Research Division
Federal Reserve Bank of St. Louis
*Working Paper Series*

# Speculation in the Oil Market

**Luciana Juvenal**
**and**
**Ivan Petrella**

Working Paper 2011-027A
http://research.stlouisfed.org/wp/2011/2011-027.pdf

October 2011

FEDERAL RESERVE BANK OF ST. LOUIS
Research Division
P.O. Box 442
St. Louis, MO 63166

---

# Speculation in the Oil Market*

Luciana Juvenal†
Federal Reserve Bank of St. Louis

Ivan Petrella‡
Katholieke Universiteit Leuven

1 October 2011

**Abstract**

The run-up in oil prices after 2004 coincided with a growing flow of investment to commodity markets and an increased price comovement between different commodities. We analyze whether speculation in the oil market played a key role in driving this salient empirical pattern. We identify oil shocks from a large dataset using a factor-augmented autoregressive (FAVAR) model. We analyze the role of speculation in comparison to supply and demand forces as drivers of oil prices. The main results are as follows: (i) While global demand shocks account for the largest share of oil price fluctuations, financial speculative demand shocks are the second most important driver. (ii) The comovement between oil prices and the price of other commodities is explained by global demand and financial speculative demand shocks. (iii) The increase in oil prices in the last decade is mainly explained by the strength of global demand. However, financial speculation played a significant role in the oil price increase between 2004 and 2008, and its subsequent collapse. Our results support the view that the financialization process of commodity markets explains part of the recent increase in oil prices.

**JEL classification:** Q41, Q43, D84, C32
**Keywords:** Oil Prices, Speculation, FAVAR

*We are very grateful to Lutz Kilian for his constructive suggestions. We thank Brett Fawley for excellent research assistance. The views expressed are those of the author and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

†Research Division, Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166-0442. *Email:* luciana.juvenal@stls.frb.org. (http://www.lucianajuvenal.com/)

‡Center for Economic Studies, Faculty of Business & Economics, Katholieke Universiteit Leuven, Naamsestraat 69, 3000 Leuven, Belgium. *E-mail*: Ivan.Petrella@econ.kuleuven.be. (http://www.ivanpetrella.com/)

*"The increase in (oil) prices has not been driven by supply and demand."*

Lord Browne, Group Chief Executive of BP (2006)

*"[...] the sharp increases and extreme volatility of oil prices have led observers to suggest that some part of the rise in prices reflects a speculative component arising from the activities of traders in the oil markets. "*

Ben Bernanke, Chairman, Federal Reserve Board (2004)

# 1 Introduction

The long-standing debate surrounding the sources of oil price fluctuations recently intensified due to the dramatic rise in oil prices. The seminal contribution of Kilian (2009) highlights that oil price shocks may have very different effects on the real price of oil depending on the origin of the shock. He concludes that oil prices have historically been driven by global demand shocks. Since his seminal contribution, an impressive list of empirical studies have investigated the effects of different types of oil shocks, agreeing with Kilian's (2009) conclusion.[1]

While this finding has gained strong support, it has been suggested that the recent run-up in oil prices may in part be driven by factors that are unrelated to supply and demand forces (see Tang and Xiong, 2011). This has fueled an ongoing debate as to whether additional regulatory limits on trading in oil futures should be imposed (see Masters, 2008), making the link between speculation and oil prices relevant from a policy standpoint.

One striking characteristic of the oil market in the past decade is that large financial institutions, hedge funds, and other investment funds have been investing billions of dollars in the futures market to take advantage of oil price changes. Indeed, commodities have become a recognized asset class within investment portfolios of financial institutions as a means to

[1] See also Baumeister, Peersman, and Robays (2010); Baumeister and Peersman (2010); Baumeister and Peersman (2011); Hicks and Kilian (2009); Kilian (2010); Kilian and Murphy (2011a, 2011b); and Kilian and Park (2009). Note that these results build on the work of Barsky and Kilian (2002), who identify the reverse causality from macroeconomic aggregates to oil prices.

diversify risks such as inflation, or equity market weakness (see Gorton and Rowenhorst, 2006). It is estimated that assets allocated to commodity index trading strategies has risen from \$13 billion in 2004 to \$260 billion as of March 2008. The increase in the volume of trading had a number of effects on commodity markets. According to Hamilton and Wu (2011), it changed the nature of risk premia in the crude oil futures market. In particular, the compensation to the long position became smaller on average but more volatile. The evidence in Tang and Xiong (2011) suggests that the growing flow of investment to commodity markets coincided with an increase in the price of oil and a higher price comovement between different commodities. In this paper we analyze whether financial speculation in the oil market was a driver of this empirical pattern.

What is speculation in the oil market? The view of speculation that we follow, which we will call financial speculation, is inspired by Hamilton (2009). He argues that speculators can affect the incentives faced by oil producers by purchasing a large number future contracts and pushing future prices to even higher levels than current prices. As producers expect a higher price of oil for future delivery, they will hold oil back from the market and accumulate inventories. This perspective on speculation is encompassed in Kilian and Murphy (2011a). In their model, the speculative demand shock is more general. It is a shock to oil inventories arising from: (i) expected short-falls of future oil supply relative to future oil demand; or (ii) speculation by traders. In this way, Kilian and Murphy (2011a) allow for financial speculation but do not separately identify it. We disentangle the speculative oil inventory demand shock and the financial speculative demand shock.[2]

In this paper we re-examine the role of speculation relative to supply and demand forces as a driver of oil prices using a factor-augmented vector autoregressive (FAVAR) model. Bernanke et al. (2005) argue that the small number of variables in a VAR may not span the information sets used by market participants, who are known to follow hundreds of data series. Therefore, a set of factors is used to summarize the bulk of aggregate fluctuations of a large dataset, which includes both macroeconomic and financial variables of the G7 countries

[2]Let us recall that Alquist and Kilian (2010) show that an unexpected increase in the uncertainty about future oil supply would have the same effect as an expected mismatch between supply and demand.

and a rich set of commodity prices. We provide extensive evidence that the information summarized in the factors is important to estimate oil shocks. This justifies the use of a FAVAR model.

We identify oil supply, global demand, speculative oil inventory demand, and financial speculative demand shocks by imposing economically meaningful sign restrictions on the impulse responses of a subset of variables in the FAVAR. Supply shocks, which were until recently the center of attention in the oil literature (see Hamilton, 2003; Kilian, 2008a; and Kilian, 2008b), refer to changes in the current physical availability of crude oil. The global demand shock captures an increase in demand for all industrial commodities triggered by the state of the global business cycle. The speculative oil inventory demand shock refers to shifts in the price of oil driven by higher demand for oil inventories, associated, for example, with market concerns about the availability of future oil supplies.[3] A financial speculative demand shock reflects an increase in oil prices driven by traders' activity in the oil futures market. Although this may not be directly linked with fundamentals, by affecting the future prices it influences the current behavior of oil market participants. We find evidence consistent with the fact that the main determinant of oil price fluctuations is global demand. However, financial speculative demand shocks are on average the second most important driver of oil price dynamics, suggesting that speculative activities may affect the incentives faced by operators in the oil market.

The use of a FAVAR allows us to investigate the transmission of oil shocks on a large number of variables. Therefore, we can investigate whether financial speculation played a role in driving the increased comovement in a large number of commodity prices observed in recent years. We find that all the identified shocks generate comovement in commodity prices, with global demand shocks being the main driver of such comovement. When we analyze the conditional correlations between oil prices and the price of other commodities, we obtain an interesting result. The largest correlations are in response to global demand shocks, consistent with the narrative in Kilian (2009). However, the financial speculative demand shock is also associated with a positive comovement between oil and other commodities'

[3] This is the speculative demand shock in Kilian and Murphy (2011a).

prices. This is consistent with the results of Tang and Xiong (2011) and adds evidence supporting the idea that the financial speculative demand shock that we identify is picking up the effects of financialization driven by the rapid growth of commodity index investment as emphasized by, among others, Singleton (2011).[4] The correlation between oil prices and the prices of other commodities is negative for the other shocks. This implies that the speculative oil inventory demand shock cannot be responsible for the comovement in commodity prices.

When we try to interpret oil price fluctuations in the last decade under the lens of our model, we find that financial speculative demand shocks began to play a relevant role as drivers of oil price increases in 2004. Interestingly, this timing is consistent with other studies that document the increase in investment flows into commodity markets in 2004 (see Tang and Xiong, 2011 and Singleton, 2011). Although financial speculation played a significant role in driving oil price increases between 2004 and 2008, and to its subsequent decline, the increase in oil prices in the last decade is mainly due to the strength of global demand, in line with Kilian (2009), and most of the literature thereafter.

The rest of the paper is organized as follows. Section 2 presents the econometric method. Section 3 describes the data, the identification strategy, and discusses the results of the standard VAR and the FAVAR. Section 4 incorporates financial speculative demand shocks into the FAVAR. Section 5 presents the main results, and Section 6 offers some concluding remarks.

# 2 Econometric Method

Since the seminal paper of Kilian (2009) a large body of literature has focused on disentangling the determinants of oil price fluctuations using structural vector autoregressions (SVARs) on a small set of variables. In this framework, structural shocks are identified as a linear combination of the residuals of the linear projection of a low-dimensional vector

[4] In their working paper version, Alquist and Kilian (2007) report evidence that from 2004 to 2007 there was an increase in traders' activity. They measure the relative importance of speculative activities by the number of noncommercial spread positions expressed as a percentage of the reportable open interest positions. They find a marked increase in the percent share of noncommercial spread positions since December 2003, suggesting that speculation intensified. The authors highlight that the most recent increase in the noncommercial spread position is unprecedented in the sample.

of variables onto their lagged values. This implies that all the relevant information for the identification of the shocks is included in the small set of variables in the VAR, i.e. that the identified structure of the shocks is fundamental (see Hansen and Sargent, 1991, Lippi and Reichlin, 1993,1994 and Fernandez-Villaverde et al., 2007). However, additional information available in other economic series excluded from the VAR may be relevant to the dynamic relation implied in the VAR model. Not including this information can have implications for the estimated model. In particular, the identification of the shocks and their related transmission mechanism can be severely biased by the omission of relevant information. One way to address this issue is by augmenting the information set of the VAR with the inclusion of a small set of principal components (factors), which summarize the information of a wider set of variables. In this section we provide a summary of the factor-augmented vector autoregressive model (FAVAR) approach that we use in the empirical section. For additional details see Bernanke et al. (2005).

