Supply Chain Uncertainty, Energy Prices, and Inflation*

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Abstract

Using US and EZ data, we document that (i) the pass-through of energy prices to inflation is state-dependent - higher when supply chain uncertainty is elevated - and (ii) energy prices become more informative about broader supply chain conditions in such states. We build a model in which firms use two inputs - energy and a specialized component - both shipped through a capacity-constrained network. Under transportation network congestion, energy can still be purchased in local liquid markets at a premium, while the specialized input faces stochastic delivery delays. Firms are unable to disentangle transitory energy price shocks from logistical disruptions, and treat energy prices as noisy signals of latent delays, updating their beliefs via Bayesian learning. This raises their perceived marginal costs. We obtain three main results: (1) both the static and the dynamic pass-through from energy shocks to output prices scale with supply chain uncertainty; (2) an incomplete-information version of the New Keynesian Phillips Curve with an endogenous, volatility-amplified cost-push term; and (3) in general equilibrium, greater sensitivity and persistence of inflation to purely transitory energy shocks. The enhanced pass-through arises from the *volatility*, not the level, of transportation shocks, consistent with the 2021–23 inflation episode.

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

JEL Classification Numbers: E31, D83.

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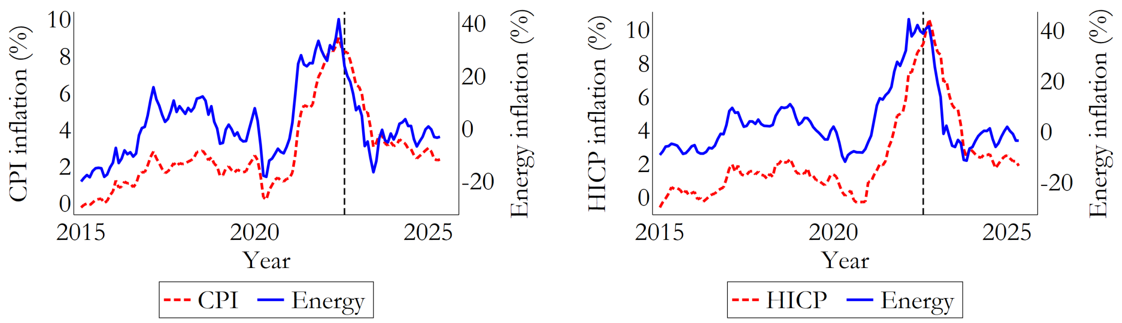
1 Introduction

Over the past three decades, inflation remained low and stable despite substantial fluctuations in energy prices.[1] However, when energy prices surged by 40% in the U.S. and the Euro area in the summer of 2022, as depicted in Figure 1, the inflation response was unexpectedly strong and persistent, displaying an unprecedented unconditional correlation with energy prices (Figure 2).[2] Dao et al. (2024) find that the international rise and fall of inflation since 2020 largely reflected the strong pass-through of the energy price shock to consumer prices. Notably, the pass-through of energy price shocks "switched regime" (De Santis and Tornese, 2025), with inflation responding more than twice as strongly as in the past – particularly in the Euro area (Pallara et al., 2023; Neri et al., 2023).



(a) U.S.

(b) Euro area

Figure 1: Price and energy inflation in the U.S. and the Euro area

Notes: The figure displays the monthly y-o-y percent change in the time series of U.S. consumer (CPIAUCSL) and energy prices (CPIENGSL) and of the Euro area-19 consumer (CP0000EZ19M086NEST) and energy price (ENRGY0EZ19M086NEST) from January 2015 to May 2025, retrieved from FRED, Federal Reserve Bank of St. Louis. The dotted vertical line marks August 2022, the peak of the energy price shock.

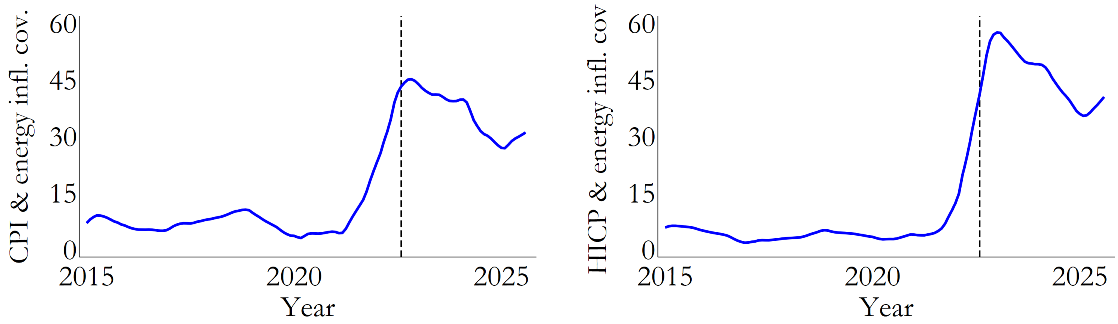
In this paper, we develop a theory of the amplification of supply shocks based on *uncertainty* in the producers' supply chains. While part of a rapidly growing literature attributes the amplified inflation response to demand-side mechanisms triggered by energy price shocks,[3] these explanations may understate the major role that supply chain disruptions played in the recent inflationary spike.[4] We argue that the unprecedented surge in the *volatility* of transportation shocks between 2021 and 2023,

[1] Blanchard and Riggi (2013).

[2] Many voices in academia suggested that the energy price shock would not result in persistent inflation – e.g., Krugman's "Team Transitory" and Ball et al. (2022) – arguing that pressure on wages in the labor market was low and stable. Policymakers also believed inflation was transitory, a product of short-lived factors, and as "these transitory supply effects abate, inflation is expected to drop back" (Powell's Press Conference July 28, 2021).

[3] For instance, Gagliardone and Gertler (2023) focus on accommodative monetary policy and the complementarity between energy and labor. Lorenzoni and Werning (2023) study the role of wage-price spirals.

[4] See Akinci et al. (2023); Liu and Nguyen (2023) for the U.S., and Banbura et al. (2023); De Santis (2024) for the Euro area.



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

Figure 2: Covariance of price and energy inflation in the U.S. and the Euro area

Notes: The figure displays the monthly rolling covariance computed over a moving window of 48 months of the y-o-y percent changes in the time series of U.S. consumer (CPIAUCSL) and energy prices (CPIENGSL) and of the Euro area-19 consumer (CP0000EZ19M086NEST) and energy prices (ENRGY0EZ19M086NEST) from January 2015 to May 2025, retrieved from FRED, Federal Reserve Bank of St. Louis. The dotted vertical line marks August 2022, the peak of the energy price shock.

by exerting persistent strain on supply chains, played a central role in amplifying the inflationary response to the energy price spike during that period. In short, supply chain *uncertainty* enhanced the pass-through of energy prices to CPI inflation.

Intuition on the main mechanism Intuitively, the economic mechanism at the heart of our framework can be illustrated as follows. Local firms employ both energy and a specialized good (e.g., microchips) as production inputs, both shipped through the same logistical routes. In the background, the economy is hit by purely *transitory* energy price disturbances. Supply chain disruptions (e.g., choke points) make the transportation capacity constraint binding, generating uncertain delivery delays. However, albeit at a premium, energy remains physically available through local liquid markets, the shipping of microchips faces a stochastic delivery delay. Because energy is a liquid, globally traded input whose price reacts quickly to congestion, firms treat it as an informative signal about unobserved delivery delays affecting the specialized input. In this context, firms can no longer clearly distinguish whether rising energy prices reflect true, and purely temporary, energy market disturbances as opposed to persistent logistical bottlenecks. Therefore, firms form Bayesian beliefs about latent delays, which raise the perceived marginal cost *beyond* the impact pass-through from higher energy prices. This signal-extraction behavior amplifies the immediate and forward-looking components of price adjustment: firms raise prices more strongly and preemptively, generating an amplified and more persistent inflation response. The amplification effect scales with the uncertainty in the supply chain (i.e., with the volatility of transportation shocks), as firms place greater weight on energy prices as indicators of underlying supply conditions.

Modern supply chains We highlight *two main features* of modern supply chains which are critical to our analysis. First, in the pre-globalization era (i.e., prior to 1990),[5] supply chains were predominantly regional or national in scope, and the concept of a globally integrated production network was largely absent. By contrast, the post-1990 economy is characterized by highly interconnected global supply chains in which even small, localized disruptions can propagate widely and persist over time. A purely mechanical shock, such as the six-day blockage of the Suez Canal in March 2021 (Tran et al., 2025), illustrates this mechanism: congestion at a single chokepoint cascades through the network much like a delay at a central airport hub, generating a domino effect on subsequent routes across multiple geographies.[6] This feature provides a rationale for treating transportation shocks in modern supply chains as highly *persistent* phenomena, generating uncertainty in shipping costs and delivery times, and therefore in firms' marginal costs.

Second, the transportation sector operates under a *capacity constraint*: most of trade (about 80 percent) is shipped via maritime routes, yet the global fleet is finite and cannot be expanded rapidly. Once this constraint becomes binding – either because the initial shock is large, or because a small shock propagates through space, as in the above example – market prices for transportation no longer serve as reliable indicators of delivery times, since rationing occurs through physical capacity rather than through price adjustment.

Firm surveys The COVID-19 pandemic, followed by an escalation in geopolitical instability, has further underscored deep structural vulnerabilities in global supply chains. According to the large-scale firm survey EIBIS,[7] still in 2023, when the COVID-19 shock had vanished, transportation disruptions represented an obstacle to business activities for more than 60% of firms in the U.S. and the E.U.

A substantial share of firms copes with the lingering effects of supply chain shocks by investing in input tracking technologies to pin down delivery lags, revealing an information shortfall.[8] As documented in Figure 3, while the share of firms reporting supply chain disruptions has moderated over time, investments in input tracking technology have remained stable.

[5] Baldwin and Freeman (2022).

[6] "Blocking something like the Suez Canal really sets in motion a number of dominoes toppling each other over – said Lars Jensen, chief executive of Denmark-based SeaIntelligence Consulting. The effect is not only going to be the simple, immediate one with cargo being delayed over the next few weeks, but will actually have repercussions several months down the line for the supply chain." `https://www.cbc.ca/news/business/suez-canal-egypt-ever-given-1.5963207`

[7] The EIBIS survey is conducted annually by the European Investment Bank (EIB). The survey covers approximately 12,000 firms across the E.U. and 800 firms in the U.S.

[8] Note that, even more strikingly, in 2022, almost *half* of the E.U. firms importing essential inputs at high risk of disruptions were investing in input tracking technologies.

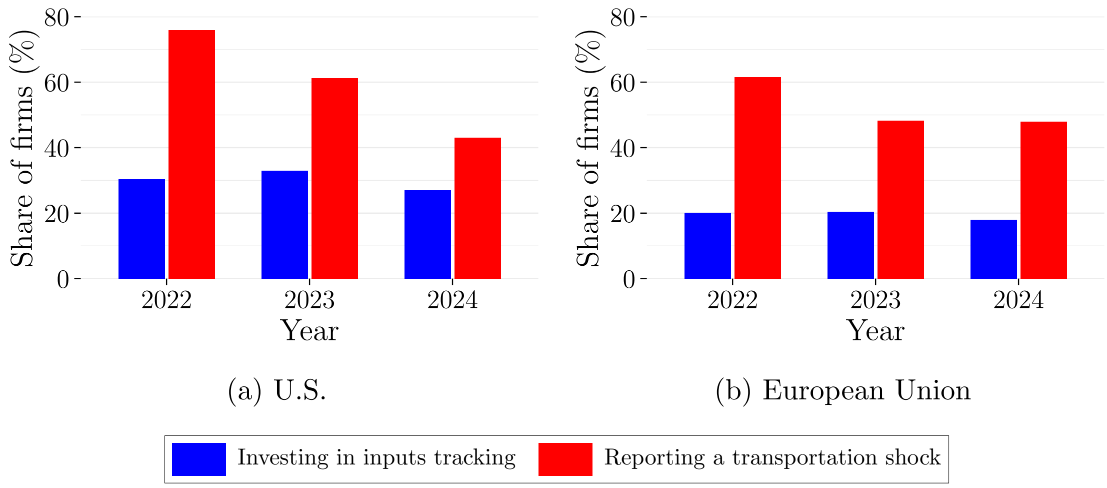


Figure 3: Share of firms investing in digital inventories and inputs tracking and reporting obstacles to logistics and transport.

Notes: The two panels above display the share of firms that report investment in digital inventories and input tracking technologies, and the share of firms that flag logistics and transport as a (minor or major) obstacle to production. In particular, this data comes from the European Investment Bank Survey (`https://data.eib.org/eibis/graph`) conducted in 2023, 2024, and 2025, with reference to the previous calendar year. The data on investment in digital inventories and input tracking is recorded as answer to the question "*Since the beginning of 2022, has your company made or are you planning to make any of the following changes to your sourcing strategy?*" and is reported for importing firms. The blue bars show the share of importing firms that reported *investments in inputs tracking* as answer to the aforementioned question. Similarly, the data on obstacles (minor or major) to logistics and transport are reported as answer to "*Since the beginning of 2022, were any of the following an obstacle to your business's activities?*". The red bars show the share of firms that reported *obstacles to logistics and transport* as answer to the aforementioned question.

Increased volatility in supply-chain transportation disruptions There is an extensive empirical literature suggesting that the volatility of transportation shocks remained close to zero for decades, but rose markedly in recent years.[9] Figure 4 displays the evolution of the rolling *variance* of the *Global Supply Chain Pressure Index* (GSCPI) in the time frame 2002–2025. The GSCPI index is a measure of transportation shocks (Benigno et al., 2022). It is a widely recognized measure that isolates the supply-side component of transportation disruptions along the global supply chain.[10] Noticeably, the variance remains relatively stable until mid-2020, and it displays an exceptional increase afterwards.

[9] See, for instance, Benigno et al. (2022); Blaum et al. (2025).

[10] The GSCPI is constructed 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.

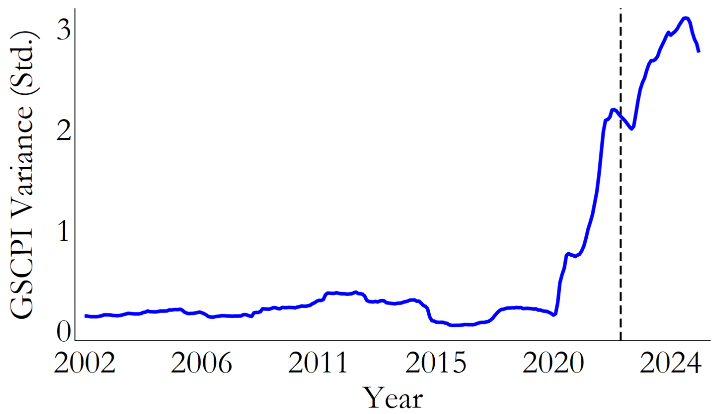


Figure 4: Evolution of the rolling variance of the GSCPI

Notes: Standardized variance of the Global Supply Chain Pressure Index (GSCPI) computed over 48-month rolling windows, plotted with monthly frequency from January 2002 to June 2025. Variance is standardized by the rolling variance computed over the whole 1998-2025 sample – so when it is 2, it means that in the last 48 months the GSCPI variance is double the long-run average. The GSCPI time series is published monthly by the New York Federal Reserve (`https://www.newyorkfed.org/research/policy/gscpi#/overview`). The dotted vertical line marks August 2022, the peak of the energy price shock.

State-dependent pass-through of energy prices to inflation Our first key empirical result is to document that, in both the U.S. and the E.A., the pass-through of energy inflation to consumer price inflation is *state-dependent*, i.e., larger in periods of supply chain uncertainty. In particular, we estimate state-dependent pass-through local projections of inflation on oil shocks instruments and find that the sensitivity of headline inflation to energy price shocks is significantly larger in periods of high supply chain volatility. This result justifies our view that greater uncertainty about transportation conditions raises the informational content of energy prices, enhancing both contemporaneous pass-through and forward-looking inflation dynamics.

Commoditized vs specialized inputs Importantly, in our framework, shared logistical chokepoints expose both *commoditized* inputs (e.g., oil and gas) and highly *specialized* components (e.g., microchips) to correlated delivery risks.[11] In our model, firms rely on two inputs – energy and a specialized component (microchips) – both transported via shared logistical routes with *finite capacity*. Shocks to the common

[11] A vivid example of correlated delivery risk regards disruptions in Russia's energy and specialized input supply. The United States imported about 20% of its key industrial metals from Russia (University of Florida News (2023), "Russia-Ukraine Global Supply Chain," `https://news.ufl.edu/2023/02/russia-ukraine-global-supply-chain/`). Following Russia's invasion of Ukraine, the U.S. halted these imports, generating shortages of critical inputs (such as nickel) even as headline prices remained stable. In parallel, the conflict drove a sharp rise in European transport costs for gas and oil, which fed into higher energy prices in the U.S (GMK.Center, "How the Russia-Ukraine war has impacted logistics routes and supply chains," `https://gmk.center/en/posts/how-the-russia-ukraine-war-has-impacted-on-logistics-routes-and-supply-chains/` and KPMG 2022 report, "Impacts of the Russia-Ukraine war on supply chains," `https://kpmg.com/us/en/articles/2022/impacts-russia-ukraine-war-supply-chains.html`).

transportation market – whether driven by demand-side factors (e.g., port congestion from the post-COVID-19 reactivation of global trade) or supply-side disruptions (e.g., geopolitical tensions at maritime chokepoints) – can make the transportation capacity constraint binding. When congestion arises, the market price of transportation naturally increases. However, input prices respond *asymmetrically*. Energy, although delayed, remains accessible through highly liquid local spot markets at a premium. Hence, the full transportation cost is embedded in the observed energy price. In contrast, specialized inputs such as microchips depend on tightly coordinated "just-in-time" supply chains, lack immediate substitutes, and cannot be easily stocked. When microchip transportation is delayed, the absence of a readily available substitute generates a non-monetary, physical time cost. Physical delays introduce a stochastic, *unobserved* cost component, not captured by market prices.

Inference problem The asymmetry across inputs gives rise to an *inference problem*. Because both inputs are exposed to the same transportation shock, the observed price of energy reflects not only raw energy fundamentals but also transportation disruptions. However, firms cannot directly observe the source of a given energy price movement. Instead, they treat energy prices as a noisy signal and infer the extent of unobserved delivery delays affecting specialized inputs. Hence, firms face a *signal extraction* problem: they form Bayesian estimates of the delay cost of specialized inputs (i.e., microchips) using energy prices as a noisy signal. When energy prices rise, firms must assess whether the increase is due to a temporary raw energy shock or a broader, persistent supply chain disruption – such as congestion that affects multiple inputs.[12]

The informativeness of energy prices depends on the volatility of transportation shocks. When the supply chain environment becomes more volatile, firms place greater weight on the signal component of energy prices. Because energy markets are highly liquid and adjust rapidly to changes in logistical conditions, energy prices serve as an *information aggregator* for hard-to-observe frictions in the supply chain. As a result, even purely transitory raw energy shocks can lead firms to revise expectations about future input costs, since such shocks may be interpreted as indicative of persistent delivery delays for other critical inputs.[13]

[12] In practice, firms are likely to aggregate multiple signals that co-vary with transportation shocks, weighting each according to its relative informativeness. A natural candidate for a signal that competes with energy price to inform the firm about transportation shocks is the transportation price. In section 2, we provide empirical evidence that under high supply chain uncertainty, firms value more energy prices than transportation prices as signals of the underlying transportation shock.

