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Energy News Shocks and their Propagation to Renewable and Fossil Fuels Use*

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Abstract

This paper investigates the impact of anticipated (news) shocks on renewable and fossil energy use on the US economy. Using structural vector autoregressions (SVARs), we identify the news shocks captured in energy stock market indexes. Our findings show that renewable and fossil energy news shocks significantly affect economic activity, revealing the tensions between the traditional fossil fuel-based industries and the emerging green technology-based ones. We further identify news shocks on Economic Policy Uncertainty (EPU) index, as policy is a key factor driving the changes in the energy mix. First, we show that the identified anticipated shocks have very different propagation mechanisms from traditional surprise shocks. Then, we find that the combination of news shocks to energy stock prices and economic policy uncertainty jointly account for about 90% of the variability of output, job openings and house prices. To interpret our findings, we use a DSGE model that incorporates fossil and renewable energy sectors and news shocks as a driving force, and we show that the propagation mechanisms of news shocks in the model are consistent with our empirical observations. Our study illustrates on the critical interaction between energy news and economic policy uncertainty in affecting the real economy in the transition from dirty to clean energy technologies.

JEL classification: E2, E6, E32, E44, Q42, Q43, Q58
Keywords: news shocks; renewable energy; economic policy uncertainty; expectations;

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1 Introduction

Recent research has shown that news and expectations surrounding the future of energy markets can have a significant impact on economic and financial indicators (Cascaldi-Garcia and Galvao (2021)). This impact extends to both renewable and fossil energy sources, as well as for oil and stock markets prices. This finding is consistent with prior studies conducted by Kilian and Murphy (2014) and Arezki et al. (2017) which have suggested that news and changes in expectations drive fluctuations in energy markets. While the consequences of fossil fuels on the real economy remains a significant concern as demonstrated by Díaz et al. (2019), it is important to note the growing emphasis on renewable energy sources and the transition to a low-carbon economy. Therefore, as policymakers and energy companies are closely monitoring the advancements made in the renewable energy sector (Reboredo et al. (2017)), the news and expectations related to these shifts suggest that the changing energy landscape may further affect economic and financial indicators.

In the context of renewable energy, such news involve new regulations and agreements related to environmental policies or major advancements in green economy technology.[1] These developments can have significant effects on relative prices, commodities markets, financial assets, and real variables such as total output, consumption, and employment through current and future investment. On the other hand, news related to fossil energy may include advancements in oil extraction technologies, or new discoveries of oil and gas resources. Arezki et al. (2017) have shown that fossil fuel discoveries can affect people's expectations, investment decisions, and government policies.

This paper investigates the impact of anticipated (news) shocks on renewable and fossil fuels energy sources in the US economy. To do so, we identify the news captured in energy stock market indexes. Our identification framework implies that two types of shocks drive the long-term variation in the variables of interest. These shocks are the traditional unanticipated (surprise) shock and the anticipated (news) shock. We find that the two shocks exhibit distinct characteristics and have contrasting propagation mechanisms, and in some cases, they can even be opposite. The news shock is the one that does not affect the variable of interest on impact, but predicts future changes on it. Moreover, the news shock propagates significantly to forward-looking variables such as industrial production, stock market indexes, financial volatility, job openings, housing prices and the US competitiveness. The main mechanism is that renewable and fossil fuel energy news shock today

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[1] There is a not exhaustive list of environmental policies and advancements in green economy technology in Appendix E and F.

can anticipate future movements in stock prices, affecting current and future economic dynamics.

Our hypothesis is that the extent to which energy news shocks contribute to economic fluctuations depends on the economy's readiness to replace fossil fuels with renewable energy and on the investment in research and development. Additionally, their contribution also depends on the tension between an old economy based on fossil fuels and a new economy based on the green technology. This tension plays a pivotal role in determining the differential impact of energy news shocks on various economic variables, ultimately affecting economic fluctuations through both the investment and preferences channels. Those investments may involve either the present expansion of production capacity, as in the case of fossil energy, or future expansion of production capacity, as in the case of renewable energy. A positive fossil fuel news shock immediately increases the economic activity and stimulates the economic activity based on fossil fuels. Conversely, a renewable energy news shock can predict future economic expansion, as it leads to an increase of the future investment in renewable energy and more efficient technology. Therefore, the propagation mechanism of energy news shocks reveals the competition between the old and new, greener economies.

To identify these news shocks, we use monthly data from October 2010 to July 2022 for the US economy. Our analysis employs structural vector autoregressions (SVARs) based on Barsky and Sims (2011) methodology. We then examine how distinct characteristics of news shocks on renewable and fossil energy impact on five key aspects of the real economy: total industrial production, the labor market, the housing market, financial market volatility, and the US competitiveness. We further identify news shocks on Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016),[2] as policy is a key factor driving the changes in the energy mix. The EPU index plays a crucial role in capturing anticipated shocks, including attitudes towards environmental awareness, and signaling future economic trends and financial market conditions.

Barsky and Sims (2011) methodology combines a forward-looking effect driven by the expectation of increased economic activity in the future with a contemporaneous effect caused by the immediate impact of the news on the economy. In an eight variables SVAR, the news shock is the one that best predicts in the medium long-run the variable situated in the first position, without affecting it on impact. We consider three options for the first variable: the renewable stock

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[2] The EPU encompass both economic factors like stock price volatilities, investment rates, and employment growth, as well as non-economic factors like partisan political tensions or military actions that can still have economic consequences. The EPU presents important spikes during the Eurozone Crises, U.S. Midterm Elections in November 2010, Gulf War I, Gulf War II, Rising tariffs & trade policy tensions, especially between U.S. and China, BREXIT, Trump election, etc. EPU - Annotated US Index

price index (specifically, the NASDAQ OMX Renewable Energy index,[3] which comprises mostly technology firms), the fossil fuel stock price index (specifically, the S&P Oil & Gas Exploration & Production Select Industry Index), and the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016). While one of the three variable alternatively occupy the first position in the SVAR, the other two join the Industrial Production Index, Jobs Openings (JOLTS), the volatility index, VIX, the US Home Price index and the US dollar Index in the benchmark SVAR.

The forecast-error variance (FEV) decomposition indicates that the combination of energy with economic policy news may explain more than 90% of the variability of economic indicators. The impulse response functions (IRFs) of renewable energy news shocks show that on impact, it increases economic policy uncertainty (EPU) and the volatility index (VIX), while decreasing job openings and persistently the fossil energy stock prices. However, the initially negative effects on job openings and industrial production turn positive in the long run with significant persistent effects, especially for job openings. On the US Home Price index, the effect in the medium to long run is positive, significant, and persistent, indicating a strong wealth effect. These long-run positive effects of renewable energy news shocks are highlighting its robust and dynamic effect on the real economy.

To interpret our empirical findings we use a DSGE model that incorporates renewable and fossil energy sectors as in Argentiero et al. (2018), augmented with news shocks. In line with Acemoglu et al. (2012), the energy sector uses renewable and fossil fuels as substitutable inputs in a CES production function. Acting as the driving force of the model, the news shocks affect household preferences and Total Factor Productivities (TFPs) in energy sectors. The model, allows us to link theoretical and empirical variables, such as the mapping between renewable and fossil energy model prices and energy stock prices,[4] the production of final goods and the US Industrial Production Index, as well as the inverse of total consumption and EPU.

Methodologically, our model combines two strands of the DSGE literature. Firstly, it incorporates an environmental component into a DSGE model, known as an E-DSGE model, to explore the impact of environmental policies during business cycles in line with Fischer and Springborn (2011), Heutel (2012), and Dissou and Karnizova (2016). Second, our paper relates to the news shocks literature.[5] While the unanticipated shock to the TFP has been incorporated into E-DSGE

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[3] We selected it from different renewable energy indexes as it specifically target companies that engage in the production and distribution of clean energy.

[4] The empirical SVAR includes NASDAQ OMX Renewable Energy and S&P Oil & Gas Exploration & Production Select Industry Index.

[5] A growing literature assigns a central role in accounting for the bulk of business cycles to news shocks (or shocks

models (see Angelopoulos et al. (2013), Annicchiarico and Di Dio (2015), and Khan et al. (2019)), to the best of our knowledge, our study is the first to incorporate the effects of energy news shocks on macroeconomic variables. The theoretical model's results highlight the consistency between the propagation mechanism of news shocks and our empirical observations.

Given the importance of transitioning towards a low-carbon economy while replacing fossil fuels intensive existing equipment, as emphasized by Díaz et al. (2019), our study contributes to the literature on how information is transmitted across renewable and fossil energy, crude oil, and stock market indices. Previous research by Apergis and Payne (2014) and Ferrer et al. (2018) suggests that renewable and oil prices tend to move in the same direction. Interestingly, our findings reveal a negative correlation between news shocks on renewable and fossil fuel energy price indexes. While Liu and Hamori (2020) support co-movements between clean stock prices and the financial volatility, VIX, we observe significant effects of renewable news shocks on the VIX only in the short term and neutral effects in the medium to long run.

Several studies suggest a close substitutability between fossil fuels and clean energy sources from the comovement between fossil fuel prices and clean energy stock prices (see Henriques and Sadorsky (2008); Xia et al. (2019); Kocaarslan and Soytas (2019)). It turns out, however, that while the two news shocks we identify have opposite impacts, we do not observe any evidence of a substitutability effect. First, news shocks in renewable energy have a positive and statistically significant effect on economic variables, while fossil energy news shocks have negative impacts. Secondly, the transmission of news shocks in renewable energy is more persistent than that of news to fossil energy, and this implies an improvement in competitiveness over the medium term. Overall, our findings indicate that renewable energy news shocks have a significant impact on the economy, with important consequences for investment decisions and policy-making.

Finally, our paper contributes to the literature that suggests EPU is a crucial factor to consider when analyzing the effects of changes in crude oil prices and their volatility as shown by Antonakakis et al. (2014), Degiannakis et al. (2018), Roubaud and Arouri (2018), and Wei et al. (2017). Our study shows comparable effects between EPU and renewable news shocks, with differences on the magnitude of the responses of the rest of the economic variables, but not the sign.

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to future fundamentals), which affect people's economic behavior such as consumption, hours, and investment by changing people's expectations about the future. (Ben Zeev and Khan (2015); Beaudry and Portier (2014); Ben Zeev et al. (2020); Dvorkin et al. (2020); Guinea et al. (2023).

Our findings show that news shocks related to renewable energy have a positive and statistically significant effects on economic variables, while fossil energy news shocks have negative impacts. Furthermore, the impact of news shocks related to renewable energy is more persistent compared to those related to fossil energy, driving a significant improvement in competitiveness over the medium term. Overall, our findings indicate that renewable energy news shocks have a significant impact on the economy, which may have significant implications for investment decisions and policy-making.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the empirical results. Section 4 presents the theoretical model and its results. Finally, Section 5 concludes and discusses the implications of the findings.

2 Data and Methodology

We use monthly U.S. data from October 2010 to July 2022. All data are publicly available from the Federal Reserve Economic Data (FRED) and the Bureau of Economic Analysis. The details regarding our series with FRED mnemonics are provided in Section A.

The Structural Vector Autoregression (SVAR) model used in this study includes eight economic indicators. The first two, represent energy stock prices, namely the NASDAQ OMX Renewable Energy renewable energy, [6] for and the S&P Oil & Gas Exploration & Production Select Industry Index for fossil energy. [7] These indicators, along with the Economic Policy Uncertainty (EPU) from Baker et al. (2016), are the variables of interest used to identify news shocks. One of these variables alternates in the first position in the SVAR model, while the other indicators include the Industrial Production Index, Job Openings: Total Nonfarm (JTSJOL), S&P/Case-Shiller U.S. National Home Price Index, the CBOE Volatility Index (VIX), and the US Dollar Index.

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[6] We selected it from different renewable energy indexes as it specifically target companies that engage in the production and distribution of clean energy. Our decision was based on the fact that this index provide a clear and targeted view of the clean energy sector, allowing for a more accurate assessment of the industry's impact over the economic variables.

[7] We examine fossil fuel energy due to its widespread use and significant impact on global energy markets. Fossil fuels, such as coal, oil, and natural gas, are major sources of energy for electricity generation, transportation, and industry. By examining fossil fuel energy indexes, we can gain valuable insights into the performance of companies involved in this sector, which can inform our understanding of the broader energy landscape. We include in our selection S&P Oil & Gas Exploration & Production Select Industry Index.

2.1 Identification Strategy

To identify news shocks, we adopt the approach introduced by Barsky and Sims (2011). This section provides a concise overview of the methodology, while Appendix B contains more detailed information. The initial assumption is that each variable, X_{it}, used for news shock identification, follows a stochastic process driven by two shocks.[8] The first shock, referred to as the surprise shock, is unanticipated and impacts X_{it} at the same time agents observe it. The second shock, known as the news shock, is anticipated by agents and affects the future level of X_{it}.

To estimate the model, we utilize a vector autoregression (VAR) model that incorporates an empirical measure of X_{it} along with other economic variables. The surprise shock is identified as the reduced-form innovation in X_{it}. The news shock is then identified as the shock that best explains the future movements in X_{it}, beyond what can be accounted for by its own innovation. Following the maximum forecast error variance (FEV) identification approach proposed by Barsky and Sims (2011),[9] we evaluate the responses to the identified shock over a period of forty-eight months to determine whether they are different from zero (refer to Appendix B for detailed information).[10]

This approach offers flexibility in that it allows, but does not require, a permanent impact on the variable of interest from either the contemporaneous shock, the news shock, or both. Additionally, the approach does not impose any restrictions regarding common trends among the various variables in the VAR model. Furthermore, as a partial identification method, this approach can be applied to VARs with multiple variables without requiring additional assumptions about other shocks.

3 Empirical results

This section presents the VAR model that includes the logs of eight variables: the three variables of interest, X_{it}: NASDAQ OMX Renewable Energy, S&P Oil & Gas Exploration & Production Select Industry Index and Economic Policy Uncertainty (EPU); Industrial Production Index (IPI); Job

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[8] X_{it} where $i = r, f$, and epu represents NASDAQ OMX Renewable Energy, r, S&P Oil & Gas Exploration & Production Select Industry Index, f, and EPU series, epu.

[9] Barsky and Sims (2011) apply the strategy proposed by Uhlig (2004a) to identify a news shock maximizing over an horizon 40 of quarters. Their methodology is based on the FEV maximization approach of Uhlig (2004b) who chooses the shock that maximally explains a weighted average of future levels of productivity. We attach equal weights to the various horizons over which news shocks are to be explained.

[10] Arezki et al. (2017) shown that the forty-eight months period is approximately the delay between a discovery of a new oil field and production of oil.

Openings (JTSJOL); S&P/Case-Shiller U.S. National Home Price Index; CBOE Volatility Index: VIX; US Dollar Index. Firstly, we will demonstrate the impacts of two identified shocks: news and surprise shocks, on the variables of interest, X_{It}. We include in this analysis the effects on the Industrial Production Index. Our objective is to highlight the differences in their characteristics and propagation mechanism, which are, in some cases, even opposite. This evidence can be considered a feature of the data that emphasizes the need for understanding how the energy news shocks affect the real economy. Then, we analyse the news shocks effects for the full VAR.

The key insight is to show that news about future leads to predictable changes economic variables. To prove this case, we focus on three variables, say X_{it}, with $i = r$ (renewable), f (fossil), and epu (EPU). To proceed, we estimate a vector autoregression (VAR) model on US monthly data for the period October 2010 - July 2022. We follow Barsky and Sims (2011) methodology to identify the news shock. This implies the combination of VAR prediction errors that have zero contemporaneous impact on X_{it}, but that account for the maximum share of the forecast-error variance (MFEV) of X_{it} over a period of forty-eight months period.[11].

We estimate a Bayesian VAR system in levels.[12] The Akaike criteria, the Hannan-Quinn information and Schwartz criteria favor between ten and twelve lags. As a benchmark, we choose to estimate a VAR with twelve lags. The results are robust to using a different number of lags, and any order of the variables in the VAR. We contrast for each realization (3000) the existence of unit roots and test the residuals to be white noise.

3.1 Empirical evidence: Surprise vs. News shocks

In this section we distinguish between the effects of surprise shocks against anticipated (news) shocks. They both hit the variable in the first position. The key difference between the two shocks is their impact at time $t = 1$. The surprise shock triggers an immediate jump in the variable of interest, whereas the news shock, by construction, does not cause an immediate response but affects the variable in subsequent periods. As such, the propagation mechanism trough the system is different. The news shock effect, mainly, propagates into forward-looking variables.

Figure 1 to 3 show the two shocks effects on the renewable stock index, NASDAQ OMX Re-

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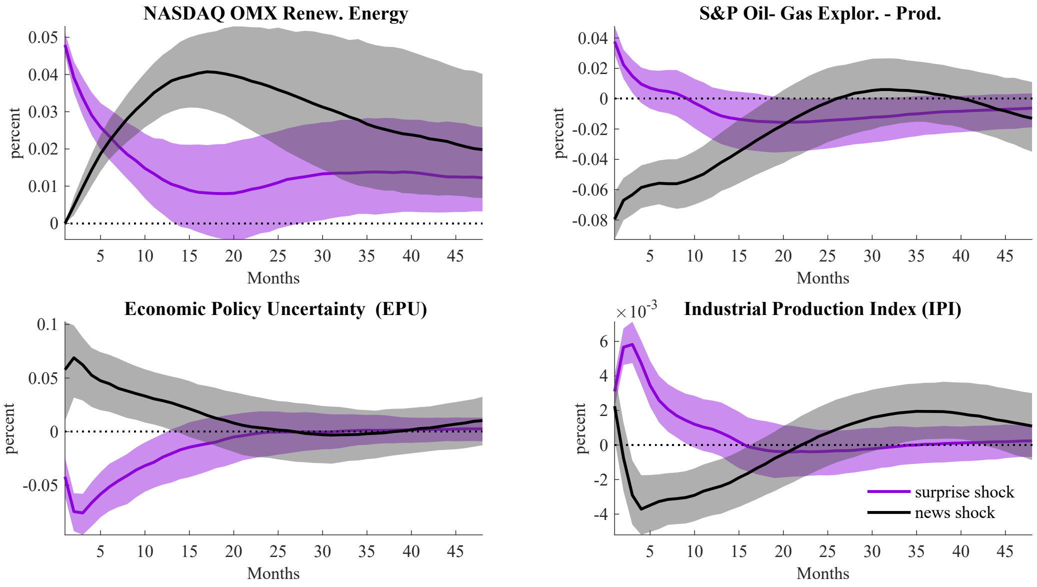
[11] Barsky and Sims (2011) apply the strategy proposed by Uhlig (2004a) to identify a news shock maximizing over an horizon 40 of quarters. Their methodology is based on the FEV maximization approach of Uhlig (2004b)

[12] We use the MATLAB main program routine provided by Kurmann and Otrok (2013).

newable Energy (Figure 1), fossil energy stock index, S&P Oil & Gas Exploration & Production Select Industry Index (Figure 2), and EPU (Figure 3). The two shocks are characterized as follows: surprise (purple) and news (grey). All three figures clearly show that the two shocks have different effects on all variables. Since we are interested in the boom and bust dynamics of economic activity, we focus on analyzing the effects on the Industrial Production Index.