The use of the FAVAR entails two major advantages with respect to low-dimensional VAR models. First, it does not require a stance on specific observable measures corresponding precisely to some theoretical constructs. In empirical models of the oil market, for example, we need to include a measure of the global demand pressures, which can be captured by an unobservable factor. Second, a natural by-product of the FAVAR is to obtain impulse response functions for any variable included in the dataset. This allows us to document the effects of identified shocks on a broader set of commodities and will be particularly useful as a validation of the different shocks identified. In fact, we can check that global demand shocks positively impact all commodity prices (as hinted by Kilian, 2009), or that speculation in the oil market transmits across different commodities as a result of portfolio rebalancing of diversified index investors (see e.g., Kyle and Xiong, 2001).

Denote by $x_{it}$ the generic variable of a panel of $N$ stationary time series, where both the $N$ and $T$ dimensions are very large. In the factor model each variable in our dataset, $x_{it}$, is expressed as the sum of a common component and an idiosyncratic component that are mutually orthogonal and unobservable:[5]

$$x_{it} = \boldsymbol{\lambda}_i \mathbf{f}_t + \xi_{it}, \tag{1}$$

where $\mathbf{f}_t$ represents $r$ unobserved factors ($N \gg r$), $\boldsymbol{\lambda}_i$ is the $r-$dimensional vector of factor loadings, and $\xi_{it}$ are idiosyncratic components of $x_{it}$ uncorrelated with $\mathbf{f}_t$.

The idiosyncratic components are poorly correlated across the cross-sectional dimension. We can think of them as shocks that affect a single variable or a small group of variables. For example, in the specific dataset under analysis the idiosyncratic components will incorporate shocks to a single country that are not large enough to affect the all other countries. The idiosyncratic components also include a measurement error that is uncorrelated across variables. Allowing for a measurement error is particularly useful in our context. The low-dimensional VARs aimed at analyzing the oil market include some proxy for global demand (see Kilian, 2009; and Baumeister and Peersman, 2011). Any observable measure of this general concept is likely to be contaminated by measurement errors.

The common component is a linear combination of a relatively small number of $r$ (static) factors. These reflect movements in global economic activity and will generally be responsible for the bulk of the comovements between the variables in the dataset.[6]

Let $\mathbf{y}_t$ denote the $M$-dimensional vector of variables describing the dynamics of the oil market. The VAR literature assumes that the relevant information set for the identification of the shocks is summarized by its lagged values. However, additional information available in other economic series not included in the VAR may be relevant to the dynamics of the oil market. Therefore, we consider that the dynamics in the oil market can be well represented by the following FAVAR:

$$\begin{bmatrix} \mathbf{y}_t \\ \mathbf{f}_t \end{bmatrix} = \boldsymbol{\Phi}(L) \begin{bmatrix} \mathbf{y}_{t-1} \\ \mathbf{f}_{t-1} \end{bmatrix} + \mathbf{u}_t \tag{2}$$

where $\boldsymbol{\Phi}(L)$ is the lag polynomial in the lag operator $L$, and $\mathbf{u}_t$ is the error term with mean zero and variance-covariance matrix $\boldsymbol{\Sigma}$.

[5] A discussion of the variables included as well as the exact stationary transformation of the data is included in Appendix A.

[6] Notice that the static factor model considered here is not very restrictive since an underlying dynamic factor model can always be written in static form (see Stock and Watson, 2005).

Kilian (2009) was the first to emphasize the importance of global demand forces in the determination of oil prices. In fact, he includes a proxy for global economic activity among the relevant variables for identifying the structural shocks. In a way this low-dimension VAR can be considered a specific version of (2), where the proxy for global economic activity is considered an observable factor. Therefore, by considering model (2) we complement the existing empirical evidence by allowing the stochastic dimension of the large dataset of macroeconomic and commodity data (i.e. the world economy) to be larger than 1. This will be true whenever the global economy is affected by more than one source of common shocks.[7] The specification (2) highlights that the low-dimensional VAR is well suited for the identification of the structural shocks affecting the oil market only when the aggregate factors do not Granger-cause the variables in $\mathbf{y}_t$ (see Giannone and Reichlin, 2006).

Our application includes the growth rate of oil production, inventories and prices in $\mathbf{y}_t$, whereas the effect of global demand is accounted for by the unobservable factors. We do not impose that any of the oil variables are an observable factor in the system.[8] This implies that the identified shocks are not necessarily global shocks but does not rule out the possibility.[9] Some evidence suggests that oil shocks are global. In fact, since the seminal papers of Hamilton (1983, 1985) oil price surges have been considered among the key driving forces behind most of the US recessions. As suggested by Engemann et al. (2010), it is likely that other countries are also affected by the oil shocks in a very similar way. Evidence in Baumeister et al. (2010) shows that industrialized countries tend to respond in a similar way to global demand and oil specific demand shocks. In related studies, Kilian et al. (2009) and Kilian and Park (2009)) emphasize the role of oil shocks as drivers of US real stock returns and external balances.

[7]This is a realistic assumption that holds even if one is not willing to assume the presence of global shocks. Indeed, the presence of interconnections among economies in the global markets gives rise to a factor representation of the data akin to (1) (see e.g. Chudick et al., 2011).

[8]The test of Bai and Ng (2006) suggests that none of these variables can be considered as a valid proxy of the unobservable common factors.

[9]An alternative way to model the oil market in a large information framework would be to estimate a dynamic factor model along the lines of Forni et al. (2009) , however in this framework we would be implicitely constraining the oil shocks to be global shocks.

## 2.1 Estimation and identification of the structural shocks

We estimate the model using a two-step procedure. In the first step, the unobserved factors and loadings are estimated using the principal components method described in Stock and Watson (2002b). In the second step, we use the estimated factors along with the oil variables to estimate our VAR model.[10] Stock and Watson (2002a) prove consistency of the principal components estimator in an approximate factor model when both cross-section and time sizes, $N$ and $T$, go to infinity. The two-step procedure is chosen for computational convenience. Moreover, the principal components approach does not require very strong distributional assumptions.[11]

Since the unobserved factors are estimated and then included as regressors in the FAVAR model the two-steps approach might suffer from the "generated regressor" problem. In order to account for estimation uncertainty, we adopt a non-overlapping block bootstrap technique along the lines of Forni and Gambetti (2010a and 2010b).

We are interested in analyzing the impact of different type of oil shocks in the framework of a FAVAR model. To give a structural interpretation to the shocks we follow the approach based on sign restrictions proposed by Uhlig (2005). We identify the shocks by imposing economically meaningful sign restrictions on the impulse responses of a subset of variables. Specifically, denote with $\mathbf{Q}$ an orthonormal matrix, so that $\mathbf{Q}'\mathbf{Q} = \mathbf{I}$. The structural shocks can be recovered as $\boldsymbol{\eta}_t = \mathbf{Q}\mathbf{u}_t$. The orthonormal matrices $\mathbf{Q}$ are found from the eigenvalue decomposition of a random $q \times q$ matrix drawn from a normal distribution with unitary variance (see Rubio-Ramirez et al., 2010). The corresponding structural impulse response function to the common component for the oil variables can be recovered as

$$\mathbf{y}_t = [\mathbf{I}_3; \mathbf{0}_{3\times r}] \left[\mathbf{I}_{3+r} - \boldsymbol{\Phi}(L)L\right]^{-1} \mathbf{Q}'\boldsymbol{\eta}_t,$$

where the moving average representation of the $i$-th variable in the dataset can be written

[10] The lag length is equal to 4. Setting a longer lag length (in line with the recommendation of Hamilton and Herrera, 2004) does not affect the results.

[11] Doz et al. (2011) show that likelihood-based and two-step procedures perform quite similarly in approximating the space spanned by latent factors. In addition, Bernanke et al. (2005) find that the single step Bayesian likelihood method delivers essentially the same results as the two-step principal components method.

as

$$x_{it} = [\mathbf{0}_{1\times 3}; \boldsymbol{\lambda}_i] \left[\mathbf{I}_{3+r} - \boldsymbol{\Phi}(L)L\right]^{-1} \mathbf{Q}' \boldsymbol{\eta}_t.$$

# 3 Empirical Analysis

## 3.1 Data

We use quarterly data from 1971 to 2009. The data consists of 151 series taken mainly from the *International Financial Statistics* (IFS) of the International Monetary Fund (IMF), the Organization for Economic Cooperation and Development (OECD), the Department of Energy (DOE), and the Energy Information Administration (EIA). A complete description of the data and sources is listed in Appendix A. The series include oil specific data such as oil production, oil prices, and inventories, as well as prices of other commodities and measures of global real economic activity. We also collected data on output, prices, financial indicators, and employment for the G7 countries. All data is transformed to reach stationarity (see Appendix A for details).[12]

## 3.2 Sufficient Information and the Choice of Factors

A natural question at this stage is whether the large data set we use contains valuable information with respect to the small-scale VAR typically used in the literature to characterize the effects of oil shocks. Therefore, we test whether the small scale VAR is infomationally sufficient to identify the shocks using the procedure described in Forni and Gambetti (2011). The method uses the Gelper and Croux (2007) multivariate extension of the out-of-sample Granger causality test proposed by Harvey et al. (1998). To implement the method we proceed as follows. We set the maximum number of static factors to be $r = 6$ and compute the corresponding 6 principal components. Then, we test whether the first 6 principal components Granger cause the variables of the VAR. If the null of no Granger causality is not rejected, the variables of the VAR are informationally sufficient. Otherwise sufficiency is rejected and the set of variables under consideration does not contain enough information

[12] In the estimation all commodity prices, including oil, are entered in real terms after deflating by the US CPI.

to estimate the structural shocks. In this case at least one factor should be added to the estimation. We repeat this procedure until the alternative hypothesis is always rejected for any number of factors up to the specified maximum number of factors (here 6).

