Slipping Through the Cracks
Refining the Pass-Through of Energy Prices to Core Inflation*

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PRELIMINARY AND INCOMPLETE

Abstract

I estimate how refined-product costs pass through to core consumer prices using input-output exposure across detailed personal consumption expenditures categories. I find that cost increases fully pass through to prices after about a year and a half. Consistent with nominal price rigidities, goods and sticky-price categories show little response for a year before adjusting, while services and categories with flexible consumer prices respond within six months. Pass-through is stronger when inflation is higher, the output gap is positive, and the labor market is tight. Expectations amplify the transmission of energy costs. Firms pass through more of a current cost increase when further refined-product cost increases are expected and inflation expectations are higher. Cost induced price increase are not accompanied by a contraction in real spending, consistent with a low elasticity of substitution across consumption categories. The rise in refined-product prices through September 2026 would raise the core PCE price level by 0.85 percent by the end of 2027, almost twice the increase implied by crude-oil prices over the same period.

JEL Codes E31, E32, Q43, D57

Keywords Inflation, Pass-Through, Energy Prices, Input-Output, Price Stickiness

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1 Introduction

> "There are just lots of ways that oil and derivatives of oil get into the production and transportation of many, many things. And those—they're big effects in headline inflation, but things like that leak into core as well" (Powell, 2026)[1]
>
> Jerome H. Powell, Chair of the Federal Reserve Board
> FOMC press conference, March 18, 2026

Energy-price shocks are often measured using crude-oil prices. But as Powell (2026) emphasizes, "[i]t's diesel prices because that's, that's transportation of food and things like that" that matter for the transmission to core consumer prices. Refined-product prices often rise more than crude-oil prices, widening crack spreads, rendering it important to understand how those prices bleed into core inflation. While monetary policy cannot reverse energy supply shocks, it can arguably affect the degree of the direct cost pass-through to core prices. In this paper, I ask how much of a cost increase due to an increase in refined-product prices reaches core consumer prices, how quickly, and under what conditions.

To answer those questions, I exploit the cross-sectional exposure across 179 core personal consumption expenditures (PCE) categories to refined-product output and estimate the differential rise in consumer prices in response to a rise in refined-product producer prices. I show that a one-dollar input-cost increase due to higher refined-product prices raises consumer prices by a dollar after about a year and a half, with pass-through reaching 1.2 at its maximum.[2] Given an average exposure of 1.1 percent across core categories, full pass-through implies that a 10 percent rise in refining prices raises core prices by 0.11 percent, and by 0.13 percent at the maximum. Using the same methodology with crude oil implies 0.09 percent. Core spending is less exposed to crude than to refined products, and the estimated pass-through per unit of exposure is smaller. Using oil prices instead of refined-product prices can severely underestimate the spillover from the rise in energy prices into core inflation. Refined-product prices reveal a substantial source of inflation pressure that crude-oil prices miss. Moreover, pass-through is weaker in a cooler economy. The state-dependent estimates imply that monetary tightening can reduce the transmission of an energy-cost increase into core prices by weakening demand.

The pass-through is larger when inflation is higher, consistent with state-dependent pricing, in which inflation changes firms' incentives to adjust prices (Dotsey et al., 1999, Golosov and Lucas, 2007). A hot labor market and a positive output gap also significantly boost the pass-through, consistent with industry supply curves becoming steeper as capacity utilization rises (Boehm and Pandalai-Nayar, 2022). When demand is strong and production is close to capacity, firms have more

[1] Refining margins also featured in Lagarde (2026), who referred to "crack spread or the refining margin" and observed, "And we know now that it's yet another bottleneck." Discussing the rise in bond yields, Warsh (2026, p. 12) referred to "so-called crack spreads" and "what that means for products that find their way into stores across the country."

[2] A coefficient above one is consistent with firms maintaining percentage rather than dollar markups, as discussed by Minton and Somale (2025).

scope to pass an input-cost increase into their prices. Monetary policy can, by cooling demand, lower the pass-through from cost-push shocks to inflation.

I also test whether pass-through depends on the expected path of refined-product prices, using forecasts from the Energy Information Administration (EIA) available at the time of each cost increase. Pass-through is stronger when further refined-product price increases are expected, consistent with firms setting prices in response to expected future marginal costs (Taylor, 2000). The same cost increase also produces a larger price response when households expect higher inflation, whether measured over the next year or the next five to ten years. Expectations about a particular input price and expectations about the general price level therefore both help explain the strength of pass-through. The first captures the expected persistence of the input-cost increase. The second captures the broader inflation environment in which firms set prices.

I next examine how quickly different categories pass through the cost increase. Services respond within six months and reach full pass-through after about fifteen months, while goods show little response during the first year. Goods then catch up and even overshoot the pass-through for services. The same pattern holds when categories are sorted by how often their consumer prices change in the CPI microdata (Montag and Villar, 2023). Flexible-price categories respond sooner, while sticky-price categories adjust later, consistent with heterogeneous nominal rigidities (Nakamura and Steinsson, 2010). The faster response of services is consistent with their more direct exposure to fuel costs, while the transmission to goods requires price adjustment at successive stages of the supply chain (Minton and Wheaton, 2023).

The cross-sectional design identifies differential pass-through across categories and leaves the common aggregate response unidentified, the missing-intercept problem in Wolf (2023). General equilibrium effects can attenuate or amplify the direct cost channel. A decline in real income can contract demand for other categories, exerting downward pressure on their prices. Higher energy prices can also raise inflation expectations (Coibion and Gorodnichenko, 2015), consistent with households using salient price changes to form beliefs about aggregate inflation (D'Acunto et al., 2021). Expectations and induced wage adjustment can raise marginal costs more broadly. I examine the common component by removing month fixed effects and including the aggregate refining-price change directly. I then use oil-supply news from Känzig (2021) to isolate supply-driven variation. The panel instrument interacts this news with lagged refining utilization and category exposure to get variation over and above the oil price. Separate aggregate time-series regressions imply that a 10 percent rise in refining prices raises aggregate core prices by 0.85 percent under IV and 0.48 percent under OLS, compared with 0.13 percent through the baseline exposure channel. These estimates suggest that the cross-sectional effect is a lower-bound estimate.

Applied to the 2026 episode, the baseline exposure estimates imply that the increase in refined-product prices through September raises core PCE prices by 0.85 percent by the end of 2027 if prices stay at their September level, and by 0.57 percent if prices follow the EIA forecast. Along the EIA path, the fourth-quarter-over-fourth-quarter contribution to core inflation is about 0.50

percentage point in 2026 and 0.08 percentage point in 2027. The category price data available through September provide an initial check on this transmission. Exposed categories' prices have risen relative to unexposed ones by about twice as much as the historical point estimates imply, with airfares leading.

Last, I replace the price changes with the change in real expenditure on those categories and estimate how real spending responds to cost increases. If the input-cost increase affects relative demand only through relative prices, the negative ratio of the quantity response to the price response identifies a relative demand elasticity. While higher refining costs raise relative consumer prices, I do not find a statistically significant decline in relative quantities. The cost-induced price increase is not accompanied by a statistically significant contraction in real spending, suggesting that demand elasticities are low.

2 Literature

This paper contributes to the literature on the macroeconomic effects of energy prices. Kilian (2009) shows that these effects depend on the source of the oil-price change. Känzig (2021) finds that adverse oil-supply news raises prices and reduces activity. I study how energy costs reach core consumer prices.[3] I estimate the magnitude and timing of transmission across consumer categories over fifty years. Matching refined-product prices to refining exposure reveals cost pressure that crude-oil prices miss and allows me to examine how transmission varies with the macroeconomic environment.[4]

Minton and Wheaton (2023) use input-output exposure and producer prices to estimate the transmission of commodity costs through production networks. They show how nominal rigidities and downstreamness affect the timing of adjustment and link expected commodity prices to forward-looking price setting. My contribution is to trace refining costs through to the prices households pay. Refined-product prices capture cost pressures from both crude oil and refining that a crude-oil measure alone misses. Matching these prices to refining exposure allows me to measure their transmission into core consumer prices, establish the lags in adjustment, and examine how pass-through varies with inflation, demand conditions, and expected refined-product prices.

Related applications use input-output exposure to measure tariff transmission to consumer prices (Minton and Somale, 2025, Minton et al., 2026). Their theoretical price effect and my input-cost increase share the dollar-for-dollar benchmark. I use repeated monthly changes in refining prices to estimate the dynamic pass-through of input costs over fifty years. Sangani (2026) finds that complete pass-through in dollar levels can coexist with incomplete pass-through in percentages.

[3] More directly on core inflation, Clark and Terry (2010) document a decline in energy pass-through after the early 1980s, and Conflitti and Luciani (2019) find a small but persistent response of the common component of core inflation to oil shocks.

[4] Hobijn (2008) measures commodity exposure using input-output tables and calculates its implications under full pass-through. I estimate the extent and timing of transmission rather than impose that benchmark.

Luo and Villar (2023) use disaggregated producer prices to show how production linkages and price rigidity jointly shape sectoral price responses. Acemoglu et al. (2016) document downstream propagation of supply shocks. Rubbo (2023) derives the implications of production networks for inflation, and Pastén et al. (2020) show how heterogeneous price rigidity changes monetary transmission across sectors. Micro evidence also distinguishes the size of pass-through from its timing. Nakamura and Zerom (2010) separate local costs, markup adjustment, and nominal rigidity in coffee prices, while Ganapati et al. (2020) estimate energy-cost pass-through in U.S. manufacturing.

The paper also connects the transmission of sectoral cost shocks to monetary stabilization. I examine how the pass-through of a given input-cost increase varies with demand conditions and the inflation environment. The state-dependent estimates connect cooling demand to lower transmission of an energy-cost increase into core prices. This demand mechanism complements the role of perceived cost persistence in Taylor (2000). In Guerrieri et al. (2022), sectoral supply disruptions can themselves generate demand shortages. The policy trade-off depends both on demand relative to productive capacity and on how demand conditions affect the transmission of input costs.

3 Data

3.1 Refined-Product Prices

My measure of the cost of refined products is the producer price index (PPI) for petroleum refineries (NAICS 324110), published monthly by the Bureau of Labor Statistics and available from 1976. It measures the price of a refinery's entire output basket, including gasoline, diesel, jet fuel, heating oil, and other products. Prices are measured at the refinery gate, before distribution margins, retail markups, and fuel taxes. I use the refining PPI rather than a retail or spot product price for two reasons. First, it is the price of the exact commodity whose cost share the input-output tables record, so the shock and the exposure are defined on the same object. Second, it is the price of refined products themselves and therefore already embeds the cost of crude oil. Hence, the estimates capture the effect of higher oil prices as well as the widening of refining margins, and they should not be added to a separate estimate of an oil price effect. The refining PPI measures the refinery's output basket, so its movements can differ from those of individual spot products because of product coverage and timing. I seasonally adjust it with X-13 and use the one-month percent change, ΔR_t, where R_t denotes the refining PPI. For the crude-oil comparison, I use crude oil with oil and gas extraction exposure. The crude-oil regressions use the same category-month observations as refining at each horizon, beginning in July 1976. I seasonally adjust crude oil with the same X-13 specification.

Figure 1 plots the two price series used in the analysis. Figure 2 shows the difference between product prices and crude oil at the product level. The crack spreads subtract the price of a barrel

of crude oil from the per-barrel spot prices of gasoline, diesel, and jet fuel.

Hurricanes Katrina and Rita shut refineries and interrupted pipelines and ports along the Gulf Coast in 2005. Fuel production and deliveries fell, inventories were drawn down, and gasoline and diesel prices rose sharply. In September 2008, gasoline prices on the Gulf Coast spiked as Hurricane Ike approached the Houston and Galveston refining centers, then fell back as refineries restarted. These episodes restricted the supply of usable fuels even when crude oil was available elsewhere (U.S. Department of Energy, 2009).

In 2022, gasoline and diesel demand approached pre-pandemic levels while refinery production remained below them, inventories were low, and Russian product exports declined. U.S. refining capacity had fallen by almost one million barrels per day since early 2020 because of refinery closures and conversions. The EIA attributed the unusually high gasoline and diesel crack spreads to this combination of strong demand and constrained product supply (U.S. Energy Information Administration, 2022).

In 2026, disruptions to trade through the Strait of Hormuz and to refining activity in Russia, China, and the Middle East tightened global fuel supplies. Foreign demand for U.S. distillate and jet fuel increased, drawing domestic production into export markets. U.S. refineries operated at high utilization rates, yet distillate inventories remained low. The EIA reports that third-quarter diesel and jet-fuel crack spreads were almost three times their year-earlier levels, while gasoline spreads more than doubled (U.S. Energy Information Administration, 2026a,b). These episodes show why crude oil and refined-product prices can diverge. Disruptions to refining and product distribution raise the cost of the fuels used in production and transportation relative to the cost of crude oil.

3.2 Consumer Prices

Category prices are the Bureau of Economic Analysis's detailed monthly PCE price indexes. The baseline panel contains 179 core categories (excluding food and energy) with a price series that can be matched to the input-output tables. The exposure summaries use the 178 categories observed in the final panel month. The 2026 cross-sectional regression uses 177 categories with the required price history and controls, of which 171 have producer-price adjustment frequencies. These are distinct availability samples, not alternative definitions of core consumption. The all-PCE sample contains 207 categories. The refining panel runs from July 1976 to August 2026. The 2026 cross-sectional evidence uses the October 29 release through September, retaining the same 177 categories. The historical regressions retain their August data cutoff. The crude-oil comparison uses consumer-price observations beginning in July 1976. I write the cumulative percent price change at horizon j as $\Delta_j P_{i,t} \equiv 100(P_{i,t+j}/P_{i,t-1} - 1)$. The horizon is attached to the change operator because every response is measured relative to the same pre-shock price, $P_{i,t-1}$.

3.3 Exposure: The Input-Output Share

The exposure of each category to refining is built from BEA's 2017 Industry-by-Commodity Total Requirements table and PCE Bridge. The Total Requirements table gives, for every commodity, the Leontief-inverse requirement of petroleum refining output per dollar of that commodity's final output, the full direct-plus-indirect requirement running through the entire supply chain. [5] The PCE Bridge maps commodities to PCE categories and splits each consumer dollar into the producer value of the commodity, the cost of transporting it to the point of sale, and the wholesale and retail margins. Each part is weighted by the refining requirement of the industry that receives it. The transportation component therefore reflects the fuel intensity of transportation, while the wholesale and retail margins reflect the requirements of those industries. Figure 3 illustrates the construction for a stylized coffee machine. The result is a time-invariant input-output (IO) share for each category, IOShare_i, the cents of every dollar spent on category i that go to refining output. The same construction for the oil and gas extraction industry gives a crude oil exposure, $\text{IOShare}_i^{\text{oil}}$.

The IO share used throughout the paper weights each piece of the purchaser dollar by the requirement of the industry that receives it,

$$\text{IOShare}_i \;=\; \frac{\sum_c \left(r_c\,\text{PV}_{ic} + r_{T,c}\,\text{TRANS}_{ic} + r_W\,\text{WHSL}_{ic} + r_R\,\text{RTL}_{ic}\right)}{\sum_c \text{PURCH}_{ic}},$$

where c runs over the commodities the PCE Bridge assigns to category i, r_c is commodity c's refining requirement, and $r_{T,c}$, r_W, r_R are the output-weighted requirements of the transportation, wholesale, and retail industries from the BEA Supply table, which records commodity output by industry. Here PV denotes producer value, TRANS transportation margins, WHSL wholesale margins, RTL retail margins, and PURCH purchaser value. Pipeline transportation enters $r_{T,c}$ only for petroleum and natural gas, the commodities it delivers. The same construction with the crude oil requirements gives the oil share.

The refining exposure is the requirement of petroleum refineries (NAICS 324110) and its price is the refining PPI, the price of that industry's output. The oil and gas extraction exposure uses NAICS 211000. I match this exposure to crude-oil prices for the crude-oil comparison.

3.4 State Variables

I examine how pass-through varies with macroeconomic conditions and category characteristics. The first macroeconomic state is twelve-month core PCE inflation through the month before the change in the refining PPI, π_{t-1}. The second is the unemployment gap, Gap_t, the unemployment rate minus the Congressional Budget Office's (CBO) estimate of the natural rate, with positive values indicating slack. I also include a pair of indicators, for months in which the refining PPI fell and for months from January 2022 onward. I also use the output gap, OutputGap_t, defined as 100

[5] Figure A.1 works through a three-industry example.

times the log of real GDP relative to the CBO's estimate of potential real GDP, available quarterly and carried forward within the quarter. The first category characteristic is an indicator for goods rather than services. The second is the frequency of price adjustment (FPA) at the producer level, from Pastén et al. (2020), who estimate the fraction of goods in each BEA industry's basket whose price changes in a typical month from BLS producer price microdata. I match it to PCE categories through the PCE Bridge, and it covers 172 of the 179 core categories once industries without a published estimate are assigned that of their parent aggregate. The third is the frequency of price change at the consumer level, from the CPI microdata statistics of Montag and Villar (2023), bridged from CPI entry-level items to PCE categories through the Consumer Expenditure Survey concordance and covering 89 categories.

Household inflation expectations come from the University of Michigan Surveys of Consumers. I use the median expected inflation rate over the next year and over the next five to ten years. Both measures are expressed in percentage points and demeaned over their respective estimation samples. The one-year series begins in January 1978 and the longer-run series in February 1979. I retain only reported readings, leaving gaps in the early longer-run series unfilled. The six- and eighteen-month regressions use expectation readings through February 2026 and February 2025, respectively.

3.5 Forecasts of Refined-Product Prices

To extend the analysis past the last PPI print, I use the Energy Information Administration's Short-Term Energy Outlook (STEO), which forecasts refiner wholesale prices for gasoline, diesel, and jet fuel monthly through December 2027. I use the October 2026 vintage.

The inputs are the wholesale petroleum product prices in Table 2 of the STEO, measured in dollars per gallon. They cover gasoline, diesel fuel, and jet fuel. The workbook dates the completion of modeling and analysis to October 1, 2026. I estimate the relation between refining-PPI growth and growth in the corresponding Gulf Coast spot prices using monthly observations through September 2026. I seasonally adjust the historical series with X-13 and apply the projected seasonal factors to the STEO paths. The forecast calculation uses growth rates, so it maps the projected wholesale-price changes through coefficients estimated on spot-price changes. Refining-PPI observations run through September and the projected changes begin in October.

For the historical expectations analysis, I use the archived retail gasoline and diesel forecasts and the archived jet-product forecasts. These vintages differ from the October 2026 wholesale paths used in the application. For the historical EIA-implied PPI paths, I first map the equal-weight retail gasoline–diesel composite into nominal refining-PPI levels using a fitted log-level relationship, then remove the refining PPI's X-13 seasonal component from both the constructed paths and the observed series. Historical factors reproduce the adjustment used in the baseline. Projected factors extend through December 2027. For quarterly forecasts, I hold the reported level constant within the quarter, adjust the three monthly values, and average them. This puts the displayed PPI paths

on the same basis as the PPI used in the regressions.

