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News, Noise and Oil Price Swings

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Non-Technical Summary

In the past years oil prices have dropped from the peak of US$ 112 in June 2014 to the trough of US$ 27 in January 2016, and before the recent financial crisis they peaked at above US$ 145 in July 2008 and bottomed out at US$ 32 in December. As of the second half of 2016, prices have recovered and now hover at around $ 50. Oil price fluctuations still continue to catch both policy makers and practitioners by surprise.

The benchmark framework for identifying oil price shocks is due to Kilian (2009), who identifies three main determinants of oil price fluctuations: oil production, global demand, and precautionary demand shocks (or oil-specific demand shock). However, we argue that fluctuations in oil prices are also driven by expectations about future developments in the oil market and they can be explained as the agents' reactions to news about oil market fundamentals. The presence of a forward-looking component in the real price of oil complicates the identification of structural shocks.

In this paper, we solve the issue of identifying the forward-looking component in the real price of oil. We argue that oil prices fluctuate due to news about future developments in the oil market. However, some news will materialize and affect oil fundamentals, while other news is pure noise and has only a temporary impact on prices. We show that the oil-specific demand shock in Kilian (2009) can be interpreted as a "news" shock and it can be disentangled into noise and fundamental (or anticipated) components.

We propose an econometric model to disentangle the impact of news on oil price fluctuation between the fundamental (or anticipated) and the noise components (shocks). Building on Forni et al. (2017a and 2017b), we assume agents receive an imperfect signal of future developments in the oil market. We use both a simple three-variable VAR in the spirit of Kilian (2009) where the spot price is interpreted as the signal, and a richer specification including non-energy commodities prices, an index of financial conditions and an additional indicator of US economic activity.

We show that the anticipated shock has a permanent effect on oil production and oil prices, but a temporary impact on global demand. On the other hand, the noise shock has no statistically significant effect on oil production, and a temporary impact on oil prices and global demand.

News, Noise and Oil Price Swings*

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Abstract

We interpret oil price fluctuations as the result of agents reaction to news about oil market fundamentals. Agents form expectations about future developments in oil production with limited information, and they only observe a noisy signal about its possible changes. We find that a large part of oil price swings is attributable to shocks that do not have any effect on oil production or global demand indexes. The finding is obtained using a VAR with dynamic rotations. We interpret this shock, through the lenses of a simple imperfect information rational expectations framework, as a noise shock in the oil market.

JEL classification: C32, E32, E62.

Keywords: Oil price shocks, Bubbles, Nonfundamentalness, SVAR, Imperfect Information.

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"Current prices are 'irrational' and should certainly be higher than $ 30 a barrel."

Khalid Al-Falih, Chairman of Saudi Aramco, 21 January 2016.

"We are very bearish for the first half of the year. In the second half, every tank and swimming pool in the world is going to fill and fundamentals are going to kick in."

Bob Dudley, BP CEO, 10 February 2016.

"Thus, the supply-demand fundamentals seem consistent with the view now taken by market participants that the days of persistently cheap oil and natural gas are likely behind us."

Ben S. Bernanke, Chairman of the Federal Reserve Bank, 15 June 2006.

1 Introduction

In the past years oil prices have dropped from the peak of US$ 112 in June 2014 to the trough of US$ 27 in January 2016, and before the recent financial crisis they peaked at above US$ 145 in July 2008 and bottomed out at US$ 32 in December. As of the second half of 2016, prices have recovered and now hover at around $ 50. While oil price fluctuations still continue to catch both policy makers and practitioners by surprise (see Baumeister and Kilian, 2016), the benchmark framework to identify oil price shocks is due to Kilian (2009), who identifies three main determinants of oil price fluctuations: oil production, global demand, and precautionary demand shocks (or oil-specific demand shock).

However, fluctuations in oil prices are also driven by expectations of future developments in the oil market and can be attributable to some extent to market reaction to news. The presence of a forward-looking component in the real price of oil makes the identification of structural shocks more complicated, as acknowledged in Kilian and Murphy (2014) where they propose to solve this issue by including oil inventories in the VAR specification.

In this paper, we solve the issue of identifying the forward looking component in the real price of oil. We propose to look at oil price movements as the result of changes in expectations of future developments in the oil market. We argue that oil prices fluctuate due to news about future developments in the oil market. However, some news will materialize and affect oil fundamentals, while other news is pure noise and has only a temporary impact on prices. We show that the oil-specific demand shock in Kilian (2009) can be interpreted as a "news" shock and it can be disentangled into noise and fundamental (or anticipated) components.

We propose an econometric model to disentangle the impact of news on oil price fluctuation between the fundamental (or anticipated) and the noise components (shocks). Building on Forni et al. (2017a and 2017b), we assume agents receive an imperfect signal of future developments in the oil market. We use both a simple three-variable VAR in the spirit of Kilian (2009) where the spot price is interpreted as the signal, and a richer specification including non-energy commodities prices, an index of financial conditions and an additional indicator of US economic activity. We show that a sizable part of oil price swings is attributable to noise shocks that do not have any effect on oil production or global demand indexes.

Recently, large swings in oil prices have been discussed extensively in the literature. In particular, the dramatic fall in oil prices in the second half of 2014 is difficult to assess and cannot be fully explained by supply and demand dynamics. Baumeister and Kilian (2016), using a four variable VAR, show that more than half of this decline was predictable in real time; they attribute about \$11 of this predictable decline to a slowing global demand and \$16 to positive shocks to current and future oil production.[1] However, they point out the importance of the movement of any variable relative to what it was expected to be.

In fact, the oil market has undergone important structural changes[2] On the one hand, the "Shale Revolution", the technology that allows the extraction using fracking, has completely changed the perception of oil supply capacity (the narrative about available supply of oil) making it appear no longer as an exhaustible resource. As pointed out in Dale (2015), estimates of recoverable oil resources are increasing "far more quickly than existing reserves are consumed" thanks mainly to new technology. On the other hand, technological progress (e.g. the electric car, see Dale and Smith, 2016) and concerns for climate change (see the 2015 UN conference in Paris) mean that "it is increasingly unlikely that the world's reserves of oil will ever be exhausted."

On a different note, oil prices reached a peak in 2008 before the Great Recession. The price movements were explained by the narrative of "Peak Oil", the expectations that, as oil production was near the peak and demand growth seemed unstoppable, prices could only increase in the future.[3] Hamilton (2009) argues that the run-up of oil prices in 2007-08 was determined by the miscalculation of the long-run price elasticity of oil demand

[1] Büyükşahin et al. (2017) instead estimate that the effect of surprise shifts in oil supply account for more than 60% of the decline in oil prices, and demand shift for the remaining part.

[2] See Dale (2015) and Wolf (2015) for an analysis and a discussion of the structural changes in the oil market (or "New Economics of Oil").

[3] See Authers (2016) for an interesting take on 'grand narratives' in oil markets.

by market participants fueled by speculation, i.e. by investors that bought oil not as a commodity but as a financial asset. In fact, he suggests that, while it might be possible to tell a story that rationalizes the oil price swing as driven only by fundamentals, the speed and the magnitude of the price collapse tend to highlight a dynamic of a speculative price bubble that burst.

On the other hand, temporary disruption in oil production (see for example the wildfires in the Canadian oil sands region in May 2016) or the expectations of conflicts[4] may have an immediate impact on prices, but, when they do not materialize, they do not affect the fundamentals (oil production).

In this paper, we argue that news, the expectations about future developments in the oil market, is the main driver in oil prices and we propose an econometric model to disentangle the effects of noise versus fundamentals.

This paper builds on an extensive literature on the identification of oil price shocks and on their impact on real economy. Kilian (2009) was the first to break with the tradition of evaluating the effects of exogenous oil price changes (Hamilton, 2003, and Kilian, 2008, among others), and to disentangle oil supply shocks, aggregate demand shocks, and oil specific shocks, i.e. precautionary demand shocks. He argues that the exogeneity assumption of oil shocks is inappropriate because of reverse causality from macroeconomic aggregate to oil prices, and because oil prices, like other commodities, are driven by supply and demand forces. He shows that oil supply shocks have contributed very little to oil price movements, while aggregate demand shocks account for the majority of the changes. Previously, Kilian (2008) shows that exogenous oil supply disruptions have only a small impact on oil prices, suggesting that shifts in the demand for oil and the uncertainly about future oil supply disruptions have instead an important role. However, even if he does not incorporate it in the analysis, he recognizes the importance of expectations. In fact, even if oil production does not move, the expectation of future oil disruptions can significantly affect the current prices, as he finds in the case of the 1990/91 Persian Gulf War episode.

