Macroeconomic Outcomes of OPEC and Non-OPEC Oil Supply Shocks in Euro Area[1]

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Abstract

Exogenous OPEC and non-OPEC oil supply cuts, which are identified within an SVAR model with unplanned oil supply outage as an external instrument, decrease industrial production and raise unemployment rate of member states in the European Union. However, the transmissions to consumer price are different when OPEC and non-OPEC oil supply cuts are respectively considered. Further analyses are implemented with datasets of different sectors and individual countries. The results are robust against different identification strategies and variations in empirical specifications. Finally, our findings signify policy implications for enhancing energy security in the European Union.

Keywords: OPEC and Non-OPEC; Oil supply shocks; European macroeconomy; VAR; External instrument

JEL Codes: Q41; Q43; C22

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1. Introduction

There has been a gradual decline in oil demand in the European Union (EU) countries since 2000 due to a range of factors including the development of green vehicles, improvements in vehicle efficiency, the blending of biofuels, and global economic downturn. However, the oil import dependency ratio as reported by McGovern et al. (2020) had continuously increased to a high of 96% in 2018,[2] which clearly identifies the importance of analysing the profound effects of oil supply shocks on the European macroeconomy. According to McGovern et al. (2020), more than half of the EU's oil imports came from non-OPEC countries (31% from Russia, 16% from Kazakhstan and Norway, and a further 5% from Azerbaijan). In addition, around 35% of the total oil imports of the EU came from OPEC countries (9% from Iraq, 8% from Saudi Arabia, 7% from Nigeria, 6% from Libya and 4% from Iran). It can be seen that the majority of oil imports of the EU came from unstable regions such as those suffering from geopolitical tensions, terrorism, border conflicts, or wars. Consequently, the EU countries face an increasing risk of oil supply outage and so it is essential to figure out the relative importance of OPEC and non-OPEC oil supply shocks to the EU's macroeconomy.

Existing literature on the oil-macroeconomy relationship has been largely focused on the US market. To name a few, the seminal work of Hamilton (1983) is among one of the first to explore how oil is associated with the macroeconomy. They document that the US macroeconomic performance is affected by fluctuations of oil price in the post-OPEC periods. Hamilton (2003) further utilizes a nonlinear model to investigate the relation between oil price changes and GDP growth. The empirical findings suggest that oil price increases play a more important role in determining economic growth than oil price decreases. Moreover, Kilian (2008) first isolates a time

[2] The oil dependency is calculated as the ratio of net oil imports to gross inland energy consumption of crude oil and petroleum product.

series of oil supply shock which causes a decrease in the US real GDP growth and a spike in inflation. One recent work by Herrera and Rangaraju (2020) attributes the impulse response estimations in existing studies to different identification strategies.

To understand the macroeconomic effects of structural oil shocks, numerous studies prefer a Structural Vector Autoregression (SVAR) model (Kilian, 2008, 2009; Kilian and Lewis, 2011; Kilian, 2014; Lütkepohl and Net˘Sunajev, 2014; Baumeister and Kilian, 2015, 2016; Güntner and Linsbauer, 2018; Baumeister et al., 2018; Känzig, 2019; Baumeister and Hamilton, 2021; Herrera and Rangaraju, 2020). Specifically, Kilian (2009) empirically uses a SVAR model to identify oil supply shock, aggregate demand shock and oil-specific demand shock, respectively. The impacts of the identified oil shocks on the US macroeconomy are varied. Bhat et al. (2018) employ a SVAR methodology to explore how the macroeconomy of India is affected by oil and food price shocks. Their results confirm that the macroeconomic activities in India are sensitive to external shocks. In addition, Nasir et al. (2019) adopt a SVAR framework to examine the association between oil price shocks and the macroeconomy of the Gulf Cooperation Council (GCC) member countries. They demonstrate that as the major oil exporters in the world, the impacts of oil price shocks on macroeconomic variables of GCC members are significant and positive.Further studies such as Cologni and Manera (2009); Kang and Ratti (2013); Cashin et al. (2014); Lee et al. (2017); Gong and Lin (2018); Ewing et al. (2018); Kamiar and Mehdi (2019) and Chen et al. (2020) also investigate the impacts of oil shocks on the economy from a variety of different perspective.

However, a drawback of the traditional SVAR model is that the conclusions are derived based on the assumptions that the desired oil supply shocks can contemporaneously affect macroeconomic variables, but the reverse impacts take time. To interpret the results with causal evidence, one should ensure that the unexpected oil supply shocks are strictly exogenous and not endogenous responses to other macroeconomic shocks. To address this main missing point of current literature, this study estimates the causal effects of an exogenous oil supply shock on the EU's macroeconomy by utilizing a proxy SVAR model in the spirit of Stock and Watson (2012) and Mertens and Ravn (2013). The desired exogenous oil supply shock is identified by using an external instrument namely unplanned oil supply outage shock. It is also worth highlighting that present findings have been primarily concentrate on the US with few studies analysing the influence of oil supply shocks on European macroeconomy so the findings of this study will be of great interest.

As mentioned above, a large proportion of oil imports into the EU came from non-OPEC countries, rather than OPEC member countries. It is natural to suspect that there are heterogenous impacts of OPEC and non-OPEC oil supply shocks on the European macroeconomy. Therefore, we respectively identify OPEC and non-OPEC oil supply shocks and compare their impacts on the EU macroeconomy by using impulse response functions (IRFs) under a novel identification scheme. In addition, forecast error variance decomposition (FEVD), historical decomposition (HD) and counterfactual analysis (CA) are conducted to complement our quantitative evidence. We also examine the responses at sectoral level and of individual member countries to provide economic implications.

The impulse response analysis shows that the identified exogenous oil supply shocks of both OPEC and non-OPEC significantly raise oil price and unemployment rate while having a dampening impact on industrial production of the EU countries. Moreover, we find that exogenous OPEC and non-OPEC oil supply shocks have different impacts on price level. Specifically, the identified oil shock of OPEC decreases price but that of non-OPEC has an opposite effect on price level. According to historical decomposition, some interesting results are noticeable. We identified negative shocks in OPEC oil supply over three sub-periods from 2009 to 2011, 2013 to 2014 and several months in the late 2019. These negative shifts caused increasing oil price and decreasing industrial production. Interestingly, the identified oil supply cuts did not cause the price to rise. As for the results of non-OPEC oil shocks, negative shifts in oil production are identified in several months of 2011 to 2013, 2016 to 2017 and late 2019. These decreases in non-OPEC oil supply elevated oil price and consumer price whose HD patterns are highly coherent. In addition, by using the counterfactual series in a typical VAR, we observe that the IRFs patterns of oil supply shocks change dramatically.

To capture wider macroeconomic responses, we provide the results of IRFs of the components of industrial production growth, inflation rate, trade and financial market variables. The identified exogenous non-OPEC oil supply shock significantly raises the components of consumer price and pulls down the categories of industrial production. However, the exogenous OPEC oil supply shock does not have significant impacts on sub-indices of consumer price. In terms of trade variables, the unexpected oil supply reduction of OPEC has significant and negative impacts on exports and imports in the short-run. As for the reactions of financial variables, a sudden decrease in OPEC oil supply increases interest rate and share price in the short-run. However, an exogenous non-OPEC oil supply shock leads to a slump in stock market for the near future. Finally, we show that the impacts of the exogenous OPEC and non-OPEC oil supply shocks on macroeconomy are varied across the EU states, which calls for more resilient capabilities to respond to oil market disruptions.

To the best of our knowledge, we are among the first to investigate the nexus between oil supply shocks and the macroeconomy of the EU through a proxy SVAR framework. This paper contributes to the existing literature in several important ways. First, we use a novel approach to identify the oil supply shock by employing unplanned oil supply outage as the exogenous instrument, which addresses the causality problem and mitigates the endogeneity problem simultaneously. Second, we distinguish the effects of the oil supply shocks from OPEC and non-OPEC on the European macroeconomy. The results show that the unexpected cuts in both OPEC and non-OPEC oil supply would decrease industrial production and increase unemployment rate. However, their impacts on consumer price are diverse, i.e., only the unanticipated decrease in non-OPEC oil supply could drive up consumer price. Third, our findings shed light on the strengthening of energy security and market stability. It is highlighted that policymakers should prioritise green energy transition and stimulate energy diversification to minimize the damaging influences of oil supply disruptions in the EU. Given the background of heightened geopolitical risk in the oil-producing regions, this study offers profound policy implications on the improvement of the EU's energy security in both the short-term and long-term. It is crucial to employ a coordinated approach across the EU to improve energy efficiency in the short-term. More importantly, we argue that in the longer term, enhancing the oil storage capacity and infrastructure as well as advancing the transition to renewable energy sources should be placed as a strategic priority, so that the EU's energy market becomes more resilient and sustainable by curtailing the exposure and vulnerability to oil supply interruptions.

The remainder of this paper is organized as follows. Section 2 introduces the methodology used in this study. Section 3 shows the results of the baseline model, robustness checks and sensitivity analysis. Section 4 captures wider macroeconomic effects of the exogenous oil supply shocks. The last section concludes the paper.

2. Methodology

Numerous literature has used VAR models to estimate the impacts of oil shocks on the macroeconomy (Kilian, 2009; Kilian and Lewis, 2011; Kilian, 2014; Baumeister et al., 2018; Baumeister and Hamilton, 2021; Herrera and Rangaraju, 2020). Although the VAR can describe the dynamics between a set of endogenous variables within a linear system, the key problem is to measure the impacts of an exogenous shocks on all the variables within the VAR. To obtain a structural interpretation, the common method is to impose restrictions on the VAR system. Following Stock and Watson (2012) and Mertens and Ravn (2013), we employ a proxy SVAR model with an external instrument to achieve identification. This methodology is capable to solve the reverse causality problem and ensure the identified oil supply shocks are exogenous. Section 2.1 introduces the proxy SVAR model. Section 2.2 shows the external instrument that will be used to identify the exogenous oil supply shocks. Section 2.3 presents model specifications.

2.1. Proxy SVAR

We consider a reduced-form VAR model,

$$Y_t = c + \sum_{j=1}^{p} \alpha_j Y_{t-j} + u_t \qquad (2)$$

where Y_t denotes a vector of $n \times 1$ observations. p is the lag order of the VAR system. c is a vector of constants, and u_t represents a vector of reduced-form residuals that are correlated with a series of structural shocks ε_t,

$$u_t = \mathrm{A}\varepsilon_t \qquad (3)$$

where A denotes an invertible matrix. The baseline estimates are built upon five variables. Specifically, the baseline model includes two oil market variables (such as oil production and real price of oil), and three macroeconomic variables (such as industrial production index, consumer price index and unemployment rate) of the EU-27 countries. The interest is to estimate the effects of exogenous oil supply shocks, therefore we locate oil production at the first position in Y_t. In other words, we only need to identify the coefficients of the first column of A, which describe the impacts of exogenous oil supply shocks. This identification strategy is superior to traditional Cholesky decomposition by assuming A is a lower triangular matrix. The Cholesky identification strategy implicitly assumes that unexpected oil supply shocks have immediate impacts on all other variables in the VAR system, but the reverse effects take time. Such assumption hides a fact that oil supply and oil price are highly correlated. The structural oil supply shock identified by Cholesky decomposition is a combination of an exogenous component and endogenous responses to other structural shocks in the system. Thus, traditional Cholesky identification cannot capture causal effects.[3]

To ensure that the desired oil supply shocks that are strictly exogenous, we use a novel identification strategy proposed by Stock and Watson (2012) and Mertens and Ravn (2013) who suggest how to identify an exogenous shock with an external instrument. Specifically, they propose two moment conditions called instrumental relevance and exogeneity condition. Suppose an external instrument $\square_t$ (that is ξ_t^k in this study), it satisfies that,

$$E[\square_t \varepsilon_{1t}^{'}] \neq 0 \qquad (4)$$

$$E[\square_t \varepsilon_{2t}^{'}] = 0 \qquad (5)$$

where $\varepsilon_{1t}^{'}$ and $\varepsilon_{2t}^{'}$ denote the oil supply shock and all other structural shocks identified in a typical SVAR model. Equation (4) and (5) ensure that the external instrument is correlated with the exogenous oil supply shock, and uncorrelated with other structural shocks. To be noted, the external instrument ξ_t^k is not the full shock series, but is only used as a proxy of an exogenous component of the true shock.[4] Then, we obtain the IRFs by using the results in Stock and Watson (2012), Mertens and Ravn (2013), and Känzig (2021). FEVD, HD and CA are computed according to the procedures in Peersman (2022) and Montiel Olea et al. (2020).

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[3] The robustness checks in Appendix E present the results of using Cholesky identification method. The results show that using traditional identified full oil supply shock can exaggerate the effects of the exogenous OPEC oil supply shock, but underestimate the impacts of the exogenous non-OPEC oil supply shock. Furthermore, the FEVD results show that the identified exogenous oil supply shocks (not the full shock series identified by Cholesky decomposition) contribute a larger proportion of variations in the EU-27 macroeconomic variables.

[4] Mertens and Ravn (2013) name the external instrument as a noisy true shock series. In the following paragraphs, we plot the external instrument ξ_t^k the identified exogenous oil supply shocks, respectively.

2.2. Unplanned Oil Supply Outage Shocks

Energy Information Administration (EIA) first tracked unplanned oil supply outage since 2009. EIA differentiates declines in production as unplanned production outage, permanent losses of production capacity, and voluntary production cutbacks. The unplanned oil supply outage (referred to as outage hereafter) is calculated as a difference between estimated effective production capacity (the level of supply that could be available within one year) and estimated production. The outage is related to weather, natural disasters, labour strikes, technical failures or accidents, political disputes, and geopolitical tensions.

Figure 1 plots the evolution of OPEC and non-OPEC unplanned oil supply outages. The first jump is due to the outbreak of the Libya civil war with the maximum loss of 1.4 million barrels per day (b/d) in 2011. Although there is a short-period drop in the subsequent months, the OPEC unplanned oil supply outage series again climbs because the Petroleum Facilities Guard militia blocks oil export terminals. In the Meanwhile, Iran was also another contributor to the outage because of the sanctions against its nuclear program since July 2011. The Iran's outage was long-lasting lasting until December 2015 when the nuclear sanctions were lifted due to the adoption of Joint Comprehensive Plan of Action (JCPOA). After that, we find a sharp increase in early 2016. There are multiple contributors to the outages in the following periods. The largest contributor is again related to Iran because the at the time US president Donald Trump announced the withdrawal from the JCPOA and re-imposed nuclear-related sanctions on Iran. Therefore, it is reasonable to conclude that increasing OPEC unplanned oil supply outages are mainly caused by the Libya civil war and Iran sanctions.