We estimate two versions of a 4-variable VAR, that has been used in the literature. The first VAR is from Kilian and Murphy (2011a) and includes the following variables: oil production, oil inventories, real oil price, and real economic activity. The latter is a measure of global real economic activity based on freight rates proposed by Kilian (2009). The second VAR replaces real economic activity by aggregate industrial production, which is the measure used by Baumeister and Peersman (2011).

Table 1 reports the (bootstrapped) $p$-values of the Granger causality test for the VAR and VAR augmented with Factors. Panel A shows the results for the VAR with the Kilian measure of economic activity and Panel B includes the results with aggregate industrial production. The first row of each table presents the $p$-value for the null that the first principal components do not Granger cause the variables of the VAR. Overall, we find that the variables of the VAR are Granger caused by the first six principal components. This implies that the VAR is not informationally sufficient and motivates the use of a FAVAR to identify the shocks. Since the null is rejected we proceed by augmenting the VAR with factors. For both specifications we cannot reject the informational sufficiency of the FAVAR when 4 factors are added to the baseline VAR.

**[Table 1 about here]**

We also implement the Bai and Ng (2002) test to determine the number of factors. This test suggests using 3 factors. We choose 4, consistent with the sufficient information test. However, our results are robust to the estimation of the FAVAR with 3 factors. When we estimate the FAVAR with a different number of factors we find that the shapes of the impulse responses of a subset of variables are largely unaffected, but their sizes are affected. Moreover, consistent with our choice of the number of factors, we find that the results do not change when including more than 3 factors.[13]

[13] Appendix B shows the impulse responses for different numbers of factors.

## 3.3 Identification

In this Section we discuss the sign restrictions imposed to estimate oil supply, global demand, and speculative oil inventory demand shocks, which are the focus of the recent literature. Our identification strategy, summarized in Table 2, builds on Kilian and Murphy (2011a, 2001b) and Baumeister and Peersman (2011). An oil supply shock is identified as any unanticipated shift in the oil supply curve that results in an opposite movement of oil production and the real price of crude oil. A negative oil supply shock is associated with a decrease in production and an increase in real oil prices. During an oil supply disruption inventories are depleted in an effort to smooth oil production and real activity contracts. We impose a sign restriction on inventories in order to disentangle this shock from the financial speculative shock we will describe in Section 4.[14]

[**Table 2 about here**]

A speculative oil inventory demand shock arises from a possibility of a sudden shortage in production or expectations of higher demand in the future. Therefore, it is associated with expected short-falls of future oil supply relative to future oil demand. This can happen in the presence of uncertainty about future oil supplies, driven, for example, by political instability in key producing countries such as Nigeria, Iraq, Venezuela or Libya. A positive speculative oil inventory demand shock raises demand for inventories, causing the level of inventories and real oil prices to increase. Inventories of crude oil increase in order for supply to meet demand in the event of supply shortfalls or unexpected shifts in demand (see Alquist and Kilian, 2010). The accumulation of inventories requires an increase in oil production. As a result of the increase in the real oil price, real activity declines.

A global demand shock is driven by unexpected changes in global economic activity. This represents shifts in demand for all industrial commodities, including oil, resulting from higher real economic activity, triggered, for example, by rapid growth in China, India, and

[14]Our approach differs from Kilian and Murphy (2011a) since they do not impose a sign restriction on inventories to identify the supply shock. However, leaving oil inventories unrestricted they find that inventories decline after a supply shock. Therefore, we are comfortable imposing this sign since it goes in line with their empirical findings.

other emerging economies (see Hicks and Kilian, 2009). This increase in the demand for oil will drive its real price up. In order to satisfy the higher demand, oil production increases. The effect on oil inventories is ambiguous.

In addition to the sign restrictions, we impose an upper bound of 0.0257 for the response of the impact elasticity of oil supply with respect to the real price, consistent with Kilian and Murphy (2011b). This bound is imposed for all shocks except for the supply shock.

## 3.4 Orthogonality

Despite the rejection of the information sufficiency of the VAR, it can still be the case that some of the shocks are correctly identified from the low-dimensional VAR. This would be the case whenever the identified structural shocks from the VAR are orthogonal to any available information at time $t$, for instance lagged values of the factors. Otherwise, the identified shock cannot be considered structural (Forni and Gambetti, 2011).

The identification by sign restriction does not identify a single model. Therefore, we investigate the orthogonality of the shocks over all sets of identified impulse responses. To summarize our findings, Table 3 reports the size of the rejection set (at the 10% level) of the $F$-test of orthogonality for each of the shocks identified from the VAR with sign restrictions. Specifically, for each possible set of shocks we test whether each of them is Granger-caused by lagged factors. We then report the number of rejected shocks over the total identified shocks. The results of the first row imply that the first factor does not Granger cause any of the shocks. This result is consistent with the view that the first factor reflects the business cycle, and consequently is captured by real economic activity. The last line of Table 3 suggests that a linear combination of 4 factors is granger causing 14% of all the identified oil supply shocks, 60% of all the identified global demand shocks and about 52% of all the identified speculative oil demand shocks.[15]

**[Table 3 about here]**

[15] The fact that the lagged first factor is orthogonal to the shocks of the VAR is consistent with the impulse responses shown in Appendix B. There is very little difference between the impulse responses of the VAR and the impulse responses of the VAR augmented with one factor. This is consistent with the work of Kilian and Murphy (2011a) in that they impose the stochastic dimension of the economy to be 1.

Overall, these results justify the choice of augmenting the low-dimension VAR with the set of factors. They also emphasize that the factors are a good representation of the bulk of aggregate fluctuation, and consequently are well suited to summarize the dynamics behind the world business cycle.

## 3.5 VAR and FAVAR

In this subsection we estimate a VAR and a FAVAR with 3 shocks and compare their results. Note that in the case of the FAVAR we impose sign restrictions on both measures of real economic activity given that the two of them have been used in the literature. The impulse responses obtained from the FAVAR and the VAR are qualitatively comparable (they are shown in Appendix C). However, some differences between the two methods emerge when we analyze the variance decomposition. Table 4 presents the forecast error variance decomposition of the oil price to the three shocks using the VARs (with the two measures of economic activity) and the FAVAR. The variance decomposition in both VARs is dominated by demand shocks at all step horizons. The speculative oil inventory demand shock also plays a significant role, accounting for about 10% to 30% of oil price fluctuations in the VARs. The sum of the three shocks account for around 90% of the oil price variation in both VARs.

**[Table 4 about here]**

The FAVAR offers a contrasting picture. Global demand shocks account for 38% of the variation in oil prices on impact and 40% in the long run. The speculative oil inventory demand shock also plays a smaller role in comparison to the VARs. Supply shocks account for up to 10% of oil price fluctuations. Overall, the total share of oil price fluctuations explained by the three shocks is attenuated in the FAVAR with respect to the VAR. In fact, in the FAVAR the three shocks explain from 49% to 56% of oil price fluctuations at all horizons.

It can be noted that the oil supply shock is the least affected by the inclusions of the factors. This is consistent with the results in the previous section. Specifically, among the 3 shocks, this is the one with the lowest rate of rejection of the orthogonality test. This highlights that the identification of this shock is not largely affected by the inclusion of the factors.

The contrasting results highlight the potential benefits of identifying the shocks using a FAVAR. The FAVAR allows us to rely on more information, which can be useful for a correct identification of the shocks and to recover their fundamental structure.

From the previous results we observe that there is a substantial unexplained component playing an important role. We conjecture that one of these components is speculation in the oil market. The next Section attends to this.

# 4 Augmented Model

In this Section we extend the FAVAR model with 3 identified shocks as previously analyzed to include financial speculative demand shocks. We first describe the main characteristics of speculation in the oil market and then we discuss the identifying restrictions to pin down the speculative shock.

## 4.1 Background on Speculation

One striking characteristic of the oil market in the past decade is that large financial institutions, hedge funds, and other investment funds have been investing billions of dollars in the futures market to take advantage of oil price changes. The Commodity Futures Trading Commission (CFTC) defines a speculator as a unit who "does not produce or use the commodity, but risks his or her own capital trading futures in that commodity in hopes of making a profit on price changes." The speculative view of oil price determination states that growing participation in oil futures by non-market players can push the price above the level that should result from purely fundamental factors. The way financial institutions operate in the commodity markets can be described as follows. They take a long position in a near-term futures contract, sell it a few weeks before expiry, and use the proceeds to take a long position in a subsequent near-term futures contract. When commodity prices are rising, the sell price should be higher than the buy, and the investor can profit without physical delivery. As more financial institutions take positions in commodity futures contracts, futures prices go up, and with it the spot price.

Commodities have become a recognized asset class within investment portfolios of financial institutions as a means to diversify risks such as inflation, or equity market weakness. Gorton and Rouwenhorst (2006) show that commodity futures have performed as well as stocks and better than bonds, with less risk. This leads to increased expenditure on energy commodities. Speculative trading occurs both on the regulated New York Mercantile Exchange (NYMEX) and on the over-the-counter (OTC) markets. In contrast to trades conducted on the NYMEX, traders on unregulated OTC exchanges are not required to keep records, which means that there are no official records on the total amount traded. Michael Masters, in testimony before the U.S. Senate in May 2008, estimated that assets allocated to commodity index trading strategies had risen from \$13 billion in 2004 to \$260 billion as of March 2008. As the evidence in Tang and Xiong (2011) suggests, growing participation in the commodities market coincided with an increase in oil prices as well as a broader increase in comovement between the return of investments in different commodities. In a related study, Hamilton and Wu (2011) document that the purchases of futures contracts increased substantially after 2004, as a vehicle for financial diversification.

This financialization of commodities might give rise (and many believe it did) to a speculative bubble in the price of oil.[16] Singleton (2011) presents evidence that there was an economically and statistically positive effect of investor flows on oil futures prices. He also highlights how the interaction of heterogeneity of views on commodity prices and associated speculative trading, might give rise to boom and bust cycles in commodity prices. Hamilton and Wu (2011) find that increased participation of financial investors in the oil market resulted in a significant change in the behavior of crude oil future contracts. In particular, the pricing of risk has increased significantly since 2005. There is also anecdotal evidence that speculation has significantly increased oil prices. Most recently, this idea attracted a great deal of media attention after the CFTC filed lawsuits against traders for manipulating the price of oil.[17] In the next subsection we propose an identification strategy to disentangle the

[16] See, for example, "The Role of Market Speculation in Rising Oil and Gas Prices: A Need to Put the Cop Back on the Beat", Permanent Subcommitee on Investigations, Committee on Homeland Security and Governmental Affairs, United State Senate, June 2006.

