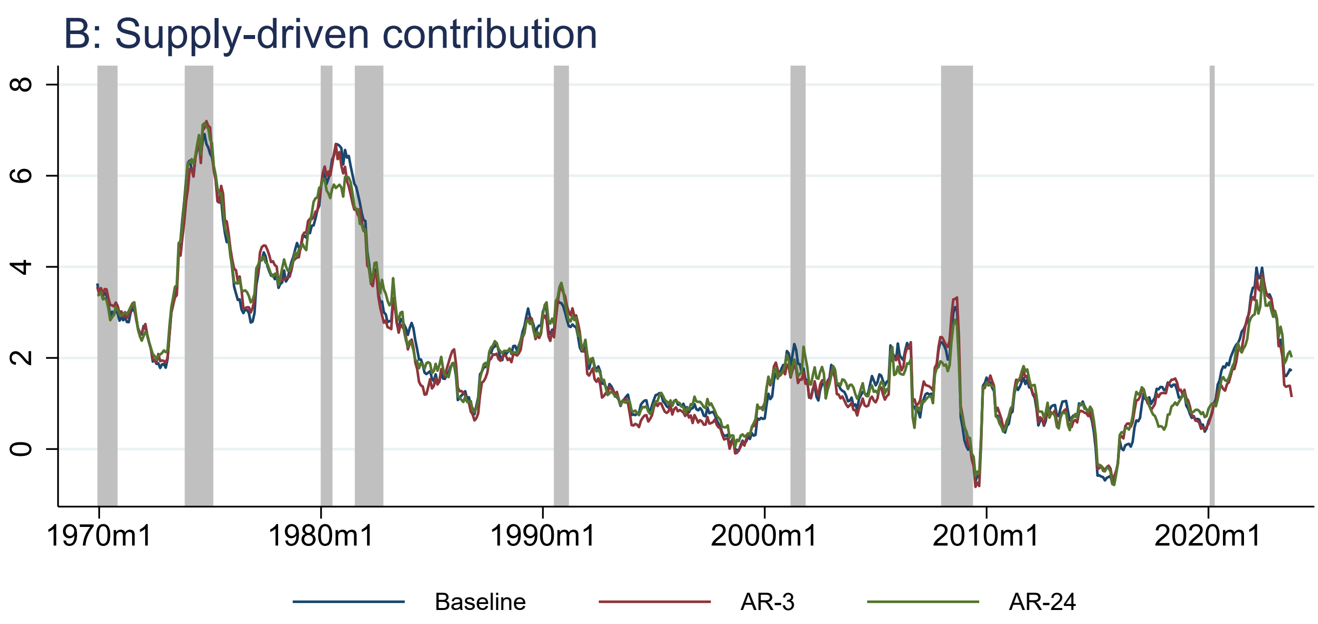
Figure A4: Cumulative Residuals (IRF), Headline PCE Inflation



Notes: Depicted are the contributions to 12-month headline PCE inflation. Smooth-1 uses the sum of the current and lagged residual to determine whether a category is supply or demand driven. Smooth-2 uses the sum of the current and two lagged residuals, and smooth-3 uses the sum of the current and three lagged residuals.

