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Oil price dynamics in times of uncertainty: Revisiting the role of demand and supply shocks[☆]

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ABSTRACT

Drivers of real oil prices have been explored extensively in the literature with little consensus. Using a new identification scheme based on forecast error variance, we identify oil-specific demand, demand, and oil supply shocks that maximize the sum of forecast error variance of three variables explained by their respective shocks. The estimation, with the sample period until 2007, suggests that the three identified shocks have similar effects as in the early literature, with oil-specific demand shocks playing a prominent role. However, in the post-crisis period supply shocks have emerged as a source of short-run increases in oil prices, and demand shocks do not have a long-run effect on prices, unlike in the pre-crisis period. By further including risk in the model, we show that the importance of supply shock in driving oil prices in the short run is not driven by global risk. These estimates overwhelmingly suggest zero short-run supply elasticity - a matter of debate in the recent literature. Aside from oil-specific demand shocks, six episodes (including COVID-19) and a time-varying VAR with stochastic volatility identified based on forecast error variance suggest that other shocks, in particular supply shocks, have also played a significant role in driving oil prices in different episodes which cannot be ignored while evaluating the oil price dynamics.

1. Introduction

Oil is an important input in production and essential for the transportation activities on the planet; hence movements in oil prices have attracted the attention of economists for a long time. In light of the recent global uncertainty driven by the pandemic and higher geopolitical risks, this paper aims to uncover the role of oil demand and supply shocks in explaining the variation in oil prices in times of different uncertainties. The existing literature suggests that oil specific demand shock has a prominent role in explaining variation in oil prices. Moreover, in recent years alternative sources of energy have become available which can be substituted for oil especially if oil prices rise significantly. There is also a push towards reducing oil consumption in order to reduce carbon emission. Hence, we analyse whether there is any change in the relative role of oil demand and supply shocks in explaining the variation in oil prices given the emphasis on decarbonization driven by concerns related to climate change in recent times.

The existing literature on oil prices can be summarized into three broad themes. The first strand of research is based on exogenous oil prices which argues that exogenous supply shocks are important drivers of oil price shock - Shapiro and Watson (1988), Rotemberg and Woodford (1996), Blanchard and Gali (2007).[1] These studies typically have oil prices as the first variable in the recursive structure.

The second line of this research in the literature argues that the sources of price change matter and all price changes are not alike. Oil price changes could be driven by oil supply, oil demand and aggregate demand in the economy. Bjornland (2000) identifies demand, supply and oil price shocks using short and long run restriction in a SVAR model and suggests that oil price shock is contractionary in the US, the UK and Germany but not in Norway. Kilian (2009) identifies three

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[1] Oil prices have been extensively used to estimate its economic consequences, i.e., its effects on output, employment, inflation and stock prices. Creti et al. (2014) argue that the interdependence between oil and stock prices is higher in oil exporting countries compared to oil importing countries.

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shocks using three variables with recursive ordering. These variables are global oil production, a global index for economic activity and real oil prices. Since oil prices can rise due to general increase in the price level that is not related to oil market, the use of real oil prices is more appropriate to identify shocks driving oil prices. The real oil price is similar to relative price of oil but not exactly the same. The relative price of oil is obtained by price of oil relative to other prices excluding oil prices, whereas real price of oil is obtained by price of oil relative to general price level that includes oil price as well. The three shocks identified in Kilian (2009) are oil supply shock, demand shock and oil specific demand shock.

Kilian (2009) argues that the demand shock and oil specific demand shock explain a large part of the variation in oil prices and that is true for oil price increases of the 1970s as well. Kilian (2009) finds little role for supply shocks unlike Hamilton (2003, 2009). Hamilton (2009) argues that earlier episodes of oil price increase were different from the oil price increase during 2007–2008 which was predominantly driven by demand shocks. In spite of this, the response of the economy during this period because of higher oil prices was similar as earlier periods. Lippi and Nobili (2012) use an open economy model and argue that global supply shocks explain much larger proportion of variation in oil prices compared to oil supply shocks. Peersman and Van Robays (2012) identify three shocks similar to Kilian (2009) across a set of industrialized countries and argue that all countries irrespective of their oil dependence experience a transitory decline in output due to demand and oil-specific demand shock. However, there is heterogeneity in their response due to oil supply shocks and countries importing oil experience a permanent decline in output due to this shock, unlike oil exporting countries. Cashin et al. (2014) also argue that the effect of the oil price shock depends upon the source and also the oil endowment/production in the country.

The period of heightened uncertainty which one can otherwise think of as an adverse supply shock can actually increase prices due to precautionary and speculative demand for oil, not for immediate use but as inventory due to expected supply disruptions in the future. Kilian and Murphy (2014) bring oil-specific speculative demand shock into the three-variable model to capture this speculative oil demand shock as distinct shock. The augmented model consists of demand, oil supply, oil-specific demand and oil-specific speculative demand shocks. They argue that the oil price run during 2007–08 was not driven by shortage in supply and speculative demand for oil. Kilian and Murphy (2014) further argue that supply shocks such as the Iranian revolution affected oil prices not because they led to a decline in global production but because it increased the precautionary/speculative demand for oil.

Aastveit et al. (2015) using a factor augmented vector auto regression (FAVAR) model argue that demand from emerging economies especially Asian economies is twice as important as demand from developed economies in explaining oil price fluctuations. Stock and Watson (2016) use a structural dynamic factor model and suggest that oil supply shocks explain a relatively small proportion of variation in oil prices and macroeconomic variables like output in the US that is similar to the findings in Kilian (2009). Baumeister and Hamilton (2019) suggest that exclusion restrictions used in traditional oil market SVAR literature can be thought of as a strong prior belief in the Bayesian tradition. They estimate a Bayesian SVAR model and argue that oil supply shocks explain much larger share of variation in oil prices than suggested by SVAR models estimated using exclusion restriction in frequentist tradition. Kanzig (2021) identifies an oil supply shock using high-frequency data and OPEC announcements and suggests that the shock has a significant effect on the US economy. This shock behaves as a traditional supply shock that decreases output and increases inflation.

The third line of research is related to the short-run oil supply curve - Kilian and Murphy (2012, 2014). Both macro and micro data have been used to estimate the short-run oil supply curve. The recursive identification of Kilian (2009) implies a zero short-run price elasticity of supply or a vertical short-run supply curve for oil. The main results of Kilian (2009) remain valid with an upward sloping curve in Kilian and Murphy (2012, 2014), albeit a very low value for the slope. Caldara et al. (2019) argue that supply elasticity is crucial in determining the short run share of supply shocks in forecast error variance (FEV) of oil prices. Caldara et al. (2019) and Baumeister and Hamilton (2019)'s estimate of the price elasticity of supply is significantly higher than Kilian and Murphy (2012, 2014) and this increases the share of supply shocks significantly at the expense of demand and oil specific demand shocks. Baumeister and Hamilton (2019) obtain a value for supply elasticity close to 0.1.

Apart from these macro studies, there are also studies based on micro data to estimate the short run oil supply curve. Results obtained in Anderson et al. (2018) indicate a zero short run elasticity and according to them prices affect production through discoveries and starting production from new oil wells. The production from existing oil wells does not respond to prices. This is because production from a oil well depends upon the oil pressure and not on the prices once the well is operational. Bjornland et al. (2021) and Aastveit et al. (2022) use data from Shale producers from the US and estimate a higher short run elasticity of oil supply.

Overall, there is still no consensus about the short run oil supply curve and there are conflicting evidences from both macro and micro data based studies. The difference in results in Anderson et al. (2018) and Bjornland et al. (2021) and Aastveit et al. (2022) could also be driven by different types of oil wells being considered in these papers. Anderson et al. (2018) consider traditional oil wells whereas Bjornland et al. (2021) and Aastveit et al. (2022) consider Shale oil wells and the Shale oil is likely to be more price sensitive.[2] This is because the Shale oil drilling is more labour intensive which makes it costly but also gives more flexibility in production compared to traditional oil wells.

As argued above, the value of supply elasticity has been a matter of debate and it is important for the contribution of different shocks in driving oil prices. Apart from this, there are some recent developments in oil price which warrant an investigation of shocks driving oil prices. Oil futures fell into negative territory for the first time in history on 20th April 2020.[3] The oil prices fell to record low (relative to the last two decades) during COVID-19 pandemic in April 2020 and then increased very rapidly at the end of 2020. It is unclear whether these were driven by demand shock or supply shock (Fig. 1).

In this paper we make three contributions to the existing literature on oil prices. First, we implement an identification based on the share in forecast error variance. Kurmann and Otrok (2013) identify the term premium shock using a similar method. We identify multiple orthogonal shocks based on the share in forecast error variance and that is similar to the approach in Carriero and Volpicella (2022). Carriero and Volpicella (2022) show the existence and uniqueness of the identified shock using this method. Forecast error variance based identification does not require any zero restrictions and is useful when it is difficult to justify zero restrictions as in Kilian (2009). Further, the proposed identification does not suffer from serious issues with sign restrictions as in Kilian and Murphy (2012, 2014). The identification using sign restriction method is implemented using accept and reject algorithm. Draws satisfying the assumed sign restrictions are kept whereas other draws are discarded. If a large number of draws are discarded, then this casts doubt on the assumed sign restrictions being used for identification. The identification based on forecast error variance allows to estimate the short-run supply elasticity of oil. Hence, the results obtained in the paper will help us to precisely understand the role of demand and supply shocks in explaining oil price movements as argued by Caldara et al. (2019).

2 https://www.bloomberg.com/news/articles/2022-02-19/how-rebounding-oil-is-making-u-s-shale-more-viable-quicktake

3 https://www.cnbc.com/2020/04/20/oil-markets-us-crude-futures-in-focus-as-coronavirus-dents-demand.html

Fig. 1. Oil Price (WTI).

Second, we augment the baseline model of Kilian (2009) with the geopolitical risk from Caldara and Iacoviello (2022). Adverse supply shocks can emerge from geopolitical (or exogenous) sources or endogenously due to the output decisions of oil producers to counter unexpected market imbalances by adjusting supplies. Flow demand can be affected by the movement in global business cycle which is influenced by geopolitical risk. Stock (precautionary) demand shocks could arise due to speculative reasons, reflecting the forward-looking behaviour of market participants, as well as shifts in precautionary demand due to geopolitical risk. Hence, demand, precautionary demand and supply seem to be mis-specified in Kilian (2009). We argue that geopolitical risk is one of the important variables influencing demand, precautionary demand and supply of oil, and hence we augment the model with geopolitical risk and obtain robust estimates for the short-run supply elasticity of oil. Third, in this paper we investigate the sharp decline and rise in oil prices during the COVID-19 pandemic apart from other episodes documented in the literature and estimate the contributions of demand and supply shocks in causing these sharp movements in oil prices.

Results obtained in this paper confirm that the demand shocks are significant drivers of oil prices. Results suggest that the short run supply elasticity is indeed zero; however, our results from the post-crisis sample provide evidence of a transition in the role of supply shock in the medium-run. The supply shocks have much higher effect on oil prices in the short run, and the impact of demand shocks does not last long, unlike the pre-crisis period. The change in the response of oil price due to demand shock appears to be driven by higher substitutability of crude oil with other forms of oil such as shale oil, as the price of crude oil increases. It can also be driven by higher substitutability of oil with unconventional energy at higher prices. Furthermore, we have estimated a TVP-VAR model with stochastic volatility where we have identified the shocks using the forecast error variance (FEV) method. The response of production and prices due to supply shocks and the share of demand and supply shocks in forecast error variance of the prices at three different time points (April 2000, April 2009 and January 2020) also demonstrate the transition evident from the split sample estimation. Results also suggest that the decline in oil price during January 2020 to April 2020 was driven by oil specific demand, and demand shock, and the contribution of demand shock is more than 15%. Uncertainty shock also played significant role in driving real oil price down. The increase in price during the pandemic was led by oil-specific demand and demand shocks.

The rest of the paper is structured as follows. Section 2 explains the methodology and gives a brief overview of the data being used in this paper. In Section 3, we discuss the main results of the paper. In Section 4, we present the results from TVP-VAR with stochastic volatility where the shocks have been identified by maximizing the sum of the share of shocks in forecast error variance of the respective variables. This is followed by concluding remarks in the last section.

2. Methodology and data

2.1. Methodology

A general structural vector autoregression model is given by

$$A_0 y_t = a + \sum_{j=1}^{p} A_j y_{t-j} + \epsilon_t$$

The reduced form model is given by

$$y_t = b + \sum_{j=1}^{p} B_j y_{t-j} + u_t$$

Where $b = A_0^{-1} a$, $B_j = A_0^{-1} A_j$ and $u_t = A_0^{-1} \epsilon_t$. The covariance matrix of the reduced form shocks $E(u_t, u_t') = \sum = \left(A_0^{-1}\right)\left(A_0^{-1}\right)'$ is known.We assume that structural shocks have unit variance. We can write the impulse response matrix at horizon h as given by:

$$IR^h = C(h) A_0^{-1}$$

Where $C(h)$ is the hth element in the expansion if $\left[I_n - \sum_{j=1}^{p} B_j L^j\right]^{-1}$. The element in row (i) and column (j) denotes the response of ith variable due to shock associated with jth variable. The matrix A_0^{-1} is unknown and needs to be estimated to calculate the structural impulse response IR^h. The reduced form covariance matrix is known and one can do Cholesky decomposition of the same as given by:

$$\sum = PP'$$

and that implies $A_0^{-1} = P$. But as shown by Uhlig (2004), the matrix P obtained by Cholesky decomposition is not the only matrix that satisfies the above decomposition as we can write:

$$\sum = PQQ'P'$$

For any orthonormal matrix Q ($QQ' = I$). This gives us $A_0^{-1} = PQ$ and hence the structural impulse response can be written as

$$IR^h = C(h)PQ$$

The response of the ith variable due to a shock associated with jth variable is

$$IR^h(i,j) = e_i' C(h)PQe_j = e_i' C(h)Pq_j = c_{ih}' q_j$$

Where q_j is jth column of Q and c_{ih}' is ith row of $C(h)P$. The important point is that $Q = I_n$ gives the identification based on Cholesky decomposition, and the additional identification such as based on sign restrictions can be achieved by imposing restrictions on Q. Kilian (2009) used $Q = I_n$ to identify the shock. But there are some obvious limitations to this. The important point is the zero restrictions implied by Kilian (2009) in a three-variable system effectively puts the price elasticity of supply to be zero. The three variable system of Kilian consists of $[\Delta Prod, EA, RP]$ where $\Delta Prod$ is % change in oil production, EA is the measure of global economic activity and RP is the relative price of oil.

In this system, the price elasticity of supply is a_{13}/a_{33} where a_{ij} are the element in the ith row and jth column of A. a_{13} is the % change in production and a_{33} gives % change in oil price due to the shock associate with relative price of oil and hence represent elasticity of supply. But a_{13} is assumed to be zero in Kilian (2009) and hence the price elasticity of supply is zero. Kilian and Murphy (2012), Baumeister and Hamilton (2019) and Caldara et al. (2019) attempt to estimate this elasticity using different methods. Kilian and Murphy (2012) use sign restrictions, Baumeister and Hamilton (2019) use Bayesian estimation and Caldara et al. (2019) use external variables to estimate the price elasticity of supply.