[13] A recent episode illustrates this mechanism clearly. Following Israel's attack on Iran in June 2025, the world's largest listed oil tanker company, Frontline, announced that it would not accept new charters through the Strait of Hormuz due to heightened security risks. The Strait handles roughly a quarter of global oil flows and is also a major route for container ships serving the Gulf region. The threat of attacks on commercial vessels – particularly by Houthi rebels backed by Iran – created a dual impact: a sharp spike in oil prices and a surge in uncertainty surrounding the delivery time of containerized goods, including specialized intermediate inputs such as semiconductors. Because oil and manufactured inputs share the same shipping corridors, the observed increase in oil prices may also have conveyed information about broader supply chain risks, leading firms to interpret it as a signal of unobserved delivery delays for other critical inputs. See Financial Times,

Kalman-filter based evidence We provide supporting empirical evidence for this information-based mechanism using a Kalman-filter estimation. We compare the *informational content* of energy prices and transportation prices (proxied by the Baltic Dry Index, a widely used indicator of transportation costs) as *signals* of underlying supply chain disruptions. Under normal conditions, when transportation markets function smoothly, transportation prices aggregate most of the relevant information about delivery times, while energy prices carry little additional signal value. However, during periods of high supply chain uncertainty – when congestion renders transportation prices less informative – firms increasingly rely on energy prices as a proxy for logistical conditions. In our estimates (for both the U.S. and the Euro area), both the loading and the Kalman gain associated with energy inflation rise sharply in high-uncertainty regimes, overtaking those of transportation prices.

Bridging empirical evidence and model We embed the above inference problem framework into a canonical New Keynesian model to study how energy price shocks transmit to output prices. Firms face two types of upstream disturbances: (i) purely transitory shocks to raw energy and (ii) persistent shocks to the supply chain (e.g., transportation or logistics). In partial equilibrium under flexible prices, supply chain uncertainty gives rise to two amplification channels: (a) stronger *impact pass-through* of energy shocks to prices, and (b) greater *propagation* of those shocks over time via firms' expectations.

A rise in energy prices increases marginal costs directly. But under uncertainty, firms also treat energy prices as signals of broader supply chain disruptions and anticipate delivery delays for other inputs. These expectations further raise marginal costs, prompting firms to adjust prices not only in response to observed energy costs but also in anticipation of unobserved input delays. This signal-driven adjustment *amplifies* the pass-through of heightened energy prices with an additional, forward-looking component.

Crucially, the strength of this amplification depends on the *volatility* of transportation shocks. Higher volatility increases uncertainty, leading firms to place greater weight on energy prices as indicators of supply chain conditions. Conversely, when volatility is low, firms rely more on prior beliefs and largely ignore energy prices, bringing the model closer to the complete-information benchmark. In the limit, under complete information, a transitory energy shock has no effect on *future* prices. In contrast, with supply chain uncertainty, firms interpret the same shock as a signal of a persistent upstream disruption, raising expected future marginal costs. As a result, even purely temporary raw energy shocks *propagate* into future price dynamics.

Incomplete information NKPC Next, we embed the framework into a general equilibrium environment with staggered price setting. Under Calvo-type nominal rigidities, we derive an *incomplete-information* version of the New Keynesian Phillips Curve (NKPC) that incorporates supply chain uncertainty. Relative to the

June 13, 2025, "Oil tanker owners reluctant to brave Strait of Hormuz, Frontline chief says."

full-information benchmark, the NKPC features an additional *endogenous* term – formally isomorphic to a *cost-push* shock – arising from firms' Bayesian estimates of delivery delays. This term is activated by energy price shocks and inherits the persistence of the underlying transportation shock.

We study how purely temporary raw energy shocks affect inflation dynamics in this setting. Compared to the full-information case, inflation responds more strongly and persistently to energy shocks. The amplification mechanism stems entirely from firms' incomplete information about upstream supply conditions. Both the enhanced contemporaneous pass-through and the forward-looking propagation of shocks contribute to a more pronounced inflation response.

The core intuition mirrors the logic of the canonical NK framework: inflation is a forward-looking variable, in that it depends on both current and expected future marginal costs. Supply chain uncertainty increases the perceived persistence of marginal cost pressures following a transitory energy shock. This raises firms' expectations of future input costs, leading them to front-load price increases. As a result, even short-lived energy price shocks produce a disproportionately large response in current inflation. Forward-looking pricing behavior thus morphs the volatility in transportation conditions into an endogenous amplification channel for inflation.

1.1 Relation to the literature

Our paper contributes to a recent literature seeking to explain the transmission of supply-side shocks to persistent inflation during 2021–2023. Lorenzoni and Werning (2023) focus on the role of wage-price spirals as an amplification mechanism. Gagliardone and Gertler (2023) highlight the complementarity between labor and oil – both as a good in consumption and as an input in production – coupled with a role for accommodative monetary policy. Ball et al. (2022); Bernanke and Blanchard (2025); Liu and Nguyen (2023) attribute the unprecedented co-movement of inflation and energy inflation in 2021–2023 to exceptional supply chain disruptions. We contribute to this strand of the literature by highlighting that it is the surge in the *volatility*, rather than in the *level*, of transportation shocks that determines a heightened co-movement between CPI inflation and energy inflation.

Our paper relates to a rapidly growing body of literature on the macroeconomic implications of supply chain shocks. Bai, Fernández-Villaverde, Li, and Zanetti (2024) formalize the transportation market with a search-and-matching model between producers seeking a transportation service and transporters meeting the demand. In their setting, transportation shocks are spikes in matching frictions, causing heightened transportation times and costs. In a more recent paper, Bai et al. (2025) adopt the same model to study the optimal conduct of monetary policy. Ascari et al. (2024); Finck and Tillmann (2022); Bini (2025) assess empirically the effects of transportation shocks, and consistently find that they cause a persistent rise in consumer prices and a decline in economic activity. Similarly, Känzig and Raghavan (2025) identify a series of exogenous transportation shocks, and document that the primary effects are an increase in supplier delivery times, a broad-based increase in shipping rates, and a rise in commodity prices. Consequently, transportation shocks also affect macroeconomic aggregates, causing a fall in industrial production and a significant and persistent increase in consumer prices. Chau et al. (2024) estimates the effect of pandemic-related supply chain shocks via a Bartik shift-share design, where shares reflect the heterogeneous sectoral exposure to supply chain shocks. They find that the full lockdown of a major supplier that accounts for 50% of total expenditure raises a sector's PPI by 14.5%. Carreras-Valle and Ferrari (2025) provide a model-based quantification of delivery delays and study their effects. In their setup, larger delays and larger supply chain uncertainty lead to more firms being constrained in production and to lower aggregate output. We contribute to this literature by emphasizing the role of supply chain *uncertainty* as a driver of heightened pass-through of energy price shocks to inflation, and by showing that under those conditions energy price shocks endogenously morph into "cost-push" shocks.

Our paper also relates to a broader literature on uncertainty (Bloom, 2014) and information frictions in price-setting (Lucas, 1973). A large body of work has developed models in which noisy private information about the state of the economy generates aggregate macroeconomic fluctuations – see e.g., Lorenzoni (2009); Angeletos and La'O (2010, 2020).[14] More recently, a growing theoretical and empirical literature documents the role of uncertainty in propagating shocks along supply chains and through production networks. Nikolakoudis (2025) embeds incomplete information into a production-network model and shows that firms infer shocks from input prices. This mechanism implies that upstream shocks matter more when productivity uncertainty is high, and downstream shocks matter more when demand uncertainty is high. On the empirical side, Cacciatore and Candian (2025) find that upstream uncertainty acts like a negative supply shock, whereas downstream uncertainty acts like an adverse demand shock. Morão (2025) constructs an energy-transportation uncertainty index and shows that spikes raise real oil prices and depress global industrial output.

Our contribution lies at the intersection of the literature on the aggregate effects of transportation supply chain shocks and the literature on uncertainty. We show that *supply chain uncertainty* works as an amplifier in the transmission of energy shocks to inflation. Finally, as in Blanchard and Riggi (2013), we study the macroeconomic effects of energy (supply) shocks within a New Keynesian model with nominal rigidities. However, our setup enriches the standard NK environment by including a model of the supply chain and a pivotal role for incomplete information.

2 Empirical evidence

In this section, we provide empirical support for the key mechanisms of our theory. We proceed in two steps. First, we document that the *pass-through* of energy prices to inflation is state-dependent – rising markedly in periods of elevated supply chain uncertainty. Second, we show, using a Kalman filter approach, that energy prices become *more informative* than transportation prices when logistical uncertainty is high.

[14]Notably, in Bui et al. (2022) model of international input network, also noisy *public* information can drive business cycles.

2.1 Transmission of energy prices to inflation

Existing empirical evidence suggests that a significant portion of the 2021–2023 inflation surge was due to supply chain and energy price shocks. The literature quantifies this contribution at between one-third and two-thirds in the U.S. (Shapiro, 2022), and even more in the Euro area (di Giovanni et al., 2022). Notably, the last two decades have recorded other energy price shocks comparable to that of 2021–2023, but the latter period was starkly distinguished by an unprecedented sensitivity of inflation to energy prices. Evidence suggests that, after 2020, the core inflation response to an energy price shock "switched regime" (De Santis and Tornese, 2025), and was four times stronger in the Euro area and two times higher in the U.S. than in the pre-2020 period (Pallara et al., 2023), reaching an impressive 70% pass-through of the energy price shock to output prices for Euro area producers (Wehrhöfer, 2024). We conjecture that, under incomplete information, heightened transportation volatility can account for this evidence. A wide empirical literature has documented the unprecedented levels and variance of transportation shocks in recent years (Attinasi et al., 2022), and has shown that they affected CPI inflation (Benigno et al., 2022; Akinci et al., 2023; Ascari et al., 2024; di Giovanni et al., 2022; Carrière-Swallow et al., 2023).

Conditional correlates: CPI and energy inflation We consider the most natural proxy for supply chain uncertainty, namely the sample variance of the GSCPI computed over rolling windows (of 48 months). In Table 1, we explore the effects of adding this measure to a simple OLS regression of U.S. CPI inflation and Euro area HICP inflation. Specifically, we run a regression of inflation on its own lags over the preceding three years, energy inflation, the y-o-y percent change in the unemployment rate, and the one-year-ahead expected inflation. In column (1), we show the coefficient associated with energy inflation, which is positive and strongly significant.

In column (2), we add the *level* of the transportation disruption index (the GSCPI) to the regression. We show that the coefficient associated with the level of the transportation shock is also positive and strongly significant. Finally, in column (3), we include the interaction of energy inflation with the *variance* of the GSCPI in the regression. Notably, this interaction term is a significant covariate of inflation that weakens and *absorbs* part of the effect of the *level* of the transportation shock. Column (3) highlights that energy inflation has both a *direct effect* on CPI inflation (as captured by the coefficient on energy inflation) and an *uncertainty-related effect* that intensifies with higher volatility of the transportation shock (as captured by the interaction term).

These baseline OLS regressions provide a first empirical motivation for our analysis, pointing to an underlying mechanism – arguably incomplete information – in which the influence of transportation shocks on inflation stems not only from their level, but also from the amplification effect of their volatility on the transmission of energy price shocks.

	U.S. CPI inflation		
	(1)	(2)	(3)
U.S. Energy Inflation	0.094***	0.088***	0.083***
	(0.005)	(0.005)	(0.005)
GSCPI		0.341***	0.153***
		(0.049)	(0.056)
Var(GSCPI) × U.S. Energy Inflation			0.027***
			(0.005)
Adj. R^2	0.867	0.889	0.903
N	240	240	240

(a) U.S.

	E.A. HICP inflation		
	(1)	(2)	(3)
E.A. Energy Inflation	0.086***	0.080***	0.065***
	(0.004)	(0.004)	(0.004)
GSCPI		0.112***	0.060**
		(0.024)	(0.023)
Var(GSCPI) × E.A. Energy Inflation			0.014***
			(0.002)
Adj. R^2	0.970	0.972	0.977
N	240	240	240

(b) Euro area

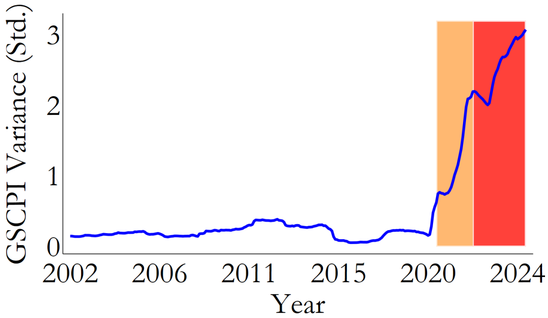
Table 1: Conditional correlates of U.S. and Euro area inflation

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Additional controls are: 3-year lags of inflation, y-o-y percent change in the unemployment rate, expected one-year-ahead inflation. For Table 1a, the data series retrieved from FRED, Federal Reserve Bank of St. Louis, are: U.S. CPI (CPIAUCSL) and energy inflation (CPIENGSL), U.S. y-o-y percent change in the unemployment rate seasonally adjusted (UNRATE), the expected one-year-ahead U.S. inflation from the Michigan Survey (MICH); for Table 1b are: Euro area HICP (CP0000EZ19M086NEST) and energy inflation (ENRGY0EZ19M086NEST). The Euro area y-o-y percent change in the unemployment rate seasonally adjusted (une_rt_m), and the expected one-year-ahead Euro area inflation (prc_hicp_mv12r) are retrieved from Eurostat, and the GSCPI is retrieved from the NY Fed. Var(GSCPI) is the 48-month rolling variance of the GSCPI time series. All variables considered have a monthly frequency from January 2002 to December 2024.

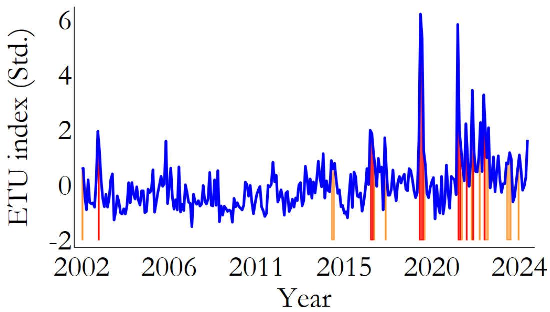
Supply chain uncertainty: low vs high states In Table 1, we consider supply chain uncertainty as a continuous variable that amplifies the conditional comovement of CPI and energy inflation. To simplify, we reduce this continuous dimension into two *states*: low and high supply chain uncertainty. Since the identification of the supply chain uncertainty states hinges heavily on the measure chosen, we consider two different measures constructed using diametrically opposed approaches.

The 48-month rolling variance of the GSCPI provides a first structural and data-driven measure of uncertainty. It captures the volatility in observed global supply chain pressures, aggregating from the bottom up various sources of transportation prices and managers' surveys across the globe. This measure reflects supply chain uncertainty from *fundamentals* rather than perceptions.
Alternatively, the *Energy Transportation Uncertainty (ETU)* index offers a perception-

based view of supply chain uncertainty. Derived from newspaper text-mining as in Caldara and Iacoviello (2022) and compiled by Morão (2025), the ETU flags articles that jointly mention energy, transportation, and uncertainty terms. It thus captures the narrative dimension of supply chain risk and measures how uncertainty over transportation is *perceived*, rather than how it materializes in economic data.



(a) Rolling variance of GSCPI



(b) ETU index

Top 10% Top 20%

Figure 5: Comparison of two measures of supply chain uncertainty, with periods of high uncertainty highlighted (rolling variance of GSCPI and ETU index).

Notes: In the left panel, the standardized variance of the GSCPI is computed over 48-month rolling windows and plotted monthly from January 2002 to December 2024. In the right panel, the standardized Energy Transportation Uncertainty (ETU) index from Morão (2025), available at `https://github.com/hmorao95/etu_world/blob/main/etuindex_data.xlsx`, is plotted over the same period. In both panels, light orange highlights the top 20% and red the top 10% of each series. The left measure captures volatility in realized global supply-chain pressures (rolling variance of GSCPI), whereas the right measure is an independent index of uncertainty related to energy transportation.

As Figure 5 shows, the two measures pin down two different high supply chain uncertainty regimes, yet both have most of their high values after 2020. Notably, the rolling variance aggregator smooths out short-run fluctuations, showing a clean break from a low to a high-uncertainty regime. On the other hand, the ETU index is more volatile and nuanced.

2.2 State-dependent local projections

Conditional on the identified supply chain uncertainty regimes, we compare the dynamic effects of exogenous *oil supply news shocks* across those states. This exercise provides further evidence that supply chain uncertainty shapes the pass-through of energy price shocks to inflation. Noticeably, our results show that the response of inflation to an oil shock is *state-dependent* – amplified when supply chain uncertainty is high.

We follow Ramey and Zubairy (2018) and estimate local projections à la Jordà (2005). Formally, consider the indicator variable U_t that flags the periods in which our chosen measure of uncertainty is above a given threshold. For the baseline specification, we consider the periods in which the 48-month rolling variance of the

GSCPI is in the top 20% of its distribution:

$$U_t = \mathbf{1}\{\text{Var}(GSCPI_t) > p_{80}\}$$

We interact U_t with the high-frequency oil supply news shocks $\{\varepsilon_t^{\text{oil}}\}$, identified by Känzig (2021). The identification of exogenous and unanticipated shocks proceeds in two steps. First, high-frequency *surprise* movements in oil futures prices are isolated around OPEC announcements.[15] 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.

Baseline LPs with GSCPI For each horizon $h = 0, \ldots, 18$, we estimate the following local projection:

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

where π_{t+h} is the 12-month U.S. or Euro area headline consumer (or core) inflation[16] at horizon h, and $\sum_{j=1}^{12} \gamma_{j,h} \pi_{t-j}$ is the set of its lags up to 12 months. The two coefficients of interest, $\{\beta_h, (\beta_h + \beta_h^H)\}$, trace the impulse responses of headline consumer 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. The impulse responses of inflation to oil news shocks when the GSCPI is used as the supply uncertainty measure are plotted in Figure 6, with their 90% and 68% confidence bands.[17]

ETU index as proxy of uncertainty A state-dependent estimation requires each regime to cover a non-trivial share of the sample and to display sufficient variation. As mentioned above, the rolling variance of the GSCPI is a smoother that reduces volatility, therefore reducing LP power and widening confidence bands in finite samples. Notably, this problem is less relevant when the uncertainty states are identified with the finer *ETU index*, possibly leading to an improved identification of the state-dependent responses of inflation to oil shocks.[18] Hence, in an alternative

[15]This methodology is analogous to that used to identify monetary policy shocks. In the monetary policy literature, high-frequency identification exploits asset price reactions in narrow event windows to isolate the effects of policy news. See, e.g., Kuttner (2001); Gürkaynak et al. (2005).