Panel (b) in Figure 1 shows the movement path of unplanned oil supply outages of non-OPEC countries. The first spike is located in February 2012 due to the independence of South Sudan. The disputes about the oil transportation fee with Sudan triggered South Sudan into closing in its oil production with a maximum loss around 0.4 million b/d over the period from 2012 to 2013 period. The outages lasted until 2019 due to the unresolved issues on domestic and interstate relations which lingered between Sudan and South Sudan. Moreover, Syria also contributes to oil disruptions over a long period from 2011 to 2014 because of the civil war and ongoing hostilities. Although Syria is not a major oil supplier in the world, most of its production exports to Europe. After 2013, the outage gradually decreased and touched the bottom at the beginning of 2015. In the following months, there is a sharp increase due to the wildfires in Canada in June 2016, which leads to an unexpected oil supply loss of 0.8 million b/d. Since 2017, the disruptions of Russia and the United States account for a majority of total non-OPEC oil supply outages due to the extreme events and weather, such as unplanned maintenance of the Druzhba pipeline and Hurricane Barry.

In summation, it is confident to conclude that the unplanned oil supply outage is viewed as an exogenous series which reflects external factors affecting the oil production in OPEC and non-OPEC countries. The following analyses are built upon this series by incorporating the outage shock series as an external instrument to identify exogenous oil supply shocks in the VAR model. To isolate the unplanned oil supply outage shock, we estimate the following regression and save the residuals as the desired outage shock series,

$$Outage_t^k = c + \sum_{i=1}^{m} \alpha_i \cdot Outage_{t-i}^k + \gamma \cdot rea_t + \sum_{j=1}^{n} \beta_j \cdot rea_{t-j} + \xi_t^k \qquad (6)$$

where $k=1$ and 2 represents the unplanned oil supply outage series of OPEC and non-OPEC countries, respectively. c is a constant term and ξ_t^k is the desired external instrument. rea_t denotes the world real economic activity index measured by Kilian (2009), which is utilized to exclude potential demand factors affecting oil supply cuts.[5] The reasons why we obtain the desired outage shock series can be summarized as follows. First, unplanned oil supply outage is persistent which could last for a long-time. To represent the sudden changes in oil supply outage, it should be necessary to incorporate the lagged terms. Second, unplanned oil supply outage could also be altered by demand side factors, we thus eliminate these possible impacts by adding real economic activity index into the model.

The results of the benchmark model are built upon the specifications of $m = n = 1$ for both OPEC and non-OPEC models. The residuals are plotted in Figure 1. In alternative robustness checks, we choose a more flexible strategy by augmenting the model with 12 lags and drop off the insignificant terms. The results using flexible lags are available in the Table B.1. in Appendix. The peak and bottom values in the evolution of OPEC and non-OPEC oil supply outage shocks are in line with the political or geopolitical events, conflicts, wars and extreme weather. Therefore, the external instrument ξ_t^k is exogenous and representative for unexpected oil supply disruptions.

【Figure 1 is here】

2.3. Empirical Specifications

As stated above, the baseline model includes five variables, such as oil production (pro_t), real price of oil (rpo_t), industrial production (ip_t), consumer price index (cpi_t) and unemployment rate (ue_t). All variables in the model are nonstationary and contain either deterministic trends or stochastic trends.[6] Some studies impose unit root and

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[5] By adding the world real economic activity index, ε_t^k can be viewed as a clean external instrument which is free of the disturbance from demand side. To verify this point, we carry out a series of Granger causality tests running from the EU's industrial production growth to OPEC and non-OPEC unplanned oil supply outage shocks, respectively. The null hypothesis of non-causality is not rejected when we consider different lags in the model. Furthermore, Hamilton (2019) measures the world economic activity by considering industrial production of main economies in the world. We also replace the rea_t to the world production index proposed by Hamilton, the results are not changed.

[6] One referee suggests to check the stability of the VAR, we thus use the method proposed by Lütkepohl (1991). According to the results of inverse roots of AR characteristic polynomial, we find that no root lies outside the unit

cointegrated relations to pre-test the variables, however Elliott (1998) suggests that this procedure can lead to size distortions. Sims et al. (1990) and Ramey (2016) suggest to estimate the VAR model at logarithms, which presents consistent estimates as well. Sims et al. (1990) also show that a VAR can be estimated in levels if the main interests are IRFs. Therefore, we estimate the benchmark model with log level variables.[7] Besides, unplanned oil supply outage shocks ξ_t^k in equation (1) are used for identifying exogenous oil supply shocks by using instrumental relevance and exogeneity condition. In our study, we identify both OPEC and non-OPEC oil supply shocks, respectively. Given 1% decrease in pro_t, the IRFs of variables in the SVAR system are comparable. The benchmark model is determined as $Y_t = [pro_t, rpo_t, ip_t, cpi_t, ue_t]'$ with the inclusion of 5 lags.[8] We estimate the typical SVAR model over the period from 2009M1 to 2019M12 for OPEC countries and from 2011M1 to 2019M12 for non-OPEC countries, respectively. This is because the unplanned oil supply outage data is unavailable before 2009M1 for OPEC countries and before 2011M1 for non-OPEC countries. In the baseline model, we use the variables of the EU-27 countries, which are drawn from Eurostat dataset.

We augment the baseline VAR model with other variables to accommodate wider macroeconomic effects. The VAR is extended to such a form, $Y_t = [pro_t, rpo_t, ip_t, cpi_t, ue_t, x_t]'$ where x_t denotes other variables that are interested. Specifically, we consider the variables of industrial production and CPI at sectoral level

circle. Therefore, we believe that the VAR satisfies the stability conditions. The related results are available in Appendix C.

[7] The IRFs of the VAR in difference are provided in appendix as well though the patterns are erratic and less informative than the results of the VAR in level. Other studies like Peersman (2022) also built the VAR by using level variables. We also implement typical unit root tests for integrating order and Johansen cointegration test for long-run relationship. The trace test shows that there are cointegrating relation among these five variables.

[8] We decide the optimal lags used in the VAR model by considering multiple methods. The conventional wisdom is using information criteria including Akaike information criterion (AIC) and Schwarz information criterion (SIC). However in the baseline model, we determine the optimal lags as 5 by using the lags exclusion testing procedure provided by EViews 10. Choosing short lags will ignore the dynamics in the impulse response patterns, but long lags may generate erratic patterns in our case. Although there are some differences in empirical results when we use different strategies, the main conclusions are not altered.

and the variables of financial market, exchange rate and trade. Additionally, the member countries of the EU-27 are also considered, and the baseline specification is changed to $Y_t = [pro_t, rpo_t, ip_t^i, cpi_t^i, ue_t^i]'$, where i refers to individuals in EU-27.

In robustness checks, comparisons are made by using different identification strategies of unplanned oil supply outage shocks. Next, we change the baseline specifications with different lags and datasets. The estimates in this study are obtained under a VAR framework which is commonly believed to be sensitive to the choice of lags. Moreover, we utilize other measurements of real price of oil (such as US refiner acquisition cost of crude oil and Brent oil price).[9] Lastly, we re-estimate the VAR with variables in difference.

3. Baseline Results

In this section, we first present the impulse response analysis of the EU-27 macroeconomic variables given one-percentage of unexpected decrease in oil supply growth (pro_t). we report 68% and 90% confidence intervals by using the Moving Block Bootstrap (MBB) method proposed by Brüggemann et al. (2016). We implement FEVD, HD and CA for additional quantitative evidence. To provide sensitivity of the baseline estimates, we consider using a flexible lags strategy to identify external instrument and an alternative Cholesky decomposition to identify the structural oil supply shock. Moreover, the changes in empirical specifications are also taken into account for robustness checks.

As mentioned above, the key identification assumption of proxy SVAR is that the instrument variable is correlated with the oil supply shock and uncorrelated with other structural shocks identified in the standard SVAR model. To avoid potential weak

[9] The real WTI crude oil price is calculated by the ratio of nominal WTI price to the US constant consumer price index. The real Brent crude oil price is computed by the ratio of nominal Brent crude oil price to the EU-27 constant harmonized consumer price index.

instrument problem, we use the method proposed by Montiel Olea et al. (2020) who suggests to use F-test in the regression of the oil supply residual from the VAR on unplanned oil supply outage shock ξ_t^k. The F-statistic and robust F-statistic are 71.953 and 46.037 in OPEC model, and 24.149 and 26.526 in non-OPEC model, respectively.[10] The F-statistics are well above the safe value suggested by Stock and Yogo (2005). Thus, we are confident that the baseline results are free of weak instrument problem.[11]

3.1. Impulse response analysis

The Proxy SVAR model can provide causal evidence of the impacts of the identified exogenous oil supply shock on macroeconomic variables of EU-27 countries. In this study, the identified exogenous oil supply shocks are defined as one percentage of decrease in oil production. Therefore, this setting allows the empirical results of OPEC and non-OPEC oil supply shocks to be comparable. The empirical results are shown in Figure 2. An unexpected decrease in OPEC and non-OPEC oil production significantly raises real price of oil. The identified exogenous oil supply shocks of OPEC maximumly cause around 2% increase in oil price, but that of non-OPEC makes maximum impacts on oil price around 4%.

As for the median responses of the EU's macroeconomic variables, the industrial production goes down and touches the bottom at around -0.25% before the median response gradually recovers to zero. In addition, the IRFs of CPI given exogenous OPEC shocks persistently drop down, however the exogenous shocks of non-OPEC raise CPI with the maximum impact of 0.08%. That is to say, the IRFs patterns of CPI disagree substantially given OPEC and non-OPEC oil supply shocks. Lastly, the unemployment rate increases around 0.6% and 0.4% after an immediate increase in

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[10] The baseline estimates are built upon an external instrument with one lag in equation (1). The reasons why we choose one lag can be summarized as follows. First, we discard the external instruments whose F statistics are insignificant. Next, when F statistics are significant, we choose the external instrument generated with minimum lags. Thus, this strategy can provide a strong external instrument and ensure sufficient observations in the baseline estimations.

[11] Following Peersman (2022) and Känzig (2021), the threshold value is 10 for the corresponding F-statistic. The robust F-statistic accounts for heteroskedasticity.

non-OPEC and OPEC oil supply. The rise in unemployment rate is somewhat more persistent than we expected.

To summarize, the identified exogenous oil supply shocks of OPEC and non-OPEC pull down industrial production with considerably negative impacts. The non-OPEC oil supply shocks make bigger impacts than OPEC oil supply shocks on real price of oil and unemployment rate. The differences are the responses of price level that non-OPEC oil supply shocks make positive impacts but OPEC oil supply shocks make negative effects. One plausible explanation is that the EU countries import more crude oil from non-OPEC countries than from OPEC countries. Previous studies mainly discussed the impacts of OPEC oil supply shocks (Kilian 2007; Känzig, 2021), however the oil supply shocks of non-OPEC countries harm European macroeconomy by decreasing industrial output, raising price level and unemployment rate.

【Figure 2 is here】

3.2. Forecast error variance decomposition

Using FEVD is important to evaluate the average relevance of identified exogenous oil supply shocks for the fluctuations of baseline variables. The FEVD results are available in Figure 3. In obvious, It is clear that the identified exogenous OPEC and non-OPEC oil supply shocks contribute over 80% of the forecast-error variance of oil supply in the short-run. Such contribution is persistent, which still remains above 50% after 20 months. The FEVD of real price given non-OPEC oil supply shocks is well above the pattern give OPEC oil supply shocks Rewrite?. This indicates that the exogenous non-OPEC oil supply shocks contribute more variations to oil price.

With respect to the FEVD results of macroeconomic indicators of the EU-27, the exogenous OPEC oil supply shocks explain about 20% of forecast-error variance in industrial production in the long-run. The contribution of OPEC oil supply disruptions to CPI is around 25% in longer horizons. The FEVD of unemployment rate given OPEC oil supply disruptions is lower than 10% in the long-run. As for the results shown in panel (b), roughly 10% of variations in industrial production are attributed to the identified exogenous non-OPEC oil supply shocks after 30 months. In addition, a sudden decrease in non-OPEC oil production contributes over 15% volitivity to CPI in the medium-run. To be noticeable, the exogenous non-OPEC oil supply shock contributes around 20% to the unemployment rate volatility in the long-run. Such contribution is persistent and long-lasting.

【Figure 3 is here】

3.3. Historical decomposition and counterfactual analysis

We are interested in the question of what would have happened if the impacts of the identified exogenous oil supply shocks on oil and macroeconomic variables are excluded? To answer this question, we follow the method of Montiel Olea et al. (2020) who propose how to identify the target exogenous structural shock series and to compute historical decomposition. Specifically, the plots of identified exogenous oil supply shocks are shown in Figure 4.[12]

【Figure 4 is here】

Figure 5 depicts the historical contribution of the identified exogenous oil supply shocks to all five variables. Some interesting findings can be summarized by combining the results shown in Figure 5 and the narrative story of OPEC and non-OPEC unplanned oil supply cuts. We first look at the historical decomposition of OPEC oil supply shocks in Panel (a) of Figure 5. First, due to the outbreak of the Libya civil war in August 2011, the identified exogenous OPEC oil supply shock raised real price of oil and decreased industrial production sharply over that period. Second, we can see that the OPEC oil

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[12] We further implement a series of diagnostic tests for the exogenous OPEC and non-OPEC oil supply shocks. The Ljung-Box Q-statistics show that there is no autocorrelation in both series.

supply disruptions drove down real price of oil after 2015, which is mainly due to the fact that the nuclear sanctions on Iran were lifted in the same year and Iran's oil production capacity was recovered. The shock also positively contributed to the rise of industrial production due to the adoption of JCPOA in this period. Third, the sudden decrease of oil supply in 2019 caused by nuclear-related sanctions on Iran led to a jump in oil price and a tiny decrease in industrial production. Fourth, the historical contribution of exogenous OPEC oil supply shock to unemployment rate remains positive in the majority of sample period. In regards to the features of historical decomposition given exogenous non-OPEC oil supply shock as shown in Panel (b) of Figure 5, the shock from 2012 to 2013 increased real price of oil, decreased industrial production, and raised inflation and unemployment rates. These results are coincident with the outbreak of disputes between South Sudan and Sudan. The similar decrease in oil production is observed in June 2016, which are related with the wildfires in Canada. It is noteworthy that as one of the largest oil suppliers in the world, Russia kept its crude oil production stable over 2014-2015 despite the combination of oil prices falling and western sanctions due to events in Ukraine at the time. Overall, it is shown that oil supply shocks can result in remarkable fluctuations of oil price and macroeconomic stances. Since major oil-producing countries have been associated with heightened geopolitical risk in the past decade, oil imports into the EU can suffer from substantial disruptions.