[17] See http://online.wsj.com/article/SB10001424052702303654804576349572125616828.html. and

speculative shock and analyze its role as a driver of oil prices.

## 4.2 Identification of Financial Speculative Demand Shock

For the reasons explained before, oil can be viewed as an asset and as such, price changes can arise from speculation (see Singleton, 2011). We identify a speculative shock using sign restrictions inspired by Hamilton (2009) and presented in the last row of Table 2. The restrictions imposed to identify a speculative shock are that the real oil price increases, inventories accumulate and oil production falls. We do not impose any restriction on real economic activity.

The rationale for these restrictions follows from Hamilton (2009). He argues that speculators can affect the incentives faced by oil producers by purchasing a large number of future contracts and pushing up future prices to even higher levels than current prices. As producers expect a high price of oil for future delivery, they will hold oil back from the market and accumulate inventories. Leaving more oil underground may enhance total profits on the producers investment given that prices are expected to rise in the future (more rapidly than the average market return). As explained by the Hotelling (1931) principle, it would pay for the producers of oil to forgo current production in order to be able to sell the oil at higher future prices. In this way, the oil producers will not accommodate the upward trend in oil prices but rather decrease production. Oil producers take future profits into account when deciding whether to produce today or tomorrow, especially in the context of speculation, when prices are expected to increase in the future.[18] In contrast to a speculative oil inventory demand shock, in a financial speculative demand shock inventories accumulate not because of a fear of a shortage of production (which will generate a need of oil storage), but because speculation itself leads to higher expected prices. The reduction in the oil available for current use, resulting from lower production and increased inventory holding, will cause the current spot oil price to rise.

http://nyti.ms/lbSAm7.

[18] There is evidence supporting this argument. For example, Davidson et al. (1974) show that after President Nixon imposed temporary price controls on oil produced in the US in 1971, the number of shut-in oil-producible zones on the US outer continental shelf jumped from 14.3 per cent of the total completions of oil producible zones in 1971 to 44.4 per cent in 1972 and 44.5 per cent in 1973.

These set of sign restrictions are also consistent with Bernanke (2004), which describes how speculation may drive oil prices up. He highlights that as speculative traders expect oil to be in short supply and oil prices to rise in the future, they purchase oil futures contracts on the commodity exchange. Oil futures contracts represent claims to oil to be delivered at a specified price and at a specified date and location in the future. If the price of oil rises as the traders expect–more precisely, if the future oil price rises above the price specified in the contract–they will be able to re-sell their claims to oil at a profit. If many speculators share this view, then their demand for oil futures will be high and, consequently, the price of oil for future delivery will rise. Higher oil futures prices in turn affect the incentives faced by oil producers. Seeing the high price of oil for future delivery, oil producers will hold oil back from today's market, adding it to inventory for anticipated future sale. This reduction in the amount of oil available for current use will in turn cause today's price of oil to rise, an increase that can be interpreted as the speculative premium in the oil price.

There are two forces that operate in opposite directions driving demand. On the one hand, the oil price increase would have a contractionary effect on demand. On the other hand, oil plays the same role as an asset and the price increase operates as a wealth effect, which induces a positive impact on demand in the short run. Consequently, we leave real economic activity unrestricted.

We highlight that in the context of speculation there are several forces driving the oil price up. The expectation of higher prices in the future gives rise to higher demand for inventories and less production, which decreases the amount of oil available. At the same time, the increased demand is reflected in higher demand pressure for oil resulting in higher oil prices. In this way speculation gives rise to a self fulfilling mechanism that sustains higher oil prices.

This perspective on speculation is encompassed by Kilian and Murphy (2011a). In their model, speculation is a shock to inventories arising from forward-looking behavior which combines three distinct types of shocks: (i) an uncertainty shock that raises precautionary demand; (ii) a shock arising from expectations of higher future demand; (iii) or speculation by traders. In this way, Kilian and Murphy (2011a) allow for financial speculation but do not separately identify it. In our paper, we identify the speculative oil inventory demand shock, which includes (i) and (ii) and financial speculation, which includes (iii).

We would like to emphasize that in order to disentangle oil supply shocks from the financial speculative demand in our framework we need to impose a negative restriction on oil inventories following an oil supply shock. As explained in Kilian and Murphy (2011a), this is implicitly imposing a consumption smoothing rationale for holding inventories in the face of supply shocks. We note that Kilian and Murphy (2011a) report evidence in favor of this type of inventory behavior, so this seems a reasonable restriction.

# 5 Empirical Results

## 5.1 Impulse responses

Figure 1 presents the median impulse responses of oil production, oil inventories, real economic activity and industrial production to an oil supply, speculative oil inventory demand, global demand and financial speculative shocks. The impulse responses, estimated using a FAVAR with the sign restrictions from Table 2, have been accumulated and are shown in levels.

[**Figure 1 about here**]

A negative oil supply shock is associated with a drop in production, which exhibits a temporary decline. Oil inventories decrease in an effort to smooth production. The real price of oil rises on impact, but this rise is only transitory. As production stabilizes, the effect on real oil prices vanishes. The latter effect is reflected in a transitory decline in aggregate industrial production and real economic activity.

A positive speculative oil inventory demand shock is associated with an immediate jump in the real price of oil. The real oil price overshoots on impact and declines gradually. Inventories exhibit a persistent increase as in Kilian and Murphy (2011a). Oil production increases while aggregate industrial production and real economic activity decline temporarily.

A positive global demand shock leads to an increase in aggregate industrial production and real economic activity. As a consequence of high demand pressures triggered by rapid growth, real oil prices exhibit a persistent increase. Oil production also rises temporarily, and oil inventories decline to satisfy the higher demand.

A positive financial speculative shock is associated with a persistent increase in oil prices. As producers expect a higher price in the future, they hold oil back from production and accumulate inventories. Real economic activity goes up on impact but reverses quickly while aggregate industrial production exhibits a small temporary rise.

## 5.2 The Price of Other Commodities

The FAVAR allows us to include a large number of variables such as the price of different commodities. A natural question is what is the impact of each of the shocks to the price of commodities? This question is of particular impact since it will allow us to check whether the speculative shock we are indentifying in fact arises from the financialization in the commodity markets as described before. If this is the case, the response of the prices of other commodities to a speculative shock should be positive and we should observe a positive comovement between oil prices and the price of other commodities. Barberis and Shleifer (2003) highlight that since index investors typically focus on strategic portfolio allocation between the commodity class and other asset classes, such as stocks and bonds, they tend to trade in and out of all commodities in a chosen index at the same time.

Analyzing the response of the price of other commodities will also allow us to investigate an additional dimension of the global demand shock. Kilian (2009) interprets this shock as an increase of demand for all industrial commodities, fueled in the last decade by high growth in China and India (see also Kilian, 2010; and Hicks and Kilian, 2009). If this is the case, demand for industrial commodities such as copper and oil will rise because these commodities are used as inputs in production. At the same time demand for non-industrial commodities is likely to rise due to increases in income. Demand pressures would be associated with an increase in the price of all commodities.

In what follows we examine the impulse responses of industrial commodities, the comovement of commodity prices in response to each of the shocks, and the conditional correlation between oil prices and the price of other commodities.

### 5.2.1 Impulse Responses of Industrial Commodities

Figure 2 presents the impulse responses of the real price of industrial commodities: Copper, aluminium, nickel, iron ore and zinc to the four shocks identified. The identification is the same as in Section 5.1. Note that the responses of these variables to the shocks were left unrestricted.

From the impulse responses it follows that the global demand shock has a positive effect on the price of all industrial commodities, consistent with the interpretation of the shock. The financial speculative demand shock also leads to a rise in the price of industrial commodities. This suggests a possible link between investment in oil futures and other commodities futures. In fact, Pindyck and Rotemberg (1990) highlight that comovement in commodity markets can be due to the behavior of speculators who are long in several commodities at the same time. The speculative oil inventory demand shock generates a decrease in the price of industrial commodities. Finally, the negative supply shock leads to a decrease in the price of industrial commodities but the effect is small. When we analyze the responses of the price of other commodities (non industrial) to each shock, we find similar behavior.[19]

[**Figure 2 about here**]

### 5.2.2 Comovement in Commodity Prices

In order to shed some light on the comovement between commodity prices we decompose the correlation between two variables into the contributions of the structural shocks of the FAVAR. This will allow us to understand which of the shocks are responsible for the increased correlation in commodity prices.

Following Den Haan and Sterk (2011), the correlation ($COR$) between the $K$th period ahead forecast errors of two variables $v_t$ and $z_t$, is

$$COR(v_t, z_t; K, s) = \frac{\sum_{k=1}^{K} v_k^{imp,s} z_k^{imp,s}}{SD(v_t; K)SD(z_t; K)}. \tag{3}$$

[19] Not shown here but available upon request.

In Equation 3, $v_k^{imp,s}$ and $z_k^{imp,s}$ are the $K$th period responses of $v$ and $z$ to a one-standard deviation innovation of the $s^{th}$ structural shock, and $SD$ denotes the total standard deviation of the $K$th period ahead forecast error given by

$$SD(b_t; K) = \left[ \sum_{k=1}^{K} COV\left(b_t, b_t; K, s\right) \right]^{1/2} \qquad \text{for } b_t = v_t, z_t,$$

where $COV$ denotes covariance, equal to $COV(v_t, z_t; K, s) = \sum_{s=1}^{S}\sum_{k=1}^{K} v_k^{imp,s} z_k^{imp,s}$, and $S$ is the number of shocks (in our case $S = 3 + r$).