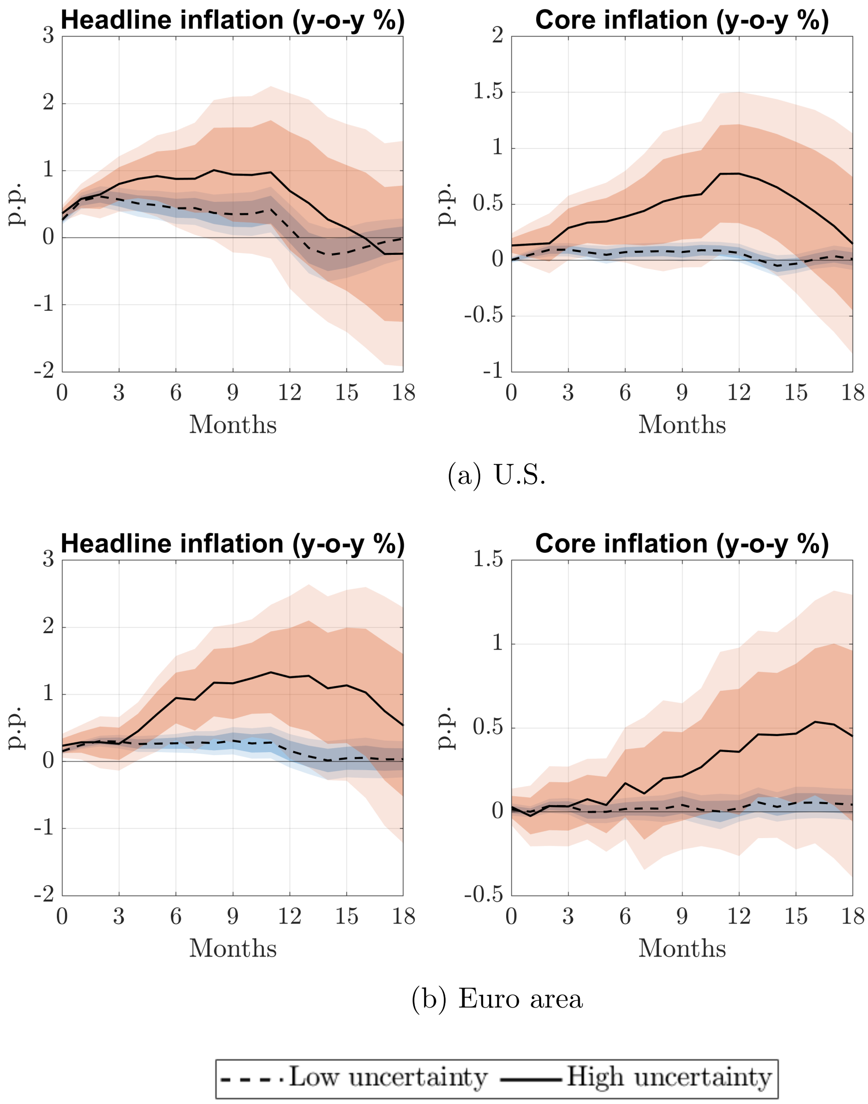
[16]For the U.S., we consider a measure of core inflation that excludes the "housing" component. This component has a disproportionate weight in U.S. core inflation (about 40%) and is completely insensitive to oil prices. As argued in Pallara et al. (2023), using the measure of core inflation that includes "housing" would therefore strongly bias downward the sensitivity of U.S. core prices to oil prices and distort the comparison with the Euro area.

[17]As noted in Ramey and Zubairy (2018), the only complication associated with the Jordà (2005) method is the serial correlation in the error terms induced by the successive leading of the dependent variable. Thus, we use the Newey and West (1987) correction to compute the standard errors.

[18]As a preliminary result, in Table 5 of Appendix B.8 we rerun the specification of Table 1 replacing the rolling variance of the GSCPI with the ETU index as a measure of supply chain uncertainty. We show that the results discussed for Table 1 are indeed robust.

set of local projections, we define:

$$U_t = \mathbf{1}\{ETU\ index > p_{80}\}$$

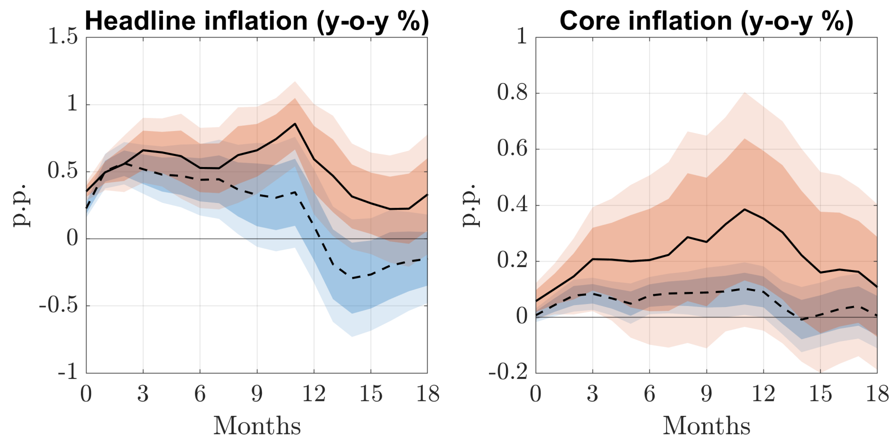


(a) U.S.

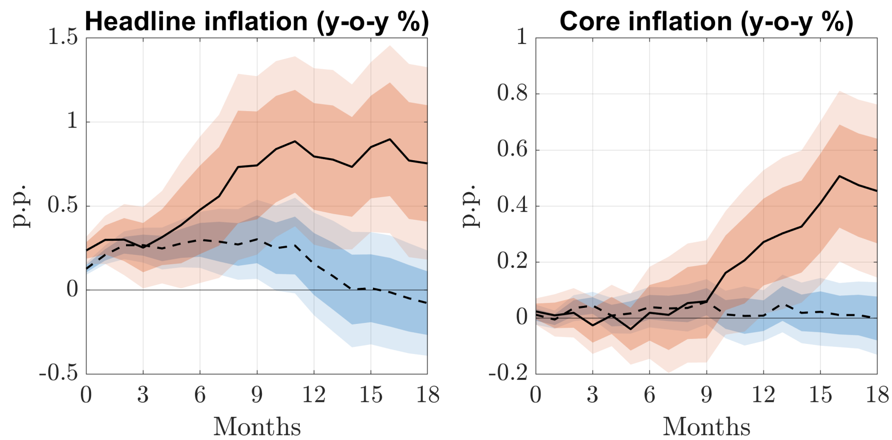
(b) Euro area

Figure 6: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across uncertainty states. High supply chain uncertainty corresponds to periods when the 48-month rolling variance of the *GSCPI* is in its top 20%.

Notes: The two panels above display the 18-month impulse response of headline and core inflation in the U.S. (Panel a) and in the Euro area (Panel b) to an oil supply news shock, computed on the time-window from January 2002 to December 2024, and normalized to increase oil price inflation by 10 percentage points on impact. The solid line represents the point estimate of the response of inflation in the high supply chain uncertainty state (top 20% of the rolling variance of GSCPI), and the orange shaded areas are the 90% and 68% Newey-West confidence bands. The dotted line represents the point estimate of the response of inflation in the low supply chain uncertainty state (bottom 80% of the rolling variance of GSCPI), and the blue shaded areas are the 90% and 68% confidence bands. The data series for the U.S. core inflation are the y-o-y percent change in the core price level series retrieved from FRED (CRESTKCPIXSLTRM159SFRBATL), while the one for the Euro area is the y-o-y percent change in the core price level series retrieved from Eurostat (TOTNRGFOODEA20MI15XM). Oil price inflation is not shown, but it is used to calibrate the size of the shock; oil inflation has monthly frequency and it is computed taking the y-o-y percent change in the series (WTISPLC) retrieved from FRED, Federal Reserve Bank of St. Louis, with no trend or seasonal adjustment. The series of oil news shocks is available at `https://github.com/dkaenzig/oilsupplynews`. See the Note of Table 1 for more details on the data series used for headline inflation.



(a) U.S.



(b) Euro area

Low uncertainty — High uncertainty

Figure 7: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across supply chain uncertainty states. High supply chain uncertainty corresponds to periods when the *ETU index* is in its top 20%.

Notes: The two panels above display the 18-month impulse response of headline and core inflation in the U.S. (Panel a) and in the Euro area (Panel b) to an oil supply news shock, computed on the time-window from January 2002 to December 2024, and normalized to increase oil price inflation by 10 percentage points on impact. The solid line represents the point estimate of the response of inflation in the high supply chain uncertainty state (top 20% of the ETU index), and the orange shaded areas are the 90% and 68% Newey-West confidence bands. The dotted line represents the point estimate of the response of inflation in the low supply chain uncertainty state (bottom 80% of the ETU index), and the blue shaded areas are the 90% and 68% confidence bands. See the Note of Figure 6 for more details on the data series used.

Figure 7 plots the state-dependent response of (headline and core) inflation in the low- and high- regimes identified as the top 20% of the ETU index distribution. Both Figure 6 and 7 show that the gap across regimes in the impulse response of inflation to oil shocks is clear and mostly statistically significant.[19] While the pass-

[19]See Appendix B.7 for a set of robustness exercises. First, Appendix B.7 reports the baseline local projection specification without state dependence, as a consistency check. It then presents state-dependent estimates in which the high-uncertainty regime is defined as the top 10% of the

through of oil price news shocks to both measures of inflation (and in both U.S. and the Euro area) is low or barely significant during periods of low supply chain uncertainty, the same pass-through increases significantly during periods of high uncertainty.

Robustness We have already discussed the main properties of the GSCPI as a benchmark index for transportation shocks. Besides the ETU index explored above, several alternative measures of transportation disturbances exist – most notably the Harper Peterson Time Charter Rates Index (HARPEX), which captures transportation costs, and the Average Congestion Rate (ACR) developed by Bai, Fernández-Villaverde, Li, and Zanetti (2024), which quantifies delivery delays. We focus on the latter, built from satellite-based measures of maritime traffic congestion, that isolates *supply-side* disruptions in transportation with minimal measurement error. These characteristics make the rolling variance of the ACR index a particularly appealing proxy for supply chain uncertainty. However, the short sample available (starting in January 2017) limits its use in our baseline analysis, especially when the sample is split into regimes for the state-dependent LP. In Figures 21 and 22 of Appendix B.8, we show that within its available time span, the ACR exhibits levels and rolling variances closely aligned with those of the GSCPI. In Table 4 of Appendix B.8, we also show that the results of the OLS regression in Table 1 are robust to the use of the ACR as a measure of transportation shocks.

2.3 The information value of energy prices

We have documented that the pass-through of energy prices to inflation is larger in periods of high supply chain uncertainty. Our interpretation is that, under uncertainty, firms need more information about ensuing delivery delays, and rely heavily on observable prices as information aggregates.

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 lose their allocative role: physical queues, not prices, determine the timely distribution of inputs. In such cases, another possibly useful signal emerges – *energy inflation*. 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 empirical model We assess the relative *information content* of two signals for firms: energy inflation and transportation prices – which are proxied

variance of the GSCPI. Finally, it shows results from a specification that controls for the contemporaneous level and a block of 12 lags of the GSCPI, ensuring that the identified state dependence reflects genuine uncertainty effects rather than the level of supply chain pressures.

by the Baltic Dry Index (BDI).[20] We consider energy inflation and BDI from January 2002 to December 2024, splitting the sample into low- and high-uncertainty regimes based on the GSCPI's rolling variance (bottom 80% and top 20%).

We estimate a Kalman filter model. In the *state* equation, we assume that the *unobserved* supply chain disruption (or 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 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 errors $\{\varepsilon_{\psi,t}\}$ 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 GSCPI series unconditional moments.[21]
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 Appendix B.9.[22]

In Figure 8, we plot – across uncertainty states – the estimated loading coefficients α_1, α_2 associated to energy inflation and to the BDI, respectively. As in the low-uncertainty state there are typically no disruptions, the transportation market runs smoothly and embeds all the information about the (sufficiently small) delivery delays. Therefore, firms rely solely on the BDI price to predict delivery delays, 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, the transportation market typically operates at its capacity limit, making transportation prices poor indicators of

[20]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.

[21]Initial priors provide an anchor to the state's scale. Without an external anchor, the pair (ψ_t, α) is only identified up to a multiplicative constant. Setting (m_0, C_0) on the GSCPI scale (and standardizing y_t) removes this confounding in practice.

[22]See Appendix B.9 for a detailed description of the MLE recursive estimation procedure under the two uncertainty regimes. The Appendix also discusses the choice of starting values and the parametric constraints imposed on the estimated parameters.

underlying disruptions. As a result, the BDI component becomes a noisier signal and receives little weight in firms' inference process. In contrast, the energy inflation signal – largely ignored under stable conditions – now gains prominence, retaining its reliability even when logistical frictions intensify. Consequently, in high-uncertainty regimes, the loading on energy inflation rises above that on transportation prices, reflecting its enhanced informational value.

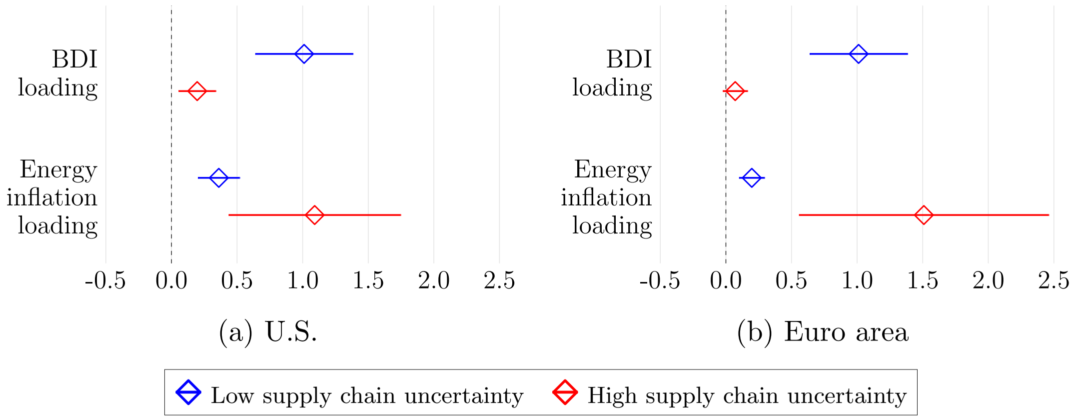


Figure 8: Loading coefficients for BDI and Energy Inflation - U.S. and Euro area

Notes: The figure presents the result of the MLE estimation of the empirical Kalman filter model. The two panels above display the estimated loadings of energy inflation (α_1) and BDI index (α_2) in the U.S. (Panel a) and in the Euro area (Panel b). For the U.S., Energy inflation is the y-o-y percentage change in the energy price series (CPIENGSL) retrieved from FRED, Federal Reserve Bank of St. Louis. For the Euro area, it is the series (ENRGY0EZ19M086NEST) retrieved from Eurostat. All variables considered have a monthly frequency over a sample from January 2002 to December 2024. The Baltic Dry Index (BDI) series is retrieved from Bloomberg. Both the energy inflation and the BDI are measured in standard deviations from their sample average. Estimation is performed via MLE, assuming uncorrelated observation shocks (i.e., the variance–covariance matrix V is diagonal). See Appendix B.9 for a robustness test with the matrix V potentially non-diagonal. The red line represents the point estimate and relative 90% confidence interval of the coefficients in the high supply chain uncertainty state (top 20% of the rolling variance of the GSCPI). The blue lines represents the point estimates and 90% confidence intervals of the loading coefficients in the low state (bottom 80% of the rolling variance of the GSCPI). See also Appendix B.9 for details on the computation of standard errors, and for a complete report of all the parameters estimated from the Kalman-filter empirical model.

The Kalman gain provides a direct measure of the *weight* that firms assign to a given signal when estimating the unobserved state. In Table 2, we show how the Kalman gain weights associated to energy inflation and the BDI vary across uncertainty states. The results are fully consistent with those inferred from the loadings plot. Under low uncertainty, when the transportation market efficiently aggregates information about delivery delays, the BDI receives a Kalman gain close to 1, while energy inflation carries almost no weight. By contrast, under high supply chain uncertainty, the transportation price signal becomes uninformative, and inference shifts almost entirely to the energy inflation signal.

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 allocates relative weights across signals according to their measurement noise – the contribution of signal j is inversely related to σ_j^2. Since energy inflation signals display much lower variance than BDI signals in the high-uncertainty regime, the Kalman gain weight of energy inflation rises relative to that of the BDI.[23]

Signal	Low uncertainty	High uncertainty
BDI	0.99	1.57×10^{-9}
Energy inflation	1.87×10^{-9}	0.92

(a) U.S.

Signal	Low uncertainty	High uncertainty
BDI	0.99	2.24×10^{-10}
Energy inflation	3.00×10^{-9}	0.66

(b) Euro area

Table 2: Kalman gain across uncertainty regimes: U.S. and Euro area.

Notes: The panels display Kalman gain entries for the BDI and energy inflation, which are the two observed equations in the Kalman filter problem. They are computed separately for the high-uncertainty regime (top 20% of the rolling variance of the GSCPI) and the low-uncertainty regime (bottom 80%). The sample spans January 2002 to December 2024. Estimation is performed via MLE, assuming uncorrelated observation shocks (i.e., the variance–covariance matrix V is diagonal).

3 A model of the supply chain

The empirical evidence presented above highlights two key facts: (i) the *pass-through* of (suitably identified) energy price shocks to inflation is amplified in periods of high supply chain uncertainty; (ii) during such episodes, energy prices become relatively *more informative* than transportation prices about underlying logistical conditions. We next develop a theoretical framework that rationalizes these 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 delays – can amplify 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 9.

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

[23]The result of a larger Kalman gain (in Table 2) and of a larger loading coefficient (in Figure 8) associated with the energy signal under high supply chain uncertainty is robust to the assumption of potentially correlated observation shocks (non-diagonal matrix) and to the use of energy prices in place of y-o-y energy inflation. See Appendix B.9.

a known premium in the event of shipping delays and supply chain disruptions. The second input is a *specialized component* M (e.g., microchips). 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.

