WORKING PAPER

UNDERSTANDING POST-PANDEMIC INFLATION FLUCTUATIONS: THE COMMODITY COST CHANNEL

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Understanding Post-Pandemic Inflation Fluctuations: The Commodity Cost Channel*

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Abstract

This paper employs a joint SVAR-IV model for the United States and the euro area to estimate the pass-through of energy and food commodity cost shocks to inflation. Exogenous commodity cost shocks—such as those triggered by the Russian invasion of Ukraine—had only a modest impact on inflation during the post-pandemic period. However, counterfactual analyses based on the pass-through estimates indicate that overall commodity cost fluctuations—including their endogenous responses to macroeconomic conditions—can almost fully account for the rise and subsequent decline of energy, food, and core CPI inflation over this period. These findings highlight that commodity costs constitute a key transmission channel through which macroeconomic developments affect inflation. Estimates of a standard Phillips Curve specification, including its slope, are shown to be severely biased when this channel is ignored.

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1 Introduction

The surge in inflation following the COVID-19 pandemic has sparked intense debate about its underlying causes.[1] While most studies examine the relative importance of various shocks—such as aggregate demand versus supply shocks—the channels through which these shocks passed through to inflation during this period remain poorly understood.

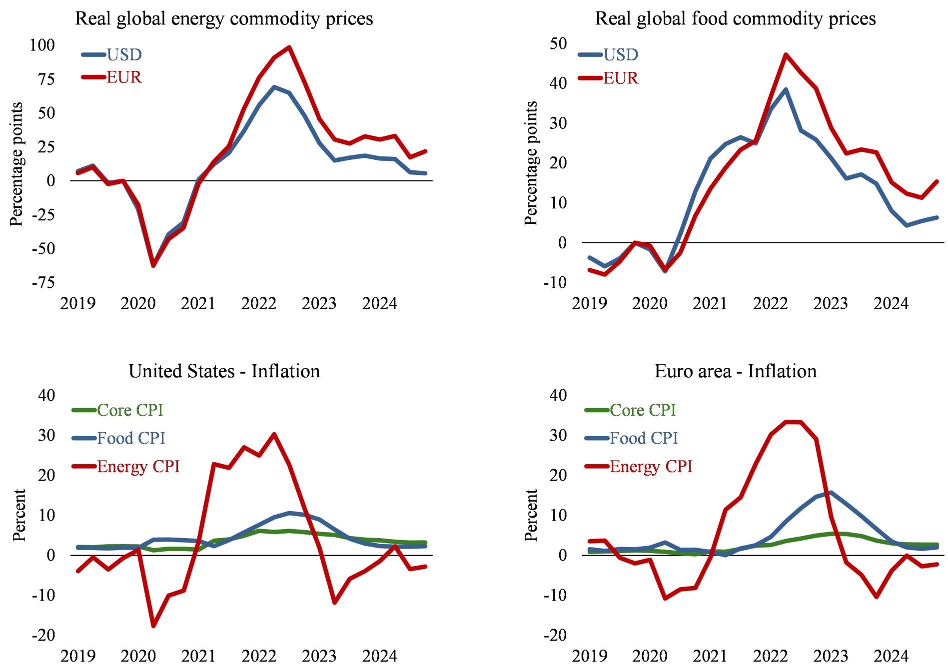
The conventional view of pass-through is grounded in the New Keynesian Phillips Curve, which links inflation to expectations and a markup over real marginal costs. In empirical applications, marginal costs are typically proxied by measures of economic slack, such as the output gap or labor market tightness, thereby overlooking the role of commodity input costs. Extensions that incorporate commodity prices generally treat them as exogenous regressors. However, this approach can be misleading, as commodity prices also respond endogenously to macroeconomic conditions, such as shifts in global demand and expected economic activity. Ignoring this endogeneity can bias coefficient estimates—including the slope of the Phillips Curve—and these specifications fail to identify the causal relationships or true pass-through effects of commodity costs.

This paper examines the role of commodity cost fluctuations—particularly global energy and food commodity prices—in shaping post-pandemic inflation dynamics in the United States (US) and the euro area. As shown in Figure 1, both commodity prices closely tracked inflation developments during this period, and the food and energy components of the CPI rose far more sharply than core CPI. While exogenous commodity market shocks may have contributed to these dynamics, in an environment of markup-based price setting, the endogenous responses of commodity prices to broader macroeconomic shocks were also likely transmitted to consumer prices. Accurately measuring the overall contribution of commodity cost fluctuations to post-pandemic inflation therefore requires accounting for both exogenous and endogenous commodity price movements, including second-round effects such as wage adjustments triggered by these price changes.

To establish causality and quantify the relevance of commodity costs, I employ a structural vector autoregression with external instruments (SVAR-IV). Specifically, I estimate a joint SVAR-IV model for the US and euro area to measure the average historical pass-through of truly exogenous global

[1] Examples are Ball et al. (2022), Eickmeier and Hofmann (2022), Bianchi and Melosi (2022), Banbura et al. (2023), Barro and Bianchi (2024), Dao et al. (2024), Comin et al. (2023), Smets and Wouters (2024), Aastveit et al. (2024), Bergholt et al. (2024), Giannone and Primiceri (2024), Bernanke and Blanchard (2025), Cassinis et al. (2025) and Mori (2025).

Figure 1: Commodity prices and inflation in the post-pandemic era



Note: Real global energy and food commodity prices are expressed as percentage changes relative to 2019Q4. Nominal prices are taken from the World Bank Pink Sheet and deflated by core CPI in US dollars and euros, respectively. Inflation figures are reported in percent. Energy CPI, Food CPI and Core CPI refer to consumer prices for energy, food, and for all items excluding energy and food, respectively.

energy and food commodity cost shocks to energy, food, and core CPI. I use the oil supply news shocks of Känzig (2021) and flow supply shocks of Baumeister and Hamilton (2019) as instruments for the identification of broad energy cost shocks—defined as a weighted average of oil, natural gas, and coal prices—and the unanticipated global harvest surprises developed by Peersman (2022) and De Winne and Peersman (2021) for food commodity cost shocks.

Both types of cost shocks tend to raise consumer prices, including core CPI. However, historical decompositions indicate that most commodity price fluctuations have been endogenous responses to broader macroeconomic developments—such as the global business cycle and monetary policy—captured by the other VAR variables, rather than exogenous disturbances. This pattern also holds in the post-pandemic period. The SVAR estimates identify two major exogenous shocks to food commodity prices: one at the onset of the pandemic in early 2020 and another following the Russian invasion of Ukraine in 2022. For energy commodities, several adverse exogenous shocks emerged around the time of the invasion. Nevertheless, the bulk of post-pandemic commodity price movements primarily reflected endogenous responses to macroeconomic fundamentals and shocks originating outside commodity markets. Consequently, while exogenous energy and food cost shocks contributed to post-pandemic inflation fluctuations, their overall impact during this period was relatively modest.

To assess the overall contribution of commodity costs—including their endogenous responses to macroeconomic conditions—I conduct a counterfactual analysis based on the pass-through estimates of exogenous shocks. Specifically, I use the SVAR model to simulate the evolution of inflation if global energy and food commodity prices had remained at their baseline levels from 2019 onward—that is, their deterministic paths in the absence of exogenous shocks and endogenous responses to other macroeconomic disturbances. To do this, I trigger the SVAR each period by a combination of energy and food cost shocks that offset all commodity price innovations, thereby keeping both variables at their baseline trajectories. This approach is analogous to counterfactuals commonly used in VAR studies to assess the effects of endogenous monetary policy (e.g., Sims and Zha 2006; McKay and Wolf 2023; Castelnuovo et al. 2024), but is less susceptible to Lucas critique concerns resulting from anticipation effects, as future commodity price movements are inherently unpredictable in efficient markets. A key assumption underlying this exercise is that the historical pass-through estimates remain representative for the post-pandemic period, and that the pass-through of exogenous and endogenous commodity cost changes to consumer prices is similar.[2]

The counterfactual analysis reveals that overall fluctuations in commodity costs can almost fully account for post-pandemic developments in US energy, food, and even core inflation. The exception is food CPI, where the rise exceeded what historical pass-through estimates would predict, suggesting that profit margins in the food supply chain may have compressed less—or even expanded—relative to past episodes. Notably, the contribution of energy and food costs to the peak of core inflation was roughly equal. An extension of the VAR to include unit labor costs indicates that elevated US wage inflation during this period can also be attributed to the commodity cost channel, reflecting second-round effects of commodity cost fluctuations. The same applies to GDP deflator inflation.

For the euro area, the baseline VAR indicates a gap between the contribution of commodity costs and the observed path of inflation during this period. However, once the depreciation of the euro

[2] In standard DSGE models, the structural pass-through of input costs to prices is also invariant to the source of the shock; only the dynamic response of markups may differ, which is treated as part of the unexplained component of inflation in the counterfactual analysis.

against the US dollar—relevant because global commodity prices are denominated in dollars—and the sharp increase in European gas prices relative to global benchmarks are taken into account, the commodity cost channel likewise explains most of the variation in energy, food, and core inflation.

