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Oil price elasticities and oil price fluctuations☆

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ABSTRACT

Studies identifying oil shocks using structural vector autoregressions (VARs) reach different conclusions on the relative importance of supply and demand factors in explaining oil market fluctuations. This disagreement is due to different assumptions on the oil supply and demand elasticities that determine the identification of the oil shocks. We provide new estimates of oil-market elasticities by combining a narrative analysis of episodes of large drops in oil production with country-level instrumental variable regressions. When the estimated elasticities are embedded into a structural VAR, supply and demand shocks play an equally important role in explaining oil prices and oil quantities.

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1. Introduction

Academics, practitioners, and policymakers attribute swings in the price of oil to a variety of forces, such as changes in global demand, disruptions in supply, and precautionary motives. However, the relative importance of these forces remains highly debated. In their chapter in the Handbook of Macroeconomics, Stock and Watson (2016) summarize the academic debate by comparing an early literature that finds an important role for oil supply shocks in driving oil market fluctuations to a more recent literature that finds that most movements in oil prices are demand-driven.[1]

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[1] The early literature, initially used to study the 1970s oil shocks, assumes that oil prices are predetermined, and interprets innovations in prices as the outcome of oil supply shocks. Examples of papers adopting this approach are Shapiro and Watson (1988), Rotemberg and Woodford (1996), and Blanchard and Galí (2010). Blanchard and Galí (2010) identify an oil shock that explains about 80% of oil prices, and interpret the shock as being mostly driven by oil supply factors. The more recent literature, promoted by Kilian (2009), assumes that the short-run oil supply elasticity is zero, and explicitly allows for oil prices to contemporaneously respond to movements in oil production and in global demand. This literature finds that oil-specific demand shocks are important drivers of oil prices.

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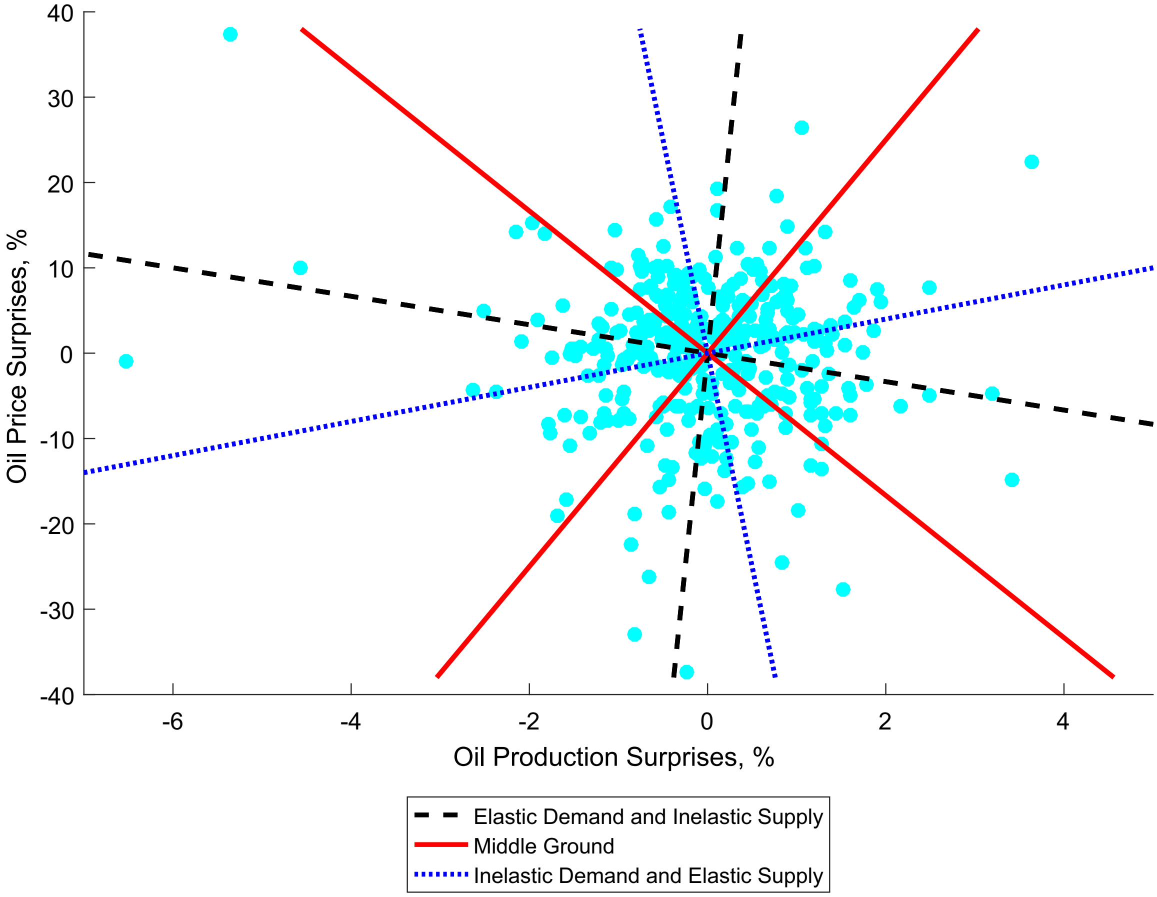

Fig. 1. Quantities and Prices in the Oil Market
Note: The figure depicts the scatter plot between the residuals from a regression of oil prices and oil production on their own lag and a constant. The solid red, black dashed, and blue dotted lines represent alternative configurations of the oil demand and the oil supply curves that are consistent with the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In this paper, we assess the relative importance of supply and demand factors in explaining oil market fluctuations, and find that supply and demand shocks are equally important in accounting for fluctuations in oil prices and oil quantities. We reach this conclusion in two steps. First, we combine narrative analysis with a panel of observations on country-specific oil production and consumption to estimate oil supply and demand elasticities. Second, we embed these elasticities in a vector autoregression (VAR) to identify the oil supply and demand equations and, consequently, the associated oil supply and oil demand shocks.

Our starting point is to show how the cross-equation restrictions that are inherent in standard VARs of the oil market impose an inverse, nonlinear relation between the short-run price elasticities of oil supply and demand. This relation— as originally noted by Baumeister and Hamilton (2017)— implies that seemingly plausible restrictions on the oil supply elasticity may map onto implausible values of the oil demand elasticity, and vice versa. For instance, if one imposes a short-run oil supply elasticity of zero, a common value in the literature, the resulting oil demand elasticity is -1, a value which is in the high end of the empirical estimates.[2] Similarly, if one imposes an oil demand elasticity of -0.05, a value in the ballpark of the empirical estimates, the resulting supply elasticity is large, close to 0.5.

We next argue that the selection of the elasticities is essential for understanding sources and consequences of oil market fluctuations, and that seemingly small changes in these elasticities have large effects on the relative importance of demand and supply forces. In particular, with a configuration of the oil market characterized by a zero supply elasticity, all movements in oil prices are attributed to oil-specific demand shocks. By contrast, setting the supply elasticity to 0.1 implies that oil supply and oil demand shocks are equally important drivers of oil price fluctuations.

To understand the relationship between oil price elasticities and oil price fluctuations, Fig. 1 shows a scatter plot between monthly surprises in oil prices and global oil production implied by simple univariate AR(1) regressions.[3] The dots

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[2] See Hamilton (2009) for a survey of the estimates of the short-run price elasticity of demand for crude oil: the average estimate of the demand elasticity is -0.06.

[3] A similar figure would obtain by plotting the reduced-form residuals for oil prices and oil production estimated using a VAR.

show that oil prices and global oil production are uncorrelated. This lack of correlation could be the outcome of very different oil market configurations. On one hand, as shown by the dashed lines in Fig. 1, the supply curve could be inelastic, while the demand curve could be very elastic. As a result, fluctuations in oil prices and oil production would be disconnected, with prices driven uniquely by demand shocks, and production driven uniquely by supply shocks. On the other hand, a market characterized by a very elastic oil supply curve and an inelastic demand curve—the dotted lines in Fig. 1—would also lead to a disconnect of movements in oil prices and oil production. In between these two extremes lies an oil market with a downward-sloping demand curve and an upward-sloping supply curve—the solid lines in Fig. 1—which would imply that demand and supply shocks jointly affect oil prices and production. These market configurations, picked among many for illustrative purposes, are equally consistent with the data but have different implications for the causes and the consequences of oil price fluctuations.

In order to estimate oil supply and demand elasticities, we combine narrative analysis with instrumental-variable regressions for a large panel of countries. For each country, we instrument the price of oil with large, exogenous drops in oil production occurring in other countries. This approach yields a supply elasticity of 0.08, and a demand elasticity of −0.08. These estimated elasticities are used as external information to identify the structural shocks in our VAR. In particular, we propose an identification scheme that minimizes the distance between the elasticities consistent with the cross-equation restrictions of the VAR, and the elasticities using external information. In doing so, we derive VAR-consistent elasticities of 0.10 for supply, and of −0.14 for demand.

Even with this identification strategy in hand, an additional challenge is to disentangle demand shocks that are specific to the oil market from demand shocks that originate from changes in global economic activity. To this end, we use three indicators of global activity that provide a broad characterization of the global demand for oil. We construct two separate indicators based on industrial production, one for emerging economies, and another for advanced economies, dating back to the mid 1980s. These indicators allow us to measure the distinct consequences of oil shocks on advanced versus emerging economies in a parsimonious model. Our third indicator is an index of industrial metal prices, which are often viewed by policymakers and practitioners as leading indicators of swings in economic activity and global risk sentiment.[4]

Our analysis delivers the following results. First, oil supply shocks are the main driving force of oil market movements, accounting for about 35% of the volatility of oil prices, and about 45% of the volatility of oil production. Shocks to global economic conditions also play an important role, explaining 35% of the volatility of oil prices, and about 20% of the volatility of oil production. Second, a drop in oil prices driven by either oil demand or supply shocks depresses economic activity in emerging economies. A drop in oil prices boosts economic activity in advanced economies only when driven by supply shocks.

Our contribution to the literature is twofold. First, we provide a transparent analysis that highlights the importance for inference of selecting the restrictions on the oil supply and demand elasticities in a VAR framework. We stress how in a structural VAR there is a tight equivalence between setting a specific value for the oil supply elasticity, on the one hand, and imposing a particular value for the oil demand elasticity on the other. Second, we propose a novel way of selecting oil supply and demand elasticities in a manner that combines external information from country-specific oil supply shocks with the cross-equations restrictions that are inherent in a just-identified VAR model.[5]

Kilian and Murphy (2012), Lippi and Nobili (2012), and Baumeister and Hamilton (2017) embed prior distributions for the elasticities in structural VARs of the oil market in order to identify shocks to oil supply and demand. Compared with these studies, we show that small differences in the elasticities have a substantial effect on inference, in particular on the decomposition of oil price movements. The use of narrative analysis on oil shocks builds off the work of Hamilton (2003) and Kilian (2008), who use country-specific episodes of exogenous disruptions in oil production to estimate the macroeconomic effects of oil supply shocks. Unlike these earlier studies, we use country-specific oil supply shocks as instruments to identify both supply and demand curves in the oil market. Our estimate of the global oil supply elasticity is within the range of estimates available in the literature, in line with the estimates by Baumeister and Hamilton (2017), but nearly three times as large as Kilian and Murphy (2012). Importantly, we find larger supply elasticities for OPEC members—especially for Saudi Arabia—than for non-OPEC producers. This finding reinforces the plausibility of our estimation approach, as OPEC producers are the group with the largest volume of oil capacity that can be used to offset disruptions in oil supply within a short period of time. Similarly, our estimates of the oil demand elasticity are in line with existing empirical studies.[6] Finally, our

[4] The use of IP indicators for advanced and emerging countries to measure global activity hews closely to the work of Baumeister and Hamilton (2017) and Aastveit et al. (2015). The use of metal prices follows the lead of Barsky and Kilian (2001), who propose the use of an index of industrial commodity prices—excluding oil—to identify broad-based shifts in global demand, as well as the more recent work of Arezki and Blanchard (2014), who exploit the idea that metal prices typically react to global activity even more than oil prices. Other studies that find a meaningful link between cyclical fluctuations in global economic activity and movements in metal prices include Pindyck and Rotemberg (1990), Labys et al. (1999), Cuddington and Jerrett (2008), Lombardi et al. (2012), Issler et al. (2014), Delle Chiaie et al. (2018), and Stuermer (2018).