4 Empirical Strategy

I identify pass-through by comparing consumer prices across categories with different exposure to the same change in refining costs. The input-output tables measure each category's direct and indirect use of refined products, including the fuel used to transport goods to the store. Multiplying this exposure by the change in the refining PPI gives a category-specific cost increase. The panel then measures how much more prices rise in categories facing larger cost increases. Category fixed effects absorb persistent differences across categories, and month fixed effects absorb common price movements. This comparison identifies the response transmitted through input costs. Section 6 examines the common component separately.

I implement this comparison in two steps. First, I calculate the price increase implied by full dollar-for-dollar pass-through along the input-output network, holding other costs and dollar margins fixed. This input-cost increase is the category's exposure times the change in the refining PPI,

$$\Delta c^{\text{IO}}_{i,t} \;=\; \text{IOShare}_i \times \Delta R_t. \tag{1}$$

I use the term input-cost increase to distinguish this accounting benchmark from the regression-based predicted price response. Figure 4 illustrates the calculation for a coffee machine. A 10 percent rise in the refining PPI increases costs by about 1.5 percent for taxi fares and 1.0 percent for airfares, compared with 0.1 percent for the average core category. The calculation captures direct and indirect input requirements. It holds wages, other input prices, and demand fixed.

In the second step, I estimate a panel local projection (Jordà, 2005) of category prices on the cost increase. For each horizon $j = 0, \ldots, 24$ months,

$$\Delta_j P_{i,t} \;=\; \beta_j \, \Delta c^{\text{IO}}_{i,t} \;+\; \alpha_i \;+\; \gamma_t \;+\; \varepsilon_{i,t}, \tag{2}$$

where α_i is a category fixed effect and γ_t a month fixed effect, and standard errors are clustered by category. The coefficient β_j is the cumulative pass-through, the share of the first-round cost increase that has appeared in the category's price j months after the change, relative to unexposed categories. A value of 1 means prices have risen by exactly the cost increase under constant dollar margins. Values above 1 are consistent with constant percentage markups. In that case, the price response scales the cost increase up by the markup.

The identifying variation is the interaction of a common refining-price change with fixed differences in IO exposure. The design therefore belongs to the shift-share class studied by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022). Month fixed effects absorb the refining-price change itself and all other price movements common to the categories. Identification requires that, conditional on the controls, other category-specific price pressures associated with refining-price

changes are unrelated to IO exposure.

The specification includes the interaction of ΔR_t and IOShare_i. Their main effects are absorbed by month and category fixed effects, respectively.

To study heterogeneity, I interact the cost increase with a state variable Z,

$$\Delta_j P_{i,t} \;=\; \beta_j \, \Delta c^{\text{IO}}_{i,t} \;+\; \delta_j \, \Delta c^{\text{IO}}_{i,t} \times Z_{i,t} \;+\; \alpha_i + \gamma_t + \varepsilon_{i,t}, \tag{3}$$

where Z varies over time for the macroeconomic states and across categories for the category characteristics. The main effect of Z is absorbed by the fixed effects. The coefficient δ_j measures how the exposure-price-change slope varies with Z. The macroeconomic and price-frequency states use their eighteen-month reference-sample means at all horizons. The expectation measures use their own estimation-sample means. Thus, β_j is the pass-through at the average state. I report the interactions at two horizons, 6 and 18 months, to separate states that change how fast pass-through arrives from states that change how large it eventually is, and I plot the implied pass-through at two values of each state across all horizons, with bands from the joint covariance of β_j and δ_j.

For the goods indicator I use the pooled interaction specification. I plot β_j for services and $\beta_j + \delta_j$ for goods, with confidence bands calculated from their joint covariance.

5 Results

5.1 Exposure to Refining Costs

Figure 5 ranks the fifteen most exposed core categories. The most exposed categories are transportation services. Taxis and ride-sharing, intracity mass transit, and intercity buses have a refining IO share of about 15 percent, air transportation and other road transportation about 10 percent, because fuel is a large part of their cost and non-fuel value added is thin. The expenditure-weighted average across the core basket is 1.10 percent for refining and 0.87 percent for crude oil. Crude exposure is smaller because part of every dollar's refining requirement is refining margin and value added on top of the crude input.

The pass-through coefficients are identified from differences in refining exposure across categories, so it matters how that exposure is distributed. Table 1 summarizes the IO share for three groups, goods, services excluding transportation, and the ten transportation services, and Figure 6 plots every category.

Exposure is concentrated in a small group. The ten transportation services have a refining IO share of 10.3 percent on average, weighted by purchaser value, against 1.2 percent for goods and 0.8 percent for other services. They account for 2 percent of core spending but 20 percent of total exposure, the IO share multiplied by purchaser value. Their contribution to identification depends on the variance of residualized exposure in the estimation sample. Even the least exposed of them, at 4.8 percent, is well above the most exposed goods (3.2 percent) and other services (3.4 percent).

Across the 178 categories in the exposure summary, the unweighted standard deviation of the IO share is 2.30 percentage points, and almost all of it separates transportation from everything else.

Within the other two groups there is much less variation, and the two groups resemble each other. The standard deviation is 0.64 for goods and 0.58 for services excluding transportation, and their 10th to 90th percentile ranges, 0.7 to 2.3 and 0.2 to 1.5, overlap substantially. Figure 7 lists the most exposed categories in each. The leading goods are household items such as cookware, film, dishes, and cleaning products (2.1 to 3.2 percent), for which both the producer's own requirement and the cost of moving and selling the good matter. For services, exposure includes refined products used directly by the provider and indirectly by its suppliers. The leading services are lotteries, water and sewage, garbage collection, and parking and tolls (2.1 to 3.4 percent), and commercial and vocational schools and membership clubs and participant sports centers at 1.4 to 1.7 percent. The sources of exposure differ between goods and services. For goods, about half of the average IO share of 1.17 percent (0.57 percentage point) comes through the transportation, wholesale, and retail margins of the PCE Bridge, which are weighted at the refining requirement of the transportation and trade industries, and the other half (0.60) through the producer's own requirement. For services, including transportation, essentially all of it is the producer's own requirement, because services carry almost no margins. Weighted by spending, services excluding transportation (0.80 percent) are less exposed than goods (1.17 percent), and all services together average 1.1 percent, so the comparison of goods with services mostly reflects whether the ten transportation services are included.

The PCE Bridge helps explain the less familiar services in this ranking. Lotteries are assigned to the broad industry for other state and local government enterprises, which also supplies part of the bridge weights for water and sewage and for parking and tolls. Their exposure inherits the production structure of that industry. Garbage collection maps to waste management, while schools and membership services map mainly to education and recreation. These requirements include fuel used by suppliers as well as fuel bought directly by the service provider. Broad industry assignments can therefore blur differences between individual services. Excluding lotteries, water supply and sewage maintenance, parking fees and tolls, garbage and trash collection, commercial and vocational schools, and membership clubs and participant sports centers leaves the baseline pass-through estimates close to those for the full sample.

5.2 The Magnitude and Dynamics of Pass-Through

Figure 8 shows the results of Equation 2. The pass-through is 0.46 after three months, 0.73 after six, and 0.85 after twelve, before reaching 1.19 after eighteen.[6] Exposed categories' prices therefore rise

[6]The results are robust to estimating a distributed-lag specification. A separate local projection of the cumulative log change in the refining PPI on its one-month percentage change gives an own-price response of 1.04 after twenty-four months (Appendix Figure A.2). The initial input-price increase therefore persists over the horizon in which consumer prices adjust.

by approximately the full input-cost increase relative to unexposed categories.[7] The lagged response is consistent with nominal rigidities delaying transmission through the network (Rotemberg, 1982, Calvo, 1983, Nakamura and Steinsson, 2010, Luo and Villar, 2023, Rubbo, 2023).

I repeat the same regression using crude-oil prices and oil and gas extraction exposure. Figure 9 plots the response, and Table 2 reports the six- and eighteen-month estimates for both measures. Using the available crude oil sample from July 1976, pass-through is 0.65 after six months and 1.03 after eighteen months.

Multiplying these estimates by average core exposure translates them into a core-price effect. A 10 percent rise in refining prices raises core PCE prices by 0.13 percent after eighteen months, compared with 0.09 percent using crude oil. Refining exposure is higher, and its estimated pass-through is also higher. One possible explanation is that refined-product prices measure the costs paid by firms more closely. Refining margins vary with capacity, outages, product demand, and the composition of output. Crude-price movements therefore need not translate one-for-one into diesel, gasoline, and jet-fuel prices. Refined-product prices incorporate this additional variation at the stage where energy enters transportation and production.

5.3 Macroeconomic Conditions and Pass-Through

I next examine whether the transmission of a given input-cost increase depends on the macroeconomic environment. Table 3 shows that pass-through is higher when inflation is higher and the unemployment gap is lower. The separate output-gap estimates reported below give a consistent pattern. Column (8) estimates pass-through to be 0.41 lower from January 2022 onward, but the difference is not statistically significant (standard error 0.32).

Figure 10 compares the estimated pass-through for inflation at 4 percent and 2 percent. When inflation is higher, pass-through is stronger at every horizon. After eighteen months, it is 2.36 at 4 percent inflation and 0.93 at 2 percent inflation. The inflation state-dependence is consistent with theories in which the inflation environment changes firms' incentives to adjust prices (Dotsey et al., 1999, Golosov and Lucas, 2007) or with theories under which inflation changes the perceived persistence of cost increases (Taylor, 2000).[8]

Figure 11 plots pass-through at the 10th and 90th percentiles of the unemployment gap, -0.8 and $+3.3$ percentage points, a tight and a slack labor market. The two paths are indistinguishable for the first nine months and then separate. The unemployment-gap interaction is -0.071 at eighteen months. After eighteen months, pass-through is 1.36 in a tight labor market and 1.07 in a slack one. Panel C of Table 4 compares the six- and eighteen-month unemployment-gap and inflation interactions in columns (9)–(12).

[7] At eighteen months, pass-through is 0.88 excluding air transportation, 1.65 excluding all ten transportation services, and 1.28 excluding shock months in 2020–2022. Excluding all ten transportation services reduces the six-month response to -0.12. Transportation services account for much of the early response, while substantial pass-through remains at eighteen months. All specifications retain category and month fixed effects and category-clustered standard errors.

[8] Section 5.5 examines this mechanism using fuel-price forecasts and inflation expectations.

The output gap, the log of real GDP relative to the CBO's potential, gives a similar picture to the unemployment gap. At eighteen months the interaction is 0.086 per percentage point. The pass-through is 1.07 at the 10th percentile of the output gap (−3.1 percent) and 1.47 at the 90th (+1.6 percent), a difference of 0.40 (0.14).

When demand is strong relative to capacity, firms have more scope to pass a cost increase into prices. This mechanism connects the results to Boehm and Pandalai-Nayar (2022), who document convex industry supply curves, and Baqaee and Farhi (2022), who analyze the interaction of supply constraints and demand across production networks. Monetary policy can therefore affect more than the aggregate demand response to an energy shock. By reducing demand relative to productive capacity, tightening can limit the pressure on other input costs and the scope for firms to pass higher energy costs into consumer prices. The inflation-output trade-off depends on this interaction between the initial cost increase and the state of demand.

Column (7) of Table 3 interacts the cost increase with an indicator for a decline in the PPI. Pass-through from months in which the PPI fell is not distinguishable from pass-through from months in which it rose, so there is no detectable downward rigidity in this sample.

5.4 Price Flexibility and the Speed of Pass-Through

I next compare the timing of price adjustment for goods and services. I interact the input-cost increase with an indicator for goods in Equation 3, keeping the same category and month fixed effects. Figure 12 plots the implied response for services and for goods from this pooled regression. At six months the goods-minus-services interaction is −0.74, so goods have passed through less of the cost increase than services. By eighteen months the difference is +0.52 and is no longer statistically distinguishable from zero. The comparison traces an early delay in goods followed by a catch-up.

The two flexibility measures are correlated only 0.37 across categories, so they carry distinct information. The producer measure is the frequency of producer-price adjustment from Pastén et al. (2020), mapped through the PCE Bridge and covering 172 categories. The consumer measure is the monthly frequency of price changes in the CPI microdata from Montag and Villar (2023), mapped to 89 PCE categories. The first measures repricing by the producing industry. The second measures changes in the price paid by the household.

Figure 13 shows the same pattern within categories sorted by how often their consumer prices change. It plots the pass-through implied by Equation 3 with the consumer-level frequency of price change as the state, for a category at the 90th percentile (a price that changes in 25.7 percent of months) and one at the 10th percentile (4.9 percent of months). The flexible-price category passes through 0.38 of the cost increase after three months and 0.64 after six. The sticky-price category passes through nothing for a year, −0.07 after three months, 0.05 after six, 0.07 after twelve. By month 18 the sticky-price category has reached 0.61 and the flexible one 0.90, and by month 24 the two bands overlap. Panel B of Table 4 reports the price-adjustment interactions at six and

eighteen months side by side. In columns (7) and (8), the consumer-frequency interaction is 2.85 at six months and 1.38 at eighteen, significant early, not significant late. The producer-level frequency of price adjustment in columns (5) and (6) gives the same early effect and a somewhat larger late one. Moving from the 10th to the 90th percentile of the producer measure raises pass-through by 0.7 at six months and by 1.1 at eighteen, both significant, and sticky-price categories by that measure show no pass-through at any horizon. The two measures agree that greater price flexibility brings the cost increase into consumer prices sooner, with a spread of 0.6 to 0.7 of the cost increase at six months. They differ on whether sticky-price categories fully catch up.

Columns (3) and (4) in Panel A of Table 4 show that the goods indicator flips sign between the two horizons, from -0.74 ($p = 0.02$) at six months to $+0.52$ (not significant) at eighteen, which is the two-horizon summary of Figure 12. Goods are slower than services, and then they catch up.

These patterns are consistent with the multisector menu-cost model of Nakamura and Steinsson (2010), in which both a firm's own frequency of adjustment and the rigidity of its input prices affect the response to a shock. The consumer-price frequency measure shows an early difference that narrows over time. The goods-services comparison provides a complementary view of the stages between the initial cost increase and the price paid by the household.

The input-output structure provides an economic explanation for the goods-services difference. In the most exposed transportation services, the firm buys fuel directly and sells the service to the household. A goods price is set at the end of a longer chain. Transportation, wholesale, and retail margins create additional stages between production and the household's purchase of a good. Nominal rigidities along the production chain can delay transmission to consumer prices even when firms anticipate future input costs (Minton and Wheaton, 2023). In microdata on coffee, Nakamura and Zerom (2010) locate much of the delay at the wholesale stage. The difference in adjustment speed does not contradict the intuition that transportation costs matter more for goods and labor costs more for services. That intuition concerns how large the cost share is, which the IO share already measures and which is similar for the two groups (an unweighted mean refining share of 1.3 percent for goods and 1.6 percent for services, including transportation). The speed result concerns how many repricing decisions lie between the refinery and the household.

Two other explanations account for part of the result but not all of it. The first is price flexibility. Goods and services have the same average producer-level frequency of price adjustment (0.138 and 0.141), and controlling for it reduces the six-month goods interaction from -0.74 to -0.50 ($p = 0.08$) without eliminating it. The second is composition. The most exposed services are transportation services, and those ten categories do adjust prices more often than other services (0.21 against 0.13), which makes services look faster. Controlling for them cuts the six-month goods interaction to -0.33, about half of the baseline, and it is no longer significant. The gap does not hinge on any single category, however. Dropping air transportation alone leaves it at -0.65 ($p = 0.03$), and dropping the 30 most exposed categories one at a time moves it only between -0.82 and -0.63. The early gap is also not a feature of one period. It is -0.99 ($p < 0.01$) in months since

1997 and -0.65 ($p = 0.02$) when 2020 to 2022 is excluded.

The early delay appears in both nondurable goods and most durable-goods categories. At longer horizons, the average goods response increases.

5.5 Expectations and Pass-Through

I next examine the price paths available to firms when a refining-cost increase occurs. Figure 14 shows EIA forecast vintages for gasoline, diesel, and jet fuel. Thin paths record individual releases and the heavier line joins the EIA's estimates for the release period. Figure 15 shows the EIA-implied forecast, which combines gasoline and diesel with equal weights and expresses their forecast paths in refining-PPI levels. The longer history begins in late 1985, when both forecasts are available. I map the composite price relative into a PPI price relative using a fitted log-level relationship, anchored to the PPI in the release period. The paths distinguish episodes in which a current cost increase was expected to persist from episodes in which it was expected to reverse.

For each release, I calculate the expected log price change over the next twelve months relative to the release-period price and interact it with the current input-cost increase in Equation 3. Table 5 reports two columns for each fuel and for the equal-weight composite. The first uses the continuous twelve-month expected change. The second uses an indicator for an expected decline. Each pair uses the longest available sample for its own forecast measure. Gasoline begins in January 1983, while diesel and the equal-weight gasoline–diesel composite begin in November 1985. Jet fuel uses its available early observations and the later series from August 2004. All samples end in February 2025.

The twelve-month diesel, jet-fuel, and gasoline–diesel composite interactions are positive. For the composite, each additional percentage point of expected price growth raises pass-through by 0.021. The expected-decline interactions are negative for gasoline, diesel, jet fuel, and the composite. Composite pass-through is 0.40 lower when a decline is expected. This comparison connects the expected persistence of an input-cost increase to how much of it reaches consumer prices.

A firm that expects to keep its price fixed for several periods takes account of costs over that interval. A current increase can therefore induce a larger response when further increases are expected than when it is expected to reverse (Taylor, 2000). Andrade et al. (2026) use tariff-related cost variation to show that firms incorporate expected future costs into current prices, with firms that adjust less often placing more weight on expected costs. The refining evidence connects this mechanism to energy costs and consumer prices.

I then turn to households' expectations about the general price level. The Michigan survey reports expected inflation over the next year and over the next five to ten years. I interact each survey reading in month t with the same cost increase and retain category and month fixed effects. Table 6 reports the implied six- and eighteen-month responses. Higher expected inflation at either forecast horizon is associated with stronger pass-through. The longer-run measure extends the comparison beyond expectations about the immediate inflation outlook.

6 The Common Component and General Equilibrium Effects

6.1 Adding Back the Common Component

The month fixed effects remove price movements shared across consumption categories. To examine those movements, columns (1) and (2) of Table 3 estimate the regression without month fixed effects and include the aggregate change in the refining PPI directly. Column (1) includes the IO share, while column (2) includes category fixed effects. Column (3) adds month fixed effects and gives the baseline exposure estimate. The eighteen-month exposure coefficients are 1.25, 1.24, and 1.19. The coefficient on the aggregate PPI change is 0.040 in column (1) and 0.041 in column (2). Combining the latter with the exposure effect gives a core-price response of about 0.054 percent per 1 percent refining-price increase, compared with 0.013 through exposure alone. This common response can reflect wages, other input costs, expectations, and demand. To separate supply-driven refining-price movements from other aggregate variation, I next turn to oil-supply news.

6.2 Instrumenting the Change in Refining Prices

The same increase in energy prices can arise from a supply disruption or stronger aggregate demand, with different implications for consumer prices (Blanchard and Galí, 2010, Kilian, 2008). I use the oil-supply news shock of Känzig (2021), measured from oil futures prices around OPEC announcements, to isolate variation associated with news about supply.

