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 dominates the dynamics of inflation at any point in time (i.e., a binary variable), it does not pin down the

[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

degree to which supply or demand is impacting inflation. With aggregate data, 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 category-level data is that one can obtain a continuous measure of the degree to which supply and demand factors are impacting aggregate inflation without resorting to using additional non-sign restrictions. This is done by averaging over the binary category-level indicators using the expenditure weights—the same weights used by the Bureau of Economic Analysis (BEA) in constructing aggregate PCE inflation from category-level inflation rates.

I use the price and quantity data from the more than 100 goods and services categories underlying the personal consumption expenditures (PCE) index. Specifically, separate price and quantity regressions are run on each category 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 likely experienced a net-demand shock and are labeled as demand-driven in that month. Categories with residuals of opposite signs likely experienced a net-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 contribution of demand-driven inflation falls during recessions and rises during economic booms. Key events also impact the series, for instance, the collapse in airline travel after September 11, 2001 reduced demand-driven inflation and 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,

[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.

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 are robust along several dimensions: using a rolling-average of past residuals instead of the current residual, ignoring labels that are possibly labeled imprecisely, relaxing the assumption of binary labeling, using alternative number of lags in the VAR, and allowing for time-varying parameters in the VAR.

As a 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. Interestingly, the same tightening induces a small positive increase in supply-driven inflation, showing some evidence of a cost-channel effect of monetary policy (Barth and Ramey (2001)). A negative oil supply shock has a small positive impact on the supply-driven contribution to core inflation, thus showing a 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 with the idea 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 interesting underlying supply and demand effects.

The supply and demand contributions can be used by researchers to help test and better

[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))

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:

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

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 $\varepsilon_i = \begin{bmatrix} \varepsilon^s_i \\ \varepsilon^d_i \end{bmatrix}$ 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, $\nu^q_{i,t}$ and $\nu^p_{i,t}$:

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

where $\nu_i = \begin{bmatrix} \nu^q_i \\ \nu^p_i \end{bmatrix}$. 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:

$$\text{+ Demand Shock}: \quad \nu^p_{i,t} > 0, \nu^q_{i,t} > 0 \rightarrow \varepsilon^d_{i,t} > 0 \tag{8}$$

$$\text{- Demand Shock}: \quad \nu^p_{i,t} < 0, \nu^q_{i,t} < 0 \rightarrow \varepsilon^d_{i,t} < 0 \tag{9}$$

$$\text{+ Supply Shock}: \quad \nu^p_{i,t} < 0, \nu^q_{i,t} > 0 \rightarrow \varepsilon^s_{i,t} > 0 \tag{10}$$

$$\text{- Supply Shock}: \quad \nu^p_{i,t} > 0, \nu^q_{i,t} < 0 \rightarrow \varepsilon^s_{i,t} < 0. \tag{11}$$

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.

2.2 Data and estimation

I employ the 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 136 categories in the PCE price index and 124 categories in the core PCE index. Data at this level disaggregation are generally available back to 1988, although some series at this level are available at earlier dates.

I run price and quantity regressions for each of the 136 categories, i, in the PCE index:

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

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

where $q_{i,t}$ is the log quantity index and $p_{i,t}$ is the log price index of category i. My main specification uses 12 lags of price and quantity as controls—the results are robust to alternative numbers of lags.[5] 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.

[5] Online appendix figure A5 and table 1 show that the main results in this study are robust using 3 lags and 24 lags.

The reduced-form residuals, $\nu^q_{i,t}$ and $\nu^p_{i,t}$, are then used to label (or sign) each category i in each month t using the restrictions defined in equations (8) to (11):

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

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

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

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

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

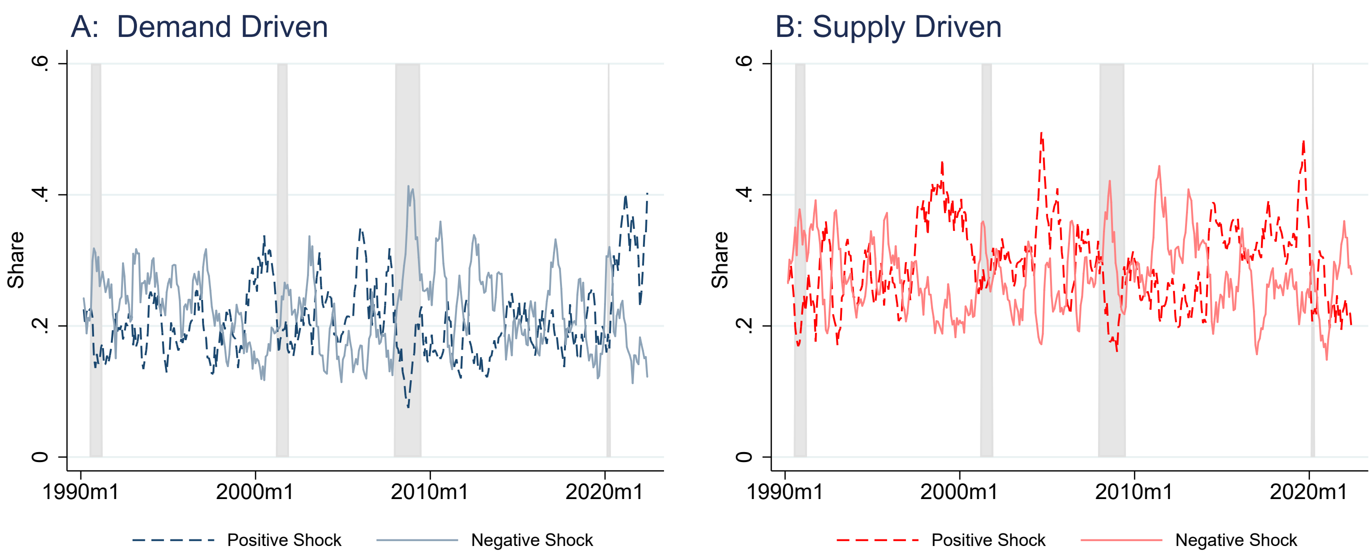
$$\gamma_{s,t} = \sum_i \mathbb{1}_{i\in s,t}\omega_{i,t} \tag{14}$$

where $s \in \{dem(+), dem(-), sup(+), sup(-)\}$. and $\omega_{i,t}$ is the expenditure weight of category i in the PCE consumption basket[6] 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 1 shows a plot of these shares. Over the entire 1990 to 2022 sample period, supply-shocks make up a larger fraction of the consumption expenditures than demand shocks—roughly 60 percent of the PCE is labeled with a supply shock. The pattern of the labeling shows some intuitive characteristics. During recessions, negative-demand shocks are more prevalent while positive demand shock are less prevalent. Positive supply shocks became more prevalent during the late 1990's stemming from an increases in the supply of

[6] The expenditure weight is a Laspyeyres weight, and is calculated a the share of consumption expenditures in period $t-1$.

Figure 1: 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 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 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 clothing, owner-occupied rent, and restaurants. Categories that experienced frequent negative supply shocks in this period include new vehicles, tobacco, audio & video equipment, sporting goods, and furniture.[7]

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:

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

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

[7] 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 and positive supply shocks in the late 1990s.

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

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

where $\omega_{i,t}$ is the expenditure weight of category i in the PCE consumption basket and $\pi_{i,t,t-1}$ 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 2 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 sum of the current and past 11 monthly supply- and demand-driven contributions: $\pi^{sup}_{t,t-12} = \sum_{k=0}^{11} \pi^{sup}_{t-k,t-k-1}$ and $\pi^{dem}_{t,t-12} = \sum_{k=0}^{11} \pi^{dem}_{t-k,t-k-1}$. The contribution of demand-driven inflation generally declines at the tail end of recessions. The Great Recession saw a decrease in both demand- and supply-driven inflation. This decline in supply driven inflation mainly stemmed from positive supply shocks among categories in the financial sector, plausibly due to accommodative monetary policy (i.e., an increase in the supply of financial services) following the financial crisis. 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. Demand-drive inflation stayed strong into 2022 at the same time supply-driven inflation began to substantially increase.[8] This acceleration in supply-driven prices at this time was likely attributable to food and energy supply

[8]See online appendix figure A2 which shows the contributions to monthly (i.e., month-to-month) PCE inflation over the 2019-2022 period.

disruptions, including those associated with the invasion of Ukraine.

3.2 Robustness

To test the robustness of the results of the methodology I go through a series of alternative estimation specifications. First, I address the concern that the residuals used to label categories may contain measurement error. Second, I address the concern that the model is misspecified.