However, the presence of a forward-looking component in oil prices complicates the identification of structural shocks. If agents react to information about future developments in supply and demand not included in the econometrician's information set, market expectations will differ from the expectations constructed by the econometrician and thus make VAR models based on supply and demand invalid.

[4]See for the example expectations of disruption in oil production in Niger after the attacks by the Niger Delta Avengers in the Spring 2016 and the oil price adjustment after the announcement of a ceasefire.

On the one hand, Kilian and Murphy (2014) propose to solve this issue by including physical oil inventories in their VAR analysis, and they confirm that oil price movements are driven mainly by global demand shocks. On the other hand, several papers focus instead on speculation as the driving force of prices not explained by (current) fundamentals. They follow Hamilton's (2009) observation that oil price fluctuations have been amplified by financial speculation as a result of the "financialization" of commodities (see Masters, 2008, Tang and Xiong, 2012).

In particular, Singleton (2014) points out how informational frictions can drift prices in commodity markets away from "fundamental" values. Fattouh et al. (2012) survey the literature on the role of speculation on oil prices, and they conclude that there is no evidence to support an important role of speculation. They instead notice that the co-movements between spot and future prices do not reflect the financialization of the oil market, but rather the presence of common economic fundamentals. Juvenal and Petrella (2015), using a dynamic factor model, show that, although speculative shocks are relevant, global demand is the main driver of oil price fluctuations. Beidas-Strom and Pescatori (2014) propose an identification strategy to distinguish between speculative demand shocks driven by *news about fundamentals* and those driven by *noise trading* using restrictions based on economic theory. However, Knittel and Pindyck (2016), using a simple model of equilibrium in the cash and storage markets, conclude that it is possible to rule out speculation as the cause of the sharp changes in prices starting in 2004.

Recently, Leluc et al. (2016) show that a (DSGE) model where agents learn over time the persistence of oil shocks can explain the observed fluctuations in oil-price futures. They abstract from other possible important factors influencing futures prices. In particular, they do not include in the analysis time-varying risk premia that have been shown to be important in understanding the dynamics in oil futures prices. Although we focus on spot prices, our analysis could be related to Leluc et al. (2016) if we offer a different interpretation to the identified shocks. In fact, the anticipated shock, which has an impact on fundamentals, could be interpreted as a permanent shock, and the noise shock, which has only a temporary effect on prices, as a temporary shock.

We build on the extensive econometric literature on the estimation of "news" shocks, disentangling the component that affects fundamentals (oil production and global real economic activity) from the noise component. In particular, Forni et al. (2017a and 2017b) propose an identification methodology based on dynamic rotation to disentangle "news" shocks in noise and fundamental component. They apply it to the estimation of "noise" shocks as a source of business cycle fluctuations, and to stock prices.

The rest of the paper is organized as follows. Section 2 introduces the model and presents how to disentangle "news shocks" into fundamental (or anticipated) and noise shocks. Section 3 analyzes the identification of the shocks in the VAR model. Section 4 presents the data and discusses the results. Section 5 concludes.

2 News and imperfect information in the oil market

In this section, we first revisit Kilian's (2009) evidence with an updated sample. Then we explain that the oil specific demand shock identified in Kilian (2009) can be interpreted as a "news shock". Finally, we introduce how we disentangle the "news shock" in anticipated and noise shocks.

We reexamine Kilian's (2009) results using the same VAR specification and the same identifying restrictions, more specifically a Cholesky decomposition. The VAR includes oil production, a forward-looking index of economic activity and the oil price, in that order. Unlike Kilian (2009), we use the Baltic Dry Index (BDI) as a measure of global economic activity. It has the advantages of being readily available, standardized and representing the current cost of moving raw materials by sea by various vessel classes over different global routes.[5] Therefore the first shock is the oil supply shock, the second is the global demand shock and the third is the oil-specific demand shock, or precautionary demand shock.

Figure 1 plots the estimated impulse response functions and Table 1 reports the variance decomposition. Confirming Kilian (2009)'s results, the precautionary demand shock appears to be a major source of fluctuations in oil prices, explaining more than 80% of their variance. This shock has no contemporaneous impact on oil production and on an index of real economic activity, but an immediate positive effect only on oil prices. However, it determines a significant and permanent future increase in oil production. This last result is particularly important because it implies that the precautionary oil-demand shock can be interpreted as a "news" shock: a shock that significantly affects future oil production but not current production. Moreover, the shock has a significant positive effect on the BDI. This result is compatible with the interpretation that an increase in oil demand could be triggered by an expected increase in global demand. Markets anticipate the future increase in demand and this triggers an immediate positive reaction in oil prices. To sum up, the existing evidence suggests that fluctuations in oil prices are, to a large extent, driven by expectations about future developments in the oil market.[6]

[5] In Section 4.1 for the details of the dataset. The BDI is a composite of the Baltic Capesize, Supramax, Panamax, and Handysize indices.

[6] News or anticipated shocks have become popular in both empirical and theoretical models. The

While it is certainly plausible that expectations have an important impact on the price of oil, it appears also reasonable and realistic to think that agents have access only to imperfect information about future development in the oil market. In fact, in many cases market expectations might be unfulfilled. As discussed in the Introduction, the periods before the recent financial crisis, 2007-2008, and the years before the recent drop in prices, i.e. 2012-2014, represent two episodes when prices appear to have been driven more by expectations about future developments in the markets than by fundamentals.

In other words, movements in prices might be, to some extent, disconnected from future changes in oil production or global demand and simply attributable to "wrong" expectations about future oil market conditions. Here we show that in an imperfect-information framework, the "news" shock can be modeled as a combination of two different disturbances: the true genuine shock, which has a delayed effect on oil production, and a "noise shock", which does not have any effects on future production. Consequently, within this framework, the shock identified in Kilian (2009) turns out to be a combination of these two components. Here we show how to disentangle the two and study their effects.[7]

As an example, and to understand the identification procedure, let us consider the following stylized model. Suppose oil production follows

$$q_t = q_{t-1} + \varepsilon_{t-1}, \tag{1}$$

where ε_t is a Gaussian, serially uncorrelated process affecting q_t with a one-period delay. We call ε_t an "anticipated shock" to oil production. We assume that the agent, at time t, observes oil production q_t and a noisy signal s_t of the anticipated shock ε_t.[8] The signal s_t here can be interpreted as the news that agents receive about possible changes in future oil production. We assume

$$s_t = \varepsilon_t + v_t. \tag{2}$$

The noise shock v_t is a Gaussian white noise, uncorrelated with ε_t at all leads and lags. The variance of the signal is just the sum of the variances of the two shocks, $\sigma_s^2 = \sigma_\varepsilon^2 + \sigma_v^2$. The agent's information set is given by $\mathcal{I}_t = \text{span}(q_{t-k}, s_{t-k}, k \geq 0)$. Given the delayed effects of the anticipated shock ε_t, this information is not sufficient to distinguish the true shock from the noise shock.

literature, so far has focused on anticipated fiscal socks (Leeper et al.) and technology shocks (Beaudry and Portier). In those cases the shock has delayed effects on fiscal variables and total factor productivity respectively.

[7] This modeling framework has been used extensively in the literature of noise shocks, see Blanchard et al ().

[8] Here we adopt a terminology that differs from the standard one.

As long as market participants react to news about future developments in oil production, in the sense that oil prices is driven by expectations *about future oil production*, then both the anticipated shock and the noise shock will affect oil price. To illustrate this point, and without aiming at a realistic model of oil price determination, suppose that agents form expectations rationally and the price of oil is determined by

$$p_t = E(q_{t+1}|\mathcal{I}_t) = q_t + E(\epsilon_t|\mathcal{I}_t).$$

Since p_{t-k} and s_{t-k} are uninformative about ϵ_t, $E(\epsilon_t|\mathcal{I}_t)$ is simply the projection of ϵ_t on s_t:

$$E(\epsilon_t|\mathcal{I}_t) = \gamma s_t$$

where $\gamma = \frac{\sigma_\varepsilon^2}{\sigma_s^2}$ is the linear projection coefficient of the projection of the anticipated production shock on the information set, i.e. the signal. Substituting equation (4) and solving for the conditional expectation we find

$$p_t = q_t + \gamma\varepsilon_t + \gamma v_t$$

The change in price will be

$$\Delta p_t = \gamma\varepsilon_t + (1-\gamma)\varepsilon_{t-1} + \gamma v_t - \gamma v_{t-1}$$

When a noise shock hits, agents react to the signal and the price increases by γ. At time $t+1$ agents realize it was just noise and the price is reduced by γ. The total long-run effect on the price is zero but noise has triggered a fluctuation in the price. As a result the noise component can generate fluctuations in the price of oil that are completely disconnected from oil production. The goal of this paper is to disentangle the anticipated shock from the noise shock and measure the empirical importance of the two for oil price fluctuations.