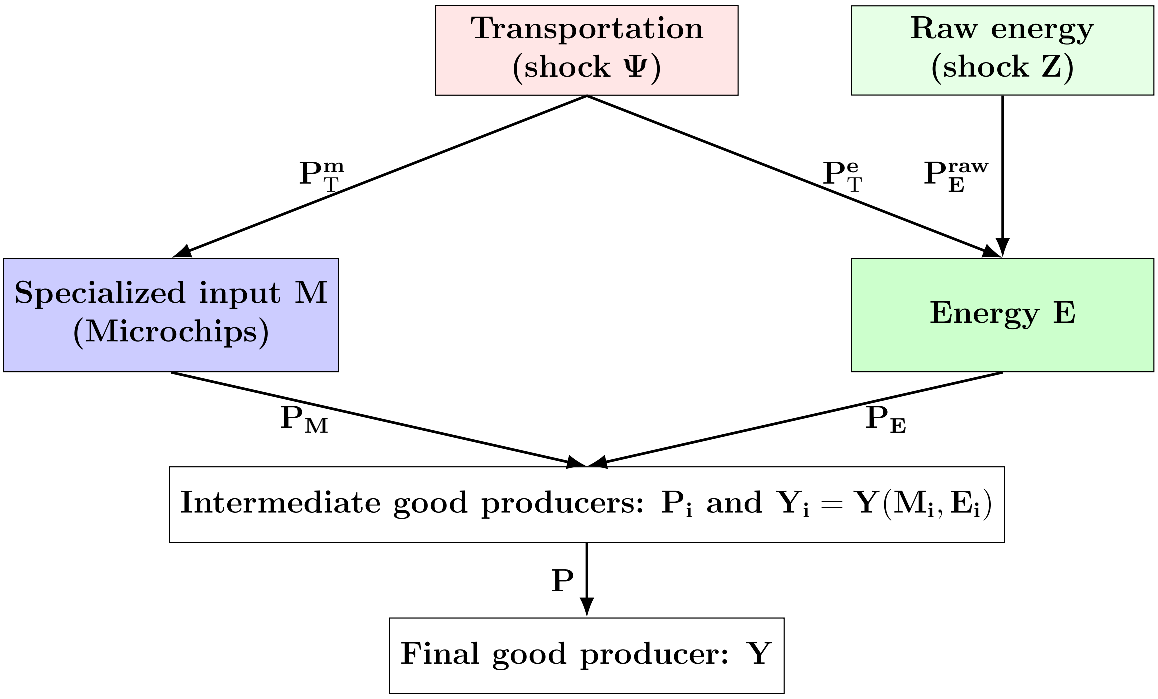


Figure 9: Model of the supply chain

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 $\varepsilon > 1$:

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{2}$$

The demand for each differentiated variety $Y_{i,t}$ is derived from cost minimization under a CES aggregator with elasticity of substitution $\varepsilon > 1$. It is given by:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon} Y_t \tag{3}$$

where $P_{i,t}$ is the price of variety i, and P_t is the aggregate price index defined as:

$$P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon} \, di \right)^{\frac{1}{1-\varepsilon}}$$

Intermediate goods There is a continuum of monopolistically competitive intermediate product firms that take the price of energy and the specialized input 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 (3) and to:

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

where $\alpha_E + \alpha_M = 1$. Producer i's optimal demand for energy reads:

$$E_{i,t} = \alpha_E \frac{P_{i,t} \, Y_{i,t}}{P_{E,t}}$$

Integrating over i:

$$E_t = \int_0^1 E_{i,t} \, di = \frac{\alpha_E}{P_{E,t}} \int_0^1 P_{i,t} \, Y_{i,t} \, di$$

Since the final good producer makes zero profits, $\int_0^1 P_{i,t} \, Y_{i,t} \, di = P_t Y_t$, we have:

$$E_t = \frac{\alpha_E \, P_t Y_t}{P_{E,t}} \tag{4}$$

Symmetrically, the optimal total demand for the specialized input reads

$$M_t = \frac{\alpha_M \, P_t Y_t}{P_{M,t}} \tag{5}$$

Finally, the nominal marginal cost of production – common across intermediate producers – is given by:

$$MC_t = \left(\frac{P_{E,t}}{\alpha_E} \right)^{\alpha_E} \cdot \left(\frac{P_{M,t}}{\alpha_M} \right)^{\alpha_M} \tag{6}$$

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, profit-maximizing energy supplier operating under perfect competition, which 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.[24]

The firm produces one unit of (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). 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:

$$E_t \;=\; \left((1-\delta)^{1/\eta}\, E_{T,t}^{1-(1/\eta)} \;+\; \delta^{1/\eta}\, E_{raw,t}^{1-(1/\eta)}\right)^{\frac{\nu}{1-(1/\eta)}} \tag{7}$$

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.[25]

The cost-minimizing demand for energy transportation reads:

$$E_{T,t} = \nu^{\eta} \cdot E_t^{\eta+\frac{1}{\nu}(1-\eta)} \cdot (1-\delta) \cdot \left(\frac{P^{e}_{T,t}}{P_{E,t}}\right)^{-\eta} \tag{8}$$

where the marginal cost price index is

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

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:

$$E_{raw,t} = \nu^{\eta} \cdot E_t^{\eta+\frac{1}{\nu}(1-\eta)} \cdot \delta \cdot \left(\frac{P^{raw}_{E,t}}{P_{E,t}}\right)^{-\eta} \tag{10}$$

Plugging the demand for raw energy (8) and for its transportation (10) into the energy supply aggregator (7) yields the equilibrium supply of energy:

[24]This modeling assumption on the determinants of energy price is realistic as, according to the U.S. Energy Information Administration (EIA), production and distribution constitute 85% of the retail oil price in the U.S. (see `https://www.eia.gov/energyexplained/heating-oil/prices-and-outlook.php`)

[25]In particular, we assume that both the energy and the specialized input markets have the same IRS production function in (7), with the same increasing returns index ν, the same elasticity of substitution η, and the same weight δ.

$$E_t = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta) \left(P^e_{T,t}\right)^{1-\eta} + \delta \left(P^{raw}_{E,t}\right)^{1-\eta} \right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{11}$$

Note that, since $\nu > 1$, the equilibrium supply of energy has a negative relation to its price $P_{E,t}$.

3.4 Market for transportation

We first lay out a few relevant facts that characterize the market for transportation of both the energy input and the specialized input. We then introduce a stylized model of the market for transportation.

3.4.1 Facts about the market for transportation

We present some distinctive features of global trade that motivate our modeling choices for the transportation market.

Fact 1. Maritime trade Over 80% of the volume of international merchandise trade is carried by sea (UNCTAD, 2024). As we will point out, maritime global trade can be viewed as a market for transportation, where transportation services are purchased at an *effective* price of transportation that is composed of a *market* price of transportation and of a *time cost* of delivery. The latter refers to the additional costs that producers can incur if their input good is shipped with delay – e.g., penalties from contract breaches, reputational losses, and discount-induced sales.

Fact 2. Finite supply of transportation Global maritime trade is extremely concentrated, due to the substantial time and cost required to construct new vessels, with only 5,589 container ships in operation worldwide.[26] Downstream firms demand a flow of transportation capacity to ship their goods, while supply is provided by a fixed number of container ships. This supply exhibits a *vertical kink*: once all ships are fully deployed and operating at maximum capacity, no further increase in transportation can occur, regardless of demand.

Fact 3. Chokepoints In the market for transportation we are considering, there are large containers following fixed itineraries centered on a handful of key seaports. In each continent, the trade network is highly concentrated around a few port hubs and major trade routes – which serve as international hubs for freight distribution – with a Gini coefficient exceeding 0.85 (Ducruet and Notteboom, 2022).[27] These hubs and their fixed routes act as "chokepoints" in the global logistics network, much like an airport hub coordinating international flights; any delay at a chokepoint generates far-reaching ripple effects on the delivery of numerous goods.

[26]See UN Trade and Development (UNCTAD, `https://unctad.org/rmt2022`).

[27]To put things in context, the U.S. income distribution has a Gini coefficient of 0.48.

3.4.2 Transportation shocks and input substitutability

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).[28] Because most globally traded goods – including energy – share the same transportation market, featuring the same chokepoints, they are exposed to the same transportation shocks. In other words, energy and microchips 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 causes traffic on a specific trade route, it causes network congestion, thereby increasing the transportation time and cost in *all* routes by the same amount.

Commoditized vs specialized input Energy is a commoditized input – perfectly substitutable and available in local spot markets. In contrast, the specialized component (e.g., microchips) cannot be easily sourced locally and lacks immediate substitutes. As a result, disruptions in global supply chains affect these inputs asymmetrically. Shortages of energy can be accommodated through local purchases at a known premium. However, for the specialized input, delivery is subject to stochastic lags, governed by logistical bottlenecks and maritime transport risks.

Commodity markets – such as those for oil and gas – rapidly and efficiently aggregate information, including risks of disruption. Prices in these markets quickly adjust to reflect changing expectations about supply chain reliability. In normal times, the price of specialized inputs incorporates such risks indirectly, via the cost of transportation. For instance, if shipping companies anticipate elevated risks when navigating key chokepoints like the Suez Canal or the Strait of Hormuz, they may opt for longer, safer routes (e.g., via the Cape of Good Hope). This rerouting raises the cost of maritime transport, which in turn affects the delivered price of specialized goods. However, when disruptions become severe, transportation networks may experience congestion or physical blockage, impairing timely delivery. At that point, while commoditized inputs like energy remain available – albeit at higher spot prices– specialized inputs face true supply uncertainty. Delivery times become unpredictable, and with them, so does the effective cost of production for firms dependent on those specialized inputs.

3.4.3 A simple model of the transportation market

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

[28]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).

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.*

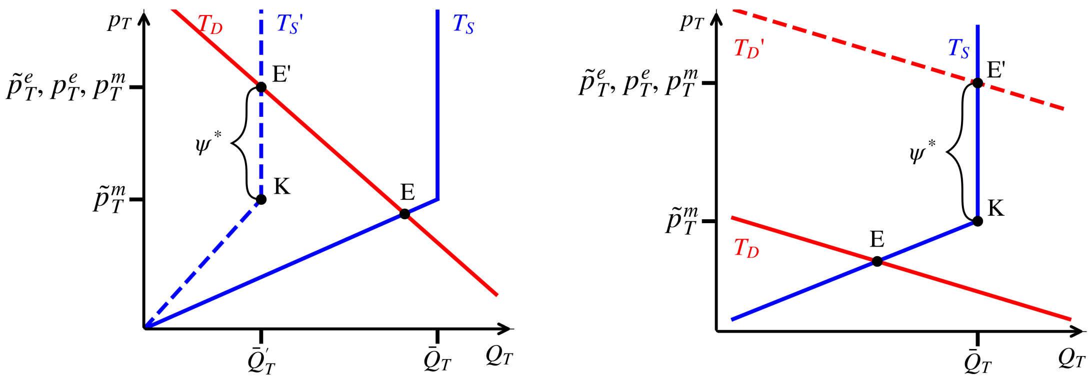
This assumption captures the fact that both energy and specialized inputs rely on shared transportation infrastructure and pass through common logistical chokepoints. We conceptualize supply chain disruptions as transportation shocks, which can originate from either the demand or the supply side of the transportation sector.

Transportation *demand* shocks arise, for example, from surges in global economic activity. A salient case is the post-COVID-19 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 decisions, reduces effective fleet availability, or impairs the flow of goods.

Graphical illustration of the transportation market We represent the transportation market in Figure 10 in terms of demand and supply in the 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, $T_S(Q_T)$, depicted in blue, is upward sloping, as a higher price of transportation stimulates more transportation capacity. Crucially, though, the transportation supply function becomes *vertical* at a given finite capacity limit $\bar{Q}_T$.

The initial equilibrium is at point E, located in the upward sloping portion of the T_S curve. Consider, first, a transportation (negative) supply shock (left panel), depicted as a leftward shift in the supply function. The main point to highlight is that, if the shock is sufficiently large, the demand and supply functions intersect in the vertical portion of the T_S curve. At point E' the capacity constraint on the transportation of the specialized input becomes binding. In the same vein, the right panel of Figure 10 depicts the effect of a transportation demand shock, as a rightward shift in the T_D function. If the shock is large enough, the supply and demand functions intersect at point E' where the capacity constraint on the transportation of the specialized input is binding.



(a) Transportation supply shock (b) Transportation demand shock

Figure 10: Transportation market (lower case variables in logs)

Notes: The figure displays the effects on the transportation market of a transportation supply shock (left panel) and a transportation demand shock (right panel). All prices are expressed in logs. p^m_T, p^e_T are, respectively, the log *effective* price of the specialized input and of energy; $\tilde{p}^m_T$, $\tilde{p}^e_T$ are the log *market* prices of the specialized input and of energy. Point E is the equilibrium before the transportation shock, point K is the kink point of the supply schedule, and point E' is the equilibrium after the transportation shock. The vertical distance E'K measures the unobserved delay cost $\psi^* \equiv \log(\Psi^*)$.

Unobserved delay cost 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 effective price of transportation for the specialized input $P^m_{T,t}$ (at point E) and the market price of transportation of the specialized input $\tilde{P}^m_{T,t}$ (at point E'). This wedge is due to an *unobserved delay cost* of transportation Ψ^*_t, corresponding to the vertical segment K-E' (where lower case variables refer to logs). Formally, we write:

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

Intuitively, when transportation supply reaches full capacity, firms begin to incur an unobservable delay cost associated with the physical delivery 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.[29] Henceforth, and without loss of generality, we normalize $\tilde{P}^m_{T,t} = 1$.

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

For the energy input, however, the market price of transportation P_T^e and the effective price $\tilde{P}_{T,t}^e$ 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:

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

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 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 a *noisy signal* of the effective price of transportation. As a result, downstream firms will have to estimate an unobserved 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

To describe the market for *raw* energy we assume that the price of 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 supply of energy equation (11) we obtain:

$$\underbrace{E_t(\Psi_t)}_{\substack{\text{equilibrium supply}\\ \text{of energy}}} = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{12}$$

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

$$\underbrace{M_t(\Psi_t^*)}_{\substack{\text{equilibrium supply} \\ \text{of specialized input}}} = (\nu\, P_{M,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta\right]^{\frac{\nu}{(1-\eta)\,(\nu-1)}} \tag{13}$$

where we have assumed that the price of the raw specific input is normalized to 1. Notice that the equilibrium supply of the specialized input depends on the unobserved delay cost Ψ_t^*.

Equilibrium price of energy The equilibrium price of energy can be derived by combining the demand by the intermediate product firm in (4) with the supply in (12):[30]

$$P_{E,t}(Y_t, \Psi_t, Z_t) = (\alpha_E Y_t P_t)^{1-\nu}\, \nu^{-\nu} \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}\right]^{\frac{\nu}{1-\eta}} \tag{14}$$

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:

$$p_{E,t} = (1-\nu)y_t + \nu\left[(1-\delta)\psi_t + \delta z_t\right] \tag{15}$$

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 (5) with (13):

$$P_{M,t}(Y_t, \Psi_t^*) = (\alpha_M Y_t P_t)^{1-\nu}\ \nu^{-\nu}\ \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta\right]^{\frac{\nu}{1-\eta}} \tag{16}$$

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 *unobserved* delay cost Ψ_t^*, as that cost *physically delays* the input transportation via the supply chain, generating an additional uncertain production cost.

[30]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 (6) and derive an expression for the equilibrium nominal marginal cost as a function of the underlying shocks:

$$MC_t(Y_t, P_t, \Psi_t, Z_t, \Psi_t^*) = A^{-\nu} \cdot (Y_t P_t)^{1-\nu} \cdot \Gamma(\Psi_t, Z_t)^{\frac{\alpha_E \nu}{1-\eta}} \cdot \Lambda(\Psi_t^*)^{\frac{\alpha_M \nu}{1-\eta}} \tag{17}$$

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

Therefore, the nominal marginal cost depends on *both* the true transportation shock Ψ_t – through its effect on the price of energy – and the unosberved delay cost Ψ_t^* – through its effect on the effective price of the specialized input.

Log-linearizing equation (17), and letting mc_t be the percent deviation of the *real* marginal cost from its steady-state value we can write:

$$mc_t = \underbrace{(1-\nu)\, y_t}_{\text{output}} + \nu\,(1-\delta) \left[\underbrace{\alpha_E\, \psi_t}_{\substack{\text{true transportation}\\ \text{shock}}} + \underbrace{\alpha_M\, \psi_t^*}_{\substack{\text{unobserved}\\ \text{delay}}} \right] + \underbrace{\alpha_E\, \nu\, \delta\, z_t}_{\substack{\text{raw energy}\\ \text{shock}}} \tag{18}$$

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 unobserved delay ψ_t^* in 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 (18) above highlights the role of transportation shocks and uncertain delays in the delivery of specialized inputs 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 estimate the unobserved component ψ_t^* before setting its price.

Signal extraction problem We assume that, at every time t, intermediate producers hold a *prior* over the distribution of transportation shocks, observe the realized price of energy and the level of aggregate output, and must infer what portion of the observed price of energy is attributable to disruptions in transportation as opposed to primitive shocks to the raw price of energy. Hence, in its estimation problem, each intermediate producer adopts the price of energy $p_{E,t}$ as a *signal* for the underlying transportation shock.[31]

[31] Notice that, without loss of generality, we presented a minimal information problem where firms learn *solely* from energy prices to estimate the state of the supply chain ψ_t. All our results extend to the general case where firms also use other concurring signals. We discuss this assumption extensively in Appendix B.1.

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.[32] For each time $t \geq 1$, the corresponding state-space model is:

$$\begin{cases} \psi_t \ = \ \rho_\psi \, \psi_{(t-1)} + \varepsilon_{\psi,t} & \varepsilon_{\psi,t} \sim \mathcal{N}(0, \, \sigma^2_\psi) \\ p_{E,t} = (1-\nu) y_t + \nu \, \Omega_t & \\ \Omega_t \equiv (1-\delta)\psi_t + \delta z_t & z_t \quad \sim \mathcal{N}(0, \, \sigma^2_Z) \end{cases} \tag{19}$$

where Ω_t is a *convolution* of the two supply shocks (to transportation and raw energy respectively), the latent transportation shock process 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^2_ψ and σ^2_Z, respectively.[33]
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. The information problem corresponds to a signal extraction problem in which 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 $\mathcal{P}_{\psi,(t-1)}$ of the Bayesian estimate of the transportation shock. From this process of Bayesian learning, the firm obtains an updated *posterior* distribution $\mathcal{P}_{\psi,t}$. 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 ($\mathbb{E}\{.\}$), 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.

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

[33] 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: $\psi_0 \sim \mathcal{N}(m_0, C)$.