[5] Baumeister and Hamilton (2017) were the first to demonstrate that one should move away from the dogmatic idea of an extremely low supply elasticity because of the extremely large values implied for the demand elasticity and to point out that there exists a wealth of external information about both elasticities that should be used for inference.

[6] See Hamilton (2009) and Baumeister and Hamilton (2017) for a summary of the existing empirical evidence on the short-run price elasticity of crude oil demand. Gelman et al. (2016), using daily transaction-level data for a large panel of individuals, find a demand elasticity of gasoline close to −0.2. Coglianese et al. (2017) estimate an elasticity of gasoline demand of −0.37 that is not statistically significant. As discussed in Hamilton (2009), since crude oil represents about half of the retail cost of gasoline, the price elasticity of demand for crude oil should be about half of that for retail gasoline.

approach of combining country-specific data on oil production with an aggregate VAR echoes the approach of the global VAR (GVAR) literature pioneered by Dees et al. (2007) and Mohaddes and Pesaran (2016).

2. Identifying oil market and global activity shocks

2.1. Model overview

The structure describing the oil market and its relationship with the global economy is given by the following structural VAR:

$$\mathbf{A}\mathbf{X}_t = \sum_{j=1}^{p} \alpha_j \mathbf{X}_{t-j} + \mathbf{u}_t, \tag{1}$$

where $\mathbf{X}$ is a vector of oil–market and macroeconomic variables, $\mathbf{u}_t$ is the vector of structural shocks, p is the lag length, and $\mathbf{A}$ and $\boldsymbol{\alpha}_j$ for $j = 1, \ldots, p$ are matrices of structural parameters. The vector $\mathbf{u}_t$ is assumed to have a Gaussian distribution with zero mean and variance–covariance matrix $E\left[\mathbf{u}_t\mathbf{u}_t'\right] = \boldsymbol{\Sigma}_u$. Without loss of generality, we normalize one entry on each row of $\mathbf{A}$ to 1 and we assume that $\boldsymbol{\Sigma}_u$ is a diagonal matrix. The reduced-form representation for $\mathbf{X}_t$ is the following:

$$\mathbf{X}_t = \sum_{j=1}^{p} \gamma_j \mathbf{X}_{t-j} + \varepsilon_t, \tag{2}$$

where the reduced-form residuals $\boldsymbol{\varepsilon}_t$ are related to the structural shocks $\mathbf{u}_t$ as follows:

$$\varepsilon_t = \mathbf{B}\mathbf{u}_t, \tag{3}$$

$$\boldsymbol{\Sigma}_\varepsilon = \mathbf{B}\boldsymbol{\Sigma}_u\mathbf{B}', \tag{4}$$

where $\mathbf{B} = \mathbf{A}^{-1}$, so that $\mathbf{u}_t$ can be alternatively expressed as $\mathbf{u}_t = \mathbf{A}\varepsilon_t$. Estimation of the reduced-form VAR allows us to obtain a consistent estimate of the $n(n+1)/2$ distinct entries of $E\left[\varepsilon_t\varepsilon_t'\right] = \boldsymbol{\Sigma}_\varepsilon$. To recover the n^2 unknown entries of $\mathbf{B}$ and $\boldsymbol{\Sigma}_u$, we make $(n-1)n/2$ identifying assumptions on the parameters of matrix $\mathbf{A}$.

To discuss our identification strategy, it is useful to distinguish between an oil–market block and a global–activity block, which we jointly characterize using five endogenous variables. The oil block includes (1) the log of world crude oil production, q_t; and (2) the log of oil prices, p_t. The global activity block consists of: (3) the log of advanced economies IP, ya_t; (4) the log of emerging economies IP, ye_t; and (5) the log of the IMF metal price index, m_t. All series are linearly detrended.[7] Oil prices and metal prices are expressed in real terms.[8]

The model, which includes a constant and 24 lags of the endogenous variables, is estimated on monthly data from 1985 to 2015 employing Bayesian techniques.[9] The sample starts in the mid-1980s, coinciding with the decision by the Organization of Petroleum Exporting Countries (OPEC) to abandon an administered official selling price and to adopt a market–based system. In addition, Baumeister and Peersman (2013a,b) show that large changes in the time-series properties of oil–market variables took place around the mid-1980s. The supplementary material shows that results under our baseline model are robust to alternative specifications.

The following five equations describe abstracting from lags—the joint modeling of the oil–market and the global–activity blocks, and summarize the restrictions that we impose on the parameters in matrix $\mathbf{A}$:

$$q_t = \eta_S p_t + u_{S,t}, \tag{5}$$

$$q_t = \eta_A ya_t + \eta_E ye_t + \eta_D p_t + u_{D,t}, \tag{6}$$

$$ya_t = \nu_Q q_t + u_{A,t}, \tag{7}$$

$$ye_t = \mu_Q q_t + \mu_A ya_t + u_{E,t}, \tag{8}$$

[7] The detrending method has modest impact on our results. The supplementary material presents results when our baseline VAR is estimated on variables that are not detrended.

[8] The supplementary material describes in detail the data and the construction of the IP indexes.

[9] We impose a Minnesota prior on the reduced-form VAR parameters by using dummy observations (Del Negro and Schorfheide, 2011). The vector of hyper-parameters of the prior is $\lambda = [1, 2, 1, 1, 1]$. The first two years of data serve as a training sample for the Minnesota prior. Results are based on 10,000 draws from the posterior distribution of the structural parameters, with the first 2000 draws used as a burn-in period.

$$m_t = \psi_Q q_t + \psi_A ya_t + \psi_E ye_t + \psi_P p_t + u_{M,t}. \tag{9}$$

Eqs. (5) and (6) describe the oil market block. Eq. (5) describes the oil supply schedule. Oil production q_t is assumed to respond contemporaneously only to changes in oil prices. The parameter η_S denotes the short-run price elasticity of supply. The supply shock $u_{S,\,t}$ captures disturbances to oil supply due to, for instance, geopolitical events, natural disasters, and technological innovations in oil extraction. Eq. (6) describes the oil demand schedule: oil demand is allowed to respond contemporaneously to the level of economic activity in advanced and emerging economies, ya_t and ye_t, and to oil prices. The parameter η_D denotes the short-run price elasticity of demand, and is defined as the change in desired demand q_t for a given change in oil prices p_t, holding activity in advanced and emerging economies constant. The oil-specific demand shock $u_{D,\,t}$ captures changes in oil prices due to, for instance, speculation and shifts in the precautionary demand for oil caused by oil price volatility.[10]

Eqs. (7) to (9) describe the global activity block. Eq. (7) determines activity in advanced economies. We assume that ya_t responds within the period only to oil production. Eq. (8) determines activity in emerging economies, ye_t. We assume that ye_t responds within the period to ya_t and to oil production. Our assumption that ye_t reacts contemporaneously to ya_t is meant to capture the idea that exports to advanced economies are an important component of aggregate demand in emerging economies. Our model assumes that the oil market has a contemporaneous and direct effect on both ya_t and ye_t only through changes in q_t, as oil is an input in the production of manufactured goods. However, changes in oil prices have an indirect contemporaneous effect on real activity by inducing changes in oil production. Eq. (9) determines metal prices, which are allowed to respond within the period to all variables in the system. The shock $u_{M,\,t}$ captures movements in global demand over and above the innovations in IP.[11]

The use of zero restrictions to model the interaction between the oil market and global activity is consistent with the assumptions in Kilian (2009), who also assumes that oil supply does not respond to shocks to global activity, while oil demand does. The key difference between Kilian's (2009) identification strategy and ours lies in the choice of the oil supply and demand elasticities η_S and η_D.

2.2. Identification of the oil market block

We now show how seemingly plausible restrictions on the oil supply elasticity η_S may map into implausible values of the oil demand elasticity η_D, and vice versa. Fig. 2 illustrates this result. The black line depicts all combinations of η_S and η_D that are consistent with the data—as summarized by setting $\mathbf{\Sigma}_\varepsilon$ at its OLS estimate—and with the zero restrictions described above. For instance, the same model can be identified restricting the oil supply elasticity to zero, a common value in the literature, only to imply an oil demand elasticity of about -1, which is at the high end of the empirical estimates; by contrast, the model can be identified restricting the oil demand elasticity to a value in the ballpark of empirical estimates (for instance -0.05), only to imply an oil supply elasticity which is implausibly large.

The blue circle indicates a pair of elasticities that represent an oil market configuration featuring moderately inelastic supply ($\eta_S^* = 0.081$) and demand ($\eta_D^* = -0.080$) elasticities. These oil price elasticities are based on the country-level, instrumental-variable panel regressions presented in Section 3. We refer to these elasticities as external information, as they are derived from data and identification assumptions that are external to the structural VAR model.

We propose to use the external information on both elasticities to discipline the identification of VAR model. Specifically, our identification strategy selects a pair of admissible elasticities η_S and η_D by minimizing the Euclidean distance between the VAR-admissible elasticities and the target elasticities. Consider η_D as a function of η_S and of the variance-covariance matrix of the estimated reduced-form residuals, $\eta_D(\eta_S;\, \mathbf{\Sigma}_\varepsilon)$. Our identification strategy solves the following problem:[12]

$$\min_{\eta_S} \begin{bmatrix} \eta_S - \eta_S^* \\ \eta_D(\eta_S;\, \mathbf{\Sigma}_\varepsilon) - \eta_D^* \end{bmatrix}' V^{-1} \begin{bmatrix} \eta_S - \eta_S^* \\ \eta_D(\eta_S;\, \mathbf{\Sigma}_\varepsilon) - \eta_D^* \end{bmatrix}, \tag{10}$$

where η_S^* and η_D^* are the target values for the supply and demand elasticities, respectively, and V is a diagonal matrix of weights. We summarize the external information into a mean component, the targets η_S^* and η_D^*, and into a variance component, which we use to calibrate the weights V. If the external information is perfectly consistent with the VAR, η_S^* and η_D^* are on the curve plotted in Fig. 2 and the distance between the VAR-implied elasticities and the targets is zero. By contrast, if the external information is not consistent with the VAR, η_S^* and η_D^* are not on the curve and the identification

[10] See for instance Beidas-Strom and Pescatori (2014) and Juvenal and Petrella (2015).