3 The econometric model

We identify the anticipated shock and the noise shock in the oil market using the identification procedure in Forni et al. (2017a), FGLS henceforth. The approach uses dynamic rotations within VAR models. We consider two VAR specifications: the three-variable specification used in Kilian (2009), and a richer specification including seven variables. For sake of exposition, we start describing the identification approach in a simple bivariate VAR.

We make three assumptions that will be maintained in both empirical specifications.

(A1) Oil production follows

$$\Delta q_t = c(L)\varepsilon_t + g(L)e_t, \tag{3}$$

where $c(0) = 0$, e_t is an $(n-2)$-dimensional white noise vector (n being either 3 or 7) with identity variance covariance matrix, orthogonal to ε_t at all leads and lags, and $g(L)$ is an $(n-2)$-dimensional row vector of polynomials in L.

(A2) The "anticipated shock" ε_t is not observed by the agents. Rather they observe a noisy signal

$$s_t = \varepsilon_t + v_t \tag{4}$$

where v_t is the "noise shock", a Gaussian white noise, uncorrelated with ε_t at all leads and lags. The agents' information set is given by $\mathcal{I}_t = \text{span}(q_{t-k}, s_{t-k}, e_{t-k}k \geq 0)$. Notice that while we assume that the anticipated shock is not observed, the other shocks e_t are assumed to be observed.

(A3) The econometrician observes a variable z_t that reveals the signal received by the agent, i.e. z_t contains the same information as s_t. The econometrician's information set is therefore $\mathcal{I}^e_t = \text{span}(q_{t-k}, z_{t-k}, e_{t-k}k \geq 0)$

While s_t is the "news shock" as discussed in Section 2 and can be interpreted as all the news appearing on the media regarding the oil market, z_t is the variable observed by the econometrician and containing the agents' reactions to news and therefore incorporating the impact of the news.

3.1 Bivariate specification

Suppose that the anticipated shock, ε_t, and the noise shock, v_t, are the only two shocks in the economy, i.e. $g(L) = 0$, then the structural representation of production and the signal is

$$\begin{pmatrix} \Delta q_t \\ s_t \end{pmatrix} = \begin{pmatrix} c(L) & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}. \tag{5}$$

The representation is non-fundamental since the determinant is zero at zero since $c(0) = 0$. The fundamental representation is

$$\begin{pmatrix} \Delta q_t \\ s_t \end{pmatrix} = \begin{pmatrix} \frac{c(L)}{b(L)} & \frac{c(L)\sigma^2_\varepsilon}{\sigma^2_s} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ s_t \end{pmatrix}, \tag{6}$$

where

$$b(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L}$$

and r_j, $j = 1, \dots, n$ are the roots of $c(L)$ which are smaller than one in modulus and $\bar{r}_j$ is the complex conjugate of r_j. The shocks u_t and s_t are orthogonal innovations for the agents' information set and

$$\begin{pmatrix} u_t \\ s_t \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_v^2}{\sigma_s^2} & -b(L)\frac{\sigma_\varepsilon^2}{\sigma_s^2} \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ v_t \end{pmatrix}. \tag{7}$$

The econometrician does not observe the signal but rather a variable z_t, which reveals the signal (assumption (A3)). The normalized (i.e. unit variance shocks) fundamental representation, i.e. the representation in terms of the econometrician's information set innovations, of Δq_t and z_t is

$$\begin{pmatrix} \Delta q_t \\ z_t \end{pmatrix} = a(L) \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s. \end{pmatrix} \tag{8}$$

It is easy to see that equation (8) is the Cholesky representation since the MA is fundamental (by assumption (A3)), the shocks have unit variance and $a_{12}(0) = \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} = 0$ since $c(0) = 0$ ($a_{ij}(L)$ is the element i, j of $a(L)$) . Moreover, the Cholesky shocks are dynamic combinations of the structural shocks

$$\begin{pmatrix} u_t/\sigma_u \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} b(L)\frac{\sigma_v}{\sigma_s} & -b(L)\frac{\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix} \tag{9}$$

so that the structural representation is

$$\begin{aligned} \begin{pmatrix} \Delta q_t \\ z_t \end{pmatrix} &= \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ d(L)\sigma_u & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} b(L)\frac{\sigma_v}{\sigma_s} & -b(L)\frac{\sigma_\varepsilon}{\sigma_s} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix} \\ &= \begin{pmatrix} c(L)\sigma_\varepsilon & 0 \\ f(L)\sigma_\varepsilon + b(L)d(L)\frac{\sigma_\varepsilon\sigma_v^2}{\sigma_s^2} & f(L)\sigma_v - b(L)d(L)\frac{\sigma_v\sigma_\varepsilon^2}{\sigma_s^2} \end{pmatrix} \begin{pmatrix} \varepsilon_t/\sigma_\varepsilon \\ v_t/\sigma_v \end{pmatrix} \end{aligned} \tag{10}$$

Estimation of representation (10) is done through the following steps (we use to denote the estimates of the corresponding parameter):

1. Estimate the Cholesky representation (8) estimating first the reduced form by OLS and then identifying using the Cholesky factor of the covariance matrix of the OLS residuals.

2. Estimate $b(L)$ by setting r_j equal to the roots of the polynomial $\hat{a}_{12}(L)$ that are smaller than one in absolute value.

3. Since $b(1) = 1$, estimate $\sigma_\varepsilon/\sigma_v$ as the ratio $\frac{\hat{a}_{12}(1)}{\hat{a}_{11}(1)}$.

4. Using $\sigma_v^2/\sigma_s^2 + \sigma_\varepsilon^2/\sigma_s^2 = 1$, $\widehat{\sigma_\varepsilon/\sigma_s}$ and $\widehat{\sigma_v/\sigma_s}$ are obtained as $\sin(\arctan(\widehat{\sigma_\varepsilon/\sigma_v}))$ and $\cos(\arctan(\widehat{\sigma_\varepsilon/\sigma_v}))$, respectively.

The fours steps provide estimates of all the elements of representations (8) and (9) and consequently of all the elements in (10).

3.2 Three-variable VAR

The first VAR specification we use in our empirical analysis is the three-variable model in Kilian (2009). The model includes the Baltic Dry Index (BDI)[9], denoted by y_t, the (log) oil world production, q_t, and the (log) price of oil, p_t. We use oil prices as the variable revealing the signal, i.e. z_t,. The rationale is that oil prices, as long as they are determined by agents expectations about current and future changes in oil production, will convey information about the signal observed by the agents. Finally let e_t be a scalar unit-variance white noise shock. Under assumptions A1-A3 the Cholesky representation of the model is given by

$$\begin{pmatrix} \Delta q_t \\ y_t \\ p_t \end{pmatrix} = a(L) \begin{pmatrix} u_t/\sigma_u \\ e_t \\ s_t/\sigma_s \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & a_{12}(L) & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} \\ a_{21}(L) & a_{22}(L) & a_{23}(L) \\ d(L)\sigma_u & a_{32}(L) & f(L)\sigma_s \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ e_t \\ s_t/\sigma_s \end{pmatrix}. \tag{11}$$

The corresponding structural representation is obtained by postmultiplying $a(L)$ by

$$\begin{pmatrix} b(L)\frac{\sigma_v}{\sigma_s} & 0 & -b(L)\frac{\sigma_\varepsilon}{\sigma_s} \\ 0 & 1 & 0 \\ \frac{\sigma_\varepsilon}{\sigma_s} & 0 & \frac{\sigma_v}{\sigma_s} \end{pmatrix} \tag{12}$$

Estimation works as before. The only difference is that now $b(L)$ is obtained setting r_j equal to the roots of the polynimial $\hat{a}_{13}(L) = \frac{\hat{c}(L)\sigma_\varepsilon^2}{\sigma_s}$, which are smaller than one in absolute value, and $\hat{\sigma}_\varepsilon/\hat{\sigma}_v$ is obtained as $\frac{\hat{a}_{13}(1)}{\hat{a}_{11}(1)}$.

