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Macroeconomic regime change and the size of supply chain disruption and energy supply shocks

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Abstract

The COVID-19 pandemic and Russia's invasion of Ukraine have complicated macroeconomic forecasting and policymaking due to unprecedented disruptions in supply chains and energy markets, suggesting a new macroeconomic regime. However, we are unable to reject the null hypothesis of no structural break in March 2020. We then examine whether these shocks have increased post-COVID-19. Their sizes were initially elevated, but then have been gradually returning to pre-pandemic levels. The linear and nonlinear models reveal that supply chain disruptions cause persistent increases in expected inflation and headline goods prices, while energy supply shocks have a transitory inflation effect. The nonlinear model shows that real GDP is adversely affected by supply shocks in low growth periods.

Keywords: Business cycles, supply-chain disruption shocks, energy shocks, nonlinearities, TVAR, narrative identification

JEL Classification: C32, E32

Non-Technical Summary

The COVID-19 pandemic and Russia's invasion of Ukraine have significantly altered the favorable conditions of the Great Moderation, due to unprecedented supply chain and energy shocks. This study assesses whether a structural break occurred in March 2020 and whether these shocks have increased in size and frequency post-COVID-19, suggesting a new macroeconomic regime. The research uses both linear and nonlinear models also to analyze the impacts of these shocks on inflation and real GDP in the euro area from January 1999 to June 2024.

A key finding is that, despite significant disruptions, there is no statistical evidence of a structural break in March 2020. This suggests the fundamental relationships in the macroeconomic data have remained stable, even amidst turmoil. Initially, the size of supply chain disruption shocks increased after the onset of the pandemic, and energy shocks rose with the shortage of gas in Europe in Autumn 2021 and the subsequent Russia's invasion of Ukraine. However, both types of shocks have been gradually returning to pre-pandemic levels. This indicates that while these shocks were initially severe, their long-term effect may be less drastic than feared.

The study distinguishes between the impacts of supply chain disruptions and energy supply shocks. Supply chain disruptions lead to persistent increases in expected inflation and headline goods prices, with effects peaking about 18 to 24 months after the initial shock. In contrast, energy supply shocks tend to have a transient effect on inflation. Both types of shocks negatively affect real GDP, but the nonlinear model reveals that their impacts vary depending on economic conditions. Specifically, during periods of low economic growth, supply chain disruptions have a more significant negative impact on GDP. Conversely, during high-growth periods, these disruptions primarily lead to increased prices.

Sectoral analysis further reveals that adverse supply shocks have a more pronounced negative effect on real economic variables when overall macroeconomic conditions are already weak. This suggests that industries are more vulnerable to supply chain and energy disruptions during economic downturns. On the other hand, during periods of economic strength, these shocks tend to drive up prices more sharply.

The findings carry important implications for policymakers. The study's findings have

important implications for policymaking. The distinct transmission mechanisms of supply chain and energy shocks necessitate tailored policy responses. The persistence of supply chain disruptions in driving inflation and their short-term impact on GDP highlight the need for policies that enhance supply chain resilience. In contrast, the transitory nature of energy supply shocks on inflation but their pronounced medium-term GDP impact calls for policies that stabilize energy markets and diversify energy sources.

The energy crisis from 2021 to 2024 has significantly challenged the chemical and other energy intensive sectors, affecting production costs and competitiveness. To help the industry navigate these challenges, governments may choose to provide financial incentives for companies to invest in energy-efficient technologies and processes. Reviewing and adjusting taxation and carbon pricing mechanisms could balance emissions reduction needs with the economic pressures faced by the industry during the energy crisis.

Similarly, the automotive and related industries have faced significant challenges due to supply chain disruptions during the post-pandemic period. While governments have encouraged automotive companies to diversify their supply chains to reduce dependence on a limited number of suppliers or geographic regions, more efforts are needed to build resilience against supply chain disruptions. Additionally, governments could partner with industry to maintain strategic reserves of critical components, such as semiconductors, to buffer against supply chain disruptions. Fostering public-private partnerships to invest in and produce critical components domestically is also vital.

I Introduction

The COVID-19 pandemic and Russia's invasion of Ukraine have likely reversed the favorable supply-side conditions of the Great Moderation, significantly impacting macroeconomic forecasting and policymaking. These events introduced unprecedented economic shocks, such as supply chain and gas disruptions, which traditional forecasting models struggled to handle, complicating policymaking decisions. The sudden and severe disruptions in global supply chains, adverse energy shocks, and drastic policy interventions created a highly volatile environment. By employing euro area data from January 1999 to June 2024, we assess whether a change in the transmission mechanism has occurred, then we evaluate whether supply chain and energy shocks in the euro area have increased in size since the COVID-19 pandemic, indicating a potential shift to a new macroeconomic regime. The analysis is carried out using linear and nonlinear models, also investigating the relationship between these shocks, real GDP and both headline and expected inflation.

First, we test for a potential structural break in March 2020 using a Chow test, which is robust in the presence of possible heteroskedasticity and is applied as a joint test across multiple time series. The test does not reject the null hypothesis of no structural break.

Second, we employ a linear structural VAR (SVAR) model to extract the stochastic trends and the shocks of interest. The model's estimation, using data available until February 2020, reveals that the dynamics of the stochastic trend remain consistent with those estimated over the entire sample period up to June 2024, indicating no structural break. We then examine the relationship between supply chain disruption shocks, energy shocks, inflation and economic activity. Statistical tests are conducted to identify any significant changes in the size of these shocks following the onset of COVID-19.

Third, the role of nonlinearities is investigated conditional on the business cycle, as it is plausible that supply chain disruption and energy supply shocks have a greater impact on headline and expected inflation during periods of robust economic expansion (e.g. high-growth regime), when the economy is likely to face resource constraints, which can amplify the impact of supply shocks. To explore this, a threshold SVAR (TVAR) model, using the level of underlying real GDP growth as the state variable, is employed. The findings will help determine whether the large estimated supply shocks from the linear model represent a new post-COVID-19 norm or are a result of model misspecification, considering the relevance of nonlinearities in shock transmission.

The nonlinear pass-through of supply chain disruption shocks and energy supply shocks on aggregate consumer prices in low and high economic growth regimes, and their implications for output are important questions that have not received much academic attention. Investigating these issues could shed some light on whether aggregate prices behave as state-dependent models suggest.

We identify these shocks through sign, magnitude, and narrative restrictions.[1] Motor vehicle output in the euro area was strongly affected by disruptions in global supply chains. It is a critical sector and, across sectors, it is characterized by the longest supply chain (Boranova et al., 2022). Therefore, to identify supply chain disruption shocks, we use the suppliers' delivery times in the motor vehicle sector, which captures the extent of supply chain delays in such sector, vehicle production and vehicle prices.

Typically, the 2020 period is shut down in empirical models through dummies (Finck and Tillmann, 2022) or handled through methods addressing heteroskedasticity (Lenza and Primiceri, 2022). In this study instead, after having shown that the stochastic trends remain stable over the entire 1999-2024 sample period, the extreme volatility characterizing March-May 2020, with automotive production essentially halting in April, is used to identify the supply chain disruption shocks (De Santis, 2024). Macroeconomic shocks are better identified when they are relatively large (Rigobon, 2003). Specifically, we assume that the supply chain disruption shocks were positive (negative) in March-April (May) 2020. This assumption is corroborated by microeconometric evidence: by using difference-in-difference approach, Lebastard et al. (2023) found that the performance of French firms more exposed to global supply chains was much worse than simple exporters in March-April 2020, while the opposite was true with the recovery in May 2020. Similarly, we assume that the supply chain disruption shocks were positive in March 2021 due to the Suez Canal blockage.

Gas supplies from Russia to the European Union (EU) were cut significantly at the

[1] Edelstein and Kilian (2009a) study the impact of US retail energy price shocks on US consumer expenditure using a linear bivariate VAR identified through timing restrictions. Sign restrictions have been proposed as a better alternative approach to identify energy supply shocks (Kilian and Murphy, 2012, 2014). The approach suggested by Kilian and Murphy (2014) was used by Güntner et al. (2024) to study the impact of gas shocks on German industrial production.

beginning of the autumn 2021, contributing to the slow replenishment of gas inventories in Europe ahead of the winter season, and at the end of February 2022 Russia invaded Ukraine. Both historical episodes caused a sudden surge in energy prices and a drop in manufacturing production of the energy-intensive sectors, such as chemical and basic metals. Therefore, to identify retail energy supply shocks, we use retail energy prices, energy production and energy-intensive manufacturing production. In addition, we assume that energy supply shocks were positive in October-November 2021 and March 2022. Similarly, we assume that energy supply shocks were positive in January 2003 due to the major strike in Venezuela, which paralyzed the oil industry, leading to sharp rises in oil and retail energy prices.

The response of the other three main variables of the structural model, medium-term expected inflation, headline HICP and real GDP, is always left unrestricted also on impact. This allows us to be completely agnostic about the impact of the two supply-shocks on the key variables of the business cycle.

The linear model reveals that supply chain disruption shocks and retail energy supply shocks act as cost-push shocks, each with distinct transmission mechanisms. Supply chain disruptions lead to persistent increases in inflation expectations and headline HICP, with effects peaking around 18 to 24 months, and cause short-term GDP declines, which subsequently rebound as the disruptions are alleviated. Conversely, energy supply shocks have an insignificant impact on expected inflation, a transitory effect on headline HICP and a pronounced medium-term impact on GDP.

The nonlinear model, through the state-dependent impulse response functions (IRFs), shows that the effects of the shocks vary with the economic state. Focusing on the main differences across states, supply chain disruption shocks exert a more substantial positive impact on headline HICP during periods of high growth, whereas they have a more adverse effect on real GDP in low growth states. Energy supply shocks negatively impact real GDP during periods of low economic growth, whereas the economy appears to be unaffected during times of economic expansion. Demand shocks significantly influence expected inflation during periods of economic underperformance, while they have a more enduring effect on headline HICP during times of expansion.

Finally, an analysis of shock magnitudes over time, derived from both the linear and the nonlinear SVAR, reveals that while the size of supply chain disruption shocks and demand shocks were elevated in 2020 and energy supply shocks were elevated in 2022 compared to pre-pandemic levels, they have been gradually returning to pre-pandemic levels in 2023 and 2024.

The literature on global value chains is large (see for a review Antras and Chor, 2022), studying the optimal allocation of ownership rights along the value chain (Antras and Chor, 2013) and investigating the effects of demand (Alfaro et al., 2019), interest rate (Antràs, 2023), financing conditions (Kim and Shin, 2023) and risk (Ersahin et al., 2023). Acemoglu and Tahbaz-Salehi (2025) show that the response of the production network generates a nonlinear amplification pattern over the business cycle. Supply chain disruptions can emerge as a powerful propagation mechanism during severe downturns, while playing a much more limited role during milder downturns.

Supply chain disruption shocks have been identified using sign and narrative restrictions (Finck and Tillmann, 2022; Celasun et al., 2022; Kemp et al., 2023; Kabaca and Tuzcuoglu, 2023; De Santis, 2024; Bai et al., 2024) or imposing prior distributions for structural parameters (Aastveit et al., 2024). di Giovanni et al. (2022) instead study the propagation of shocks through interconnected sectors defining the supply chain disruptions as labour shortages. Other studies analyse the impact of rising shipping costs on inflation finding a positive statistical significant effect (Herriford et al., 2016; Carrière-Swallow et al., 2023).

As for the retail energy supply shocks, De Santis (2024) and De Santis and Tornese (2025) use sign, magnitude and narrative restrictions on retail energy prices and the energy-intensive sector. Another strand of the literature for the United States looks at gasoline prices (Edelstein and Kilian, 2009a; Kilian and Zhou, 2022a). Energy supply shocks are typically studied through the global crude oil market and using linear frameworks.[2] Oil prices have also been used in non-linear models. Herrera et al. (2011) find a strong nonlinear response of U.S. energy-intensive production to oil prices.[3] Baumeister and Peersman (2013) investigate

[2]Among others, see Kilian (2009); Kilian and Murphy (2012, 2014); Aastveit et al. (2015); Baumeister and Kilian (2016); Baumeister and Hamilton (2019); Caldara et al. (2019); Känzig (2021); Aastveit et al. (2021); Kilian and Zhou (2022b); Baumeister (2023); Aastveit et al. (2024). Another strand of the literature has looked at gasoline prices (Kilian and Zhou, 2022a) and jointly at global oil market and the European gas market (Casoli et al., 2024).

[3]Kilian and Vigfusson (2011) find little evidence of nonlinearity in the relation between oil prices and U.S. GDP growth, but they address the question using linear methods. One key criticism made by Hamilton (2011) to Kilian and Vigfusson (2011)'s approach is that one cannot rely on linear models to address nonlinearities.

the time-varying effects of oil supply shocks on the US economy, but the method is agnostic about the reason why the effects of the shocks may have changed over time. Holm-Hadulla and Hubrich (2017) use a Markov Switching model without distinguishing the source of oil price shocks, while (Mumtaz et al., 2018) identify demand and supply oil price shocks using a TVAR with sign restrictions, finding that stock prices respond negatively to oil supply shocks only when oil inflation is low. Knotek and Zaman (2021) assess the asymmetric responses of consumer spending to energy prices using the reduced form residuals for the analysis.

