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Demand-Driven Inflation

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Abstract

Post-covid inflation was predominantly driven by unexpectedly strong demand forces—both in the United States and in the Euro Area. We establish this result using a sequence of structural VARs with progressively richer specifications, interpret it through the lens of standard AD-AS analysis and an estimated DSGE model, and provide independent support for this conclusion using survey forecasts and real-time data. These demand forces reflected a combination of surprisingly robust pent-up demand following the pandemic restrictions, stronger-than-expected expansionary fiscal policies, and an unusually accommodative monetary stance. Together, they mitigated the recessionary effects of adverse supply shocks and supported the recovery, albeit at the cost of higher inflation. The economic intuition is simple: When a central bank responds forcefully to inflationary pressures, as the Fed and the ECB have done in recent decades, the aggregate demand curve is relatively flat, so supply disturbances move real activity much more than inflation. A large inflation surge, therefore, requires a shift or rotation of the aggregate demand curve.

1 Introduction

We document that the evolution of post-pandemic inflation has been remarkably similar in the United States (US) and the Euro Area (EA). US inflation accelerated in the first half of 2021,

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reached its peak in the second quarter of 2022, and has since gradually declined. Inflation in the EA followed the very same path, only delayed by approximately six months. In this paper, we study the causes of this inflation episode—the first of its kind since the Great Inflation of the 1970s.

Such similar inflation experiences across the Atlantic are unlikely to be mere coincidences. Our central finding is that unexpectedly strong demand was the dominant driver of the post-pandemic inflation surge in both regions. At the onset of the pandemic, both economies were hit by large adverse supply and demand shocks that severely depressed economic activity. As the recovery unfolded, however, aggregate demand rebounded much more rapidly than anticipated, outpacing aggregate supply and generating inflation. This stronger-than-expected recovery in demand reflected a combination of unusually accommodative monetary policy, expansionary fiscal policy, and the release of pent-up demand as pandemic-related restrictions were lifted.

The conclusion that post-pandemic inflation was primarily demand driven may appear at odds with the widespread view that adverse supply shocks were the dominant force, especially in Europe. However, the inflationary effects of supply disturbances cannot be assessed independently of the monetary policy regime under which they occur. In economies such as the US and the EA, central banks have historically responded aggressively to inflationary pressures, regardless of whether they originated from demand or supply shocks. In the standard AD-AS framework, such a strong systematic response to inflation makes the aggregate demand curve relatively flat. As a result, shocks that shift aggregate supply have comparatively large effects on real activity and smaller effects on inflation. That is, had the Fed and the ECB reacted to the pandemic-era supply disruptions in line with their pre-pandemic behavior, and had those supply shocks been the only disturbances affecting the economy, we would have experienced substantially less inflation, albeit at the cost of a weaker recovery. Instead, unexpectedly strong demand forces—including accommodative economic policies—partly offset the contractionary effects of the supply shocks, resulting in a stronger recovery but also higher inflation. We take no stand here on whether that trade-off was desirable. Indeed, the appropriate policy response may well have involved accepting temporarily higher inflation in order to cushion the effects of the pandemic on economic activity. Our point is simply that any decomposition of inflation into demand and supply components is inherently relative to the monetary policy regime, with the pre-pandemic conduct of policy providing the natural benchmark.

We investigate these issues using three complementary approaches, each relying on a different degree of structural economic modeling. First, we estimate a sequence of Structural Vector Autoregressions, beginning with a parsimonious bivariate specification identifying aggregate supply and demand shocks, and progressively enriching the framework to distinguish the roles of energy-supply shocks, monetary policy and fiscal policy. We also show that our conclusions are robust to allowing for a distinct covid factor, following Stock and Watson (2025), that captures the unusual macroeconomic dynamics associated with the pandemic. Second, we provide an economic interpretation of these empirical findings using both the intuition of the standard AD-AS framework and an estimated New Keynesian DSGE model. Rather than providing an alternative quantitative decomposition, the structural model illustrates why the relative importance of demand and supply shocks depends on the systematic conduct of monetary policy, clarifying the interpretation of counterfactual exercises commonly used in the recent literature. Finally, we provide largely model-free evidence based on ECB staff projections, the US Survey of Professional Forecasters, and real-time macroeconomic data.

The survey evidence reveals that forecasters in both the US and the EA systematically underestimated not only the persistence of inflation but also the strength of the recovery in real activity during 2021 and 2022. These forecast errors provide independent support for the demand-driven interpretation emerging from our structural analysis. Moreover, we document that real-time GDP releases painted a substantially more pessimistic picture of economic activity than subsequently revised data. As a result, policymakers operating in real time perceived considerably more economic slack than later revisions revealed. This finding suggests that real-time misperceptions likely contributed to the unusually accommodative policy stance. It also helps explain why inflation came to be widely interpreted as primarily supply driven—a narrative that continues to influence policy discussions, as reflected in the background materials prepared for the recent strategy reviews of both the Federal Reserve and the ECB (Hajdini et al., 2025 and European Central Bank, 2025).

The rest of the paper is organized as follows. Section 2 compares the inflation experience in the US and the EA. Section 3 presents the empirical evidence and progressively enriches the baseline framework to distinguish the roles of different demand and supply forces. Section 4 develops the economic interpretation of these findings using standard AD-AS analysis and a New Keynesian DSGE model. Section 5 provides model-free evidence from survey forecasts and real-time data. Section 6 discusses our contribution in the context of the rapidly growing literature on post-pandemic inflation. Section 7 concludes.

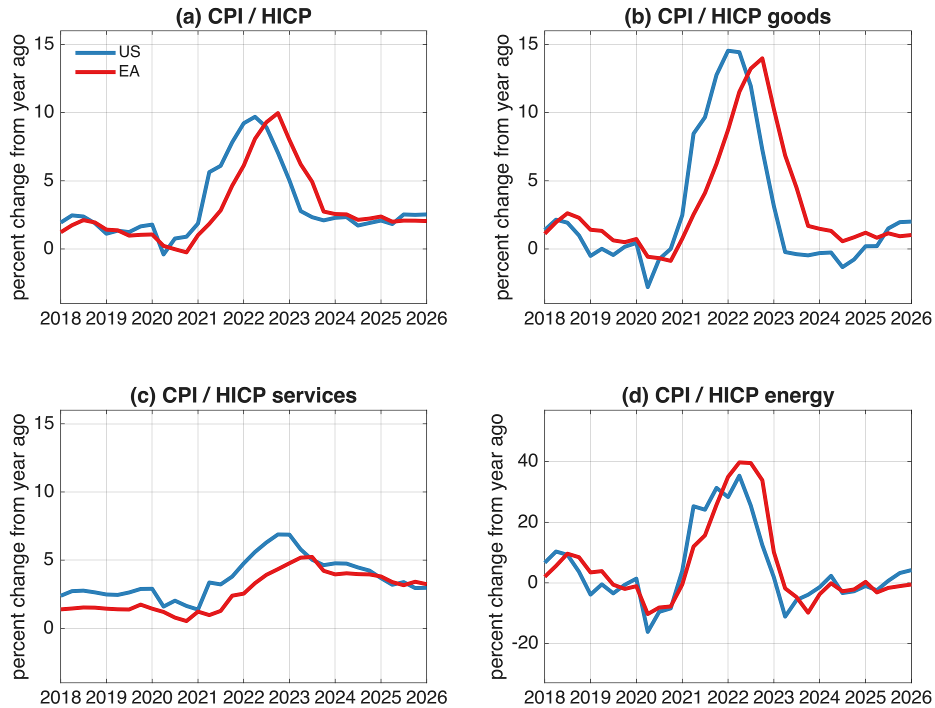

Figure 1: Inflation in the US and the EA. Sources: data from the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

2 Inflation in the US and the EA

This section sets the stage for the analysis that follows by comparing recent inflation dynamics in the US and the EA. It highlights the striking similarity in the evolution of headline inflation and several of its components on both sides of the Atlantic.

Figure 1 illustrates this point by plotting year-on-year inflation since 2018. Panel (a) focuses on the most widely monitored measure of EA inflation, based on the Harmonized Index of Consumer Prices (HICP), and compares it to the US Consumer Price Index (CPI). To make such comparison more meaningful, US CPI inflation has been adjusted to exclude "Owners' equivalent rent of residences," since the EA HICP does not comprise any rent imputation for owner occupied houses (see appendix A). These data tell a clear story: The rise in prices was delayed by a few quarters in the EA, relative to the US. But aside from this timing difference, the trajectory of inflation has been remarkably similar in both regions. Panels (b) and (c) further corroborate this similarity, by distinguishing between inflation for consumption goods and services. This distinction matters because goods inflation has peaked earlier and higher than services inflation, as is well known. But figure 1 shows that these dynamics too are common to the two regions across the Atlantic.

The last panel of figure 1 focuses on energy-price inflation, which has drawn considerable attention in the wake of the Russian invasion of Ukraine. Panel (d) shows that energy inflation has also moved in tandem in the US and the EA. It peaked slightly higher and declined with a modest delay in the EA, but this discrepancy appears relatively minor compared to the overall magnitude of the rise and fall in energy prices since 2020. This similarity in aggregate energy inflation masks important differences across its components, to which we return in section 3.

In the remainder of the paper, we investigate the drivers of the post-pandemic inflation surge, with a focus on distinguishing between demand- and supply-side forces. According to the conventional view rooted in monetary theory, central banks should "look through" supply shocks—allowing their temporary effects on inflation to dissipate—while actively countering demand-driven inflationary pressures. Understanding the relative contributions of these shocks is therefore important for the design of effective stabilization policies.

3 Demand- or supply-driven inflation?

To study the drivers of inflation dynamics, we estimate the following Structural Vector Autoregression (SVAR) model,

$$y_t = c + B_1 y_{t-1} + ... + B_p y_{t-p} + \Gamma \varepsilon_t, \tag{1}$$

where y_t is an $n \times 1$ vector of macroeconomic variables. They are assumed to evolve as a function of their own lagged values $(y_{t-1}, ..., y_{t-p})$ and an $n \times 1$ vector of economically interpretable shocks (ε_t). The vector c and the matrices $B_1, ..., B_p$ and Γ are objects of conformable dimensions that consist of estimable parameters.

We begin by focusing on the simplest specification of (1) that can disentangle supply and demand forces. More specifically, we set $n = 2$ and let y_t only include (the logarithm of) real GDP and the CPI (in the case of the US) or the HICP (for the EA). We identify demand and supply disturbances using sign restrictions (Uhlig, 2005; Rubio-Ramirez, Waggoner and Zha, 2010), assuming that *demand shocks* generate positive comovement between real activity and prices, while the comovement induced by *supply shocks* is negative. In essence, supply shocks are disturbances that create a trade-off between output and inflation stabilization, while demand shocks do not.[1] The model is estimated using four lags $(p = 4)$ and quarterly data from 1997:Q1 to 2019:Q4. The analysis starts in 1997 because of data availability for the EA, and because there

[1] Interestingly, Madeira, Madeira and Santos Monteiro (2023) document that supply shocks—identified using sign restrictions like ours—increase dissent among FOMC voting members. Demand disturbances, instead, reduce it.

is evidence of a change in US inflation dynamics since the 1990s (Cogley, Primiceri and Sargent, 2010; Del Negro, Lenza, Primiceri and Tambalotti, 2020). The estimation sample ends in 2019 because we want to keep a clear distinction between pre- and post-pandemic dynamics. In addition, macroeconomic volatility has been very elevated during the acute phase of the pandemic, and the inclusion of these data might distort inference (Lenza and Primiceri, 2022). To address the curse of dimensionality due to the limited sample length, we adopt Bayesian inferential methods with the Minnesota and the sum-of-coefficients priors, following the technical implementation of Giannone, Lenza and Primiceri (2015). Importantly, the sum-of-coefficients prior helps reduce the estimation uncertainty of the model's deterministic component documented by Bergholt et al. (2025).

Using the model estimated on the 1997-2019 sample, we decompose the behavior of output and inflation since 2020:Q1 into demand- and supply-driven components. The results of this historical decomposition are reported in figure 2, for both the US and the EA. In all four panels, the solid line corresponds to the actual realization of the data, while the dashed-dotted line represents the model forecast for the corresponding variable as of 2019:Q4. The discrepancy between these two lines is the forecast error—the extent to which the data have turned out to be different from the pre-pandemic model-based prediction. The estimated model infers the shares of these forecast errors that have been driven by unexpected changes in demand (yellow bars) or supply conditions (green bars).

Panel (a) illustrates that demand factors have supported economic activity since 2021, while supply shocks have acted as a substantial drag on output. When it comes to US inflation, more than half of its rise and fall can be attributed to demand disturbances, as shown in panel (c). The figure paints a similar picture for the EA, with the difference that supply factors exert a larger negative contribution to the EA GDP. On the contrary, demand shocks play an even more dominant role for inflation in the EA, relative to the US. Adverse supply shocks contribute substantially to EA inflation only in 2022, i.e. during the first year of the Russian invasion of Ukraine.