Let n_t denote the news shock, U_{t-1} lagged refining capacity utilization, and IOShare_i category exposure. I define $z_{i,t} = \text{IOShare}_i n_t U_{t-1}/\bar{U}$, where $\bar{U}$ is mean utilization. Scaling the shock by utilization allows its effect on refined-product prices to vary with the state of refining capacity. The first stage projects the input-cost increase on this instrument and its lag,

$$\Delta c_{i,t}^{\text{IO}} = a_i + d_t + \eta_0 z_{i,t} + \eta_1 z_{i,t-1} + v_{i,t}. \tag{4}$$

The second-stage local projection uses the fitted cost increase,

$$\Delta_j P_{i,t} = \alpha_i + \gamma_t + \beta_j^{\text{IV}} \widehat{\Delta c}_{i,t}^{\text{IO}} + \varepsilon_{i,t}. \tag{5}$$

Both stages use the same horizon-specific observations and category and month fixed effects. Table 7 reports the two first-stage coefficients. Their joint F statistic is 107 at six months and 106 at eighteen months. Table 8 compares OLS and IV on identical observations. Pass-through is 0.83 under IV against 0.73 under OLS at six months, and 1.45 against 1.19 at eighteen months.

For the aggregate response, I estimate a separate time-series local projection of cumulative core PCE inflation on the refining-PPI change. Its first stage uses n_t and n_{t-1} as instruments, and its

second stage replaces the refining-price change with the fitted value. This regression has an intercept and no category or month fixed effects. Figure 16 plots its OLS and IV responses alongside the baseline exposure-implied response. At eighteen months, a 10 percent refining-price increase implies a core-price increase of 0.85 percent under aggregate IV, 0.48 percent under aggregate OLS, and 0.13 percent through category exposure. The aggregate point estimates suggest additional transmission beyond the differential response across categories.

6.3 Historical Decomposition

I use the estimated responses to trace the core-inflation contribution implied by the historical sequence of refining-price changes. For each month, I apply the response at the corresponding horizon to every preceding monthly refining-price change. The difference between the resulting price-level paths twelve months apart gives the contribution to twelve-month inflation. I repeat the calculation with the baseline exposure response and with the aggregate OLS and IV responses from the previous section.

Figure 17 plots the three implied contributions alongside actual twelve-month core PCE inflation and extends them through 2027 with refining prices held at their September 2026 level. Figure 18 uses the EIA price path for the extension. The shaded region marks the forecast period in both figures. In 2022, the exposure channel contributes 0.64 percentage point on average, about an eighth of that year's 5.4 percent core inflation. The corresponding averages are 2.47 percentage points using aggregate OLS and 4.42 using aggregate IV. In September 2022, the three contributions are 0.75, 2.90, and 5.09 percentage points. The comparable pooled crude-oil exposure contribution is 0.54 percentage point. The aggregate calculations assign a larger role to refining-price movements because they also include the common price response. They provide an accounting exercise based on the estimated responses, rather than a decomposition into independently identified structural shocks.

The exposure estimate uses the pooled pass-through coefficients. The state-dependent estimates imply a larger contribution when inflation and demand are high. Recursive estimates also indicate that the transmission pattern predates the inflation surge. Refining estimates through December 2021 imply a 0.53-percentage-point exposure contribution to September 2022 core inflation.

7 The 2026 Episode

7.1 Predicted Build-Up

The 2026 episode allows the estimated timing of pass-through to be applied to a sequence of recent cost increases. I begin with observed refining-price changes through September and hold the refining PPI constant thereafter. For each monthly change since January, I apply the response at its age,

multiply by average core exposure, and sum across months. The solid line in Figure 20 shows the resulting path.

The observed increases imply a 0.85 percent rise in core PCE prices by the end of 2027. Applying the same calculation to crude-oil prices through September gives 0.50 percent. Full dollar-for-dollar pass-through of the sum of the monthly refining-cost increases gives 0.79 percent.[9] The estimated path eventually exceeds that benchmark because the pass-through coefficient rises above one. The contribution continues to build after refining prices stop rising, as the earlier cost increases reach consumer prices.

7.2 Incorporating the Forecast for Refined-Product Prices

I next replace the assumption of unchanged refining prices with the October 2026 EIA paths for gasoline, diesel, and jet fuel through December 2027. To translate these paths into refining-PPI changes, I estimate a bridge using monthly log growth rates. The fitted regression is

$$\widehat{g}_t^{\text{PPI}} = 0.088 + 0.281 g_t^{\text{gas}} + 0.216 g_t^{\text{diesel}} + 0.196 g_t^{\text{jet}}, \tag{6}$$

where each growth rate is 100 times the log change. The sample contains 243 monthly growth observations from July 2006 through September 2026, and the R^2 is 0.70. I apply the coefficients to the EIA-implied paths, then convert the projected log changes to arithmetic percent changes before applying the local projections.

Figure 19 shows the implied refining-PPI path. Prices decline by about 28 percent between September 2026 and December 2027 but remain above their January 2026 level. In Figure 20, this decline reduces the end-2027 core-price effect to 0.57 percent, compared with 0.85 percent if refining prices remain at their September level. On a fourth-quarter-over-fourth-quarter basis, the forecast path contributes 0.50 percentage point to core inflation in 2026 and 0.08 percentage point in 2027.

7.3 Cross-Sectional Evidence from the 2026 Episode

Eight months of realized price data since the shock began allow a first check of whether exposed categories are behaving as the estimates say they should. For each core category, the price change from January to September 2026 is regressed, with expenditure weights, on the category's refining IO share, its average eight-month price change over 2000 to 2019, its 2024 inflation, and its 2025 inflation. Column (3) additionally controls for producer-price adjustment frequency on the 171 categories with an estimate. The plotted comparison uses column (2), without this additional control.

For the plotted comparison, I remove the same inflation controls from both the price change and refining exposure using expenditure weights. The slope between these residuals equals the

[9] This benchmark sums monthly percentage changes, consistent with the linear projection, whereas applying the average IO share to the compounded January–September PPI increase gives 0.99 percent.

exposure coefficient in the joint regression in column (2) of Table 9. The benchmark for that slope is what the panel local projections predict for changes of this age, $\sum_t \beta_{T-t}\,\Delta R_t$ over February to September, with T denoting September 2026. This benchmark is 0.39. Full pass-through of the 90 percent cumulative rise in the refining PPI would be 0.90.

Figure 21 shows the result. On all 177 core categories the slope is 0.76 (standard error 0.25), about twice the panel-implied slope and within two standard errors of it. Multiplied by the average core IO share, these slopes say that exposed categories' relative price increases through September amount to a core PCE effect of about 0.83 percent, against the 0.42 percent the build-up predicts. The cross section thus shows at least as much pass-through as history implies, and more in the point estimate. Expenditure weights and transportation services account for much of the cross-sectional relationship. The unweighted slope is 0.23 and not significant. Air transportation, the exposed category with the largest weight, has excess inflation of 12.9 percent through September. Excluding it lowers the slope to 0.44. Table 9 reports the underlying regressions. Splitting by goods and services, the slope is 0.82 for services and negative for goods, where the most exposed goods categories have not risen, which is what the speed results of subsection 5.4 predict at this stage. Eight months in, the pass-through seen so far is concentrated in flexible-price transportation services, while the historical goods response develops later. Appendix Figure A.3 compares the measured core PCE price effects to date with the historical prediction and traces the projected effects through 2027 under unchanged refining prices and the EIA forecast.

The intercept of the cross-sectional regression is positive. Core categories ran hotter than their own history in 2026 whether or not they use refined products. This is the missing-intercept issue in Wolf (2023). The cross section identifies relative price effects and cannot attribute movements shared by all core categories to refining costs.

8 The Demand Side

The price response also raises a question about substitution across consumption categories. I replace the dependent variable with the category's cumulative change in its real PCE quantity index, keeping the same cost increase, fixed effects, and clustering. Table 10 reports the resulting regressions at six, twelve, eighteen, and twenty-four months. The increase in relative prices is not accompanied by a statistically significant contraction in relative quantities.

To connect this comparison to demand, consider CES preferences with a common elasticity of substitution σ. Relative quantities then satisfy

$$\log(q_i/q_k) = -\sigma \log(p_i/p_k) + \log(a_i/a_k), \tag{7}$$

where a_i/a_k captures relative demand weights. If the refining-cost increase changes relative demand only through relative prices, the responses satisfy $\beta_j^q = -\sigma\beta_j^p$ to a first-order approximation. The quantity-price ratio therefore provides a way to study substitution using cost-driven relative-price

variation. A small response of quantities to higher relative prices would indicate that consumers have limited scope to shift spending toward less exposed categories.

The degree of substitution matters for the propagation of sectoral shocks. When inputs or consumption categories are difficult to replace, a cost increase in one part of the economy can have effects that are not well summarized by its initial expenditure share. Baqaee and Farhi (2019) show how substitution, production linkages, and reallocation generate nonlinear aggregate responses to microeconomic shocks. Guerrieri et al. (2022) show how sectoral supply disruptions can create demand shortages when cross-sector substitution is low relative to intertemporal substitution and markets are incomplete. These mechanisms connect the quantity response to the wider question of how an energy-cost increase changes demand and productive capacity across sectors.

9 Conclusion

Refined-product prices reveal energy-cost pressures that crude oil alone misses. Using input-output exposure across 179 core PCE categories and fifty years of monthly prices, I find that refining-cost increases pass through fully after about eighteen months. Flexible-price categories respond within six months, while sticky-price categories adjust later. Pass-through is stronger when inflation is high.

A 10 percent rise in refining prices implies a 0.13 percent increase in core PCE prices, compared with 0.09 percent for crude oil. Applying the estimated responses to the 2026 episode through September gives a 0.57 percent increase in core prices by the end of 2027 along the EIA fuel-price path, compared with 0.85 percent if refining prices remain at their September level.

The estimates show how refining-cost pressure is transmitted across consumer categories and when it appears in core inflation. A separate aggregate component can reflect expectations, other input costs, and demand responses.

The cross-sectional evidence through September 2026 shows a larger point estimate than the historical response implies. Airfares and other transportation services move first, while exposed goods adjust more slowly. This sequence matters for interpreting incoming inflation data. The early response in services does not exhaust the cost pressure implied by the observed refining-price increases. These findings place the transmission of energy costs at the center of the monetary-policy trade-off. The state-dependent estimates link cooling demand to a smaller contribution of energy costs to core inflation. The relevant policy comparison weighs this reduction in pass-through against the cost of weaker activity.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016) "Networks and the macroeconomy: An empirical exploration", *NBER Macroeconomics Annual*, 30, pp. 273–335.

Andrade, Philippe, Alexander M. Dietrich, John Leer, Raphael S. Schoenle, Jenny Tang, and Egon Zakrajšek (2026) "The future in today's prices: Evidence from a survey of U.S. firms", Working Paper 26-11, Federal Reserve Bank of Boston.

Baqaee, David Rezza and Emmanuel Farhi (2019) "The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem", *Econometrica*, 87 (4), pp. 1155–1203.

Baqaee, David Rezza and Emmanuel Farhi (2022) "Supply and demand in disaggregated Keynesian economies with an application to the COVID-19 crisis", *American Economic Review*, 112 (5), pp. 1397–1436.

Blanchard, Olivier J. and Jordi Galí (2010) "The macroeconomic effects of oil price shocks: Why are the 2000s so different from the 1970s?", Jordi Galí and Mark Gertler eds. *International Dimensions of Monetary Policy*, Chicago, University of Chicago Press, pp. 373–421.

Boehm, Christoph E. and Nitya Pandalai-Nayar (2022) "Convex supply curves", *American Economic Review*, 112 (12), pp. 3941–3969.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022) "Quasi-experimental shift-share research designs", *Review of Economic Studies*, 89 (1), pp. 181–213.

Calvo, Guillermo A. (1983) "Staggered prices in a utility-maximizing framework", *Journal of Monetary Economics*, 12 (3), pp. 383–398.

Clark, Todd E. and Stephen J. Terry (2010) "Time variation in the inflation passthrough of energy prices", *Journal of Money, Credit and Banking*, 42 (7), pp. 1419–1433.

Coibion, Olivier and Yuriy Gorodnichenko (2015) "Is the Phillips curve alive and well after all? inflation expectations and the missing disinflation", *American Economic Journal: Macroeconomics*, 7 (1), pp. 197–232.

Conflitti, Cristina and Matteo Luciani (2019) "Oil price pass-through into core inflation", *The Energy Journal*, 40 (6), pp. 221–247.

D'Acunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber (2021) "Exposure to grocery prices and inflation expectations", *Journal of Political Economy*, 129 (5), pp. 1615–1639.

Dotsey, Michael, Robert G. King, and Alexander L. Wolman (1999) "State-dependent pricing and the general equilibrium dynamics of money and output", *The Quarterly Journal of Economics*, 114 (2), pp. 655–690.

Ganapati, Sharat, Joseph S. Shapiro, and Reed Walker (2020) "Energy cost pass-through in US manufacturing: Estimates and implications for carbon taxes", *American Economic Journal: Applied Economics*, 12 (2), pp. 303–342.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020) "Bartik instruments: What, when, why, and how", *American Economic Review*, 110 (8), pp. 2586–2624.

Golosov, Mikhail and Robert E. Lucas, Jr. (2007) "Menu costs and Phillips curves", *Journal of Political Economy*, 115 (2), pp. 171–199.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning (2022) "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?", *American Economic Review*, 112 (5), pp. 1437–1474.

Hobijn, Bart (2008) "Commodity price movements and PCE inflation", *Current Issues in Economics and Finance, Federal Reserve Bank of New York*, 14 (8).

Jordà, Òscar (2005) "Estimation and inference of impulse responses by local projections", *American Economic Review*, 95 (1), pp. 161–182.

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

Kilian, Lutz (2008) "The economic effects of energy price shocks", *Journal of Economic Literature*, 46 (4), pp. 871–909.

Kilian, Lutz (2009) "Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market", *American Economic Review*, 99 (3), pp. 1053–1069.

Lagarde, Christine (2026) "Monetary Policy Statement (with Q&A)", European Central Bank, September 10, press conference, Berlin.

Luo, Shaowen and Daniel Villar (2023) "Propagation of shocks in an input-output economy: Evidence from disaggregated prices", *Journal of Monetary Economics*, 137, pp. 26–46.

Minton, Robert, Madeleine Ray, and Mariano Somale (2026) "Detecting tariff effects on consumer prices in real time – Part II", FEDS Notes, Board of Governors of the Federal Reserve System, April 8, https://doi.org/10.17016/2380-7172.4040.

Minton, Robert and Mariano Somale (2025) "Detecting tariff effects on consumer prices in real time", FEDS Notes, Board of Governors of the Federal Reserve System, May 9, https://doi.org/10.17016/2380-7172.3786.

Minton, Robert and Brian Wheaton (2023) "Delayed inflation in supply chains: Theory and evidence", SSRN Working Paper 4470302.

Montag, Hugh and Daniel Villar (2023) "Price-setting during the COVID-19 era", FEDS Notes, Board of Governors of the Federal Reserve System, August 29.

Nakamura, Emi and Jón Steinsson (2010) "Monetary non-neutrality in a multisector menu cost model", *The Quarterly Journal of Economics*, 125 (3), pp. 961–1013.

Nakamura, Emi and Dawit Zerom (2010) "Accounting for incomplete pass-through", *Review of Economic Studies*, 77 (3), pp. 1192–1230.

Pastén, Ernesto, Raphael Schoenle, and Michael Weber (2020) "The propagation of monetary policy shocks in a heterogeneous production economy", *Journal of Monetary Economics*, 116, pp. 1–22.

Powell, Jerome H. (2026) "Transcript of Chair Powell's Press Conference", Board of Governors of the Federal Reserve System, March 18, p. 24.

Rotemberg, Julio J. (1982) "Sticky prices in the United States", *Journal of Political Economy*, 90 (6), pp. 1187–1211.

Rubbo, Elisa (2023) "Networks, Phillips curves, and monetary policy", *Econometrica*, 91 (4), pp. 1417–1455.

Sangani, Kunal (2026) "Complete pass-through in levels", *The Quarterly Journal of Economics*, 141 (2), pp. 1077–1135.

Taylor, John B. (2000) "Low inflation, pass-through, and the pricing power of firms", *European Economic Review*, 44 (7), pp. 1389–1408.

U.S. Department of Energy (2009) "Comparing the energy infrastructure impacts of the 2005 and 2008 hurricanes",Technical report, Office of Electricity Delivery and Energy Reliability.

U.S. Energy Information Administration (2022) "EIA Expects High Refinery Margins to Contribute to Increasing Fuel Production This Summer", Today in Energy, June 10.

U.S. Energy Information Administration (2026a) "Petroleum Markets Responded to Disruptions in the Middle East in the Second Quarter", Today in Energy, July 15.

U.S. Energy Information Administration (2026b) "Crude Oil Prices and Refinery Margins Generally Increased Throughout the Third Quarter", Today in Energy, October 5.

Warsh, Kevin (2026) "Transcript of Chairman Warsh's Press Conference", Board of Governors of the Federal Reserve System, September 16.

Wolf, Christian K. (2023) "The missing intercept: A demand equivalence approach", *American Economic Review*, 113 (8), pp. 2232–2269.

Table 1. Variation in Refining Exposure by Group

Exposure in percent of purchaser value						
Group	N	Weighted mean	Weighted SD	Mean	SD	P10–P90
Goods	64	1.17	0.52	1.32	0.64	0.69–2.25
Services excl. transport	104	0.80	0.54	0.86	0.58	0.21–1.45
Transportation services	10	10.32	2.53	9.78	4.03	4.95–14.80
All core	178	1.10	1.51	1.52	2.30	0.40–2.37

Group	Maximum	Share of spending	Share of total exposure
Goods	3.18	25.7	27.4
Services excl. transport	3.35	72.2	52.6
Transportation services	14.80	2.1	20.0
All core	14.80	100.0	100.0

Note. Refining exposure is measured as a percent of purchaser value. Weighted statistics use 2017 purchaser values. Total exposure is the exposure share multiplied by purchaser value. The sample contains the 178 core categories with a price in the final panel month. Transportation services include passenger transport, delivery, moving, storage, and freight.