We prefer to use energy prices in the model, because oil and petroleum products now account for less than 15% of the energy mix (see Longaric et al., 2025). In the European Union, oil and oil products are crucial, particularly in the transportation sector and the petrochemical industry for producing plastics, chemicals, and other goods. However, their overall share in the energy mix has decreased in favor of natural gas and renewable energy sources. In industrial production, the primary energy sources are electricity and natural gas, each comprising approximately one-third of the EU's industrial energy mix, with oil and petroleum products, along with renewables and biofuels, each contributing 11%. Although natural gas and other fossil fuels remain vital for energy production, the share of renewables in the EU's electricity generation is steadily increasing. Electricity prices are closely tied to fossil fuels due to the marginal pricing system, where prices are set by the costliest facility in use at any given time. As a result, gas often determines the price. Moreover, while oil can be easily transported globally, gas typically flows through pipelines. Therefore, a gas shortage cannot be easily substituted. The 2022 Russian invasion of Ukraine and the ensuing energy dispute with Europe highlighted the critical role of gas and the challenges in reducing reliance on Russian energy in the short term.

Given these considerations, this paper focuses on linear and nonlinear effects arising from retail energy supply shocks using a composite energy index, which includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment. Similarly, the analysis considers all activities directly related to energy production in the euro area, rather than focusing solely on oil production. This broader perspective more accurately captures fluctuations in the overall energy market and reflects the diverse energy

He also showed that nonlinearities are the consequence of large movements in oil prices.

mix used in production.

The paper is structured as follows. Section II presents the model. Section III describes the shocks' identification strategy. Section IV discusses the key results. Section V concludes.

II Framework

We employ a Bayesian SVAR, where supply and demand shocks are identified using sign, magnitude and narrative restrictions. Given that the macroeconomic responses could depend on the state of the economy a TVAR is also estimated, where transitions across states (i.e., low- and high-growth regimes) are defined by an endogenously determined underlying real GDP growth.

II.A Linear specification

The reduced-form VAR takes the following form

$$\mathbf{X}_t = \mathbf{c} + \mathbf{\Pi}(\mathbf{L})\mathbf{X}_{t-1} + \mathbf{u}_t, \tag{1}$$

$$\mathbf{u}_t \sim N(0, \mathbf{\Omega}), \tag{2}$$

where $\mathbf{u}_t$ denotes the $n \times 1$ vector of forecast errors, $\mathbf{\Omega}$ the covariance matrix of the residuals, $\mathbf{c}$ the vector of intercepts and $\mathbf{\Pi}$ the lag polynomial.

The model is structured into three primary blocks: a macroeconomic block (comprising inflation expectations, headline inflation, and real GDP), an energy block (including energy prices, energy production, and the output of the energy-intensive sector), and an automotive sector block (encompassing vehicle producer prices, vehicle production, and suppliers' delivery times in the vehicle sector). The vector $\mathbf{x}_t = [\pi_t^e, p_t, p_t^v, p_t^e, y_t, y_t^v, y_t^e, y_t^i, s_t^v]'$ defines the nine variables of the SVAR, where π_t^e denotes the SPF 2-year inflation expectations,[4] p_t headline HICP, p_t^v the vehicle producer price, p_t^e the energy price, y_t real GDP, y_t^v the vehicle

[4]The European Central Bank's SPF collects information on the expected rates of inflation in the euro area at several horizons, ranging from the current year to the longer term. The SPF began in 1999. The aggregate results and microdata are published four times a year. The quarterly observations are linearly interporlated to obtain the monthly frequency.

production, y_t^e energy production,[5] y_t^i the output of the energy-intensive sector and s_t^v the suppliers' delivery times of the vehicle sector. All variables, except s_t^v and π_t^e, are defined in logs.

The stability condition of a SVAR requires that all the roots, r, of $\mathbf{\Pi}$

$$|\mathbf{\Pi}(r)| = |\mathbf{I_n} - \mathbf{\Pi}_1 r - \mathbf{\Pi}_2 r^2 - .... - \mathbf{\Pi}_p r^p| = 0, \tag{3}$$

lie outside the unit circle, $|r > 0|$. This guarantees that the system of equations is stationary.

Inference on the reduced form parameters of the SVAR is performed in a Bayesian framework using a standard Monte Carlo algorithm of the type described by Kadiyala and Karlsson (1997), which allows to draw from the posterior of the model parameters.

For the parameters, we assume natural conjugate Normal-Inverse-Wishart (N-IW) priors. The IW priors for Ω have $n + 2$ degrees of freedom and diagonal scale matrix with the i-th diagonal elements equal to the mean squared error from estimating an AR(1) for the i-th variable. Conditional on Ω, the priors for Π are Normal with Minnesota-type mean and variance (Doan et al., 1984), and complemented with a dummy-initial observation prior (Sims, 1993) that is consistent with the assumption of cointegration.

Detailed information on the dataset is provided in the Appendix with the time series shown in Figure A1. The monthly sample spans over the period going from January 1999 to June 2024.[6] We convert real GDP to a monthly frequency, applying the method proposed by Chow and Lin (1971) and utilizing monthly data from industrial production and real retail sales. While the quarter-on-quarter real GDP growth rates align with observed values, the intra-quarter dynamics follow those of industrial production and real retail sales. Thus, this monthly real GDP series serves as a coincident business cycle indicator, capturing both supply and demand factors, but the GDP series is fully recovered in quarterly terms.[7] A robustness check is conducted using industrial production, which is available on a monthly

[5]We take the MIG (Main Industrial Groupings) energy production definition by Eurostat. It includes extraction of crude petroleum and natural gas, mining of coal and lignite, mining of uranium and thorium ores, manufacture of coke and refined petroleum products, production and distribution of electricity, gas, steam, and air conditioning.

[6]We set the lag order p to 6 in order to estimate less parameters given the sample size. The use of six lags in a monthly VAR is not unusual (e.g., for example, Ludvigson et al., 2021; Caggiano et al., 2021; Cascaldi-Garcia and Galvao, 2021).

[7]A similar procedure was undertaken by Bernanke and Mihov (1998) and Uhlig (2005).

frequency, instead of real GDP.

The Suppliers' Delivery Times Index from Standard and Poor's (S&P) Global Purchasing Managers' Index (PMI) business surveys assess the degree of supply chain delays within an economy, acting as a crucial indicator of capacity constraints. In these surveys, purchasing managers in the vehicle sector report whether their suppliers are taking more or less time, on average, to deliver inputs to their factories. This information is particularly vital due to the industry's just-in-time strategy, highly personalized car configurations, and strict safety requirements necessitating specific chips.

During the 2020-2022 period, a shortage of chips and other essential components for assembling new motor vehicles led to an unprecedented reduction in supply. Container vessel activity faced significant disruptions due to the pandemic. The global misallocation of containers, following the collapse of world trade in March and April 2020, and the rescheduling of numerous cargo vessels arriving late at their destinations, resulted in considerable supply bottlenecks.[8] These disruptions in cargo activity affected all manufacturing sectors, particularly those with the longest supply chains, such as the automotive industry.

Another factor exacerbating these supply bottlenecks was the renewed lockdown measures due to the spread of the Delta variant in certain Asia-Pacific countries, including Malaysia, Singapore, Thailand, and Vietnam. These regions are crucial to semiconductor chip production, and the lockdowns generated a crisis in the supply of semiconductors.

Therefore, the use of suppliers' delivery times of the vehicle sector together with automotive production and car prices are a suitable candidate to identify disruption in supply chains.[9] Notice that the suppliers' delivery times rose during the global financial crisis in 2008-2009 and the sovereign debt crisis in 2010-2011 because they were driven by negative demand shocks, which tend to shorten the suppliers' delivery times, given that more resources are available to satisfy diminished demand. Instead, the index dropped in March

[8] According to UNCTAD, the average time spent by container vessels in ports in the first half of 2021 was 11% higher compared to the pre-pandemic average in 2018-19. In Europe, due to congestion, scheduling delays, and infrastructure constraints, German and French ports experienced a significant increase in average port stays—42% and 25% higher than their 2018-19 averages, respectively—exceeding even those seen in the United States.

[9] The motor vehicle industry is present in several euro area countries covering 93.6% of euro area GDP in 2021 and, therefore, making the sector a good proxy for the analysis. According to the European Automobile Manufacturers' Association, or ACEA, motor vehicles were produced in the following 12 euro area countries: Austria, Belgium, Finland, France, Germany, Italy, Lithuania, the Netherlands, Portugal, Slovakia, Slovenia and Spain.

and April 2020, it jumped back in May 2020 and it recovered in the summer 2020 to drop again in the autumn 2020. The sharp lengthening recorded after the pandemic hit in March 2020 can be exploited, because it was driven by supply considerations, as we can exclude the hypothesis that demand rose sharply in that period. Instead, the lengthening recorded in the autumn 2020 can be either driven by the sharp recovery in demand (for work-related electronic equipment) or by adverse supply shocks to the supply chain. We exploit the extreme volatility during the spring 2020 to identify the supply chain disruption shocks.

Gas and renewable sources like wind, solar, geothermal and hydropower have become important alternative sources in the last two decades for energy supplies' security motives and for environmental issues. Their prices are only weakly correlated with oil prices. Therefore, we employ the HICP category "Energy (ENRGY)" for goods and services, rather than oil prices to identify energy shocks. The retail energy price includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment. As for energy production, we take the MIG (Main Industrial Groupings) energy production definition by Eurostat. It includes extraction of crude petroleum and natural gas, mining of coal and lignite, mining of uranium and thorium ores, manufacture of coke and refined petroleum products, production and distribution of electricity, gas, steam, and air conditioning.

The energy intensive sector is defined by aggregating the production of chemicals, chemical products and basic metals using time-varying weights provided by Eurostat. The energy-intensive sector accounts on average for about 10% of euro area industrial production.

II.B Nonlinear specification

We are also interested in exploring the nonlinearities involved in the propagation of supply chain disruptions, energy supply issues, and aggregate demand shocks. Throughout the paper, we present results derived from both the linear SVAR and the TVAR models. We do this because it is important to identify which aspects of the results are captured by both models and which aspects are overlooked by the linear SVAR. The SVAR is the standard model in practitioners' toolkit and it represents a specifically restricted version of the more general TVAR.

The reduced-form TVAR takes the following form

$$\begin{aligned}\mathbf{X}_t = (\mathbf{c}_{Low} + \mathbf{\Pi}_{Low}(\mathbf{L})\mathbf{X}_{t-1})I\{z_{t-1} < z^*\}+ \\ (\mathbf{c}_{High} + \mathbf{\Pi}_{High}(\mathbf{L})\mathbf{X}_{t-1})I\{z_{t-1} \geq z^*\} + \mathbf{u}_t,\end{aligned} \tag{4}$$

$$\mathbf{u}_t \sim N(0, \mathbf{\Omega}_t), \tag{5}$$

$$\mathbf{\Omega}_t = \mathbf{\Omega}_{Low} I\{z_{t-1} < z^*\} + \mathbf{\Omega}_{High} I\{z_{t-1} \geq z^*\}, \tag{6}$$

where $\mathbf{u}_t$ denotes the $n \times 1$ vector of forecast errors, $\mathbf{\Omega}_t$ the state-contingent covariance matrix of the residuals, z_t the state variable, z^* a threshold of z_t, $\mathbf{c}_{Low}$ and $\mathbf{c}_{High}$ the vector of intercepts in the two regimes and $\mathbf{\Pi}_{Low}$, $\mathbf{\Pi}_{High}$ the lag polynomials. The regime switches are governed by the indicator function I and are indexed by $t-1$ to avoid endogeneity problems.

As for linear VARs, the stability condition of a TVAR requires that all the roots, r, of $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$

$$|\mathbf{\Pi}_S(r)| = |\mathbf{I_n} - \mathbf{\Pi}_{S,1}r - \mathbf{\Pi}_{S,2}r^2 - .... - \mathbf{\Pi}_{S,p}r^p| = 0, \quad S \in (Low, High), \tag{7}$$

lie outside the unit circle, $|r > 1|$. This guarantees that the system of equations is stationary within each regime.[10]

The state variable, z_t, is assumed to depend on current and past month-on-month real GDP growth using an exponentially weighted moving average (EWMA), which gives larger weights, α, to the most recent observations and geometrically declining weights to past real GDP growth rates, $z_t = \sum_{i=0}^{\infty} \alpha(1-\alpha)^i(y_{t-i} - y_{t-1-i})$. Hence, z_t is a function of the entire history of y_t and can be written as:

$$z_t = \alpha(y_t - y_{t-1}) + (1-\alpha)z_{t-1}, \quad \alpha \in (0, 1). \tag{8}$$

[10]The condition that all the roots in each regime lie outside the unit circle ensures that the system is locally stationary, ruling out explosive behaviours. In this context Franses and Dijk (2000) discuss the issue of stationarity in high-order non-linear models, suggesting that a pragmatic way to investigate the stationarity properties of such models is to perform a deterministic simulation. This involves computing the values of the variables, given starting values, while setting all shocks equal to zero. Essentially, the simulations we employ to generate non-linear IRFs are similar in spirit to the one suggested by the authors, and show that none of our posterior draws display explosive or oscillating (across regimes) behaviours. Thus, the model aligns with the definition of global stationarity given by Franses and Dijk (2000).

