Proposal for the NBER Macroeconomics Annual:

(Mis-)Identification of the Drivers of Inflation: Supply, Demand, or Both?*

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Overview

The post-pandemic surge in inflation has made it a priority to understand the relative importance of supply-side and demand-side forces in driving inflation dynamics. While the broad narrative of the origins of supply and demand disturbances—strong recovery of demand during economic reopening, supply chain disruptions, and rising energy prices due to the Russian invasion of Ukraine—is generally agreed upon, it has proven challenging to provide solid empirical evidence to determine their quantitative relevance for the run-up in inflation. Decomposing inflation movements into supply and demand contributions is central to formulating appropriate monetary policy responses. Despite substantial research efforts and policy interest, no consensus has emerged to date on the fundamental drivers of the inflation surge.[1]

Many studies resort to simple bivariate vector autoregressive (VAR) models of inflation and output to disentangle supply and demand shocks. In this paper, we show that two widely-used methods that rely on sign information, one based on sectoral data (Shapiro, 2026) and one based on aggregate data (Giannone and Primiceri, 2024, 2026; Bergholt et al., 2024a,b, among others), suffer from fundamental identification problems that impair estimating the slopes of supply and demand curves which are key to quantifying the relative importance of supply and demand determinants

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[1]Some studies suggest that demand factors were the main driver of inflation (e.g., Giannone and Primiceri, 2024, 2026; Bergholt et al., 2024a), some find equal contributions of supply and demand (e.g., Kabaca and Tuzcuoglu, 2023; Bekaert et al., 2024), while others identify supply shocks as the dominant source (e.g., Ascari et al., 2024; Caldara et al., 2025).

of inflation. Both approaches draw point inference in under-identified models which is not only statistically erroneous, but, more importantly, gives the misleading impression that we can obtain an exact decomposition of inflation.

We make three contributions. First, we provide a comprehensive methodological critique of the approach proposed by Shapiro (2026), demonstrating that labeling inflation as demand- or supply-driven based on forecast error sign patterns is invalid, because the sign of only *one* structural shock is identified at any point. Given the widespread adoption of this approach in central bank circles to inform monetary policy decisions as well as in academic studies, it is imperative to clarify the lack of structural interpretation and misguided nature of this method. Second, we consider structural VARs identified with conventional sign restrictions. We characterize the sign-constrained identified set, showing that the range of admissible supply and demand slopes spans configurations producing contradictory historical decompositions. Since it is neither economically nor statistically justifiable to select a single value of structural parameters from the sign-identified set without further identifying assumptions, the standard way of conducting inference based on the median is incorrect and gives a false sense of precision. Third, we offer a truly structural decomposition of inflation dynamics based on a flexible, economically-motivated approach to identification that draws on multiple sources of imperfect identifying information in the spirit of Leamer (1983), Baumeister and Hamilton (2015, 2018, 2024), and Baumeister, Loria, and Maih (2026). In fact, Leamer (1983) convincingly argues that "a model with an infinite number of parameters will allow inference from a finite data set only if there is some prior information that effectively constrains the ranges of the parameters" (p.36).[2] In light of this, we propose a fully Bayesian approach that incorporates economic knowledge through informative priors on structural parameters and other objects of interest. This not only provides a transparent and inferentially-sound decomposition of inflation into supply and demand components, but also delivers a methodological blueprint for either extending the model to break down demand and supply into more granular drivers of inflation or for addressing similar modeling problems in other contexts.

Since there seems to be a lot of confusion about the implications of identification in structural VARs which are widely used for policy analysis, we believe that our paper would be a valuable contribution to the NBER Macro Annual that clarifies widely-held misconceptions based on the pressing question of the role of supply and demand for inflation dynamics and provides a constructive way forward. In what follows, we elaborate more on the issues highlighted above and our proposed

[2]Leamer (1983) continues by pointing out that "economists have inherited from the physical sciences the myth that scientific inference is objective, and free of personal prejudice. This is utter nonsense." (p.36) He emphasizes that "if we want to make progress, the first step we must take is to discard the counterproductive goal of objective inference" (p.37). He summarizes this approach by saying "the 'facts' used for statistical inference about θ are first the data, symbolized by x, second a conditional probability density, known as sampling distribution $f(x|\theta)$, and third, explicitly for a Bayesian and implicitly for 'all others,' a marginal or prior probability density function $f(\theta)$.

solution to provide credible estimates of the fundamental drivers of inflation.