In Kilian (2009)'s identification, the first shock in the Cholesky representation is the oil supply shock, the second the global demand shock and the third the oil-specific demand shock. In our empirical setting, while the second shock remains the global demand shock, the two remaining shocks have a very different interpretation. Indeed the first shock is simply the innovation in quantity production, instead the third represents the signal. These two shocks in our setup do not have a structural interpretation, since, as shown above, they are actually combinations of the present and the past of the true structural shocks, the anticipated quantity shock and the noise shock. Our identifying procedure will be able to disentangle the two shocks.

[9]For further details see Section 4.1.

3.3 Seven-variable VAR

We extend the model to include other variables that can have confounding effects on the identification of the shocks. In particular, let w_t be a 4×1 dimensional vector including the BDI, a general index of commodity prices, the Chicago Fed index of the US economic activity (mnemonic CFNAI) and the the Chicago Fed index of US financial stress (mnemonic ANFCI). Let p_t denote oil price. We now use the three-month the oil price future as the signal-revealing variable z_t. Let $e_t = [e_t^{1\prime}\ e_t^{2}]'$ be a 5×1 dimensional vector of white noise shocks with identity matrix variance, where e_t^1 is a subvector of dimension 4×1 and e_t^2 is a scalar. Consider the Cholesky representation of the model

$$\begin{pmatrix} \Delta q_t \\ w_t \\ z_t \\ p_t \end{pmatrix} = a(L) \begin{pmatrix} u_t/\sigma_u \\ e_t^1 \\ s_t/\sigma_s \\ e_t^2 \end{pmatrix} = \begin{pmatrix} \frac{c(L)\sigma_u}{b(L)} & a_{1,2:5}(L) & \frac{c(L)\sigma_\varepsilon^2}{\sigma_s} & a_{17}(L) \\ a_{2:5,1}(L) & a_{2:5,2:5}(L) & a_{2:5,6}(L) & a_{2:5,7}(L) \\ d(L)\sigma_u & a_{6,2:5}(L) & f(L)\sigma_s & a_{67}(L) \\ a_{71}(L) & a_{7,2:5}(L) & a_{76}(L) & a_{77}(L) \end{pmatrix} \begin{pmatrix} u_t/\sigma_u \\ e_t^1 \\ s_t/\sigma_s \\ e_t^2 \end{pmatrix} \tag{13}$$

where $a_{i:k,l:j}(L)$ denote the submatrix formed by the rows from i to k and columns from l to j of $a(L)$. The corresponding structural representation is obtained by post-multiplying $a(L)$ by

$$\begin{pmatrix} b(L)\frac{\sigma_v}{\sigma_s} & \mathbf{0}' & -b(L)\frac{\sigma_\varepsilon}{\sigma_s} & 0 \\ \mathbf{0} & I_4 & \mathbf{0} & \mathbf{0} \\ \frac{\sigma_\varepsilon}{\sigma_s} & \mathbf{0}' & \frac{\sigma_v}{\sigma_s} & 0 \\ 0 & \mathbf{0}' & 0 & 1 \end{pmatrix} \tag{14}$$

where 0 is a 4×1 vector of zeros and I_4 is a 4×4 identity matrix. Again the only difference in the estimation is that now $b(L)$ is obtained setting r_j equal to the roots of $\hat{a}_{16}(L)$ which are smaller than one, and $\sigma_\varepsilon/\sigma_v$ is obtained as $\frac{\hat{a}_{16}(1)}{\hat{a}_{11}(1)}$.

4 Empirics

4.1 Data

In this section, we describe the data used in the empirical study.

We use monthly data from 1990.01 to 2016.03. To measure oil prices we use Brent crude oil spot prices deflated using US CPI, as in the bulk of the literature. We use data on world oil production from the Energy Information Administration (EIA). To proxy for global real economic activity we use the *Baltic Dry Index* (BDI), an economic indicator issued daily by the London-based *Baltic Exchange* providing "an assessment of the price of moving the major raw materials by sea." It is an average of the cost of booking various cargoes of raw material on various routes. BDI is a leading indicator of economic activity because it provides a measure of the demand for shipping raw materials used to produce intermediate and final goods. Unlike other markets, it is not affected by speculation since it is based on actual orders.[10]

BDI is very similar to the Global Real Economic Activity index developed in Kilian (2009),which is constructed using data manually collected from *Drewry's Shipping Monthly* on dry cargo single voyage ocean freight rates and it is explicitly designed to capture shifts in the demand for industrial commodities in the global business cycle. BDI is available since 1985 and it was developed by Baltic Exchange, "the world's leading source of independent maritime market data"[11], to allow the dealings to occur electronically.[12] BDI has the same advantages of Kilian's index in providing a direct measure of global economic activity without the need for exchange rates conversion. However, it has the further advantage of being standardized, ready to use and providing the (weighted) average of different sizes of oceangoing transport vessels (Capsize, Panamax, Supramax and Handysize) over different routes. Nevertheless, it suffers from the same potential drawback of being affected by the business cycle of the supply of cargo as Kilian's index. In fact, while the supply of cargoes is inelastic in the short term (it takes at least two years to build a ship), an increase in demand can push prices very quickly. Moreover, during a boom there might be a delay in building up capacity that lasts after reaching the peak and determines a trough in shipping prices.[13]

In the seven-variable specification, we use the three-month oil price futures as the signal-revealing variable, z_t. Although Alquist and Kilian (2010) show that oil futures prices fail to improve the accuracy of simple no-change forecasts, they are used by many international institutions (e.g. ECB and IMF, among others) as a proxy for markets' expectations of oil spot price and as predictors of spot prices to construct inflation and output gap projections. Therefore, they remain a good signal on which market participants (economic agents) form their expectations about future oil price movements.[14]

[10]See Gross (2003) and the *balticexchange.com* for more detailed information.

[11]See balticexchange.com for more information

[12]BDI is available on shipping publications like *Lloyd's List*, but also on Bloomberg and Reuters.

[13]For more details see Kilian (2009) section I.A.

[14]Pagano and Pisani (2009) interpret the difference between oil futures prices and the realized oil spot prices (forecast error) as a measure of the oil futures risk premium. This risk premium varies over the business cycle and that could be explained using a real-time US business cycle indicator. They show that out-of-sample forecasting exercise using risk-adjusted forecasts are more precise that those obtained with unadjusted futures, random walk or futures adjusted for a constant risk premium, particularly at

Moreover, we use the Chicago Fed National Activity Index (CFNAI) as an additional indicator of country-specific economic activity, and the [Adjusted] National Financial Conditions Index (ANFCI) as an indicator of financial conditions.

The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[15] (Source Chicago Fed). On the other hand, the ANFCI "isolates a component of financial conditions uncorrelated with economic conditions to provide an update on financial conditions relative to current economic conditions".

Finally, we use also the non-energy commodities price index from the IFS-IMF database to control for developments in other commodities' markets that could bias our findings.

4.2 Three-variable VAR

Figure 2 plots the effects of the signal s_t and the innovation u_t on the three variables included in the model: oil production, the Baltic Dry Index and the oil price. The solid line represents the point estimates, the dark gray area the 68% confidence bands, and the light gray area the 90% confidence bands. The signal has a positive and persistent effect on oil production. Moreover the effect is significant for the first year after the shock hits suggesting that change in prices do actually predict, to some extent, future changes in the oil production.

Figure 3 plots the effects of the anticipated and noise shocks on the three variables. The anticipated shock increases oil production with a delay and the effect is permanent. The BDI and the oil price increase as well, although the effect is temporary. The positive co-movement of prices and production suggests that the anticipated shock can be interpreted as an oil demand shock. BDI responds very little suggesting that the increase does not seem to be driven by a significant higher level of global activity. The noise shock triggers a substantial and significant increase in oil prices but has no effects on oil production. The second finding is important since the result is consistent with the assumption that oil production is noise free and is used for the identification of the noise

horizons longer than 6 months. Baumeister and Kilian (2014) propose a general solution to pin down the best possible estimate of the market expectations for any set of risk premium estimates. Also Hamilton and Wu (2014) document significant changes in the pricing of risk premia after the volume of futures trading began to grow significantly after 2005.