For the parameters of both regimes, we assume natural conjugate Normal-Inverse-Wishart (N-IW) priors. The IW priors for Ω_{low} and Ω_{high} have $n+2$ degrees of freedom and diagonal scale matrix with the i-th diagonal elements equal to the mean squared error from estimating an AR(1) for the i-th variable. Conditional on Ω_{low} and Ω_{high}, the priors for Π_{low} and Π_{high} are Normal with Minnesota-type mean and variance, and complemented with a dummy-initial observation prior.

Inference on the reduced form parameters of the TVAR is performed in a Bayesian framework using a multivariate version of the sampler developed in Chen and Lee (1995). The posterior draws of reduced form parameters are then transformed into structural parameters that satisfy the desired restrictions employing the rejection sampler of Rubio-Ramirez et al. (2010). Narrative restrictions are therefore informative about the identification of shocks in the regime in which the event took place. The sampler is described in the Appendix.

One disadvantage of the TVAR model is its abrupt regime changes, which occur when the threshold variable crosses a specific value. To mitigate the issue of sudden and erratic "jumps" between regimes from one month to the next, a condition is imposed that requires the threshold variable to remain in the same regime for at least two consecutive periods before transitioning. This adjustment ensures more stable and meaningful shifts between states, addressing the erratic behaviour inherent in the original TVAR specification.

A natural alternative to this approach would be the use of a Smooth-Transition SVAR. However, it is important to note that, unlike TVARs, a Smooth-Transition dynamic for reduced-form parameters does not translate into a Smooth-Transition dynamic for structural parameters, which are the basis for IRFs. Specifically, assuming a smooth transition between the two regimes in Equation (6) does not imply that the impact matrix (which defines the contemporaneous reaction of variables to a shock) is a weighted average of the impact matrices from the two extreme regimes. This crucially means that any narrative restriction imposed would be uninformative for identifying structural shocks in periods other than the one to which the narrative refers.

II.C The state variable

In several studies, the state variable is computed using a moving average of the last months of the variable of interest (e.g. Tenreyro and Thwaites, 2016; Ramey and Zubairy, 2018; Knotek and Zaman, 2021). This approach tends by construction to postpone the potential change in regime, if the shock is not relatively large. The solution proposed by others is to take a centered moving average, between $t-h$ and $t+h$ (e.g. Auerbach and Gorodnichenko, 2012; Ascari and Haber, 2022). However, this provides inconsistent estimates, because the state variable ought to be predetermined, so that it is uncorrelated with the shock happening at time t or in future periods.

We construct the state variable, z_t, using (8). Assigning a relatively larger weight to the most recent observations allows for better capturing the timing of regime changes. We calibrate α such that z_t comoves closely with year-on-year real GDP growth, a measure closely monitored by policymakers and market participants. This is achieved with $\alpha = 0.125$. Specifically, z_t is calculated using month-on-month real GDP growth starting from January 1995, as a sufficient number of observations are required to estimate the underlying real GDP growth, with $\alpha = 0.125$. Over the sample period January 1999 - June 2024, the correlation between underlying real GDP growth, z_t, and year-on-year real GDP growht is 84% (see Figure 1). The median of our annualised monthly state variable is 1.6% and of the annual real GDP growth rate is 1.3%. This threshold choice is further supported by a grid search over possible percentile values of the observations. The marginal likelihood is maximized at the 53rd percentile, suggesting a threshold for z_t at 1.7% annualized. Using the median has the advantage that the potential differential results in the two regimes do not depend on the number of observations.

III Shocks' Identification

The reduced form residuals can be written as

$$\mathbf{u}_t = \mathbf{B}_0^{-1} \epsilon_t, \tag{9}$$

in the linear specification, where $\mathbf{B}_0^{-1}$ is the structural impact multiplier matrix, and ϵ_t is the vector of standard Normal structural shocks. and as

$$\mathbf{u}_t = (\mathbf{B}_{0,Low}^{-1} I\{z_{t-1} < z^*\} + \mathbf{B}_{0,High}^{-1} I\{z_{t-1} \geq z^*\})\epsilon_t, \tag{10}$$

in the nonlinear setting, where $\mathbf{B}_{0,Low}^{-1}$ and $\mathbf{B}_{0,High}^{-1}$ are the structural impact multiplier matrices in the low- and high-inflation regimes. The differences in the propagation of shocks across regimes is then due to differences in the impact matrices $\mathbf{B}_{0,Low}^{-1}$ and $\mathbf{B}_{0,High}^{-1}$ and differences in lag polynomial $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$.

Given the reduced form parameters, the set of permissible impact matrices is infinite and the impact matrices cannot be identified uniquely from the data. Shocks are therefore identified using sign, magnitude and narrative restrictions. We adapt the narrative identification method of Antolín-Díaz and Rubio-Ramírez (2018) to the non-linear setting, refraining from applying the importance weighting step as suggested by Giacomini et al. (2020).

III.A Sign, Magnitude and Narrative Restrictions

The restrictions imposed on shocks are summarized in Table 1. Sign and magnitude restrictions allow to estimate a set identified model. Narrative restrictions are imposed to sharpen the identification of the shocks.

Sign restrictions. We posit that supply chain disruption shocks lead to reductions in the one-step-ahead forecast errors for vehicle output and suppliers' delivery times, while simultaneously causing an increase in motor vehicle prices. Similarly, we hypothesize that adverse energy supply shocks result in higher one-step-ahead forecast errors for energy prices, and lower forecast errors for energy production and the manufacturing output of energy-intensive goods. These assumptions are consistent with those proposed by Kilian and Murphy (2012), Baumeister and Hamilton (2019) and De Santis (2024). The responses of real GDP, headline prices, and expected inflation are determined endogenously at impact. This approach is taken to circumvent the necessity for *a priori* judgments regarding the sign and timing of shock propagation on aggregate economic activity.

As suggested by Canova and Paustian (2011), improved inference related to the shocks of interest can be achieved by identifying additional macroeconomic shocks, even if they are not the primary focus of the analysis. Therefore, in addition to identifying two supply shocks, we also identify specific demand shocks, which affect both energy prices and the pressure on the supply chains. We assume that demand shocks cause one-step-ahead forecast errors for headline HICP, energy HICP and GDP to move in the same direction, while causing the one-step-ahead forecast errors for suppliers' delivery times to move in the opposite direction. The remaining shocks are left unlabeled.

Magnitude restrictions. The sign restrictions alone are insufficient to distinguish between the two supply shocks. To disentangle them, we employ magnitude restrictions that affect the forecast error variance decomposition (FEVD) of specific variables at the point of impact. Arias et al. (2021) compare the effects of two shocks on the same variable, enabling them to impose magnitude restrictions on the impulse response functions (IRFs) at impact. In contrast, we compare the effects of a specific shock on two different variables with distinct variances. Therefore, we normalize the effects through the FEVD. In other words, rather than imposing bounds on the FEVD as in Volpicella (2022), we impose inequality restrictions between FEVDs of different shocks. Specifically, we assume that supply chain disruption shocks contribute more to the FEVD of suppliers' delivery times at impact than to the Energy HICP, whereas energy supply shocks contribute more to the FEVD of the Energy HICP at impact than to suppliers' delivery times. This distinction is illustrated in Table 1 with '++' versus '+'. Like any identification restriction, the one we have described is not entirely without consequence. However, we believe it is generally acceptable. This assumption simply posits that, on impact, a supply chain disruption shock causes a greater proportion of the unexpected variation observed in automotive suppliers' delivery times compared to the variation it induces in the Energy HICP. Similarly, on impact, the energy supply shock contributes more to the unexpected variation in the Energy HICP than it does to the unexpected time variation seen in suppliers' delivery times.

Narrative sign restrictions. Among the admissible models that satisfy the sign and magnitude restrictions, we follow the suggestion of Antolín-Díaz and Rubio-Ramírez (2018) and assume that the supply chain disruption shocks and energy supply shocks must be positive on a specific date t.

Table 1: Sign, magnitude and narrative restrictions

	Supply chain disruption	**Energy supply**	**Demand**
Variables	Panel A: *Sign restrictions on the impact matrix* B_0^{-1}		
Expected inflation 2-year ahead			
Headline HICP			+
Real GDP			+
Vehicle prices	+		
Vehicle output	-		
Vehicle suppliers' delivery times	-		-
Energy prices		+	+
Energy output		-	
Energy-intensive output		-	
Variables	Panel B: Magnitude restrictions on the FEVD at $h = 0$		
Vehicle suppliers' delivery times	++	+	
Energy HICP	+	++	
Dates	Panel C: *Narrative sign restrictions*		
03/20 - 04/20	+		-
05/20	-		+
10/21 - 11/21		+	
03/22		+	
Dates	Panel D: *Sign contribution restrictions*		
04/20 (low growth)	$\mathrm{FE}^{s^v}_t$		
03/21 (high growth)	$\mathrm{FE}^{s^v}_t$		
01/03 (low growth)		$\mathrm{FE}^{p^e}_t$	
03/22 (high growth)		$\mathrm{FE}^{p^e}_t$	

In March and April 2020, the economy froze due to the restrictions introduced by the governments to contain the pandemic. Intermediate goods could not be supplied timely and the demand of goods and services dropped because people were forced to stayed at home. Therefore, we assume that supply chain disruption shocks were positive, while demand shocks were negative, in March and April of 2020. The sharp fall in economic activity was followed by a dramatic rise in May 2020. In order to characterize the V-shape recovery, we assume that in May 2020 supply chain disruption shocks were negative and demand shocks were positive.

In March 2021, the Suez Canal was totally blocked for six days by a 400 metre-long container ship. The obstruction created a massive traffic jam in the vital passage, straining supply chains already burdened by the coronavirus pandemic. Therefore, we assume that the supply chain disruption shocks were positive in that month. A similar assumption is made by Finck and Tillmann (2022), while Furceri et al. (2022) use the Suez Canal obstruction in March 2021 as an exogenous instrument for the identification of shipping shocks.

On December 2, 2002, a major strike started in Venezuela, primarily targeting the state oil company PDVSA. The strike aimed to oust President Chávez, who was perceived as anti-business and threatening to private property. It paralyzed the oil industry, which is vital to Venezuela's economy, leading to severe economic disruption. The Brent oil price rose month-on-month by 8.2% and 12.4% in December 2002 and January 2003, respectively. The pass-through to energy prices implied an increase in euro area energy prices by 3.2% in January 2023. Ultimately, the strike failed after weeks of turmoil, and Chávez's government regained control of PDVSA. Therefore, we assume that energy supply shocks were positive in that month.

In autumn 2021 and again in March 2022, euro area energy prices rose sharply, as a result of the cut in Russian gas supplies to Europe via the Yamal-Europe pipeline and in the aftermath of the Russian invasion of Ukraine. Almost 30% of the EU crude oil imports, 40% of the EU natural gas imports and 50% of EU solid fossil fuel (mostly coal) imports originated from Russia. By keeping deliveries to Europe deliberately tight, Russia engineered an energy crunch and the ballooning of gas prices. Over the same period, the production of the energy intensive sector (chemicals and basic metals) dropped. We assume that energy supply shocks are positive in these three months.[11]

The demand shocks are fully captured by the sign restrictions, including the discretionary reaction of fiscal policy, which has been rather significant over the period 2020-22. However, there are some effects of reopening that can be captured only through narrative restrictions. We assume that all demand shocks were negative in March and April 2020, as households were constrained to consume being forced to stay at home. At the same time, we assume that all demand shocks were positive in May 2020 with the partial reopening of the activities.

In the appendix, we also consider other narratives that might have affected demand. The success of the vaccination programme against Covid-19 allowed governments to lift the restrictions from March 2021. In Germany, for example, hairdressers were allowed to reopen from March 1, 2021. Subsequently, Germany announced the reopening to tourists on June 15th. In March and June 2021, euro area monthly real GDP growth is estimated to have risen by 2.5% and 2.1% month-on-month, respectively.[12] Finally, we assume that the demand

[11]Given the sharp rise in energy prices in March 2022 following the invasion of Ukraine, we also assume that the 1-step ahead forecast error of energy prices is mostly explained by energy supply shocks.

[12]In March and June 2021, retail sales rose by 3.9% and 2.5% month-on-month, and service production rose by 3.5% and 3.7%respectively, mainly due to higher demand for high contact-intensive services, such as hotels, restaurant, arts, entertainment and transport.

shocks were positive in May 2022, as output rose strongly in that month, despite the war in Ukraine. Most of the unexpectedly robust growth was due to strong activity in the services sector following the lifting of most pandemic-related restrictions (see ECB, 2022). In the Appendix, we assume that all demand shocks in these three months are positive and show that the results are robust to such assumptions.