【Figure 5 is here】

Accordingly, we construct the counterfactual variables based on above results and plot them in Figure 6.[13] Undoubtedly, the counterfactual variables deviate from the original evolution over the periods related to economic events, natural disasters, labour strikes, technical failures or accidents, political disputes, and geopolitical tensions. Consequently, we are interested in the dynamics of IRFs of counterfactual variables and

[13] The counterfactual series are constructed by using the original series to minus the historical decomposition.

the differences between the counterfactual IRFs and baseline IRFs. To achieve this, we build a typical VAR model with the classical recursive identification scheme, which accommodates all counterfactual variables. The results are shown in Figure 7. Given 1% decrease in OPEC oil production, the oil price dramatically goes down. This pattern is significantly different from the baseline IRFs. In addition, the IRFs of industrial production and unemployment rate are not significant. As for the results of non-OPEC oil supply shocks, the main findings remain but larger impacts on macroeconomic variables are identified comparing with the baseline IRFs. In summation, we conclude that the identified exogenous oil supply shocks have significant impacts on baseline variables. Excluding the impacts of the identified exogenous oil supply shocks would change the transmission of the sudden decreases of oil supply to the European macroeconomy.

【Figure 6 and 7 are here】

3.4. Robustness checks and sensitivity analysis

This section presents the results of robustness checks. we first consider using other specifications to obtain the desired external instrument. Next, we discuss the robustness of the empirical results by considering different specifications in section 4.4.2 3.4.2?.

3.4.1. Construction of external instrument

The baseline estimates are built upon unplanned oil supply outage shocks which are identified by using fixed lags. The lag selection is crucial to model specification and the identification of oil supply outage shock. Therefore, we augment the baseline model by incorporating more lags into the model. To determine the optimal lags, we first augment the model with 12 lags and drop off the terms that are insignificant. The estimates are shown in Table A.1 in appendix. We choose $m=1$ and $n=4$ for OPEC model, and $m=1$ and $n=3$ for non-OPEC model, respectively. We utilize this newly constructed instrument to identify oil supply shocks within a Proxy SVAR model. Other empirical specifications are the same as the ones used in the baseline model. The results of IRFs are shown in Figure D.1 in Appendix. The results of IRFs using alternative external instrument are similar to the baseline results. Thus, the results are robust against different constructing methods of the instrument.

3.4.2. Alternative proxy SVAR specifications

This section discusses the robustness of the baseline results. The particular interest is assessing the robustness of the IRFs of the identified exogenous oil supply shocks on the EU-27 variables.

Using information criteria. In the baseline estimates, we determine the lag as 5 for the VAR model by using the lags exclusion tests provided by EViews 10. As we have discussed in the main text, another strand of literature determines the lags with information criteria. Therefore, we check the robustness of the baseline IRFs by using Akaike Information criteria (AIC) and Schwarz Information Criterion (SIC). The results are reported in Figure D.2 and Figure D.3 in appendix. According to the results of SIC, the lags of both OPEC and non-OPEC models are determined as 1. Based on the AIC, we choose 3 lags for the OPEC model and 11 lags for the non-OPEC model. Obviously, the IRFs obtained by using short lags are similar to the baseline IRFs. There are some differences in the IRFs between the baseline model and the model with long lags. Although there are erratic fluctuations in panel (b) Figure B.3., the main conclusions are not changed.

Different datasets. It is necessary to check the robustness of the results by using other datasets. First, we consider alternative measurements of oil price by using US refiner acquisition cost of crude oil and Brent oil price which are deflated by the US constant CPI index and the constant harmonized CPI index of the EU-27 countries. The results are shown in Figure D.4 and Figure D.5 in appendix. The IRFs patterns contain no significant changes in comparison with the baseline IRFs, indicating the baseline estimations are robust. We further replace the macroeconomic variables of EU-27 countries to EU-19 countries and EU-28 countries, respectively.[14] Other specifications are the same as the ones used in the baseline model. The main conclusions shown in are not altered when we consider different groups of countries.

VAR in difference. As is shown in the baseline model, the benchmark VAR is estimated with log level variables. Sims et al. (1990) present that a log-level specification could deliver consistent estimates when the variables are cointegrated or have stochastic trends. In addition, Elliott (1998) also demonstrates that imposing the unit root and cointegration relation could lead to large size distortions in the estimates. In spite of this, we re-estimate the VAR model by using differencing variables and the empirical results are available in Figure D.6. It is hard to interpret the empirical results because of the frequent fluctuations in the IRFs patterns.

3.5. Policy Implications

According to the baseline estimations, the identified exogenous non-OPEC oil supply shock pulls down industrial growth, raise price level and unemployment rates, whose impacts are significant and persistent. The exogenous OPEC oil supply shocks make significant and negative impacts on industrial production and CPI. However, the unemployment rate increases given the identified exogenous oil supply shocks. In other words, the transmissions of oil supply shocks to the price level of Europe significantly vary across OPEC and non-OPEC countries. Through historical decomposition and counterfactual analysis, there are visible gaps over the periods related to unplanned oil supply outages between the original evolution and the counterfactual in the baseline variables.

[14] The EU-19 countries include Belgium, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Austria, Portugal, Slovenia, Slovakia and Finland. The EU-28 countries include Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Portugal, the United Kingdom, Austria, Finland, Sweden, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovenia, Slovakia, Bulgaria, Romania, and Croatia.

The EU is an energy dependent region, whose energy security is challenged by unexpected energy disruptions from its producers in the last decades due to political disputes, geopolitical risks, extreme events and weather. Since 2000, the EU has dramatically increased its imports from Russia, but reduced its imports from other countries. Some countries even view Russia as their sole oil producer. However, treating Russia as the main oil producer does not satisfy Europe's diplomatic freedom (Acevedo and Lorca-Susino, 2020). If Russia abruptly cuts oil supply to the EU countries, the negative impacts will lead to economic downturn, roaring price and deteriorating labour market. Although the US shares a common value with European countries and has become the largest oil exporter in the world, the oil imports from the US are significantly lower than the needed amount of the EU countries. In other words, the US cannot guarantee necessary oil demand of the EU countries.

Seeking another oil supplier which has a common value with the EU countries and sufficient production capacity to supply the EU countries is not an easy task. Due to different locations of each country, the oil infrastructures are also varied across different nations. Some inland countries (e.g. Eastern European countries) do not have large ports for oil tankers instead relying solely on pipelines, which indicates that getting rid of oil dependency on Russia is difficult for certain EU countries. As a consequence, it is crucial for the EU to establish and consolidate a win-win strategic partnership regarding energy issues with non-OPEC oil exporters, especially Russia, despite the geopolitical tensions.

Enhancing energy security and ensuring market stability should be placed as a priority in both the short and long term. To alleviate the negative influence of unexpected oil supply disruptions of OPEC and non-OPEC oil suppliers, the adoption of alternative energy seems to be a good solution. Under the framework of the European Green Deal, policymakers should consider accelerating the development of energy efficient technologies and the expansion of the utilisation of alternative renewable energy sources, such as biomass, hydropower, geothermal, wind, and solar. This can not only contribute to reduce the oil demand and dependence of the EU-27 countries but also facilitate the green transition. Furthermore, the European Central Bank, the national central banks as well as fiscal authorities of the EU-27 member states should play their part by acting cohesively and decisively in attenuating the potential stagflation problem caused by oil market turbulence.

4. Wider Effects

To provide more economic implications, the baseline model is extended to incorporate macroeconomic variables in different sectors and of the EU member countries. The empirical specifications are the same as the settings used in the baseline model.

4.1. Sectoral Responses

In the baseline estimates, we focus on the responses of macroeconomic variables at the aggregate level. The sectoral responses could be heterogenous because of its different dependencies of industries on oil consumption. The empirical specifications are the same as the ones used in the baseline models.

Industrial production. According to the baseline IRFs, the median responses of industrial production given OPEC and non-OPEC oil supply shocks are significantly negative for most of the horizons. The sectoral responses suggest the similar findings which are available in Figure 8. Specifically, we investigate the responses of industrial production of intermediate goods, energy, capital goods, durable goods, and non-durable goods. As is shown in panel (a), given one percentage of unexpected decrease in OPEC oil production, the median responses of all subcategories are significantly negative excluding non-durable goods. For the results of non-OPEC shocks in panel (b), the median responses of capital goods, durable goods and non-durable goods are significantly negative in the long-run. The IRFs of intermediate goods are insignificant, which is different from the results of OPEC shocks. In regard to the IRFs of energy, only the short-run response is significant and positive.

【Figure 8 is here】

Consumer price index. To capture the dynamic impacts of oil supply shocks on the price of different goods, we analyse the sub-components of CPI , including goods (overall index excluding services), industrial goods, non-energy industrial goods, energy, non-energy industrial goods (durables only), non-energy industrial goods(semi-durables), non-energy industrial goods (non-durables only), services (overall index excluding goods) and overall index excluding energy. The results are presented in Figure 9. Panel (a) shows that the IRFs given OPEC oil supply shocks. Obviously, the identified exogenous OPEC oil supply shocks exert significantly negative impacts on goods (excluding services), non-energy industrial goods, semi-durable goods, non-durable goods and overall goods (excluding energy). Interestingly, the IRFs of energy are insignificant over different horizons. With respect to the results of non-OPEC shocks, the IRFs of goods (excluding services), industrial goods, energy, durable goods and non-durable goods are significantly positive. In particular, the impacts of non-OPEC oil supply shocks have bigger impacts on energy CPI than the other indices.

【Figure 9 is here】

Exchange rate and trade. According to McGovern et al. (2020), the proportion of energy imports to total primary goods imports is nearly 65%. Therefore, it is natural to suspect that the identified exogenous oil supply shocks have a causal impact on the EU's International trade. Specifically, the responses of real effective exchange rate (REER), exports and imports are provided in Figure 10. As we can see from panel (a), a sudden decrease in OEPC oil supply would raise REER but pull down exports and imports. In terms of the unexpected non-OPEC oil supply cuts, the REER first goes up and then drops down before recovering to zero.

【Figure 10 is here】

Financial market. The share price is a leading indicator to reflect potential fluctuations in macroeconomic conditions. Therefore, we compute the IRFs of interest rate and share price, which are plotted in Figure 11. Given one percentage of unexpected decrease in oil supply, the response of interest rate shortly goes up given the OPEC shock. Recall that the identified OPEC oil supply outage shock pulls down CPI, monetary authorities may take into account this point and implement tight monetary policy. However, the IRFs of interest rate given non-OPEC shock is insignificant. These findings suggest that the monetary authorities are more sensitive to the threats of OPEC oil supply shocks. Next, we also consider the responses of share price. The empirical results suggest that non-OPEC oil supply shocks significantly pulls down share price with the magnitude of roughly -2% after the immediate decrease in oil production. In contrast, the median response given OPEC oil supply shocks is not significant over different horizons.

【Figure 11 is here】

4.2. Cross-countries differences

After presenting the responses of the macroeconomic variables of aggregate EU countries, it is necessary to understand the responses of its member countries. One issue that has been mentioned in McGovern et al. (2020) is that the oil dependency varies across the EU member countries. For countries like Denmark and Italy, they can choose the importing methods by shipping or pipelines. However, some Eastern and Central European countries are highly dependent on Russia’s supply. Specifically, the ratio of oil importing sourced from Russia is over 80% for Finland and Slovakia, and above 60% for Bulgaria, Czechia, Hungary, Lithuania and Poland. Therefore, it is natural to suspect that the identified exogenous OPEC and non-OPEC oil supply shocks have heterogeneous impacts on macroeconomic conditions of different member countries.

The specifications are the same as the ones used in the baseline model. The model is specified as $Y_t = [pro_t, rpo_t, ipg_t^i, ir_t^i, ue_t^i]'$, where i refers to individual countries of EU-27. To save space, we present the results of France, Germany, Netherlands, Denmark, Slovakia, Hungary, Poland, and Bulgaria given OPEC and non-OPEC shocks in Figure 12 and 13, respectively.[15] The rationale behind the selection of countries is that France, Germany, Netherlands and Denmark represent the countries in the Northwest Europe whist Slovakia, Hungary, Poland and Bulgaria is a group of Eastern European countries that imports more than 50 % of oil from non-OPEC countries such as Russia. It is evident that the identified exogenous oil supply shocks of OPEC and non-OPEC impose heterogenous impacts on industrial production, CPI and unemployment rate across the European countries. The reasons can be attributed to the different dependency on oil imports. In addition, the location of member countries also matters to a country's oil import structure. However, one finding that stands out is the detrimental effects of the identified exogenous non-OPEC oil supply shock. We will discuss these results in more details in the rest of this section.

As can be seen from Figure 12 that depicts the IRFs given OPEC shocks, one consistent finding is that the exogenous OPEC oil supply shocks raise CPI steeply in the short-run and decrease CPI in the long-run. In addition, the unemployment rate of Denmark, Poland and Bulgaria tends to increase as OPEC oil supply suddenly decreases, indicating that economic welfare can be harmed due to exposures to oil supply risk.

Figure 13 presents the IRFs patterns of selected countries given non-OPEC oil supply shocks. For Eastern European countries like Hungary, Slovakia, Poland and Bulgaria, we find that the unexpected decrease in oil supply can result in increased CPI persistently, which is accompanied with reduced purchasing power and standards of living. However, the inflation in France, Germany, Netherlands and Denmark is not

[15] We report the results of all the EU-27 member countries in the appendix.

escalated given non-OPEC oil shocks. This can be partially explained by the diverse exposure to the risk of oil supply and security of oil imports between North Western and Eastern European countries. On one hand, France, Germany and Denmark are capable of the domestic crude oil production and are equipped with large scale oil storage facility, implying that these countries are more resilient when encountered with sudden disruptions of oil imports. On the other hand, Bulgaria, Hungary, Poland and Slovakia are located in the Eastern part of Europe and have limited oil supply options due to landlocked geographical position. As a consequence, these countries are more reliant on oil importing from other countries and suffering from greater exposure to oil supply shocks and subsequent economic instability. Furthermore, Figure 13 shows that non-OPEC oil supply shocks bring down industrial production and elevate unemployment across the selected EU countries, which can cause lowered economic growth and policymakers will have to adjust monetary policy accordingly in response to the economic damage and prevent the economy falling into recession.

【Figures 12 and 13 are here】

It can be seen that significant heterogeneity exists among the EU-27 states vis-à-vis the association between underlying macroeconomic conditions and oil supply shocks. Therefore, policymakers should consider implementing proactive actions by accounting for the heterogenous features of macroeconomic response in order to mitigate the adverse impacts of oil supply shocks and promote energy security across the member states of the EU. Despite the heightened geopolitical instability in the oil exporting countries, we suggest that the authorities in the EU strengthen the capital investment in oil related infrastructure and further expand the adoption of renewable energy in the transition to a green economy.