Figure 3 presents the cross-sectional average pairwise correlation of all commodity prices in response to the shocks identified. Two results are of interest. First, we observe that the correlations are positive for all shocks. The largest response on impact occurs in the case of the global demand shock. This confirms the nature of the shock, which originates in an increase in demand for all commodities. The results that include only industrial commodities are very similar.[20]

**[Figure 3 about here]**

In order to further evaluate the comovement between commodity prices we calculate the conditional correlations between the impulse responses of oil prices and the impulse response of the prices of other commodities. We compute the correlation for the real oil price with different portfolios of commodity indexes, calculated as an equal-weighted real price index for each commodity sector. Figure 4 presents the correlations.

We obtain three main results. First, the largest correlations are in response to a global demand shock. In this way our results are consistent with the view that the commodity price boom is due to rapid growth of the global economy. Second, the financial speculative demand shock is associated with a positive correlation between oil and other commodities' prices. This result shows that the type of speculative shock that we are capturing is precisely the one that results from the financialization process driven by the rapid growth of commodity index investment as emphasized by Singleton (2011) and Tang and Xiong (2011). Third, the

[20]Not included here to preserve space but available upon request.

correlations between oil prices and the prices of other commodities are negative in the case of oil supply and speculative oil inventory demand shocks. This implies that the speculative oil inventory demand shock cannot be responsible for the comovement in commodity prices. The correlation in the case of the financial speculative shock is smaller than for the global demand shock. This result should be taken with care since it is an average result. Financial speculation can still be an important driver of the increased correlation in periods where it has played a more relevant role.

[**Figure 4 about here**]

## 5.3 The Drivers of Oil Market Variables

In this subsection we assess how much of the variation in oil market variables (oil prices, oil inventories, and oil production) over the sample is accounted for by each of the shocks analyzed before. The variance decomposition for oil prices is shown in Table 5. The first point to note about the results is that they are very stable with respect to the FAVAR with three shocks shown in Table 4. It is generally suggested that identifying more shocks would tend to narrow the set of valid impulse response functions. However, in our case, identifying an additional shock does not alter the results, suggesting that we are pinning down the valid set of impulse responses. Like before, global demand shocks are the most important driver of oil prices, accounting for up to 44% of oil price fluctuations. Financial speculative demand shocks are the second most important driver, explaining up to 15% of oil price movements. The speculative oil inventory demand shock is particularly important on impact (13%) but decreases to 8% at longer horizons. The oil supply shock is the least relevant driver, explaining less than 10% of the variation in oil prices at all horizons.

[**Table 5 about here**]

Our results highlight that Kilian's (2009) conclusion that global demand shocks are the main drivers of oil fluctuations remains robust. In addition, we show that financial speculative shocks are the second most important driver of oil prices.

Given the importance attributed to the modeling of oil inventories (see Kilian and Murphy, 2011a), it is illustrative to show their variance decomposition, presented in Table 6. In the short run 24% of the variation in oil inventories is driven by oil supply shocks, consistent with production smoothing in response to a supply shock. Interestingly, speculative oil inventory demand explains up to 12% of inventory fluctuations. The global demand shock contributes up to 15% of inventory movements. In turn, financial speculative shocks explain only 10% of the fluctuations in oil inventories. At longer horizons, the share of global demand declines to 9%, while the share of oil supply increases to 33%. The explanatory power of speculative oil inventory demand and financial speculative shocks is similar to the short run. These results suggest that fluctuations in oil inventories are due to speculative oil inventory motives as well as production smoothing in response to oil supply shocks. In this way our findings are consistent with Kilian and Murphy (2011a).

[**Table 6 about here**]

In Table 7 we present the variance decomposition of oil production. In the short run oil supply shocks explain around 18% of oil production fluctuations. The financial speculative shock affects the incentives faced by producers, who lower oil production in anticipation of predictable increases in the price of oil. In this way, it is expected that speculative shocks play a role as a driver of oil production. In fact, they explain around 17% of oil production fluctuations.

[**Table 7 about here**]

## 5.4 Speculation and Oil Prices in the Past Decade

In the previous subsection we showed how much of the variation in oil prices is explained by each of the shocks. Note that this is an average measure for the whole period analyzed and consequently does not provide information on whether the financialization of commodity markets in recent years led to an increase in the price of oil. In order to investigate this it is instructive to calculate the historical decomposition of the oil price to the 4 shocks identified. Figure 5 presents the results.

**[Figure 5 about here]**

Figure 5 shows that global demand, and therefore real forces, are the main driver of oil price increases. We also observe that speculation was responsible for a large proportion of the oil price increase between 2004 and 2008. The Figure suggests that financial speculation contributed around 15% to oil price increases in this period. It is interesting to note that the financial speculative shock begins to play a relevant role as a driver of oil price increases in 2004, which is the time when significant index investment started to flow into commodities markets (see, Tang and Xiong, 2011). This confirms that we are picking up the form of speculative shock arising from the financialization of commodity markets. The trend in prices due to global demand clearly started before 2004. This could have been a triggering factor to speculative forces given that speculation is likely to rise when demand is increasing (see Singleton, 2011 and Tang and Xiong, 2011).

Another aspect to emphasize is that speculative oil inventory demand shocks would have implied basically no fluctuations in the oil price between 2004 and mid 2006. These years are associated with the start of the surge in oil prices. This shock, however, accounted for a large share of the spike in 2006-2007. We also note that very little of the decline during the last recession is due to speculative oil inventory demand shocks.

The V-shaped decline in the real price of oil in late 2008 is mainly driven by the recession associated with the global financial crisis, and reflected by the global demand shock. However, we note that the financial speculative demand shock also played a significant role in the V-shaped decline as the financial crisis hurt the risk appetite of financial investors for commodities in their portfolios (see Tang and Xiong, 2011), consequently pushing prices down.

# 6 Conclusion

Our study is motivated by the empirical pattern of increased price comovements between different commodities after 2004, the year in which significant investment started to flow into commodity markets. One of the objectives of this paper is to shed light on the sources of these price increases and assess whether speculation played a key role in driving this empirical pattern.

We identify oil shocks from a large dataset, including both macroeconomic and financial variables of the G7 countries and a rich set of commodity prices using a FAVAR model. The use of a FAVAR allows us to investigate the transmission of the oil shocks on a large number of variables. Therefore, we can investigate whether speculation played a role in driving the increased comovement in a large number of commodity prices observed in recent years. When we analyze the conditional correlations between oil prices and the price of other commodities, we find that the largest correlations are in response to global demand shocks, consistent with Kilian (2009). Interestingly, the financial speculative shock is also associated with a positive comovement between oil and other commodities' prices. This is consistent with the results of Tang and Xiong (2011) and adds evidence supporting the idea that the financial speculative demand shock that we identify is picking up the effects of financialization driven by the rapid growth of commodity index investment , as emphasized by, among others, Singleton (2011). The correlation between oil prices and the prices of other commodities is negative for the other shocks. This implies that the speculative oil inventory demand shock cannot be responsible for the comovement in commodity prices.

The speculative view of oil price determination suggests that a growing participation in oil futures by non-market players can push the price above the level that should result from purely fundamental factors. Our findings confirm that while global demand shocks account for the largest share of oil price fluctuations, financial speculative demand shocks are the second most important driver.

We find that the increase in oil prices in the last decade is mainly due to the strength of global demand, consistent with previous studies. However, financial speculation significantly contributed to the oil price increase between 2004 and 2008. Our analysis pins down the start of speculative forces driving oil prices in 2004, which is the time when significant investment started to flow into commodity markets. We find that the decline in the real price of oil in late 2008 is mainly driven by the negative global demand shock associated with the recession after the financial crisis. However, we note that the financial speculative shock also played a significant role in the decline as the financial crisis eroded the balance sheet of many financial institutions, which affected their demand for commodity assets in their portfolio, consequently pushing prices down.

# References


Alquist, R., and L. Kilian (2007): "What Do We Learn from the Price of Crude Oil Futures?," CEPR Discussion Papers 6548, C.E.P.R. Discussion Papers.

——— (2010): "What do we learn from the price of crude oil futures?," *Journal of Applied Econometrics*, 25(4), 539–573.

Bai, J., and S. Ng (2002): "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70(1), 191–221.

——— (2006): "Evaluating latent and observed factors in macroeconomics and finance," *Journal of Econometrics*, 131(1-2), 507–537.

Barberis, N., and A. Schleifer (2003): "Style Investing," *Journal of Financial Economics*, 66(1), 161–199.

Barsky, R. B., and L. Kilian (2002): "Do We Really Know that Oil Caused the Great Stagflation? A Monetary Alternative," in *NBER Macroeconomics Annual 2001, Volume 16*, NBER Chapters, pp. 137–198. National Bureau of Economic Research, Inc.

Baumeister, C., and G. Peersman (2010): "Sources of the Volatility Puzzle in the Crude Oil Market," Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium 10/634, Ghent University, Faculty of Economics and Business Administration.

——— (2011): "Time-Varying Effects of Oil Supply Shocks on the US Economy," Working papers of faculty of economics and business administration, ghent university, belgium, Ghent University, Faculty of Economics and Business Administration.

Baumeister, C., G. Peersman, and I. V. Robays (2010): "The Economic Consequences of Oil Shocks: Differences across Countries and Time," in *Inflation in an Era of Relative Price Shocks*, ed. by R. Fry, C. Jones, and C. Kent, RBA Annual Conference Volume. Reserve Bank of Australia.

Bernanke, B. (2004): "Oil and the Economy," Speech presented at the Distinguished Lecture Series, Darton College, Albany, Georgia.

Bernanke, B., J. Boivin, and P. S. Eliasz (2005): "Measuring the Effects of Monetary Policy: A Factor-augmented Vector Autoregressive (FAVAR) Approach," *The Quarterly Journal of Economics*, 120, 387–422.

Chudik, A., M. H. Pesaran, and E. Tosetti (2011): "Weak and strong cross-section dependence and estimation of large panels," *Econometrics Journal*, 14(1), C45–C90.

Davidson, P., L. H. Falk, and H. Lee (1974): "Oil: Its Time Allocation and Project Independence," *Brookings Papers on Economic Activity*, 5(1974-2), 411–448.

Den Haan, W., and V. Sterk (2011): "The Myth of Financial Innovation and the Great Moderation," *Economics Journal*, 121(553), 707–39.