We identify multiple shocks based on their share in forecast error variance decomposition. This method is purely agnostic and driven by data. We put very minimal restrictions on identification. Unlike the Bayesian approach of Baumeister and Hamilton (2019), our method is not subject to issues with prior and hyper-parameters, which often make Bayesian inference problematic. The forecast error variance of the ith variable due to a shock associated with jth variable at horizon h is given by

$$\sum_{h=0}^{h=h} IR^h(i,j)IR^h(i,j)' = \sum_{h=0}^{h=h} q_j' c_{ih} c_{ih}' q_j = q_j' \left(\sum_{h=0}^{h=h} c_{ih} c_{ih}' \right) q_j$$

The forecast error variance of the ith variable due to all shocks is given by $\sum_{h=0}^{h=h} c_{ih}' c_{ih}$. Hence the share of jth variable in the forecast error variance of ith variable is given by

$$FEV(i,j,h) = \frac{q_j' \left(\sum_{h=0}^{h=h} c_{ih} c_{ih}' \right) q_j}{\sum_{h=0}^{h=h} c_{ih}' c_{ih}}$$

We define

$$FEV(i,h) = \frac{\left(\sum_{h=0}^{h=h} c_{ih} c_{ih}' \right)}{\sum_{h=0}^{h=h} c_{ih}' c_{ih}}$$

We identify multiple columns (all columns as well) of Q using the following optimization problem

$$Q_{1,k}^* = \arg\max_{Q_{1:k}} \sum_{i=1}^{k} q_i' FEV(i,h) q_i$$

Subject to

$$q_j' FEV(j,h) q_j \geq q_j' FEV(i,h) q_j \quad \text{for} \quad j = 1, \ldots, k, \forall i \in I_{-j}$$

$$Q_{1:k}' Q_{1:k} = I_n$$

This effectively implies that we maximize the sum of the share of each shock in the forecast error variance of the respective variables. We put very reasonable restrictions. These constraints imply that each shock explains a higher forecast error variance of the variable associated with it, compared to the other variables. For example, the first shock explains a higher share of the forecast error variance of the first variable than its share in the forecast error variance of the second and third variables. The same is true for the remaining shocks. Using the fact $\sum_{i=1}^{k} q_i' FEV(i,h) q_i = \sum_{i=1}^{k} trace(q_i' FEV(i,h) q_i)$, we write the above problem as a minimization problem

$$Q_{1,k}^* = \arg\min_{Q_{1:k}} - \sum_{i=1}^{k} trace(q_i' FEV(i,h) q_i)$$

Subject to

$$q_j' FEV(i,h) q_j \leq q_j' FEV(j,h) q_j \quad \text{for} \quad j = 1, \ldots, k, \forall i \in I_{-j}$$

$$Q_{1:k}' Q_{1:k} = I_n$$

We solve the above problem using the fmincon function in Matlab with nonlinear constraints. We do not face any situation of the constraints not being satisfied.

The reduced form shocks u_t and the structural shocks ϵ_t are related as

$$u_t = A_0^{-1} \epsilon_t$$

Which we can write as:

$$u_t = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \epsilon_t$$

We assume recursive structure because Cholesky decomposition implies recursive relationship among the variables. Since we use % change in production and log of real oil prices, we can interpret a_{13}/a_{33} as the impact elasticity of the supply of oil with respect to the real price of oil. a_{13} and a_{33} are the impact responses of supply and real oil prices due to oil specific demand shock, helping identify the supply curve. This is very similar to the classic identification of demand and supply where the supply curve is identified using changes in demand curve. The elasticity is zero in Kilian (2009) because $a_{13} = 0$ (zero restriction) as assumed in Cholesky decomposition of the covariance matrix of the reduced form shock. Non-zero restriction is essential for estimating supply elasticity, and based on sign restrictions, Kilian and Murphy (2012) consider an upper bound of 0.0258. Identification scheme used in this paper implies

$$A_0^{-1} = PQ$$

where P is the Cholesky decomposition of reduced form covariance matrix. Q is the orthogonal matrix estimated using the optimization explained above, A_0^{-1} contains coefficients of contemporaneous relationship between reduced form and structural shocks. Hence $u_t = A_0^{-1} \epsilon_t$ can be written as:

$$u_t = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} q_{11} & q_{12} & q_{13} \\ q_{21} & q_{22} & q_{23} \\ q_{31} & q_{32} & q_{33} \end{bmatrix} \epsilon_t$$

Now the impact response of supply due to oil specific demand shock is given by the product of first row of P and third column of Q. Similarly the impact response of oil price due to oil specific demand shock is given by the product of third row of P and third column of Q. Hence the elasticity is given by

$$\text{Supply Elasticity} = \frac{\begin{bmatrix} p_{11} & 0 & 0 \end{bmatrix} \begin{bmatrix} q_{13} \\ q_{23} \\ q_{33} \end{bmatrix}}{\begin{bmatrix} p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} q_{13} \\ q_{23} \\ q_{33} \end{bmatrix}} \geq 0$$

We restrict the elasticity to be positive to ensure that we obtain an economically meaningful supply curve.

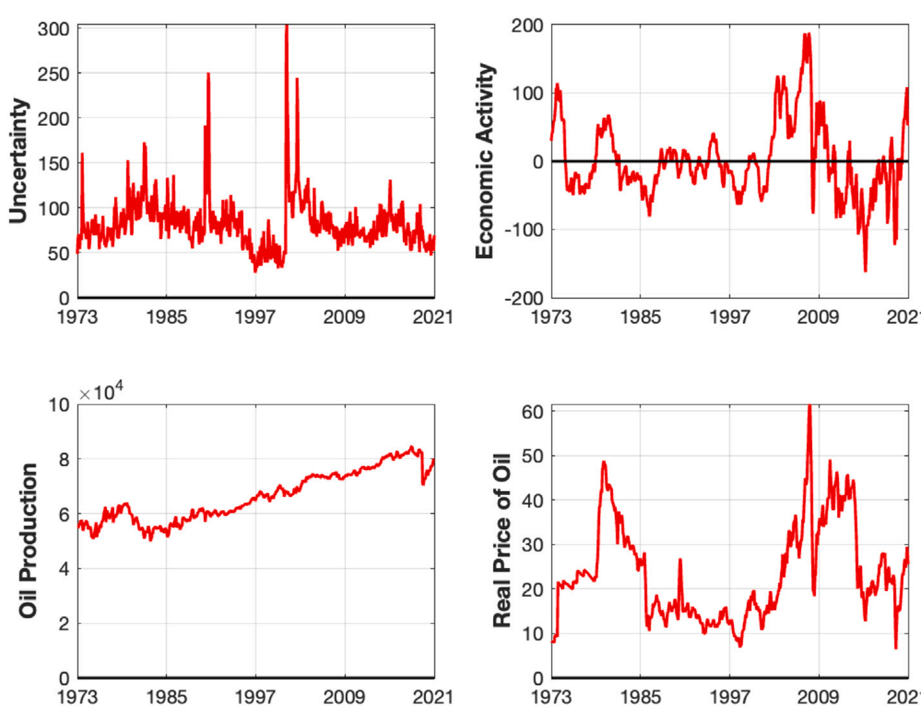

Fig. 2. Variables being used in the paper. Oil production is in million barrels/day.

2.2. Data

We obtain Global oil production (million barrels/day) from Energy Information Administration (EIA). We specifically use the series INTL.57-1-WORL-TBPD.M. The crude oil price used in this paper is the West Texas Intermediate (WTI) price available at the St. Louis Federal reserve website. We deflate the oil price using the consumer price index (CPIAUCSL series from the St. Louis Federal reserve website at base 1982-84 = 100) to obtain real oil price. There are benefits of working with real price. The demand shock and other supply shocks can increase nominal prices of oil because of their effect on consumer inflation. Hence, the relative price movement is pure movement in oil prices which is not driven by movements in overall inflation. Economic conditions index is the updated data, obtained from Dallas Fed. The economic activity index used in Kilian (2009) has a coding error and the updated data has fixed that error. Uncertainty data used in this paper is historical geopolitical risk from Caldara and Iacoviello (2022).[4] Fig. 2 gives the data series used in this paper. The time period covered is between January 1973 to December 2021. Appendix A gives the link of the data sources used in this paper.

3. Results and analysis

3.1. Three variable models

We use two types of identification scheme in this paper. The first one is using the Cholesky decomposition as in Kilian (2009) and the second one is based on share in forecast error variance decomposition explained in the previous section. Also, we do three sub-sample estimates for each of these two methods. The first one is using the data from 1973–2007 which allows us to compare the results in Kilian (2009). The second sample period is for the time period 1973–2021 and the third sample is for the time period 2008–2021. We use twenty four lags in first two sub-samples and 6 lags in the case of third sub-sample because of small sample size.

Fig. 3 gives the impulse responses from the first sub-sample. These are responses due to one standard deviation shock. We use production growth in the estimation and accumulate the response of production growth and plot it. The supply shock decreases production by 1.5% on impact and the production is lower by almost 0.5% even after 20 months.

This suggests that the supply shock adversely affects production even in the medium run. As expected, the supply shock does not have any effect on the global economic activity and its effect on the price level is short-lived and the maximum increase in real price due to the supply shock is almost 1%. The impact response of production due to the demand shock is zero, and up to five months, the production does not change. After five months, production increases but the maximum increase in production is less than 0.5%.

The delayed response of production due to the demand shock also indicates that it is difficult to change production from existing oil fields due to exogenous shocks to prices. Demand shock has a permanent effect on economic activity as expected. Also the demand shock has a persistent effect on oil prices and the oil price increases by almost 5% by 20th month of the demand shock. Oil specific demand shock does not affect production, and increases economic activity. It also has an impact response on relative price, with magnitudes higher than 7% but unlike the demand shock this effect decreases with time. There is not much difference in the response of model variables from these two identification schemes. FEV based identification suggests slightly lower response of prices due to demand shock and higher response of activity due to oil-specific demand shock. Hence we can say that zero restriction based identification scheme in Kilian (2009) attributes slightly higher role for demand shocks in explaining oil prices.

[4] Ftiti and Jawadi (2019) estimate several measures of oil price volatility which could be considered as a measure of oil price uncertainty but not uncertainty in general. Ftiti and Hadhri (2019) and Kumar et al. (2023) use economic policy uncertainty and equity and bond market volatility as measures of uncertainty. We use geopolitical risk as we believe that these are true risks which should affect the oil market. Also, these measures of uncertainties are correlated with each other and hence the results should not vary a lot based on the use of these uncertainties. Also, the focus in this paper is not on the uncertainty itself, and uncertainty is more like a control variable in the absence of which we may have uncertainty being absorbed by demand or supply shocks or both, Kumar et al. (2021).