Taken together, these results point to tightness in global energy and food markets as the primary driver of post-pandemic inflation. More broadly, they underscore the potential biases in Phillips Curve estimates when the role of commodity markets and endogeneity of commodity prices is ignored. To illustrate, in the final part of the paper, I estimate a standard Phillips Curve for US inflation using labor market tightness as a proxy for real marginal costs. The estimated slope is statistically significant. Augmenting the model with food and energy commodity prices as exogenous regressors does little to change the results. However, when I account for endogeneity by instrumenting commodity prices with the exogenous shocks identified in the SVAR, the Phillips Curve steepens considerably, and the coefficients on both commodity price variables increase substantially.[3]

The results also helps reconcile several seemingly divergent findings in the literature. VAR-based studies typically attribute the post-pandemic inflation surge primarily to demand shocks (e.g., Giannone and Primiceri 2024; Bergholt et al. 2024; Mori 2025), whereas studies relying on the Phillips Curve framework find little evidence for a demand-driven explanation, as traditional indicators of slack remained subdued and inflation expectations were well anchored (e.g., Ball et al. 2022; Dao et al. 2024; Bernanke and Blanchard 2025). These studies instead emphasize price shocks relative to wages. Similarly, Smets and Wouters (2024), using a New Keynesian DSGE model, conclude that the rise and fall in US inflation was largely driven by price mark-up shocks. My findings suggest that demand shocks may indeed have played a central role, but their inflationary effects were not transmitted through conventional domestic channels, such as labor market tightness or the output gap, but primarily through overheated global commodity markets. Because these markets are typically absent from Phillips Curve and DSGE models, the pass-through of demand shocks is likely absorbed in the form of mark-up shocks. Finally, Comin et al. (2023) highlight the importance of binding supply constraints along production chains, including restricted access to imported inputs. My results point to international commodity markets as the primary source of these constraints, with only food CPI inflation potentially amplified by additional frictions along the production chain.

[3]The steepening of the slope is consistent with Gagliardone et al. (2025), who find a steeper slope for a cost-based Phillips Curve relative to the conventional output gap-based formulation of the Phillips Curve.

2 Pass-Through of Food and Energy Commodity Cost Shocks

2.1 Joint SVAR-IV Model for the US and Euro Area

To measure the pass-through of commodity cost fluctuations to inflation—and to assess their role in the post-pandemic era—I estimate a joint SVAR-IV model for the US and the euro area using quarterly data from 1970 to 2024 with $p = 4$ lags. Specifically, the dynamics of an $n \times 1$ vector of observed endogenous variables Y_t are described by the following reduced-form VAR(p) model:

$$Y_t = b + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \mu_t \tag{1}$$

where p is the lag order, μ_t is an $n \times 1$ vector of reduced-form innovations, b is an $n \times 2$ vector of constants and time trends, and $B_1, \ldots, B_p$ are $n \times n$ coefficient matrices. The reduced-form innovations are related to the structural shocks:

$$\mu_t = S\varepsilon_t \tag{2}$$

where S is an $n \times n$ structural impact matrix and ε_t is an $n \times 1$ vector of unobserved structural shocks. These shocks can be recovered if S is (partially) invertible; that is, $\varepsilon_t = S^{-1}\mu_t$. Stock and Watson (2012) and Mertens and Ravn (2013) demonstrate that the coefficients of a single column i of S— sufficient to recover structural shock i—can be estimated with an instrumental variable Z_t if the standard relevance and exogeneity conditions hold. As I identify two structural shocks using external instruments, their correlation may be non-zero. To orthogonalize both shocks, I assume that energy cost shocks can contemporaneously influence food commodity prices both directly and indirectly through other VAR variables via general equilibrium effects, whereas food commodity cost shocks can only affect energy prices on impact through general equilibrium effects.[4]

To capture the dynamics in global commodity markets, the VAR model includes global real energy and food commodity prices (denominated in US dollars), world industrial production, the real S&P 500 equity price index, and the US one-year interest rate. Commodity price data are obtained from the World Bank's *Pink Sheet* dataset. Energy commodity prices represent a weighted average of global crude oil, natural gas, and coal prices. Food commodity prices are a trade-weighted index of bench-

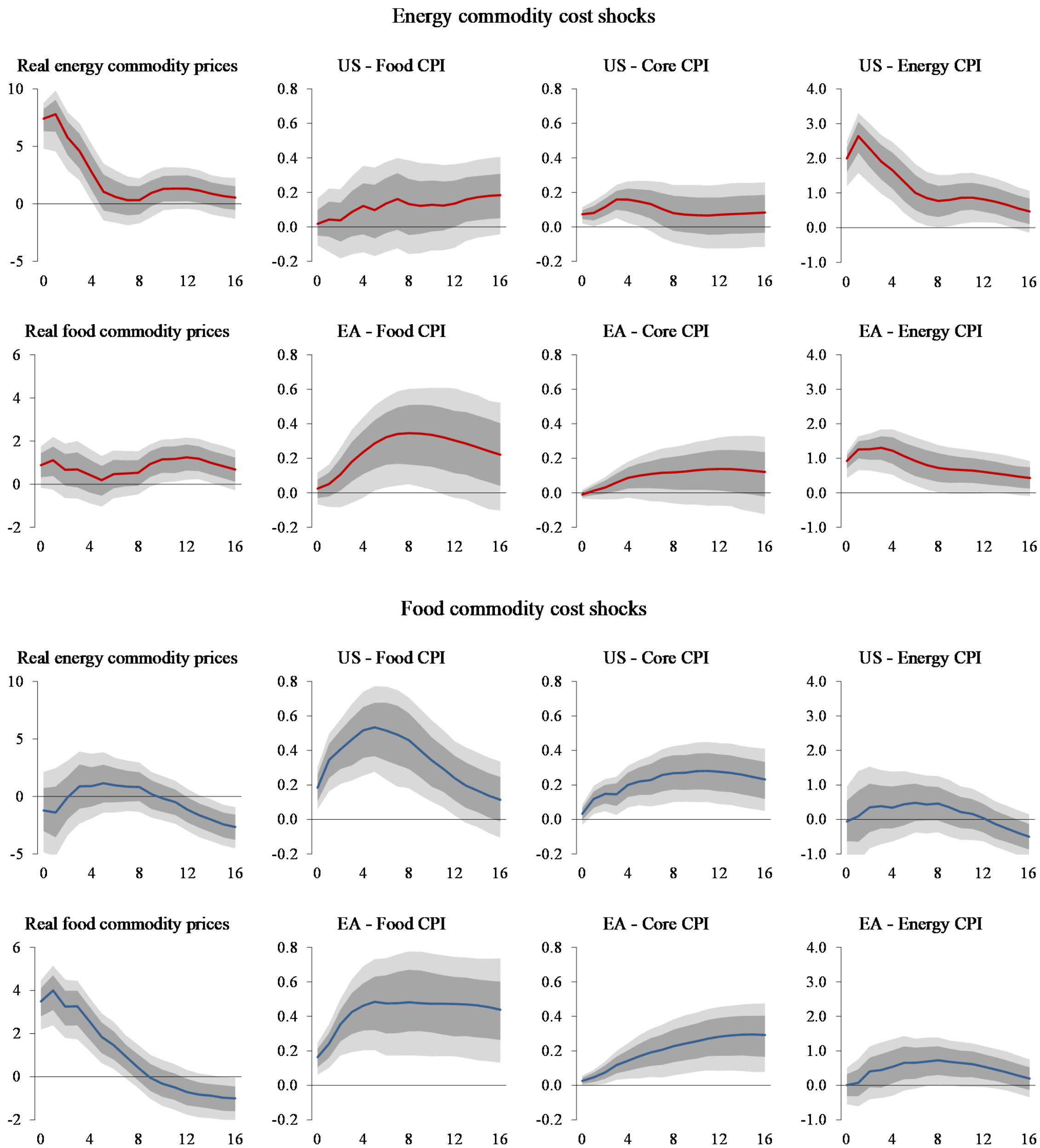
[4]This strategy is analogous to that employed by Mertens and Ravn (2013) to identify personal and corporate income tax shocks using two instrumental variables. See also Castelnuovo et al. (2024). The (overlapping) sample period of the instruments spans 1975-2023, implying that the first stage of the SVAR-IV is estimated over a slightly shorter sample period.

mark prices for key food items, including cereals, vegetable oils, meat, sugar, bananas, and oranges. Nominal prices are deflated by US core CPI. The remaining global variables reflect fluctuations in (expected) global economic activity and the dominant role of the US in international markets. World industrial production is measured by the index of Baumeister and Hamilton (2019), while the S&P 500 real equity price index is taken from Robert Shiller's publicly available dataset. The SVAR-IV also includes real GDP, energy CPI, food CPI, and core CPI for both economies, along with the bilateral euro-US dollar exchange rate. US macroeconomic variables are sourced from the FRED database. For the euro area, data from 1970Q1 to 1994Q4 are taken from the ECB's Area-Wide Model dataset, while data from 1995Q1 onward come from Eurostat. Euro area food and energy prices prior to 1995 are based on the historical series constructed in Peersman (2022). All variables (except the interest rate) are expressed as 100 times their natural logarithms.

Given the dominance of crude oil in the global energy commodity price index, I use two types of oil supply shocks as external instruments for the identification of structural shocks to global energy commodity costs: (i) a quarterly average of oil supply news shocks from Känzig (2021), and (ii) the flow oil supply shocks from Baumeister and Hamilton (2019). For the former, I rely on the revised series by Mori and Peersman (2024), who correct for distortions in the original shocks due to omitted variables. The joint (robust) F-statistic for these instruments is 23.1 (21.0).