In simpler terms, at the onset of the pandemic, both economies were severely impacted by significant negative supply and demand shocks, which drastically reduced economic activity. As conditions started to improve, aggregate demand rebounded faster than predicted, and aggregate supply slower than expected. But our results suggest that the former has contributed more to the surge in inflation. Appendix B characterizes the statistical uncertainty surrounding our decomposition and reports a series of robustness checks concerning technical aspects of the implementation, including the prior specification and identification strategy, which can matter

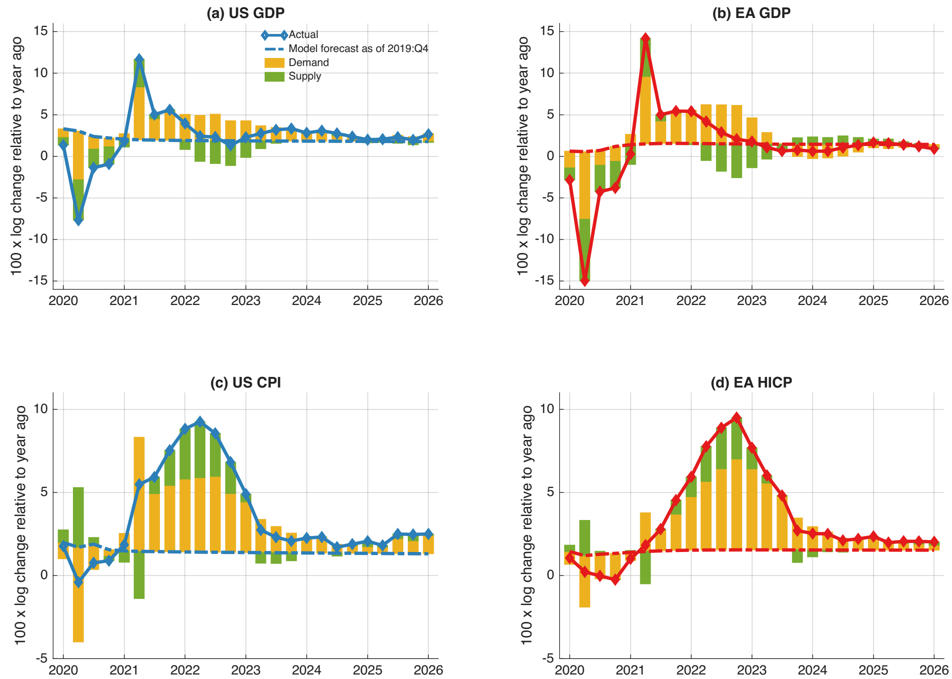

Figure 2: Historical decomposition of GDP and inflation dynamics. Sources: data from the Bureau of Economic Analysis, the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

in set-identified models (Baumeister and Hamilton, 2015).

This finding may appear surprising, given the widespread view that adverse supply shocks were the primary drivers of the post-covid inflation surge, particularly in the EA. To explain this result, section 4 develops its economic intuition using both an estimated DSGE model and a simple AD-AS framework. Before turning to that analysis, however, we first strengthen the empirical case. The baseline specification deliberately distinguishes only between aggregate demand and aggregate supply shocks, each of which encompasses many underlying disturbances. The next three subsections therefore pursue two objectives. First, they assess the robustness of the baseline decomposition. Second, they open these demand and supply "boxes" to identify which underlying shocks mattered most. The richer models largely reallocate shocks within the demand and supply categories, rather than across them, leaving the main conclusion unchanged: Demand forces remain the dominant driver of the inflation surge. They also provide additional insights, pointing to an important role for both monetary and fiscal policy on the demand side, and to energy on the supply side.

3.1 Controlling for a distinct covid factor

The baseline model attributes the entire post-2020 movement in output and inflation to demand and supply shocks. The pandemic, however, may have disrupted the economy in ways that the historical comovement of activity and prices does not fully capture. Stock and Watson (2025) document this possibility using a dynamic factor model estimated on a panel of 128 monthly indicators of real economic activity. They show that the small number of factors that describe pre-pandemic comovement cannot fully account for the behavior of these series after early 2020. A single additional factor—active from 2020 and essentially dormant by early 2023—absorbs most of this residual variation. This "covid factor" has no structural interpretation. It is a statistical summary of the atypical comovement among macroeconomic variables during the pandemic. The most prominent manifestation of these dynamics was the unprecedented reallocation of consumption and production away from in-person services toward goods. If these dynamics are indeed distinct from conventional demand and supply disturbances, our identified shocks may partly absorb them, and the corresponding historical decompositions would inherit whatever the factor explains. This subsection therefore asks how much of the post-pandemic inflation surge can be attributed to such a factor, and how much remains driven by demand and supply.

To address this question, we take the Stock–Watson covid factor as given and treat it as exogenous. We then purge the identified demand and supply shocks of the component explained by the covid factor. Specifically, we project each identified shock onto the contemporaneous value of the covid factor and its four lags. As in Stock and Watson (2025), we set the covid factor to zero outside the 2020:Q1–2023:Q1 period over which it is active. The residuals from these projections are interpreted as the purged demand and supply shocks and used to construct the historical decomposition. The remaining variation in the data is attributed to the covid component. We adopt this procedure rather than including the factor directly in the VAR because, by construction, it is zero before 2020 and therefore contains no variation over the pre-pandemic estimation sample. Including it in the VAR would therefore leave the estimated model unchanged.

The top row of figure 3 shows the historical decomposition based on the purged demand and supply shocks and adds the covid component in black. For GDP growth, the covid factor accounts for a substantial share of the movements during the early phases of the pandemic, in line with the findings of Stock and Watson (2025). For inflation, in contrast, the covid factor plays only a minor role, as shown in panel b of the figure. Over the period 2021–2023, demand accounts for more than half of excess CPI inflation.

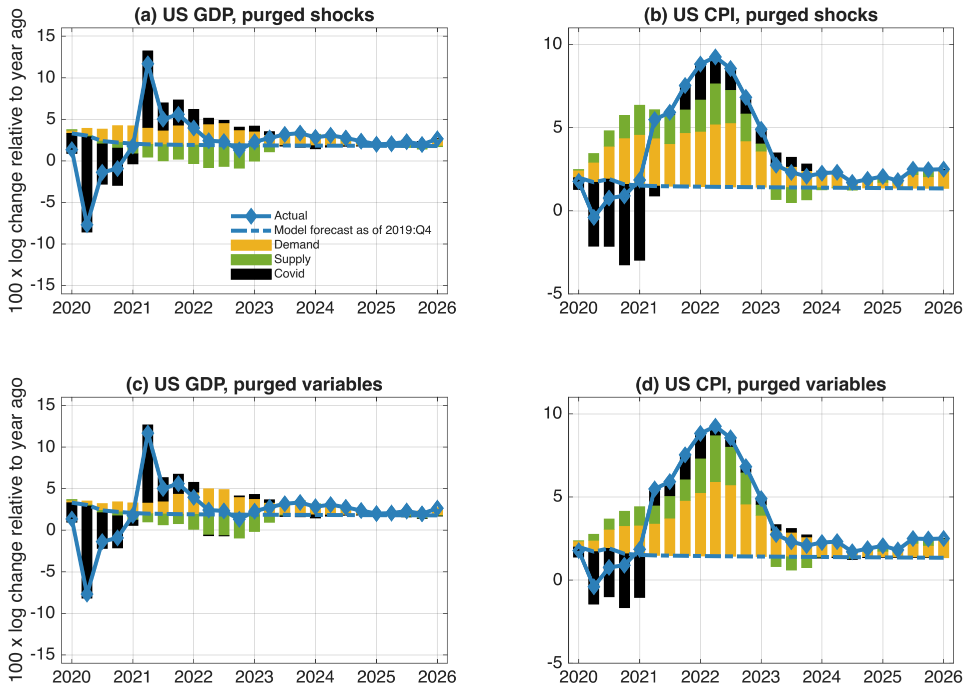

Figure 3: Historical decomposition of GDP and inflation dynamics, after controlling for the covid factor of Stock and Watson (2025). Sources: data from the Bureau of Economic Analysis and the Bureau of Labor Statistics; accessed via Haver Analytics; computations by authors and Stock and Watson (2025).

An alternative way of removing the covid-specific dynamics is to purge the data rather than the shocks. We regress each variable in the model on the contemporaneous value of the Stock–Watson covid factor and its four lags, then estimate the SVAR on the resulting residuals and construct the corresponding historical decomposition. The bottom row of figure 3 reports the results, which are very similar to those just described. In essence, the covid component captures the exceptional movements in real activity associated with the pandemic, rather than the persistent inflation of 2021–2023, leaving the demand-driven interpretation of the inflation surge essentially unchanged.

This robustness exercise is deliberately conservative. By construction, any variation shared between the covid factor and the identified demand and supply shocks is attributed to the covid component rather than to demand or supply. Consequently, the estimated contributions of demand and supply should be interpreted as lower bounds. This conservatism is reinforced by the fact that the projection is estimated only over the post-2020 period, a short sample in which the factor is driven largely by the exceptional movements of 2020. As a result, the procedure is likely to attribute a larger share of the identified shocks to the covid component than would be obtained using a longer estimation sample. Even under this conservative assignment, demand still accounts for a large share of excess CPI inflation between 2021 and 2023. Thus, introducing an explicit covid factor changes the decomposition of output during the early phases of the pandemic, but it has little effect on the decomposition of inflation. The exercise is available only for the US, since the Stock–Watson covid factor has no counterpart for the EA.

3.2 Opening the supply box

In this section, we open the supply box by distinguishing between energy-supply shocks and all other supply disturbances, including supply chain disruptions, markup shocks, and productivity shocks, which we group into a single non-energy-supply shock. As documented in section 2, energy prices fluctuated dramatically during the post-covid period and featured prominently in the policy debate, particularly in the view that the inflation surge in the EA was primarily driven by the energy crisis.

To identify energy supply shocks, we enrich the model with the two components of energy prices, household and transportation energy (appendix A describes the data). Aggregate energy prices behaved very much alike in the two economies, but the two components evolved differently. Household energy prices increased much more in the euro area than in the United States, as also noted by Tenreyro (2023), in large part because of the greater influence of the Russian invasion of Ukraine on European electricity and gas prices. The retail price of transportation fuels, on the contrary, displayed a considerably larger swing in the US. These differences almost exactly balance out in the aggregate price of energy.

As a first step in assessing the importance of energy price fluctuations, figure 4 decomposes headline inflation into the contributions of non-energy prices, household energy, and transportation fuels. This accounting decomposition shows that energy accounted for roughly one-third of inflation at its peak in both economies.

Figure 4 is informative, but these contributions are purely mechanical, and they should not be interpreted as measuring the causal importance of energy supply shocks for two reasons. First, energy shocks have indirect effects that propagate to the other components of the consumer basket, so the purple bars may understate their overall contribution. Second, energy prices are strongly influenced by the global business cycle and should not be viewed as purely exogenous drivers of post-covid inflation. Like commodity prices, shipping costs and delivery times, they are sufficiently procyclical to be used in constructing real-time indexes of economic conditions (section 6 discusses this literature in detail). Stronger economic activity raises the

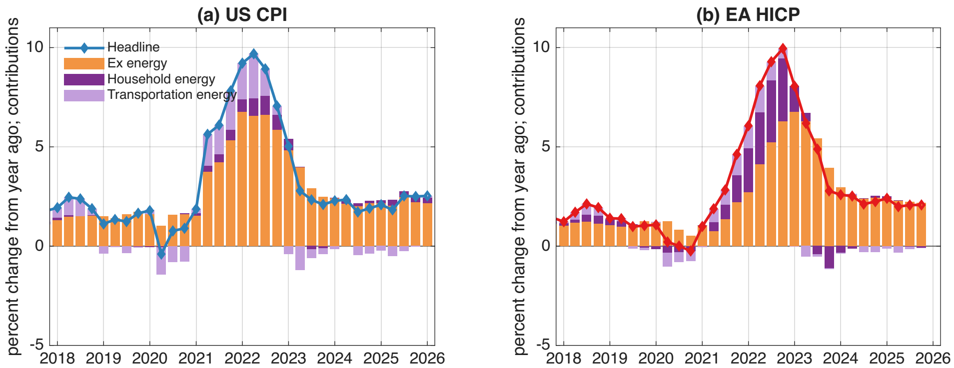

Figure 4: Accounting decomposition of headline inflation into the contributions of prices excluding energy, household energy and transportation energy. Accounting decomposition based on the official basket weights and the chain-linking conventions of the two indexes. Sources: data from the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

demand for energy and its price, implying that part of the measured contribution of energy may itself reflect demand rather than energy supply.

To move beyond the accounting decomposition and identify the causal effects of energy and other supply shocks, we build a model that includes output, non-energy prices and household- and transportation-energy prices. The model features four shocks: one demand shock, two energy-supply shocks, and one non-energy-supply shock. We identify them through the co-movement they generate: (i) *demand shocks* move output, non-energy prices and energy prices in the same direction; (ii) *non-energy-supply shocks* move non-energy prices in the opposite direction from output, while energy prices move with output; (iii) the two *energy-supply shocks* move energy prices in the opposite direction from output. We distinguish the two energy-supply disturbances by requiring each to reduce at least one of the two energy price components and to have different effects on household and transportation energy, so that neither is simply a relabeling of the other. The restrictions treat the pair symmetrically and therefore identify the two shocks only up to their labels, so we report their combined effect. In this richer model we impose the sign restrictions for four consecutive quarters, rather than only on impact, to ensure a meaningful distinction between the shocks.

Figure 5 reports the historical decomposition of non-energy inflation into the four structural shocks. It shows that energy-supply shocks are a key source of inflation within the supply block, but that their contribution in both economies does not exceed 2 percentage points at the peak. As shown in appendix C, these shocks have their largest effects on EA household energy prices, consistent with the prominence of natural gas in the European energy crisis and with the narrative emphasized by policymakers and the media. In the US, by contrast, energy-supply shocks

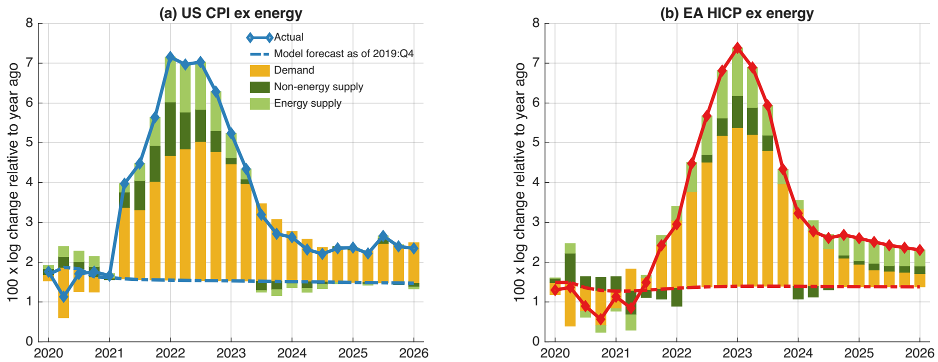

Figure 5: Historical decomposition of non-energy inflation dynamics, based on a model including GDP, non-energy prices, and household- and transportation-energy prices. The contributions of the two energy-supply shocks are reported jointly. Sources: data from the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

operate also through transportation fuels. Their impact on overall inflation, however, remains limited because most of the increase in energy prices was itself driven by demand rather than by energy supply. Opening the supply box therefore only reinforces the main conclusion of the paper: Despite being only one of the four structural shocks in the model, demand remains the main driver of post-covid inflation in both the US and the EA.

