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Supply chain uncertainty, energy prices, and inflation

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Abstract

Using U.S. and Euro area data, we document that (i) the pass-through of energy prices to inflation is state-dependent - stronger when supply chain uncertainty is elevated - and (ii) in such states, energy prices become more informative about logistical conditions. We develop a model in which firms combine energy and a specialized input transported through a capacity-constrained transportation network. When congestion binds, energy remains available in local markets at a premium, whereas the specialized input is subject to delivery delays. Because energy prices reflect both raw energy shocks and transportation conditions, firms treat them as noisy signals of supply disruptions and update beliefs through Bayesian learning. This signal-extraction channel increases perceived marginal costs, generating an uncertainty wedge that amplifies and propagates energy shocks. Within a general-equilibrium New Keynesian model, the mechanism raises the impact elasticity and the persistence of inflation in response to transitory energy shocks. This challenges the conventional monetary policy prescription to "look through" supply disturbances.

Keywords: supply chain uncertainty, transportation shocks, energy price shocks, incomplete information, pass-through, inflation.

JEL Classification Numbers: E31, D83.

Non-technical summary

Energy price shocks do not always have the same effects on inflation. This study shows that the effects of energy shocks on consumer prices are state-dependent - stronger when logistical networks are under stress and supply chain uncertainty is high. The recent past provides clear examples of this pattern. Between 2021 and 2023, inflation increased sharply across advanced economies, including the euro area and the United States. This episode coincided with large energy price increases, severe disruptions to global transportation routes, and unusually volatile supply chain conditions. More recently, the Iran conflict in 2026 has triggered a sharp oil price spike alongside a renewed surge in supply chain uncertainty, again raising concerns about an outsized inflation response.

The paper studies why this happens and how firms' pricing decisions are affected by uncertainty about the timely availability of production inputs. The central idea behind the study is simple. Modern global supply chains depend on tightly interconnected transportation networks in which energy and specialized components are shipped along common routes. When bottlenecks or disruptions hit supply chains, firms become uncertain not only about current costs, but also about how severe and persistent the supply disruption will be. In this environment, firms look for signals. Because energy is traded in liquid global markets and its price reacts quickly to congestion, energy prices become a convenient indicator of broader supply chain conditions. As a result, firms interpret higher energy prices not only as a cost shock, but also as a sign that supply bottlenecks may be worsening and that specialized inputs could arrive later than expected. This fundamentally changes firms' pricing behavior: prices increase not only to cover current energy costs, but also to account for expected supply disruptions.

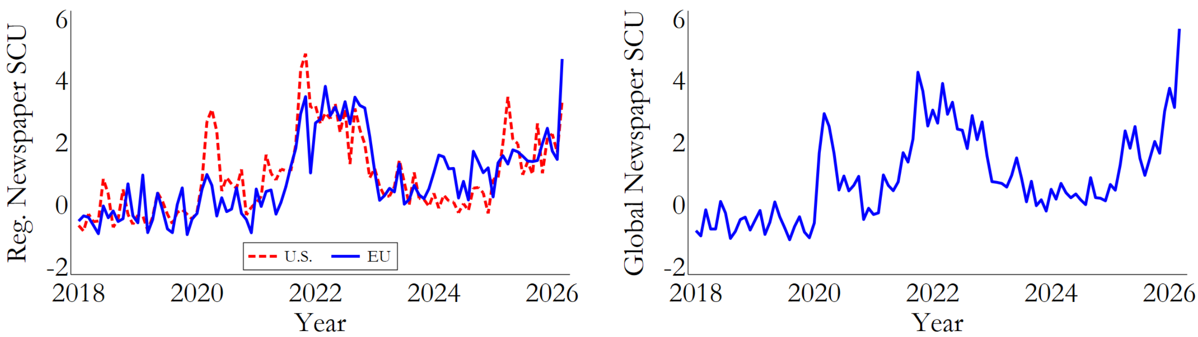
Using data for both the United States and the euro area, the paper provides evidence supporting this mechanism. First, in a set of local projections of inflation on exogenous oil shocks, we show that consumer prices react much more strongly to oil (energy) shocks during periods of high supply chain uncertainty than during normal times. This result holds across four independent measures of supply chain uncertainty and is robust to additional controls and placebo tests. Second, we estimate a Kalman filter on the data separately for high- and low-supply-chain-uncertainty regimes to evaluate the relative informativeness of energy and transportation prices as signals of logistical conditions. We find that when supply chains are unstable, energy prices become more informative about logistical conditions than more traditional transportation price indicators. Third, textual evidence from firms' earnings calls shows that managers' discussions of energy costs and supply bottlenecks move together most strongly when supply chain uncertainty is high, consistent with firms treating energy prices as a signal of broader disruptions.

To interpret these findings, the paper develops a microfounded New Keynesian model in which firms form Bayesian beliefs about unobserved upstream supply chain conditions using energy prices as noisy signals. The model's key result is that supply chain uncertainty introduces an endogenous uncertainty wedge into the New Keynesian Phillips Curve - an additional component that is absent under complete information and is activated by energy price shocks. When supply chain uncertainty is elevated, firms place greater weight on energy prices as signals of persistent logistical disruptions, so that even purely transitory energy shocks generate an inflation response that is both larger on impact and more persistent than in a world with stable supply chains.

The policy implications are important. Policymakers often argue that central banks should "look through" energy price shocks, as their inflationary effects will fade quickly. This paper shows that this logic can break down when supply chains are highly volatile. In such periods, even transitory energy price shocks can become entrenched in inflation expectations in ways that generate severe and long-lasting inflationary pressures. Monetary policy should be state-contingent, conditioning its response not only on the level of energy prices but also on the volatility of upstream supply chain conditions.

1 Introduction

Over the past three decades, inflation remained low and stable despite substantial fluctuations in energy prices.[1] Yet this stability was not unconditional: episodes of elevated supply chain disruption have repeatedly coincided with stronger inflation responses to energy shocks. The 2021-23 surge - when energy prices rose by 40% in the U.S. and Euro area - is a salient example, with the pass-through more than twice as strong as in the past.[2] More recently, the Iran conflict in 2026 triggered a sharp oil price spike alongside a renewed surge in supply chain uncertainty, again raising concerns about an outsized inflation response. Figure 1 shows that supply chain uncertainty - measured via newspaper text-mining - spiked during 2021-23 and again with the onset of the Iran war in February and early March 2026, which has generated an unprecedented shock to global shipments of energy, raw materials, and intermediate inputs. We view these episodes as manifestations of a potentially structural *complementarity*: when supply chain uncertainty is elevated, energy disturbances become significantly more inflationary.



(a) U.S. and EU

(b) Global

Figure 1: Supply chain uncertainty

Notes: Region-specific supply chain uncertainty (SCU) indexes for the U.S. (red) and the Euro area (blue), and a global SCU index. From January 1, 2018, to March 15, 2026. These indexes measure the share of newspaper articles mentioning SCU in region-specific and global outlets from the Factiva Dow Jones database, following the text-mining approach of Caldara et al. (2020). See Online Appendix B.1 for details.

Modern supply chains. In this paper, we develop a theory of the amplification and propagation of supply shocks based on *uncertainty* in the producers' supply chains. Our analysis is grounded in two defining characteristics of globally integrated production networks. The first is shared

[1] Blanchard and Riggi (2013).

[2] The pass-through "switched regime" (De Santis and Tornese, 2025), particularly in the Euro area (Pallara et al., 2023; Neri et al., 2023).

logistical *chokepoints*. Energy and specialized manufacturing components rely on the same maritime infrastructure and pass through a small number of critical nodes, so congestion at a single point cascades across geographies (Ducruet and Notteboom, 2022; Känzig and Raghavan, 2025; Bai et al., 2024). Episodes such as the Suez Canal blockage in 2021 or the shutdown of the Strait of Hormuz in 2026 illustrate how localized disruptions generate correlated delivery risks for seemingly unrelated inputs. The second is the *asymmetric* response of commoditized and specialized inputs to transportation shocks. Energy is available in liquid local spot markets at a known premium even under severe congestion, so its price continuously reflects transportation conditions. Specialized inputs - such as semiconductors or EV batteries - are non-substitutable and cannot be sourced locally when supply chains are disrupted: delivery delays manifest as unobserved *time costs* rather than market prices.

Signal extraction and uncertainty wedge. These two features jointly give rise to a signal-extraction problem for downstream firms. Because *both* energy and specialized inputs share the same transportation network, a rise in energy prices may reflect either a transitory raw energy shock or a broader, persistent supply chain disruption affecting delivery times across inputs. Firms cannot directly observe which shock is activated. They therefore treat the observed energy price as a *noisy signal* of the latent transportation shock, and update their beliefs via Bayesian learning.

The informativeness of this signal is *state-dependent*. When supply chain uncertainty is low, transportation markets operate smoothly and prices clear delivery conditions for all inputs, leaving little residual information in energy prices. When supply chain uncertainty is elevated, however, the capacity constraint on specialized input transportation binds, transportation prices lose their allocative role, and energy prices - which always clear through liquid spot markets - emerge as the more reliable aggregator of logistical conditions. Firms optimally place greater weight on the energy price signal precisely when uncertainty is highest.

We formalize this mechanism in a general-equilibrium New Keynesian model. Firms combine energy and a specialized input, both routed through a capacity-constrained transportation network. The signal-extraction problem generates an *uncertainty wedge* in the New Keynesian Phillips Curve: an endogenous, energy-activated component of marginal cost that is absent under complete information. Even a purely transitory energy shock triggers this wedge when supply chain uncertainty is elevated, raising both the *impact* pass-through to inflation and its *persistence* through forward-looking price-setting. The volatility of transportation shocks - not merely their level - thus becomes a key determinant of inflation dynamics.

Empirical evidence. We document three complementary facts that validate the mechanism.

(i) State-dependent pass-through. Using state-dependent local projections with exogenous oil supply news shocks (Känzig, 2021), we show that the response of both headline and core inflation to energy price shocks is significantly larger - and more persistent - when supply chain uncertainty is in the top quintile of its distribution. This result holds across four independent measures of supply chain uncertainty, is robust to controlling for the level of supply chain pressures, and is not specific to the COVID-19 inflation episode. Crucially, it does *not* arise for gas shocks, which travel via pipelines rather than maritime routes, nor for generic uncertainty measures such as the VIX, the Economic Policy Uncertainty index, or general macroeconomic uncertainty. Supply chain uncertainty is the uniquely activating state.

(ii) Informational content of energy prices. Using a Kalman-filter estimated separately for high- and low-uncertainty regimes, we show that the informational loading on energy prices increases sharply in high-uncertainty states, while that on transportation prices - proxied by the Baltic Dry Index - falls. Under normal conditions, transportation prices are the primary signal of logistical disruptions; conversely, under elevated uncertainty, energy prices displace them. This shift in relative informativeness is consistent with the mechanism at the heart of our model.

(iii) Evidence from earnings calls. Textual analysis of earnings call transcripts from publicly listed U.S. and Euro area firms reveals that references to energy costs and supply chain disruptions co-move most strongly precisely when supply chain uncertainty is elevated. Firms across diverse sectors - from manufacturers to financial intermediaries - treat energy prices as indicative of broader supply bottlenecks, not merely as an independent cost item. This narrative evidence corroborates the signal-extraction interpretation.

Policy implications. Our framework challenges the conventional "look-through" prescription for monetary policy. The standard view holds that central banks should disregard transitory energy price shocks, since their temporary nature implies limited consequences for trend inflation. We show that this prescription is *state-dependent*. When supply chain uncertainty is elevated, even purely transitory energy shocks are perceived by firms as signals of persistent cost pressures, leading to stronger and more persistent inflation dynamics through precautionary pricing and expectation de-anchoring. Under a passive look-through stance, the endogenous amplification from the uncertainty wedge is unaddressed and generates inflationary pressure that mimics a genuinely persistent supply disturbance. Monetary policy should therefore condition on the prevailing degree of supply chain uncertainty - not only on the level of energy prices.

Related literature. Our paper relates to several strands of the literature. First, it speaks to work on the macroeconomic implications of supply chain shocks. Bai, Fernández-Villaverde, Li, and Zanetti (2024) formalize the transportation market via a search-and-matching model in which transportation shocks generate heightened delivery times and costs. Empirically, Ascari et al. (2024); Finck and Tillmann (2022); Bini (2025) find that transportation shocks cause persistent increases in consumer prices and declines in economic activity, while Känzig and Raghavan (2025) documents that exogenous shipping disruptions raise commodity prices, depress industrial production, and generate broad-based inflation. Chau et al. (2024) use a Bartik shift-share design to show that a full lockdown of a supplier accounting for 50% of expenditure raises sectoral PPI by 14.5%. Carreras-Valle and Ferrari (2025) quantify delivery delays and show that greater supply chain uncertainty constrains more firms and lowers aggregate output. Ball et al. (2022); Bernanke and Blanchard (2025); Liu and Nguyen (2023) attribute the 2021-2023 inflation surge primarily to exceptional supply chain disruptions.

We contribute to this literature in two ways. First, we emphasize supply chain *uncertainty* as a driver of heightened pass-through from energy prices to inflation. Second, we build an incomplete-information version of the canonical New Keynesian (NK) model and derive a version of the NK Phillips Curve in which marginal costs decompose into a standard complete-information component and a novel uncertainty-driven endogenous component, activated by energy price shocks and amplified by supply chain uncertainty.

Our paper also relates to the broader literature on uncertainty (Bloom, 2014) and information frictions in price-setting (Lucas, 1973). A large body of work shows that noisy private information generates aggregate fluctuations (Lorenzoni, 2009; Angeletos and La'O, 2010; Angeletos and La'O, 2020).[3] More recently, Nikolakoudis (2025) embeds incomplete information into a production-network model and shows that upstream shocks matter more under high productivity uncertainty, while downstream shocks matter more under high demand uncertainty - a pattern confirmed empirically by Cacciatore and Candian (2025). Morão (2025) constructs an energy-transportation

[3] In Bui, Huo, Levchenko, and Pandalai-Nayar (2022), noisy *public* information also drives macroeconomic fluctuations through an international input network.

uncertainty index and documents that uncertainty spikes raise real oil prices and depress global industrial output. Our contribution lies at the intersection of these two literatures. As in Blanchard and Riggi (2013), we study energy supply shocks in a NK environment with nominal rigidities - but enrich the standard framework with an explicit model of the supply chain and a central role for incomplete information, showing that supply chain uncertainty acts as an amplifier in the transmission of energy shocks to inflation.

2 Empirical Evidence

We provide empirical support for our theory in three steps. First, we document that the *pass-through* of energy prices to inflation is state-dependent, rising markedly under elevated supply chain uncertainty. Second, using a Kalman-filter approach, we show that energy prices become *more informative* than transportation prices when logistical uncertainty is high. Third, *textual analysis* of earnings-call transcripts reveals that the correlation between energy and supply chain language in managers' communications is strongest precisely when supply chain uncertainty is most severe.

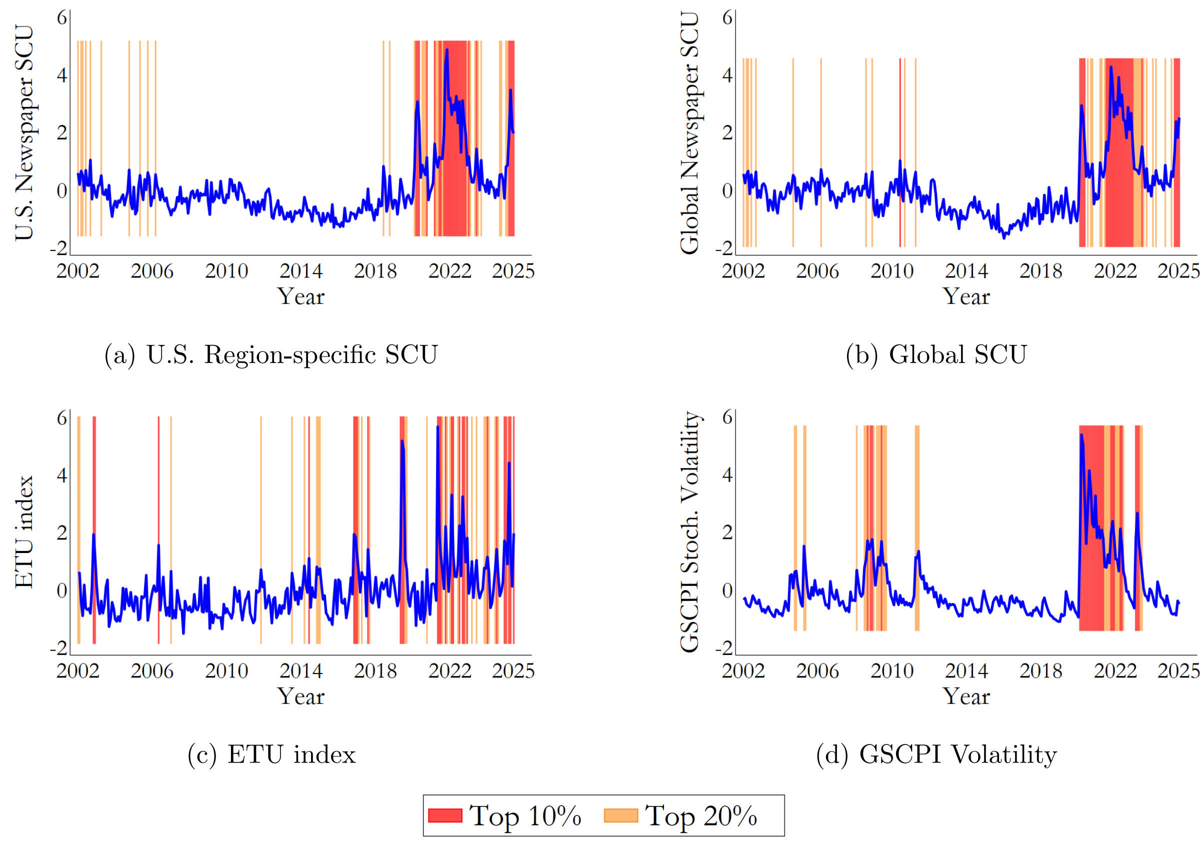
2.1 Measures of Supply Chain Uncertainty

We introduce *four* alternative measures of supply chain uncertainty (SCU) drawing on different sources. Three are perception-based indexes derived from newspaper text-mining in the spirit of Caldara and Iacoviello (2022), capturing how supply chain uncertainty is *perceived* rather than how it materializes in economic data. The fourth offers an objective, data-driven measure of supply chain volatility. All four measures are plotted in Figure 2.

Baseline measure Our baseline measure of SCU is the U.S. (EU) Region-specific Supply Chain Uncertainty index, which captures media attention to supply-chain uncertainty in the Factiva Dow Jones database of newspaper articles about the U.S. (EU). In Online Appendix B.1, we plot the *European Union Region-specific SCU*, and we compare it with the U.S. regional index. The regional indexes capture the incidence of newspaper articles whose headline (or lead paragraph) mentions words from the semantic groups of "supply chain" and "uncertainty."[4] The Region-specific SCU therefore captures supply chain *perceptions* of households and firms in each

[4]This measure of supply chain risk was introduced in Hassan et al. (2025).

region - the U.S. and the EU, respectively. Since supply chains and (maritime) transportation routes are mostly concentrated within continents (Ducruet and Notteboom, 2022), the Region-specific SCU has the appropriate geographic scope to be our baseline measure of supply chain uncertainty.



(a) U.S. Region-specific SCU

(b) Global SCU

(c) ETU index

(d) GSCPI Volatility

Figure 2: Measures of supply-chain uncertainty (SCU)

Notes: Light orange (red) highlights observations in the top 20% (10%). All series standardized.

Global SCU The Global Supply Chain Uncertainty captures media attention to supply-chain uncertainty in *global* newspapers covered by the Factiva Dow Jones database. The index is constructed using the same text-analysis methodology as the Region-specific SCU measure. Relative to the Region-specific index, however, the Global SCU has a broader, worldwide, geographic scope.

ETU index The Energy Transportation Uncertainty (ETU) index captures uncertainty surrounding energy delivery and transportation in supply chains. This is a more detailed measure of supply chain uncertainty that relates specifically to the sector of energy transportation. The index is constructed by Morão (2025) from newspaper articles, identifying texts that jointly mention terms related to energy, transportation, and uncertainty.

GSCPI volatility Unlike the previous indicators, the GSCPI Volatility index is an *objective* measure of *volatility* in global supply chain conditions. We construct it by estimating a stochastic volatility model for the Global Supply Chain Pressure Index (GSCPI) compiled by Benigno et al. (2022).[5] The GSCPI summarizes observed supply chain pressures by combining information from transportation costs and purchasing managers' surveys across the globe.[6] We estimate the GSCPI Volatility index in two steps. First, we model the GSCPI as an autoregressive process with time-varying volatility. Second, we estimate the model using the Bayesian particle filter algorithm of Born and Pfeifer (2014) and extract the filtered conditional variance of the innovations to the GSCPI process. The resulting series is the GSCPI Volatility index, a novel structural and data-driven measure of supply chain uncertainty. Notably, this measure reflects supply chain uncertainty deriving from *fundamentals* rather than perceptions. We defer the remaining details regarding the construction of the four SCU indexes to Online Appendix B.1.

2.2 State-Dependent Local Projections

We compare the dynamic effects of exogenous oil supply news shocks across different states of supply chain uncertainty. We follow the approach in Ramey and Zubairy (2018) and estimate state-dependent local projections (Jordà, 2005) of inflation (headline and core) on oil supply news shocks over the sample from January 2002 to June 2025.[7] Let U_t be an indicator variable that flags periods in which the observations of our preferred measure of supply chain uncertainty SCU_t exceed a given threshold p:

$$U_t = \mathbf{1}\{SCU_t > p\} \tag{1}$$

In the baseline specification, we consider the periods in which the Region-specific SCU index is in the top 20% of its distribution.[8] We interact U_t with the high-frequency oil supply news shocks $\{\varepsilon_t^{\text{oil}}\}$, identified by Känzig (2021). The identification proceeds in two steps. First, high-

[5] The GSCPI is an index of global supply chain bottlenecks, published monthly by the NY Fed.

[6] Other measures of transportation disruptions exist - such as the satellite-based Average Congestion Rate (ACR) index of Bai, Fernández-Villaverde, Li, and Zanetti (2024) - but they are less suitable for our purposes due to limited sample availability (see Online Appendix B.2).

[7] Euro area core inflation is available from January 2002; oil supply news shocks until June 2025.

[8] The results are qualitatively unchanged for any threshold above the median. Available upon request.

frequency surprise movements in oil futures prices are isolated around OPEC announcements. Second, these surprises are used as an instrument in a standard oil market VAR, yielding the series of structural oil supply news shocks employed in the local projection. The resulting series, plotted in Figure 3, is approximately white noise and, crucially, does not show visible clustering of unusually large shocks in high-uncertainty regimes. This is important for two main reasons. First, it indicates that oil news shocks do *not* exhibit a systematic correlation with episodes of supply chain disruption and uncertainty.[9] Second, it shows that the high pass-through of energy shocks during the 2021–23 inflation cannot be attributed to a *non-linear* effect arising from the unusually large size of energy shocks.

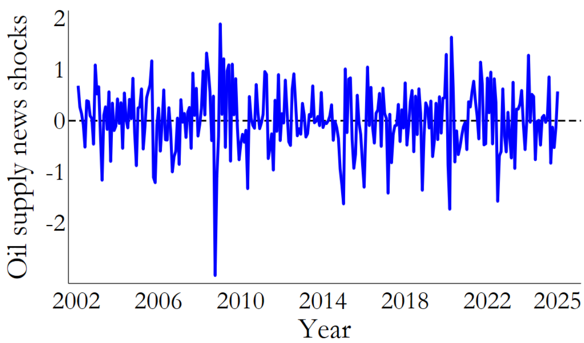


Figure 3: Oil supply news shocks

Notes: Oil supply news shocks identified by Känzig (2021) plotted with monthly frequency from January 2002 to June 2025.

Baseline state-dependent LPs For each horizon $h = 0, \ldots, 18$, we estimate the following local projection:[10]

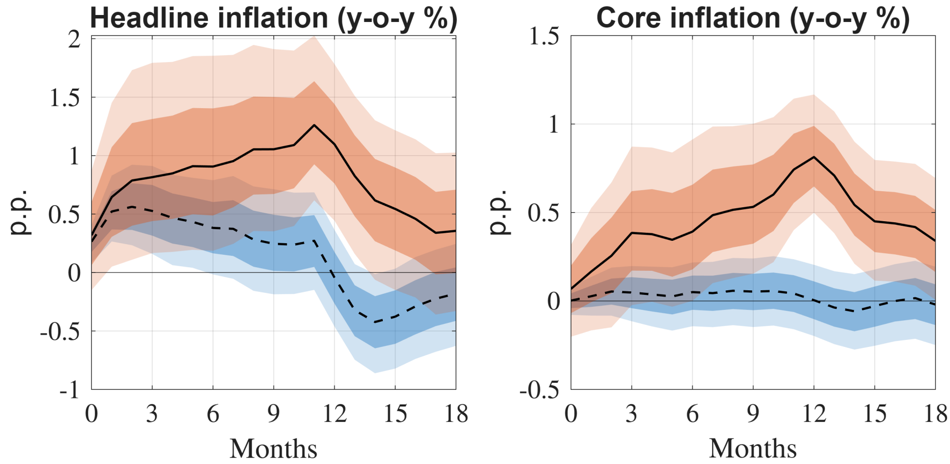
$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{oil}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \nu_{t+h} \tag{2}$$

where π_{t+h} is the 12-month U.S. or Euro area headline consumer (or core) inflation[11] at horizon h, and $\sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j}$ is the set of its lags up to 12 months.