Doz, C., D. Giannone, and L. Reichlin (2011): "A two-step estimator for large approximate dynamic factor models based on Kalman filtering," *Journal of Econometrics*, 164(1), 188–205.

Engemann, K. M., K. L. Kliesen, and M. T. Owyang (2010): "Do oil shocks drive business cycles? Some U.S. and International Evidence," Working papers, Federal Reserve Bank of St. Louis.

Fernandez-Villaverde, J., J. F. Rubio-Ramirez, T. J. Sargent, and M. W. Watson (2007): "ABCs (and Ds) of Understanding VARs," *American Economic Review*, 97(3), 1021–1026.

Forni, M., and L. Gambetti (2010a): "The dynamic effects of monetary policy: A structural factor model approach," *Journal of Monetary Economics*, 57(2), 203–216.

——— (2010b): "Macroeconomic Shocks and the Business Cycle: Evidence from a Structural Factor Model," Cepr discussion papers, C.E.P.R. Discussion Papers.

——— (2011): "Testing for Sufficient Information in Structural VARs," UFAE and IAE Working Papers 863.11, Unitat de Fonaments de l'AnÃălisi EconÃšmica (UAB) and Institut d'AnÃălisi EconÃšmica (CSIC).

Forni, M., D. Giannone, M. Lippi, and L. Reichlin (2009): "Opening The Black Box: Structural Factor Models With Large Cross Sections," *Econometric Theory*, 25(05), 1319–1347.

Gelper, S., and C. Croux (2007): "Multivariate out-of-sample tests for Granger causality," *Computational Statistics & Data Analysis*, 51(7), 3319–3329.

Giannone, D., and L. Reichlin (2006): "Does information help recovering structural shocks from past observations?," *Journal of the European Economic Association*, 4(2-3), 455–465.

Gorton, G., and K. G. Rouwenhorst (2006): "Facts and Fantasies about Commodity Futures," *Financial Analysts Journal*, 62(02), 47–68.

Hamilton, J. D. (1983): "Oil and the Macroeconomy since World War II," *Journal of Political Economy*, 91(2), 228–48.

Hamilton, J. D. (1985): "Historical Causes of Postwar Oil Shocks and Recessions," *The Energy Journal*, 6(1), 97–116.

——— (2003): "What is an oil shock?," *Journal of Econometrics*, 113(2), 363–398.

——— (2009): "Causes and Consequences of the Oil Shock of 2007-08," *Brookings Paper on Economic Activity*, (Spring 2009), 215–261.

Hamilton, J. D., and A. M. Herrera (2004): "Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy: Comment," *Journal of Money, Credit and Banking*, 36(2), 265–86.

Hamilton, J. D., and C. Wu (2011): "Risk Premia in Crude Oil Futures Prices," Working paper, University of California, San Diego.

Hansen, L. P., and T. J. Sargent (1991): "Two difficulties in interpreting vector autoregressions," in *Rational Expectations Econometrics*, ed. by L. P. Hansen, and T. J. Sargent, pp. 77 – 120. Westview Press, Boulder.

Harvey, D. I., S. J. Leybourne, and P. Newbold (1998): "Tests for Forecast Encompassing," *Journal of Business & Economic Statistics*, 16(2), 254–59.

Hicks, B., and L. Kilian (2009): "Did Unexpectedly Strong Economic Growth Cause the Oil Price Shock of 2003-2008?," CEPR Discussion Papers 7265, C.E.P.R. Discussion Papers.

Hotelling, H. (1931): "The Economics of Exhaustible Resources," *Journal of Political Economy*, 39(2), 137–75.

Kilian, L. (2008a): "A Comparison of the Effects of Exogenous Oil Supply Shocks on Output and Inflation in the G7 Countries," *Journal of the European Economic Association*, 6(1), 78–121.

——— (2008b): "Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?," *The Review of Economics and Statistics*, 90(2), 216–240.

——— (2009): "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, 99(3), 1053–69.

——— (2010): "Oil Price Shocks, Monetary Policy and Stagflation," in *Inflation in an Era of Relative Price Shocks*, ed. by R. Fry, C. Jones, and C. Kent, RBA Annual Conference Volume. Reserve Bank of Australia.

Kilian, L., and D. Murphy (2011a): "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil," Working paper, University of Michigan.

——— (2011b): "Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market VAR Models," Journal of the european economic association, forthcoming.

KILIAN, L., AND C. PARK (2009): "The Impact Of Oil Price Shocks On The U.S. Stock Market," *International Economic Review*, 50(4), 1267–1287.

KILIAN, L., A. REBUCCI, AND N. SPATAFORA (2009): "Oil shocks and external balances," *Journal of International Economics*, 77(2), 181–194.

KYLE, A., AND W. XIONG (2001): "Contagion as a Wealth Effect," *Journal of Finance*, 56(4), 1401–1440.

LIPPI, M., AND L. REICHLIN (1993): "The Dynamic Effects of Aggregate Demand and Supply Disturbances: Comment," *American Economic Review*, 83(3), 644–52.

——— (1994): "VAR analysis, nonfundamental representations, blaschke matrices," *Journal of Econometrics*, 63(1), 307–325.

MASTERS, M. W. (2008): "Testimony of Michael W. Masters, Managing Member / Portfolio Manager, Masters Capital Management, LLC.," Testimony before the u.s. senate committee on homeland security and governmental affairs,(hsgac.senate.gov/public/$_files/052008masters.pdf$).

PINDYCK, R. S., AND J. J. ROTEMBERG (1990): "The Excess Co-movement of Commodity Prices," *Economic Journal*, 100(403), 1173–89.

RUBIO-RAMIREZ, J. F., D. F. WAGGONER, AND T. ZHA (2010): "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference," *Review of Economic Studies*, 77(2), 665–696.

SINGLETON, K. J. (2011): "Investor Flows and the 2008 Boom/Bust in Oil Prices," Working paper, Stanford University.

STOCK, J. H., AND M. W. WATSON (2002a): "Forecasting Using Principal Components From a Large Number of Predictors," *Journal of the American Statistical Association*, 97, 1167–1179.

Stock, J. H., and M. W. Watson (2002b): "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, 20(2), 147–62.

Stock, J. H., and M. W. Watson (2005): "Implications of Dynamic Factor Models for VAR Analysis," NBER Working Papers 11467, National Bureau of Economic Research, Inc.

Tang, K., and W. Xiong (2011): "Index Investment and Financialization of Commodities," Working paper, Princeton University.

Uhlig, H. (2005): "What are the effects of monetary policy on output? Results from an agnostic identification procedure," *Journal of Monetary Economics*, 52(2), 381–419.

**Table 1. Test for Sufficient Information**

Panel A. 4 variable-VAR with Kilian measure of real global economic activity

| | VAR | VAR+1F | VAR+2F | VAR+3F | VAR+4F |
|---|---|---|---|---|---|
| 1F | 0.0680 | — | — | — | — |
| 2F | 0.0280 | 0.3420 | — | — | — |
| 3F | 0.0100 | 0.0060 | 0.0360 | — | — |
| 4F | 0.0060 | 0.0320 | 0.0000 | 0.0160 | — |
| 5F | 0.0260 | 0.1000 | 0.1700 | 0.1000 | 0.2820 |
| 6F | 0.0180 | 0.0940 | 0.1020 | 0.1320 | 0.3480 |

Panel B. 4 variable-VAR with aggregate industrial production

| | VAR | VAR+1F | VAR+2F | VAR+3F | VAR+4F |
|---|---|---|---|---|---|
| 1F | 0.1720 | — | — | — | — |
| 2F | 0.0800 | 0.3740 | — | — | — |
| 3F | 0.0020 | 0.0940 | 0.0560 | — | — |
| 4F | 0.0840 | 0.1700 | 0.0020 | 0.0240 | — |
| 5F | 0.2320 | 0.1560 | 0.0000 | 0.0080 | 0.9440 |
| 6F | 0.1140 | 0.0320 | 0.0000 | 0.0000 | 0.4920 |

**Notes:** Bootstrapped $p$-values of the Granger causality test for the VAR and VAR augmented with Factors.

**Table 2. Sign Restrictions**

| Shock: | Oil production | Oil Inventories | Real Oil Prices | Real Activity |
|---|---|---|---|---|
| Oil Supply | − | − | + | − |
| Speculative Oil Inventory Demand | + | + | + | − |
| Global Demand | + | | + | + |
| Financial Speculative Demand | − | + | + | |

**Notes:** All shocks are normalized to imply an increase in the price of oil. Blank entries denote that no sign restriction is imposed. The sign restrictions are imposed only on impact.

**Table 3. Orthogonality Test**

| | Oil Supply | Speculative Oil Inventory Demand | Global Demand |
|---|---|---|---|
| 1 | 0.0000 | 0.0000 | 0.0000 |
| 2 | 0.5520 | 0.4880 | 0.5190 |
| 3 | 0.2600 | 0.5920 | 0.6030 |
| 4 | 0.1390 | 0.5210 | 0.5980 |

**Notes:** Size of the rejection set (at the 10% level) of the $F$-test of orthogonality for each of the shocks identified from the VAR with sign restrictions.

**Table 4. Variance Decomposition of the Real Oil Price**

| Horizon | | Oil Supply | Speculative Oil Inventory Demand | Global Demand |
|---|---|---|---|---|
| 1 | VAR (KM) | 0.0693 | 0.3070 | 0.5572 |
| | VAR (AIP) | 0.0934 | 0.3181 | 0.5010 |
| | FAVAR | 0.0609 | 0.1254 | 0.3769 |
| 2 | VAR (KM) | 0.0575 | 0.2185 | 0.6435 |
| | VAR (AIP) | 0.0916 | 0.2608 | 0.5439 |
| | FAVAR | 0.0443 | 0.0712 | 0.4242 |
| 3 | VAR (KM) | 0.0575 | 0.1795 | 0.7016 |
| | VAR (AIP) | 0.0582 | 0.2769 | 0.5532 |
| | FAVAR | 0.0297 | 0.0469 | 0.4461 |
| 4 | VAR (KM) | 0.0233 | 0.1514 | 0.7138 |
| | VAR (AIP) | 0.0475 | 0.3057 | 0.5348 |
| | FAVAR | 0.0272 | 0.0384 | 0.4449 |
| 8 | VAR (KM) | 0.0250 | 0.0735 | 0.7954 |
| | VAR (AIP) | 0.0661 | 0.2058 | 0.6359 |
| | FAVAR | 0.0573 | 0.0467 | 0.3834 |
| 12 | VAR (KM) | 0.0243 | 0.0918 | 0.7762 |
| | VAR (AIP) | 0.0664 | 0.2239 | 0.6066 |
| | FAVAR | 0.0951 | 0.0696 | 0.3372 |

**Notes:** VAR (KM) denotes that the VAR was estimated using the Kilian measure of real economic activity. VAR (AIP) denotes that the VAR was estimated using aggregate industrial production.