Figure 1: IRF: News vs. surprise shocks on NASDAQ Renewable Energy Index

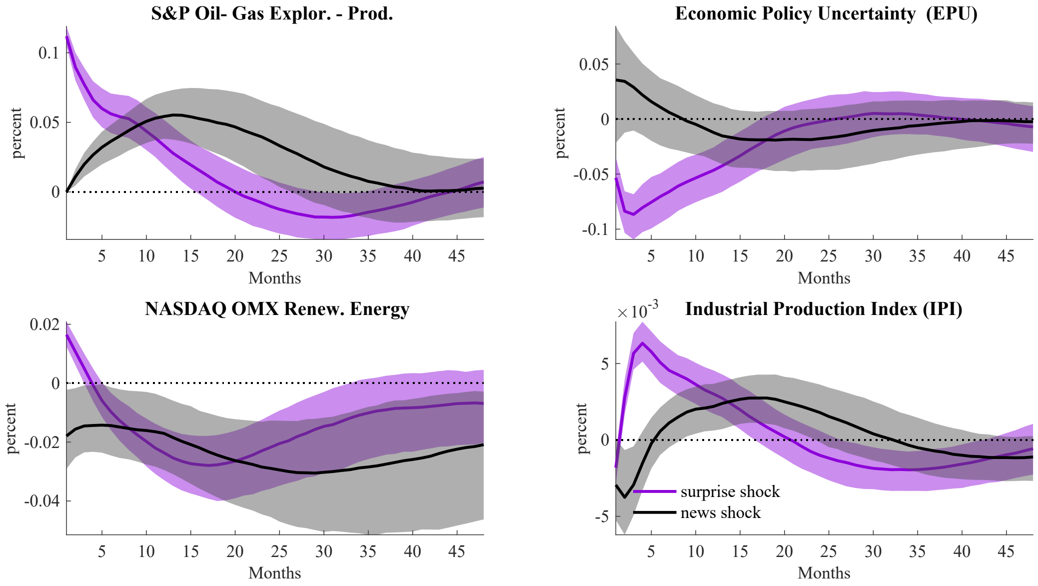


Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Renewable energy stock index. The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Specifically, in Figure 1, the surprise shock on IPI leads to a relatively short-lived expansion, while the news shock results in an initial jump, followed by a short-run recession and a long-run expansion. We interpret the dynamics as follows: New technology may be a pleasant surprise, but it alone is not enough to sustain long run growth. Instead, the news of a breakthrough development in renewable technology initially triggers optimism, but the shift of resources to this new technology can cause a temporary economic downturn until the greener technology is fully implemented.

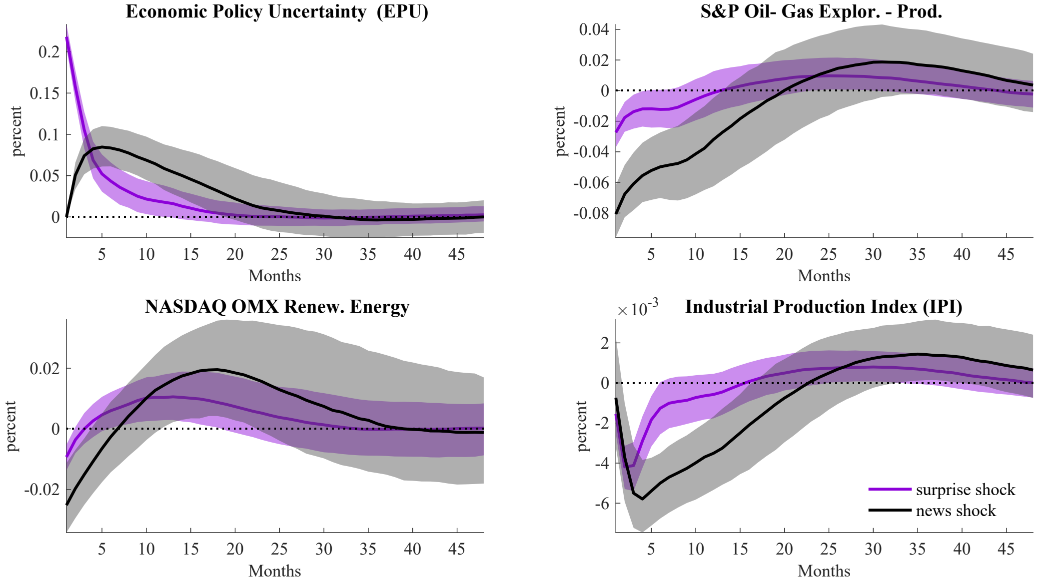
The surprise of new technology is is good, but not enough to sustain long run growth. This is in contrast to Figure 2, where the news shock on fossil energy initially results in an impact fall the IPI, followed by a persistent expansion. Our interpretation is as follows: good news for the fossil sector may be bad news for the economy, but if we continue with business as usual, the economy will eventually recover and experience a boom. Figure 3, on the other hand, shows a recession for

Figure 2: IRF: News vs. surprise shocks on SP Oil & Gas Exploration & Prod. Select Industry Index



Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Fossil energy stock index. The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure 3: IRF: News vs. surprise shocks on Economic Policy Uncertainty



Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Fossil Energy stock index (solid line). The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

both shocks, with varying degrees of persistency: the news shock has a more persistent effect, while the surprise shock has a less persistent effect. The impact on the economy is consistent with the fact that Economic Policy Uncertainty (EPU) actually provides continuous coverage of news shocks. However, since the difference between news and surprise in constructing EPU is tiny, the effects of the shocks are not different. Nevertheless, an increase in Economic Policy Uncertainty can be harmful to economic activity.

We believe that the evidence provided, which shows the contrasting effects of news and surprise shocks on different variables, is an important characteristic of the data that should be considered when analyzing the dynamics of the economy. The findings also highlight the tension between the fossil and renewable energy sectors, where good news for one sector may lead to bad news for the other, and vice versa. This tension may have implications for economic policy and the transition to more sustainable energy sources.

3.2 Impulse Response Functions and Forecast Error Variance: Discussion

Based on this key evidence, we will now discuss the overall effects of news shocks. This exploration is justified by the fact that news shocks account for a high share of forecast error variance, as we will see. Figures C.1 to C.6 report the impulse response functions, (IRF), and the forecast error variance, (FEV) of the full SVAR. The solid lines correspond to the posterior median estimates, and the bands display the 16-84% posterior intervals. These bands are constructed by drawing from the posterior distribution of the parameters of the estimated model. We extract the shocks that maximize the fraction of the FEV due to X_{it}, $i = r, f, epu$, over the forecast horizon of 48 months weighting each of the forecasts equally.[13] The choice is motivated by the fact that we want to capture short- and medium-run movements of X_{it} while providing reliable estimates at the long end of the forecasting horizon. Next, we discuss the results for news shocks along the different variables.

3.2.1 Effects of Renewable energy News Shocks

We consider that a positive realization of the renewable news shock implies an expected increase in investment in greener technology. This anticipates new or improved efficiency of the green technology in the medium-to-long-run, resulting in a boom. Figure C.1 presents the renewable news shock IRF for all variable in SVAR. The dynamics on IPI, which we discussed above, are reflected in the

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[13] When using the Barsky and Sims' method to identify future X_{It} news shocks, we find that the results are not sensitive to the choice of forecast horizons. We have considered truncation horizons from 24 to 60 periods and the results are very similar.

job opening variable, (JTSJOL), which initially falls but increases significantly and persistent in the long run. We consider this effect as representing medium long run new work opportunities in sectors that use the greener, more efficient technology. Additionally, the same news shock leads to a persistent and significant increase in housing prices in the medium-to-long run. We consider this the wealth effect triggered by the renewable news shock.

The financial markets volatility increases on impact with a short lived effect, while the US competitively increases mainly in the long run, once the new technology was fully implemented. The IRF also show that a positive news shock on renewable energy triggers a deep persistent fall on fossil energy sector highlight that good news for one sector may lead to bad news for the other.

Figure C.2 confirms the significance of news shock results. According to the FEV, renewable news shocks account for over 66% of volatility in the fossil sector. Similarly, housing prices experience up to 75% volatility in the medium-long run due to this factor. Moreover, it explains a significant portion of fluctuations in the IPI, up to 45%, and more than 60% of job openings in the long run. Table C.1 presents the median contribution of the renewable news shock.

3.2.2 Fossil fuel news shocks

We consider that a positive realisation of fossil news shock results in increased economic activity by adding new fossil resources. Figure C.3 presents the fossil news shock IRF for all variable in SVAR. In this case, the effect on IPI, that we discussed already above, impact differently the labor market dynamics. The job openings exhibit a significant and persistent decline in the medium to long run, which we interpret as a short-term stagnation followed by missed opportunities to switch from an economy based on fossil resources to a greener ecenomy. Moreover, the same news shock leads to a persistent and substantial decrease in housing prices in the medium to long run, resulting in a decline in wealth due to the news shock. The financial markets' volatility increases on impact, but with a short-lived effect, while the same shock has a neutral effect on the US competitiveness.

The IRF also indicates that a positive news shock on fossil energy triggers a deep and persistent fall in the renewable energy sector. We interpret this findings as highlighting the tension between the fossil and renewable energy sectors rather than a substitutability effect.

Figure C.4 shows the FEV of the news shock. The fossil news shocks account for over 55% of volatility in the renewable sector. Similarly, housing prices experience up to 52% volatility in the medium-long run due to this factor. Moreover, it explains up to 38% of fluctuations in the IPI, and up to 45% of job openings in the long run. Table C.2 presents the median contribution of the fossil fuel news shock.

3.2.3 Economic Policy Uncertainty news shocks

An Economic Policy Uncertainty (EPU) news shock refers to an increase in uncertainty surrounding economic activity. Figure C.5 shows that the effects of EPU news shocks are comparable to those of renewable news shocks. However, an increase in EPU can be detrimental to economic activity. It leads to a persistent decline in the IPI and job openings, with a minor effect on the house price index. It also increases financial volatility represented by VIX and reduces US competitiveness in the medium term. Moreover, an EPU news shock decreases the fossil stock index while increasing the renewable stock index. We interpret this as a sign that renewable energy investments could be considered safe and reliable during times of market volatility or economic uncertainty, like in investments in low-risk assets such as gold, government bonds, or cash.

Figure C.6 shows the FEV of the news shock on EPU. This shock accounts for over 45% of volatility in IPI. Similarly, housing prices experience around 31% volatility in the long run due to this factor. Moreover, it explains up to 43% of fluctuations job opening, up to 40% of financial market volatility and up to 48% of US Dollar Index. Table C.3 presents the median contribution of the EPU news shock.

3.3 SVAR Results Interpretation

This analysis produces several interesting results. Based on the IRFs and FEV decomposition analysis, we conclude that renewable news has a strong impact on economic variables. The reaction is particularly strong on impact on variables such as IPI, financial volatility, and fossil stock prices, while other variables such as job openings, housing prices, and the US Dollar Index exhibit significant effects that accumulate over time. In both the short and long run, all variables are affected. It is noteworthy that the renewable news shock produces an increase in Economic Policy Uncertainty. This may be due to the fact that breakthrough technological developments or new policies to mitigate climate change are capable of disrupting a stable economy such as the US.

The fossil news shock has opposite effects on various variables. While it reduces job openings, housing prices, and renewable stock prices, it increases financial volatility on impact and the industrial production in medium term. Notably, the shock has no effect on EPU, suggesting that the system equilibrium is maintaining the status quo by relying on fossil resources while keeping political uncertainty low. This framework promotes economic activity by avoiding significant changes.

The impact of news shocks on Economic Policy Uncertainty (EPU) is significant over all variables, highlighting the importance of economic policy uncertainty. The news shock not only reduces job openings and the fossil resources index significantly on impact, but also persistently decreases industrial production. Negative effects extend to the US dollar index, resulting in a decrease in US competitiveness. The shock has a strong effect on financial volatility, which increases. Although the renewable index falls on impact, it increases in the medium term. These results suggest that during periods of economic policy uncertainty, renewable resources are gaining preference over fossil fuels due to their potential for stability and sustainability.

To ensure the robustness of our results, we estimated the SVAR by excluding the COVID-19 crisis period from the data sample. The results of this estimation, presented in Appendix D, show qualitatively similar results with insignificant differences in magnitudes.

4 A model with two energy sectors

To interpret the empirical findings, we incorporate news shocks into the model proposed by Argentiero et al. (2018). The model that integrates both fossil and renewable energy represents an economy composed of four sectors, with one dedicated to producing final consumer goods and the other three engaged in manufacturing intermediate goods. The driving forces of the model include stochastic stationary contemporaneous shocks as in Argentiero et al. (2018), augmented with news shocks. The news shocks are hitting the households preferences shifter, and the Total Factor Productivities, TFPs, in the fossil and renewable energy sector. In particular, as the empirical analysis suggests, the news shocks have distinct long-term implications based on their persistence parameter ϕ_i which is shock-specific. This effectively captures the propagation mechanism within each energy sector and preferences in response to the news shock.

4.1 Economy's supply side

The final output, Y_t, is generated within a competitive framework using a Cobb-Douglas production function that exhibits constant returns to scale. This function incorporates three inputs: capital, $K_{y_{t-1}}$, labor, N_{y_t}, and energy services E_t:

$$Y_t = \bar{A}_y \, K_{y_{t-1}}^{\alpha} \, N_{y_t}^{\beta} \, E_t^{1-\alpha-\beta}, \tag{4.1}$$

where $\bar{A}_y$ represents a constant TFP.

The energy sector is the first of the three intermediate goods sectors. It operates on a competitive setting, utilizing renewable and fossil inputs. Renewable energy sources, RES, account for a share of η and are denoted as E_{ert}, while fossil fuels make up a share of ζ and are represented by E_{ef_t}:

$$E_t = \bar{A}_e \, \left(\eta \, E_{er_t}^{-\epsilon} + \zeta \, E_{ef_t}^{-\epsilon}\right)^{-\frac{1}{\epsilon}}, \tag{4.2}$$

where $\bar{A}_e$ represents a constant TFP and ϵ represents the elasticity of substitution between RES and fossil fuels.

The fossil fuel sector constitutes the second intermediate goods sector and operates with a constant returns to scale function, producing its output competitively. A resource extraction firm, which utilizes private capital, $K_{ef_{t-1}}$, and labor, N_{ef_t}, extracts fossil fuels from a deposit stock, S_{t-1}.

$$E_{ef_t} = A_{ef_t} \, K_{ef_{t-1}}^{\nu} \, N_{ef_t}^{\theta} \, S_{t-1}^{1-\nu-\theta}, \tag{4.3}$$

where A_{ef_t} is the fossil fuel sector total factor productivity, that we assume follows an AR(1) stochastic process:

$$\log A_{ef_t} = (1-\phi_{ef}) \log \bar{A_{ef}} + \phi_{ef} \log A_{ef_{t-1}} + \varepsilon_{ef_t}, \tag{4.4}$$

where the shock, ε_{ef_t}, is an i.i.d. process with zero mean and standard deviation σ_{ε}, and $\bar{A_{ef}}$ indicates the TFP steady state value in the fossil energy sector.

The third intermediate goods sector is comprised of the RES industry, which operates in a perfectly competitive market. The constant returns to scale production function (4.5) incorporates accumulated R&D capital stock (Cincera and Veugelers (2014)), K_{rt-1}, in addition to capital and labor, K_{ert-1} and N_{ert}. The presence of the R&D capital stock is crucial in driving innovation and fostering the development of clean energy, as highlighted by Fischer and Newell (2008).

$$E_{ert} = A_{ert}\, K_{ert-1}^{\kappa}\, N_{ert}^{\iota}\, K_{rt-1}^{1-\kappa-\iota}, \tag{4.5}$$

where A_{ert} is the renewable sector productivity, which is assumed to follow a stochastic process driven by a shock, ε_{ert}, which is an i.i.d. process with zero mean and standard deviation σ_{ε}:

$$\log A_{ert} = (1-\phi_{er}) \log \bar{A_{er}} + \phi_{er} \log A_{ert-1} + \varepsilon_{ert}, \tag{4.6}$$

where $\bar{A_{er}}$ indicates the TFP steady state value in the renewable energy sector.

We assume that the government extends monetary support for the R&D capital by offering a subsidy, denoted as μ_{rt}, which is entirely funded through a tax on fossil fuels, τ. This subsidy plays a crucial role in fostering innovation and facilitating R&D spillovers associated with K_{rt-1}, ultimately aiding the transition to cleaner energy sources. To maintain a balanced government budget, all revenues generated from environmental taxation are allocated towards R&D investments. Consequently, the following equation holds true for each period, denoted as t:

$$E_{ef_t}\, \tau = \mu_{rt}\, K_{rt-1}, \tag{4.7}$$

The left hand side of the equation represents tax revenues generated from fossil fuels, which are equal to the public investment in the form of a subsidy for R&D capital, K_{rt}, on the right hand side of the equation.

Following Varga et al. (2022) we assume that the fossil deposit stock has a known size S_t, and there is a depreciation rate of fossil deposit δ_g. As such, the maximisation problem involves the following resource constraint:

$$S_t = (1+\delta_g)\, S_{t-1} - E_{ef_t}. \tag{4.8}$$

The total capital stock, K_t, is distributed among the economic sectors - total output, energy, fossil fuels, and renewable energy sources, RES. Meanwhile, the research and development, R&D capital, K_{rt} is specifically allocated to the RES sector.

$$K_t = \sum_{j} K_{j_t}, \tag{4.9}$$

where $j = \{y, ef, er, r\}$.

Each type of capital stock, K_{j_t}, evolves according to a law of motion:

$$X_{j_t} = K_{j_t} - (1 - \delta_j)\ K_{j_{t-1}}, \tag{4.10}$$

where $j = \{y, ef, er, r\}$, and δ_i is the corresponding rates of capital depreciation.

4.2 Economy's demand side

There is a continuum of households indexed by $j \in (0, 1)$ with preferences defined for the private consumption, C_t, and labor services, N_t. These latter are allocated to final output production, N_{y_t}, fossil fuel sector, N_{ef_t} and RES sector, N_{ert} on a period-by-period basis. Each household seeks to maximize the expected value of an intertemporal utility function:

$$E_t \sum_{t\ =0}^{\infty} \rho^t (C_t,\ N_{y_t},\ N_{ef_t},\ N_{ert}), \tag{4.11}$$

with ρ^t corresponding to the subjective discount factor.

The utility function assumes the following CRRA form:

$$U_t = \left(\Upsilon_t \frac{C_t^q}{1-q} - \frac{{N_{yt}}^{1+\chi}}{1+\chi} - \frac{{N_{ef_t}}^{1+\omega}}{1+\omega} - \frac{{N_{er_t}}^{1+\psi}}{1+\psi} \right), \tag{4.12}$$

where Υ_t is a taste shifter (Stockman and Tesar (1995)), whose law of motion is described by an AR(1) process with uncorrelated residuals $\epsilon_{\Upsilon t}$:

$$log\Upsilon_t = (1 - \phi_\Upsilon) log\bar{\Upsilon} + \phi_\Upsilon log\Upsilon_{t-1} + \varepsilon_{\Upsilon t}, \tag{4.13}$$

where $\bar{\Upsilon}$ represents the steady state preferences shifter.

The period utility function is subject to the following intertemporal budget constraint, which states that the total flow of consumption and investment, cannot exceed total income:

$$Y_t = C_t + X_t, \tag{4.14}$$

where $X_t = \sum_j X_{j_t}$, where $j = \{y, ef, er, r\}$.