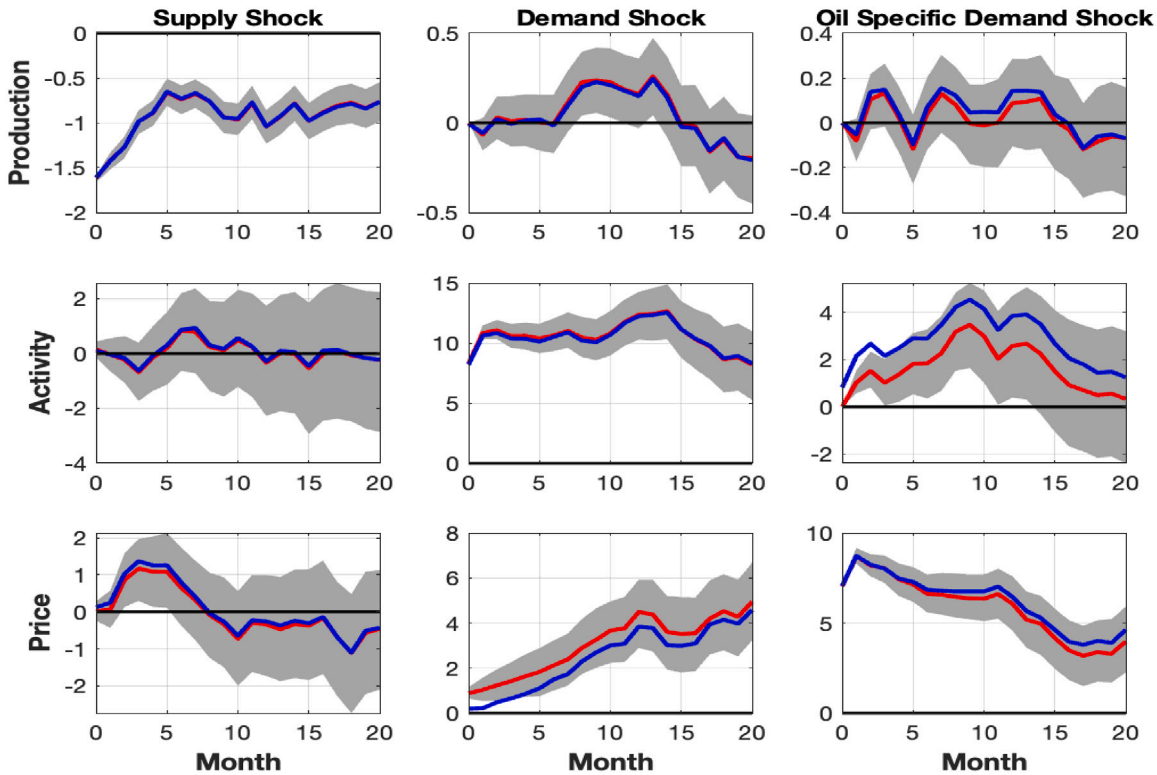

Fig. 3. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

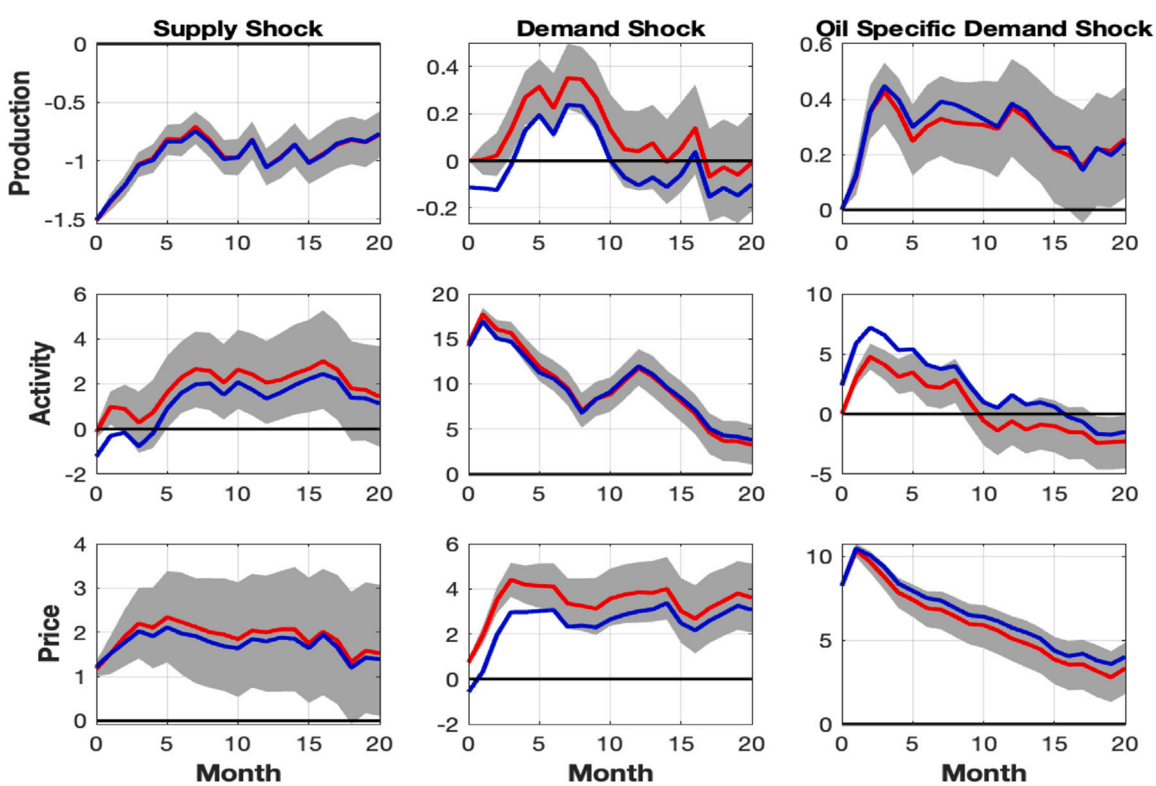

Fig. 4. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

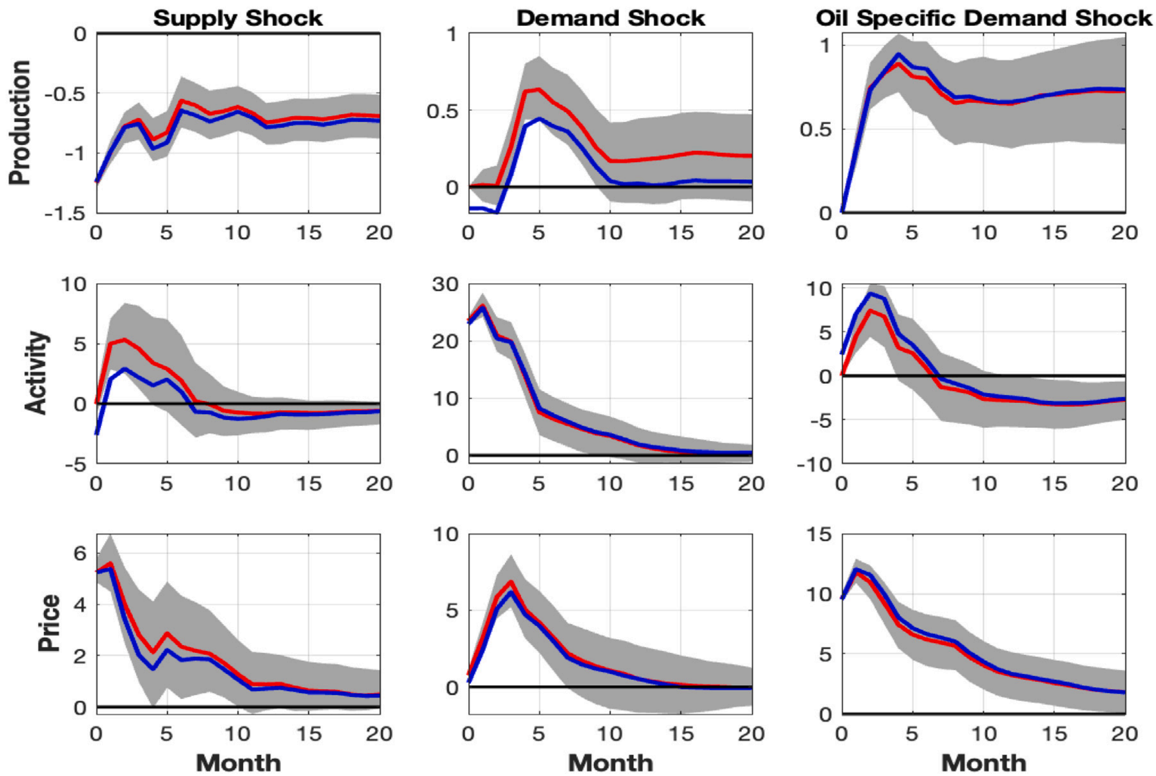

Fig. 5. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 2008–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4 gives the impulse responses from the second sub-sample. Extending the sample to post crisis period brings some noticeable differences. We find more persistent response of supply shock on prices unlike the pre-crisis period. Also we find that the impact of demand shock on prices does not keep increasing and stabilize at a level lower than in the pre-crisis period. These two together imply that medium run price movement contains significantly higher contribution of supply shock than the demand shock compared to the pre-crisis period. We also find that the impact response of real price due to oil specific demand shock is higher in the full sample compared to the pre-crisis sample.

Fig. 5 gives the impulse responses from the post-crisis sample. It is important to clarify that the post-crisis sample is estimated with a smaller lag length of six compared to twenty four lag length used in previous two estimations reported above. Hence, there is possibility of lower persistence in results that could be driven by lag length selection. But we believe that six lag length is not small and should not be driving significant differences. We find that the impact response of production due to supply shock is lower than 1.5% reported earlier. We also find that the impact response of price due to supply shock is much higher than the demand shock and if we just compare supply and demand then the supply shock turns out to be the dominant driver of oil price in the short run. Comparing two identification methods, we find that the response of prices due to supply shock is slightly lower from identification based on forecast error variance.

Interestingly we also find that the response of price due to supply shock persists slightly longer than the demand shock, and the demand shock does not have permanent effect on prices unlike reported earlier. These responses suggest significant changes in the factors influencing real oil price in the short and medium run in the post crisis period. Also, the impact response of price due to oil specific demand shock is highest in the post crisis period, and the response of economic activity due to oil specific demand shock vanishes quickly.

As explained above the short run elasticity of oil supply is the ratio of impact response of production and real price due to oil specific demand shock. In the case of Cholesky decomposition, the elasticity is zero by design as the impact response of production due to oil specific demand shock is zero. In the identification based on forecast error variance method it is not zero but constrained to be greater than equal to zero. As we can see from figures 4, 5 and 6, in all these cases, the impact response of production due to oil specific demand shock is zero and hence the short run supply elasticity is zero. These results suggest that the identification scheme based on Cholesky decomposition used in Kilian (2009) is not rejected by the data as even if we do not restrict the short run supply elasticity to be zero and estimate it, we still obtain a zero value.

Fig. 6 gives the forecast error variance decomposition from the first sub-sample. More than 80% of the variation in production in the medium run is explained by the supply shock and both demand and oil-specific demand shocks explain less than 10% of the variation in the production in the medium run. The supply shock explains .02% of the variation in price in the medium-run, demand shock explains 20% and the remaining is explained by the oil-specific demand shock. Comparing two methods, we find that forecast error variance based identification suggests slightly higher role for oil-specific demand shock in explaining prices at the cost of demand and supply shocks.

Fig. 7 gives the forecast error variance decomposition from the second sub-sample. The noticeable difference arises in the share of supply shock in explaining the variation in real oil price which increased to 5%. Similar to the pre-crisis period, we find that forecast error variance method suggests higher share for oil-specific demand shock in explaining prices at the cost of demand and supply shocks. But both Cholesky decomposition and forecast error variance method suggest that the share of supply shocks in explaining the variation in price has doubled relative to the pre-crisis value. Fig. 8 gives the forecast error variance decomposition from the post-crisis sample. In post crisis sample, the supply shock explains more than 20% of the variation in

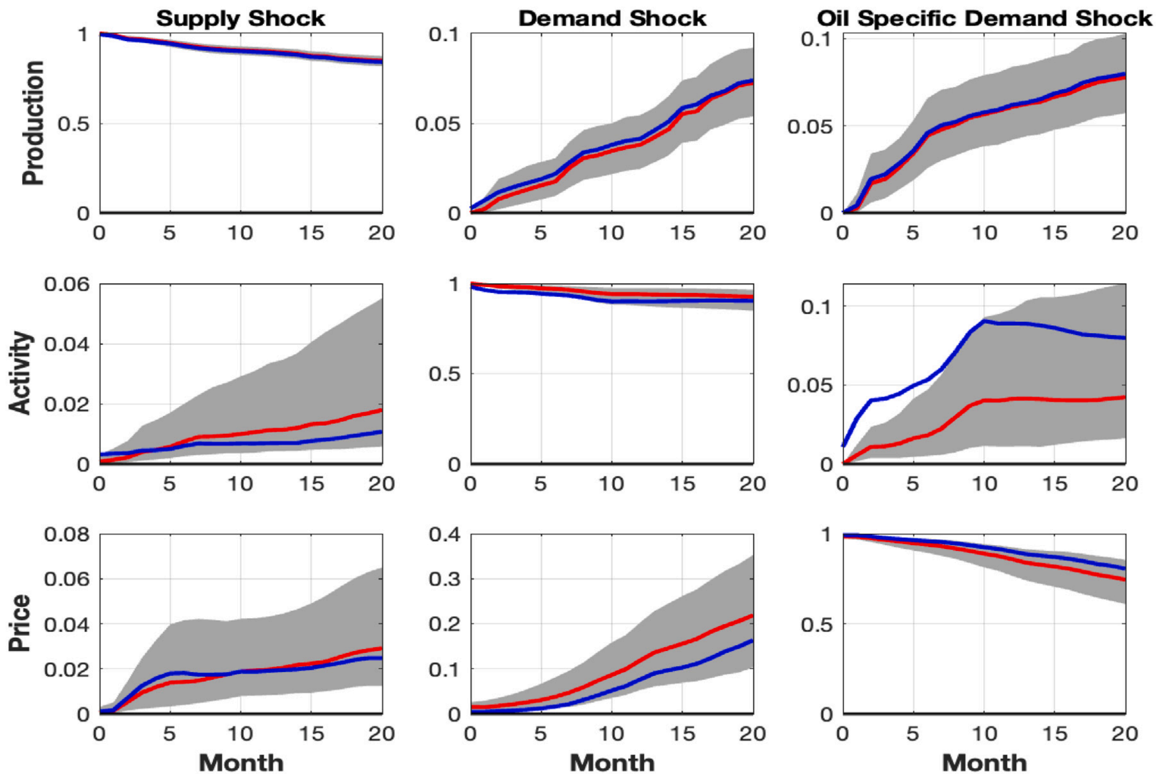

Fig. 6. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

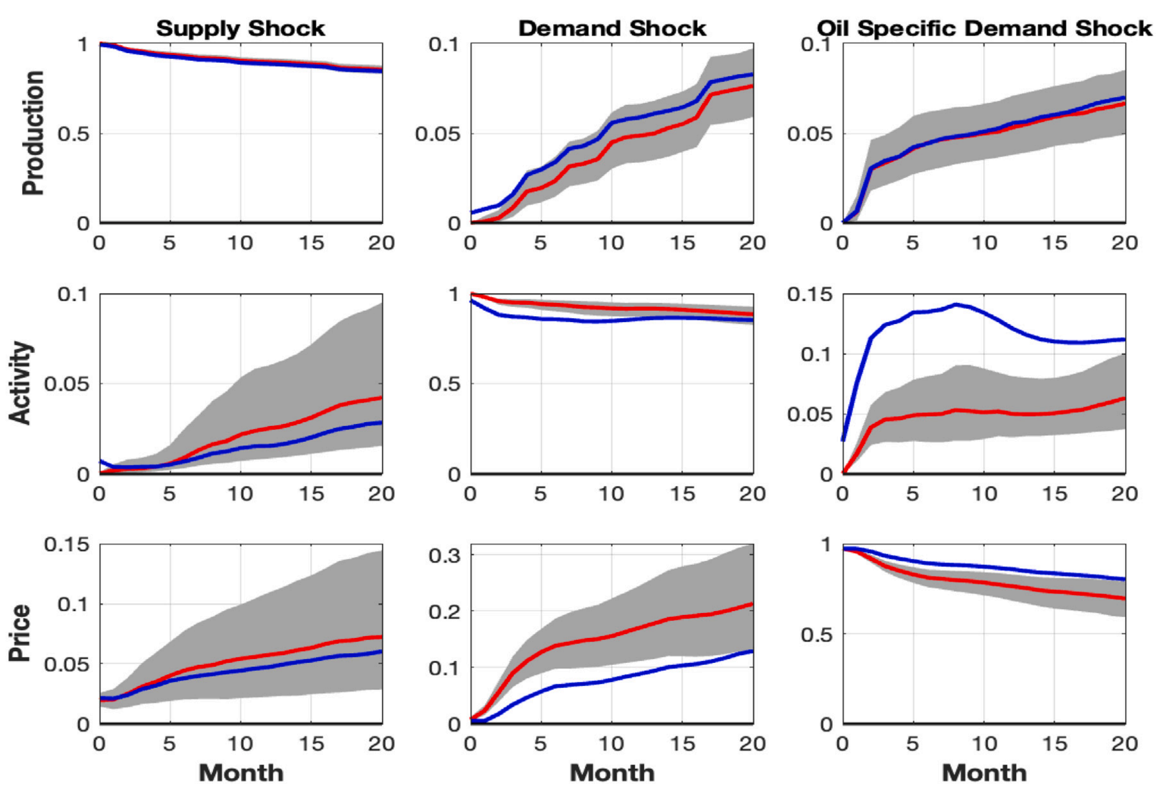

Fig. 7. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample: 1973–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

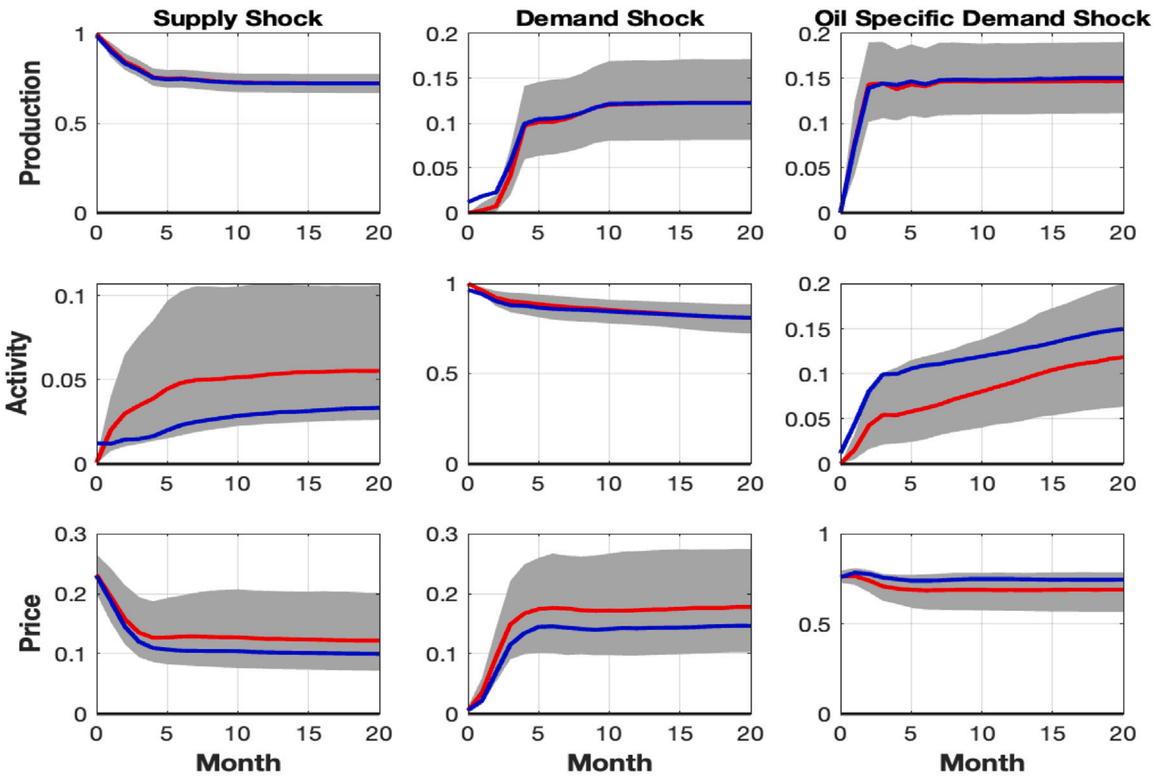

Fig. 8. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 2008–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

oil prices in the beginning which stabilizes at 10% in the medium term. This is more than 4 times the share of supply shock in pre-crisis sample which is a significant increase.