Table 2. Pass-Through of Refining and Crude Oil Costs

	6 months		18 months	
	(1) Refining	(2) Crude oil	(3) Refining	(4) Crude oil
$\Delta c_{i,t}^{\mathrm{IO}}$	0.727***	0.652**	1.194***	1.026***
	(0.248)	(0.260)	(0.399)	(0.382)
Category fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
R^2	0.191	0.190	0.372	0.371
Observations	101,665	101,665	99,509	99,509
First shock month	Jul 1976	Jul 1976	Jul 1976	Jul 1976

Note. The dependent variable is the cumulative category price change from $t-1$ to $t+j$, in percent. Every column uses the specification in column (3) of Table 3. Refining prices are paired with refining exposure and crude-oil prices with oil and gas extraction exposure. Crude oil uses the St. Louis Fed spliced price series WTISPLC. The refining and crude-oil columns use identical category-month observations at each horizon, beginning in July 1976. Parentheses report category-clustered standard errors. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3. Pass-Through and State Dependence at an 18-Month Horizon

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔR_t	0.040***	0.041***							
	(0.007)	(0.007)							
IOShare_i	6.521								
	(5.302)								
$\Delta c_{i,t}^{\text{IO}}$	1.251***	1.242***	1.194***	1.250***	1.190***	0.600*	1.297*	1.234***	1.676***
	(0.404)	(0.403)	(0.400)	(0.403)	(0.400)	(0.353)	(0.664)	(0.407)	(0.490)
$\Delta c_{i,t}^{\text{IO}} \times \text{Gap}_t$				-0.071***					
				(0.025)					
$\Delta c_{i,t}^{\text{IO}} \times \text{Goods}_i$					0.516				
					(0.629)				
$\Delta c_{i,t}^{\text{IO}} \times \text{FPA}_i$						7.844**			
						(3.847)			
$\Delta c_{i,t}^{\text{IO}} \times \mathbf{1}[\Delta R_t < 0]$							-0.199		
							(0.669)		
$\Delta c_{i,t}^{\text{IO}} \times \mathbf{1}[t \geq 2022]$								-0.410	
								(0.320)	
$\Delta c_{i,t}^{\text{IO}} \times \pi_{t-1}$									0.717***
									(0.222)
Category FE	No	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	No	No	✓	✓	✓	✓	✓	✓	✓
R^2	0.003	0.222	0.372	0.372	0.372	0.388	0.372	0.372	0.372
Observations	99,509	99,509	99,509	99,509	99,509	95,476	99,509	99,509	99,509

Note. The dependent variable is the category price change from $t-1$ to $t+18$, in percent. $\Delta c_{i,t}^{\text{IO}} = \text{IOShare}_i \Delta R_t$ is the input-cost increase. Columns (1) to (3) progressively add category and month fixed effects. Columns (4) to (9) add one interaction to column (3). Gap is the unemployment gap, FPA is producer-price adjustment frequency, and π_{t-1} is twelve-month core PCE inflation through $t-1$. Continuous states are demeaned. Indicator reference states are services, a PPI increase, and a pre-2022 month. The main cost coefficient is pass-through at the reference state. Category and month fixed effects absorb the corresponding main effects. The FPA sample contains 172 categories. Standard errors are clustered by category in every column. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4. Pass-Through and Its State Dependence at 6 and 18 Months

Dependent variable: cumulative category price change, $\Delta_h P_{i,t}$ (percent)				
A. Baseline and goods versus services				
State variable Z	Baseline		Goods indicator	
Horizon	6 months (1)	18 months (2)	6 months (3)	18 months (4)
$\Delta c_{i,t}^{\mathrm{IO}}$	0.727***	1.194***	0.733***	1.190***
	(0.249)	(0.400)	(0.251)	(0.400)
$\Delta c_{i,t}^{\mathrm{IO}} \times Z$			-0.744**	0.516
			(0.310)	(0.629)
R^2	0.191	0.372	0.191	0.372
Observations	101,665	99,509	101,665	99,509
B. Frequency of price adjustment				
State variable Z	Producer prices		Consumer prices	
Horizon	6 months (5)	18 months (6)	6 months (7)	18 months (8)
$\Delta c_{i,t}^{\mathrm{IO}}$	0.402	0.600*	0.267	0.717***
	(0.257)	(0.353)	(0.196)	(0.218)
$\Delta c_{i,t}^{\mathrm{IO}} \times Z$	5.149**	7.844**	2.852***	1.383
	(2.482)	(3.847)	(1.044)	(1.477)
R^2	0.198	0.388	0.244	0.488
Observations	97,548	95,476	51,835	50,767
C. Macroeconomic conditions				
State variable Z	Unemployment gap		Core PCE inflation	
Horizon	6 months (9)	18 months (10)	6 months (11)	18 months (12)
$\Delta c_{i,t}^{\mathrm{IO}}$	0.744***	1.250***	0.923***	1.676***
	(0.262)	(0.403)	(0.285)	(0.490)
$\Delta c_{i,t}^{\mathrm{IO}} \times Z$	-0.015	-0.071***	0.294***	0.717***
	(0.025)	(0.025)	(0.098)	(0.222)
R^2	0.191	0.372	0.191	0.372
Observations	101,487	99,509	101,665	99,509
Category fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓

Note. The dependent variable is the cumulative category price change from $t-1$ to $t+h$. Each pair reports the same specification at 6 and 18 months. Columns (1) and (2) are the baseline. Other pairs add an interaction of the input-cost increase with the indicated state Z. Goods equals one for goods and zero for services. Producer-price adjustment frequency is from Pastén et al. (2020), and consumer-price adjustment frequency is from Montag and Villar (2023). Core inflation is lagged twelve-month core PCE inflation. Continuous states are demeaned over the eighteen-month sample. All specifications include category and month fixed effects. Parentheses report category-clustered standard errors. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5. Expected Fuel Prices and Pass-Through

	Gasoline		Diesel		Jet fuel		Composite	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expectation	12-month	Decline	12-month	Decline	12-month	Decline	12-month	Decline
$\Delta c_{i,t}^{\mathrm{IO}}$	0.857**	1.084***	0.922***	1.214***	0.903*	1.239**	0.867***	1.068***
	(0.362)	(0.364)	(0.332)	(0.378)	(0.505)	(0.614)	(0.329)	(0.380)
$\Delta c_{i,t}^{\mathrm{IO}} \times E_t^{\mathrm{fuel}}$	0.006	-0.507***	0.040***	-0.657***	0.006*	-0.759**	0.021**	-0.401**
	(0.009)	(0.175)	(0.012)	(0.192)	(0.004)	(0.362)	(0.009)	(0.196)
Category FE	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.328	0.328	0.344	0.344	0.341	0.341	0.344	0.344
Observations	87,194	87,194	81,983	81,983	47,310	47,310	81,983	81,983
First month	Jan 1983	Jan 1983	Nov 1985	Nov 1985	Jan 1983	Jan 1983	Nov 1985	Nov 1985

Note. The dependent variable is the eighteen-month cumulative category price change. $\Delta c_{i,t}^{\mathrm{IO}}$ is the refining input-cost increase. In odd-numbered columns, E_t^{fuel} is the expected twelve-month log price change in percentage points, demeaned over the sample. In even-numbered columns it is an indicator for an expected twelve-month decline. The composite equally weights gasoline and diesel and requires both forecasts. Each pair uses all available observations for its own measure through February 2025. Jet-fuel coverage is intermittent, with early observations in 1983–1984 and regular coverage from August 2004. Gasoline and diesel use retail forecasts and jet fuel uses the archive jet-product forecasts. Category and month fixed effects are included. The original release calendar is retained and missing product forecasts are not filled across releases. Parentheses report category-clustered standard errors. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6. Household Inflation Expectations and Pass-Through

	6 months		18 months	
	(1)	(2)	(3)	(4)
Michigan horizon	1 year	5 to 10 years	1 year	5 to 10 years
$\Delta c^{\mathrm{IO}}_{i,t}$	0.980***	0.756***	1.750***	1.178***
	(0.297)	(0.219)	(0.524)	(0.352)
$\Delta c^{\mathrm{IO}}_{i,t} \times E^{\pi}_{t}$	0.657***	0.360**	1.470***	0.896***
	(0.168)	(0.167)	(0.424)	(0.285)
Category fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
R^2	0.189	0.182	0.369	0.342
Observations	98,954	82,364	96,798	80,216

Note. The dependent variable is the cumulative category price change from $t-1$ to $t+j$. E^{π}_{t} is the Michigan survey median expected inflation rate over the next year or over the next five to ten years, in percentage points. Each expectation measure is demeaned over its estimation sample. The specification is column (3) of Table 3, augmented by the expectations interaction. Only months with a reported survey reading are used. Longer-run observations are intermittent before regular monthly coverage, so the two measures have different samples. Parentheses report category-clustered standard errors. Sources are the University of Michigan Surveys of Consumers and FRED. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7. First Stage for the IO-Implied Refining Cost Increase

	(1)	(2)
Response sample	6 months	18 months
$\mathrm{IOShare}_i n_t U_{t-1}/\bar{U}$	5.144***	5.164***
	(0.512)	(0.514)
$\mathrm{IOShare}_i n_{t-1} U_{t-2}/\bar{U}$	4.001***	3.989***
	(0.484)	(0.490)
Category fixed effects	✓	✓
Month fixed effects	✓	✓
Joint F	107.3	105.9
Observations	101,309	99,509

Note. The dependent variable is $\Delta c^{\mathrm{IO}}_{i,t}$. Each column uses the observations in the corresponding horizon of Table 8. The instruments are defined in the text. Parentheses report time-score Newey–West standard errors with twelve lags. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8. Instrumental-Variable Estimates of Pass-Through

	(1)	(2)	(3)	(4)
Horizon	6 months	6 months	18 months	18 months
Estimator	OLS	IV	OLS	IV
$\Delta c_{i,t}^{\mathrm{IO}}$	0.727^{***}	0.835^{**}	1.194^{***}	1.448^{***}
	(0.248)	(0.352)	(0.399)	(0.434)
Category fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
R^2	0.192	0.192	0.372	0.372
Observations	101,309	101,309	99,509	99,509
First-stage joint F		107.3		105.9

Note. The dependent variable is $\Delta_j P_{i,t}$. OLS and IV use identical observations at each horizon. The two instruments are refining exposure multiplied by the oil-supply news shock and lagged refining capacity utilization, dated t and $t-1$. Both stages include category and month fixed effects. Standard errors in parentheses are clustered by category. The first-stage joint F uses the fixed-effect-residualized panel and a time-score Newey–West covariance with twelve lags. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9. Price Change since January 2026 on Refining Exposure

	(1)	(2)	(3)	(4)
IOShare_i	0.756***	0.759***	0.778***	0.816***
	(0.243)	(0.246)	(0.244)	(0.240)
Goods_i				0.662
				(2.285)
$\text{IOShare}_i \times \text{Goods}_i$				-1.431
				(1.227)
FPA_i			-0.217	
			(1.473)	
Average 8-month change, 2000–2019	-0.449	-0.454	-0.486	-0.524
	(0.349)	(0.356)	(0.371)	(0.394)
Inflation, 2024	0.387***	0.379***	0.421**	0.309***
	(0.144)	(0.147)	(0.177)	(0.110)
Inflation, 2025		0.019	0.007	0.062
		(0.119)	(0.122)	(0.135)
Constant	0.717	0.687	0.618	1.045*
	(0.555)	(0.567)	(0.697)	(0.539)
Expenditure weights	✓	✓	✓	✓
R^2	0.211	0.211	0.211	0.238
Observations	177	177	171	177

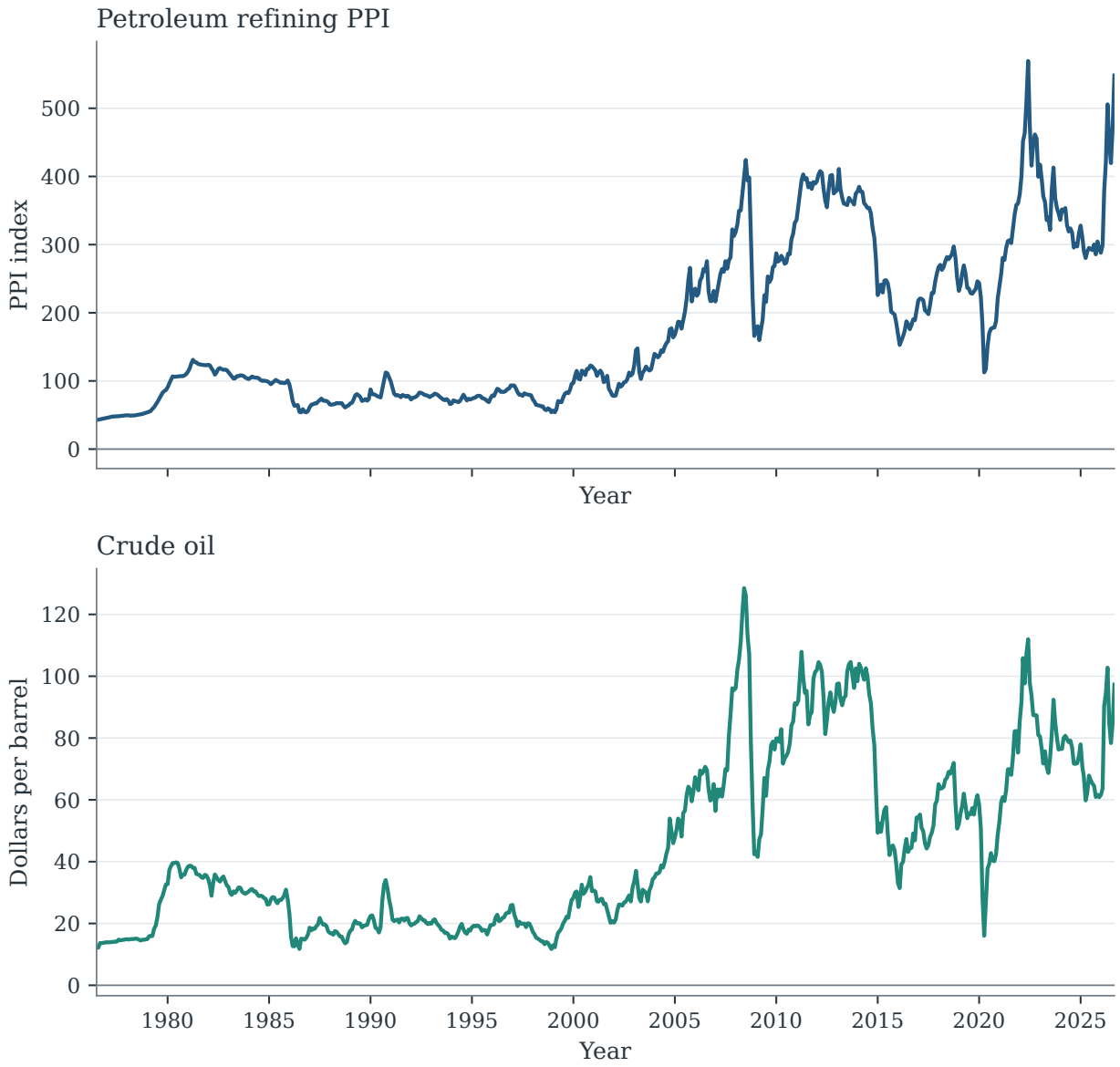
Note. One observation per core PCE category (177). The dependent variable is the category's percent price change from January to September 2026. IOShare_i is refining exposure in percent of purchaser value. Controls include the average eight-month price change over 2000–2019 and December-to-December inflation in 2024 (column 1) and in 2024 and 2025 (columns 2 to 4). Column (3) adds producer-price adjustment frequency on the 171 categories with an estimate. Column (4) adds a goods indicator and its interaction with exposure. All columns use the existing purchaser-value weights. Column (2) is the specification behind Figure 21. The historical panel responses imply a slope of 0.39 at this horizon. The cumulative rise in refining PPI from January to September is 90 percent. Normalizing the exposure coefficients by this cumulative rise gives 0.84 in column (2) and 0.86 in column (3), against 0.43 for the historical-response benchmark. PCE data are from the October 29, 2026 release. Historical pass-through coefficients are unchanged. Heteroskedasticity-robust standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10. Real Quantity Responses to Refining Costs

Horizon	(1) 6 months	(2) 12 months	(3) 18 months	(4) 24 months
$\Delta c_{i,t}^{\mathrm{IO}}$	1.784*	2.596	2.541	3.303
	(1.076)	(2.377)	(4.143)	(5.073)
Category fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
R^2	0.068	0.033	0.019	0.019
Observations	100,461	99,397	98,329	97,261

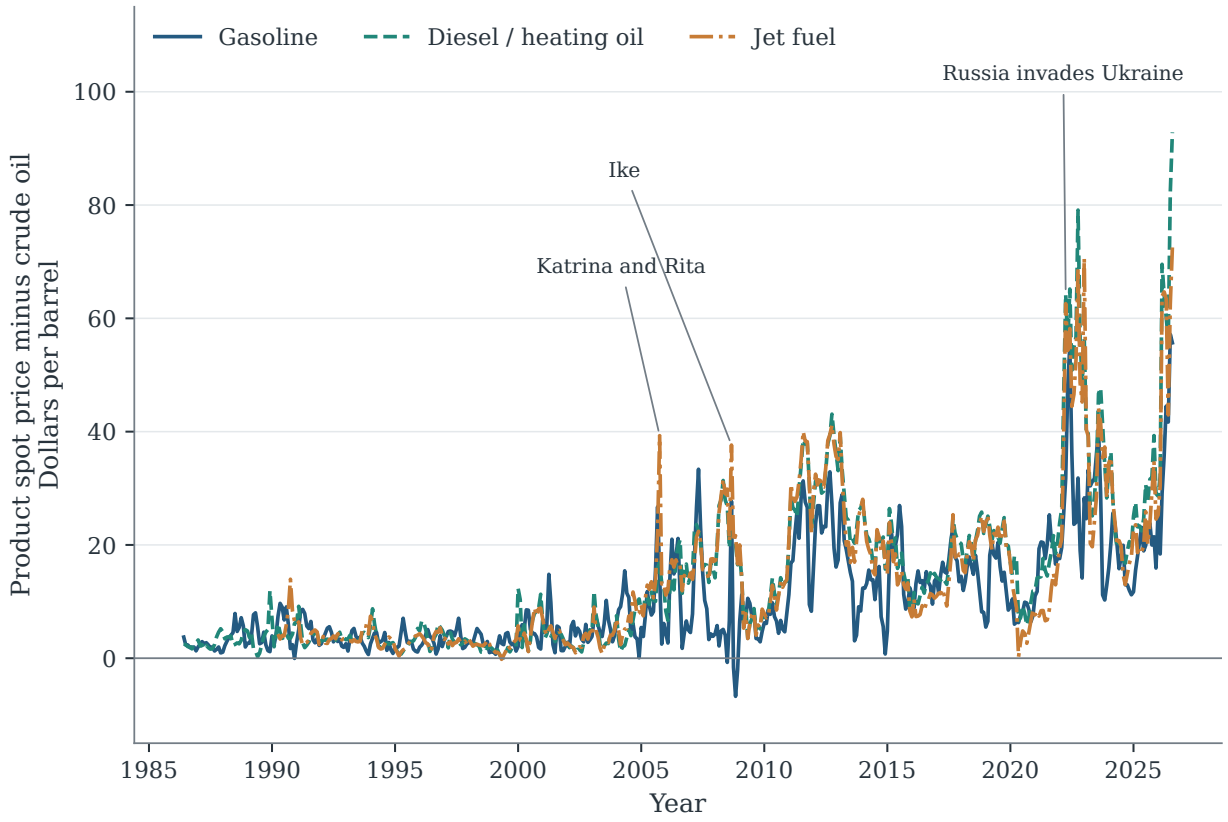
Note. The dependent variable is the cumulative change in the BEA real PCE quantity index from $t-1$ to $t+j$, in percent. The regressor is the refining input-cost increase. All columns use the full available sample, including 2020 to 2022, and the same specification as the baseline price regression. Each horizon uses observations with both price and quantity data. Standard errors in parentheses are clustered by category. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 1. Refining and Crude Oil Prices



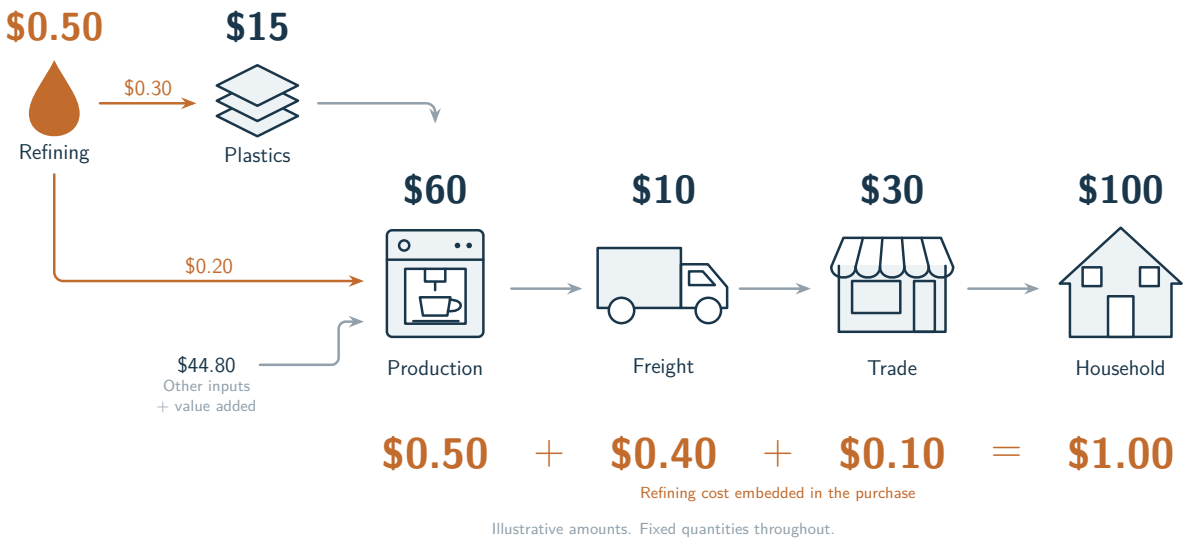
Note. The top panel shows the petroleum-refining producer price index. The bottom panel shows the crude-oil price series in dollars per barrel over the consumer-price panel period. Both series extend through September 2026. Sources are BLS and FRED.