4.3 News shocks

In this setting, the news shocks, $\varepsilon_{t-6}^{\text{news}}$, are introduced to fossil and renewable TFPs sectors and to the preferences shifter as follows:

$$\log A_{er_t} = (1 - \phi_{er}) \log \bar{A}_{er} + \phi_{er} \log A_{er_{t-1}} + \varepsilon_{er_t} + \varepsilon_{t-6}^{\text{news}}, \tag{4.15}$$

$$\log A_{er_t} = (1 - \phi_{er}) \log \bar{A}_{er} + \phi_{er} \log A_{er_{t-1}} + \varepsilon_{er_t} + \varepsilon_{t-6}^{\text{news}}, \tag{4.16}$$

$$\log \Upsilon_t = (1 - \phi_{\Upsilon}) \log \bar{\Upsilon} + \phi_{\Upsilon} \log \Upsilon_{t-1} + \varepsilon_{\Upsilon_t} + \varepsilon_{t-6}^{\text{news}}. \tag{4.17}$$

Although we report only results for the news shock, ${\varepsilon^{\text{news}}}_{t-6}$, we also consider a contemporaneous i.i.d. shock, ε_{it}, $i = er, ef, \Upsilon$.

The news shock hits the economy in steady state. Agents receive news about a one percent increase in A_{er_t}, A_{ef_t} and Υ_t up to six periods ahead: ε_{t-6}^{news} is an innovation that materializes in period t, but that agents learn about in period $t - 6$.

4.4 Calibration

This section discusses the choice of parameter values we consider useful in studying the propagation mechanism of news shocks. Our strategy is to calibrate parameters so that the steady state of the model economy matches the average values in US monthly data for the 1995-2018 period. The stochastic structure that governs the evolution of the news shocks is taken from the time series properties of the corresponding. The goal of the quantitative experiments next is to provide an interpretation of the responses we estimated in data. Table 1 summarizes the calibrated parameters. As indicated above most parameters are in conformity with either the long-run or the stochastic properties of the data.

Parameters' definitions & Calibration

Parameter	Target	Definition	Value
α	K_{y_t}/Y_t	Final output elasticity with respect to capital	0.2215
β	N_{y_t}/Y_t	Final output elasticity with respect to labor	0.6015
δ_y	X_{y_t}/K_{y_t}	Capital depreciation rate: final output	0.0119
δ_{ef}	X_{ef_t}/K_{ef_t}	Capital depreciation rate: fossil fuels	0.0134
δ_{er}	X_{ert}/K_{ert}	Capital depreciation rate: RES	0.0115
δ_r	X_{rt}/K_{rt}	Capital depreciation rate: R&D	0.014
δ_s	Calibrated	Fossil deposit depreciation rate	0.0129
ϵ	Calibrated	Elasticity of substitution between RES and fossil fuels	0.4966
ζ	Calibrated	Fossil fuels share in energy production	0.8066
η	Calibrated	RES sharein energy production	0.1934
θ	N_{ef_t}/E_{ef_t}	Fossil fuels elasticity with respect to labor	0.2033
ν	K_{ef_t}/E_{ef_t}	Fossil fuels elasticity with respect to capital	0.5645
ι	N_{ert}/E_{ert}	RES elasticity with respect to labor	0.3222
κ	K_{ert}/E_{ert}	RES elasticity with respect to private capital	0.6466
q	Calibrated	Relative risk aversion coefficient	0.8816
$\bar{A}_y$	Estimated	Constant TFP in the final output	0.8528
$\bar{A}_e$	Estimated	Constant TFP in energy sector	0.8766
ϕ_{ef}	Estimated	Shock persistence of TFP in fossil fuels sector	0.8510
ϕ_{er}	Estimated	Shock persistence of TFP in RES sector	0.8399
ϕ_{Υ}	Estimated	Shock persistence in taste shifter	0.8760
χ	Calibrated	Inverse of RES Frisch elasticity of labor supply	3.24507
ω	Calibrated	Inverse of fossil fuels Frisch elasticity of labor supply	3.6257
ψ	Calibrated	Inverse of final output Frisch elasticity of labor supply	3.6056
ρ	Calibrated	Discount factor	.9963
τ	Calibrated	Tax rate on fossil fuels' production	.015

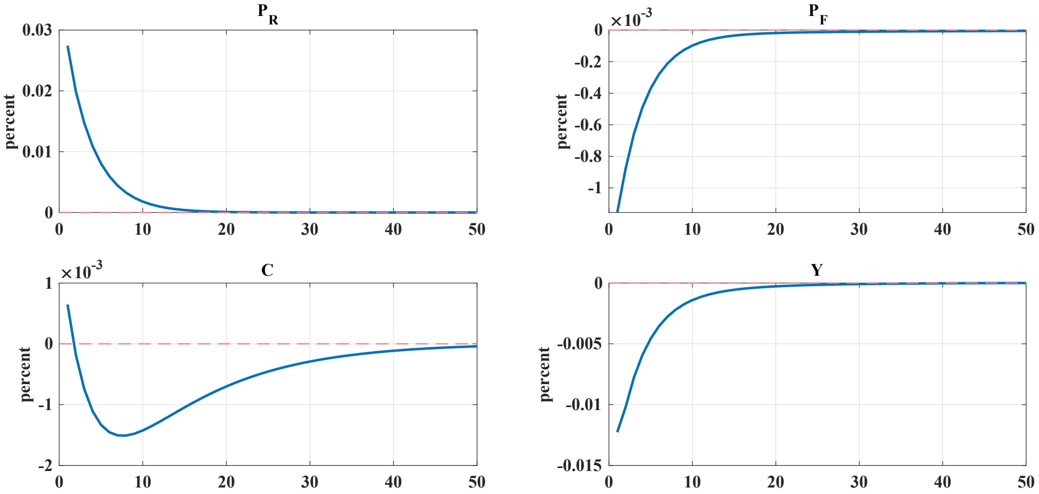
Table 1: Parameters' definitions

4.5 Model responses to news shocks

In the next step of our analysis, we examine the theoretical impulse response functions (IRFs) to news shocks in our benchmark model. We use the same variable mapping as introduced in Section 1, and our model's response to the news shock aligns with the empirical results presented in Section 3. We focus on four variables: the renewable energy price (P_R), corresponding to the renewable energy index; the fossil energy price (P_F), corresponding to the fossil energy index; total output (Y), corresponding to the empirical Industrial Production Index; and total consumption (C), representing the inverse of the empirical Economic Policy Uncertainty. We present the IRFs for a 48-period horizon, consistent with the empirical analysis.

Figure 4 displays the IRFs of the model's aggregate variables after a 1% positive news shock on the price of renewable energy. The fossil energy price and total output both decrease on impact, but with low persistence. Specifically, the output falls by approximately 1.3%, while the fossil price falls by around 0.01%. In contrast, total consumption on impact increases, but subsequently declines and exhibits significant persistence in returning to its steady state.

Figure 4: News shock on Renewable Prices



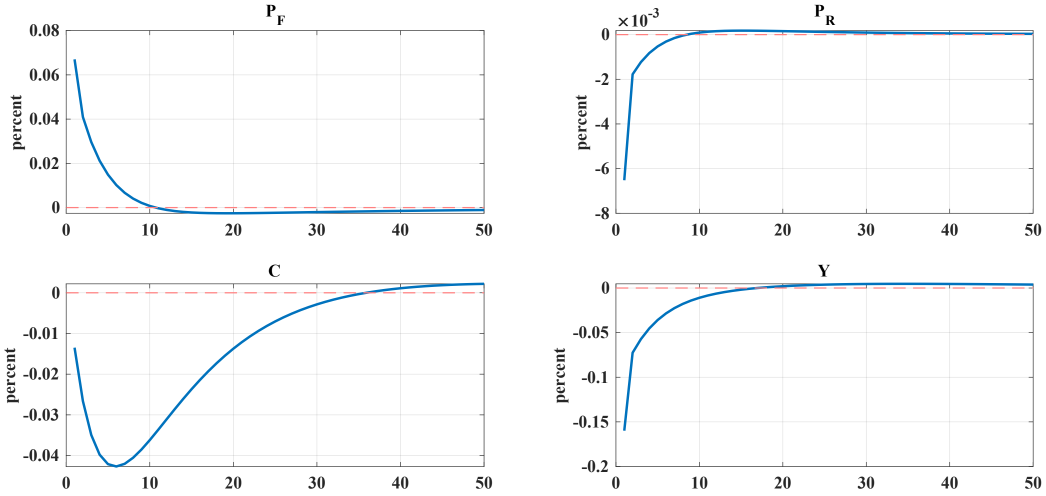
Notes: The units of the vertical axes are percentage deviations from the steady state.

Figure 5 illustrates the IRFs of the model's aggregate variables in response to a 1% positive news shock on the price of fossil energy. The results show that both the renewable energy price and total output on impact decrease with a larger magnitude, but lower persistence than the shock produced by the renewable energy. In particular, the output falls by 1.6%, while the fossil price falls by approximately 0.08%. Additionally, the total consumption also declines by 0.12% and demonstrates significant persistence in returning to its steady state.

Figure 6 illustrates the IRFs of the model's aggregate variables in response to a 1% positive news shock on the preference shifter. The consumption response appears to be short-lived and transitory, while the responses of fossil energy prices, total output, are more persistent and have a long-run impact. Those variables recover the initial fall and increase over the long run with a high degree of persistency.

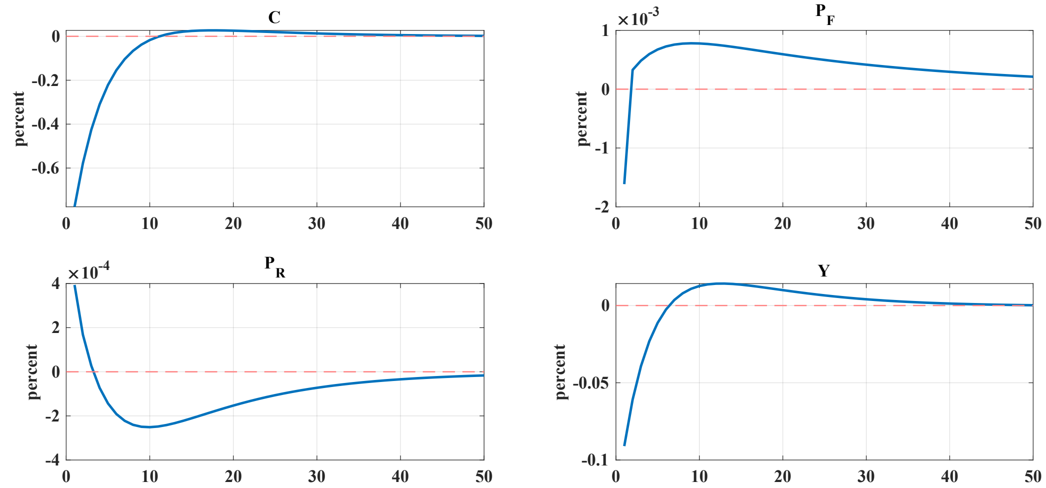
Overall, Figure 4 to 6 suggest that the model is capable of capturing the dynamic responses of key macroeconomic variables to news shocks in line with the empirical results. However, it is important to note that the review only covers one specific shock, and the model's performance may vary for different types of shocks.

Figure 5: News shock on Fossil Fuel Prices



Notes: The units of the vertical axes are percentage deviations from the steady state.

Figure 6: News shock on Preferences shifter



Notes: The units of the vertical axes are percentage deviations from the steady state.

5 Conclusion

This study aims to investigate the impact of anticipated (news) shocks on renewable and fossil fuel energy and economic policy uncertainty. Our hypothesis is that the contribution of energy news shocks to economic fluctuations depends on various factors: the society's attitudes towards environmental awareness, the readiness of the economy to shift from fossil fuels to renewable energy and the level of investment in research and development. Moreover, this impact is influenced by the tension between the traditional, fossil fuel-based economy and the emerging, green technology-based economy.

To demonstrate our hypothesis, we first use the Barsky and Sims (2011) estimation approach. We aim to ensure that we are identifying a news shock, rather than a traditional surprise shock or its lag. We begin by comparing the effects of news shocks with those of surprise shocks in a SVAR model comprising eight variables. We observe important differences between them, and that the news shock has significant and mostly opposite effects to the surprise shock. Next, we examine how news shocks affect other variables and propagate through the real economy. We find energy news shocks have significant impacts on economic and financial variables.

The analysis of impulse response function indicates that renewable energy news shocks have stronger and more persistent effects than fossil fuel news shocks. Economic Policy Uncertainty news shocks exhibit similar characteristics as the renewable shocks but to a lesser extent. Additionally, renewable news shocks explain a considerable variation in the Industrial Production Index (up to 45%), job openings (over 55%), and US Home Price Index (up to 77%). On the other hand, the news shocks identified on fossil energy explain the variance of IPI, job openings, and home prices to a lesser extent (38%, 45%, and 55%, respectively). The combination of the three variables of interest of news shocks explains a significant forecast error variance contribution (90%) of the SVAR variables, leaving only 10% to be explained by other shocks.

Overall, this study will provide valuable insights into the dynamics of the news energy shocks and its impact on the real economy and economic policy uncertainty. By exploring the nexus between renewable and non-fossil energy sources and economic policy uncertainty, we can gain insight into how news shocks in one sector affect the other. This understanding is critical as the energy sector is a significant driver of economic growth and development.

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Appendix

A DATA

Board of Governors of the Federal Reserve System (US), Industrial Production: Total Index [INDPRO], retrieved from FRED, Federal Reserve Bank of St. Louis; INDPRO

To measure the total production of the industrial sector, we use the Industrial Production Index (INDPRO). In addition, we incorporate Total Nonfarm Job Openings (JTSJOL) to gain insights into the effects of renewable and fossil energy policies on the labor market[14]. Unlike the unemployment rate, which is a lagging variable, the JTSJOL as a forward-looking variable can help shed light on the potential impact of energy and economic policy news shocks on employment.

As a measure of the housing market health, we use the S&P/Case-Shiller U.S. National Home Price Index. House prices were included in order to identify the wealth effect of the news shocks, as shown by Guinea et al. (2023). As a measure of financial market volatility, we incorporate the CBOE Volatility Index (VIX). While some of the volatility can be attributed to the energy indexes, we acknowledge that financial volatility is also influenced by other sectors of the economy. Finally, the US Dollar Index is included to assess the competitiveness of the US in international trade, as well as how changes in energy prices and policies affect its exchange rate (Dvorkin et al. (2020)).

A.1 Real economy

A.1.1 Industrial Production Index (IPI)

Industrial Production Index (IPI)[15] refers to a monthly economic indicator that measures the production output of the US manufacturing, mining, and utilities sectors. The indicator is published by the Federal Reserve Board and is considered an important measure of the country's industrial sector's health. The index provides a snapshot of the overall performance of the industrial sector by

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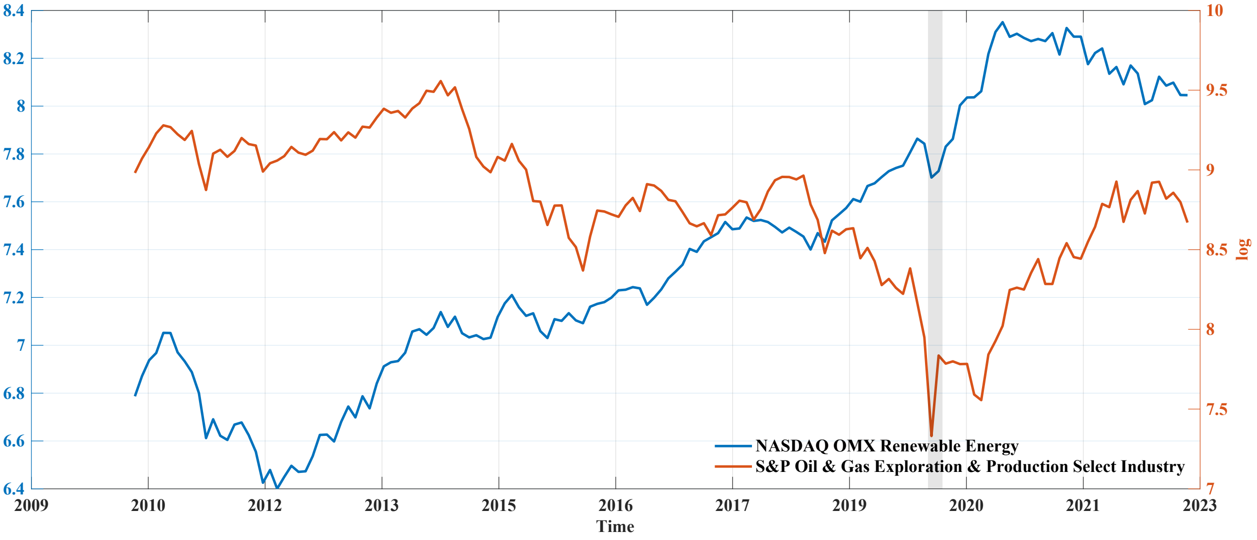
[14] The job openings level is a key indicator of demand for labor. It reflects the need for additional employees, and it can provide insights into shifts in the economy. Job openings level often increases when approaching an economic expansion or decreases when approaching an economic contraction. One way to evaluate the number of job openings is to compare it with the number of unemployed people. These measures tend to move in opposite directions. Penn and Nezamis (2022)

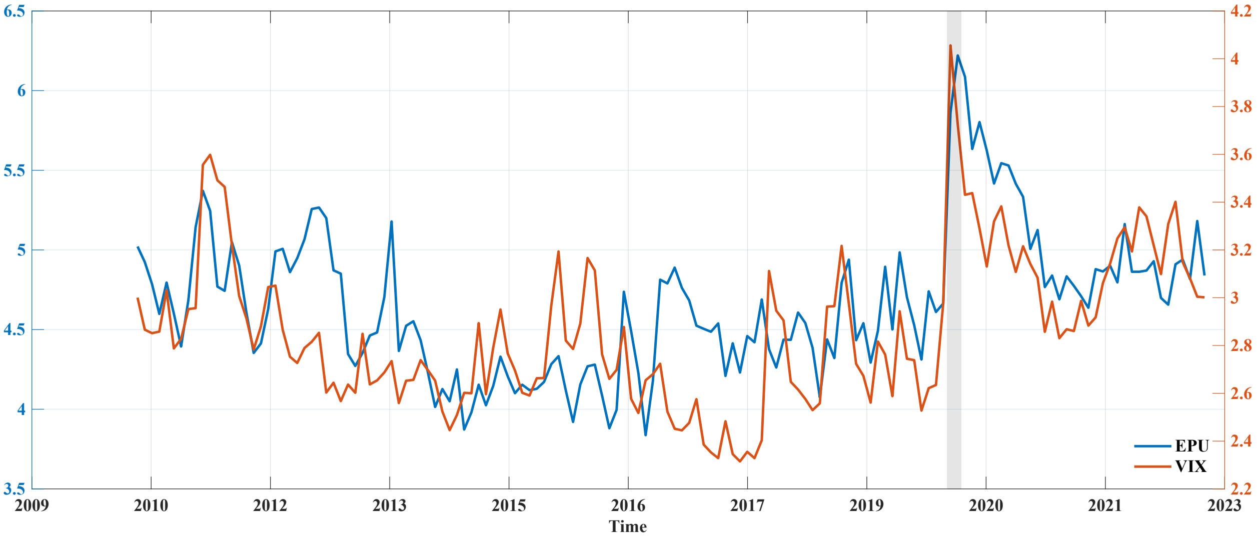
[15] Board of Governors of the Federal Reserve System (US), Industrial Production: Total Index [INDPRO], retrieved from FRED database FRED, Federal Reserve Bank of St. Louis, March 17, 2023.