3.2. Extended models

As argued before, geopolitical risk is an important variable influencing all the three variables in the baseline model used in the previous section. Hence we augment the model with the geopolitical risk and estimate three sub-sample models. Fig. 9 gives the impulse response from the first sub-sample.

Risk/uncertainty shock plays a significant role in driving production, activity and prices. Uncertainty shock decreases production on impact, which becomes insignificant quickly and becomes negative and insignificant again. Uncertainty shock also increased economic activity in the medium run. The identification based on forecast error variance method gives a negative impact response of activity due to uncertainty shock and the response of activity is always lower than the one given by Cholesky decomposition. This is in line with the finding in the literature that uncertainty shock is contractionary (Kumar et al., 2021) which is quite prominent in the post-crisis sample. Interestingly, this uncertainty shock increases price level by almost 2% in the medium run. The supply shock does not affect uncertainty which is expected. The response of activity due to supply shock is as before but now the supply shock does not increase prices as found in the model without uncertainty shock. The demand and oil-specific demand shocks do not affect uncertainty and the responses of other variables due to these two shocks are similar to the one reported before from model without uncertainty shock.

Fig. 10 gives the impulse responses from the second sub-sample. The effect of uncertainty shock on production in the medium run is now more pronounced. Its effect on activity is subdued and it decreases price significantly on impact and the increase in price in the medium run is not significant unlike in the pre-crisis sample. The response due to other shocks remains similar except that the response of production due to oil specific demand shock identified using FEV method is almost zero. Fig. 11 gives the impulse response from the post-crisis sample. The effect of uncertainty shock on economic activity in the medium-run is now more pronounced and it decreases activity significantly and does not increase in the medium-run unlike the pre-crisis period.

The uncertainty shock does not affect production, but decreases the real price significantly. The maximum decline in price due to uncertainty shock is almost 4% and even in the medium run, real prices are lower by almost 2%. Its effect on activity is subdued and it decreases price significantly on impact and the increase in price in the medium run is not significant unlike in the pre-crisis sample. The response due to other shocks remains similar except that the response of production due to oil specific demand shock identified using FEV method is almost zero.

Fig. B.1 in appendix gives the forecast error variance decomposition from the first sub-sample. The role of supply shock in explaining the variation in production is reduced. Uncertainty shock explains around 10% of the variation in production and oil-specific demand shock identified using forecast error variance method explains around 15%. Uncertainty shock also explains more than 5% of the variation in price in the medium-run. Fig. B.2 in appendix gives the forecast error variance decomposition from the second sub-sample. Uncertainty shock explains around 10% of the variation in production but less variation in prices compared to the pre-crisis period (Fig. B.1). Fig. B.3 in the appendix gives the forecast error variance decomposition from the post-crisis sample. Uncertainty shock explains more than 10% of the variation in production and prices (Fig. B.1).

Effectively in the post crisis period, the importance of uncertainty shock in explaining prices increases significantly. In the medium-run, all the other three shocks explain around 10% of the variation in prices and the remaining 70% of the price variation is explained by oil-specific demand shock. Since there is not much change in the contribution of demand and supply shocks reported in Fig. 8 (without uncertainty),

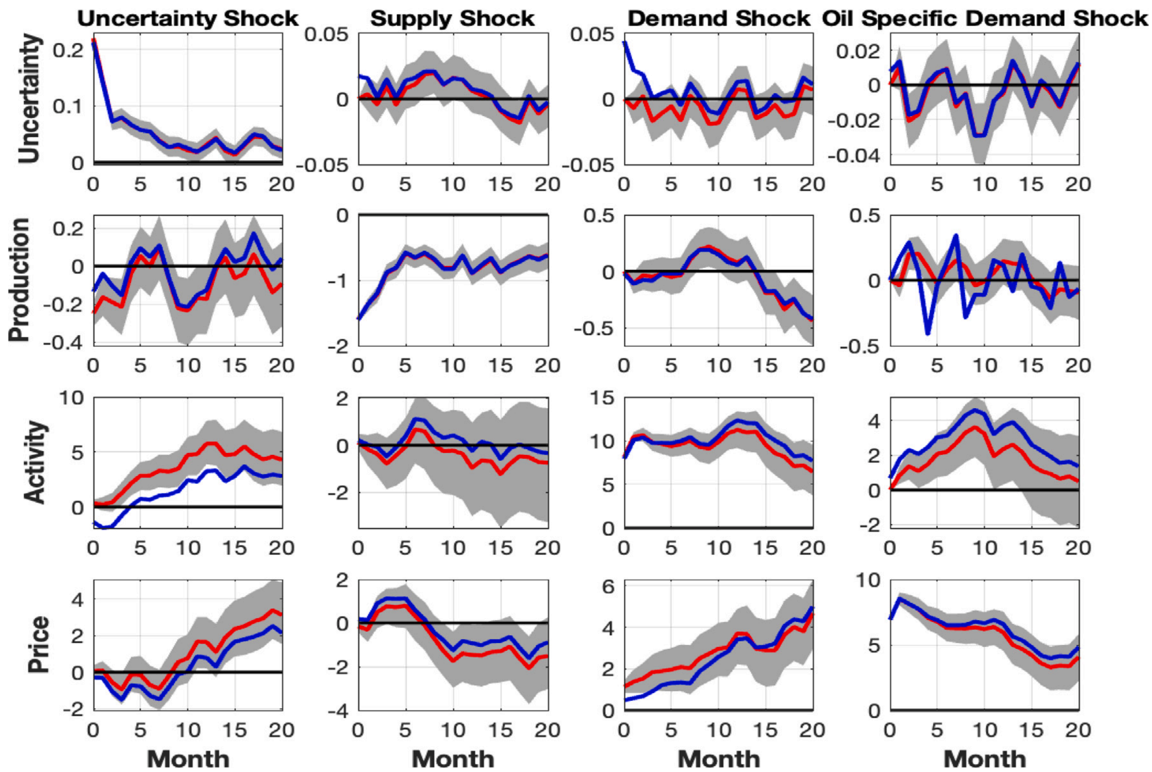

Fig. 9. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

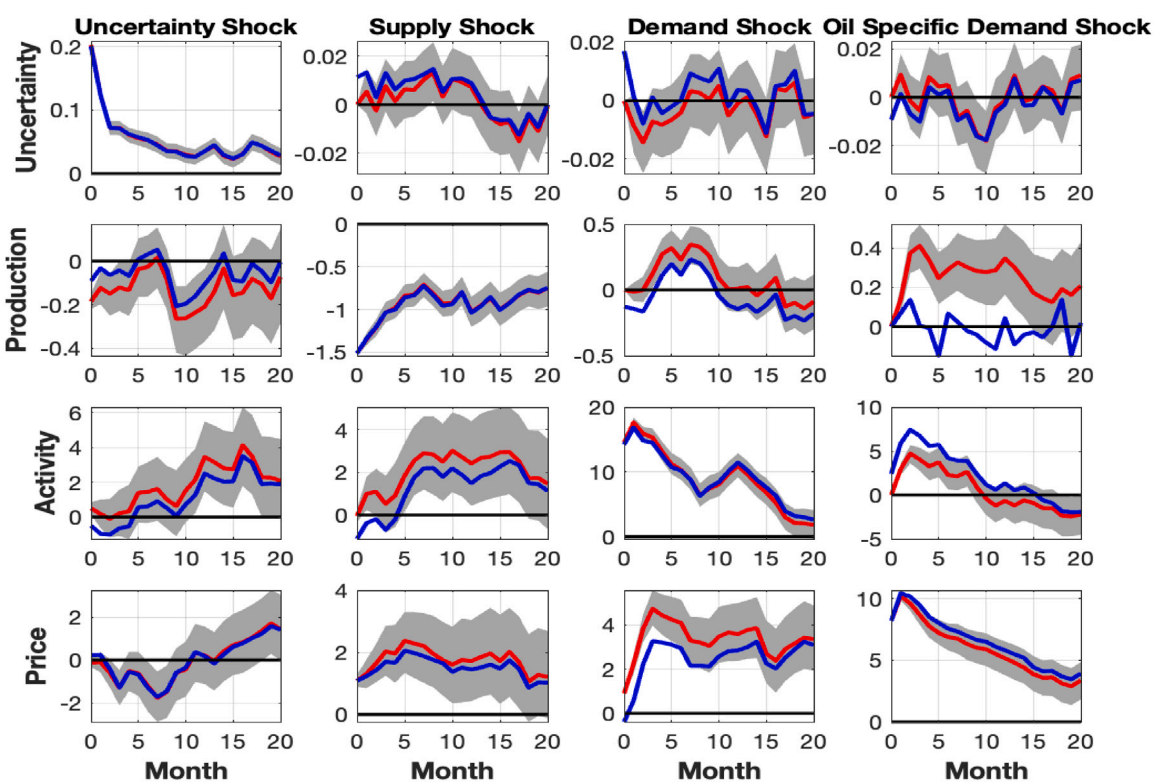

Fig. 10. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

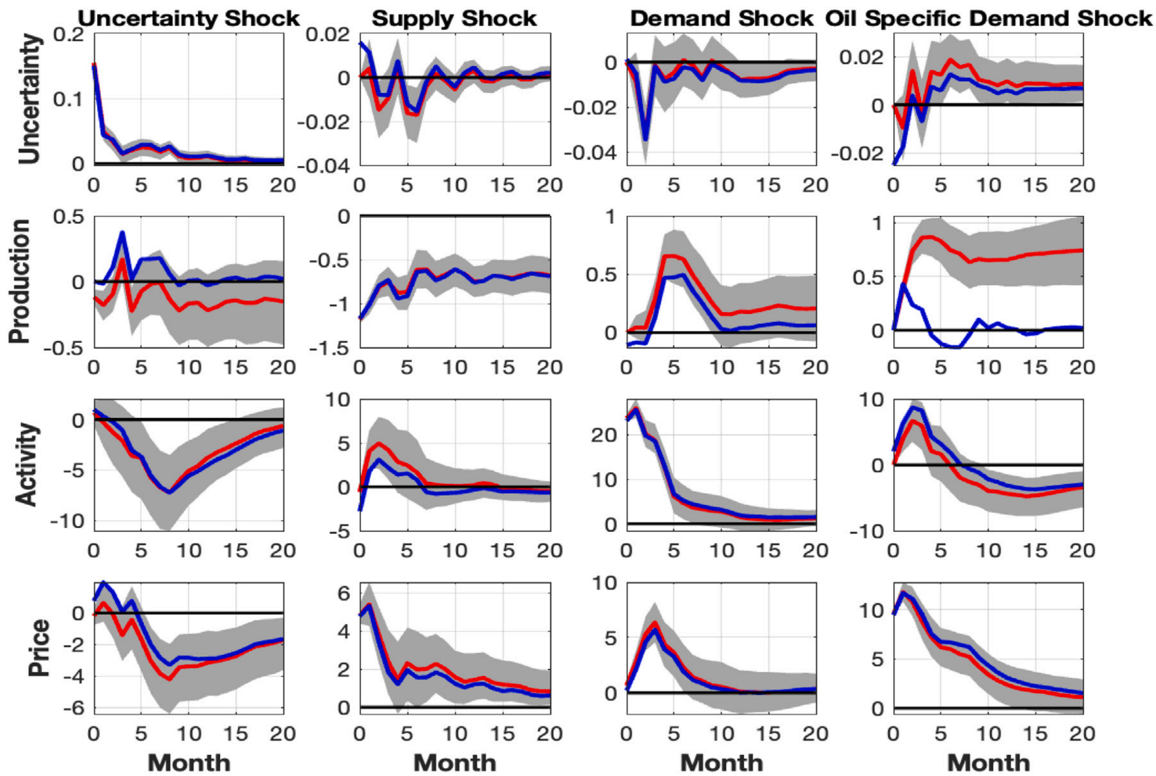

Fig. 11. Blue and red lines are responses due to shocks identified using FEV method and Cholesky decomposition respectively. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

we can say that in the absence of uncertainty, a higher proportion of variation in prices is attributed to the oil-specific demand shock. Also, it makes sense as it is expected that oil-specific demand shock will capture the role of uncertainty shock in absence of the uncertainty shock in the model.

3.3. Major episodes: Historical decomposition

The reduced form vector auto-regression model is given by:

$$y_t = b + \sum_{j=1}^{p} B_j y_{t-j} + u_t$$

where $u_t = A_0^{-1}\epsilon_t$

The moving average representation is given by

$$y_t = C(h)u_t$$

which can be written in terms of structural shock as:

$$y_t = C(h)A_0^{-1}\epsilon_t$$

Hence we can write

$$y_t = \sum_{s=0}^{t-1} C(s)A_0^{-1}\epsilon_{t-s} + \sum_{s=t}^{\infty} C(s)A_0^{-1}\epsilon_{t-s}$$

where C_s is the corresponding matrix from the moving average representation

$$y_t \sim \sum_{s=0}^{t-1} C(s)A_0^{-1}\epsilon_{t-s}$$

Based on the identification scheme used in this paper:

$$y_t \sim \sum_{s=0}^{t-1} C(s)PQ\epsilon_{t-s}$$

We know P from the Cholesky decomposition and Q is obtained from the optimization explained above. Write the above expression as

$$y_t \sim \sum_{s=0}^{t-1} H_s\epsilon_{t-s}$$

Then the third row contains the contribution of different shocks in prices. The value of y_t obtained from y should be compared with the demeaned y_t in the data as we have an intercept in the VAR model. Since we discard observation before time 0, the actual value and the value obtained from above may not coincide and we should discard some observations to eliminate the effect of left-out shocks. Appendix C at the end (Figs. C.1–C.6) reports the share of each shock in driving change in y up to each point in the sample. These may not add up to actual value due to residual error but we ignore that. Further, we can calculate the value of difference between y_{t+h} and y_t using the above. This is the total change in y during the time period h caused by the three shocks. We also know the contribution of each shock in this total change in y and hence we can calculate the share of each shock in driving change in y during time period h. In case of increase in real price, the difference between y_{t+h} and y_t is positive and the shocks which are having positive contribution are causing the price to rise and shocks having negative contribution is pushing price down. We consider six major episodes. Most of these episodes except recent ones have been explored extensively in the literature, see, Kilian (2009); Hamilton (2013); Caldara et al. (2019); Antolin-Diaz and Rubio-Ramirez (2018). Since, we use bootstrap to estimate the confidence band, we create the 68% confidence band around the share of individual shocks as well. All the historical decomposition in the paper are based on shocks identified using forecast error variance based identification explained in the methodology section.

The first episode is the time period during the Iranian revolution. The time period does not include Iraq's invasion of Iran in September 1980. The real oil price was doubled during the one year time period.