[15]The CFNAI corresponds to the index of economic activity developed by Stock and Watson (1999).

shock.

Table 2 reports the variance decomposition of the three variables. Noise appears to be the major source of fluctuations in oil price, explaining around 80-90% in the short run and around half of fluctuations at longer horizons. On the contrary, the noise component explains nothing of the fluctuations in oil production and a negligible part of the variance of the BDI. Global demand shocks represent the second most important source of fluctuations in oil prices and they explain, as expected, the bulk of fluctuations in the BDI. On the contrary the anticipated shock has little effects on oil prices while is very important for fluctuations in oil production.

Figure 4 plots the historical decomposition of (log) oil process. The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component of oil prices. Consistent with the variance decomposition results, the noise component is responsible for sizable swings in oil prices. Findings suggest there are several major episodes of oil price swings (bubbles) driven by noise shocks. The first occurs in the period 1997-1999, is negative, and could be associated with the aftermath of the Asian crisis. It could be interpreted, for instance, that the decline in oil prices was driven by "wrong" expectations that oil demand would have remained subdued for long. The second is dated 2004-2005 and is also negative. The third is in 2008-2009, when first it reached a peak and then turned negative. The first part of these dynamics could be interpreted as the effect of the "peak oil" narrative: the idea that oil demand would have outstripped oil supply in the near future. The expectations of an increase in oil prices led to a spike in the oil price. Brent crude oil reached US$145.85 in July 2008. However, the aftermath of Lehman's bankruptcy and the beginning of the financial crisis caused a drastic oil price drop and the noise component turned negative. This could be interpreted as the overestimation of the negative effects of the financial crisis. This interpretation is consistent with Hamilton (2009) arguing that the 2007-2008 oil shock was the result of a miscalculation of the long-run price elasticity of oil demand, exacerbated by speculative investing. The fourth swing in 2011-2014 is positive. This could be interpreted as the effects of "wrong" expectations regarding the increase in demand in emerging markets, but also regarding the pace of adjustment in supply. In fact, the "shale revolution", the new technology that allows the extraction of oil using fracking, increased the supply of oil considerably. From the very low levels in 2010, they have recently reached over 4.5 Mb/day.[16] Finally, from mid-2014 the noise component turned and remained negative. This reverse coincides with the sudden drop in oil prices driven by a mix of slow recovery and realization that "oil is not an exhaustible resource"

[16]See Dale (2015) for further analysis.

(Dale, 2015). This could be interpreted as an (excessive) negative outlook regarding the future oil demand.

4.3 Seven-variable VAR

In order to better identify the shocks, we control for further factors that could confound our results.

Figure 5 plots the effects of the signal s_t and the innovation u_t on prices and oil production. The signal has a positive, permanent and significant effect on oil production. In this specification the effects are much larger and more significant than those estimated with the three-variable VAR. The findings suggest that the oil price futures are a much better predictor of futures changes in oil production than the price itself.

Figure 6, 7 and 8 plot the responses of the variables included in the model to the anticipated shock and the noise shock. We do not report the response of oil price future since it is extremely similar to that of oil prices. Several interesting findings emerge. First, the noise shock, consistent with the identifying assumptions, has no effect on production, but has a large positive effect on oil prices. From Table 3 it emerges that the noise shock is a major factor of price fluctuations. Indeed the shock explains about 35-40% of the variance within a four year horizon. However, it is important to notice that the figures are smaller than in the three-variables case. This depends, to a large extent, on the fact that we included and ordered commodity prices before oil prices in the VAR, which has the effect of mitigating the importance of the shock. Still noise remains the main driver of oil price fluctuations in the short run.

Second, the noise shock produces significant effects on US variables. Economic activity is significantly reduced and financial stress significantly increased. Nonetheless the effects are quantitatively small since the shock explains at most 5% of the variance of the economic activity indicator. Global demand is virtually unaffected and commodity prices react sluggishly to the noise shock.

Third, the anticipated shock has huge effects on oil production, which increases permanently and significantly, and it explains about 80% of the variance of production, but the effects on prices are small, the shock explains 15% of the variance on impact and 10% at an horizon of four years. As before, prices react positively and significantly suggesting that our anticipated shock captures disturbances on the demand side. The impact on the remaining variables are negligible.

Figure 9-12 plot the historical decomposition of the (log) oil prices, the BDI index, the US economic activity index and the financial stress index. The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component of oil prices. As before, the noise component is responsible for sizable swings in oil prices. In particular, the negative swing driven by the noise shock in 1997-1999 remains large. However, the 2004-2005 negative swing is much more contained. The peak in 2007-2008 is instead better identified and consistent with Hamilton's analysis. The subsequent drop occurs in 2010 and 2011 in line with the evolution of the global financial crisis. Instead, the positive swing is better identified to the period 2012-2014, while the recent drop in mid-2014 remains the same yet is of a smaller size.

5 Conclusions

In this paper we revised Kilian's (2009) VAR model and we interpret the oil-specific demand (or precautionary) shock as a news shock. We use the *dynamic rotation* methodology developed in FGLS (2017) to disentangle the news shock in anticipated and noise shocks. We show that the anticipated shock has a permanent effect on oil production and oil prices, but a temporary impact on global demand. On the other hand, the noise shock has no statistically significant effect on oil production, and a temporary impact on oil prices and global demand.

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Shock	Variable	Horizon (months)			
		0	12	48	80
Oil supply	Production	1.00	0.88	0.85	0.82
	BDI	0.00	0.02	0.04	0.04
	Oil price	0.00	0.00	0.06	0.13
Global demand	Production	0.00	0.04	0.03	0.02
	BDI	0.99	0.93	0.90	0.88
	Oil price	0.03	0.15	0.22	0.22
Precautionary	Production	0.00	0.06	0.11	0.14
	BDI	0	0.04	0.05	0.06
	Oil price	0.95	0.84	0.70	0.64

Table 1: Variance decomposition in the Cholesky representation of the 3-variable VAR.

Shock	Variable	Horizon (months)			
		0	12	48	80
Noise	Production	0.00	0.34	0.26	0.19
	BDI	0.00	6.64	9.55	12.78
	Price	91.50	82.31	64.02	56.55
Anticipated	Production	6.93	92.59	96.06	97.39
	BDI	0.00	2.03	2.93	2.93
	Price	6.81	3.83	11.86	20.14
Demand	Production	0.00	7.05	3.67	2.40
	BDI	100.00	91.32	87.50	84.28
	Price	1.67	13.85	24.11	23.29

Table 2: Variance decomposition in the 3-variable VAR.

Shock	Variable	Horizon (months)			
		0	12	48	80
Noise	Production	0.00	2.46	0.87	0.57
	BDI	0.00	2.18	3.87	4.00
	CPrices	0.00	0.11	6.25	9.94
	CFNAI-MA3	0.00	4.98	5.60	5.68
	NFCI	0.00	1.87	1.41	2.21
	Future	64.91	33.31	27.94	22.99
	Price	55.91	37.16	34.23	30.19
Anticipated	Production	0.00	79.52	80.29	79.71
	BDI	0.00	2.08	2.05	3.47
	CPrices	0.00	0.31	5.73	5.17
	CFNAI-MA3	0.00	2.96	2.34	2.75
	NFCI	0.00	0.91	0.88	1.16
	Future	18.44	9.47	15.61	25.75
	Price	15.89	8.02	9.65	16.13

Table 3: Variance decomposition in the 7-variable VAR.