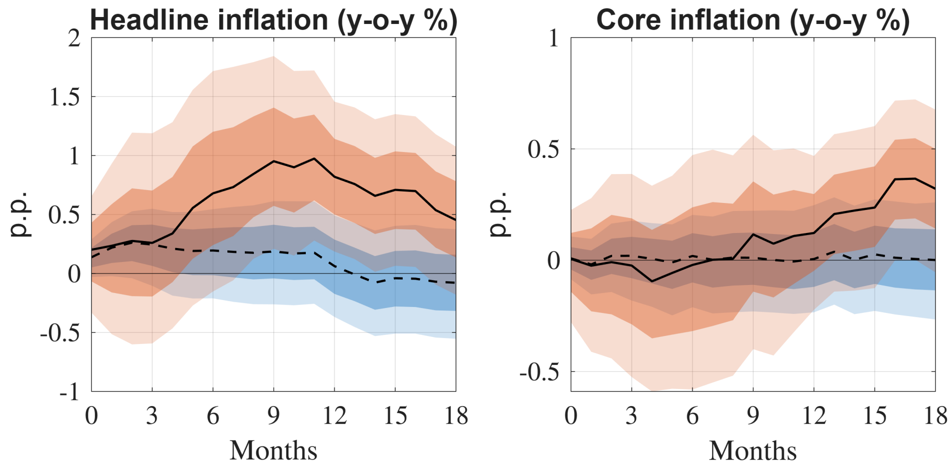
[9] State-dependent local projections identify the response to a large shock if the shock is exogenous and independent of the state (Gonçalves et al., 2024). This condition is plausible here, since high- and low-supply-chain-uncertainty regimes are arguably independent of the exogenous energy shocks we study.

[10] We also include a set of 11 monthly seasonal dummies as in Känzig (2021).

[11] For the U.S., we consider a measure of core inflation that excludes the "housing" component. As argued in Pallara et al. (2023), including "housing" would bias downward the sensitivity of U.S. core prices to oil prices and distort the comparison with the Euro area.



(a) U.S.



(b) Euro area

Figure 4: Headline and core inflation responses to an oil news shock across *Region-specific SCU* states - U.S. and Euro area

Notes: Responses are normalized to generate a 10 p.p. increase in oil inflation. Solid (dotted) line: high (low) SCU state (top 20% / bottom 80% of Region-specific SCU). Orange (blue) shaded areas: 90% and 68% confidence bands.

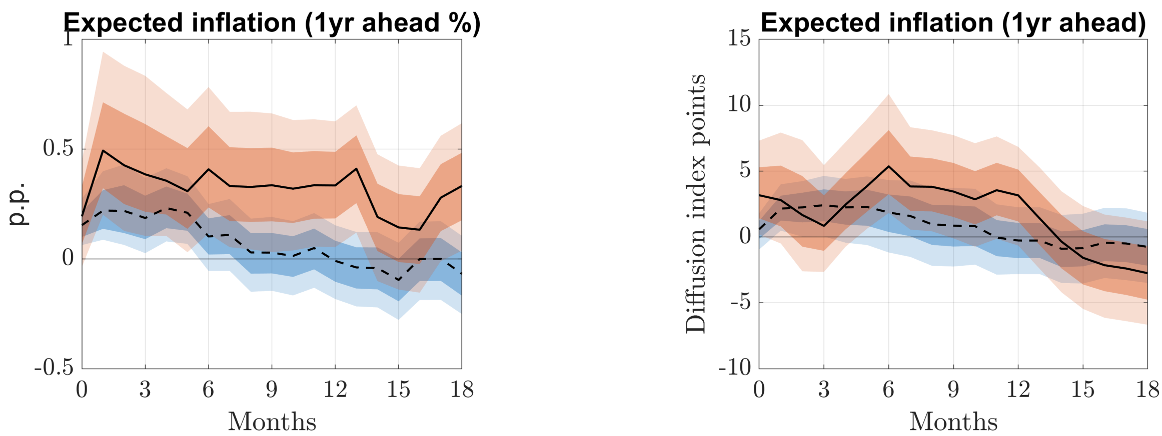
The two coefficients of interest, $\{\beta_h, (\beta_h + \beta_h^H)\}$, trace the impulse responses of inflation to an exogenous news shock of a drop in oil supply, comparing low and high supply chain uncertainty regimes. We normalize the oil supply news shock size to generate a 10 percentage point increase in oil price inflation in the U.S. and the Euro area.

Figure 4 plots the impulse responses with 90% and 68% confidence bands.[12] There is a clear and statistically significant difference across regimes: in a *low* SCU regime, the inflation response is

[12] Moving block bootstrap with block size 12.

muted and often indistinguishable from zero; conversely, in a *high* SCU regime, both headline and core inflation are significantly amplified and more persistent, in both the U.S. and the Euro area.

Inflation expectations We test whether the amplification of energy shocks to inflation is a persistent process that can de-anchor households' expectations. We run a local projection of one-year-ahead consumers' expected inflation on oil shocks. The series for the U.S. is the one-year-ahead expected inflation from the Michigan survey. The series for the Euro area is a diffusion index of one-year-ahead expected inflation retrieved from the Business and Consumer Survey (BCS) Data of the European Commission. Figure 5 shows the impulse response in the U.S. and in the Euro area. Under low uncertainty, the response of one-year-ahead expected inflation to a (transitory) oil shock is muted, as households and firms correctly interpret the transitory nature of the oil shock. Under high uncertainty, however, inflation expectations rise persistently above zero, as a (transitory) oil shock transmits to the economy as a persistent disturbance. The result is particularly strong in the U.S. sample, while in the Euro area it becomes visible only over the medium horizon.



(a) U.S. (b) Euro area

Figure 5: Expected inflation responses to an oil news shock across *Region-specific SCU* states - U.S. and Euro area

Notes: Responses are normalized to generate a 10 p.p. increase in oil inflation. Solid (dotted) line: high (low) SCU state (top 20% / bottom 80% of Region-specific SCU). Orange (blue) shaded areas: 90% and 68% confidence bands.

Results across SCU measures We test the robustness of our results using the alternative measures of supply chain uncertainty introduced above: the Global SCU, the ETU index, and the

GSCPI Volatility index. Online Appendix B.3 reports the impulse responses of headline and core inflation to an oil news shock, conditional on each of these measures. Across all specifications, the results are consistent: in both the U.S. and the Euro area, the response of inflation is significantly larger and more persistent during periods of high supply chain uncertainty.

2.2.1 Robustness

Why oil and not gas? In the Euro area, the 2022 energy shock highlighted the role of gas alongside oil. We estimate local projections of inflation on exogenous gas supply shocks identified from TTF futures by Alessandri and Gazzani (2025), and find that the transmission of *gas* shocks is *invariant* to supply chain uncertainty (see Online Appendix B.4). This placebo confirms that our amplification result for oil is not a mechanical non-linearity: it arises because oil is traded globally via maritime routes and thus embeds transportation conditions, whereas gas travels mainly through pipelines in regional markets.

Uncertainty beyond supply chains Arguably, the amplification of energy shocks might be a general feature of uncertainty states. However, re-running the baseline LPs using general measures of uncertainty such as EPU, VIX, equity volatility, trade policy uncertainty, and the macro uncertainty index of Jurado et al. as state variables yields no significant state dependence, confirming that supply chain uncertainty uniquely triggers the information mechanism. Results are reported in the Online Appendix B.5.

Was it only COVID-19? Some periods of elevated supply chain uncertainty overlap with the COVID inflation spike. The Online Appendix B.6 addresses this with two exercises: adding a COVID dummy capturing the *level* shift during the inflationary spike (April 2020 - December 2022), and adding monthly categorical variables for April-December 2020 to absorb any month-specific shock during the lockdown months. Both exercises confirm that our results hold beyond the COVID episode.

Disentangling uncertainty from supply chain pressures Heightened supply chain uncertainty tends to coincide with elevated supply chain pressures, raising the concern that the estimated state dependence reflects *first-moment* rather than second-moment effects. The Online Appendix B.7 addresses this with two exercises. First, we augment the baseline LP with the contemporaneous level and 12 lags of the GSCPI. Second, we add the interaction between the GSCPI and the oil shock, absorbing any non-linear effect driven by supply chain pressure levels. In both cases, the state-dependent effects remain essentially unchanged, confirming that they capture genuine uncertainty effects.

2.3 Information Value of Energy Prices

When firms are unsure about the state of their supply chain, nearby prices provide signals about underlying disruptions. Suitable measures of the price of transportation are the most immediate candidates, as they reflect congestion and delivery bottlenecks. However, we argue that when a major shock hits a critical chokepoint of the transportation network, *congestion constraints* become binding and transportation prices may lose their allocative role: physical queues, not prices, determine the timely distribution of inputs. In such cases, *energy inflation* may emerge as another possibly useful signal. Because energy is a homogeneous, globally traded commodity whose price continuously clears the market, it might become a more reliable aggregator of information even when the transportation network is under stress.

Kalman filter We assess the relative information content of two alternative signals for firms: energy inflation and transportation prices - which are proxied by the Baltic Dry Index (BDI).[13] We consider energy inflation and BDI from January 2002 to June 2025, splitting the sample into low- and high-uncertainty regimes based on the Region-specific SCU. We estimate a Kalman filter model. In the *state* equation, we assume that the *true* transportation shock follows the AR(1) process:

$$\psi_t \; = \; \rho_\psi \, \psi_{t-1} \; + \; \varepsilon_{\psi,t}, \qquad \varepsilon_{\psi,t} \sim \mathcal{N}(0, \sigma_\psi^2), \quad \sigma_\psi^2 > 0, \quad |\rho_\psi| < 1$$

In the *observation* equation, we consider a vector $y_t \in \mathbb{R}^2$ that is built from two competing (standardized) signals - energy inflation $\pi_{E,t}$, and the price of transportation p_t^{BDI} - each with

[13] The Baltic Dry Index (BDI) is a widely used benchmark for shipping rates, retrieved from Bloomberg. The BDI is a composite of time-charter rates for major dry bulk vessels (e.g., Panamax, Supramax). Noticeably, it covers the transportation costs of raw materials and commodities, but not of manufactured goods.

its own loading in the vector F:

$$\underbrace{\begin{bmatrix} \pi_{E,t} \\ p_t^{BDI} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}}_{F} \psi_t \ + \ \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}\big(0, V\big), \quad V = \begin{bmatrix} v_1 & 0 \\ 0 & v_2 \end{bmatrix}, \ v_1, v_2 > 0$$

The two sequences of innovations $\{\varepsilon_{\psi,t}\}$ and $\{\varepsilon_t\}$ are mutually independent and independent of the initial prior for the state process (ψ_0). Specifically, ψ_0 has a Gaussian distribution:

$$\psi_0 \sim \mathcal{N}(m_0, \, C_0)$$

with prior parameters calibrated to the unconditional moments of the GSCPI series. The full set of parameters in the model is stacked in the vector θ:

$$\theta \ = \ (\alpha_1, \alpha_2, \rho_\psi, \, v_1, v_2, \, \sigma_\psi^2)$$

We estimate θ recursively via MLE, following the procedure detailed in the Online Appendix C.1. Figure 6 plots - across uncertainty states - the estimated loading coefficients α_1, α_2 associated to energy inflation and to the BDI, respectively. In the low-uncertainty state there are typically no major disruptions, hence the transportation market runs smoothly and embeds all the information about the (sufficiently small) transportation shocks. In this case, firms rely solely on the BDI price, whose loading weight is high and relatively higher than that on energy inflation. Information from energy inflation is barely useful, and the loading contribution is close to zero. Conversely, under high supply chain uncertainty, transportation markets operate near capacity, making transportation prices poor indicators of underlying disruptions. As a result, the BDI index becomes a noisier signal and receives little weight in firms' inference. In contrast, energy inflation - largely uninformative in normal times - retains its reliability and gains prominence. Accordingly, in high-uncertainty regimes, the loading on energy inflation exceeds that on transportation prices, reflecting its greater informational value. This shift reflects the fundamental logic of the Kalman filter: under higher uncertainty, the filter places more weight on the data because the prior is less informative. In particular, the filter places more weight on the more precise signal. Since the energy inflation signal is less noisy than the BDI in the high-uncertainty regime, its Kalman gain rises relative to the BDI's. See Online Appendix C.2

for the full estimation results.[14]

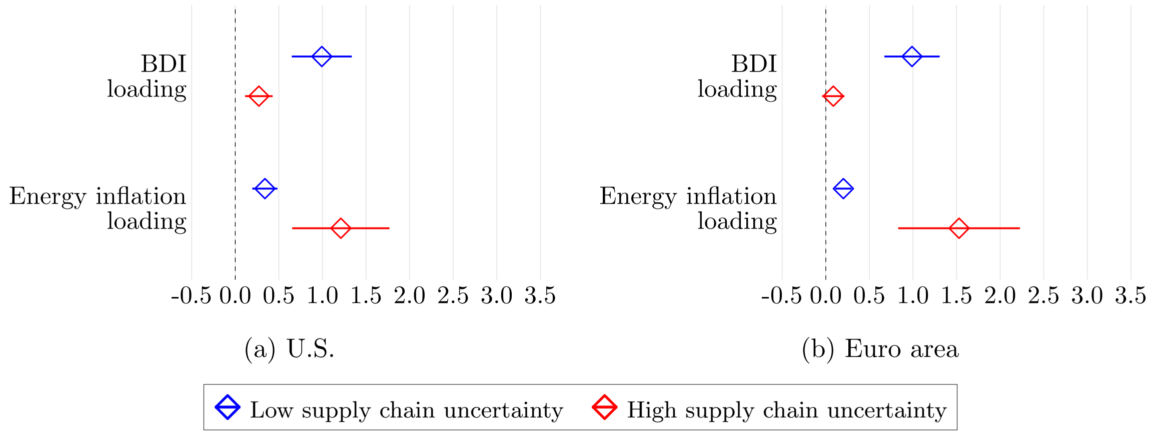


Figure 6: Loading coefficients for BDI and Energy Inflation - U.S. and Euro area

Notes: MLE-estimated loadings of energy inflation and BDI on the latent transportation shock, January 2002 - June 2025. Red (blue): high (low) SCU state (top 20% / bottom 80% of Region-specific SCU), with 90% confidence intervals. All variables in standard deviations. See Appendix C.1 for estimation details.

2.4 Evidence from Earnings Calls

In this section, we use textual data to assess whether energy prices become more informative for firms in periods of elevated supply chain uncertainty. Using earnings call transcripts from NL Analytics (January 2002 - June 2025), we construct indicators of the salience of supply chain disruptions and energy cost pressures in managers' communications for publicly listed firms in the United States and the Euro area. Earnings calls are well suited to this purpose. Managers discuss performance and outlook under tight time constraints and close scrutiny, which limits superficial discussion and forces prioritization. As a result, the share of the call devoted to a given topic provides a meaningful measure of its perceived importance.

Text-based analysis We carry out a text-based analysis of earnings calls following the approach in Hassan et al. (2025, 2019) and Caldara et al. (2020). We gather transcripts from a sample of earnings calls released quarterly by publicly listed firms headquartered in the U.S. or the Euro area, and count the share of sentences that contain at least one *keyword* from the semantic group of "supply chain" (pressure, disruption, bottleneck, etc.) and "energy," over the total number of sentences - see the Online Appendix C.4 for more details. To give content to these textual indicators, we consider sentences in which managers explicitly mention *both* supply

[14]Online Appendix C.2 also shows that the results are robust to using energy prices instead of year-on-year energy inflation.

chains and energy. In the Online Appendix C.4.1, we report some representative examples. The main pattern that emerges is that managers across very different sectors - from consumer services and fossil-fuel producers to banks - emphasize the "double effect" of supply chain distortions and raw material or energy inflation, treating them as intertwined rather than independent sources of risk. This narrative is consistent with our interpretation that firms view energy prices not only as a cost component, but also as a *salient signal* about the state of supply bottlenecks.

We consider two separate quarterly time series: the share of sentences that mention at least one supply chain keyword, $w_{SC,t}$, and the share of sentences that mention at least one energy keyword, $w_{E,t}$.[15]

In Table 1, we explore the correlation of the two indexes. Unconditionally, the two indicators co-move strongly: periods with more frequent mentions of supply chain issues also feature more references to energy markets. To move beyond unconditional co-movement, we compute the conditional correlation between these indicators and its state dependence with respect to supply chain uncertainty. Formally, we estimate regressions of the following form:

$$\underbrace{w_{SC,t}}_{\substack{\text{supply chain}\\ \text{words}}} = \alpha + \beta_1 \pi_{E,t} + \beta_2 \underbrace{w_{E,t}}_{\substack{\text{energy}\\ \text{words}}} + \beta_3 \left[\mathrm{SCU_t} \times w_{E,t}\right] + \varepsilon_t, \tag{3}$$

where $\pi_{E,t}$ denotes energy inflation and SCU_t is the Region-specific SCU, our preferred measure of supply chain uncertainty.

The estimates deliver two main results. First, conditional on energy inflation $\pi_{E,t}$, firms mention energy-related terms more often in those periods when they also discuss supply chain disruptions. This suggests that energy prices are not only treated as an independent cost item, but also as informative signals about supply bottlenecks. Second, the correlation between the share of energy words and the share of supply chain words is stronger in periods when supply chain uncertainty is elevated, indicating that firms rely more on energy signals precisely when uncertainty and informational frictions are more severe. Panels (a) and (b) of Table 1 report the estimates for the US and the Euro area, respectively, and show positive, statistically significant conditional correlations, with an amplifying role for the interaction between energy mentions and supply chain uncertainty.

[15] The earnings call-based indicators for both the U.S. and the Euro area are well aligned to the GSCPI index (correlation over 0.7 in the January 2002 - June 2025 period).

(a) U.S.

	Supply chain keyword		
	(1)	(2)	(3)
Energy keyword	0.537***	0.680***	0.373***
	(0.088)	(0.072)	(0.067)
Energy inflation		0.043***	0.023***
		(0.006)	(0.005)
SCU × Energy keyword			0.447***
			(0.056)
Adj. R^2	0.280	0.555	0.737
N	94	94	94

(b) Euro area

	Supply chain keyword		
	(1)	(2)	(3)
Energy keyword	0.647***	0.608***	0.478***
	(0.079)	(0.064)	(0.058)
Energy inflation		0.047***	0.011
		(0.007)	(0.008)
SCU × Energy keyword			0.370***
			(0.059)
Adj. R^2	0.413	0.621	0.733
N	94	94	94

Table 1: Conditional correlates of supply chain keywords in the U.S. and Euro area

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Keyword indicators compiled at quarterly frequency from earnings call transcripts of publicly listed U.S. and Euro area firms. Sample: 2002 Q1 - 2025 Q2. See Online Appendix C.4 for details.

2.5 Summary of Empirical Evidence

Three facts emerge from the empirical evidence. First, the pass-through of energy price shocks to inflation is significantly amplified under high supply chain uncertainty - robustly across four SCU measures, outside the COVID period, and independent of shock size. Second, energy prices become more informative than transportation prices about logistical conditions precisely when SCU is elevated. Third, earnings-call transcripts show that references to energy and supply chain disruptions co-move most strongly under high SCU. Together, these facts point to a structural complementarity between energy price disturbances and supply chain uncertainty in driving inflation dynamics.

3 A Model of the Supply Chain

In this section we develop a theoretical framework that rationalizes the above findings. The model formalizes how firms' incomplete information about supply chain disruptions - combined with their reliance on energy prices as a noisy signal of transportation shocks - can amplify and propagate the transmission of energy shocks to marginal costs and inflation.

3.1 Stylized Supply Chain Structure

We build a model of the supply chain for the production of differentiated intermediate goods. The model is qualitatively illustrated in Figure 7.

A final good producer aggregates a continuum of differentiated varieties, indexed by i, to produce a homogeneous output Y. Each downstream intermediate firm i produces its variety Y_i by combining two distinct inputs. The first input is *energy*, E, a commoditized good that is traded in liquid global markets and is therefore perfectly substitutable. Although a significant share of global energy - particularly crude oil and liquefied natural gas - is transported via maritime routes, energy can be stored and is always available for purchase on the local spot market, albeit at a known premium, in the event of transportation shocks and shipping delays. The second input is a *specialized component* M (e.g., EV batteries). In contrast to energy, this input is non-substitutable, and its availability critically depends on uninterrupted transportation through the supply chain. Delays in shipping cannot be easily offset by local sourcing or inventory buffers, making delivery times uncertain and production more vulnerable.

The energy input is produced by combining two upstream inputs that are subject to stochastic shocks: raw energy Z and transportation Ψ. In contrast, the availability of the specialized input depends solely on transportation. The market for transportation provides services for both energy and the specialized input, and it is thus central to the model. We begin by formally describing the production process of the downstream firms and then move up to the upstream transportation and raw energy markets.

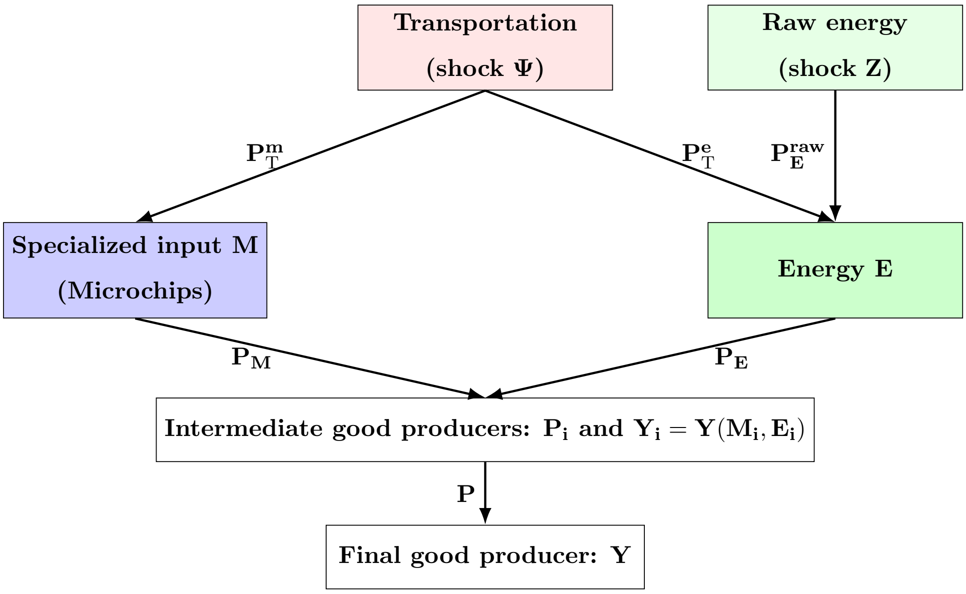


Figure 7: Model of the supply chain

3.2 Final and Intermediate Product Firms

The downstream portion of the production chain is populated by a final good firm and a continuum of intermediate producers.

Final good There is a perfectly competitive final firm producing a homogeneous good Y_t as a CES composite of the continuum of differentiated goods $Y_{i,t}$, indexed by $i \in [0,1]$, with elasticity of substitution $\varepsilon > 1$:

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{4}$$

Optimal demand for each differentiated variety $Y_{i,t}$ is given by

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon} Y_t \tag{5}$$

where $P_{i,t}$ is the price of variety i, and P_t is the aggregate price index given by $P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon} \, di \right)^{\frac{1}{1-\varepsilon}}$.

Intermediate goods There is a continuum of monopolistically competitive intermediate product firms that take the price of energy (E_t) and the specialized input (M_t) as given. Each firm i chooses the optimal output price ($P_{i,t}$), quantity ($Y_{i,t}$), and inputs ($E_{i,t}, M_{i,t}$) to maximize profits:

$$\max_{P_{i,t},Y_{i,t},E_{i,t},M_{i,t}} \{P_{i,t}Y_{i,t} - [P_{E,t}E_{i,t} + P_{M,t}M_{i,t}]\}$$

subject to 5 and the production function:

$$Y_{i,t} = E_{i,t}^{\alpha_E} M_{i,t}^{\alpha_M}$$

where $\alpha_E + \alpha_M = 1$. Cost-minimization yields aggregate input demands

$$E_t = \frac{\alpha_E \, \mathcal{M}^{-1} P_t Y_t}{P_{E,t}}, \qquad M_t = \frac{\alpha_M \, \mathcal{M}^{-1} P_t Y_t}{P_{M,t}}, \tag{6}$$

where $\mathcal{M} \equiv \frac{\varepsilon}{\varepsilon-1}$ is the markup. The nominal marginal cost of production - common across intermediate producers - is given by:

$$MC_t = \left(\frac{P_{E,t}}{\alpha_E}\right)^{\alpha_E} \cdot \left(\frac{P_{M,t}}{\alpha_M}\right)^{\alpha_M} \tag{7}$$

3.3 Supply of Energy

We focus on the energy supplier, as its market is perfectly symmetric to that of the specialized input supplier.