To identify exogenous food commodity cost shocks, I use an updated version of the unanticipated global harvest shocks developed in De Winne and Peersman (2016, 2021) and Peersman (2022). This approach exploits the lag—ranging from three to ten months—between planting and harvesting of the world's four major staple crops: corn, wheat, rice, and soybeans. This lag ensures that harvest volumes in a given quarter are not influenced by contemporaneous macroeconomic conditions, while still being vulnerable to exogenous disturbances such as weather variation or crop diseases. By regressing a composite quarterly index of global harvest volumes on lagged macroeconomic variables (i.e., six lags of global real food, grains, and oils & meals commodity prices, world industrial production, the S&P real equity price index, real energy commodity prices, the OECD global composite leading indicator, the US dollar effective exchange rate and the US one-year interest rate), the residuals from this regression can be interpreted as unanticipated global harvest shocks. For further details, see the aforementioned studies. The first-stage (robust) F-statistic for this instrument is 17.7 (11.8).

Figure 2: Pass-through of exogenous global energy and food commodity cost shocks



Note: Impulse responses to one standard deviation shocks. The horizon of the responses (x axes) is quarterly. 68 and 90% confidence intervals constructed using a moving block bootstrap with 5,000 replications and a block size of 6.

2.2 Dynamic Effects of Exogenous Commodity Cost Shocks

Figure 2 presents the impulse responses of the relevant price variables to one-standard-deviation shocks in real global energy and food commodity prices. The responses of the other variables are provided in the appendix. These are similar to existing studies. Specifically, energy commodity cost shocks lead to a significant decline in output and equity prices, a drop in interest rates, and a depreciation of the dollar. Food shocks also lead to a significant decline in economic activity and equity prices, but to an increase in the US interest rate, and an appreciation of the dollar against the euro.

Energy commodity cost shocks typically persist for about 1 year. These shocks also exert upward pressure on food commodity prices, likely due to the role of energy in the production, processing, and distribution of food commodities, and the potential substitution of biofuels for refined energy products. Higher energy commodity prices drive up the energy CPI, though more pronounced in the US than in the euro area. The shocks also significantly affect core and food CPI. Specifically, a 10% increase in global energy commodity prices raises core CPI by 0.21% in the US and 0.19% in the euro area. The peak increases in food CPI are 0.25% and 0.47%, respectively. Accordingly, food CPI also increases relative to core CPI—particularly in the euro area—suggesting that the post-pandemic surge in global energy prices has also contributed to the disproportionate rise in food inflation.

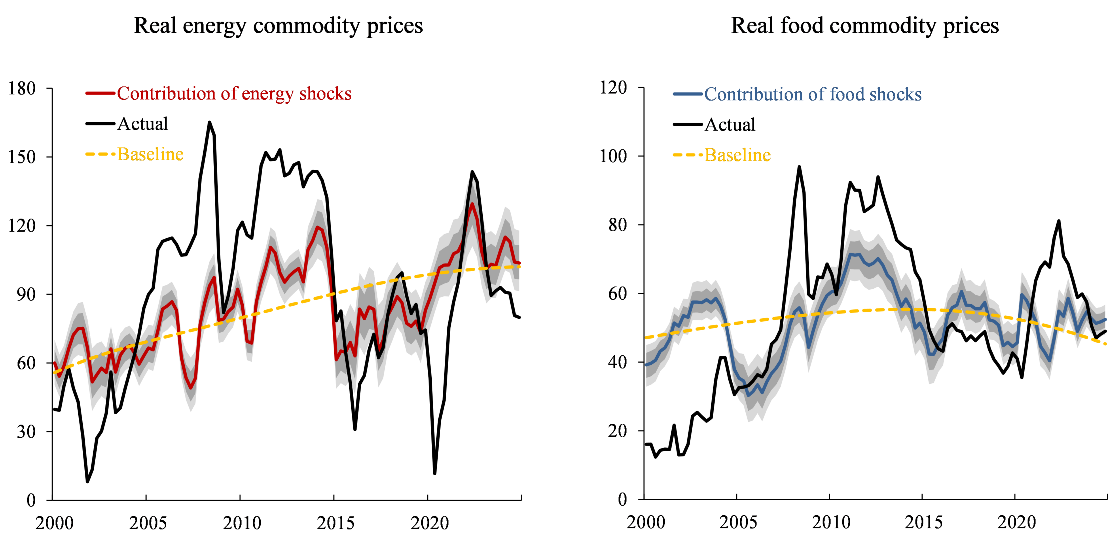
The rise in food commodity prices following an exogenous food cost shock is more persistent, lasting approximately 2 years. The shock triggers a persistent rise in food CPI in both economies. Specifically, a 10% increase in real food commodity prices results in a peak increase in food CPI of 1.53% in the US and 1.39% in the euro area. As shown in De Winne and Peersman (2016) and Peersman (2022), the pass-through is smaller than the share of food commodities in the food CPI, indicating that changes in food commodity costs have historically been partially absorbed through profit margins at various stages of the production chain. Notably, core CPI also increases persistently in both economies, though to a lesser extent. These broader inflationary effects are partly driven by second-round effects—such as rising inflation expectations and/or wages—as documented in the aforementioned studies. In the euro area, the depreciation of the euro against the US dollar amplifies these effects by raising import prices, which also contributes to the increase in euro area energy CPI.

In the appendix (Figure A2), I show that the pass-through estimates remain broadly similar when the VAR model is re-estimated over the sample periods 1982–2024 and 1970–2019, respectively. The main exception is a somewhat weaker pass-through of energy shocks to food and core CPI in the euro area during the 1970–2019 period. If anything, this suggests that the pass-through of energy costs to inflation appears to have been stronger in the post-pandemic era compared with earlier periods.

2.3 Contribution to Food and Energy Commodity Price Fluctuations

Figure 3 displays the cumulative contributions of energy and food commodity cost shocks to fluctuations in real energy and food commodity prices, respectively, relative to their baseline trajectories as implied by the SVAR model. The baseline reflects the evolution of prices in the absence of any exogenous shocks and endogenous responses to macroeconomic developments. The figure also includes the actual observed real prices of both commodities. As can be observed, most historical deviations from the baseline are attributable to endogenous responses to broader macroeconomic conditions, rather than to exogenous shocks.[5]

Figure 3: Contribution to global food and energy commodity price fluctuations



Note: Percentage points cumulative contribution of the shocks relative to the baseline evolution implied in the VAR, together with the actual real price of both commodities. The remaining gaps are endogenous responses to other macroeconomic shocks. 68 and 90% confidence intervals constructed using a moving block bootstrap.

[5]Over the full sample period 1970-2024, exogenous energy shocks account for 19% of the forecast error variance in real energy commodity prices at the two-year horizon, while exogenous food shocks explain 29% of the variation in food commodity prices. Typical examples of exogenous commodity market shocks include supply or expected supply disturbances, but they may also reflect demand-driven factors—such as speculative activity or precautionary demand—as long as the price innovations are specific to commodity markets and not endogenous responses to other variables in the VAR system.

A similar pattern holds in the post-pandemic period. In the case of energy commodities, a series of adverse exogenous shocks emerged around the time of the Russian invasion of Ukraine in 2022. The war severely destabilized global energy markets, as Russia—then the world's second-largest producer of oil and natural gas—faced extensive sanctions and logistical disruptions. The subsequent realignment of global energy trade, particularly Europe's rapid shift away from Russian energy imports, further contributed to sustained price increases.

The SVAR identifies two major exogenous food commodity cost shocks. The first occurred in early 2020 at the onset of the pandemic, driven by widespread concerns about labor shortages affecting harvests. In response, several major food-exporting countries (e.g., Russia, Vietnam) imposed export restrictions to secure domestic food supply, while importing nations increased stockpiling to ensure food security. A second significant shock followed the Russian invasion of Ukraine in 2022. Both countries are key players in global agricultural markets, and the conflict disrupted exports through the Black Sea and Red Sea trade routes, further tightening global food supply chains.

Overall, while a few large exogenous shocks played a role—particularly in the case of the invasion of Ukraine—most of the variation in commodity prices during this period reflects endogenous responses to evolving macroeconomic conditions. For instance, energy commodity prices rose by 132% between 2020Q2 and 2022Q2, of which roughly 35 percentage points can be attributed to exogenous disruptions. The remaining increase largely stemmed from the strong post-pandemic recovery, which boosted global demand for commodities. In addition, expansionary monetary policies worldwide improved financial conditions and lowered inventory-holding costs, further fueling commodity demand.[6]