3.2.1 Measurement error

One concern with the methodology is that the residuals, $\nu^p_{i,t}$ and $\nu^p_{i,t}$, used to determine whether a category is labeled as supply- or demand-driven may include measurement error. I address this concern in a few ways. As a first exercise, I change the definition of the indicator function to that based on a smoothed version of the residual:

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

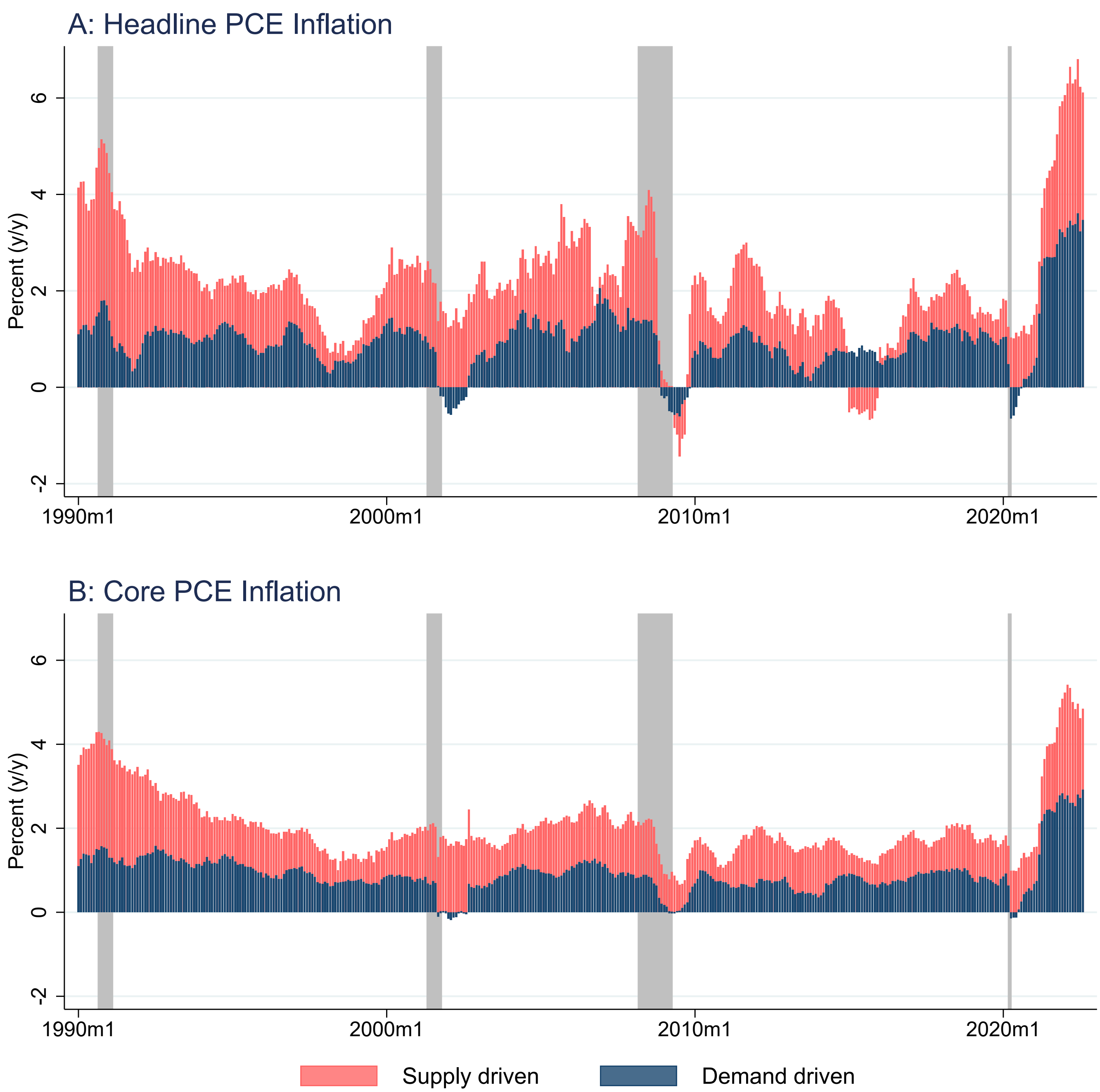
$$\mathbb{1}_{i\in dem,t} = \begin{cases} 1 & \text{if } \sum_{j=0}^{J} \nu^p_{i,t-j} > 0, \sum_{j=0}^{J} \nu^q_{i,t-j} > 0 \text{ or } \sum_{j=0}^{J} \nu^p_{i,t-j} < 0, \sum_{j=0}^{J} \nu^q_{i,t-j} < 0 \\ 0 & \text{otherwise.} \end{cases}$$

which entails substituting the current residual, with a rolling sum of current and previous residuals. The idea here is that the current residual might be contaminated with noise, which could be dissipated some by taking the rolling sum (or equivalently, average). The drawback here is that this uses perhaps stale information to define the label in the current period. I test three different smoothing specifications where $J = \{1, 2, 3\}$. I report the cross-correlations of the implied 12-month supply- and demand-driven contributions to headline inflation in Table 1, labeled as "Smooth-1," "Smooth-2," and "Smooth-3."[9] The correlations are all quite high with the baseline specification, ranging from 0.88 to 0.934.

As a second exercise, I ignore labels that are possibly labeled imprecisely. Specifically, I relabel a category as "ambiguous" if either of the price or quantity residuals is "close to

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

Figure 2: 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).

zero." 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 0.05 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.[10]

As a final exercise to address measurement error, I relax the assumption that the labeling is definitive (or binary). Instead I assume that the labeling is stochastic (or probability-based). Specifically, one can replace equation (15) from that which is based on indicator functions to that which is based on probability weights:

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

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 and intuitive appeal. One set is constructed using the posterior distribution from Bayesian estimation of (12) and (13). The other set is constructed using an assumed parametric distribution of the residuals, similar to that used in the precision labeling exercise above. 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),"[11] are both above 0.95 for supply-driven and above 0.93 for demand-driven.

[10]The first panel of online appendix figure A3 shows the result of this re-labeling. Increasing the threshold to 0.10 standard deviations (or 25 percent of observations) results in correlations of 0.97 and 0.98 for the demand and supply contributions respectively. The second panel of online appendix figure A3 uses multiple precision cut-offs representing those category-months with a residuals up to 0.10 standard deviations and 0.25 standard deviations from zero.

[11]The series are shown graphically in the online appendix figure A7

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

Variables	Baseline	Smooth-1	Smooth-2	Smooth-3	AR-3	AR-24	Wt. (Param.)	Wt. (Bayes.)	Rolling	Precision
					Supply-driven contribution					
Baseline	1.000									
Smooth-1	0.929	1.000								
Smooth-2	0.925	0.936	1.000							
Smooth-3	0.917	0.961	0.967	1.000						
AR-3	0.933	0.867	0.814	0.832	1.000					
AR-24	0.946	0.902	0.925	0.898	0.816	1.000				
Wt. (Param.)	0.958	0.923	0.939	0.938	0.897	0.925	1.000			
Wt. (Bayes.)	0.965	0.921	0.877	0.889	0.984	0.878	0.936	1.000		
Rolling	0.958	0.884	0.876	0.875	0.889	0.895	0.960	0.934	1.000	
Precision	0.963	0.889	0.845	0.854	0.954	0.868	0.895	0.966	0.909	1.000
					Demand-driven contribution					
Baseline	1.000									
Smooth-1	0.887	1.000								
Smooth-2	0.869	0.887	1.000							
Smooth-3	0.873	0.935	0.938	1.000						
AR-3	0.923	0.820	0.731	0.782	1.000					
AR-24	0.936	0.874	0.882	0.867	0.808	1.000				
Wt. (Param.)	0.937	0.858	0.861	0.887	0.891	0.908	1.000			
Wt. (Bayes.)	0.954	0.877	0.797	0.838	0.984	0.859	0.918	1.000		
Rolling	0.945	0.850	0.821	0.832	0.891	0.865	0.918	0.919	1.000	
Precision	0.989	0.890	0.873	0.879	0.907	0.925	0.922	0.942	0.946	1.000

Notes: Shown are the contemporaneous correlations of 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. AR-3 uses a 3-lag VAR to compute the residuals. AR-24 uses a 24 lag VAR to compute the residuals. Rolling window estimates the VAR using 10-year rolling windows, using the residual of the final period window to label the category. 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 0.025 category-specific standard deviations from zero.

3.2.2 Model misspecification

Another concern is model misspecification, which could result in biased estimates of the residuals $\nu_{i,t}^{p}$ and $\nu_{i,t}^{p}$. 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."[12] 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 model misspecification bias is the assumption that the coefficients in equations (12) and (13)—γ_j^{qq},γ_j^{qp}, γ_j^{pp}, and γ_j^{pq}—are fixed over time. To address this possible misspecification bias, I estimate (12) and (13) using 10-year rolling-windows which allows the coefficients to vary over time. The first window begins in January 1988, the first period PCE data are available at the detailed level, and ends in December 1997. This generates residuals in January 1998. 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. One downside of this method is that it allows for the supply- and demand-driven contribution series to begin only in 1998, the end of the first 10-year window. The correlations (reported as "Rolling" in Table 1) again are quite large with the baseline specification—0.96 for supply-driven and 0.95 for demand-driven.[13]

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

[12]The series are shown graphically in the online appendix Figure A5.
[13]The series are shown graphically in the online appendix figure A6.

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 of (Jorda (2005)) which is similar to the standard vector auto-regression (VAR) approach but less restrictive. That is, 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:

$$\pi^{j}_{t+h,t-1} = \alpha^h_j HFI_t + \beta^h_j OS_t + \mathbf{A}^h_j \sum_{\tau=0}^{6} \mathbf{Y}_{t-\tau} + \zeta_{j,t+h}. \tag{17}$$

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). 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.[14] 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)).[15] The oil supply shocks (OS) are constructed by Baumeister and Hamilton (2019) and represent surprise decreases in the supply of oil.[16] Results using alternative oil supply shocks—oil supply news shocks by Känzig (2021)—produce qualitatively similar results.[17] Controls, $\mathbf{Y}_t$, include current and six lags of the monthly demand and supply contributions, unemployment rate, the excess

[14]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 2019 sample period used in Eberly, Stock, and Wright (2019). See online appendix figure A10.

[15]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.

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

[17]See online appendix figure A9.

bond premium, and credit spreads (Gilchrist and Zakrajšek (2012)). I estimate (17) over the full sample period, 1990-2022.