5. Concluding Remarks

This study contributes to existing studies by using unplanned oil supply shocks as an external instrument to identify exogenous oil supply shocks of OPEC and non-OPEC countries. Under a framework of Proxy SVAR model, we compare the impacts of the identified exogenous OPEC and non-OPEC oil supply shocks on European macroeconomy. By utilizing impulse response analysis, forecast-error variance decomposition and historical decomposition, we find that unexpected non-OPEC oil supply cut is more detrimental to the EU's macroeconomy in comparison with the impacts of OPEC oil supply reduction. These findings have important implications to energy security and environmental protections in Europe.

The EU is an oil-dependent region, importing its majority of oil from areas suffering from geopolitical tensions, terrorism, border conflicts, or wars. In spite of this, the EU member countries have limited choices to import oil due to the restrictions of location and infrastructure. However, the empirical findings suggest that the identified exogenous non-OPEC oil supply shock is more harmful to European macroeconomic conditions. From the short-term perspective, the detrimental effects of non-OPEC oil supply shocks are unavoidable. Increasing oil imports from OPEC countries is not a good alternative since some OPEC countries are currently disturbed by wars, geopolitical risks (such as Iraq and Iran). Although the US has become the largest oil-producing country in the world and shares a common value with the EU countries, the US does not endorse any commitments of energy related agreements with the EU countries (Acevedo and Lorca-Susino,2020). With the shale gas revolution, the US seems to achieve energy independence and is not disturbed by the trade-off between "energy economic security" and "energy diplomatic freedom". However, the EU countries still need to balance such a trade-off since Russia has served as a main oil supplier to the EU. The governments of the EU countries are suggested to put more emphasis on non-OPEC unplanned oil supply disruptions which are empirically verified as a main threat to the EU's macroeconomy.

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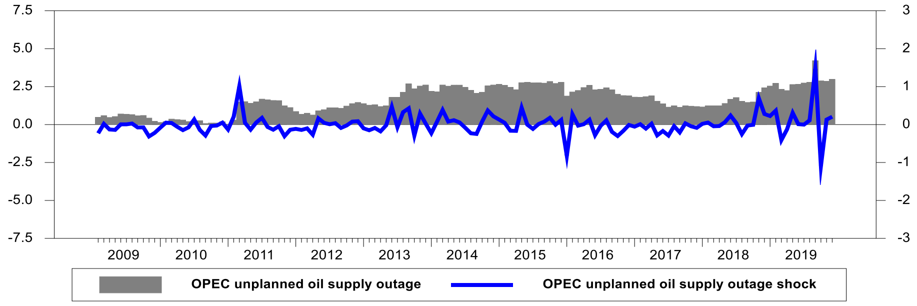
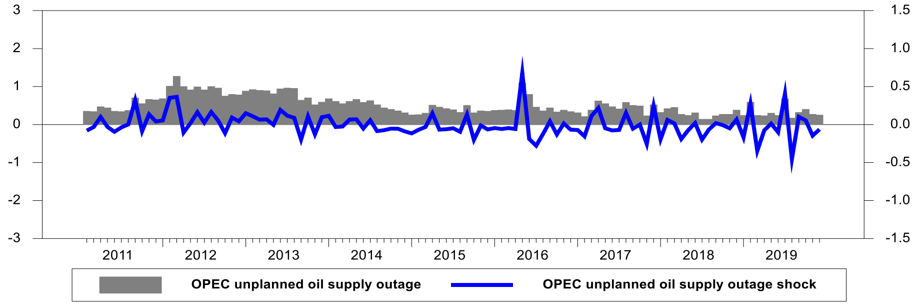
Figure 1 The evolution of unplanned oil supply outages and their identified shocks

Panel (a) OPEC



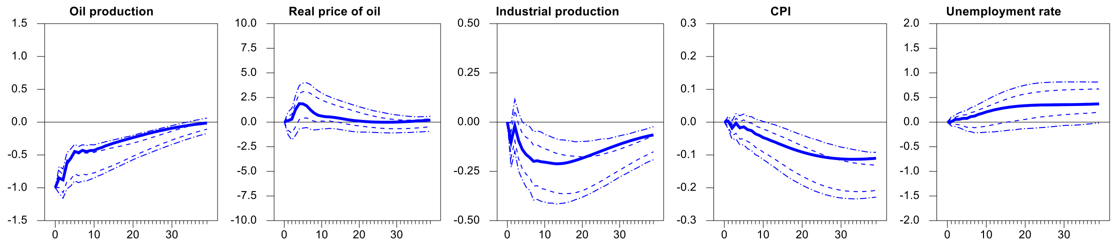
Panel (b) Non-OPEC



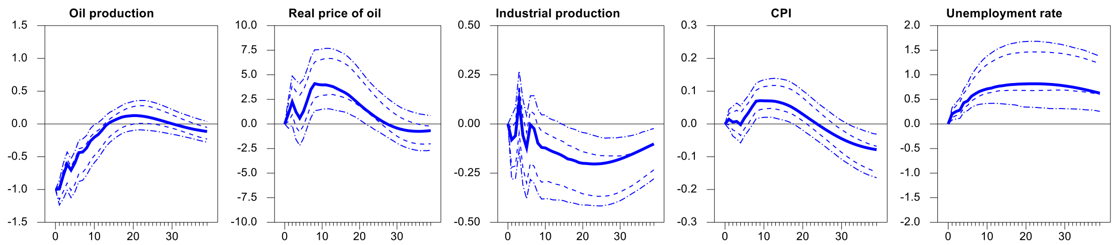
Note: the unplanned oil supply outage of both OPEC and non-OPEC countries can be found from the EIA's website. The shock series is obtained from equation (1). The lags for both OPEC and non-OPEC countries are determined as 1, respectively.

Figure 2 Effects of exogenous oil supply shocks

Panel (a) OPEC



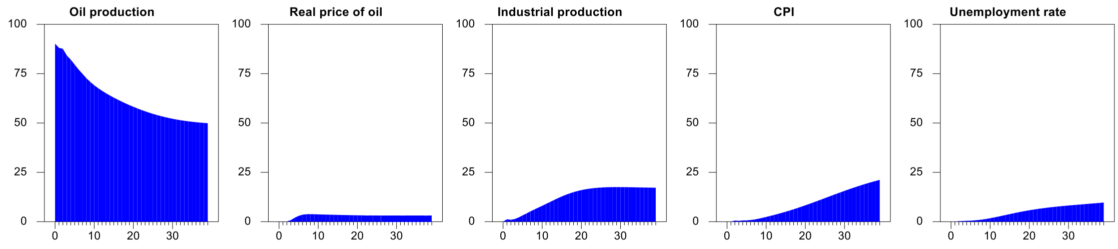
Panel (b) Non-OPEC



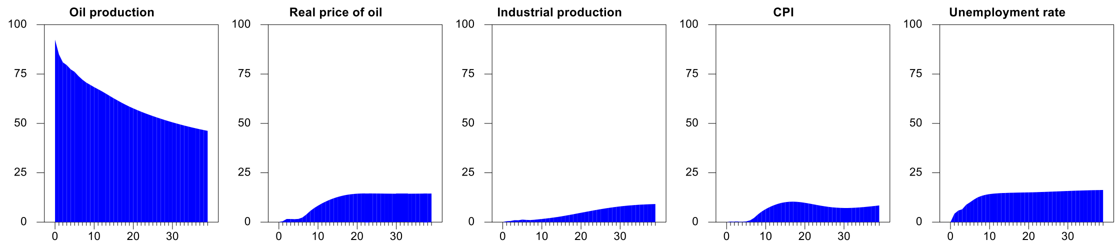
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5 by using lags exclusion tests provided by EViews 10.

Figure 3 Contribution of oil production shocks to forecast error variance decomposition

Panel (a) OPEC



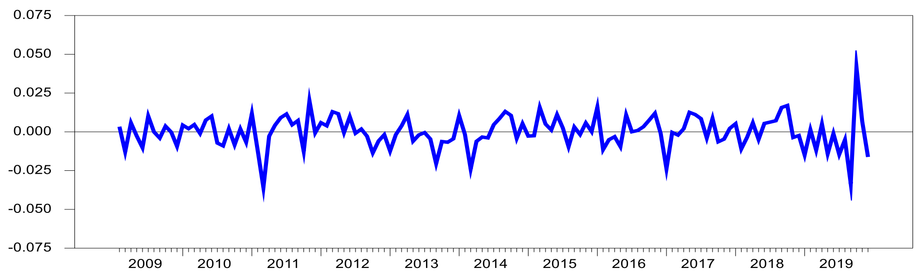
Panel (b) Non-OPEC



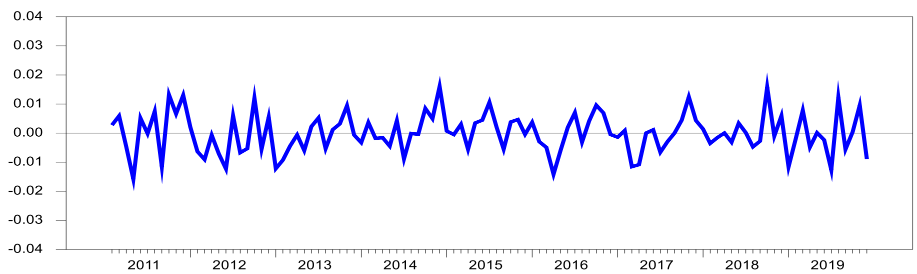
Note: the horizons are monthly.

Figure 4 The evolution of identified exogenous oil supply shocks

Panel (a) OPEC



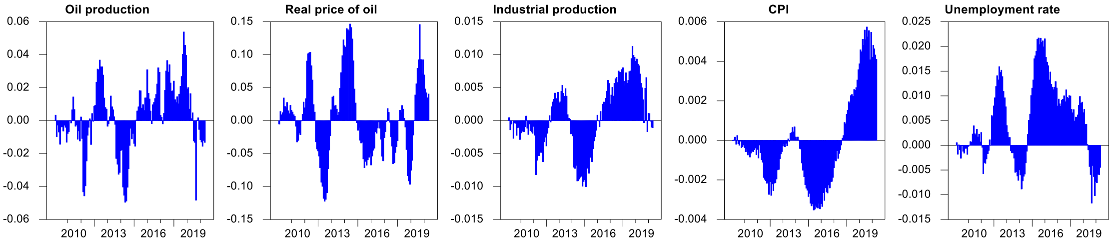
Panel (b) Non-OPEC



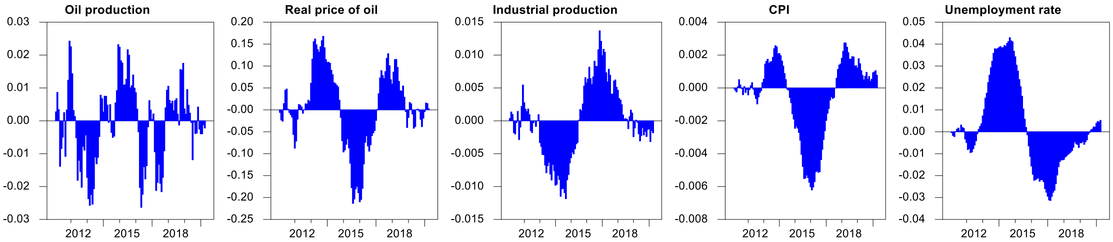
Note: the identified exogenous oil supply shocks can be obtained from a typical SVAR model by satisfying the instrumental relevance and exogeneity conditions.

Figure 5 Historical decomposition of oil production shocks

Panel (a) OPEC



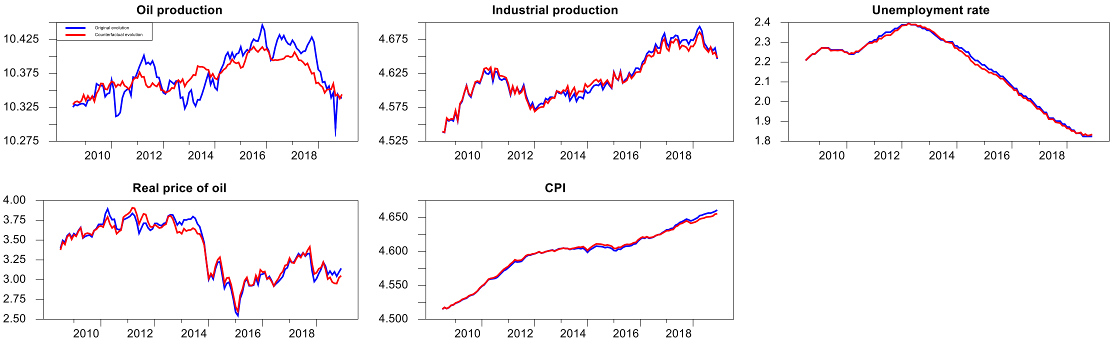
Panel (b) Non-OPEC



Note: time series of exogenous oil supply shocks and contribution to key variables in the baseline model.