One qualification concerns the interpretation of the identified energy-supply shocks. We estimate the model separately for each economy, so the shocks are classified from that economy's perspective. However, energy prices in a region reflect not only local economic conditions but also conditions abroad, and how our model captures foreign disturbances depends on their correlation with domestic shocks. Suppose, for example, that demand booms abroad. If the boom is global, and therefore by definition correlated with domestic demand, it is captured by the demand shock, because it raises both activity and energy prices at home. If, instead, foreign demand is unrelated to domestic demand, its adverse effect on the home economy operates through higher energy prices and is therefore captured by the energy-supply shocks. These considerations affect the interpretation of the identified supply shocks, but not the central conclusion. In particular, some of the energy-supply shocks identified for the EA may in fact reflect commodity prices driven up by strong demand elsewhere (see Bergholt et al., 2026). If anything, this observation further strengthens the conclusion that demand was the dominant driver of the post-covid inflation surge.

3.3 Opening the demand box

So far, we have shown that demand, rather than supply, was the dominant driver of the post-pandemic inflation surge. We now open the demand box to distinguish monetary and fiscal policy shocks from the remaining sources of demand, such as pent-up demand, excess savings, reopening effects and confidence, which we group into a single other demand shock. Policy is the natural place to look, given the prominent role that both monetary and fiscal interventions played during the pandemic and the subsequent debate over their contribution to inflation.

We summarize the stance of the two policies using two broad indicators: the 1-year interest rate for monetary policy and the ratio of the primary deficit to potential output for fiscal policy. Measuring monetary policy is particularly challenging because policy rates were constrained by the effective lower bound. We therefore use the 1-year Treasury yield in the US, which reflects the expected path of future policy rates and thus captures part of the effects of unconventional monetary policy. Swanson and Williams (2014) argue that 1- and 2-year Treasury yields remained surprisingly unconstrained until 2010, although they became more constrained thereafter. For symmetry, we use the corresponding 1-year rate in the EA.

The primary deficit combines government transfers, spending, taxes and subsidies in a single comprehensive measure. This breadth is an advantage here because the fiscal mix differed markedly across the two economies, with transfers dominating in the US, and subsidies and energy support playing a larger role in the EA.[2] The construction of the primary deficit and of potential output follows Mori (2026) for the US and Ascari et al. (2026) for the EA; details are provided in appendix A.

The model is the mirror image of the supply specification. It features four structural shocks: three demand shocks—monetary policy, fiscal policy, and other demand—and one supply shock. As in the baseline, demand shocks move output and prices in the same direction, whereas the supply shock moves them in opposite directions. The responses of the two policy indicators, the interest rate and the primary deficit, then distinguish the three demand shocks. A monetary policy shock moves the interest rate in the opposite direction from output, whereas the remaining demand shocks move it in the same direction, reflecting the systematic response of monetary policy to stronger economic activity and higher inflation. The primary deficit, in turn,

[2] Some authors have instead focused on individual fiscal instruments. Arias, Rubio-Ramírez and Shin (2026), for example, provide a detailed analysis of the inflationary effects of fiscal transfers. Mori (2026) separately identifies government spending and revenue shocks and finds results similar to those based on the primary deficit, with the post-pandemic fiscal impulse arising mainly from the revenue side.

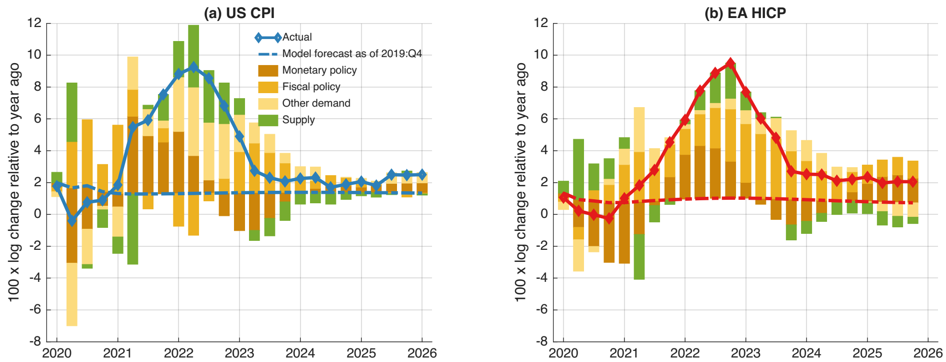

Figure 6: Historical decomposition of inflation dynamics, based on a model including GDP, prices, the 1-year interest rate and the primary-deficit-to-potential-GDP ratio. Sources: data from Eurostat, the European Central Bank, the Bureau of Labor Statistics, the Bureau of Economic Analysis, the Board of Governors of the Federal Reserve System and the Congressional Budget Office; accessed via Haver Analytics; computations by authors.

helps identify fiscal disturbances. Only a fiscal shock raises both the deficit and output simultaneously. Monetary and other demand expansions, instead, narrow the deficit through the automatic stabilizers. As in the supply model, we impose the sign restrictions for four consecutive quarters to ensure a meaningful distinction among the shocks.

Figure 6 shows that the two economies have much in common. In both, demand remains the dominant driver of the inflation surge, with monetary and fiscal policy shocks each making substantial contributions. Monetary policy became accommodative only in 2021, as interest rates remained low while inflation rose, and added to demand until 2022. The main difference between the two economies lies in the timing of fiscal policy. In the US, fiscal support came early through successive rounds of transfers to households, most notably the stimulus checks of 2020 and the first half of 2021. Its contribution reaches more than 4 percentage points in early 2021. Thereafter, as fiscal support faded, the remaining increase in inflation is attributed mainly to monetary accommodation and the other demand shock. In the EA, fiscal expansion began later and lasted longer. As a result, monetary and fiscal policy shocks contributed simultaneously during the later phase of the inflation surge rather than sequentially.

One qualification concerns the interpretation of the other-demand shock, since part of it may ultimately reflect monetary and fiscal policy disturbances. First, the 1-year interest rate does not fully capture the accommodation provided through forward guidance, asset purchases, credit support, and other unconventional instruments. That accommodation may therefore be absorbed by the other demand shock rather than by the monetary policy shock. Second, the large fiscal transfers that left households with an unusual accumulation of savings need not stimulate spending immediately, so the portion that is initially saved and spent only later may also appear as other demand rather than as a fiscal shock. These considerations suggest that the decomposition, if anything, understates the overall contribution of policy shocks, since part of what is attributed to other demand shocks ultimately reflects monetary or fiscal interventions. Finally, our framework also does not separately identify the unconventional fiscal measures introduced during the energy crisis, such as energy subsidies and reductions in VAT or excise duties on energy products (Dao et al., 2023). These measures combine demand and supply effects: to the extent that they raise disposable income, they are identified as fiscal expansions; to the extent that they lower energy prices and firms' production costs, they are identified as favorable supply shocks. A final qualification concerns the interpretation of the monetary policy shock itself. Because the model is estimated using final data vintages, part of what it identifies as a deviation from the systematic policy response may instead reflect that same systematic response applied to real-time measures of economic activity that were subsequently revised upward—an issue we return to in section 5.

These qualifications concern the interpretation of the policy shocks, not the paper's central conclusion. Opening the demand box therefore confirms that demand was the dominant force behind the inflation surge in both economies. Why demand played such a dominant role, despite the prominence of supply shocks in the public debate, is the question we turn to next.

4 Understanding the dominant role of demand factors for post-covid inflation

This section develops the economic rationale for our conclusion that demand-side forces played a fundamental role in the post-covid inflation surge. To illustrate this point, we use both an estimated DSGE model and a simple framework based on aggregate demand (AD) and aggregate supply (AS) curves. Readers less interested in the details of the structural model may skip directly to section 4.1, which presents the intuition graphically.

The model is a standard New Keynesian economy, populated by a representative household, a continuum of monopolistically competitive firms, and a government. The representative household maximizes

$$E_t\sum_{s=0}^{\infty}\beta^s b_{t+s}\left[\log\left(C_{t+s}-hC_{t+s-1}\right)-\varphi\int_0^1\frac{L_{t+s}\left(i\right)^{1+\nu}}{1+\nu}di\right],$$

subject to the budget constraint

$$\int_0^1 P_t(i)\, C_t(i)\, di + B_t + T_t \leq R_{t-1}B_{t-1} + \Pi_t + \int_0^1 W_t(i)\, L_t(i)\, di.$$

Here, B_t denotes holdings of government bonds, T_t lump-sum taxes net of transfers, R_t the gross nominal interest rate, and Π_t the profits that firms distribute to the household. Aggregate consumption, C_t, is a Dixit-Stiglitz aggregator of differentiated consumption goods,

$$C_t = \left[\int_0^1 C_t(i)^{\frac{1}{1+\theta_t}}\, di\right]^{1+\theta_t},$$

and P_t is the associated price index. $L_t(i)$ denotes labor of type i, which is used to produce differentiated good i, and it is supplied in a competitive market at the nominal wage $W_t(i)$. The parameters h and ν govern the degree of internal habit formation and the inverse Frisch elasticity of labor supply.

The variables θ_t and b_t are exogenous disturbances that follow

$$\log\theta_t = (1-\rho_\theta)\log\theta + \rho_\theta \log\theta_{t-1} + \varepsilon_{\theta,t}$$

$$\log b_t = \rho_b \log b_{t-1} + \varepsilon_{b,t}.$$

The former can be interpreted as a cost-push shock: It moves firms' desired markups and thus inflation for any given level of marginal cost. Although formally a disturbance to firms' market power, in practice θ_t acts as a catch-all for supply-side forces omitted from our stylized production structure. These forces include changes in the price of energy and imported inputs, as well as the supply-chain bottlenecks that figured prominently in the aftermath of the pandemic, all of which drive a wedge between prices and wages. The shock b_t, in contrast, is an intertemporal preference disturbance that perturbs the household discount factor. In equilibrium, it operates as an aggregate demand disturbance: An increase in b_t raises the marginal utility of current consumption relative to the future, inducing households to bring consumption forward and thereby raising aggregate demand at any given real interest rate. As is typical of demand shocks, an increase in b_t therefore moves output and inflation in the same direction.

Each differentiated consumption good is produced by a monopolistically competitive firm with the linear technology

$$Y_t(i) = A_t L_t(i),$$

where A_t denotes aggregate labor productivity. We model A_t as a unit-root process whose growth rate, $z_t \equiv \log(A_t/A_{t-1})$, follows the exogenous process

$$z_t = (1-\rho_z)\gamma + \rho_z z_{t-1} + \varepsilon_{z,t}.$$

As in Calvo (1983), in every period a fraction ξ of firms cannot reoptimize their prices and instead update them according to the indexation rule

$$P_t(i) = P_{t-1}(i)\,\pi_{t-1}^{\iota}\pi^{1-\iota},$$

where ι is an exogenous parameter, and π_{t-1} and π denote the gross rate of inflation in period $t-1$ and in steady state, respectively. Firms that are able to reoptimize choose $\widetilde{P}_t(i)$ to maximize the present value of expected profits,

$$E_t \sum_{s=0}^{\infty} \xi^s \beta^s \Lambda_{t+s} \left\{ \tilde{P}_t(i) \left(\prod_{j=0}^{s-1} \pi_{t+j}^{\iota} \pi^{1-\iota} \right) Y_{t+s}(i) - W_{t+s}(i)\, L_{t+s}(i) \right\},$$

subject to the demand for their good and the production function. Λ_{t+s} is the marginal utility of nominal income of the representative household, which owns the firms.

As in Smets and Wouters (2007) and Justiniano, Primiceri and Tambalotti (2010), monetary policy sets the policy rate according to the rule

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left[\left(\frac{\left(\prod_{j=0}^{3} \pi_{t-j}\right)^{1/4}}{\pi_t^*} \right)^{\phi_\pi} \left(\frac{Y_t}{Y_t^*}\right)^{\phi_Y} \right]^{1-\rho_R} \left[\frac{Y_t/Y_{t-1}}{Y_t^*/Y_{t-1}^*} \right]^{\phi_{dY}} e^{\eta_{R,t}},$$

where R is the steady-state gross nominal interest rate, and Y_t^* is a statistical measure of potential output, obtained using the exponential filter of Cúrdia et al. (2015).[3] Under this rule, the central bank smooths interest rates and responds to the level and growth rate of the output gap, as well as to deviations of annual inflation from a time-varying inflation target. Following Ireland (2007) and Cogley, Primiceri and Sargent (2010), we model the inflation target π_t^* as the exogenous process

$$\log \pi_t^* = (1-\rho_*) \log \pi + \rho_* \log \pi_{t-1}^* + \varepsilon_{*,t}.$$

[3]Specifically, $\log Y_t^* = 0.9 \log Y_{t-1}^* + 0.1 \log Y_t + 0.9\gamma$. The drift term ensures that Y_t^*/Y_t equals one along the balanced growth path.