3 Understanding Post-Pandemic Inflation Developments

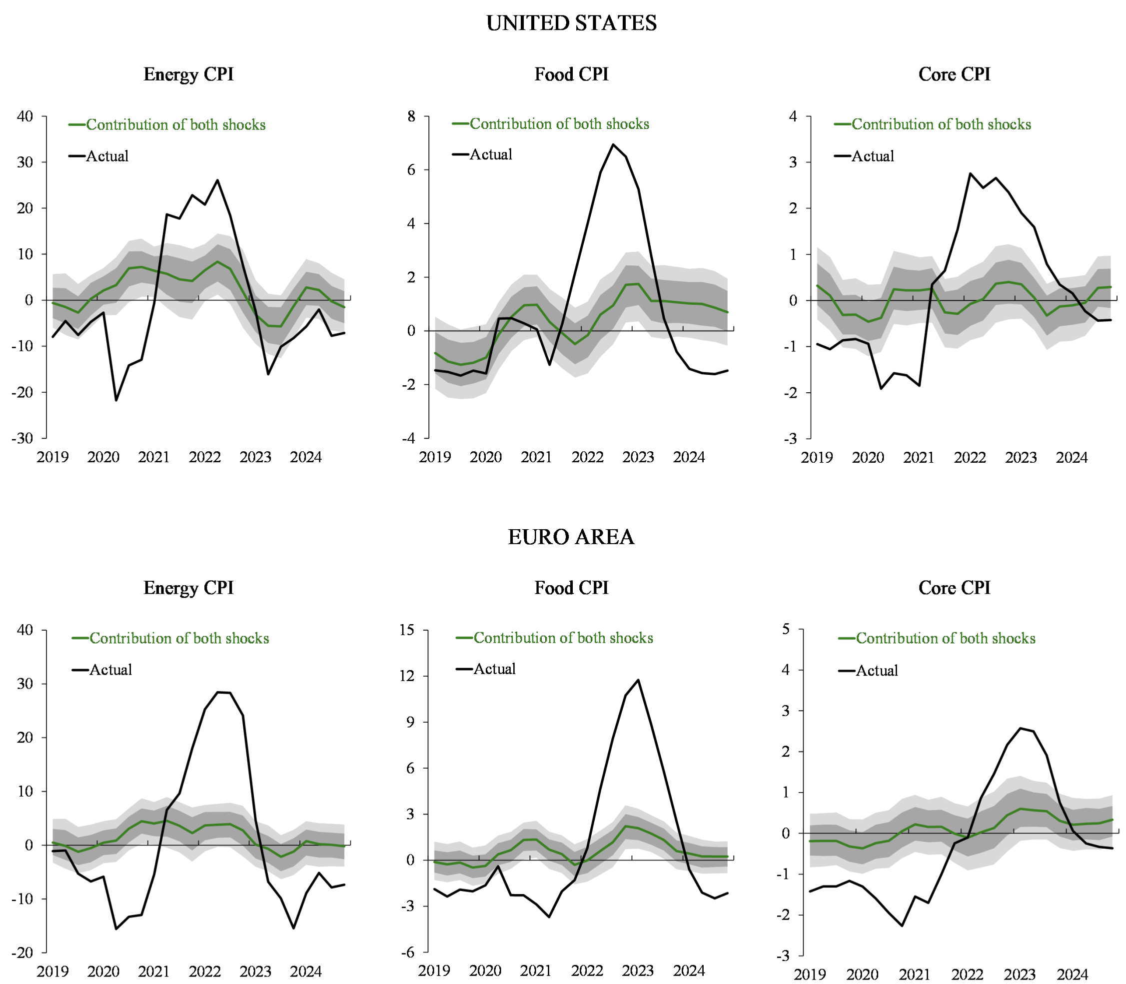
3.1 Contribution of Exogenous Commodity Market Shocks

The combined cumulative contribution of exogenous energy and food commodity cost shocks to post-pandemic fluctuations in energy, food, and core consumer price inflation is illustrated in Figure 4. Inflation is measured as the annual growth rate of the energy CPI, food CPI, and core CPI, with the

[6]The VAR estimates, for example, indicate a significant negative impact of reduced-form US interest rate innovations on food commodity prices. Moreover, when the US interest rate is excluded from the VAR, a much larger share of post-pandemic food commodity price fluctuations is attributed to exogenous shocks (see Figure A3). Together, these findings suggest that expansionary monetary policy significantly contributed to the surge in food commodity prices.

series and the cumulative contributions presented as deviations from baseline inflation rates. In both the US and the euro area, exogenous commodity cost shocks had a statistically significant impact on the surge in energy and food CPI inflation, although their overall magnitudes were relatively modest. Also their influence on core inflation was muted.

Figure 4: Contribution of exogenous commodity cost shocks to inflation



Note: Percentage points cumulative contribution of both shocks (i.e., the sum of the effects of exogenous energy and food cost shocks), together with actual energy, food and core CPI annual inflation relative to the baseline evolution implied in the VAR. 68 and 90% confidence intervals constructed using a moving block bootstrap.

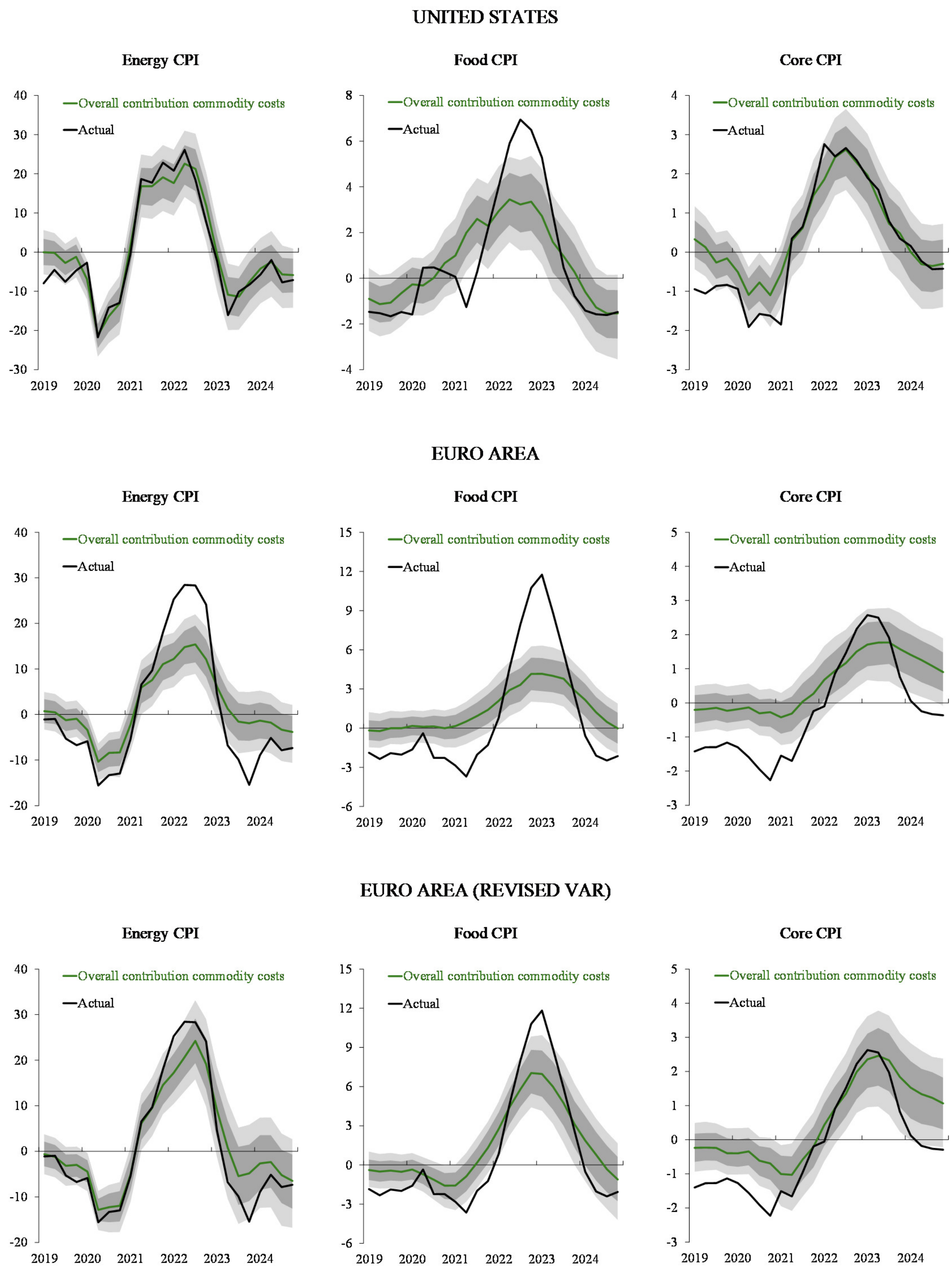
3.2 Overall Contribution of Commodity Cost Fluctuations

As discussed in section 2.3, most post-pandemic commodity price fluctuations were endogenous responses to broader macroeconomic developments rather than purely exogenous shocks. To gauge the *overall* contribution of energy and food commodity costs to inflation—including the dynamic effects of these endogenous price movements—I conduct a counterfactual analysis based on the estimated pass-through of exogenous shocks. Specifically, I use the SVAR model to measure the evolution of inflation under the assumption that energy and food commodity prices had remained at their baseline levels from 2019 onward—that is, their deterministic paths in the absence of any shocks. To implement this counterfactual, from 2019Q1 onward, the SVAR system is iteratively triggered by a combination of (exogenous) energy and food commodity cost shocks that precisely offset the deviation of energy and food commodity prices from their baselines, thereby keeping both price series on their baseline trajectories. Importantly, the shocks are imputed sequentially, accounting for the lagged effects of shocks from previous periods. Because there are two shocks and two target variables, a unique pair of shocks in each period ensures that both commodity price series follow the intended paths.

A key advantage of this counterfactual strategy is that it does not require identifying the specific shocks driving endogenous commodity price fluctuations. Instead, it assumes that the pass-through of changes in input costs to prices is broadly similar across all types of commodity price changes, regardless of their origin. In most DSGE models, for example, the structural features governing price-setting—such as price stickiness, contract structures, and the degree of competition—are invariant to the source of cost shocks. As a result, the mechanical pass-through of input costs to prices is the same whether these changes stem from exogenous disturbances or arise endogenously in response to macroeconomic conditions. What may differ, however, are the dynamic responses of markups and other endogenous variables to the underlying shocks. By design, the counterfactual analysis isolates only the contribution of commodity costs; any variation in markups linked to the nature of the underlying shocks is reflected in the portion of inflation labeled as unexplained in the figures.