[11] Our restrictions imply that metal prices can directly respond to contemporaneous movements in oil prices, but rule out the reverse interaction. We estimated a model that imposes the alternative assumption that oil prices respond contemporaneously to metal prices—by allowing metal prices to enter into the oil demand equation—while imposing $\psi_P = 0$. We found very similar results to those reported below. In addition, removing metal prices from the VAR model slightly diminishes the importance of global activity shocks to explain movements in oil market variables, but has a very modest influence on the remaining results of the paper. See Section 4.4 and the supplementary material for details.

[12] We parameterized the problem by expressing η_D as a function of η_S so that matrix $\mathbf{A}$ satisfies the necessary and sufficient conditions for identification of Rubio-Ramírez et al. (2010). Thus, the structural parameters (ν_Q, μ_Q, μ_A, η_A, η_E, η_D, ψ_Q, ψ_A, ψ_E, ψ_P, $\mathbf{\Sigma}_u$) are uniquely identified given information from $\mathbf{\Sigma}_\varepsilon$.

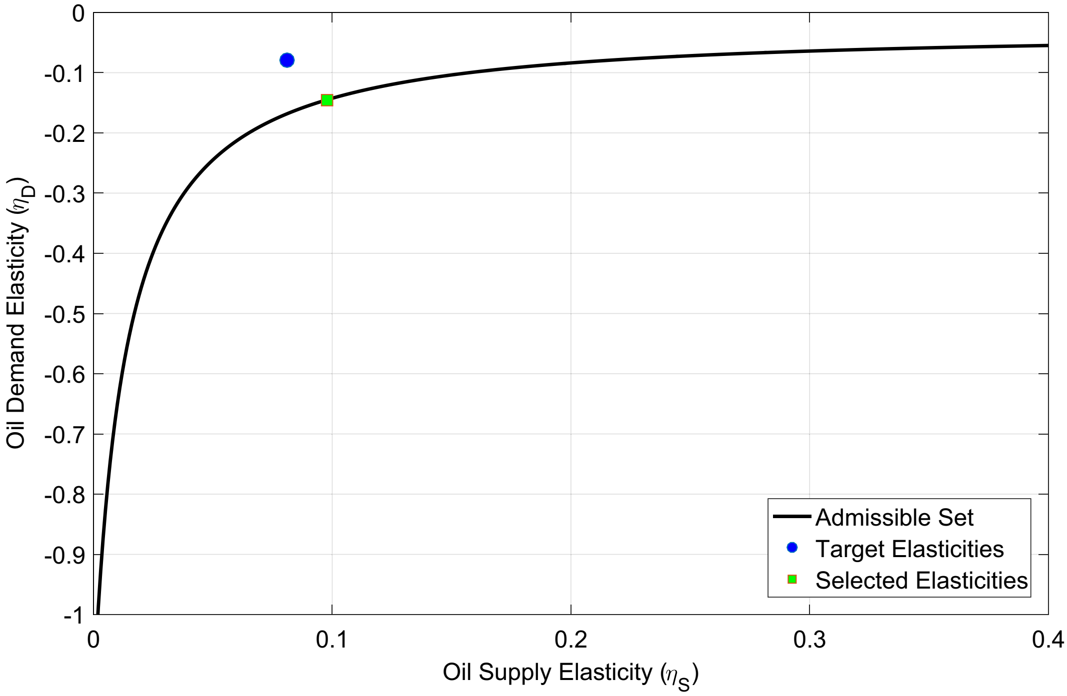


Fig. 2. Oil Demand and Supply Elasticities Implied by the VAR Model: Baseline VAR Specification
Note: The solid line plots the relationship between the price elasticity of oil supply and oil demand implied by the baseline structural VAR model described in Section 2. The blue circle corresponds to the elasticities estimated in Section 3 ($\eta_S^* = 0.081, \eta_D^* = -0.080$). The green square corresponds to the elasticities selected by our identification scheme ($\eta_S = 0.10, \eta_D = -0.14$). See Section 2 for additional information. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

selects the pair of elasticities on the curve that are as close as possible to the targets, assigning a larger weight to the elasticity that is more precisely estimated.

In our application, the identification selects $\eta_S = 0.10$ and $\eta_D = -0.14$, denoted by the green square in Fig. 2. Both values are close to their target.

In sum, standard VAR models of the oil market face a trade–off in the selection of the oil supply and demand elasticities. For instance, the same model can be identified restricting the oil supply elasticity to using a common value in the literature (for instance 0), only to imply an oil demand elasticity which is at the high end of the empirical estimates; by contrast, the model can be identified restricting the oil demand elasticity to a value in the ballpark of empirical estimates (for instance -0.05), only to imply an oil supply elasticity which is implausibly large. Our approach eases this potential tension by making use of external information on both elasticities to select a model with oil elasticities that are as close as possible to empirically plausible values.

2.3. The role of oil demand and oil supply elasticities

One could argue that an oil supply elasticity of, say, 0.01 is not meaningfully different from an elasticity of, say, 0.05. In this subsection, we show that this is not the case. Small changes in the oil price elasticities have large and material implications for quantifying the determinants of fluctuations in oil prices and oil production. Fig. 3 illustrates this result by plotting—for our baseline model—the share of the forecast error variance at horizon zero for oil prices and for oil production that is attributable to oil shocks, as a function of the oil supply elasticity η_S.

Consider the case in which the supply elasticity is assumed to be zero, the value used in Kilian (2009). By assumption, setting a zero supply elasticity implies that oil production is exogenous within the month, as the supply curve is perfectly inelastic. Accordingly, as shown by the red line in the right panel of Fig. 3, all of its forecast error variance is accounted for by the oil supply shock. However, an additional implication of setting a zero supply elasticity is that, as shown in the left panel, almost all of the forecast error variance of oil prices—about 95%—is explained by the oil-specific demand shock. This is due to the fact that the demand curve implied by the VAR is highly elastic. Thus, setting $\eta_S = 0$ implies a disconnect between the drivers of oil production and the drivers of oil prices: oil production moves in response to shocks to oil supply, whereas oil prices move in response to shocks to oil demand.

Fig. 3 also shows that small variations in the oil supply elasticity significantly alter the relative importance of oil-specific supply and demand shocks in accounting for fluctuations in the price of oil. In particular, a value of η_S close to 0.1, similar

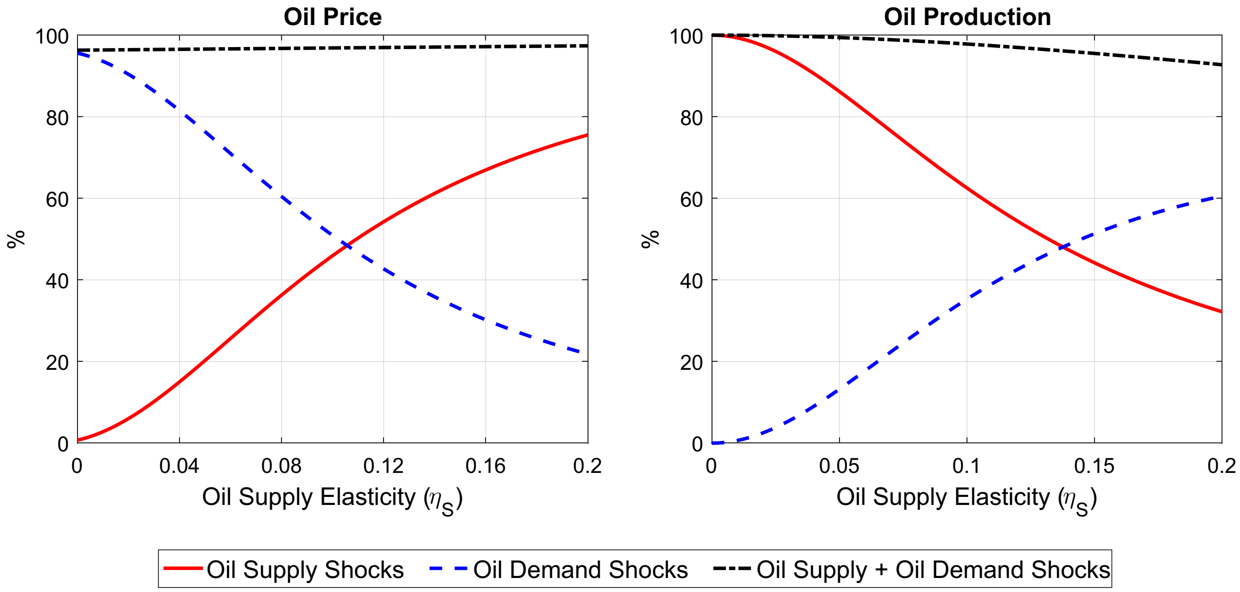


Fig. 3. Forecast Error Variance Decomposition – Impact Horizon Baseline VAR Specification
Note: Fraction of forecast error variance in oil price (left panel) and oil production (right panel) at horizon zero explained by oil supply shocks (solid red line), oil demand shocks (dashed blue line), and the sum of oil supply and oil-specific demand shocks (dashed-dotted black line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to that selected by our identification strategy, implies that the two shocks are equal drivers of oil prices and oil production. Thus, for sufficiently upward-sloping supply curves and sufficiently downward-sloping demand curves, the two oil shocks jointly affect oil prices and production, and there is no disconnect between drivers of oil production and drivers of oil prices.[13]

3. IV Estimates of oil supply and demand elasticities

This section provides empirical evidence about the price elasticity of global supply and demand for crude oil by estimating instrumental variable (IV) panel regressions. This evidence provides the basis for the target elasticities that we impose to identify the structural VAR.

3.1. A Stylized model of the global oil market

Our starting point is a small, stylized empirical model that provides the basis for estimating oil supply and oil demand elasticities starting from individual countries' oil production data. The empirical model posits that the global oil market consists of N countries, and has the following structure:

$$\Delta q_{S,i,t} = \eta_S \Delta p_t + u_{S,i,t}, \forall i = 1, \ldots, n, \tag{11}$$

$$\Delta q_{D,i,t} = \eta_D \Delta p_t + u_{D,i,t}, \forall i = 1, \ldots, n, \tag{12}$$

$$\sum_{i=1}^{N} \omega_{S,i} \Delta q_{S,i,t} = \sum_{i=1}^{N} \omega_{D,i} \Delta q_{D,i,t}. \tag{13}$$

Eq. (11) is the oil supply schedule in country i. According to this equation, the log change in country i's production of crude oil ($\Delta q_{S,\,i,\,t}$) for month t depends on the log change in the price of crude oil Δp_t and on a country-specific oil supply shock $u_{S,\,i,\,t}$. Eq. (12) is the oil demand schedule in country i. According to this equation, the log change in country i's consumption of crude oil ($\Delta q_{D,\,i,\,t}$) for month t depends on the log change in the price of crude oil and on a country-specific oil demand shock $u_{D,\,i,\,t}$. The coefficients η_S and η_D denote the price elasticity of supply and demand, respectively. We assume, for

[13] The supplementary material places our identification strategy in the context of the old and new VAR literature—surveyed in Stock and Watson (2016)—studying the macroeconomic effects of oil shocks.

simplicity, that there are common demand and common supply elasticities across countries, but we relax these assumptions in the robustness exercises presented below.