Finally, $\eta_{R,t}$ is a monetary policy disturbance given by

$$\eta_{R,t} = \varepsilon_{R,t} + \sum_{k=1}^{K} \varepsilon_{R,k,t-k},$$

where $\varepsilon_{R,t}$ is the conventional contemporaneous policy surprise, while $\varepsilon_{R,k,t-k}$ is an anticipated policy shock that becomes known to agents at time $t-k$, but affects the policy rule at time t. Anticipated policy shocks are important for the estimation of this model because they allow us to constrain the future path of the interest rate, as necessary to enforce the zero lower bound or to capture policymakers' forward guidance, as in Laséen and Svensson (2011), Campbell et al. (2012), Del Negro and Schorfheide (2013), and Del Negro, Giannoni, and Patterson (2023). Accordingly, the variance of these anticipated shocks is constrained to be equal to zero before 2008:Q4. We include anticipated shocks up to the horizon spanned by the 1-year rate.

The government issues one-period nominal bonds and levies lump-sum taxes that adjust to satisfy its intertemporal budget constraint, so that fiscal policy is Ricardian. In equilibrium, all markets clear; in particular, $Y_t(i) = C_t(i)$ for every good i. All structural innovations, $\varepsilon_{\theta,t}$, $\varepsilon_{b,t}$, $\varepsilon_{z,t}$, $\varepsilon_{*,t}$, $\varepsilon_{R,t}$, $\{\varepsilon_{R,k,t-k}\}_{k=1}^{K}$, are mutually independent, serially uncorrelated, normally distributed random variables with mean zero and standard deviations σ_θ, σ_b, σ_z, σ_*, σ_R, $\{\sigma_{R,k}\}_{k=1}^{K}$, respectively.

To solve the model, we collect the first-order conditions and constraints from the agents' optimization problems into a system of rational expectations difference equations that characterizes the equilibrium. Because of technological progress, the real variables of the economy are non-stationary. We therefore rewrite the equilibrium conditions in terms of deviations of the real variables from the technology process A_t. We then log-linearize the resulting system around its non-stochastic steady state and solve the linearized model using standard methods (e.g., Sims, 2002).

4.1 Building intuition: A simple AD/AS representation of the model

To build intuition, we first consider a very special case of the previous model, which strips out all dynamics and complications. In particular, and only for the purposes of this subsection, suppose that $h = \iota = \phi_Y = \phi_{dY} = \rho_R = \rho_b = \rho_\theta = \rho_* = \sigma_z = \sigma_R = \sigma_{R,1} = \ldots = \sigma_{R,K} = 0$, and that the policy rule responds to current rather than annual inflation. Under these restrictions—and assuming $\phi_\pi > 1$, so that the equilibrium is unique—there are no internal dynamics: Habit formation, indexation, and interest-rate smoothing are shut down, all shocks are i.i.d., and, in equilibrium, all expectations of future variables are zero. The model therefore boils down to three simple and familiar equations:

$$\hat{\pi}_t = \kappa \hat{x}_t + \varepsilon_{\theta,t} \tag{2}$$

$$\hat{x}_t = -\hat{R}_t + \varepsilon_{b,t} \tag{3}$$

$$\hat{R}_t = \phi_\pi \left(\hat{\pi}_t - \hat{\pi}_t^*\right), \tag{4}$$

where $\kappa = \frac{(1-\beta\xi)(1-\xi)(1+\nu)}{\xi(1+\nu(1+1/\theta))}$, $\hat{x}_t$ is the deviation of output from its log-linear trend—which, in this special case, coincides with the model's output gap, since flexible-price output is log linear—and hats denote log deviations from steady state. Equation (2) is the Phillips curve, relating inflation to the output gap and to cost-push shocks, which play the role of supply shocks; it characterizes the aggregate supply (AS) side of the economy. Equation (3) is the IS equation, derived from the households' Euler equation, where $\varepsilon_{b,t}$ is the preference shock. Equation (4) is a simplified policy rule, in which the nominal interest rate responds only to inflation's deviations from the target. Substituting the policy rule into the IS equation yields the aggregate demand (AD) of this economy:

$$\hat{\pi}_t = -\frac{1}{\phi_\pi}\hat{x}_t + \frac{1}{\phi_\pi}\varepsilon_{b,t} + \hat{\pi}_t^*. \tag{5}$$

We stress that this special case is a device for intuition, not measurement. The restrictions eliminate exactly the propagation mechanisms to which the estimation in section 4.2 will attribute an important role, and the implied slopes should not be taken quantitatively. Its value is to make transparent three qualitative properties that survive in the full model. First, supply and demand shocks are identified by opposite comovements: Cost-push disturbances shift the AS curve and move inflation and output in opposite directions, whereas demand disturbances shift the AD curve and move them in the same direction. Second, shifts in aggregate demand comprise both non-policy and policy sources: A surge in private demand ($\varepsilon_{b,t}$) and an increase in the central bank's inflation target ($\hat{\pi}_t^*$) both shift the AD curve up. As equation (5) shows, however, the target shifts the curve one-for-one, while the effect of private demand is dampened by the strength of the policy response. Third, the slope of aggregate demand is governed by the systematic conduct of monetary policy: The stronger the central bank's reaction to inflation (ϕ_π), the flatter the AD curve.

The full model relaxes this tight mapping in several ways: With persistent shocks, expectations of the future enter both the supply and the demand block, so that most disturbances no longer shift exclusively one curve; responses build gradually over time; and the comovement of inflation and output conditional on each shock—the empirical counterpart of the slopes—depends on the shock and on the horizon considered. We turn to an estimated version of the full model in section 4.2. Before doing so, however, we retain the qualitative structure of the AD/AS framework, but discipline the slopes of the two curves with the data rather than with the model. The logic follows from the first property above: Supply shocks move the economy along the AD curve, so the relative responses of inflation and GDP to the supply shocks identified in section 3 trace out its slope; symmetrically, the relative responses to the identified demand shocks trace out the slope of AS. We measure these relative responses at a one-year horizon; see appendix B. These slopes are estimated on pre-pandemic data, so their use here embodies the assumption that covid altered the size and mix of demand and supply disturbances, but not their transmission mechanism. We return to the role of this assumption at the end of the section. To draw the static version of these curves in figure 7, we use the responses of year-on-year inflation and of GDP's deviation from trend at the one-year horizon. Armed with this framework, we can return to the interpretation of the post-covid surge in inflation.

Figure 7 depicts the AD and AS curves estimated in this way, in the US and the EA. Initially, they cross at a level of output's deviation from trend normalized to 0, and inflation equal to 2 percent. The figure also reports the average level of output's deviations from its pre-covid trend and inflation in 2020, 2021, 2022 and 2023, from figure 2. The first thing to notice is that the AD curve is quite flat in both economies, and more so in the EA than in the US. This characteristic of the AD curve is due to the Fed and the ECB's strong reputation as (near) inflation targeters. To understand why being an effective inflation targeter results in a flat AD, we can refer to the simple model above. For example, think of the extreme situation of a central bank that never lets inflation deviate from a 2-percent target, no matter the cost in terms of output deviations from trend—the limit $\phi_\pi \to \infty$ in equation (5). The resulting slope of the AD curve would be exactly zero. In such an extreme case, supply shocks shifting the AS curve would have a large impact on real activity, but no effect on inflation, and private demand disturbances would be fully offset by the policy response. The only way to experience higher inflation would then be through an increase in the central bank's own inflation target. More generally, away from this extreme, inflationary shifts in aggregate demand can originate from private demand shocks that

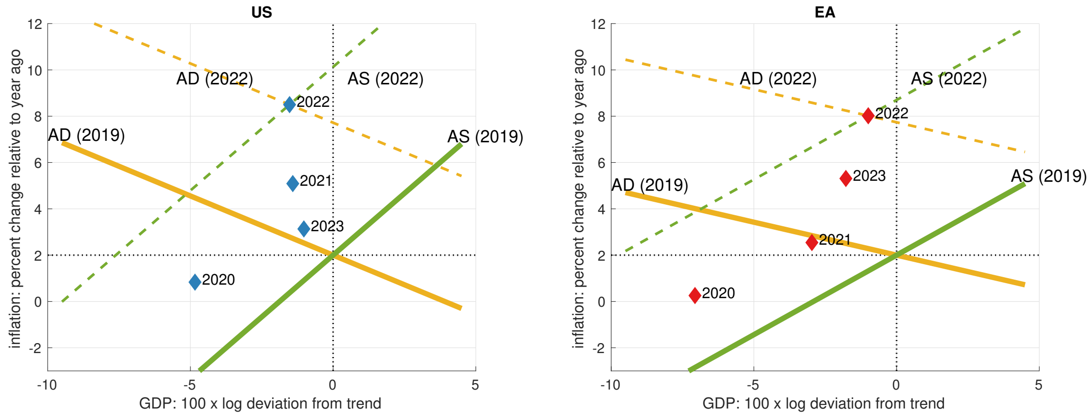

Figure 7: AD and AS curves in the US and the EA. Sources: data from the Bureau of Economic Analysis, the Bureau of Labor Statistics, and Eurostat; accessed via Haver Analytics; computations by authors.

the central bank accommodates only imperfectly, or from monetary expansions engineered by the central bank itself—either $\varepsilon_{b,t}$ or $\hat{\pi}_t^*$ in equation 5.

The estimated AD curves depicted in figure 7 for the US and the EA are not as flat as in the extreme example of strict inflation targeting that we have just described, but they are not far from that benchmark. For example, the ECB has a single mandate of price stability, and it is intuitive that this priority has resulted in a fairly flat AD curve in the EA until 2019. If this curve has been as flat also during the pandemic, the negative supply shocks experienced by the EA economy since 2020 have likely had a large contractionary effect on real activity, but a limited impact on inflation. This intuition is consistent with the empirical findings of figure 2. Similarly, the only way for inflation to rise to the levels observed in 2022 is for the AD curve to shift upwards, as shown by the dashed yellow line in figure 7, which explains our result that demand factors have played a dominant role for post-pandemic inflation.

The flatness of the AD curve also finds support outside our framework. Because supply shocks move the economy along the demand curve, any identified supply disturbance provides information about its slope. Känzig (2021), for example, identifies oil supply news shocks from futures-price movements around OPEC announcements, and the ratio of the inflation and output responses to these shocks at a one-year horizon is broadly consistent with the slope of the AD curve that we estimate. Gagliardone and Gertler (2026) obtain similar estimates.

The intuition that we have just provided leverages the assumption that the transmission mechanism of demand and supply shocks, and thus the slopes of the AD and AS curves, has not changed after covid. But what if they did? Would our interpretation of the empirical findings of section 3 be different? The answer to this question is “not a whole lot.” Let us understand why in the context of figure 7. First, consider a steepening of the AS curve after 2020, or a nonlinearity that makes inflation more responsive to economic activity when the economy operates in a tight region. Benigno and Eggertsson (2023), for example, argue that the post-pandemic Phillips curve became substantially steeper as labor markets tightened. The possibility of important nonlinearities was also taken seriously by Fed staff in their efforts to understand the unusually large inflation forecast errors of the pandemic period (Peneva, Rudd and Villar, 2025). But even with a more responsive AS curve, a substantial outward shift in the AD curve would still be needed to account for the high level of inflation together with the level of economic activity. Indeed, if the economy had moved onto a steeper portion of the AS curve, a given increase in demand would generate an even larger rise in inflation, precisely as emphasized by Benigno and Eggertsson (2023).

But what about a change in the slope of the AD curve? Mechanically, a steeper AD curve since 2021 could rationalize the observed dynamics of real activity and inflation with smaller demand shocks, i.e. smaller shifts of the AD. But a steepening of the AD curve would correspond to a weakening of the monetary policy systematic reaction to inflation, possibly reflecting "shocks to the preferences of the monetary authority, perhaps due to [...] shifts in the relative weight given to unemployment and inflation" (Christiano, Eichenbaum and Evans, 1999, pp. 71-72). Therefore, for the purpose of interpreting the recent inflation run-up, a steepening of the AD curve is essentially equivalent to an upward shift, as both imply a historically unprecedented monetary policy accommodation of inflationary pressures (see, also, Bianchi, Faccini and Melosi, 2023). Put differently, relative to the pre-pandemic conduct of monetary policy, both a steeper and an upward-shifted AD curve imply unusually strong demand forces. The distinction between a shift and a rotation is therefore of secondary importance for our interpretation of the post-pandemic inflation episode, as both reflect a departure from the historical monetary policy regime, a point discussed more fully in section 4.3.[4] This interpretation is also consistent with Nakamura, Riblier and Steinsson (2025), who argue that the inflationary consequences of shocks should be understood in the context of the broader monetary policy regime, rather than through a mechanical application of a Taylor rule. As Reis (2026) puts it, "supply shocks may have caused the inflation surge, but demand policies and expectations are what allowed them to happen."

[4] Cuciniello (2024) uses financial daily data to infer the public perception of the ECB responsiveness to inflation, and how it has changed over time. He finds that, if anything, the perceived short-run ECB responsiveness to inflation has increased since 2022, not diminished. This result speaks against a possible rotation of the AD curve and in favor of a shift.

4.2 An estimated DSGE

The simplified model is useful for building intuition, but its assumptions are too stark for serious quantitative analysis. To overcome this limitation, we now turn to an estimated version of the full DSGE model presented above. We estimate the model for the US economy using Bayesian methods and data on real GDP per capita, the GDP deflator, the federal funds rate, and the 1-year Treasury rate. The 1-year rate complements the federal funds rate by helping discipline the expected path of policy and, therefore, the anticipated policy shocks. The parameters are estimated over the same pre-pandemic sample used for the SVAR in section 3. Conditional on those estimates, we then infer the shocks driving the post-2019 data. Details on the priors and posterior distributions are reported in appendix D. The results are broadly consistent with previous work on the US economy. In particular, we highlight two implications. The monetary policy rule responds strongly to inflation, with a posterior mode of $\phi_\pi = 2.48$. The model also implies a relatively flat Phillips curve. In the full DSGE, current inflation depends on lagged and expected future inflation and on real marginal cost, with a coefficient on the latter estimated at 0.0034. This slope is in line with estimates from other DSGE models over similar sample periods (e.g. Del Negro et al., 2020), and with the broader evidence of a flat Phillips curve from the cross-state variation exploited by Hazell et al. (2022).