This approach is analogous to counterfactuals commonly used in VAR studies to estimate the effects of endogenous monetary policy (e.g., Sims and Zha 2006; McKay and Wolf 2023; Castelnuovo et al. 2024), which similarly assume that monetary policy influences the economy only through the policy rate, irrespective of whether rate changes are systematic or shock-driven. Unlike certain monetary policy counterfactuals—which may be sensitive to the Lucas critique due to agents anticipating future imputed shocks to enforce the contemplated counterfactual policy rule—these simulations are less vulnerable to such concerns, as future (exogenous and endogenous) commodity price movements are inherently unpredictable in efficient markets and tend to follow a random walk.

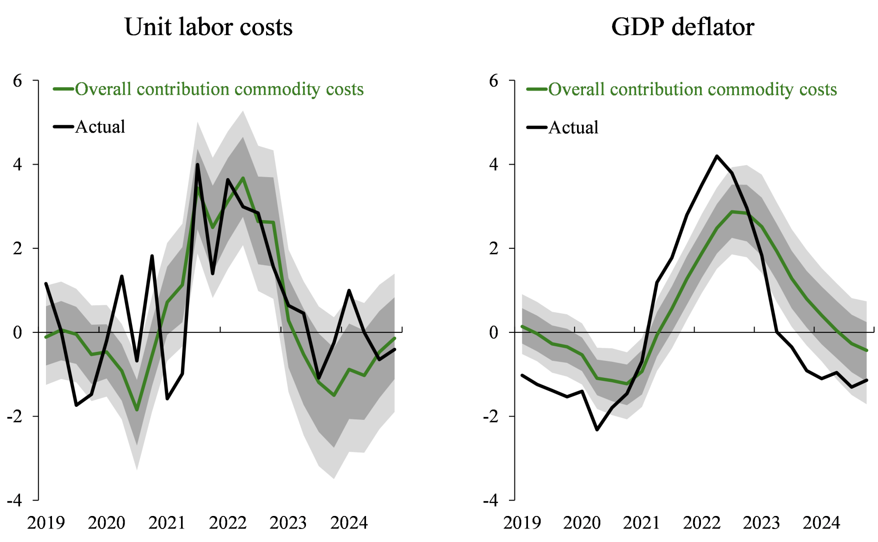
Figure 5: Overall contribution of commodity cost fluctuations to inflation



Note: Percentage points cumulative contribution of exogenous and endogenous energy and food commodity cost fluctuations, together with actual energy, food and core CPI annual inflation relative to the baseline evolution implied in the VAR. 68 and 90% confidence intervals constructed using a moving block bootstrap. The revised euro area SVAR accounts for the depreciation of the euro and higher European gas prices in the post-pandemic era.

The results of the counterfactual analysis are shown in Figure 5, where the "overall contribution of commodity costs" represents the difference between the actual and counterfactual paths of energy, food, and core consumer price inflation. The figure shows that the commodity cost channel can almost fully account for post-pandemic US inflation dynamics. In particular, the large swings in the deviation of the annual growth rate of the energy CPI from its baseline are almost entirely explained by commodity cost fluctuations. Strikingly, the same holds for core inflation. While actual core inflation was about 1.5–2.0 percentage points below its baseline in 2020, roughly half of this gap can be attributed to lower commodity costs. Moreover, the surge in core inflation between 2021 and 2024 can be fully explained by fluctuations in global energy and food prices. For food CPI, commodity costs were also the dominant driver, although with some discrepancies: food inflation ran below the historical contribution of commodity costs in 2021, but substantially above it during 2022–2023. Section 3.3 provides a more detailed cumulative analysis. As shown in the appendix (Figure A4), energy and food costs contributed roughly equally to the peak of US core inflation. The appendix also shows that the results are very similar when the VAR is estimated over the 1982–2024 sample period (Figure A5).

Figure 6: Contribution to annual growth of unit labor costs and GDP deflator in the US



Note: Percentage points cumulative contribution of exogenous and endogenous energy and food commodity cost fluctuations, together with actual annual growth of ULC and GDP deflator relative to the baseline evolution implied in the VAR. 68 and 90% confidence intervals constructed using a moving block bootstrap.

Furthermore, as documented in Figure 6, extending the baseline SVAR to include unit labor costs reveals that the commodity cost channel also accounts well for wage growth during this period, suggesting that the post-pandemic evolution of wages has been consistent with the historical second-round effects of commodity price shocks. The same applies to the annual growth rate of the GDP deflator.

For the euro area, the baseline VAR suggests a gap between the contribution of commodity costs and the observed inflation path. Two important qualifications apply. First, because commodity prices are denominated in US dollars, commodity costs in the euro area were additionally affected by the depreciation of the euro against the dollar during this period. Second, commodity costs in the euro area have been further amplified by the sharper increase in European natural gas prices relative to global benchmarks: between 2021 and 2023, European gas prices rose on average 41 percentage points more than global gas prices, while natural gas has a weight of 10.8% in the global energy commodity price index. When the SVAR-IV model is re-estimated using global energy and food commodity prices expressed in euros, and the energy price index is adjusted to account for the European–global natural gas price discrepancy—results that are shown in the lower panel of Figure 5—the commodity cost channel also explains most of the developments in euro area energy, food, and core inflation.

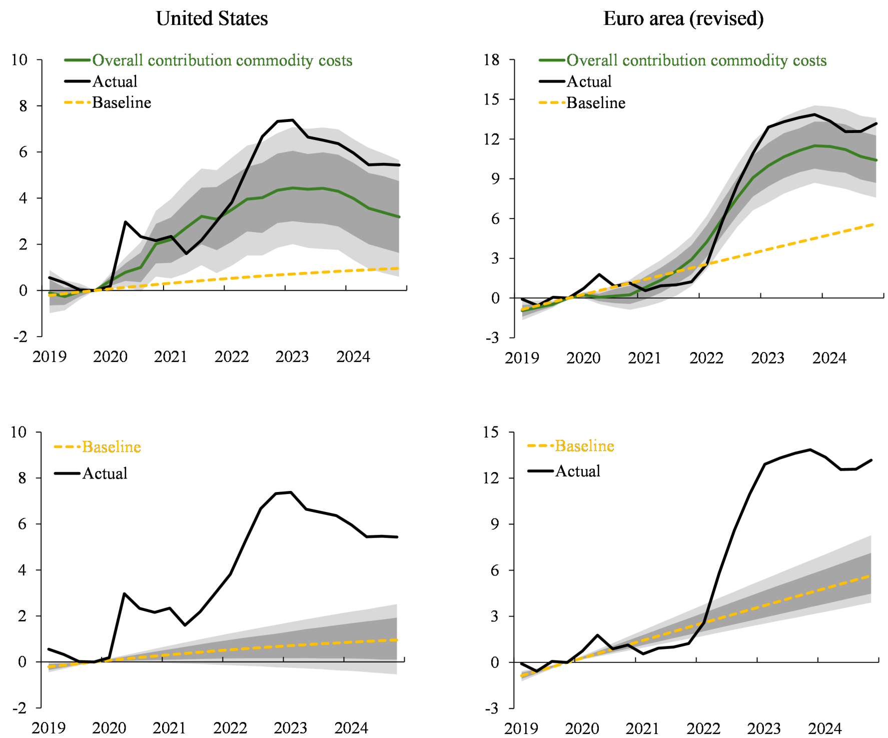
3.3 The Disproportionate Rise in Food CPI

To assess whether commodity costs can also explain the divergence between food and core CPI, Figure 6 presents the cumulative contribution to their relative evolution since 2019Q4. The euro area results are based on the revised SVAR model. Several observations stand out. First, food and energy commodity costs account for a substantial share of the widening gap between food and other consumer prices. Second, in the euro area, food CPI has exhibited a structurally higher baseline trend relative to core CPI—about 1.1 percentage points per year over this period—which has further contributed to the divergence. Nonetheless, a sizeable portion of the gap between food and core CPI in both regions remains unexplained. Put differently, food prices have risen more than historical pass-through estimates would predict. It is unlikely that wages or other input costs have increased more in the food sector than elsewhere: services are typically more labor-intensive, while other goods sectors depend more heavily on industrial inputs, which also rose sharply in price during this period. A more plausible explanation is that profit margins along the food supply chain declined less than usual—or even increased—in response to commodity costs.[7] Potential explanations include strong food demand in this era, increased

[7]When the SVAR model is re-estimated using data only up to 2019Q4, the baseline trend in the euro area appears to be flatter at the onset of the pandemic. This suggest that part of the stronger-than-usual post-pandemic pass-through may be

market concentration in the food sector, and supply chain disruptions specific to food.

Figure 7: Contribution to the disproportionate rise in food CPI



Note: Percentage points cumulative contribution of commodity costs relative to the baseline evolution implied in the VAR, together with the actual evolution of food consumer prices relative to core CPI. The bottom panel only shows the baseline evolution. 68 and 90% confidence intervals constructed using a moving block bootstrap.

4 Does it Matter for the Estimation of Phillips Curves?

The results in section 3 indicate that Phillips Curve estimates may be biased when commodity markets and the endogeneity of commodity prices are ignored.[8] To examine this possibility, I estimate a standard Phillips Curve for US inflation using labor market slack as a proxy for real marginal costs.

absorbed into the model's baseline, leading to an underestimation of the "unexplained" component of the disproportionate rise in food CPI.