1 Methodology

The common starting point across studies is a dynamic aggregate supply and demand model that takes the following form:

$$q_t = \beta_s p_t + \boldsymbol{b}_s' \boldsymbol{y}_{t-1} + u_{st} \tag{1}$$

$$q_t = \beta_d p_t + \boldsymbol{b}_d' \boldsymbol{y}_{t-1} + u_{dt} \tag{2}$$

where q_t is output, p_t is the price, β_s is the short-run price elasticity of supply, β_d is the short-run price elasticity of demand, $\boldsymbol{y}_{t-1} = (1, q_{t-1}, p_{t-1}, ..., q_{t-m}, p_{t-m})$ contains a constant and lagged observables up to lag m, and $\boldsymbol{b}_s'$ and $\boldsymbol{b}_d'$ capture the structural dynamics. The structural supply shock u_{st} and the structural demand shock u_{dt} are contemporaneously uncorrelated with each other and thus have a diagonal variance matrix $\boldsymbol{D}$. By the Frisch-Waugh-Lovell theorem, this system of structural equations can be expressed in terms of reduced-form forecast errors $\hat{e}_{qt}$ and $\hat{e}_{pt}$ that are obtained by projecting q_t and p_t onto $\boldsymbol{y}_{t-1}$:[3]

$$\hat{e}_{qt} = \beta_s \hat{e}_{pt} + u_{st} \tag{3}$$

$$\hat{e}_{qt} = \beta_d \hat{e}_{pt} + u_{dt} \tag{4}$$

The identification problem amounts to recovering the structural parameters from the reduced-form covariance matrix $\boldsymbol{\Omega}$. Specifically, in this two-equation model, there are four structural parameters to be estimated – the two elasticities (β_s, β_d) and the variances of the two structural shocks (d_s, d_d) – but the data only provide three pieces of information, namely the three parameters $(\omega_{qq}, \omega_{pq}, \omega_{pp})$ in $\boldsymbol{\Omega}$ given that it is symmetric. Earlier contributions by Leamer (1981), Fry and Pagan (2011), Baumeister and Hamilton (2015), and Uhlig (2017) have used simple bivariate market models to illustrate the fundamental challenges of identification in simultaneous equation systems, the usefulness of inequality constraints on structural parameters, and the key role of elasticities. Recently, this model has been used by Bergholt et al. (2024a,b), Giannone and Primiceri (2024, 2026), Shapiro (2026), among others, to address a key policy question: To what extent was the post-pandemic surge in inflation driven by supply vs demand? Quantifying the relative importance of supply and

[3]This is equivalent to estimating a reduced-form VAR(m) in output and price and computing the one-step-ahead forecast errors where the forecast errors are linear combinations of the unobserved structural shocks as can be seen from writing (1) and (2) in matrix form:

$$\begin{bmatrix} \hat{e}_{qt} \\ \hat{e}_{pt} \end{bmatrix} = \begin{bmatrix} 1 & -\beta_s \\ 1 & -\beta_d \end{bmatrix}^{-1} \begin{bmatrix} u_{st} \\ u_{dt} \end{bmatrix}$$

demand shocks for inflation dynamics is essential for monetary policy analysis but crucially hinges on a credible identification strategy. Here we revisit the usefulness of two prominent approaches based on sign restrictions on elasticities for the decomposition of inflation and highlight different shortcomings of each that invalidate the economic conclusions drawn in those studies.

1.1 Pitfalls of the Shapiro (2026) Approach

One popular approach that has been followed in dozens of studies was developed by Shapiro (2026) based on a sectoral analysis of items in the US consumption basket.[4] The approach consists of three steps. First, reduced-form errors are obtained for each sector using bivariate VARs estimated by OLS over rolling windows. Second, based on the sign pattern of forecast errors, sectoral month-on-month inflation is labeled as supply- or demand-driven. Third, the results of the first two steps are aggregated and converted to year-on-year inflation. The final outcome is a presumed decomposition of (something close to) headline PCE inflation into supply and demand.