Figure 8 reports the historical decomposition of inflation at the posterior mode. Its interpretation is the same as that of the SVAR-based decompositions in section 3, but it is derived from the estimated DSGE model. According to the model, a large share of the post-covid inflation surge is again attributed to demand-side disturbances. The DSGE, however, sharpens this conclusion by assigning the predominant role within the demand component to monetary policy—specifically, to an unusually accommodative policy stance—rather than to private demand shocks. As in the SVAR, these shocks may partly capture real-time misperceptions of economic conditions, as discussed in section 5.

To interpret this difference from the SVAR, note that the DSGE is at once less and more flexible. It is less flexible, because its responses are disciplined by tight cross-equation restrictions. At the same time, it is more flexible in its treatment of monetary policy because it distinguishes anticipated from unanticipated policy shocks—a separation the SVAR cannot make, and one that matters in a sample featuring the zero lower bound, forward guidance, and the pandemic. Indeed, the model attributes most of the initial inflation surge to monetary policy shocks, both anticipated and unanticipated ones, while cost-push and private demand shocks become important only later. Overall, the message is consistent with that of the SVARs, although the DSGE

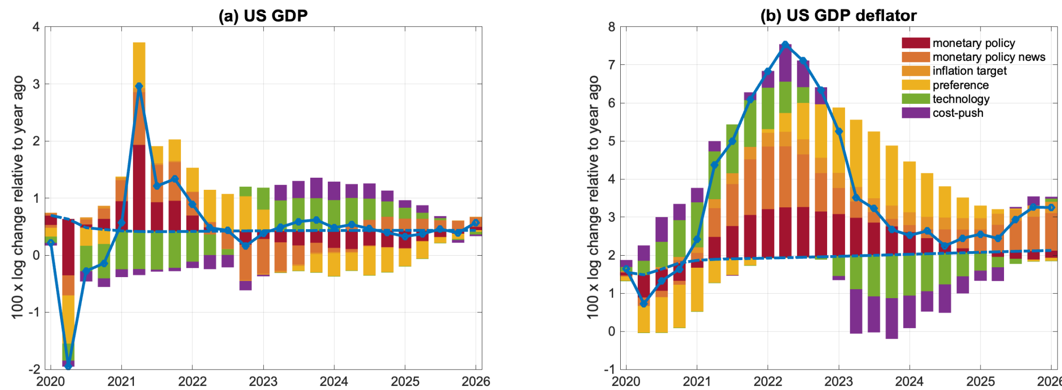

Figure 8: Historical decomposition of GDP and inflation dynamics based on the estimated DSGE model. Sources: data from the Bureau of Economic Analysis; accessed via Haver Analytics; computations by authors.

assigns a relatively larger role to monetary policy within the demand component.

4.3 Which monetary policy regime?

The decomposition reported in the previous subsection is conditional on the estimated monetary policy rule. This is not a limitation of our framework, but a feature of the question itself: The attribution of inflation to demand and supply forces is necessarily defined relative to a monetary policy regime. Every empirical exercise in this literature therefore makes a choice about that regime, whether or not it is stated explicitly. In a SVAR, the estimated reduced form embeds the systematic policy response prevailing over the estimation sample; in a DSGE model, that response is explicitly specified in the policy rule. The choice is unavoidable, and we prefer to make it explicit. The value of the DSGE model in this context is that, despite the additional structural assumptions it requires, it allows us to vary the policy rule and explore directly how the demand–supply decomposition depends on the systematic conduct of monetary policy. This subsection does exactly that, before turning to the question of which regime provides the most natural benchmark.

Table 1 illustrates this dependence by showing how the share of post-pandemic inflation attributed to demand varies across monetary policy regimes. It reports the share of the cumulative forecast error in year-on-year inflation between 2021:Q1 and 2023:Q4, relative to the 2019:Q4 forecast, accounted for by demand disturbances—monetary policy, inflation-target, and preference shocks. In both panels, the shaded cell corresponds to the estimated policy parameters. Panel A varies the response to inflation, ϕ_π: The share attributed to demand falls from 0.90 under

Panel A. *Varying the response to inflation*

ϕ_π	1.05	1.50	2.00	**2.48**	3.00	5.00
Demand share	0.82	0.85	0.88	**0.90**	0.92	0.95

Panel B. *Varying the response to the output gap*

ϕ_Y	0.00	**0.16**	0.40	0.60	0.80	1.00
Demand share	1.08	**0.90**	0.67	0.52	0.42	0.34

Table 1: The demand–supply decomposition and the systematic conduct of monetary policy. The table reports the share of the cumulative forecast error in year-on-year inflation over 2021:Q1–2023:Q4, relative to a forecast origin of 2019:Q4, that is attributed to demand disturbances (monetary policy, inflation-target, and preference shocks) under counterfactual monetary policy rules. All other model parameters are held fixed at their posterior mode, including ϕ_Y in Panel A and ϕ_π in Panel B. The shaded cells correspond to the estimated policy rule and are identical across the two panels.

the estimated rule to 0.82 when ϕ_π is lowered to 1.05. Panel B varies the response to the output gap and delivers a similar message, with a stronger response to output substantially reducing the share attributed to demand. The same data and the same model thus yield conclusions ranging from predominantly demand-driven to predominantly supply-driven inflation, depending on the assumed systematic conduct of monetary policy.

The reason is not that policy alters the disturbances themselves. The pandemic, supply-chain disruptions, fiscal transfers, and the reopening of the economy did not depend on how the Fed or the ECB conducted monetary policy. What does depend on the policy regime is how these disturbances propagate and, therefore, how much of the observed movements in prices and quantities each of them accounts for. As we have seen in section 4.1, a given adverse supply shock generates a large increase in inflation and a small contraction in activity under an accommodative regime, and the reverse under a regime that responds aggressively to inflation. Moreover, structural shocks are not observed; they are inferred from the data through the lens of a model that necessarily embeds an assumption about the systematic conduct of policy. Changing that assumption therefore changes not only the estimated effects of the shocks, but also the shocks inferred from the data.

The question, then, is not whether to condition on a monetary policy regime, but which regime to condition on. For any episode one wishes to decompose—post-pandemic inflation in our case—three benchmarks are conceivable. The first is an external benchmark, such as strict inflation targeting or a regime that holds the real interest rate constant. The second is the regime prevailing during the episode itself. The third is the policy regime prevailing before the episode, presumed to have been in place for some time. We adopt the third for a number of reasons.

The first benchmark has the advantage of fixing a well-defined policy regime, but it does not escape the dependence just described: Since the shocks are themselves inferred under the assumed policy rule, conditioning on a regime that holds the real interest rate constant, say, delivers a set of disturbances no less regime-specific than any other. More importantly, a decomposition under such a benchmark is hard to interpret. It answers the question of what demand and supply would have contributed had policy followed a rule that it did not in fact follow—a perfectly legitimate counterfactual, but one that describes a hypothetical economy governed by a policy regime that never prevailed, rather than the one whose inflation we are trying to explain. It also requires a fully specified structural model, and cannot be implemented with the semi-structural methods that, as noted above, are the workhorse of this literature and of section 3 of this paper. Table 1, however, allows readers who favor such a benchmark to locate it along the continuum of policy rules and read off the corresponding decomposition.

This leaves the regimes prevailing before and during the episode as the two natural alternatives. It is worth noting at the outset that the data themselves offer little guidance for choosing between them. Over an episode as short as the post-pandemic inflation surge, it is difficult to distinguish whether policy followed the historical rule combined with a sequence of unusually expansionary policy shocks or a different systematic rule geared toward greater accommodation.

But even if the data could distinguish between these two interpretations, we would still favor the pre-pandemic regime. To understand why, suppose the economy is hit by an adverse supply shock and monetary policy accommodates it to a historically unusual degree, causing inflation to rise substantially. Conditioning on the regime prevailing during the episode—that is, on the exceptionally accommodative rule—would attribute most of the increase in inflation to the supply shock, because under that rule this is precisely the response the shock would generate. Yet the observed inflation reflects two distinct forces: the original supply disruption and the unusually accommodative policy response. By construction, using the latter as the benchmark policy regime attributes to supply what is partly the consequence of a demand-side policy choice.

This concern is not merely hypothetical. At least two prominent accounts of pandemic-era US monetary policy fit precisely this pattern. The first is that the Fed deliberately looked through supply disturbances that it expected to be temporary, accommodating them more than its historical conduct of policy would have implied—a course of action that may be optimal for a central bank whose credibility keeps long-run expectations anchored (Nakamura, Riblier and Steinsson, 2025). The second is the revision of the FOMC's long-run strategy in 2020, which introduced an explicit tolerance for inflation running temporarily above target (Papell and Prodan-Boul, 2024). Both provide a reason why the historical rule might have ceased to describe policy during the pandemic. Economically, however, both describe a deliberate departure from the historical conduct of policy that allowed inflation to rise more than it otherwise would have. If the demand–supply decomposition is conditioned on the policy regime prevailing during the episode, this departure is absorbed into the regime, and the resulting inflation is largely attributed to the supply shocks that policy chose to accommodate. Under our pre-pandemic policy benchmark, instead, the inflation associated with greater accommodation is attributed to demand, which we regard as the appropriate accounting, since accommodation is a monetary policy action rather than a supply disturbance.

The pre-pandemic benchmark also has another important advantage: it is the regime under which expectations were formed. Our exercise decomposes forecast errors—the extent to which output and inflation differed from what could have been predicted as of 2019:Q4—and those predictions were made by agents, forecasters, and policymakers operating under the historical regime. Conditioning the decomposition on the same regime under which those expectations were formed therefore makes the exercise internally coherent. Under this benchmark, demand accounts for close to three-quarters of the excess inflation of 2021–2023.

5 Real-time vs. revised data: evidence on forecast errors

The previous sections have shown, using structural VARs, a DSGE model, and the intuition of the standard AD–AS framework, that demand shocks were the dominant driver of the post-pandemic inflation surge and that monetary policy remained unusually accommodative during this period. In this section, we provide complementary evidence that is largely independent of the structure of those models. We do so by examining real-time forecasts of inflation and real activity. Besides providing model-free support for the demand-driven interpretation of the inflation surge, these forecasts also shed light on one factor that may have contributed to the unusually accommodative stance of monetary policy.

Economic models such as SVARs and DSGEs explain historical fluctuations through sequences of structural shocks that are ultimately inferred from the models' forecast errors—that is, the

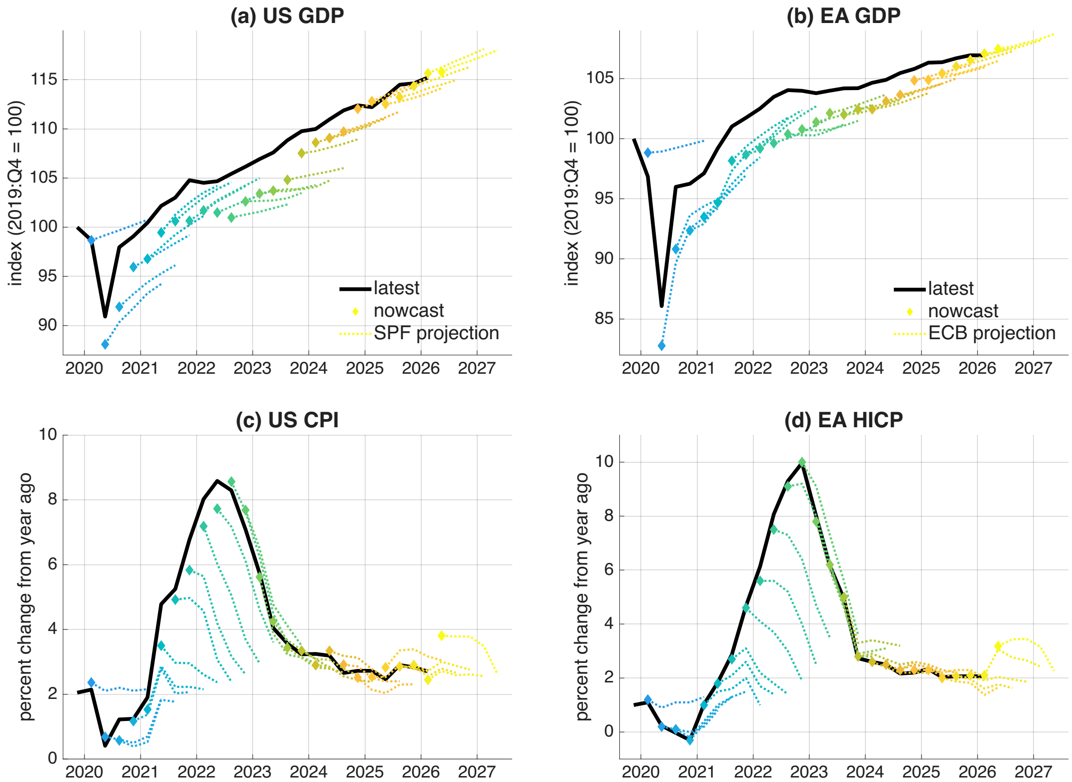

Figure 9: GDP and inflation in the US and the EA: data and projections. Sources: data from the Bureau of Economic Analysis, the Bureau of Labor Statistics, the European Central Bank, Eurostat, and the Federal Reserve Bank of Philadelphia; accessed via Haver Analytics, the website of the European Central Bank and the Federal Reserve Bank of Philadelphia; computations by authors.

discrepancy between realized outcomes and the paths that the models would have predicted. In line with Reis (2026), a more direct and less model-dependent way to study those forecast errors is to examine the expectations of central banks and professional forecasters in real time. For the EA, we use the ECB's real-time staff projections for HICP inflation and real GDP since 2020. For the US, the Federal Reserve's Greenbook forecasts remain unavailable because of the five-year publication lag. As a proxy, we therefore use projections from the Survey of Professional Forecasters (SPF), focusing on CPI inflation and real GDP.