Figure 3 shows the results on the contributions to core PCE inflation, along with one-standard deviation and 90th percentile confidence intervals.[18] A monetary policy tightening—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.[19] The same tightening induces a smaller 0.5 percentage point increase in the supply-driven contribution to inflation, but the estimates are not statistically distinguishable from zero. The positive, albeit noisy, impact of a monetary policy tightening on supply-driven could imply some evidence of a cost-channel effect, 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 3 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 4, 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

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

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

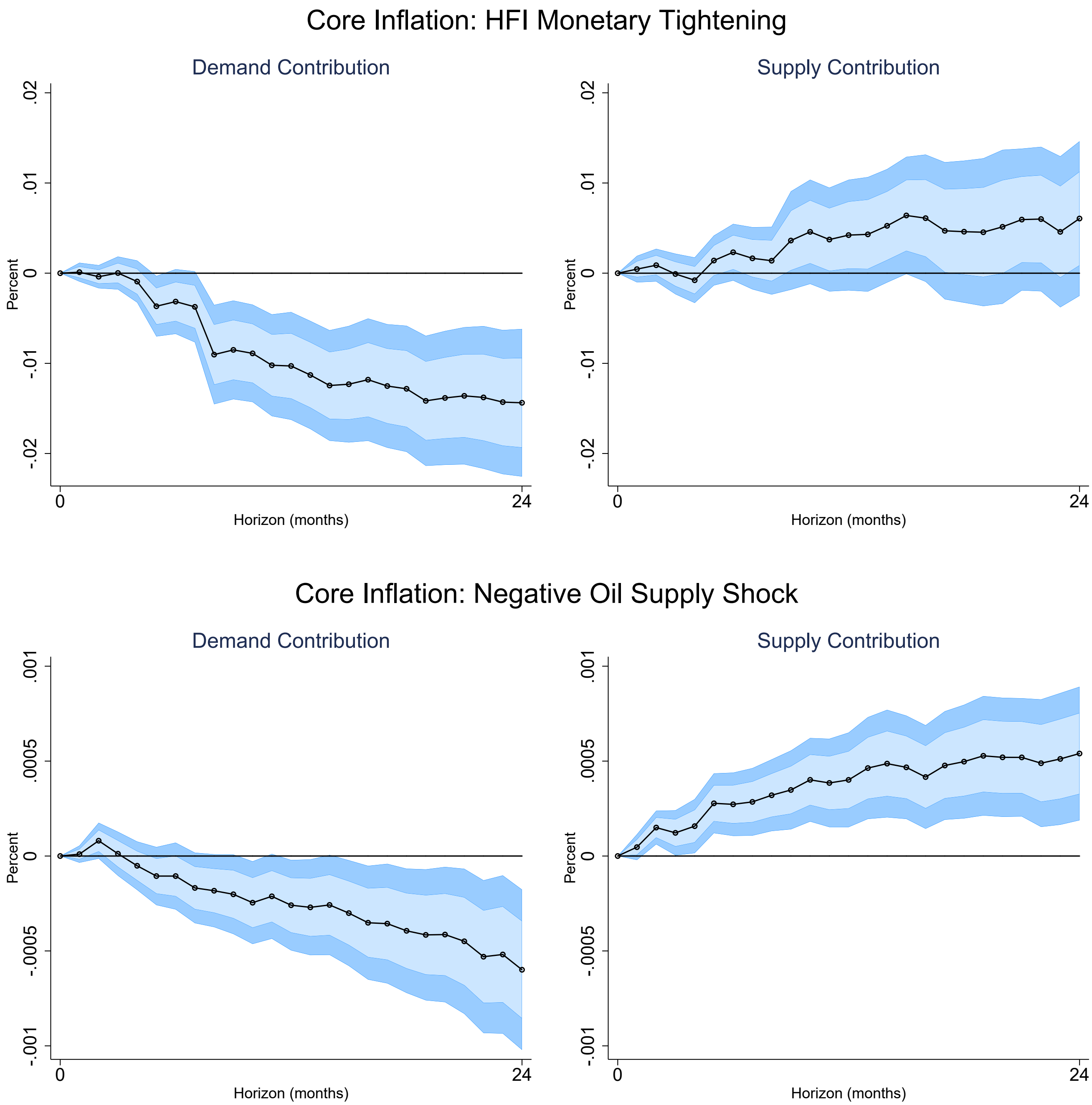
this effect. The bottom panel of figure 4 shows that the quantity and prices of fuel oil move in oppositive directions—corroborating the externally identified negative supply. However, the quantity and price of "other fuels" (i.e., propane, kerosene, and firewood) move in the same direction, indicative of a demand shock. Thus, the inflation decomposition reveals an increase in demand for oil substitutes stemming from the decline in oil supply.

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.

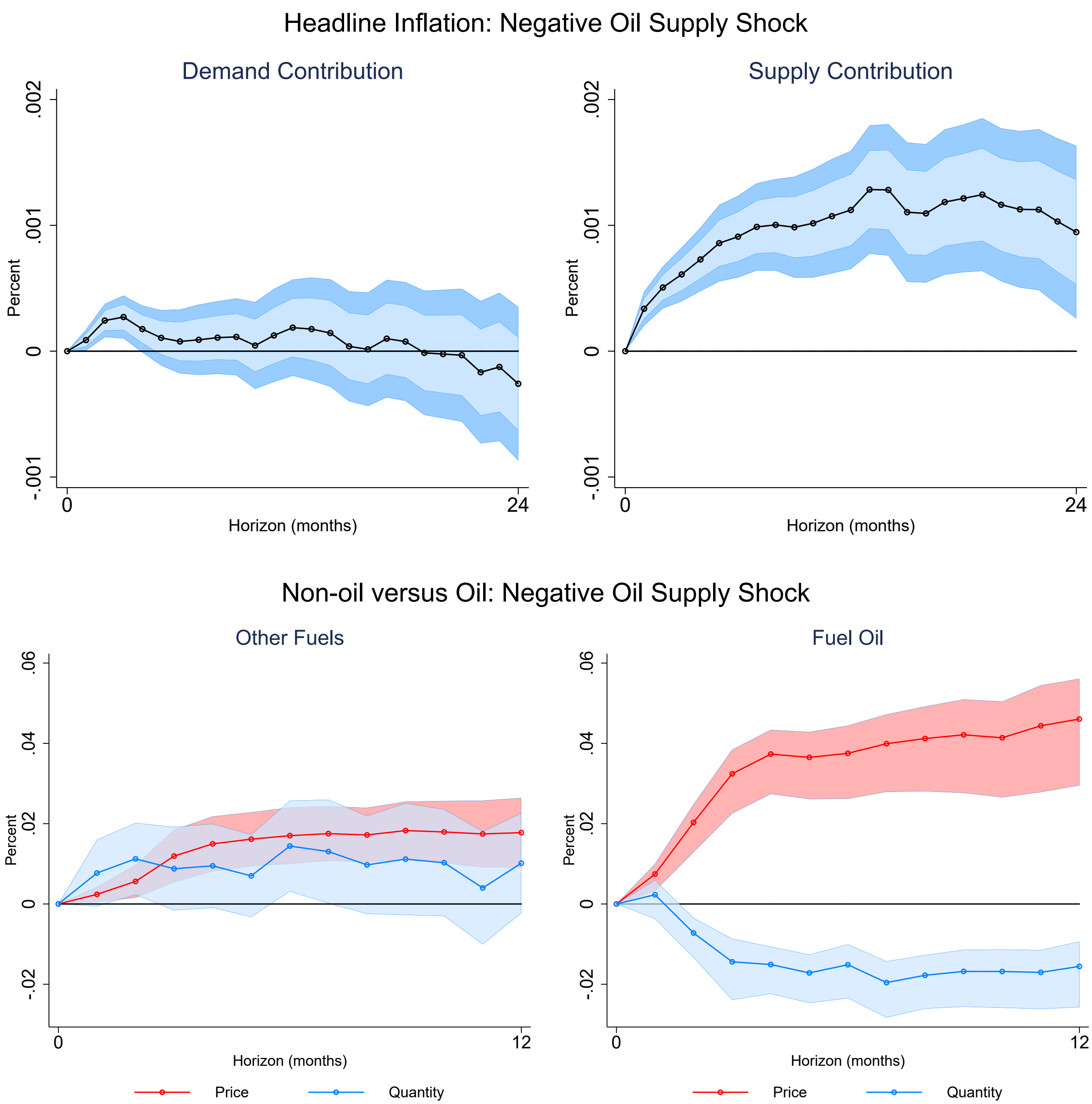
The supply- and demand-contributions can be updated and used by researchers to help answer a host of existing and future economic questions. For instance, one could test whether monetary or fiscal policy impacts the economy differently when inflation is high due to supply versus demand reasons. They 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 3: 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 1990-2022.

Figure 4: 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 1990-2022.

References

Aizcorbe, A. (2006): "Why did semiconductor price indexes fall so fast in the 1990s? A decomposition," *Economic Inquiry*, 44(3), 485–496.

Bachmeier, L. J., and I. Cha (2011): "Why don't oil shocks cause inflation? Evidence from disaggregate inflation data," *Journal of Money, Credit and Banking*, 43(6), 1165–1183.

Ball, L., D. Leigh, and P. Mishra (2022): "Understanding US Inflation During the COVID Era," *Brookings Papers on Economic Activity*.

Barnichon, R., and G. Mesters (2020): "Identifying modern macro equations with old shocks," *The Quarterly Journal of Economics*, 135(4), 2255–2298.

——— (2022): "A Sufficient Statistics Approach for Macro Policy Evaluation," Federal Reserve Bank of San Francisco.

Barth, M. J., and V. A. Ramey (2001): "The cost channel of monetary transmission," *NBER macroeconomics annual*, 16, 199–240.

Baumeister, C., and J. D. Hamilton (2019): "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks," *American Economic Review*, 109(5), 1873–1910.

Blanchard, O. J., and J. Gali (2007): "The Macroeconomic Effects of Oil Shocks: Why are the 2000s so different from the 1970s?," .

Blinder, A. S., and J. B. Rudd (2013): "The supply-shock explanation of the Great Stagflation revisited," *The Great Inflation: The rebirth of modern central banking*, pp. 119–175.

