Supply Chain Uncertainty, Energy Prices, and Inflation*

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Abstract

Using U.S. and EA data, we document that (i) the pass-through of energy prices to inflation is state-dependent – stronger when supply chain uncertainty is elevated – and (ii) in such states, energy prices become more informative about broader supply chain conditions. We develop a theory in which firms use two inputs – energy and a specialized component – both shipped through a capacity-constrained network. Under congestion, energy can still be sourced in local liquid markets at a premium, while the specialized input faces stochastic transportation shocks. Because energy is a liquid, globally traded input whose price reflects congestion, firms treat it as a noisy signal of unobserved delays and update their beliefs via Bayesian learning. This belief channel raises perceived marginal costs and generates an uncertainty-driven component of marginal cost that amplifies and propagates energy shocks. Both the static and the dynamic pass-through from energy prices to output prices scale with supply chain uncertainty. Embedding this mechanism in a New Keynesian model, we show that higher supply chain uncertainty increases the sensitivity and persistence of inflation to transitory energy shocks, and relate these findings to the 2021–23 inflation episode. Our findings call for a reconsideration of the so-called "look-through" approach of monetary policy to supply shocks.

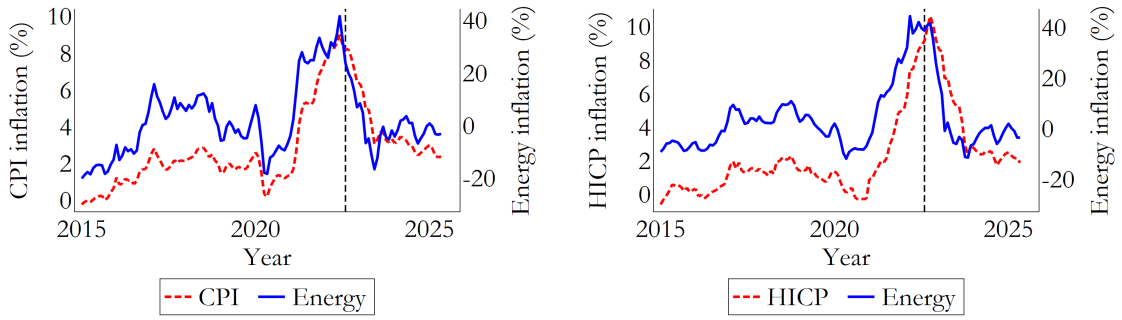
Keywords: supply chain uncertainty, transportation shocks, energy price shocks, incomplete information, pass-through, inflation.

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*Correspondence: alfonso.merendino@ecb.europa.eu (alfonso.merendino@studbocconi.it), and tommaso.monacelli@unibocconi.it. All errors are our own. Marcella Lucchini provided excellent research assistance. We thank for valuable comments the participants to the annual 2025 Federal Reserve Bank of Boston research conference, and to a seminar at the European Central Bank-DGE. We also thank Ludwig Straub and Giacomo Candian for very insightful discussions.

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.

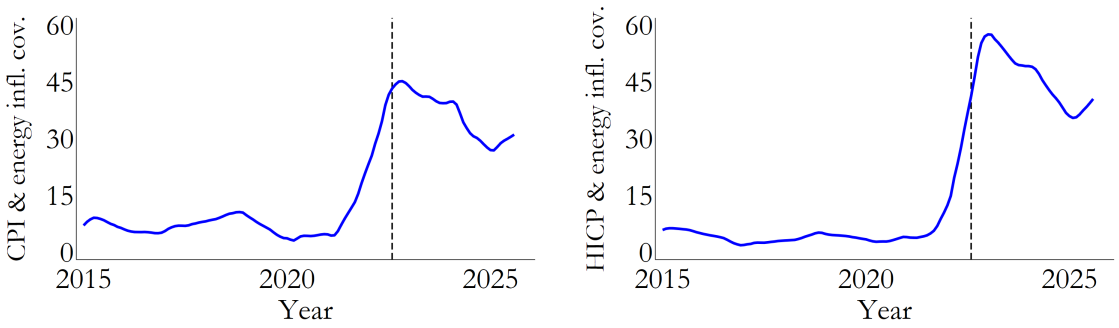
In this paper, we develop a theory of the amplification of supply shocks based on *uncertainty* in the producers' supply chains. While part of a rapidly growing literature attributes the recent amplified inflation response to demand-side mechanisms triggered by energy price shocks,[3] these explanations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

[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] For the role of supply chain disruptions in the recent inflation spike 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.

of supply chain uncertainty) between 2021 and 2023, 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. However, while the recent 2021-23 inflation episode is a natural laboratory for our theory, we view our approach as pointing to a more general, and possibly structural, *complementarity* between supply (energy) disturbances and supply chain uncertainty in driving inflation dynamics.

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., EV batteries) as production inputs, both shipped through the same logistical routes. In the background, the economy is hit by purely *transitory* energy price disturbances. Transportation shocks (e.g., disruptions at chokepoints) make the transportation capacity constraint binding, generating uncertain delivery delays. However, while energy remains physically available through local liquid markets - albeit at a premium - the shipping of EV batteries faces a stochastic delivery delay. Because energy is a liquid, globally traded input whose price reflects the true state of congestion, firms treat it as an informative signal about unobserved delivery delays affecting the specialized input. Yet energy prices are also noisy signals, as they are hit by primitive, and independent, raw energy shocks. Hence, 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 transportation shocks, 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 transportation 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.

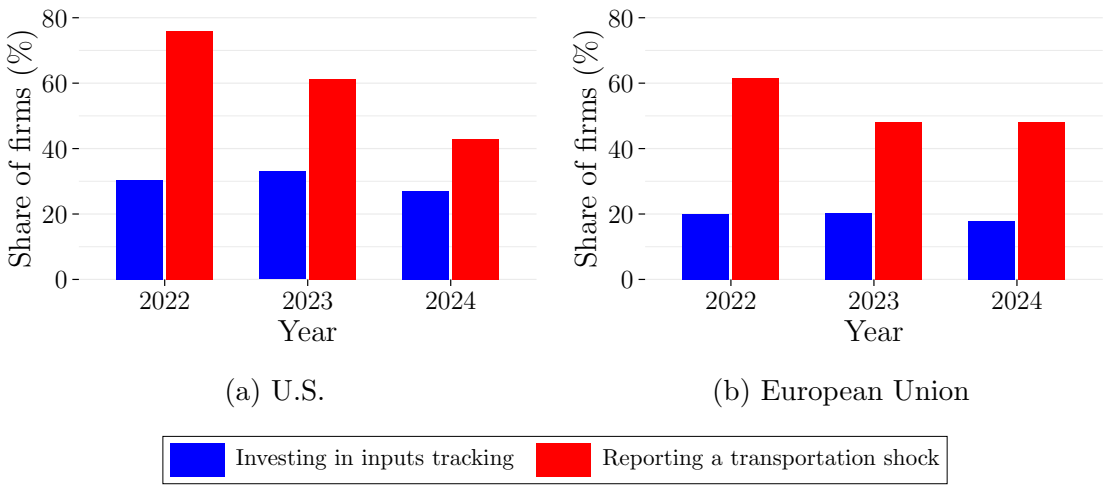


Figure 3: Share of firms investing in digital inventories and inputs tracking and reporting obstacles to logistics and transport

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 EIBIS (European Investment Bank Investment 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 an answer to the aforementioned question.

Increased volatility in supply-chain transportation shocks 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, Anderl and Caporale (2024).

[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.

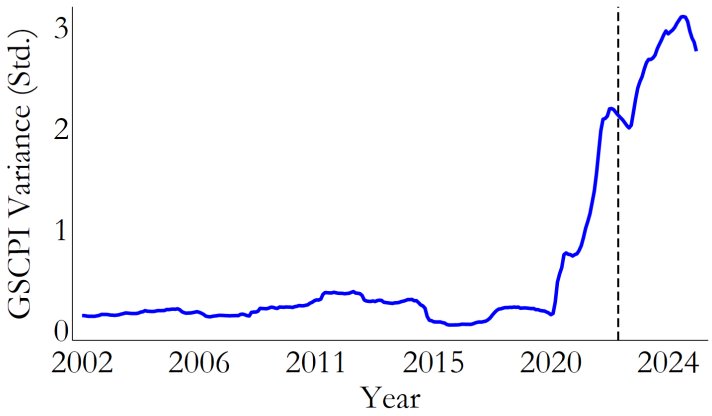


Figure 4: Evolution of the rolling variance of the GSCPI

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 value. 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 EA, 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 (both headline and core) inflation to energy price shocks is significantly larger in periods of high supply chain uncertainty. Importantly, we also find that this causal state-dependent effect of energy price shocks on inflation is not driven only by the recent post-Covid period, but holds more generally.

Commoditized vs specialized inputs In our framework, shared logistical chokepoints expose both *commoditized* inputs (e.g., oil and gas) and highly *specialized* components (e.g., EV batteries) to correlated delivery risks. In our model, firms rely on two inputs – energy and a specialized component (EV batteries) – both transported via shared logistical routes with *finite capacity*. Shocks to the common 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 EV batteries depend on tightly coordinated "just-in-time" supply chains, lack immediate substitutes, and cannot be easily stocked. When EV batteries transportation is delayed, the absence of a readily available substitute generates a non-monetary, physical time cost. Transportation shocks and the ensuing physical frictions introduce a stochastic 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 transportation shocks affecting delays of specialized inputs. Hence, firms face a *signal extraction* problem: they form Bayesian estimates of the transportation shocks hitting specialized inputs (i.e., EV batteries) 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.[11]
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.[12]

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 (the latter proxied by the Baltic Dry Index, a widely used indicator of transportation costs) as *signals* of underlying transportation shocks and delays. 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

[11] 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.

[12] 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 delivery delays for other critical inputs. See Financial Times, June 13, 2025, "Oil tanker owners reluctant to brave Strait of Hormuz, Frontline chief says."

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. Yet 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 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. Noticeably, the propagation effect is *non-linear* in the degree of supply chain uncertainty. At short horizons, where learning is still incomplete, higher uncertainty raises the pass-through of energy price shocks on expected future prices. At longer horizons, however, higher uncertainty accelerates firms' Bayesian learning, hence reducing the persistence of energy price shocks on output prices.

Incomplete-information NKPC Finally, we embed the above 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.[13] Relative to the full-information benchmark, the NKPC features an "uncertainty wedge" - an additional *uncertainty-related* marginal cost component arising from firms' Bayesian estimates of transportation shocks and delivery delays. The endogenous uncertainty wedge is activated by energy price shocks and inherits the persistence of the underlying transportation shock. We study how purely temporary raw energy shocks affect

[13]Noticeably, we define as NKPC the Phillips curve in its primitive form, i.e., with current inflation being a function - besides expectations - of the real marginal cost as a main driving force.

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 relates to several strands of the literature. First, it speaks to work on the macroeconomic implications of supply chain shocks. Bai, Fernández-Villaverde, Li, and Zanetti (2024) formalize the transportation market 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, Fernandez-Villaverde, Li, and Zanetti (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 high-frequency 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. Ball et al. (2022); Bernanke and Blanchard (2025); Liu and Nguyen (2023) highlight that the 2021–2023 inflation spike was mainly driven by exceptional supply chain disruptions.

We contribute to this strand of the literature in two ways. First, we emphasize the role of supply chain *uncertainty* as a driver of heightened pass-through of energy price shocks to inflation. Second, we derive an incomplete-information version of the New Keynesian Phillips Curve in which marginal costs are decomposed into a standard complete-information component and a novel, uncertainty-driven endogenous

component that is activated by energy price shocks and whose impact is amplified and propagated by supply chain uncertainty.

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 in uncertainty 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 three 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. Third, using *textual analysis* of firms' earnings-call transcripts, we show that the correlation between the share of "energy" words and the share of "supply chain" words in managers' communications is particularly high when supply chain uncertainty is elevated, indicating that firms rely more on energy signals precisely when supply chain uncertainty is more severe.

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,

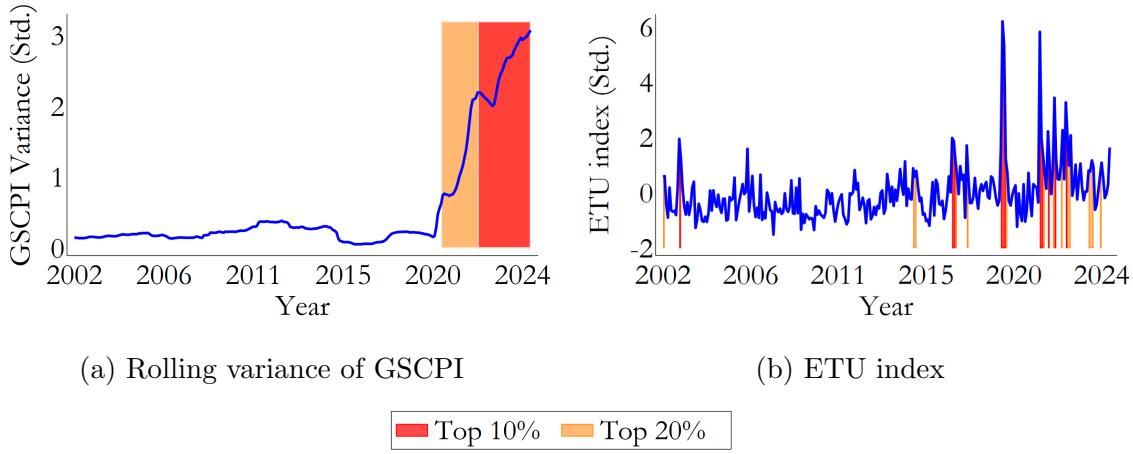
[14] Notably, in the model of Bui, Huo, Levchenko, and Pandalai-Nayar (2022) with an international input network, also noisy *public* information have an effect on macroeconomic fluctuations.