Figure 6 Counterfactual evolution

Panel (a) OPEC



Panel (b) Non-OPEC

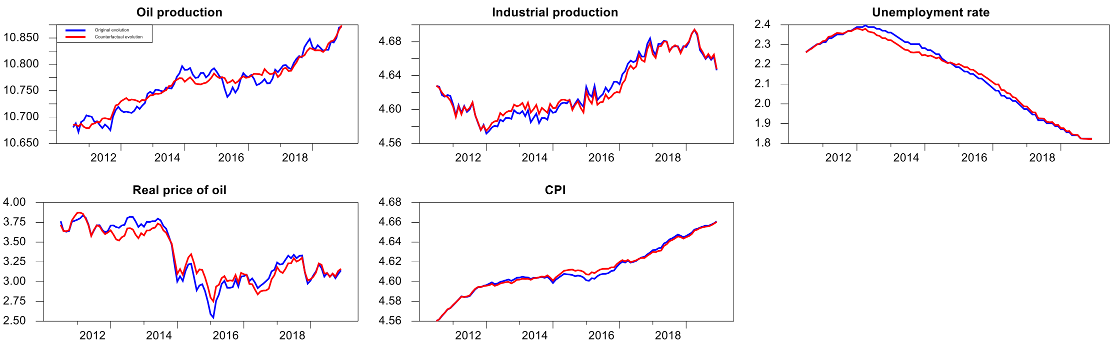
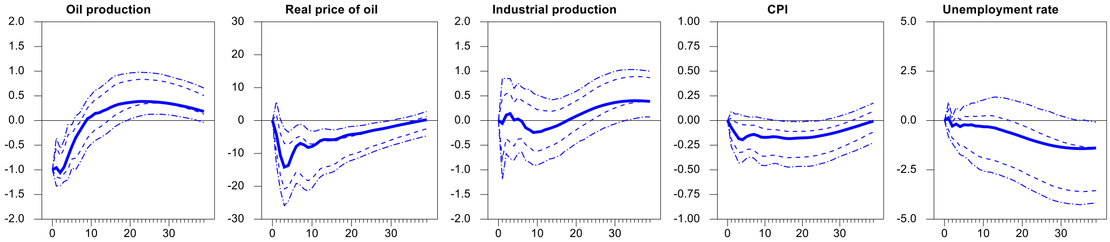
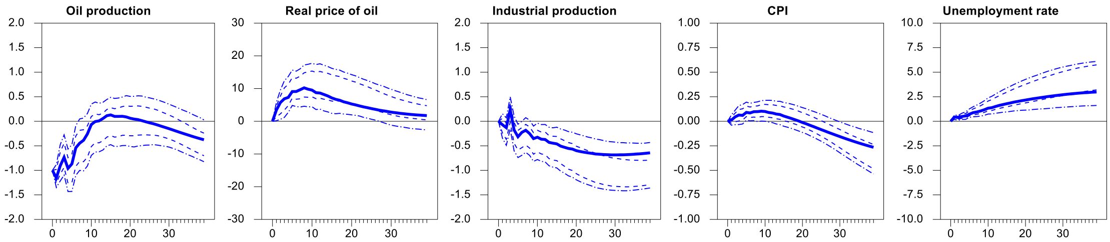


Figure 7 Counterfactual impulse responses (typical VAR model)

Panel (a) OPEC



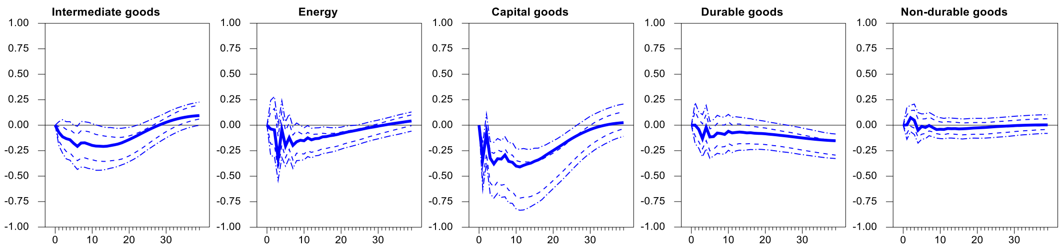
Panel (b) Non-OPEC



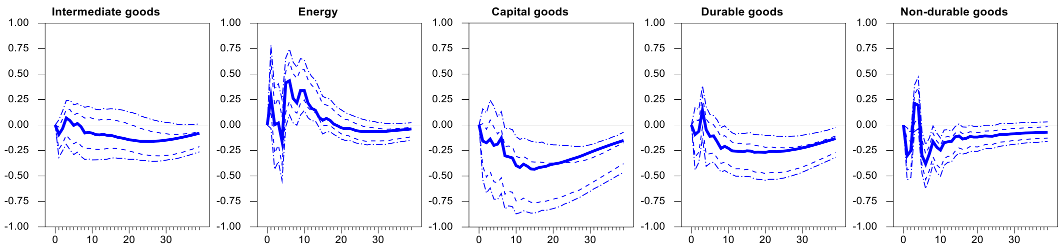
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 8 The IRFs of sub-indices of industrial production

Panel (a) OPEC



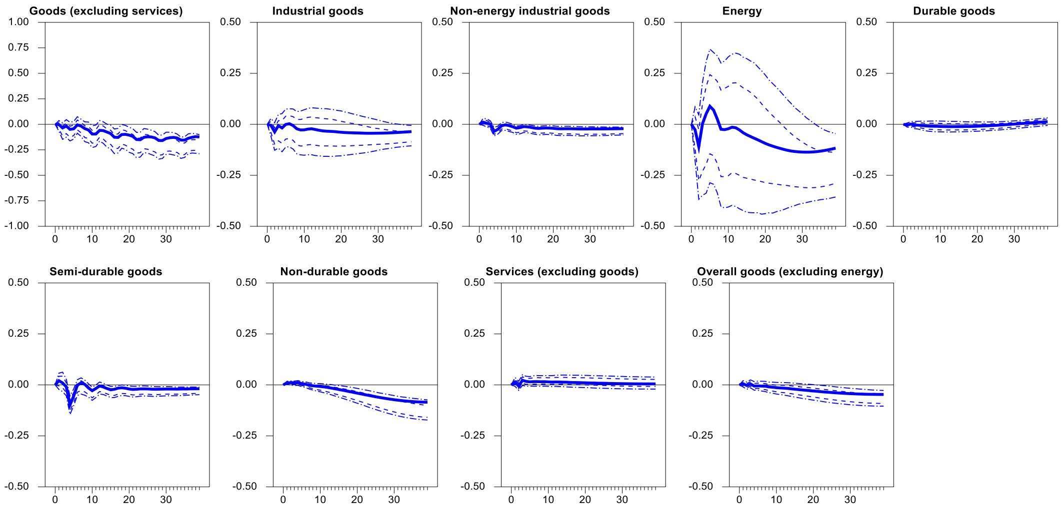
Panel (b) Non-OPEC



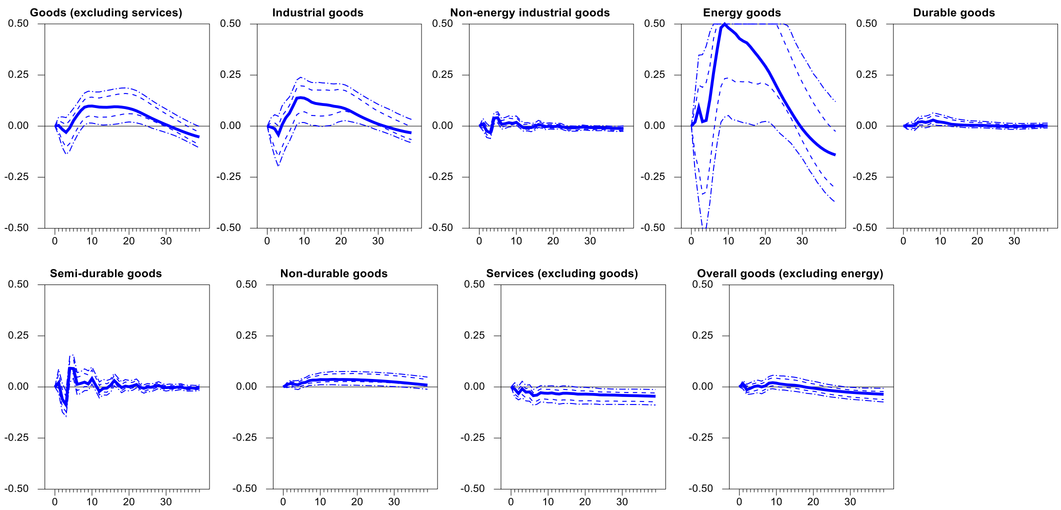
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 9 The IRFs of sub-indices of CPI

Panel (a) OPEC



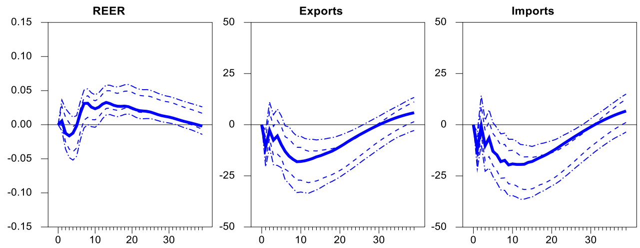
Panel (b) Non-OPEC



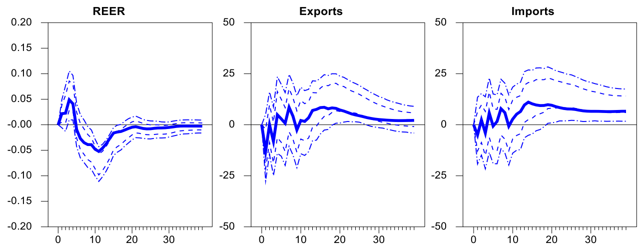
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 10 The IRFs of sub-indices of trade variables

Panel (a) OPEC



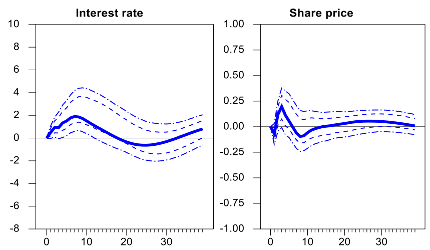
Panel (b) Non-OPEC



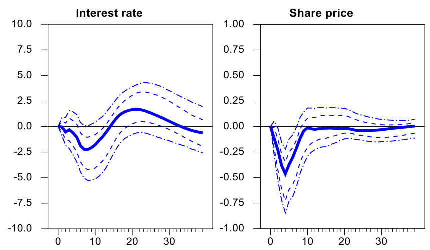
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 11 The IRFs of sub-indices of financial variables