Boissay, F., F. Collard, J. Galí, and C. Manea (2021): "Monetary policy and endogenous financial crises," Discussion paper, National Bureau of Economic Research.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005): "Nominal rigidities and the dynamic effects of a shock to monetary policy," *Journal of political Economy*, 113(1), 1–45.

Clemens, J., and J. Gottlieb (2017): "In the shadow of a giant: Medicare's influence on private physician payments," *Journal of Political Economy*, 125(1), 1–39.

Clemens, J., J. Gottlieb, and A. Shapiro (2014): "How Much Do Medicare Cuts Reduce Inflation?," *FRBSF Economic Letter*, 28.

Clemens, J., J. Gottlieb, and A. Shapiro (2016): "Medicare payment cuts continue to restrain inflation," *FRBSF Economic Letter*, 15.

Conflitti, C., and M. Luciani (2019): "Oil price pass-through into core inflation," *The Energy Journal*, 40(6).

Copeland, A., and A. Shapiro (2016): "Price setting and rapid technology adoption: The case of the PC industry," *Review of Economics and Statistics*, 98(3), 601–616.

Eberly, J. C., J. H. Stock, and J. H. Wright (2019): "The federal reserve's current framework for monetary policy: A review and assessment," .

Edelstein, P., and L. Kilian (2009): "How sensitive are consumer expenditures to retail energy prices?," *Journal of Monetary Economics*, 56(6), 766–779.

Faust, J. (1998): "The robustness of identified VAR conclusions about money," in *Carnegie-Rochester conference series on public policy*, vol. 49, pp. 207–244. Elsevier.

Fry, R., and A. Pagan (2011): "Sign restrictions in structural vector autoregressions: A critical review," *Journal of Economic Literature*, 49(4), 938–60.

Gerardi, K., and A. Shapiro (2009): "Does competition reduce price dispersion? New evidence from the airline industry," *Journal of Political Economy*, 117(1), 1–37.

Ghassibe, M., and F. Zanetti (2022): "State dependence of fiscal multipliers: the source of fluctuations matters," *Journal of Monetary Economics*.

Gilchrist, S., and E. Zakrajšek (2012): "Credit spreads and business cycle fluctuations," *American economic review*, 102(4), 1692–1720.

Gürkaynak, R. S., B. Sack, and E. Swanson (2005): "The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models," *American economic review*, 95(1), 425–436.

Hamilton, J. D. (1983): "Oil and the macroeconomy since World War II," *Journal of political economy*, 91(2), 228–248.

——— (2008): "Oil and the Macroeconomy," *The new Palgrave dictionary of economics*, 2.

Hooker, M. A. (2002): "Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime," *Journal of money, credit and banking*, pp. 540–561.

Jorda, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161–182.

Jordà, Ò., C. Liu, F. Nechio, F. Rivera-Reyes, et al. (2022): "Why Is US Inflation Higher than in Other Countries?," *FRBSF Economic Letter*, 7.

Jump, R. C., and K. Kohler (2022): "A history of aggregate demand and supply shocks for the United Kingdom, 1900 to 2016," *Explorations in Economic History*, p. 101448.

Känzig, D. R. (2021): "The macroeconomic effects of oil supply news: Evidence from OPEC announcements," *American Economic Review*, 111(4), 1092–1125.

Kuttner, K. N. (2001): "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of monetary economics*, 47(3), 523–544.

Lee, K., and S. Ni (2002): "On the dynamic effects of oil price shocks: a study using industry level data," *Journal of Monetary economics*, 49(4), 823–852.

Primiceri, G. E. (2006): "Why inflation rose and fell: policy-makers' beliefs and US postwar stabilization policy," *The Quarterly Journal of Economics*, 121(3), 867–901.

Ravenna, F., and C. E. Walsh (2006): “Optimal monetary policy with the cost channel,” *Journal of Monetary Economics*, 53(2), 199–216.

Rotemberg, J. J., and M. Woodford (1996): “Imperfect Competition and the Effects of Energy Price Increases on Economic Activity,” *Journal of Money, Credit and Banking*, 28(4), 549–577.

Rudebusch, G. D., and T. Wu (2008): “A macro-finance model of the term structure, monetary policy and the economy,” *The Economic Journal*, 118(530), 906–926.

Smets, F., and R. Wouters (2003): “An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area,” *Journal of the European Economic Association*, 1(5), 1123–1175.

Uhlig, H. (2005): “What are the effects of monetary policy on output? Results from an agnostic identification procedure,” *Journal of Monetary Economics*, 52(2), 381–419.

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:

$$\pi_{t,t-1} = \underbrace{\sum_i \phi_{i,t}^{sup} \omega_{i,t} \pi_{i,t,t-1}}_{\text{supply-driven } (\pi_{t,t-1}^{sup})} + \underbrace{\sum_i \phi_{i,t}^{dem} \omega_{i,t} \pi_{i,t,t-1}}_{\text{demand-driven } (\pi_{t,t-1}^{dem})} . \tag{18}$$

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 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:

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

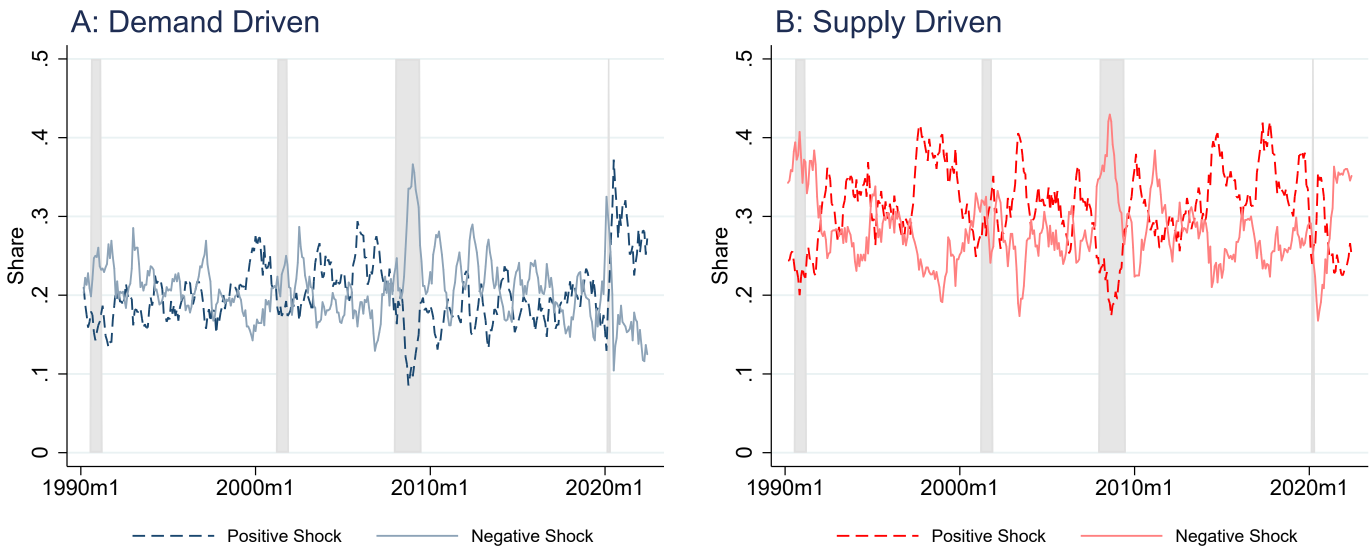
Parametric weights: For any given month t and category i, the parametric model assumes that the probability that category i experienced a supply (demand) shock increases the larger the values of $\nu_{i,t}^{p}$ and $\nu_{i,t}^{q}$, conditional on residuals being of the opposite (same) sign. The variable $\lambda_{i,t} = \nu_{i,t}^{p} \cdot \nu_{i,t}^{q}$ 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 $\nu_{i,t}^p$ and $\nu_{i,t}^q$ is close to zero, the algorithm assumes a roughly equal probability that the category experienced either a supply or demand shock.