Figure A.1: NASDAQ OMX Renewable Energy vs. S&P Oil & Gas Exploration & Production Select Industry



Note: The variables are in logs.

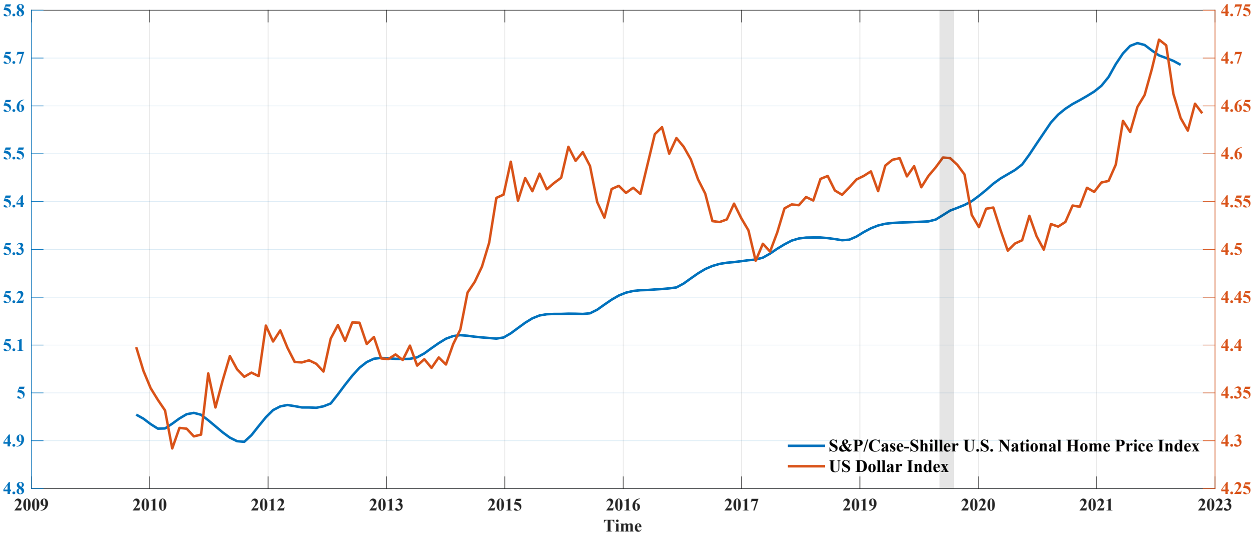
Figure A.2: EPU vs. VIX



Note: The variables are in logs.

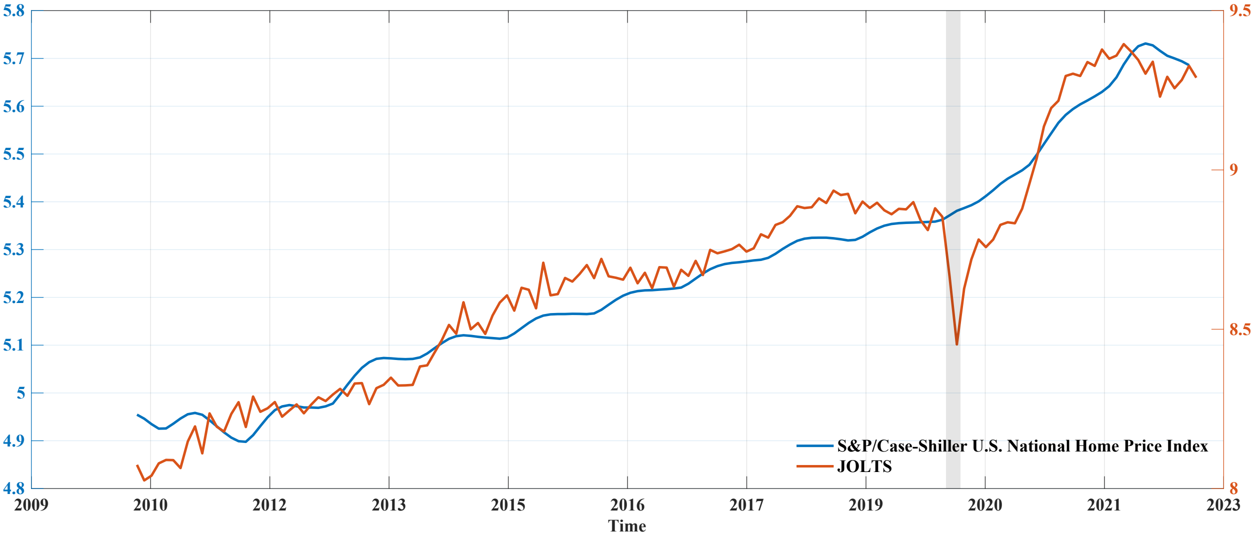
measuring the percentage change in total output, both in terms of volume and value. The data used to construct the INDPRO index is obtained from a survey of industrial companies, and it covers a broad range of products, including durable and non-durable goods. INDPRO is closely watched by economists, policymakers, and investors as it provides insights into the overall health of the US economy and is considered an important leading indicator of economic growth.

Figure A.3: S&P/Case-Shiller U.S. National Home Price Index vs. US Dollar Index



Note: The variables are in logs.

Figure A.4: S&P/Case-Shiller U.S. National Home Price Index vs. JOLTS



Note: The variables are in logs.

A.1.2 S&P/Case-Shiller U.S. National Home Price Index

The S&P/Case-Shiller U.S. National Home Price Index[16] is a measure of the performance of the U.S. residential real estate market. It is calculated and released monthly by Standard & Poor's, and is based on a composite of single-family home prices across 20 major metropolitan areas in the United States. The index is designed to track changes in the price of residential real estate over

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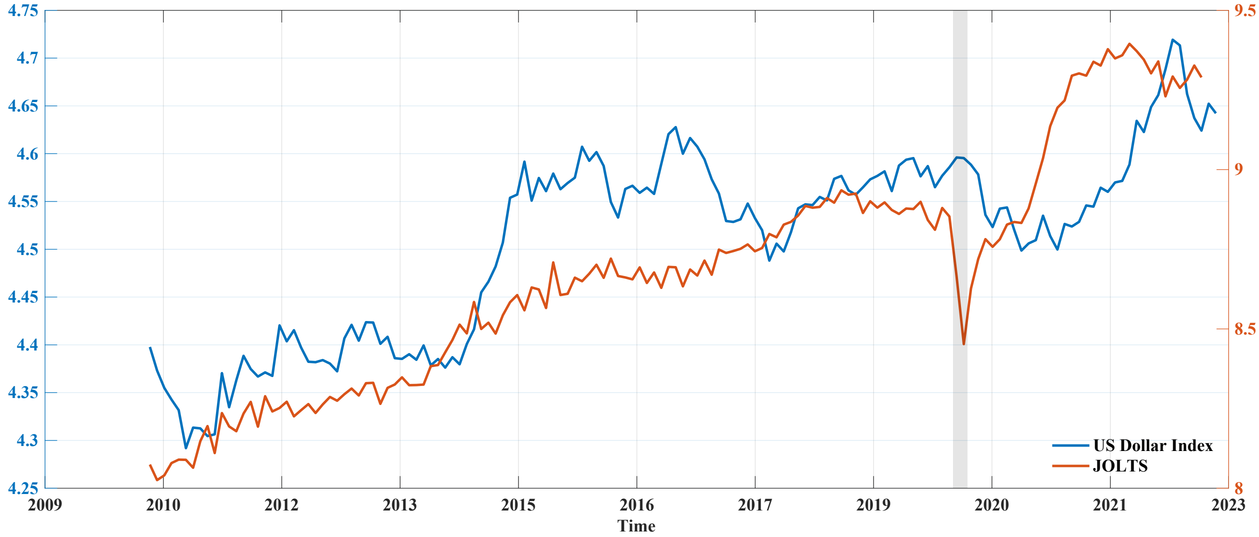
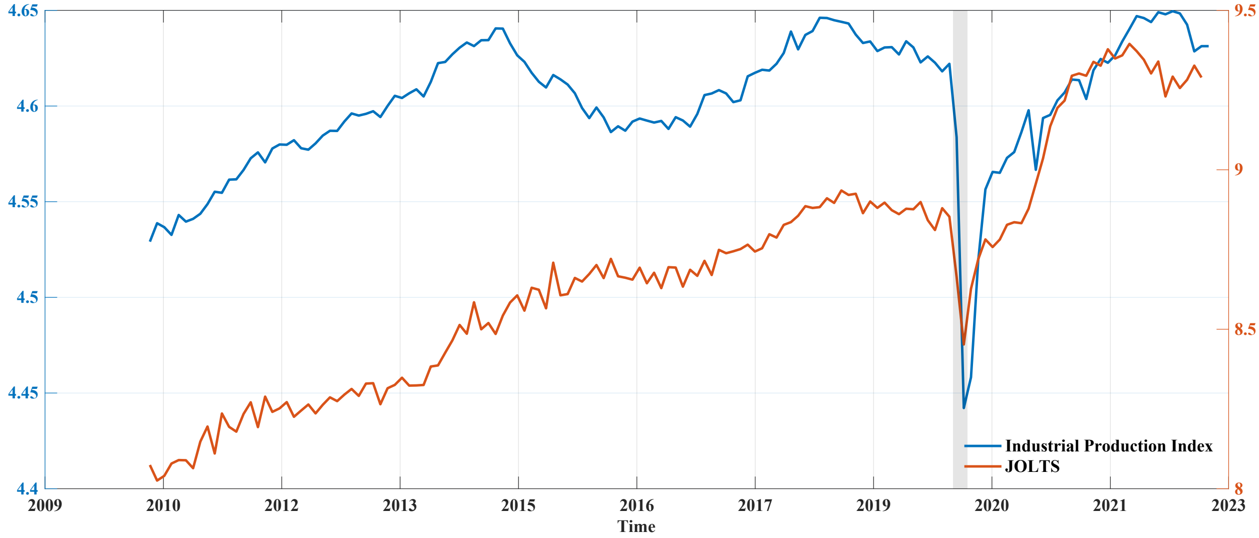
[16] S&P Dow Jones Indices LLC, S&P/Case-Shiller U.S. National Home Price Index [CSUSHPINSA], retrieved from FRED database, FRED Federal Reserve Bank of St. Louis, March 16, 2023.

Figure A.5: US Dollar Index vs. JOLTS



Note: The variables are in logs.

Figure A.6: Industrial Production Index vs.JOLTS



Note: The variables are in logs.

time, and is considered to be a leading indicator of overall economic conditions, as rising home prices are often associated with a strong economy. The index is widely used by economists, policymakers, and investors to gauge the health of the housing market and to make investment decisions.

A.1.3 Job Openings: Total Nonfarm (JTSJOL)

The Job Openings: Total Nonfarm (JTSJOL)[17] figure represents the total number of job openings in the United States across all nonfarm industries. This includes jobs in sectors such as manufacturing, construction, retail, and healthcare. It is an indicator included in the Job Openings and Labor Turnover Survey (JOLTS), which is a monthly report released by the Bureau of Labor Statistics (BLS) in the United States. It provides information on job openings, hires, and separations in various industries and regions of the country. The JOLTS report includes data on both private and public sector jobs. The JOLTS report provides an important indicator of the health of the labor market.

Investors and policymakers closely monitor the JOLTS report as it can provide insight into the overall strength of the economy and the labor market. A high JTSJOL number indicates a strong demand for workers, which can lead to wage growth and economic expansion. Conversely, a low JTSJOL number suggests a weaker labor market with fewer job opportunities.

A.2 US Dollar Index

The "US Dollar Index", also known as DXY, is a financial index that measures the value of the US dollar relative to a basket of six major foreign currencies: the euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc. The index was created in 1973, and its purpose is to provide a benchmark for the value of the US dollar against other major currencies.

The US Dollar Index is weighted according to the trade volume of the currencies included in the basket. The euro has the highest weighting, with a value of 57.6%, followed by the Japanese yen at 13.6%, the British pound at 11.9%, the Canadian dollar at 9.1%, the Swedish krona at 4.2%, and the Swiss franc at 3.6%.

The US Dollar Index is widely used by traders and investors to track the strength of the US dollar against other major currencies. A rising index value indicates a stronger US dollar, while a falling index value indicates a weaker US dollar. The index is also closely watched by central banks, as changes in the value of the US dollar can have significant implications for international trade and

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[17] U.S. Bureau of Labor Statistics, Job Openings: Total Nonfarm [JTSJOL], retrieved from FRED database, FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/JTSJOL, March 16, 2023.

financial markets.

The reference website for DXY is the Intercontinental Exchange (ICE) website, which provides real-time and historical data for the index. (Intercontinental Exchange (ICE))

A.3 NASDAQ OMX Renewable Energy

The "NASDAQ OMX Renewable Energy" is a stock index that tracks the performance of companies engaged in renewable energy and related businesses. It includes companies involved in various subsectors, such as solar power, wind power, hydro power, geothermal power, and biomass energy.

The index is designed to provide investors with a benchmark for tracking the performance of renewable energy companies and to serve as a tool for portfolio diversification. It is weighted based on market capitalization, with larger companies having a greater impact on the index's performance.

The NASDAQ OMX Renewable Energy index was launched in 2008 and is maintained by the NASDAQ OMX Group, Inc. The index is calculated in real-time and is disseminated every 15 seconds during trading hours. Some of the companies included in the index are Tesla Inc., First Solar Inc., and Canadian Solar Inc.

The NASDAQ OMX Group, Inc. is a global exchange operator that provides trading, clearing, exchange technology, regulatory, securities listing, and public company services. Within this group, there is a separate index known as the NASDAQ OMX Clean Edge Global Wind Energy Index, which tracks the performance of companies in the wind energy industry.NASDAQ OMX Global Indexes

A.4 CBOE Volatility Index: VIX

The CBOE Volatility Index, or VIX[18], is a real-time market index that represents the market's expectations for volatility over the next 30 days. The VIX is calculated using the prices of S&P 500 index options and reflects the level of fear or stress in the stock market. When the VIX is high, it indicates that investors expect significant market volatility and are willing to pay more for options to protect their portfolios. Conversely, a low VIX indicates that investors expect little

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[18] Chicago Board Options Exchange, CBOE Volatility Index: VIX [VIXCLS], retrieved from FRED database FRED, Federal Reserve Bank of St. Louis, March 18, 2023.

market volatility and are less concerned about potential losses. The VIX is often referred to as the "fear index" because it is seen as a measure of investor sentiment and risk appetite.

B VAR IDENTIFICATION

We identify news shocks using Barsky and Sims (2011) methodology. Let $\mathbf{y}_t$ be a $k \times 1$ vector of observables of length T. Let the reduced form moving average representation in the levels of the observables be given as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t \tag{B.1}$$

where $B(L)$ is a $k \times k$ matrix polynomial in the lag operator, L, of moving average coefficients and u_t is the $k \times 1$ vector of reduced-form innovations. We assume there exists a linear mapping between innovations and structural shocks, ε_t, given as:

$$\mathbf{u}_t = \mathbf{A}_0\varepsilon_t \tag{B.2}$$

This implies the following structural moving average representation:

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\varepsilon_t \tag{B.3}$$

Where $\mathbf{C} = \mathbf{B}(\mathbf{L})\mathbf{A}_0$ and $\varepsilon_t = \mathbf{A}_0^{-1}\mathbf{u}_t$. The impact matrix must satisfy $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$, where $\mathbf{\Sigma}$ is the variance-covariance matrix of reduced-form innovations. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, $\tilde{A}$ (we choose the convenient Cholesky decomposition), the entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a orthonormal matrix ($D' = D^{-1}$ and $DD' = I$, identity matrix).

The h step ahead forecast error is:

$$\mathbf{y}_{t+h} - E_{t-1}\mathbf{y}_{t+h} = \sum\nolimits_{\tau=0}^{h}\mathbf{B}_{\o}\tilde{\mathbf{A}}_0\mathbf{D}\varepsilon_{t+h-\tau} \tag{B.4}$$

where $B\tau$ is the matrix of moving average coefficients at horizon τ. The contribution to the forecasterror variance of variable i attributable to structural shock j at horizon h is then:

$$\Omega_{i,j}(h) = \frac{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_{\text{\o}} \tilde{\mathbf{A}}_0 \mathbf{D} \mathbf{e}_j \mathbf{e}_j' \mathbf{D}' \tilde{\mathbf{A}}_0' \mathbf{B}_{\text{\o}}{}' \right) \mathbf{e}_i}{\mathbf{e}_i' \left(\sum_{\tau=0}^{h} \mathbf{B}_{\text{\o}} \mathbf{\Sigma} \mathbf{B}_{\text{\o}}' \right) \mathbf{e}_i} \tag{B.5}$$

$$= \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \tilde{\mathbf{A}}_0 \gamma \gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'}$$

The $\mathbf{e}_i$ denote selection vectors with one in the ith place and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the jth column of $\mathbf{D}$, which will be denoted by γ. $\tilde{\mathbf{A}}_0\gamma$ is $k \times 1$ is a vector corresponding to the jth column of a possible orthogonalization and has the interpretation as an impulse vector. The selection vectors outside the parentheses in both numerator and denominator pick out the ith row of the matrix of moving average coefficients, which is denoted by $\mathbf{B}_{i,\tau}$.

Let q_t^i occupy the first position in the system, and let the unanticipated shock be indexed by 1 and the news shock by 2. Our identifying assumption implies that these two shocks account for all variation of q_t^i at all horizons. Eqs. (**??**) and (**??**), imply that these two shocks account for all variation in q_t^i

$$\Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \quad \forall h \tag{B.6}$$

It is general not possible to force this restriction to hold at all horizons. Instead, we propose picking parts of the impact matrix to come as close as possible to making this expression hold over a finite subset of horizons. With the surprise shock identified as the innovation in observed technology, $\Gamma_{1,1}(h)$ will be invariant at all h to alternative identifications of the other $k-1$ structural shocks. As such, choosing elements of A_0 to come as close as possible to making the above expression hold is equivalent to choosing the impact matrix to maximize contributions to $\Gamma_{1,2}(h)$ over h.

Since the contribution to the forecast error variance depends only on a single column of the impact matrix, this suggests choosing the second column of the impact matrix to solve:

$$\gamma* = \arg\max \sum_{\mathbf{h}=\mathbf{0}}^{\mathbf{H}} \Omega_{1,2}(h) = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \tilde{\mathbf{A}}_0 \gamma \gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{i,\tau}'}{\sum_{\tau=0}^{h} \mathbf{B}_{i,\tau} \mathbf{\Sigma} \mathbf{B}_{i,\tau}'} \tag{B.7}$$

s.t.

$$\tilde{\mathbf{A}}_0(1,j) = 0 \quad \forall j > 1 \tag{B.8}$$

$$\gamma(1,1) = 0 \tag{B.9}$$

$$\gamma'\gamma = 1 \tag{B.10}$$

So as to ensure that the resulting identification belongs to the space of possible orthogonalization of the reduced form, the problem is expressed in terms of choosing γ conditional on an arbitrary orthogonalization, $\tilde{A}_0$. H represents the finite truncation horizon[19]. The first two constraints impose that the news shock has no contemporaneous effect on the level of q_t^i. The third restriction (that γ have unit length) ensures that γ is a column vector belonging to an orthonormal matrix.