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).

Supply chain uncertainty: low vs high states We consider the most natural proxy for supply chain uncertainty, namely the sample variance of the GSCPI computed over rolling windows (of 48 months). 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.

Two measures of supply chain uncertainty 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.[15]

[15]The ETU index captures the proportion of articles discussing energy transportation uncertainty over a universe of English-language media sources worldwide. An article is classified as relevant when an energy-related keyword appears in the headline or lead paragraphs and when terms related to energy, transportation, and uncertainty occur within a five-word proximity. Further details on the construction of the index, keyword lists, and source selection are provided in Morão (2025).



(a) Rolling variance of GSCPI

(b) ETU index

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 (Global Supply Chain Pressure Index) is computed over 48-month rolling windows. The GSCPI time series is published monthly by the New York Federal Reserve and is available at `https://www.newyorkfed.org/research/policy/gscpi#/overview`. 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`. Both indexes are plotted with monthly frequency from January 2002 to December 2024. 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 of supply chain uncertainty 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 the approach in Ramey and Zubairy (2018) and estimate state-dependent local projections (Jordà, 2005) of inflation on oil supply news shocks over the sample from January 2002 to December 2024. Let U_t be an indicator variable that flags periods in which our preferred measure of uncertainty exceeds a given threshold. In 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.[16] Second, these surprises are used as an instrument in a standard oil market VAR, yielding the series of structural oil supply news shocks employed in the local projection. The resulting series, plotted in Figure 6, is approximately white noise and, crucially, does not show visible clustering of unusually large shocks in high-uncertainty regimes. This is important for two main reasons. First, it indicates that oil news shocks do *not* exhibit a systematic correlation with episodes of supply chain disruption and uncertainty.[17] Second, it shows that the high pass-through of energy shocks during the 2021–23 inflation episode *cannot* be attributed to a *non-linear* effect arising from the unusually large size of energy shocks.

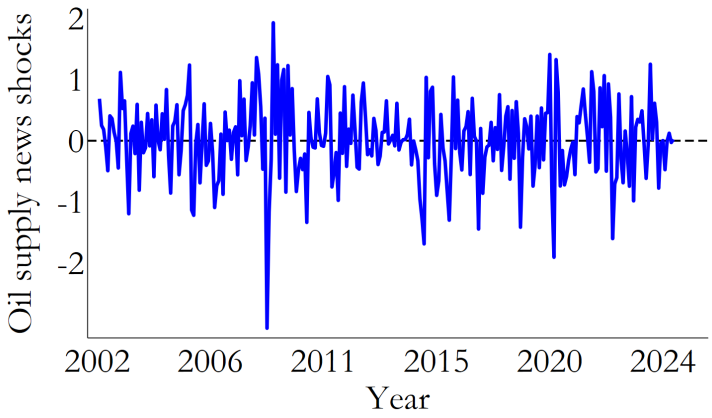


Figure 6: Evolution of oil supply news shocks

Notes: Oil supply news shocks identified by Känzig (2021) plotted with monthly frequency from January 2002 to December 2024. Source: `https://github.com/dkaenzig/oilsupplynews`

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

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

where π_{t+h} is the 12-month U.S. or Euro area headline consumer (or core) inflation[19] at horizon h, $\sum_{j=1}^{12} \gamma_{j,h}^{\pi} \pi_{t-j}$ is the set of its lags up to 12 months, and $COVID_t$ is a

[16] 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).

[17] As highlighted in Gonçalves, Herrera, Kilian, and Pesavento (2024), the impulse response estimates of a state-dependent local projection to a large shock are valid if the shock is exogenous and independent of the state of the economy. This condition holds in our setting, since the regimes of high and low supply chain uncertainty are independent of the exogenous (supply-side) energy shocks under consideration.

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

[19] 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

categorical variable which equals 1 from April 2020 to December 2023 and 0 otherwise. 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 both *headline* and *core* inflation to oil news shocks when the GSCPI is used as the supply uncertainty measure are plotted in Figure 7, with their 90% and 68% confidence bands based on 1'000 bootstrap replications.[20] Noticeably, there is a clear and statistically significant difference across the two regimes (high and low supply chain uncertainty). Under low uncertainty, the response of inflation is muted and sometimes even not statistically different from zero. Conversely, under high supply chain uncertainty, the responses of both measures of inflation, both in the US and the Euro area, are significantly larger.

Was it only COVID-19? As it is clear from Figure 5, many periods of elevated supply chain uncertainty overlap with the COVID-19 inflation spike. A natural question is whether supply chain uncertainty has an amplification effect *beyond* the COVID-19 inflation spike. With the inclusion of the categorical variable, $COVID_t$, we precisely aim to show that our results do *not* depend on the specific COVID-19 inflation episode, and instead hold more generally.

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. Hence, in an alternative set of local projections, we define:

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

Figure 8 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 7 and 8 show that the gap across regimes in the impulse response of inflation to oil shocks is clear and mostly statistically significant. While the pass-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.

2.2.1 Robustness

We perform a series of robustness exercises on the baseline specification.

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.

[20] To compute the confidence bands, we use a moving block bootstrap with block size set to 12.

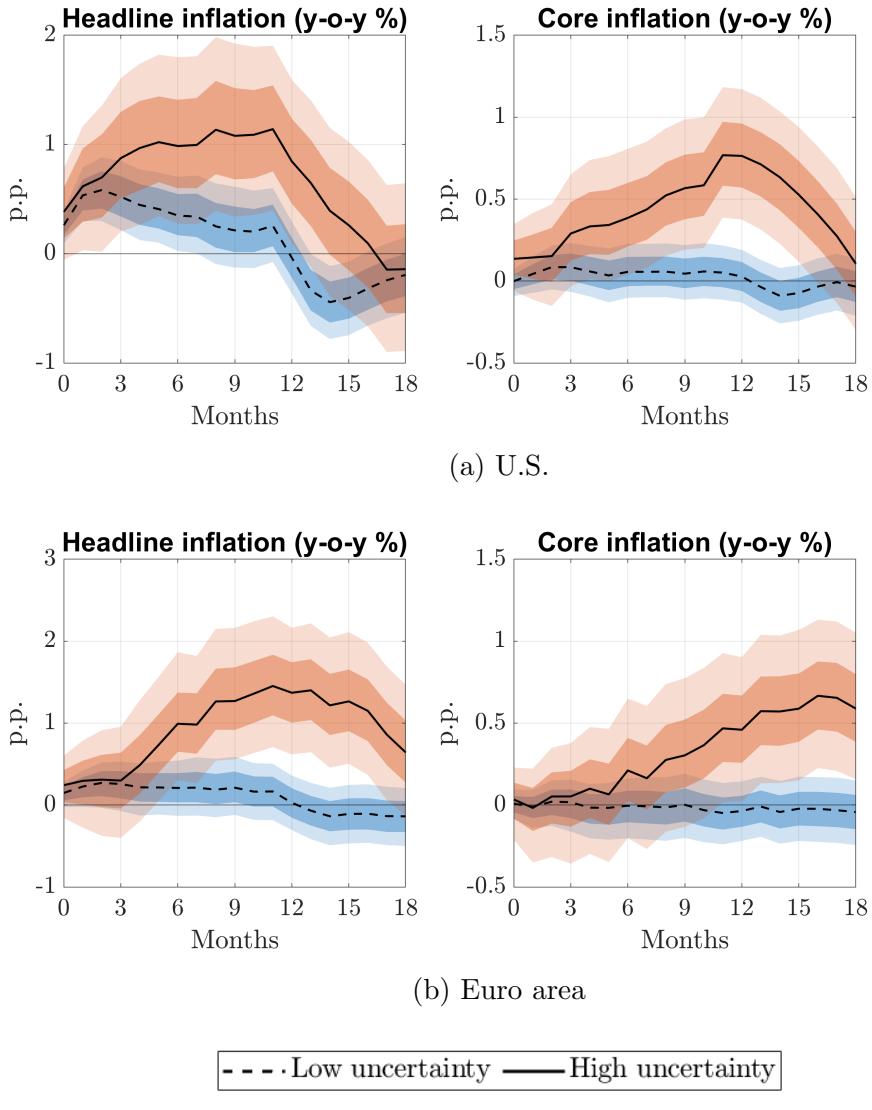
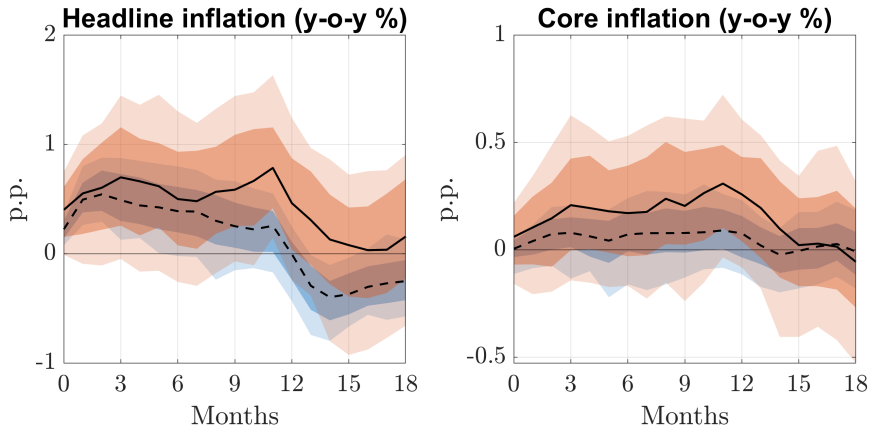
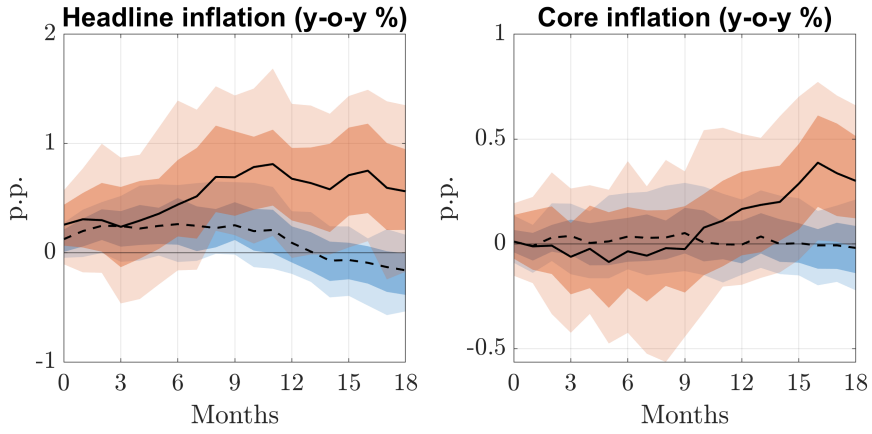


Figure 7: Headline and core inflation responses to an oil news shock across Var(GSCPI) uncertainty states – U.S. and Euro area

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% bootstrapped 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 series for the U.S. CPI headline (CPIAUCSL) and core (CRESTKCPIXSLTRM159SFRBATL) inflation are retrieved from FRED. The series for the Euro area HICP headline (CP0000EZ19M086NEST) and core (TOTNRGFOODEA20MI15XM) inflation are retrieved from Eurostat. 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`.



(a) U.S.



(b) Euro area

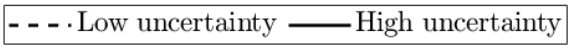


Figure 8: Headline and core inflation responses to an oil news shock across ETU index uncertainty states – U.S. and Euro area

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% bootstrapped 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 to Figure 7 for more details on the data series used.

Disentangling uncertainty from supply chain pressures Periods of heightened supply chain uncertainty tend to coincide with episodes of intense supply chain pressures. The strong co-movement between our first- and second-moment measures raises the concern that the estimated state dependence might simply be capturing additional inflationary effects of elevated supply chain pressures. To address this, Appendix B.8 reports a robustness exercise in which we re-estimate the local projections of inflation on a series of exogenous oil shock instruments using a richer specification that includes controls also for the contemporaneous level and a block of 12 lags of the GSCPI, as well as for the uncertainty indicator U_t. The state-dependent effects are essentially unchanged, indicating that they reflect genuine uncertainty effects rather than the level of supply chain pressures.

Alternative measures of transportation shocks We have already discussed the main properties of the GSCPI as a benchmark index for transportation shocks. Beyond the GSCPI, several alternative measures of transportation disturbances exist – most notably the Harper Peterson Time Charter Rates Index (HARPEX), the measure of climate-related supply chain shocks computed in Blaum et al. (2025), 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 2016) 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.9, we show that within its available time span, the ACR exhibits levels and rolling variances aligned with those of the GSCPI.

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 transportation shocks and 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 alternative signals for firms: energy inflation and transportation prices – which are proxied by the Baltic Dry Index (BDI).[21] 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 *true* transportation shock follows the AR(1) process:

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

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

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

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

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

with prior parameters calibrated to the GSCPI series unconditional moments.[22]
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.10.[23]

Figure 9 plots – across uncertainty states – the estimated loading coefficients $\alpha_1,\ \alpha_2$ 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) transportation shocks. Therefore, firms rely solely on the BDI price, whose loading weight is high and relatively higher than that on energy inflation. Information from energy inflation is barely useful, and the loading contribution is close to zero.