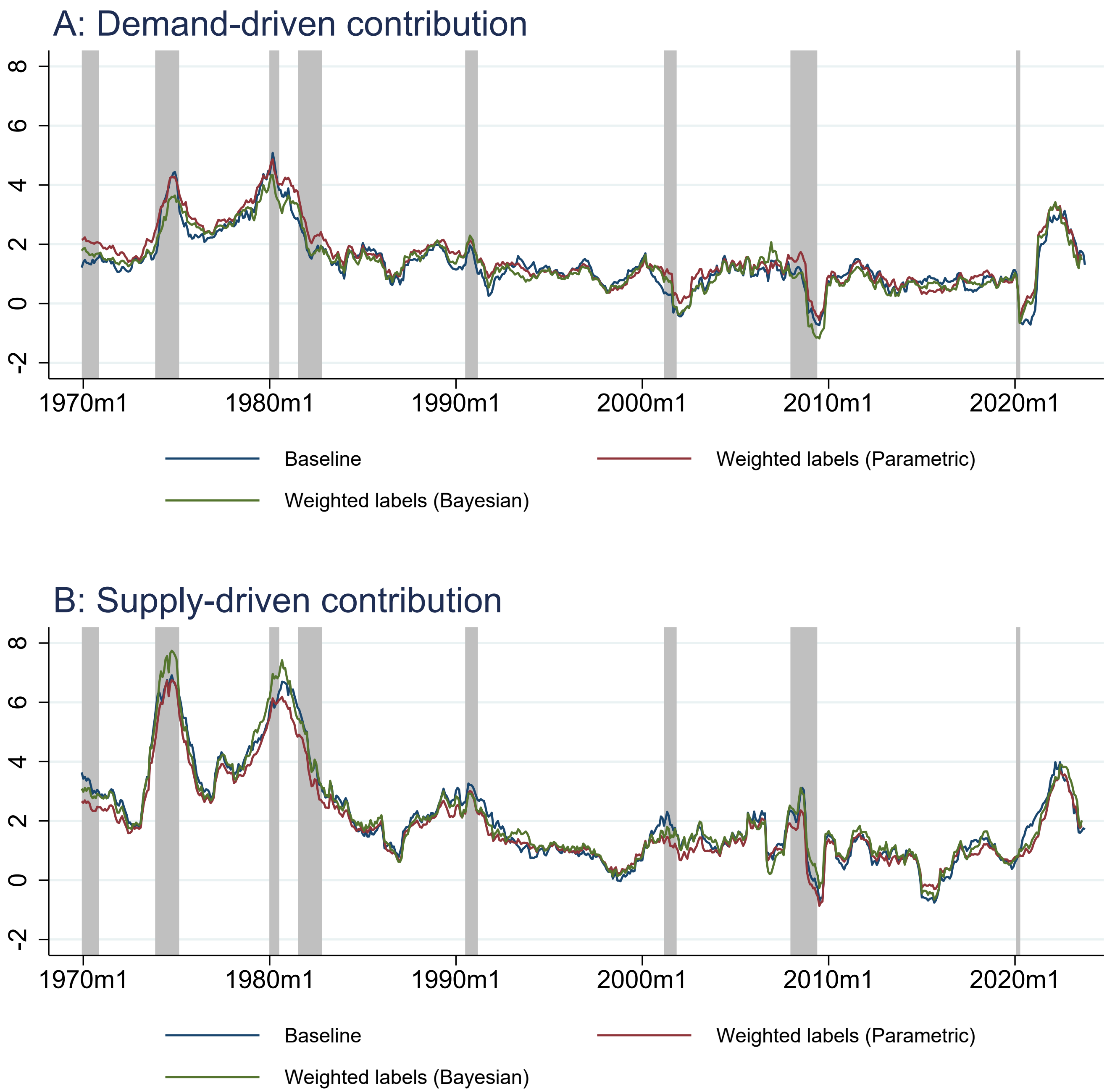
Figure A5: Alternative auto-regression lags, Headline PCE Inflation