**Table 5. Variance Decomposition of the Real Oil Price (FAVAR)**

| Horizon | Oil Supply | Speculative Oil Inventory Demand | Global Demand | Financial Speculative Demand |
|---|---|---|---|---|
| 1 | 0.0461 | 0.1308 | 0.3995 | 0.1054 |
| 2 | 0.0342 | 0.0731 | 0.4424 | 0.1189 |
| 3 | 0.0233 | 0.0478 | 0.4596 | 0.1307 |
| 4 | 0.0228 | 0.0384 | 0.4501 | 0.1473 |
| 8 | 0.0467 | 0.0560 | 0.4104 | 0.1171 |
| 12 | 0.0782 | 0.0784 | 0.3725 | 0.1078 |

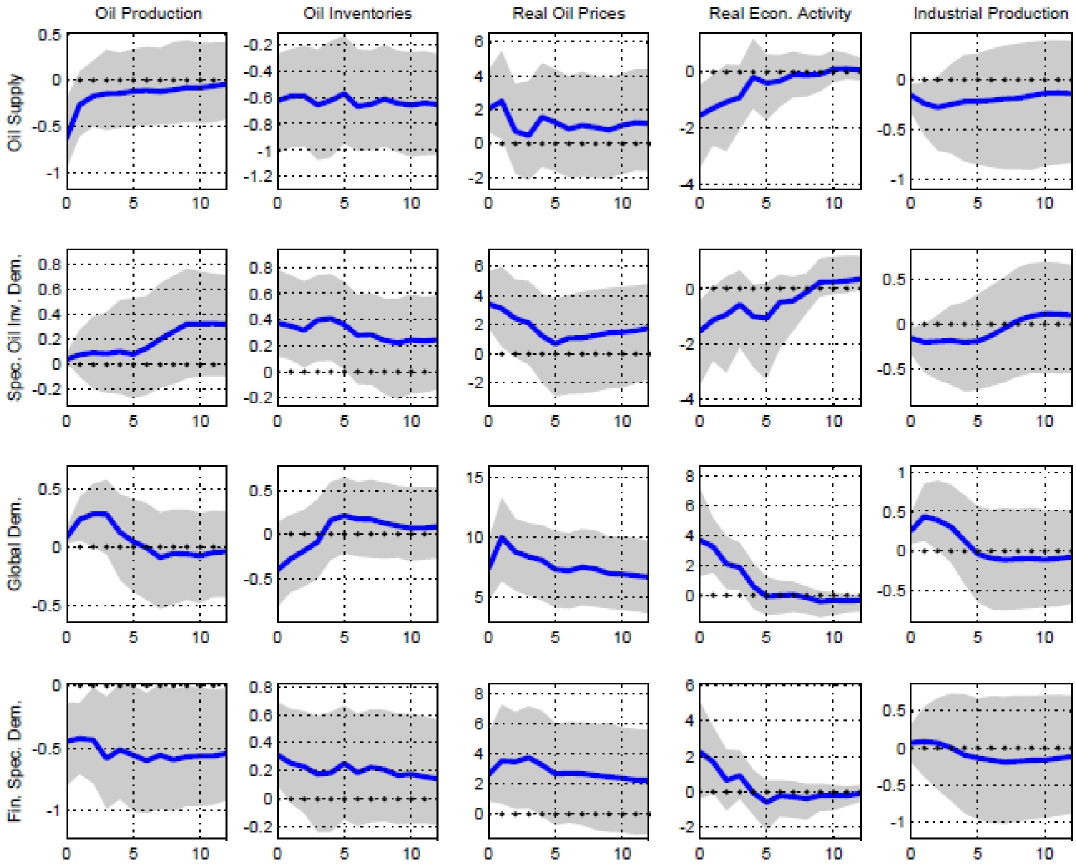
**Table 6. Variance Decomposition of Oil Inventories (FAVAR)**

| Horizon | Oil Supply | Speculative Oil Inventory Demand | Global Demand | Financial Speculative Demand |
|---|---|---|---|---|
| 1 | 0.2325 | 0.1015 | 0.1524 | 0.1003 |
| 2 | 0.2402 | 0.1234 | 0.1287 | 0.1028 |
| 3 | 0.2688 | 0.1220 | 0.1122 | 0.1018 |
| 4 | 0.3148 | 0.1219 | 0.0859 | 0.0841 |
| 8 | 0.3331 | 0.0852 | 0.1154 | 0.1112 |
| 12 | 0.3255 | 0.1121 | 0.0896 | 0.0959 |

**Table 7. Variance Decomposition of Oil Production (FAVAR)**

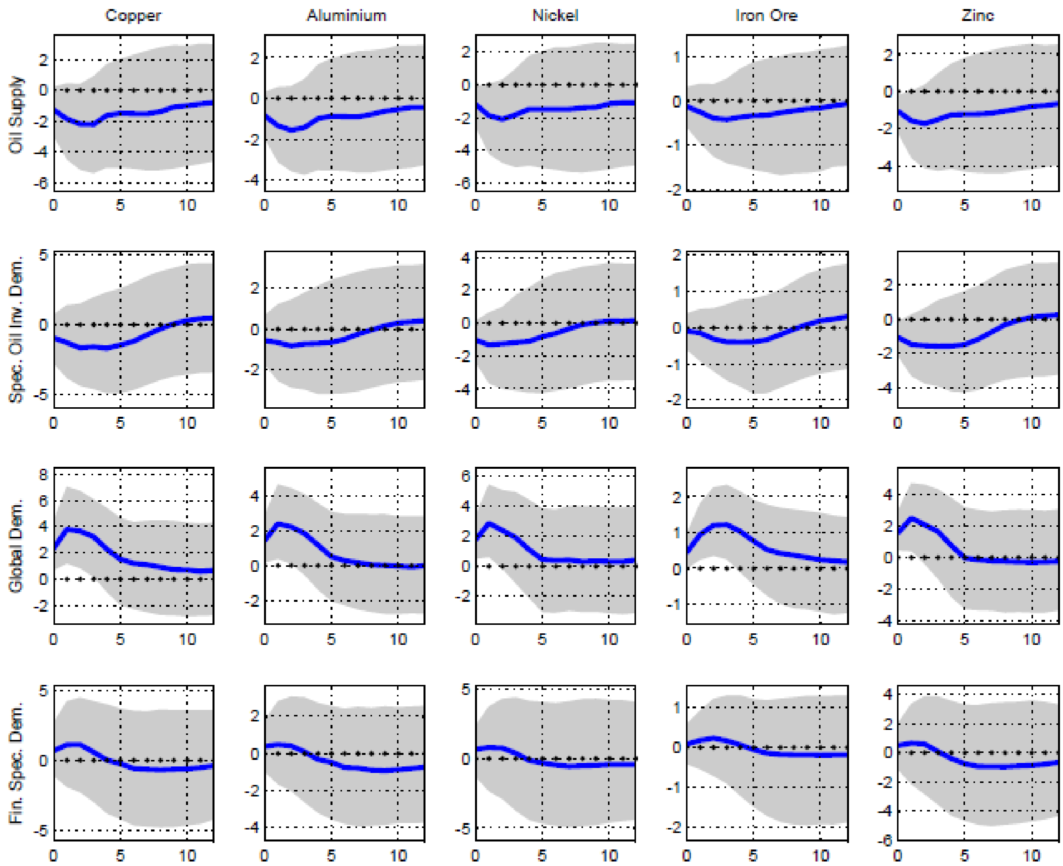
| Horizon | Oil Supply | Speculative Oil Inventory Demand | Global Demand | Financial Speculative Demand |
|---|---|---|---|---|
| 1 | 0.3113 | 0.0025 | 0.0065 | 0.1839 |
| 2 | 0.1683 | 0.0321 | 0.0970 | 0.1849 |
| 3 | 0.1212 | 0.0522 | 0.1286 | 0.1593 |
| 4 | 0.1152 | 0.0439 | 0.1051 | 0.2041 |
| 8 | 0.1034 | 0.1464 | 0.0830 | 0.2010 |
| 12 | 0.1158 | 0.1763 | 0.0730 | 0.1886 |

**Figure 1. Impulse Responses: Main Variables**




**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, global demand, and financial speculative demand shocks using a FAVAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

**Figure 2. Impulse Responses: Industrial Commodities**




**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, global demand, and financial speculative demand shocks using a FAVAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