[8]Figure A6 in the appendix presents the overall contribution of commodity cost fluctuations to core CPI inflation when the counterfactual analysis is conducted over the full sample period. Given the length of the period considered, such a counterfactual should be interpreted with more than the usual degree of caution. The results suggest that the dominant role of commodity cost fluctuations in explaining core inflation during the post-pandemic period has been quite unique in a historical context. Commodity costs also played an important role in the 1970s and early 1980s, but in other periods, fluctuations in core inflation were clearly not driven by commodity costs. This changing role over time reinforces the concern that Phillips Curve estimates that omit commodity market developments may be biased.

Table 1: Phillips Curve estimates - United States

		V/U	$U-U^n$	RCP_{energy}	RCP_{food}
Baseline: $\pi_{core}-\pi^e$	OLS	1.007***			
		(0.162)			
	OLS	1.139***		0.002	0.011***
		(0.162)		(0.002)	(0.003)
	IV	1.637***		0.018***	0.028**
		(0.289)		(0.007)	(0.012)
Unemployment gap	OLS		-0.338***	0.004*	0.011***
			(0.072)	(0.002)	(0.003)
	IV		-0.861***	0.034**	0.038**
			(0.234)	(0.013)	(0.017)
1985-2024 sample period	OLS	0.801***		0.000	0.009**
		(0.147)		(0.001)	(0.004)
	IV	1.153***		0.021***	0.012
		(0.214)		(0.007)	(0.014)
CPI inflation	OLS	1.347***		-0.004	0.017***
		(0.297)		(0.003)	(0.003)
	IV	2.306***		0.029**	0.044**
		(0.564)		(0.012)	(0.022)
GDP deflator inflation	OLS	0.863***		-0.000	0.009***
		(0.224)		(0.002)	(0.003)
	IV	1.433***		0.020**	0.022*
		(0.399)		(0.009)	(0.013)

Note: The dependent variable $\pi_{core}-\pi^e$ is the gap between core inflation and inflation expectations. V/U denotes ratio of vacancies to unemployed (four-quarter average). $U-U^n$ is the gap between the unemployment rate and noncyclical rate of unemployment (four quarter average). RCP_{energy} and RCP_{food} are the global real energy and food commodity prices, respectively (four-quarter averages). All estimations also include a constant. Baseline sample period: 1971-2024. The IV estimations use the exogenous shocks identified in the SVAR-IV as instruments (eight-quarter averages). Robust standard errors in parentheses. Significance as * p<0.10 , ** p<0.05, *** p<0.01.

Following Ball et al. (2022) and Dao et al. (2024), I regress the inflation gap, defined as the difference between core inflation and longer-term inflation expectations ($\pi_{core}-\pi^e$), on a constant and the average vacancy-to-unemployment ratio (V/U) over the current and previous three quarters. Expected inflation is measured using ten-year forecasts from the Survey of Professional Forecasters

(SPF).[9] Table 1 shows that the estimated slope from an OLS estimation is positive and statistically significant. Furthermore, adding the average of real energy and food commodity prices over the current and previous three quarters as exogenous regressors has little effect on the slope coefficient.

When I address endogeneity by instrumenting commodity prices with the exogenous energy and food cost shocks identified in the SVAR (eight-quarter averages), the slope steepens considerably, and the coefficients on both commodity price variables rise substantially. As documented in Table 1, this result is robust to alternative measures of labor market slack—such as the gap between the unemployment rate and the noncyclical rate of unemployment—and to re-estimating the Phillips Curve since the beginning of the Great Moderation (1985–2024). Similar conclusions are obtained when estimating Phillips Curves for CPI inflation and the GDP deflator. Taken together, these findings underscore the critical role of commodity market tightness in shaping inflation dynamics and demonstrate that ignoring commodity market developments can lead to biased Phillips Curve estimates.

5 Conclusions

This paper has shown that global commodity markets were the central transmission channel of post-pandemic inflation in the US and the euro area. Using a structural VAR with external instruments, I estimated the pass-through of exogenous energy and food commodity cost shocks and used these estimates to assess the broader contribution of commodity price fluctuations—including their endogenous responses to global macroeconomic conditions—to inflation outcomes during 2020–2024. The main finding is that exogenous commodity market shocks such as the Russian invasion of Ukraine contributed to inflation, but explain only a modest share of inflation variation in this period. Instead, once the pass-through of endogenous responses of global energy and food commodity prices to macroeconomic fundamentals are taken into account, commodity cost fluctuations can explain nearly the entire rise and fall in energy, food, and core CPI inflation in both regions. Furthermore, estimates of a standard Phillips Curve specification, including its slope, are shown to be seriously distorted when the endogeneity of commodity prices is ignored.

[9] The assumption that core inflation responds one-for-one to movements in longer-term expected inflation is consistent with the New Keynesian framework of Hazell et al. (2022). The results are robust to relaxing this restriction or augmenting the specification with a lagged dependent variable. Ball et al. (2022) and Dao et al. (2024) also allow for nonlinearities by modeling a cubic relationship between the inflation gap and labor market tightness. Since my focus is on whether Phillips Curve estimates are distorted when commodity market dynamics are ignored, nonlinearities are beyond the scope of this paper. Nonetheless, the findings remain robust when a cubic specification is included.

These results help bridge divergent findings in the recent literature. VAR-based studies emphasize demand shocks, while Phillips Curve estimates highlight supply or markup shocks. My findings suggest these views are consistent once commodity markets are properly integrated: global demand pressures operated primarily through commodity market tightness rather than through conventional measures of domestic slack. The broader implication is that commodity markets should be treated as a core element of inflation modeling rather than as exogenous disturbances.

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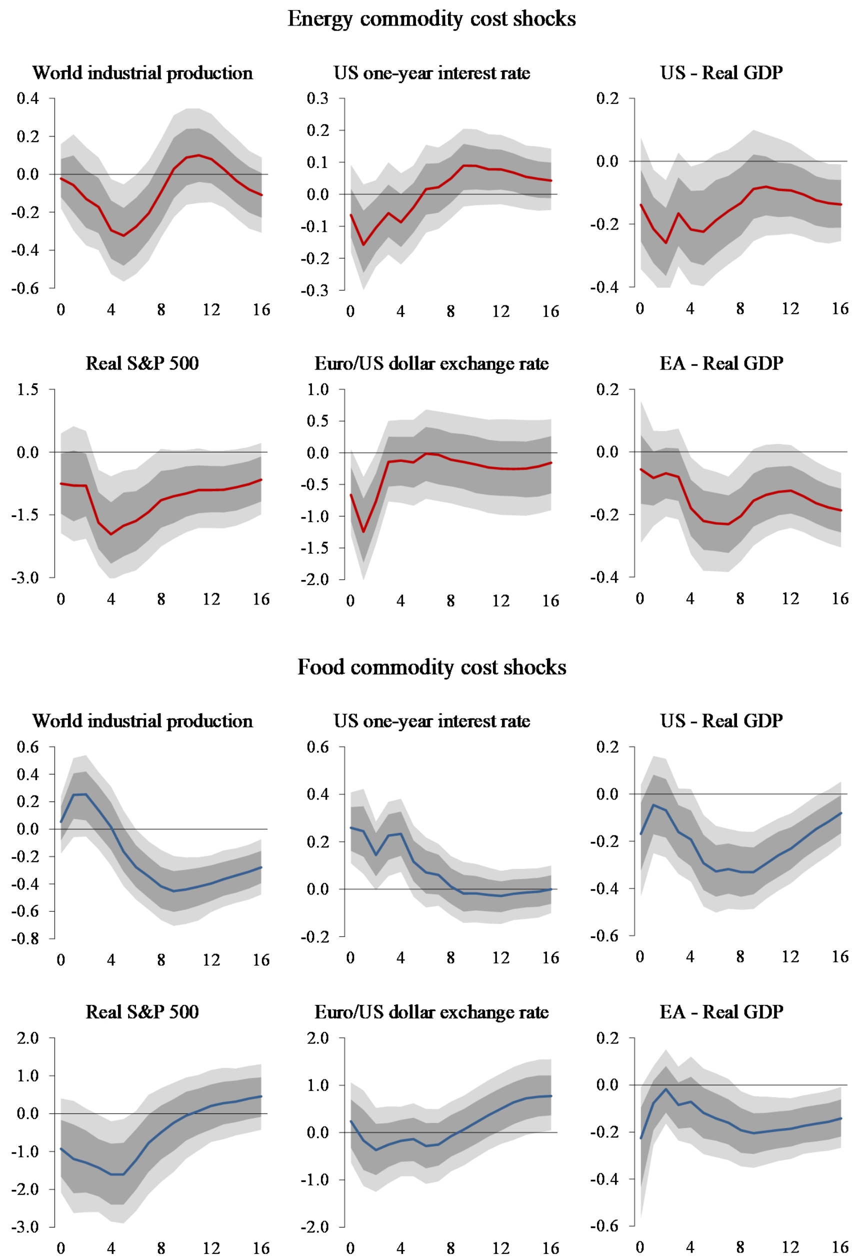
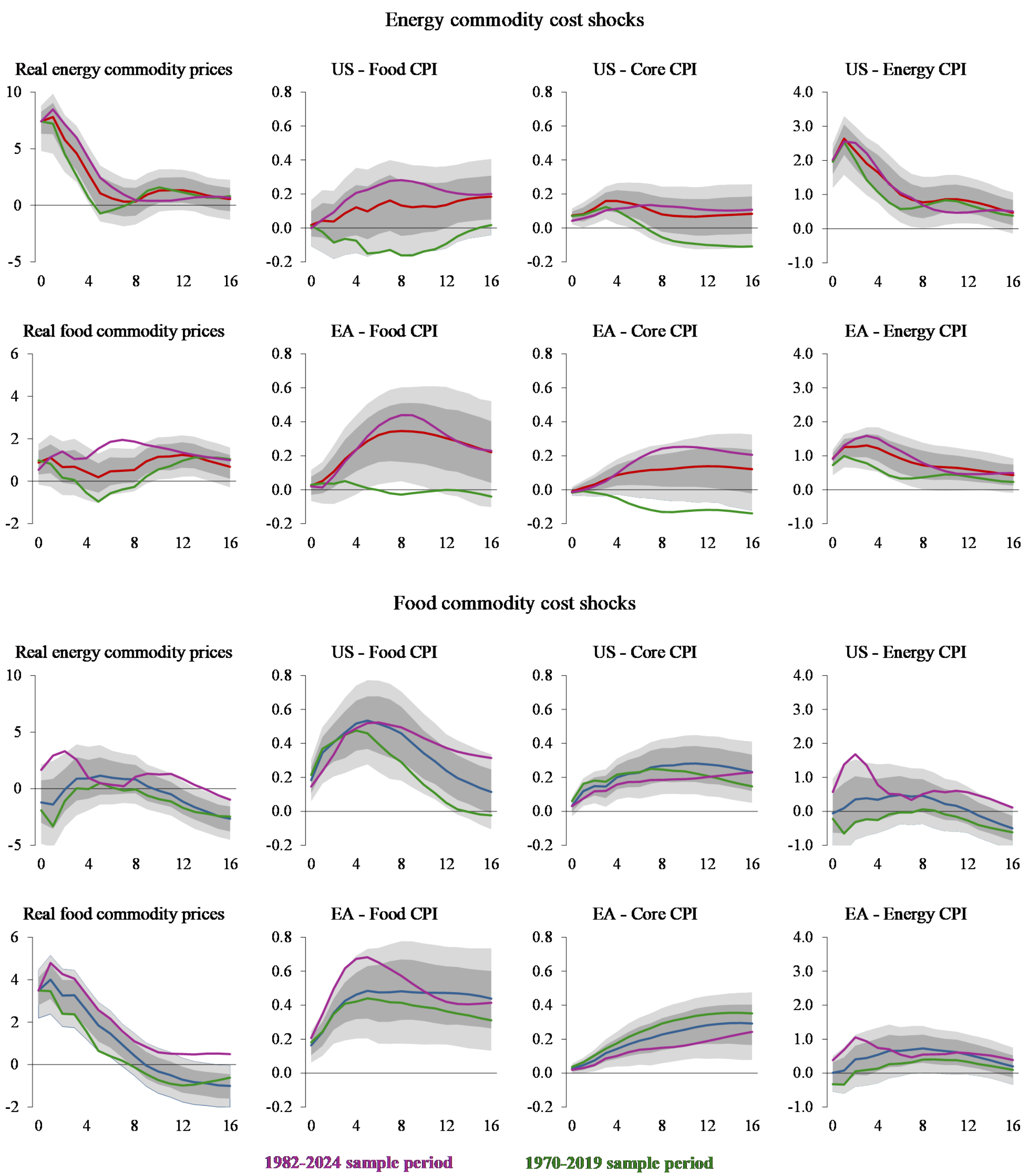
Appendix