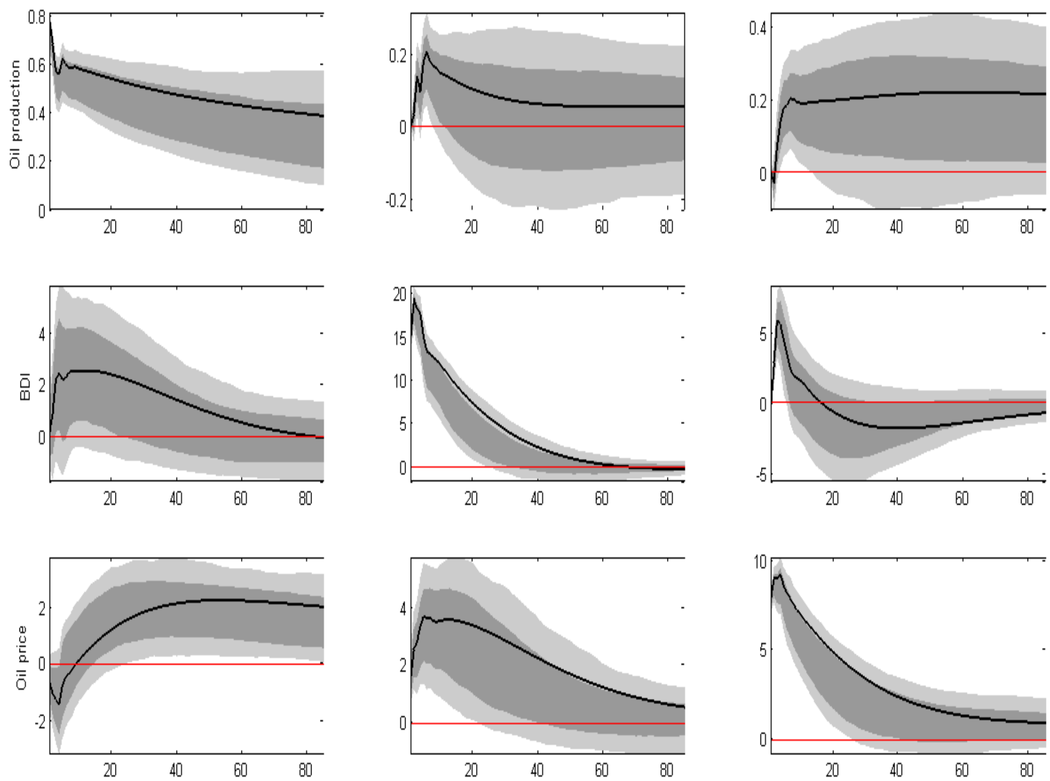

Figure 1: Impulse response functions to the three shocks (Kilian's VAR). The news shock is the one in the third column in the 3-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

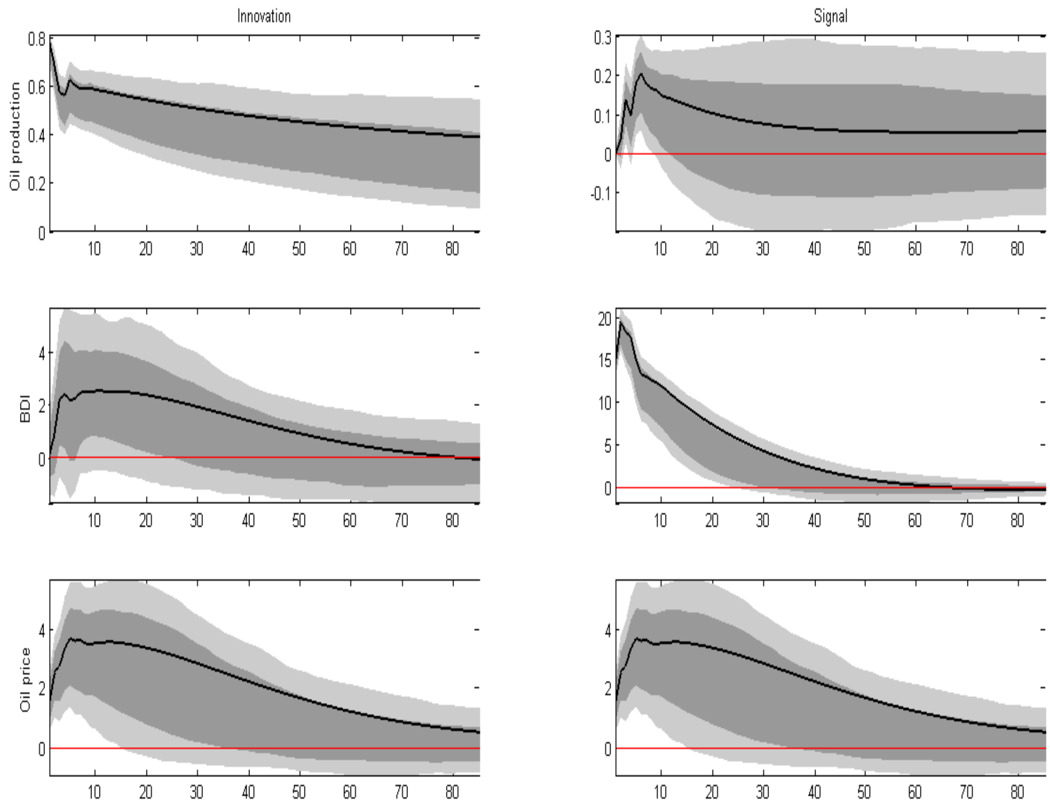

Figure 2: Impulse response functions to signal s_t and innovation u_t on the three variables in the model: the oil production, the Baltic Dry Index, and the oil price. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

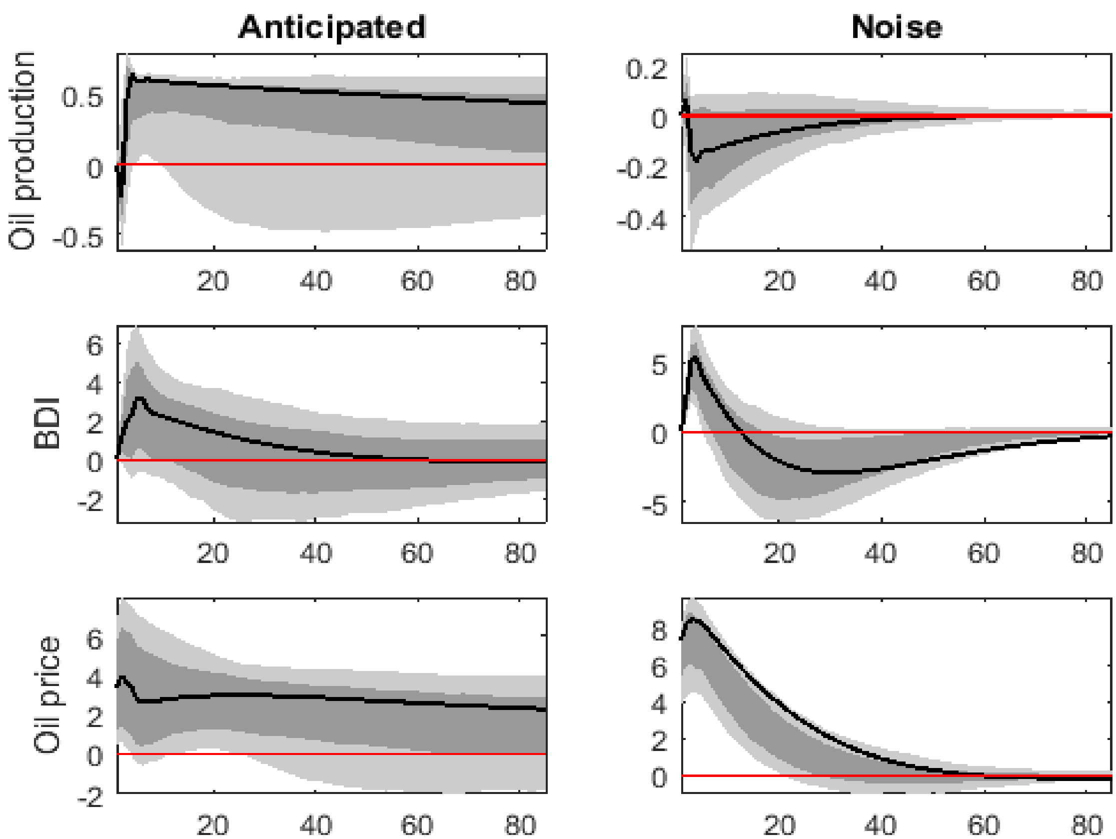

Figure 3: Impulse response functions to an anticipated shock (left column) and a noise (right column) shock in the 3-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