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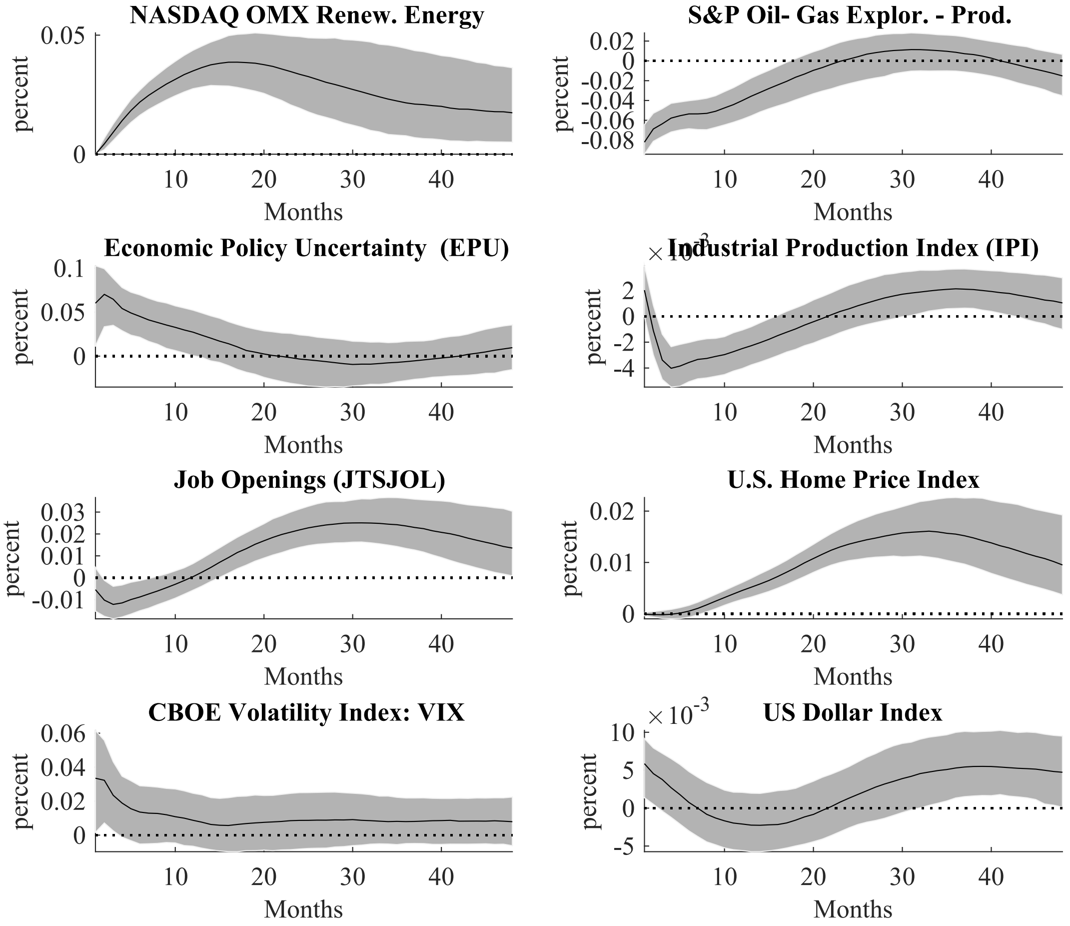
[19] The finite truncation horizon in this paper is 10 periods

C Empirical evidence of energy news shocks

This appendix illustrates the empirical results from a VAR identification of oil news shocks.

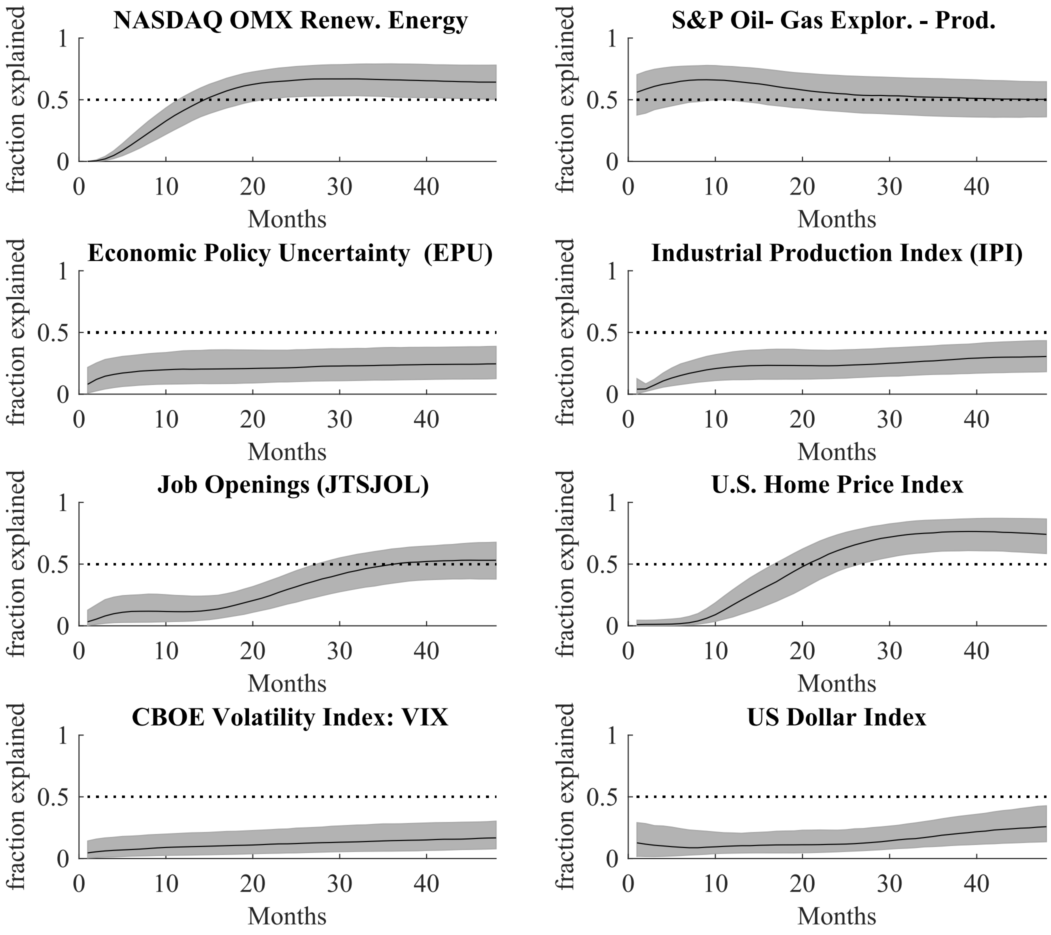
C.1 Renewable news shock

Figure C.1: IRF - Renewable energy



Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure C.2: FEV - Renewable energy



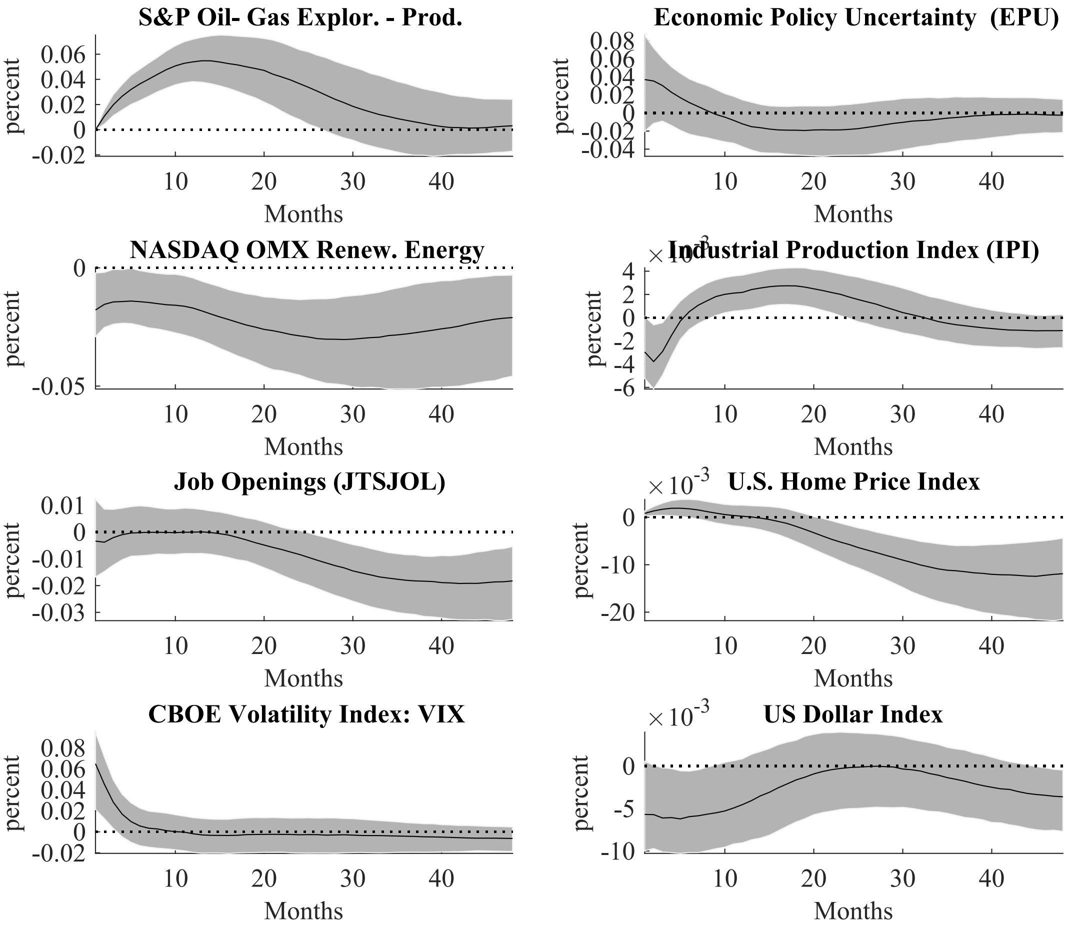
Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

	NASDAQ Renew.	SP Oil & Gas	EPU	IPI	Jobs Opening	US Home Price	CBOE VIX	US Dollar Index
Median contribution	0.66	0.67	0.38	0.45	0.60	0.75	0.19	0.32
Period	41	8	48	48	15	25	48	47

Table C.1: Median contribution to FEV of a renewable news shock

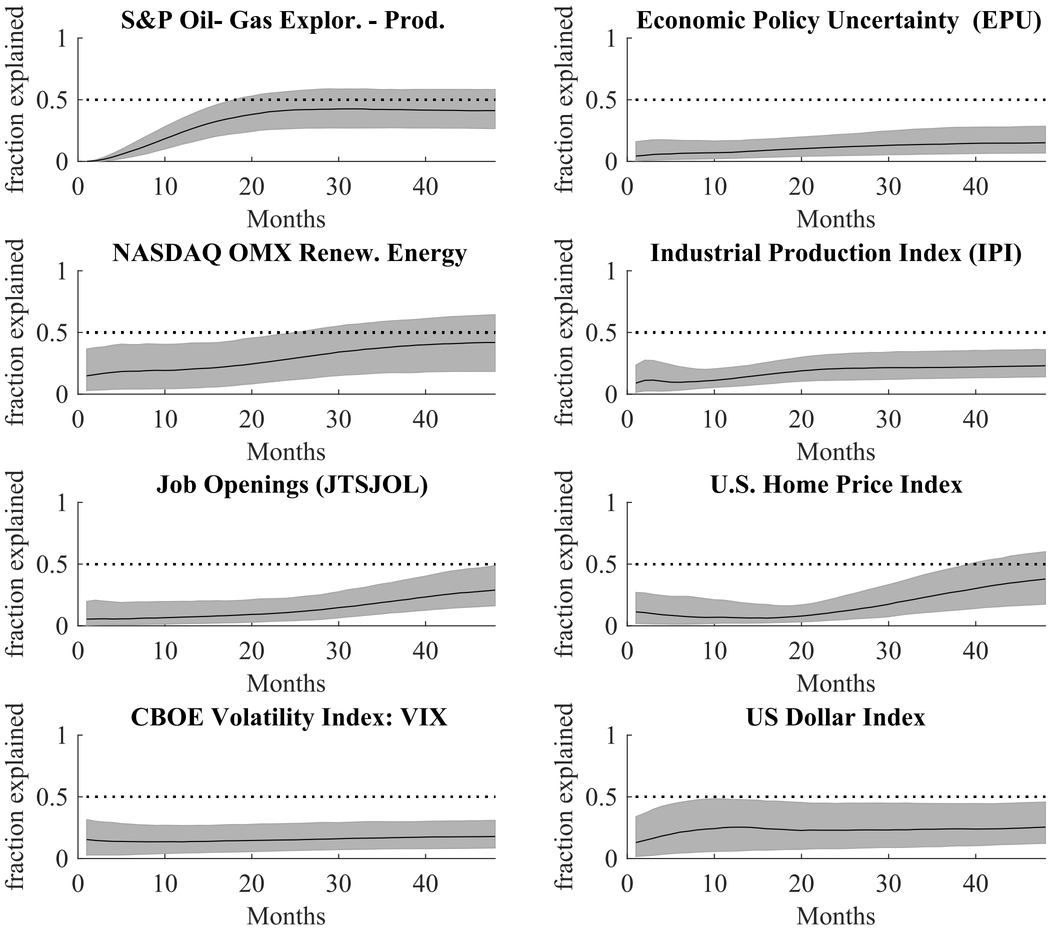
C.2 Fossil news shock

Figure C.3: IRF - Oil & Gas



Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure C.4: FEV - Oil & Gas



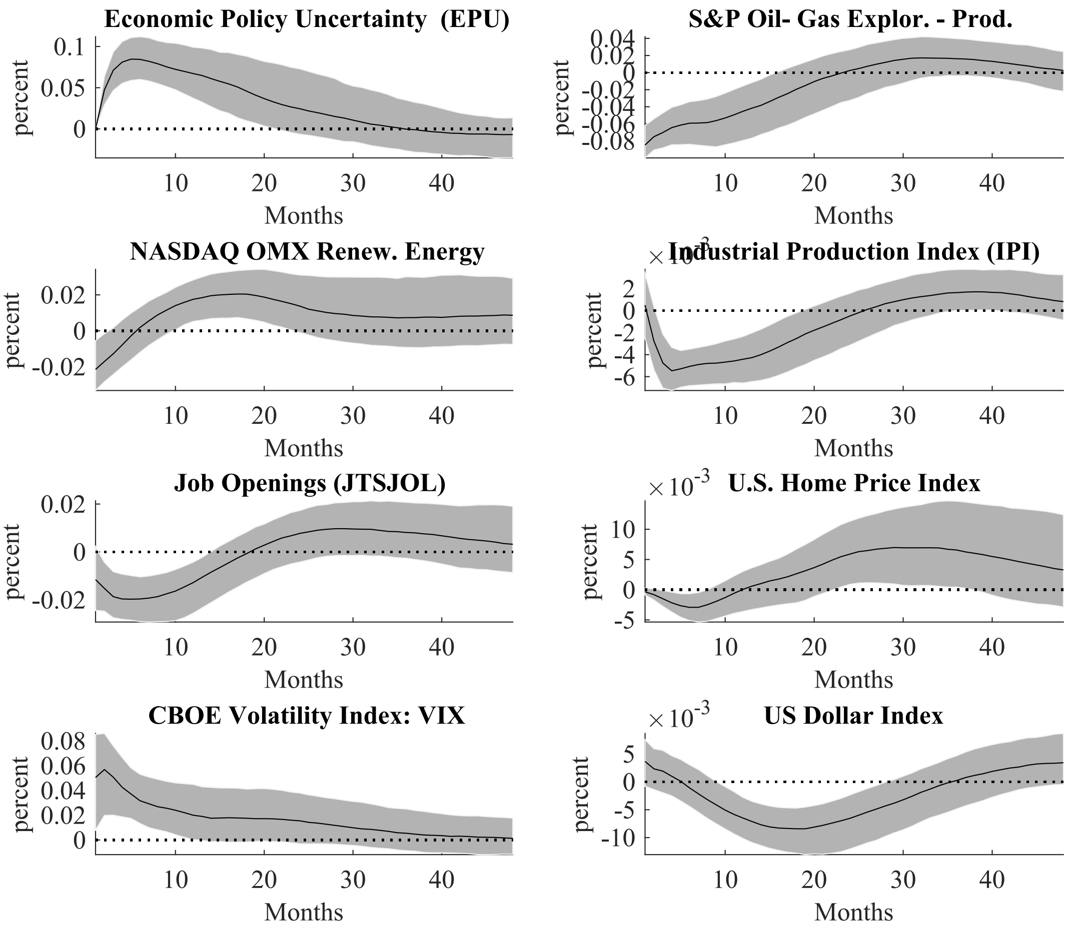
Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

	SP Oil & Gas	EPU	NASDAQ Renew.	IPI	Jobs Opening	US Home Price	CBOE VIX	US Dollar Index
Median contribution	0.47	0.17	0.46	0.32	0.39	0.42	0.15	0.28
Period	30	48	47	46	46	1	48	45

Table C.2: Median contribution to FEV of a fossil fuel news shock

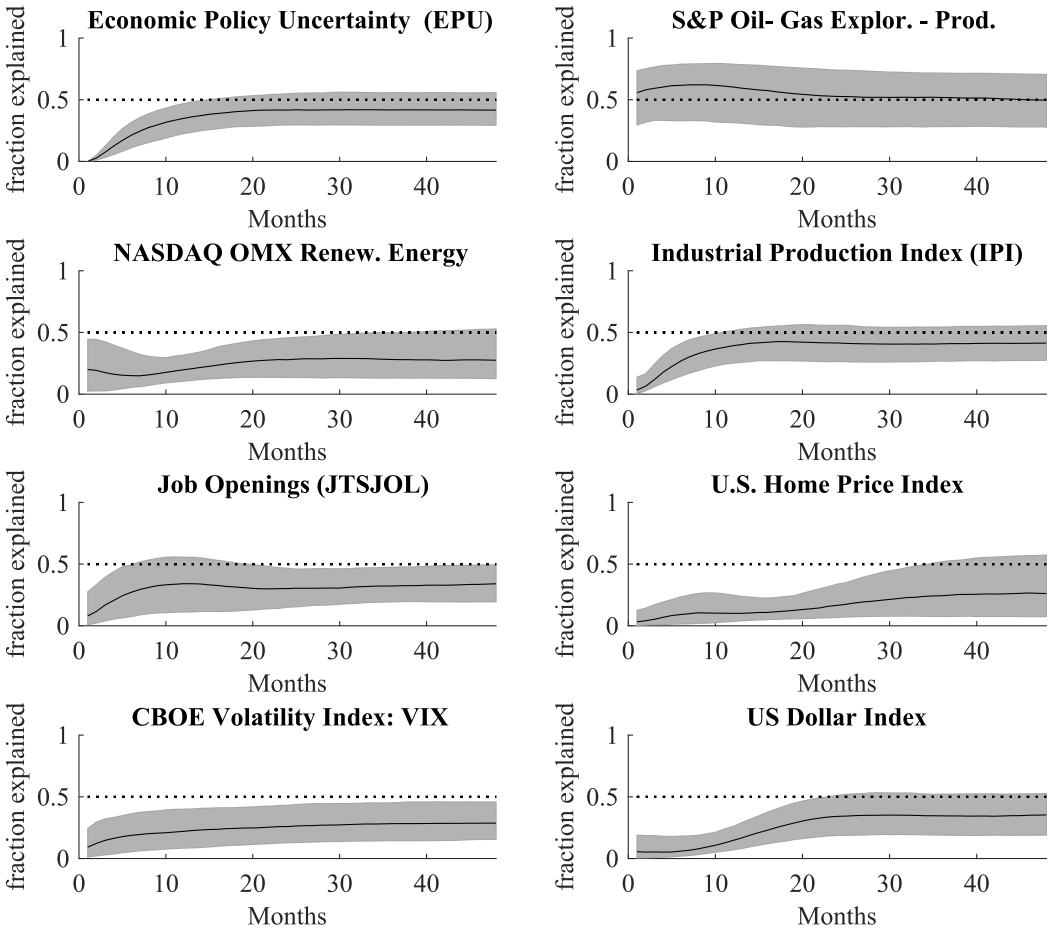
C.3 Economic Policy Uncertainty news shock