Figure 2. Crack Spreads, 1986 to 2026



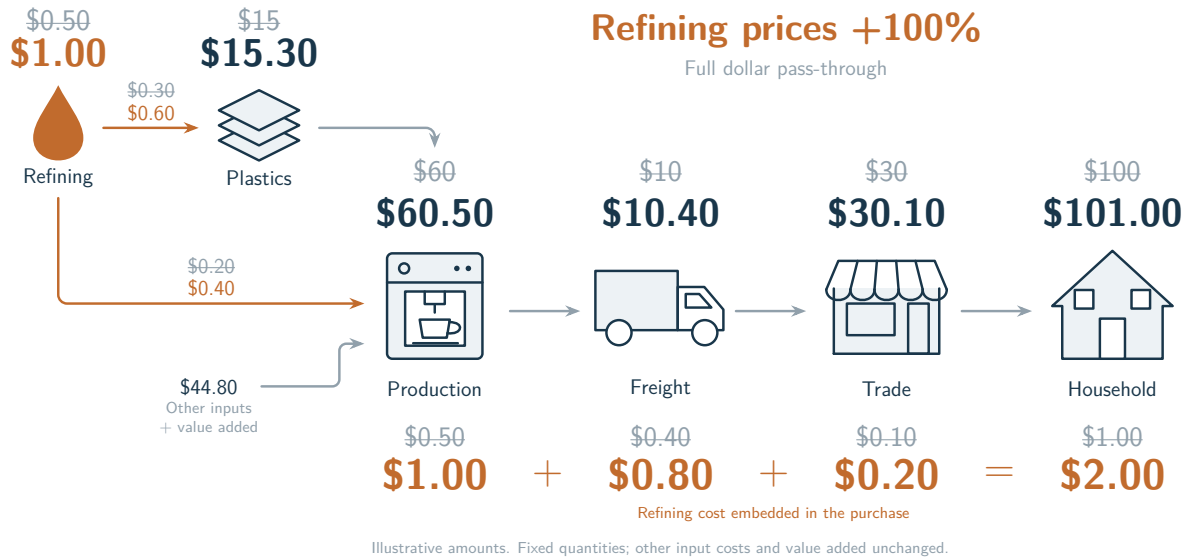
Note. Product spot price minus crude oil, dollars per barrel, monthly averages of daily data, 1986 through August 2026. Gasoline and jet fuel are Gulf Coast spot throughout. The distillate series uses New York Harbor heating oil through May 2006 and Gulf Coast diesel from June 2006.
Source. U.S. Energy Information Administration. Via FRED.

Figure 3. From Input-Output Linkages to a Consumer Dollar, A Stylized Example



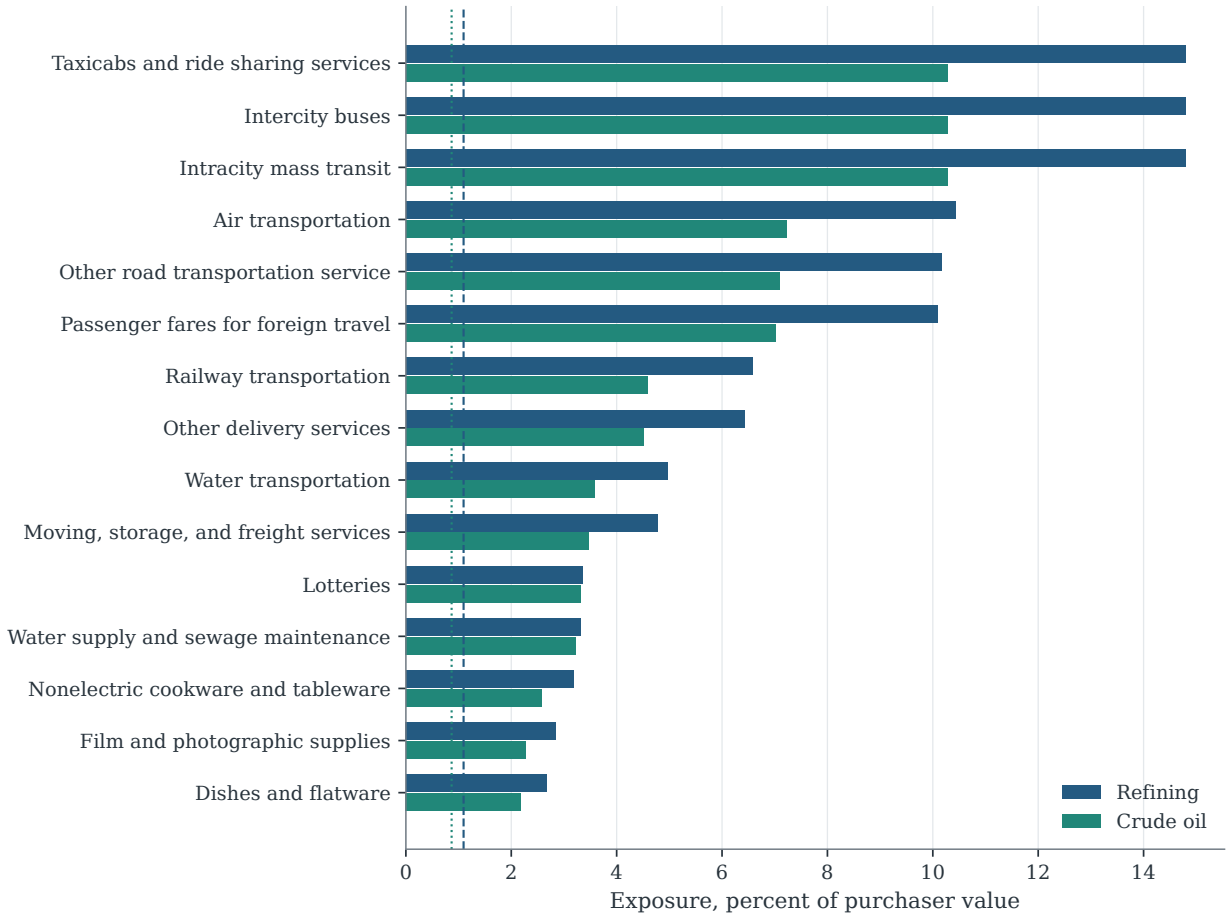
Note. In a stylized coffee machine's supply chain, refining output enters production both directly and indirectly, through plastics, and the resulting producer value is marked up through freight and trade margins to the $100 purchaser price. Of the $100 purchaser price, $1.00, or 1 cent of exposure per purchaser dollar, ultimately pays for refining output across all three stages (production, freight, trade). Illustrative amounts, not estimated from data.

Figure 4. The Full-Pass-Through Benchmark under a Refining Shock, A Stylized Example



Note. The same stylized coffee machine supply chain as Figure 3, under the Step 1 benchmark of a 100 percent refining-price shock with fixed quantities and full dollar pass-through at every stage, all other nominal input costs and value added held unchanged. The $1.00 of embedded refining cost rises to $2.00, and the purchaser price rises by exactly that dollar amount, from $100 to $101. Illustrative amounts, not estimated from data.

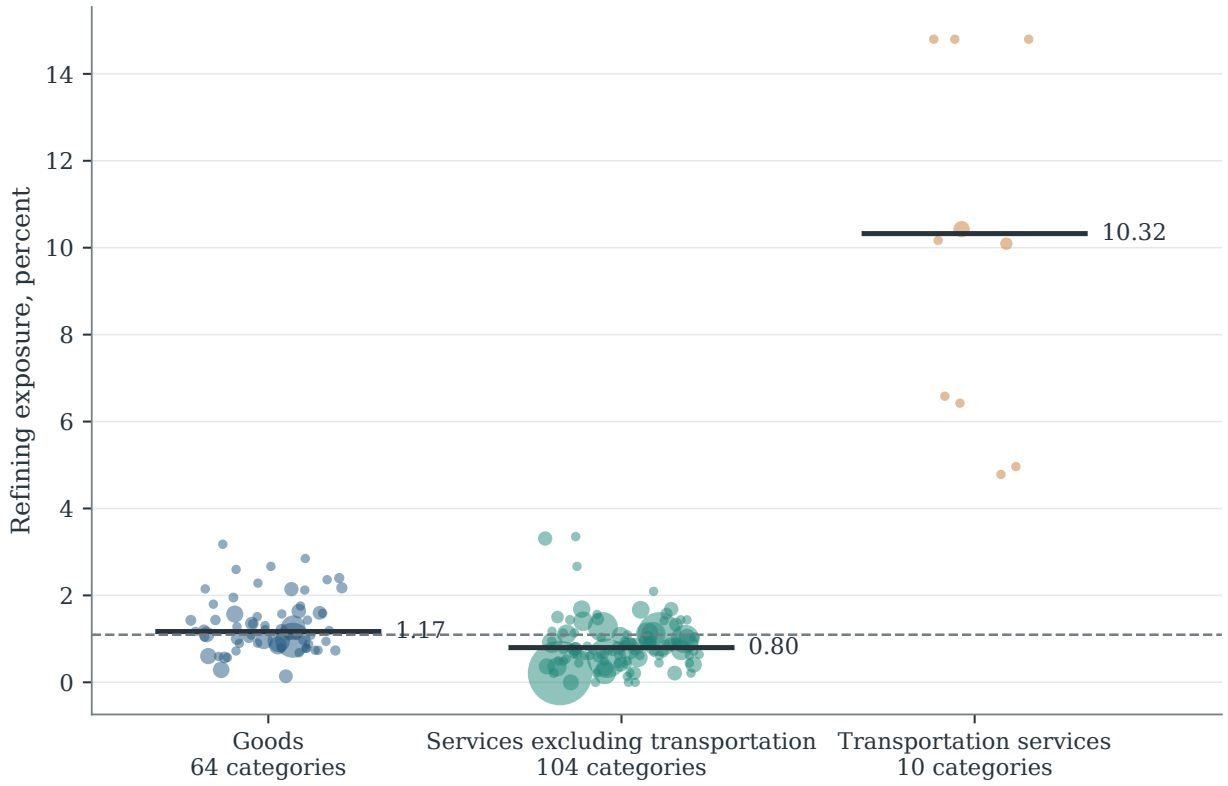
Figure 5. Most Exposed Core PCE Categories, Refining and Crude Oil



Note. Top 15 of 179 core (excluding food and energy) PCE categories, ranked by refining-channel IO share, with the oil-channel IO share plotted alongside for the same categories. The IO share is the purchaser-value-weighted average Total Requirements coefficient, including direct and indirect requirements through the full supply chain. Dashed vertical lines mark the expenditure-weighted average IO share across the core basket (1.10 percent for refining and 0.87 percent for crude oil).

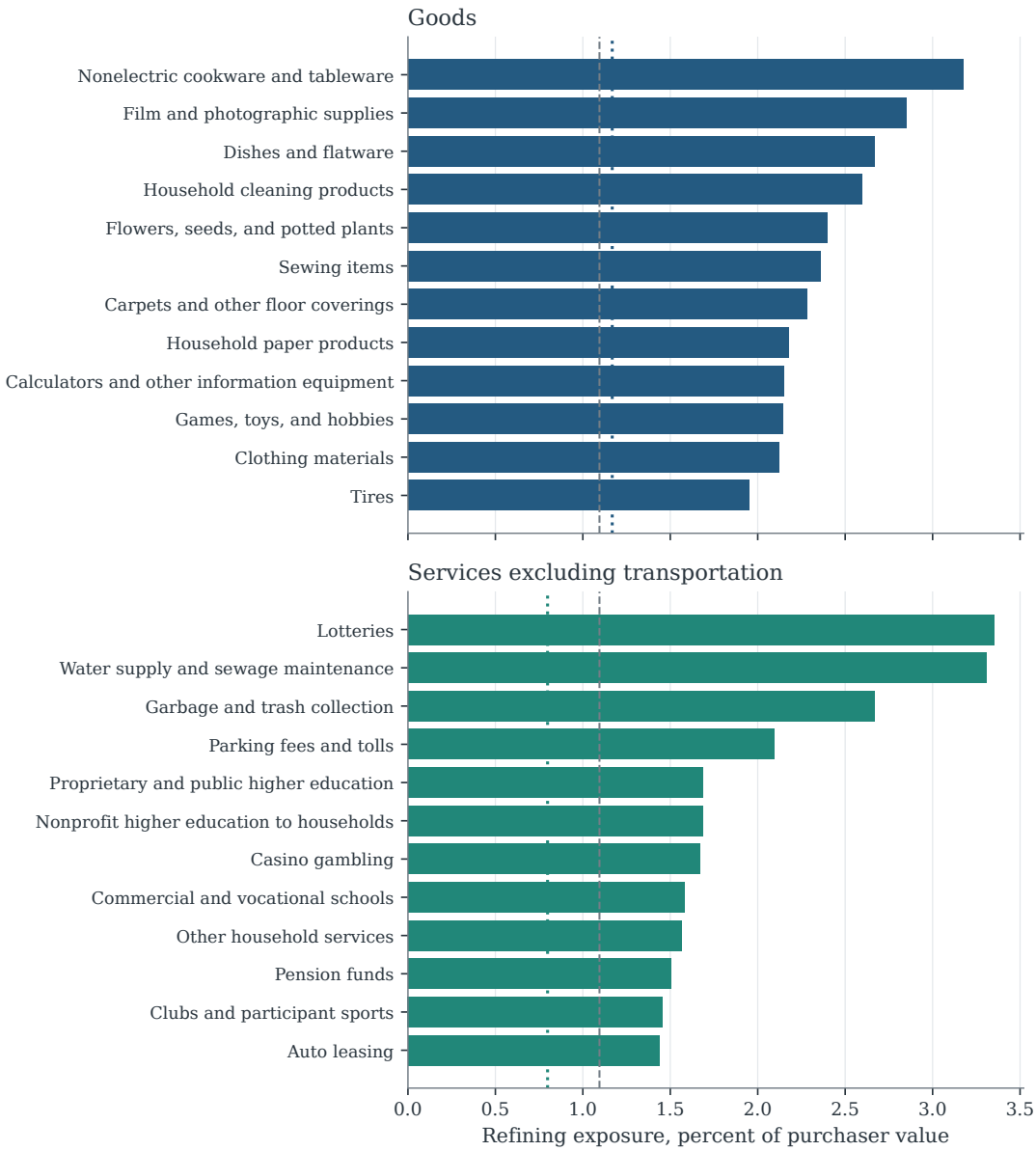
Source. Bureau of Economic Analysis, 2017 Industry-by-Commodity Total Requirements table and PCE Bridge. Author's calculations.

Figure 6. Distribution of Refining Exposure by Group



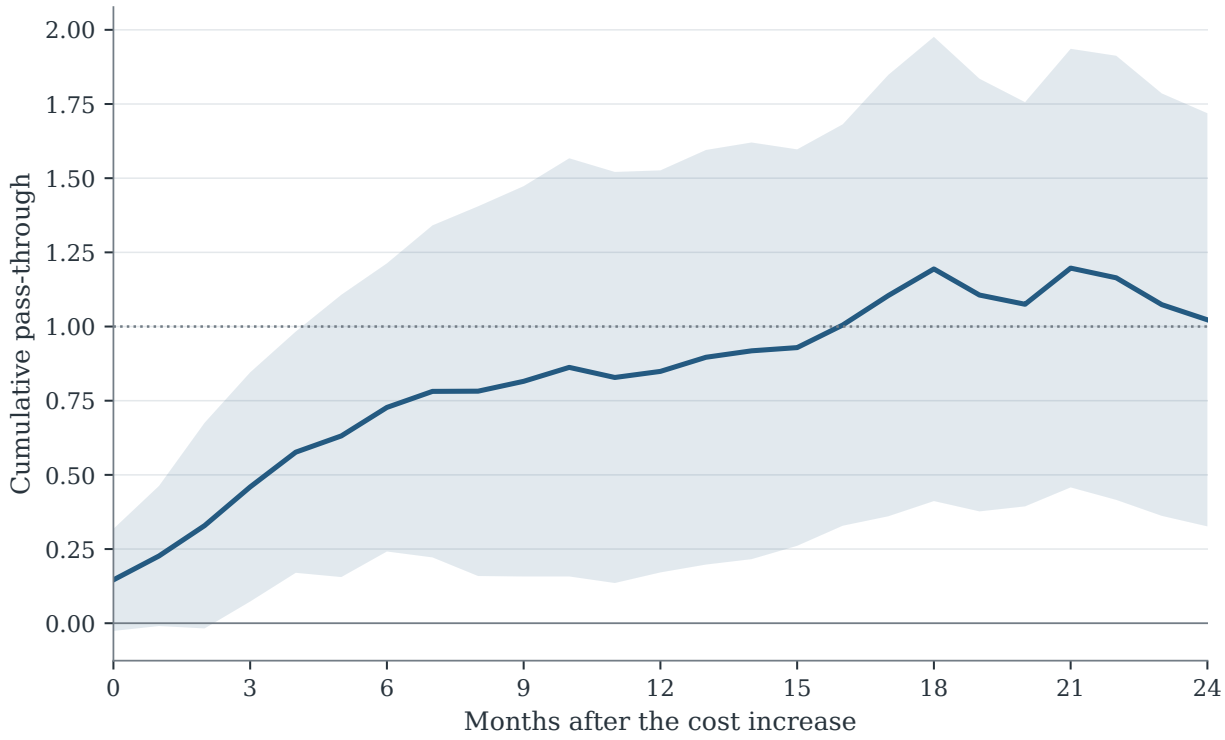
Note. Refining IO share of every core category, by group. Dot size is the category's purchaser value. The solid line marks the expenditure-weighted group average. The dashed line marks the core average of 1.10 percent.