Panel (a) OPEC

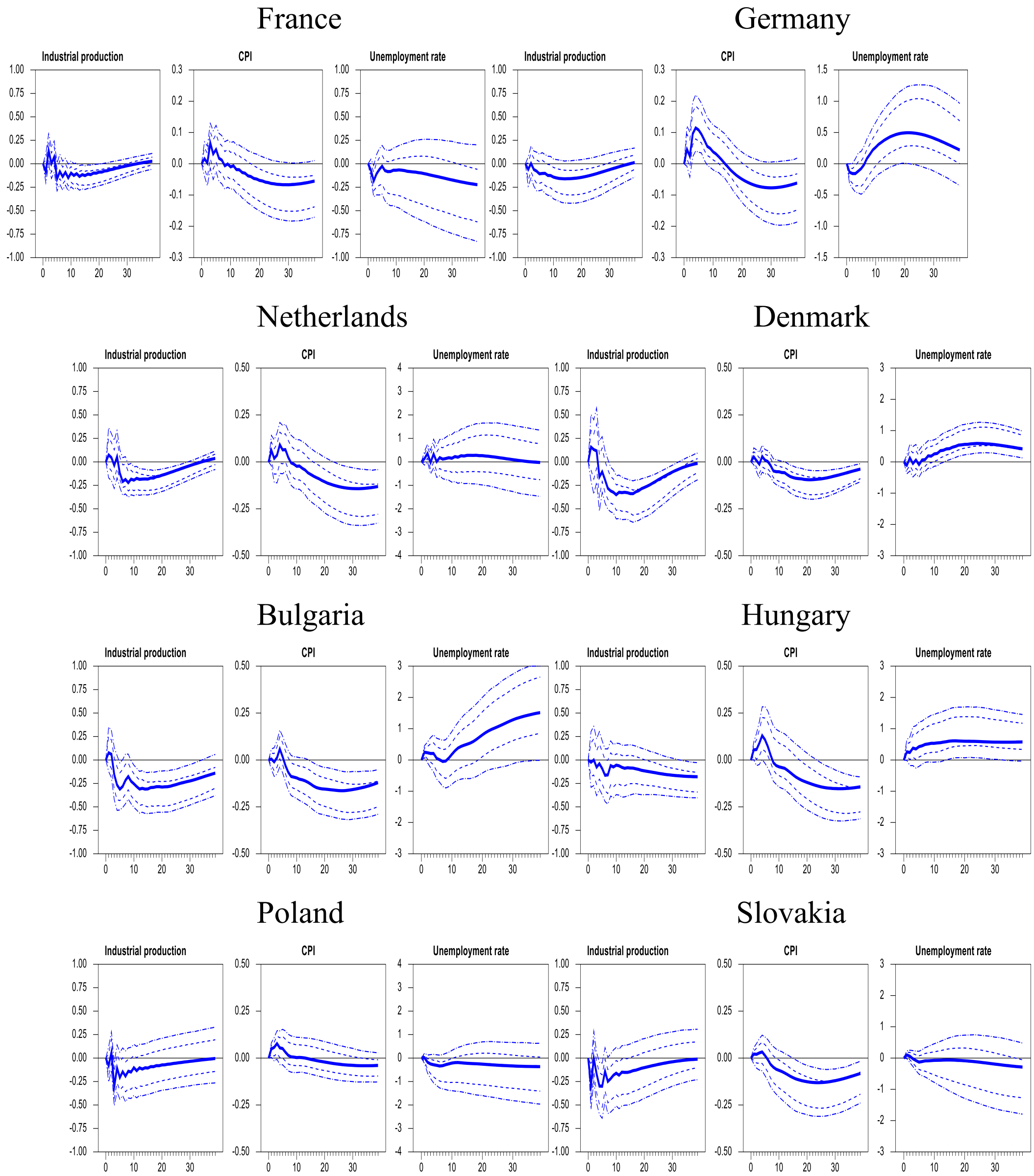


Panel (b) Non-OPEC



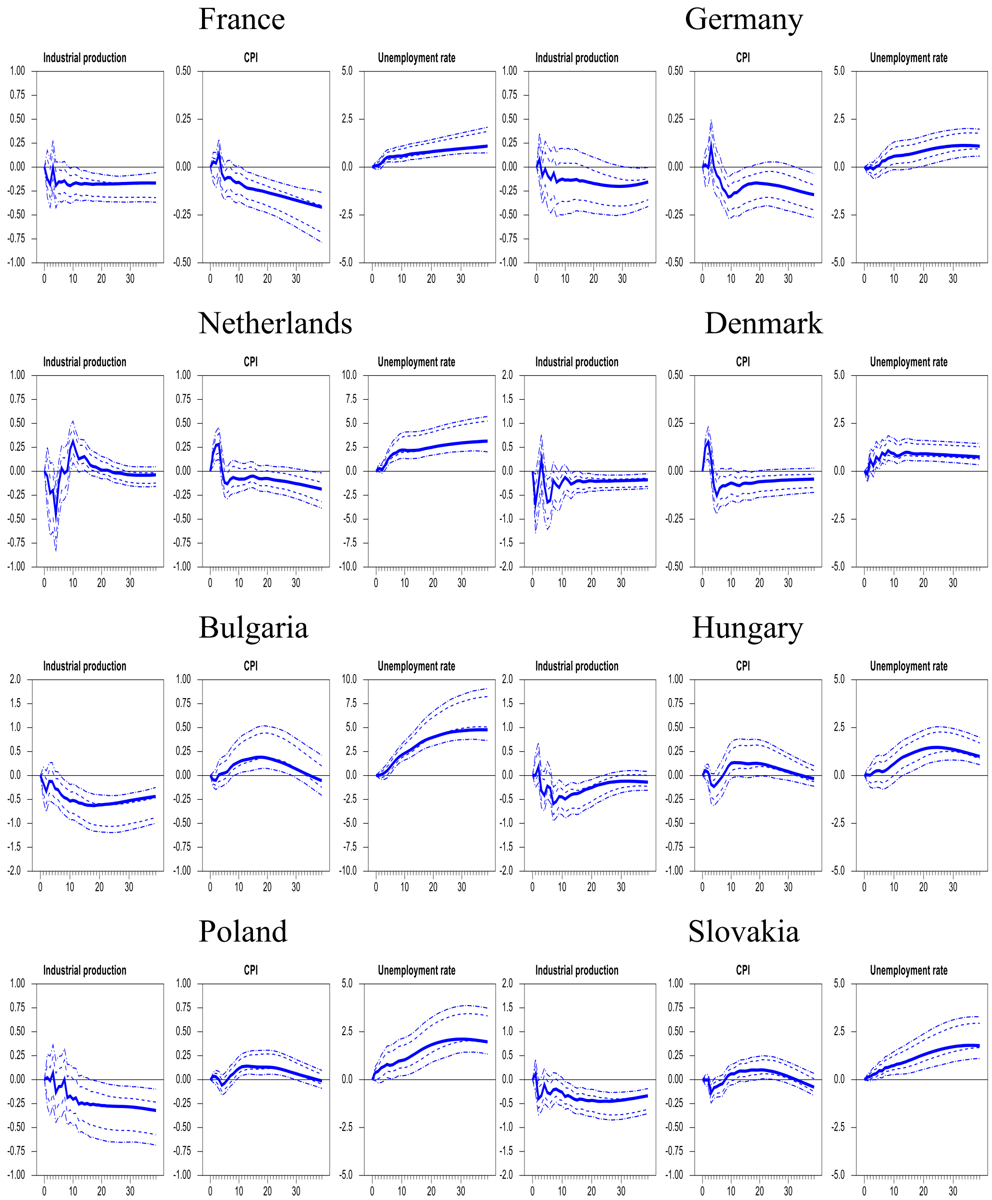
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 12 The IRFs given OPEC shocks of selected member countries



Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Figure 13 The IRFs given non-OPEC shocks of selected member countries



Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5.

Appendix. Supplementary Materials

In this chapter, we provide supplementary materials including data source and additional results of sensitivity analysis and robustness checks.

A. Data descriptions

We present the details of data source used in this study. The oil supply outage series, oil supply (OPEC and non-OPEC) and oil prices, are available at Energy Information Administration (EIA). The industrial production index, CPI, unemployment rate, interest rate, share price, real effective exchange rate, exports, imports and their sub-indices are selected from the Eurostat database.

Table A.1. The outline of dataset

	Description	Source	Region/Country/Sectors	Period
Outage	*Unplanned oil supply outage*	EIA	OPEC	2009M1-2019M12
		EIA	Non-OPEC	2011M1-2019M12
pro	*Oil production*	EIA	OPEC	2009M1-2019M12
		EIA	Non-OPEC	2011M1-2019M12
rpo	*Real price of oil*	EIA	WTI	2009M1-2019M12
		EIA	Imported Crude Oil Price	2009M1-2019M12
		EIA	Brent	2009M1-2019M12
ip	*Industrial production*	Eurostat	EU-27	2009M1-2019M12
		Eurostat	EU-19	2009M1-2019M12
		Eurostat	EU-28	2009M1-2019M12
		Eurostat	Member countries	2009M1-2019M12
		Eurostat	Intermediate goods	2009M1-2019M12
		Eurostat	Energy	2009M1-2019M12
		Eurostat	Capital	2009M1-2019M12
		Eurostat	Durable goods	2009M1-2019M12
		Eurostat	Non-durable goods	2009M1-2019M12
cpi	*Consumer price index*	Eurostat	EU-27	2009M1-2019M12

		Eurostat	EU-19	2009M1-2019M12
		Eurostat	EU-28	2009M1-2019M12
		Eurostat	Member countries	2009M1-2019M12
		Eurostat	Goods (excluding services)	2009M1-2019M12
		Eurostat	Industrial goods	2009M1-2019M12
		Eurostat	Non-energy industrial goods	2009M1-2019M12
		Eurostat	Energy	2009M1-2019M12
		Eurostat	Durable goods	2009M1-2019M12
		Eurostat	Semi-durable goods	2009M1-2019M12
		Eurostat	Non-durable goods	2009M1-2019M12
		Eurostat	Services (excluding goods)	2009M1-2019M12
		Eurostat	Overall goods (excluding energy)	2009M1-2019M12
ue	*Unemployment rate*	Eurostat	EU-27	2009M1-2019M12
		Eurostat	EU-19	2009M1-2019M12
		Eurostat	EU-28	2009M1-2019M12
		Eurostat	Member countries	2009M1-2019M12
ir	*Interest rate*	Eurostat	EU-27	2009M1-2019M12
sp	*Share price*	Eurostat	EU-27	2009M1-2019M12
reer	*Real effective exchange rate*	Eurostat	EU-27	2009M1-2019M12
ex	*Exports*	Eurostat	EU-27	2009M1-2019M12
im	*Imports*	Eurostat	EU-27	2009M1-2019M12

B. Cointegrated relations in the VAR

As we presented, the VAR is estimated by using log level variables (Sims et al., 1990; Ramey, 2016). Sims et al. (1990) present that a log-level specification could deliver consistent estimates when the variables are cointegrated or have stochastic trends. Therefore, we implement the Johansen cointegration test to investigate if long-run relations are presented among the variables. The trace test statistics indicate that there are 2 cointegrating equations at 10% significance level for both OPEC and non-OPEC models. The results are reported in Table B.1.

Table B.1. Trace Test

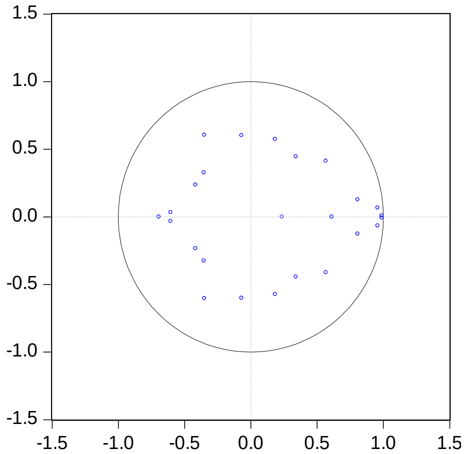
Hypothesized No. of CE(s)	OPEC		Non-OPEC	
	Trace statistic	0.1 critical value	Trace statistic	0.1 critical value
None *	95.825	65.820	101.074	65.820
At most 1 *	51.979	44.494	51.200	44.494
At most 2	24.137	27.067	25.319	27.067
At most 3	7.258	13.429	9.671	13.429
At most 4	0.830	2.706	0.028	2.7056

Note: trace test indicates 2 cointegrating equations at the 0.1 level. * denotes rejection of the hypothesis at the 0.1 level. The OPEC model covers from 2009M1 to 2019M12, and the non-OPEC model is estimated with the sample from 2011M1 to 2019M12. Other empirical specifications are the same as the ones used in the benchmark model.

C. Diagnostic statistics in the VAR

To present the stability of the VAR, we plot the following inverse roots of the characteristic AR polynomial in OPEC model (Lütkepohl, 1991). In obvious, we find that no root lies outside the unit circle and the VAR satisfies the stability condition. Since the Proxy SVAR provides another strategy to identify the exogenous oil supply shocks, the diagnostic statistics based on the typical SVAR residuals cannot deliver too much information.

Figure C.1. Inverse roots of AR characteristic polynomial



D. Robustness checks and sensitivity analysis

This section presents the results of robustness checks and sensitivity analysis. First, we consider different constructions of external instrument by using flexible lags. Next we utilize Akaike information criterion and Schwarz information criterion to select optimal lags used in baseline VAR model. Then we select other data sources including different measurements of oil price and Euro macroeconomic indicators. In addition, we also report the IRFs of the VAR in difference.

D.1. Different constructions of external instrument

In the benchmark model, we choose optimal lags by using lags exclusion test provided by EViews 10. In robustness checks, we employ another strategy with flexible lags. To determine the optimal lags, we first augment the model with 12 lags and drop off the terms that are insignificant.

Table D.1 Regression estimates

	OPEC		Non-OPEC	
	Coefficients	*t* stat.	Coefficients	*t* stat.
c	0.138	1.753	0.036	0.666
α_1	0.875	8.501	0.506	4.267
α_2	-0.012	-0.092	0.18	1.362
α_3	0.16	1.145	0.091	0.697
α_4	-0.142	-0.829	0.056	0.44
α_5	0.021	0.116	0.122	0.944
α_6	-0.046	-0.249	0.03	0.217
α_7	0.282	1.533	-0.131	-0.936
α_8	-0.27	-1.448	-0.009	-0.066
α_9	0.171	0.901	-0.057	-0.406
α_{10}	0.051	0.269	0.105	0.735
α_{11}	-0.248	-1.297	0.199	1.318
α_{12}	0.08	0.599	-0.188	-1.482
γ	0.391	2.652	-0.094	-1.051
β_1	-0.583	-2.821	0.033	0.257

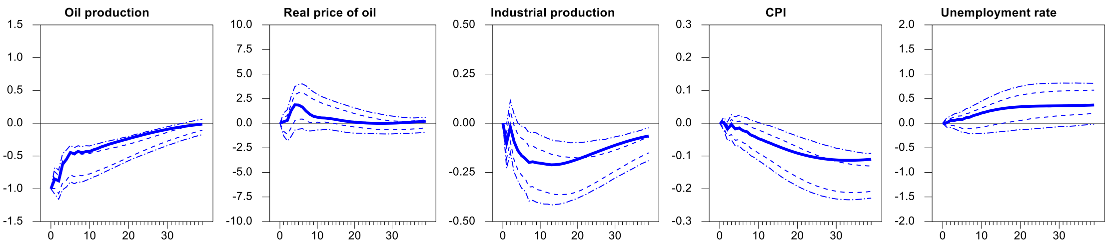
β_2	0.358	1.692	0.098	0.769
β_3	-0.485	-2.282	-0.218	-1.764
β_4	0.393	1.788	0.088	0.706
β_5	-0.211	-0.938	0.09	0.715
β_6	0.045	0.2	-0.001	-0.009
β_7	-0.163	-0.734	-0.022	-0.161
β_8	0.239	1.085	-0.089	-0.682
β_9	-0.064	-0.291	0.254	1.993
β_{10}	-0.182	-0.849	-0.152	-1.171
β_{11}	0.308	1.444	0.067	0.499
β_{12}	-0.083	-0.577	-0.078	-0.817
R^2	0.911		0.732	
$\hat{R}^2$	0.888		0.647	
LM_{SC}	0.841 (0.362)		0.537 (0.471)	
LM_{HET}	0.988 (0.491)		0.464 (0.983)	

Note: The estimations are built upon equation (1). LM_{SC} and LM_{HET} refer to Breusch-Godfrey serial correlation test and Breusch-Pagan-Godfrey heteroskedasticity tests, respectively.

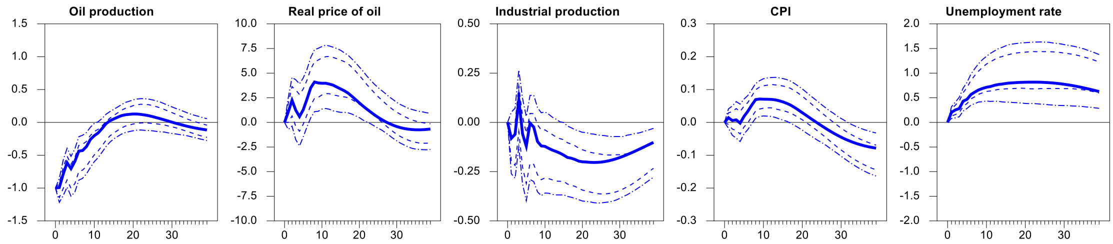
We use the alternative unplanned oil supply outage shocks for robustness checks. Figure B.1 shows the IRFs patterns given the newly constructed instrumental variables. The empirical specifications are the same as the ones used in the baseline model. In obvious, there are no visible changes in comparison with the baseline IRFs. Thus, employing different external instrument does not alter the main conclusions.

Figure D.1 IRFs of different constructions of external instrument

Panel (a) OPEC



Panel (b) Non-OPEC



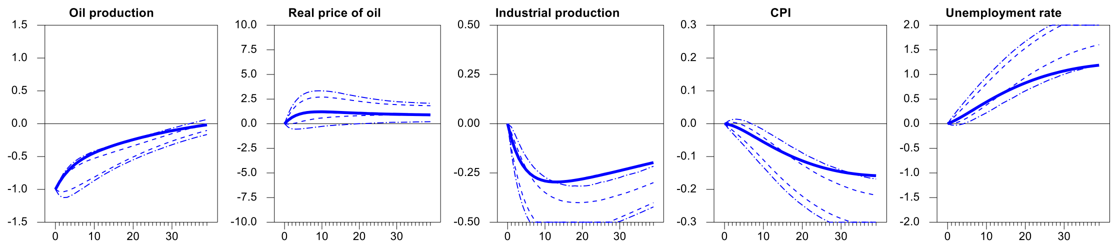
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizons are monthly. The lags for the VAR system are determined as 5 by using lags exclusion tests in EViews 10.

D.2. Using information criteria

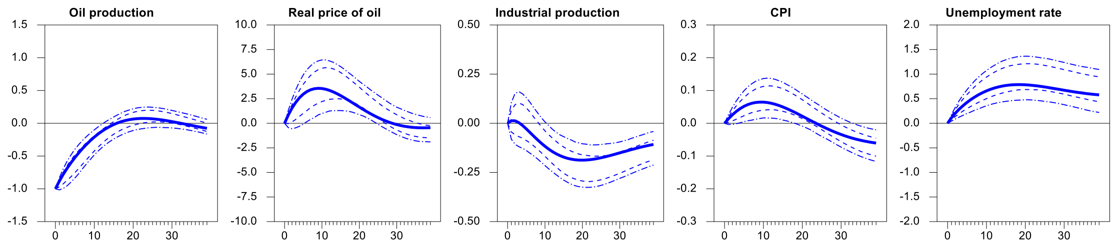
The optimal lags of the benchmark model are determined as 5 through the lags exclusion tests provided by EViews 10. Other empirical studies prefer selecting the lags through information criteria. To complement to this field, we use Schwarz information criterion (SIC) and Akaike information criterion (AIC) for robustness checks. According to SIC, both OPEC and non-OPEC models choose 1 lag. We present the IRFs results of SIC in Figure D.2. The patterns are similar to the baseline plots in Figure 3.