Figure A1: Impact of global energy and food commodity cost shocks on other variables



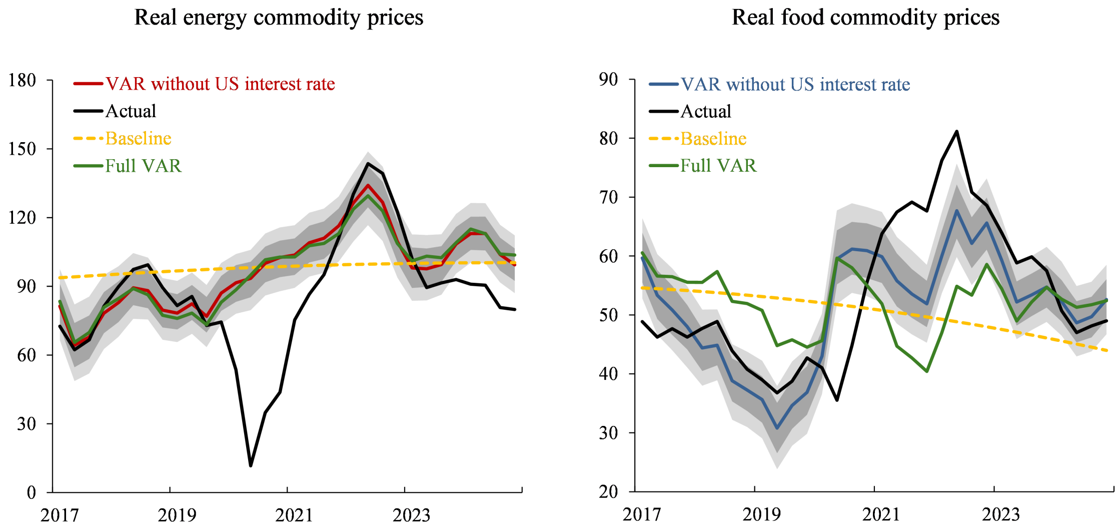
Note: Impulse responses to one standard deviation shocks. The horizon of the responses (x axes) is quarterly. 68 and 90% confidence intervals constructed using a moving block bootstrap with 5,000 replications and a block size of 6.

Figure A2: Pass-through of commodity cost shocks across sample periods



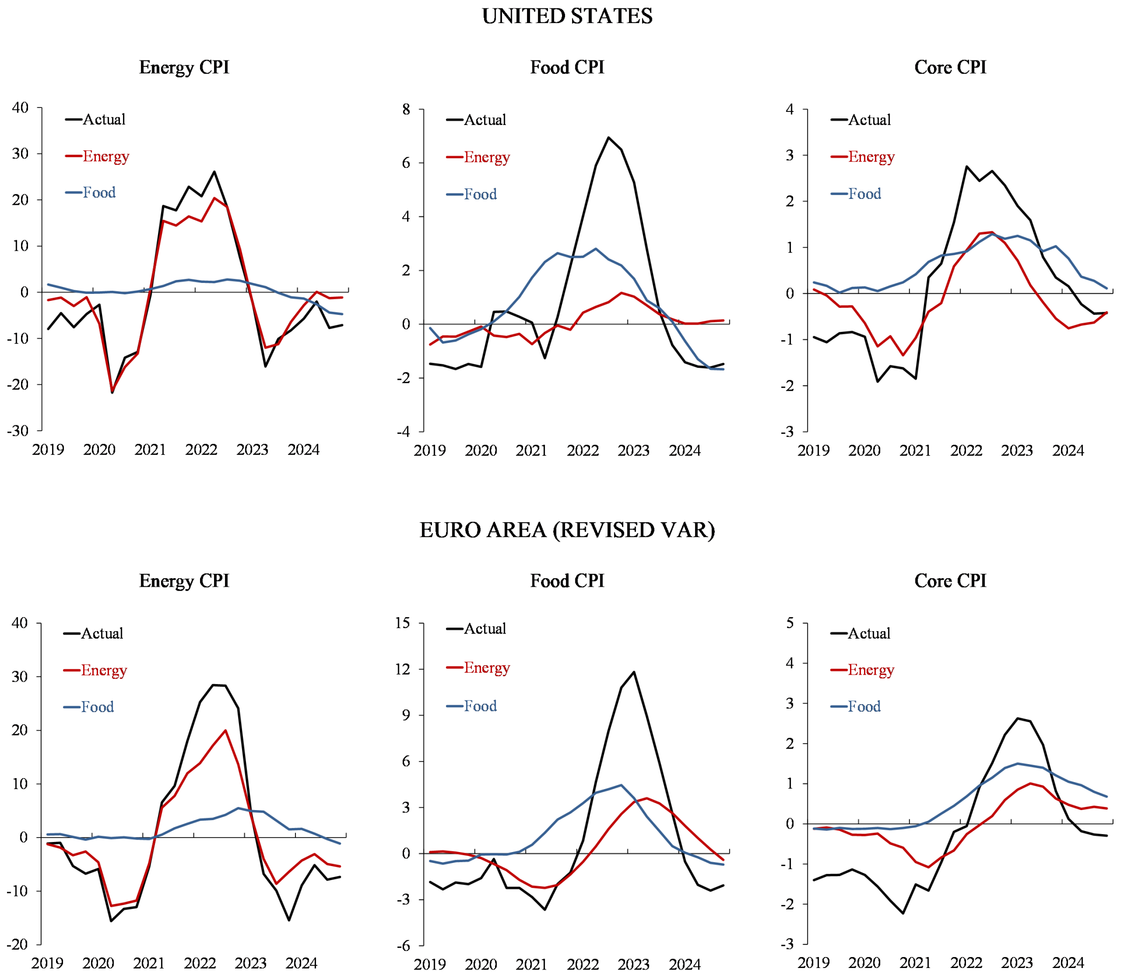
Note: Baseline VAR impulse responses estimated over the full sample period, together with 68 and 90% confidence intervals (as reported in Figure 2). The violet and green lines show the point estimates for the sample periods 1982–2024 and 1970–2019, respectively. The shocks are normalized to the scale of the full-sample estimates. The first-stage (robust) F-statistics for the 1982–2024 sample are 15.7 (12.6) and 13.0 (9.4) for energy and food commodity cost shocks, respectively, and for the 1970–2019 sample 26.5 (21.5) and 10.4 (8.6), respectively.