Figure 7. Most Exposed Goods and Services Excluding Transportation



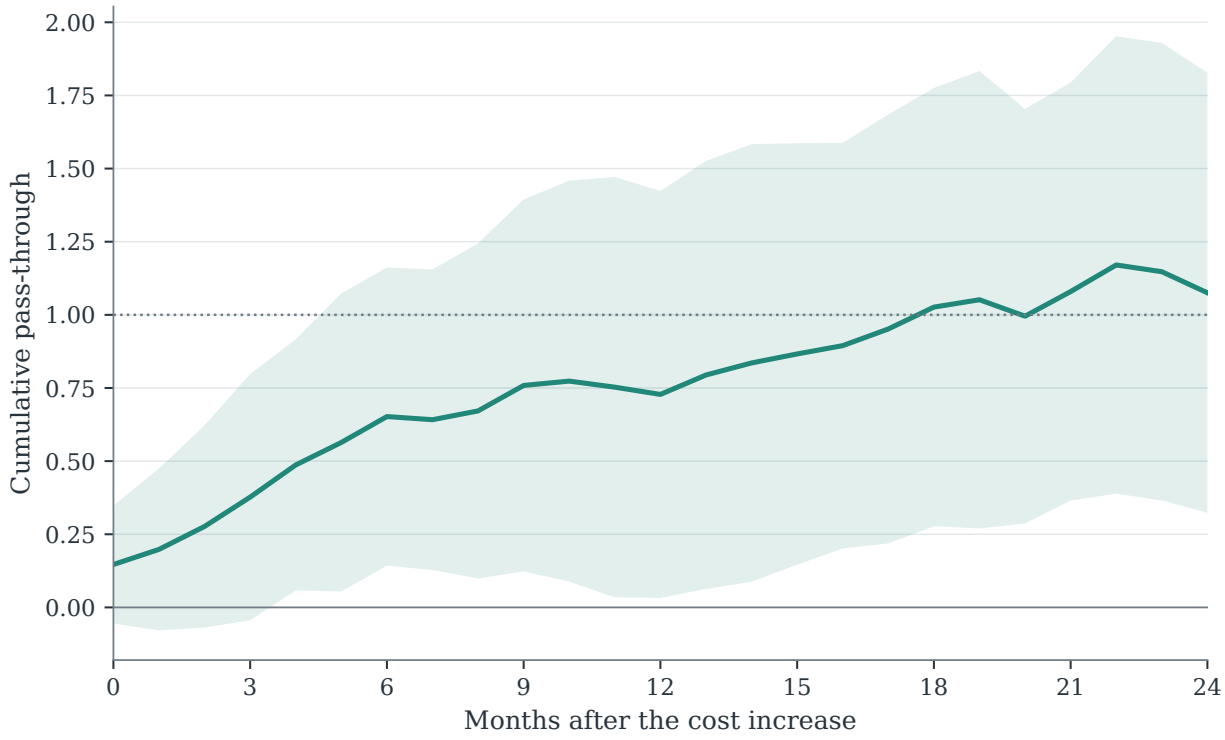
Note. The 12 most exposed core goods (top) and core services excluding the ten transportation services (bottom), refining IO share in percent of purchaser value, on a common axis. Dashed line, core average of 1.10 percent. Dotted line, group average, weighted by purchaser value.

Figure 8. Estimated Pass-Through, Petroleum Refining



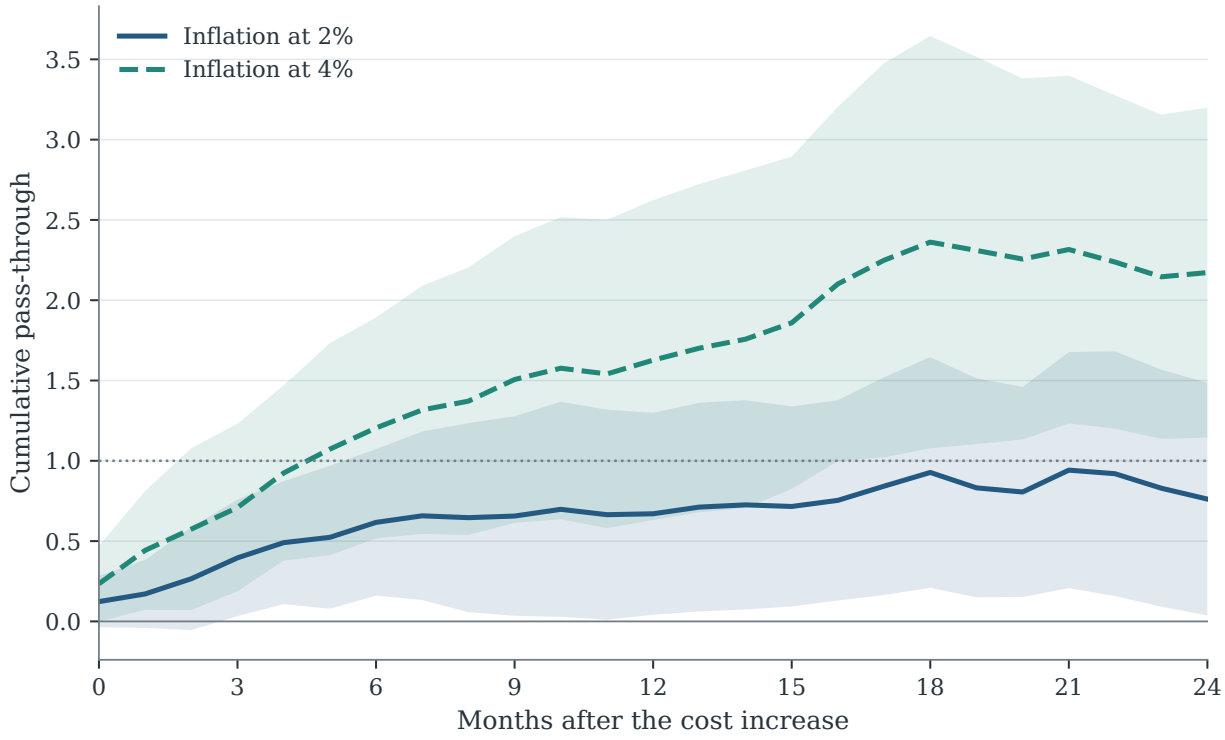
Note. Panel local projection of Equation 2, estimated by horizon $j = 0, \ldots, 24$ months with category and month fixed effects. Refining PPI shock, July 1976 through August 2026, N =98,429–102,749 across horizons. Standard errors are clustered by category. Shaded bands are 95 percent confidence intervals. The dotted line at one is full pass-through of the input-cost increase. *Source.* Bureau of Economic Analysis, Bureau of Labor Statistics, and author's calculations.

Figure 9. Estimated Pass-Through of Crude Oil Costs



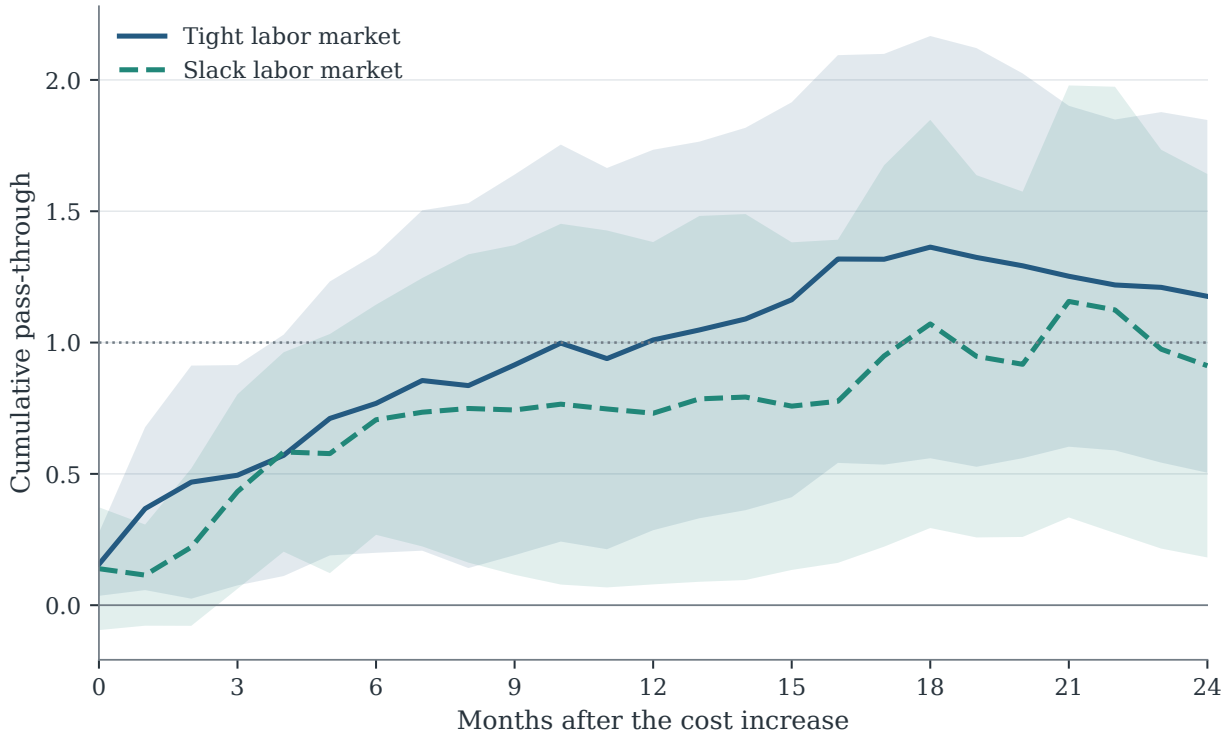
Note. Panel local projections using crude-oil price series and oil and gas extraction exposure, with category and month fixed effects. The available estimation sample begins in July 1976. The shaded band is a 95 percent confidence interval using category-clustered standard errors. The line at one marks full pass-through.

Figure 10. Pass-Through at High and Low Inflation



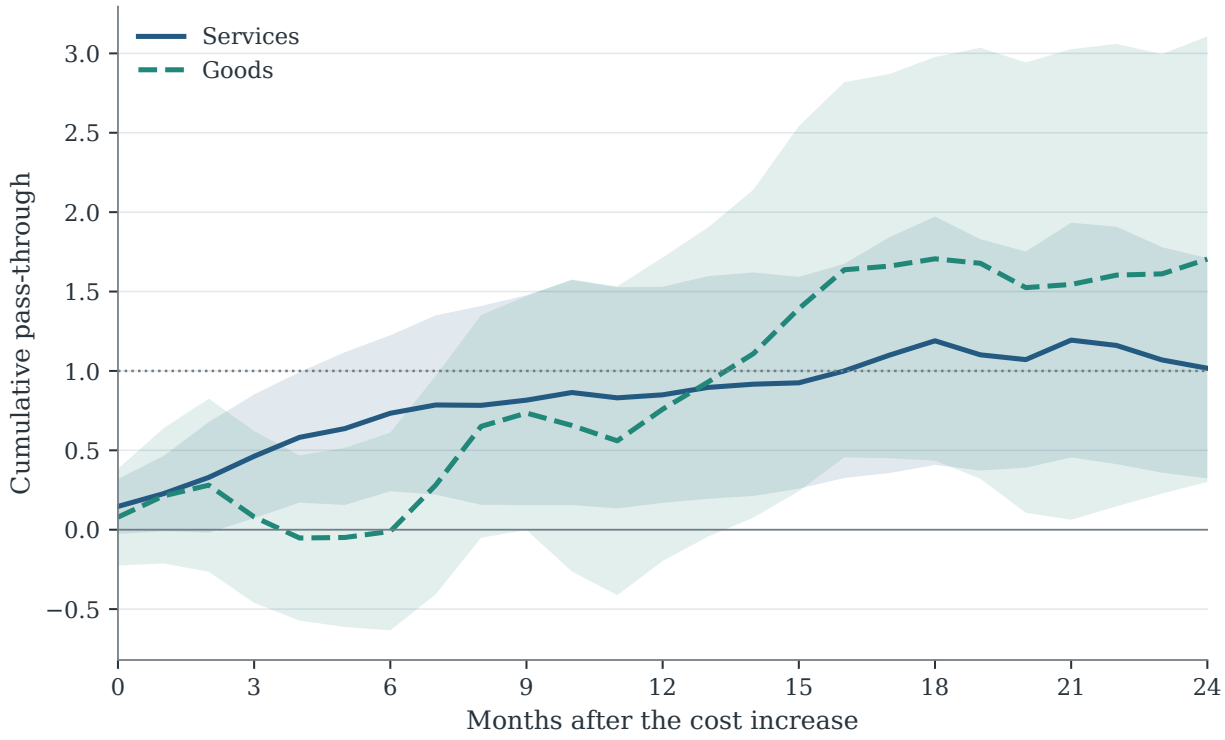
Note. Cumulative pass-through by horizon, refining only, category and month fixed effects, category-clustered standard errors, and 95 percent bands. Pass-through at 4 and 2 percent twelve-month core PCE inflation through the month before the change, from column (9) of Table 3, $\beta_j + \delta_j(\pi - \bar{\pi})$. Bands use the joint covariance of the two coefficients. The dotted line at one is full pass-through.

Figure 11. Pass-Through in Tight and Slack Labor Markets



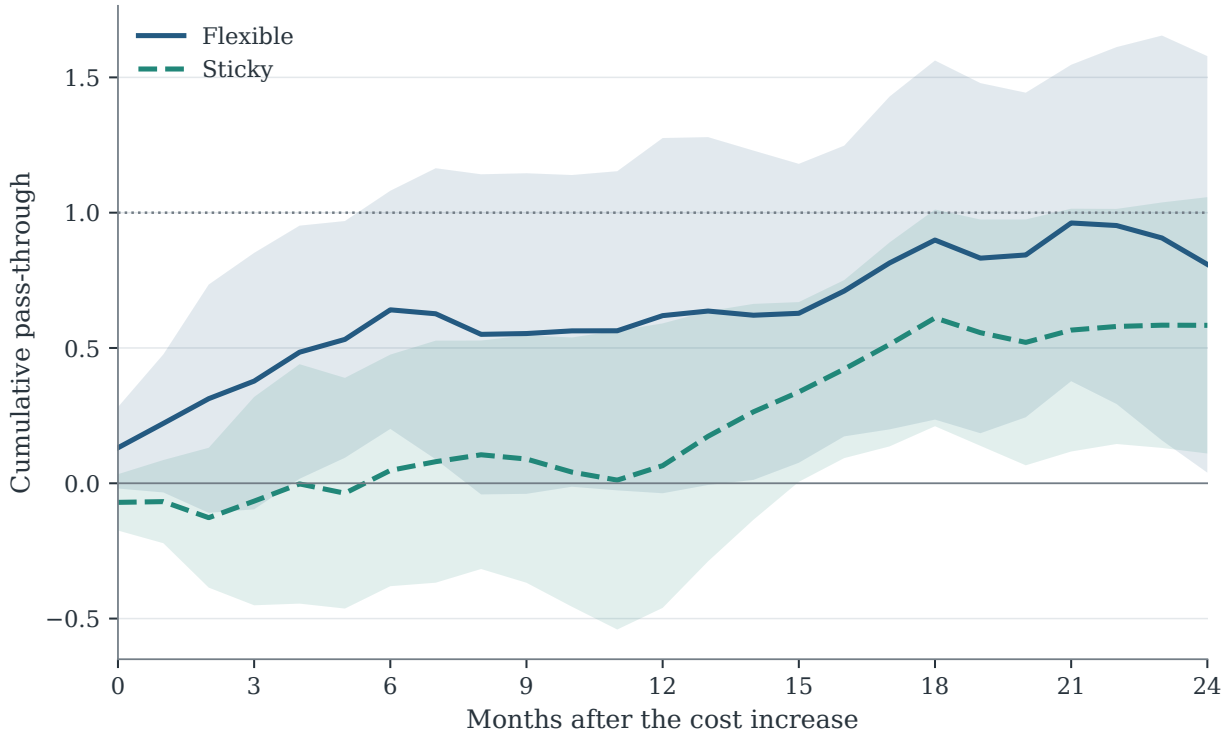
Note. Cumulative pass-through by horizon, refining only, category and month fixed effects, category-clustered standard errors, and 95 percent bands. Unemployment gap at its 10th percentile (−0.8 percentage point, tight) and 90th percentile (+3.3 percentage points, slack), from column (4) of Table 3. Bands use the joint covariance of the main and interaction coefficients. The dotted line at one is full pass-through.

Figure 12. Pass-Through for Goods and Services



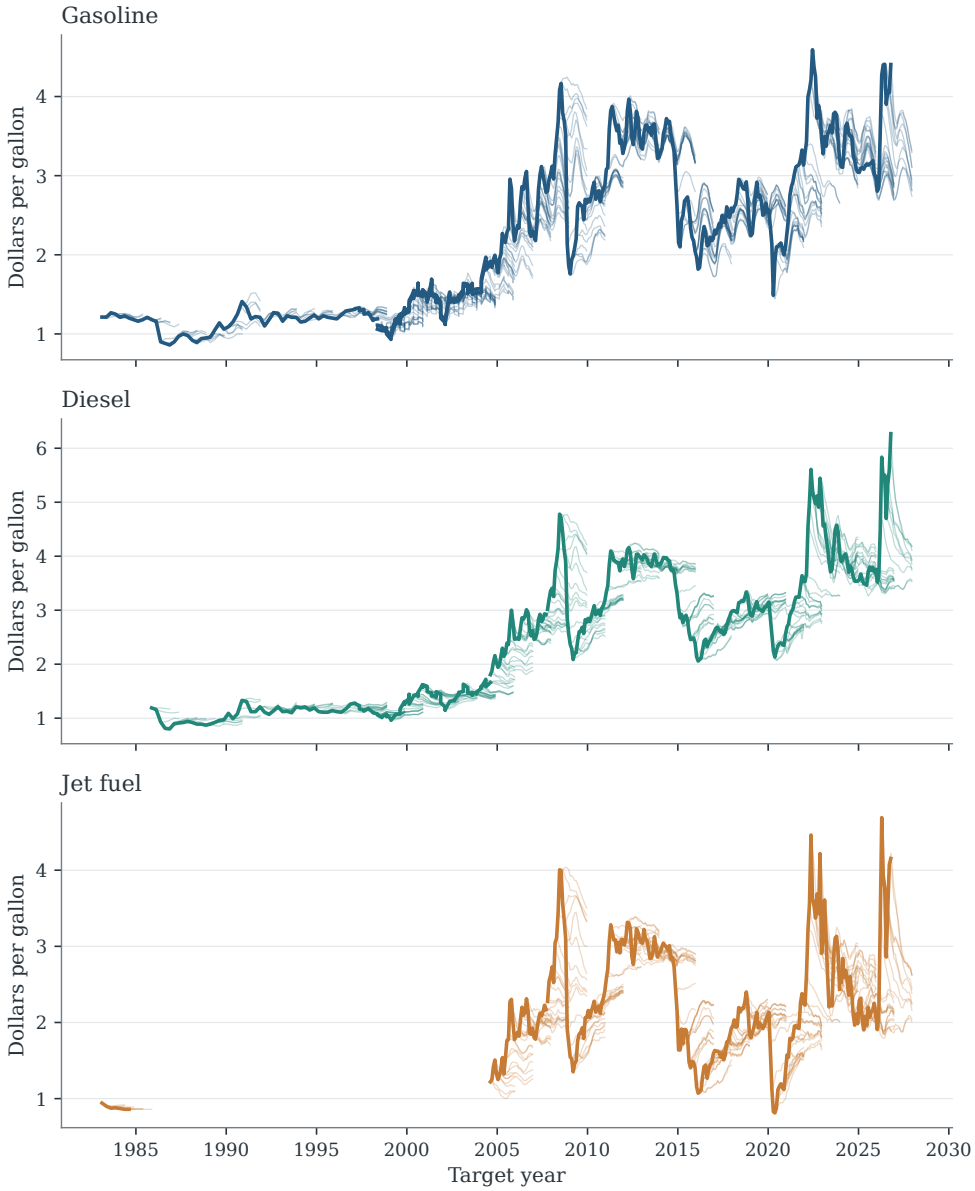
Note. Implied services and goods responses from the pooled interaction in Equation 3. The services path is β_j and the goods path is $\beta_j + \delta_j$. Category and month fixed effects are common to both paths. The shaded bands are 95 percent intervals calculated using the joint category-clustered covariance matrix. The dotted horizontal line marks full pass-through.