Figure C.5: IRF - EPU



Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure C.6: FEV - EPU



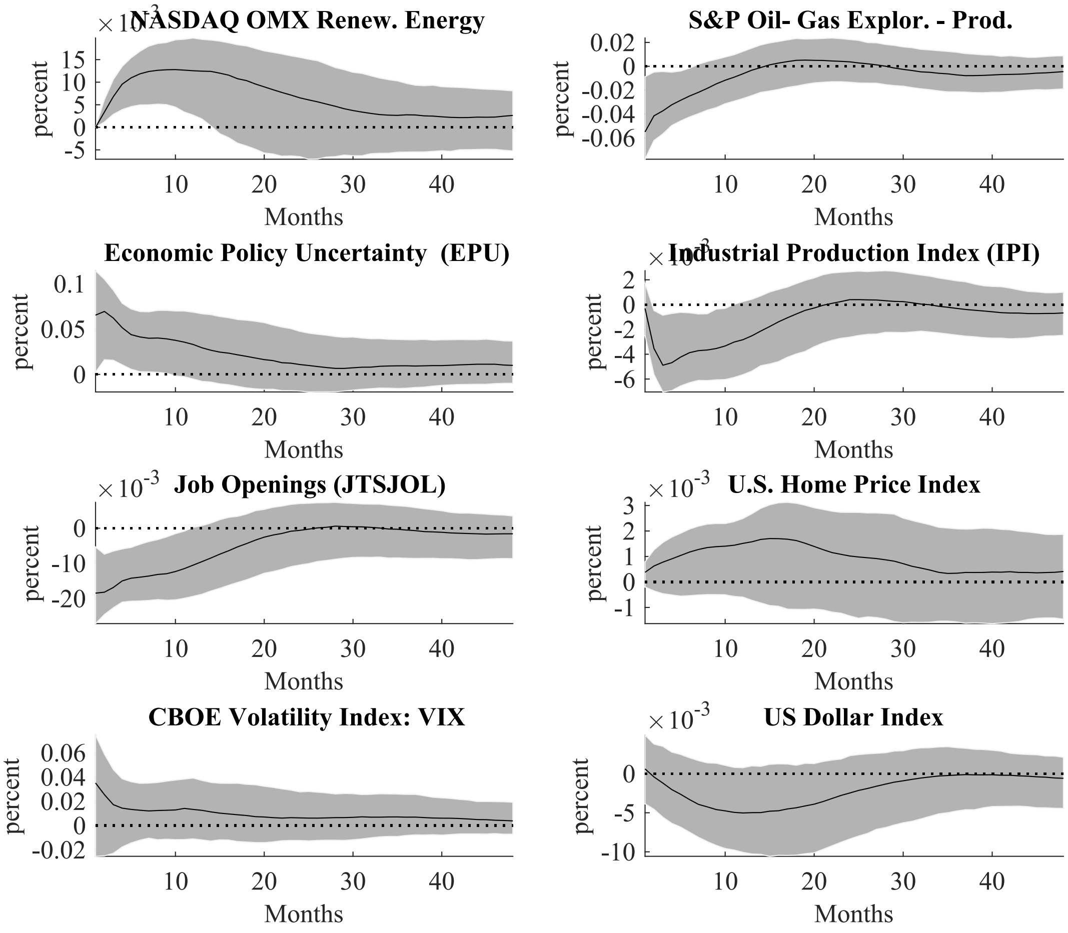
Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

	EPU	SP Oil & Gas	NASDAQ Renew.	IPI	Jobs Opening	US Home Price	CBOE VIX	US Dollar Index
Median contribution	0.44	0.71	0.27	0.45	0.43	0.31	0.38	0.40
Period	46	6	48	45	48	48	48	48

Table C.3: Median contribution to FEV of an EPU news shock

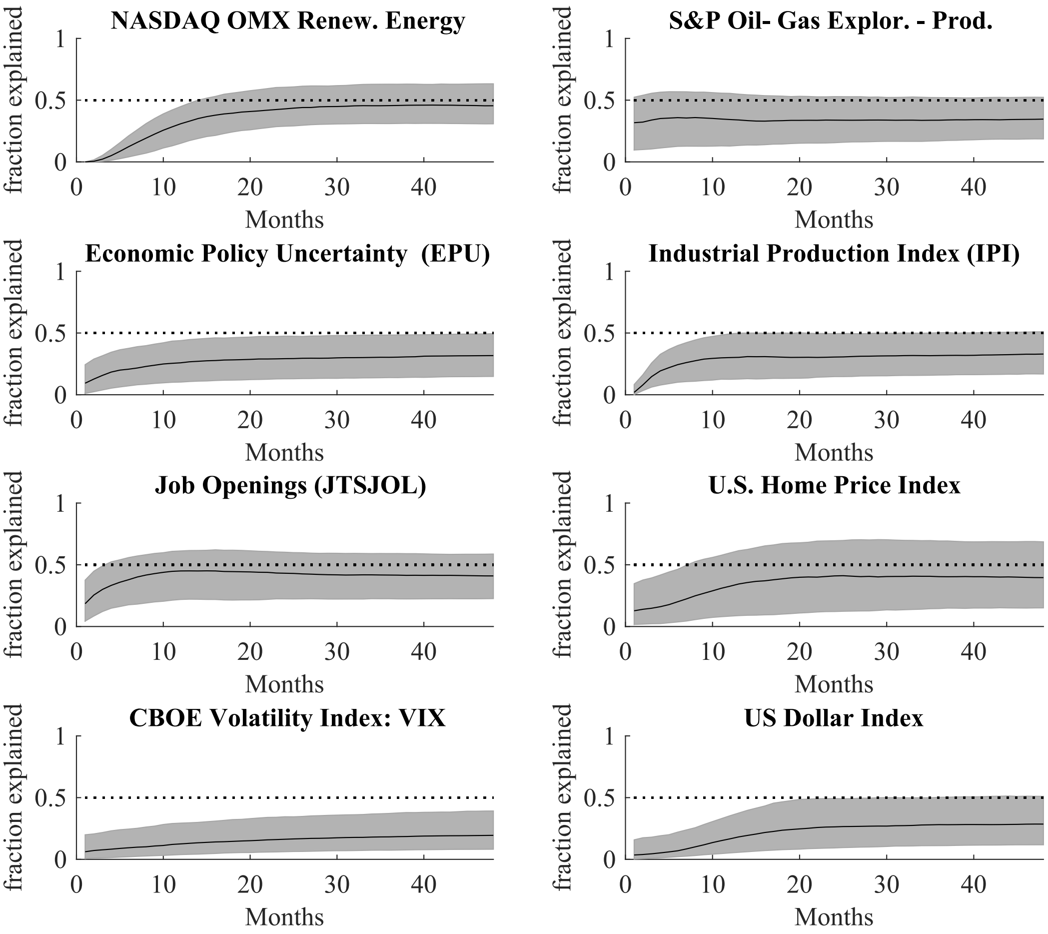
D Empirical evidence of energy news shocks - pre-COVID sample

Figure D.7: IRF - Renewable energy: Pre-COVID 19 estimation



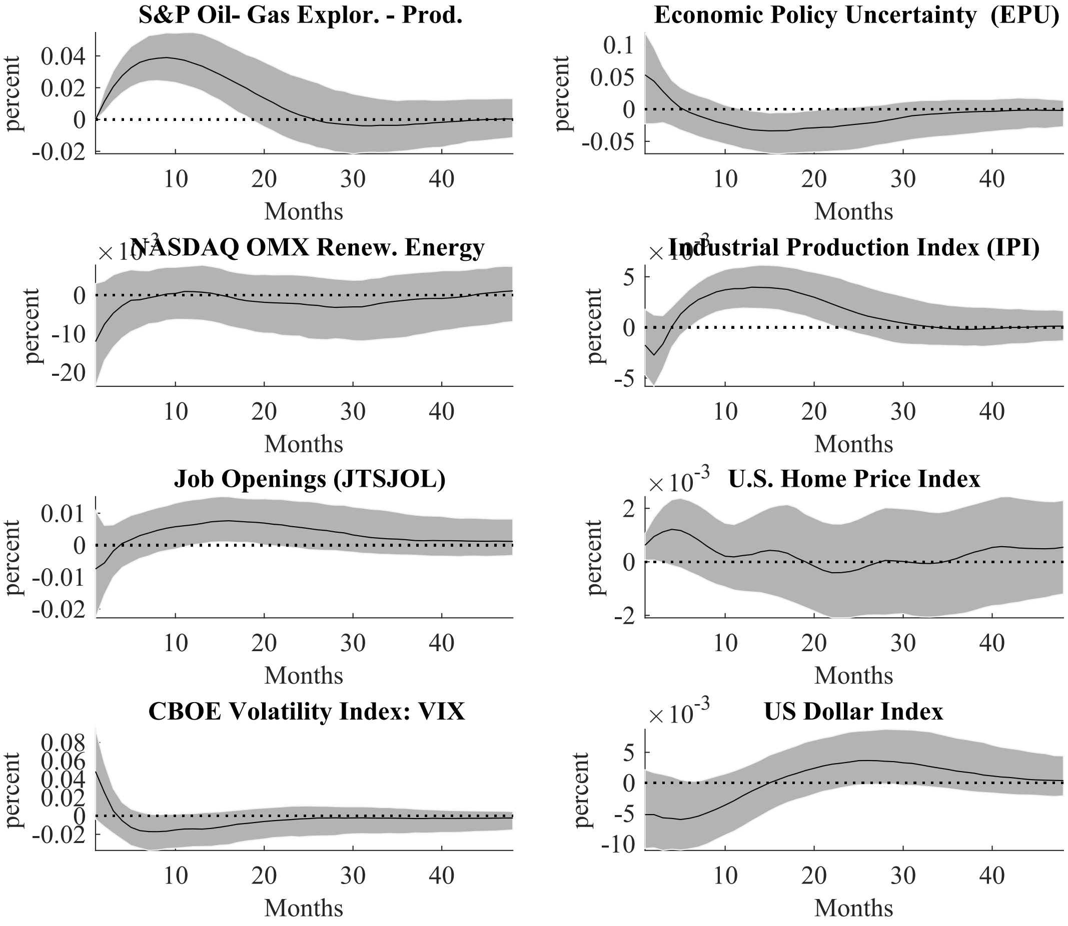
Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure D.8: FEV - Renewable energy: Pre-COVID 19 estimation



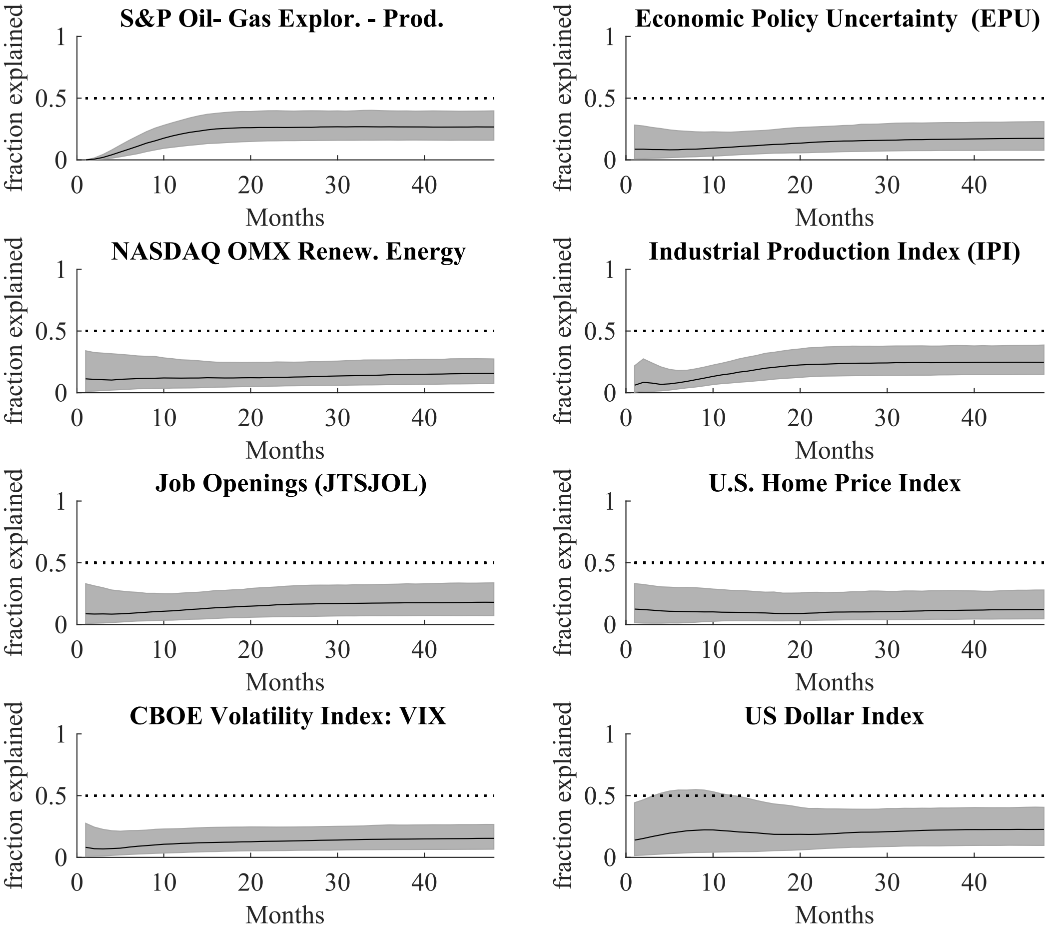
Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

Figure D.9: IRF - Oil & Gas: Pre-COVID 19 estimation



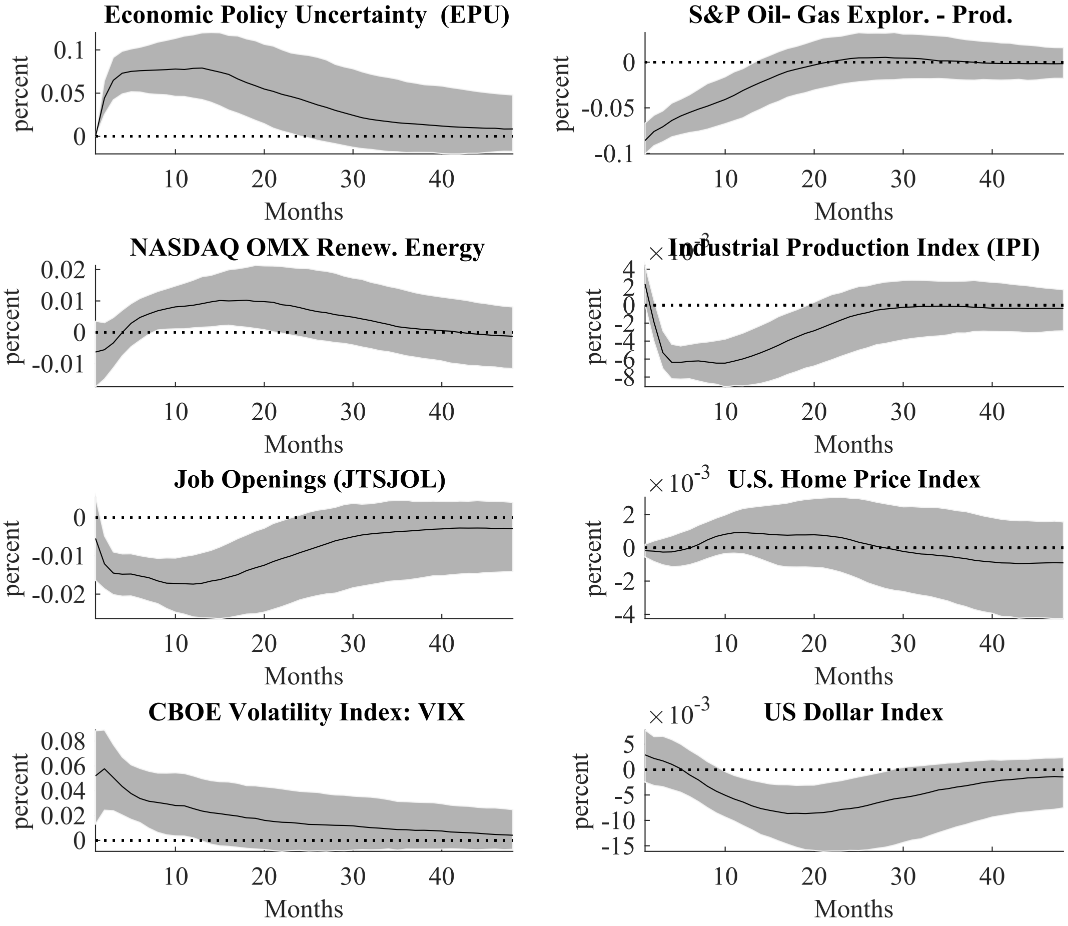
Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure D.10: FEV - Oil & Gas: Pre-COVID 19 estimation



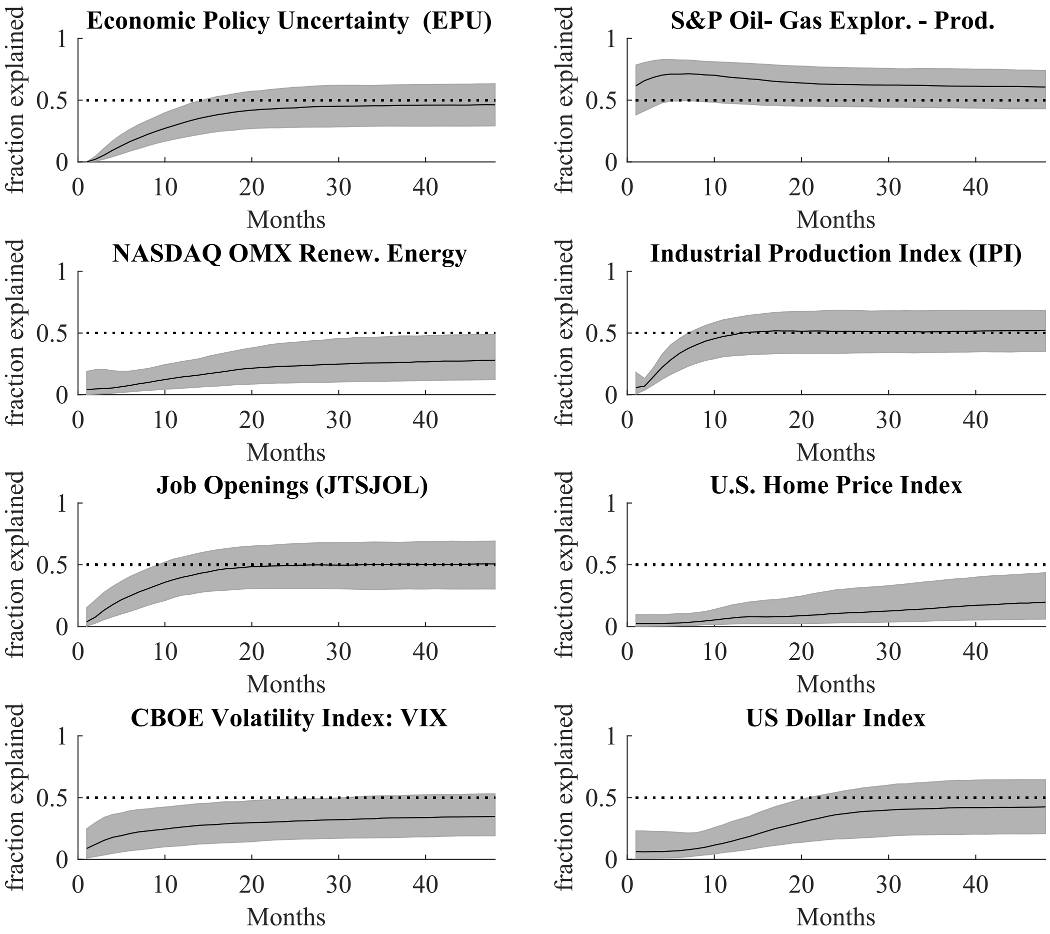
Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

Figure D.11: IRF - EPU: Pre-COVID 19 estimation



Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure D.12: FEV - EPU: Pre-COVID 19 estimation



Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

E Agreements and Protocols List

The list is not exhaustive

The Conference of the Parties (COP) is a series of international meetings held under the United Nations Framework Convention on Climate Change (UNFCCC). These conferences bring together representatives from countries that have signed the Convention to discuss and negotiate action on global climate change. The COP meetings are typically held annually, and are an important forum for international cooperation and action on one of the most pressing issues facing the world today.