Kalman filter The *optimal linear estimator* of ψ_t given $p_{E,t}$ is well-defined under the Gaussian linear specification in (19). The point estimate ψ_t^* evolves according to the Kalman filter updating equation:

$$\psi_t^* = \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\}}_{\text{guess with old info}} + \underbrace{\mathbb{K}(\mathcal{S})}_{\text{weight to new info}} \underbrace{\Big(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\Big)}_{\text{error correction with new signal}} \tag{20}$$

where $\mathbb{K}(\mathcal{S})$ is the *Kalman gain*, in turn a function of the *signal-to-noise* ratio $\mathcal{S}$.[34]

Equation 20 above describes the *recursive* learning process of the intermediate firm. At time $t-1$, the firm formulates a guess for the future state process value of ψ_t. Consequently, it makes a $t-1$ forecast for the time t energy price $p_{E,t}$. At time t, the firm observes the energy price $p_{E,t}$ and incorporates information by comparing the actual energy price with the time $t-1$ forecast. This comparison obtains an *error correction* term: $\Big(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\Big)$. This new signal information component contributes to the estimate of the transportation latent process ψ_t^*. The extent of this contribution is determined by the Kalman gain $\mathbb{K}(\mathcal{S})$, which is a measure of the *informativeness* of the energy price $p_{E,t}$. Notice that the Kalman gain $\mathbb{K}(\mathcal{S})$ is strictly increasing in the signal-to-noise ratio $\mathcal{S} \equiv \sigma_\psi^2/\sigma_Z^2$.[35]

Marginal cost under uncertainty As argued above, and highlighted in (16), the specialized input price $p_{M,t}$ depends on the *unobserved delay cost* ψ_t^*, which is estimated according to the Kalman filter updating equation in (20):

$$p_M(\psi_t^*) = (1-\nu)\, y_t + \nu\,(1-\delta) \cdot \underbrace{\Big[\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} + \mathbb{K}(\mathcal{S})\Big(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\Big)\Big]}_{\psi_t^*} \tag{21}$$

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:

$$mc_t = \alpha_E \underbrace{p_{E,t}}_{\text{energy price}} + \alpha_M \underbrace{\big[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\big]}_{\text{specialized input price: } p_M(\psi_t^*)} \tag{22}$$

Once uncovered the dependence of the specialized input price from the energy price in (21), it is clear that the marginal cost depends on the energy price through two distinct channels. For one, an increase in the energy price raises the marginal cost through a *direct effect* by a coefficient α_E. Furthermore, and due to the existence of supply chain uncertainty, the energy price also informs the firm of a possible transportation delay ψ_t^*, further raising the marginal cost through an *uncertainty effect*. Notice that the elasticity of the uncertainty channel is increasing in the IRS parameter $\nu > 1$.

[34] 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 Appendix B.4 for a detailed discussion.

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

3.8 Pass-through of energy prices under uncertainty

We are now in the position to study the impact and propagation of primitive energy price shocks on the intermediate product price under supply chain uncertainty. Notice that we consider the role of uncertainty at *first order*, that is, in a log-linearized setup that abstracts from second-order effects.

Optimal pricing The optimal log intermediate product price under uncertainty is a constant markup $\mu \equiv \log(\frac{\varepsilon}{\varepsilon-1})$ over the nominal marginal cost of production:

$$p_t = \mu + \underbrace{\alpha_E p_{E,t} + \alpha_M \left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]}_{mc_t^n} \tag{23}$$

where mc_t^n is the firm's nominal marginal cost, and $\varepsilon > 1$ is the price elasticity of demand.[36] 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 energy price shocks.

Proposition 1 (Impact pass-through of energy prices). *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 is:*

$$\frac{dp_t}{dp_{E,t}} = \underbrace{\alpha_E}_{\textit{direct effect}} + \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\textit{uncertainty effect}} \tag{24}$$

Proof. Consider the marginal cost equation (22) and combine it with equation (20). That yields:

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

In particular,

$$\frac{\partial \psi_t^*}{\partial p_{E,t}} \equiv \mathbb{K}(\mathcal{S}).$$

□

The above proposition shows that an increase in the price of energy raises the intermediate firm's marginal cost – and, one-to-one, its optimal output price – via two channels:

- *Direct effect*: A rise in the energy price directly increases the marginal cost of production and, therefore, the optimal output price with elasticity given by the share of energy in production. This effect would be present also under complete information.

[36] In the present subsection (i.e., subsection 3.8), with a slight abuse of notation for the sake of readability, let $p_{E,t}$ be the *nominal* energy cost, y_t be the *nominal* output in deviation from steady state, and ψ_t^* be the *nominal* unobserved delay cost.

- *Uncertainty effect*: Under incomplete information about the supply chain, a rise in the energy price is also informative about the unobserved delay cost, which increases the marginal cost above and beyond the direct effect. Notably, this effect is stronger when prior knowledge about the supply chain is more uncertain – i.e., the Kalman gain coefficient $\mathbb{K}(\mathcal{S})$ is higher – and firms rely more on the energy price to gain information about the unobserved delay cost.

Precautionary pricing The rise in the intermediate product price driven by the uncertainty effect mirrors the standard precautionary-pricing mechanism found in macroeconomic models with time-varying uncertainty (see Fernández-Villaverde et al. (2015) and references therein). Notice that the existing literature generally associates precautionary pricing with the nominal Calvo price rigidity: the anticipation of future marginal costs by firms prompts them to raise prices preemptively, thereby insuring against the risk of being left with prices that subsequently prove to be too low in the event of an increase in future marginal costs. In contrast, Proposition 1 suggests that our supply chain uncertainty mechanism triggers a precautionary-pricing motive *even* in the absence of any nominal price rigidity.

Dynamic energy price pass-through Next, we emphasize the mechanism through which supply chain uncertainty endogenously generates *persistence* in the pass-through of otherwise transitory energy price shocks to intermediate product prices. Let $\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+k)}\}$ be the expected optimal future intermediate product price at horizon $t+k$, conditional on the information set at time t. We consider an increase in today's energy price $p_{E,t}$ originating from a purely *transitory i.i.d.* raw energy shock z_t. The following proposition characterizes the pass-through on product prices at different horizons:[37]

Proposition 2 (Dynamic pass-through of energy prices). *Under supply chain uncertainty, the pass-through of a purely transitory time-t energy price shock z_t to the future expected optimal output price at horizon $k \geq 1$ is:*

$$\frac{d\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+k)}\}}{dp_{E,t}} = \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\textit{impact effect of uncertainty}} \cdot \underbrace{\left[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\right]^k}_{\textit{dynamic effect of uncertainty}} > 0 \quad (25)$$

Proof. Proof in Appendix A.1. □

The dynamic pass-through of energy prices at time horizon k reflects the fraction of the uncertainty effect of the impact pass-through that survives at the time horizon $t+k$. It is therefore made of two components:

First, the familiar *impact effect of uncertainty* – $\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})$ – that is increasing with $\mathbb{K}(\mathcal{S})$, the Kalman gain and, consequently, with the signal-to-noise ratio $\mathcal{S} \equiv \sigma^2_\psi / \sigma^2_Z$ and with supply chain uncertainty σ^2_ψ.

[37] Notice that this corresponds to a partial equilibrium pass-through, as we still treat output y_t as given.

Second, the *dynamic effect of uncertainty* – $\left[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\right]^k$ – that regulates the *persistence* of the pass-through as the time horizon k increases. This dynamic component depends *negatively* on the Kalman gain and, consequently, on the supply chain uncertainty σ_ψ^2.

Notice that, under *complete* information, the dynamic pass-through of energy prices to output prices is zero:

Corollary 3.1. *Under complete information, the time t+k pass-through of any given time-t energy price shock is zero.*

Proof. Under complete information, the Kalman gain $\mathbb{K}(\mathcal{S}) = 0$. Equation (25) then yields $\frac{\partial \mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+k)}\}}{\partial p_{E,t}} = 0$. $\square$

Proposition 2 shows that when firms observe, under supply chain uncertainty, a surge in energy prices, they initially *misinterpret* that surge as deriving from a persistent underlying transportation shock, and revise their optimal future intermediate product price accordingly. This misinterpretation produces a non-zero dynamic pass-through beyond the date of the shock. Over time, through its recursive Bayesian learning procedure, the firm understands that the increase in the energy price was solely due to a purely *i.i.d.* raw energy shock, and that there is no persistent transportation disturbance. As learning takes place, the firm's future optimal good price converges to the complete-information benchmark. As shown above, the dynamic pass-through under complete information is zero for any time $t+k$, as firms immediately understand that there is no persistent transportation shock, and therefore do not revise their future optimal good price upward.

Figure 11 displays the effect on the optimal intermediate product price p_t and on the unobserved delay cost ψ_t^* 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.

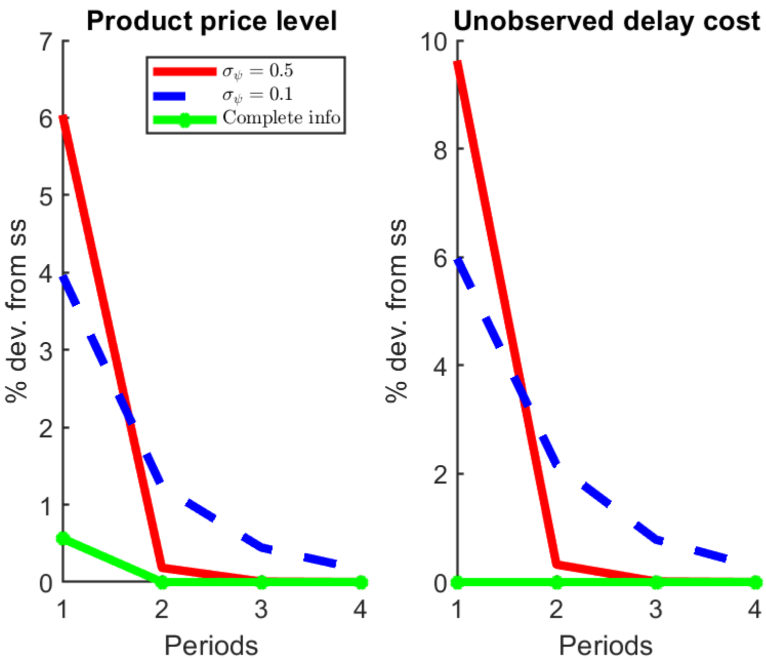


Figure 11: Impulse responses of the optimal intermediate product price and of the unobserved delay cost to an *i.i.d.* raw energy price shock

Notes. The panel depicts the response of the optimal intermediate product price to an *i.i.d.* 10% positive shock in the raw energy price z_t with volatility $\sigma_Z = 0.1$. The green line describes the case of *complete* information (i.e., $\sigma_\psi = 0$), the red line describes the case of *low supply chain uncertainty* $\sigma_\psi = 0.1$ and the blue line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.5$. The remaining parameter values are $\alpha_E = 0.09$, $\alpha_M = 0.91$, $\eta = 0.01$, $\delta = 0.5$, $\rho_\psi = 0.9$, $\sigma_Z = 0.1$, $\nu = 1.25$.

Proposition 1 and 2 determine how supply chain uncertainty shapes the dynamic response of the intermediate product price to a transitory (raw) energy price shock. Figure 11 illustrates how higher supply chain uncertainty (a higher variance of the transportation shock) increases the *impact* response of the product price level to an i.i.d. energy price shock.

Non-linear effect of uncertainty on dynamic pass-through The key mechanism operates as follows. Higher supply chain uncertainty increases firms' reliance on energy prices to infer the unobserved delay cost. Two forces shape the dynamics. First, greater uncertainty amplifies the *impact* pass-through of energy prices to output prices, as firms react more strongly to the informational content of observed shocks. Second, greater uncertainty determines a *non-linear* effect on *the dynamic* pass-through for any given horizon k, as uncertainty accelerates Bayesian updating, pushing firms to extract marginally more information from energy prices, learning more quickly, and therefore reducing the persistence of the output price response.

Figure 12 illustrates the non-linear effect on the dynamic pass-through. The Figure shows the effect of varying supply chain uncertainty σ_ψ on the dynamic pass-through of energy prices at different horizons k. 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. Importantly, 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.

Taken together, these effects imply that greater supply chain uncertainty leads to a stronger – but less persistent – dynamic estimate of the unobserved delay cost, and thus a more pronounced yet shorter-lived pass-through of raw energy price shocks to output prices.

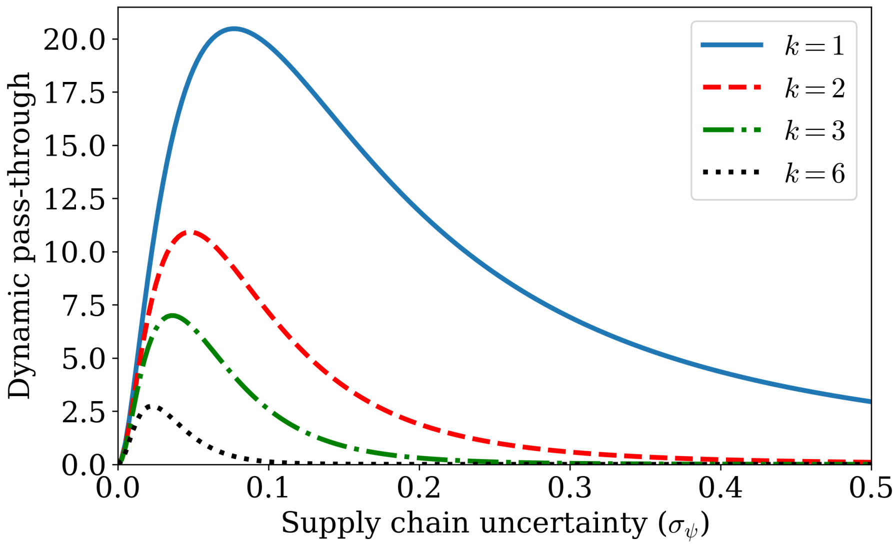


Figure 12: Effect of varying supply chain uncertainty on the dynamic energy price pass-through at different horizons k

Notes. The panel depicts the dynamic pass-through of energy ($\times 100$), as computed in Proposition 2, on supply chain uncertainty σ_ψ^2. The plot includes four different horizons $k = 1, 2, 3,$ and 6. Parameter values are $\alpha_E = 0.09$, $\alpha_M = 0.91$, $\eta = 0.01$, $\delta = 0.5$, $\rho_\psi = 0.9$, $\sigma_Z = 0.1$, $\nu = 1.25$.

3.9 Staggered price setting

So far we have worked under the assumption that the prices of intermediate good varieties are flexible. We now assume that prices are infrequently adjusted according to a standard Calvo-type mechanism. Each intermediate producer can revise its price at random intervals with common probability $(1-\theta)$. The log optimal forward-looking pricing condition reads:[38]

$$p_t = (1-\theta\beta)\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(\mu + mc^n_{(t+k)})\right\} \tag{26}$$

where $\beta \in (0,1)$ is the household discount factor reflecting the household's preference for present versus future consumption, μ is the log desired markup, and $mc^n_{(t+k)}$ is the expected nominal 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 price as a function of the stream of current and expected future nominal marginal costs. Importantly, the operator $\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\cdot\}$ denotes expectations formed under uncertainty.[39]

3.9.1 New Keynesian Phillips Curve (NKPC) under uncertainty

Following steps outlined in Appendix B.6, we can manipulate equation (26) above to obtain the *incomplete-information* version of the NKPC:

$$\pi_t = \beta \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\}}_{\text{future expected inflation}} + \frac{(1-\theta)(1-\theta\beta)}{\theta} \cdot \underbrace{mc_t(\psi^*_t)}_{\text{estimated current marginal cost}} \tag{27}$$

Note the key departure from the complete-information NKPC: both the current real marginal cost in deviation from its steady state (mc_t) and future inflation ($\pi_{(t+1)}$) feature an *unobserved* delay cost, that is estimated via the state-space model in (19). Both components – the estimated current marginal cost and the estimated future inflation – 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 (27).

Amplification via estimated current real marginal cost As established in Proposition 1, an increase in the current energy-price level 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 higher anticipated unobserved delay 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 estimated future inflation As shown in Proposition 2, under supply chain uncertainty, an energy price shock is (at least partially) interpreted

[38]With a slight abuse of notation, let p_t represent the optimal *reset price* – i.e., the price that minimizes the present discounted value of the stream of current and future quadratic deviations of the reset price from the static optimal price (i.e., markup over current marginal cost).

[39]Notice that, in principle, the Calvo pricing model introduces another layer of uncertainty due to the randomness in the timing of adjustment. For model consistency, we need to assume that the share θ of resetting firms and the unobserved delivery delay ψ^*_t are independent processes. See Appendix B.5 for more details.

by firms as a signal of a *persistent* upstream disturbance, expected to raise unobserved delay costs 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 into 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.

Endogenous cost-push component The overall effect of energy prices as a signal of present and future unobserved delay costs can be isolated by rewriting equation (27) as a familiar complete-information NKPC augmented by an *uncertainty-related* endogenous *cost–push* component. Supply (energy) shocks are therefore made more inflationary by uncertainty, in line with Monnery and Minton (2025). The next proposition illustrates this result.

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

$$\pi_t = \underbrace{\beta\, \mathbb{E}\left\{\pi_{(t+1)}\right\} + \frac{(1-\theta)(1-\theta\beta)}{\theta} \cdot mc_{complete\ info,t}}_{\text{Standard complete-information NKPC}} + \underbrace{G \cdot u_t}_{\substack{\text{Uncertainty} \\ \text{cost-push shock}}} \tag{28}$$

where $\mathbb{E}\{\cdot\}$ *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 cost-push component due to the unobserved delay cost 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.2. □

Supply chain uncertainty adds a novel cost-push component to the standard complete-information NKPC. This component is due to an increase in unobserved delay costs. Under uncertainty, the increase in energy prices has not only an inflationary effect via the firms' true marginal cost, but it also serves as a signal of unobserved delay costs – causing a fully fledged endogenous *cost-push* inflationary effect.

The u_t component is an $AR(1)$ process with driving force

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

that is activated by the convolution of supply shocks $(1-\delta)\varepsilon_{\psi,t}+\delta z_t$, and increasing in both the Kalman gain $\mathbb{K}(\mathcal{S})$ and the IRS index ν. On the contrary, the persistence of the cost-push component

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

is lower than that of the transportation shock ρ_ψ, by an amount that increases with the Kalman gain $\mathbb{K}(\mathcal{S})$, the IRS index ν, and the share of the specialized input in production $(1-\delta)$.

As in the earlier partial equilibrium analysis, consider the illustrative case of a purely transitory shock to raw energy prices. Under complete information, the Phillips Curve implies a mild and short-lived inflation response: firms experience a temporary increase in marginal costs, prompting modest price adjustments. In contrast, under incomplete information, supply chain uncertainty arises, and the endogenous u_t component is activated. Although the underlying shock is *i.i.d.*, firms interpret the rise in energy prices as a signal of a persistent upstream transportation disruption. This belief raises their expectations of future marginal costs, leading to stronger and more persistent inflation. As a result, the inflation response exhibits greater amplification and persistence – even in the face of a purely transitory energy price shock.

Notably, the larger the supply chain uncertainty σ_ψ^2, the higher the signal to noise ratio $\mathcal{S}$ and, in turn, the Kalman gain $\mathbb{K}(\mathcal{S})$. Ceteris paribus, this pushes the cost-push component u_t up, but reduces its persistence. In fact, larger supply chain uncertainty implies that firms learn more from energy price data when making an estimate of possible unobserved delay costs. Therefore, on impact, firms mistake a large part of the increase in energy prices as a persistent transportation shock generating delay costs, but over time, they learn rapidly that there are actually no persistent unobserved delay costs, and therefore quickly revert their price towards the complete-information benchmark. All in all, larger supply chain uncertainty produces a stronger yet more short-lived dynamic estimate of the unobserved delay cost, and therefore of the Phillips Curve response of inflation.