Figure D.2 IRFs using information criteria (Schwarz information criterion)

Panel (a) OPEC



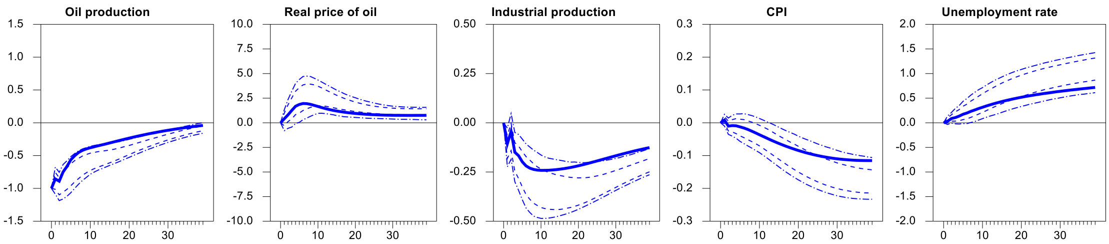
Panel (b) Non-OPEC



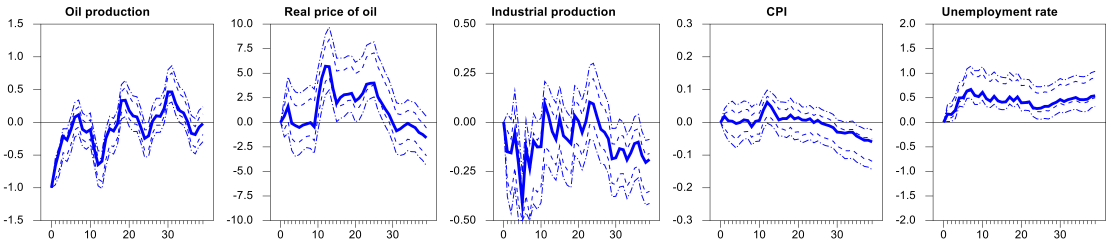
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags chosen by Schwarz information criterion are 1.

However the AIC disagrees substantially for the lags in OPEC and non-OPEC model. Specifically, the lags of OPEC model are determined as 3 and of non-OPEC model are chosen as 11. Although the IRFs patterns of non-OPEC model capture more dynamics, the main conclusions are not altered.

Figure D.3 IRFs using information criteria (Akaike information criterion)
Panel (a) OPEC



Panel (b) Non-OPEC

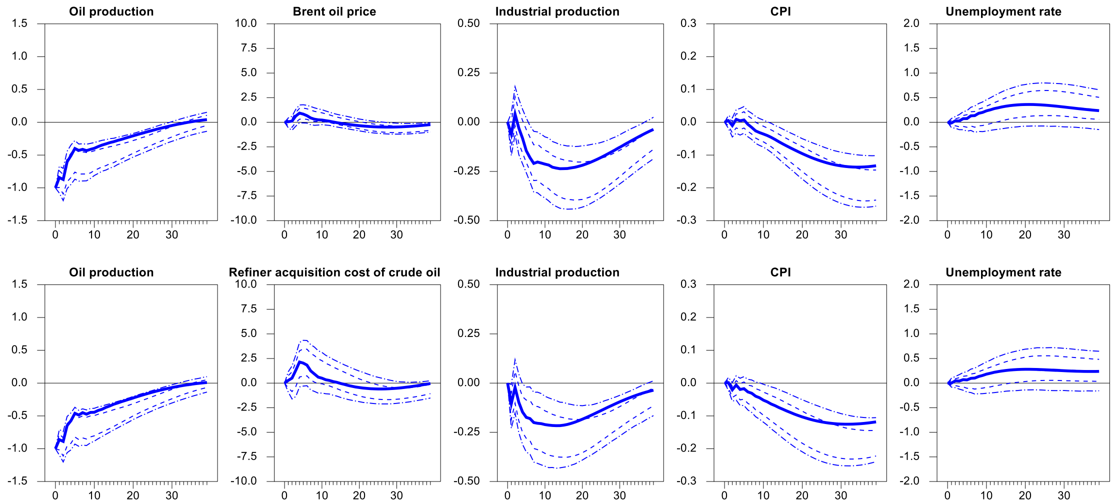


Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags of OPEC and non-OPEC models chosen by Akaike information criterion are 3 and 11, respectivley.

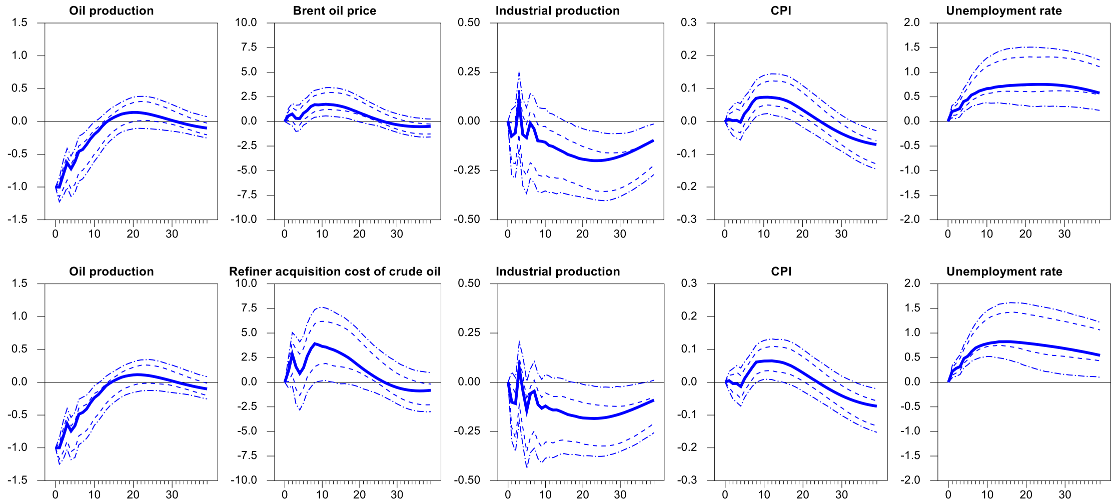
C.3. Different variables

This section checks the robustness against different variables. First, to represent oil price, we choose WTI price in our baseline estimates. There are other indices such as US refiner acquisition cost of crude oil and Brent oil prices which are used for robustness checks. Other empirical specifications are not changed. The IRFs of robustness checks against different measurements of oil prices are available in Figure D.4. In brief, the results are robust when we choose different proxies of oil price.

Figure D.4 IRFs of different measurements of oil price
Panel (a) OPEC



Panel (b) Non-OPEC

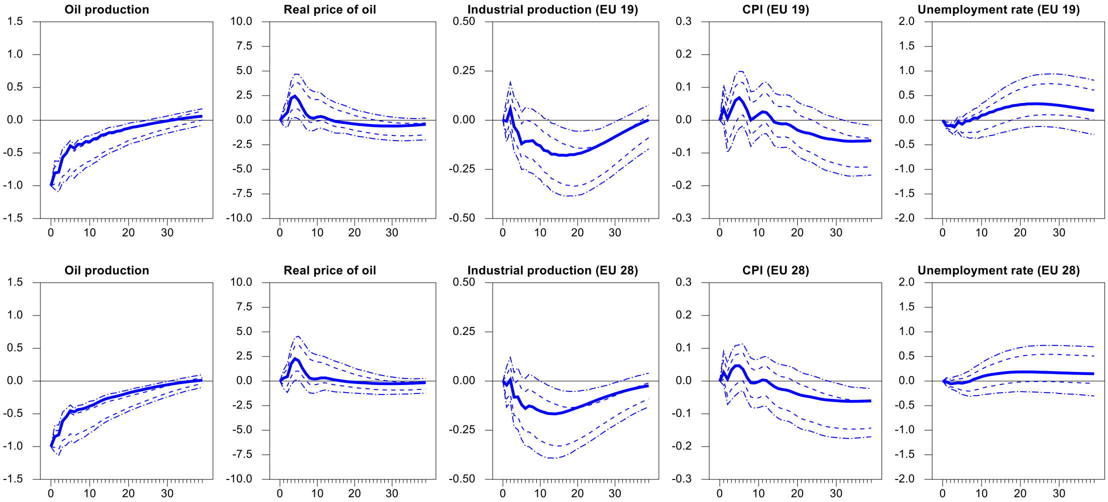


Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags for the VAR system are determined as 5.

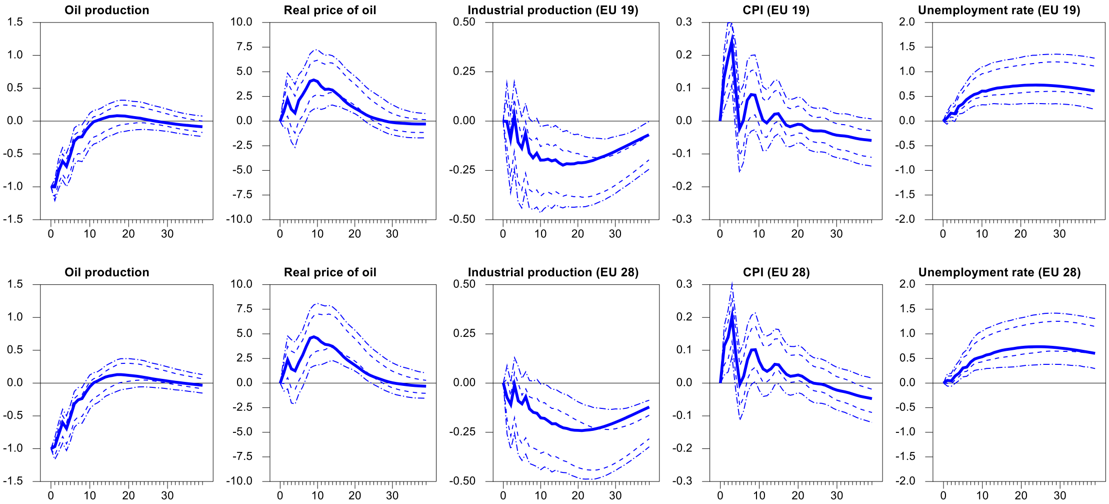
To represent EU's macroeconomic conditions, we choose the aggregate indices of EU-27 member countries. There are other measurements of EU's macroeconomic conditions by including different individual countries. Here we consider the aggregate industrial production index, CPI and unemployment rate of EU-19 and EU-28 countries for robustness checks. Still, the identified exogenous oil supply shocks would raise oil price and unemployment rate but pull down industrial production.

Figure D.5 IRFs of different measurements of Euro macroeconomic variables

Panel (a) OPEC



Panel (b) Non-OPEC



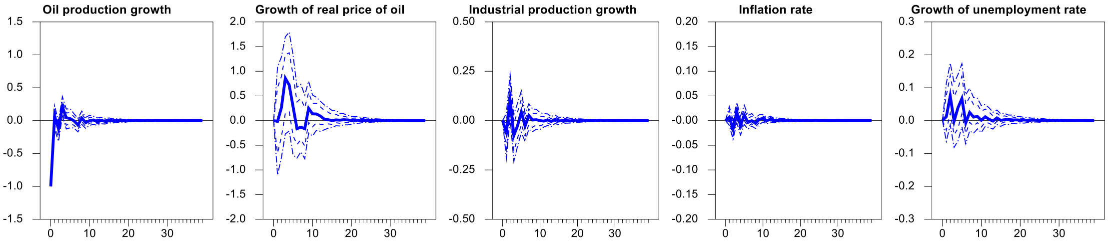
Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags for the VAR system are determined as 5.

C.4. VAR in difference

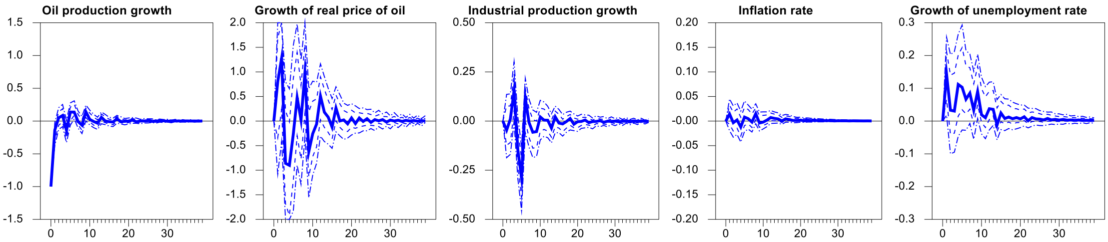
Although the cointegrated relations are presented in Section B, we estimate the VAR with variables in difference. We still specify the model like the benchmark estimates. The empirical findings are shown in Figure D.6. The following IRFs patterns contain frequent fluctuations which disappear in long horizons. In essence, the IRFs results of the VAR in difference are hard to interpret and are significantly different from the baseline results. Therefore, estimating the model with differencing variables is not plausible (Sims et al., 1990; Ramey, 2016).

Figure D.6 IRFs of VAR in difference

Panel (a) OPEC



Panel (b) Non-OPEC



Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags for the VAR system are determined as 12.

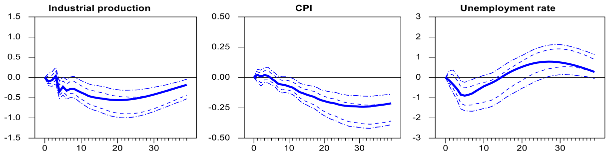
E. Additional results of member countries

This section presents the IRFs results of all EU-27 states which include Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden. The optimal lags are determined as 5. The confidence intervals by using Moving Block Bootstrap (MBB) method proposed by Brüggemann et al. (2016) are reported at 68% and 90% confidence levels. The specifications are the same as the ones used in the baseline model. The model is specified as $Y_t = [pro_t, rpo_t, ipg_t^i, ir_t^i, ue_t^i]'$, where i refers to individual countries of EU-27.