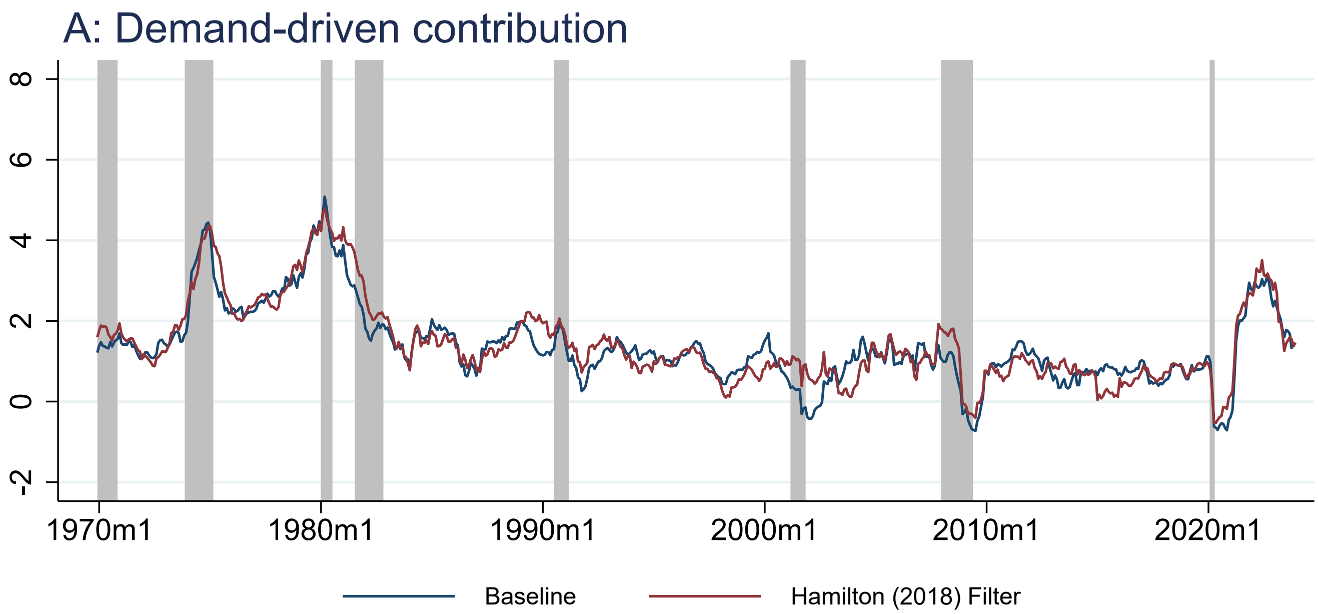
Notes: Depicted are the contributions to 12-month headline PCE inflation. AR-3 uses a 3-lag VAR to compute the residuals. AR-24 uses a 24 lag VAR to compute the residuals.

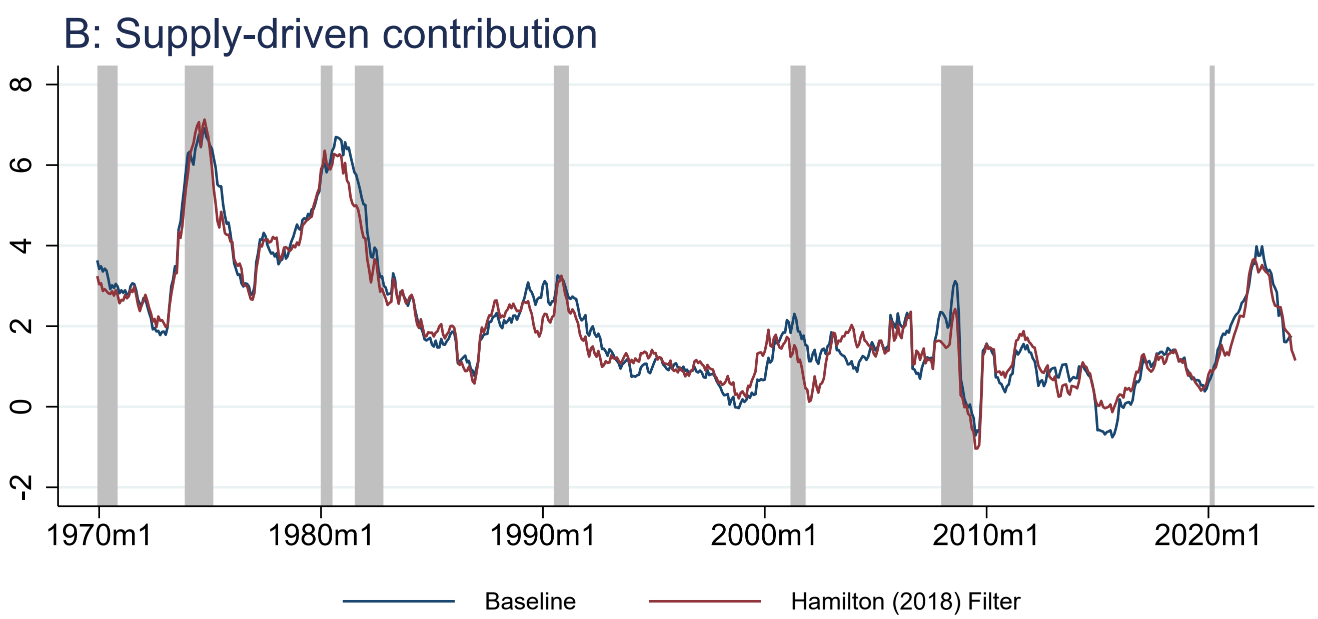
Figure A6: Weighted labeling, Headline PCE Inflation