Finally, Eq. (13) is the global market-clearing condition. According to this condition, changes in global oil production (weighted by the country's production share ω_S) must be equal to changes in global oil consumption (weighted by the country's consumption share ω_D). This formulation of the global oil market allows for individual countries to run oil trade imbalances. Through this formulation we implicitly assume that changes in global oil inventories play a secondary role in shaping the ups and downs of oil supply and oil demand. This working hypothesis is supported by the analysis in the supplementary material, in which we show that augmenting the baseline VAR to include the change in global oil inventories has only a modest effect on the results.

We can express the change in the equilibrium oil price as follows:

$$\Delta p_t = \sum_{i=1}^{N} c_{S,i} u_{S,i,t} + \sum_{i=1}^{N} c_{D,i} u_{D,i,t}, \tag{14}$$

where the reduced-form coefficients $c_{S,\,i}$ and $c_{D,\,i}$ depend on the elasticities η_S and η_D, and on the country weights $\omega_{S,\,i}$ and $\omega_{D,\,i}$.[14] Eq. (14) shows that the equilibrium oil price depends on the supply and demand shocks realized in each country. The straightforward implication is that running country–specific OLS regressions based on either Eq. (11) or Eq. (12) would yield biased estimates of η_S and η_D, since, for each country i, the regressor Δp_t is correlated with the shocks $u_{S,\,i,\,t}$ and $u_{D,\,i,\,t}$. In order to circumvent this problem, we use large exogenous drops in oil production in *other* countries as instrumental variables for oil prices in Eqs. (11) and (12). Intuitively, if events leading to oil supply disruptions in other countries are truly exogenous, they should affect oil supply and oil demand in a particular country only through their effect on prices. This way, we obtain unbiased estimates of η_S and η_D by regressing production and consumption in each country against the component of prices that is explained by the exogenous shocks in other countries.[15]

Our approach yields unbiased estimates when the oil supply and oil demand shocks identified in a specific country are orthogonal to oil shocks taking place in other countries within the same month. In our application, this condition is violated during the Iraq invasion of Kuwait in August 1990, which led to supply disruptions in multiple countries. For this reason, we classify shocks that take place in multiple countries within the same month as one single episode, and impose the orthogonality assumption at the episode-level aggregation. Additionally, our stylized model rules out any interactions between the oil market and global economic activity, unlike in our structural VAR model, in which industrial production affects, and responds to, global oil production. We control for these channels by controlling for industrial production in the estimation of the country-specific regressions.

3.2. Construction of the instruments

We describe the construction of the instruments in three steps. First, we use the example of the Gulf War to revisit the evidence on the oil supply elasticity presented in Kilian and Murphy (2012), in which a single episode of a large drop in oil production in two countries is used to infer the global oil supply elasticity. Second, we generalize this example using data on oil production for 21 countries for the sample from 1985 to 2015, and compile a list of 29 episodes of large, country-specific drops in oil production. Third, we use narrative records to classify these episodes as either exogenous (e.g., the result of wars or natural disasters) or endogenous (e.g., the response to falling oil prices). For each individual country we construct an instrument that sums for, each month, all the exogenous drops in oil production occurring in the other countries.

3.2.1. The example of the gulf war

Prima facie, the events of the Gulf War appear ideal candidates to derive estimates of the oil supply elasticity. On August 2, 1990, Iraqi forces invaded Kuwait. Within one month, oil production in Iraq and Kuwait fell by about 4 and 2.9% of global production, respectively. Amidst such drop in production and the associated fears about a potential escalation of the war, the real price of crude oil rose in August 1990 by 45.3%. Kilian and Murphy (2012) argue that in August 1990 there was ample spare capacity in global oil production, as well as unanimous willingness among oil producers to increase production to offset the adverse price effects of market fears about a wider war. In August 1990, all oil producers excluding Iraq and Kuwait increased production only by 1.17%. According to their analysis, the implied oil supply elasticity could not exceed $\eta_S = 1.17/45.3 \equiv 0.0258$, a value that they take as an upper bound. However, case studies can be deceptive, and the same event can easily lend itself to multiple interpretations. In fact, our interpretation is that geopolitical events that unfolded in August 1990 show how even this single episode can be used to rationalize an oil supply elasticity that is larger than this upper bound.

[14] With two countries only, the equilibrium price can be written as follows (omitting the time subscripts for simplicity): $\Delta p = -\frac{\omega_{S,1}u_{S,1}+\omega_{S,2}u_{S,2}}{\eta_S-\eta_D} + \frac{\omega_{D,1}u_{D,1}+\omega_{D,2}u_{D,2}}{\eta_S-\eta_D}$, so that $c_{S,1} = \frac{-1}{\eta_S-\eta_D}\omega_{S,1}$, and $c_{D,1} = \frac{1}{\eta_S-\eta_D}\omega_{D,1}$, for instance. Accordingly, a sufficient condition for supply shocks to reduce the price and demand shocks to increase the price is that the supply elasticity η_S is positive and the demand elasticity η_D is negative.

[15] Mohaddes and Pesaran (2016) use a GVAR to analyze the international transmission of country-specific oil supply shocks. As in the GVAR approach, we study the global oil market by exploiting the information contained in country-level data on oil production and oil consumption. However, an upshot of our approach is that we focus on episodes of large changes in a country's oil production in order to derive estimates of both oil demand and oil supply elasticity.

Table 1
Large country-specific drops in crude oil production.

Date	Country	Event	Exogenous?	% of Global oil prod.	% of Domestic oil prod.	Narrow crit.[a]	Broad crit.[b]
Jan 1985	Iran	War	✓	−1.03	−22.32		✓
May 1985	Saudi Arabia	OPEC		−1.62	−25.36		✓
Jun 1985	Nigeria	OPEC		−0.67	−24.15		✓
Jan 1986	Nigeria	OPEC		−0.79	−27.28		✓
Apr 1986	Norway	Strike	✓	−0.97	−62.36		✓
Apr 1986	Qatar	N\A		−0.28	−48.46		✓
Jul 1986	Egypt	OPEC		−0.26	−20.13		✓
Sep 1986	Nigeria	OPEC		−0.79	−26.35		✓
Sep 1986	Saudi Arabia	OPEC		−2.64	−25.09	✓	✓
Oct 1986	Egypt	OPEC		−0.21	−12.71		✓
Jan 1987	Saudi Arabia	OPEC		−2.06	−22.46	✓	✓
Mar 1987	Ecuador	Earthquake	✓	−0.40	−82.56		✓
Sep 1987	Iran	War	✓	−0.97	−22.24		✓
Jan 1988	U.A.E.	OPEC		−0.81	−28.63		✓
Jan 1989	Saudi Arabia	OPEC		−2.82	−26.10	✓	✓
Aug 1990	Iraq	War	✓	−4.03	−70.59	✓	✓
Aug 1990	Kuwait	War	✓	−2.90	−94.59	✓	✓
Aug 1990	U.A.E.	Geopolitics	✓	−0.66	−19.51		✓
May 1992	Russia	Anticipated		−0.86	−6.32		✓
Oct 1995	Mexico	Hurricanes	✓	−1.37	−30.37		✓
Jun 1997	Iraq	Geopolitics	✓	−1.07	−54.33		✓
Dec 2000	Iraq	Geopolitics	✓	−2.07	−51.87	✓	✓
Jun 2001	Iraq	Geopolitics	✓	−2.61	−61.96	✓	✓
Apr 2002	Iraq	Geopolitics	✓	−1.95	−51.69		✓
Dec 2002	Venezuela	Geopolitics	✓	−2.83	−65.68	✓	✓
Apr 2003	Iraq	War	✓	−1.88	−96.14		✓
Sep 2005	U.S.A.	Hurricane	✓	−1.33	−18.94		✓
Sep 2008	U.S.A.	Hurricane	✓	−1.39	−20.51		✓
Mar 2011	Libya	Civil War	✓	−1.38	−77.61		✓

Note: The entries in the table list large drops in oil production identified by using the criteria described below.
[a] Narrow criterion: Domestic oil production in month t drops by more than 2 percent of global oil production.
[b] Broad criterion: Domestic oil production in month t drops by: (1) more than 0.66% of global oil production, and (2) more than 19.5% and (3) more than 4 standard deviations; OR domestic oil production in month t drops by: (1) more than 1 percent of global oil production, and (2) more than 50 percent; OR domestic oil production relative to a 6-month moving average drops by more than 5 standard deviations.

In August 1990 oil production in the United Arab Emirates (U.A.E.) was disrupted by geopolitical events that were clearly linked to the inception of the Gulf War. In other words, there was a shock to $u_{S,\,i}$ for the U.A.E. that was also related to the same sequence of events that ultimately led to the shocks $u_{S,\,i}$ in Iraq and Kuwait. On July 17, 1990, then-Iraq's President Saddam Hussein openly threatened to use force against Arab oil-exporting nations if they did not curb their excess production. Even though President Hussein did not mention countries by name, all commentators agreed that the threats were clearly aimed at the U.A.E and Kuwait (Ibrahim, 1990). During the same week, Abu Dhabi National Oil Co. announced that it intended to reduce crude production by up to 30% for an indefinite period. While this action was officially taken to ensure that the U.A.E. complied with the OPEC production agreement, the timing and the fact that the U.A.E. had been in violation of the agreement for a prolonged period suggest that the move was taken in reaction to the pressure imposed by the unprecedented barrage of strong political intimidation by Iraq's top officials. All told, the U.A.E. lowered oil production in August by 19.5 percent, about 0.66% of global production. The implication for the analysis at hand is that oil production in the U.A.E. should be excluded from global oil production for the calculation of the oil supply elasticity. Consequently, since in August 1990 global oil production excluding Iraq, Kuwait, and the U.A.E. increased by 1.97 percent, the estimate of η_S becomes 0.045, nearly twice as large as the estimate in Kilian and Murphy (2012).

3.2.2. Identifying large drops in oil production

We generalize the analysis of the Gulf War by using quantitative criteria to detect similar episodes of large drops in oil production.

Table 1 presents the candidate country–month pairs selected using our criteria. Our first criterion—the narrow criterion—selects observations for which oil production in country i during month t drops by more than 2% of global oil production, a threshold inspired by the drop in oil production experienced by Iraq and Kuwait in August 1990. As shown in the table, the narrow criterion selects only eight country–month pairs: Saudi Arabia in September 1986, January 1987, and January 1989; Iraq and Kuwait in August 1990; Iraq in December 2000 and June 2001, and Venezuela in 2002.

Our second criterion—the broad criterion—defines multiple thresholds calibrated to select a larger set of drops in a country's oil production. These drops are either large relative to a country's own past production, or relative to global production. In particular, the three thresholds that comprise the broad criterion—described in the note to Table 1—are designed to capture the drops in oil production of Iraq, Kuwait, *and the U.A.E.* in August 1990. All told, as shown in Table 1, the broad criterion singles out 29 country–month pairs.

3.3. Narrative analysis: Sources of oil shocks

After selecting candidate country–month pairs, we move to the construction of the instruments, starting with the identification of the causes underlying each episode. Our goal is to classify these episodes as either endogenous—cuts in production taken in response to oil price changes—or as exogenous, cuts in production due, for instance, to geopolitical events or natural disasters. The supplementary material describes our narrative classification in greater detail.

Two sources are the backbones of the narrative characterization and classification of the episodes selected through our quantitative criteria. For the episodes before 1991, we rely exclusively on the Oil Daily published by the Energy Intelligence Group. For the episodes from 1991 onward, we rely on information from the Oil Market Report (OMR) of the International Energy Agency (IEA). To complement the information from the Oil Market Report, we also use the Oil Daily.