Conversely, under high supply chain uncertainty, the transportation market typically operates at its capacity limit, making transportation prices poor indicators of

[21] 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.

[22] In general linear Gaussian state-space models, the pair (ψ_t, α) is only identified up to a multiplicative constant. Initial priors on (m_0, C_0), the standardization of y_t, and the global constraint to the parameters detailed in B.10, provide an anchor to the state's scale and remove this scaling indeterminacy.

[23] See Appendix B.10 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.

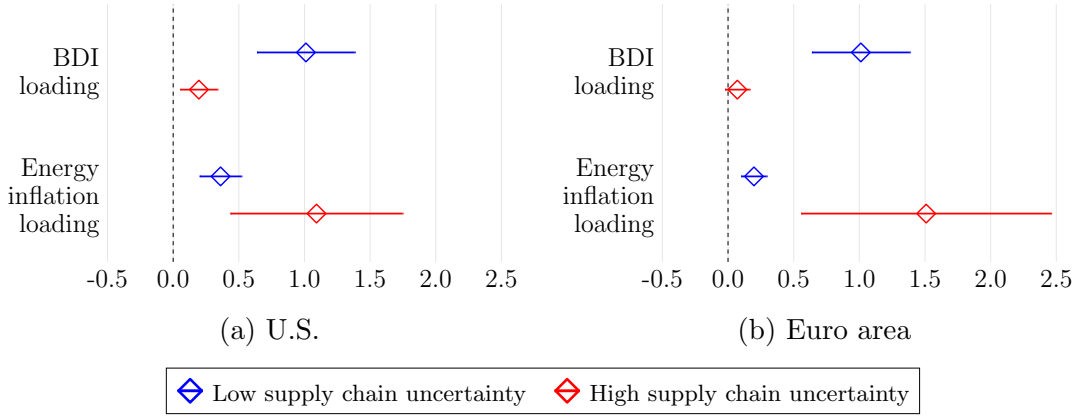


Figure 9: Loading coefficients for BDI and Energy Inflation – U.S. and Euro area

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.10 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.10 for details on the computation of standard errors, and for a complete report of all the parameters estimated from the Kalman-filter empirical model.

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 the one on transportation prices, reflecting its enhanced informational value.

The Kalman gain provides a direct measure of the *weight* that firms assign to a given signal when estimating the true state. In Table 1, 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 transportation shocks, 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.[24]

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 1: 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).

2.4 Evidence from firms' earnings calls

In this section, we use textual data to examine more directly whether energy prices become especially informative for firms in periods of elevated supply chain uncertainty. We use earnings call transcripts from NL Analytics spanning January 2002 to December 2024, and we construct indicators of the salience of supply chain disruptions and energy cost pressures in managers' communications. The sample covers publicly listed firms headquartered either in the United States or in the Euro area, allowing us to build separate indicators for the two regions.

Earnings calls are well suited for our purposes. Managers report on past performance and discuss future challenges under tight time constraints, while their statements are closely monitored by investors and supervisors. Scarce time and high stakes constrain superficial discussion and compel firms to rank topics and prioritize key issues. In this environment, the share of the call devoted to a specific theme provides an informative measure of its perceived importance.

Text-based analysis We carry out a text-based analysis of earnings calls following the approach in Hassan et al. (2025, 2019) and Caldara et al. (2019). We gather transcripts from a sample of earnings calls released quarterly by publicly listed firms headquartered in the U.S. or the EA, and count the share of sentences that contain at least one *keyword* from the semantic group of "supply chain" (pressure, disruption, bottleneck, etc.) and "energy," respectively, over the total number of sentences – see Appendix C for more details.

[24]The result of a larger Kalman gain (in Table 1) and of a larger loading coefficient (in Figure 9) 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.10.

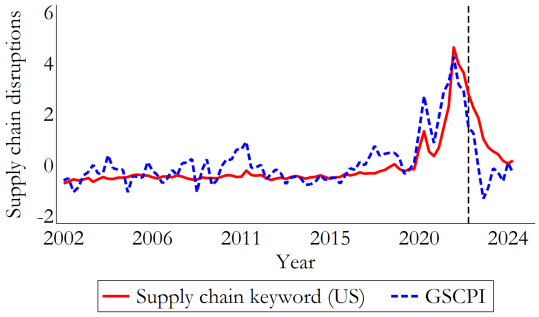
To give content to these textual indicators, we consider sentences in which managers explicitly mention *both* supply chains and energy – Table 2 reports some representative examples. The main pattern that emerges is that managers across very different sectors – from consumer services and fossil-fuel producers to banks – emphasize the "double effect" of supply chain distortions and raw material or energy inflation, treating them as intertwined rather than independent sources of risk. This narrative is consistent with our interpretation that firms view energy prices not only as a cost component, but also as a *salient signal* about the state of supply bottlenecks.

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

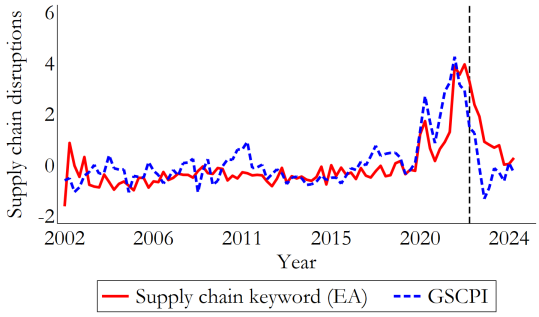
Table 2: Representative sentences with both energy and supply chain keywords

Turning back to the identification of the two keyword groups in earnings call sentences – "supply chain" and "energy" – we consider two separate quarterly time series: the share of sentences that mention at least one supply chain keyword, $w_{SC,t}$, and the share of sentences that mention at least one energy keyword, $w_{E,t}$.

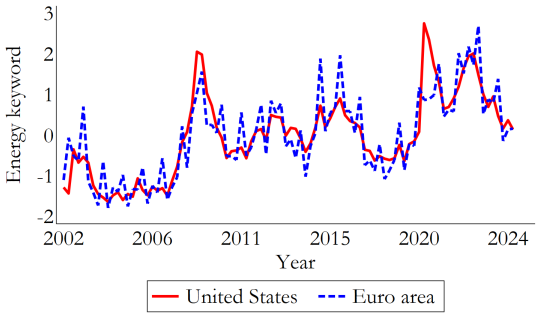
In Figure 10, we plot the evolution of the index of supply chain keywords in the U.S. and the Euro area – compared to the evolution of the GSCPI index – and the evolution of the energy keywords indicators in the U.S. and the Euro area.



(a) Supply chain keywords – U.S.



(b) Supply chain keywords – Euro area



(c) Energy keywords – U.S. and Euro area

Figure 10: Evolution of supply chain and energy keywords in firms' earnings calls

Notes: Panels (a) and (b) compare the GSCPI index (see the note to Figure 4 for more details) with the index of supply chain keywords at quarterly frequency, from Q1 2002 to Q4 2024, in the U.S. and in the Euro area, respectively. Panel (c) plots the energy keyword indexes at quarterly frequency, from Q1 2002 to Q4 2024, for the U.S. and the Euro area. See Appendix C for details on the construction of the keyword indexes.

In Table 3, we explore the correlation of the two indexes. Unconditionally, the two indicators co-move strongly: periods with more frequent mentions of supply chain issues also feature more references to energy markets. To move beyond unconditional co-movement, we study the conditional correlation between these indicators and its state dependence with respect to supply chain uncertainty. Formally, we estimate regressions of the following form:

$$\underbrace{w_{SC,t}}_{\substack{\text{supply chain}\\ \text{words}}} = \alpha + \beta_1 \pi_{E,t} + \beta_2 \underbrace{w_{E,t}}_{\substack{\text{energy}\\ \text{words}}} + \beta_3 \left[\text{Var}(GSCPI)_t \times w_{E,t}\right] + \varepsilon_t, \tag{2}$$

where $\pi_{E,t}$ denotes energy inflation and $\text{Var}(GSCPI)_t$ is the rolling variance of the GSCPI, our benchmark measure of supply chain uncertainty.

The estimates deliver two main results. First, conditional on energy inflation π_E, firms mention energy-related terms more often in those months when they also discuss supply chain disruptions. This suggests that energy prices are not only treated as an independent cost item, but also as informative signals about supply bottlenecks. Second, the correlation between the share of energy words and the share of supply chain words is stronger in periods when supply chain uncertainty is elevated, indicating that firms rely more on energy signals precisely when uncertainty and

informational frictions are more severe.[25] Tables 3a and 3b report the estimates for the United States and the Euro area, respectively, and show positive, statistically significant conditional correlations, with an amplifying role for the interaction between energy mentions and supply chain uncertainty.

	Supply chain keyword		
	(1)	(2)	(3)
Energy keyword	0.533***	0.675***	0.143
	(0.090)	(0.073)	(0.086)
Energy inflation		0.043***	0.027***
		(0.006)	(0.005)
Var(GSCPI) × Energy keyword			0.721***
			(0.089)
Adj. R^2	0.273	0.553	0.739
N	92	92	92

(a) U.S.

	Supply chain keyword		
	(1)	(2)	(3)
Energy keyword	0.647***	0.605***	0.325***
	(0.080)	(0.065)	(0.084)
Energy inflation		0.048***	0.031***
		(0.007)	(0.007)
Var(GSCPI) × Energy keyword			0.391***
			(0.085)
Adj. R^2	0.412	0.625	0.693
N	92	92	92

(b) Euro area

Table 3: Conditional correlates of supply chain keywords in the U.S. and Euro area

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The supply chain and energy keyword indicators are compiled at quarterly frequency from a sample of transcripts of publicly listed firms' earnings calls headquartered in the U.S. (top panel) and in the Euro area (bottom panel). See Appendix C for more details. U.S. energy inflation (CPIENGSL) is retrieved from FRED and Euro area energy inflation (ENRGY0EZ19M086NEST) is retrieved from Eurostat. All variables are at quarterly frequency from 2002 Q1 to 2024 Q4.

2.5 Summary of empirical evidence

To summarize, the empirical evidence presented above highlights three main facts. First, the *pass-through* of (suitably identified) energy price shocks to inflation is amplified in periods of high supply chain uncertainty. This effect is not specific to the Covid-inflation period and does not depend on the size of the energy shock being particularly large during that period. Second, during periods of high supply chain uncertainty, energy prices become relatively *more informative* than market-based

[25] Ersahin et al. (2024) analyze firm-level earnings calls with different text analysis methods and find a highly significant correlation of supply chain risk with commodity price risk in firms' reports (Table IA.4 of the Online Appendix).

transportation prices about underlying logistical conditions. Third, a text-based analysis of firms' earnings calls suggests that references to energy prices are strongly associated to references to supply chain conditions ("pressure" / "disruption"), especially during periods of high supply chain uncertainty. Overall, this evidence points to a complementarity between energy price disturbances and supply chain uncertainty in driving inflation dynamics.

3 A model of the supply chain

In this section we develop a theoretical framework that rationalizes the above findings. The model formalizes how firms' incomplete information about supply chain disruptions – combined with their reliance on energy prices as a noisy signal of transportation shocks – can amplify 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 11.
A final good producer aggregates a continuum of differentiated varieties, indexed by i, to produce a homogeneous output Y. Each downstream intermediate firm i produces its variety Y_i by combining two distinct inputs. The first input is *energy*, E, a commoditized good that is traded in liquid global markets and is therefore perfectly substitutable. Although a significant share of global energy—particularly crude oil and liquefied natural gas—is transported via maritime routes, energy can be stored and is always available for purchase on the local spot market, albeit at a known premium in the event of transportation shocks and shipping delays. The second input is a *specialized component* M (e.g., EV batteries). In contrast to energy, this input is non-substitutable, and its availability critically depends on uninterrupted transportation through the supply chain. Delays in shipping cannot be easily offset by local sourcing or inventory buffers, making delivery times uncertain and production more vulnerable.