Figure 13. Pass-Through and Consumer Price Flexibility



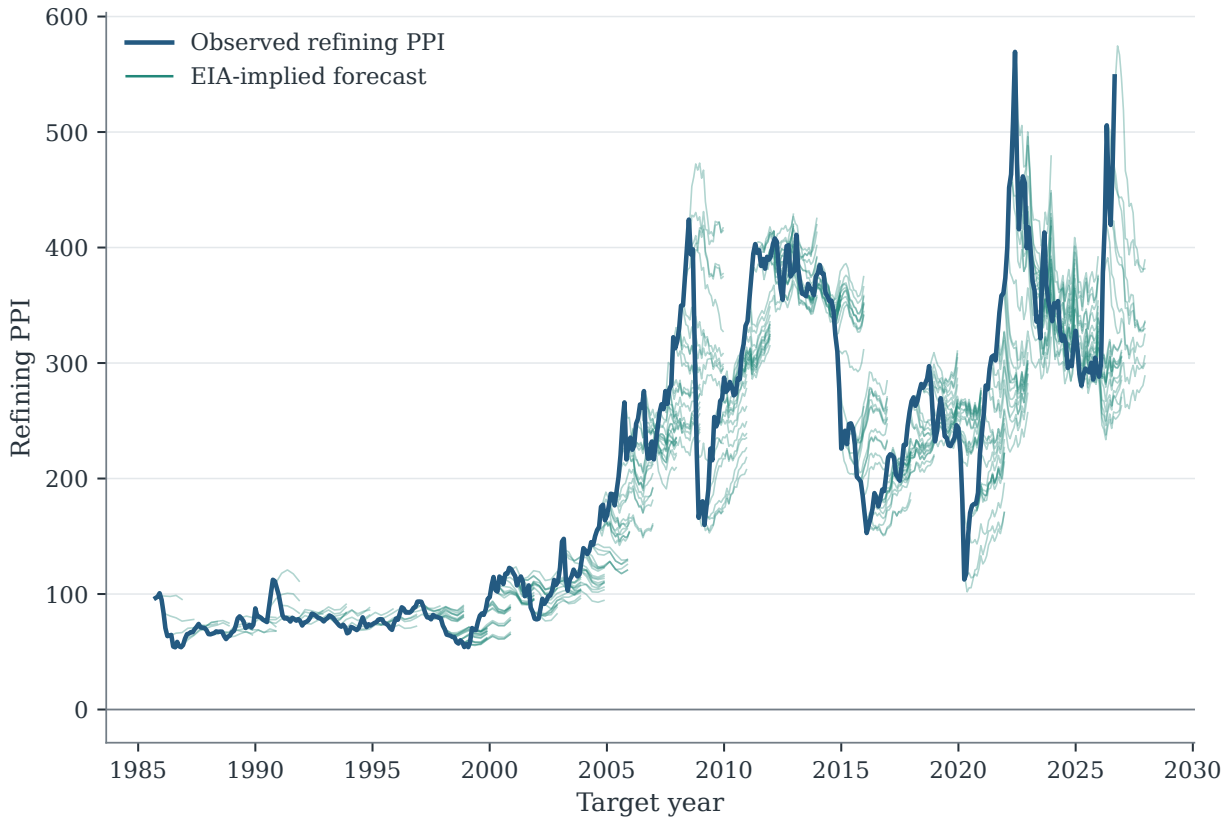
Note. Implied pass-through at the 90th and 10th percentiles of consumer-price adjustment frequency from Montag and Villar (2023), 25.7 and 4.9 percent of months, respectively. The percentiles are calculated across the 89 categories in the eighteen-month estimation sample and held fixed across horizons. The specification is the consumer-frequency interaction reported in columns (7) and (8) of Table 4, estimated at each horizon. The bands use the joint category-clustered covariance of the main and interaction coefficients. The horizontal line at one marks full pass-through.

Figure 14. EIA Forecast Paths for Gasoline, Diesel, and Jet Fuel



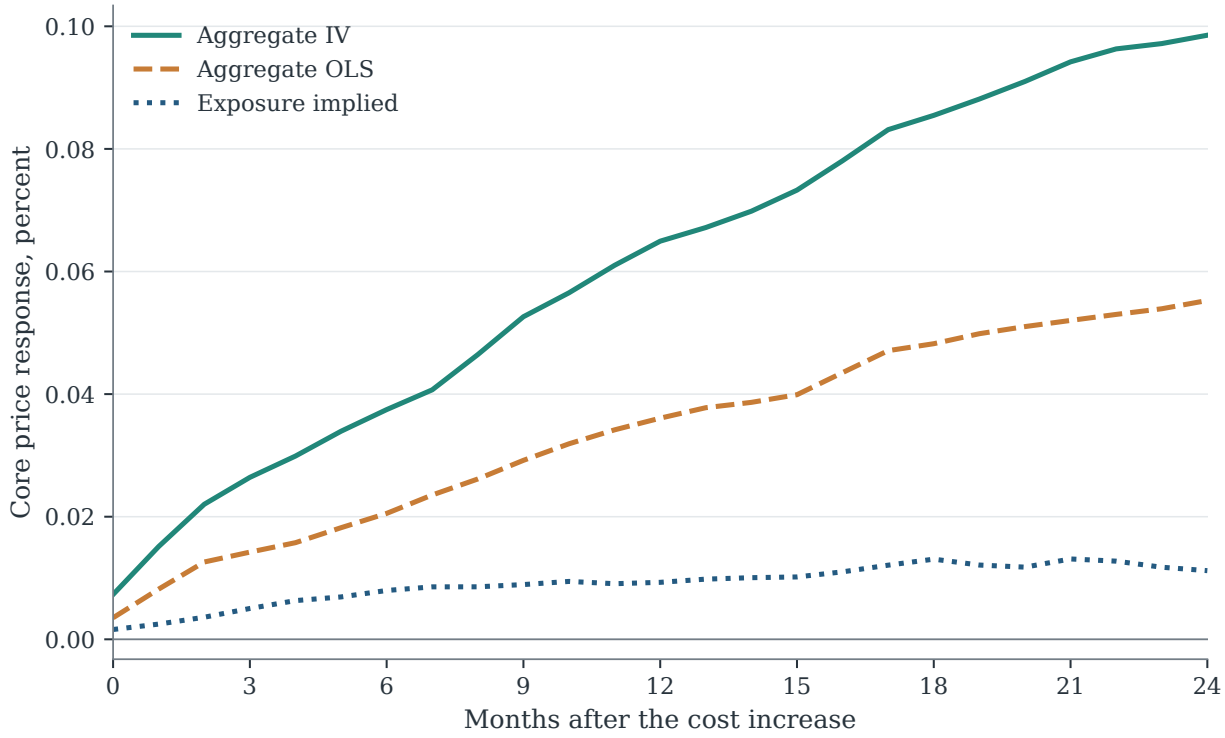
Note. Each thin colored line records one forecast vintage in nominal dollars per gallon. Heavier lines join the EIA estimates for the release period. Gasoline and diesel follow the original retail series. Jet fuel follows the archived jet-product series. Gaps indicate missing series coverage.

Figure 15. EIA-Implied Forecast



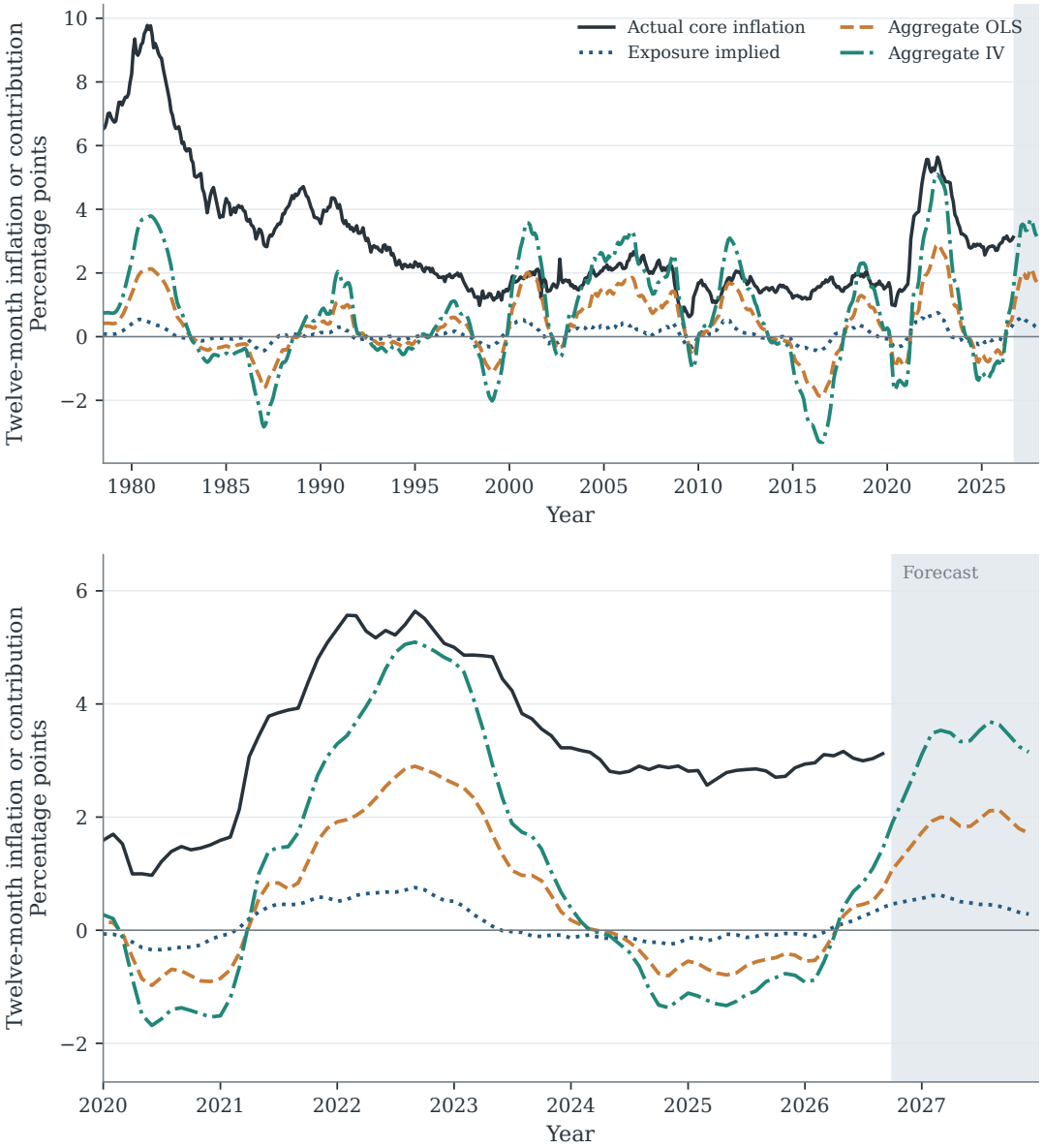
Note. Thin paths show the EIA-implied refining-PPI forecast from each release, beginning in the fourth quarter of 1985, constructed as described in the data section. The underlying composite gives gasoline and diesel equal weights. The thick line is observed refining PPI. These are constructed paths, not published EIA PPI forecasts.

Figure 16. Core PCE Responses Under Aggregate IV, Aggregate OLS, and Category Exposure



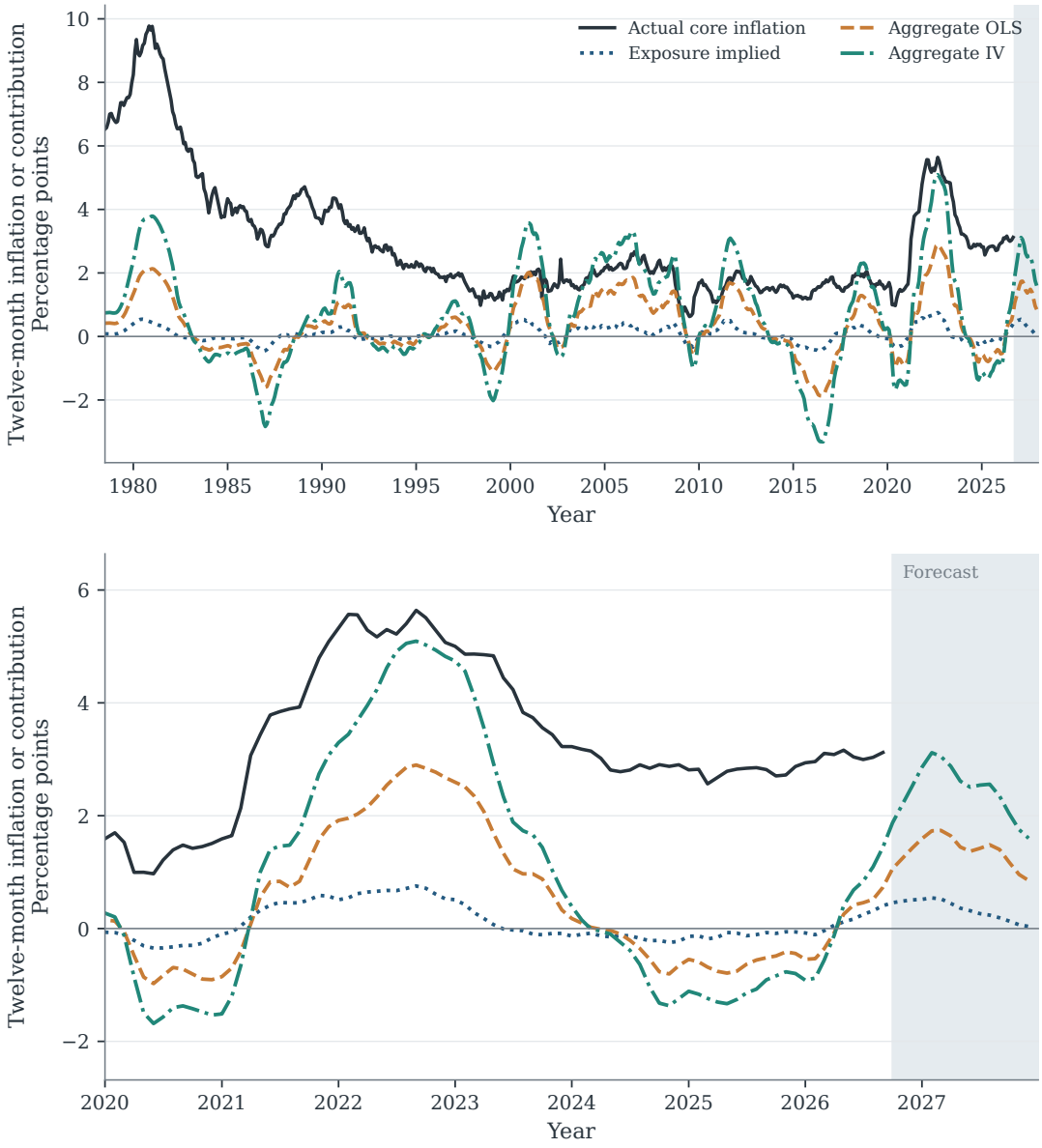
Note. Core-price response to a 1 percent monthly refining-PPI increase. Aggregate OLS and IV use time-series local projections. The aggregate IV instruments are the oil-supply news shock and its lag. The exposure-implied response is the baseline panel coefficient multiplied by average core refining exposure. This figure compares point-estimate paths.

Figure 17. Core Inflation Contributions with Refining Prices Held Fixed



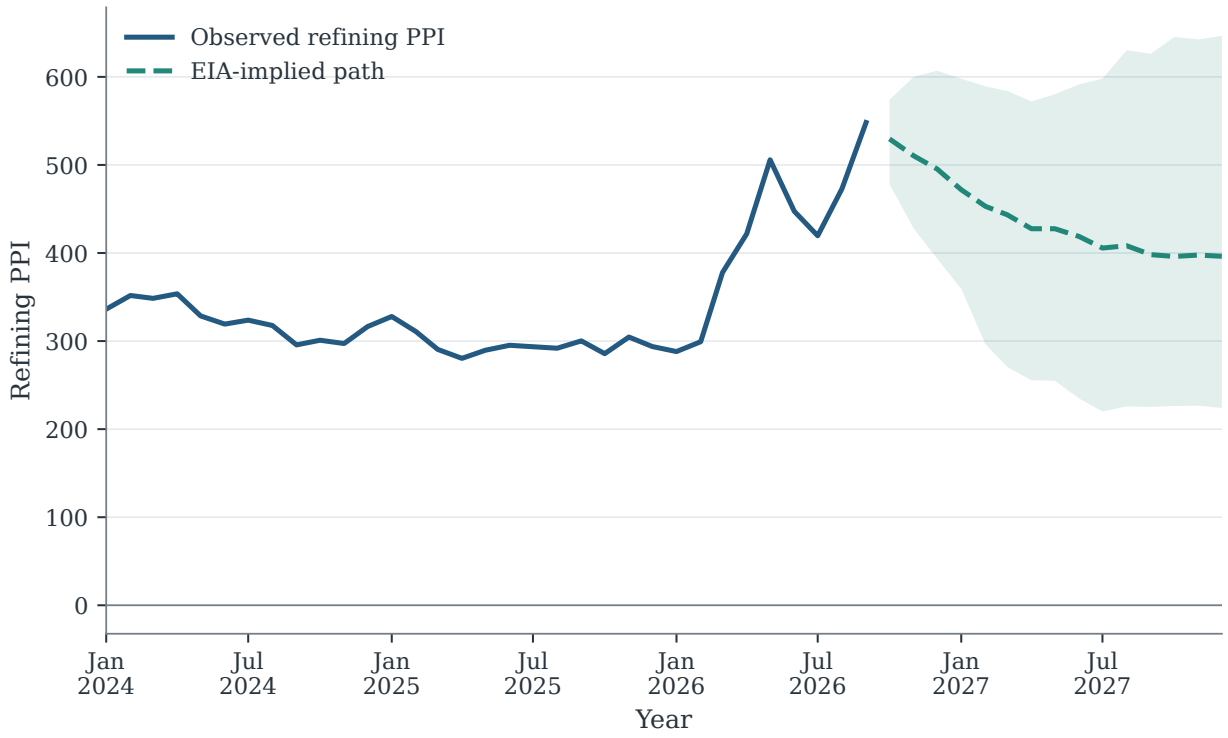
Note. Historical monthly refining-PPI changes are passed through the estimated exposure, aggregate OLS, and aggregate IV responses. Actual twelve-month core PCE inflation is included for comparison. Each line is the difference between implied price-level contributions twelve months apart. Responses beyond month 24 are held at their month-24 level. These are response-based accounting contributions, not a structural-shock decomposition. The lower panel enlarges the recent period. The forecast region begins in October 2026. Refining prices stay at their September level through December 2027. Shading marks dates and is not a confidence interval.