In our sample, the quantitative criteria detect two instances of concurrent large production drops in more than one country. In April 1986, large production drops occurred in Qatar and Norway. We classify the drop in Qatar as endogenous, and the drop in Norway as exogenous. In August 1990, large production drops occurred in Iraq, Kuwait, and the U.A.E., which we classify as exogenous.

Based on our narrative analysis, we find that country-month pairs identified using the narrow criterion exhibit, on average, larger drops than those selected with the broad criterion, an outcome which had to be expected. Interestingly, we also find that endogenous episodes were typically characterized by drops that were, on average, smaller than those associated with exogenous episodes. More specifically, through the narrow criterion we select three endogenous and five exogenous country–month pairs, with all five exogenous episodes related to wars and geopolitical events. Among these eight episodes, the average production drop expressed as percent of global oil production was 2.5 and 2.9% for endogenous and exogenous episodes, respectively. Using the broad criterion, we select 12 endogenous and 17 exogenous country–month pairs. Among these 29 episodes, the average production drop was 1.15 and 1.7 percent for endogenous and exogenous episodes, respectively. Furthermore, when we aggregate the August 1990 drops for Iraq, Kuwait, and the U.A.E. into a single episode, the average output drop for the 15 exogenous episodes was 1.9%.

3.3.1. Endogenous large oil production drops

Out of the 29 episodes selected through the broad criterion, we classify 12 of them as endogenous. Ten of these 12 episodes involved output cutbacks by oil producers aimed at curbing conditions of oversupply glutting the global oil market and, therefore, at either stabilizing or shoring up prices. Eight of these cutbacks emerged as outcomes of decisions taken by OPEC countries, namely Saudi Arabia, Nigeria, and the U.A.E. These decisions to restrain production were part of efforts by OPEC to bring its overall output in line with the agreed quota structure and to help support prices. As such, they represented the responses of cartel members to developments in the global oil market that caused global production and benchmark prices to deviate from their preferred targets. Two other episodes of deliberate output cutbacks involved one non-OPEC producer, Egypt, and reflected its willingness to cooperate with the cartel's efforts to keep global production in check and help stabilize prices.

The remaining two country-month pairs classified among the endogenous episodes are related to production drops in Qatar during April 1986 and in Russia during May 1992. For the former, we were not able to find any information about a major event leading to an exogenous disruption in oil production. Considering that Qatar is an OPEC member, we classify the April 1986 drop as endogenous. As for the May 1992 episode involving Russia, it was largely anticipated by market participants, being the continuation of a decline in crude oil output amidst the deep economic and political crisis that followed the dissolution of the Soviet Union.

3.3.2. Exogenous large oil production drops

Wars and adverse geopolitical events account for nine of the 15 exogenous episodes. Among these, the Gulf War in August 1990 represents the largest event encompassing the concurrent cutbacks in production in Iraq, Kuwait and the United Arab Emirates. The set of large, exogenous output drops caused by wars and geopolitical events also includes two episodes in the course of the Iran–Iraq war that had started in 1980. In January 1985 and September 1987, Iran experienced two drops in oil production following attacks by Iraqi warplanes on oil tankers calling at Iranian ports and on Iranian oil installations. Moving down Table 2 timeline of wars and geopolitical events, between the late 1990s and the early 2000s, Iraq suffered four large output drops prompted by developments relative to the United Nations' "oil–for–food" program. During April 2003 and March 2011, output drops in Iraq and Libya, respectively, were caused by the disruptions following the military actions that marked the start of the Iraq War and by the attacks of government forces on rebel-held oil fields and infrastructure in the context of the Libyan civil war.

Large exogenous output drops were also triggered by other categories of events in oil producing countries such as natural disasters and domestic political tensions. During March 1987, two devastating earthquakes in Ecuador led to extensive damage of its oil production and transportation equipment. Hurricane Roxanne in Mexico in October 1985, hurricanes Katrina and Rita in September 2005 and hurricanes Gustav and Ike in September 2008 in the U.S. caused severe damages to oil infrastructures, leading to substantial losses of crude output. As for output drops caused by domestic political tensions,

Table 2
Exogenous drops in oil production included in the instruments.

Date	Country	Event	% of Global oil prod.	Narrow instrument[a]	Broad instrument[b]
Jan 1985	Iran	Iran-Iraq War	−1.03		✓
Apr 1986	Norway	Strike	−0.97		✓
Mar 1987	Ecuador	Earthquake	−0.40		✓
Sep 1987	Iran	Iran-Iraq War	−0.97		✓
Aug 1990	Iraq+Kuwait+U.A.E.	Gulf War	−7.59	✓	✓
Oct 1995	Mexico	Hurricanes	−1.37		✓
Jun 1997	Iraq	Geopolitics	−1.07		✓
Dec 2000	Iraq	Geopolitics	−2.07	✓	✓
Jun 2001	Iraq	Geopolitics	−2.61	✓	✓
Apr 2002	Iraq	Geopolitics	−1.95		✓
Dec 2002	Venezuela	Political Unrest	−2.83	✓	✓
Apr 2003	Iraq	Iraq War	−1.88		✓
Sep 2005	U.S.A.	Hurricane	−1.33		✓
Sep 2008	U.S.A.	Hurricane	−1.39		✓
Mar 2011	Libya	Civil War	−1.38		✓

Note: The entries in the table list the episodes of large drops in oil production that comprise the narrow and broad instruments. See text for additional details.
[a] Narrow instrument: Drops in oil production that satisfy the narrow criterion discussed in Table 1 and are classified as oil supply shocks in the narrative analysis.
[b] Broad instrument: Drops in oil production that satisfy the broad criterion discussed in Table 1 and are classified as oil supply shocks in the narrative analysis.

during April 1986 a sizable portion of Norwegian crude production was shut off after a major strike by unionized caterers working on offshore fields and the subsequent lockout of oil production workers of all affiliated offshore unions, whereas during December 2002 a general national strike in Venezuela led to a substantial fall in its oil output.

3.3.3. *Comparison to existing narrative shock series*

Fig. 4 plots the time series of the exogenous production shortfalls. For comparison, our time series is plotted alongside the measure of oil supply shocks constructed following Kilian (2008). The latter is based on large drops in oil production in some OPEC countries relative to a counterfactual based on the production of other OPEC countries which did not experience such shocks and which were otherwise subject to the same global macroeconomic conditions and economic incentives.[16]

When we compare our non-zero shocks with Kilian's shocks in the same month—as shown in the inset panel—the magnitudes are similar, and correlation between the two series is very high (0.92). However, when the comparison is extended to the full set of observations in which the two series overlay, the correlation drops to 0.68, as Kilian's series, by construction, displays large swings also in periods without well-defined exogenous movements in oil production. Importantly, our shocks series signals a larger exogenous oil supply drop in August 1990—consistent with the inclusion of the United Arab Emirates along Iraq and Kuwait in the group of countries that were responsible for the shortfall in oil production—and includes shocks to non-OPEC producers.

3.4. *Estimation results*

We use monthly data from 1985 to 2015 on production and consumption of crude oil available from the U.S. Department of Energy. Data on crude oil production are available for 21 countries, while data on petroleum consumption are available for eight OECD countries. We estimate the following instrumental variable specifications:

$$\Delta p_{i,\tau} = \pi_i + \gamma \Delta v_{i,\tau} + \epsilon_{i,\tau}, \tag{15}$$

$$\Delta q^S_{i,\tau} = \alpha_{S,i} + \eta^S \widehat{\Delta p}_{i,\tau} + u^S_{i,\tau}, \tag{16}$$

$$\Delta q^D_{i,\tau} = \alpha_{D,i} + \eta^D \widehat{\Delta p}_{i,\tau} + \Psi \mathbf{X}_{i,\tau} + u^D_{i,\tau}, \tag{17}$$

where π_i, $\alpha_{S,\,i}$, and $\alpha_{D,\,i}$ are country fixed effects, τ is the time-subscript identifying the episodes of exogenous drops in oil production. Eq. (15) is the first-stage regression, where $\Delta v_{i,\tau}$ is the instrument, given by the percent change in global oil production directly accounted for by the episodes listed in Table 2. Eqs. (16) and (17) are the IV regressions for supply

[16] We reconstruct Kilian's monthly series following the methodology described in his paper, since Kilian's published oil shocks (downloaded from http://www-personal.umich.edu/~lkilian/oilshock.txt) are only made available at quarterly frequency. When the monthly shocks are converted to a quarterly frequency, the resulting series is virtually indistinguishable from the published series (their correlation is 0.9929).

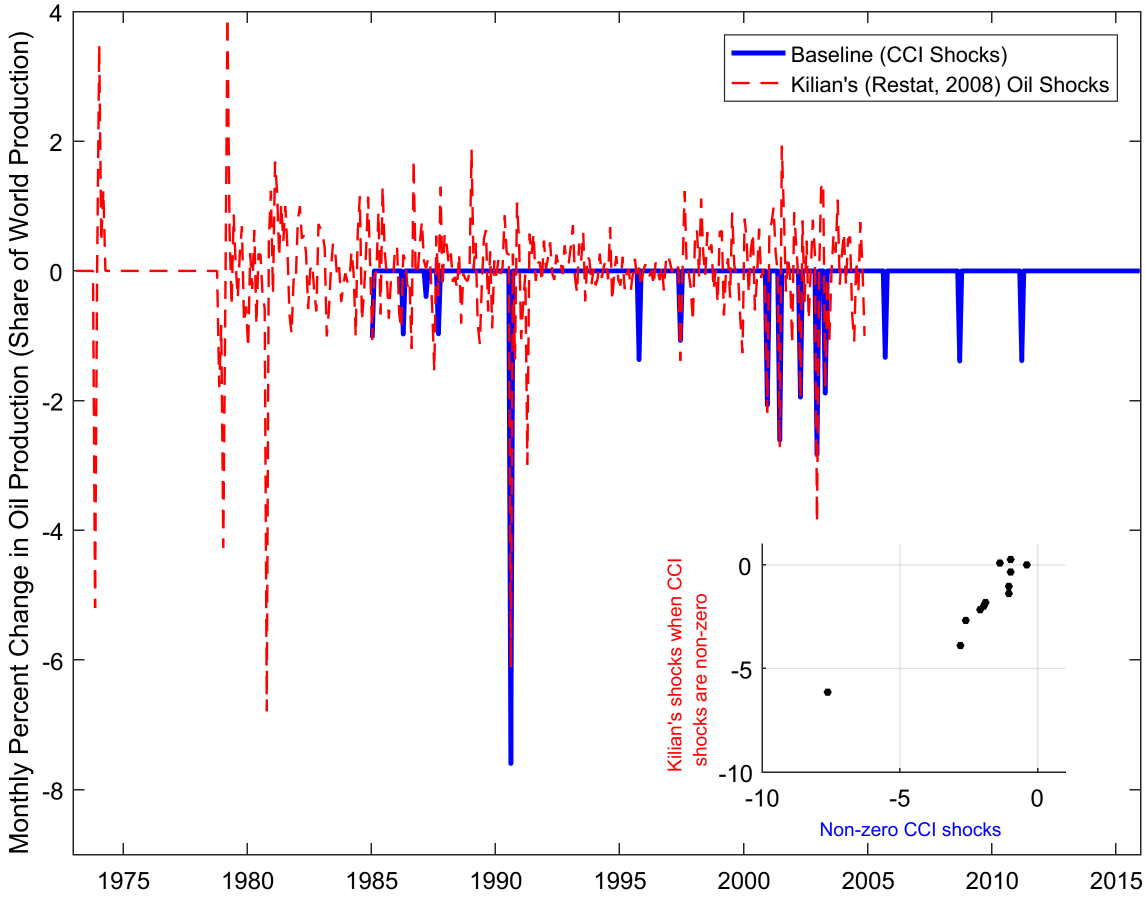


Fig. 4. Aggregate Series of Oil Supply Shocks

Note: Time-series comparison between the oil shocks series in this paper based on identified shocks from the narrative analysis and Kilian's (2008) measure of oil supply shocks. The inset panel is a scatter plot of the observations corresponding to months in which our oil supply shocks measure takes non-zero values.

and demand. In line with the structural VAR presented in Section 2, Eq. (17) controls for contemporaneous and lagged country–specific, advanced economies, and emerging economies log changes in IP, all denoted by the vector $\mathbf{X}_{i,\tau}$. For each country i, we construct country-specific instruments by excluding exogenous episodes involving that country. For instance, the instrument for the U.S. excludes the months of September 2005 and September 2008, the two months during which hurricanes Katrina and Gustav disrupted crude oil and petroleum products production in the U.S.