Signed contribution restrictions. To refine the identification of demand from supply shocks, we impose specific restrictions on key dates, ensuring that supply-disruption shocks and energy supply shocks are the primary contributors to the one-step-ahead forecast errors in vehicle suppliers' delivery times and energy prices, respectively.

For vehicle output suppliers' delivery times, this assumption is applied in April 2020 and March 2021 (refer to Panel D of Table 1). In particular, the sharp decline in vehicle suppliers' delivery times observed after the onset of the pandemic can be leveraged to identify supply chain disruption shocks, as it cannot be driven by a significant demand increase during that period. It is worth mentioning that, during April 2020, the underlying real GDP growth experienced a contraction, whereas economic activity surged beyond its median value around March 2021. These periods align to provide at least one signed contribution restriction for each economic regime, making them highly informative for identifying supply chain disruption shocks.

For energy prices, the sign contribution restriction is applied in January 2003, a period marked by low growth, and in March 2022, a period characterized by high growth. These assumptions allow us to effectively identify energy shocks.

Following De Santis and Van der Weken (2022), the identification is less restrictive than Antolín-Díaz and Rubio-Ramírez (2018), as we allow the unrestricted shocks to have an even larger contribution to the one-step ahead forecast error of the vehicle output suppliers' delivery times and energy prices, if the contribution of that unrestricted shock moves such forecast errors in the opposite direction.

III.B Nonlinear Structural Impulse Responses

Structural shocks, ϵ_t, may have nonlinear effects on $\mathbf{X}_t$. They depend on the history of the data, Γ_{t-1}, and on the sign and magnitude of the structural shocks, ϵ_t, with effects from

t to $t+k$. z_{t-1} is a function of y_{t-1} and, therefore, z_t, z_{t+1},...., z_{t+k-1} are endogenously determined in the TVAR. To construct the structural response functions, the feedback from future changes in z_{t-1} into the dynamics of macroeconomic system outght to be taken into account.

Following Balke (2000) in a TVAR setting and Koop et al. (1996),[13] who proposed the construction of the response functions using the conditional expectations, we compute the nonlinear structural IRFs as the difference between the expectations of the realizations $\mathbf{X}_{t+k}$ at horizon k, conditional on a given value of structural shock of interest, ϵ_t, and the information set at time $t-1$, Γ_{t-1}, and the expectations of the realizations $\mathbf{X}_{t+k}$ conditioned only on Γ_{t-1}:

$$IRF_{\mathbf{X},S}(k,\epsilon_t,\Gamma_{t-1}) \equiv \mathbb{E}(\mathbf{X}_{t+k}|\ \Gamma_{t-1},\epsilon_t) - \mathbb{E}(\mathbf{X}_{t+k}|\ \Gamma_{t-1}), \tag{11}$$

where $S \in \{Low, High\}$ indicates whether the shock at time t impacts the economy while it is in the low- or high-growth state. The conditional expectations are calculated by simulating forward the model. In such simulation, all structural shocks are drawn from their distribution, with the exception of the shock of interest at time t, which is set equal to the value ϵ_t in the construction of $\mathbb{E}(\mathbf{X_{t+k}}|\Gamma_{t-1},\epsilon_t)$.

It is worth emphasizing that the switch among regimes is treated as endogenous, as the economy can shift from low to high economic growth regimes or *viceversa* over the simulation horizon, depending on the sign and the size of the shock, the estimated parameters and the specific history of the system prior to the shock. The starting points are assumed to be the mean of all the in-sample observations in each regime, in order to obtain the most representative picture of the dynamics associated to each regime.

IV Business Cycle Response to Economic Shocks

IV.A Structural break and stochastic trends

Since the identification relies on the extraordinary volatility occurred during and after the Covid-19 period, we first assess whether there are no significant structural breaks in 2020.

[13] Koop et al. (1996) were not concerned about structural identification, they used the reduced form residuals. Given that we focus on structural identification, the algorithm differs from Koop et al.'s approach. See also Kilian and Lütkepohl (2017, Chapter 18) for a discussion of state dependent IRFs.

We formally test for a potential structural break in March 2020 using a Chow test. This test checks the hypothesis that the slope parameters of the VAR model do not change in the post-March 2020 period. To make the test robust to the possible presence of heteroskedasticity, we compute the p-value employing the wild bootstrap approach proposed by Hafner and Herwartz (2009).[14]

It is worth noting that a sufficient assumption for standard inference to apply is that the system is stable, as in Eq. 7. Nonetheless, correct inference can still be achieved even if a unit root is present, provided that the lag length of the estimated model exceeds the true lag length, as discussed by Dolado and Lütkepohl (1996). Given that the AIC, BIC, and HQ information criteria recommend using 5, 1, and 2 lags respectively, it is highly likely that our estimated models are lag-augmented, and hence that the conditions outlined by Dolado and Lütkepohl (1996) apply.

The Chow test does not reject the hypothesis of no structural break, yielding a p-value of 0.26. This indicates that there is no evidence of a change in the co-movement of the variables after the Covid-19 outbreak. Furthermore, we conducted the same test to verify that also the slope parameters of the TVAR remained constant within both regimes after March 2020. The p-values, 0.14 for the high-growth regime and 0.97 for the low-growth regime, are significantly higher than any reasonable confidence level, further supporting the stability of these parameters.

Additionally, we compare the dynamics of the stochastic trend implied by a model estimated with data available until February 2020 with those estimated for the post-March 2020 period. Consistent with previous findings, a joint Chow test on the slope parameters of AR(6) models estimated for the stochastic trends of all variables does not reject the hypothesis of no breaks, yielding a p-value of 0.20. All in all, the difference between the observed values and their stochastic trend can be explained by macroeconomic shocks, which we need to identify.

[14]We perform 1000 bootstrap iterations, computing the Wald statistics based on White-type heteroskedasticity-robust covariance matrices. The results do not change increasing the number of bootstrap draws or using homoskedasticity-based covariance matrices. Moreover, we performed the same tests employing the recursive design block bootstrap of Brüggemann et al. (2016), obtaining similar results.

IV.B Macroeconomic impact of economic shocks

We identify the shocks as detailed in Table 1 utilizing sign, magnitude, and narrative restrictions.[15] The identification of supply shocks is achieved by leaving the responses of the professional forecasters' 2-year inflation expectations, headline HICP, and real GDP unrestricted. Consequently, their IRFs provide significant insights. The results for the sectoral variables are discussed in Section IV.D.

The IRFs of the linear model are presented in Panel A of Figure 2. Each subplot features the median IRFs (solid blue line) and the corresponding 68% posterior pointwise credible intervals.

The results indicate that both supply chain disruption shocks and retail energy supply shocks act as cost-push shocks, albeit with markedly different transmission mechanisms. The 2-year inflation expectations of professional forecasters and the headline HICP rise a few months after adverse supply chain disruption shocks, with the effects being highly persistent, as noted by De Santis (2024). Similarly, Finck and Tillmann (2022) observe that consumer prices increase following a global supply chain shock. In contrast, Aastveit et al. (2024) report that the peak impact on both inflation and inflation expectations occurs approximately two years after the onset of a global supply chain shock. Specifically, the economic significance of these shocks on the professional forecasters' 2-year inflation expectations and headline prices becomes apparent after few months, intensifying over time and peaking around 18 and 24 months, respectively. In contrast, the effects of energy supply shocks on headline inflation is transitory. A one-standard deviation energy supply shock results in an immediate increase of 1.1% in energy prices and 0.1% in HICP, aligning with the 10% weighting of energy goods in the consumer basket. The response of retail energy prices peaks quickly, which is consistent with the findings of Känzig (2021) regarding real oil prices. However, the decline in energy prices following this peak is gradual. The impact on headline HICP is notably persistent and enduring, again similar to the findings by Känzig (2021) on US consumer prices.

As for real economic activity, real GDP declines following both shocks disrupting supply chains and energy markets. Notably, the short-term impact on real GDP is slightly

[15] The acceptance rate for the share of rotations that meet the imposed restrictions is 0.3% in the linear model. In contrast, it is 7.4% in the nonlinear model conditioned on a low economic growth regime and 1.4% in the nonlinear model conditioned on a high economic growth regime.

more pronounced following a supply chain disruption shock with a rebound after about six months, which occurs as supply chain disruptions alleviate (see the dynamics of the supply delivery times in Figure (4)). Conversely, the medium-term effects on economic activity are more significant after a retail energy supply shock, as energy prices return to the pre-shock equilibrium gradually after about 2 years (see the dynamics of energy prices in Figure (4)).

The state-dependent IRFs of the nonlinear model are displayed in Panel B of Figure 2. The responses to various shocks are contingent upon the prevailing macroeconomic state. For this analysis, supply chain disruption shocks are normalized by assuming a 10-point decline in suppliers' delivery times in both states. In the high-growth regime, the expected and headline inflation trajectories mirror those of the linear model, while the credible set for real GDP includes zero, indicating no significant impact. Conversely, in the low-growth regime, the impact on expected and headline inflation is more subdued, and real GDP experiences a decline. These findings support the view that when the economy is underperforming (below the median), supply chain disruption shocks have a significantly negative impact on output. Conversely, when the economy is expanding (above the median) and the supply of intermediate inputs, labor, and capital is already constrained, such disruptions lead to a sharper increase in prices. In a low-growth regime, real GDP rebounds after a few months, suggesting a convex relationship between supply chain disruption shocks and activity, when the economy is underperforming. Once disruptions are gradually resolved, pent-up demand is satisfied.

The state-dependent IRFs following retail energy supply shocks are also intuitive. These shocks are normalized by assuming that they increase energy prices by 10%. They result in a positive, albeit temporary, impact on expected and headline inflation. However, they have a negative impact on economic activity only when the economy is underperforming (below the median).

Finally, demand shocks, which are normalized by assuming a 1% increase in headline HICP, appear to have a more pronounced effect on headline HICP in the medium term in the high growth regime, while expected inflation seems no much affected by temporary demand shocks. On average, positive demand shocks seem to have a larger effect only at impact on real GDP when the economy is underperforming.

IV.C Supply and demand shocks

The three identified shocks are depicted in Figure 3, with the linear model results on the left and the nonlinear model results on the right. Demand shocks were significantly negative, reaching two standard deviations (in absolute values), during the initial impact of the COVID-19 pandemic in March 2020 and five standard deviation in April 2020. Similarly, supply chain disruption shocks were highly adverse during this period, amounting to about one standard deviation in March 2024 and six standard deviations in April 2020. In contrast, energy supply shocks played a smaller role during this time-frame, about one standard deviation in March 2020 and two standard deviations in April 2020. Throughout 2021 and 2022, the economy continued to experience multiple adverse supply chain disruption shocks of smaller magnitude. Energy supply shocks began to emerge as a crucial factor influencing the macroeconomy after the summer of 2021, coinciding with gas rationing from Russia. This trend was further exacerbated following the invasion of Ukraine in February 2022, when the energy supply shock reached four standard deviations.

The features described are common to the shocks identified by both the linear and nonlinear specifications, which are broadly similar yet distinct. This similarity can be explained by the fact that a linear specification offers a weighted average of the dynamic relationships between variables in the two regimes (see, for example, the related discussion in Kolesár and Plagborg-Møller (2024)). The weights are always positive and depend on the distribution of the observables. Consequently, the linear specification, which applies the same identification assumptions, generally provides good estimates of the structural shocks, especially during periods when such shocks are substantial. However, this does not imply that the nonlinearities suggested by the data are unimportant. In fact, in many cases, the shocks indicated by the two models differ significantly, as demonstrated in Figure 3.

Table 2 provides a comprehensive summary of one additional finding of the paper, specifically examining whether the magnitude of shocks has changed over time following the outbreak of the pandemic. The regression equation used is specified as follows:

$$\text{abs}(\epsilon_t) = \alpha + \beta_{2020} D_{2020,t} + \beta_{2021} D_{2021,t} + \beta_{2022} D_{2022,t} + \beta_{2023} D_{2023,t} + \beta_{2024} D_{2024,t} + v_t,$$

where abs(ϵ_t) represents the absolute value of the shocks, $D_{year,t}$ are time dummies characterized by monthly observations taking a value of 1 for the specific month of the year and 0 otherwise, and v_t denotes the OLS errors. Therefore, the regression effectively compares the average size of shocks during the five pandemic and post-pandemic years with the overall average size from the pre-pandemic period. It employs monthly observations, with estimates representing the monthly average value for each corresponding year to aid interpretation and minimize volatility. The combination of monthly time series data and the randomness in determining the absolute value of the shocks accounts for the relatively low adjusted R-squared in the regression. Nonetheless, our primary focus is on identifying the mean shift through this analysis. Table 2 reveals significant differences in the size of the three identified shocks between the past five years and the rest of the sample, as indicated by some large t-statistics.