Energy supplier We consider a single energy supplier that produces (final) energy, E_t, by combining transportation services, $E_{T,t}$, and raw energy, $E_{raw,t}$. To capture empirically observed economies of scale in energy logistics - reflecting, for example, the tendency of tankers to operate near full capacity - we assume that the underlying production function exhibits increasing returns to scale (IRS).

We model the energy sector as a regulated natural monopoly and impose efficient (marginal-cost) pricing, abstracting from the associated fiscal transfers. In the special case of constant returns ($\nu = 1$), the equilibrium allocation is isomorphic to that of a representative price-taking supplier. The energy supplier takes both the price of raw energy, $P_{\mathrm{E},t}^{raw}$, and the per-unit cost of transportation, $P_{\mathrm{T},t}^{e}$, as given. Moreover, we allow for a high degree of complementarity between the two inputs, so that the marginal productivity of raw energy is positive only if coupled with transportation services, and vice versa. The energy production function, therefore, reads:

$$E_t = \left((1-\delta)^{1/\eta} E_{T,t}^{1-(1/\eta)} + \delta^{1/\eta} E_{raw,t}^{1-(1/\eta)}\right)^{\frac{\nu}{1-(1/\eta)}} \tag{8}$$

where δ is the share of raw energy in the production of final energy, $\eta \to 0$ is the (low) elasticity of substitution reflecting complementarity between transportation and raw energy, and $\nu > 1$ indexes increasing returns.[16]

Combining cost-minimizing input demands with the aggregator (8) yields the inverse equilibrium cost-schedule of energy (see Online Appendix D.5):

$$E_t = (\nu P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\left(P_{T,t}^e\right)^{1-\eta} + \delta \left(P_{E,t}^{raw}\right)^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{9}$$

Note that, since $\nu > 1$, equation (9) describes a negative relation of (final) energy to its price $P_{E,t}$.

3.4 Market for Transportation

There are two key elements of our analysis. First, transportation markets in the supply chain are subject to disruptions, and those disruptions affect *both* types of inputs. Second, commoditized and specialized inputs react asymmetrically to transportation shocks.

Transportation shocks The transportation of production inputs is subject to shocks. Those shocks increase the *effective* cost of delivery (Alessandria et al., 2023; Dunn and Leibovici, 2023).[17] The effective price of transportation services combines the *market price* of shipping with the *time cost* of delivery delays. The latter captures the costs firms incur when inputs arrive late, including contractual penalties, reputational losses, and discount-driven sales. Because most globally traded goods - including energy - are carried by sea and share the same transportation market,[18] featuring the same chokepoints, they are exposed to the same transportation shocks. In other words, energy and EV batteries do not need to share the same cargo ships to be exposed to the same transportation shocks. Even if the two inputs travel separately, when a transportation shock disrupts traffic on a specific trade route, it generates network congestion,

[16] In particular, we assume that both the energy and the specialized input markets have the same IRS production function in (8), with the same increasing returns index ν, the same elasticity of substitution η, and the same weight δ.

[17] The positive correlation between transportation shocks and the transportation price is due to the prevalence of spot contracts in maritime trade, particularly "trip-charters," whereby shipowners are compensated on a per-day basis (Brancaccio et al., 2023).

[18] Over 80% of international merchandise trade travels by sea (UNCTAD, 2024).

thereby increasing the effective transportation cost and time on *all* other routes as well, by the same amount.

Commoditized vs specialized input Energy is perfectly substitutable and available in local spot markets, so shortages can always be accommodated at a known premium. The specialized input, by contrast, cannot be easily sourced locally and lacks close substitutes - delivery is subject to stochastic lags governed by logistical bottlenecks. When disruptions become severe, while energy remains available at higher spot prices, specialized inputs face true supply uncertainty.

3.4.1 A Simple Model of the Transportation Market

We formalize the above discussion in a stylized model of the transportation market. We start with a few assumptions.

Assumption 3.1. *The supply of transportation of the specialized input has finite capacity.*

This assumption reflects the idea that the energy input is perfectly substitutable and can always be sourced from local spot markets. In contrast, the specialized input lacks local substitutes and is therefore vulnerable to binding supply constraints arising from disruptions in global transportation and logistics.

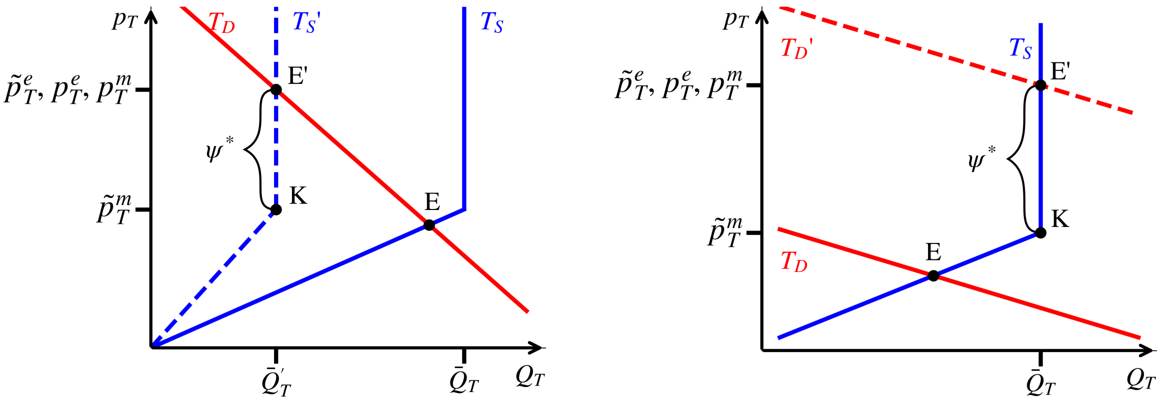
Assumption 3.2. *Both energy and the specialized input are subject to the same transportation shock.*

This assumption captures the fact that both energy and specialized inputs rely on shared transportation infrastructure and pass through common logistical chokepoints.[19] We conceptualize supply chain disruptions as transportation shocks, which can originate from either the demand or the supply side of the transportation sector. Transportation *demand* shocks arise, for example, from surges in global economic activity. A salient case is the post-COVID recovery, during which a synchronized increase in demand across major economies led to severe congestion at key maritime ports. This congestion strained the global shipping network and drove up the market price of transportation services (i.e., cargo rates). By contrast, transportation *supply* shocks reflect disruptions to the effective capacity of the shipping system. These may stem from physical bottlenecks at critical nodes, or from heightened geopolitical risk that alters routing

[19] Note this does not imply that the law of one price is being imposed across the two transportation services.

decisions, reduces effective fleet availability, or impairs the flow of goods.

Graphical illustration of the transportation market We represent the transportation market in Figure 8 in terms of demand and supply in the price-quantity space (P_T, Q_T). The transportation demand curve $T_D(Q_T)$, depicted in red, is downward sloping, for standard reasons. The supply curve $T_S(Q_T)$, in blue, is upward sloping and becomes *vertical* at capacity limit $\bar{Q}_T$. A sufficiently large negative supply shock or positive demand shock moves the equilibrium to point E', where the capacity constraint becomes binding.



(a) Transportation supply shock

(b) Transportation demand shock

Figure 8: Transportation market (lower case variables in logs)

Notes: Effects of a transportation supply shock (left) and demand shock (right) in logs. p^m_T, p^e_T: log effective prices; $\tilde{p}^m_T$, $\tilde{p}^e_T$: log market prices. E: pre-shock equilibrium; K: kink point; E': post-shock equilibrium. The vertical distance K-E' measures the estimated transportation shock $\psi^* \equiv \log(\Psi^*)$.

Estimated transportation shock The above illustration motivates a distinction between the *effective* and the *market* price of transportation for each input. When the transportation supply constraint is not binding, the market price of transportation reflects the effective price for both inputs. When, instead, the supply constraint becomes binding, there is a wedge between the market price of transportation for the specialized input $\tilde{P}^m_{T,t}$ (at point K) and the effective price of transportation of the specialized input $P^m_{T,t}$ (at point E'). This wedge is *unobserved* by the firm and determines an *estimated* transportation shock Ψ^*_t, corresponding to the vertical segment K-E' (where lower case variables refer to logs). Formally, we write:

$$\underbrace{P^m_{T,t}}_{\substack{\text{effective}\\ \text{price}}} = \underbrace{\tilde{P}^m_{T,t}}_{\substack{\text{market}\\ \text{price}}} \cdot \underbrace{\Psi^*_t}_{\substack{\text{estimated}\\ \text{transportation shock}}}$$

Intuitively, when transportation supply reaches full capacity, firms begin to incur a delay time cost associated with a disruption in the physical transportation of the specialized input. If key transportation routes become severely impaired - due to congestion at logistical chokepoints - downstream firms face uncertainty in delivery times, which in turn is reflected in their pricing and production decisions. Notably, market transportation prices for the specialized input are unable to play their allocative role and clear the market because of the existence of physical impairments in the delivery of the specialized input.[20] Henceforth, and without loss of generality, we normalize $\tilde{P}^m_{T,t} = 1$.

For the energy input, however, the effective price $P^e_{T,t}$ and the market price of transportation $\tilde{P}^e_{T,t}$ always coincide, even conditional on the transportation capacity constraint being binding. Consistent with Assumption 3.2, the price of transportation of energy is subject to the same shock Ψ_t. Formally:

$$\underbrace{P^e_{T,t}}_{\substack{\text{effective}\\ \text{price}}} = \underbrace{\tilde{P}^e_{T,t}}_{\substack{\text{market}\\ \text{price}}} = \underbrace{\Psi_t}_{\substack{\text{true transportation}\\ \text{shock}}}$$

Hence the energy market price of transportation efficiently incorporates all the information contained in the *true* transportation shock Ψ_t. This property of the energy transportation price reflects the fact that firms can always source energy from local spot markets, though potentially at a premium. These local markets efficiently incorporate information about transportation shocks and their implications, with prices adjusting immediately to reflect changes in global shipping conditions and risk. Henceforth, we work under the assumption that transportation shocks are large enough that the transportation capacity constraint is binding.

Assumption 3.3. *Transportation (supply and demand) shocks are large enough that the transportation capacity constraint of the specialized input becomes binding.*

The above assumption motivates the existence of a signal extraction problem. Away from the capacity constraint (i.e., in normal times), the market price of transportation is perfectly

[20] This concept is also present in the model of the transportation market from Bai, Fernández-Villaverde, Li, and Zanetti (2024).

correlated with the effective price of transportation for both inputs. When the transportation supply constraint is binding, however, the market price of transportation for the specialized input becomes *uninformative* of the effective price of transportation. As a result, downstream firms will have to estimate a time delay cost associated with the transportation of the specialized input. We turn to the analysis of the signal extraction problem and its determinants in the sections below.

3.5 Raw Energy

The price of *raw* energy $P_{E,t}^{raw}$ evolves according to a stochastic process Z_t. Formally, we have:

$$P_{E,t}^{raw} = Z_t$$

The process Z_t will play an important role in firms' signal extraction problem to be analyzed below.

3.6 Equilibrium in the Energy and Specialized Input Markets

We are now ready to describe the equilibrium in both the market of energy and the market of the specialized input. Plugging the expressions for the price of transportation of energy and the price of raw energy into the equilibrium cost-schedule of energy (9) we obtain:

$$\underbrace{E_t(\Psi_t)}_{\substack{\text{equilibrium supply}\\ \text{of energy}}} = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{10}$$

Symmetrically, we can obtain the equilibrium supply of the specialized input:

$$\underbrace{M_t(\Psi_t^*)}_{\substack{\text{equilibrium supply}\\ \text{of specialized input}}} = (\nu\, P_{M,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{11}$$

where we have assumed that the real price of the raw specific input is normalized to 1. Notice that the equilibrium supply of the specialized input depends on the estimated transportation shock Ψ_t^*.

Equilibrium price of energy The equilibrium price of energy can be derived by combining the demand from the intermediate product firm in (6) with the supply in (10):[21]

$$P_{E,t}(Y_t, \Psi_t, Z_t) = (\alpha_E \mathcal{M}^{-1} Y_t P_t)^{1-\nu} \, \nu^{-\nu} \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta} \right]^{\frac{\nu}{1-\eta}} \tag{12}$$

The equilibrium price of energy depends negatively on the quantity produced Y_t due to IRS ($\nu > 1$), and positively on both the true transportation shock Ψ_t and the raw energy shock Z_t, due to complementarity in production ($\eta < 1$). This reflects a key feature of our model, whereby the price of energy responds by fully internalizing all the information originating from the supply chain. In particular, this implies, as specified earlier, that the effective and market price of transportation of energy are always equalized ($P_T^e = \tilde{P}_T^e$).

Log-linearizing the above expression, the equilibrium relative price of energy in deviation from its steady-state value can be written:

$$p_{E,t} = (1-\nu) y_t + \nu \left[(1-\delta)\psi_t + \delta z_t \right] \tag{13}$$

where $p_{E,t} \equiv \log(\frac{P_{E,t}}{P_t P_E})$, $\psi_t \equiv \log(\frac{\Psi_t}{P_t})$ and $z_t \equiv \log(\frac{Z_t}{P_t})$. The above equation clarifies that, at first order, the elasticities of the energy price to the primitive shocks ψ_t and z_t are increasing in the IRS parameter ν:

$$\frac{\partial p_{E,t}}{\partial \psi_t} = \nu \cdot (1-\delta) \; ; \; \frac{\partial p_{E,t}}{\partial z_t} = \nu \cdot \delta$$

Equilibrium price of specialized input A symmetric equation can be obtained for the relative price of the specialized input combining equation (6) with (11):

$$P_{M,t}(Y_t, \Psi_t^*) = \left(\alpha_M \mathcal{M}^{-1} Y_t P_t\right)^{1-\nu} \, \nu^{-\nu} \, \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta \right]^{\frac{\nu}{1-\eta}} \tag{14}$$

Notice that the equilibrium price of the specialized input depends on aggregate output (as long as $\nu \neq 1$) and, unlike the price of energy, on the *estimated* transportation shock Ψ_t^*, as that cost physically delays the input transportation via the supply chain, generating an additional uncertain production cost.

[21] Note that in practice, energy prices reflect both current production and the existing inventories' buffer stocks. In particular, inventories adjust endogenously to add persistence to energy prices in the short run. For simplicity, we abstract from explicitly modeling inventories.

3.6.1 Equilibrium Marginal Cost

We now consider equation (7) and derive an expression for the equilibrium nominal marginal cost as a function of the underlying shocks:

$$MC_t(Y_t, P_t, \Psi_t, Z_t, \Psi_t^*) = A^{-\nu} \cdot (Y_t P_t)^{1-\nu} \cdot \Gamma(\Psi_t, Z_t)^{\frac{\alpha_E \nu}{1-\eta}} \cdot \Lambda(\Psi_t^*)^{\frac{\alpha_M \nu}{1-\eta}} \tag{15}$$

where $A \equiv \nu\, \alpha_E^{\alpha_E}\, \alpha_M^{\alpha_M}$, $\Gamma(\Psi_t, Z_t) \equiv (1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}$, $\Lambda(\Psi_t^*) \equiv (1-\delta)(\Psi_t^*)^{1-\eta} + \delta$.

The nominal marginal cost depends on *both* the true transportation shock Ψ_t - through its effect on the price of energy - and the estimated transportation shock Ψ_t^* - through its effect on the effective price of the specialized input. Log-linearizing equation (15), and letting mc_t be the percent deviation of the *real* marginal cost from its steady-state value we can write:

$$mc_t = \underbrace{(1-\nu)\, y_t}_{\text{output}} + \nu\,(1-\delta) \left[\underbrace{\alpha_E\, \psi_t}_{\substack{\text{true transportation} \\ \text{shock}}} + \underbrace{\alpha_M\, \psi_t^*}_{\substack{\text{estimated transportation} \\ \text{shock}}} \right] + \underbrace{\nu\, \delta\, \alpha_E\, z_t}_{\substack{\text{raw energy} \\ \text{shock}}} \tag{16}$$

where ψ_t, ψ_t^*, z_t are all in real units. In its log-linear representation, the real marginal cost is affected by four components, each with its own elasticity governed by the IRS parameter $\nu > 1$: *(i)* the aggregate level of output y_t; *(ii)* the *true* transportation shock ψ_t, which directly increases the market price of energy; *(iii)* the estimated transportation shock ψ_t^* which adds a delay time cost to the delivery of the specialized input; *(iv)* the raw energy shock z_t, which directly increases the price of energy.

3.7 Supply Chain Uncertainty

The marginal cost equation (16) highlights the role of *true* and *estimated* transportation shocks as key determinants of the intermediate firm's marginal cost. This framework naturally gives rise to a *signal-extraction* problem, in that the firm needs to form an estimate ψ_t^* of the (log) transportation shock before setting its price.

Signal extraction problem At every period t, intermediate producers face an inference problem. They observe the realized real energy price $p_{E,t}$ and aggregate output y_t, but cannot distinguish whether a movement in $p_{E,t}$ reflects a primitive shock to raw energy costs or a broader disruption to the transportation network. Each firm therefore treats the energy price as a *noisy signal* of the latent transportation shock ψ_t, and forms a Bayesian estimate of the delivery delay cost for the specialized input.[22]

State-space model We represent the above information problem in terms of a *state-space* model. Specifically, we assume that the transportation shock ψ_t is the (latent) state process evolving as a Gaussian linear Markov process. Meanwhile, the energy price equation is the noisy observation equation.[23] For each time $t \geq 1$, the corresponding state-space model is:

$$\begin{cases} \psi_t \;=\; \rho_\psi\, \psi_{(t-1)} + \varepsilon_{\psi,t} & \varepsilon_{\psi,t} \sim \mathcal{N}(0,\, \sigma_\psi^2) \\ p_{E,t} = (1-\nu) y_t + \nu\, \Omega_t & \\ \Omega_t \equiv (1-\delta)\psi_t + \delta z_t & z_t \quad \sim \mathcal{N}(0,\, \sigma_Z^2) \end{cases} \tag{17}$$

where Ω_t is a *convolution* of the two supply shocks (to transportation and raw energy respectively), the latent process of transportation shocks ψ_t has known persistence ρ_ψ, and $\{\varepsilon_{\psi,t}, z_t\}_{t\geq 1}$ are two independent sequences of Gaussian innovations with mean zero and known variances σ_ψ^2 and σ_z^2, respectively.[24]

The model above makes $p_{E,t}$ in the observation equation a noisy function of the latent state ψ_t, perturbed by a second unobserved shock z_t, with Ω_t becoming the noisy signal and z_t the underlying noise. Through the signal extraction problem the firm breaks down the convolution of supply shocks Ω_t in order to isolate the *true* transportation shock, ψ_t, from the *noise* of the raw energy shock, z_t.

Bayesian learning Firms update their beliefs about the latent state ψ_t via Bayesian learning. At every time t, each firm receives new information from the (log) energy price $p_{E,t}$, and optimally combines it with old information contained in the *prior* distribution $\mathcal{P}_{\psi,(t-1)}$. From this process of Bayesian learning, the firm obtains an updated *posterior* distribution $\mathcal{P}_{\psi,t}$.

[22] Without loss of generality, we restrict firms' information set to the energy price $p_{E,t}$ as the sole signal for ψ_t. This is motivated by our previous result that, under elevated supply chain uncertainty, the market price of transportation loses its informativeness precisely when it would otherwise be the natural candidate signal. All results extend to the general case in which firms pool multiple signals via an optimal Bayesian filter, provided $p_{E,t}$ receives strictly positive weight.

[23] For the formal details on the problem of incomplete information considered and its solution, see Online Appendix D.2 and D.3.

[24] Note that as an additional assumption, we also require that the prior distribution of ψ_t at time $t = 0$ is Gaussian with known mean and variance parameters m_0 and C: $\psi_0 \sim \mathcal{N}(m_0, C)$.

Finally, each intermediate firm employs the posterior distribution to produce the optimal point estimate of the current transportation shock, given by:

$$\psi_t^* \equiv \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\psi_t\}$$

To distinguish the standard expectation operator under complete information ($\mathbb{E}_t\{.\}$), we adopt a specific notation for the formulation of the expected value of the transportation shock conditional on the history of energy prices:

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\psi_t\} = \int_{\mathbb{R}} \psi_t \ d\mathcal{P}_{\psi,t}(\psi_t \mid p_{E,(0:t)})$$

where $p_{E,(0:t)}$ is the history of energy prices from period 0 to t.

Kalman filter The optimal linear *estimator* of ψ_t given $p_{E,t}$ is well-defined under the Gaussian linear specification in (17). The point estimate ψ_t^* evolves according to the Kalman filter updating equation:

$$\psi_t^* = \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\}}_{\text{guess with old info}} + \underbrace{\mathbb{K}(\mathcal{S})}_{\text{weight to new info}} \underbrace{\left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)}_{\text{error correction with new signal}} \tag{18}$$

where $\mathbb{K}(\mathcal{S})$ is the *Kalman gain*, in turn a function of the *signal-to-noise* ratio $\mathcal{S}$.[25] The Kalman gain $\mathbb{K}(\mathcal{S})$ is strictly increasing in the signal-to-noise ratio $\mathcal{S} \equiv \sigma_\psi^2/\sigma_Z^2$, and converges to a steady-state value (see Online Appendix D.4).[26]

Marginal cost under uncertainty As highlighted in (14), the specialized input price $p_{M,t}$ depends on the *estimated* transportation shock ψ_t^*, which is estimated according to the Kalman filter updating equation in (18):

$$p_M(\psi_t^*) = (1-\nu)\, y_t + \nu\,(1-\delta) \cdot \underbrace{\left[\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} + \mathbb{K}(\mathcal{S})\left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)\right]}_{\psi_t^*} \tag{19}$$

[25] We assume the Kalman gain converges to a steady state. Accordingly, $\mathbb{K}(\mathcal{S})$ denotes the steady-state gain - the limit of the time-varying gain when the filter is asymptotically stable. See Online Appendix D.4 for a detailed discussion.

[26] See Petris et al. (2009) for a reference.

Notably, the specialized input price depends on the energy price $p_{E,t}$, and on the Kalman gain $\mathbb{K}(\mathcal{S})$.

The marginal cost of the intermediate firm depends on the prices of the two inputs in production - energy and the specialized input:

$$mc_t = \alpha_E \underbrace{p_{E,t}}_{\text{energy price}} + \alpha_M \underbrace{\left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]}_{\text{specialized input price: } p_M(\psi_t^*)} \tag{20}$$

The real marginal cost depends on the energy price through two distinct channels. The first is a *direct effect*: an increase in the energy price raises marginal cost with elasticity α_E, exactly as under complete information. The second is an *uncertainty effect*: because the energy price serves as a noisy signal of the latent transportation shock, firms revise upward their estimate of delivery delays for the specialized input, ψ_t^*, which feeds into the specialized input price $p_M(\psi_t^*)$ and raises marginal cost by an additional amount. Two properties of this channel are worth noting. First, it is absent when $\alpha_M = 0$: if firms use no specialized input, energy prices carry no information about costs that matter, and the uncertainty effect is muted. Second, the effect is increasing in ν. With stronger increasing returns, the transportation sector operates more efficiently when shipment volume is high. A transportation shock then not only reduces carrier availability and raises transportation costs directly (first-round effect), but also lowers logistics efficiency by disrupting the scale economies of the sector (second-round effect)

3.8 Pass-Through of Energy Prices under Uncertainty

We are now in a position to study the impact and propagation of primitive energy price shocks on the intermediate product price under supply chain uncertainty.

Optimal pricing The optimal (log) real *relative* price of the intermediate good under uncertainty is a constant markup $\mu \equiv \log(\mathcal{M})$ over the real marginal cost of production:

$$p_t = \mu + \underbrace{\alpha_E p_{E,t} + \alpha_M \left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]}_{mc_t} \tag{21}$$

The pass-through of energy price movements onto the intermediate product price can be decomposed into an *impact* and a *dynamic* component.

Impact energy price pass-through The following Proposition derives the impact price pass-through of *i.i.d.* energy price movements that originate from primitive raw energy price shocks.