The dashed lines in figure 9 report these projections. The diamonds indicate nowcasts of GDP and inflation, since the ECB and SPF projections are typically finalized in the middle month of each quarter—when forecasters generally have access only to the preliminary estimate of GDP for the previous quarter and the price index for the first month of the current quarter. The solid lines show the latest available vintage of realized data. Appendix A.2 provides data sources and further details on the computations underlying figure 9.

Consider first the second row of figure 9, which displays the inflation projections for the US and the EA. It is evident that both the SPF and the ECB systematically underestimated the duration of the inflation surge in 2021 and 2022, anticipating that inflation would subside fairly quickly. Watson (2026) similarly documents the unusually large inflation forecast errors during this period. These forecast errors are also consistent with the widely accepted narrative that many central bankers initially viewed the rise in inflation as largely transitory, revising this assessment only later (see, for example, Lagarde, 2023, Powell, 2024, and the retrospective on the Fed staff's inflation forecast errors of Peneva, Rudd and Villar, 2025).

Turning to the first row of figure 9, we see that both the SPF and the ECB not only under-predicted inflation, but also underestimated the strength of the recovery. Their GDP forecasts systematically fell short of realized outcomes, suggesting that forecasters expected considerably more economic slack than actually materialized. Consistent with this, Peneva, Rudd, and Villar (2025) find that the unemployment gap closed more quickly than Fed staff had anticipated. This finding suggests that policymakers operating in real time anticipated a weaker recovery than actually materialized, and they may have been more willing to tolerate higher inflation in order to support economic activity. Forecast errors for inflation and output were therefore both positive in the two economies during 2021–22, a pattern that is consistent with our earlier finding that demand forces were unexpectedly strong. The International Monetary Fund (2022) and Koch and Noureldin (2024) find the same positive correlation of inflation and output forecast errors, relative to the predictions of the World Economic Outlook, across many advanced and emerging economies.

What accounts for this systematic under-prediction of real GDP? Figure 10 provides a clue. It replicates the projections from figure 9, but instead of comparing them to the most recent vintage of revised data, it compares them to the preliminary GDP releases available at the time—namely, the BEA's "advance estimates" and Eurostat's "flash estimates." The contrast is striking: The forecasts from the SPF and the ECB align much more closely with the preliminary data than with the revised data. In other words, by comparing the solid lines in figures 10 and 9, it becomes clear that the BEA and Eurostat substantially revised their GDP estimates upward for much of the 2020–2024 period. In real time, then, economic activity appeared broadly consistent with prevailing forecasts, making the buildup of demand pressures harder to detect and contributing to the widespread view that inflation was largely supply driven. In sum, real-time data painted a substantially more pessimistic picture of economic activity than later revisions revealed, likely shaping both projections and policy decisions. This observation should not be interpreted as

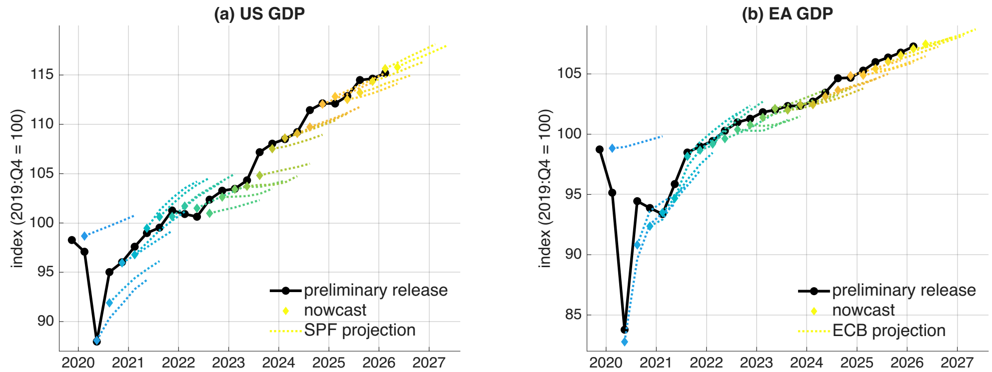

Figure 10: GDP in the US and the EA: preliminary data releases and projections. Sources: data from the European Central Bank, Eurostat, and the Federal Reserve Bank of Philadelphia; accessed via the website of the European Central Bank, Eurostat, and the Federal Reserve Bank of Philadelphia; computations by authors.

a criticism of policymakers. Allowing inflation to exceed its usual range may well have been the appropriate response to support a faster recovery. Our point is simply that this reaction was unusual by historical standards, and that real-time misperceptions of economic slack likely played a role in the unusually accommodative policy stance.

6 Relation to the existing literature

Several studies have attempted to quantify the relative roles of demand and supply factors in explaining inflation dynamics since the outbreak of the covid pandemic.

Ball, Leigh, and Mishra (2022), Harding et al. (2023), Benigno and Eggertsson (2023), Jordà and Nechio (2023) and Erceg et al. (2024) discuss how such decomposition might be affected by the non-linearity of the supply curve. In their work, the pandemic brought about a series of large shocks that moved the equilibrium of the economy to a region characterized by a steeper supply curve. Relative to these papers, we study the role of the slope of the demand curve, which depends on the monetary policy reaction function.

Gonçalves and Koester (2022) and Lane (2022) estimate bivariate vector autoregressive (VAR) models like ours separately for many goods and service categories, using EU data and a methodology developed by Shapiro (2022, 2024) for the US economy (see also the supply-demand decomposition tool of the Federal Reserve Bank of San Francisco, 2026). Their findings suggest that demand and supply factors have had a comparable role in explaining inflation dynamics. See also Braun, Flaaen and Hacıoğlu Hoke (2024), who find that, for U.S. manufactured goods, supply disruptions explain the early surge in prices, while demand becomes increasingly important later. These studies, however, might underestimate the role of demand, since the sectoral demand curves are less flat than at the aggregate level, given that monetary policy responds to aggregate, not sectoral, inflationary pressures.

Bańbura, Bobeica and Martinez Hernández (2023) find a large contribution of supply shocks to EA inflation. Differently from us, their VAR includes a richer set of variables and several structural shocks. But their results are likely to overstate the influence of supply factors because their model is saturated with both supply indicators and supply disturbances, and it is estimated using the approach of Korobilis (2022) in which few common shocks drive all the reduced-form residuals. Caldara, Iacoviello, and Yu (2025) introduce a new text-based shortage index and argue that "post-pandemic shortages and inflation were primarily driven by supply forces, with demand factors playing a less important role" (p. 1). However, the priors in their statistical model are centered on values that imply a much steeper AD curve than the AS curve. One contribution of our paper is to clarify how such assumptions can significantly influence the results. De Santis (2024), Ascari, Bonam and Smadu (2024), and Bai et al. (2024) highlight the impact of global supply chain bottlenecks and disruptions for EA and US inflation. Yet, their impulse responses do not adequately account for the effect of demand shocks on supply chain pressure indexes. This appears inconsistent with an extensive literature that documents the strong positive correlation between economic activity and commodity prices, shipping costs, and delivery times (for example, see Kilian, 2009, Kilian and Zhou, 2018, Baumeister and Hamilton, 2019, Alquist, Bhattarai and Coibion, 2020, Delle Chiaie, Ferrara and Giannone, 2022, Baumeister and Korobilis, 2022, and Bernanke and Blanchard, 2025). Furthermore, the model specifications in these papers do not incorporate priors that discipline the behavior of the deterministic component and limit its estimation uncertainty (Giannone, Lenza and Primiceri, 2019; Bergholt et al., 2025). As argued by Bergholt et al. (2025), this omission can significantly affect the results of historical decomposition analyses.[5]

The papers closest to our work are Ascari et al. (2023), Bergholt et al. (2025), Faria e Castro (2024), and Garcia-Revelo, Levieuge and Sahuc (2024), who point to demand disturbances as key factors for the rise of inflation in the US and the EA. Mori (2026) and Ascari et al. (2026) highlight the importance of fiscal shocks in both regions, while Hazell and Hobler (2025), Reis (2026) and Barro and Bianchi (2025) underscore the fiscal influences on inflation in the US and

[5] De Santis (2024) utilizes the dummy-initial observation prior, but this prior is ineffective at correcting the problem highlighted by Bergholt et al. (2025) if imposed on the coefficients of a VAR specified in log levels (Giannone et al., 2019). Bai et al. (2024) do not use any of the priors recommended by Bergholt et al. (2025), but they check the robustness of their results using the prior-robust approach proposed by Giacomini and Kitagawa (2021).

several other countries.

Our results on the sources of inflationary pressures are consistent with theirs. In addition, we explain the intuition of these results, and why a chief role for demand disturbances is inevitable if the AD curve is as flat as we would expect for central banks that are credible (near) inflation targeters. Our results are also broadly in line with those of Comin, Johnson and Jones (2023), Bocola et al. (2024), Gagliardone and Gertler (2026) and Nakamura, Riblier and Steinsson (2025), all of whom emphasize an important role for accommodative monetary policy in the post-pandemic inflation surge in the US. Di Giovanni et al. (2022) quantify the relative role of demand and supply shocks based on a calibrated two-period multi-sector model with perfectly competitive factors and good markets. Their analysis is limited to the cumulative inflation experience until 2021:Q4, without modeling dynamics. Nevertheless, their calibrated closed-economy model attributes more than 50 percent of the surge of inflation to demand forces, even in the EA.[6] In subsequent iterations of their work, Di Giovanni et al. (2023a and b) find an even larger contribution of aggregate demand shocks, fully consistent with our results. In addition, these articles decompose demand disturbances into domestic and global components, like Ha et al. (2023), Aastveit et al. (2024), Forbes, Ha and Kose (2024) and Bergholt et al. (2026), something that we do not attempt to do in this paper.

Guerrieri et al. (2023) present a comprehensive report on the behavior of inflation in the US and the EA. These authors study the price response to monetary policy and oil-supply shocks, documenting that the former is more uniform across sectors than the latter. But this study does not divide the recent dynamics of inflation into demand- and supply-driven components. Relatedly, Rubbo (2024) divides US inflation into components driven by industry-specific and aggregate shocks. She finds that industry-specific demand and supply disturbances were key determinants of inflation during the early phase of the pandemic, but aggregate factors have dominated its dynamics since the beginning of 2021.

Bernanke and Blanchard (2025) evaluate the contribution of product- and labour-market shocks for US post-covid inflation. Their approach has been applied by Arce et al. (2024) and Vilmi and Oinonen (2024) to EA data, and by Menz (2024), De Walque and Lejeune (2024), Pisani and Tagliabracci (2024), Aldama, Le Bihan and Le Gall (2024), Ghomi, Hurtado and Montero

[6]The open-economy version of their model attributes less than one half of EA inflation to domestic shocks. However, this share does not speak to the question whether inflation is demand or supply driven, because it is based on the counterfactual assumption that "domestic goods demanded by Euro Area households can be substituted with the goods produced abroad, and these regions (the US and RoW) have not been hit by expansionary demand shocks or contractionary labor supply shocks, thus keeping prices of their goods (which are reflected in Euro Area import prices) lower than domestic prices in the Euro Area" (Di Giovanni et al., 2022, pp. 48).

(2024), Bonam, Hebbink and Pruijt (2024), Haskel, Martin and Brandt (2024), Bounajm, Roc and Zhang (2023), and Nakamura et al. (2024) to data from Germany, Belgium, Italy, France, Spain, the Netherlands, the UK, Canada and Japan. All these articles, whose results are summarized by Bernanke and Blanchard (2024), find a large impact of food and energy prices on aggregate inflation. Similar insights emerge from the analysis of EA data by Lane (2022), and from the study of the behavior of headline and core inflation in 21 countries by Dao et al. (2024), who build on earlier work of Ball, Leigh and Mishra (2022) for the US and Dao et al. (2023) for the EA. But they all treat food and energy prices, as well as supply shortages, as exogenous variables, making it difficult to map their results into a demand-supply decomposition useful for policy analysis. As we show in section 3 and appendix C, their conclusions are not necessarily in conflict with ours, because energy prices are largely driven by the same fluctuations in aggregate demand that have ultimately generated inflation.

Our analysis also relates to the literature on the role of real-time data in monetary policy. Orphanides (2001) shows that reliance on real-time information can lead to systematic misperceptions that materially affect policy decisions. Orphanides and Van Norden (2002) emphasize the difficulty of assessing economic slack in real time, documenting that output gap estimates often diverge substantially from later revisions. Orphanides (2004) argues that during the 1970s, real-time data overstated economic slack, while revised data later revealed that the economy was in fact close to overheating. He concludes that this misperception contributed to an overly accommodative stance, which in turn fueled the Great Inflation. We find that the post-pandemic period exhibits a similar pattern. Real-time data understated the strength of the recovery, creating the impression of a more unfavorable inflation–activity trade-off and reinforcing the belief that inflation was primarily driven by supply shocks. In contrast, revised data reveal that demand forces were, in fact, the likely dominant driver of inflation during this episode.

7 Concluding remarks

This paper revisits the drivers of post-pandemic inflation in the US and the EA and presents evidence that demand-side forces played a dominant role in both regions. Using a sequence of structural VARs and an estimated DSGE model, we show that aggregate demand rebounded much more strongly than anticipated, while the contribution of supply shocks to inflation—though not negligible—was more modest. We also provide complementary evidence from survey forecasts and real-time data. Forecasters in both the US and the EA systematically underestimated not only the persistence of inflation but also the strength of the recovery in economic activity during 2021 and 2022. These forecast errors provide independent support for the demand-driven interpretation emerging from our structural analysis.

Our interpretation is grounded in a clear economic intuition: In economies where central banks have historically responded forcefully to inflationary pressures, steep and persistent increases in inflation are unlikely to result from supply shocks alone. Instead, they require a shift in the aggregate demand curve—driven by exceptionally strong private or public demand, an unusually accommodative policy stance, or some combination of the two.

A Data

This appendix describes the details of the data used throughout the paper.