The intercept α calculates the average size of the monthly shocks over the sample period from 1999 to 2019, prior to the pandemic. This intercept is approximately equal to half a standard deviation for each of the two types of supply shocks and one third of a standard deviation for the demand shock. The monthly average coefficients for individual years (β_t) measure the additional monthly impact in each corresponding year relative to the average size, α.

The shocks in 2020 were extraordinarily large. On average, monthly supply chain disruption shocks were 1.14 standard deviations in the SVAR and 0.92 in the TVAR. Similarly, monthly demand shocks averaged 1.00 standard deviations in the SVAR and 0.80 in the TVAR, while monthly energy supply shocks averaged 0.64 standard deviations in the SVAR and 0.84 in the TVAR. By 2021, the magnitude of shocks returned to levels similar to those observed in the pre-pandemic period. However, in 2022, energy supply shocks became predominant, averaging 1.68 standard deviations per month in the SVAR and 1.27 in the TVAR. This increase in energy supply shocks can be attributed to the tensions between Russia and Ukraine and the ensuing conflict.

As robustness check, we conducted a similar analysis, incorporating two dummy variables so that we have more observations during each period: one for the period before June 2021 and another for after June 2021. Prior to this date, supply shocks were predominantly

Table 2: The Size of the Shocks after the Covid-19

	Supply chain disruption		**Energy**		**Demand**	
Panel A: SVAR	**Coef**	**t-Stat**	**Coef**	**t-Stat**	**Coef**	**t-Stat**
Intercept	0.497	(15.924)	0.517	(17.572)	0.327	(12.743)
2020	0.639	(4.413)	0.121	(0.890)	0.672	(5.650)
2021	0.195	(1.344)	0.091	(0.663)	0.055	(0.459)
2022	0.147	(1.015)	1.160	(8.493)	0.311	(2.610)
2023	0.257	(1.778)	0.033	(0.242)	0.173	(1.451)
2024	0.426	(2.105)	-0.238	(-1.246)	0.148	(0.892)
Adj. R-squared	0.069		0.189		0.102	
Panel B: TVAR	**Coef**	**t-Stat**	**Coef**	**t-Stat**	**Coef**	**t-Stat**
Intercept	0.489	(17.439)	0.501	(16.093)	0.407	(16.979)
2020	0.435	(3.347)	0.336	(2.333)	0.398	(3.586)
2021	0.052	(0.398)	0.146	(1.012)	-0.130	(-1.167)
2022	-0.001	(-0.004)	0.765	(5.302)	0.158	(1.427)
2023	0.071	(0.548)	0.255	(1.766)	0.323	(2.910)
2024	0.368	(2.023)	-0.024	(-0.119)	0.313	(2.018)
Adj. R-squared	0.033		0.091		0.069	
Panel C: SVAR	**Coef**	**t-Stat**	**Coef**	**t-Stat**	**Coef**	**t-Stat**
Intercept	0.497	(15.910)	0.517	(16.212)	0.327	(12.560)
2020M1-2021M6	0.519	(4.337)	0.133	(1.084)	0.459	(4.599)
2021M7-2024M6	0.224	(2.562)	0.362	(4.056)	0.199	(2.728)
Adj. R-squared	0.067		0.048		0.076	
Panel D: TVAR	**Coef**	**t-Stat**	**Coef**	**t-Stat**	**Coef**	**t-Stat**
Intercept	0.489	(17.421)	0.501	(15.789)	0.407	(16.659)
2020M1-2021M6	0.359	(3.337)	0.294	(2.419)	0.220	(2.359)
2021M7-2024M6	0.068	(0.864)	0.350	(3.943)	0.192	(2.811)
Adj. R-squared	0.031		0.056		0.033	

associated with supply chain issues, as indicated in Panel C. Conversely, supply shocks occurred after June 2021 were mainly related to energy concerns as indicated in Panel D.

Qualitatively, the results from both the linear and nonlinear models are similar. However, when the model is estimated while conditioning on economic activity, the shocks appear somewhat smaller compared to the pre-pandemic period (see Panel B of Table 2). This discrepancy occurs because the SVAR attributes part of the observed dynamics, which cannot be explained by a linear model, to structural shocks. In contrast, the TVAR captures these dynamics as nonlinear relationships, resulting in a more accurate fit.

Overall, the post-pandemic shocks have been consistently larger than those recorded in previous periods, but they are gradually decreasing in size over time. This trend suggests that the economy in 2023 and 2024 has been slowly returning to pre-pandemic equilibrium levels.

IV.D Sectoral Impact

The impact on sectors is illustrated in Figure 4. Both adverse supply shocks lead to an increase in vehicle and energy prices. However, the nature of the shocks affects the sectors differently. A supply chain disruption shock causes a decline in vehicle output and has a marginal negative impact on the output of the energy and energy-intensive sectors. In contrast, an energy supply shock results in a significant drop in all three sectors, with the impact being temporary for the automotive sector but persistent for the energy and energy-intensive sectors. These results are line with the findings of Lee and Ni (2002), who found that oil price shocks decrease the supply in oil-intensive industries and the demand across various sectors, notably the automobile industry; and of Edelstein and Kilian (2009b), who observed a decline in demand for automotive goods following energy shocks.

It is important to note that suppliers' delivery times are influenced by both demand and supply forces. First, demand shocks have a strong negative impact on vehicle output and extend suppliers' delivery times, with this lengthening of the supply chain lasting approximately nine months. Subsequently, the dynamics fully mean-revert, with a peak shortening of delivery times occurring after 16 months. Suppliers' delivery times for vehicle output return to their equilibrium level after about two and a half years. Second, supply chain disruption shocks also extend the delivery time for materials and equipment, with this delay lasting around 12 months. The dynamics then mean-revert, with the peak shortening of delivery times occurring after 24 months. Suppliers' delivery times for vehicle output return to their pre-shock equilibrium after approximately five years.

Interestingly, energy supply shocks are associated with a shortening of the supply chain, possibly because firms strive to enhance production efficiency to offset the rise in energy costs.

Demand shocks also tend to increase the production of vehicles and energy-intensive sectors, which are left unrestricted at impact.

The results of the nonlinear model align closely with those of the linear model for nominal variables in a high-growth regime and for real variables in a low-growth regime. In other words, adverse supply shocks have a more pronounced negative impact on real variables when the macroeconomic conditions are already weak. Conversely, these shocks lead to a sharper increase in prices when macroeconomic conditions are strong and favorable. Similar conclusions can be derived from analyzing demand shocks.

IV.E Robustness checks

IV.E.1 Using industrial production

The key finding that supply chain disruption and retail energy supply shocks act as cost-push shocks with distinct transmission mechanisms remains coherent when industrial production (excl. construction) is used as a measure of output instead of real GDP (see Figure 5). The impact of supply chain disruptions shocks on expected inflation and headline HICP is particularly persistent in the high industrial production growth regime. In the low growth regime, these disruptions lead to short-term declines in industrial production. In the high growth regime, the credible set for industrial production includes zero, similar to the baseline scenario. Similarly, energy supply shocks have a transitory effect on expected inflation and headline HICP. They negatively impact aggregate industrial production in both regimes, whereas real GDP appears to be most affected in the low-growth regime.

IV.E.2 The narrative restrictions on the demand shocks

In the appendix, we consider other narrative restrictions that might have affected demand. The success of the vaccination programme against Covid-19 allowed governments to lift the restrictions from March 2021. In Germany, for example, hairdressers were allowed to reopen from March 1, 2021. Subsequently, Germany announced the reopening to tourists on June 15th. In March and June 2021, euro area monthly real GDP growth is estimated to have risen by 2.5% and 2.1% month-on-month, respectively.[16] Finally, we assume that the demand shocks were positive in May 2022, as output rose strongly in that month, despite the war in

[16] In March and June 2021, retail sales rose by 3.9% and 2.5% month-on-month, and service production rose by 3.5% and 3.7%respectively, mainly due to higher demand for high contact-intensive services, such as hotels, restaurant, arts, entertainment and transport.

Ukraine. Most of the unexpectedly robust growth was due to strong activity in the services sector following the lifting of most pandemic-related restrictions (see ECB, 2022). In the Appendix, we assume that all demand shocks in these three months are positive and show that the results are robust to such assumptions (see Figures A2 and A3 of the Appendix).

V Conclusions

The COVID-19 pandemic and Russia's invasion of Ukraine have significantly altered the favorable conditions of the Great Moderation, due to unprecedented supply chain and energy shocks. This study assesses whether a structural break occurred in March 2020 and whether these shocks have increased in size and frequency post-COVID-19, suggesting a new macroeconomic regime. Finally, we examine their impact on inflation and GDP using linear (SVAR) and nonlinear (TVAR) models.

The statistical tests cannot reject the null hypothesis of no structural break. Moreover, the findings reveal that supply chain disruption shocks, retail energy supply shocks and demand shocks were initially elevated, but they have been gradually returning to pre-pandemic levels.

Supply chain disruption and retail energy supply shocks act as cost-push shocks with distinct transmission mechanisms. Supply chain disruptions lead to persistent increases in inflation expectations and headline HICP, peaking around 18 to 24 months, and cause short-term GDP declines. In contrast, energy supply shocks have a transitory effect on inflation and a pronounced medium-term impact on GDP. The nonlinear model shows that the effects of these shocks vary with economic conditions, being more significant on prices during high GDP growth periods and on real economic activity during low GDP growth periods.

Shocks are identified across three sectors: automotive, energy, and energy-intensive industries. Sectoral analysis indicates that adverse supply shocks exert a more pronounced negative impact on real variables when macroeconomic conditions are already weak. Conversely, these shocks lead to a sharper increase in prices when macroeconomic conditions are strong and favorable. Similar conclusions can be drawn from the analysis of demand shocks.

The study's findings have important implications for policymaking. The distinct transmission mechanisms of supply chain and energy shocks necessitate tailored policy responses. The persistence of supply chain disruptions in driving inflation and their short-term impact on GDP highlight the need for policies that enhance supply chain resilience. In contrast, the transitory nature of energy supply shocks on inflation but their pronounced medium-term GDP impact calls for policies that stabilize energy markets and diversify energy sources.

An alternative approach to our analysis could involve identifying shocks both within and between the proposed macro, energy, and automotive blocks. However, undertaking such an analysis would require a significantly more structured model. Specifically, accurately capturing the structural relationships between these blocks would involve identifying both demand and supply shocks unique to each sector, thereby imposing additional constraints on the estimated model. We acknowledge the potential value of this approach and will explore how these questions can be addressed in future research endeavors.

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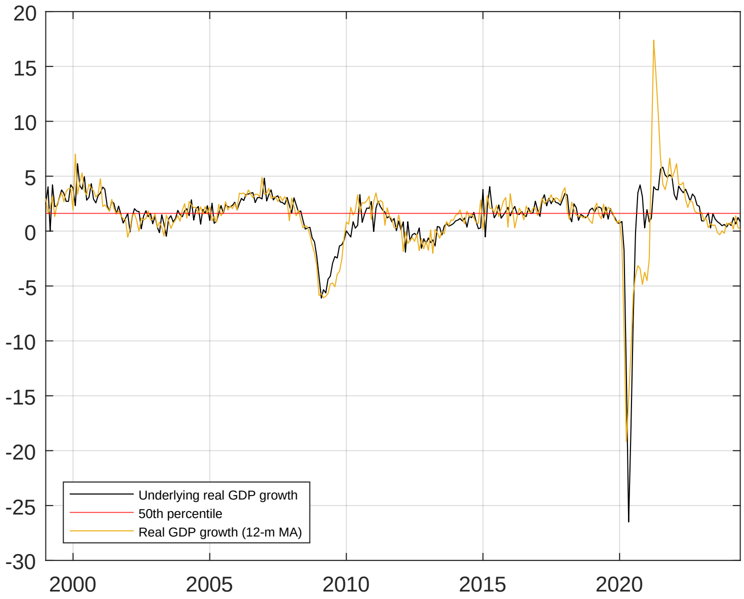
Tables and Figures