Figure A3: Contribution of exogenous energy and food commodity cost shocks to their respective price indices



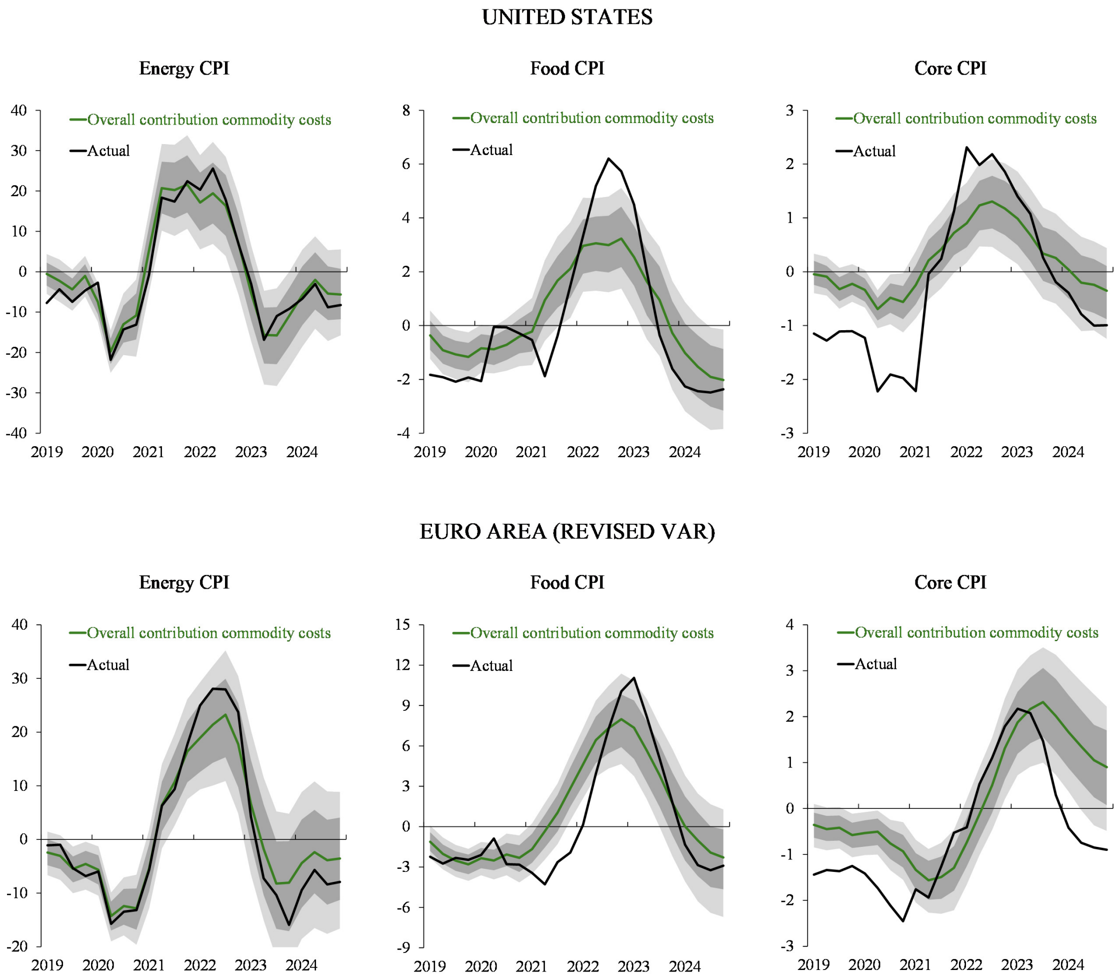
Note: Percentage points cumulative contribution of the shocks relative to the baseline evolution implied in the VAR, together with the actual real price of both commodities. Baseline (full VAR) results (green lines) are compared with those from a VAR specification that excludes the US interest rate.

Figure A4: Overall contribution of energy and food commodity cost fluctuations to inflation



Note: Percentage points cumulative contribution of exogenous and endogenous energy (red) and food (blue) commodity cost fluctuations, together with actual energy, food and core CPI annual inflation relative to the baseline evolution implied in the VAR. The revised euro area SVAR accounts for the depreciation of the euro and higher European gas prices in the post-pandemic era.

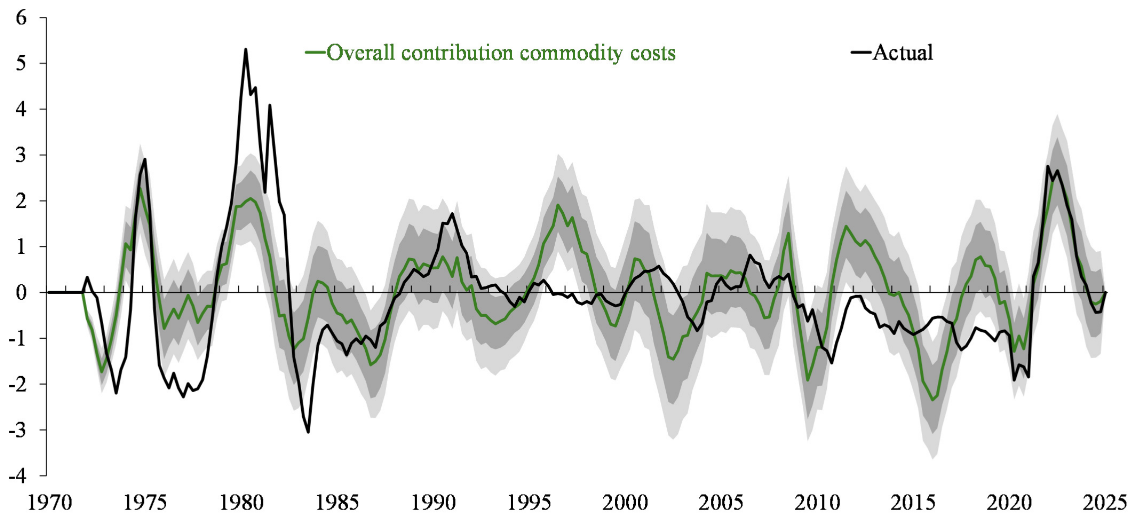
Figure A5: Overall contribution of commodity cost fluctuations based on the VAR estimated over the 1982–2024 sample period



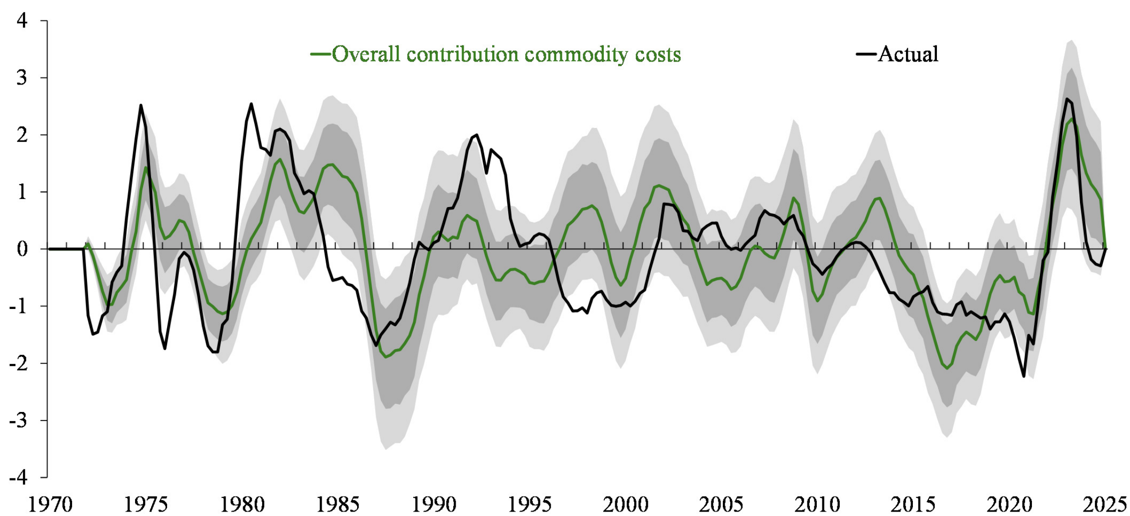
Note: Percentage points cumulative contribution of exogenous and endogenous energy and food commodity cost fluctuations, together with actual energy, food and core CPI annual inflation relative to the baseline evolution implied in the VAR. 68 and 90% confidence intervals constructed using a moving block bootstrap. The revised euro area SVAR accounts for the depreciation of the euro and higher European gas prices in the post-pandemic era.

Figure A6: Overall contribution to core CPI inflation - full sample period

Core CPI inflation - United States



Core CPI inflation - Euro area (revised)



Note: Percentage points cumulative contribution of exogenous and endogenous energy and food commodity cost fluctuations, together with actual core CPI annual inflation relative to the baseline evolution implied in the VAR. 68 and 90% confidence intervals constructed using a moving block bootstrap. The revised euro area SVAR accounts for the depreciation of the euro and higher European gas prices in the post-pandemic era.