Panels (A) and (B) in Table 3 report results from the estimation of Eqs. (16) and (17). The OLS column presents the estimates when, trivially, $\widehat{\Delta p} = \Delta p$, while the last two columns show the IV estimates using the narrow and broad instruments discussed in the previous section.[17]

Starting with Panel (A), column 1 reports the OLS estimate of the global oil supply elasticity η_S, which is 0.021. Column 2 presents the IV estimates using the narrow instrument. The oil supply estimate constructed using IV is 0.054, larger than its OLS counterpart and statistically different from zero.[18] The last column presents the IV estimates using the broad instrument. The estimated oil supply elasticity is even larger, 0.081, and remains statistically significant (with a standard error of 0.037). As shown in the table, our instrumental variables are strong instruments for oil prices, with F-statistics above 15. Importantly, if we treat the August 1990 drop in production in the U.A.E. as endogenous, using the narrow instrument, the estimate of η_S drops to 0.029. This number is very close to the 0.026 estimate of Kilian and Murphy (2012) discussed

[17] The IV regressions do not include the months in which no exogenous oil shocks occur. We verified that including the months without exogenous oil shocks in our regressions has little bearing for our estimates.

[18] The standard errors in Table 3 are double clustered by country and time using Stata's IVREG2 command—see Baum et al. (2002). Clustering by country addresses the concern that either the data or the elasticities might be more precisely estimated for some countries than for others. Clustering by time addresses the concern that the countries are subject to a common shock each month.

Table 3
Panel estimates of the price elasticity of crude oil supply and demand.

	1. OLS	2. Narrow IV	3. Broad IV
(A.) *Price elasticity of crude oil supply*			
η_S	0.021	0.054	0.081
	[0.017]	[0.019]	[0.037]
First-stage F stat.	–	16.25	16.61
Total Obs.	7719	77	293
Countries	21	21	21
Unique Episodes	372	4	15
(B.) *Price elasticity of crude oil demand*			
η_D	−0.017	−0.031	−0.080
	[0.036]	[0.037]	[0.079]
First-stage F stat.	–	16.25	16.61
Total Obs.	2976	32	118
Countries	8	8	8
Unique Episodes	372	4	15

Note: The dependent variables in each specification are $\Delta q_{S,\,i,\,t}$ (panel A) and $\Delta q_{D,\,i,\,t}$ (panel B), the monthly change in the production and consumption, respectively, of crude oil in country *i*. The entries in the rows of the table corresponding to η_S and η_D denote the estimates of the coefficients associated with the monthly change in the real price of crude oil. The second column reports OLS estimates, while columns 3 and 4 show the IV estimates using the narrow and broad instruments described in Table 2 and in the text. Standard errors—clustered by time and country—are reported in brackets. All specifications include country fixed effects. The OLS specifications include month-of-the-year dummies. The OLS and Broad IV specifications in panel B include current and lagged log changes in country *i*'s industrial production, in advanced economies' aggregate industrial production, and in emerging economies' aggregate industrial production.

earlier. By contrast, using the broad instrument, the estimate of η_S is 0.056.[19] The use of a larger set of episodes induces a larger estimate of the oil supply elasticity irrespective of the classification of the drop in oil production in the U.A.E.

The results for the oil supply elasticity are robust to the use of alternative estimation methods. For instance, using the broad instrument, the estimate of the oil supply elasticity becomes 0.133 using the mean group estimator of Pesaran and Smith (1995). In addition, to rationalize our aggregate estimate of the supply elasticity, it is instructive to look at country–specific estimates, which uncover some heterogeneity across countries, confirming the wisdom that not all oil producers respond uniformly to movements in oil prices. When we estimate the broad instrument specification allowing for different oil supply elasticities across (1) Saudi Arabia, (2) OPEC countries excluding Saudi Arabia, and (3) non-OPEC countries, we find values of 0.212, 0.191, and −0.004, respectively.[20] These results are consistent with the observation that OPEC producers have the largest volume of spare capacity that can be used to offset disruptions in oil supply within a short period of time.

Panel (B) shows the estimates of η_D, the oil demand elasticity. The OLS estimate is −0.017. A higher elasticity in absolute value is obtained using the narrow instrument: in this case, the elasticity is −0.031, although it appears less precisely estimated than its oil supply counterpart, with a standard error of 0.037. Finally, using the broad instrument, the demand elasticity becomes larger in absolute value, with a point estimate of −0.080, and associated standard error of 0.079. The results for the oil demand elasticity obtained using the broad instrument are also robust to the use of alternative estimators. For instance, the estimate of the oil demand elasticity is −0.055 using the mean group estimator of Pesaran and Smith (1995).

All told, the demand estimates—albeit less precise than their supply counterparts—are consistent with the existing empirical evidence. In line with Dahl (1993) and Cooper (2003), we find that the demand elasticity of crude oil is small and around −0.05. Compared to these studies, our contribution is to provide an alternative identification strategy based on IV regressions. The demand elasticity of crude oil is substantially smaller than the demand elasticity of gasoline, which is typically estimated to be around −0.3. There are at least three reasons for this difference. First, as discussed in Hamilton (2009), crude oil represents about half the retail cost of gasoline, and thus the price elasticity of demand for crude oil should be about half that for retail gasoline. Second, data on petroleum consumption measure, among other things, refinery production and crude oil products supplied. The contracts underlying the deliveries of such products are typically negotiated at least a month in advance, and thus petroleum consumption might be less responsive to changes in prices within a given month relative to gasoline consumption. Third, similarly to the oil supply elasticity, the events of August 1990 have a large weight in shaping the estimates of the oil demand elasticity. In that month, despite a large rise in oil prices, oil consumption fell sharply in the European countries included in our dataset, but rose in Korea, Japan, Canada, and the United States.

[19] The estimate of η_S by Kilian and Murphy (2012) has a natural interpretation as an IV regression based on two observations: one baseline observation in which changes in oil prices and changes in oil production are assumed to be zero, and another in which prices rise by 45.3%, and the endogenous response of global production is 1.17%.

[20] The associated standard errors are 0.152, 0.086, and 0.023, respectively. As OPEC producers account for about 40% of global output, the "production-weighted" average of these estimates is again close to the estimated value of 0.081 for the global supply elasticity reported in Table 3.

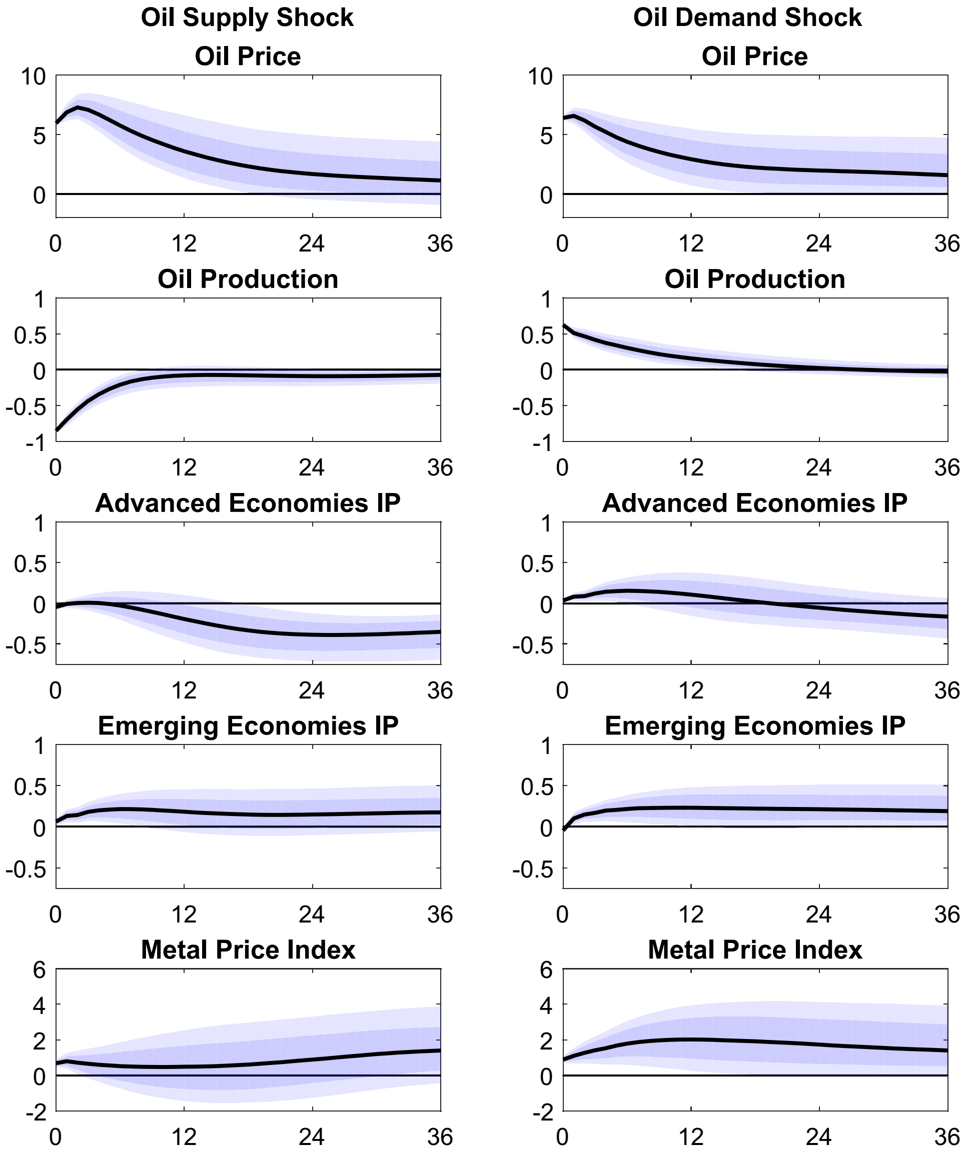


Fig. 5. Impulse Responses to Oil Market Shocks
Note: The solid lines in the left column depict median responses of the specified variable to a one standard-deviation oil supply shock, while those in the right column depict median responses to a one standard-deviation oil demand shock; The light shaded bands represent the 90% pointwise credible sets and the dark shaded bands represent the 68% pointwise credible sets. All variables are expressed in log changes (multiplied by 100).