3.10 General equilibrium

We can now embed our model of inflation behavior under uncertainty into an otherwise standard general-equilibrium New Keynesian model.

Households A representative household chooses sequences of consumption, labor, and bonds $\{C_t, N_t, B_t\}_{t=0}^{\infty}$ to solve

$$\max_{\{C_t,N_t,B_t\}_{t=0}^{\infty}} \mathbb{E}_0\left\{\sum_{t=0}^{\infty}\beta^t\left(\frac{C_t^{1-\sigma}}{1-\sigma}-\frac{N_t^{1+\varphi}}{1+\varphi}\right)\right\} \tag{29}$$

subject to the budget constraint, which must hold for all $t\geq 0$:

$$P_tC_t+B_t\leq W_tN_t+R_tB_{(t-1)}+\int_0^1 D_t(i)\,di \tag{30}$$

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:

$$C_t^{-\sigma} = \beta(1+i_t)\mathbb{E}_t \left\{ C_{(t+1)}^{-\sigma} \frac{P_t}{P_{(t+1)}} \right\} \tag{31}$$

where i_t is the nominal net return on bonds. 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:

$$\frac{W_t}{P_t} = C_t^{\sigma} N_t^{\varphi} \tag{32}$$

The transversality condition:

$$\lim_{T\to\infty} \mathbb{E}_0 \left[\beta^T C_T^{-\sigma} \frac{B_T}{P_T} \right] = 0 \tag{33}$$

Intermediate product firms We introduce labor in production and assume that each intermediate firm 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 $\alpha_N + \alpha_E + \alpha_M = 1$:

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

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

$$1 + i_t = \beta^{-1} \left(\frac{\Pi_t}{\bar{\Pi}} \right)^{\phi_\pi}$$

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 (14)-(16), 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 (29)-(30); *(ii)* firms form expectations about the unobserved delay cost according to the optimal Bayesian estimator ψ_t^* in (20); *(iii)* prices satisfy the household's and firms' first-order conditions; *(iv)* all markets clear.

3.11 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.[40] 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 unobserved transportation shock, 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 transportation market, δ, ν, and η. We calibrate the share of raw energy and transportation involved in energy production using the respective values of $\delta = 0.5$ and $1 - \delta = 0.5$.[41] 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 specialized input transportation market.[42] The remaining parameters are calibrated as in the standard Galí (2015). In particular, the elasticity of substitution between labor and leisure $\sigma = 1$; impatience discount factor $\beta = 0.99$; Calvo parameter $\theta = 0.75$; inverse Frisch elasticity $\varphi = 1$; Taylor rule coefficient $\varphi_\pi = 1.5$; goods market markup $\mu = 1.2$. A summary of the key calibrated parameters is presented in Table 3. We consider three cases for the standard deviation of the transportation shock σ_ψ. First, we calibrate $\sigma_\psi = 0$ to reproduce the case of complete information. Second, we calibrate $\sigma_\psi = 0.1$ to reproduce the long period of low volatility in transportation shocks from 2002 to 2021. Third, we calibrate $\sigma_\psi = 0.5$ to reproduce the unprecedented – approximate fivefold – increase in the rolling standard deviation

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

[41]According to the U.S. Energy Information Administration (EIA), retail gasoline pump prices are split evenly between crude oil costs and distribution costs (about 50% each). See `https://www.eia.gov/petroleum/gasdiesel/`

[42]All the results are robust to values of $\delta, \nu, \eta \in (0, 1)$.

of transportation shocks that occurred in 2021–2023.

	Description	Value
α_N	Share of labor in output production	0.66
α_E	Share of energy in output production	0.03
α_M	Share of specialized input in output production	0.31
ρ_ψ	Persistence of transportation shock	0.90
σ_z	Standard deviation of energy price shock	0.10
δ	Share of raw energy in energy production	0.50
ν	Increasing returns to scale index	1.25
η	Elasticity of substitution between raw energy and transportation	0.01

Table 3: Key model parameters

3.11.1 Effect of an energy price shock under uncertainty

Figure 13 and 14 display the impulse responses of goods inflation, output, real unobserved delay costs, raw energy price, quantity of energy, specialized input, employment, and real wage to an *i.i.d.* 10% positive raw energy price shock under three alternative scenarios: *(i)* complete-information benchmark; *(ii)* low supply chain uncertainty, and *(iii)* high supply chain uncertainty.

When the 10% raw energy price shock hits, the energy price jumps on impact and reverts immediately. Under complete information, firms know that this increase is due to the raw energy price shock, and they correctly infer no transportation disturbance. Therefore, the unobserved delay cost is zero (see Figure 13), inflation rises modestly by about 0.25 p.p. on impact and is back to steady state after one quarter, and output falls mildly – by about 0.10% on impact – with full reversion within one quarter.

Under uncertainty, the same energy price realization is interpreted as a noisy signal of a latent supply chain disruption. Consequently, the unobserved delay cost spikes near 5% in the case of low uncertainty and to 10% on impact in the case of high uncertainty. By Proposition 3, the unobserved delay cost due to uncertainty feeds a cost-push term in the Phillips Curve that increases inflation on impact. The inflation surge scales monotonically with uncertainty: roughly 0.60 p.p. for low and 0.70 p.p. for high uncertainty. Accordingly, supply chain uncertainty also makes the effects on output contraction more severe, as output falls on impact by about 0.25%. The dynamics of output depends almost entirely on the demand of energy and of the specialized input, which respond negatively to the price increase (Figure 14). On the one hand, the energy price is always observed without noise, so energy use drops by roughly 6% *across uncertainty regimes*. On the other hand, the price of transportation of the specialized input is unobserved, so the information regime actually matters. Under complete information, the use of the specialized input decreases by 0.1% just due to its complementarity with energy; under uncertainty, instead, the unobserved delay cost increases the price of the specialized and depresses its demand, which falls severely by about 0.30% on impact.

Labor market margins are also dependent on the level of supply chain uncertainty. Under complete information, production slows down mildly and firms substitute toward labor as energy becomes relatively more expensive, so employment rises by about 0.20% on impact and the real wage spikes close to 0.90%. Under uncertainty, higher perceived marginal costs depress output, reducing labor demand and wages. Notably, this effect counteracts the substitution effect, yielding almost a muted response of aggregate employment and real wages.

Finally, we highlight how higher supply chain uncertainty *amplifies the initial impact* yet *reduces the persistence* of a transitory energy price shock on macroeconomic variables. When uncertainty rises, the Bayesian filter assigns greater weight to the contemporaneous energy price signal in the learning process, leading agents to update their beliefs about supply chain delays more aggressively. Consequently, comparing the low-uncertainty regime ($\sigma_\psi^2 = 0.1$) with the high-uncertainty regime ($\sigma_\psi^2 = 0.5$), beliefs about delays adjust more rapidly, the *unobserved delay cost* in Figure 13 collapses earlier, and all impulse responses converge faster back to steady state.

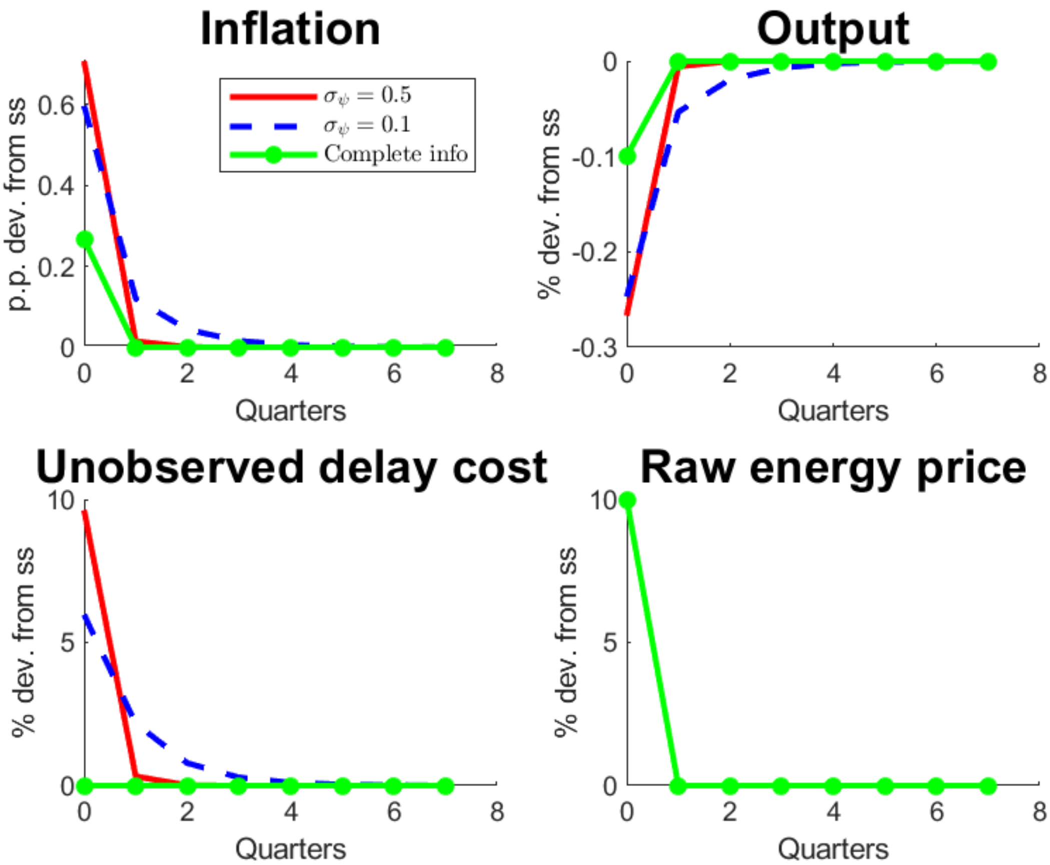


Figure 13: Impulse responses of inflation, output, unobserved delay cost, and raw energy to an *i.i.d.* raw energy price shock.

Notes. The panels depict the responses of inflation, output, real unobserved delay cost ψ_t^*, and real raw energy cost to an *i.i.d.* 10% positive shock in the raw energy price z_t with volatility $\sigma_z = 0.1$. The green line describes the case of *complete* information (i.e., $\sigma_\psi = 0$), the blue line describes the case of *low supply chain uncertainty* $\sigma_\psi = 0.1$, and the red line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.5$.

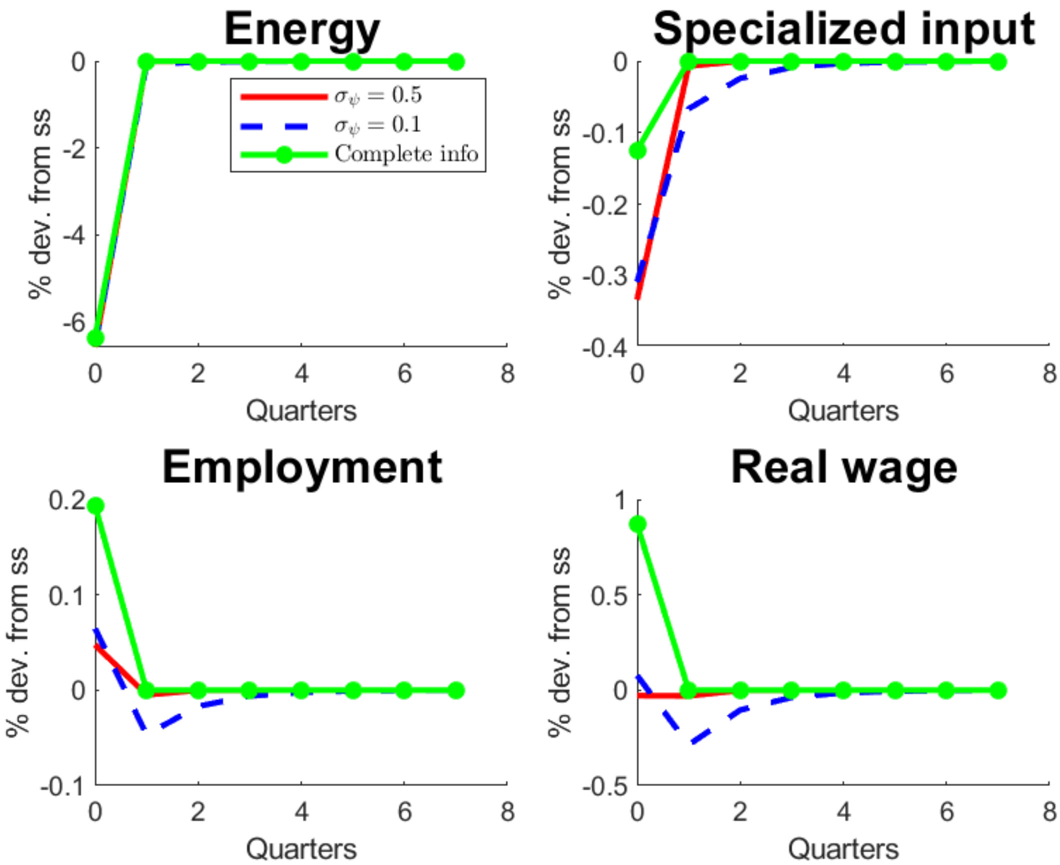


Figure 14: Impulse responses of energy, specialized input, employment, and real wage to an *i.i.d.* raw energy price shock.

Notes. The panels depict the responses of energy, specialized input, employment, and real wage to an *i.i.d.* 10% positive shock in the raw energy price z_t with volatility $\sigma_z = 0.1$. The green line describes the case of *complete* information (i.e., $\sigma_\psi = 0$), the blue line describes the case of *low supply chain uncertainty* $\sigma_\psi = 0.1$, and the red line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.5$.

4 Conclusions

This paper offers a novel explanation for the unusually strong and persistent response of inflation to energy price shocks during the 2021–2023 inflation episode. Motivated by the empirical observation that this response coincided with a sharp rise in the volatility of transportation conditions, we develop a theory of inflation amplification grounded in firms' *uncertainty* about their supply chains.

In our framework, firms rely on both energy and specialized inputs transported through shared logistical routes. When transportation disruptions make the transportation capacity constraint binding, delivery delays for the specialized input become unpredictable. Firms face a signal extraction problem: they use observed energy prices – affected by both raw energy fundamentals and transportation costs – as noisy signals to infer 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.

We embed this signal-based mechanism in a canonical New Keynesian model and show that supply chain uncertainty generates an additional cost-push component in the underlying 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. Our model predicts that higher uncertainty amplifies both the *impact* and the *persistence* of inflation following an energy shock, consistent with the stylized patterns observed in the recent inflation episode.

These findings may have important policy implications. In the presence of supply chain uncertainty, energy shocks can mimic persistent inflationary pressures. Central banks may therefore need to adopt *state-contingent* responses, calibrating the strength of their policy reaction to the prevailing degree of volatility in supply conditions – such as those captured by the rolling variance of the Global Supply Chain Pressure Index (GSCPI) and by the ETU index.

Our framework paves the way for a full new set of empirical investigations. The next natural step is to measure the amplification channel we propose in an estimated quantitative DSGE setup – assessing how much of the recent inflationary response stems from firms' learning under supply chain uncertainty. This would clarify the extent to which incomplete information and volatility-induced amplification shape the transmission of global shocks to domestic inflation.

A Proofs

A.1 Proof of Proposition 2

Consider the expression for the optimal intermediate product price (23) at horizon $k \geq 1$ and differentiate with respect to time-t energy price. That yields:

$$\frac{d\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+k)}\}}{dp_{E,t}} = \alpha_M \cdot \nu \cdot (1-\delta) \cdot \frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} \tag{34}$$

The Kalman filter updating equation in (20), forwarded k periods, reads:

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

The partial derivative follows the recursive formulation

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

Consider the expected $t{+}k$ period energy price conditional on the time-t information set:

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

The derivative with respect to the energy price is:

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

Then, the overall partial derivative reads:

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

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

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \mathbb{K}(\mathcal{S}) \cdot \Big[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\Big]^k = \mathbb{K}(\mathcal{S}) \cdot L^k \tag{35}$$

Substituting into (34) 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. Interestingly, this condition is the same that ensures the stationarity of the cost-push shock u_t (see the proof of Proposition 3 below). Moreover, the condition has a deeper interpretation in control theory, as it guarantees that there exists a *steady-state* Kalman gain $\mathbb{K}(\mathcal{S})$ and that the Kalman filter is asymptotically stable. See Appendix B.4 for more details.

A.2 Proof of Proposition 3

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 unobserved delay cost $mc(\psi_t^*)$:

$$mc(\psi_t^*) = \alpha_E p_{E,t} + \alpha_M \left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]$$

Write it in deviation from its complete-information counterpart,[43] 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

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

We get:

$$u_t = \rho_\psi u_{(t-1)} + \mathbb{K}(\mathcal{S}) \left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right) - \varepsilon_{\psi,t}$$

Rewrite the motion law of u_t as

$$u_t = \rho_\psi u_{(t-1)} + \mathbb{K}(\mathcal{S}) \cdot FE(p_{E,t}) - \varepsilon_{\psi,t}.$$

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 $t-1$:[44]

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

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

[44] 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^*. This assumption is discussed in section B.1.

The forecast error is precisely the *surprise* that the firm experiences when it observes $p_{E,t}$ and compares it against the forecast $\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}$.
Decompose further the forecast error:

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

Now we can rewrite u_t as

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

where $L \equiv \rho_\psi\left[1 - \mathbb{K}(\mathcal{S})\cdot\nu\cdot(1-\delta)\right]$. As anticipated in the proof of Proposition 2 (see Appendix A.1), we impose the natural stability condition $L < 1$ to guarantee the stationarity of the cost-push shock.

Now, we aim to rewrite the *incomplete-information NKPC* to isolate the cost-push effect of estimated delays. 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 unobserved elements:

$$(i) \qquad mc_t(\psi^*_t)$$

$$(ii) \quad \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\}$$

For (i), use the rewriting

$$mc_t(\psi^*_t) = mc_{\text{complete info},t} + \alpha_M\cdot\nu\cdot(1-\delta)\cdot u_t \tag{36}$$

where $u_t \equiv \psi^*_t - \psi_t$.

For *(ii)*, lag one period ahead the *incomplete-information NKPC*:

$$\pi_{(t+1)} = \beta\mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{\pi_{t+2}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{mc_{(t+1)}\} \tag{37}$$

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

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{t+2}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{(t+1)}\} \tag{38}$$

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

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+1+j}\} \tag{39}$$

Plug (36) into equation (39) above:

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j\left(\mathbb{E}\{mc_{\text{complete info},t+1+j}\} + \alpha_M\cdot\nu\cdot(1-\delta)\cdot\mathbb{E}\{u_{t+1+j}\}\right) \tag{40}$$

Use equations (36)-(40) to rewrite the *incomplete-information NKPC*:

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

Recursively,

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

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 $L \equiv \rho_\psi\left[1-\mathbb{K}(\mathcal{S})\,\nu\,(1-\delta)\right] < 1$.