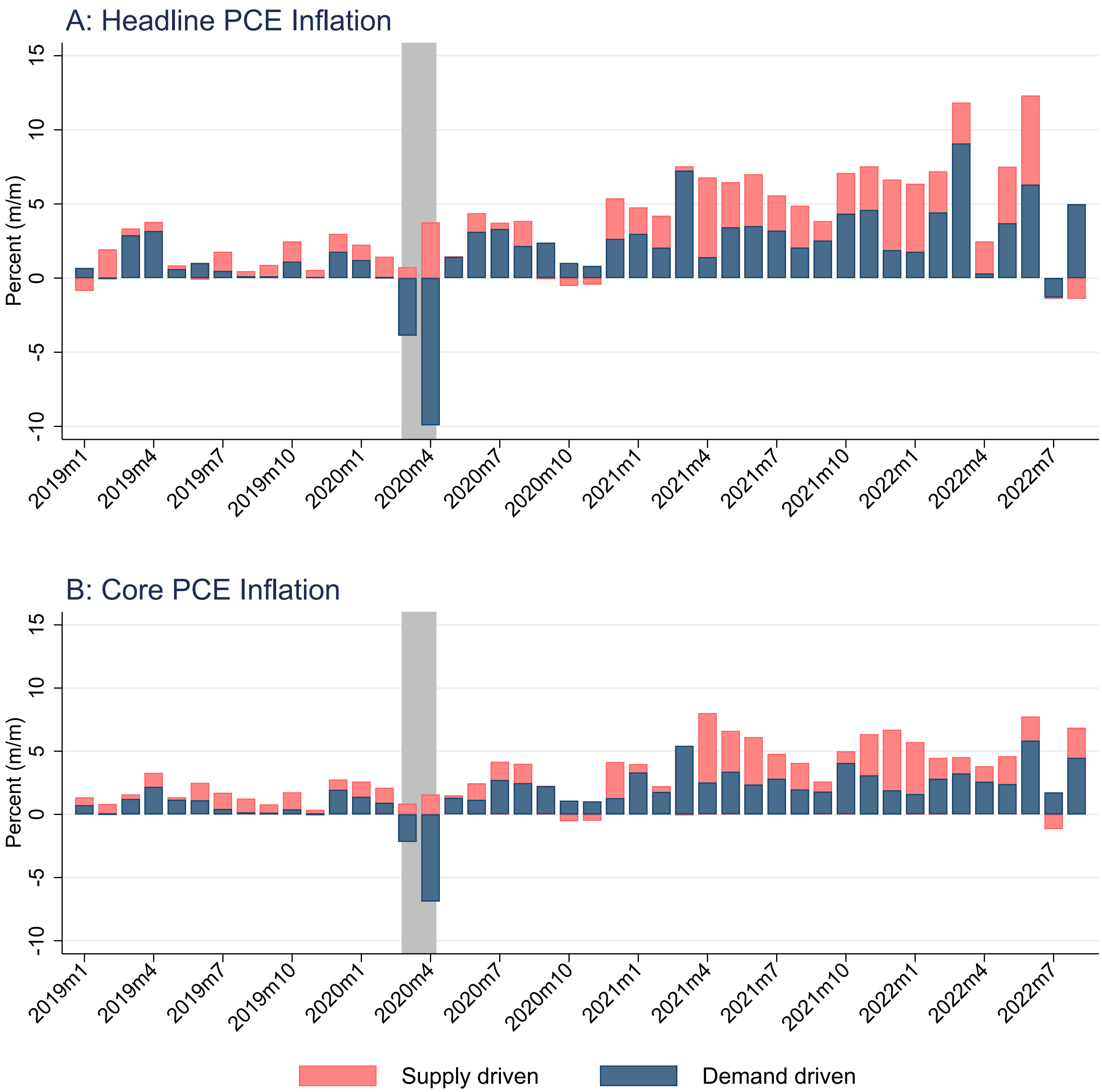
A.2 Figures and Tables

Figure A1: Unweighted share of categories by shock type



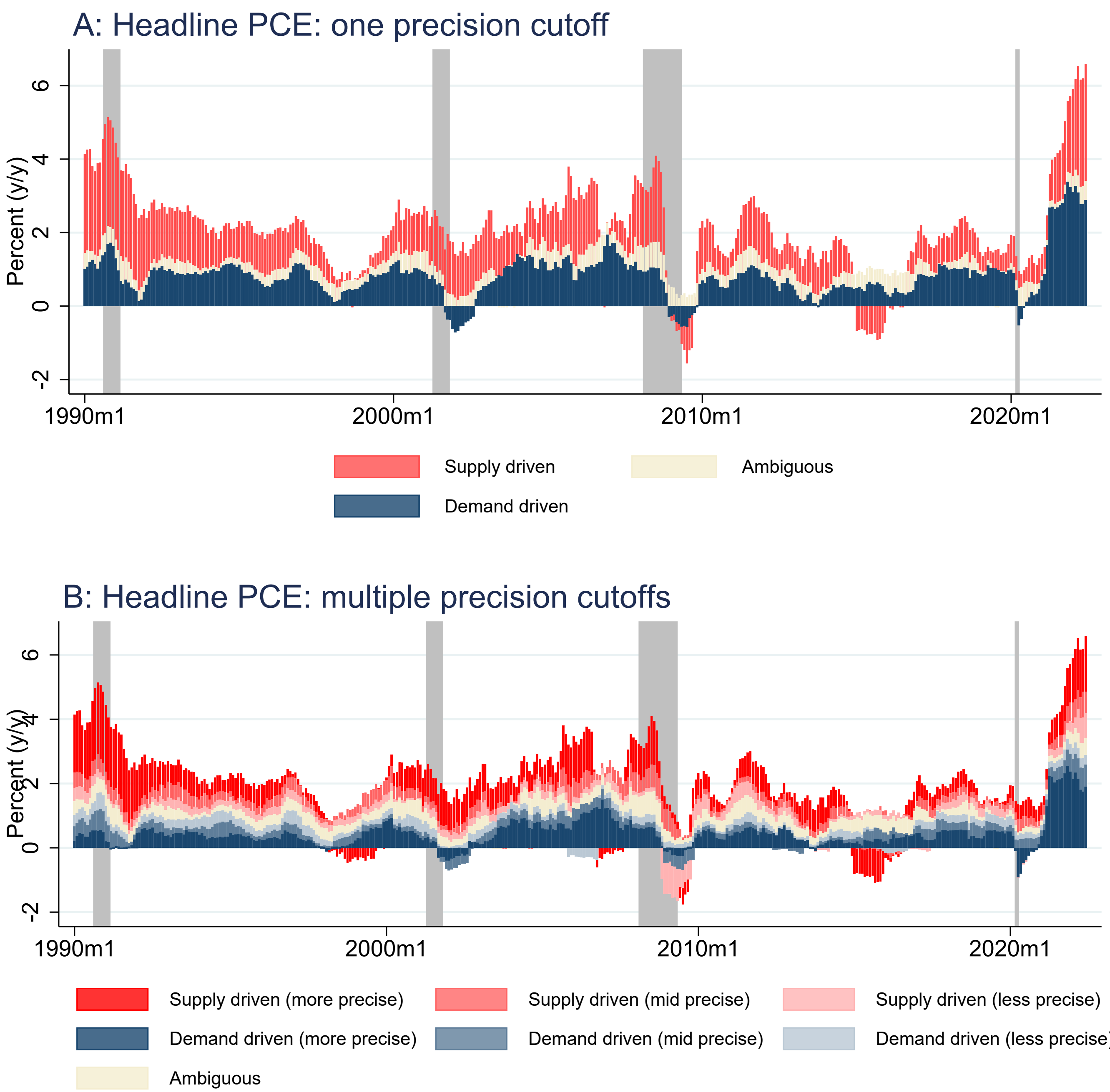
Notes: Plotted is the unweighted share of PCE categories that are labeled as supply or demand driven in a given month, centered five-month moving average. Panel A shows the share of categories that were labeled demand driven, and then further decomposed into whether the category experienced a negative 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 in the time of COVID-19 (month-to-month inflation)



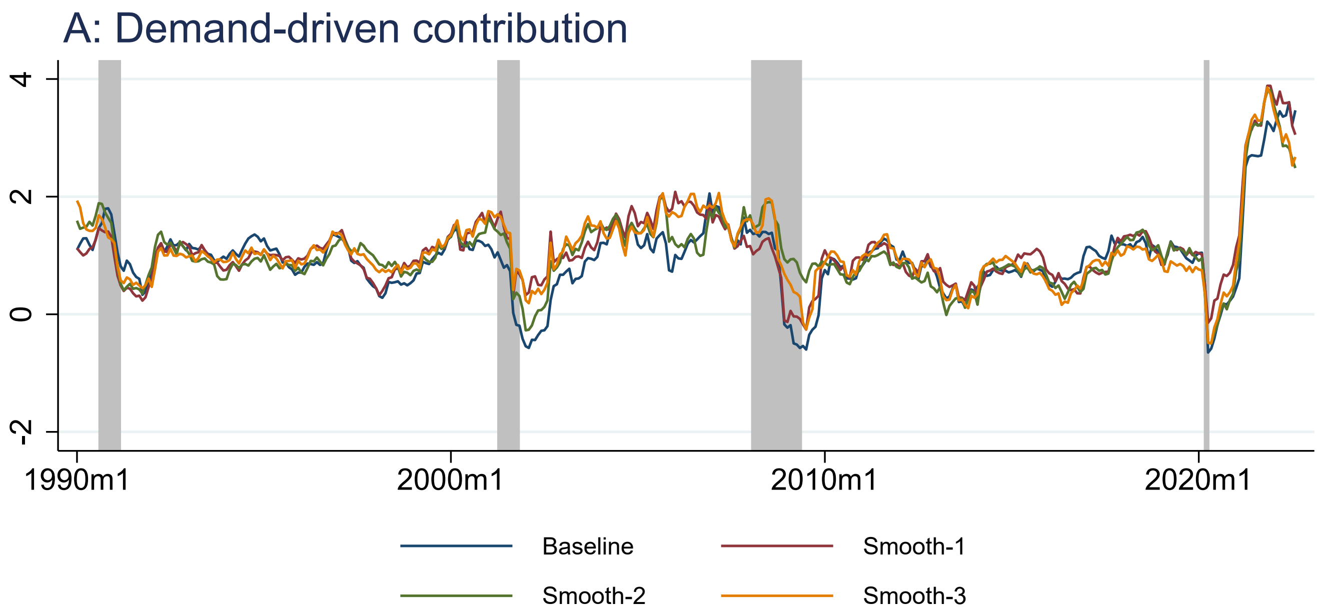
Notes: Panel A the contributions to the monthly change in headline PCE inflation and panel B shows the contributions to the monthly-change in core PCE inflation. Both series are divided intro contributions determined as supply-driven (red) and demand-driven (blue).