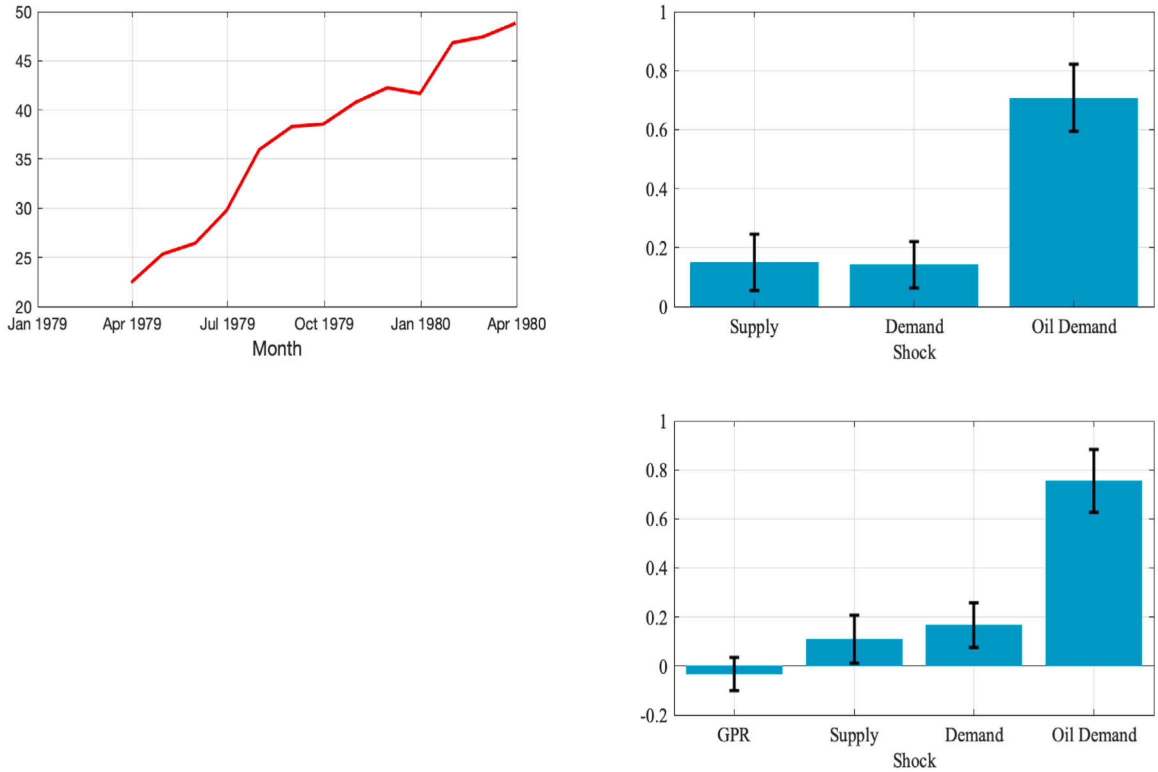

Fig. 12. Increase in real oil price during Iranian revolution (April 1979–April 1980) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

We find that almost 7̃0% of this was driven by oil-specific demand shock and remaining 30% was shared equally by supply and demand shocks (Fig. 12). Once we bring uncertainty into the model, the contribution of oil-specific demand shock increases slightly whereas the contribution of supply shock decreases. This brings us to the point mentioned in the introduction that uncertainty shocks are not only likely to influence precautionary demand but also important for the correct identification of supply shock as well.

The second episode is the time period during the infamous gulf war of 1990s. Again the real oil price was almost doubled during the six month time period. We find that almost 85% of this was driven by oil-specific demand shock and remaining 15% was due to supply shock. The demand shock had no role in driving price during this time period (Fig. 13). Once we bring uncertainty into the model, the contribution of all other shocks excluding uncertainty decreases, although the contribution of uncertainty shock is not significant.

The third episode is the surge in oil prices during the great financial crisis. Again the real oil price was almost doubled during June 2007–June 2008. We find that almost 75% of this was driven by oil-specific demand shock and remaining 25% was due to demand shock (Fig. 14). Supply shock has no significant role in driving price during this time period. But once we bring uncertainty into the model, the supply shock is significant and negative. This implies that supply was favourable during this time period and in the absence of favourable supply, price would have increased even more.

The fourth episode is of decline in oil price which was very sharp during the global financial crisis. This was predominantly driven by oil-specific demand shock contributing 80% and demand shock contributing 20% (Fig. 15). Even the inclusion of uncertainty does not change the contribution of oil-specific demand shock and demand shock. We can say that the uncertainty and supply shocks played no role in the decline in real oil price during the great financial crisis.

Next we move to the sharp decline and fall in price during the COVID-19 pandemic. With the start of the pandemic, the real prices of oil declined sharply and within a matter of just four months during January 2020 to April 2020, it became one fourth. We find that this decline was predominantly driven by oil-specific demand shock with 80% contribution and remaining 20% contribution of demand shock, Fig. 16. But uncertainty too played some minor role. Including uncertainty in the model decreases the contribution of oil-specific demand shock at the expense of uncertainty shock. The supply shock played negligible role in driving down price during the COVID-19 pandemic. The contribution of both demand and uncertainty shock makes sense because the COVID-19 pandemic brought unprecedented uncertainty and very sharp decline in global economic activity.

The final episode is the most recent surge in real oil prices. The real oil prices became almost doubled during the period October 2020 to October 2021 (Fig. 17). We find that this was primarily driven by oil-specific demand shocks. The supply shock was again favourable and almost countered the upward pressure on prices caused by the demand shock although the contribution of supply shock is not significant whereas the contribution of demand shock is significant. Bringing uncertainty does not change the contribution of shocks significantly but slightly increases the magnitude of demand shock and decreases the magnitude of supply shock. Although these results suggest that the oil specific demand shock has been the predominant drivers of real oil prices as argued by Kilian (2009), these results suggest that other shocks have also played significant role in different episodes. Out of the six episodes considered, in only two episodes (Iranian revolution and gulf war) supply shocks caused significant increase in oil price. Demand shock played significant role in four episodes i.e. Iranian revolution and COVID-19, surge and decline during global financial crisis and decline during the COVID-19 pandemic. Although uncertainty shock played significant role in driving down the price during COVID-19 pandemic only, it has been found to be influencing the contribution of other shocks in different episodes considered in this paper.

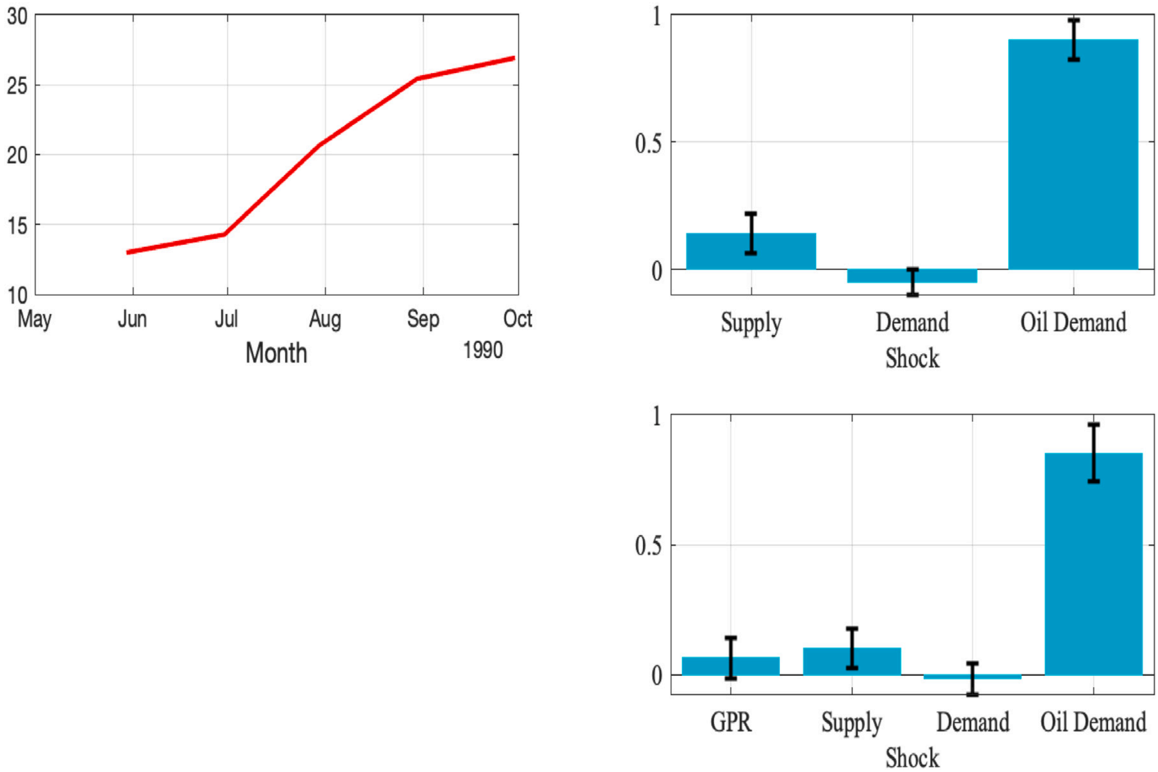

Fig. 13. Increase in real oil price during gulf war (June 1990–October 1990) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

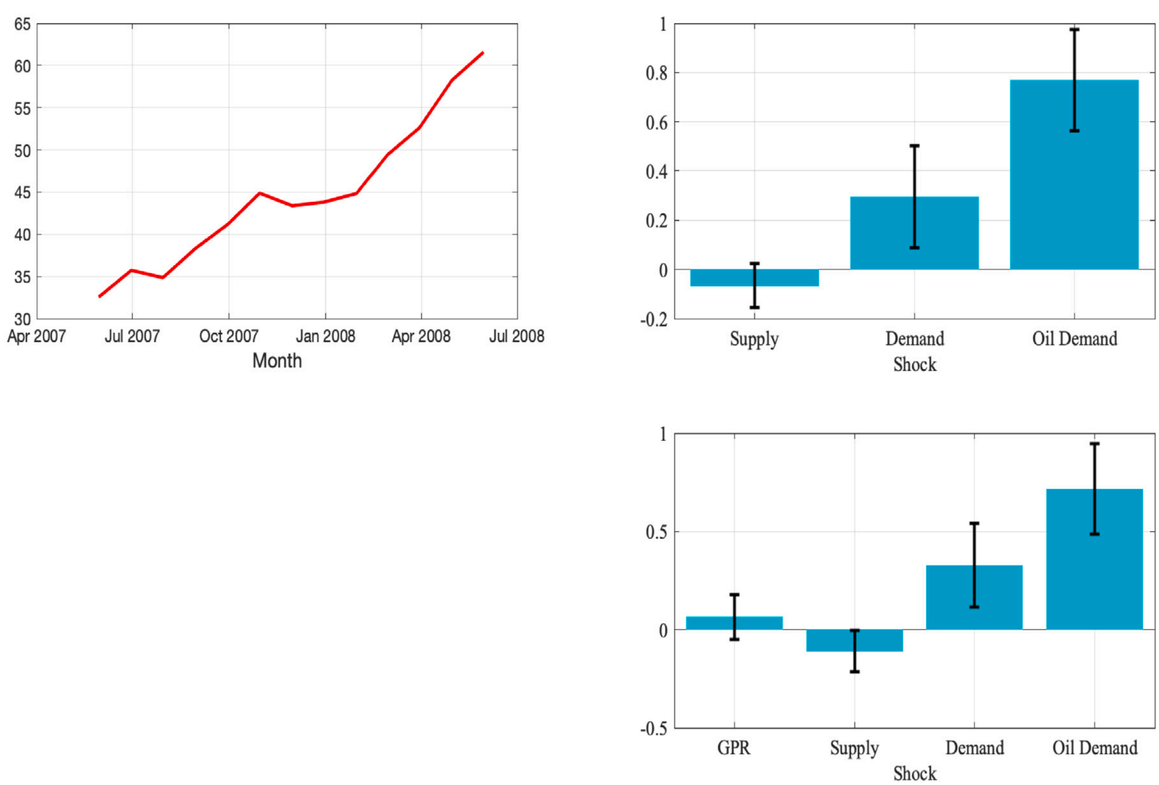

Fig. 14. Increase in real oil price during global financial crisis (June 2007–June 2008) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

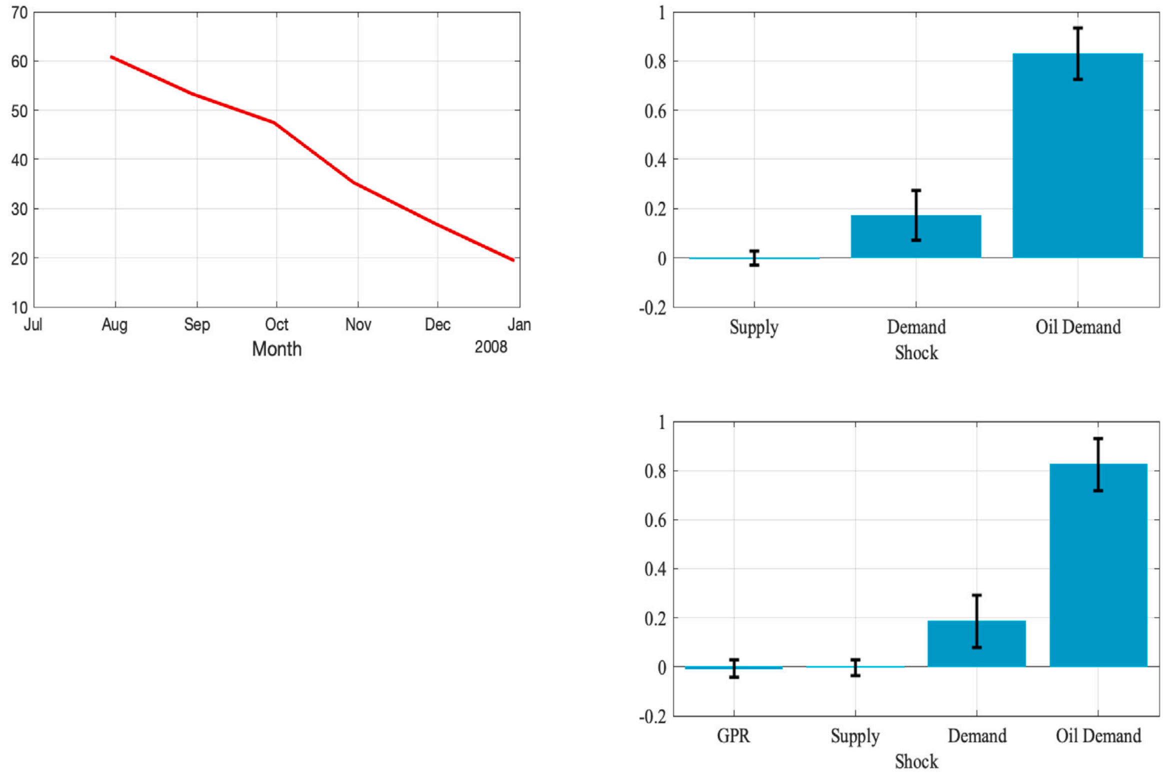

Fig. 15. Decline in real oil price during global financial crisis (July 2008–December 2008) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