A.1 Data used in sections 2, 3 and 4

The data are quarterly and seasonally adjusted, and they are accessed through Haver Analytics unless otherwise noted.

Real GDP for the euro area is Eurostat's chain-linked volume measure, using the changing-composition definition of the euro area. For the United States, it is the Bureau of Economic Analysis measure of real GDP, expressed in billions of chained dollars at seasonally adjusted annual rates.

For the euro area, consumer prices are measured by the Harmonized Index of Consumer Prices (HICP) compiled by Eurostat, using the changing-composition definition of the euro area. Alongside the overall index, we use its energy component and, within energy, the subcomponents for electricity, gas, and other fuels, and for fuels and lubricants for personal transport. For the United States, we start from the components of the Consumer Price Index for All Urban Consumers (CPI-U) compiled by the Bureau of Labor Statistics, and align them with the HICP so that prices are measured on a comparable basis across the two economies. Relative to the US CPI, the HICP excludes owners' equivalent rent of residences, classifies electricity, gas, and other fuels as goods rather than services, and classifies food away from home as services rather than goods. We therefore align the US CPI with the HICP by:

- removing owners' equivalent rent of residences (OERR),

- reclassifying food away from home from goods to services; and
- reclassifying energy services from services to goods.

The CPI component indexes are annual chain-linked Laspeyres indexes that measure price changes by comparing prices in each month with those of December of the previous year. Constructing indexes that differ from those published by the Bureau of Labor Statistics therefore requires first unchaining the component indexes, aggregating them using their relative importance weights, and then chain-linking the resulting aggregate. We follow the procedure described in Eurostat (2018) and Perrins and Nielsen. Constructed in this way, the overall index excludes owners' equivalent rent, and the index excluding energy is built in the same manner. Household energy prices correspond to the CPI household energy component (electricity, utility gas and household fuels), and transportation energy prices are obtained by chain-linking the components of energy excluding household energy, so that where a published aggregate exists our indexes replicate it exactly.

For the EA, the interest rate is the 12-month EURIBOR. For the US, it is the 1-year constant-maturity Treasury yield. The DSGE model also uses the federal funds rate.

For the EA, the primary deficit is the general government primary balance from the ECB Government Finance Statistics, with the sign reversed. Because no official quarterly measure of potential output is available, we express the primary deficit as a percentage of a trend measure of nominal GDP. Following Ascari et al. (2024), this trend is obtained by fitting a sixth-order polynomial in time to the logarithm of nominal GDP. The quarterly fiscal series begin in 2002:Q4, which determines the starting date of the euro-area sample in specifications that include fiscal variables. For the US, the primary deficit is constructed from the National Income and Product Accounts as the negative of net general government saving minus general government interest payments—that is, the federal deficit net of interest outlays—and is expressed as a percentage of nominal potential GDP estimated by the Congressional Budget Office.

A.2 Data used in section 5

This appendix provides the data sources for the projections displayed in figures 9 and 10, along with details on the underlying computations.

A.2.1 SPF projections of US GDP and inflation

The source of the SPF projections and real-time data for the United States is the Federal Reserve Bank of Philadelphia, which maintains both databases. For comprehensive documentation and descriptions, see Croushore and Stark (2003 and 2019).

To construct panel (a) of figures 9 and 10, we use the SPF median forecast of real GDP, available at this link. The SPF releases projections quarterly, typically in the middle of each quarter, at which point forecasters have access to the BEA's advance estimate of GDP for the previous quarter. Forecasters are asked to predict real GDP for six horizons: the previous quarter, the current quarter (nowcast), and the next four quarters. Denote the median forecast issued in quarter t by $\left\{Y_{t+h|t}^{SPF}\right\}_{h=-1}^{4}$, where $h = -1$ refers to the previous quarter and $h = 0$ to the current quarter. The figures plot the set of forecast paths $\left\{Y_{t+h|t}^{SPF}\right\}_{h=0}^{4}$, for each projection round t =2020:Q1, ..., 2024:Q4. The September 2023 comprehensive revision of real GDP moved the reference year for chained-dollar estimates from 2012 to 2017. We therefore rescale the level projections issued before 2023:Q4 by the factor 1.073 to place them on the 2017 basis.

To construct panel (c) of figure 9, we use the SPF median forecast of the US CPI inflation rate, available at this link. At the time of release, forecasters know the CPI for the first month of the current quarter. Forecasters are asked to predict *quarterly* CPI inflation for six horizons: the previous quarter, the current quarter (nowcast), and the next four quarters. Let $\left\{\pi_{t+h|t}^{SPF}\right\}_{h=-1}^{4}$ denote the median forecast issued in quarter t. We then obtain the implied forecasts for *year-on-year* inflation as

$$\Pi_{t+h|t}^{SPF} = 100 \times \left[\prod_{j=0}^{3}\left(1 + \frac{\pi_{t+h-j|t}^{SPF}}{100}\right)^{\frac{1}{4}} - 1\right], \qquad h = 0, ..., 4,$$

where $\pi_{t-3|t}^{SPF}$ and $\pi_{t-2|t}^{SPF}$ are computed using the CPI data vintages available at the time the forecast was issued. The figure plots the set of forecast paths $\left\{\Pi_{t+h|t}^{SPF}\right\}_{h=0}^{4}$, for each projection round t =2020:Q1, ..., 2024:Q4.

A.2.2 ECB projections of EA GDP and inflation

The ECB projections are taken from the ECB Macroeconomic Projection Database, accessible through the ECB website. Real-time data for the EA are obtained from Eurostat through this link.

To construct panel (b) of figures 9 and 10, we use the ECB projections of real GDP. The ECB publishes its projections quarterly, typically in the second half of the middle month of each quarter. At the time of release, Eurostat's flash estimate of GDP for the previous quarter is available to forecasters. The ECB provides projections of *quarter-on-quarter* real GDP growth for the current quarter (nowcast) and several subsequent quarters. Denote these projections by $\left\{g^{ECB}_{t+h|t}\right\}_{h=0}^{4}$, where t indexes the quarter in which the forecast is issued. To obtain the corresponding projected levels of GDP, we compute

$$Y^{ECB}_{t+h|t} = Y^{Eurostat}_{t-1|t} \times \prod_{j=0}^{h} \left(1 + \frac{g_{t+j|t}}{100}\right),$$

where $Y^{Eurostat}_{t-1|t}$ represents Eurostat's flash estimate of GDP in the previous quarter, as available at the time of the forecast. The figures plot the set of projected GDP paths $\left\{Y^{ECB}_{t+h|t}\right\}_{h=0}^{4}$ for each projection round $t =$2020:Q1, ..., 2024:Q4.

To construct panel (d) of figure 9, we use the ECB projections of HICP inflation. At the time of release, Eurostat's revised estimate of the HICP for the first month of the current quarter is available to forecasters. The ECB provides projections of *year-on-year* HICP inflation for the current quarter (nowcast) and several subsequent quarters—denote them by $\left\{\Pi^{ECB}_{t+h|t}\right\}_{h=0}^{4}$. The figure plots the set of forecast paths $\left\{\Pi^{ECB}_{t+h|t}\right\}_{h=0}^{4}$, for each projection round $t =$2020:Q1, ..., 2024:Q4.

B Assessing uncertainty and robustness to priors

This appendix assesses uncertainty surrounding the results of our baseline model. We report the full posterior distributions of some key objects of interest, examine the extent to which they differ from their priors, and assess the robustness of our results to alternative prior specifications.

The results presented in the main text are based on a standard Bayesian VAR with Minnesota and sum-of-coefficients priors. We treat the informativeness of these priors as unknown and conduct inference on the corresponding hyperparameters, following the hierarchical approach of Giannone, Lenza and Primiceri (2015). We identify the structural shocks through sign restrictions, specifying a uniform prior, conditional on the reduced-form parameters, over the set of orthogonal matrices, as in Rubio-Ramírez, Waggoner and Zha (2010). This choice induces a uniform joint prior distribution over the identified set for the vector of impulse responses (Arias, Rubio-Ramírez and Waggoner, 2025). In what follows, we refer to this specification as the baseline model.

Figure 11 displays the prior and posterior densities of the ratios of the responses of log prices and GDP to demand and supply shocks at a one-year horizon. We refer to these ratios as the slopes of the supply and demand curves, respectively. To facilitate comparison, the figure reports the negative of the demand-curve slope. The densities are estimated non-parametrically using 500,000 draws from the prior and posterior distributions.[7]

Notice that the prior distributions of the two slopes are fairly diffuse and symmetric across demand and supply: They place substantial probability on a wide range of slopes and display no systematic tendency to favor a flatter demand curve or a steeper supply curve. The data, however, update the two distributions in opposite directions. For the supply curve, the posterior shifts to the right of the prior, indicating a steeper supply curve. For the demand curve, the posterior shifts to the left, indicating a flatter demand curve. The posterior medians of the supply- and demand-curve slopes are 1.06 and 0.53 for the US, and 0.63 and 0.27 for the EA. These are the values used to depict the AS and AD curves in figure 7.[8]

Figure 12 reports the prior and posterior distributions of the demand share of the cumulative forecast error in year-on-year inflation over the inflation surge. For the US, the window runs from 2021:Q1 to 2023:Q4, relative to the 2019:Q4 forecast. For the EA, the window is shifted forward by two quarters to account for the observed delay in the run-up of inflation. The demand share is not restricted to the $[0, 1]$ interval because the contributions of demand and supply shocks can have opposite signs. Panels (a) and (b) report results for the baseline model, while the remaining panels consider alternative priors to assess the robustness of our findings.

In the baseline model, the prior distribution of the demand share is quite diffuse and symmetric around 0.5. The posterior, by contrast, shifts markedly toward 1 in both economies, with medians of about 90 percent. The posterior probability that demand accounts for more than

[7] The densities are estimated using MATLAB's `ksdensity` function with its default Gaussian kernel with bandwidth $\omega = \hat{\sigma} \cdot (4/(3N))^{1/5}$, where N is the number of draws and $\hat{\sigma}$ is a robust measure of dispersion corresponding to the median absolute deviation from the median divided by 0.67. We impose boundary reflection at zero. Because the slopes are ratios of impulse responses, their distributions can exhibit Cauchy-type tails; the robust scale therefore prevents extreme draws from having an undue influence on the bandwidth. The figure displays the densities only over the interval from 0 to 4, but draws above 4 are retained when estimating the densities. The displayed densities are not renormalized, so the area under each curve equals the probability mass between 0 to 4.

[8] The prior distributions differ across the US and the EA only because of differences in the volatility of prices and output in the two regions. In particular, the prior implies smaller slopes in the EA because inflation is less volatile relative to output growth than in the US. These differences arise from the standard implementation of the Minnesota prior and the Inverse-Wishart prior for the residual covariance matrix. Both are scaled using residual variances from univariate AR(1) models for the VAR variables, so differences in the relative volatility of prices and output across the two economies translate into differences in the induced prior distributions of the slopes. As we show below, however, these differences have essentially no bearing on our results.

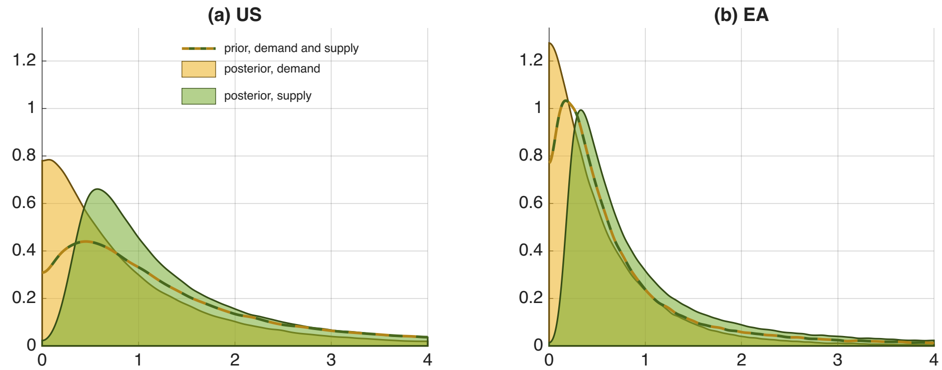

Figure 11: Prior and posterior distribution of the supply-curve slope and the negative of the demand-curve slope, computed as the ratio of the responses of log prices and GDP to demand and supply shocks respectively, at the one-year horizon. Sources: data from the Bureau of Economic Analysis, the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

two-thirds of the increase in inflation exceeds 70 percent. Thus, neither the priors nor the sign restrictions themselves favor a demand-driven interpretation; it is the data that shift substantial probability mass toward a predominant role for demand.

The remaining panels of figure 12 report three robustness exercises. In the first, we impose a flat prior on the demand share, eliminating the slight tendency of the baseline prior to place more mass near 0 and 1. We implement this prior by reweighting the original prior and posterior draws by the inverse of their density under the baseline prior. In the second exercise, we return to the baseline model and impose the additional restriction that demand shocks have only transitory effects on real activity, consistent with standard economic theory—or, equivalently, that the aggregate supply curve becomes steep at long horizons. Specifically, we require the GDP response to a demand shock after twenty quarters to be no more than one-tenth of its maximum response over the first two years. In the last exercise, following Baumeister and Hamilton (2015), we place priors directly on the impact price elasticities of demand and supply, defined as the ratios of the impact responses of log GDP to those of log prices following supply and demand shocks, respectively. As in their work, these priors are Student$-t$ distributions centered at 1 for supply and -1 for demand, with scale 0.6 and 3 degrees of freedom, truncated to satisfy the corresponding sign restrictions. For this exercise, we adopt the calibration of Baumeister and Hamilton (2015) for all remaining prior hyperparameters and use their posterior simulation algorithm.