4. VAR results

In our identification strategy, we set the target supply and demand elasticities to the point estimates reported in Table 3 for the case of the broad instrument, that is, $(\eta_S^*, \eta_D^*) = (0.081, -0.080)$. We choose the estimates obtained using the broad instrument as they rely on a large set of observations, and as they hew closely to the VAR admissible set shown in Fig. 2. We set the weights matrix V in Eq. (10) to be diagonal, with the entries equal to the variances associated with the point estimates of the elasticities from Table 3. The resulting elasticities are $\eta_S = 0.10$ and $\eta_D = -0.14$.

4.1. Impulse responses

The solid lines in the left column of Fig. 5 show the impulse responses to a one-standard deviation oil supply shock. An unanticipated disruption in oil supply reduces production by about 0.8% and leads to a persistent increase in oil prices, which rise by 6% on impact and remain elevated thereafter. On the activity side, IP in advanced economies declines gradually, bottoming out at -0.4% two and a half years after the shock. In contrast, IP in emerging economies rises somewhat, peaking after six months at 0.2% above its pre-shock level.

The increase in industrial production among emerging countries is puzzling given that our sample does not include some of the largest oil exporters, thus being, in the aggregate, oil independent.[21] To investigate this result, we compute the response to an oil supply shock of country-specific IP for the eight largest emerging economies. The responses are indicative of a broad-based increase in industrial production, except for Mexico and India.[22] These responses also seem to corroborate the evidence of an "Asian puzzle:" Aastveit et al. (2015) find, using a FAVAR model, that activity—measured by GDP—in many emerging Asian economies rises after a negative oil supply shock, even for oil-importing countries. They suggest that the "Asian puzzle" can be explained by the low consumption and high investment shares in GDP, by their high trade openness, and by the prevalence, in many countries, of price controls that attenuate the pass-through of changes in oil prices.[23]

The right column of Fig. 5 shows the responses to an oil demand shock. The shock leads to an increase in oil prices of about 6% and induces a rise in oil production of about 0.6%. The near-term response of IP in advanced and emerging economies is similar, with IP increasing mildly in both groups of economies for six months. Thereafter, real activity contracts in advanced economies while remaining elevated in emerging economies, even though the responses are quantitatively small.

Fig. 6 traces out the effects of the three global activity shocks. The left and middle columns plot the responses to a shock to activity in the advanced and emerging economies, respectively, while the right column shows the responses to a metal price shock. The three shocks generate correlations that are typical of demand-driven business cycle fluctuations: The increase in real activity in advanced and emerging economies—the latter accompanied by a persistent increase in metal prices—is associated with a rise in both oil prices and oil production.

Positive shocks to activity in emerging economies and positive shocks to metal prices induce a persistent increase in oil prices. By contrast, higher activity in advanced economies induces only a mild and short-lived increase in oil prices. The positive response of IP in advanced and emerging economies to a shock to the metal price index supports the view that metal prices are a leading indicator of current and expected global activity. Additionally, our findings are also consistent with the literature that emphasizes shocks to commodity prices as drivers of business cycles in emerging economies (IMF, 2015).

4.2. Forecast error variance decomposition

Table 4 shows the variation in the two-year-ahead forecast error variance in oil prices, oil production, advanced economies' IP and emerging economies' IP that is attributable to the five structural shocks identified by our structural VAR model. As shown in the first row of Table 4, about two-thirds of the fluctuations in oil prices are due to disturbances that originate in the oil market, with supply and demand shocks accounting for 37 and 27%, respectively. Movements in global demand—mostly captured by innovations in emerging economies' IP and in metal prices—explain the remaining one-third.[24] The second row of Table 4 shows that oil production is mostly driven by oil supply and oil demand shocks, which account for 43% and 36% of its volatility, respectively.

The third and fourth rows of Table 4 show that, on average, oil-specific shocks contribute little to the volatility in real activity. Oil supply shocks account for 8 and 5% of the forecast error variance of advanced economies' and emerging economies' IP, respectively. The contribution of oil-specific demand shocks is about 1 and 8% for advanced and emerging economies' activities, respectively. Although activity variables are mostly driven by their own shocks, we find that shocks to metal prices account for about 19 and 28% of the forecast error variance of IP in advanced and emerging economies, respectively.

4.3. Historical decomposition

Fig. 7 displays the historical decomposition of oil prices and oil production in terms of the contribution of the separate structural shocks. One takeaway is that while on average demand and supply factors both matter for the oil market, their relative importance varies across episodes. To illustrate this point, we zoom in on four important episodes involving large changes in the price of oil: the Gulf War, the Asian financial crisis, the global financial crisis, and the 2014–2015 oil price slump.[25]

Panel 7a reports the decomposition for the period of the Gulf War. In line with the narrative analysis, the model attributes all the drop in oil production in August 1990 and the associated increase in oil prices to an oil supply shock, caused

[21] Monthly data on IP are not available for many OPEC countries, including Saudi Arabia, Iran, Iraq, and Nigeria.

[22] The disaggregated VAR impulse responses are shown in the supplementary material.

[23] Peersman and Van Robays (2012) find that oil supply shocks that temporarily increase oil prices boost activity in all emerging economies in Asia as well as in Brazil and Peru. Iacoviello (2016) finds that oil-exporting countries experience a rise in consumption and GDP following supply-driven increases in oil prices.

[24] The point estimates reported in the table are computed using the OLS estimates of the reduced-form parameters. The sample used for the estimation of the reduced-form coefficients includes both actual data and the dummy observations used to implement the Minnesota prior.

[25] We compute the historical decomposition using the OLS estimates of the reduced-form parameters. The sample used for the estimation of the reduced-form coefficients includes both actual data and the dummy observations used to implement the Minnesota prior. We calculate the cumulative effects on each variable of shocks that materialized from the onset of the event onwards, setting all previous shocks to zero, which explains why the vertical bars in Fig. 7 do not sum to the actual data.

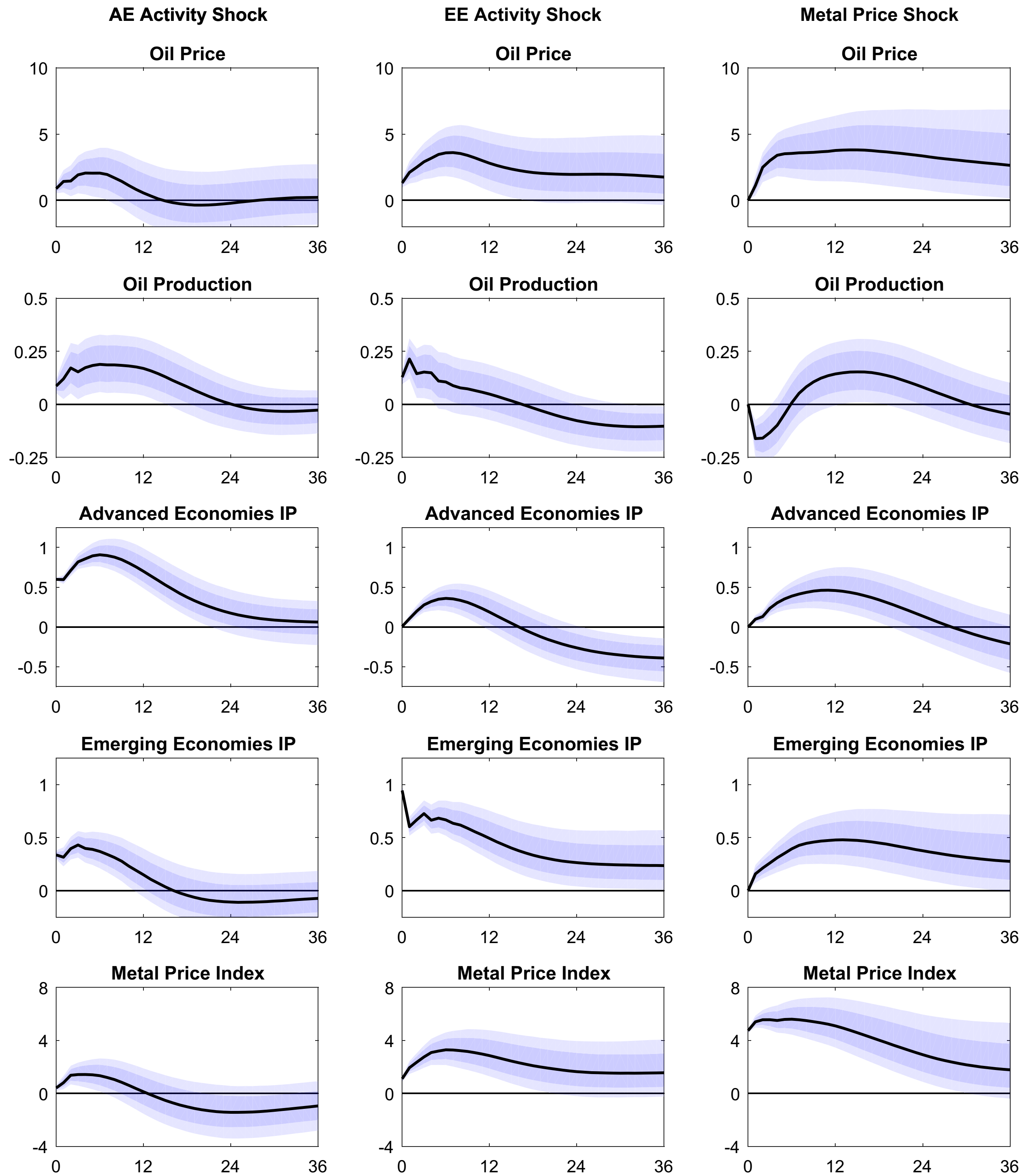


Fig. 6. Impulse Responses to Global Activity Shocks
Note: The solid lines in the left column depict median responses of the specified variable to a one standard-deviation shock to advanced economies' activity, those in the middle column depict median responses to a one standard-deviation shock to emerging economies' activity, and those in the right column depict median responses to a one standard-deviation metal price shock; The light shaded bands represent the 90 percent pointwise credible sets and the dark shaded bands represent the 68 percent pointwise credible sets. All variables are expressed in log changes (multiplied by 100).

Table 4
Forecast error variance decomposition of selected variables 24-month ahead.

Shock	Oil supply	Oil demand	AE activity	EE activity	Metal prices
Oil prices	36.6	26.5	2.5	13.1	21.3
	[24.3; 46.7]	[16.6; 36.2]	[1.7; 7.7]	[5.9; 22.8]	[9.9; 32.8]
Oil production	42.6	36.0	9.8	4.1	7.6
	[32.1; 49.5]	[25.8; 42.2]	[4.7; 17.5]	[2.8; 9.3]	[3.9; 15.5]
AE activity	8.1	1.4	64.2	7.6	18.8
	[2.4; 18.1]	[0.9; 6.8]	[48.0; 70.9]	[5.1; 13.3]	[8.7; 29.9]
EE activity	5.1	7.5	10.4	48.7	28.3
	[1.5; 13.6]	[2.0; 16.5]	[7.0; 16.6]	[34.1; 59.0]	[14.9; 39.6]

Note: The entries in the table denote the share of the forecast error variance of a specified variable at the 24-month horizon that is attributable to five structural shocks. The 16th and 84th percentiles of the posterior distributions are reported in bracket. See Section 4.2 for details.

by simultaneous drop in production in Iraq, Kuwait, and the U.A.E. Starting in September 1990, the model attributes the continued rise in oil prices both to oil supply and oil demand, in roughly equal proportions.