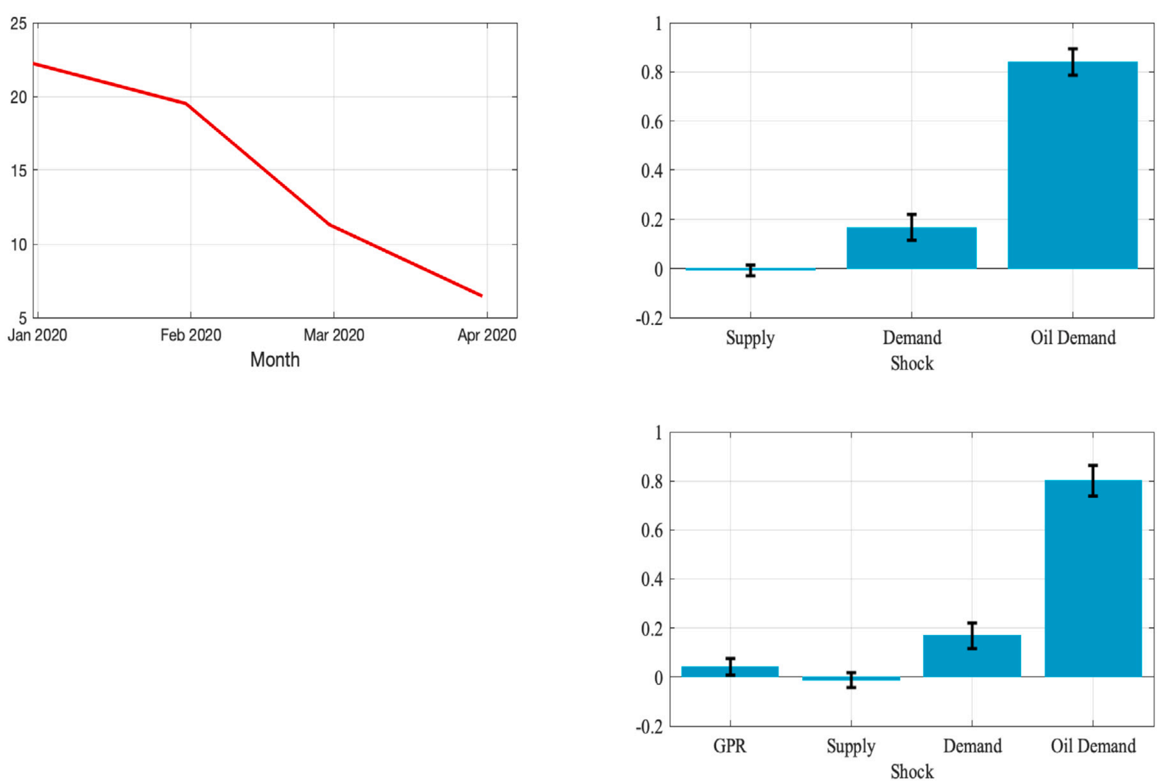

Fig. 16. Decline in real oil price during COVID-19 pandemic (January 2020–April 2020) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

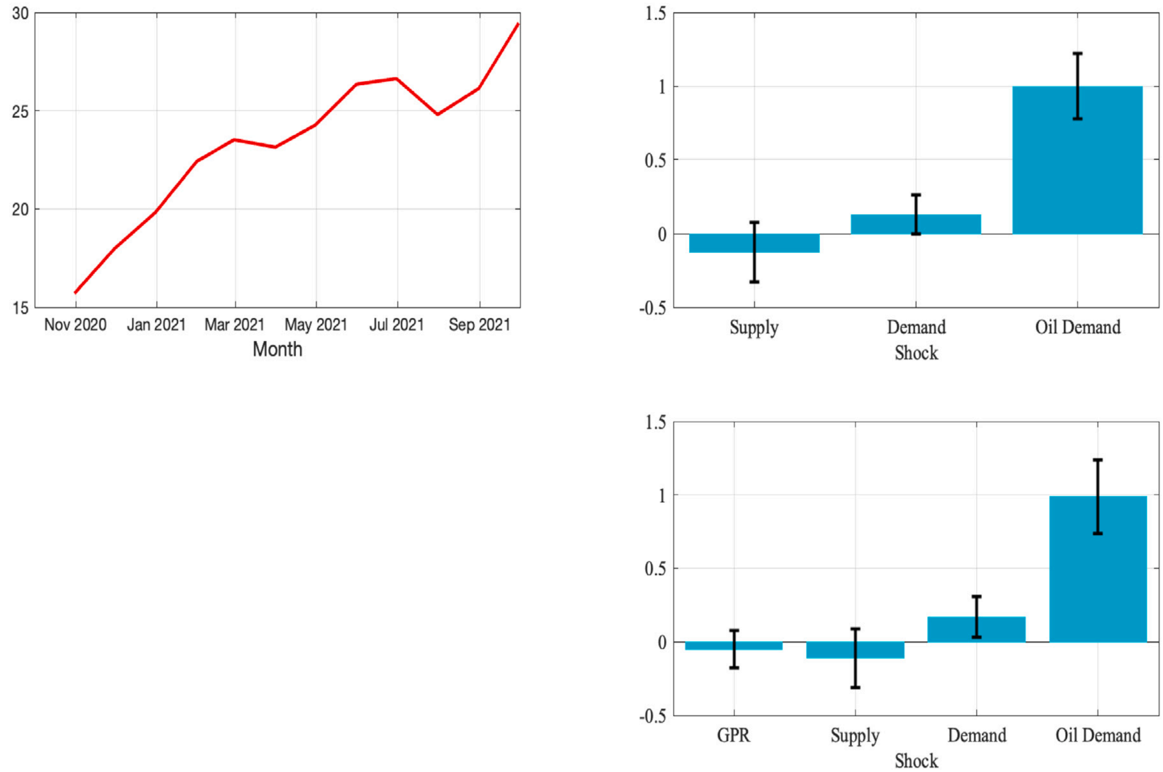

Fig. 17. Increase in real oil price during COVID-19 pandemic (November 2020–October 2021) and contribution of different shocks in driving oil price during this time period. GPR is geopolitical risk from Caldara and Iacoviello (2022). These shocks are identified using forecast error variance method.

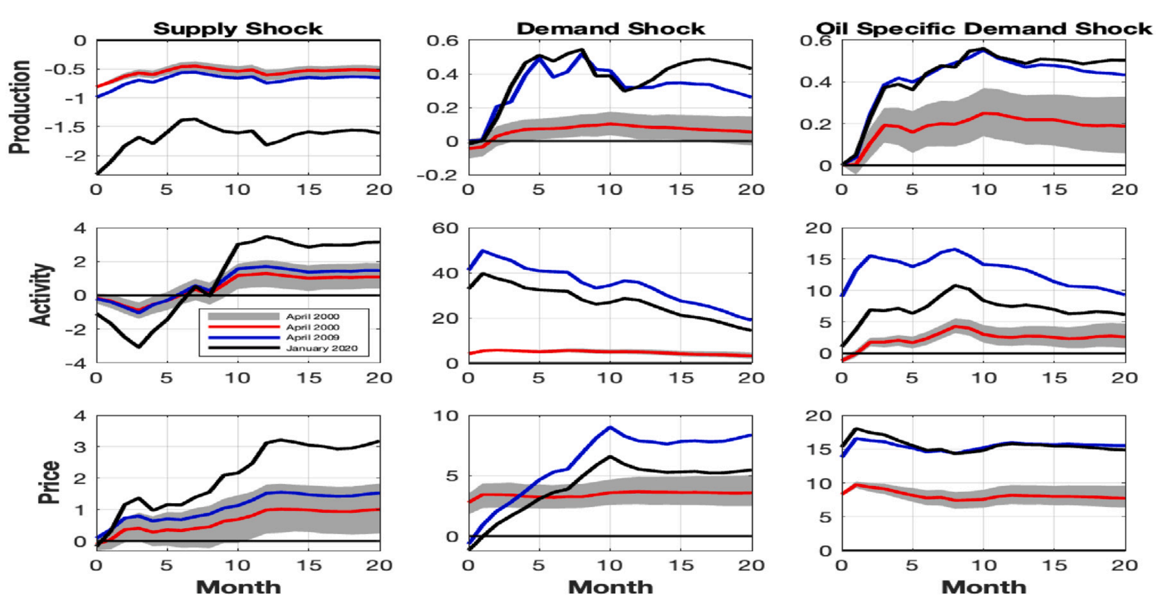

Fig. 18. Red, blue, and black lines are responses due to shocks identified from TVP-VAR using the FEV method for the months of April 2000, April 2009 and January 2020. The shaded area is a 68% confidence band for the month of April 2000. Responses given by black lines suggest the increasing influence of supply shocks in determining prices in recent times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Evidence from time-varying parameter VAR

The results presented in the previous section clearly demonstrate an increasing role of supply shocks in determining oil price in the recent sample. To further substantiate this point, we estimate a time-varying parameter vector auto-regression (TVP-VAR) model. The model is based on Primiceri (2005). The observables y_t are assumed to follow a vector autoregression with time-varying coefficients and a time-varying

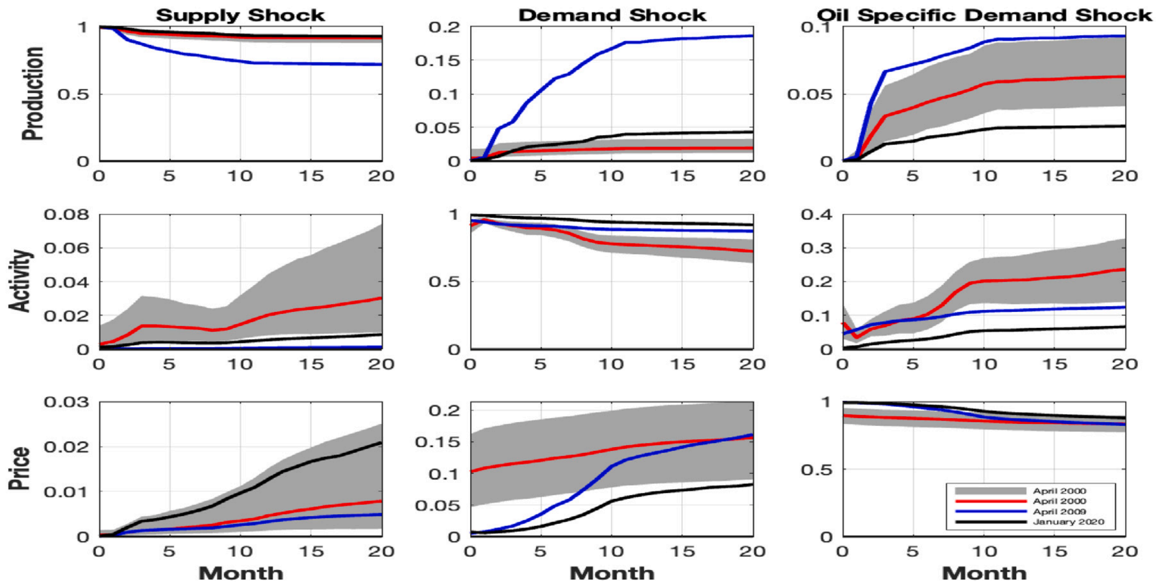

Fig. 19. Red, blue, and black lines are the share of shocks identified from TVP-VAR identified using the FEV method in forecast error variance of variables at these months: April 2000, April 2009 and January 2020. The shaded area is a 68% confidence band for the month of April 2000. Responses given by black lines suggest the increasing influence of supply shocks in determining prices in recent times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

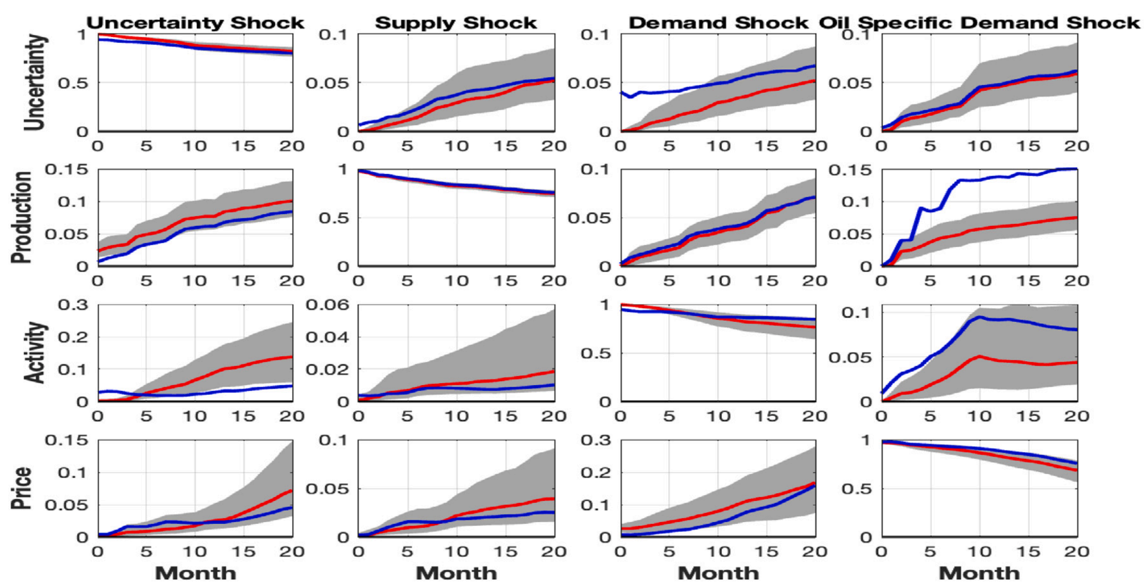

Fig. B.1. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

covariance matrix for the innovations. The model is given by:

$$A_{0,t}y_t = a_t + \sum_{j=1}^{p} A_{j,t}y_{t-j} + \Sigma_t\epsilon_t$$

$$E(\epsilon_t\epsilon_t') = I$$

where $A_{0,t}$ is the low triangular matrix which in the case of 3 variable VAR is given by:

$$A_{0,t} = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{2,1,t} & 1 & 0 \\ \alpha_{3,1,t} & \alpha_{3,2,t} & 1 \end{bmatrix}$$

and Σ_t is the diagonal triangular matrix which in the case of 3 variable VAR is given by:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 \\ 0 & \sigma_{2,t} & 0 \\ 0 & 0 & \sigma_{3,t} \end{bmatrix}$$

We assume diagonal elements of $A_{0,t}$ as 1 and Σ_t as a diagonal matrix without loss of generality. The reduced form for the same is given by:

$$y_t = A_{0,t}^{-1}a_t + \sum_{j=1}^{p} A_{0,t}^{-1}A_{j,t}y_{t-j} + A_{0,t}^{-1}\Sigma_t\epsilon_t$$