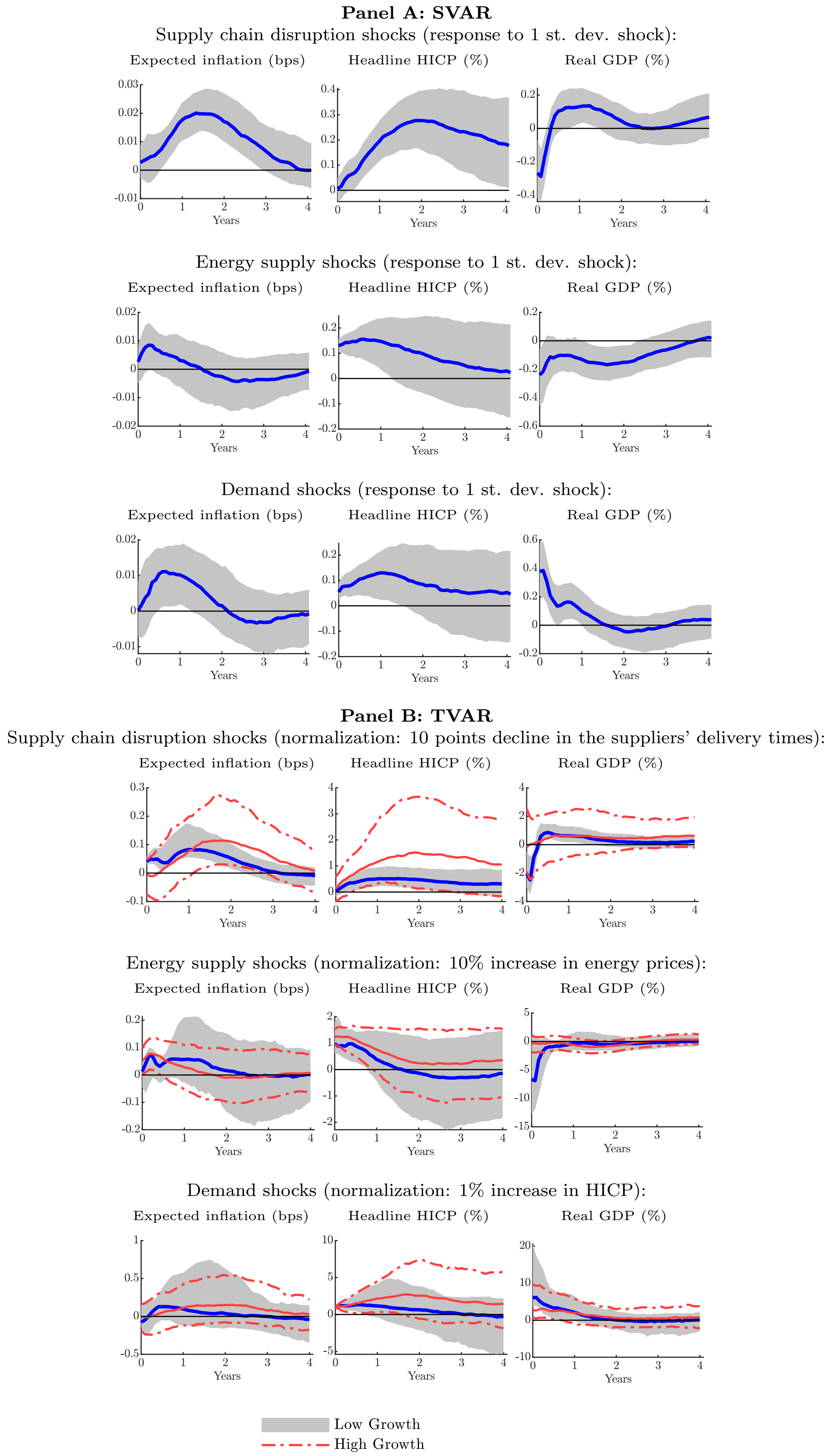
Figure 1: Real GDP Growth: Underlying Rate and 12-month Moving Average

(annualised and %)



Note: The state variable is calculated as $z_t = \alpha(y_t - y_{t-1}) + (1-\alpha)z_{t-1}$, where y_t is the log of real GDP and $\alpha = 0.125$. The exponential weighted moving average is shown annualised and in percent. Real GDP growth (12-m MA) is computed as $100(y_t - y_{t-12})$. Sample period: Jan. 1999 - Jun. 2024.

Figure 2: Macro Impact of Supply and Demand Shocks

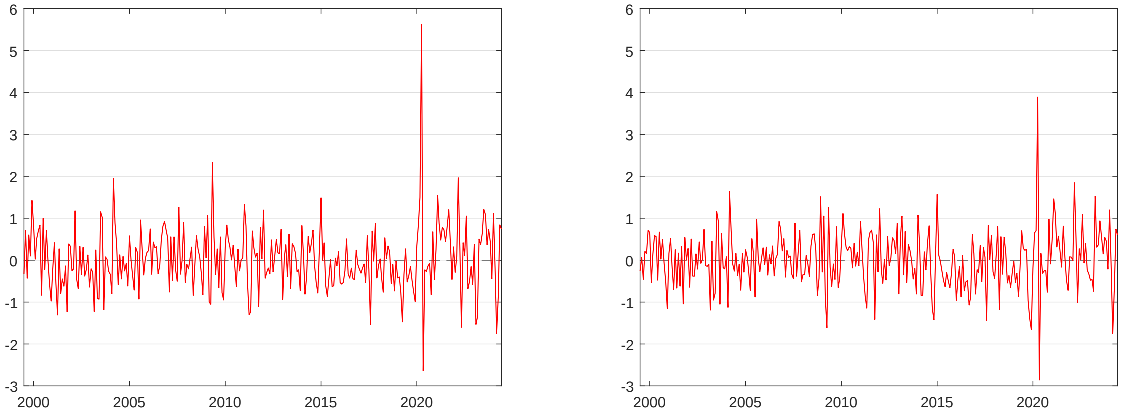


Notes: Each panel shows the median IRFs and the corresponding posterior 68% credible sets. The red (blue) lines of the TVAR model are associated to the high (low) growth regime. The VAR and the TVAR contain nine variables, $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y_t, y^v_t, y^e_t, y^i_t, s^v_t]'$: the SPF 2-year inflation expectations, headline HICP, the vehicle producer price, the energy price, real GDP, the vehicle production, energy production, the output of the energy-intensive sector and the suppliers' delivery times of the vehicle sector. All variables, except the SPF 2-year inflation expectations and the suppliers' delivery times of the vehicle sector, are defined in logs. The identifying assumptions are collected in Table 1.