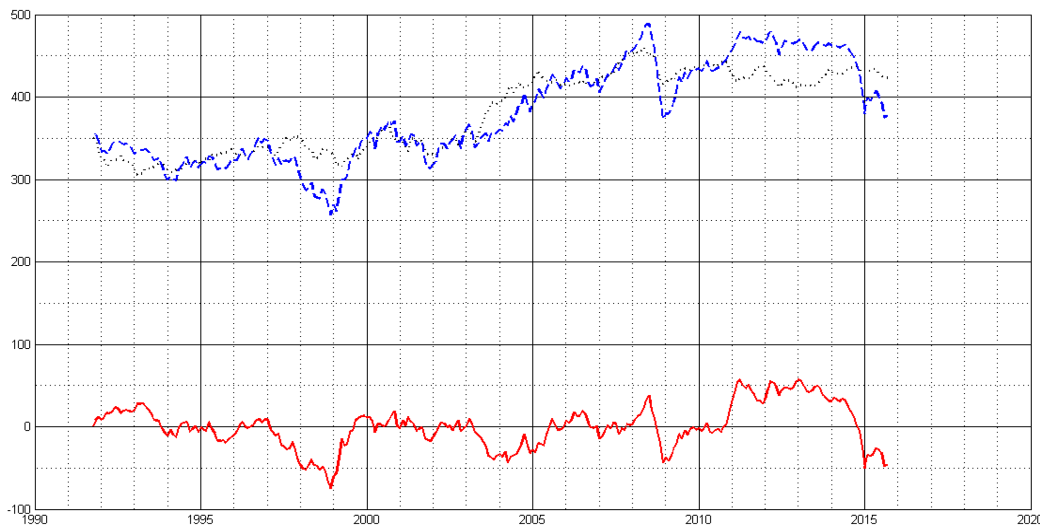

Figure 4: Historical decomposition of oil price (three-variable VAR). The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component.

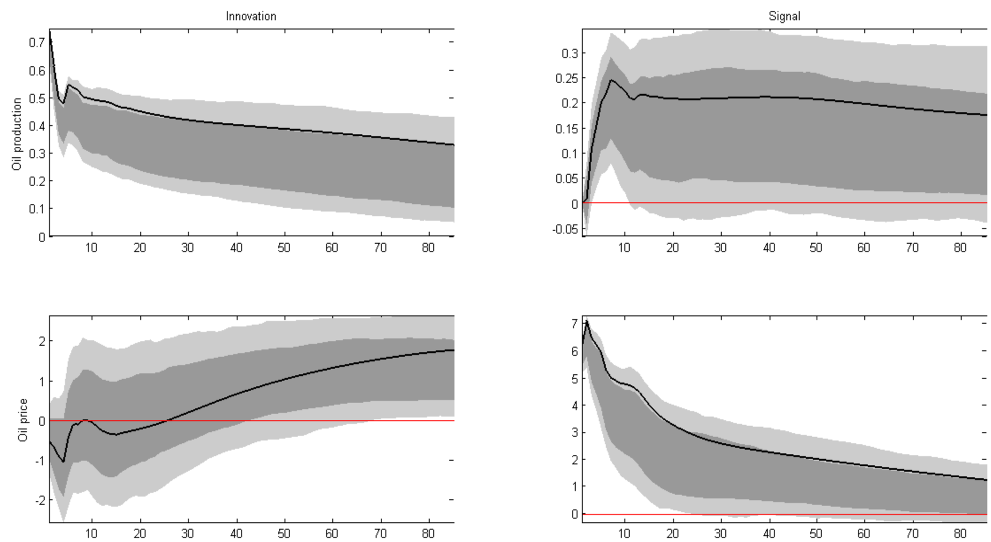

Figure 5: Impulse response functions to the innovation u_t (left column) and the signal (right column) in the 7-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

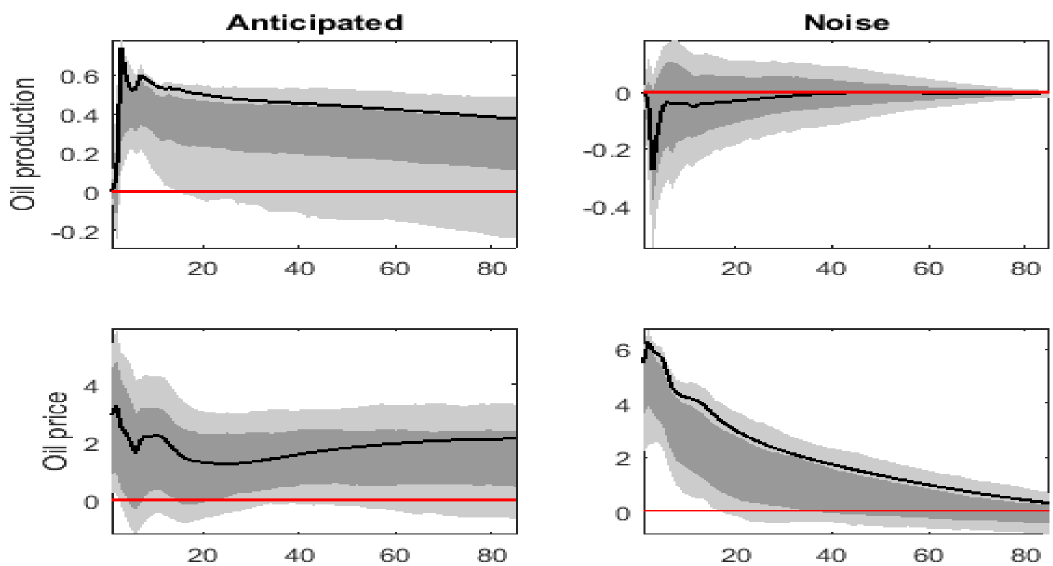

Figure 6: Impulse response functions to an anticipated shock (left column) and a noise shock (right column) in the seven-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

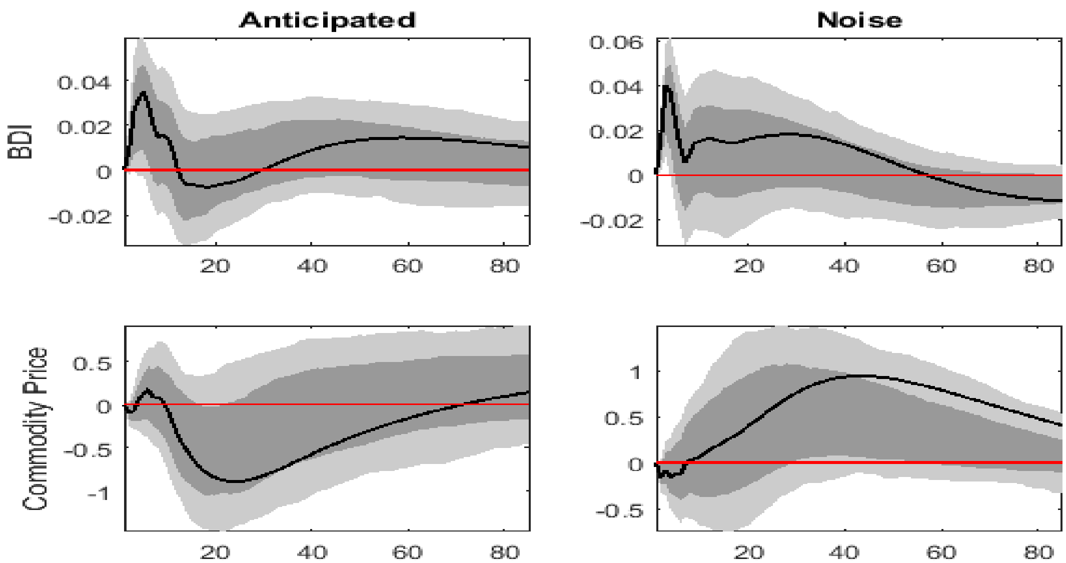

Figure 7: Impulse response functions to a news or anticipated shock (left column) and a noise (right column) shock in the seven-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