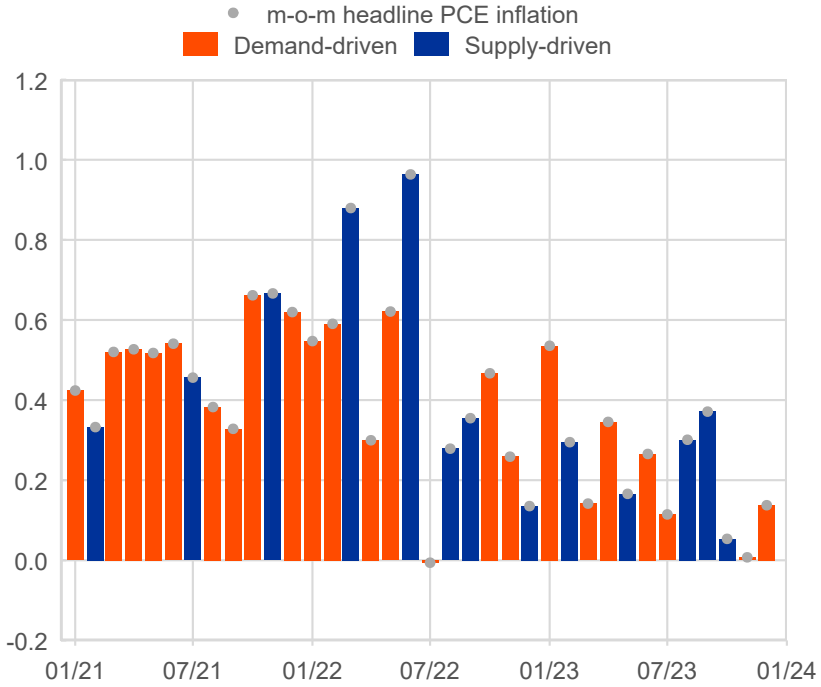
Despite its popularity, the details of the underlying identification assumptions to disentangle the supply- from the demand-driven components of inflation has not been scrutinized by any of the researchers who have applied this approach or used the decomposition as input into their own analysis. The plan is to review the construction of this decomposition and demonstrate the pitfalls inherent in each step of this procedure which has substantive consequences for policymakers and researchers who have relied on the breakdown of inflation into supply and demand factors. While all three steps are problematic, we will mostly focus on the second step which encapsulates a fundamental misunderstanding of identification.

In a nutshell, while Shapiro (2026) assumes an upward-sloping supply curve ($\beta_s > 0$ in (3)) and a downward-sloping demand curve ($\beta_d < 0$ in (4)), this allows him only to infer the sign of *one* of the structural shocks based on the sign correlation of the forecast errors, while the sign and the size of the other structural shock remains unknown. Even though it is therefore impossible to rely on this approach to infer anything about the relative importance of demand and supply shocks, the observed monthly inflation at time t is labeled as 'demand-driven' if the correlation of $\hat{e}_{qt}$ and $\hat{e}_{pt}$ in sector i is positive, and as 'supply-driven' if the correlation is negative. The direct consequence of this is that each sectoral inflation observation is either entirely explained by demand or by supply. However, this has nothing to do with identification. In fact, the magnitudes of both structural shocks and their effects on inflation remain essentially unidentified, and the slopes of the supply and demand curves are undetermined beyond the sign.

These implications of the labeling step are hidden behind the aggregation which yields a seem-

[4] See Tables A1 and A2 for a list of papers that either apply the same method to other data sets or use the data of his decomposition for empirical analysis.

Figure 1: Decomposition of Headline PCE Inflation using the Shapiro (2026) Method