Proposition 1 (Impact Pass-Through). *Under supply chain uncertainty, the time-t pass-through to the optimal intermediate product price of a given time-t increase in the energy price, originating from an i.i.d. raw energy shock z_t, is:*

$$\frac{dp_t}{dp_{E,t}} = \underbrace{\alpha_E}_{\text{direct effect}} + \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\text{uncertainty effect}} \tag{22}$$

Proof. See Appendix A.1. □

Energy prices raise the optimal price via: (i) a *direct* cost-push effect (via coefficient α_E, as under complete information); and (ii) an *uncertainty effect* via the transportation signal, stronger when the Kalman gain $\mathbb{K}(\mathcal{S})$ is higher.[27]

Dynamic energy price pass-through We wish to study how a purely *transitory* i.i.d. energy shock at t affects the path of optimal reset prices chosen at each horizon $\{p_{t+k}\}_{k\geq 1}$, holding future energy price realizations fixed.[28] We can state the following Proposition.

Proposition 2 (Dynamic Pass-Through). *Under supply chain uncertainty, the pass-through to the future expected real output price at horizon $k \geq 1$ of a purely transitory time-t increase in energy price, originating from an i.i.d. raw energy shock z_t, is:*

$$\frac{dp_{(t+k)}}{dp_{E,t}} = \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\text{impact effect of uncertainty}} \cdot \underbrace{\left[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\right]^k}_{\text{persistence effect of uncertainty}} > 0 \tag{23}$$

Proof. Proof in Appendix A.2. □

The dynamic pass-through has an *impact* component $\alpha_M \nu(1-\delta)\mathbb{K}(\mathcal{S})$, increasing in uncertainty σ_ψ^2, and a *persistence* component $[\rho_\psi(1-\mathbb{K}(\mathcal{S})\nu(1-\delta))]^k$, decreasing in uncertainty. Under complete information ($\mathbb{K}=0$), the dynamic pass-through is zero.

[27] Notice that Proposition 1 shows that supply chain uncertainty triggers a precautionary-pricing motive even without nominal price rigidity - a feature absent from the standard literature (Fernández-Villaverde et al., 2015).

[28] This is a partial-equilibrium pass-through, with aggregate output y_t treated as exogenous.

Proposition 2 shows that, under supply chain uncertainty, a surge in the energy price leads firms to initially *misinterpret* it as evidence of a persistent transportation shock, causing them to revise their future optimal price upward. This misinterpretation generates a non-zero dynamic pass-through beyond the date of the shock. Over time, recursive Bayesian learning corrects this mistake: as firms come to recognize that the price surge was driven solely by a transitory *i.i.d.* raw energy shock, their optimal price converges to the complete-information benchmark - under which dynamic pass-through is zero, since firms immediately understand that no persistent transportation disturbance has occurred.

Figure 9 displays the effect on the path of the optimal product price $\{p_{t+k}\}_{k\geq 0}$ and of the estimated transportation shock $\{\psi^*_{t+k}\}_{k\geq 0}$ of an *i.i.d.* raw energy price shock z_t. For each panel, there are three cases, corresponding to complete information, low supply chain uncertainty, and high supply chain uncertainty respectively. Clearly, and relative to the case of complete information, higher supply chain uncertainty (higher σ_ψ) amplifies the *impact* response of the product price level to an *i.i.d.* energy price shock.

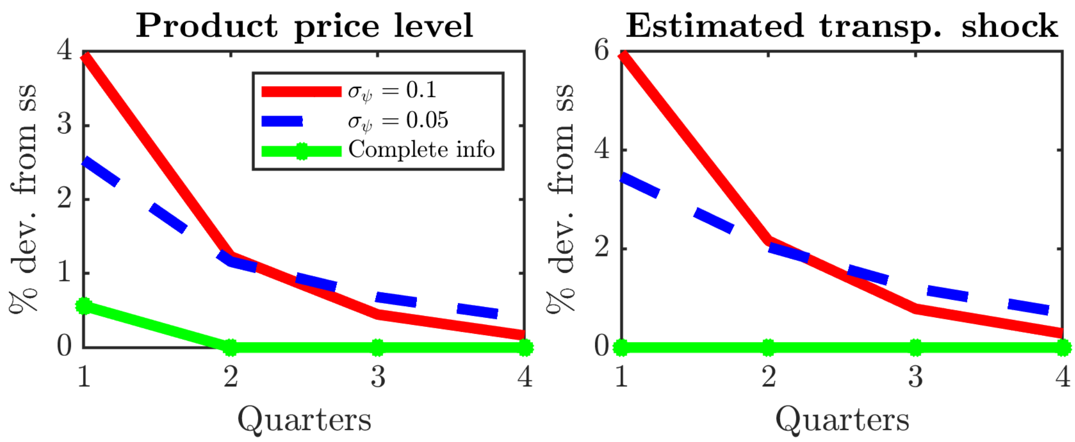


Figure 9: Impulse responses of the optimal intermediate product price and of the estimated transportation shock to an *i.i.d.* raw energy price shock: alternative values of the variance of the transportation shock σ_ψ.

Notes: Responses to an *i.i.d.* 10% positive shock in the raw energy price z_t with volatility $\sigma_z = 0.1$. The remaining parameter values are $\alpha_E = 0.09$, $\alpha_M = 0.91$, $\eta = 0.01$, $\delta = 0.5$, $\rho_\psi = 0.9$, $\sigma_Z = 0.1$, $\nu = 1.25$.

Non-linear effect of uncertainty Figure 10 shows how the dynamic pass-through $\frac{dp_{(t+k)}}{dp_{E,t}}$ varies with the degree of supply chain uncertainty σ_ψ at different horizons $k \geq 1$. Relative to the complete-information case ($\sigma_\psi = 0$), higher uncertainty increases the pass-through at short horizons. However, the effect is *hump-shaped*: as uncertainty rises, firms initially place greater weight on energy prices as signals, but learn faster, which reduces the persistence of the response at longer horizons. Hence, the relationship between uncertainty and dynamic pass-through is highly non-linear and horizon-dependent. At short horizons, where learning is still incomplete, higher uncertainty raises the pass-through more substantially. At longer horizons, however, faster learning dampens the transmission channel.

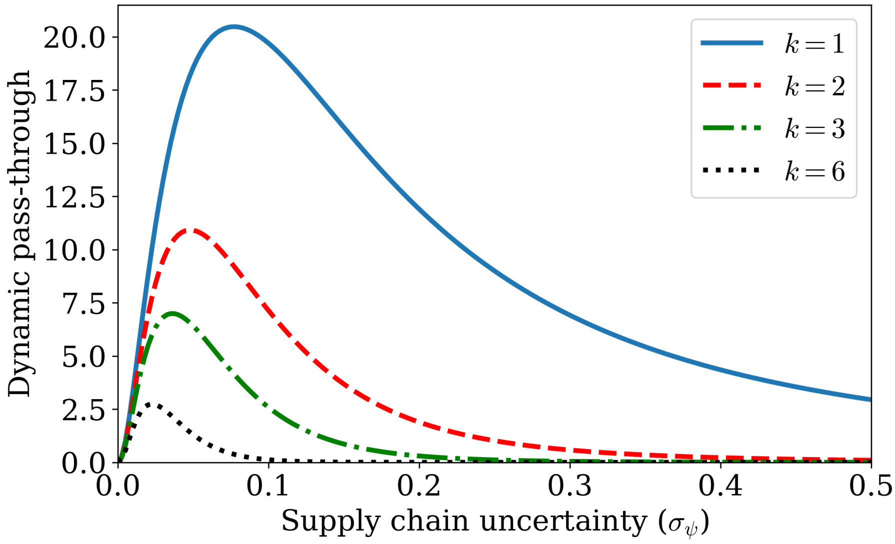


Figure 10: Effect of varying supply chain uncertainty σ_ψ on the dynamic energy price pass-through at different horizons k.

3.9 Staggered Price Setting

We now introduce Calvo-type price stickiness: each intermediate producer resets its price with probability $(1-\theta)$ each period. The optimal real reset price satisfies:

$$p_t = (1-\theta\beta)\mathbb{E}_{\mathcal{P}_{\psi},t}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(\mu + mc_{(t+k)})\right\} \tag{24}$$

where $\beta \in (0,1)$ is the household discount factor, and $mc_{(t+k)}$ is the expected real marginal cost at horizon $t+k$ (common across firms). The above condition states that, due to each price being reset only at random intervals, each intermediate firm is setting its relative price as a function of the stream of current and expected future real marginal costs. Importantly, the operator $\mathbb{E}_{\mathcal{P}_{\psi},t}\{\cdot\}$ denotes expectations formed under uncertainty.[29]

[29]Notice that, in principle, the Calvo pricing model introduces another layer of uncertainty due to the randomness in the timing of adjustment. We assume that the Calvo time before a new adjustment and the estimated transportation shock ψ_t^* evolve as independent stochastic processes. See Online Appendix D.6 for more

3.9.1 New Keynesian Phillips Curve (NKPC) under Uncertainty

Following the steps outlined in Online Appendix D.7, we can manipulate equation (24) above to obtain the *incomplete-information* version of the NKPC:

$$\pi_t = \beta \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\}}_{\substack{\text{expected} \\ \text{inflation}}} + \frac{(1-\theta)(1-\theta\beta)}{\theta} \cdot \underbrace{mc_t(\psi_t^*)}_{\substack{\text{estimated current} \\ \text{marginal cost}}} \tag{25}$$

Note the key departure from the complete-information NKPC: both the current real marginal cost in deviation from its steady state (mc_t) and expected future inflation ($\pi_{(t+1)}$) feature an *estimated* transportation shock, as detailed in the state-space model (17). Both components are sensitive to energy prices ($p_{E,t}$) and serve as two distinct *amplification* channels of the pass-through of energy prices to goods inflation in the NKPC in (25).

Amplification via estimated current real marginal cost As established in Proposition 1, an increase in the current energy price raises firms' marginal cost through two distinct channels. First, there is a *direct effect* - identical to the one that is obtained under a standard complete-information version of the pricing model. Second, there is an additional *uncertainty effect* that operates via the role of energy prices as a signal of an underlying transportation shock, and therefore of higher delay time costs. These combined cost–push forces lead intermediate firms to reset the optimal price upward, which in turn aggregates into higher overall inflation.

Amplification via expected future inflation As shown in Proposition 2, under supply chain uncertainty, an energy price shock is (at least partially) interpreted by firms as a signal of a *persistent* upstream disturbance, which raises expected transportation delays in future periods. Anticipated delays, in turn, increase firms' expectations of future marginal costs, prompting them to revise upward their expected optimal prices. When these adjustments are aggregated across firms, they result in an increase in expected inflation, and, due to the forward-looking nature of price setting, into current inflation as well. Put differently, persistence breeds amplification: the endogenously persistent component of marginal costs induced by supply chain uncertainty translates, via firms' forward-looking pricing behavior, into a magnified inflation response to energy shocks.

details.

Uncertainty wedge and the NKPC The overall effect of energy prices as a signal of present and future unobserved transportation shocks can be isolated by rewriting equation (25) as a familiar complete-information NKPC augmented by an *uncertainty-related* endogenous wedge. Supply (energy) shocks are therefore made more inflationary by uncertainty, in line with the evidence in Monnery and Minton (2025). The next proposition illustrates this result.

Proposition 3 (Phillips Curve under Uncertainty)**.** *Under supply chain uncertainty, the New Keynesian Phillips Curve can be written as:*

$$\pi_t = \underbrace{\beta\,\mathbb{E}_t\left\{\pi_{(t+1)}\right\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\cdot mc_{complete\ info,t}}_{\text{complete-information NKPC}} + \underbrace{G\cdot u_t}_{\substack{\text{uncertainty}\\ \text{wedge}}} \tag{26}$$

where $\mathbb{E}_t\{\cdot\}$ denotes the expected value under complete information about the transportation shock, $G \equiv \frac{(1-\theta)(1-\theta\beta)}{\theta}\cdot\alpha_M\cdot\nu\cdot(1-\delta)$ is a multiplicative constant, and u_t is an uncertainty-related endogenous component due to the estimated transportation shock and evolving as:

$$u_t = L\cdot u_{(t-1)} + \mathbb{K}(\mathcal{S})\cdot\nu\cdot[(1-\delta)\varepsilon_{\psi,t} + \delta z_t]$$

where the persistence is $L \equiv [1-\mathbb{K}(\mathcal{S})\cdot\nu\cdot(1-\delta)]\cdot\rho_\psi$.

Proof. Proof in Appendix A.3. □

Supply chain uncertainty adds a novel endogenous component to the standard complete-information NKPC, arising from estimated transportation shocks and delay time costs. Under uncertainty, rising energy prices not only raise firms' true marginal costs directly, but also serve as a signal of delivery delays - triggering a fully endogenous inflationary effect.

The uncertainty wedge u_t is an AR(1) process driven by the convolution of supply shocks $(1-\delta)\varepsilon_{\psi,t} + \delta z_t$, scaled by the Kalman gain $\mathbb{K}(\mathcal{S})$ and the IRS index ν. Its persistence $L \equiv [1-\mathbb{K}(\mathcal{S})\cdot\nu\cdot(1-\delta)]\cdot\rho_\psi$ is strictly lower than that of the underlying transportation shock ρ_ψ, with the gap increasing in $\mathbb{K}(\mathcal{S})$, ν, and the transportation share $(1-\delta)$.

To fix ideas, consider a purely transitory raw energy shock. Under complete information, the Phillips curve implies a mild, short-lived inflation response. Under incomplete information, the same shock activates the endogenous wedge u_t: firms misread the rise in energy prices as evidence of a persistent transportation disruption, raising their expectations of future marginal costs and generating amplified, more persistent inflation - even though the underlying shock is *i.i.d.*

The role of supply chain uncertainty σ^2_ψ is instructive. A higher σ^2_ψ raises the signal-to-noise ratio $\mathcal{S}$ and hence the Kalman gain $\mathbb{K}(\mathcal{S})$, amplifying the impact of u_t but simultaneously compressing its persistence. Intuitively, greater uncertainty makes energy prices more informative, so firms initially attribute a larger share of any price rise to persistent transportation shocks - but also learn faster that no such shock occurred, reverting more quickly to the complete-information benchmark. The net result is a sharper but more short-lived inflation response.

4 General Equilibrium

We now embed our model of pricing behavior under uncertainty into an otherwise standard general-equilibrium New Keynesian model. We introduce labor in production and assume that each intermediate producer i employs a CRS production function that requires labor $N_{i,t}$, energy $E_{i,t}$, and the specialized input $M_{i,t}$ with production elasticities, respectively, α_N, α_E, α_M, where $\alpha_N + \alpha_E + \alpha_M = 1$:

$$Y_{i,t} = N_{i,t}^{\alpha_N} E_{i,t}^{\alpha_E} M_{i,t}^{\alpha_M} \tag{27}$$

A monetary policy authority sets the nominal interest rate according to a Taylor-type interest rate rule with inflation coefficient $\phi_\pi > 1$. The demand side of the model is standard, so we delegate further details to the Online Appendix D.8.

Calibration We provide an illustrative calibration of the model parameters using commonly used values found in the literature. As for the share of inputs in output production, the labor share is set to $\alpha_N = 2/3$, as in Galí (2015), the energy share to $\alpha_E = 0.03$, as in Gagliardone and Gertler (2023), and the specialized input share residually to $\alpha_M = 1 - \alpha_N - \alpha_E$. Persistence of the transportation shock is set to $\rho_\psi = 0.9$, consistent with Ascari et al. (2024). Notice that, in line with the rest of the paper, we consider the illustrative case of a purely transitory raw energy price shock with zero persistence.[30] This abstraction from a transportation shock effectively isolates the role of the transportation *volatility* and uncertainty in the transmission of energy price shocks to output prices: regardless of the actual *level* of the true transportation shock,

[30] This is uncommon in the literature, as Blanchard and Riggi (2013) and Gagliardone and Gertler (2023) assign to oil shocks persistence over 0.95.

its *volatility* amplifies the pass-through to goods inflation. The standard deviation of the raw energy price shock is normalized to $\sigma_z = 0.1$.

There are three parameters in the energy market, δ, ν, and η. We calibrate the share of raw energy in energy production to $\delta = 0.5$.[31] We set the IRS (Increasing Returns to Scale) index over one, to capture the empirically observed economies of scale in global maritime transportation of energy, $\nu = 1.25$. Similarly, we set the elasticity of substitution between raw energy and transportation close to zero to capture the high degree of complementarity between raw energy and transportation services, $\eta = 0.01$. We assume that the same parameters δ, ν, and η apply to the market for the specialized component. The remaining parameters are calibrated as in the standard Galí (2015). In particular, the coefficient of relative risk aversion $\sigma = 1$; impatience discount factor $\beta = 0.99$; Calvo parameter $\theta = 0.75$; inverse Frisch elasticity $\varphi = 1$; Taylor rule coefficient $\phi_\pi = 1.5$; goods market markup $\mu = 1.2$. We consider three values for the standard deviation of the transportation shock: $\sigma_\psi = 0$ for complete information, $\sigma_\psi = 0.05$ for the low-volatility period of 2002-2021, and $\sigma_\psi = 0.1$ for the sharp rise in supply chain uncertainty in 2021-2023 and in 2026.

Energy price shock under uncertainty Figure 11 displays the impulse responses of selected variables to an *i.i.d.* 10% positive raw energy price shock under the three uncertainty scenarios. On impact, the raw energy price jumps 10% and reverts immediately, raising the energy price and depressing energy demand. Under complete information, firms correctly attribute the shock to raw energy - inferring no transportation disturbance - so inflation and output mean-revert within one quarter.

Under uncertainty, firms cannot isolate the source of the energy price movement and partially attribute it to an underlying transportation disruption. This belief channel raises the estimated transportation shock by approximately 4% on impact under low uncertainty and 6% under high uncertainty. By Proposition 3, this feeds into the uncertainty wedge in the Phillips curve, amplifying inflation and deepening the output contraction. Since the energy price is directly observed, the belief channel does not distort energy demand, which falls nearly identically across regimes. The specialized input, however, depends on the *estimated* transportation shock, so its response varies materially with uncertainty.

[31] According to the U.S. Energy Information Administration (EIA), around half of retail gasoline pump prices is determined by crude oil costs. See `https://www.eia.gov/petroleum/gasdiesel/`

Labor market dynamics also depend on uncertainty. Under complete information, firms substitute toward labor as energy costs rise, so both employment and real wages increase on impact. Under uncertainty, higher perceived marginal costs depress output and labor demand, largely offsetting this substitution effect and producing a near-muted aggregate labor market response.

Finally, higher supply chain uncertainty *amplifies* the initial impact while *reducing persistence*. A higher σ_ψ raises the signal-to-noise ratio, leading firms to update beliefs about transportation delays more aggressively on impact - but also to learn faster that no persistent shock occurred. Comparing the low- and high-uncertainty regimes, the estimated transportation shock collapses earlier and all impulse responses converge faster to the complete-information benchmark.

4.1 Monetary Policy and Energy Shocks: Look-Through?

A standard argument in the monetary policy debate holds that central banks should "look through" supply-driven energy price shocks. The logic is straightforward: energy shocks are typically viewed as *transitory* and therefore neutral for inflation expectations. In canonical New Keynesian models under complete information, such shocks raise marginal costs only temporarily and do not warrant a policy response, as inflation reverts quickly once the shock dissipates. This reasoning featured prominently in academic and policy debates, including during the early phases of the post-pandemic inflation surge.[32]

Our framework calls for a reassessment of this doctrine. In the model, raw energy shocks are strictly transitory by construction - yet, under elevated supply chain uncertainty, they are no longer innocuous. The key departure is firms' incomplete information about upstream supply conditions: a purely transitory energy shock can be misperceived as signalling a persistent rise in future marginal costs. This belief channel alters inflation dynamics in two ways. First, firms raise prices more aggressively on impact, reflecting both direct energy costs and precautionary pricing against perceived future bottlenecks. Second, inflation becomes more persistent, as forward-looking price-setting embeds the endogenous propagation generated by firms' learning dynamics. Crucially, both effects are state-dependent. In low-uncertainty environments, the economy converges to the standard benchmark and energy shocks can indeed be looked through. In high-uncertainty states, the same shocks generate endogenous inflationary pressure that closely mimics the response to genuinely persistent supply disturbances.

[32] See, for instance, U.S. Fed Chair Jerome Powell's speech on November 9, 2023.

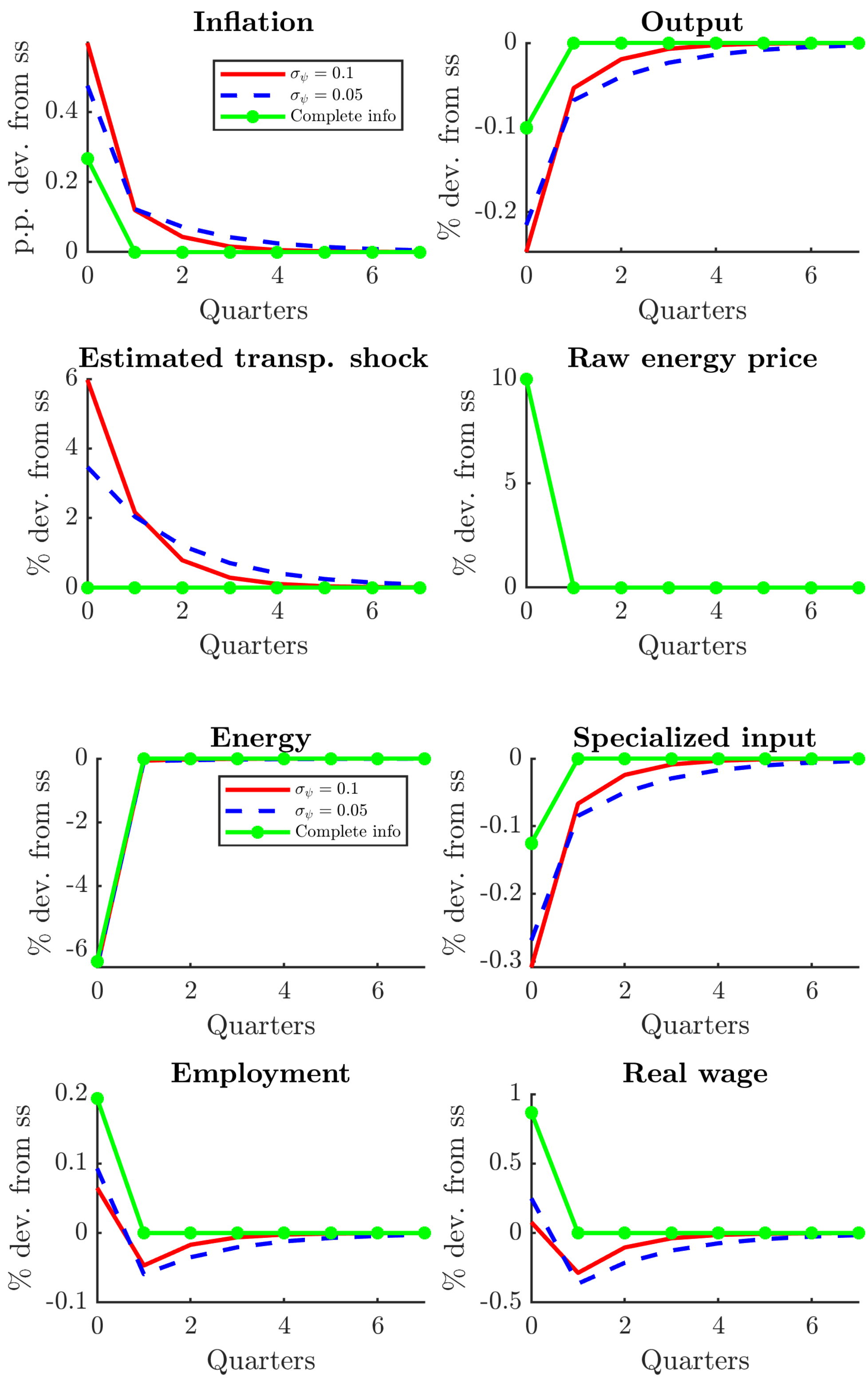


Figure 11: Impulse responses to an *i.i.d.* raw energy price shock: complete information (green) vs alternative levels of supply chain uncertainty (red and blue)

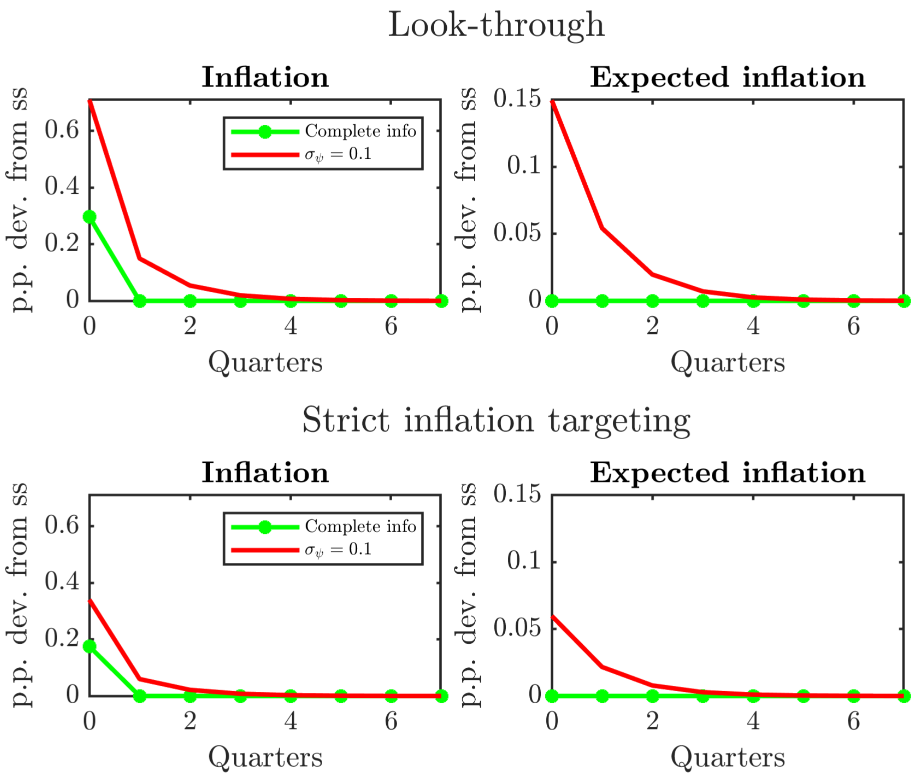


Figure 12: Impulse responses of inflation and one-quarter-ahead expected inflation to an *i.i.d.* raw energy price shock under alternative monetary policy regimes: look-through ($\phi_\pi = 1.0001$) vs strict inflation targeting ($\phi_\pi = 4$).