Conference of the Parties - COP27, representatives from countries around the world gathered to discuss and negotiate action to address the global climate crisis. The conference was seen as a critical moment for international cooperation on climate change, and a number of key goals and agreements were set out, including a commitment to limit global temperature rise to 1.5 degrees Celsius and a pledge to phase out unabated coal power.

The United States' Clean Power Plan, implemented in 2015, aimed to reduce greenhouse gas emissions from power plants by setting state-specific targets for carbon dioxide emissions.

China's National Sword Policy, launched in 2017, banned the import of certain types of waste, including plastics and mixed paper, in an effort to reduce pollution and improve domestic waste management.

The UK's 25-Year Environment Plan, launched in 2018, outlines a long-term strategy for protecting and enhancing the natural environment, including targets for reducing plastic pollution and improving air and water quality.

The Canadian government's proposed Clean Fuel Standard, expected to be implemented in 2022, would require fuel suppliers to reduce the carbon intensity of their products over time, with the goal of reducing greenhouse gas emissions from the transportation sector.

United Nations Framework Convention on Climate Change (UNFCCC): Adopted in 1992, this treaty is a framework for international cooperation to address climate change. Its goal is to stabilize greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous human interference with the climate system.

Kyoto Protocol: Adopted in 1997, this treaty is an extension of the UNFCCC and sets legally binding emission reduction targets for developed countries. It was the first international agreement to require countries to reduce their greenhouse gas emissions.

Montreal Protocol: Adopted in 1987, this treaty is designed to protect the ozone layer by phasing out the production and consumption of ozone-depleting substances, such as chlorofluorocarbons (CFCs). While not specifically focused on climate change, the Montreal Protocol is an important international agreement that has helped to reduce greenhouse gas emissions.

Copenhagen Accord: Agreed upon in 2009, this political agreement was reached at the United Nations Climate Change Conference in Copenhagen, Denmark. It recognized the scientific consensus on the need to keep global warming below 2 °C, and called on developed countries to provide financial and technological assistance to developing countries to help them reduce their greenhouse gas emissions.

Paris Agreement: The Paris Agreement is a legally binding international treaty on climate change, signed by 195 countries in 2015. The agreement aims to limit global warming to below 2 degrees Celsius above pre-industrial levels, with a long-term goal of limiting the increase to 1.5 degrees Celsius.

European Green Deal: The European Green Deal is a comprehensive plan by the European Commission to make the EU's economy sustainable. It aims to make Europe climate-neutral by 2050, while boosting the economy and improving quality of life for people.

Renewable Energy Directive: The Renewable Energy Directive is an EU law that sets targets for the share of renewable energy in the EU's energy mix. It requires the EU to reach a 32% share of renewable energy by 2030.

Emissions Trading System: The EU Emissions Trading System is a market-based system for reducing greenhouse gas emissions. It sets a cap on the total amount of emissions from certain industries and allows companies to trade emission allowances.

Single-Use Plastics Directive: The Single-Use Plastics Directive is an EU law that aims to reduce the amount of single-use plastics in the EU. It bans certain single-use plastic products and requires member states to take measures to reduce the consumption of others.

LIFE programme: The LIFE programme is an EU funding programme for environmental and climate action projects. It supports projects that help reduce greenhouse gas emissions, protect biodiversity, and promote sustainable development.

F Green technology advancements

Solar power technology - advancements in solar panel efficiency, storage and integration with grid networks have made it a viable alternative to fossil fuels.

Wind power technology - improved turbine designs, blade materials and control systems have made wind energy more efficient and cost-effective.

Electric vehicles - advancements in battery technology have improved the range and charging time of electric vehicles, making them more practical for everyday use.

Energy storage - the development of new battery technologies, such as lithium-ion, has enabled large-scale energy storage, allowing renewable energy to be used even when the sun is not shining or the wind is not blowing.

Smart grid technology - the integration of renewable energy sources into the power grid has been made possible by advances in smart grid technology, which enables real-time monitoring and management of energy production and distribution.

Green buildings - the use of energy-efficient building materials, lighting, heating and cooling systems, and renewable energy sources has made buildings more sustainable and reduced their environmental impact.

Carbon capture and storage - technology for capturing and storing carbon dioxide emissions from fossil fuel power plants has the potential to significantly reduce greenhouse gas emissions.

Hydrogen fuel cells - advancements in hydrogen fuel cell technology have made it a potential alternative to fossil fuels for powering vehicles and other applications.

Vertical farming - the use of indoor vertical farming systems that use LED lighting and hydroponics can significantly reduce water usage and carbon emissions associated with traditional agriculture.

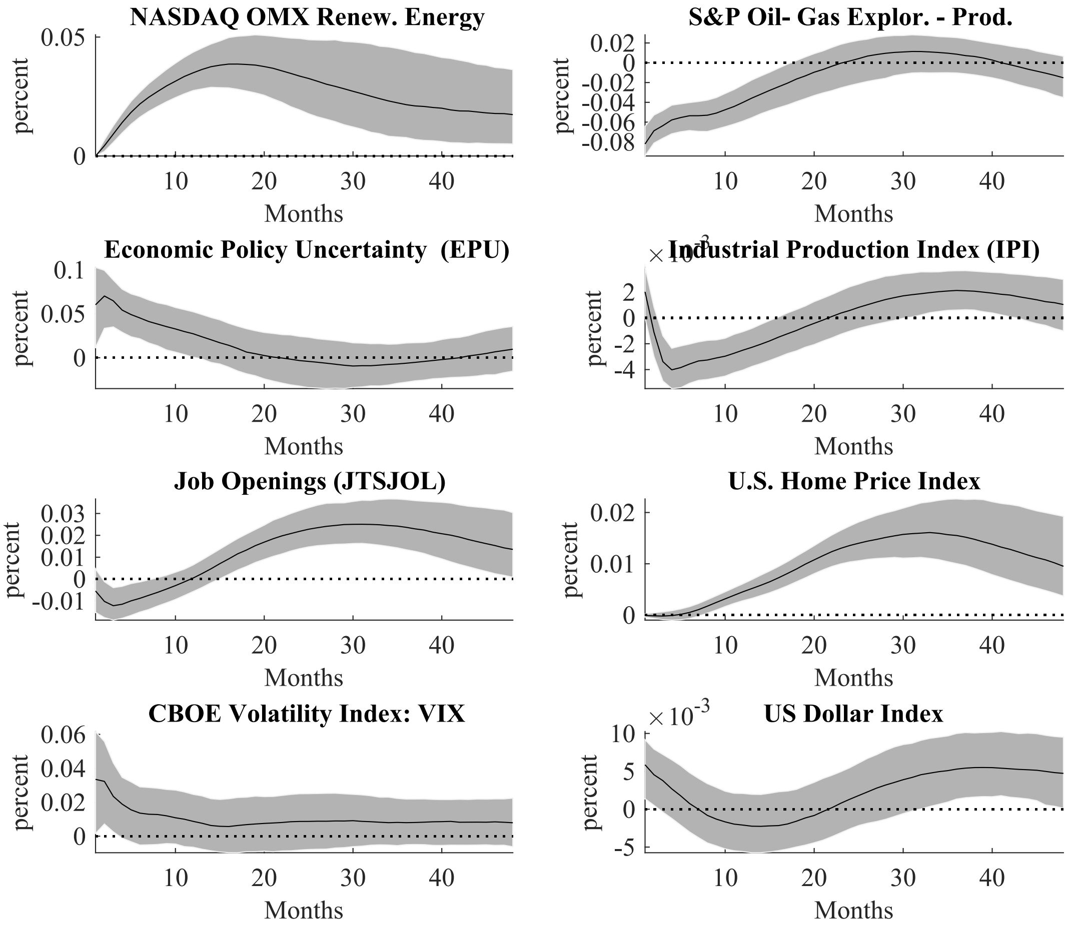
Ocean energy - developments in wave and tidal energy technology could provide a reliable and renewable source of electricity in coastal areas.

Appendix for Online Use

G VAR Identification

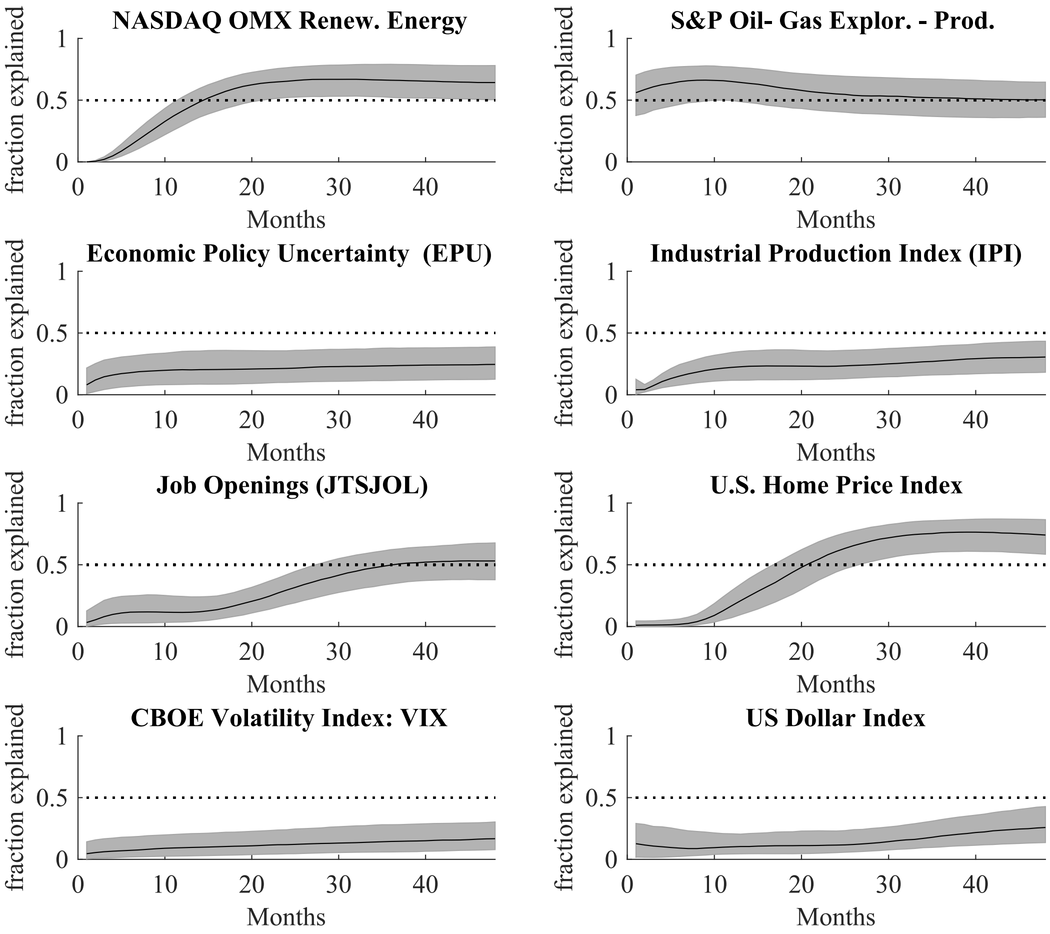
G.1 Renewable news shock

Figure G.13: IRF - Renewable energy



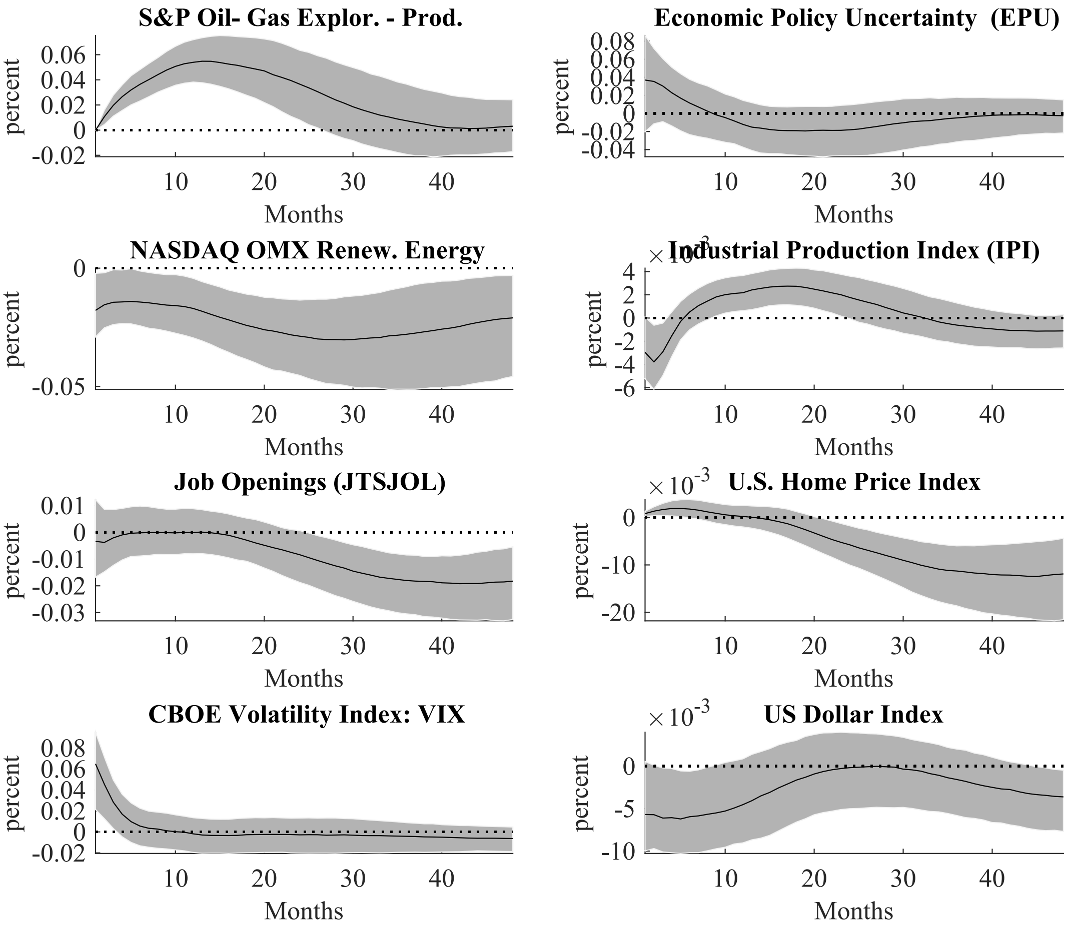
Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure G.14: FEV - Renewable energy



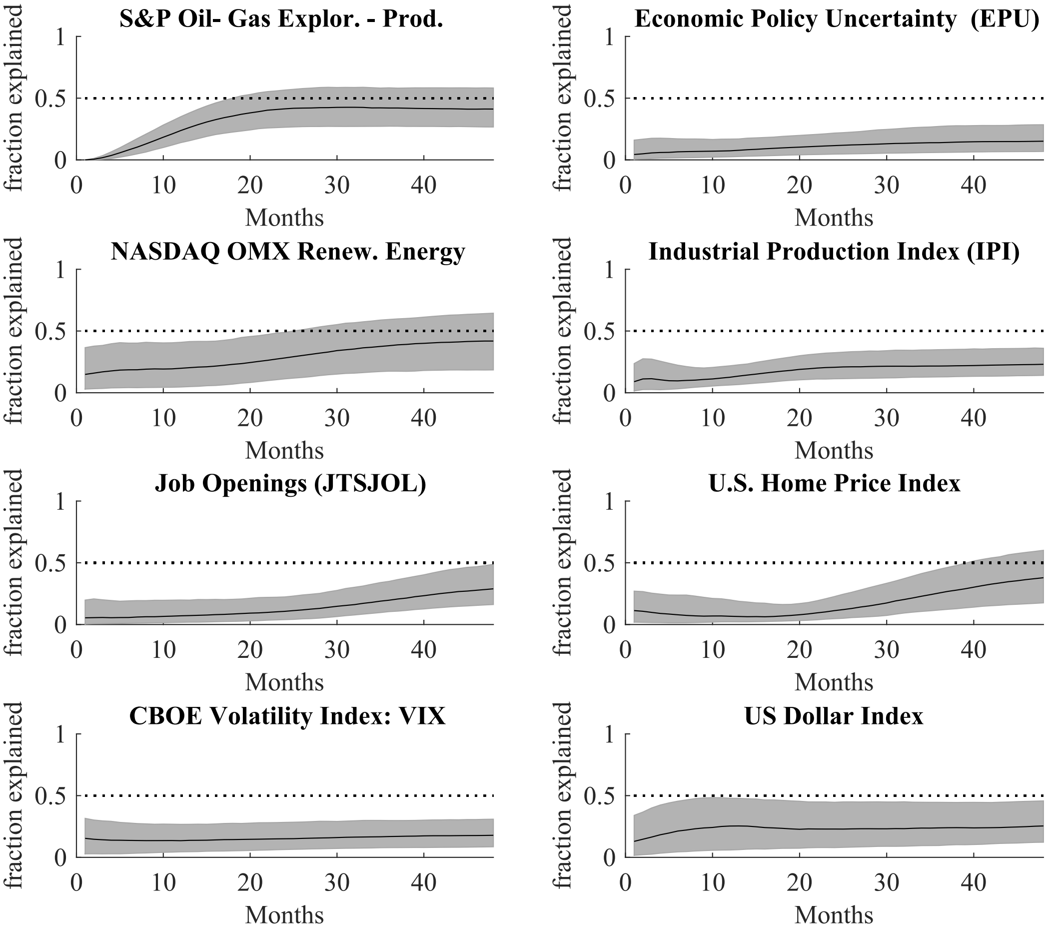
Notes: Median responses to a news shock on Renewable energy (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