Notes: Depicted are the contributions to 12-month headline PCE inflation. Weighted labels assign non-binary probability weights by category-month. "Bayesian" indicates weights are constructed from the posterior distribution of a Bayesian estimation of equations (12) and (13). "Parametric" indicate weights are constructed from an assumed normal distribution of the multiple of supply and demand residuals $\lambda_{i,t} = \nu_{i,t}^{p} \cdot \nu_{i,t}^{q}$.

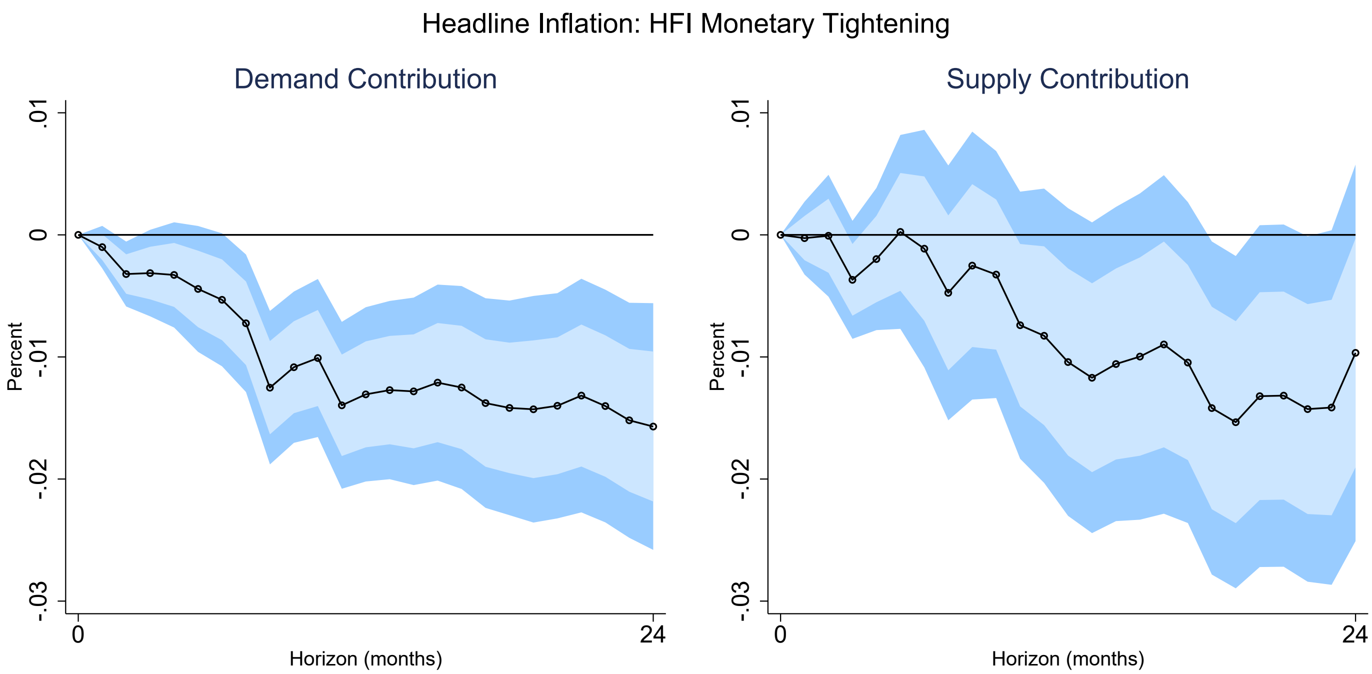
Figure A7: Hamilton (2018) Filter, Headline PCE Inflation