Figure 3: Estimated Supply Chain Disruption, Energy Supply, and Demand Shocks

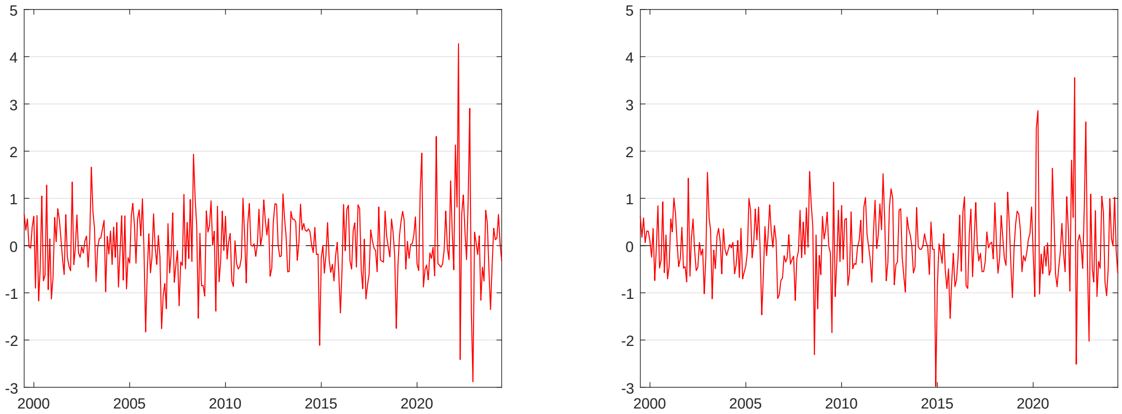
Supply chain disruption shocks

SVAR TVAR



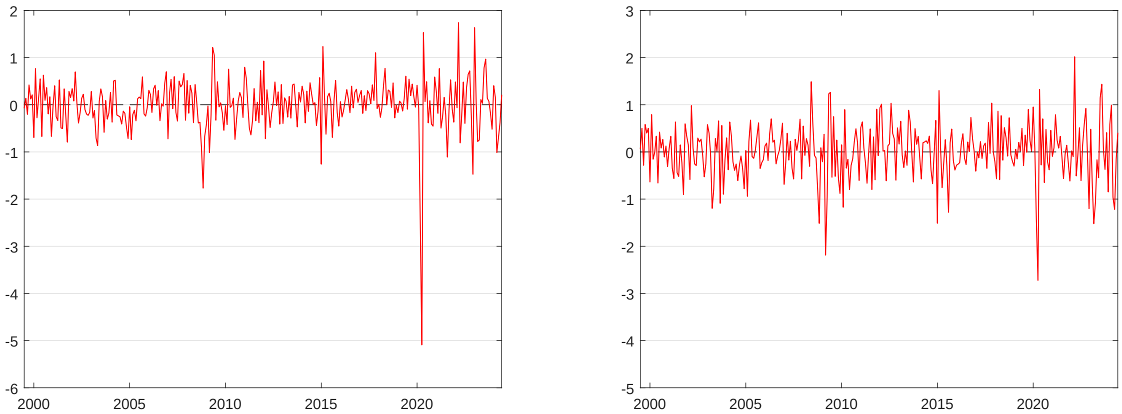
Energy supply shocks

SVAR TVAR



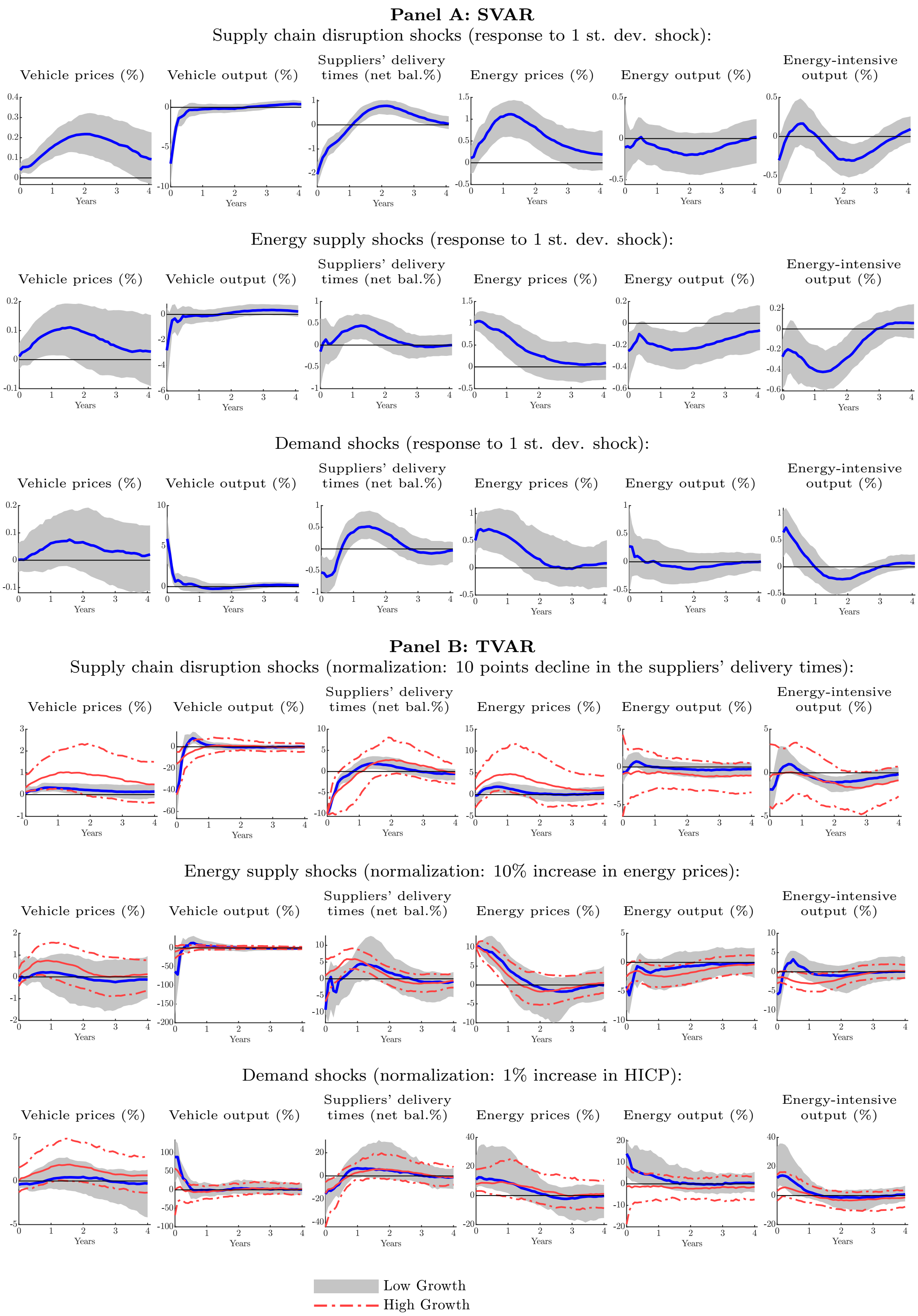
Demand shocks

SVAR TVAR



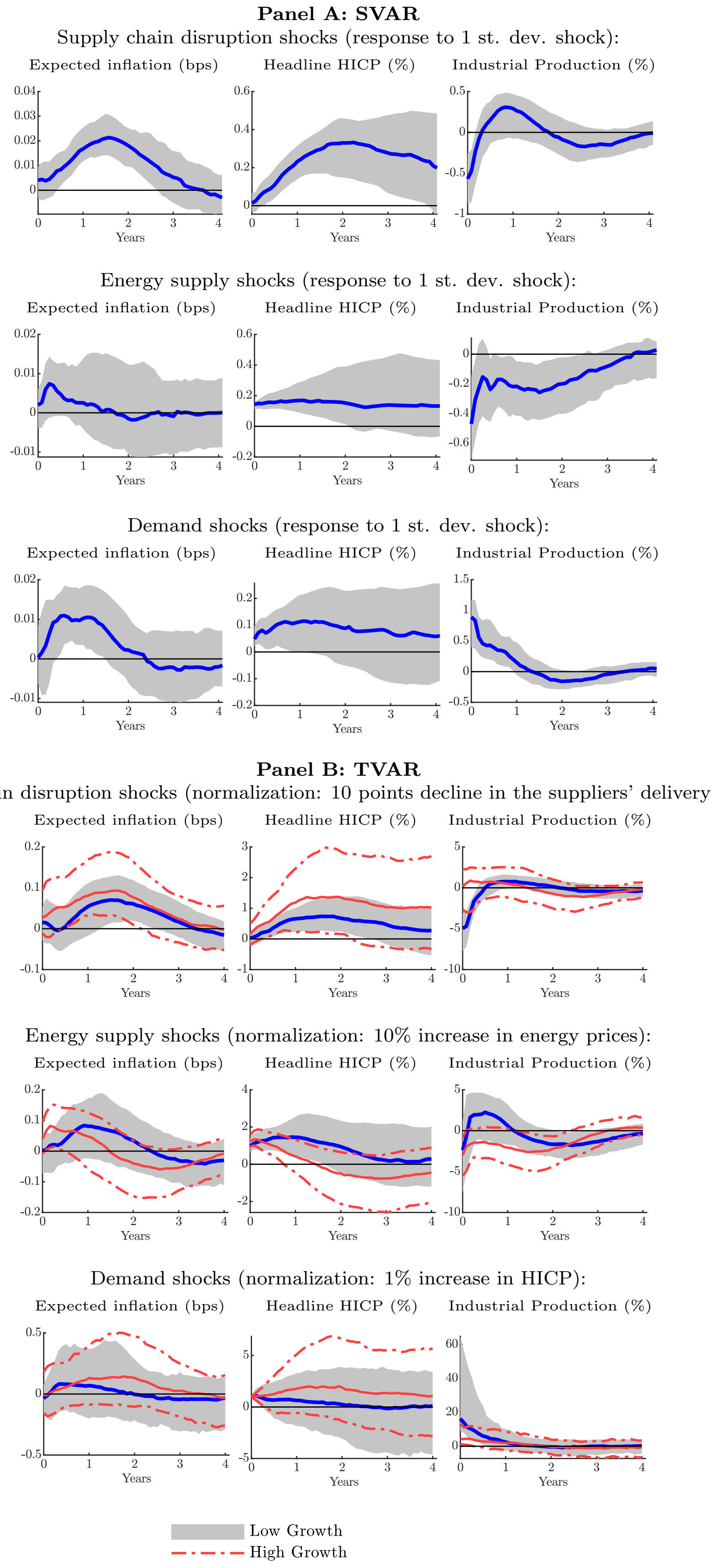
Notes: The figure shows the posterior median of the identified supply chain disruption shocks, retail energy supply shocks, and demand shocks. The structural shocks are estimated using a linear VAR containing nine variables, $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y_t, y^v_t, y^e_t, y^i_t, s^v_t]'$: the SPF 2-year inflation expectations, headline HICP, the vehicle producer price, the energy price, real GDP, the vehicle production, energy production, the output of the energy-intensive sector, and the suppliers' delivery times of the vehicle sector. All variables, except the SPF 2-year inflation expectations and the suppliers' delivery times of the vehicle sector, are defined in logs. The identifying assumptions are collected in Table 1.

Figure 4: Sectoral Impact of Supply and Demand Shocks



Notes: Each panel displays the median Impulse Response Functions (IRFs) along with their corresponding posterior 68% credible intervals. The red lines in the TVAR model represent the high growth regime, while the blue lines correspond to the low growth regime. Both the VAR and TVAR models incorporate nine variables, denoted as $mathbfx_t = pi_t^e, p_t, p_t^v, p_t^e, y_t, y_t^v, y_t^e, y_t^i, s_t^{v\prime}$: these include the SPF 2-year inflation expectations, headline HICP, vehicle producer price, energy price, real GDP, vehicle output, energy output, output of the energy-intensive sector, and suppliers' delivery times in the vehicle sector. All variables, except the SPF 2-year inflation expectations and suppliers' delivery times in the vehicle sector, are expressed in logarithms. The identifying assumptions are detailed in Table 1.

Figure 5: Macro Impact of Shocks: SVAR versus TVAR using Industrial Production



Notes: Each panel shows the median IRFs and the corresponding posterior 68% credible sets. The red (blue) lines of the TVAR model are associated to the high (low) growth regime. The VAR and the TVAR contain nine variables, $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y^{ip}_t, y^v_t, y^e_t, y^i_t, s^v_t]'$: the SPF 2-year inflation expectations, headline HICP, the vehicle producer price, the energy price, industrial production (excl. construction), the vehicle production, energy production, the output of the energy-intensive sector and the suppliers' delivery times of the vehicle sector. All variables, except the SPF 2-year inflation expectations and the suppliers' delivery times of the vehicle sector, are defined in logs. The identifying assumptions are collected in Table 1.

Appendix

A Data

We provide in this section information on key variables used to identify the supply shocks (see Figure A1).

A.A Supply chains and energy prices

The suppliers' delivery times index from Standard and Poor's (S&P) global (previously IHS Markit's) Purchasing Manager Index (PMI) business surveys captures the extent of supply chain delays in an economy, which in turn acts as a useful barometer of capacity constraints.[17]

Purchasing managers of the vehicle sector participating in business surveys are asked if it is taking their suppliers more or less time to provide inputs to their factories on average. The precise question wording is: "Are your suppliers' delivery times slower, faster or unchanged on average than one month ago?" The percentage of companies reporting an improvement, deterioration or no change in delivery times are weighted to derive a 'diffusion index' as follows: $\alpha + \beta/2$, where α and β are the percentages of survey panel responding 'Faster' and 'Same', respectively. Hence readings of 50 indicate no change in delivery times on the prior month, readings above 50 indicate that delivery times have improved (become shorter, or faster) and readings below 50 indicate that delivery times have deteriorated (become longer, or slower).[18]

In each euro area country, the panel of companies is carefully selected to accurately represent the true structure of the chosen sector of the economy as determined by official data. A weighting system is also incorporated into the survey database that weights each response according to the workforce size.

The lengthening of the motor vehicle suppliers' delivery times in March and April 2020,

[17]The aggregate manufacturing suppliers' delivery times index became widely watched in the 1990s by high-profile users such as US Fed Chair Alan Greenspan, who cited the index (produced at the time by the NAPM - now known as the ISM) as his preferred leading indicator of inflation. According to the Wall Street Journal of 6 April 1996, "Mr Greenspan, speaking in congressional testimony, said that suppliers' deliveries are "far more relevant than the Fed's own capacity utilization figures at gauging price pressures in the economy".

[18]The index is seasonally adjusted to strip out normal variations in delivery performance for the time of year.

its shortening in May 2020 and its lengthening again since the autumn 2020 is noticeable. Vehicle production moved in tandem with the suppliers' delivery times dropping after the pandemic restrictions, recovering immediately, but then dropping again in the autumn 2020. Vehicle prices started to rise sharply since the end of 2020. This suggests that supply chain disruption shocks played a key role in this period.

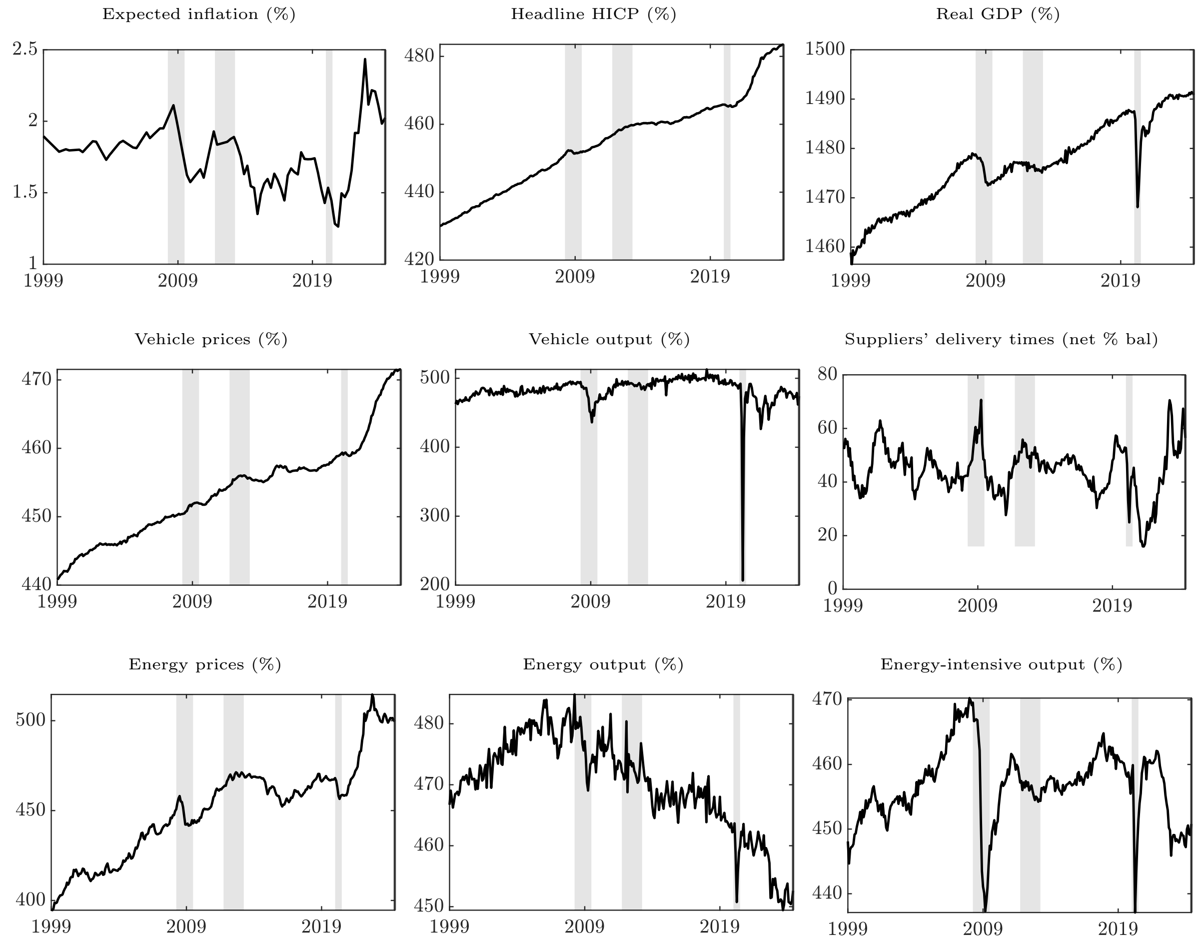
A.B Energy prices

Energy supply shocks are typically studied through the global crude oil market[19] However, the prices of other sources of energy, are only weakly correlated with oil prices. According to monthly data provided by the U.S. Energy Information Administration (EIA), available for a long period between January 1997 and December 2019, the correlation between the Henry Hub natural gas spot price and the West Texas Intermediate (WTI) spot price is 20%. Gas and renewable sources like wind, solar, geothermal and hydropower have become important alternative sources in the last two decades for energy supplies' security motives and for environmental issues. Therefore, we employ the HICP category "Energy (ENRGY)" for goods and services, rather than oil prices to identify energy shocks. The retail energy price includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment.

The remarkable drop in energy-intensive output together with the surge in energy prices since the autumn 2021 suggest that energy supply shocks might have played a key role in the dynamics of the business cycle since then. The energy-intensive sector is defined by aggregating the production of chemicals, chemical products and basic metals, as they are by far the largest-scale users of energy (e.g. EIA, 2021; Gunnella et al., 2022). We use time-varying weights provided by Eurostat to construct the index. These sub-sectors account on average for about 10% of euro area industrial production

[19] Among others, see Kilian (2009); Baumeister and Peersman (2013); Kilian and Murphy (2014); Aastveit et al. (2015); Baumeister and Kilian (2016); Baumeister and Hamilton (2019); Caldara et al. (2019); Känzig (2021); Aastveit et al. (2021); Kilian and Zhou (2022b).

Figure A1: Dataset



Notes: The models contain nine variables, $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y_t, y^v_t, y^e_t, y^i_t, s^v_t]'$: the SPF 2-year inflation expectations, headline HICP, the vehicle producer price, the energy price, real GDP, the vehicle production, energy production, the output of the energy-intensive sector and the suppliers' delivery times of the vehicle sector. The SPF 2-year inflation expectations is in percentage points, and the suppliers' delivery times of the vehicle sector is in net percent balances. All other variables are defined in logs multiplied by 100.