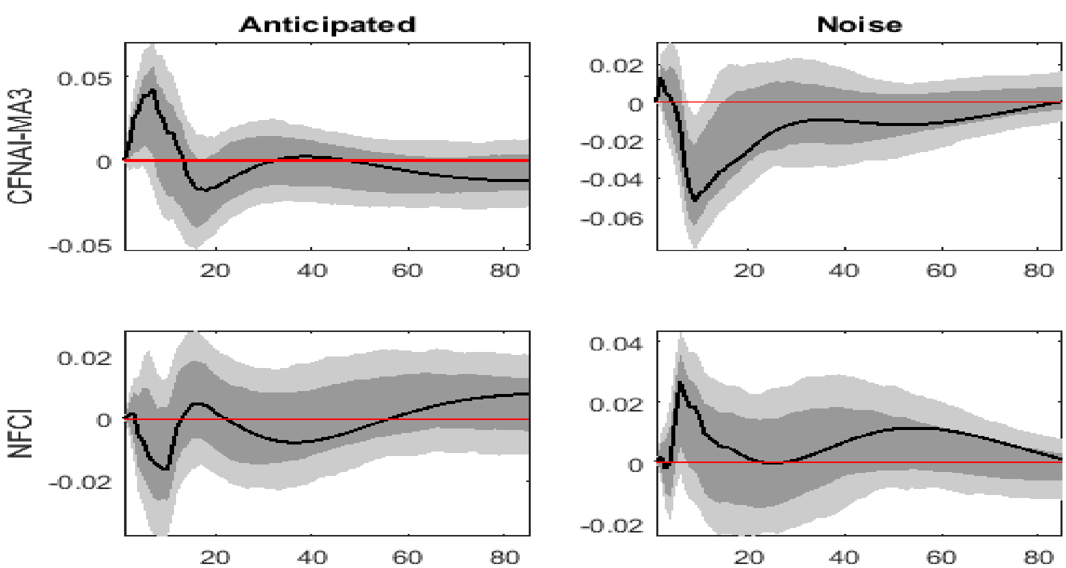

Figure 8: Impulse response functions to a news or anticipated shock (left column) and a noise (right column) shock in the seven-variable VAR. Solid line: point estimate. Light gray area: 90% confidence bands. Dark gray area: 68% confidence bands.

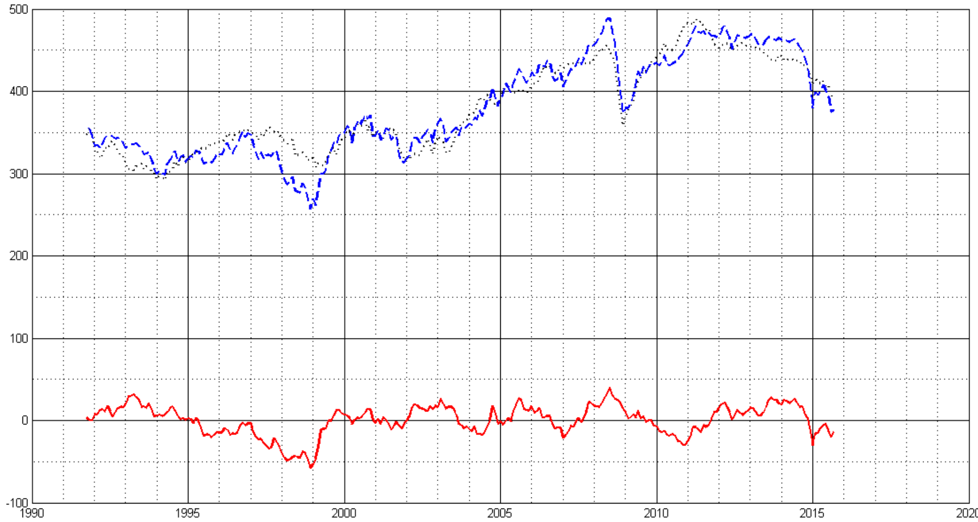

Figure 9: Historical decomposition of oil price (seven-variable VAR). The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component.

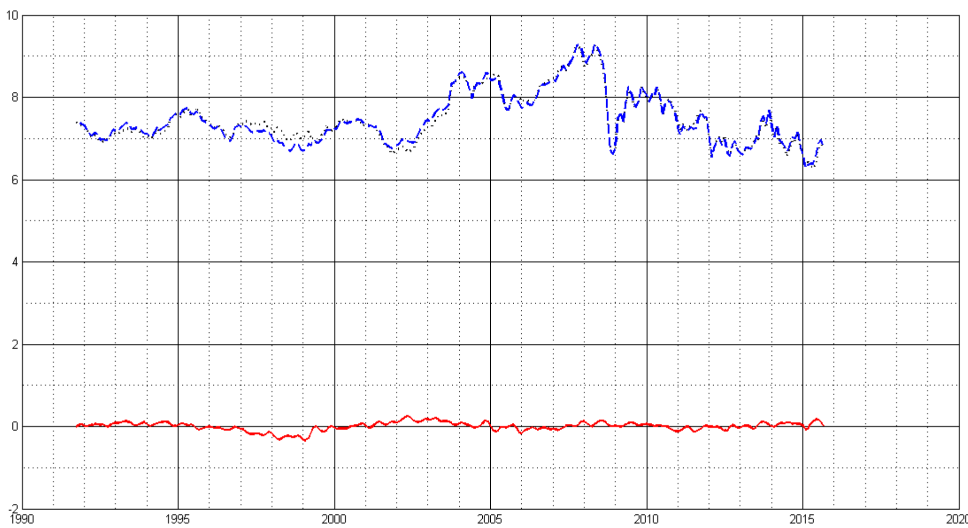

Figure 10: Historical decomposition of the BDI index (seven-variable VAR). The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component.

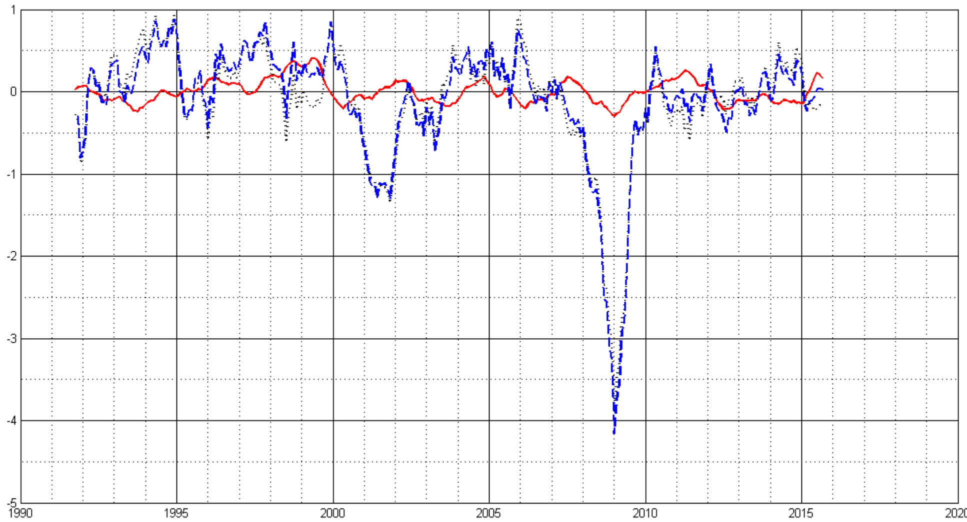

Figure 11: Historical decomposition of the economic activity index (seven-variable VAR). The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component.

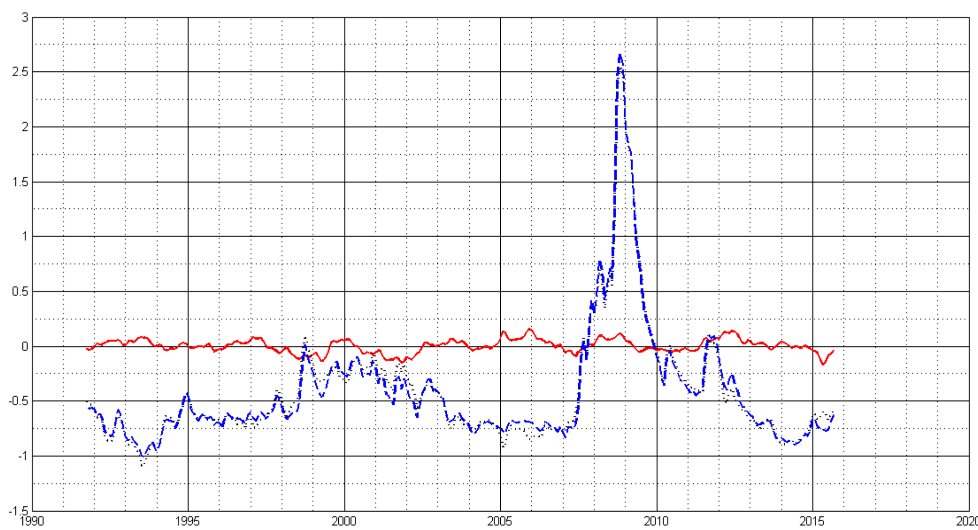

Figure 12: Historical decomposition of the financial stress index (seven-variable VAR). The blue line is the observed series, the black line is the observed series minus the noise component and the red line is the noise component.