Figure 12 illustrates this point. The top panel displays the responses of current and expected inflation to an *i.i.d.* raw energy shock under a look-through policy - defined as a value of ϕ_π barely above 1, the minimum required to satisfy the Taylor principle. Under complete information (green lines), the shock raises inflation for one period with no effect on expectations. Under supply chain uncertainty (red lines), the same look-through policy generates an endogenously more persistent response in both current and expected inflation. The bottom panel shows that switching to aggressive inflation targeting ($\phi_\pi = 4$) significantly dampens the response of inflation relative to the passive case.

5 Conclusions

This paper develops a theory of inflation amplification of supply shocks grounded in firms' *uncertainty* about their supply chains. We argue that the complementarity between energy price disturbances and supply chain uncertainty is a structural feature of modern production structures built on highly interconnected supply chains, increasingly exposed to disruptions whether for economic or geopolitical reasons.

In our framework, firms rely on both energy and specialized inputs transported through shared logistical routes. When transportation disruptions render the capacity constraint binding, delivery delays become unpredictable and firms face a signal extraction problem: observed energy prices - contaminated by both raw energy fundamentals and transportation costs - serve as noisy signals of broader supply chain conditions. This inference mechanism amplifies the pass-through of energy shocks to marginal costs and induces persistence in price-setting even when the underlying shock is transitory.

Embedding this mechanism in a canonical New Keynesian model, we show that supply chain uncertainty generates an endogenous uncertainty wedge in the Phillips Curve, activated by volatility in transportation conditions. In general equilibrium, it is the *volatility* of supply shocks - not just their level - that becomes a key determinant of inflation dynamics, amplifying both the *impact* and *persistence* of inflation in response to energy shocks.

These findings carry important policy implications. When supply chain uncertainty is elevated, transitory energy shocks can mimic persistent inflationary pressures, suggesting that optimal monetary policy should be *state-contingent* - calibrated to the prevailing degree of volatility in supply conditions.

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A Appendix

A.1 Proof of Proposition 1 (Impact Pass-Through)

Combining the marginal cost equation (20) with the Kalman filter updating rule (18):

$$\frac{dp_t}{dp_{E,t}} = \alpha_E + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \frac{\partial \psi_t^*}{\partial p_{E,t}}.$$

From (18), $\psi_t^* = \mathbb{E}_{\mathcal{P}_{\psi,t-1}}\{\psi_t\} + \mathbb{K}(\mathcal{S})(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,t-1}}\{p_{E,t}\})$, so $\partial \psi_t^* / \partial p_{E,t} = \mathbb{K}(\mathcal{S})$. Substituting yields the result. □

A.2 Proof of Proposition 2 (Dynamic Pass-Through)

Consider the expression for the optimal intermediate product price (21) at horizon $k \geq 1$ and differentiate with respect to time-t energy price. That yields:

$$\frac{dp_{(t+k)}}{dp_{E,t}} = \alpha_E \cdot \frac{dp_{E,(t+k)}}{dp_{E,t}} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} \tag{A.28}$$

First, note that the energy shock is transitory, *i.i.d.*, and therefore does not change the future energy price path, therefore it holds:

$$\frac{dp_{E,(t+k)}}{dp_{E,t}} = 0$$

Second, we compute the effect of energy prices through uncertainty: $\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}}$ Consider the Kalman filter updating equation in (18), forwarded k periods ahead:

$$\psi^*_{(t+k)} = \rho_\psi \, \psi^*_{(t+k-1)} + \mathbb{K}(\mathcal{S}) \cdot \big(p_{E,(t+k)} - \mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\}\big).$$

The partial derivative follows the recursive formulation

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \rho_\psi \frac{\partial \psi^*_{(t+k-1)}}{\partial p_{E,t}} - \mathbb{K}(\mathcal{S}) \cdot \frac{\partial \mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\}}{\partial p_{E,t}} \tag{A.29}$$

We are now interested in the expected $t+k$ energy price conditional on the time-$t+k-1$ information set:[33]

$$\mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\} = (1-\nu)\,\mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{y_{(t+k)}\} + \nu(1-\delta)\,\rho_\psi \psi^*_{(t+k-1)}$$

The derivative with respect to the energy price is:

$$\frac{\partial \mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\}}{\partial p_{E,t}} = \nu \cdot (1-\delta) \cdot \rho_\psi \cdot \frac{\partial \psi^*_{(t+k-1)}}{\partial p_{E,t}} \tag{A.30}$$

Then, equation (A.29) rewrites as:

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = [\rho_\psi \;(1-\nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S}))] \cdot \frac{\partial \psi^*_{(t+k-1)}}{\partial p_{E,t}}$$

Iterating forward yields:

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \frac{\partial \psi^*_t}{\partial p_{E,t}} \cdot \Big[\rho_\psi\,[1-\mathbb{K}(\mathcal{S})\,\nu\,(1-\delta)]\Big]^k$$

Substitute using $\frac{\partial \psi^*_t}{\partial p_{E,t}} = \mathbb{K}(\mathcal{S})$:

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \mathbb{K}(\mathcal{S}) \cdot \Big[\rho_\psi \cdot (1-\mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\Big]^k = \mathbb{K}(\mathcal{S}) \cdot L^k \tag{A.31}$$

Substituting into (A.28) yields the result. We introduce the notation $L \equiv \rho_\psi\,[1-\mathbb{K}(\mathcal{S})\,\nu\,(1-\delta)]$ and we impose $|L| < 1$, the natural stability condition for the dynamic pass-through of energy prices. This condition also guarantees the stationarity of the uncertainty wedge u_t (see the proof of Proposition 3). In control theory, this condition has a deeper interpretation. It ensures the existence of a steady-state Kalman gain $\mathbb{K}(\mathcal{S})$ and the asymptotic stability of the Kalman filter. See Online Appendix D.4 for more details.

[33] When solving its information problem at time $t+k-1$, we assume that the firm observes contemporaneous aggregate output $y_{(t+k-1)}$. Under this information set, the time-$t+k-1$ energy price $p_{E,(t+k-1)}$ provides no additional signal about the future output beyond what is already embedded in $y_{(t+k-1)}$, so that $\frac{\partial y_{(t+k)}}{\partial p_{E,t}} = 0$.

A.3 Proof of Proposition 3 (Phillips Curve under Uncertainty)

Let ψ_t^* be the transportation shock estimated via the Kalman filter:

$$\psi_t^* = \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} + \mathbb{K}(\mathcal{S}) \left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)$$

Define deviations of the estimated transportation shock from the true value: $u_t \equiv \psi_t^* - \psi_t$ Consider the marginal cost of production of the intermediate firm, which depends on the estimated transportation shock: $mc(\psi_t^*) = \alpha_E p_{E,t} + \alpha_M \left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]$. Write it in deviation from its complete-information counterpart,[34] which depends on the actual transportation shock $mc_{\text{complete info},t}(\psi_t)$

$$mc(\psi_t^*) - mc_{\text{complete info},t}(\psi_t) = \alpha_M \cdot \nu \cdot (1-\delta) \cdot (\psi_t^* - \psi_t) = \alpha_M \cdot \nu \cdot (1-\delta) \cdot u_t$$

Rewrite the optimal price as

$$p_t(\psi_t^*) = p_{\text{complete info},t}(\psi_t) + \alpha_M \cdot \nu \cdot (1-\delta) \cdot u_t$$

Notice that u_t evolves as

$$\begin{aligned} u_t &= \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} + \mathbb{K}(\mathcal{S}) \left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right) - \psi_t \\ &= \rho_\psi \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_{(t-1)}\} + \mathbb{K}(\mathcal{S}) \left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right) - (\rho_\psi \psi_{(t-1)} + \varepsilon_{\psi,t}) \\ &= \rho_\psi u_{(t-1)} + \mathbb{K}(\mathcal{S}) \cdot FE(p_{E,t}) - \varepsilon_{\psi,t} \end{aligned}$$

where $FE(p_{E,t}) = p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}$ is the forecast error. Consider the information set including all the information at time t, *except* for the observation of the energy price $p_{E,t}$. Let $\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}$ be the expected value of the energy price at time t, computed with the information set at time $t-1$:[35] $\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} = (1-\nu)\, y_t + \nu(1-\delta)\, \rho_\psi\, \psi_{(t-1)}^*$ The forecast error is precisely the *surprise* that the firm experiences when it observes $p_{E,t}$ and compares it against the forecast

[34] The optimal final good price under the assumption that the transportation shock is observable.

[35] Where we write y_t in place of $\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{y_t\}$ because y_t is observed when the firm updates the optimal estimate of ψ_t^*.

$\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}$. Decompose further the forecast error:

$$\begin{aligned} FE(p_{E,t}) &= p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} \\ &= \nu \left[(1-\delta)\psi_t + (1-\delta)\varepsilon_{\psi,t} + \delta z_t - (1-\delta)\,\rho_\psi\,\psi^*_{(t-1)}\right] \\ &= \nu \left[(1-\delta)\,\rho_\psi\psi_{(t-1)} + (1-\delta)\varepsilon_{\psi,t} + \delta z_t - (1-\delta)\,\rho_\psi\,\psi^*_{(t-1)}\right] \\ &= \nu \left[(1-\delta)\,\rho_\psi\,(\psi_{(t-1)} - \psi^*_{(t-1)}) + (1-\delta)\varepsilon_{\psi,t} + \delta z_t\right] \\ &= \nu \left[-(1-\delta)\,\rho_\psi\,u_{(t-1)} + (1-\delta)\varepsilon_{\psi,t} + \delta z_t\right] \end{aligned}$$

Then, we can rewrite u_t as

$$\begin{aligned} u_t &= \rho_\psi u_{(t-1)} + \mathbb{K}(\mathcal{S})\,\nu\left[-(1-\delta)\,\rho_\psi\,u_{(t-1)} + (1-\delta)\varepsilon_{\psi,t} + \delta z_t\right] \\ &= [1 - \mathbb{K}(\mathcal{S})\,\nu\,(1-\delta)]\,\rho_\psi u_{(t-1)} + \mathbb{K}(\mathcal{S})\,\nu \cdot [(1-\delta)\varepsilon_{\psi,t} + \delta\, z_t] \\ &= L \cdot u_{(t-1)} + \mathbb{K}(\mathcal{S}) \cdot \nu \cdot [(1-\delta)\varepsilon_{\psi,t} + \delta z_t] \end{aligned}$$

where $L \equiv \rho_\psi\,[1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta)]$. As anticipated in the proof of Proposition 2 (see Appendix A.2), we impose the natural stability condition $|L| < 1$ to guarantee the stationarity of the uncertainty wedge u_t. We aim to rewrite the *incomplete-information NKPC* to isolate the effect of estimated transportation shocks. Start from the *incomplete-information NKPC*:

$$\pi_t = \beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta} mc_t(\psi^*_t)$$

Focus separately on the two components that depend on estimated elements:

$$(i) \quad mc_t(\psi^*_t) \qquad (ii) \quad \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\}$$

For (i), rewrite the marginal cost purging out the incomplete information component in the error u_t:

$$mc_t(\psi^*_t) = mc_{\text{complete info},t} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot u_t \tag{A.32}$$

where $u_t \equiv \psi^*_t - \psi_t$. For *(ii)*, lag one period ahead the *incomplete-information NKPC*:

$$\pi_{(t+1)} = \beta\mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{\pi_{(t+2)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{mc_{(t+1)}\} \tag{A.33}$$

Apply the time t expectation operator $\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\,.\,\}$. By the law of iterated expectations, obtain

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+2)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{(t+1)}\} \tag{A.34}$$

Assume that the time t expectation of inflation at an infinite horizon converges. Then, integrate forward and obtain

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+j+1}\} \tag{A.35}$$

Note that, for any time t, the expectations of the marginal cost at $t+j+1$, computed under the incomplete information measure, can be rewritten as:

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+j+1}\} = \mathbb{E}_t\{mc_{t+j+1}(\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\psi_{t+j+1}\})\} = \mathbb{E}_t\{mc_{t+j+1}(\psi^*_{t+j+1})\}$$

Consider (A.32) that extracts the incomplete information component from the marginal cost, and iterate it $j+1$ periods ahead:[36]

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+j+1}\} = \mathbb{E}_t\{mc_{t+j+1}(\psi^*_{t+j+1})\} = \mathbb{E}_t\{mc_{\text{complete info},t+j+1}\} + \alpha_M\cdot\nu\cdot(1-\delta)\cdot\mathbb{E}_t\{u_{t+j+1}\} \tag{A.36}$$

and plug (A.36) into equation (A.35) above:

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j\left(\mathbb{E}_t\{mc_{\text{complete info},t+j+1}\} + \alpha_M\cdot\nu\cdot(1-\delta)\cdot\mathbb{E}_t\{u_{t+j+1}\}\right) \tag{A.37}$$

[36] Note that, for any time t, the expectations computed under the incomplete information measure $\mathbb{E}_t\{u_{t+j+1}\} \equiv \mathbb{E}_t\{\psi^*_{t+j+1} - \psi_{t+j+1}\} \equiv \mathbb{E}_t\{\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\psi_{t+j+1}\} - \psi_{t+j+1}\} \equiv \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\psi_{t+j+1}\} - \mathbb{E}_t\{\psi_{t+j+1}\}$

Use equations (A.32)-(A.37) to rewrite the *incomplete-information NKPC*:

$$\begin{aligned}
\pi_t &= \beta \cdot \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta} mc_t(\psi_t^*) \\
&= \frac{(1-\theta)(1-\theta\beta)}{\theta} \sum_{j=0}^{\infty} \beta^{j+1} \left(\mathbb{E}_t\{mc_{\text{complete info},t+j+1}\} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{E}_t\{u_{t+j+1}\} \right) + \\
&\quad + \frac{(1-\theta)(1-\theta\beta)}{\theta} \left(mc_{\text{complete info},t} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot u_t \right) \\
&= \frac{(1-\theta)(1-\theta\beta)}{\theta} \sum_{j=0}^{\infty} \beta^{j} \left(\mathbb{E}_t\{mc_{\text{complete info},t+j}\} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{E}_t\{u_{t+j}\} \right)
\end{aligned}$$

Recursively,

$$\pi_t = \beta \mathbb{E}_t\{\pi_{(t+1)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta} \; mc_{\text{complete info},t} + G \cdot u_t$$

where $G = \frac{(1-\theta)(1-\theta\beta)}{\theta} \cdot \alpha_M \cdot \nu \cdot (1-\delta)$, and u_t has motion law as described in Proposition 2:

$$u_t = L \cdot u_{(t-1)} + \mathbb{K}(\mathcal{S}) \cdot \nu \cdot [(1-\delta)\varepsilon_{\psi,t} + \delta z_t]$$

where, as in Proposition 2, we assume $L \equiv \rho_\psi \left[1 - \mathbb{K}(\mathcal{S})\, \nu\, (1-\delta)\right] < 1$.

Online Appendix

Supply Chain Uncertainty, Energy Prices, and Inflation

Alfonso Merendino and Tommaso Monacelli

Contents

B Appendix on Local Projections

B.1 Four Measures of SCU

In this Appendix, we present the four main measures of supply chain uncertainty that we consider for this work. The first three are based on text-mining from newspaper sources: (i) the Region-specific SCU, (ii) the Global SCU, (iii) the ETU index. The fourth measure, (iv) GSCPI Volatility, is based on prices and other fundamental economic data.

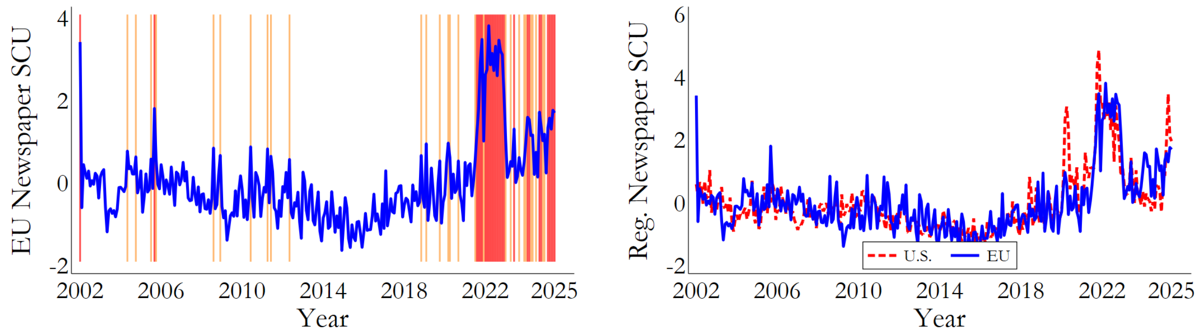
B.1.1 Baseline Measure of SCU

Region-specific Supply Chain Uncertainty The Region-specific Supply Chain Uncertainty is a measure of the incidence of *supply chain* and *uncertainty* words in the media. Figure B.13 below shows the evolution of the EU Region-specific Supply Chain Uncertainty (SCU) and compares it with the U.S. Region-specific measure. It is computed for both the U.S. and the Euro area, separately. We extract it from English-language newspapers in the Factiva Dow Jones database about the U.S. and Euro area, respectively. To avoid false positives, we restricted our search to newspapers in the economic categories: "Commodity/Financial Market News," "Corporate/Industrial News," "Economic News," "Political/General News," "Selection of Top Stories/Trends/Analysis." The process to construct the index starts by flagging newspaper articles whose headline or first paragraph contains at least one word from the *supply chain* dictionary *and* a word from the *uncertainty* dictionary. Then, the index is computed as the share of flagged articles over all articles in the month, standardized to have zero mean and unit variance over the full sample period. Both the *supply chain* and the *uncertainty* dictionary are introduced in (Hassan et al., 2025) to measure "Supply Chain Risk." In particular, the *supply chain* dictionary contains the words:

supplier, supplier network, supply assurance, supply base, supply bottleneck, supply chain, supply challenge, supply constraint, supply crunch, supply disruptions, supply front, supply impact, supply issue, supply logistic, supply network, supply partner, supply pressure, supply problem, supply shock, supply shortage, supply side, supply squeeze, supply tightness

As for the *uncertainty* dictionary, we consider the full list of synonyms for "risk," "risky," "uncertain," and "uncertainty" from the Oxford Thesaurus Dictionary (2016). It contains the words:[37]

ambivalence, ambivalent, apprehension, bet, chancy, chance, changeable, changeableness, changeability, changeful, chariness, chanciness, danger, defenseless, debatable, diffidence, diffident, dilemma, dicey, disquiet, disquietude, doubt, doubtful, doubtfulness, dubious, dubiety, endanger, equivocation, equivocating, erratic, exposed, faltering, fear, fickleness, fitful, fitfulness, fluctuating, fluctuant, gamble, gnarly, hairy, halting, hazard, hazardous, hazy, hesitant, hesitating, hesitancy, iffy, incalculable, indecision, indecisive, incertitude, inconstancy, insecure, insecurity, instability, irregular, irresolute, irresolution, jeopardize, jeopardy, likelihood, menace, misgiving, niggle, oscillating, parlous, pending, peril, perilousness, possibility, precarious, precariousness, probability, prospect, qualm, queries, query, question, questions, reservation, risk, risked, riskier, riskiest, riskiness, risky, risking, risks, scruple, skepticism, speculative, sticky, suspicion, tentative, tentativeness, threat, torn, treacherous, tricky, unclear, unconfident, undecided, undependable, undetermined, unpredictability, unpredictable, unforeseeable, unreliable, unreliability, unresolved, unsettled, unsure, unsureness, untrustworthy, unstable, uncertainties, uncertainty, vacillating, vacillation, vagueness, variable, variability, varying, venture, wariness, wager, wavering



(a) EU Region-specific SCU

(b) U.S. vs EU Region-specific SCU

Figure B.13: Comparison of EU vs U.S. Region-specific Supply Chain Uncertainty

Notes: In the left panel, light orange highlights observations in the top 20% and red in the top 10% of each series. All series are standardized over the full sample 2002-2025.

B.1.2 Additional Measures of SCU

Global Supply Chain Uncertainty The Global Supply Chain Uncertainty index is constructed from English-language global newspapers from the Factiva Dow Jones database. We follow the

[37] We follow Hassan et al. (2019) in this approach.

same procedure as the Region-specific SCU index, and we adopt the same dictionaries. Different from the index above, however, we consider *global* newspapers (not region-specific media).

Energy Transportation Uncertainty (ETU) The ETU index is calculated with a text-mining approach that computes the proportion of articles discussing energy transportation uncertainty over a universe of English-language media sources worldwide. An article is classified as relevant when an energy-related keyword appears in the headline or lead paragraphs and when terms related to energy, transportation, and uncertainty occur within a five-word proximity. To be considered, an article must contain words that belong to all three categories: *Energy* (e.g., oil, gas, petroleum, energy), *Transportation* (e.g., pipeline, midstream, shipping, rail), and *Uncertainty* (e.g., threat, risk, concern, warn).

Notably, as highlighted in Morão (2025), the ETU index can track the main episodes of narrow energy-transport disruption rather than broad supply-chain stress. Spikes in the ETU series reflect events such as the 2019 tanker attacks in the Gulf of Oman and near the Strait of Hormuz, which sharply raised fears over the security of one of the world's key oil-shipping corridors. Also, the index rises in 2021 with the Colonial Pipeline cyberattack, a ransomware attack that temporarily shut down the largest refined-fuel pipeline system on the U.S. East Coast. For further details on the construction of the index, series' spike examples, dictionaries used, and source selection see Morão (2025).

GSCPI Stochastic Volatility The GSCPI Stochastic Volatility is the median of the filtered series of transportation volatility estimated using a stochastic volatility model. The GSCPI (Global Supply Chain Pressure Index) is a measure of transportation bottlenecks (Benigno et al., 2022). The GSCPI is constructed from the bottom up by aggregating country-specific measures of supply chain efficiency, primarily derived from Purchasing Managers Index (PMI) surveys across key global economies. Additionally, it incorporates transportation costs, including indices like HARPEX and the Baltic Dry Index. The GSCPI isolates only the supply-side component of these measures. The series is compiled and published monthly by the New York Federal Reserve.[38] We leverage this measure of supply chain pressures derived from economic data to estimate a stochastic volatility model of supply chain disruptions. We standardize the series of the GSCPI to have mean zero and unit variance over the 2002-2025 sample. We then model

[38] The series is available at: `https://www.newyorkfed.org/research/policy/gscpi#/overview`.

the standardized GSCPI, denoted by ψ_t, as an autoregressive process with stochastic volatility, $\sigma_{\psi,t}$, given by

$$\begin{aligned} \psi_t &= \rho_\psi \psi_{t-1} + \exp(\sigma_{\psi,t})\varepsilon_t, && \varepsilon_t \sim \mathcal{N}(0,1), \\ \sigma_{\psi,t} &= (1-\rho_\sigma)\bar{\sigma}_\psi + \rho_\sigma \sigma_{\psi,t-1} + \eta_\psi u_t, && u_t \sim \mathcal{N}(0,1). \end{aligned} \tag{B.38}$$

The model we adopted for the evolution of the GSCPI emphasizes the distinction between the *level* of transportation bottlenecks and the *uncertainty* and unpredictability surrounding them. In this specification, $\rho_\psi \psi_{t-1}$ captures the predictable component of supply chain pressures, while $\exp(\sigma_{\psi,t})\varepsilon_t$ captures the unpredictable component, that is, the innovation to the GSCPI process. The time-t conditional variance of innovations to the GSCPI process is $\exp(2\sigma_{\psi,t})$. This is the object of interest in our analysis. It measures the amount of uncertainty surrounding supply chain conditions at each point in time: when $\sigma_{\psi,t}$ rises, shocks to supply chain pressures become more dispersed, and the GSCPI becomes harder to forecast.