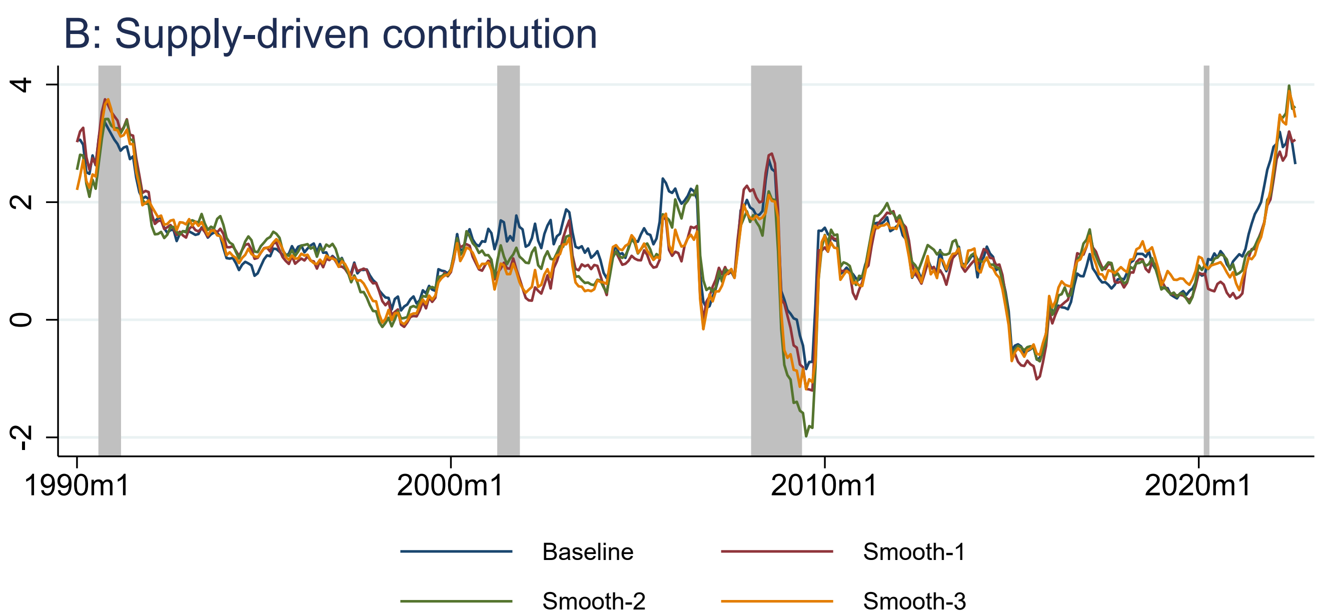
Figure A3: Precision Labeling



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 0.025 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 0.05 and 0.025 category-specific standard deviations.

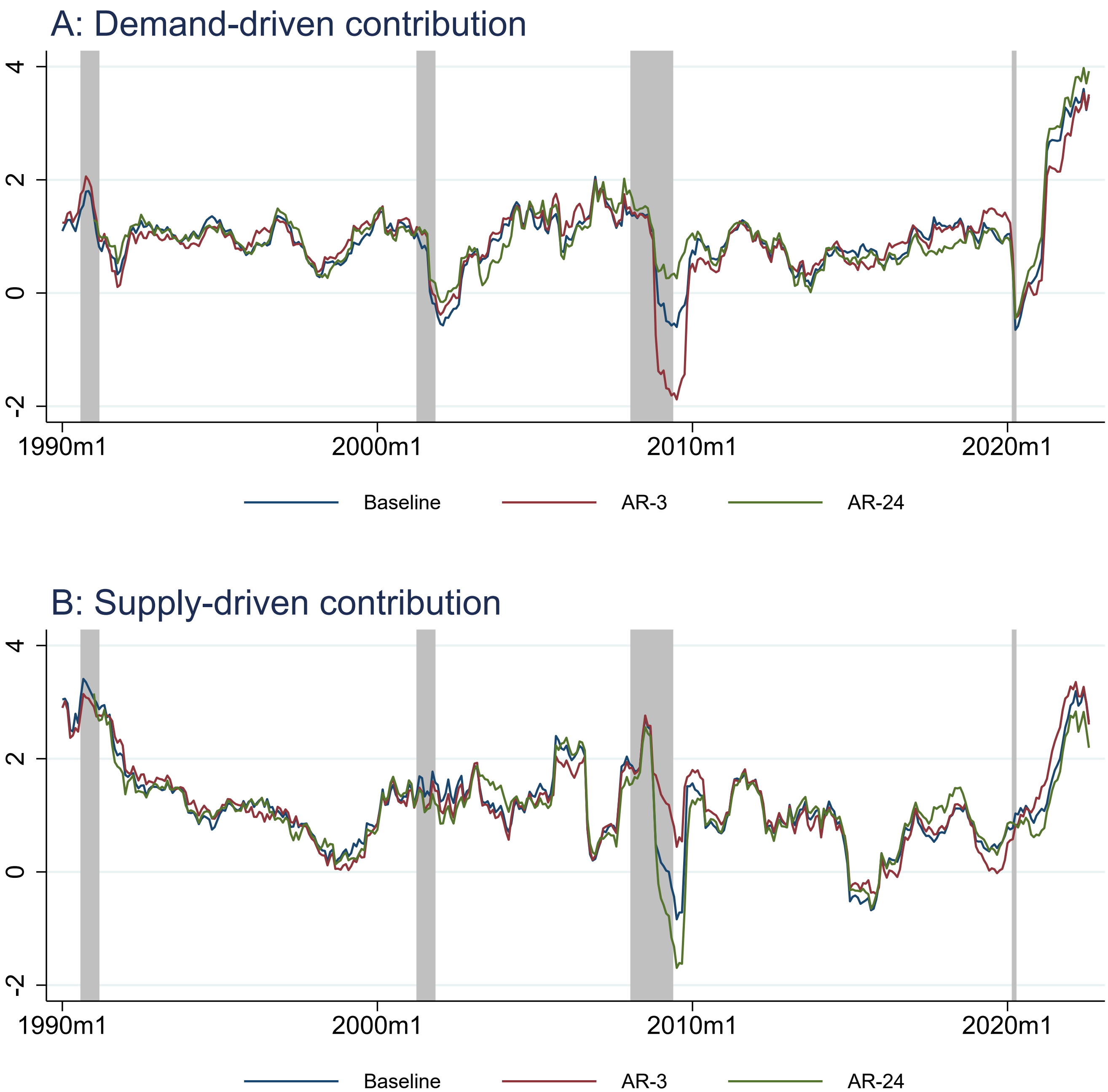
Figure A4: Smoothed Residuals, Headline PCE Inflation





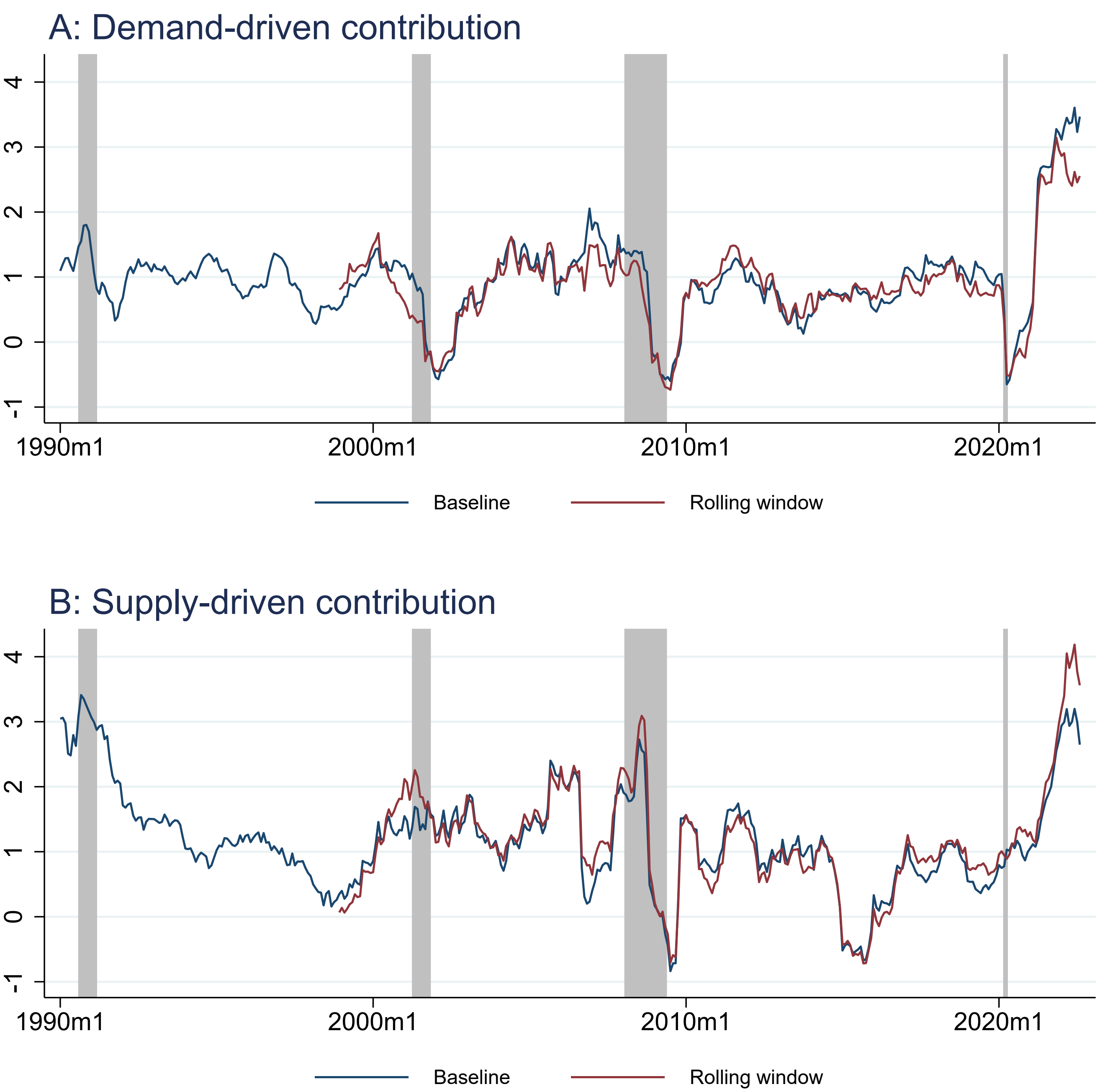
Notes: Depicted are the contributions to 12-month headline PCE inflation. Smooth-1 uses the sum of the current and lagged residual to determine whether a category is supply or demand driven. Smooth-2 uses the sum of the current and two lagged residuals, and Smooth-3 uses the sum of the current and three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