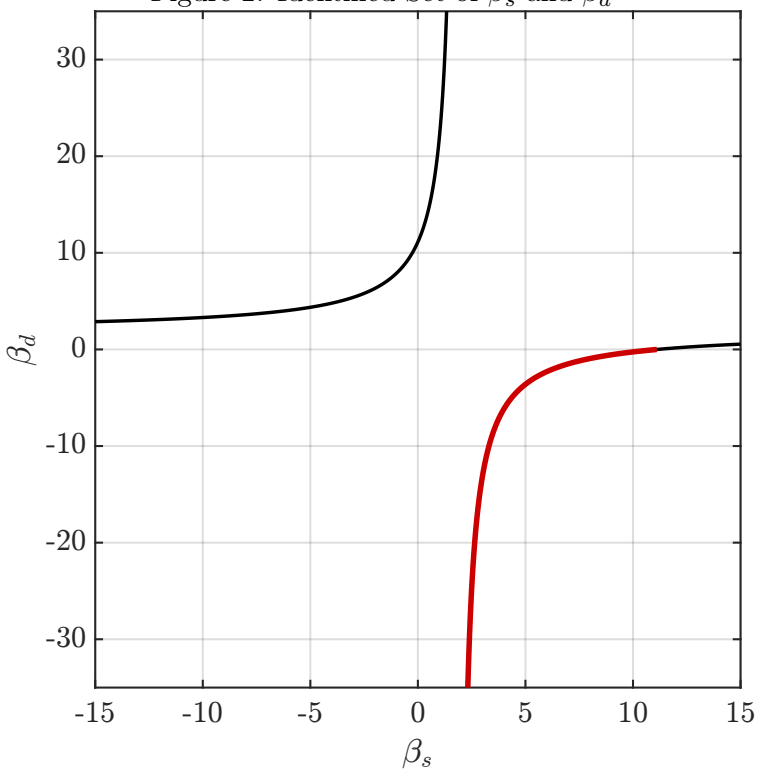
ingly reasonable decomposition of headline inflation. The best way to illustrate the fatal flaw of this strategy to identification is to apply it directly to aggregate inflation. Figure 1 shows that this would result in headline inflation being entirely attributed to supply in one month and entirely attributed to demand in another month – just like it was the case for each sector i. Not only is this inconsistent with the decomposition of headline inflation derived from aggregating up sectoral contributions, but this all-or-nothing result is also not plausible given that disturbances happen on both sides of the market each month.

Other problems that arise from (a) concatenating reduced-form errors from rolling-window VARs, (b) converting the contribution to aggregate month-on-month inflation to year-on-year inflation, (c) using different levels of disaggregation, and (d) ignoring the effects of past structural shocks for current inflation dynamics will also be documented and discussed. The last issue has also been noted by Read (2024).

1.2 Inference Issues with the Conventional Sign-Restriction Approach

Recall that the identification problem in the bivariate supply and demand model stems from the fact that there are four structural parameters but only three quantities that can be recovered from the data by OLS, which means that there is in infinite number of possible solutions for the structural model. In other words, there are many possible pairs of (β_s, β_d) that maximize the likelihood,

Figure 2: Identified Set of β_s and β_d



and without further identifying assumptions, there is no way to choose one pair over any other. Conditional on the OLS estimate of $\hat{\mathbf{\Omega}}$, we can derive all combinations of (β_s, β_d) by assuming that we know the value of β_s in equation (3). In that case, we can recover the structural supply shock $u_{st} = \hat{\epsilon}_{qt} - \beta_s \hat{\epsilon}_{pt}$ and then estimate β_d from an IV regression of $\hat{\epsilon}_{qt}$ on $\hat{\epsilon}_{pt}$ using the structural supply shock as an instrument (see Baumeister and Hamilton, 2024):

$$\hat{\beta}_d(\beta_s) = \frac{\sum_{t=1}^{T}(\hat{e}_{qt} - \beta_s \hat{e}_{pt})\,\hat{e}_{qt}}{\sum_{t=1}^{T}(\hat{e}_{qt} - \beta_s \hat{e}_{pt})\,\hat{e}_{pt}} = \frac{(\hat{\omega}_{qq} - \beta_s \hat{\omega}_{pq})}{(\hat{\omega}_{pq} - \beta_s \hat{\omega}_{pp})}. \tag{5}$$

The function $\hat{\beta}_d(\beta_s)$ describes the identified set for β_s and β_d which is plotted in Figure 2 using the reduced-form VAR specification of Bergholt et al. (2024a).[5]

Imposing the sign restrictions that $\beta_s > 0$ and $\beta_d < 0$ as in Bergholt et al. (2024a,b) and Giannone and Primiceri (2024, 2026) shrinks the identified set to:

$$\hat{S}_{\text{sign}} = \left\{ \beta_s, \beta_d : \beta_d = \frac{\hat{\omega}_{qq} - \beta_s \hat{\omega}_{pq}}{\hat{\omega}_{pq} - \beta_s \hat{\omega}_{pp}},\ \beta_s \in \left[\frac{\hat{\omega}_{pq}}{\hat{\omega}_{pp}}, \frac{\hat{\omega}_{qq}}{\hat{\omega}_{pq}} \right],\ \beta_d \in (-\infty, 0] \right\} \tag{6}$$

which corresponds to the red line segment in Figure 2. This implies that β_s lies in the interval