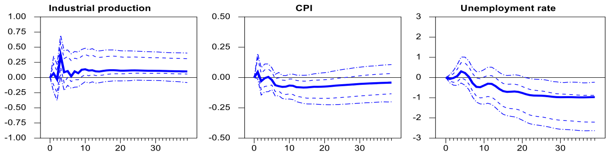
Figure E.1. Additional IRFs Results of member countries

Panel (a) OPEC

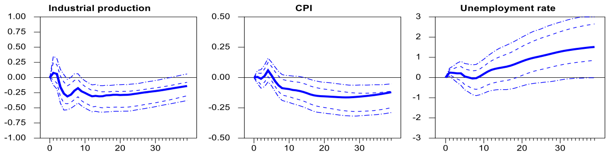
Austria



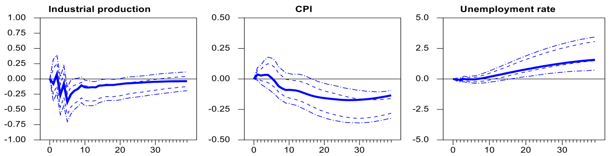
Belgium



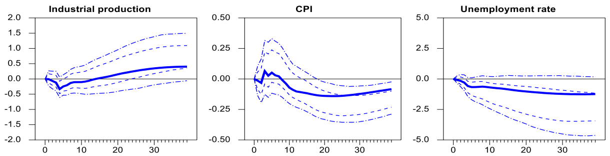
Bulgaria



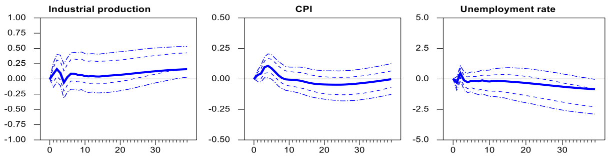
Croatia



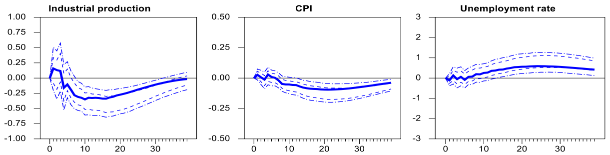
Cyprus



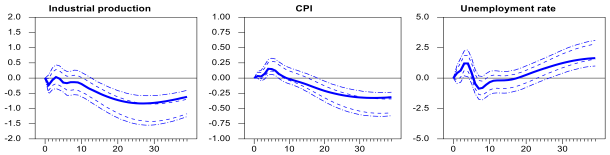
Czechia



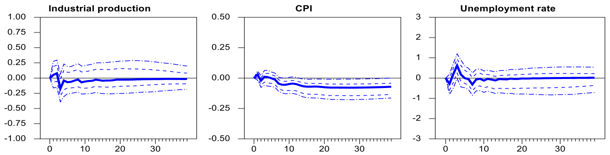
Denmark



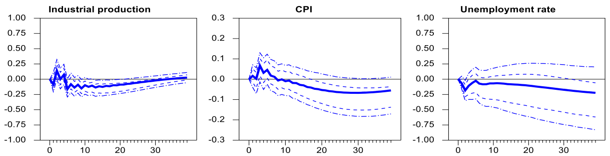
Estonia



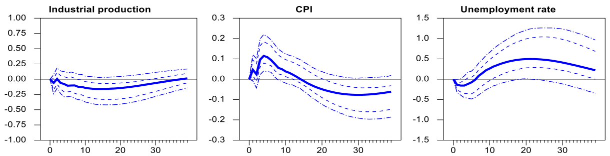
Finland



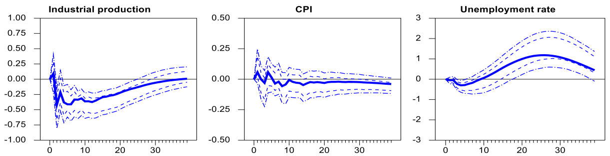
France



Germany



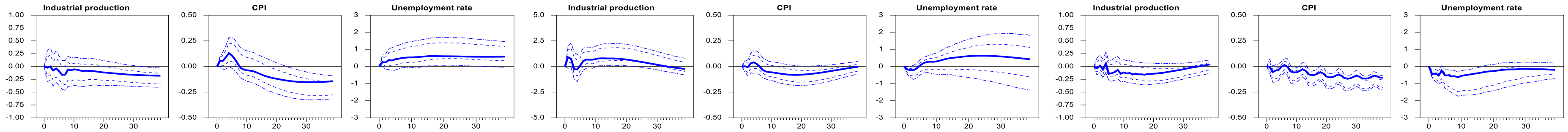
Greece



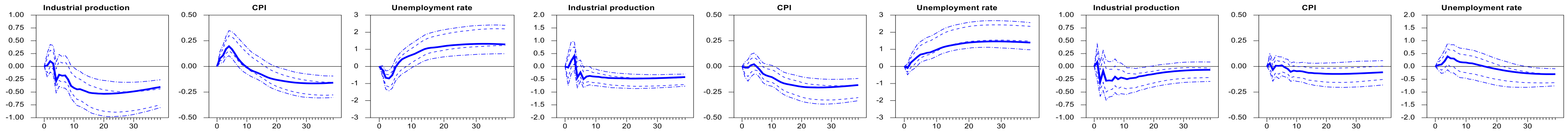
Hungary

Ireland

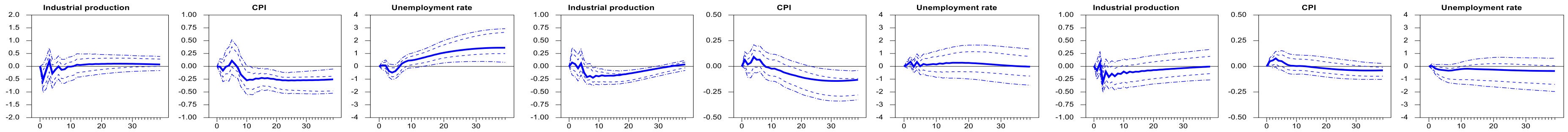
Italy



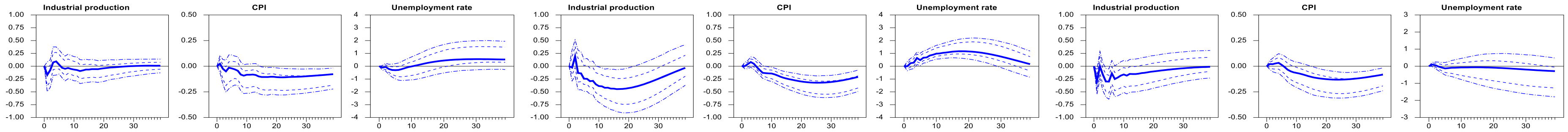
Latvia | Lithuania | Luxembourg



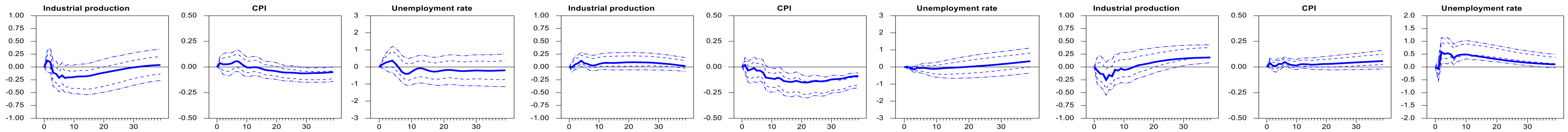
Malta | Netherlands | Poland



Portugal | Romania | Slovakia

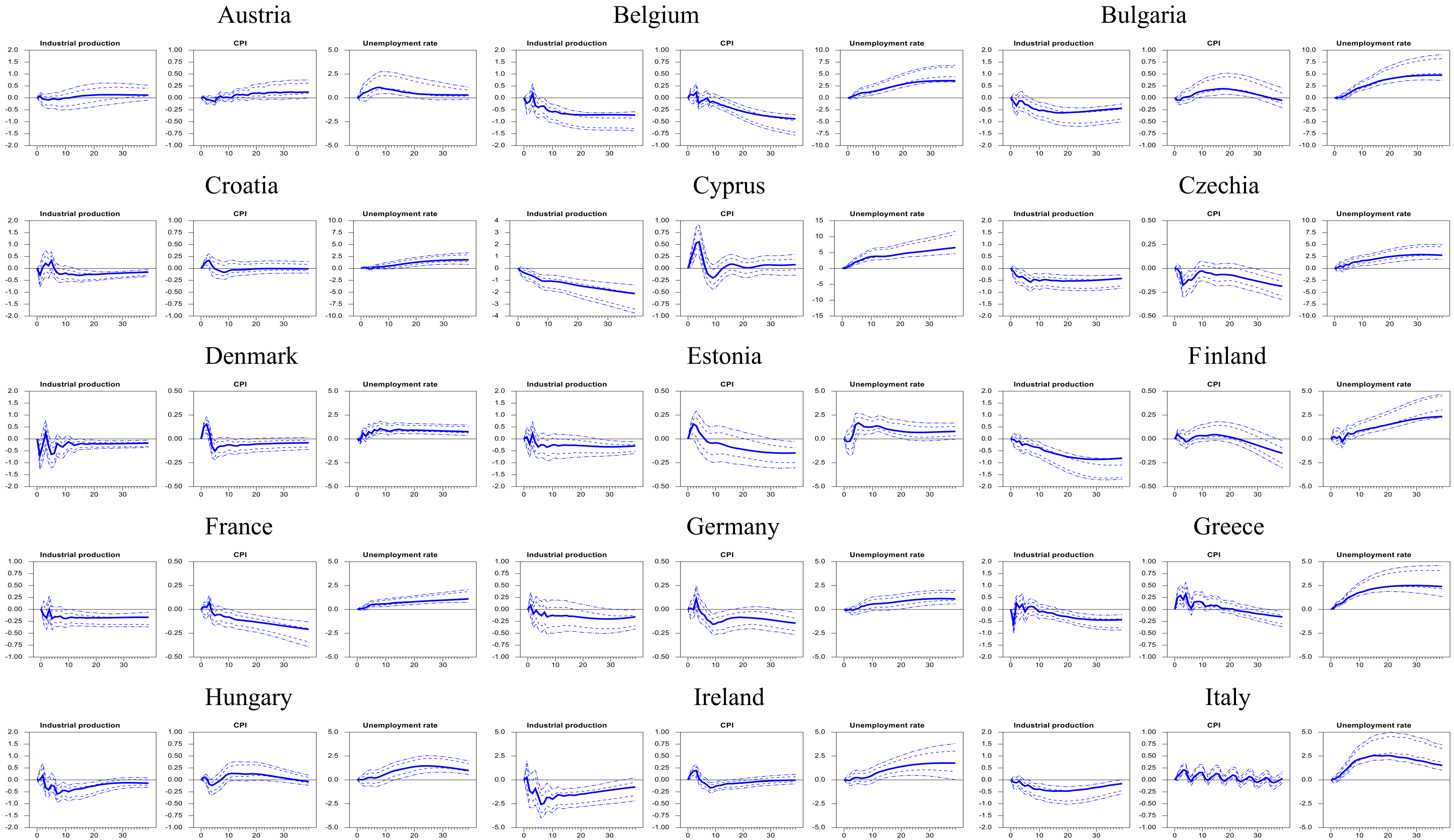


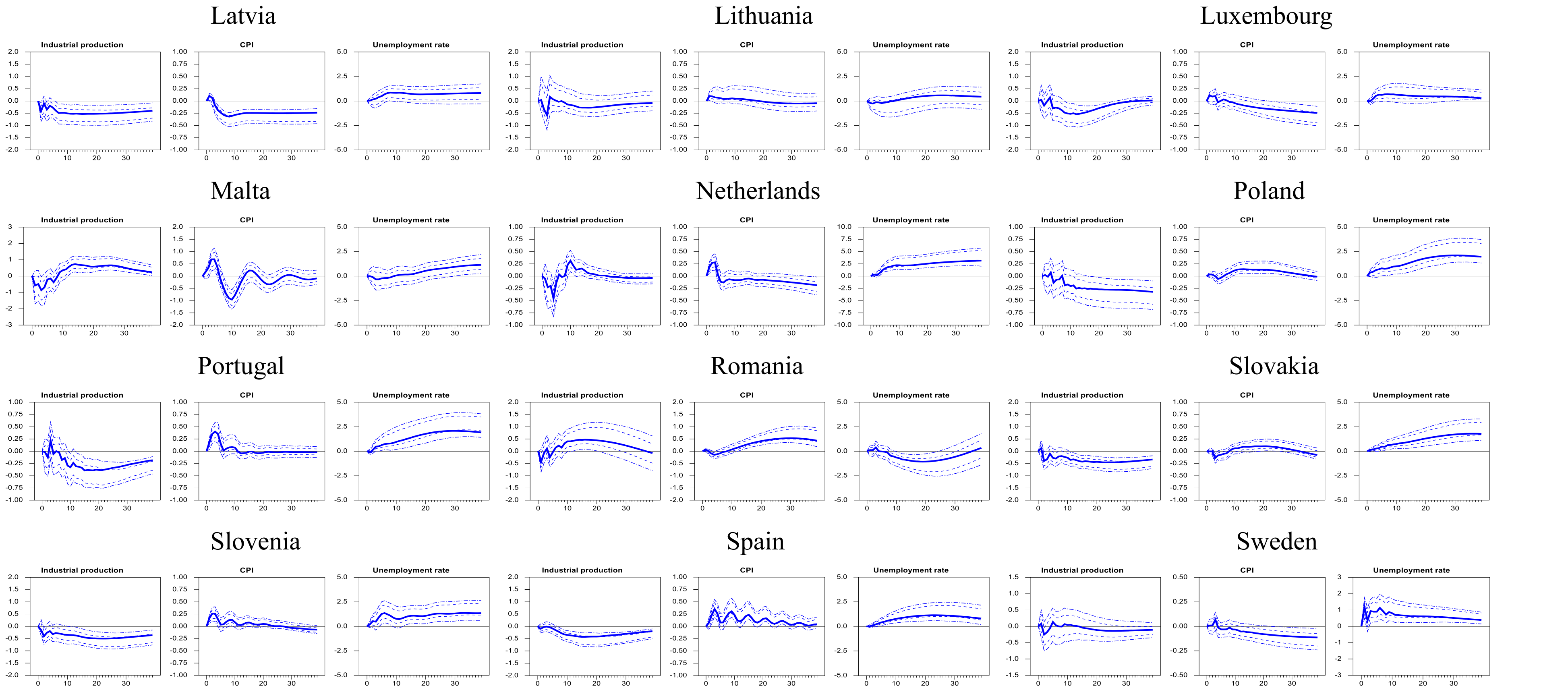
Slovenia | Spain | Sweden



Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags for the VAR system are determined as 5. The lags for the VAR system are determined as 5 by using lags exclusion tests provided by EViews 10.

Panel (b) Non-OPEC results





Note: the confidence intervals are constructed by using a moving block bootstrapping method (Brüggemann et al., 2016) at 68% and 90% significance levels. The horizon is monthly. The lags for the VAR system are determined as 5 by using lags exclusion tests provided by EViews 10.