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



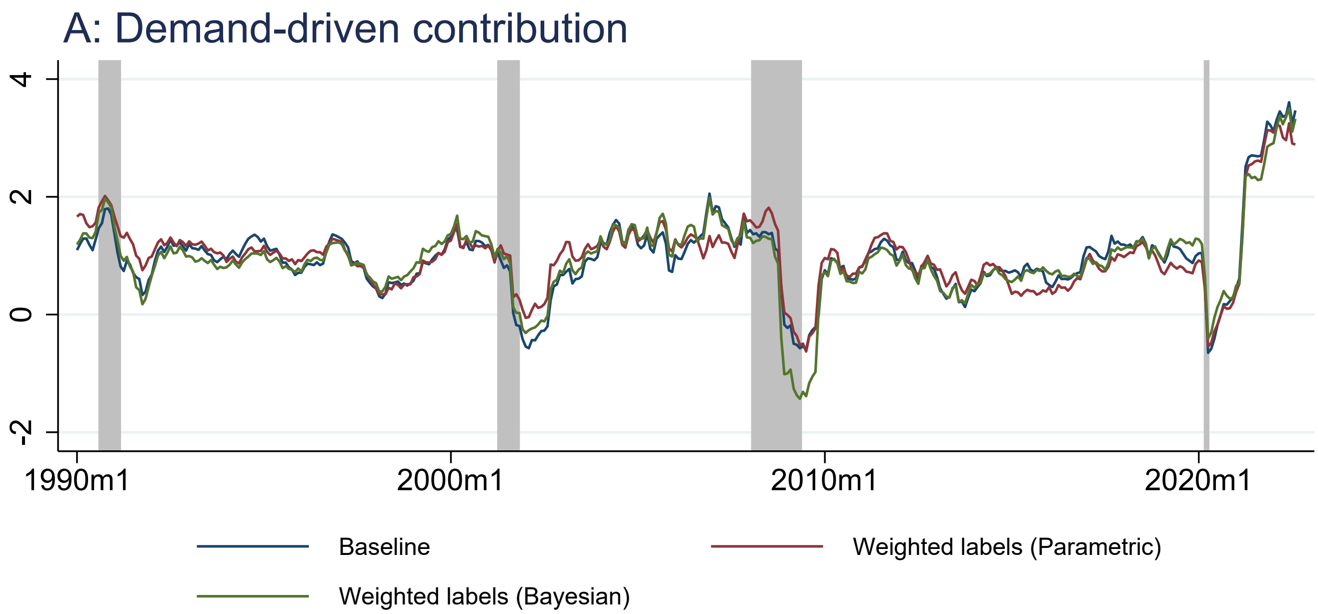
Notes: Depicted are the contributions to 12-month headline PCE inflation. AR-3 uses a 3-lag VAR to compute the residuals. AR-24 uses a 24 lag VAR to compute the residuals.

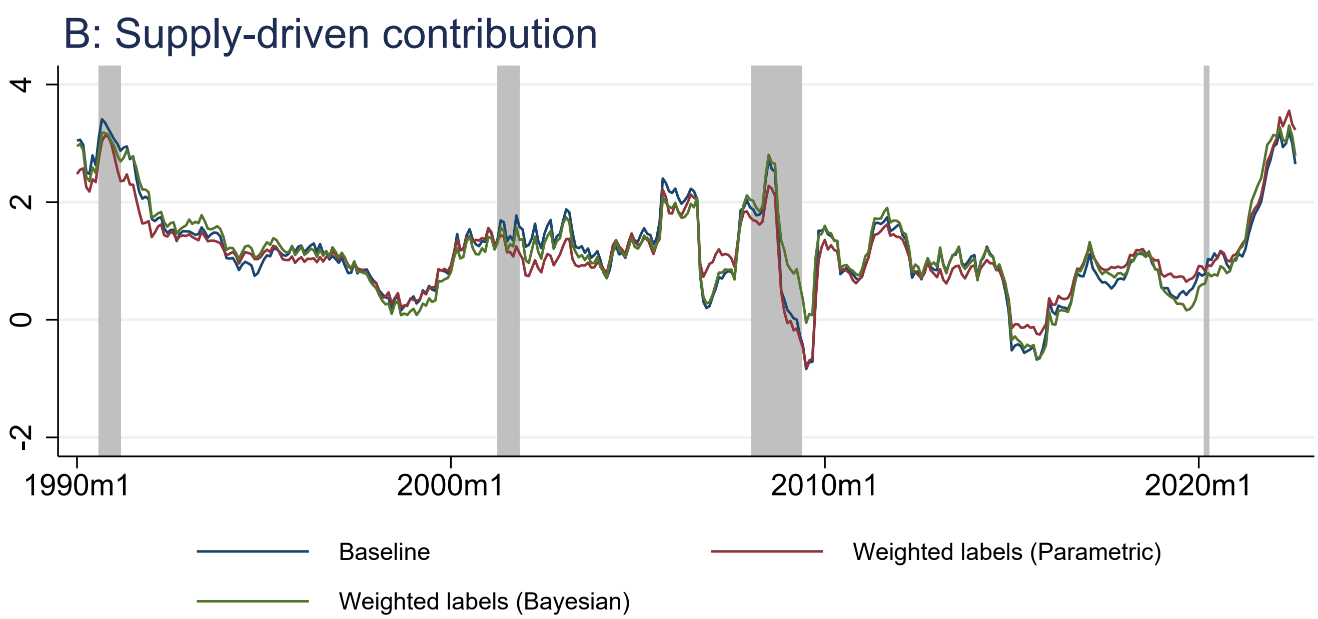
Figure A6: Rolling-window residuals, Headline PCE Inflation



Notes: Depicted are the contributions to 12-month headline PCE inflation. Rolling window estimates the VAR using 10-year rolling windows, using the residual of the final period window to label the category.

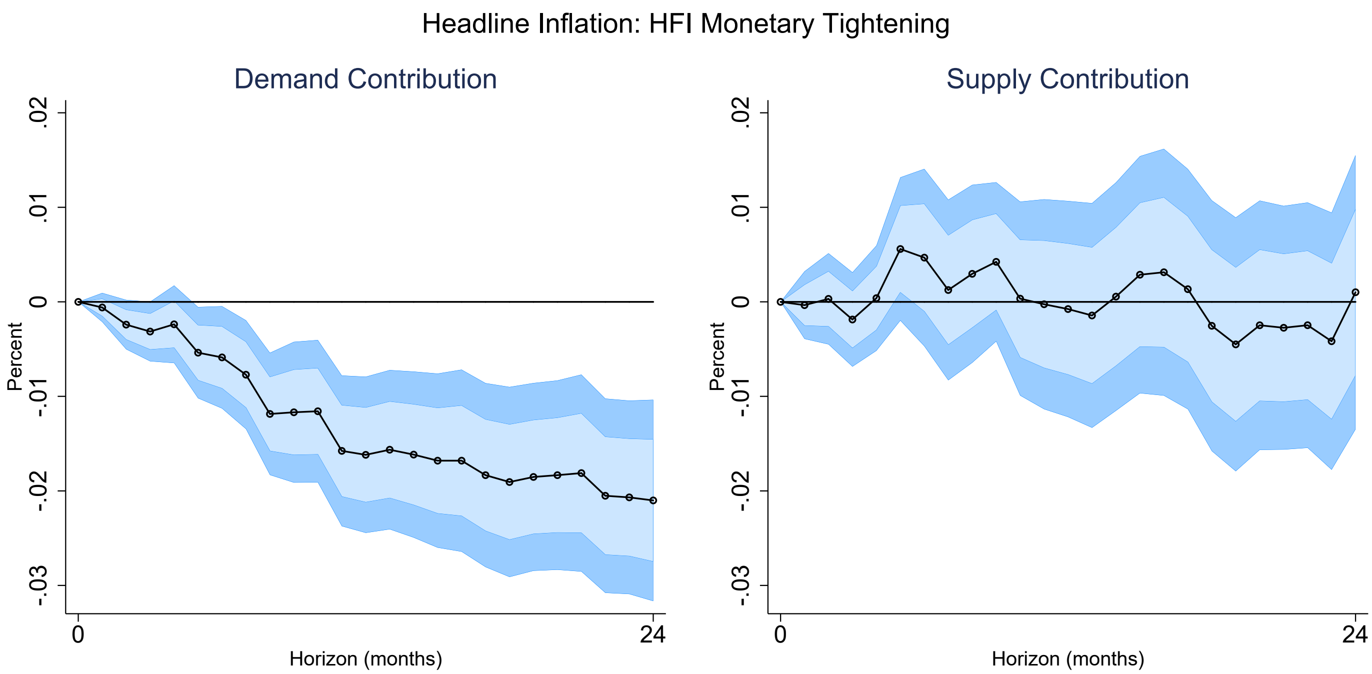
Figure A7: Weighted labeling, Headline PCE Inflation