Which can be further written as:

$$y_t = b_t + \sum_{j=1}^{p} B_{j,t}y_{t-j} + u_t$$

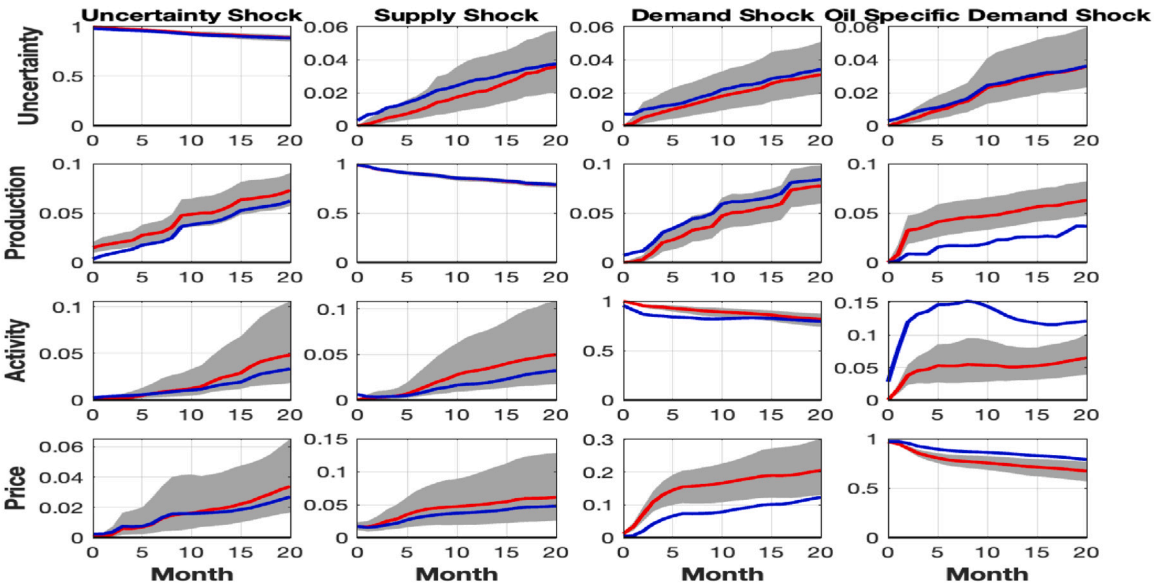

Fig. B.2. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

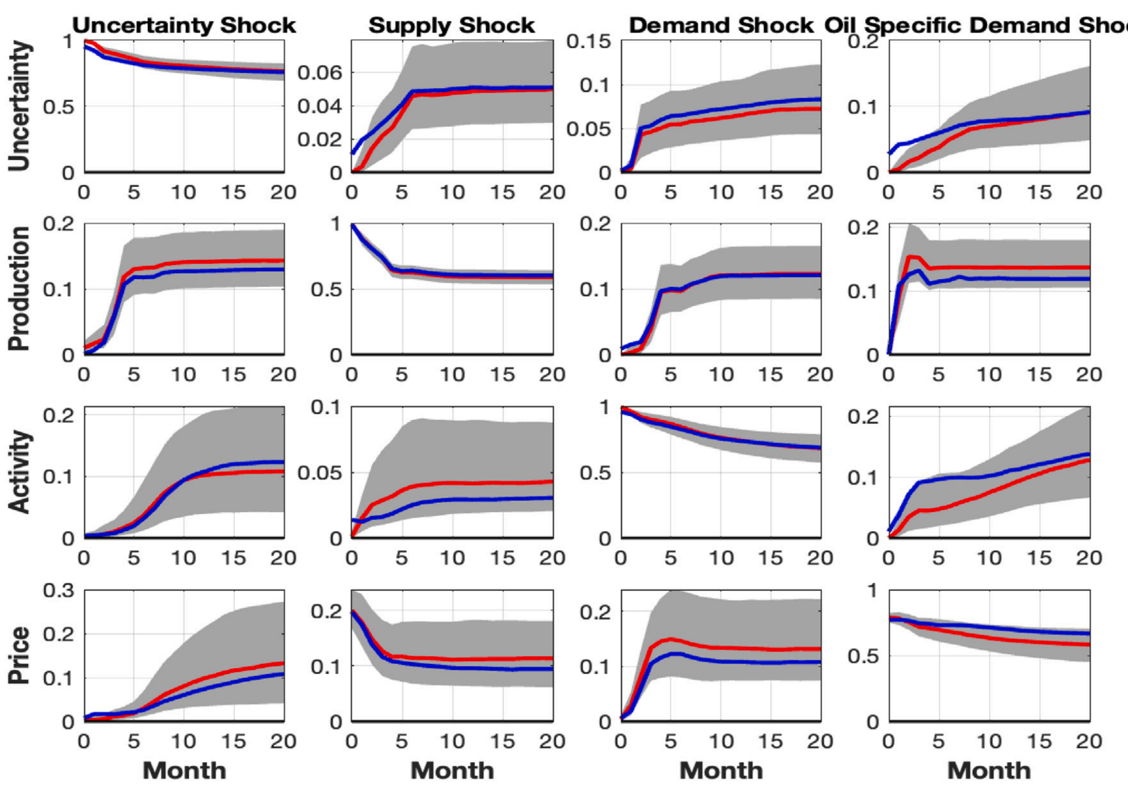

Fig. B.3. Blue and red lines are share of shocks identified using FEV method and Cholesky decomposition respectively in forecast error variance of variables. The shaded area is a 68% confidence band for the responses identified using Cholesky decomposition. Sample 1973–2007. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Where b_t is a $n\times$ 1 vector of time-varying constant terms and $B_{j,t}$ is $n \times n$ matrix containing time-varying coefficient. We have

$$u_t = A_{0,t}^{-1} \Sigma_t \epsilon_t$$

$$E(u_t u_t') = E(A_{0,t}^{-1} \Sigma_t \epsilon_t \left(A_{0,t}^{-1} \Sigma_t \epsilon_t \right)')$$

$$\Omega_t = A_{0,t}^{-1} \Sigma_t \Sigma_t' (A_{0,t}')^{-1}$$

The above structural model can be written as:

$$y_t = X_t' B_t + A_{0,t}^{-1} \Sigma_t \epsilon_t$$

Where

$$X_t' = I_n \otimes [1 \quad y_t' \quad y_{t-1}' \quad y_{t-p}']$$

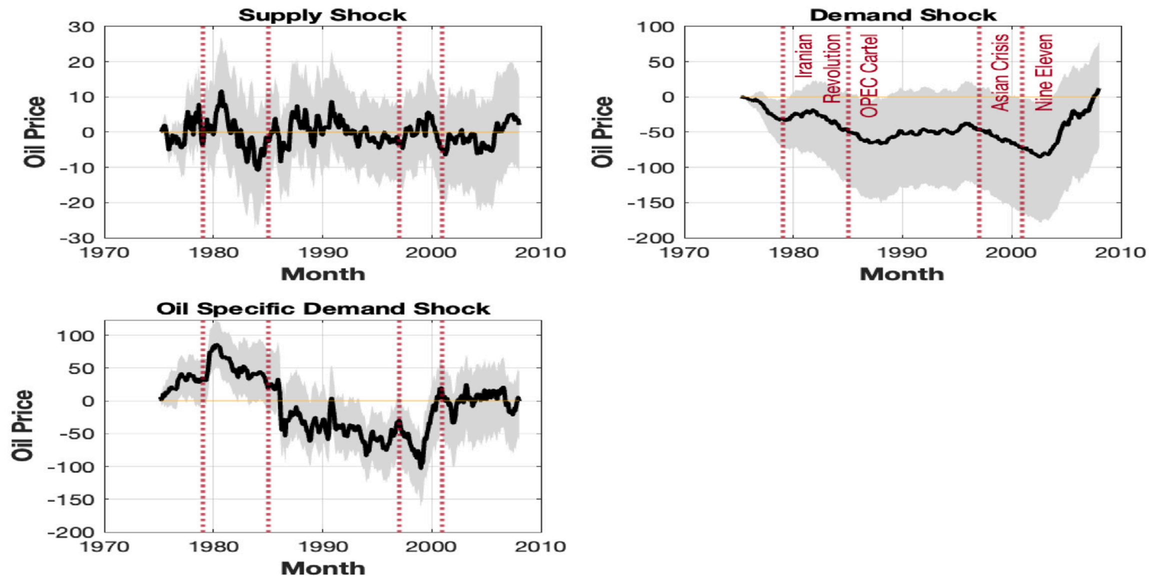

Fig. C.1. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 1973–2007.

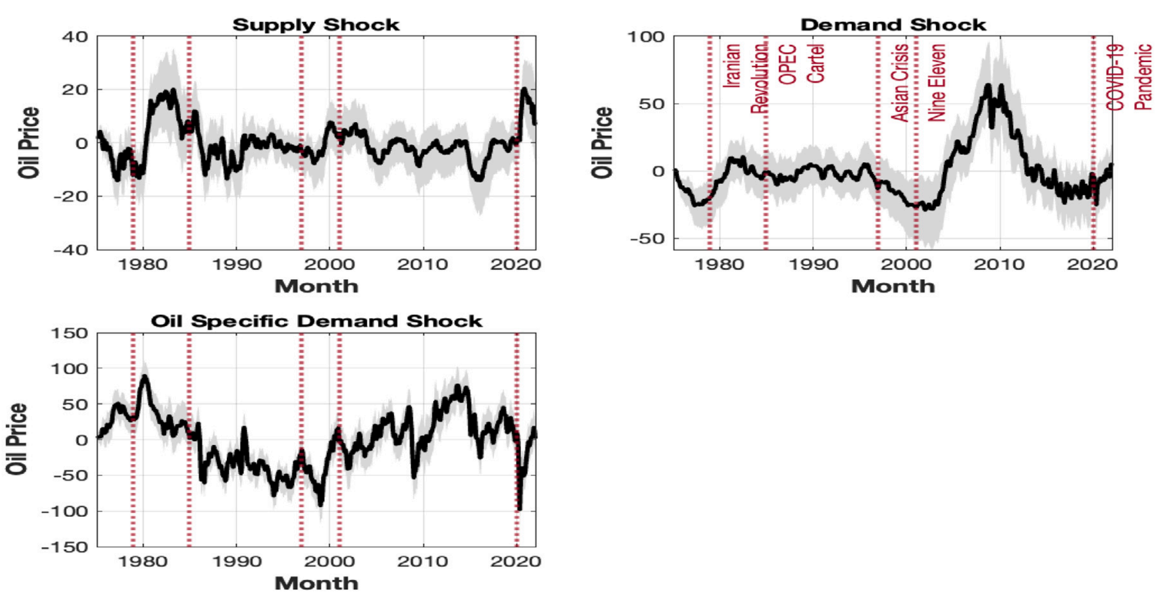

Fig. C.2. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 1973–2021.

And stacking all the coefficients gives:

$B_t = vec\left[b_t \quad B_{1,t} \quad B_{2,t} \quad B_{p,t}\right]$

The non-zero and non-one elements of A_t :

$\alpha_t = [\alpha_{2,1,t} \quad \alpha_{3,1,t} \quad \alpha_{3,2,t}]'$

The non-zero elements of Σ_t :

$\sigma_t = [\sigma_{1,t} \quad \sigma_{2,t} \quad \sigma_{3,t}]'$

The dynamics of the time-varying parameters are specified as:

$$B_t = B_{t-1} + \eta_t$$

$$\alpha_t = \alpha_{t-1} + \xi_t$$

$$log\sigma_t = log\sigma_{t-1} + \vartheta_t$$

all the innovations are assumed to be jointly normally distributed with

$$V = E\begin{bmatrix} \epsilon_t \\ \eta_t \\ \xi_t \\ \vartheta_t \end{bmatrix}\begin{bmatrix} \epsilon_t & \eta_t & \xi_t & \vartheta_t \end{bmatrix} = \begin{bmatrix} I_3 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

so that the standard deviations in σ_t evolve as independent geometric random walks. Following Primiceri (2005), it will be assumed that S is block-diagonal, with one non-zero element in the first column of the first row and three distinct non-zero elements in the second and third columns of the second and third rows. We estimate the three variable model with 12 lags and the extended model including uncertainty with 6 lags. We use less number of lags, as with 24 lags the Gibbs-sampler finds it difficult to make draws for large number of parameters based

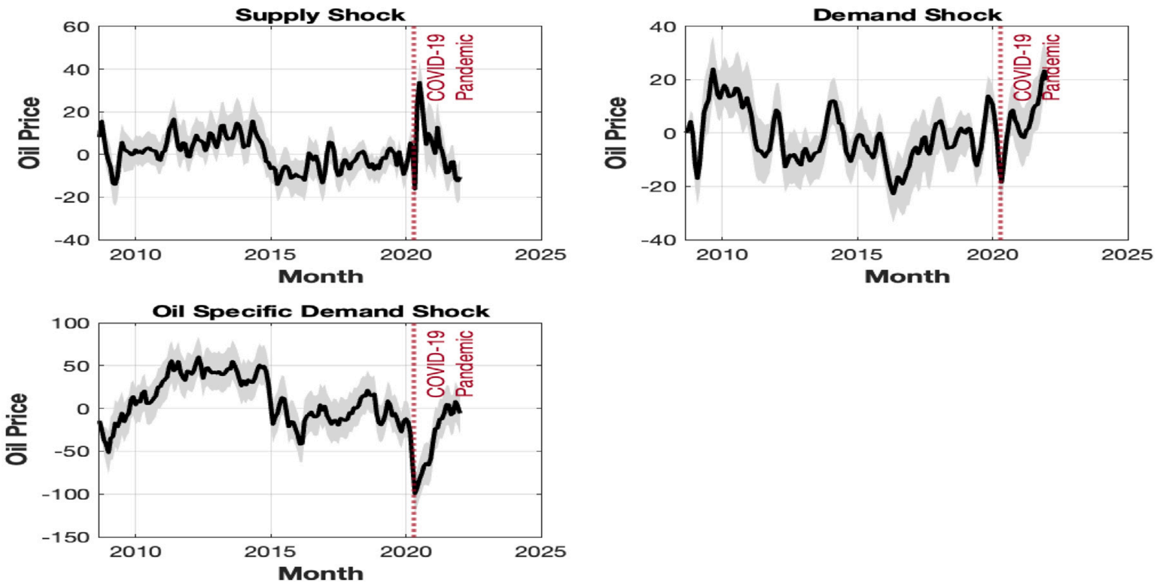

Fig. C.3. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 2008–2021.

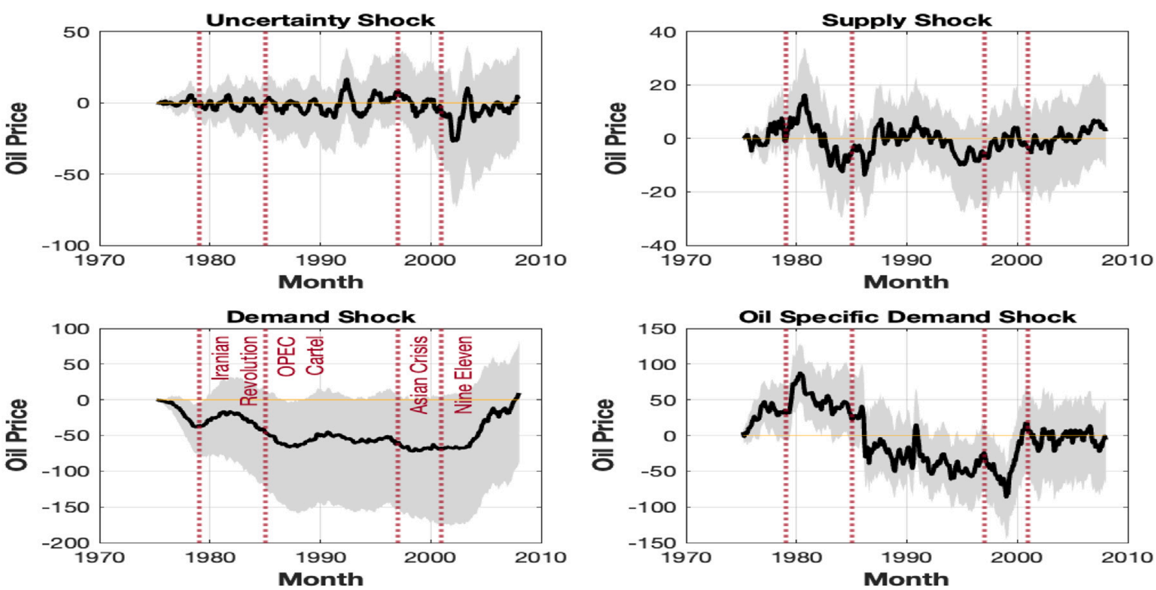

Fig. C.4. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 1973–2007.

on hyper-parameters in Primiceri (2005).[5] We use a training sample of 15 years i.e. 180 observations to set the priors for the TVP-VAR. Once we have the parameters and variance covariance matrix for each point of time, we implement the forecast error variance based identification to identify the structural shock at each point of time as explained in the previous section.