[5] Specifically, they estimate a VAR(4) for U.S. real GDP growth and GDP deflator inflation over the sample 1983Q2-2022Q4 which delivers $\hat{\mathbf{\Omega}} = \begin{bmatrix} \hat{\omega}_{qq} & \hat{\omega}_{pq} \\ \hat{\omega}_{pq} & \hat{\omega}_{pp} \end{bmatrix} = \begin{bmatrix} 1.1180 & 0.1024 \\ 0.1024 & 0.0517 \end{bmatrix}$.

$[1.98, 10.92]$ but β_d is unbounded, meaning that it could be any non-positive number.[6] The key implication here is that all the pairs of values on the red line are equally consistent with the observed data and the sign constraints. This poses a problem for inference given that absent additional information it is impossible to deem one pair of values in the sign-restricted set as more likely than any other, leaving the researcher with a set of possible answers that is far too wide to draw any meaningful economic conclusions.

Most researchers estimate sign-restricted VARs using the algorithm proposed by Arias, Rubio-Ramírez, and Waggoner (2018), which builds on earlier work by Uhlig (2005) and Rubio-Ramírez, Waggoner, and Zha (2010). They 'circumvent' the inference problem by reporting the median of the identified set based on the idea that the structural parameters are generated from a Haar-Normal-inverse-Wishart distribution subject to sign restrictions (see Hamilton, 2026). While the data are informative about the reduced-form parameters of the VAR model, they are uninformative about the orthogonal matrix $\mathbf{Q}$ which is drawn from an independent Haar distribution. Given that the Haar distribution constitutes a uniform measure over the set of all orthogonal matrices, the putative assumption is that it does not influence estimates of structural objects of interest such as elasticities or historical decompositions. This is not the case. A prior that is uniform with respect to one parameter is not uniform with respect to nonlinear transformations of that parameter which implies that the traditional sign-restriction algorithm imputes informative prior distributions for structural quantities that are independent of the data and void of economic content.

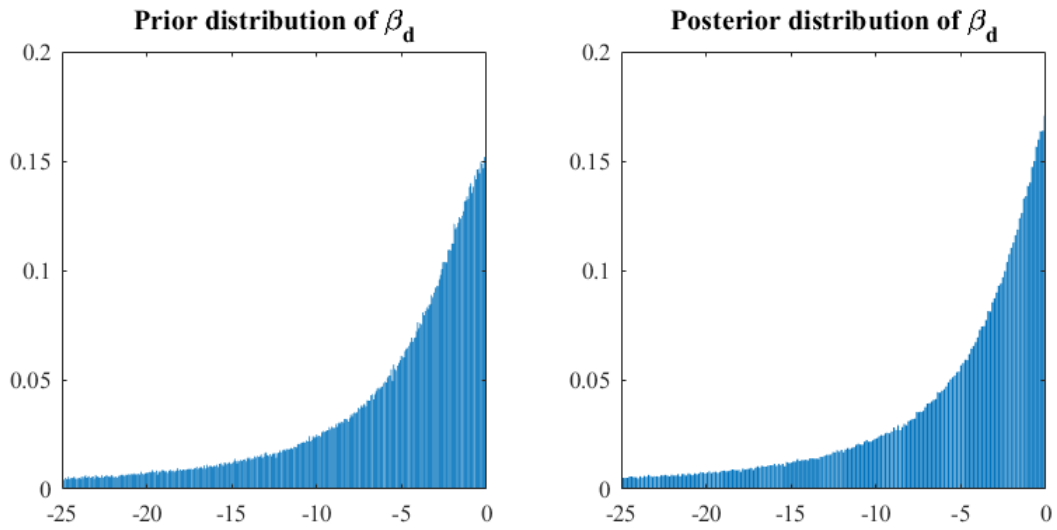
To drive home this point, we illustrate the informativeness of the uniform Haar prior for the demand elasticity by running the Arias et al. (2018) algorithm with the sign restrictions imposed, but without the data. Specifically, we use the weakest possible prior for $\hat{\mathbf{\Omega}}$ which is an inverse Wishart distribution with $\nu = n + 2 = 4$ degrees of freedom and a scale matrix $\mathbf{S}$ calibrated using univariate autoregressions in the tradition of the Minnesota prior, as suggested by Arias et al. (2025).[7] The left panel of Figure 3 shows the histogram of retained draws for β_d before seeing the data, whereas the right panel shows the same histogram after seeing the data. The two are basically indistinguishable which means that the posterior is entirely driven by the (implicit) prior.