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

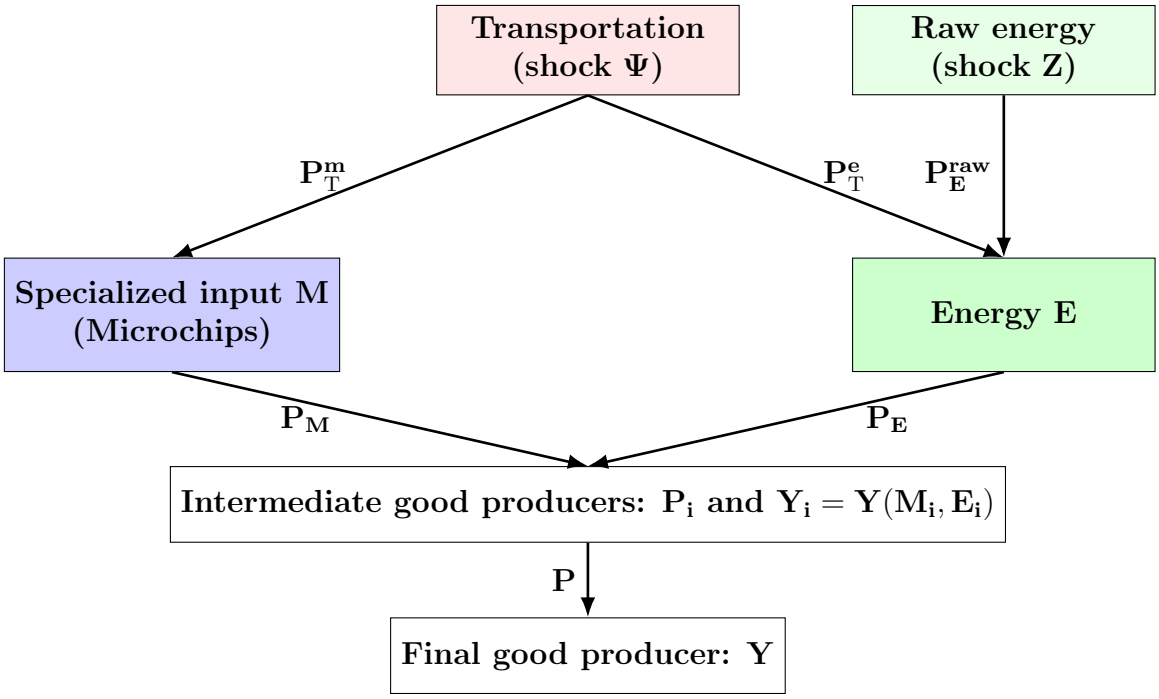


Figure 11: Model of the supply chain

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 $\varepsilon > 1$:

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{3}$$

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:

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

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 (4) 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:

$$E_t = \frac{\alpha_E\, P_t Y_t}{P_{E,t}} \tag{5}$$

Symmetrically, the optimal total demand for the specialized input reads

$$M_t = \frac{\alpha_M\, P_t Y_t}{P_{M,t}} \tag{6}$$

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

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

3.3 Supply of energy

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

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

We model the energy sector as a regulated natural monopoly: the regulator sets the energy price equal to marginal cost (the efficient pricing rule), and lump-sum transfers finance any resulting operating losses. In the special case of constant returns ($\nu = 1$), this market structure is isomorphic to a representative price-taking supplier under perfect competition. The energy supplier takes both the price of raw energy, $P_{\mathrm{E},t}^{raw}$, and the per-unit cost of transportation, $P_{\mathrm{T},t}^{e}$, as given.

Moreover, we allow for a high degree of complementarity between the two inputs, so that the marginal productivity of raw energy is positive only if coupled with transportation services, and vice versa. The energy production function, therefore, reads:

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

where δ is the share of raw energy in the production of final energy, $\eta \to 0$ is the low elasticity of substitution reflecting complementarity between transportation and raw energy, and $\nu > 1$ indexes increasing returns.[26]

The cost-minimizing demand for energy transportation reads:

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

where the marginal cost price index is

$$P_{E,t} = \frac{1}{\nu} \cdot E_t^{\frac{1}{\nu}-1} \cdot \left[(1-\delta)\left(P_{T,t}^{e}\right)^{1-\eta} + \delta\left(P_{E,t}^{\text{raw}}\right)^{1-\eta}\right]^{\frac{1}{1-\eta}} \tag{10}$$

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:

$$E_{raw,t} = \nu^{\eta} \cdot E_t^{\eta+\frac{1}{\nu}(1-\eta)} \cdot \delta \cdot \left(\frac{P_{E,t}^{raw}}{P_{E,t}}\right)^{-\eta} \tag{11}$$

Plugging the demand for raw energy (11) and for its transportation (9) into the energy supply aggregator (8) yields the inverse equilibrium cost-schedule of energy:

$$E_t = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\left(P_{T,t}^{e}\right)^{1-\eta} + \delta\left(P_{E,t}^{raw}\right)^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{12}$$

Note that, since $\nu > 1$, equation (12) determines a negative relation of (final) energy 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.

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

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 around 5'600 container ships in operation worldwide.[27] In the market for transportation, economies of scale play a central role. The capacity of the largest container ships has risen from about 58 TEU on the first containership in 1956 to more than 24,000 TEU on the newest ultra-large vessels.[28] 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).[29] 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.

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).[30] Because most globally traded goods – including energy – share the same transportation market, featuring the same chokepoints, they are

[27] In 2022, 5,589 ships were operating worldwide, see UNCTAD, Review of Maritime Transport 2022, `https://unctad.org/rmt2025`, and Bai, Fernández-Villaverde, Li, and Zanetti (2024).

[28] TEU (twenty-foot equivalent unit) is the standard measure of container capacity.

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

[30] 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).

exposed to the same transportation shocks. In other words, energy and EV batteries do not need to share the same cargo ships to be exposed to the same transportation shocks. Even if the two inputs travel separately, when a transportation shock 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., EV batteries) 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.

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.[31] We conceptualize supply chain disruptions as transportation shocks, which

[31]Note this does not imply that the law of one price is being imposed across the two transporta-

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).

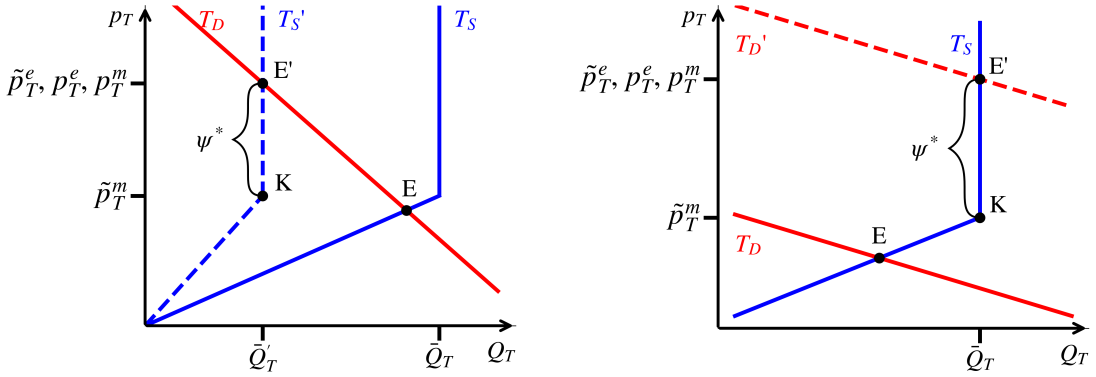
By contrast, transportation *supply* shocks reflect disruptions to the effective capacity of the shipping system. These may stem from physical bottlenecks at critical nodes, or from heightened geopolitical risk that alters routing decisions, reduces effective fleet availability, or impairs the flow of goods.

Graphical illustration of the transportation market We represent the transportation market in Figure 12 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 12 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.

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tion services.



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

Figure 12: 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_T^m, p_T^e are, respectively, the log *effective* price of the specialized input and of energy; $\tilde{p}_T^m$, $\tilde{p}_T^e$ 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 K–E' measures the estimated transportation shock $\psi^* \equiv \log(\Psi^*)$.

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

$$\underbrace{P_{T,t}^m}_{\substack{\text{effective}\\ \text{price}}} = \underbrace{\tilde{P}_{T,t}^m}_{\substack{\text{market}\\ \text{price}}} \cdot \underbrace{\Psi_t^*}_{\substack{\text{estimated}\\ \text{transportation shock}}}$$

Intuitively, when transportation supply reaches full capacity, firms begin to incur a delay time cost associated with a disruption in the physical transportation of the specialized input. If key transportation routes become severely impaired – due to congestion at logistical chokepoints – downstream firms face uncertainty in delivery times, which in turn is reflected in their pricing and production decisions. Notably, market transportation prices for the specialized input are unable to play their allocative role and clear the market because of the existence of physical impairments in the delivery of the specialized input.[32] Henceforth, and without loss of generality, we normalize $\tilde{P}_{T,t}^m = 1$.

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

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

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

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

The above assumption motivates the existence of a signal extraction problem. Away from the capacity constraint (i.e., in normal times), the market price of transportation is perfectly correlated with the effective price of transportation for both inputs. When the transportation supply constraint is binding, however, the market price of transportation for the specialized input becomes *uninformative* of the effective price of transportation. As a result, downstream firms will have to estimate a time delay cost associated with the transportation of the specialized input. We turn to the analysis of the signal extraction problem and its determinants in the sections below.

3.5 Raw energy

To describe the market for *raw* energy we assume that the price of energy $P^{raw}_{E,t}$ evolves according to a stochastic process Z_t. Formally, we have:

$$P^{raw}_{E,t} = Z_t$$

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

3.6 Equilibrium in the energy and specialized input markets

We are now ready to describe the equilibrium in both the market of energy and the market of the specialized input.
Plugging the expressions for the price of transportation of energy and the price of raw energy into the equilibrium cost-schedule of energy (12) we obtain:

$$\underbrace{E_t(\Psi_t)}_{\substack{\text{equilibrium supply}\\ \text{of energy}}} = (\nu\, P_{E,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{13}$$

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

$$\underbrace{M_t(\Psi_t^*)}_{\substack{\text{equilibrium supply} \\ \text{of specialized input}}} = (\nu\, P_{M,t})^{\frac{\nu}{1-\nu}} \cdot \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta\right]^{\frac{\nu}{(1-\eta)(\nu-1)}} \tag{14}$$

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 estimated transportation shock Ψ_t^*.

Equilibrium price of energy The equilibrium price of energy can be derived by combining the demand by the intermediate product firm in (5) with the supply in (13):[33]

$$P_{E,t}(Y_t, \Psi_t, Z_t) = (\alpha_E Y_t P_t)^{1-\nu}\, \nu^{-\nu} \left[(1-\delta)\Psi_t^{1-\eta} + \delta Z_t^{1-\eta}\right]^{\frac{\nu}{1-\eta}} \tag{15}$$

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:

$$p_{E,t} = (1-\nu) y_t + \nu \left[(1-\delta)\psi_t + \delta z_t\right] \tag{16}$$

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

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

Equilibrium price of specialized input A symmetric equation can be obtained for the relative price of the specialized input combining equation (6) with (14):

$$P_{M,t}(Y_t, \Psi_t^*) = (\alpha_M Y_t P_t)^{1-\nu}\ \nu^{-\nu}\ \left[(1-\delta)(\Psi_t^*)^{1-\eta} + \delta\right]^{\frac{\nu}{1-\eta}} \tag{17}$$

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

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

3.6.1 Equilibrium marginal cost

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

$$MC_t(Y_t, P_t, \Psi_t, Z_t, \Psi_t^*) = A^{-\nu} \cdot (Y_t P_t)^{1-\nu} \cdot \Gamma(\Psi_t, Z_t)^{\frac{\alpha_E \nu}{1-\eta}} \cdot \Lambda(\Psi_t^*)^{\frac{\alpha_M \nu}{1-\eta}} \tag{18}$$

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

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

Log-linearizing equation (18), and letting mc_t be the percent deviation of the *real* marginal cost from its steady-state value we can write:

$$mc_t = \underbrace{(1-\nu)\, y_t}_{\text{output}} + \nu\,(1-\delta) \left[\underbrace{\alpha_E\, \psi_t}_{\substack{\text{true transportation} \\ \text{shock}}} + \underbrace{\alpha_M\, \psi_t^*}_{\substack{\text{estimated transportation} \\ \text{shock}}} \right] + \underbrace{\alpha_E\, \nu\, \delta\, z_t}_{\substack{\text{raw energy} \\ \text{shock}}} \tag{19}$$

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

3.7 Supply chain uncertainty

The marginal cost equation (19) above highlights the role of *true* and *estimated* transportation shocks as key determinants of the intermediate firm's marginal cost. This framework naturally gives rise to a *signal-extraction* problem, in that the firm needs to form an *estimate* ψ_t^* of the transportation shock before setting its price. Below we formalize the signal-extraction problem: firms use energy prices, contaminated by both raw energy shocks and congestion shocks, to infer the the true transportation shock.

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.[34]

[34]Notice that, without loss of generality, we presented a minimal information problem where firms learn *solely* from energy prices to estimate the latent state of transportation 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.[35] For each time $t \geq 1$, the corresponding state-space model is:

$$\begin{cases} \psi_t \;=\; \rho_\psi \, \psi_{(t-1)} + \varepsilon_{\psi,t} & \varepsilon_{\psi,t} \sim \mathcal{N}(0,\, \sigma_\psi^2) \\ p_{E,t} = (1-\nu) y_t + \nu \, \Omega_t & \\ \Omega_t \equiv (1-\delta)\psi_t + \delta z_t & z_t \quad \sim \mathcal{N}(0,\, \sigma_Z^2) \end{cases} \tag{20}$$

where Ω_t is a *convolution* of the two supply shocks (to transportation and raw energy respectively), the latent process of transportation shocks ψ_t has known persistence ρ_ψ, and $\{\varepsilon_{\psi,t}, z_t\}_{t\geq 1}$ are two independent sequences of Gaussian innovations with mean zero and known variances σ_ψ^2 and σ_z^2, respectively.[36]
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 ($\mathbb{E}_t\{.\}$), we adopt a specific notation for the formulation of the expected value of the transportation shock conditional on the history of energy prices:

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

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

[35] For the formal details on the problem of incomplete information considered and its solution, see Appendix B.3 and B.4.