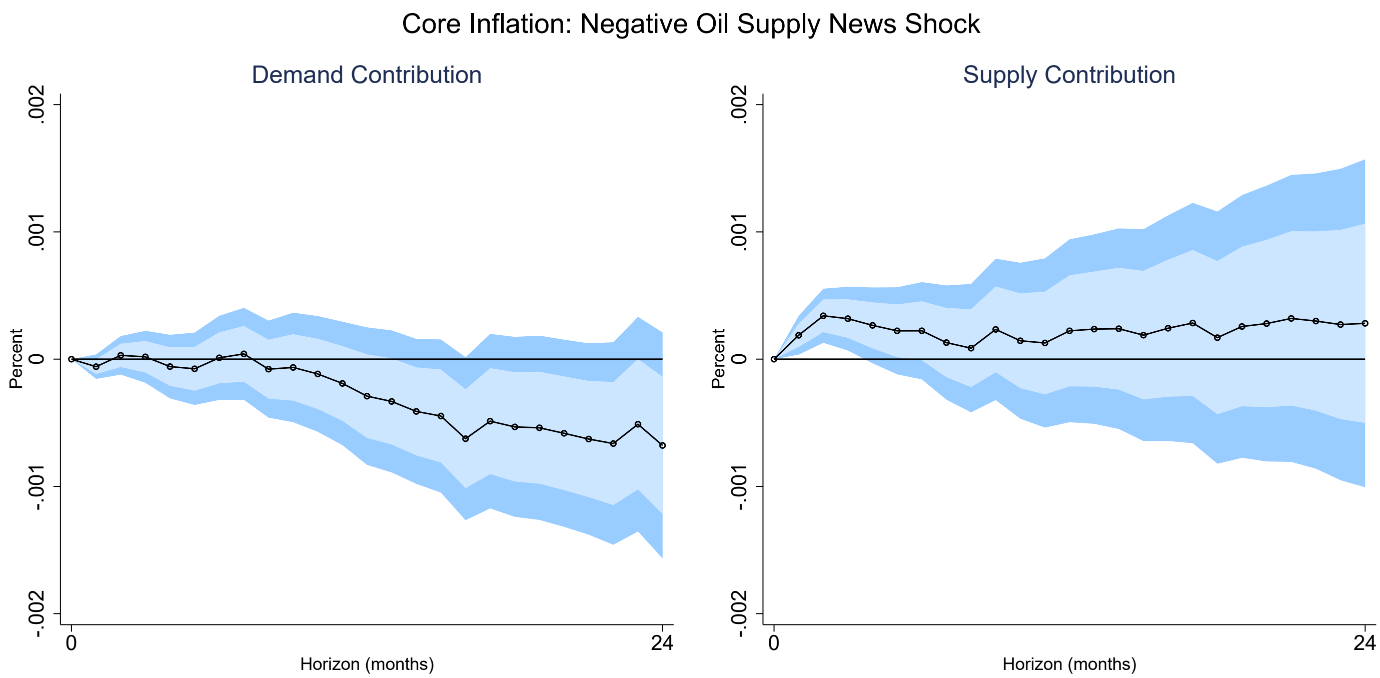
Notes: Depicted are the contributions to 12-month headline PCE inflation. The log price and log quantity indexes are filtered using Hamilton (2018), with horizon set to 24 months, before main estimation.