B Posterior Sampler for the Structural TVAR Model

Since the state variable, z_{t-1}, and its threshold value, z^*, are pre-specified, the Monte Carlo sampler used to draw from the posterior of the structural TVAR parameters is just the same as the one employed for the linear model, but applied to one regime at a time. More specifically, conditionally on z_{t-1} and z^*, the sample can be split in two sub-samples, whose observations can be denoted X_t^S, with $S \in (Low, High)$ and $t = 1, ..., T_S$, T_S being the number of observations in regime S. Given Natural-Conjugate Normal-Inverse Wishart priors on the reduced form parameters ($p(vec(\Pi'_S), \Omega_S) = p(\Omega_S)p(vec(\Pi'_S)|\Omega_S)$, with $p(\Omega_S)$ being Inverse Wishart with $\underline{\nu}$ degrees of freedom and scale $\underline{\Phi}$ and $p(\Pi_S|\Omega_S)$ being Gaussian with mean $vec(\underline{\Pi})$ and variance $\Omega \otimes \underline{V}$), and uniform *Haar* prior on the space of orthonormal rotation matrices, Q, that map the lower triangular Cholesky factor of Ω_S, $chol(\Omega_S)$, into a candidate $B_{0,S}^{-1}$, the posterior of the structural parameters associated with regime S can be explored via a direct Monte Carlo sampler that runs through the following steps:

1. Draw Ω_s from IW($\bar{\nu}$,$\bar{\Phi}$);

2. Draw $vec(\Pi'_s)$ from N($vec(\bar{\Pi})$,$\Omega \otimes \bar{V}$);

3. Draw candidates $B_{0,S}^{-1} = chol(\Omega_S)Q$ using the algorithm described by Rubio-Ramirez et al. (2010) and retain a draw (if any) that satisfy the desired restrictions;

where $\bar{\nu} = \underline{\nu} + T_S$, $\bar{\Phi} = \underline{\Phi} + \sum_{t=1}^{T_S} X_t^S (X_t^S)' + \underline{\Pi}\underline{V}^{-1}\underline{\Pi} - \bar{\Pi}\bar{V}^{-1}\bar{\Pi}$, $\bar{V} = (\underline{V}^{-1} + \sum_{t=1}^{T_S} X_{t-1}^S (X_{t-1}^S)')^{-1}$ and $\bar{\Pi} = \bar{V}(\underline{V}^{-1}\underline{\Pi} + \sum_{t=1}^{T_S} X_{t-1}^S (X_t^S)')$.

C Additional Robustness Checks

The restrictions imposed on shocks are summarized in Table A1. Relative to Table 1, we assume that demand shocks were positive in March 2021, June 2021 and May 2022.

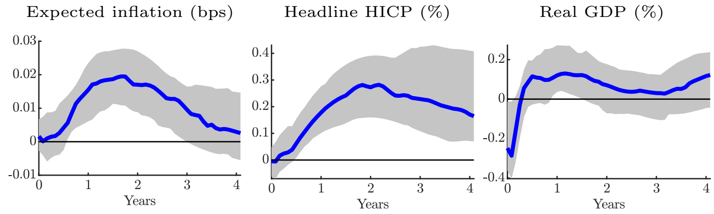
Table A1: Sign, magnitude and narrative restrictions including 2021/2022 demand Narratives

	Supply chain disruption	**Energy supply**	**Demand**
Variables	Panel A: *Sign restrictions on the impact matrix* B_0^{-1}		
Expected inflation 2-year ahead			
Headline HICP			+
Real GDP			+
Vehicle prices	+		
Vehicle output	-		
Vehicle suppliers' delivery times	-		-
Energy prices		+	+
Energy output		-	
Energy-intensive output		-	
Variables	Panel B: Magnitude restrictions on the FEVD at $h = 0$		
Vehicle suppliers' delivery times	++	+	
Energy HICP	+	++	
Dates	Panel C: *Narrative sign restrictions*		
03/20 - 04/20	+		-
05/20	-		+
10/21 - 11/21		+	
03/22		+	
03/21			+
06/21			+
05/22			+
Dates	Panel D: *Sign contribution restrictions*		
04/20 (low growth)	FE$^{s_t^v}$		
03/21 (high growth)	FE$^{s_t^v}$		
01/03 (low growth)		FE$^{p_t^e}$	
03/22 (high growth)		FE$^{p_t^e}$	

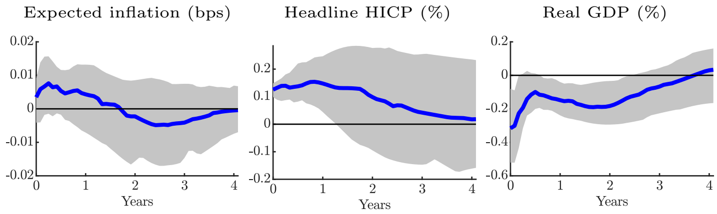
Figure A2: Macro Impact of Supply and Demand Shocks: SVAR versus TVAR including 2021/2022 Demand Narratives

Panel A: SVAR

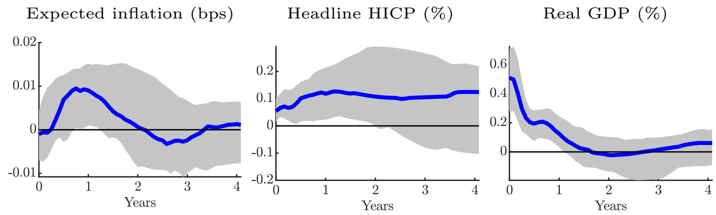
Supply chain disruption shocks (response to 1 st. dev. shock):



Energy supply shocks (response to 1 st. dev. shock):

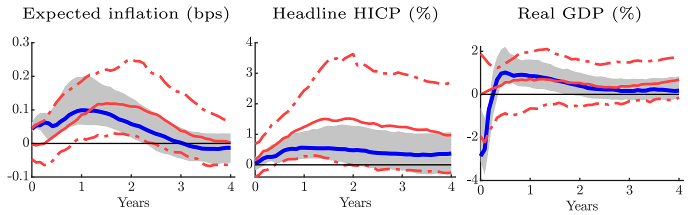


Demand shocks (response to 1 st. dev. shock):

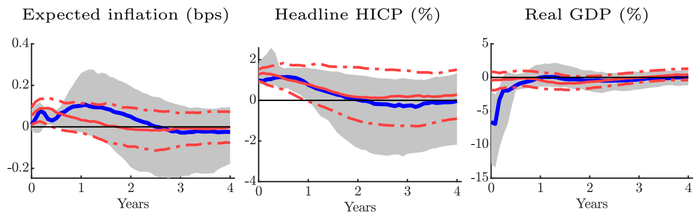


Panel B: TVAR

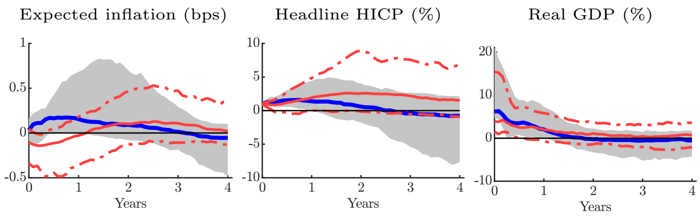
Supply chain disruption shocks (normalization: 10 points decline in the suppliers' delivery times):

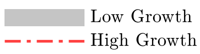


Energy supply shocks (normalization: 10% increase in energy prices):



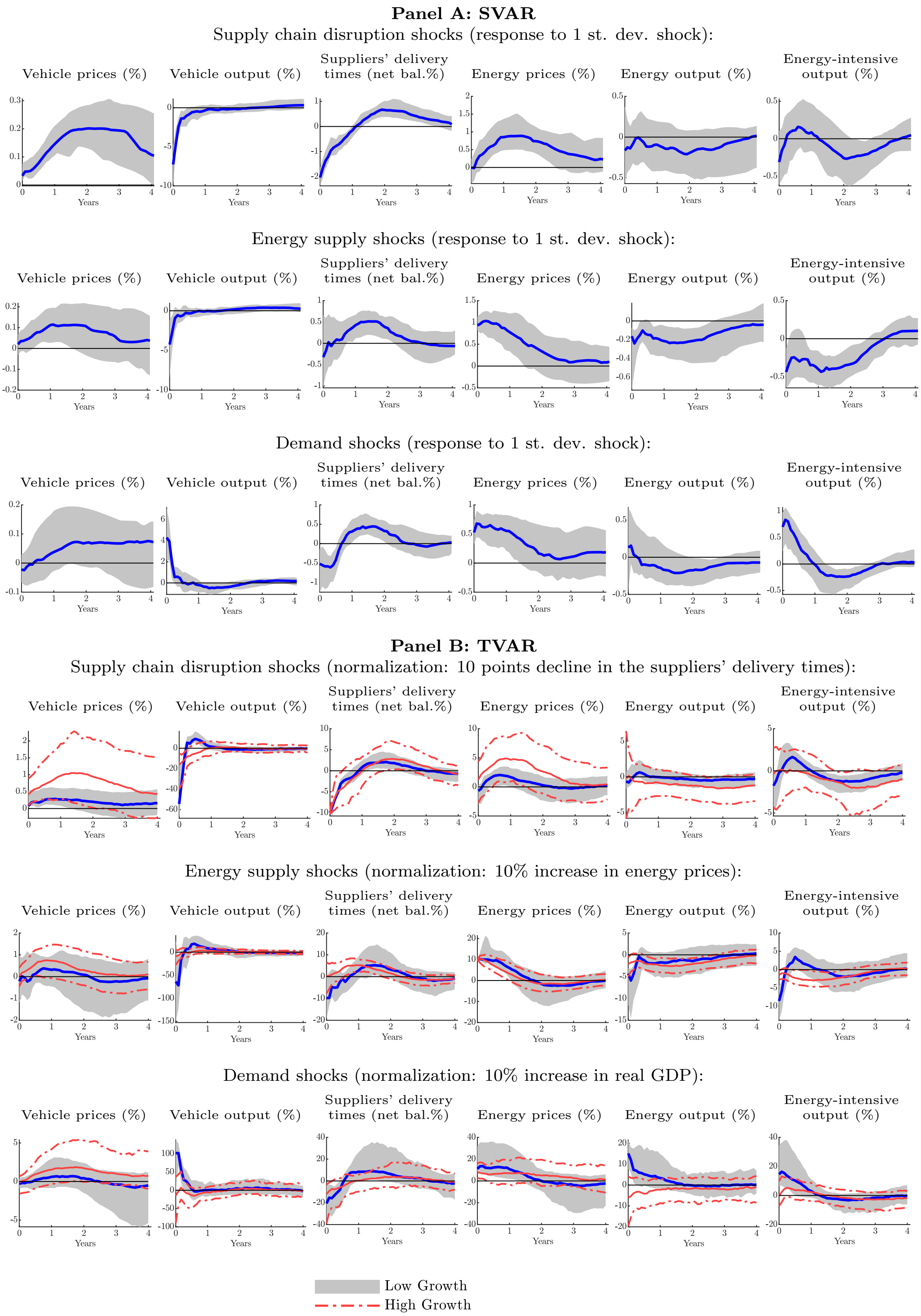
Demand shocks (normalization: 10% increase in real GDP):





Notes: Each panel shows the median IRFs and the corresponding posterior 68% credible sets. The red (blue) lines of the TVAR model are associated to the high (low) growth regime. The VAR and the TVAR contain nine variables, $\mathbf{x}_t = [\pi^e_t, p_t, p^v_t, p^e_t, y_t, y^v_t, y^e_t, y^i_t, s^v_t]'$: the SPF 2-year inflation expectations, headline HICP, the vehicle producer price, the energy price, real GDP, the vehicle production, energy production, the output of the energy-intensive sector and the suppliers' delivery times of the vehicle sector. All variables, except the SPF 2-year inflation expectations and the suppliers' delivery times of the vehicle sector, are defined in logs. The identifying assumptions are collected in Table A1.

Figure A3: Sectoral Impact of Supply and Demand Shocks: SVAR versus TVAR including 2021/2022 Demand Narratives



Notes: Each panel displays the median Impulse Response Functions (IRFs) along with their corresponding posterior 68% credible intervals. The red lines in the TVAR model represent the high growth regime, while the blue lines correspond to the low growth regime. Both the VAR and TVAR models incorporate nine variables, denoted as $mathbf{f}x_t = pi_t^e, p_t, p_t^v, p_t^e, y_t, y_t^v, y_t^e, y_t^i, s_t^{v}{}'$: these include the SPF 2-year inflation expectations, headline HICP, vehicle producer price, energy price, real GDP, vehicle output, energy output, output of the energy-intensive sector, and suppliers' delivery times in the vehicle sector. All variables, except the SPF 2-year inflation expectations and suppliers' delivery times in the vehicle sector, are expressed in logarithms. The identifying assumptions are detailed in Table A1

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