Across all three exercises, the posterior continues to place substantial probability on demand accounting for the majority of the inflation surge. Therefore, allowing for posterior uncertainty and substantial variation in the priors and identification assumptions leaves our main conclu-

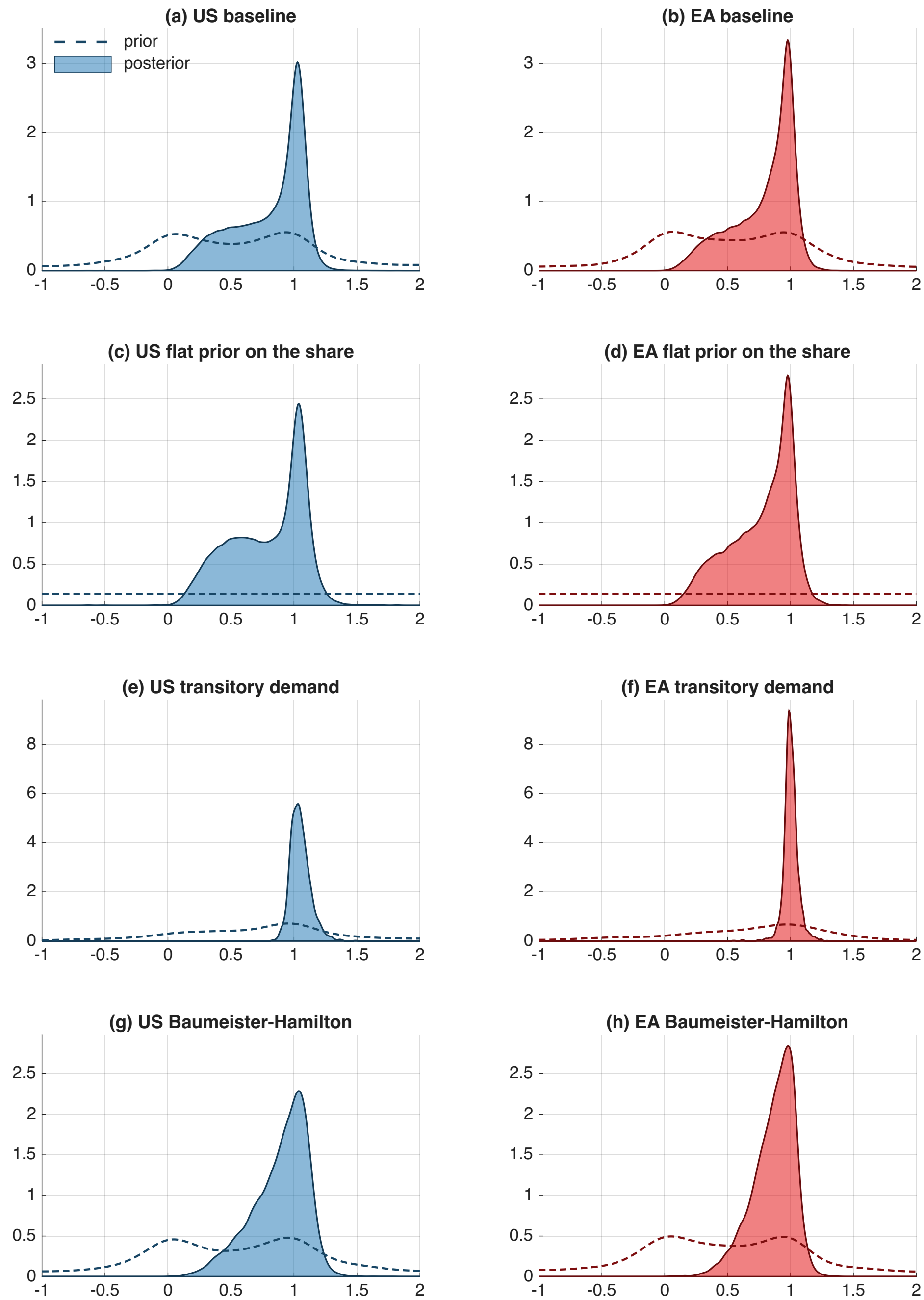

Figure 12: The share of the cumulative forecast error in year-on-year inflation over the inflation surge (2021:Q1–2023:Q4 for the US and 2021:Q3–2024:Q2 for the EA), relative to the 2019:Q4 forecast, attributed to demand disturbances. Results based on alternative priors. Sources: data from the Bureau of Economic Analysis, the Bureau of Labor Statistics and Eurostat; accessed via Haver Analytics; computations by authors.

sion unchanged: Demand shocks are the predominant drivers of the inflation surge in both economies.

C Additional results for section 3

This appendix contains some additional results concerning the larger models estimated in section 3.

C.1 The supply model

Figure 13 complements the analysis of section 3.2 by reporting the historical decomposition of all the variables of the supply model, GDP, prices excluding energy and the two energy price components, in the two economies.

C.2 The demand model

Figure 14 complements the analysis of section 3.3 by reporting the historical decomposition of all the variables of the demand model, GDP, prices, the one-year interest rate and the primary deficit. It is worth noting that, although the increase in the US primary deficit appears initially substantially larger than in the EA, the cumulative deviation of the primary deficit-to-potential-GDP ratio from its 2019:Q4 level is only moderately larger in the US.

D DSGE estimation details

The purpose of this appendix is to document the estimation of the DSGE model presented in section 4, and to report selected posterior results. As discussed in the main text, we estimate the log-linearized model using standard Bayesian methods over the sample 1998:Q1–2019:Q4. Although the SVAR estimation begins in 1997, it is conditional on the initial $p = 4$ observations; thus, the estimation sample is effectively the same pre-pandemic sample used for the SVAR in section 3.

The estimation uses data on real GDP per capita, the GDP deflator, the federal funds rate, and the 1-year Treasury rate. The one-year rate complements the federal funds rate by helping

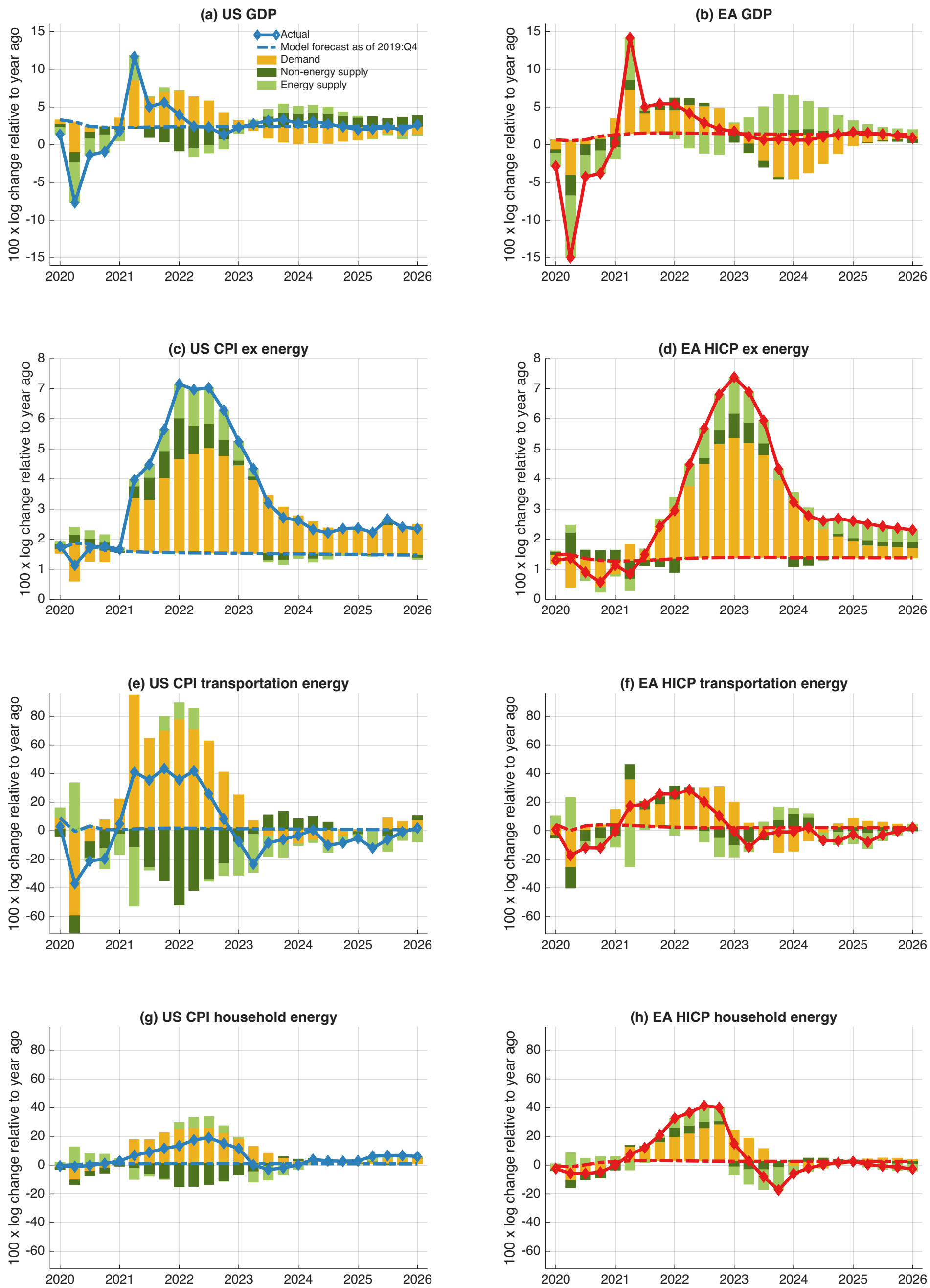

Figure 13: Historical decomposition based on a model including GDP, non-energy prices, and household- and transportation-energy prices. The contributions of the two energy-supply shocks are reported jointly. Sources: Data from Eurostat, the European Central Bank, the Bureau of Labor Statistics, and the Bureau of Economic Analysis; accessed via Haver Analytics; computations by authors.

Figure 14: Historical decomposition based on a model including GDP, prices, the 1-year interest rate and the primary-deficit-to-potential-GDP ratio. Sources: Data from Eurostat, the European Central Bank, the Bureau of Labor Statistics, the Bureau of Economic Analysis, and the Board of Governors of the Federal Reserve System; accessed via Haver Analytics; computations by authors.

discipline the expected path of monetary policy and, therefore, the anticipated policy shocks. Accordingly, we include anticipated policy shocks at horizons $k = 1$, 2, and 3, corresponding to the horizon spanned by the 1-year rate. To reflect the fact that forward guidance became an important policy instrument only after the onset of the zero lower bound, we constrain the variances of the anticipated policy shocks to zero before 2008:Q4. Consistent with this assumption, the 1-year Treasury rate is excluded from the set of observables prior to 2008:Q4, so that the federal funds rate is the only interest-rate series informing the estimation over the earlier part of the sample.

We calibrate a few parameters that are weakly identified. We set the inverse Frisch elasticity of labor supply (ν) to 2 and the steady-state price markup (θ) to 0.1. These parameters affect the dynamics of the observables almost exclusively through the slope of the Phillips curve, and are therefore poorly identified separately from the degree of price stickiness ξ. In addition, as in Cogley, Primiceri and Sargent (2010), we calibrate ρ_* to 0.995, restricting π_t^* to only capture low-frequency movements in inflation. We also set the steady-state value of inflation to 2 percent annually. Finally, to discipline the estimation of the anticipated policy shocks, we impose the following structure on their standard deviations: $\sigma_{R,k} = \sigma_{R,1}\delta^{k-1}$, for $k = 1, 2, 3$, and estimate $\sigma_{R,1}$ and δ.

All remaining parameters are estimated. Table 2 reports the priors, as well as the posterior estimates of the model parameters. Overall, the posterior estimates are broadly consistent with previous estimates for the US economy. In particular, the estimated monetary policy rule exhibits substantial interest-rate smoothing and a relatively strong response to inflation, consistent with the interpretation developed in section 4.

		Prior			Posterior		
		Density	Mean	Std	Mode	Median	[5, 95]
100γ	steady-state growth rate	N	0.45	0.05	0.43	0.43	[0.36, 0.50]
$100(\beta^{-1}-1)$	discount factor	G	0.25	0.10	0.13	0.15	[0.07, 0.29]
h	habit formation	B	0.50	0.10	0.37	0.37	[0.28, 0.47]
ξ	price stickiness	B	0.66	0.10	0.71	0.71	[0.61, 0.80]
ι	price indexation	B	0.50	0.10	0.33	0.32	[0.21, 0.47]
ϕ_π	response to inflation	N	1.50	0.50	2.48	2.52	[2.05, 3.08]
ϕ_Y	response to output gap	N	0.125	0.075	0.16	0.16	[0.07, 0.24]
ϕ_{dY}	response to output-gap growth	N	0.125	0.075	0.15	0.15	[0.11, 0.20]
ρ_R	interest-rate smoothing	B	0.60	0.20	0.90	0.90	[0.88, 0.93]
ρ_z	technology growth	B	0.40	0.20	0.31	0.29	[0.08, 0.56]
ρ_θ	cost-push	B	0.60	0.20	0.13	0.16	[0.05, 0.35]
ρ_b	preference	B	0.60	0.20	0.97	0.97	[0.95, 0.98]
δ	anticipated-shock decay	N	1.00	0.25	0.86	0.85	[0.62, 1.07]
$100\sigma_R$	monetary policy	IG1	0.15	1	0.10	0.10	[0.08, 0.12]
$100\sigma_z$	technology growth	IG1	1	1	0.53	0.55	[0.37, 0.80]
$100\sigma_\theta$	cost-push	IG1	0.15	1	0.12	0.12	[0.10, 0.14]
$100\sigma_*$	inflation target	IG1	0.025	1	0.011	0.013	[0.008, 0.023]
$100\sigma_b$	preference	IG1	1	1	2.68	2.89	[2.14, 4.55]
$100\sigma_{R,1}$	anticipated monetary policy	IG1	0.15	1	0.051	0.054	[0.041, 0.072]

Table 2: Prior densities and posterior estimates. N, G, B and IG1 denote the Normal, Gamma, Beta and Inverse-Gamma-1 distributions. Posterior statistics are based on $100,000$ draws from the posterior distribution.

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