B Appendix

B.1 Information problem

Section 3.7 lays out the simple information problem faced by the firm at time t: it observes the aggregate state *except* the transportation shock ψ_t^*, and backs it out from the energy price $p_{E,t}$ *alone*. This is a very tractable simplification. However, we can allow for additional signals – most naturally the transportation price $\tilde{p}_{T,t}^m$. Noticeably, when the capacity constraint binds (Section 3.4.3), however, $\tilde{p}_{T,t}^m$ carries no information about ψ_t^*. By contrast, other variables may be informative, and firms could consider them as concurrent signals to the energy price. In this case, the optimal Bayesian filter pools them, weighting each contribution by its informativeness (i.e., the signal-to-noise ratio). Our results go through this extension as long as $p_{E,t}$ receives strictly positive weight in that filter. Put differently, the univariate specification presented in this paper is a useful simplification; admitting multiple signals merely rescales the Kalman gains without altering the qualitative dynamics.

According to the information problem described in 3.7, the timing implies the following 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:

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

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:

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

Crucially, unobserved y_t at the time of updating affects the cost-push term u_t by adding a (positive) 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 estimating the transportation shock ψ^*_t.

B.2 Details on the state-space model

The system of equations (19) is just a particular Gaussian linear case of a more general state-space model. In this section, we describe this more general version and lay out its technical details. There are three technical assumptions behind the Bayesian model in section 3.7.

Assumption B.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 B.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,

$$\begin{aligned} \psi_t &\sim \mathcal{P}_\psi(d\,\psi_t \mid \psi_{(t-1)}), \\ p_{E,t} &\sim \mathcal{P}_{p_E}(d\,p_{E,t} \mid \psi_t). \end{aligned} \tag{41}$$

Figure 15 illustrates the information flow in this model with an acyclic directed graph of the state-space model.

$$\begin{tikzcd} \psi_0 \arrow[r] & \psi_1 \arrow[r] \arrow[d] & \psi_2 \arrow[r] \arrow[d] & \cdots \arrow[r] & \psi_{t-1} \arrow[r] \arrow[d] & \psi_t \arrow[r] \arrow[d] & \psi_{t+1} \arrow[r] \arrow[d] & \cdots \\ & p_{E,1} & p_{E,2} & & p_{E,t-1} & p_{E,t} & p_{E,t+1} & \end{tikzcd}$$

Figure 15: Acyclic directed graph of the state-space model

B.3 Bayesian learning

We follow a standard Bayesian-filtering approach – see, e.g., Colarieti and Monacelli (2022)). We assume that the firm knows the structure of the state-space model in (41), that it holds a prior $\mathcal{P}_{\psi,0}(\cdot)$ over ψ_0, and that it *learns* in a Bayesian way using the history of energy prices $\{p_{E,t}\}_{t\geq 0}$. The learning procedure involves two key conditional distributions, which are iteratively updated: the filtering distribution and the state-predictive distribution.

At time t, the filtering distribution, denoted as $\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)})$, is the probability distribution of the current transportation shock at time t, given the history of energy prices at time t:[45]

[45] This expression is derived from Bayes' Theorem and from the assumption of conditional inde-

$$\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}) \propto \mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t) \cdot \mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,0:(t-1)}). \tag{42}$$

Here, $\mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t)$ refers to the probability of observing the current energy price given the transportation shock, and $\mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,0:(t-1)})$ is the prior filtering distribution from the previous time step.

The state-predictive distribution, denoted as $\mathcal{P}_{\psi,t}(d\psi_{(t+1)} \mid p_{E,(0:t)})$, represents the probability distribution of the transportation shock at time $t+1$, conditional on the energy price history at time t:

$$\mathcal{P}_{\psi,t}(d\,\psi_{(t+1)} \mid p_{E,(0:t)}) = \int_{\mathbb{R}} \mathcal{P}_{\psi}(d\,\psi_{(t+1)} \mid \psi_t) \cdot \mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}). \tag{43}$$

The learning procedure is inherently recursive. The state-predictive distribution at time t becomes the prior distribution for calculating the filtering distribution at time $t+1$, and this process continues over time.

B.4 Kalman gain at steady state

Consider the state-space model in (19) and the Bayesian estimate of the unobserved transportation shock in (20). In this equation, the Kalman gain $\mathbb{K}(\mathcal{S})$ is assumed to be constant over time. This special assumption requires some context.

The Kalman gain is the measure of the informativeness of the new observation $p_{E,t}$ about the unobserved state ψ_t. As usual, the Kalman gain is higher when firms have lower knowledge about the unobserved state, and they need to rely more on new observations. In the model we consider, the learning process about the unobserved state equation occurs in a *dynamic environment*, that is, one in which the Kalman gain changes over time. That is because, at every time t, firms may change their knowledge about the unobserved state, and therefore change the Kalman gain $\mathbb{K}_t$. Note that, at every updating, two conflicting processes are going on: on the one hand, the observation $p_{E,t}$ brings new information about $\psi_{(t-1)}$, on the other hand the state of the system has changed to ψ_t, with the additional uncertainty carried by $\varepsilon_{\psi,t}$. This additional uncertainty is represented by the innovation variance σ^2_{ψ}. While in the early periods of the estimation process prior system knowledge is low, and therefore observations $p_{E,t}$ are very informative, as time proceeds, firms typically build confidence in their prior guesses about the system, and each new observation $p_{E,t}$ brings in a lower amount of information about $\psi_{(t-1)}$. The changing informativeness of observations over time is reflected in the dynamics of the Kalman gain $\mathbb{K}_t$, which is very high in the early periods of the system and decreases gradually over time. At some point, this additional information about $\psi_{(t-1)}$ will be exactly

pendence of energy prices, i.e., $\mathcal{P}_{\psi,t}(dp_{E,t} \mid \psi_t, p_{E,(0:t-1)}) = \mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t)$:

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

balanced by the loss of information represented by the additional variance σ_ψ^2 brought in by the new state of the system ψ_t. When this *steady state* point arrives, the Kalman gain forever stabilizes to a constant value $\mathbb{K}_t \equiv \mathbb{K}(\mathcal{S})$. In this paper, we assume that our Gaussian linear system has reached the *steady state*, and that the Kalman gain is at its constant value $\mathbb{K}(\mathcal{S})$:[46]

$$\mathbb{K}(\mathcal{S}) = \frac{C\,\nu\,(1-\delta)}{\nu^2\,\delta^2\,\sigma_Z^2\; + C\,\nu^2\,(1-\delta)^2}$$

The expression for $\mathbb{K}(\mathcal{S})$ depends positively on C, that is, the solution of the algebraic Riccati equation:

$$C = \rho_\psi^2\,C - \frac{\rho_\psi^2\,\nu^2(1-\delta)^2\,C^2}{\nu^2\delta^2\,\sigma_Z^2\;+\;\nu^2(1-\delta)^2\,C} + \mathcal{S}\cdot\sigma_Z^2.$$

where, in turn, C depends positively on the signal-to-noise ratio $\mathcal{S} \equiv \sigma_\psi^2/\sigma_Z^2$. The existence of a positive value C that satisfies the Riccati equation is a necessary condition for the existence of the system's steady state and, therefore, of a steady-state Kalman gain. A standard result in control theory states that a sufficient parametric condition for the Kalman filter to be asymptotically stable is that $L \equiv \rho_\psi(1-\mathbb{K}(\mathcal{S})\cdot\nu\cdot(1-\delta)) < 1$ (see Petris et al. (2009) for a reference). Notably, this is exactly the condition we imposed to guarantee the stationarity of the u_t process in the proofs of Propositions 2 and 3 above.

B.5 Calvo price stickiness under supply chain uncertainty

Let the *optimal* intermediate product (log) price under *complete information* be:

$$\tilde{p}_{\text{complete info},t}(\theta,\psi_t) = \mu + mc_{\text{complete info},t}(\theta,\psi_t)$$

Note that all intermediate firms set the same price $\tilde{p}_{\text{complete info},t}(\theta,\psi_t)$.

Under incomplete information (uncertainty) and Calvo pricing, the first-order condition for profit-maximization pins down the optimal reset price $p_t(\theta,\psi_t^*)$:

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

Rewrite it as

$$p_t(\theta,\psi_t^*) = \mathbb{E}_{\mathcal{P}_\theta}\left\{\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\tilde{p}_t(\theta,\psi_t)\right\}\right\} = \int\int \tilde{p}_t(\theta,\psi_t)\; d\mathcal{P}_{\psi,t}(\psi_t)\; d\mathcal{P}_\theta(\theta)$$

where $\mathcal{P}_\theta$ is the probability density function associated with the share of firms resetting their price at each time t, independently of history. For model consistency, and reasonably, we assume that the two probability densities $\mathcal{P}_{\psi,t}, \mathcal{P}_\theta$ are independent –

[46]For a proof, see Petris et al. (2009).

formally, for all t, $\mathcal{P}_\theta \perp\!\!\!\perp \mathcal{P}_{\psi,t}$. Then, the integral is exchangeable, and the order of integration does not matter.

$$p_t(\theta, \psi_t^*) = \mathbb{E}_{\mathcal{P}_\theta}\left\{\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\tilde{p}_t(\theta, \psi_t)\right\}\right\} = \int\int p_t(\theta, \psi_t)\ d\mathcal{P}_{\psi,t}(\psi_t)\ d\mathcal{P}_\theta(\theta) =$$
$$= \int\int p_t(\theta, \psi_t)\ d\mathcal{P}_\theta(\theta)\ d\mathcal{P}_{\psi,t}(\psi_t) = \mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\mathbb{E}_{\mathcal{P}_\theta}\left\{p_t(\theta, \psi_t)\right\}\right\}$$

In practical terms, this means that in a setup with two unknown components – the time to wait until the next price update (θ), and the unobserved delay cost (ψ_t^*) – firms can choose the order they prefer to aggregate information about θ and ψ_t^*. We do not need to impose any restriction on the order in which firms will process information about the two sources of uncertainty.

B.6 Derivation: the 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, that is the first-order condition for profit maximization in (26). Rewrite it in terms of the future expected real marginal cost $mc_{(t+k)}$:

$$p_t = (1-\theta\beta)\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(p_{(t+k)} + mc_{(t+k)})\right\} \tag{44}$$

We denote with $p_{t,\text{agg}}$ 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 (44). We therefore obtain:

$$p_{t,\text{agg}} = \theta p_{t-1,\text{agg}} + (1-\theta)p_t. \tag{45}$$

Rewrite equation (44) recursively as

$$p_t = (1-\theta\beta)mc_t^n + \theta\beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+1)}\}, \tag{46}$$

where mc_t^n is the nominal marginal cost in deviation from its steady state, and 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 solving the state-space model in (19). Rewrite equation (45) as

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

Combine it with equation (46) to finally obtain the *incomplete-information NKPC*:

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

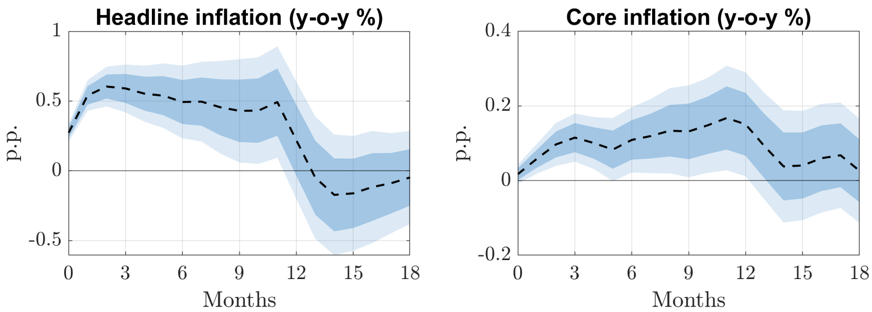
where mc_t is the real marginal cost under incomplete information in deviation from its steady state.

B.7 Local Projections

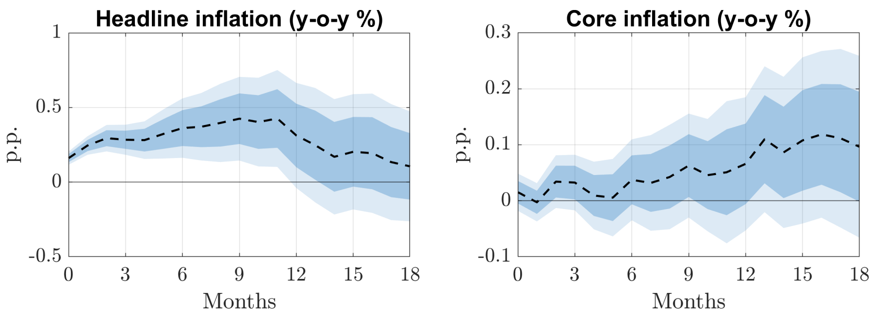
LP with no state-dependence As a consistency check, we estimate a linear local projection with no state-dependence. For each horizon $h = 0, \ldots, 18$, we estimate the following set of regressions:

$$\pi_{t+h} = \alpha_h + \beta_h \varepsilon_t^{\text{oil}} + \sum_{j=1}^{12} \gamma_{j,h} \pi_{t-j} + \nu_{t+h}$$

where all variables are defined as in the main text. The impulse responses of headline and core inflation to an oil news shock are plotted in Figure 16 with 90% and 68% Newey-West confidence bands.



(a) U.S.

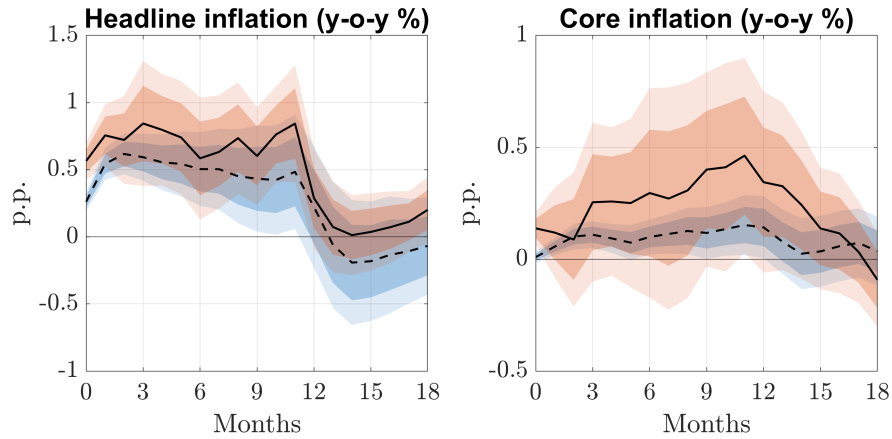


(b) Euro area

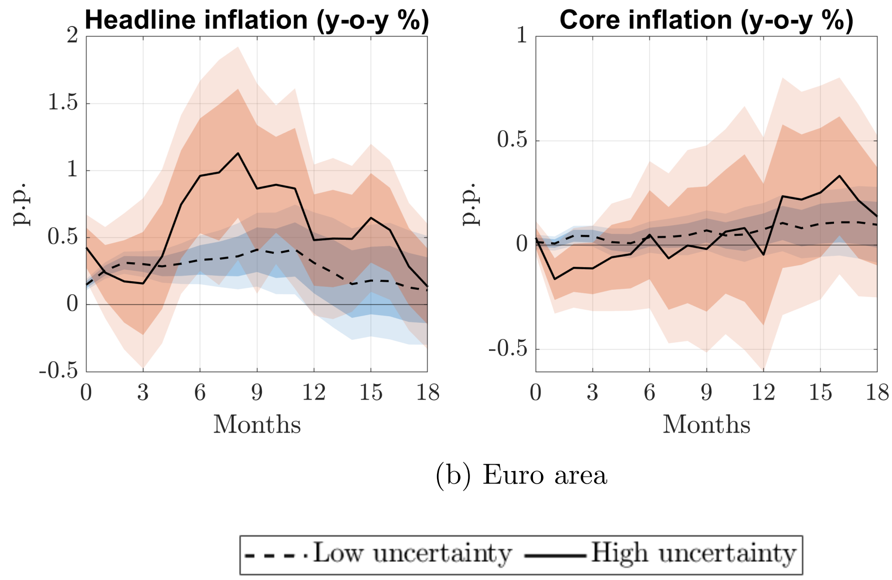
Figure 16: Impulse response of headline and core consumer inflation to an oil news shock generating a 10 percentage point increase in oil price inflation in the U.S. and the Euro area.

Notes: See the Note of Figure 16 for more details on the specification and on the data series used.

State-dependent LP: Top 10% vs Bottom 90% We consider the two measure of uncertainty described in the main text, namely the rolling variance of the GSCPI and the ETU index. For both measures, we adopt a different identification of the *high supply chain uncertainty regime*, restricting its size to the top 10% of the distribution of the measure of uncertainty. We show that the results of the state-dependent local projection in 2 are broadly preserved with the new regime identification.



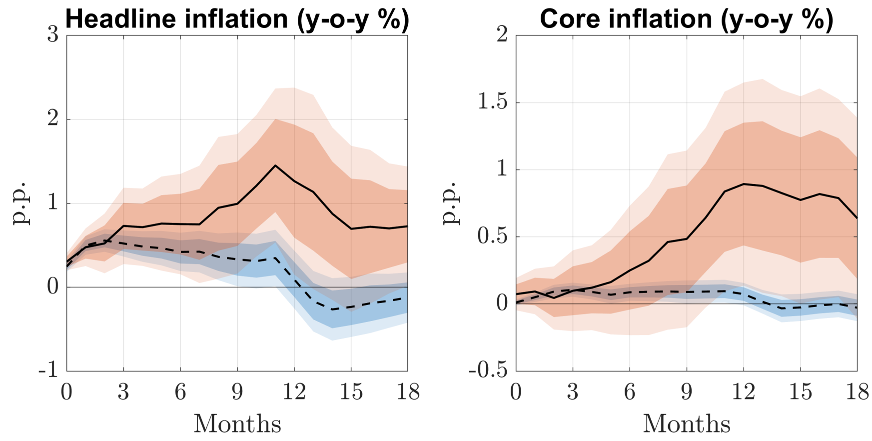
(a) U.S.



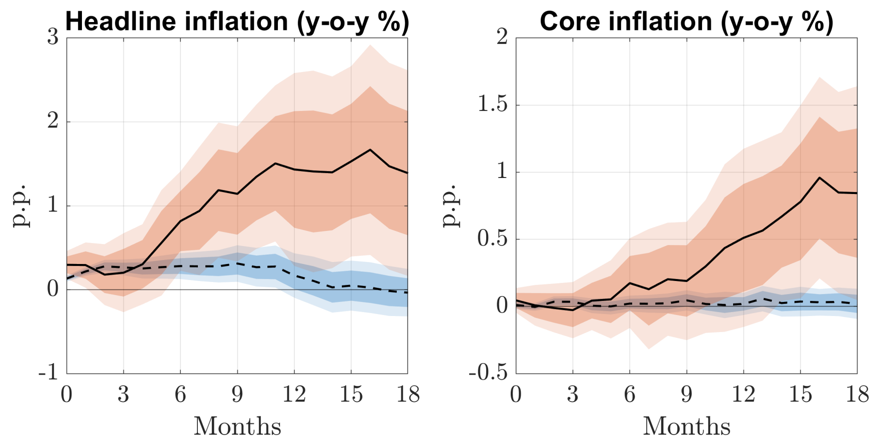
(b) Euro area

Figure 17: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across uncertainty states. High supply chain uncertainty corresponds to periods when the 48-month rolling variance of the GSCPI is in its top 10%.