We estimate the model using Bayesian methods.[39] We use a particle filter to evaluate the likelihood of the model, and a filtering step to recursively recover the latent volatility state $\sigma_{\psi,t}$ using information available up to date t. This yields, at each date, an estimate of the latent log-volatility and therefore of the corresponding conditional variance of GSCPI innovations. Our final series is thus the filtered estimate of $\exp(2\sigma_{\psi,t})$, which we label GSCPI Volatility index and interpret as a narrow measure of transportation volatility. Figure B.14 plots the GSCPI Volatility index against the level of the GSCPI, showing that the two series (level and variance) co-move only to a limited extent.

[39]The estimation is carried out using the Particle Filter algorithm from Born and Pfeifer (2014), available at `https://github.com/JohannesPfeifer/Particle_Filtering/blob/master/README.md`. We estimate the stochastic volatility process on the 2002–2025 sample of the GSCPI, taking 60,000 draws from the posterior distribution of the parameters and discarding the first 10,000 draws.

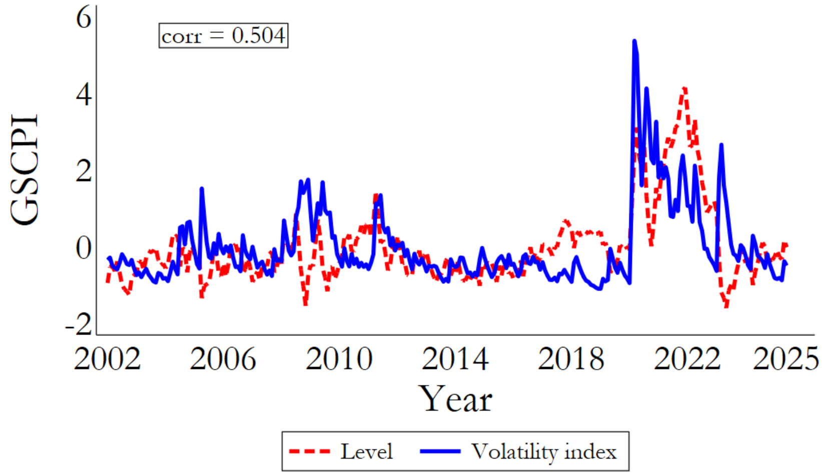


Figure B.14: Evolution of GSCPI: Level versus Volatility

Notes: The figure plots the level and Volatility index of the GSCPI, at monthly frequency from January 2002 to June 2025. Each series is expressed in standard deviations from its respective 2002-2025 average.

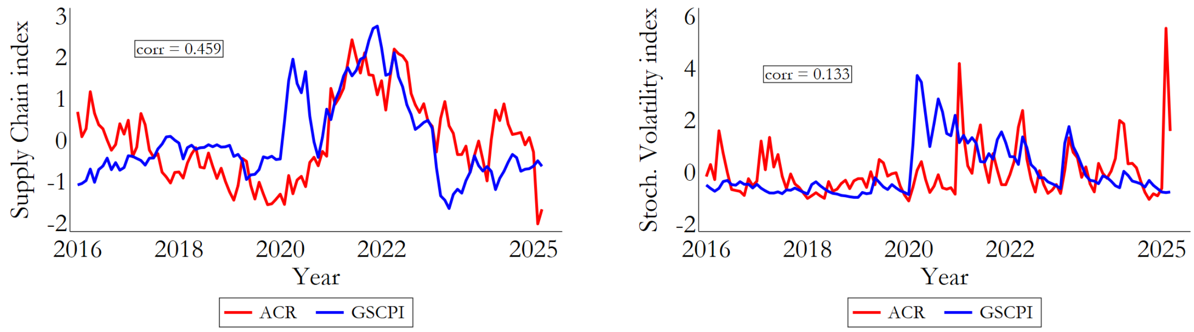
B.1.3 Note on Figure 1

Figure 1 in the main text presents the Region-specific and Global SCU indexes from January 1, 2018 to March 15, 2026. Note that the series plotted in Figure 1 are manually refined by excluding articles that mention the word "Anthropic." This adjustment is important to reduce noise because the potential classification of Anthropic as a "supply-chain risk" in the U.S. generated substantial media coverage and an artificial spike in the newspaper-based SCU series that is unrelated to genuine supply-chain uncertainty.

B.2 Average Congestion Rate (ACR) Index

Beyond the GSCPI, several alternative measures of transportation disruptions are available to construct data-driven measures of supply chain volatility. Among others, the Harper Peterson Time Charter Rates Index (HARPEX), the climate-related supply-chain shock measure proposed by Blaum et al. (2025), and the Average Congestion Rate (ACR) index developed by Bai, Fernández-Villaverde, Li, and Zanetti (2024). The ACR is a new index that measures real-time container ship congestion at major ports worldwide using high-frequency satellite data. The ACR can directly capture *physical* delivery bottlenecks and shipping disruptions, and the ACR variance is an appealing proxy for supply chain uncertainty. However, the short sample available (from January 2016 to March 2025) limits its use for our state-dependent Local Projections.

In Figure B.15a below, we plot the ACR against the GSCPI, and we show that the two have a comparable evolution. We also estimate the ACR Volatility index following a procedure that mirrors the one for the GSCPI Volatility in (B.38). We plot the ACR Volatility against the GSCPI Volatility index in Figure B.15b, and we show that they also partly co-move.

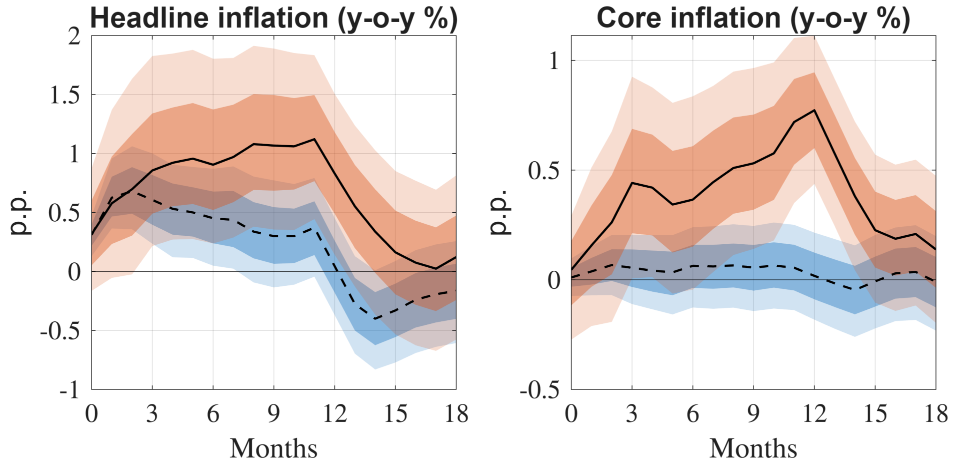


(a) Evolution of GSCPI versus ACR index (b) GSCPI vs. ACR volatility index

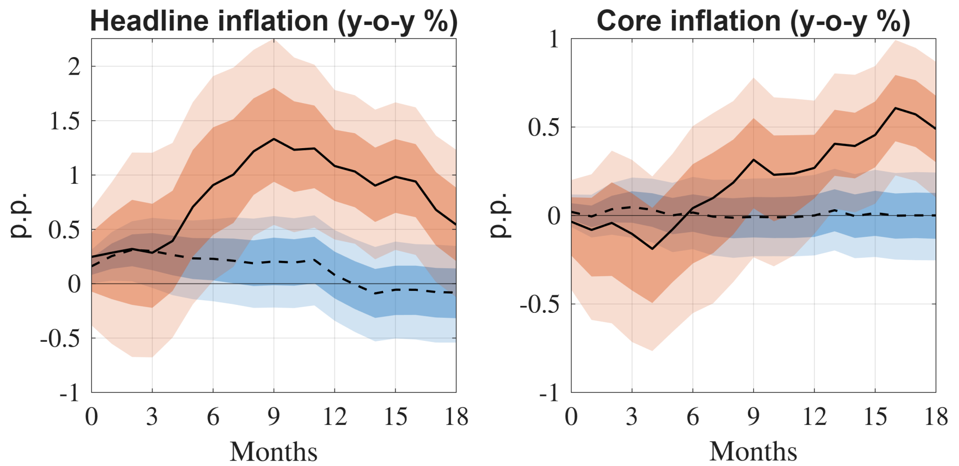
Notes: Left panel: level of the GSCPI and of ACR, plotted with monthly frequency from January 2016 to March 2025. GSCPI and ACR are expressed in standard deviations from their respective 2016-2025 averages. Right panel: plot of the ACR and the GSCPI Volatility indexes with monthly frequency from January 2016 to March 2025.

B.3 LP Estimates under Global SCU, ETU Index, and GSCPI Volatility

We consider the three additional SCU measures: Global SCU, the ETU index, and GSCPI Volatility. For each measure, the high-uncertainty regime is defined as the top 20% of its distribution. Figures B.16, B.17, and B.18 show the state-dependent impulse responses of inflation to an exogenous oil shock, where the high-SCU regime is identified by Global SCU, the ETU index, and GSCPI Volatility, respectively.

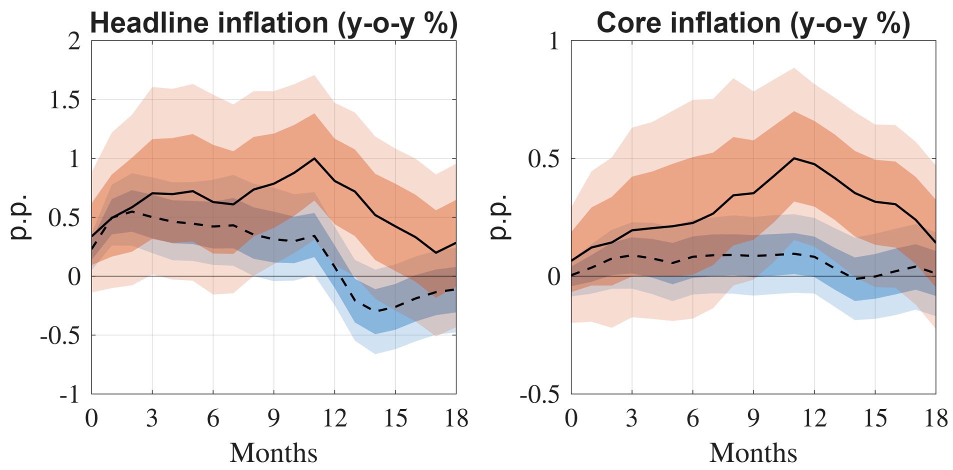


(a) U.S.

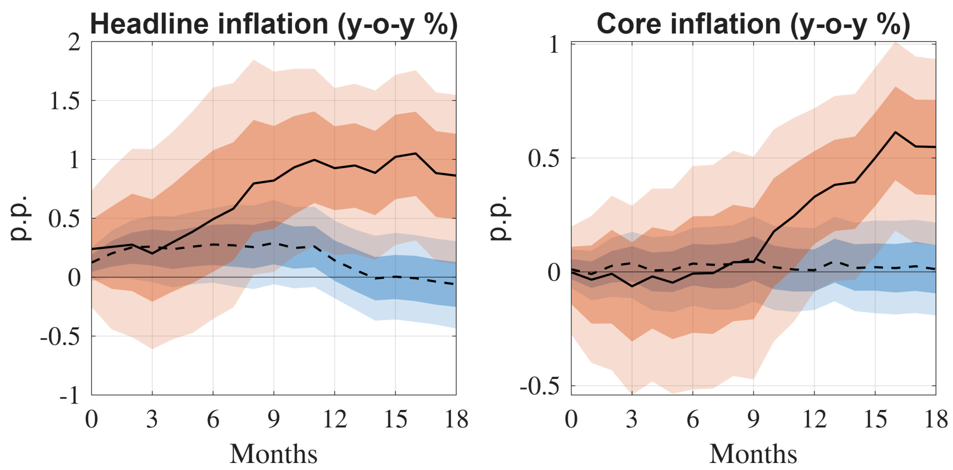


(b) Euro area

Figure B.16: Headline and core inflation responses to an oil news shock across *Global SCU* uncertainty states - U.S. and Euro area



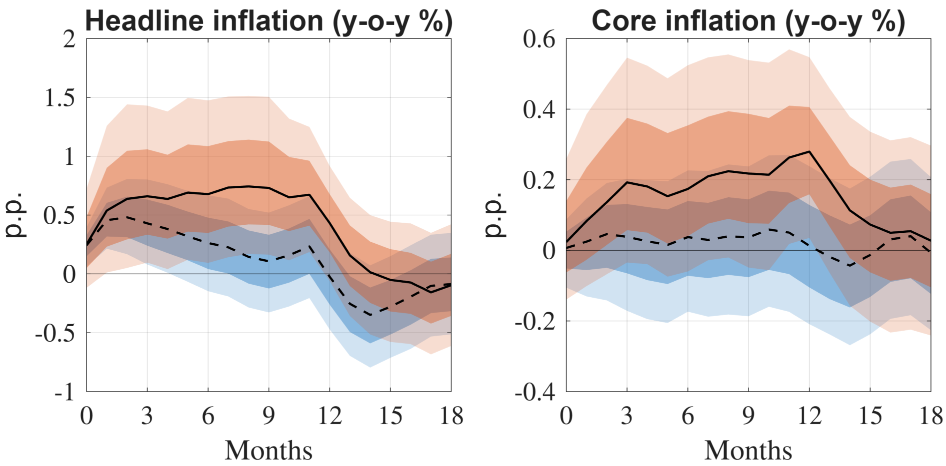
(a) U.S.



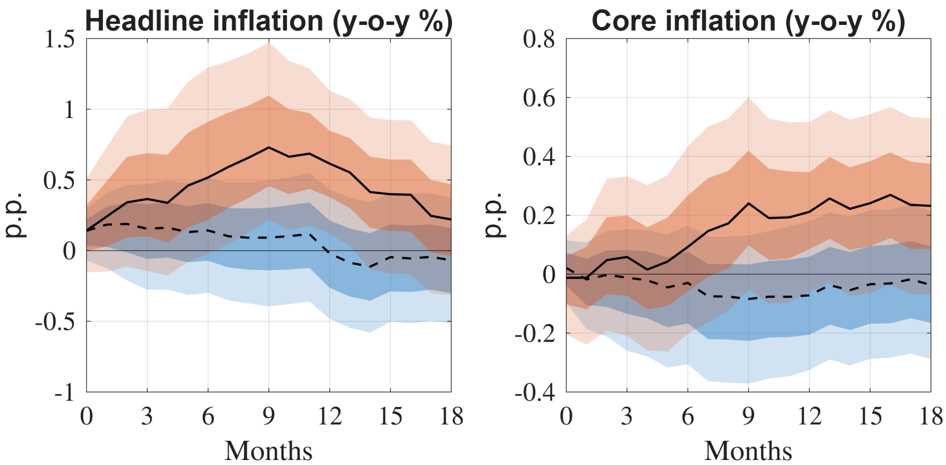
(b) Euro area

- - - Low uncertainty —— High uncertainty

Figure B.17: Headline and core inflation responses to an oil news shock across *ETU index* uncertainty states - U.S. and Euro area



(a) U.S.



(b) Euro area

- - - Low uncertainty —— High uncertainty

Figure B.18: Headline and core inflation responses to an oil news shock across *GSCPI Volatility* uncertainty states - U.S. and Euro area

B.4 LP of Inflation on Gas Shocks

In this appendix, we describe the procedure used to estimate local projections of inflation on gas shocks. The empirical approach mirrors the one adopted for oil shocks. We rely on the exogenous high-frequency gas supply news shocks for the Euro area compiled by Alessandri and Gazzani (2025). Their identification is based on the one-month Dutch TTF future, a standard proxy for European gas prices. The TTF (Title Transfer Facility) is a virtual gas trading hub in the Netherlands and serves as Europe's benchmark wholesale gas price (European

Commission, 2018). Because front-month TTF futures are highly liquid and absorb market-relevant information almost immediately, they provide a clean high-frequency signal of unexpected shifts in European gas supply conditions. The identification of gas supply news shocks then proceeds in two steps and includes a narrative component, following the approach of Känzig.

First, large unexpected movements in front-month TTF prices driven by supply news are identified from Refinitiv news. This step isolates a series of gas price surprises around exogenous gas supply events. Second, these surprises are used as an instrument in a structurally identified VAR to recover the final monthly series of structural gas shocks, $\{\varepsilon_t^{\text{gas}}\}_{t\geq 0}$.

We compute the impulse response of inflation to a gas shock that raises the energy price by 10%. We mirror the local projections of inflation on oil in the main text. For each horizon $h = 0, \ldots, 18$:

$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{gas}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{gas}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \nu_{t+h} \tag{B.39}$$

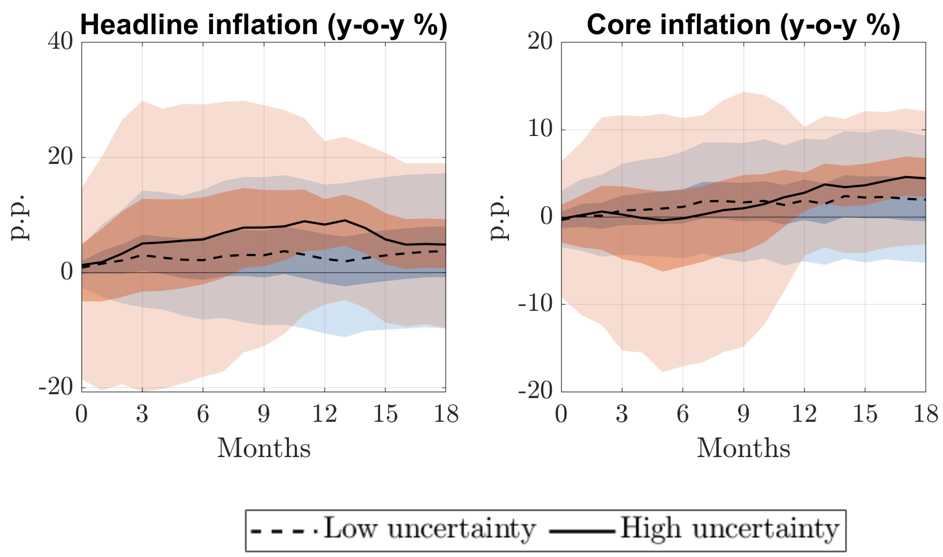


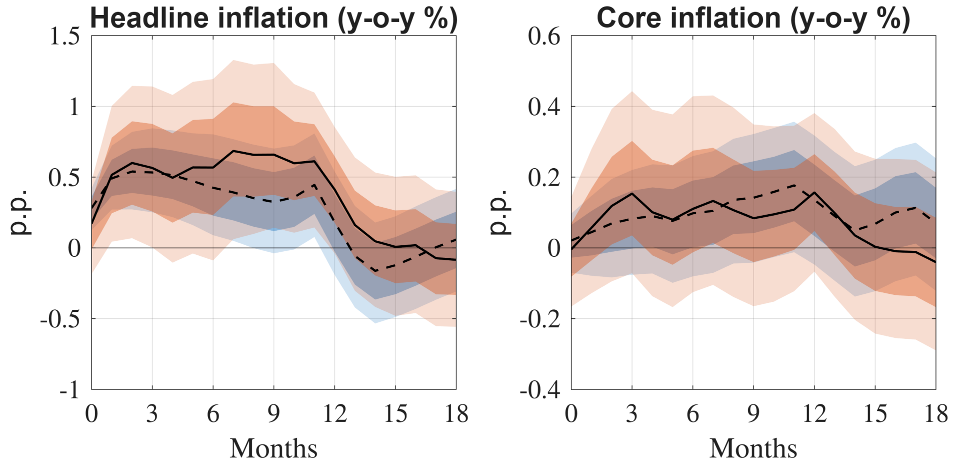
Figure B.19: Headline and core inflation responses to a *gas news shock* across Region-specific SCU uncertainty states - Euro area

Notes: Responses are normalized to generate a 10 p.p. increase in energy inflation. Solid (dotted) line: high (low) SCU state (top 20% / bottom 80% of Region-specific SCU). Orange (blue) shaded areas: 90% and 68% confidence bands.

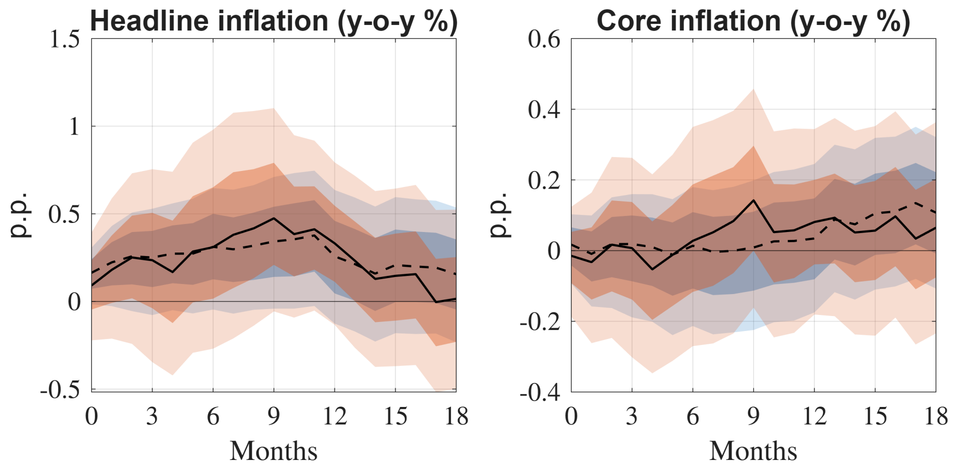
B.5 LP Estimates under EPU Index

In this appendix, we show that the amplification of energy shocks is *not* a general feature of uncertainty. We present the state-dependent local projection of inflation on oil shocks for different states of a representative measure of broad uncertainty, the *Economic Policy Uncertainty (EPU) index*. Notably, the EPU index is *unrelated* to supply-chain uncertainty. We also reproduce the local projections for different states of other broad-uncertainty measures that are *unrelated* to supply-chain uncertainty: World Trade Uncertainty Index (WTUI), Global Energy Uncertainty Index (EUI), Equity Market Volatility (EMV), Trade Policy Uncertainty (TPU), the VIX, and the Macro Uncertainty measure of Jurado et al.[40] For all measures, we find that the inflationary response to an oil shock is muted, or even dampened, under high uncertainty. This result is consistent with the standard broad-uncertainty channel, whereby higher uncertainty raises the option value of waiting, depresses investment, lowers output and inflation (Bloom, 2014).

[40] The results are available upon request from the authors.



(a) U.S.