[36] 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 (20). The point estimate ψ_t^* evolves according to the Kalman filter updating equation:

$$\psi_t^* = \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\}}_{\text{guess with old info}} + \underbrace{\mathbb{K}(\mathcal{S})}_{\text{weight to new info}} \underbrace{\left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)}_{\text{error correction with new signal}} \tag{21}$$

where $\mathbb{K}(\mathcal{S})$ is the *Kalman gain*, in turn a function of the *signal-to-noise* ratio $\mathcal{S}$.[37]

Equation 21 above describes the *recursive* process of the intermediate firm learning about the latent transportation shock ψ_t. At time $t-1$, the firm formulates a guess for ψ_t, and 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: $\left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)$. 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 $\mathcal{S} \equiv \sigma_\psi^2/\sigma_Z^2$.[38]

Marginal cost under uncertainty As argued above, and highlighted in (17), the specialized input price $p_{M,t}$ depends on the *estimated transportation shock* ψ_t^*, which is estimated according to the Kalman filter updating equation in (21):

$$p_M(\psi_t^*) = (1-\nu)\, y_t + \nu\,(1-\delta) \cdot \underbrace{\left[\mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{\psi_t\} + \mathbb{K}(\mathcal{S})\left(p_{E,t} - \mathbb{E}_{\mathcal{P}_{\psi,(t-1)}}\{p_{E,t}\}\right)\right]}_{\psi_t^*} \tag{22}$$

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

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

$$mc_t = \alpha_E \underbrace{p_{E,t}}_{\text{energy price}} + \alpha_M \underbrace{\left[(1-\nu)\, y_t + \nu\,(1-\delta)\, \psi_t^*\right]}_{\text{specialized input price: } p_M(\psi_t^*)} \tag{23}$$

Once uncovered the dependence of the specialized input price from the energy price in (22), 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 shock and delay cost, further raising the marginal cost through an *uncertainty effect*. Notice that the elasticity of the uncertainty channel is increasing in the IRS parameter $\nu > 1$.

[37] 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.5 for a detailed discussion.

[38] 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 marginal cost of production:[39]

$$p_t = \mu + \underbrace{\alpha_E p_{E,t} + \alpha_M \left[(1-\nu)\, y_t + \nu\,(1-\delta)\,\psi_t^*\right]}_{mc_t} \tag{24}$$

where mc_t is the firm's marginal cost, and $\varepsilon > 1$ is the price elasticity of demand. The pass-through of energy price movements onto the intermediate product price can be decomposed into an *impact* and a *dynamic* component.

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

Proposition 1 (Impact pass-through 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, originating from an i.i.d. raw energy shock z_t, is:*

$$\frac{dp_t}{dp_{E,t}} = \underbrace{\alpha_E}_{\textit{direct effect}} + \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\textit{uncertainty effect}} \tag{25}$$

Proof. Consider the marginal cost equation (23) and combine it with equation (21). 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:

[39] More precisely, equation (24) pins down the optimally set log intermediate product price *relative to the aggregate price*. In subsection 3.8, for the sake of readability, we will denote this quantity with p_t and consider it as the firm optimal price metric in Proposition 1 and 2.

- *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.

- *Uncertainty effect*: Under incomplete information about the supply chain, a rise in the energy price is also informative about a transportation shock ψ_t^*, increasing 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 transportation shock.

Precautionary pricing The rise in the intermediate product price driven by the uncertainty effect mirrors the precautionary-pricing mechanism highlighted 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 We show below that supply chain uncertainty endogenously generates *persistence* in the pass-through of otherwise transitory raw energy shocks to intermediate product prices. Let p_{t+k}^* denote the optimal intermediate product price chosen at date $t+k$, where beliefs about the transportation shock are updated using the Kalman filter. We study how a change in the time-t energy-price signal $p_{E,t}$ affects future prices through its effect on the entire subsequent belief-updating path. Specifically, we consider a one-time increase in $p_{E,t}$ generated by a purely *transitory*, *i.i.d.* raw energy shock z_t, and we evaluate its dynamic effect on the path of optimal p_{t+k} holding the subsequent realizations $\{p_{E,t+1}, \ldots, p_{E,t+k}\}$ fixed. The following proposition characterizes the resulting dynamic pass-through on product prices at different horizons:[40]

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

$$\frac{dp_{(t+k)}}{dp_{E,t}} = \underbrace{\alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{K}(\mathcal{S})}_{\textit{impact effect of uncertainty}} \cdot \underbrace{\left[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\right]^k}_{\textit{dynamic effect of uncertainty}} > 0 \qquad (26)$$

[40]Notice that this is a partial-equilibrium pass-through, as we treat aggregate output y_t as exogenous and observed at time t.

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 *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 $\mathcal{S} \equiv \sigma_\psi^2/\sigma_Z^2$ and with supply chain uncertainty σ_ψ^2.

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 $t+k$ dynamic pass-through of any given time-t increase in energy price, originating from an i.i.d. raw energy shock z_t, is zero.*

Proof. Under complete information, the Kalman gain $\mathbb{K}(\mathcal{S}) = 0$. Equation (26) then yields $\frac{\partial p_{(t+k)}}{\partial p_{E,t}} = 0$. □

Proposition 2 shows that, under supply chain uncertainty, when firms observe 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 13 displays the effect on the path of optimal product prices $\{p_{t+k}\}_{k\geq 0}$ and of estimated transportation shocks $\{\psi^*_{t+k}\}_{k\geq 0}$ of an *i.i.d.* raw energy price shock z_t. For each panel, there are three cases, corresponding to complete information, low supply chain uncertainty, and high supply chain uncertainty.

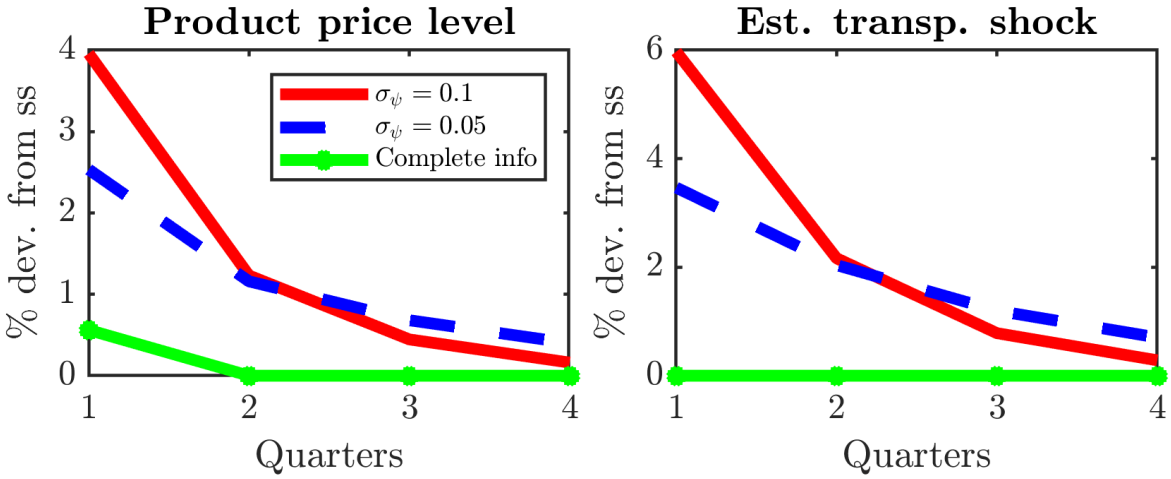


Figure 13: Impulse responses of the optimal intermediate product price and of the estimated transportation shock to an *i.i.d.* raw energy price shock, for alternative values of the variance of the transportation shock σ_ψ

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 blue line describes the case of *low supply chain uncertainty* $\sigma_\psi = 0.05$ and the red line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.1$. The remaining parameter values are $\alpha_E = 0.09$, $\alpha_M = 0.91$, $\eta = 0.01$, $\delta = 0.5$, $\rho_\psi = 0.9$, $\sigma_Z = 0.1$, $\nu = 1.25$.

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 13 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 estimate the underlying transportation shock. 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 14 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 transportation shock, and thus a more pronounced yet shorter-lived pass-through of raw energy price shocks to output prices.

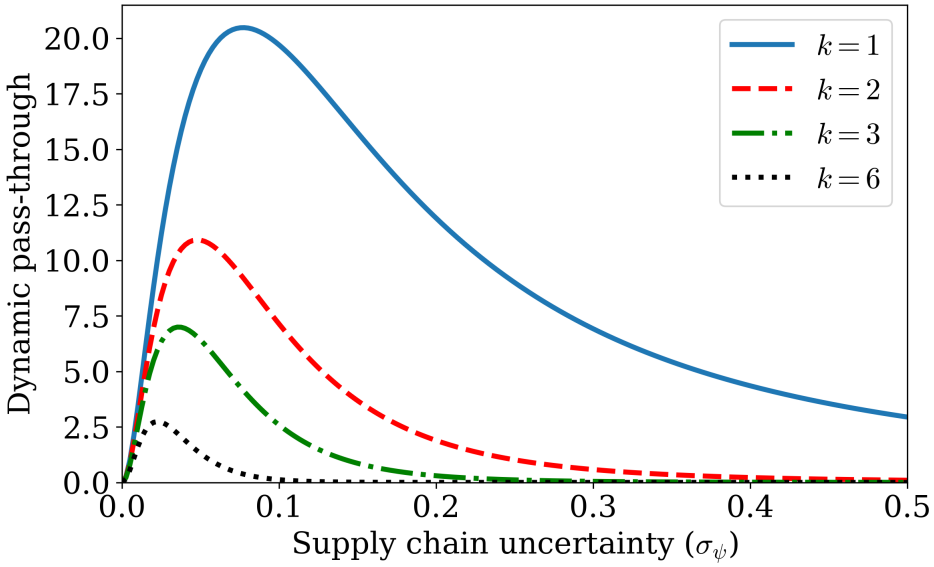


Figure 14: Effect of varying supply chain uncertainty σ_ψ on the dynamic energy price pass-through at different horizons k

Notes. The panel depicts the dynamic pass-through of energy ($\times 100$), as computed in Proposition 2, on supply chain uncertainty σ_ψ. 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:[41]

$$p_t = (1-\theta\beta)\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(\mu + mc^n_{(t+k)})\right\} \tag{27}$$

[41] 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).

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.[42]

3.9.1 New Keynesian Phillips Curve (NKPC) under uncertainty

Following steps outlined in Appendix B.7, we can manipulate equation (27) above to obtain the *incomplete-information* version of the NKPC:

$$\pi_t = \beta \underbrace{\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\}}_{\substack{\text{future expected} \\ \text{inflation}}} + \frac{(1-\theta)(1-\theta\beta)}{\theta} \cdot \underbrace{mc_t(\psi^*_t)}_{\substack{\text{estimated current} \\ \text{marginal cost}}} \tag{28}$$

Note the key departure from the complete-information NKPC: both the current real marginal cost in deviation from its steady state (mc_t) and expected future inflation ($\pi_{(t+1)}$) feature an *estimated* transportation shock, as detailed in the state-space model (20). Both components – the estimated current marginal cost and the expected 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 (28).

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 an underlying transportation shock, and therefore of higher delay time costs. These combined cost–push forces lead intermediate firms to reset the optimal price upward, which in turn aggregates into higher overall inflation.

Amplification via expected future inflation As shown in Proposition 2, under supply chain uncertainty, an energy price shock is (at least partially) interpreted by firms as a signal of a *persistent* upstream disturbance, which raises expected transportation delays in future periods. Anticipated delays, in turn, increase firms' expectations of future marginal costs, prompting them to revise upward their expected optimal prices. When these adjustments are aggregated across firms, they result 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

[42]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 estimated transportation shock ψ^*_t are independent processes. See Appendix B.6 for more details.

supply chain uncertainty translates, via firms' forward-looking pricing behavior, into a magnified inflation response to energy shocks.

Uncertainty wedge and the NKPC The overall effect of energy prices as a signal of present and future unobserved transportation shocks can be isolated by rewriting equation (28) as a familiar complete-information NKPC augmented by an *uncertainty-related* endogenous wedge. Supply (energy) shocks are therefore made more inflationary by uncertainty, in line with 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:*

$$\pi_t = \underbrace{\beta\,\mathbb{E}\left\{\pi_{(t+1)}\right\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\cdot mc_{complete\ info,t}}_{complete\text{-}information\ NKPC} + \underbrace{G\cdot u_t}_{\substack{uncertainty\\ wedge}} \tag{29}$$

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

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

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

Proof. Proof in Appendix A.2. □

Supply chain uncertainty adds a novel endogenous component to the standard complete-information NKPC. This component is due to estimated transportation shocks and delay time 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 delay costs – causing a fully fledged endogenous inflationary effect.

The uncertainty wedge u_t 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 is increasing in both the Kalman gain $\mathbb{K}(\mathcal{S})$ and the IRS index ν. On the contrary, the persistence of the uncertainty-driven 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 transportation in the

production of energy (and specialized input) $(1-\delta)$.

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 uncertainty wedge 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 transportation shocks. 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 transportation shocks, 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 transportation shocks, and therefore of the Phillips Curve response of inflation.

4 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

$$\max_{\{C_t,N_t,B_t\}_{t=0}^{\infty}} \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) \right\} \tag{30}$$

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

$$P_t C_t + B_t \leq W_t N_t + R_t B_{(t-1)} + \int_0^1 D_t(i)\, di \tag{31}$$

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:

$$C_t^{-\sigma} = \beta(1+i_t)\mathbb{E}_t\left\{C_{(t+1)}^{-\sigma}\frac{P_t}{P_{(t+1)}}\right\} \tag{32}$$

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:

$$\frac{W_t}{P_t} = C_t^{\sigma} N_t^{\varphi} \tag{33}$$

The transversality condition:

$$\lim_{T\to\infty} \mathbb{E}_0\left[\beta^T C_T^{-\sigma}\frac{B_T}{P_T}\right] = 0 \tag{34}$$

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:

$$1 + i_t = \beta^{-1}\left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\pi} \tag{35}$$

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 (15)-(17), 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 (30)-(31); *(ii)* firms form expectations about the transportation shock according to the optimal Bayesian estimator ψ_t^* in (21); *(iii)* prices satisfy the household's and firms' first-order conditions; *(iv)* all markets clear.