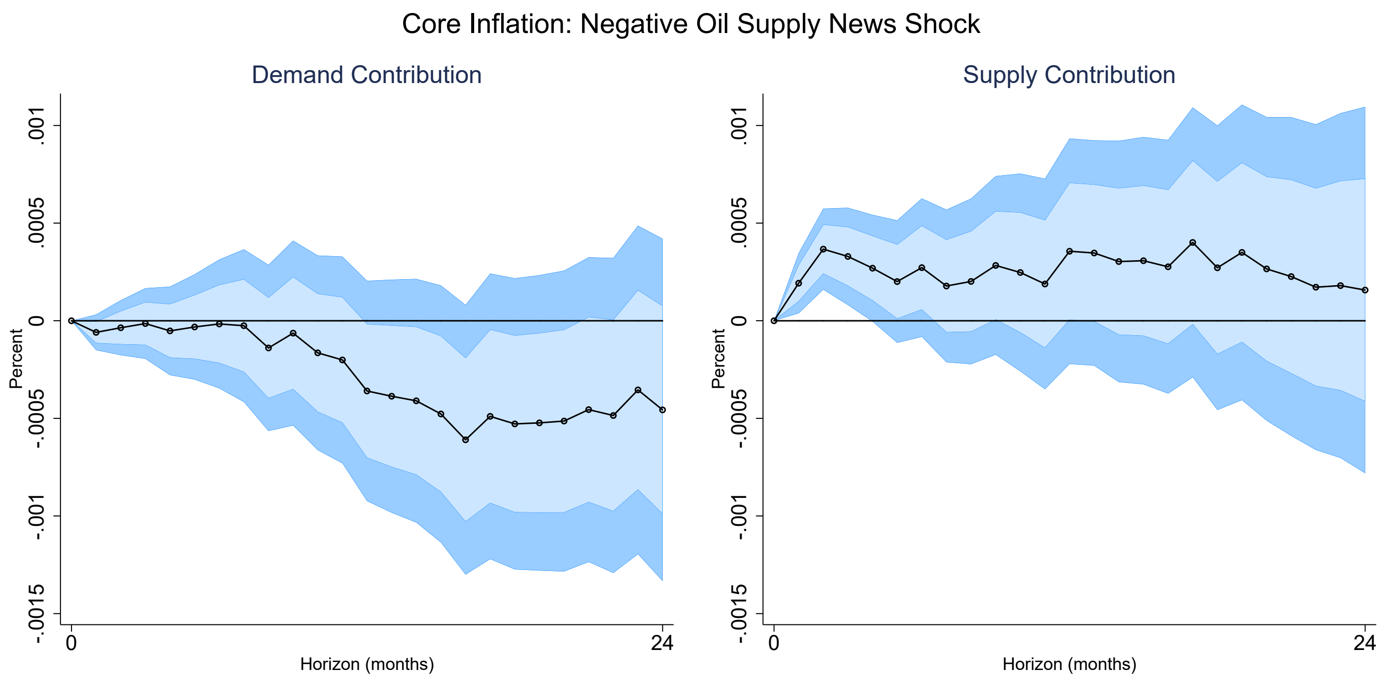
Notes: Depicted are the contributions to 12-month headline PCE inflation. Weighted labels assign non-binary probability weights by category-month. "Bayesian" indicates weights are constructed from the posterior distribution of a Bayesian estimation of equations (12) and (13). "Parametric" indicate weights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

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



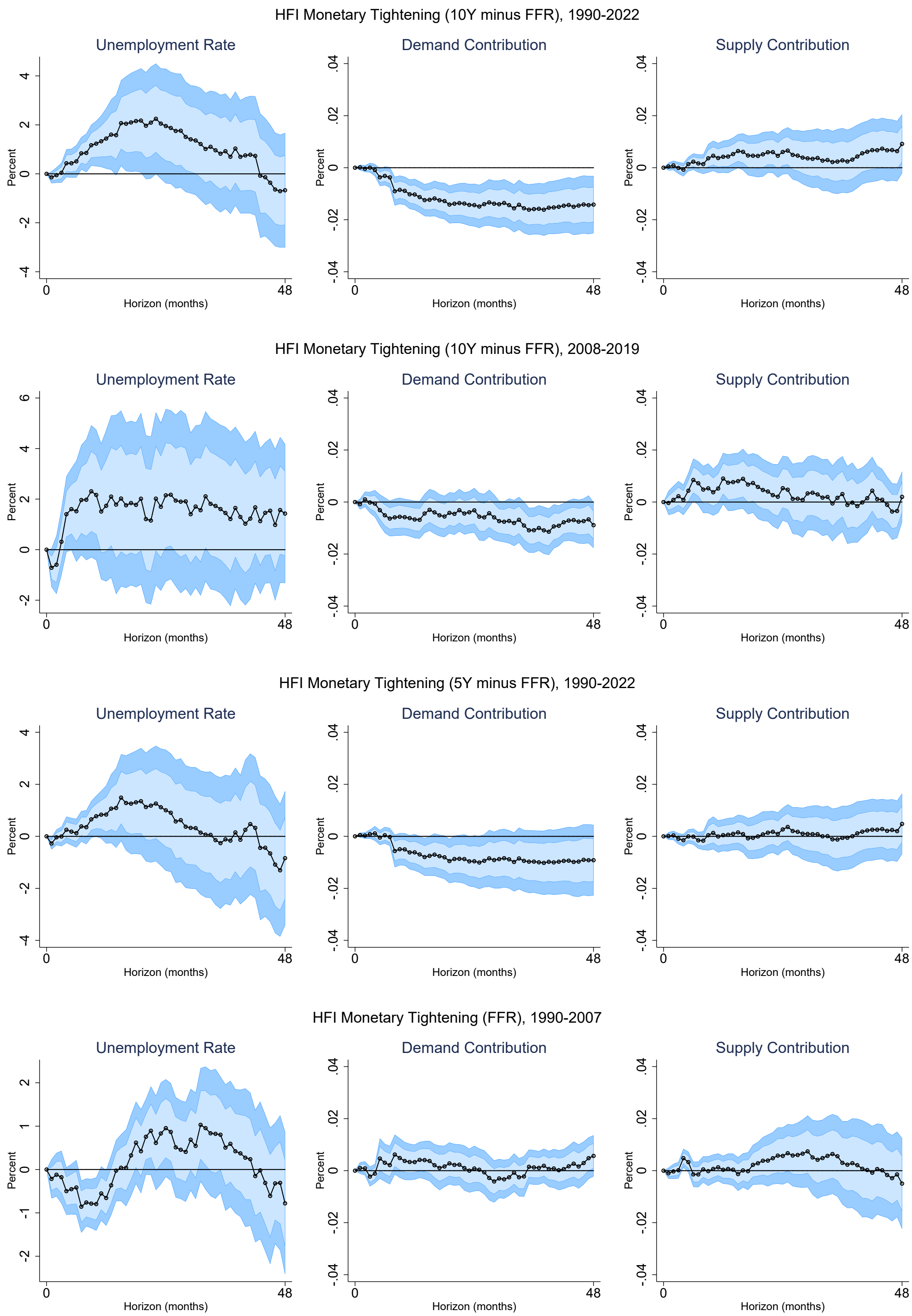
Notes: Panels A and B show the cumulative impulse response of the demand and supply contributions, respectively, to headline PCE inflation to a high frequency identified (HFI) monetary surprises (Gürkaynak, Sack, and Swanson (2005)). Shown are the 90th percentile and one-standard deviation confidence bands. Sample period is 1990-2022.

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 1990-2022.

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



Notes: Row 1 reproduces results in Figure 3. 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
Info Processing Equip	0.58	0.30	0.008
Women's & Girls' Clothing	0.47	0.20	0.017
Hotels and Motels	0.44	0.19	0.007
Used Light Trucks	0.50	0.27	0.006
Air Transportation	0.42	0.23	0.007
Used Autos	0.39	0.22	0.006
New Light Trucks	0.31	0.15	0.015
Financial Services Furnished w/out Payment	0.25	0.10	0.023
Furniture	0.31	0.16	0.010
Life Insurance	0.22	0.08	0.009

	Positive Supply Shocks (Late 1990s)		
	1997-1999	Full Sample	Exp. Weight
New Autos	0.44	0.23	0.011
Financial Service Charges, Fees/Commissions	0.44	0.23	0.023
Telecommunication Services	0.50	0.32	0.015
Games, Toys & Hobbies	0.61	0.43	0.005
Gasoline & Other Motor Fuel	0.42	0.24	0.026
Info Processing Equip	0.72	0.55	0.008
Sporting Equip, Supplies, Guns & Ammunition	0.50	0.35	0.006
Video & Audio Equip	0.64	0.50	0.009
Shoes & Other Footwear	0.39	0.26	0.007
Jewelry	0.44	0.32	0.006

	Positive Demand Shocks (Post Covid)		
	2021-2022	Full Sample	Exp. Weight
Women's & Girls' Clothing	0.53	0.17	0.017
Imputed Rent of Owner-Occupied Nonfarm Hous	0.79	0.49	0.116
Purchased Meals & Beverages	0.79	0.51	0.054
Men's & Boys' Clothing	0.42	0.18	0.011
Hair/Dental/Shave/Misc Pers Care Prods ex Elec Prod	0.37	0.14	0.005
Info Processing Equip	0.26	0.03	0.008
Games, Toys & Hobbies	0.32	0.09	0.005
Water Supply & Sewage Maintenance	0.68	0.48	0.006
Jewelry	0.37	0.17	0.006
Electricity	0.47	0.29	0.015

	Negative Supply Shocks (Post Covid)		
	2021-2022	Full Sample	Exp. Weight
New Light Trucks	0.68	0.33	0.015
Tobacco	0.68	0.46	0.009
New Autos	0.53	0.32	0.011
Video & Audio Equip	0.32	0.12	0.009
Sporting Equip, Supplies, Guns & Ammunition	0.42	0.25	0.006
Furniture	0.47	0.32	0.010
Other Motor Vehicle Services	0.47	0.32	0.007
Info Processing Equip	0.26	0.12	0.008
Games, Toys & Hobbies	0.32	0.17	0.005
Nonalc Bev Purch for Off-Premises Cons	0.53	0.40	0.009

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.