The split sample estimation (pre and post-crisis) being done in the previous section showed the increasing role of supply shocks in determining prices in recent times. To substantiate this further, we have estimated the TVP-VAR and have identified the shocks using the forecast error variance (FEV) method. To the best of our knowledge, this is the first paper to use FEV-based identification in a TVP-VAR with stochastic volatility.

[5] The TVP-VAR model with stochastic volatility is estimated using the Matlab codes available at https://sites.google.com/site/dimitriskorobilis/matlab/code-for-vars?authuser=0

Fig. 18 gives the responses at three points in time (April 2000, April 2009 and January 2020) from three variable TVP-VAR. As we can see from the figure, the reduction in supply due to adverse supply shock has been increasing over time and also the response of prices due to adverse supply shock has been increasing over time. Fig. 19 gives the share of these shocks in the FEV of the model variables and this also clearly demonstrates the transition. In recent times the share of supply shocks in the FEV of prices has increased whereas the share of demand shock in the FEV of prices has decreased. Fig. D.1 in appendix gives the responses at three points in time (April 2000, April 2009 and January 2020) from four variable TVP-VAR. As we can see from the figure, the reduction in supply due to adverse supply shock has increased in recent times and also the response of prices due to adverse supply shock has been increasing over time. Both three and four variable VARs suggest that the response of prices due to supply shocks has been more persistent in recent times, and the supply shocks keep prices higher in the medium run. Also, both the three and four variables VAR suggest the diminished share of demand shocks in

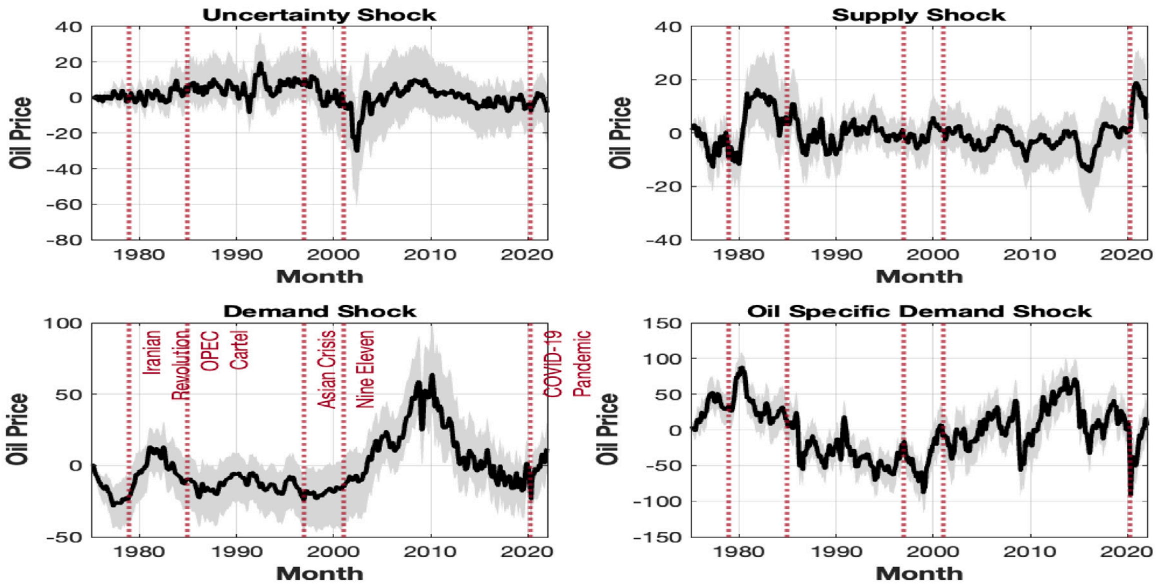

Fig. C.5. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 1973–2021.

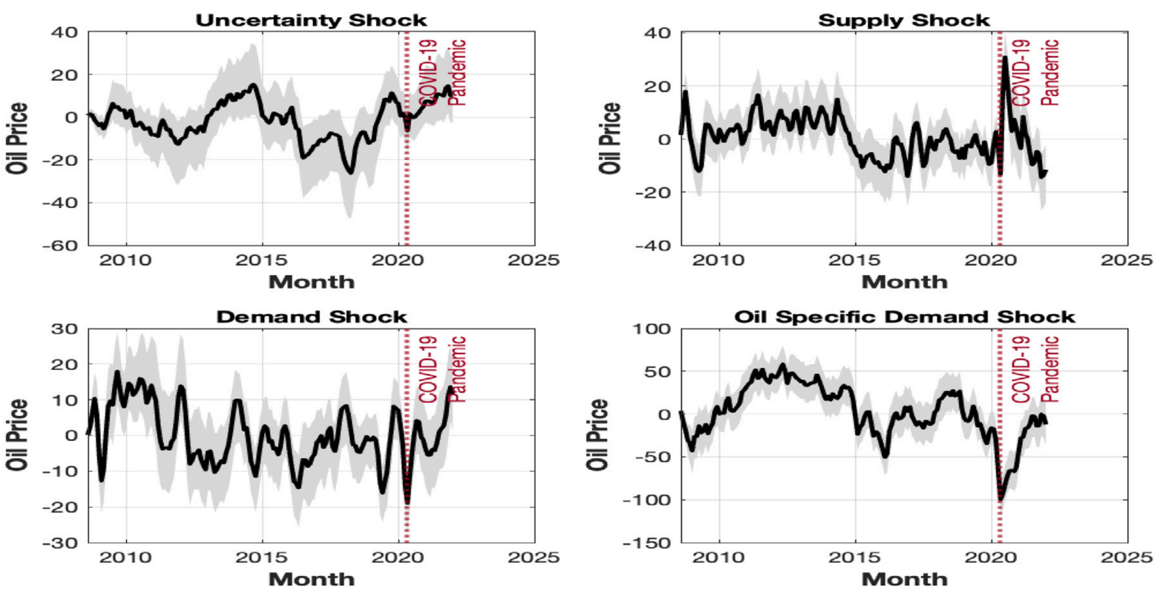

Fig. C.6. Historical Decomposition based on FEV method. The shaded area is a 68% confidence band. Sample 2008–2021.

forecast error variance of prices (Fig. D.2 in appendix). These results give overwhelming evidence in support of the split sample evidence presented in the previous section which demonstrates a transition in oil price dynamics with an increasing role of supply shocks at the expense of demand shocks.

5. Concluding remarks

Understanding the drivers of oil prices is important for business cycle stabilization and other macroeconomic policies. The short run supply elasticity of oil is important for determining the contribution of different shocks in driving the oil prices and has been a matter of debate. We address these methodological issues using a new identification scheme which does not restrict the short run supply elasticity to be zero unlike Cholesky decomposition. The identification obtained in this paper using share in forecast error variance is also minimal, non-controversial and better than accept and reject algorithm used in sign restriction based identification as argued before.

We estimate the contribution of four shocks – supply, demand, precautionary demand and geopolitical risk – in driving oil prices. Results suggest that precautionary demand and demand shocks are predominant in driving oil prices but the effect of demand shock on oil prices is not long-lasting in the recent periods unlike before global financial crisis. This is likely to be driven by higher substitutability between crude oil and other forms of energy such as Shale oil and sources of unconventional energy at higher prices. The results obtained in the paper confirm that short run supply elasticity is indeed zero as assumed in Kilian (2009). This makes sense as the oil production from existing oil wells are determined by the pressure in oil wells and do not respond to price movements as argued by Anderson et al. (2018). This does not mean that the price elasticity of oil supply is zero in the medium-term too.

In the post-crisis sample, the effect of demand shock on oil prices is less prominent, unlike the pre-crisis sample, where the effect was increasing over time. This is reflecting the recent shift towards other sources of energy (shale oil or renewable sources of energy). Further,

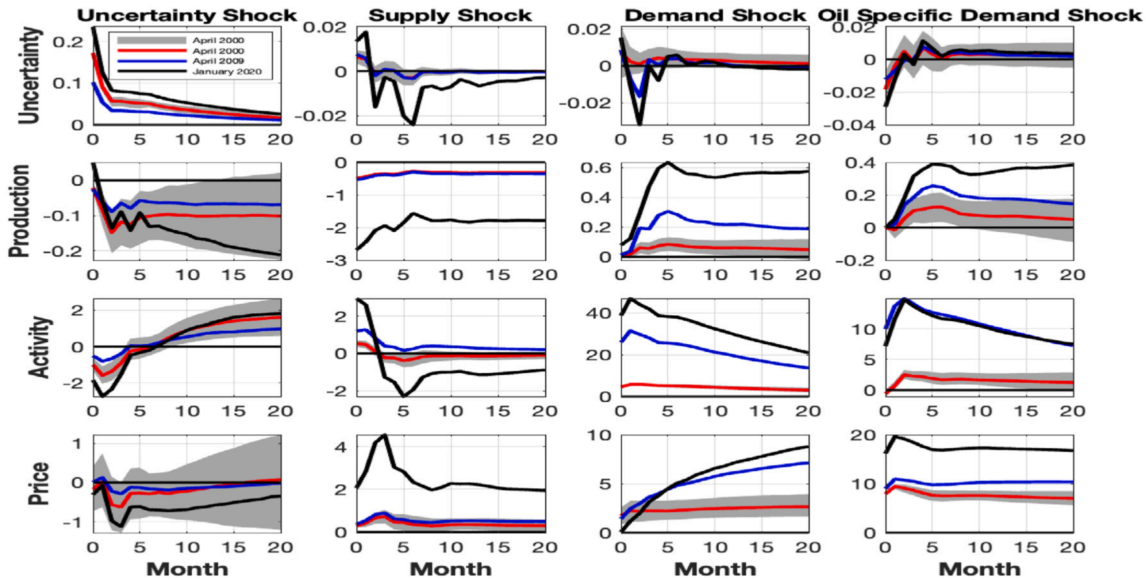

Fig. D.1. Red, blue, and black lines are responses due to shocks identified from TVP-VAR using the FEV method for the months of April 2000, April 2009 and January 2020. The shaded area is a 68% confidence band for the month of April 2000. Responses given by black lines suggest the increasing influence of supply shocks in determining prices in recent times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

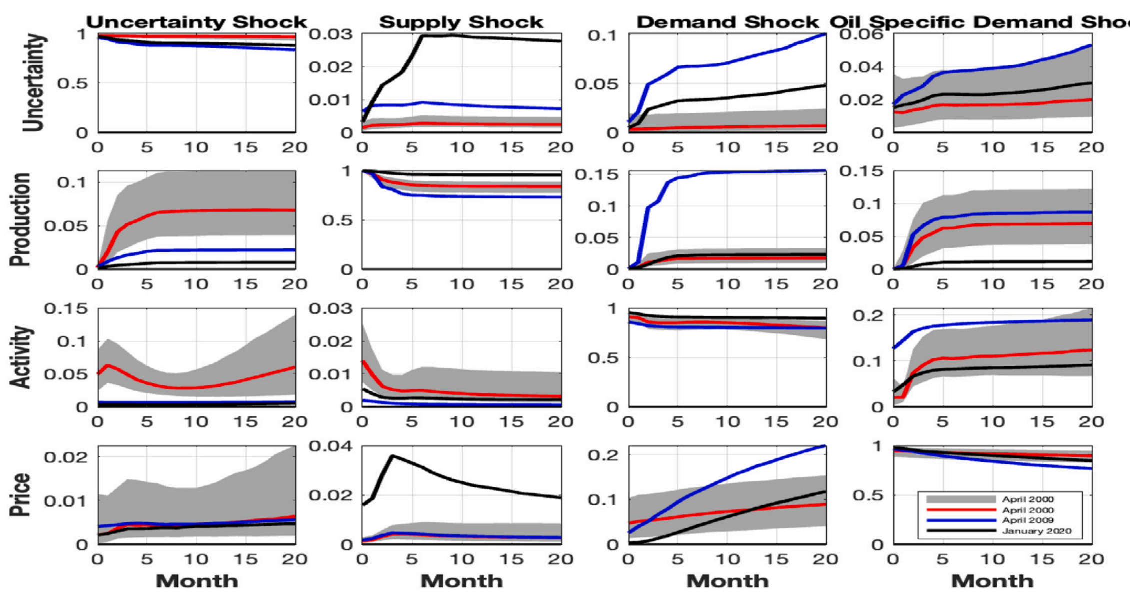

Fig. D.2. Red, blue, and black lines are the share of shocks identified from TVP-VAR identified using the FEV method in forecast error variance of variables at the following months: April 2000, April 2009 and January 2020. The shaded area is a 68% confidence band for the month of April 2000. Responses given by black lines suggest the increasing influence of supply shocks in determining prices in recent times. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the results suggest that the response of oil prices due to supply shocks is significantly higher in the recent sample, and supply shocks explain significantly higher fraction of variance of oil prices, unlike the pre-crisis sample. These results indicate a transition in the determination of oil prices where supply shocks have a relatively significant role, unlike in the pre-crisis sample period. To substantiate the results from split sample estimation, we have estimated a TVP-VAR and have identified the shocks using the forecast error variance method. The response of production and prices due to supply shocks and the share of demand and supply shocks in forecast error variance of the prices at three points in time (April 2000, April 2009 and January 2020) also demonstrate the transition evident in the split sample estimation.

Understanding the sharp movement in oil prices during the COVID-19 pandemic is another objective of this paper and the result suggests that the sharp decline in oil prices during January 2020 to April 2020 was driven by oil specific demand and demand shock, and the contribution of demand shock is 20%. Uncertainty shocks also played some role in the decline in prices during the beginning of the pandemic. The contribution of demand and uncertainty shocks in the decline in oil prices makes sense, as we know that COVID-19 pandemic brought unprecedented uncertainty and led to complete collapse of global economic activity due to widespread lock-downs. The subsequent increase in oil prices during (2020–21) was primarily driven by oil specific demand and demand shocks. Although it is true that oil-specific demand shocks are predominant drivers of real oil-prices as argued by Kilian (2009), six episodes considered in this paper suggest that other shocks, namely supply shocks, have also played significant roles in driving oil prices in different episodes which cannot be ignored while evaluating the oil price dynamics.

CRediT authorship contribution statement

Abhishek Kumar: Conceptualization, Methodology, Analysis, Data curation, Writing – original draft, Writing – review & editing. **Sushanta Mallick:** Conceptualization, Methodology, Analysis, Data curation, Writing – original draft, Writing – review & editing.

Appendix A. Data sources

Oil Production https://www.eia.gov/international/data/world/petroleum-and-other-liquids/monthly-petroleum-and-other-liquids-production?pd=

Price https://fred.stlouisfed.org/series/CPIAUCSL

WTI https://fred.stlouisfed.org/series/WTISPLC

Economic Condition Index https://www.dallasfed.org/research/igrea

Uncertainty Data https://www.matteoiacoviello.com/gpr.htm

Appendix B. FEVD from four variable models

See Figs. B.1–B.3.

Appendix C. Historical decomposition

See Figs. C.1–C.6.

Appendix D. Results of TVP-VAR from four variable models

See Figs. D.1 and D.2.

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