Figure G.15: IRF - Oil & Gas



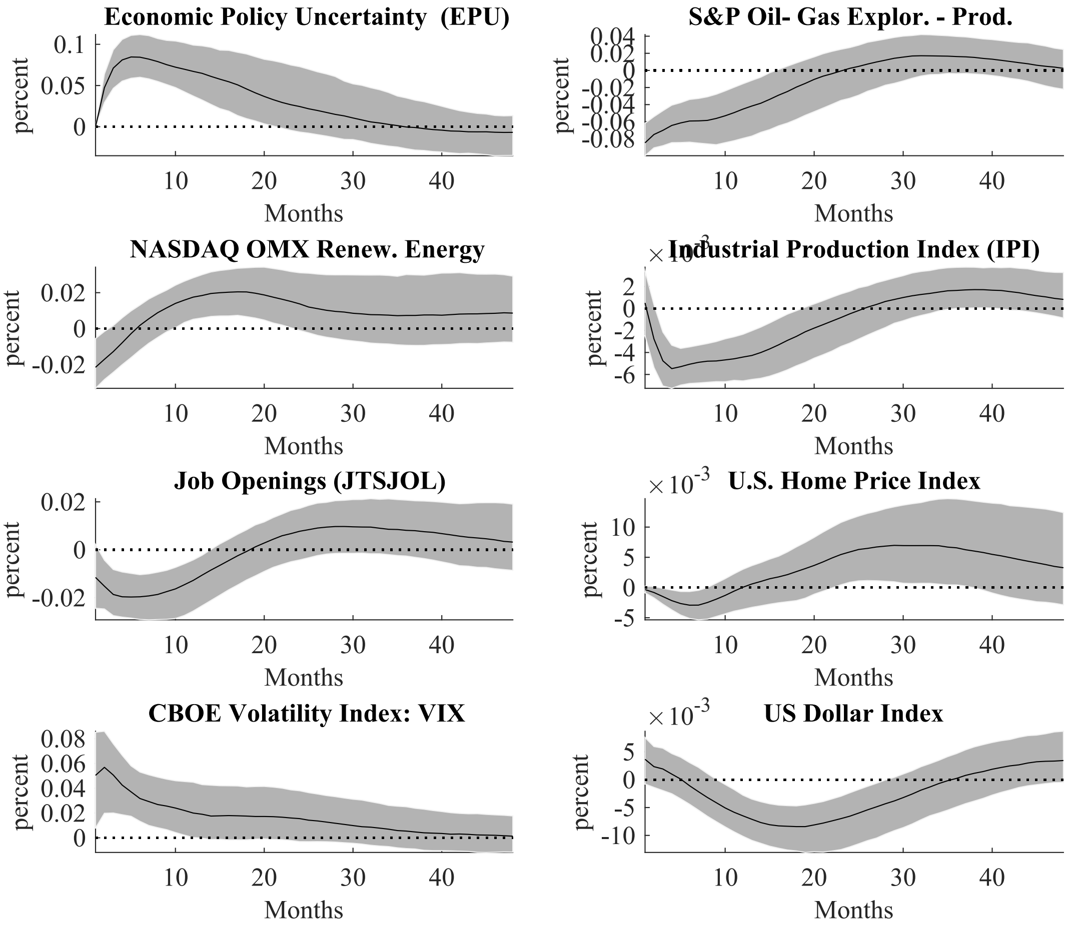
Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure G.16: FEV - Oil & Gas



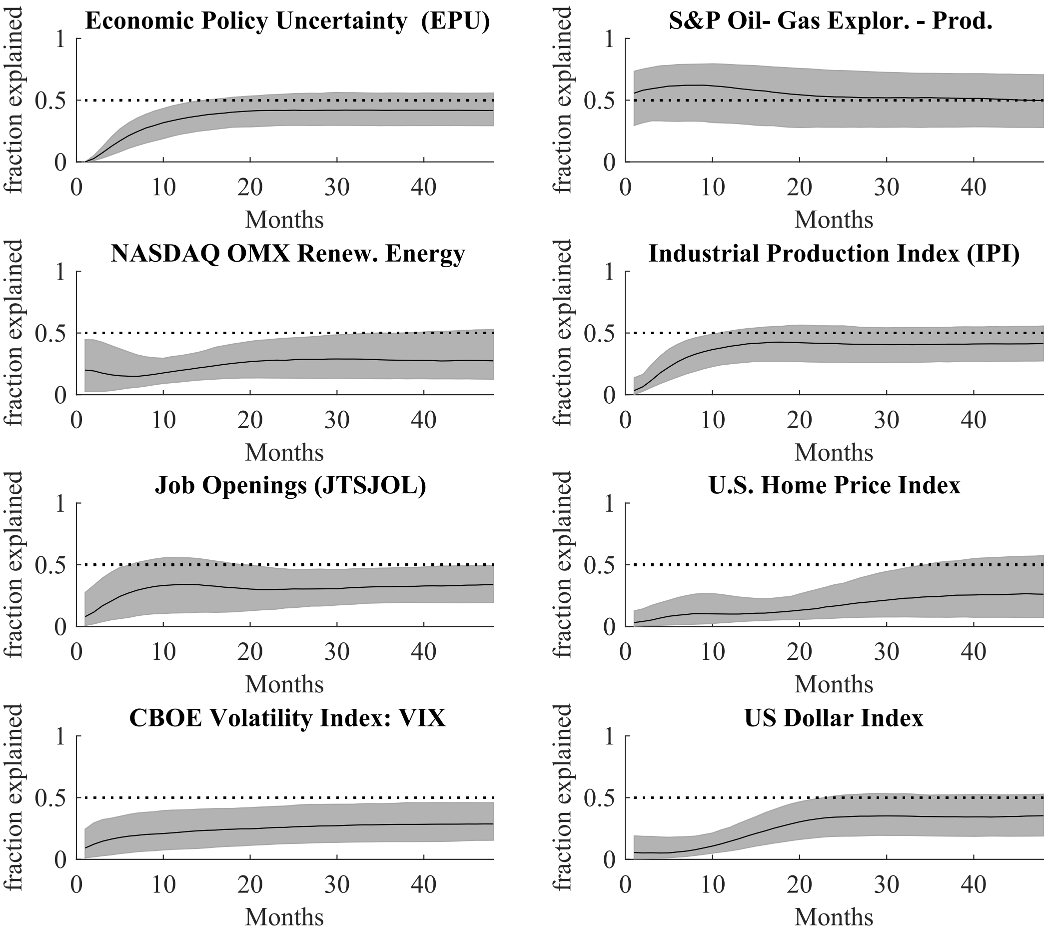
Notes: Median responses to a news shock on Oil & Gas (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

Figure G.17: IRF - EPU



Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure G.18: FEV - EPU



Notes: Median responses to a news shock on EPU (solid line). The shaded gray areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage.

	EPU	SP OIL	NASDAQ Renew	IPI	Jobs Opening	US Home Prices	VIX	US Dollar Idx
Median contribution	0.42	0.62	0.29	0.43	0.34	0.27	0.29	0.35
Period	31	9	30	18	13	46	47	48

Table G.4:

Confidence Interval	Lags	Bayesian Prior
68	10	1

Table G.5:

G.2 SVAR - FEV median contribution

	SP OIL	EPU	NASDAQ Renew	IPI	Jobs Opening	US Home Prices	VIX	US Dollar Idx
Median contribution	0.33	0.16	0.19	0.24	0.20	0.22	0.16	0.24
Period	39	48	48	48	48	48	48	36

Table G.6:

Confidence Interval	Lags	Bayesian Prior
68	11	1.04

Table G.7:

	NASDAQ Renew	SP OIL	EPU	IPI	Jobs Opening	US Home Prices	VIX	US Dollar Idx
Median contribution	0.67	0.60	0.28	0.32	0.45	0.76	0.19	0.36
Period	48	7	48	48	48	38	48	48

Table G.8:

Confidence Interval	Lags	Bayesian Prior
68	12	1.08

Table G.9:

H A model with two energy sectors

H.1 The Competitive Equilibrium

In this subsection, we derive optimal conditions that characterize the decentralized equilibrium of firms and households given a set of parameters whose values will be discussed in the next section. The representative household's problem is solved by maximizing the following dynamic Lagrangian function:

$$L = \max_{(C_t, N_t^i, K_t^i)_{t=0}^{\infty}} E \sum_{t=0}^{\infty} \rho^t \left(\Upsilon_t \frac{C_t^q}{1-q} - \frac{{N_{yt}}^{1+\chi}}{1+\chi} - \frac{{N_{ef_t}}^{1+\omega}}{1+\omega} - \frac{{N_{er_t}}^{1+\psi}}{1+\psi} \right) \tag{H.1}$$

s.t.

$$C_t + \sum_j X_{j_t} \leq \sum_i W_{it} N_{it} + \sum r_{j_t} K_j + \sum_k \Pi_{kt}$$

, where $j = \{y, ef, er, r\}$, $i = \{y, ef, er\}$ and $k = \{y, e, ef, er\}$

H.2 FOC

$$\frac{\alpha Y_t}{N_{y_t}} = \frac{{N_{yt}}^{\chi}}{\Upsilon_t \, C_t^{-q}} \tag{H.2}$$

$$\Upsilon_t \, C_t^{-q} = \rho \, \Upsilon_{t+1} \, C_{t+1}^{-q} \left(1 + \frac{\beta \, Y_{t+1}}{K_{y_t}} - \delta_y \right) \tag{H.3}$$

$$P_{et} = \frac{Y_t \, (1 - \alpha - \beta)}{E_t} \tag{H.4}$$

$$P_{ef_t} + \tau = \zeta \, P_{et} \, {A_{\bar{e}}}^{-\epsilon} \left(\frac{E_t}{E_{ef_t}} \right)^{1+\epsilon} \tag{H.5}$$

$$P_{er_t} = \eta \, P_{et} \, {A_{\bar{e}}}^{-\epsilon} \left(\frac{E_t}{E_{er_t}} \right)^{1+\epsilon} \tag{H.6}$$

$$\Upsilon_t\, C_t^{-q} = \rho\, \Upsilon_{t+1}\, C_{t+1}^{-q}\, \left(1 + \frac{{N_{ef}}_{t+1}^{\omega}}{\Upsilon_{t+1}\, C_{t+1}^{-q}}\, \frac{{N_{ef}}_{t+1}}{{K_{ef}}_t}\, \frac{\nu}{\theta} - \delta_{ef}\right) \tag{H.7}$$

$$P_{ef\,t} + \tau - \frac{\frac{{N_{ef}}_t^{\omega}}{\Upsilon_t\, C_t^{-q}}}{\theta\, \frac{{E_{ef}}_t}{{N_{ef}}_t}} = \rho\, \left(\left(1 - \delta_s\right)\, \left(\tau + {P_{ef}}_{t+1} - \frac{\frac{{N_{ef}}_{t+1}^{\omega}}{\Upsilon_{t+1}\, C_{t+1}^{-q}}}{\theta\, \frac{{E_{ef}}_{t+1}}{{N_{ef}}_{t+1}}}\right) - \frac{{E_{ef}}_{t+1}\, \left(1 - \theta - \nu\right)\, \frac{\frac{{N_{ef}}_{t+1}^{\omega}}{\Upsilon_{t+1}\, C_{t+1}^{-q}}}{\theta\, \frac{{E_{ef}}_{t+1}}{{N_{ef}}_{t+1}}}}{S_t}\right) \tag{H.8}$$

$$S_t = \left(1 - \delta_s\right)\, S_{t-1} - {E_{ef}}_t \tag{H.9}$$

$$\frac{{N_{ert}}^{\psi}_t}{\Upsilon_t\, C_t^{-q}} = \iota\, \frac{E_{ert}\, P_{ert}}{N_{ert}} \tag{H.10}$$

$$\Upsilon_t\, C_t^{-q} = \rho\, \Upsilon_{t+1}\, C_{t+1}^{-q}\, \left(1 - \delta_g + \left(1 - \iota - \kappa\right)\, \frac{P_{ert+1}\, E_{ert+1}}{{K_{eg}}_t} + mu_{rt}\right) \tag{H.11}$$

$$\Upsilon_t\, C_t^{-q} = \rho\, \Upsilon_{t+1}\, C_{t+1}^{-q}\, \left(1 + \kappa\, \frac{P_{ert+1}\, E_{ert+1}}{K_{ert}} - \delta_{er}\right) \tag{H.12}$$

$$Y_t = C_t + {X_y}_t + {X_{ef}}_t + X_{ert} + X_{rt} \tag{H.13}$$

$${E_{ef}}_t\, \tau = {mu_g}_t\, K_{rt-1} \tag{H.14}$$

$${X_y}_t = {K_y}_t - \left(1 - \delta_y\right)\, {K_y}_{t-1} \tag{H.15}$$

$${X_{ef}}_t = {K_{ef}}_t - \left(1 - \delta_{ef}\right)\, {K_{ef}}_{t-1} \tag{H.16}$$

$$X_{ert} = K_{ert} - \left(1 - \delta_{er}\right)\, K_{ert-1} \tag{H.17}$$

$$X_{rt} = K_{rt} - \left(1 - \delta_r\right)\, K_{rt-1} \tag{H.18}$$

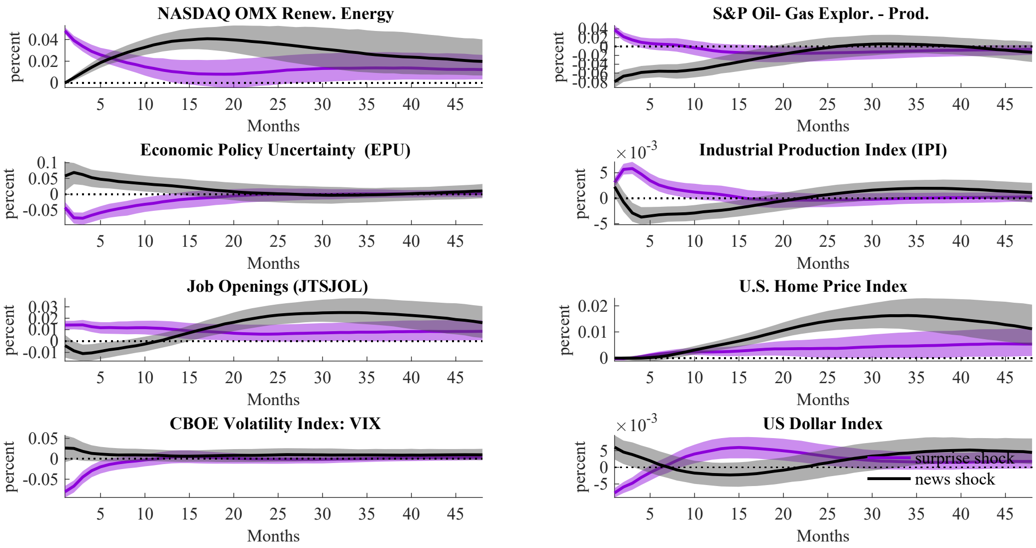
$$A_{ef_t} = \left(1 - \phi_{ef}\right)\, A_{\bar{ef}} + \phi_{ef}\, A_{ef_{t-1}} + {\varepsilon^{ef}}_t + \varepsilon^{news}_{t-1} \tag{H.19}$$

$$A_{ert} = \left(1 - \phi_{er}\right)\, A_{\bar{er}} + \phi_{er}\, A_{ert-1} + {\varepsilon^{er}}_t \tag{H.20}$$

$$\Upsilon_t = \left(1 - \phi_{\Gamma}\right)\, \bar{\Upsilon} + \phi_{\Gamma}\, \Upsilon_{t-1} + {\varepsilon^{\Upsilon}}_t \tag{H.21}$$

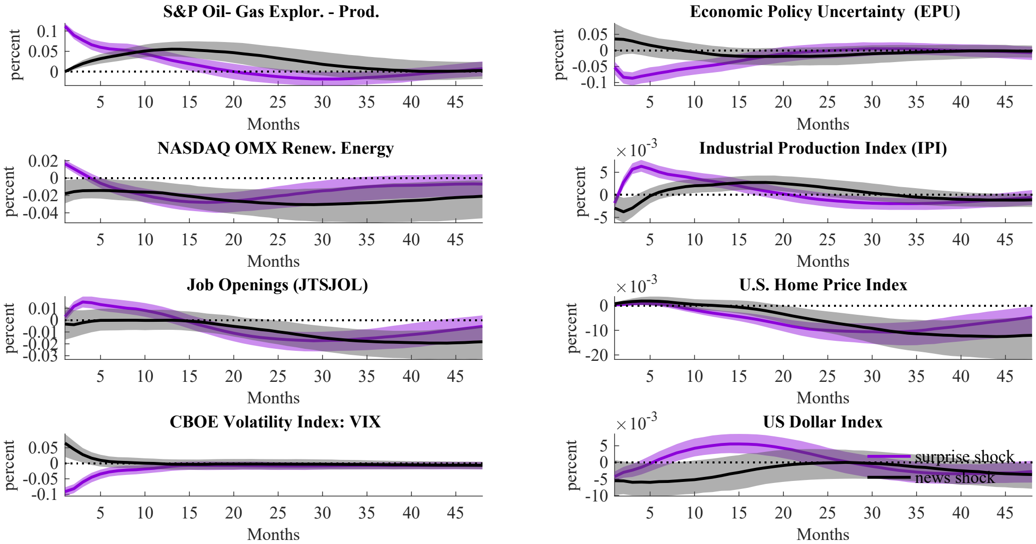
I All IRF

Figure I.19: IRF: News vs. surprise shocks on NASDAQ Renewable Energy Index



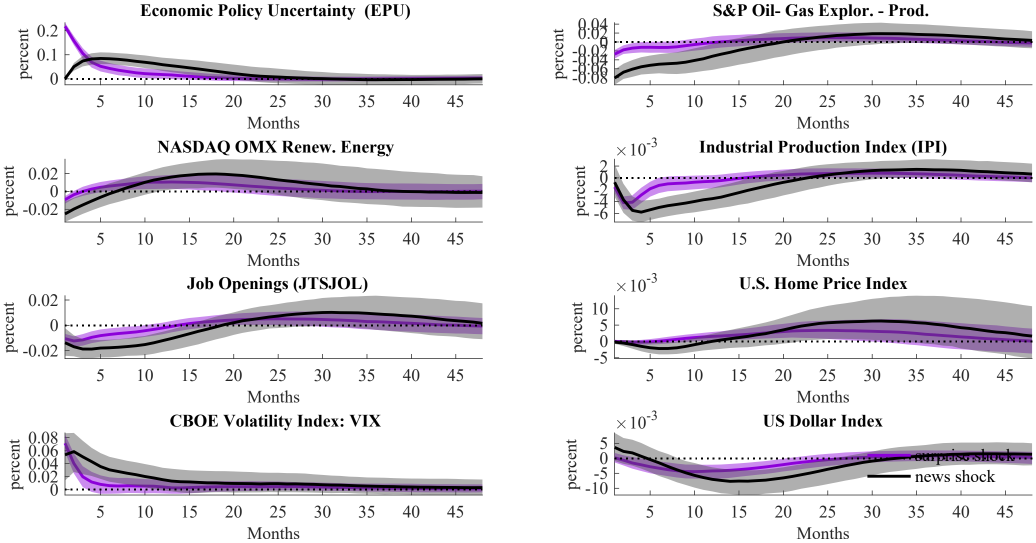
Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Renewable energy stock index. The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure I.20: IRF: News vs. surprise shocks on SP Oil & Gas Exploration & Prod. Select Industry Index



Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Fossil energy stock index. The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.

Figure I.21: IRF: News vs. surprise shocks on Economic Policy Uncertainty



Notes: Median responses to a news shock (gray solid line) and a surprise shock (purple solid line) on Fossil Energy stock index (solid line). The shaded gray and purple areas are the 16% and 84% posterior bands generated from the posterior distribution of VAR parameters. The units of the vertical axes are percentage deviations.