4.1 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.[43] This abstraction from a transportation shock effectively isolates the role of the transportation *volatility* and uncertainty in the transmission of energy price shocks to output prices: regardless of the actual *level* of the true transportation shock, its *volatility* amplifies the pass-through to goods inflation. The standard deviation of the raw energy price shock is normalized to $\sigma_z = 0.1$.

There are three parameters in the energy market, δ, ν, and η. We calibrate to $\delta = 0.5$ the share of raw energy in energy production.[44] We set the IRS (Increasing Returns to Scale) index over one, to capture the empirically observed economies of scale in global maritime transportation of energy, $\nu = 1.25$. Similarly, we set the elasticity of substitution between raw energy and transportation close to zero to capture the high degree of complementarity between raw energy and transportation services, $\eta = 0.01$. We assume that the same parameters δ, ν, and η apply to the market for the specialized component.[45] 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 4. 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 $\sigma_\psi = 0.05$ to reproduce the long period of low volatility in transportation shocks from 2002 to 2021. Third, we calibrate $\sigma_\psi = 0.1$ to reproduce the unprecedented – approximate fivefold – increase in the rolling standard deviation 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 4: Key model parameters

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

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

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

4.1.1 Effect of an energy price shock under uncertainty

Figure 15 and 16 display the impulse responses of goods inflation, output, real estimated transportation shock, 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 shock hits, the raw energy price jumps up on impact by 10% and reverts immediately. As a direct consequence, energy price increases and energy demand falls (see the top left panel of Figure 16). Under complete information, firms know that this increase in the energy price is due to the raw energy shock, and they correctly infer that there is no underlying transportation disturbance (see the green line in the bottom left panel of Figure 15). Noticeably, because firms know that the shock underlying the increase in energy price is purely transitory, inflation and output exhibit a rapid and complete mean reversion within one quarter.

Under uncertainty, firms need to carry out a signal-extraction process on the energy price increase. Firms wrongly assign a portion of the energy price realization to an underlying transportation disruption and, consequently, the estimated transportation shock spikes near 4% on impact in the case of low uncertainty and to 6% in the case of high uncertainty. By Proposition 3, the estimated transportation shock feeds the *uncertainty wedge* in the Phillips Curve, that increases inflation on impact. Accordingly, supply chain uncertainty also makes the effects on output contraction more severe, as output falls on impact by about 0.2%. 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 16). On the one hand, the energy price is always observed without noise, so energy use drops by the same amount across uncertainty regimes. On the other hand, the *effective* price of transportation of the specialized input depends on the estimated transportation shock, and therefore varies across uncertainty regimes.

Labor market margins are also dependent on the level of supply chain uncertainty. Under complete information, firms substitute toward labor as energy becomes relatively more expensive, so employment and the real wage both rise on impact. Under uncertainty, higher perceived marginal costs depress output, reducing labor demand and wages. Notably, this effect counteracts the substitution effect, yielding an almost 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 ($\sigma_\psi = 0.05$) with the high-uncertainty regime ($\sigma_\psi = 0.1$), beliefs about delays adjust more rapidly, the *estimated transportation shock* in Figure 15 collapses earlier, and all impulse responses converge faster.

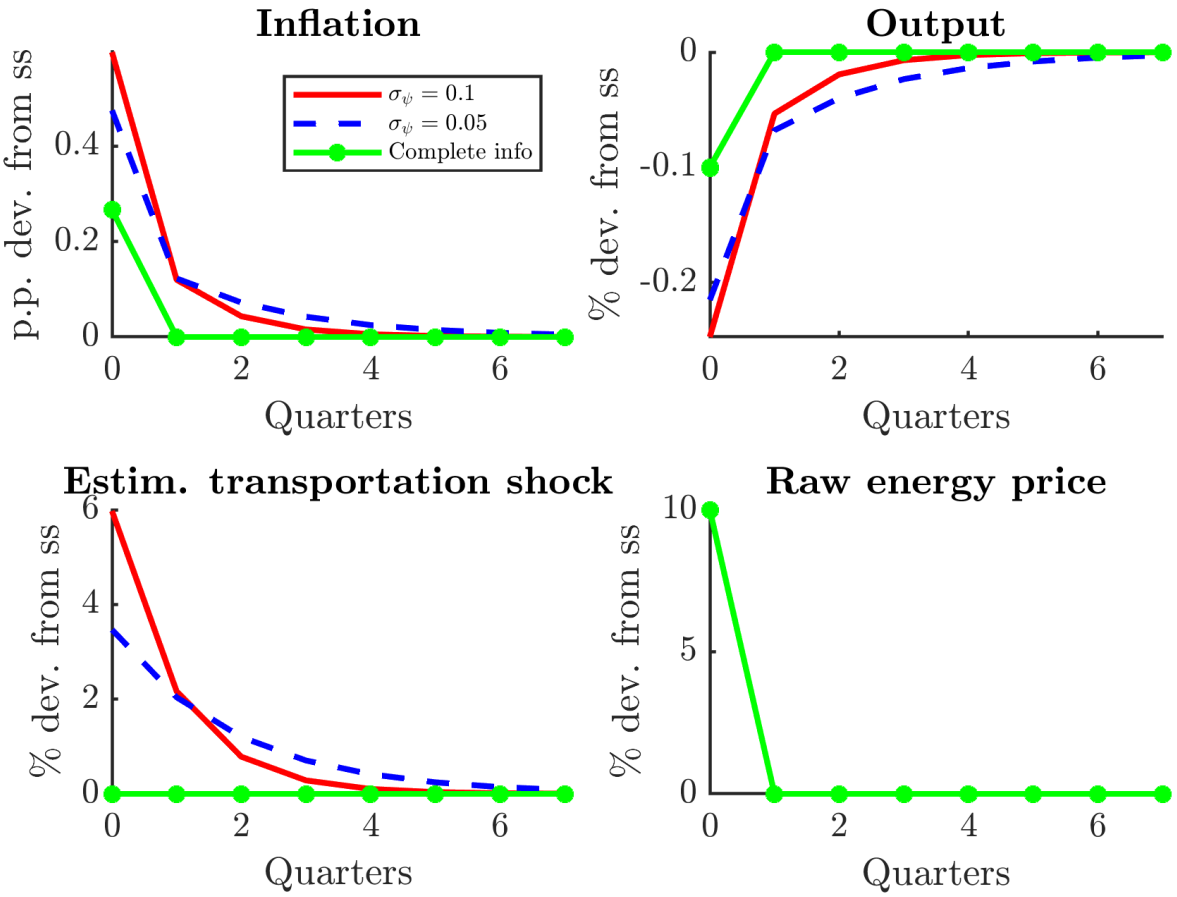


Figure 15: Impulse responses of inflation, output, estimated transportation shock, and raw energy price to an *i.i.d.* raw energy price shock

Notes. The panels depict the responses of inflation, output, real estimated transportation shock 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* $\sigma_\psi = 0.05$, and the red line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.1$.

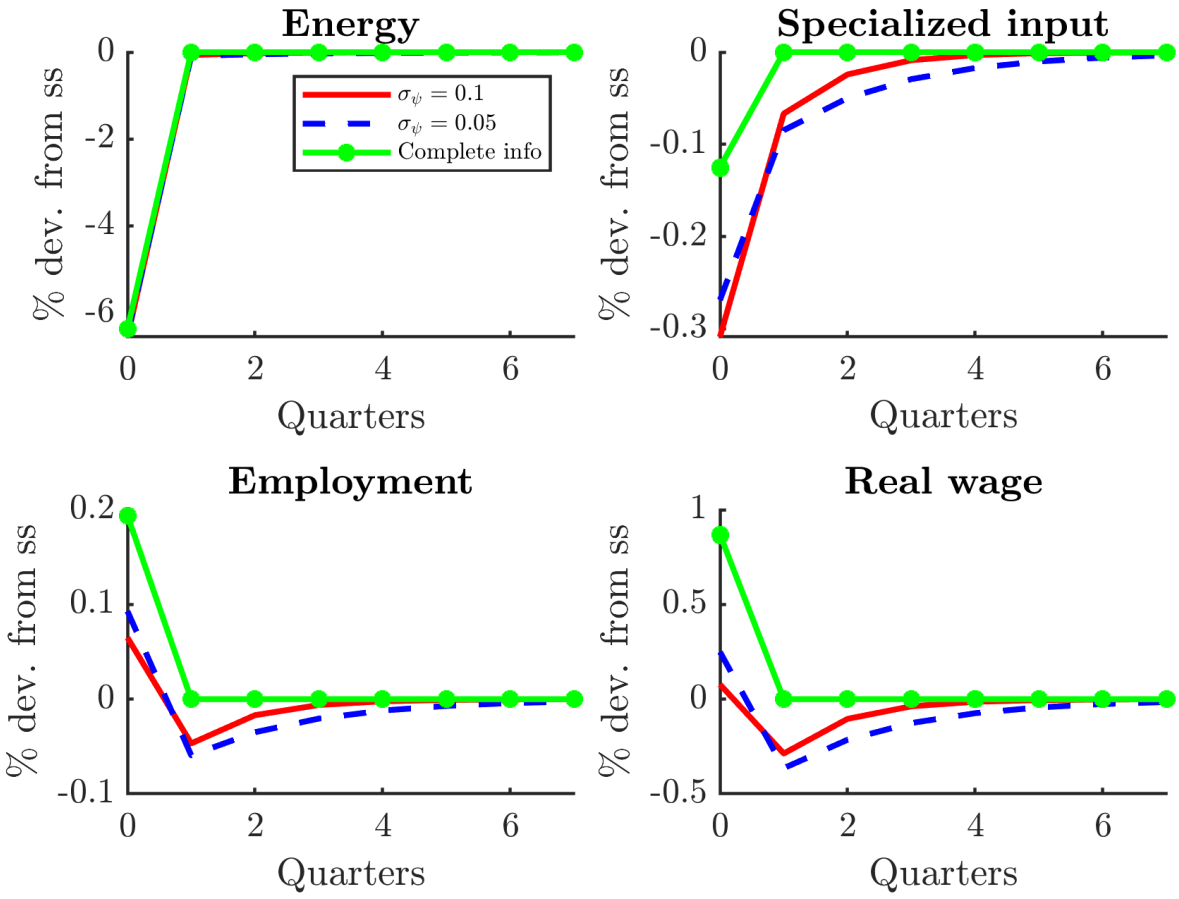


Figure 16: Impulse responses of energy, specialized input, employment, and real wage to an *i.i.d.* raw energy price shock

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* $\sigma_\psi = 0.05$, and the red line describes the case of *high supply chain uncertainty* $\sigma_\psi = 0.1$.

4.2 Monetary policy and energy shocks: look-through?

A standard argument in the monetary policy debate holds that central banks should "look through" supply-driven energy price shocks. The logic is well known: energy shocks are typically viewed as transitory and therefore neutral for inflation expectations. In canonical New Keynesian models under complete information, such shocks raise marginal costs only temporarily and therefore do not warrant a policy response, as inflation and expectations revert quickly once the shock dissipates. This reasoning has characterized both academic and policy narratives for a long time and featured prominently during the early phases of the post-pandemic inflation surge.[46]

Our framework calls for a reassessment of the look-through doctrine. In the

[46]See, for example, the U.S. Fed Chair Jerome Powell speech on November 9, 2023(`https://www.federalreserve.gov/newsevents/speech/powell20231109a.htm?`).

model, raw energy shocks are strictly temporary by construction. Yet, when supply chain uncertainty is elevated, these shocks are no longer innocuous for inflation dynamics. The key departure from the standard view lies in firms' incomplete information about upstream supply conditions. In states of the world with sufficiently elevated supply chain uncertainty even a purely transitory energy shock can be misperceived as indicative of a persistent increase in future marginal costs. This belief channel fundamentally alters the inflationary consequences of energy shocks. First, firms raise prices more aggressively on impact, reflecting not only the direct cost of energy but also precautionary pricing against perceived future bottlenecks. Second, inflation becomes more persistent, as forward-looking price setting embeds the endogenous propagation generated by firms' learning dynamics. Crucially, both amplification and propagation are state-dependent: they scale with the volatility of transportation shocks, our measure of supply chain uncertainty. In environments of low uncertainty, the economy converges back to the standard benchmark in which energy shocks can indeed be looked through. In high-uncertainty states, however, the same shocks generate endogenous inflationary pressure that closely resembles the response to genuinely persistent supply disturbances.

Figure 17 illustrates this point in the context of our model. The top panel displays the response of current and expected inflation to an *i.i.d.* raw energy shock under a "look-through" policy. The latter is a policy of very mild response to the rise in inflation, corresponding to a value of the policy parameter ϕ_π barely above 1.[47] Green lines describe the case of complete information, whereas solid red lines describe the case of supply-chain uncertainty. Under complete information, an *i.i.d.* energy shock increases inflation for only one period, before dying out, and noticeably has no effect on inflation expectations. Conversely, under supply chain uncertainty, a look-through policy generates an endogenously more persistent response of both current and expected inflation. The bottom panel describes the effects of the same *i.i.d.* energy shock under a more aggressive policy of inflation targeting, corresponding to a value of the feedback policy parameter $\phi_\pi = 4$. The key implication of a more aggressive inflation targeting policy is that, under supply chain uncertainty, the response of both current and expected inflation are dampened relative to the passive case of a look-through policy.