The bottom line is that the quantitative results about the slopes of the aggregate supply and aggregate demand curves in Giannone and Primiceri (2024, 2026) and the historical contributions of supply and demand shocks to inflation in Bergholt et al. (2024a) and Giannone and Primiceri (2024, 2026) are meaningless since they are based on a single point picked from the retained draws that characterize the sign-restricted identified set, primarily the median, which has no statistical nor

[6] Which of the two elasticities is bounded depends on the sign of the correlation among the forecast errors; if the covariance is positive, the supply elasticity is bounded; instead, if the covariance is negative, the demand elasticity is bounded (see Baumeister and Hamilton, 2015). The width of the bounded interval is in turn determined by the how strongly the reduced-form residuals are correlated (see also Read, 2024).

[7] Specifically, we retain 500,000 draws for $\mathbf{\Omega}$ from $W_2^{-1}(4\mathbf{S}, \mathbf{4})$ and $\mathbf{Q}$ from $U(\mathscr{O}_n)$ that satisfy the sign restrictions.

Figure 3: Prior and Posterior Distributions of β_d Using the Haar Prior



economic justification.[8] Picking a different pair (β_s, β_d) from the red line would imply a different decomposition and thus a different narrative of the drivers of inflation. In sum, a researcher who claims to have relied on no information about the structure other than the sign restrictions should not interpret the histogram in Figure 3 as conveying the posterior plausibility of different values of β_d. The apparent implication from these histograms that some values of β_d are relatively unlikely ex post comes from the prior distribution and not from anything in the data or the sign restrictions. A researcher who does not acknowledge having used information beyond the sign constraints can only report that any non-positive value of β_d is consistent with the observed data which precludes any economic interpretation.

1.3 Main Innovation

In addition to demonstrating that existing approaches are unable to settle the question about the relative contribution of supply and demand shocks to the post-pandemic inflation surge, we propose a transparent and economically-motivated approach to identification that can shed light on the quantitative relevance of the structural drivers of inflation.

In set-identified VARs, the credibility of the prior is key because the influence of the prior (which encapsulates the identifying assumptions) does not vanish, even asymptotically (see Baumeister and Hamilton, 2015; Giacomini and Kitagawa, 2021). We therefore give careful consideration to motivating our prior choices by drawing on existing knowledge that economists largely agree upon and expressing it in the form of probability distributions. While prior information remains

[8] Bergholt et al. (2024a) also show results for the three models closest to the median.

necessarily subjective, we make our prior beliefs about the economic structure explicit and defend them, answering Leamer's (1983) call "to put much more effort into identifying qualitatively different and convincing kinds of evidence" (p.34) and "to report economically and informatively the mapping from assumptions to inferences" (p.38).

Specifically, our approach exploits the mapping between structural VAR parameters and New Keynesian model primitives. For example, the supply elasticity equals the inverse Phillips curve slope ($\beta_s = 1/\kappa$), while the demand elasticity reflects monetary policy responsiveness and intertemporal substitution ($\beta_d = -\phi_\pi/(\sigma + \phi_y)$), as shown by Bergholt et al. (2024b). We derive prior information from meta analyses of Phillips curve estimates and values commonly used in the DSGE literature. We supplement priors for the short-run price elasticities with information about the dynamic effects of supply and demand shocks and knowledge about shocks in key historical episodes. We then estimate the structural supply and demand model, building on the flexible framework proposed by Baumeister, Loria, and Maih (2026) that extends the fully Bayesian approach of Baumeister and Hamilton (2015) to accommodate multiple sources of inexact prior information.