Figure A8: IRFs of headline PCE inflation to HFI monetary policy shocks



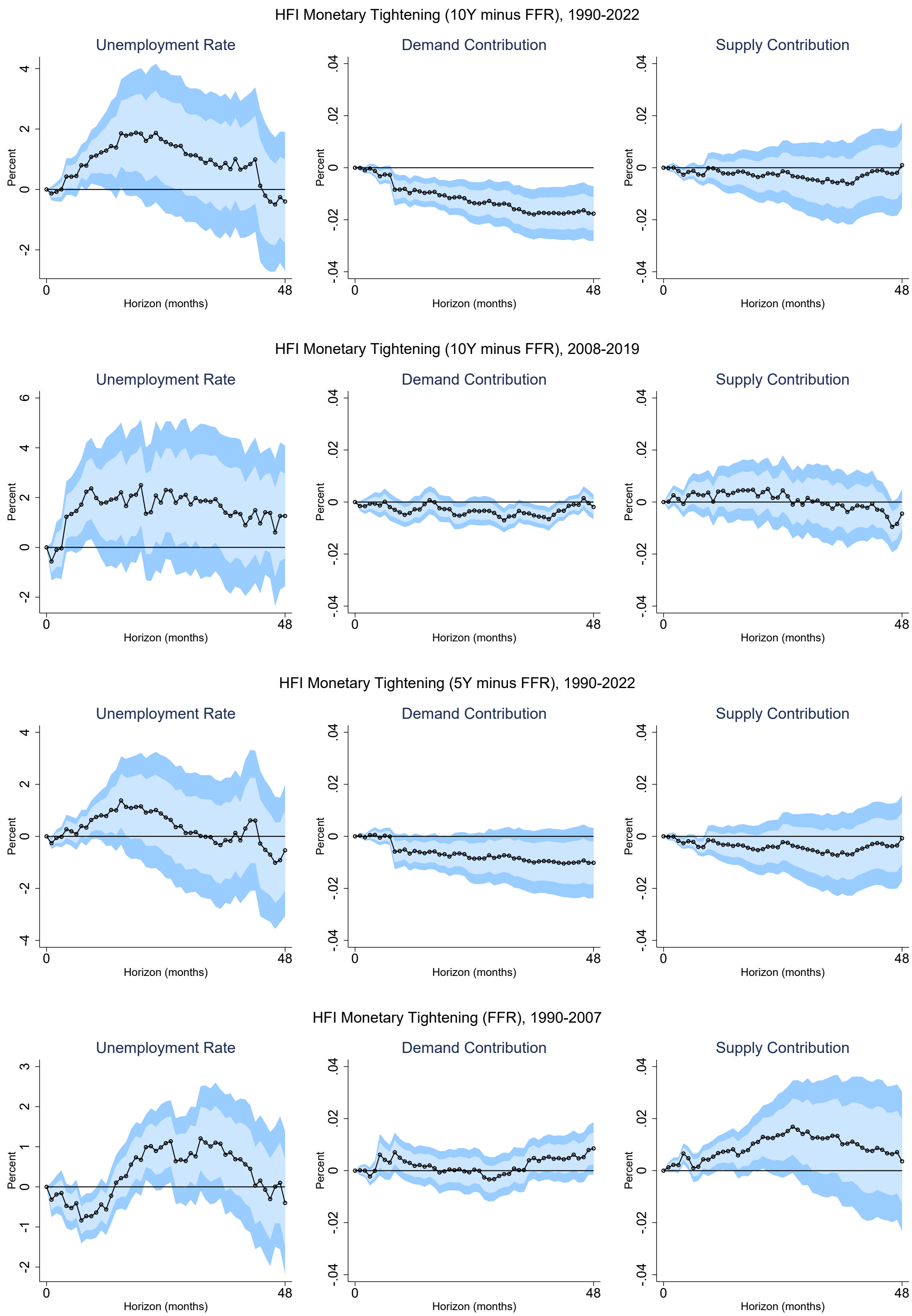
Notes: Panels A and B show the cumulative impulse response of the demand and supply contributions, respectively, to headline PCE inflation to a high frequency identified (HFI) monetary surprises (Gürkaynak, Sack, and Swanson (2005)). Shown are the 90th percentile and one-standard deviation confidence bands. Sample period is 1990-2016.