Figure 18. Core Inflation Contributions along the EIA Price Path



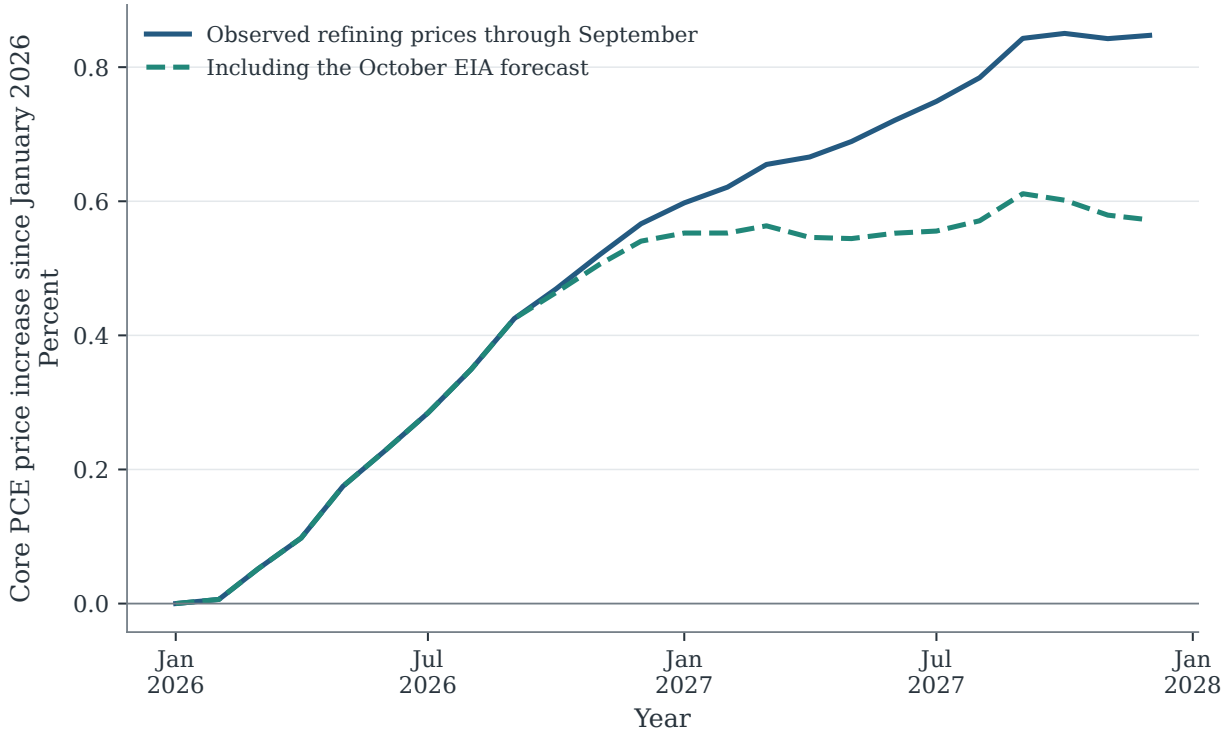
Note. The three response paths and historical inputs are the same as in Figure 17. From October 2026 onward, refining prices follow the path implied by the October STEO through Equation 6. The lower panel enlarges the recent period. The shaded region marks the forecast dates. It is not a confidence interval. Actual core PCE inflation is shown through September 2026 using the October 29 release.

Figure 19. Refining PPI and the EIA-Implied Path



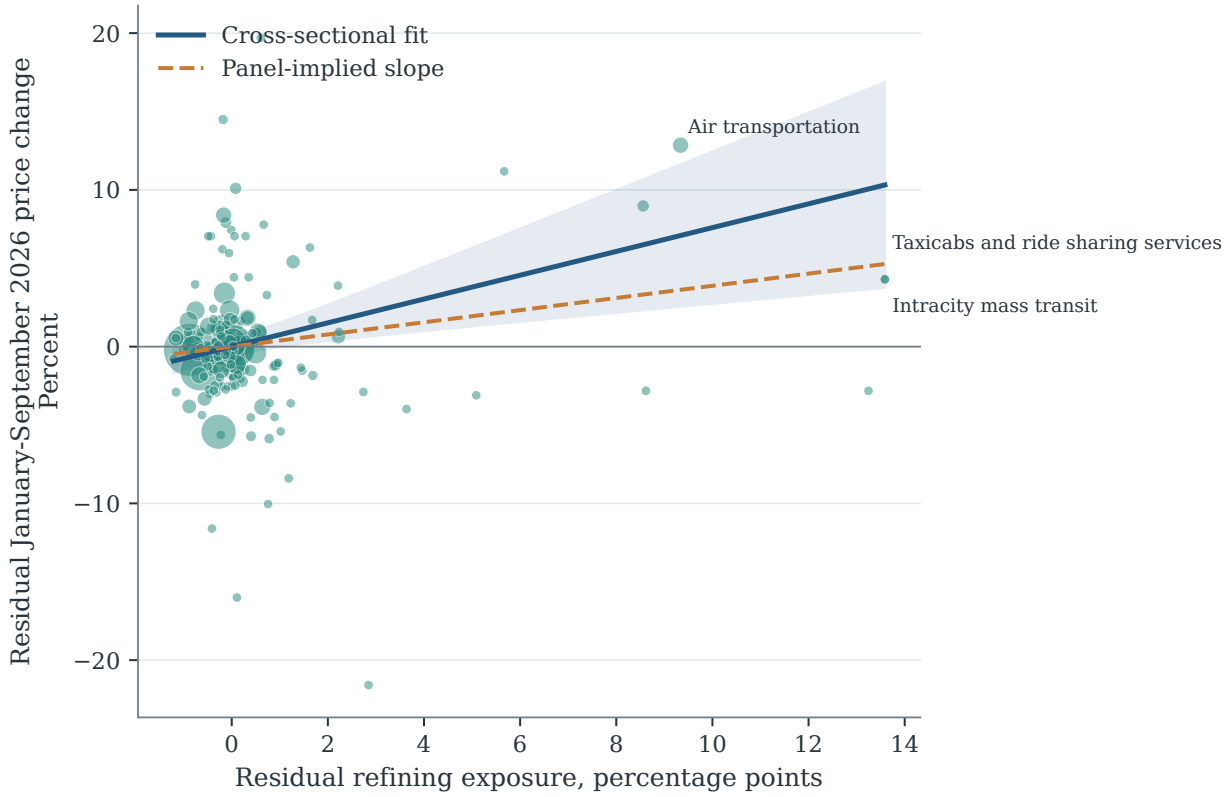
Note. Refining PPI, observed through September 2026 and projected from October 2026 through December 2027 using the October STEO and Equation 6. The shaded region is the simulated 95 percent interval, incorporating bridge-coefficient uncertainty, serially dependent bridge residuals, and historical joint fuel-forecast errors.

Figure 20. Core-Price Path Using Observed and Forecast Refining Prices



Note. Predicted cumulative core PCE price change relative to January 2026. One path holds refining prices fixed after September. The other incorporates the October 2026 STEO fuel forecasts through December 2027. Both use the same baseline pass-through coefficients and average IO exposure. The figure shows point estimates for the two paths.

Figure 21. Excess Inflation against Refining Exposure, January to September 2026



Note. Each dot is one category, sized by expenditure weight. The vertical axis shows the residual January-to-September 2026 price change after removing the category's average eight-month change over 2000–2019 and its inflation in 2024 and 2025, using expenditure weights. The horizontal axis shows refining exposure, in percentage points, after removing the same controls with the same expenditure weights. The solid line and band show the expenditure-weighted fit and its 95 percent confidence interval using heteroskedasticity-robust standard errors. The slope is 0.76 (standard error 0.25). The dashed line shows the slope the panel local projections of Figure 8 imply at this horizon, $\sum_t \beta_{T-t}\,\Delta R_t$ over the shock months February to September 2026, which is 0.39. All 177 observations are displayed. Historical pass-through coefficients are unchanged.
Source. Bureau of Economic Analysis, October 29, 2026 release. Bureau of Labor Statistics. Author's calculations.

Appendix

Figure A.1. The Leontief Inverse, A Stylized Example

A = Appliances P = Plastics R = Refining

Rows supply inputs to columns.

$$A = \begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 0 & 0 & 0 \\ 0.20 & 0 & 0 \\ \mathbf{0.01} & 0.10 & 0 \end{pmatrix} \end{array} \qquad A^2 = \begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \mathbf{0.02} & 0 & 0 \end{pmatrix} \end{array}$$

$$\mathbf{0.02} = 0.10 \times 0.20, \qquad A^3 = 0$$

$$\underbrace{(I-A)^{-1}}_{L} = \underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{array}}_{I} + \underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 0 & 0 & 0 \\ 0.20 & 0 & 0 \\ \mathbf{0.01} & 0.10 & 0 \end{pmatrix} \end{array}}_{A} + \underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \mathbf{0.02} & 0 & 0 \end{pmatrix} \end{array}}_{A^2}$$

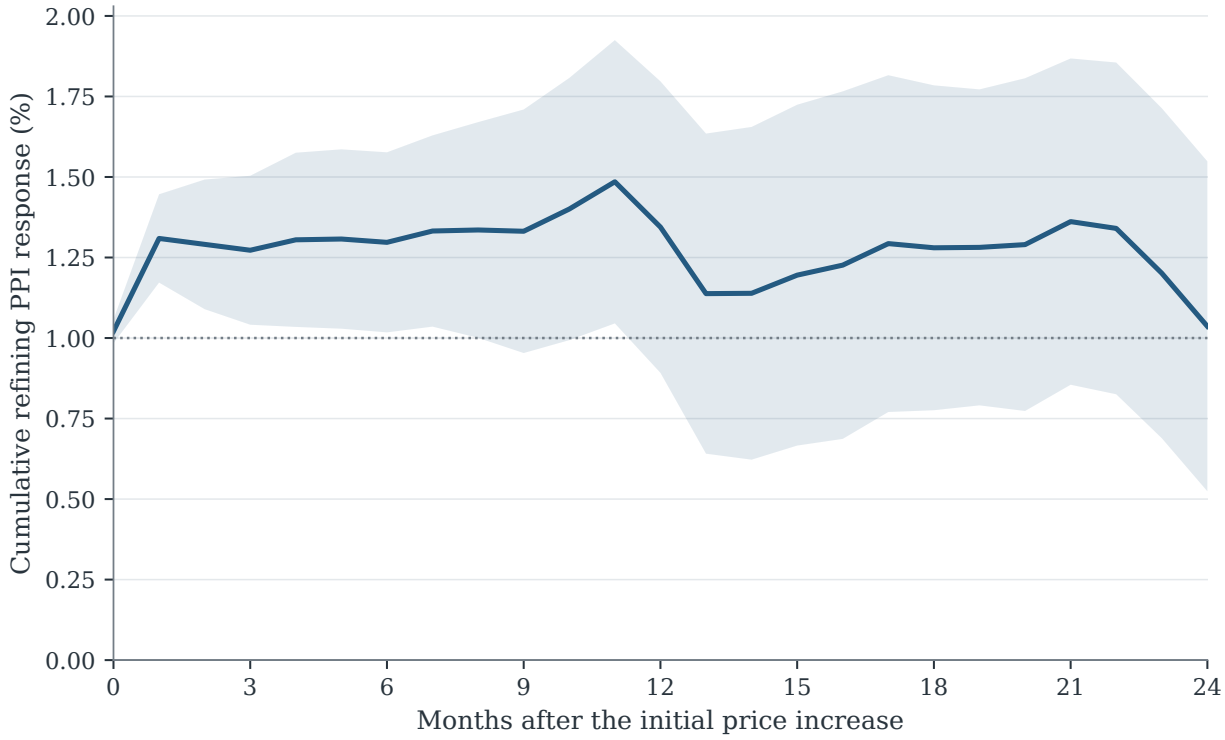
$$\boxed{L = \begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 1 & 0 & 0 \\ 0.20 & 1 & 0 \\ \mathbf{0.03} & 0.10 & 1 \end{pmatrix} \end{array}} \qquad \mathbf{0.03} = \mathbf{0.01} + \mathbf{0.02}$$

$$\underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{array}{c} \begin{array}{ccc} A & P & R \end{array} \\ \begin{pmatrix} 1 & 0 & 0 \\ 0.20 & 1 & 0 \\ \mathbf{0.03} & 0.10 & 1 \end{pmatrix} \end{array}}_{L} \underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{pmatrix} 100 \\ 0 \\ 0 \end{pmatrix}}_{y} = \underbrace{\begin{array}{c} \\ A \\ P \\ R \end{array} \begin{pmatrix} 100 \\ 20 \\ \mathbf{3} \end{pmatrix}}_{x}$$

Illustrative example. Dollar values at producer prices.

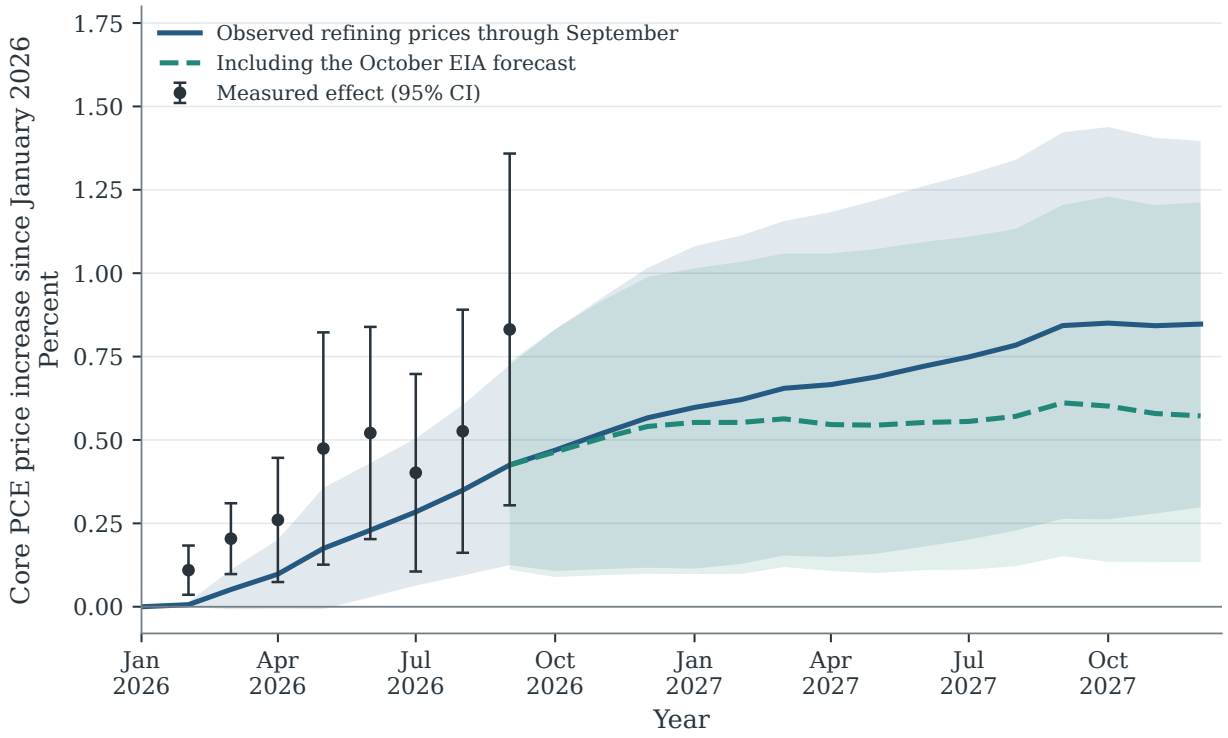
Note. A stylized three-industry example (appliances, plastics, refining) illustrating how the Leontief inverse $L = (I - A)^{-1}$ accumulates direct and indirect requirements. Refining supplies plastics directly (row R, column P, 0.10) and appliances directly (row R, column A, 0.01), plus indirectly through plastics (0.10×0.20=0.02), for a total requirement of 0.03 dollars of refining output per dollar of appliance output. Illustrative coefficients, not estimated from data.

Figure A.2. Persistence of Refining Prices



Note. Cumulative response of the seasonally adjusted petroleum-refining PPI to a one-percent monthly increase. For each horizon $h = 0, \ldots, 24$, the figure reports β_h from $100[\log R_{t+h} - \log R_{t-1}] = \alpha_h + \beta_h \Delta R_t + u_{t,h}$, where ΔR_t is the arithmetic monthly percentage change used in the baseline panel. The regression includes an intercept and no lag controls. The shaded band is the pointwise 95 percent confidence interval based on Newey–West standard errors with $h + 1$ Bartlett lags. The dotted line denotes one-for-one persistence. The data vintage ends in August 2026; estimation origins start in July 1976 and end in August 2026 minus h months. At 24 months, the coefficient is 1.036 (standard error 0.261; 578 observations). The impact coefficient differs slightly from one because the outcome uses log changes and the regressor uses arithmetic percentage changes. This is the price path associated with an observed refining-price increase.
Source. Bureau of Labor Statistics; author's calculations.

Figure A.3. Predicted and Measured Core PCE Effects through 2027



Note. Dots show the measured cumulative core PCE price-level effect since January 2026, estimated month by month using the expenditure-weighted cross-sectional specification in column (2) of Table 9 and multiplied by average core refining exposure. Whiskers are pointwise 95 percent confidence intervals using heteroskedasticity-robust standard errors. The price data are from the October 29, 2026 release, with 177 categories at each date. The solid path applies the historical panel-local-projection coefficients to observed refining-PPI changes through September, holding refining prices constant thereafter. Its shaded 95 percent band uses the joint covariance matrix of the historical coefficients. The dashed path adds the October 2026 EIA fuel forecasts through December 2027. Its shaded band is the existing simulated 95 percent interval, incorporating panel-coefficient, bridge-coefficient, bridge-residual, and joint fuel-forecast uncertainty. The paths are conditional projections, not extrapolations of the measured dots. All effects are relative to January 2026.
Source. Bureau of Economic Analysis; Bureau of Labor Statistics; U.S. Energy Information Administration; author's calculations.