Panel 7b focuses on the Asian Financial Crisis. The decline in the demand of oil from emerging economies—which the model captures through shocks to emerging economies' activity and to metal prices—induced downward pressure on oil prices, accounting for about one-third of their decline. Throughout this period, our model also attributes a nontrivial role in the decline of the price of oil to supply shocks. We rationalize this finding by noting that, despite a lower demand for oil from emerging countries, a few oil exporters, most notably Iraq, increased production.

Panel 7c shows the decomposition during the global financial crisis from July 2008 to December 2009. Initially, the model attributes much of the decline in the price of oil to negative oil-specific demand shocks, because of the simultaneous decline in oil production and the relatively small movements in measures of global activity. Global activity shocks become prominent drivers of oil prices toward the end of 2008, when IP for both advanced and emerging economies begins to rapidly decline. Supply shocks over 2007–2008 (showing up as unexpected increases in global oil production) were partly responsible for the decline in oil prices.

Finally, Panel 7d displays the estimated historical decompositions for the July 2014–December 2015 period, characterized by a major slump in the real price of oil. Our decomposition attributes most of this decline to supply shocks, likely resulting from the enduring expansion in shale oil production in Canada and the United States.[26]

4.4. Accounting for the VAR results

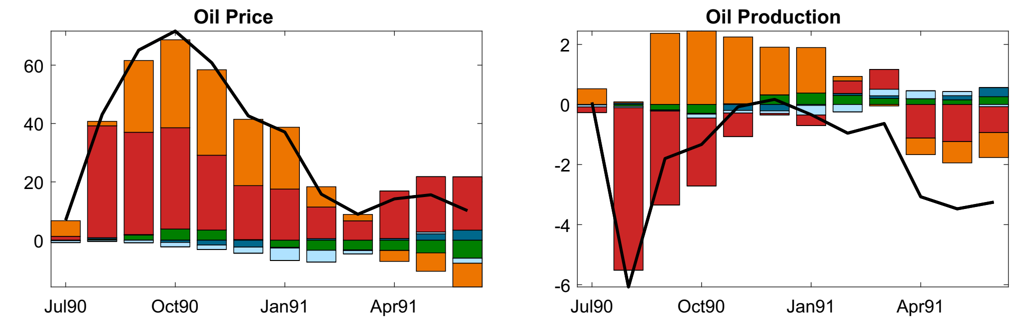
What are the modeling assumptions driving the main results? Table 5 compares the two-year forecast error variance decomposition of oil prices in our VAR to that of alternative models which differ for the choice of variables, sample period, and identification assumptions.[27] The central finding is that the short-run oil supply elasticity is the key determinant for the importance of oil supply shocks in oil price fluctuations.

The top row summarizes our baseline VAR, estimated from 1985 through 2015, and featuring a supply elasticity of 0.10 and a demand elasticity of -0.14. Under our baseline identification, shocks to oil supply and shocks to global demand account for 36.5 and 37 percent of the fluctuations in oil prices, respectively. By contrast, under an identification scheme in which the oil supply elasticity is restricted to be zero (row 2), the volatility of oil prices that is explained by oil supply shocks drops to 2 percent, while the contribution of global demand shocks remains as high as in the baseline. Rows 3, 4 and 5 modify the baseline VAR with a different set of variables, each time re-estimating supply and demand elasticities by using the minimum distance approach described in Section 2. Rows 3 and 4 show that adding oil inventories to our VAR, as done by Kilian and Murphy (2014) and Baumeister and Hamilton (2017), does not materially change our results. Row 5 considers the role of the metal price index. Dropping metal prices from our specification enhances the contribution of oil supply shocks to fluctuations in oil prices, while reducing the contribution of global demand shocks. Row 6 replaces our activity indicators with Kilian (2009)'s indicator of real activity based on ocean freight rates (*rea*). Oil supply shocks remain important drivers of oil prices, while global demand shocks contribute to 33.5 percent of the volatility of oil prices, somewhat less than in our baseline VAR.

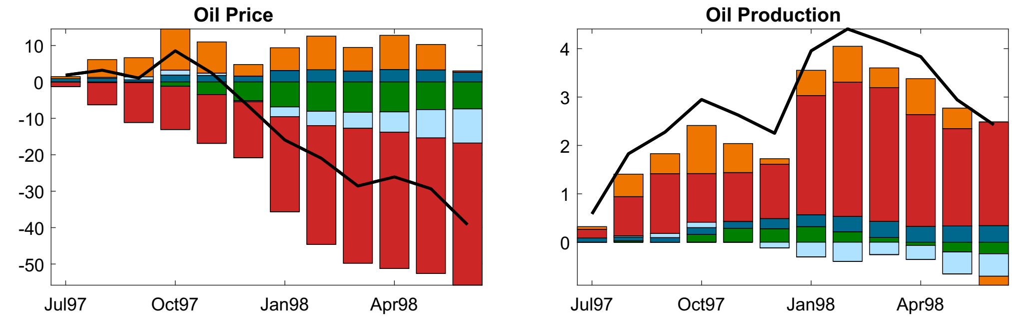
Rows 7 and 8 show that the elasticities play a crucial role in explaining the role of supply shocks to oil price fluctuations using the variables and the sample period in Kilian (2009) (see the supplementary material for details). The assumption of a zero short-run oil supply elasticity results here in a VAR-consistent demand elasticity of -3.48, a very large number, and implies that oil supply shocks play a negligible role in accounting for oil price fluctuations. By contrast, when we minimize the distance between the elasticities derived in our panel and those that are implied by Kilian's VAR specification, we derive

[26] Büyükşahin et al. (2017) have also found that unanticipated shifts in supply accounted for more than 60% of the 2014–2015 decline in oil prices and unanticipated demand shifts for the remaining part.

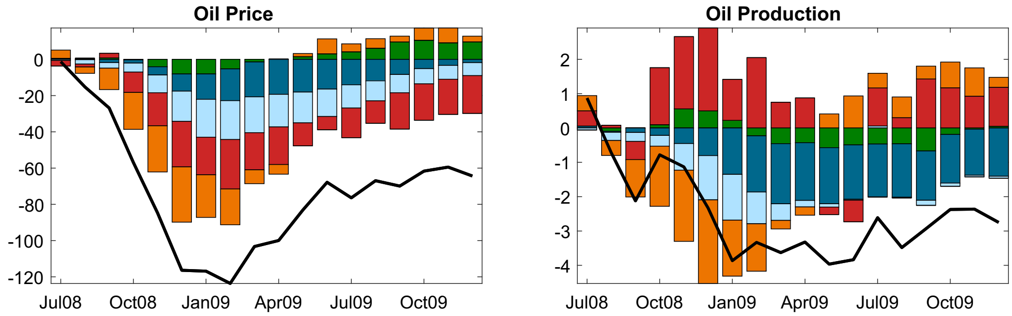
[27] The supplementary material contains details as well as a number of other robustness checks.



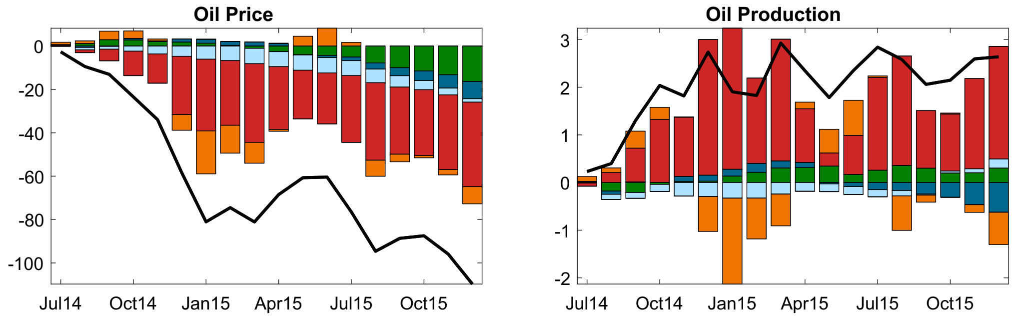
(a) The Gulf War



(b) The Asian Financial Crisis



(c) The Global Financial Crisis



(d) The 2014–15 Oil Price Slump

Fig. 7. Historical Decomposition
Note: The shaded regions in each panel depict the historical contributions of oil supply (red), oil demand (orange), advanced economies (dark blue), emerging economies (light blue), and metal price (green) shocks to the specified variable, while the solid lines depict the actual series. All variables are expressed in log changes (multiplied by 100) from the initial period of the episode. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Accounting for the VAR results.

Variables	Sample	Identification: oil price elasticities[a]	Share of oil prices explained by oil supply shocks	Share of oil prices explained by global demand shocks[b]
q, p, ya, ye, m	1985–2015	$\eta_S = 0.10,\ \eta_D = -0.14$	36.6	36.9
q, p, ya, ye, m	1985–2015	$\eta_S = 0,\ \eta_D = -1.14$	1.8	38.7
$q, p, ya, ye, m, \Delta i$	1985–2015	$\eta_S = 0.09,\ \eta_D = -0.13$	34.2	38.8
$q, p, rea, \Delta i$	1985–2015	$\eta_S = 0.09,\ \eta_D = -0.13$	46.2	34.7
q, p, ya, ye	1985–2015	$\eta_S = 0.10,\ \eta_D = -0.15$	46.9	27.8
q, p, rea	1985–2015	$\eta_S = 0.10,\ \eta_D = -0.15$	45.5	33.5
$\Delta q, p, rea$	1973–2007	$\eta_S = 0,\ \eta_D = -3.48$	1.5	28.9
$\Delta q, p, rea$	1973–2007	$\eta_S = 0.18,\ \eta_D = -0.36$	23.3	29.3

Note: Each row displays oil supply elasticities, oil demand elasticities, and the 24-month ahead forecast error variance decomposition of oil prices for alternative VAR models that change the sample, the number of variables, or the identification scheme.

[a] The elasticities are estimated with the minimum distance approach described in the paper, except in the two cases (second specification and second-to-last specification) when the supply elasticity is restricted to be equal to zero.

[b] For each VAR, global demand shocks combine the shocks to all activity indicators.

VAR-consistent elasticities of 0.18 for supply, and of −0.36 for demand. These elasticities in turn imply that supply shocks account for about one quarter of the two-year volatility in oil prices.

In sum, our findings show that the selection of the elasticities is the key reason why our baseline VAR attributes an important role to oil supply shocks as drivers of oil prices.

5. Conclusion

Using external information from a large panel of countries, we impose restrictions on the short-run price elasticities of oil supply and oil demand in order to identify a structural VAR model of the global oil market. In the estimating framework, global demand for oil is jointly captured by industrial production in advanced and emerging economies as well as by an index of metal prices. Shocks to oil supply and shock to global demand each account for about one-third of the fluctuations in oil prices at business cycle frequencies. An increase in oil prices driven by oil supply shocks depresses industrial production in advanced economies, while it boosts industrial production in emerging economies, thus helping explain the muted effects of changes in oil prices on global economic activity.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2018.08.004.

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