Notes: See the Note of Figure 6 for more details on the specification and data series used.



(a) U.S.



(b) Euro area

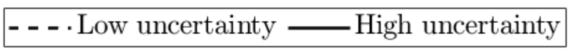


Figure 18: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across uncertainty states. High supply chain uncertainty corresponds to periods when the ETU index is in its top 10%.

Notes: See the Note of Figure 7 for more details on the specification and data series used.

State-dependent LP with a control for the level of the GSCPI supply chain shock In the main local projection exercise in section 2.1, we estimate a parsimonious model with minimal controls to emphasize the impact of exogenous oil news shocks on inflation. Here, we run a more complex specification, including as controls also the level of the transportation disruption, the GSCPI (T_t), and its lags. For each horizon $h = 0, \ldots, 18$, we therefore estimate the following local projection:

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

where U_t flags the high supply chain uncertainty regime, identified in Figure 19 and 20 using the rolling variance of the GSCPI and the ETU index, respectively.

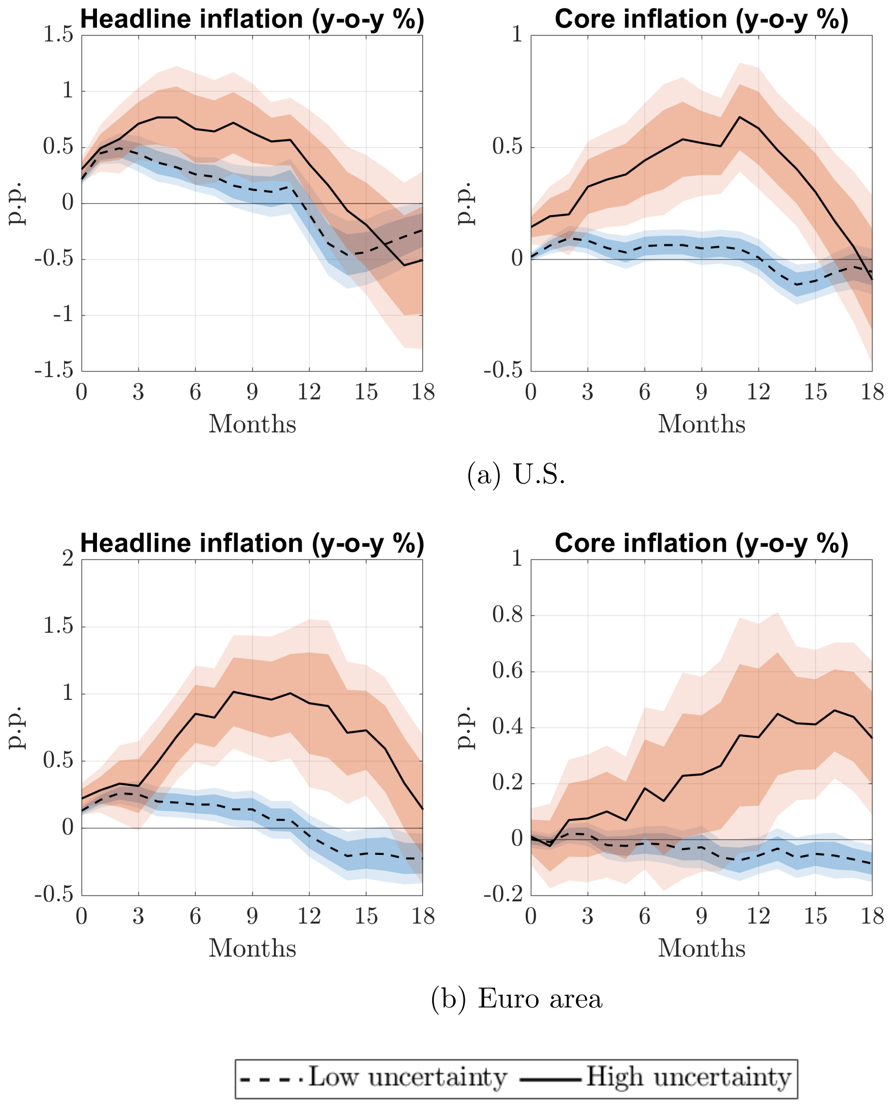
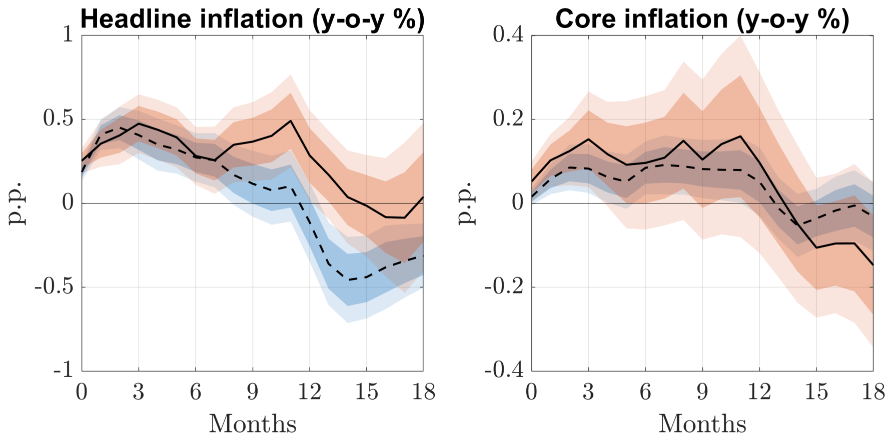
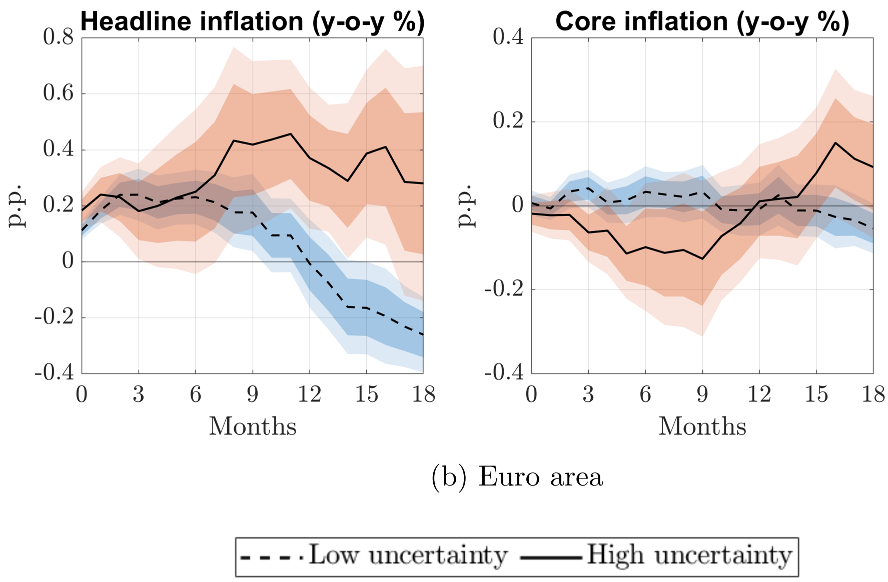


Figure 19: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across uncertainty states. High supply chain uncertainty corresponds to periods when the 48-month rolling variance of the GSCPI is in its top 20%. Additional controls for past and present transportation disruptions.

Notes: See the Note of Figure 6 for more details on the specification and data series used.



(a) U.S.



(b) Euro area

Figure 20: Headline and core inflation responses to an oil news shock in the U.S. and the Euro area, across uncertainty states. High supply chain uncertainty corresponds to periods when the ETU index is in its top 20%. Additional controls for past and present transportation disruptions.

Notes: See the Note of Figure 7 for more details on the specification and data series used.

B.8 Different measures of supply chain uncertainty

The Average Congestion Rate (ACR) index compiled by Bai, Fernández-Villaverde, Li, and Zanetti (2024) We plot the evolution of the GSCPI and the ACR index over the sample spanning from January 2017 – when the ACR sample is first available – to December 2024. We observe that the two indexes, and their rolling variances, have a comparable behavior.

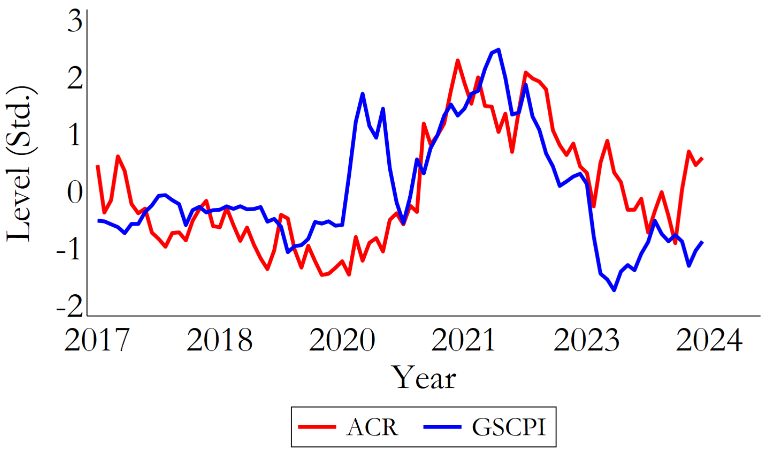


Figure 21: Level of GSCPI versus ACR index

Notes: Level of the GSCPI and of ACR, plotted with monthly frequency from January 2017 to June 2024. Each series is expressed in standard deviations from its respective 2017-2024 average. The ACR time series is available here: `https://globalportcongestion.github.io/blog/congestion.html`

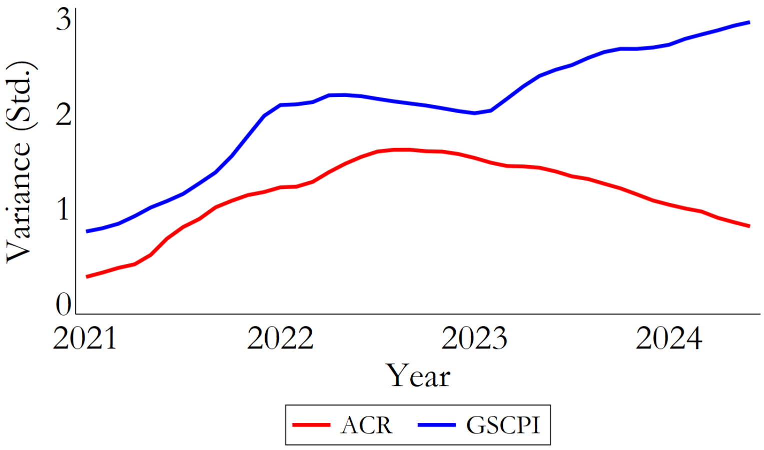


Figure 22: Rolling variance of GSCPI versus ACR index

Notes: Standardized variance of the GSCPI and of ACR computed over 48-month rolling windows, plotted with monthly frequency from January 2021 to June 2024. Each variance is standardized by its respective rolling variance computed over the whole 2021-2024 sample.

We use the ACR, alternative measure of transportation shocks, to test whether the amplified co-movement of energy prices and inflation under high supply chain uncertainty is a result dependent on the measure of supply chain uncertainty adopted. Therefore, in Table 4, we reproduce the same exercise and result by adopting the rolling variance of the ACR in place of the GSCPI.

	U.S. CPI inflation		
	(1)	(2)	(3)
U.S. Energy Inflation	0.109***	0.114***	-0.109**
	(0.017)	(0.016)	(0.044)
ACR		-0.356**	-0.272
		(0.166)	(0.190)
Var(ACR) $\times$ U.S. Energy Inflation			0.120***
			(0.023)
Adj. R^2	0.935	0.940	0.947
N	54	54	43

(a) U.S.

	E.A. HICP inflation		
	(1)	(2)	(3)
E.A. Energy Inflation	0.099***	0.098***	0.056***
	(0.005)	(0.005)	(0.015)
ACR		0.015	0.087
		(0.052)	(0.076)
Var(ACR) $\times$ E.A. Energy Inflation			0.026***
			(0.009)
Adj. R^2	0.994	0.994	0.995
N	54	54	43

(b) Euro area

Table 4: Conditional correlates of U.S. and Euro area inflation

Notes: standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The measure of supply chain uncertainty considered is the ACR index (Average Congestion Rate) compiled by Bai, Fernández-Villaverde, Li, and Zanetti (2024). The additional controls and all the data series used are identical to the ones specified in Table 1. All variables considered have a monthly frequency over a sample from January 2017 to June 2024, due to data availability.

Robustness We show a robustness check for Table 1. In Table 5, we reproduce the same exercise and result by adopting the ETU index in place of the rolling variance of the GSCPI.

	U.S. CPI inflation		
	(1)	(2)	(3)
U.S. Energy Inflation	0.094***	0.088***	0.090***
	(0.005)	(0.005)	(0.005)
GSCPI		0.341***	0.304***
		(0.049)	(0.054)
ETU × U.S. Energy Inflation			0.005*
			(0.003)
Adj. R^2	0.867	0.889	0.890
N	240	240	240

(a) U.S.

	E.A. HICP inflation		
	(1)	(2)	(3)
E.A. Energy Inflation	0.086***	0.080***	0.077***
	(0.004)	(0.004)	(0.004)
GSCPI		0.112***	0.086***
		(0.024)	(0.024)
ETU × E.A. Energy Inflation			0.006***
			(0.002)
Adj. R^2	0.970	0.972	0.974
N	240	240	240

(b) Euro area

Table 5: Conditional correlates of U.S. and Euro area inflation

Notes: standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The measure of supply chain uncertainty considered is the ETU index (Energy Transportation Uncertainty) compiled by Morão (2025). The additional controls and all the data series used are identical to the ones specified in Table 1. All variables considered have a monthly frequency over a sample from January 2002 to December 2024.

B.9 Kalman filter estimation

B.9.1 Procedure

We provide additional details on the Kalman-filter procedure outlined in 2.3.

Estimation with two uncertainty regimes Let supply chain uncertainty be $Var(GSCPI)$ – i.e., the 48-month rolling variance. Define the 80th-percentile threshold

$$\text{thr} \;=\; \text{quantile}(Var(GSCPI); 0.80),$$

and partition $\{1, \ldots, T\}$ into

$$\mathcal{T}_{\text{low}} = \{t : \; Var(GSCPI)_t \leq \text{thr}\}, \qquad \mathcal{T}_{\text{high}} = \{t : \; Var(GSCPI)_t > \text{thr}\}.$$

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

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

by maximizing the regime-specific prediction-error log-likelihood:

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

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 prediction error, and is $h_t(\theta_j) = y_{j,t} - \mu_t(\theta_j)$.[47]

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 (19). 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:

$$v_i = \exp(\eta_i), \quad \sigma^2_\psi = \exp(\omega), \quad \alpha_i = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\, SE(\kappa_i),$$
$$\rho_\psi = \rho_{\psi,\min} + (\rho_{\psi,\max} - \rho_{\psi,\min})\, SE(r_\psi)$$

where $(\eta_1, \eta_2, \omega, \kappa_1, \kappa_2, r_\psi)$ are the optimizer's free parameters, SE(.) is the standard error, and Table 6 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 6: 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 optimization reasons.[48]

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

[48] 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.

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 $\hat{R}_t = \hat{\rho}^2_\psi \hat{C}_{t-1} + \hat{\sigma}^2_{\psi,t}$

(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 $\hat{f}_t = \hat{F}_t \hat{a}_t$ and $\hat{Q}_t = \hat{F}_t \hat{R}_t \hat{F}'_t + \hat{V}_t$

(iii) the filtering distribution of $\hat{\psi}_t$: $\hat{\psi}_t|y_{1:t} \sim \mathcal{N}(\hat{m}_t, \hat{C}_t)$ with $\hat{m}_t = \hat{a}_t + \hat{R}_t \hat{F}_t \hat{Q}_t^{-1} \hat{e}_t$, $\hat{C}_t = \hat{R}_t - \hat{R}_t \hat{F}'_t \hat{Q}_t^{-1} \hat{F}_t \hat{R}_t$ 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 $\hat{\theta}_{t,j}$. Thus, the t-index reflects *sequential re-estimation*: conditional on a fixed $\hat{\theta}_j$ these matrices are constant, but as $\hat{\theta}_{t,j}$ updates over time, the implied system parameters inherit a time index.[49]

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

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

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 $V(\hat{\theta})$.

B.9.2 Additional results

Figure 8 in the main body shows graphically the contribution energy and transportation prices' loading coefficients under low and high supply chain uncertainty. In this appendix, we report all the estimated parameters under the two uncertainty regimes.

[49] We write $\hat{\sigma}^2_{\psi,t}$ as the estimated variance of the state process's residual. Similarly, $\hat{V}_t$ is the estimated variance-covariance matrix of the observation equations' residuals. $\hat{\rho}_\psi$ is the estimated persistence of the state process, while $\hat{F}_t$ is computed as the vector of $[\hat{\alpha}_{1,t}; \hat{\alpha}_{2,t}]'$.

Parameter	Low uncertainty	High uncertainty
Energy loading α_1	0.36	1.09
	(0.10)	(0.40)
BDI loading α_2	1.01	0.20
	(0.23)	(0.09)
Persistence ρ_ψ	0.96	0.95
	(0.02)	(0.03)
Obs. var. (energy) v_1	0.72	0.00
	(0.07)	(0.00)
Obs. var. (BDI) v_2	0.00	0.16
	(0.00)	(0.03)
State var. σ_ψ^2	0.08	0.10
	(0.04)	(0.07)

(a) U.S.

Parameter	Low uncertainty	High uncertainty
Energy loading α_1	0.20	1.51
	(0.06)	(0.58)
BDI loading α_2	1.01	0.07
	(0.23)	(0.06)
Persistence ρ_ψ	0.96	0.97
	(0.02)	(0.03)
Obs. var. (energy) v_1	0.39	0.00
	(0.04)	(0.00)
Obs. var. (BDI) v_2	0.00	0.20
	(0.00)	(0.04)
State var. σ_ψ^2	0.08	0.08
	(0.04)	(0.06)

(b) Euro area

Table 7: Kalman parameters by uncertainty regime: U.S. and Euro area.

Notes: The panels display the estimated coefficients and corresponding standard errors for the Kalman filter problem. Estimates are computed separately for the high-uncertainty regime (top 20% of the 48-month rolling variance of the GSCPI) and the low-uncertainty regime (bottom 80%). Parameters are obtained via MLE over the period January 2002–December 2024, assuming uncorrelated observation shocks (i.e., the variance–covariance matrix of the observation vector V is diagonal).

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