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Table A1: Papers applying the Shapiro (2026) method

Author & Year	Institution	Title	Citations
		Institutional	
Gonçalves and Koester, 2022	ECB	The role of demand and supply in underlying inflation – decomposing HICPX inflation into components	51
Lane, 2022	ECB	Inflation Diagnostics	-
Sheremirov, 2022	Fed Boston	Are the Demand and Supply Channels of Inflation Persistent? Evidence from a Novel Decomposition of PCE Inflation	13
Brůha et al., 2022	Czech National Bank	Inflation through the lens of demand factors	1
OECD, 2022	OECD	OECD Economic Outlook, Volume 2022 Issue 2: Preliminary version	-
Beckers et al., 2023	Reserve Bank Australia	Estimating the relative contributions of supply and demand drivers to inflation in Australia	14
Reserve Bank of Australia, 2023	Reserve Bank Australia	Supply and Demand Drivers of Inflation in Australia	-
Lazaretou and Palaiodimos, 2023	Bank of Greece	Impact assessment of high inflation on Greek public finances. Does the type of inflation matter? Evidence from a highly indebted country	0
Avalos et al., 2023	BIS	Monetary policy, financial conditions and real activity: is this time different?	3
AMRO, 2023	AMRO	AMRO's 2023 Annual Consultation Report on the Philippines	1
Firat, 2023	IMF	Demand vs. Supply Decomposition of Inflation: Cross-Country Evidence with Applications	37
Dudson, 2024	Reserve Bank New Zealand	Decomposing Supply and Demand Driven Retail Inflation in New Zealand	0
Dupor and Hogan, 2025	Fed St. Louis	Was the Post-Lockdown Inflation Surge Mainly Supply Driven?	1
Bakhshaliyev and Ahmadov, 2025	Central Bank Azerbaijan	Decomposition of inflation in Azerbaijan into supply and demand components according to supermarket data	0
Akarsu and Aktuğ, 2025	Central Bank Turkey	Decomposing supply- and demand-driven inflation in Turkey	0
		Academia	
Chen and Tombe, 2023	Academia	The Rise (and Fall?) of Inflation in Canada: A Detailed Analysis of Its Post-Pandemic Experience	26
Adjemian et al., 2023	Academia	Decomposing food price inflation into supply and demand shocks	10
Punongbayan, 2025	Academia	Supply and demand components of Philippine inflation, 2001–2024	0
Zhirnov and Khatuntsev, 2025	Academia	The Contribution of Supply and Demand Factors to the Dynamics of Primary Housing Prices in Russia	0

Table A2: Papers using the resulting supply/demand series from the Shapiro (2026) decomposition

Author & Year	Institution	Title	Citations
		Institutional	
Shapiro, 2023	San Francisco Fed	How much do labor costs drive inflation?	14
Hofmann et al., 2024	BIS	Targeted Taylor rules: monetary policy responses to demand-and supply-driven inflation	12
Cieslak, 2024	Fed Kansas City	Commentary: Bond Market Perceptions of Monetary and Fiscal Policy	0
Dietrich, 2024	Danmarks nationalbank	Consumption categories, household attention, and inflation expectations: Implications for optimal monetary policy	20
Lansing, 2025	Fed San Francisco	Demand versus Supply: Which is More Important for Inflation?	2
Najjar and Shapiro, 2025	Fed San Francisco	Does monetary policy tightening reduce inflation?	3
Boissay et al., 2025	Fed San Francisco / BIS	Monetary tightening, inflation drivers and financial stress	12
Hofmann et al., 2025	BIS	Targeted Taylor rules: some evidence and theory	10
Knox and Timmer, 2025	Federal Reserve Board	Stagflationary Stock Returns	4
Ahn and Nguyen, 2025	Federal Reserve Board	Who's at Risk? Effects of Inflation on Unemployment Risk	1
Hajdini et al., 2025	Federal Reserve Board	Inflation since the Pandemic: Lessons and Challenges	18
		Academia	
Ann Xing et al., 2022		Robust Empirical Regularities on the Heterogeneity of Inflation Across Consumer Goods	0
Binder et al., 2024		Partisan expectations and COVID-era inflation	34
Garcia et al., 2025		Echoes of Inflation: CEO Early-life Inflation Experience, Inflation Attention, and Corporate Decisions	0
Kakhbod et al., 2025		In the Fed's Mind	0