(b) Euro area

Low uncertainty — High uncertainty

Figure B.20: Headline and core inflation responses to an oil news shock across *Economic Policy Uncertainty* states - U.S. and Euro area

B.6 LP Estimates with Additional COVID Controls

We compute the local projections of inflation on oil shocks including additional COVID controls. First, we run a robustness exercise that accounts for the observed exceptional COVID-19 inflation spike from the outbreak to the end of 2022. We introduce a categorical variable $COVID_t$ that is a COVID-inflation period intercept from April 2020 to December 2022. Figure B.21 plots the impulse responses of inflation to an oil shock from the set of regressions, over horizons $h = 0, \dots, 18$:

$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{oil}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \gamma_h^C COVID_t + \nu_{t+h}$$

Second, we run a robustness exercise to control for the unusual inflation dynamics during the COVID-19 closure period (April to December 2020). For each horizon h, we introduce a set of COVID-month additional controls $\{C_t^{4/20} \dots C_t^{12/20}\}$ that control for month-specific shocks in the period April to December 2020. Figure B.22 plots the impulse responses of inflation to an oil shock from the set of regressions, over horizons $h = 0, \dots, 18$:

$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{oil}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \sum_{m \in \{4/20, \dots, 12/20\}} \gamma_{m,h}^C C_t^m + \nu_{t+h}$$

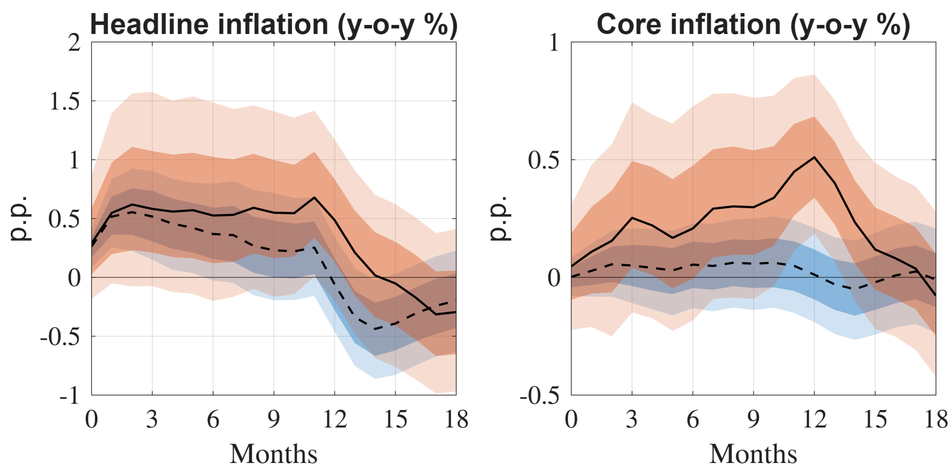
B.7 LP Estimates with Additional Supply Chain Pressure Controls

We compute the local projections of inflation on oil shocks including additional controls for supply chain pressures. First, we run a robustness exercise that accounts for the *level* supply chain pressures, the GSCPI (T_t) and its lags. Figure B.23 plots the impulse responses of inflation to an oil shock from the set of regressions, over horizons $h = 0, \dots, 18$:

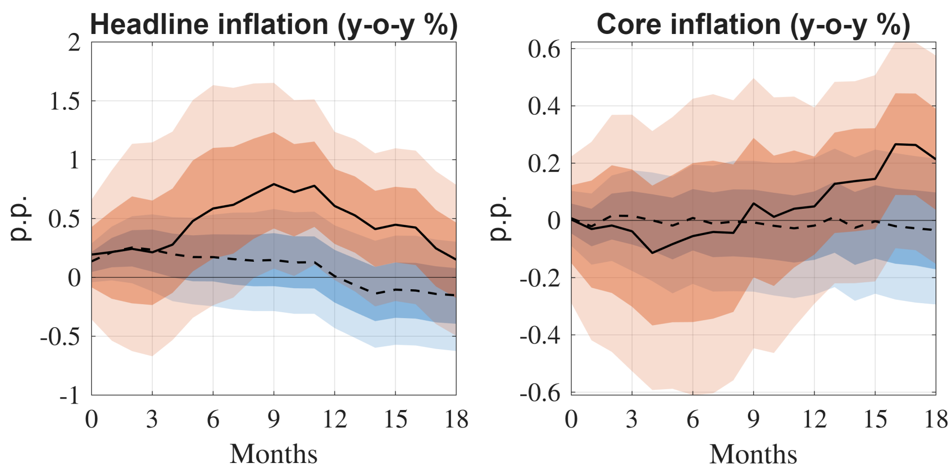
$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{oil}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \sum_{j=0}^{12} \gamma_{j,h}^{T} T_{t-j} + \nu_{t+h}$$

Second, we run a robustness exercise to control for the interaction of oil shocks with supply chain (first-moment) pressures. Figure B.24 plots the impulse responses of inflation to an oil shock from the set of regressions, over horizons $h = 0, \ldots, 18$:

$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \beta_h^H U_t \cdot \varepsilon_t^{\text{oil}} + \gamma_h^U U_t + \sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j} + \gamma_h^T T_t + \gamma_h^{T,H} T_t \cdot \varepsilon_t^{\text{oil}} + \nu_{t+h}$$



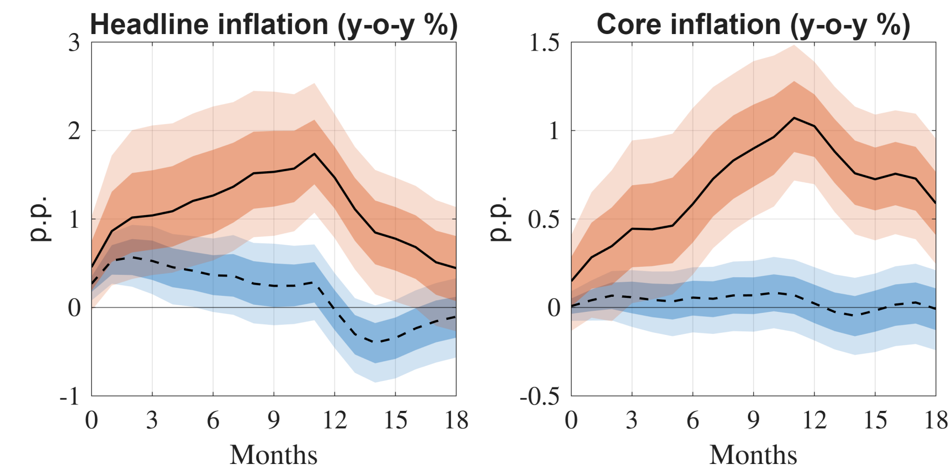
(a) U.S.



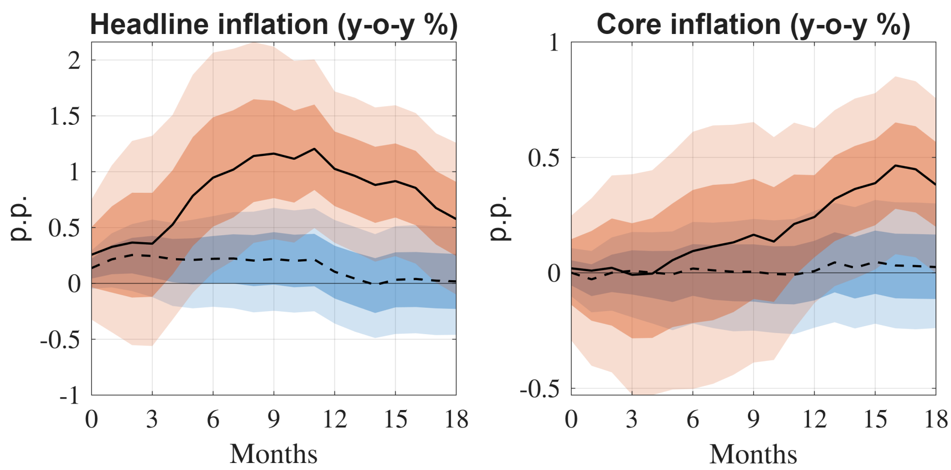
(b) Euro area

Low uncertainty — High uncertainty

Figure B.21: Headline and core inflation responses to an oil news shock with a *COVID-level additional control* across Region-specific SCU uncertainty states - U.S. and Euro area



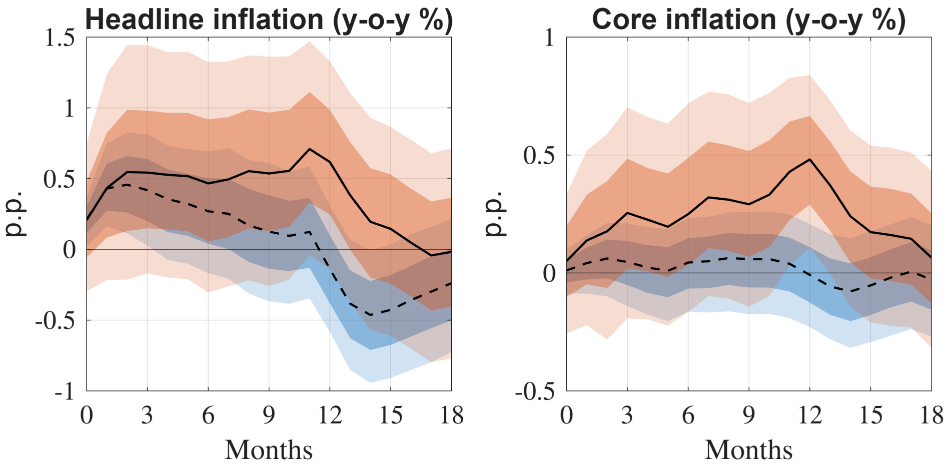
(a) U.S.



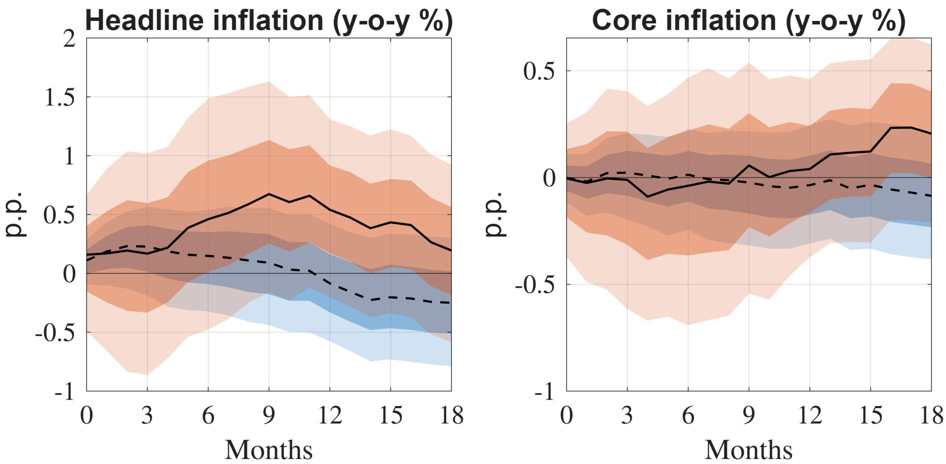
(b) Euro area

Low uncertainty — High uncertainty

Figure B.22: Headline and core inflation responses to an oil news shock with a *set of COVID-month additional controls* across Region-specific SCU uncertainty states - U.S. and Euro area



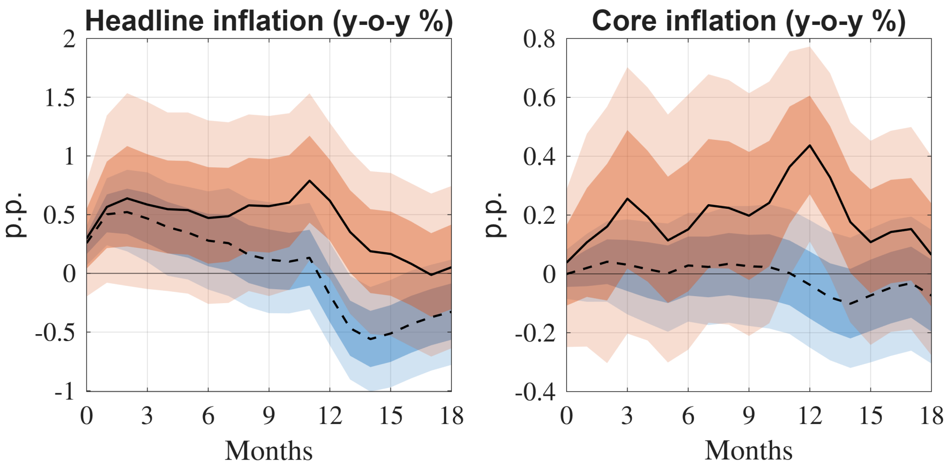
(a) U.S.



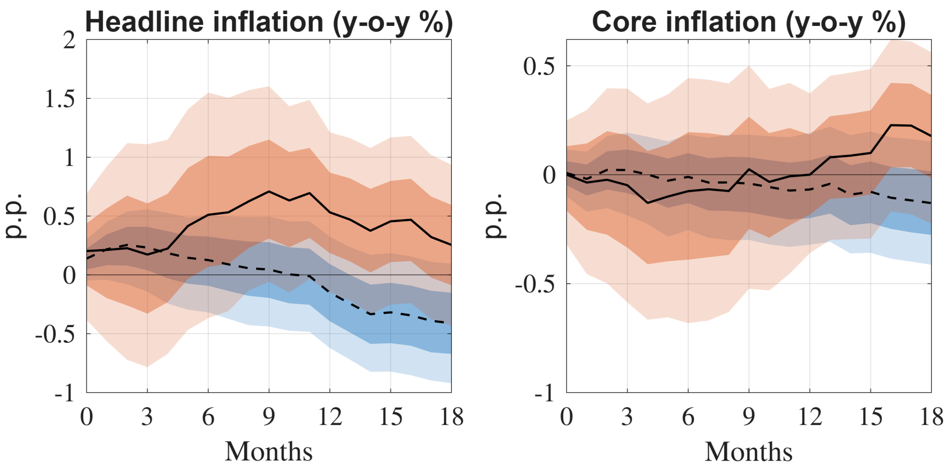
(b) Euro area

- - - Low uncertainty —— High uncertainty

Figure B.23: Headline and core inflation responses to an oil news shock with a *set of supply-chain pressures controls* across Region-specific SCU uncertainty states - U.S. and Euro area



(a) U.S.



(b) Euro area

Low uncertainty — High uncertainty

Figure B.24: Headline and core inflation responses to an oil news shock with a *supply-chain pressure control interacted with the oil news shock* across Region-specific SCU uncertainty states - U.S. and Euro area

C Empirical Appendix

C.1 Kalman Filter Estimation: Procedure

We provide additional details on the Kalman-filter estimation procedure outlined in the empirical section of the main text. We work under the assumption of uncorrelated observation shocks (i.e., the variance-covariance matrix of the observation vector V is diagonal).

Estimation with two uncertainty regimes Let SCU denote Region-specific supply chain uncertainty. Define the 80th-percentile threshold over all time periods as

$$\text{thr} \;=\; \text{quantile}(SCU;\, 0.80).$$

We then partition the set of time periods $\{1, \ldots, T\}$ into

$$\mathcal{T}_{\text{low}} = \{t : \; SCU_t \le \text{thr}\}, \qquad \mathcal{T}_{\text{high}} = \{t : \; SCU_t > \text{thr}\}.$$

For each regime $j \in \{\ell, h\}$ estimate the vector of parameters:

$$\theta_j \;=\; (\alpha_{1,j}, \alpha_{2,j}, \rho_{\psi,j},\, v_{1,j}, v_{2,j},\, \sigma^2_{\psi,j})$$

We estimate θ_j recursively (expanding window) within each regime: $\hat{\theta}_{\tau,j}$ uses observations up to $\tau < T$ (restricted to $\mathcal{T}_j$). The estimates reported in Table 6 correspond to the terminal $\hat{\theta}_{\tau,j}$ for $\tau = T$.

We estimate the parameters by maximizing the regime-specific log-likelihood:

$$\hat{\theta}_{\tau,j} \;=\; \arg\max_{\theta_j} \sum_{t \in \mathcal{T}_j : t \le \tau} \ell_t(\theta_j), \quad \ell_t(\theta_j) \;=\; -\tfrac{1}{2}\Big(\log(2\pi)^2 + \operatorname{logdet} \Sigma(\theta_j) + h_t(\theta_j)^\top \Sigma(\theta_j)^{-1} h_t(\theta_j) \Big).$$

The form of the log-likelihood derives from the fact that, conditional on θ_j, the vector $y_{t,j}$ (i.e., the vector of observations $\pi_{E,t}$ and p_t^{BDI}) is distributed as
$y_{t,j}|\theta_j \sim \mathcal{N}(\mu(\theta_j), \Sigma(\theta_j))$. Hence, the likelihood follows a normal distribution where $\Sigma(\theta_j)$ is the variance-covariance matrix of $y_{t,j}$ conditional on θ_j. Additionally, $h_t(\theta_j)$ is defined as the

residual, and is $h_t(\theta_j) = y_{j,t} - \mu_t(\theta_j)$.[41]

Starting values in the recursive estimation We set (m_0, C_0) from GSCPI moments to preserve the state's scale. Additionally, we initialize the loading associated to energy to $\alpha_1 = \nu \times (1-\delta)$, following the model formulation. We initialize α_2 to the same value. Hence, following our calibration of ν and δ, we initialize α_1 and α_2 to $1.25 * 0.5 = 0.625$. The initial values of v_1 and v_2 are set following theory to

$$v_1^0 = Var(\pi_{E,t}) * (1 - \alpha_1^2), \quad v_2^0 = Var(p_t^{(BDI)}) * (1 - \alpha_2^2)$$

Similarly, the initial value for the state innovation variance is set to

$$\sigma^2_{\psi,0} = Var(\psi_t) * (1 - \rho_\psi^2)$$

The persistence of the state process is initialized to its calibration value: $\rho_\psi = 0.9$.

Parametric constraints to the MLE estimation To enforce constraints in optimization we use:

$$v_i = \exp(\eta_i), \quad \sigma_\psi^2 = \exp(\omega), \quad \alpha_i = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\,\Lambda(\kappa_i),$$

$$\rho_\psi = \rho_{\psi,\min} + (\rho_{\psi,\max} - \rho_{\psi,\min})\,\Lambda(r_\psi)$$

where $(\eta_1, \eta_2, \omega, \kappa_1, \kappa_2, r_\psi)$ are the optimizer's free parameters and $\Lambda(.)$ is the logistic function $\Lambda(x) = \frac{1}{1+e^{-x}}$. Table C.2 shows the constraint values.

	Description	Value
$\alpha_{\min}$	Minimum value of energy and transportation loading	-2
$\alpha_{\max}$	Maximum value of energy and transportation loading	2
$\rho_{\psi,\min}$	Minimum persistence of ψ	0.7
$\rho_{\psi,\max}$	Maximum persistence of ψ	0.99

Table C.2: Parameter bounds for calibration and estimation

Notice that we set $\alpha_{min} < 0$ even if we expect that the loading coefficient will be positive for

[41]Notice that the symbol $\pi \approx 3.14$ is part of the normalizing constant of the normal distribution, unrelated to inflation.

optimization reasons.[42]

Filtering process For each regime j, we use the estimated parameters of the Kalman filter $\hat{\theta}_j$, and apply the Kalman formulae to derive the predictive and filtering distributions. Starting from $\psi_{t-1}|y_{1:t-1} \sim \mathcal{N}(\hat{m}_{t-1}, \hat{C}_{t-1})$

(i) the 1-step ahead predictive distribution of ψ_t: $\psi_t|y_{1:t-1} \sim \mathcal{N}(\hat{a}_t, \hat{R}_t)$
with $\hat{a}_t = \hat{\rho}_\psi \hat{m}_{t-1}$ and $\hat{R}_t = \hat{\rho}_\psi^2 \hat{C}_{t-1} + \hat{\sigma}^2_{\psi,j}$

(ii) the 1-step ahead predictive distribution of y_t: $y_t|y_{1:t-1} \sim \mathcal{N}(\hat{f}_t, \hat{Q}_t)$
with $\hat{f}_t = \hat{F}_j \hat{a}_t$ and $\hat{Q}_t = \hat{F}_j \hat{R}_t \hat{F}_j' + \hat{V}_j$

(iii) the filtering distribution of $\hat{\psi}_t$: $\hat{\psi}_t|y_{1:t} \sim \mathcal{N}(\hat{m}_t, \hat{C}_t)$
with $\hat{m}_t = \hat{a}_t + \hat{R}_t \hat{F}_j \hat{Q}_t^{-1} \hat{e}_t$, $\hat{C}_t = \hat{R}_t - \hat{R}_t \hat{F}_j' \hat{Q}_t^{-1} \hat{F}_j \hat{R}_t$ and $\hat{e}_t = y_t - \hat{f}_t$

We iterate for all the time periods in each of the two regimes, and finally splice the two sequences to form a single monthly series on the common calendar:

$$\hat{\psi}_t^* = \begin{cases} \hat{\psi}_{t,\ell}^*, & t \in \mathcal{T}_{\text{low}}, \\ \hat{\psi}_{t,h}^*, & t \in \mathcal{T}_{\text{high}}. \end{cases}$$

Notice that all of these objects are *estimated*: they are functions of the estimated parameter vector $\hat{\theta}_j$.[43]

Computation of standard errors Standard errors for the MLE coefficients in the vector $\hat{\theta}$ are computed exploiting the asymptotic properties of MLE:

$$\sqrt{n}(\hat{\theta} - \theta) \approx \mathcal{N}(0, I(\theta)^{-1})$$

[42] Indeed, whenever we set $\alpha_{min} \geq 0$, the MLE stops on a boundary where the regularity conditions fail, the score becomes one-sided, and the observed Fisher information (the Hessian of the log-likelihood) is singular. As a result, the optimizer we adopt cannot find stable coefficient estimates. Allowing α_{min} below zero keeps the solution in the interior, preserves curvature, and the optimizer then settles on a positive estimate if supported by the data.

[43] We write $\hat{\sigma}^2_{\psi,j}$ as the estimated variance of the state process's residual. Similarly, $\hat{V}_j$ is the estimated variance-covariance matrix of the observation equations' residuals (regime specific). $\hat{\rho}_\psi$ is the estimated persistence of the state process, while $\hat{F}_j$ is computed as the vector of $[\hat{\alpha}_{1,j}; \hat{\alpha}_{2,j}]'$.

where $I(\theta)$ is the Fisher information matrix of the true parameter and n is the sample size. In particular,

$$I(\theta) = \mathbb{E}[-\nabla^2 \ell_i(\theta)]$$

where $\nabla^2 \ell_i(\theta)$ is the Hessian of the log-likelihood. We estimate $I(\theta)$ with the observed Hessian of $\hat{\theta}$. Hence, the estimated variance-covariance matrix is $V(\hat{\theta}) \approx \frac{I(\theta)^{-1}}{n}$. The standard errors are the square roots of the diagonal entries of $V(\hat{\theta})$.

C.2 Kalman Filter Estimation: Additional Results

The main body shows graphically the contribution of energy and transportation prices' loading coefficients under low and high supply chain uncertainty. Table C.3 reports all the estimated parameters under the two uncertainty regimes, and Table C.4 compares the computed Kalman gain under the two uncertainty regimes. Figure C.25 and Table C.5 show the estimated loading coefficients and the Kalman gains when we use energy prices in place of y-o-y energy inflation.

Parameter	Low uncertainty	High uncertainty
Energy loading α_1	0.34	1.21
	(8.75×10^{-2})	(0.34)
BDI loading α_2	0.99	0.27
	(0.21)	(9.58×10^{-2})
Persistence ρ_ψ	0.96	0.91
	(1.80×10^{-2})	(5.04×10^{-2})
Obs. var. (energy) v_1	0.68	1.88×10^{-8}
	(6.40×10^{-2})	(1.11×10^{-6})
Obs. var. (BDI) v_2	8.05×10^{-10}	0.23
	(3.78×10^{-8})	(4.29×10^{-2})
State var. σ^2_ψ	9.39×10^{-2}	0.19
	(3.86×10^{-2})	(0.10)

(a) U.S.

Parameter	Low uncertainty	High uncertainty
Energy loading α_1	0.20	1.53
	(5.64×10^{-2})	(0.42)
BDI loading α_2	0.99	8.66×10^{-2}
	(0.19)	(7.76×10^{-2})
Persistence ρ_ψ	0.95	0.92
	(1.99×10^{-2})	(4.49×10^{-2})
Obs. var. (energy) v_1	0.43	1.15×10^{-9}
	(4.07×10^{-2})	(8.51×10^{-8})
Obs. var. (BDI) v_2	5.03×10^{-10}	0.40
	(2.01×10^{-8})	(7.54×10^{-2})
State var. σ^2_ψ	0.11	0.17
	(4.23×10^{-2})	(9.26×10^{-2})

(b) Euro area

Table C.3: Kalman parameters for BDI and Energy inflation - U.S. and Euro area

Notes: MLE-estimated coefficients and corresponding standard errors for the Kalman filter problem, January 2002 - June 2025. Red (blue): high (low) SCU state (top 20% / bottom 80% of Region-specific SCU), with 90% confidence intervals.

Signal	Low uncertainty	High uncertainty
Energy inflation	4.09 $\times 10^{-10}$	0.83
BDI	1.01	1.51 $\times 10^{-8}$

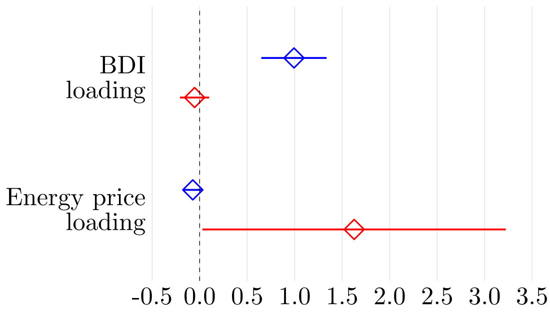
(a) U.S.

Signal	Low uncertainty	High uncertainty
Energy inflation	2.40 $\times 10^{-10}$	0.65
BDI	1.01	1.06 $\times 10^{-10}$

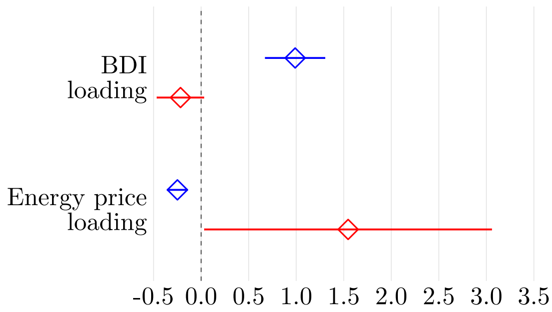
(b) Euro area

Table C.4: Kalman gain for BDI and Energy inflation - U.S. and Euro area

Notes: MLE-estimated Kalman gains for the BDI and energy prices, computed for the high (low) SCU state (top 20% / bottom 80% of Region-specific SCU), January 2002 - June 2025.



(a) U.S.