[47] This is the minimum value of ϕ_π such that the Taylor principle is satisfied in equation (35).

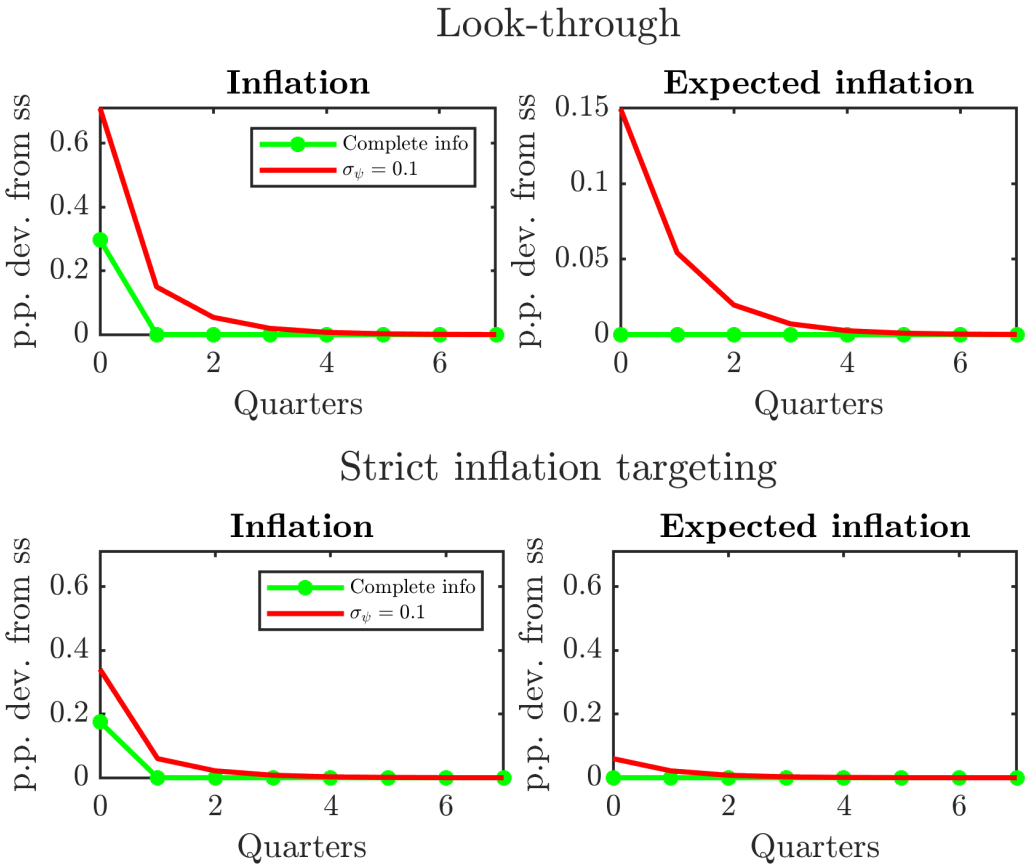


Figure 17: Impulse responses of inflation and one-quarter-ahead expected inflation to an *i.i.d.* raw energy price shock, for alternative monetary policies

Notes: The panel depicts the response of inflation and expected inflation to an *i.i.d.* 10% positive shock in the raw energy price z_t with volatility $\sigma_z = 0.1$, under alternative monetary policies: (i) top panel, look-through $\phi_\pi = 1.0001$ and (ii) bottom panel, strict inflation targeting $\phi_\pi = 4$. In each panel, the green line describes the case of *complete* information (i.e., $\sigma_\psi = 0$) and the red line describes the case of *supply chain uncertainty* $\sigma_\psi = 0.1$.

Taken together, these results deliver a clear normative implication. The appropriateness of "looking through" energy shocks is not invariant to the state of the supply chain. When supply uncertainty is sufficiently high, transitory energy shocks can de-anchor firms' expectations of marginal costs and, through them, inflation dynamics. In such states, a passive policy response risks validating the endogenous amplification mechanism highlighted in the paper. More generally, our results suggest that optimal monetary policy should be *state-contingent*, conditioning not only on the level of energy prices but also on the volatility of upstream supply conditions. Ignoring this interaction may lead policymakers to underestimate the inflationary consequences of supply shocks precisely when they are most potent.

5 Conclusions

This paper develops a theory of inflation amplification of supply (energy) shocks grounded in firms' *uncertainty* about their supply chains. We consider the 2021–2023 energy shock and inflation spike, both in the U.S. and in the Euro area, as a natural laboratory for our theory. In that period, the inflationary effects of energy shocks were largely amplified by unprecedented volatility in supply chain conditions, bringing the mechanism to daylight. However, we argue that the mechanism emphasized in the paper – the complementarity between energy price disturbances and supply chain uncertainty – is potentially a structural feature of modern production structures built on highly interconnected supply chains that are increasingly exposed to disruptions, whether for economic or geopolitical reasons.

In our framework, firms rely on both energy and specialized inputs transported through shared logistical routes. When transportation disruptions 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-wedge 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 supply shocks to domestic inflation.

A Proofs

A.1 Proof of Proposition 2

Consider the expression for the optimal intermediate product price (24) at horizon $k \geq 1$ and differentiate with respect to time-t energy price. That yields:

$$\frac{dp_{(t+k)}}{dp_{E,t}} = \alpha_E \cdot \frac{dp_{E,(t+k)}}{dp_{E,t}} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} \tag{36}$$

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

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

Second, we compute the effect of energy prices through uncertainty:

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}}$$

Consider the Kalman filter updating equation in (21), forwarded k periods ahead:

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

The partial derivative follows the recursive formulation

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \rho_\psi \frac{\partial \psi^*_{(t+k-1)}}{\partial p_{E,t}} - \mathbb{K}(\mathcal{S}) \cdot \frac{\partial \mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\}}{\partial p_{E,t}} \tag{37}$$

We are now interested in the expected $t+k$ energy price conditional on the time-$t+k-1$ information set:[48]

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

The derivative with respect to the energy price is:

$$\frac{\partial \mathbb{E}_{\mathcal{P}_{\psi,(t+k-1)}}\{p_{E,(t+k)}\}}{\partial p_{E,t}} = \nu \cdot (1-\delta) \cdot \rho_\psi \cdot \frac{\partial \psi^*_{(t+k-1)}}{\partial p_{E,t}} \tag{38}$$

Then, equation (37) rewrites as:

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

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

Iterating forward yields:

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

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

$$\frac{\partial \psi^*_{(t+k)}}{\partial p_{E,t}} = \mathbb{K}(\mathcal{S}) \cdot \Big[\rho_\psi \cdot (1 - \mathbb{K}(\mathcal{S}) \cdot \nu \cdot (1-\delta))\Big]^k = \mathbb{K}(\mathcal{S}) \cdot L^k \tag{39}$$

Substituting into (36) yields the result. We introduce the notation $L \equiv \rho_\psi \left[1 - \mathbb{K}(\mathcal{S})\, \nu\, (1-\delta)\right]$ 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 uncertainty wedge 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.5 for more details.

A.2 Proof of Proposition 3

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

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

Define deviations of the estimated transportation shock from the true value:

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

Consider the marginal cost of production of the intermediate firm, which depends on the estimated transportation shock $mc(\psi^*_t)$:

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

Write it in deviation from its complete-information counterpart,[49] 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

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

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

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 $t-1$:[50]

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

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

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

Then we can rewrite u_t as

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

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 uncertainty wedge u_t.

We aim to rewrite the *incomplete-information NKPC* to isolate the effect of estimated transportation shocks. Start from the *incomplete-information NKPC*:

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

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

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

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

[50] 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.

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

$$mc_t(\psi_t^*) = mc_{\text{complete info},t} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot u_t \tag{40}$$

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

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

$$\pi_{(t+1)} = \beta \mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{\pi_{(t+2)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,(t+1)}}\{mc_{(t+1)}\} \tag{41}$$

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

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \beta \mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+2)}\} + \frac{(1-\theta)(1-\theta\beta)}{\theta}\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{(t+1)}\} \tag{42}$$

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

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j \mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+j+1}\} \tag{43}$$

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

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

Consider (40) that extracts the incomplete information component from the marginal cost, and iterate it $j+1$ periods ahead:[51]

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{mc_{t+j+1}\} = \mathbb{E}_t\{mc_{t+j+1}(\psi^*_{t+j+1})\} = \mathbb{E}_t\{mc_{\text{complete info},t+j+1}\} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{E}_t\{u_{t+j+1}\} \tag{44}$$

and plug (44) into equation (43) above:

$$\mathbb{E}_{\mathcal{P}_{\psi,t}}\{\pi_{(t+1)}\} = \frac{(1-\theta)(1-\theta\beta)}{\theta}\sum_{j=0}^{\infty}\beta^j\left(\mathbb{E}_t\{mc_{\text{complete info},t+j+1}\} + \alpha_M \cdot \nu \cdot (1-\delta) \cdot \mathbb{E}_t\{u_{t+j+1}\}\right) \tag{45}$$

Use equations (40)-(45) to rewrite the *incomplete-information NKPC*:

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

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

Recursively,

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

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 Multiple signals

Section 3.7 lays out the simple information problem faced by the firm at time t: it observes the aggregate state *except* the true transportation shock ψ_t, and backs its estimate ψ_t^* out from the energy price $p_{E,t}$ *alone*. This is a very tractable simplification we make in this model as the other candidate signal in the model, namely the market transportation price $\tilde{p}^m_{T,t}$, is not informative of the transportation shock when the capacity constraint binds (Section 3.4.3).

However, in reality, 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.

B.2 Timeline of the information problem

According to the information problem described in section 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^*:

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

5. The deviation of the estimated transportation shock from the true value rewrites as
$$u_t \equiv \psi_t^* - \psi_t = \rho_\psi\big(1 - \mathbb{K}\,\nu(1-\delta)\big)\,u_{t-1} + \mathbb{K}\,\nu\,\delta\,z_t$$
assuming $\varepsilon_{\psi,t} = 0$.

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

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

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

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

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 forming the estimate ψ_t^* of the transportation shock.

B.3 Details on the state-space model

The system of equations (20) 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,

$$\begin{aligned} \psi_t &\sim \mathcal{P}_{\psi}(d\,\psi_t \mid \psi_{(t-1)}), \\ p_{E,t} &\sim \mathcal{P}_{p_E}(d\,p_{E,t} \mid \psi_t). \end{aligned} \tag{46}$$

Figure 18 illustrates the information flow in this model with an acyclic directed graph of the state-space model.

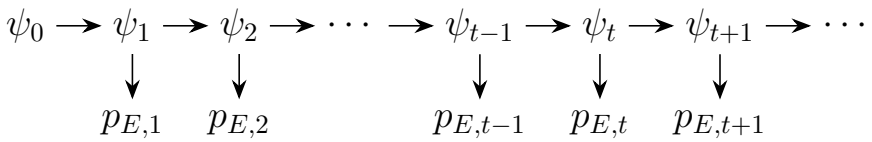


Figure 18: Acyclic directed graph of the state-space model

B.4 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 (46), 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:[52]

$$\mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}) \propto \mathcal{P}_{p_E}(dp_{E,t} \mid \psi_t) \cdot \mathcal{P}_{\psi,(t-1)}(d\,\psi_t \mid p_{E,0:(t-1)}). \tag{47}$$

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:

$$\mathcal{P}_{\psi,t}(d\,\psi_{(t+1)} \mid p_{E,(0:t)}) = \int_{\mathbb{R}} \mathcal{P}_{\psi}(d\,\psi_{(t+1)} \mid \psi_t) \cdot \mathcal{P}_{\psi,t}(d\,\psi_t \mid p_{E,(0:t)}). \tag{48}$$

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

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

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.5 Kalman gain at steady state

Consider the state-space model in (20) and the Bayesian estimate of the unobserved transportation shock in (21). 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 balanced by the loss of information represented by the additional variance σ^2_ψ 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 $\mathbb{K}(\mathcal{S})$:[53]

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

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

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

where, in turn, C depends positively on the signal-to-noise ratio $\mathcal{S} \equiv \sigma^2_\psi/\sigma^2_Z$. 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

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

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.6 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 – 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 estimated 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.7 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 (27). Rewrite it in terms of $mc_{(t+k)}$, i.e., the future expected real marginal cost of production in deviation from the steady state, μ:

$$p_t = (1 - \theta\beta)\mathbb{E}_{\mathcal{P}_{\psi,t}}\left\{\sum_{k=0}^{\infty}(\theta\beta)^k(p_{(t+k)} + mc_{(t+k)})\right\} \tag{49}$$

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 (49). We therefore obtain:

$$p_{t,\text{agg}} = \theta p_{t-1,\text{agg}} + (1-\theta)p_t. \tag{50}$$

Rewrite equation (49) recursively as

$$p_t = (1-\theta\beta)mc_t + \theta\beta\mathbb{E}_{\mathcal{P}_{\psi,t}}\{p_{(t+1)}\}, \tag{51}$$

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

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

which is computed under the estimated probability distribution over the transportation shock $\mathcal{P}_{\psi,t}(\psi_{(t+1)})$, derived solving the state-space model in (20). Rewrite equation (50) as

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

Combine it with equation (51) to finally obtain the *incomplete-information NKPC*:

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

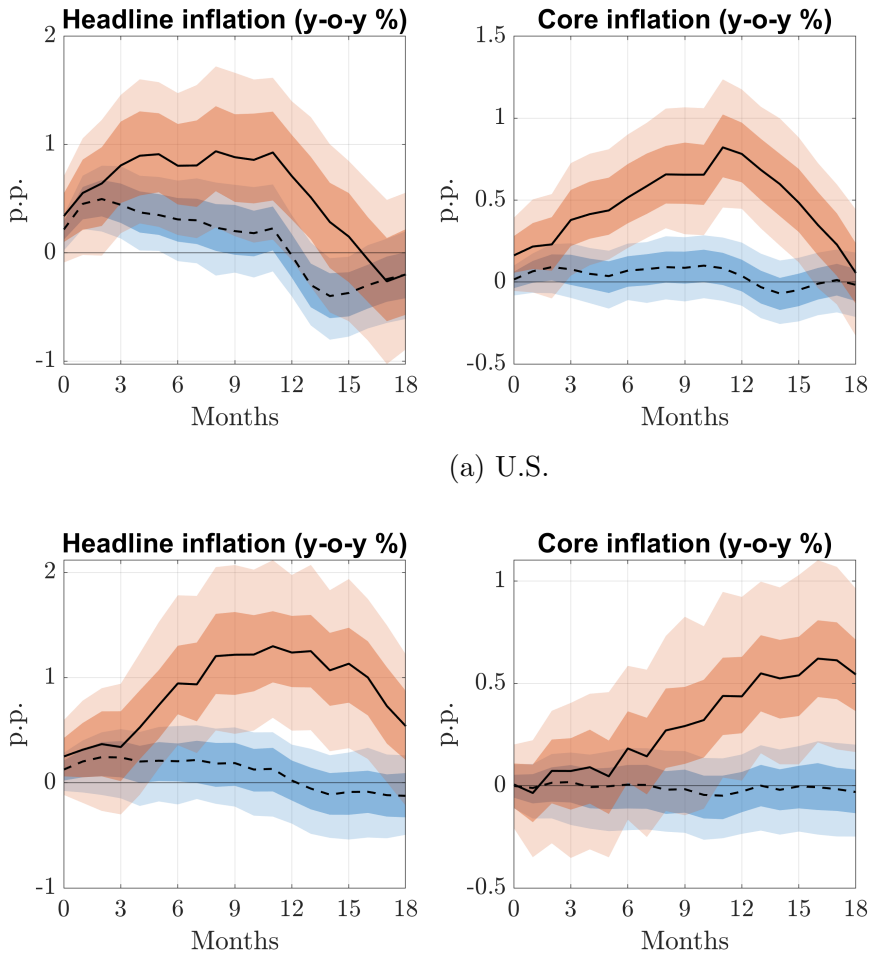
where we remark that mc_t is the real marginal cost in deviation from its steady state *under incomplete information*.

B.8 Robustness of Local Projection estimates

State-dependent LP with additional controls In the main local projection exercise in section 2.2, 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), its lags, and the interacted dummy term U_t. For each horizon $h = 0, \ldots, 18$, we therefore estimate the following local projection:

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

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.

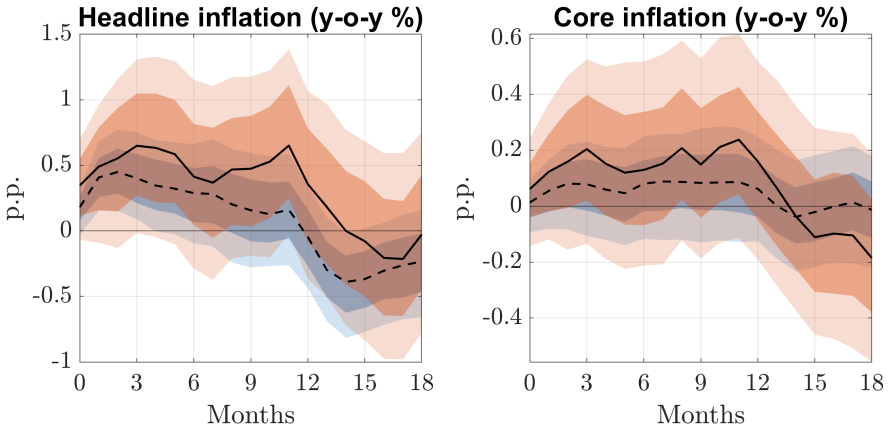


(a) U.S.

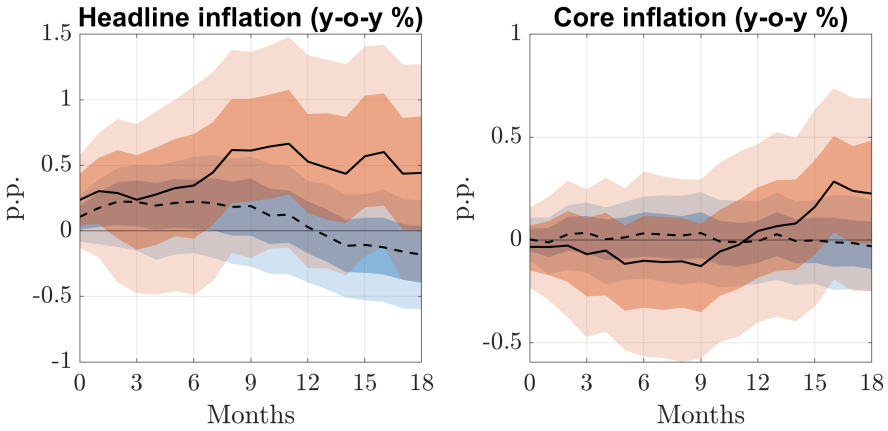
(b) Euro area

Figure 19: Headline and core inflation responses to an oil news shock across Var(GSCPI) uncertainty states – U.S. and Euro area. Additional controls for past and present transportation disruptions

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



(a) U.S.



(b) Euro area

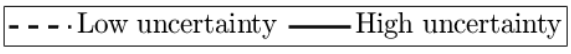


Figure 20: Headline and core inflation responses to an oil news shock across ETU index uncertainty states – U.S. and Euro area. Additional controls for past and present transportation disruptions

Notes: See the note to Figure 8 for more details on the specification and data series used.

B.9 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 January 2016 – when the ACR sample is first available – to December 2024. We observe that the two indexes, and their rolling variances, have a comparable behavior.

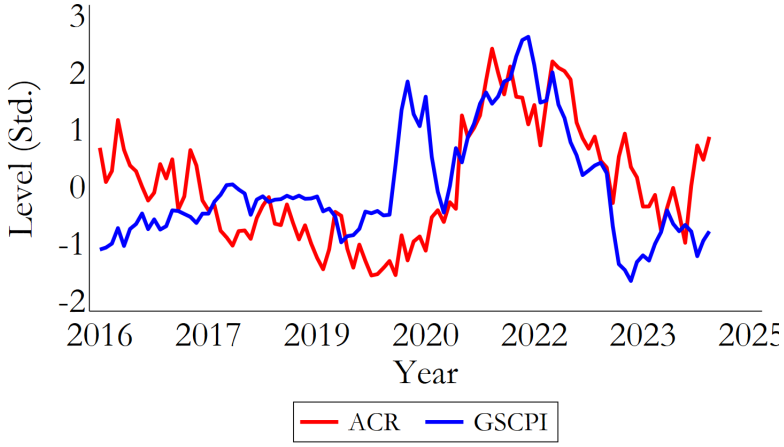


Figure 21: Evolution of GSCPI versus ACR index

Notes: Level of the GSCPI and of ACR, plotted with monthly frequency from January 2016 to June 2024. Each series is expressed in standard deviations from its respective 2016-2024 average. The ACR time series is available here: `https://globalportcongestion.github.io/blog/congestion.html`

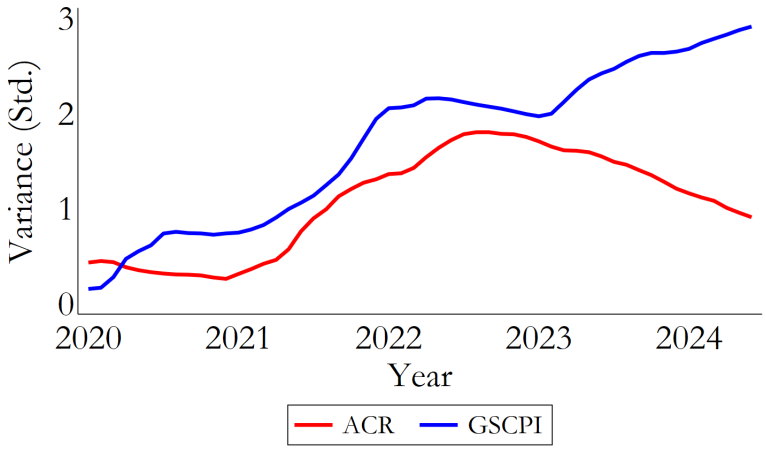


Figure 22: Rolling variance of GSCPI versus ACR index

Notes: Standardized variance of the GSCPI and of ACR computed over 48-month rolling windows, plotted with monthly frequency from January 2020 to June 2024. Each variance is standardized by its respective rolling variance computed over the whole 2020-2024 sample.

B.10 Kalman filter estimation

B.10.1 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:

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

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

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

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

The form of the log-likelihood derives from the fact that, conditional on θ_j, the vector $y_{t,j}$ (i.e., the vector of observations $\pi_{E,t}$ and p_t^{BDI}) is distributed as $y_{t,j}|\theta_j \sim \mathcal{N}(\mu(\theta_j), \Sigma(\theta_j))$. Hence, the likelihood follows a normal distribution where $\Sigma(\theta_j)$ is the variance-covariance matrix of $y_{t,j}$ conditional on θ_j. Additionally, $h_t(\theta_j)$ is defined as the residual, and is $h_t(\theta_j) = y_{j,t} - \mu_t(\theta_j)$.[54]

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 (20). 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

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

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:

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

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

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

where $(\eta_1, \eta_2, \omega, \kappa_1, \kappa_2, r_\psi)$ are the optimizer's free parameters and $\Lambda(.)$ is the logistic function $\Lambda(x) = \frac{1}{1+e^{-x}}$. Table 5 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 5: 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.[55]

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

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

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

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

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

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

Notice that all of these objects are *estimated*: they are functions of the estimated parameter vector $\hat{\theta}_j$.[56]

[55] 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.

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

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.10.2 Additional results

Figure 9 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.

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^2_ψ	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^2_ψ	0.08	0.08
	(0.04)	(0.06)

(b) Euro area

Table 6: 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). Although the panels reports some observation variances as 0.00, these are very small but strictly positive estimates (due to rounding), since $v_i = \exp(\eta_i) > 0$. In those regimes, the corresponding signal is treated as much more informative than the other, which is reflected in the highly unbalanced Kalman gains.

C Earnings calls indicators

C.1 Description of the textual measures

We construct region-specific (United States or Euro area) quarterly indicators of firms' exposure to supply chain and energy shocks using a sample of firms' earnings call transcripts retrieved from NL Analytics, spanning January 2002 to December

2024. We follow Hassan et al. (2019, 2025); Caldara et al. (2019) to build the two indexes. We gather transcripts from all the earnings calls of publicly listed firms headquartered in the U.S. or the EA in a given quarter, and we count the share of sentences that contain at least one *keyword* from the semantic group of supply chain and energy, respectively. We then standardize the resulting time series relative to their sample means and standard deviations. These measures capture the intensity with which firms discuss supply chain disruptions and energy price developments over time.

C.2 Keyword lists

To construct the keywords list for the supply chain semantic category, we refer to Hassan et al. (2025).

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

To construct the keywords list for the energy semantic category, we refer to the list of keywords part of Baker, Bloom, and Davis (2016) "Economic Policy Uncertainty,"[57] and compiled by Dang et al. (2023). We then remove some generic terms from the list[58] and obtain the final list of keywords.

Energy price keywords
1973 oil crisis, offshore drilling, West Texas intermediate, endangered species, natural gas price, climate change, oil platform, WTI, energy security, oil export, crude oil, OPEC, American petroleum institute, fracking, oil supplies, energy efficiency, Pollution, carbon tax, green energy, photovoltaics, Environment, solar energy, common ethanol fuel mixtures, internal combustion engine, shale oil, gasoline price, well logging, electric car, natural gas, sustainable energy, greenhouse gases, alternative energy, energy sector, oil and natural gas corporation, wind power, energy shock, natural resource, carbon intensity, fossil fuel, oil shale, energy shocks, oil export ban, COGIS, going green, petroleum reservoir, energy price shock, oil well, drilling mud, hydrocarbon, residual oil, energy price shocks, pipeline, energy market, liquefied petroleum gas, sustainability, energy insecurity, solar cell, ethanol price, oil and gas, wind energy, energy instability, carbon footprint, global warming, oil reserves, British thermal unit, energy crisis, COGCC, hybrid electric vehicle, petroleum industry, clean energy act 2011, energy price volatility, directional drilling, liquefied natural gas, renewable energy, corn ethanol, oil crisis, energy independence, offshore fracking, sour gas, energy conservation, ethanol fuel, oil price, wildcat well, energy tax, geothermal energy, petroleum, Brent crude, gasoline, horizontal drilling, proven reserves, clean energy, greenhouse effect, Kyoto protocol, solar power, compost, kerosene

[57] `https://www.policyuncertainty.com/energy_uncertainty.html`
[58] Namely, *energy, oil, shock, shocks, crisis, crises.*

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