Figure A9: IRFs of core PCE inflation to (Känzig (2021)) oil supply news shocks



Notes: Panels A and B show the impulse responses of the demand and supply contributions, respectively, to core PCE inflation to a negative oil supply news shock (Känzig (2021)). Shown are the 90th percentile and one-standard deviation confidence bands. Sample period is 1990-2016.

Figure A10: IRFs of unemployment and core PCE inflation to HFI monetary policy shocks



Notes: Row 1 reproduces results in Figure 6. Row 2 replicates the sample period used by Eberly, Stock, and Wright (2019). Row substitutes the surprise to the on-the-run 10 year Treasury with the surprise to the on-the-run 5-year Treasury. Row estimates impact of the surprise to the fed funds rate, the difference between the expected fed funds rate and the actual funds rate. I use the average of the surprise to the current month, one-month-ahead, and two-month-ahead surprise and estimate it over the same sample period as Eberly, Stock, and Wright (2019).

Table A1: Top 10 highest relative frequency shocks by type and period

	Negative Demand Shocks (Recessions)		
	Recessions	Full Sample	Exp. Weight
Motor Vehicle Insurance	0.54	0.28	0.006
Purchased Meals & Beverages	0.45	0.30	0.055
Used Autos	0.37	0.24	0.007
Shoes & Other Footwear	0.29	0.17	0.009
Air Transportation	0.33	0.21	0.006
Imputed Rent of Owner-Occupied Nonfarm Hous	0.31	0.20	0.108
Hotels and Motels	0.32	0.22	0.006
Communication	0.28	0.19	0.019
Women's & Girls' Clothing	0.29	0.20	0.024
Jewelry	0.23	0.15	0.006

	Positive Demand Shocks (Post Covid)		
	2021-2022	Full Sample	Exp. Weight
Water Supply & Sewage Maintenance	0.57	0.17	0.005
Hotels and Motels	0.57	0.24	0.006
Gasoline & Other Motor Fuel	0.57	0.25	0.030
Purchased Meals & Beverages	0.57	0.26	0.055
Electricity	0.52	0.24	0.017
Women's & Girls' Clothing	0.38	0.15	0.024
Men's & Boys' Clothing	0.43	0.21	0.015
Net Motor Vehicle/Oth Transportation Insur	0.43	0.24	0.006
Financial Services Furnished w/out Payment	0.38	0.20	0.020
Social Assistance	0.33	0.16	0.006

	Negative Supply Shocks (Post Covid)		
	2021-2022	Full Sample	Exp. Weight
Rental of Tenant-Occupied Nonfarm Housing	0.95	0.29	0.037
Imputed Rent of Owner-Occupied Nonfarm Hous	0.95	0.30	0.108
Life Insurance	0.62	0.21	0.009
New Light Trucks	0.57	0.26	0.011
Tobacco	0.52	0.21	0.012
New Autos	0.48	0.25	0.022
Net Motor Vehicle/Oth Transportation Insur	0.48	0.27	0.006
Video & Audio Equip	0.48	0.29	0.010
Beer	0.48	0.32	0.007
Nursing Homes	0.43	0.28	0.011

Notes: Shown are the share of months the category is labeled in a given period for categories with an average expenditure weight of at least 0.5% over the full sample period. For example, Info Processing Equip was labeled as having a negative demand shock 30 percent of all of months and 58 percent of months in recessions. Categories are ordered according to the difference in frequency between the given period and full sample. "Exp. weight" shows the average expenditure weight over the full sample.