(b) Euro area

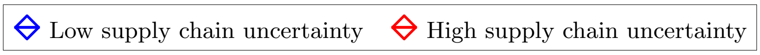


Figure C.25: Loading coefficients for BDI and Energy Prices - U.S. and Euro area

Notes: MLE-estimated loadings of energy prices and BDI on the latent transportation shock, January 2002 - June 2025. Red (blue): high (low) SCU state (top 20% / bottom 80% of Region-specific SCU), with 90% confidence intervals.

Signal	Low uncertainty	High uncertainty
Energy price	-2.71 $\times 10^{-10}$	0.61
BDI	1.01	-3.28 $\times 10^{-8}$

(a) U.S.

Signal	Low uncertainty	High uncertainty
Energy price	-4.30 $\times 10^{-10}$	0.65
BDI	1.01	-6.85 $\times 10^{-4}$

(b) Euro area

Table C.5: Kalman gain for BDI and Energy Prices - U.S. and Euro area

Notes: MLE-estimated Kalman gains for the BDI and energy prices, computed for the high (low) SCU state (top 20% / bottom 80% of Region-specific SCU), January 2002 - June 2025.

C.3 SCU Text-mining Measures Extracted from Earnings Calls

As mentioned above, both Region-specific and Global SCU are computed from public newspapers. In this appendix, we reconstruct the same measures from firms' communications. We analyze earnings-call transcripts from 2002Q1 to 2025Q2 processed by NL Analytics (2026) (Hassan et al., 2019, 2025). Note that firms hold earnings calls meetings with a quarterly frequency. Therefore, the index resulting from the analysis of earnings calls has a quarterly frequency. The process to construct the index starts by flagging the sentences in firms' earnings calls that contain at least one word from a *supply chain* and an *uncertainty* dictionary. Then, the index is computed as the average number of flagged sentences per earnings call, standardized to have mean zero and unit variance over the full sample period.

We obtain two measures of supply chain uncertainty (Global and Region-specific) based on firms' earnings calls. We find that each of the two measures is highly correlated with its newspaper-based counterpart (see Figure C.26).[44] We select the newspaper-based measures as our preferred benchmark because they are available at a monthly frequency.

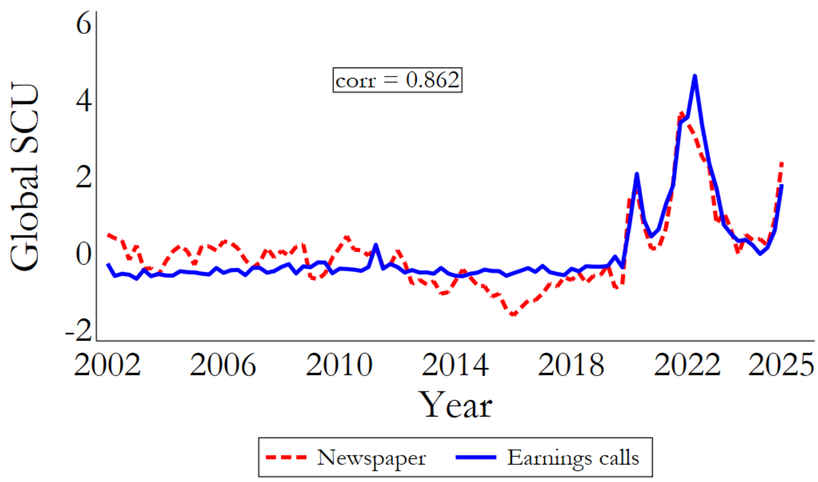


Figure C.26: Global SCU index extracted from newspapers versus earnings calls
Notes: Level of the Global SCU extracted from newspapers and earnings calls, plotted with quarterly frequency from 2002 Q1 to 2025 Q2. Each series is expressed in standard deviations from its respective sample average.

C.4 Appendix: Earnings Calls Evidence

We construct region-specific (United States or Euro area) quarterly indicators of firms' exposure to supply chain and energy shocks using a sample of firms' earnings call transcripts retrieved from NL Analytics, spanning 2002 Q1 to 2025 Q2. We follow Hassan et al. (2019, 2025); Caldara et al. (2020) to build the two indexes. We gather transcripts from all the earnings calls of publicly listed firms headquartered in the U.S. or the EA in a given quarter, and we count the share of sentences that contain at least one *keyword* from the semantic group of supply chain and energy,

[44]Note that the plot of earnings calls-based Region-specific SCU is available upon request.

respectively. We then standardize the resulting time series relative to their sample means and standard deviations. These measures capture the intensity with which firms discuss supply chain disruptions and energy price developments over time.

C.4.1 Representative sentences from earnings calls

To give content of the keyword measures, we report illustrative sentences from earnings calls that contain a keyword from *both* the supply chain and energy semantic groups.

From the earnings calls	Firm	Sector	Date
Energy cost is the biggest driver and trigger of our inflation cost because after a few spikes, all these increasing costs translate into the entire supply chain within a range of 1 to 3 months.	Amrest Holdings SE	Cyclical Consumer Services	2023-03-01
... it's not only the inflation, but it's a double effect from supply chain distortions and raw material energy inflation.	Hannover Rueck SE	Insurance	2022-03-10
We're seeing pressures across the supply chain, given the hike in oil price.	Newpark Resources Inc	Energy (Fossil Fuels)	2021-08-04
This has impacted the global economies profoundly, evident from the surge in crude oil and commodity prices and further global supply chain disruptions.	HDFC Bank Ltd	Banking & Investment Services	2022-04-16
The supply chain impact is much more difficult and demanding to rest than the energy price impact.	Raiffeisen Bank International AG	Banking & Investment Services	2021-11-03

Table C.6: Representative sentences with both energy and supply chain keywords

C.4.2 Keyword lists

For the supply chain semantic category, we use the *supply chain dictionary* introduced in B.1. For the energy semantic category, we adopt the *energy dictionary* developed by Dang et al. (2023) and hosted in Baker, Bloom, and Davis (2016) "Economic Policy Uncertainty."[45] We then remove some generic terms from the list[46] and obtain the final list of keywords.

Energy price keywords

1973 oil crisis, offshore drilling, West Texas intermediate, endangered species, natural gas price, climate

[45] https://www.policyuncertainty.com/energy_uncertainty.html

[46] Namely, *energy, oil, shock, shocks, crisis, crises.*

change, oil platform, WTI, energy security, oil export, crude oil, OPEC, American petroleum institute, fracking, oil supplies, energy efficiency, Pollution, carbon tax, green energy, photovoltaics, Environment, solar energy, common ethanol fuel mixtures, internal combustion engine, shale oil, gasoline price, well logging, electric car, natural gas, sustainable energy, greenhouse gases, alternative energy, energy sector, oil and natural gas corporation, wind power, energy shock, natural resource, carbon intensity, fossil fuel, oil shale, energy shocks, oil export ban, COGIS, going green, petroleum reservoir, energy price shock, oil well, drilling mud, hydrocarbon, residual oil, energy price shocks, pipeline, energy market, liquefied petroleum gas, sustainability, energy insecurity, solar cell, ethanol price, oil and gas, wind energy, energy instability, carbon footprint, global warming, oil reserves, British thermal unit, energy crisis, COGCC, hybrid electric vehicle, petroleum industry, clean energy act 2011, energy price volatility, directional drilling, liquefied natural gas, renewable energy, corn ethanol, oil crisis, energy independence, offshore fracking, sour gas, energy conservation, ethanol fuel, oil price, wildcat well, energy tax, geothermal energy, petroleum, Brent crude, gasoline, horizontal drilling, proven reserves, clean energy, greenhouse effect, Kyoto protocol, solar power, compost, kerosene

D Model Appendix

D.1 Timeline of the Information Problem

The signal extraction problem outlined in the main text follows this timing sequence:

1. At $t-1$, firms form the prior $\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} = \rho_\psi \psi^*_{t-1}$;
2. At t, the economy clears and $(y_t, p_{E,t})$ are realized and observed;
3. Firm considers y_t as an *observed* exogenous variable, and considers it in its information set when computing the expected energy price as used in the Kalman update:

$$\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} = (1-\nu)\, y_t + \nu(1-\delta)\, \rho_\psi\, \psi^*_{(t-1)}$$

4. Firm updates its prior with new signal $p_{E,t}$, computing the energy price forecast error, $FE(p_{E,t})$, which reflects the uncertainty over ψ^*_t:

$$FE(p_{E,t}) = p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} = \nu(1-\delta)\,\left(\psi_t - \rho_\psi\, \psi^*_{(t-1)}\right) + \nu\delta z_t$$

5. The deviation of the estimated transportation shock from the true value rewrites as

$$u_t \equiv \psi^*_t - \psi_t = \rho_\psi\big(1 - \mathbb{K}\,\nu(1-\delta)\big)\, u_{t-1} + \mathbb{K}\,\nu\,\delta\, z_t$$

assuming $\varepsilon_{\psi,t} = 0$.

Note that the timing sequence described tacitly assumes that output y_t is observed when the firm updates its estimate of the transportation shock ψ_t^*. To assess whether this assumption is restrictive, we explore the implications of considering output y_t as an endogenous state variable in the Kalman filter, unobserved at time t. Then,

$$\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} = (1-\nu)\,\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{y_t\} + \nu(1-\delta)\,\rho_\psi\,\psi^*_{(t-1)}$$

and the forecast error would acquire an extra term on output:

$$FE(p_{E,t}) = p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\} = \nu(1-\delta)\,\left(\psi_t - \rho_\psi\,\psi^*_{(t-1)}\right) + (1-\nu)\,\big(y_t - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{y_t\}\big)$$

Crucially, unobserved y_t at the time of updating affects the cost-push term u_t by adding a term to the forecast error and therefore increasing the impact on its motion law. However, it does not change the persistence

$$L = \rho_\psi\big(1 - \mathbb{K}\,\nu(1-\delta)\big)$$

that governs the dynamics in Proposition 2 and Proposition 3. Overall, this makes the argument that our results are valid (if anything amplified) in a more general model in which also output is unobserved to the firm when forming the estimate ψ_t^* of the transportation shock.

D.2 Details on the State-space Model

In the main body, we represent the signal-extraction problem of the firm with a particular Gaussian linear case of a more general state-space model representation. In this section, we describe the more general version with two assumptions.

Assumption D.1 (Transportation shocks are a Markov chain)**.** *At time t, the sequence of transportation shocks $\{\psi_t\}_{t\geq 0}$ is a Markov chain in $\mathbb{R}$, following the motion law $\psi_t \sim \mathcal{P}_\psi(\cdot \mid \psi_{(t-1)})$. The probability measure $\mathcal{P}_\psi$ is defined on the probability space $(\mathbb{R}, \mathcal{B}(\mathbb{R}), \mathcal{P}_\psi)$ such that $\mathcal{P}_\psi\left(\cdot \mid \psi_{0:(t-1)}\right) = \mathcal{P}_\psi\left(\cdot \mid \psi_{(t-1)}\right)$.*

Assumption D.2 (Conditional independence of energy prices)**.** *Conditionally on $\{\psi_t\}_{t\geq 0}$, the sequence of energy prices $\{p_{E,t}\}_{t\geq 0}$ are independent, and $p_{E,t}$ depends on ψ_t only. Let the conditional probability measure of energy prices be $\mathcal{P}_{p_E|\psi}(\cdot \mid \psi_t)$. The energy price probability measure is $\mathcal{P}_{p_E}(\cdot) = \int_{\mathbb{R}} \mathcal{P}_{p_E|\psi}(\cdot \mid \psi_t)\, d\mathcal{P}_\psi(\cdot)$.*

We now describe the fundamental process governing the pair *transportation shock ψ_t, energy price $p_{E,t}$* using a generic state-space framework. Formally,

$$
\begin{aligned}
\psi_t &\sim \mathcal{P}_{\psi}(d\,\psi_t \mid \psi_{(t-1)}), \\
p_{E,t} &\sim \mathcal{P}_{p_E}(d\,p_{E,t} \mid \psi_t).
\end{aligned}
\tag{D.40}
$$

Figure D.27 illustrates the information flow in this model with an acyclic directed graph of the state-space model.

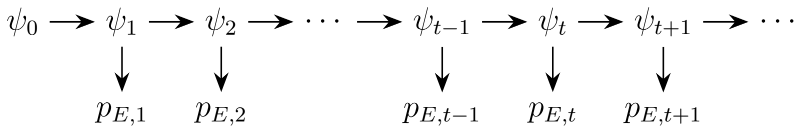


Figure D.27: Acyclic directed graph of the state-space model

D.3 Bayesian Learning

We follow a standard Bayesian-filtering approach; see, e.g., Colarieti and Monacelli (2022). The firm knows the state-space model in (D.40), holds a prior $\mathcal{P}_{\psi,0}(\cdot)$ over ψ_0, and learns from the history of energy prices $\{p_{E,t}\}_{t\geq 0}$. The learning problem is summarized by two recursively updated objects: the filtering distribution and the state-predictive distribution.

At time t, the filtering distribution $\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)})$ gives the distribution of the current transportation shock conditional on the history of energy prices:[47]

$$
\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}) \propto \mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t) \cdot \mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,0:(t-1)}).
\tag{D.41}
$$

The state-predictive distribution $\mathcal{P}_{\psi,t}(d\psi_{t+1} \mid p_{E,(0:t)})$ gives the distribution of next period's transportation shock conditional on the same information set:

$$
\mathcal{P}_{\psi,t}(d\,\psi_{t+1} \mid p_{E,(0:t)}) = \int_{\mathbb{R}} \mathcal{P}_{\psi}(d\,\psi_{t+1} \mid \psi_t) \cdot \mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}).
\tag{D.42}
$$

The learning problem is recursive: the state-predictive distribution at time t becomes the prior for the filtering distribution at time $t+1$.

[47] This expression is derived from Bayes' Theorem and from the assumption of conditional independence of energy prices, i.e., $\mathcal{P}_{\psi,t}(dp_{E,t} \mid \psi_t, p_{E,(0:t-1)}) = \mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t)$:

$$
\begin{aligned}
\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}) &= \frac{\mathcal{P}_{\psi,t}(dp_{E,t} \mid \psi_t, p_{E,(0:t-1)})}{\mathcal{P}_{\psi,t}(d\,p_{E,(0:t)} \mid p_{E,(0:t-1)})} \cdot \mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,(0:t-1)}) \\
&\propto \mathcal{P}_{p_E}(d\,p_{E,t} \mid \psi_t) \cdot \mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,(0:t-1)}).
\end{aligned}
$$

D.4 Kalman Gain at Steady State

In the main text, we present a signal-extraction problem. The resulting Kalman gain $\mathbb{K}(\mathcal{S})$ is assumed to be constant over time. This assumption requires some context. The Kalman gain measures the informativeness of the new observation $p_{E,t}$ about the unobserved state ψ_t. In the model we consider, learning occurs in a *dynamic environment*, so the Kalman gain changes over time. At each date, two conflicting processes are at work: $p_{E,t}$ brings new information about ψ_{t-1}, but the state changes to ψ_t, with the additional uncertainty carried by $\varepsilon_{\psi,t}$, represented by the innovation variance σ^2_ψ. In the early periods, prior system knowledge is low and observations are highly informative. As time proceeds, firms build confidence in their prior guesses about the system, so each new observation brings less information and the Kalman gain declines over time.

At some point, the information brought by the new observation is exactly balanced by the loss of information associated with the additional variance σ^2_ψ. When this *steady-state* point is reached, the Kalman gain stabilizes at a constant value, $\mathbb{K}_t \equiv \mathbb{K}(\mathcal{S})$. In this paper, we assume that the linear Gaussian system has reached this *steady state*:

$$\mathbb{K}(\mathcal{S}) = \frac{C\,\nu\,(1-\delta)}{\nu^2\,\delta^2\,\sigma^2_Z + C\,\nu^2\,(1-\delta)^2}, \qquad C = \rho^2_\psi\,C - \frac{\rho^2_\psi\,\nu^2(1-\delta)^2\,C^2}{\nu^2\delta^2\,\sigma^2_Z + \nu^2(1-\delta)^2\,C} + \mathcal{S}\sigma^2_Z$$

The expression for $\mathbb{K}(\mathcal{S})$ depends positively on the signal-to-noise ratio ($\mathcal{S} \equiv \sigma^2_\psi/\sigma^2_Z$) through C (the solution of the algebraic Riccati equation). The existence of a positive value C satisfying the Riccati equation is necessary for the existence of the system's steady state and of a steady-state Kalman gain. A standard result in control theory (see Petris et al. (2009)) states that a sufficient parametric condition for asymptotic stability of the Kalman filter is

$$L \equiv \rho_\psi\big(1 - \mathbb{K}(\mathcal{S})\cdot\nu\cdot(1-\delta)\big) < 1$$

Notably, this is exactly the condition imposed in the proofs of Propositions 2 and 3 to guarantee the stationarity of the u_t process.

D.5 Derivation of Equilibrium Energy

We add details to the derivation of equilibrium energy outlined in the main body. We consider a single energy supplier that produces (final) energy, E_t, by combining transportation services, $E_{T,t}$, and raw energy, $E_{raw,t}$. The energy supplier takes both the price of raw energy, $P^{raw}_{\mathrm{E},t}$, and the per-unit cost of transportation, $P^e_{\mathrm{T},t}$, as given. The energy production function:

$$E_t \;=\; \Big((1-\delta)^{1/\eta}\,E_{T,t}^{1-(1/\eta)} \;+\; \delta^{1/\eta}\,E_{raw,t}^{1-(1/\eta)}\Big)^{\frac{\nu}{1-(1/\eta)}} \tag{D.43}$$

The cost-minimizing demand for energy transportation reads:

$$E_{T,t} = \nu^{\eta} \cdot E_t^{\eta+\frac{1}{\nu}(1-\eta)} \cdot (1-\delta) \cdot \left(\frac{P^e_{T,t}}{P_{E,t}}\right)^{-\eta} \tag{D.44}$$

where the marginal cost price index is

$$P_{E,t} = \frac{1}{\nu} \cdot E_t^{\frac{1}{\nu}-1} \cdot \left[(1-\delta)\left(P^e_{T,t}\right)^{1-\eta} + \delta\left(P^{\text{raw}}_{E,t}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{D.45}$$

Note that the quantity of supply chain transportation demanded by the energy supplier decreases with the relative price of transportation, and conversely, it increases with the returns to scale ν, with the relative importance of supply chain transportation in production $(1-\delta)$, and with the quantity of energy supplied E_t. Similarly, the optimal demand for raw energy reads:

$$E_{raw,t} = \nu^{\eta} \cdot E_t^{\eta+\frac{1}{\nu}(1-\eta)} \cdot \delta \cdot \left(\frac{P^{raw}_{E,t}}{P_{E,t}}\right)^{-\eta} \tag{D.46}$$

Plugging the demand for raw energy (D.46) and for its transportation (D.44) into the energy supply aggregator (D.43) yields the inverse equilibrium cost-schedule of energy:

$$E_t = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\left(P^e_{T,t}\right)^{1-\eta} + \delta\left(P^{raw}_{E,t}\right)^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{D.47}$$

Note that, since $\nu > 1$, equation (D.47) determines a negative relation of (final) energy to its price $P_{E,t}$.

D.6 Calvo Price Stickiness under SCU

Under sticky prices and incomplete information, firms face two sources of uncertainty: the Calvo duration for which the current price remains in place (θ_D) and the supply-chain conditions (ψ_t). Firms make a forecast of the Calvo duration (θ_D) and transportation shock (ψ_t). Firms combine these estimated quantities into a function $\tilde{p}(.)$ that produces the optimal time t reset price. If both sources of uncertainty are represented by probability measures, the optimal price is:
$p_t = \mathbb{E}_{\mathcal{P}_\theta}\left\{\mathbb{E}_{\mathcal{P}_{\psi,t}}\left[\tilde{p}_t(\theta_D,\psi_t)\right]\right\}$. Assuming independence between Calvo pricing uncertainty and supply-chain uncertainty, $\mathcal{P}_\theta \perp\!\!\!\perp \mathcal{P}_{\psi,t}$ for all t, the order of integration is irrelevant:

$$p_t = \iint \tilde{p}_t(\theta_D,\psi_t)\, d\mathcal{P}_{\psi,t}(\psi_t)\, d\mathcal{P}_\theta(\theta_D) = \iint \tilde{p}_t(\theta_D,\psi_t)\, d\mathcal{P}_\theta(\theta_D)\, d\mathcal{P}_{\psi,t}(\psi_t).$$

Hence, firms can equivalently integrate first over the duration for which the current price remains in place or first over supply-chain uncertainty.

D.7 Derivation: NKPC under Uncertainty

Consider the intermediate producer that can revise its price at random intervals with Calvo probability $(1-\theta)$. Consider the formula for the optimal reset price p_t, i.e., the first-order condition for firm profit maximization. Rewrite it in terms of $mc_{(t+k)}$, i.e., the future expected real marginal cost of production in deviation from the steady state, μ:

$$p_t = (1-\theta\beta)\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(p_{(t+k)} + mc_{(t+k)})\right\} \tag{D.48}$$

We denote by $p_{t,\text{agg}}$ the aggregate price at time t (so that $\pi_t = p_{t,\text{agg}} - p_{t-1,\text{agg}}$). Under sticky prices, the share $(1-\theta)$ of intermediate firms that can reset their good price each period chooses the same optimal reset price p_t as in (D.48). We therefore obtain:

$$p_{t,\text{agg}} = \theta p_{t-1,\text{agg}} + (1-\theta)p_t. \tag{D.49}$$

Rewrite equation (D.48) recursively as

$$p_t = (1-\theta\beta)mc_t + \theta\beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+1)}\}, \tag{D.50}$$

where the forecast of the future optimal price under incomplete information is

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+1)}\} = \int_{\mathbb{R}} p_{(t+1)}(\psi_{(t+1)})\, d\mathcal{P}_{\psi,t}(\psi_{(t+1)}),$$

which is computed under the estimated probability distribution over the transportation shock $\mathcal{P}_{\psi,t}(\psi_{(t+1)})$, derived by solving the state-space model in the main text. Rewrite equation (D.49) as

$$p_t = \frac{\pi_t}{1-\theta} + p_{t-1,\text{agg}}.$$

Combine it with equation (D.50) to finally obtain the *incomplete-information NKPC*:

$$\pi_t = \beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}mc_t$$

where we remark that mc_t is the real marginal cost in deviation from its steady state *under incomplete information.*

D.8 Details on General Equilibrium

We detail the description of the demand side of the general-equilibrium model outlined in the main body.

Households A representative household chooses sequences of consumption, labor, and bonds $\{C_t, N_t, B_t\}_{t=0}^{\infty}$ to solve the maximization problem subject to the budget constraint, which must hold for all $t \geq 0$

$$\max_{\{C_t, N_t, B_t\}_{t=0}^{\infty}} \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) \right\}, \qquad P_t C_t + B_t \leq W_t N_t + R_t B_{(t-1)} + \int_0^1 D_t(i)\, di \quad \text{(D.51)}$$

where P_t is the nominal price of consumption C_t, W_t is the nominal wage rate for unit of labor N_t, and R_t is the nominal return on the one-period risk-free bond B_{t-1}. Profits from monopolistic good-producing intermediate firms are $D_t(i)$. The household takes $\{P_t, W_t, R_t\}$ and B_{-1} as given. Deriving the first-order conditions yields the familiar consumption Euler equation:

$$C_t^{-\sigma} = \beta R_t \mathbb{E}_t \left\{ C_{(t+1)}^{-\sigma} \frac{P_t}{P_{(t+1)}} \right\} \quad \text{(D.52)}$$

The expected value operator, $\mathbb{E}_t\{.\}$, indicates that the household's decision depends on expectations formed under *full information* available at time t. The intratemporal optimality condition reads:

$$\frac{W_t}{P_t} = C_t^{\sigma} N_t^{\varphi} \quad \text{(D.53)}$$

The transversality condition:

$$\lim_{T \to \infty} \mathbb{E}_0 \left[\beta^T C_T^{-\sigma} \frac{B_T}{P_T} \right] = 0 \quad \text{(D.54)}$$

Monetary policy We assume that monetary policy is conducted by means of the following interest rate rule:

$$R_t = \beta^{-1} \left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\phi_\pi} \quad \text{(D.55)}$$

where $\phi_\pi > 1$ is the elasticity of the nominal interest rate to deviations of inflation from the target $\bar{\Pi}$.

Market clearing We require that the energy and the specialized input markets clear, that the bond market clears ($B_t = 0$), and aggregate labor supply equals labor demand $\int_0^1 N_t(i)\, di = N_t$. The final good production equals household consumption such that $Y_t = C_t$.

Equilibrium In the New Keynesian model with supply chain uncertainty, a competitive equilibrium is a set of allocations and prices such that: *(i)* the representative household solves (D.51); *(ii)* firms form expectations about the transportation shock according to the optimal Bayesian estimator ψ_t^*; *(iii)* prices satisfy the household's and firms' first-order conditions; *(iv)* all markets clear.

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