**Figure 3: Pariwise correlation all commodities**

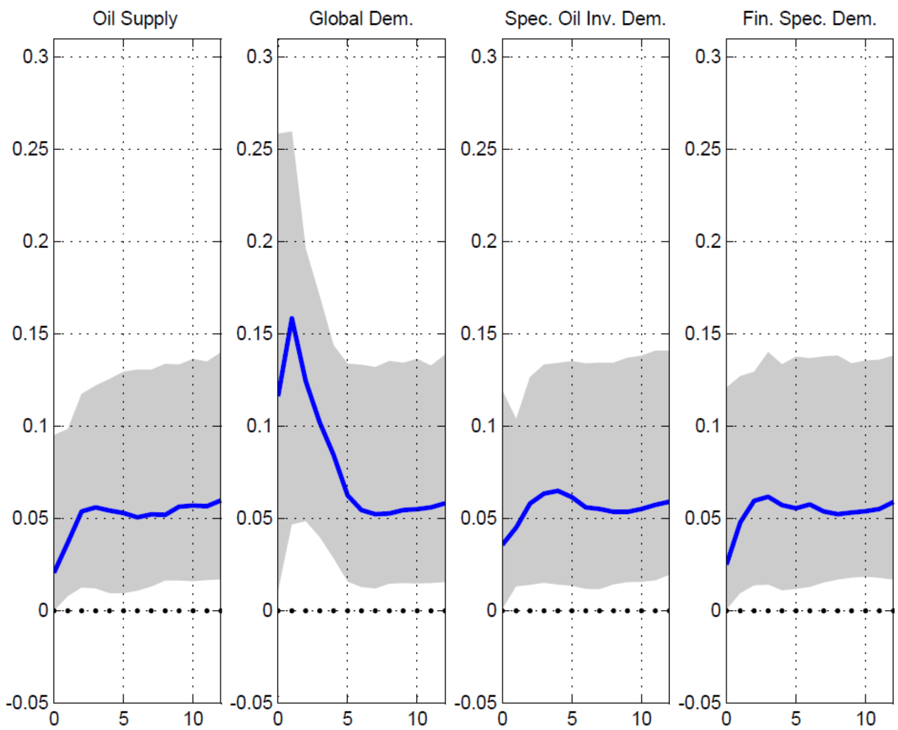
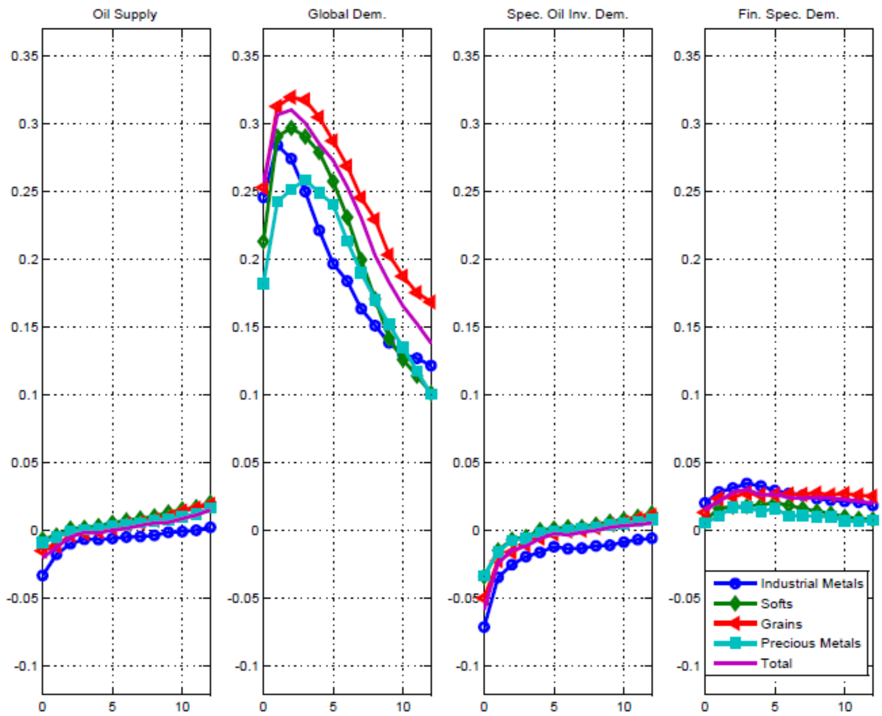
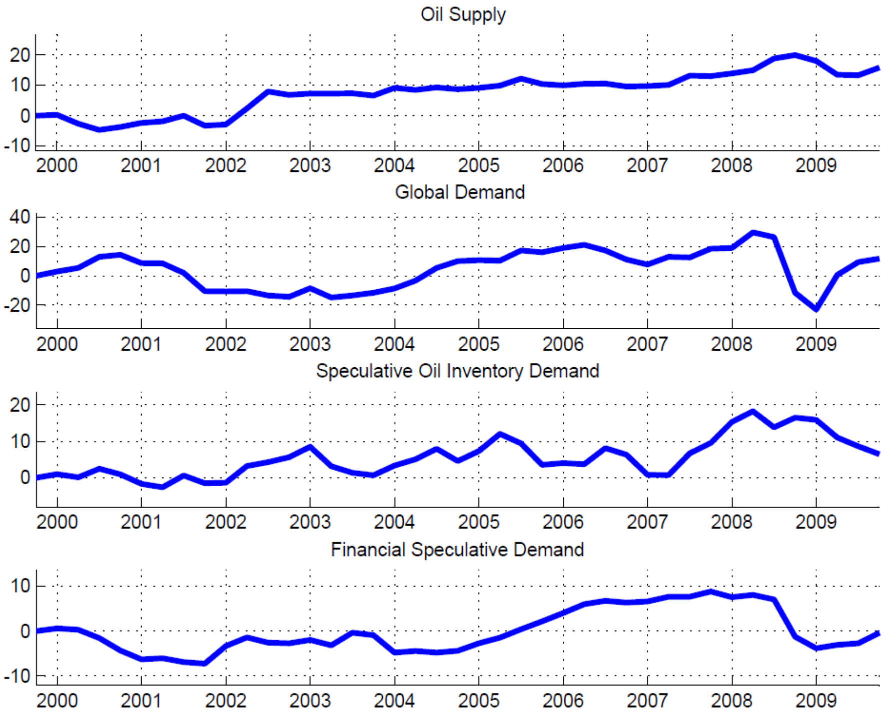


**Figure 4. Conditional Correlations**




**Notes:** The figure shows the correlation for the real oil price with different portfolios of commodity indexes, calculated as an equal-weighted real price index for each commodity sector. The sectors are: industrial metals, softs, grains, and precious metals. Industrial metals include copper, aluminium, nickel, iron ore, and zinc; softs are composed of cotton, tobacco, sugar, coffee, and cacao; grains are sunflower oil, palm oil, soybeans, wheat, rice, and maize; precious metals include gold and silver.

**Figure 5. Historical Decomposition of the Oil Price for the Last Decade**



# Appendix A. Data

| Variable | Unit | Source | Start Date | End Date | Seasonally Adjusted | Stationarity Transformation |
|---|---|---|---|---|---|---|
| **Oil and Aggregate Variables** | | | | | | |
| World Oil Production | Thousands of barrels per day (monthly average) | DOE | 1971 Q1 | 2009 Q4 | Y | 4 |
| Aggregate Industrial Production | Index | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Average World Price of Oil | USD/barrel (nominal) (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Inventories of Oil | Millions Barrel | EIA | 1971 Q1 | 2009 Q4 | Y | 4 |
| Oil Price Spot-Future Spread | USD/barrel (nominal) | NY MEX | 1983 Q1 | 2009 Q4 | N | 3 |
| Index of Global Economic Activity | Index | Kilian (2009) | 1971 Q1 | 2009 Q4 | N | 1 |
| **Commodity Prices** | | | | | | |
| Gold | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Silver | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Copper | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Aluminium | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Nickel | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Iron Ore | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Zinc | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Rubber | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Timber | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Cotton | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Tobacco | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Sunflower oil | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Palm oil | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Sugar | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Soybeans | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Wheat | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Rice | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Maize | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Coffee | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| Cacao | (Real, deflated by US CPI) | IFS | 1971 Q1 | 2009 Q4 | N | 4 |
| **Real GDP** | | | | | | |
| US | MILL, USD | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| UK | MILL, POUNDS | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| France | MILL, EUROS | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| Germany | MILL, EUROS | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| Italy | MILL, EUROS | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| Canada | MIL, CAD | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| Japan | MILL, YEN | OECD | 1971 Q1 | 2009 Q4 | Y | 4 |
| **Personal Consumption** | | | | | | |
| US | Bil. USD | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| UK | Bil. GBP | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| France | Bil. EUR | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| Germany | Bil. EUR | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Italy | Bil. EUR | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Canada | Bil. CAD | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Japan | Bil. JPY | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| **Industrial Production** | | | | | | |
| US | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| UK | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| France | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Germany | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Italy | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Canada | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Japan | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 4 |

Notes: (1) denotes level, (2) denotes first difference, (3) denotes log, (4) denotes log difference, and (6) denotes first difference of annual growth rates.

| Variable | Unit | Source | Start Date | End Date | Seasonally Adjusted | Stationarity Transformation |
|---|---|---|---|---|---|---|
| **Employment** | | | | | | |
| US | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| UK | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| France | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Germany | % | OECD MEI/Statistisches Bundesamt Deutschland | 1971 Q1 | 2009 Q4 | Y | 2 |
| Italy | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Canada | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Japan | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| **Unemployment** | | | | | | |
| US | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| UK | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| France | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Germany | % | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 2 |
| Italy | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Canada | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| Japan | % | OECD Economic Outlook | 1971 Q1 | 2009 Q4 | Y | 2 |
| **Employee Earnings** | | | | | | |
| US | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| UK | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| France | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Germany | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Italy | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Canada | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Japan | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| **CPI** | | | | | | |
| US | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| UK | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| France | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Germany | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Italy | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Canada | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Japan | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| **PPI** | | | | | | |
| US | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 6 |
| UK | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 6 |
| France | Index (2005=100) | IFS | 1993Q1 | 2009 Q4 | Y | 6 |
| Germany | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 6 |
| Italy | Index (2005=100) | IFS | 1981Q1 | 2009 Q4 | Y | 6 |
| Canada | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 6 |
| Japan | Index (2005=100) | IFS | 1971 Q1 | 2009 Q4 | Y | 6 |
| **Overnight Rates** | | | | | | |
| US | % | IFS | 1971 Q1 | 2009 Q4 | N | 2 |
| UK | % | IFS | 1971Q4 | 2009 Q4 | N | 2 |
| France | % | IFS | 1971 Q1 | 2009 Q4 | N | 2 |
| Germany | % | IFS | 1971 Q1 | 2009 Q4 | N | 2 |
| Italy | % | BIS | 1971Q1 | 2009 Q4 | N | 2 |
| Canada | % | BIS | 1971 Q1 | 2009 Q4 | N | 2 |
| Japan | % | IFS | 1971 Q1 | 2009 Q4 | N | 2 |
| **10-Year Rates** | | | | | | |
| US | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |
| UK | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |
| France | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |
| Germany | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |
| Italy | % | IFS | 1971 Q1 | 2009 Q4 | N | 2 |
| Canada | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |
| Japan | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 2 |

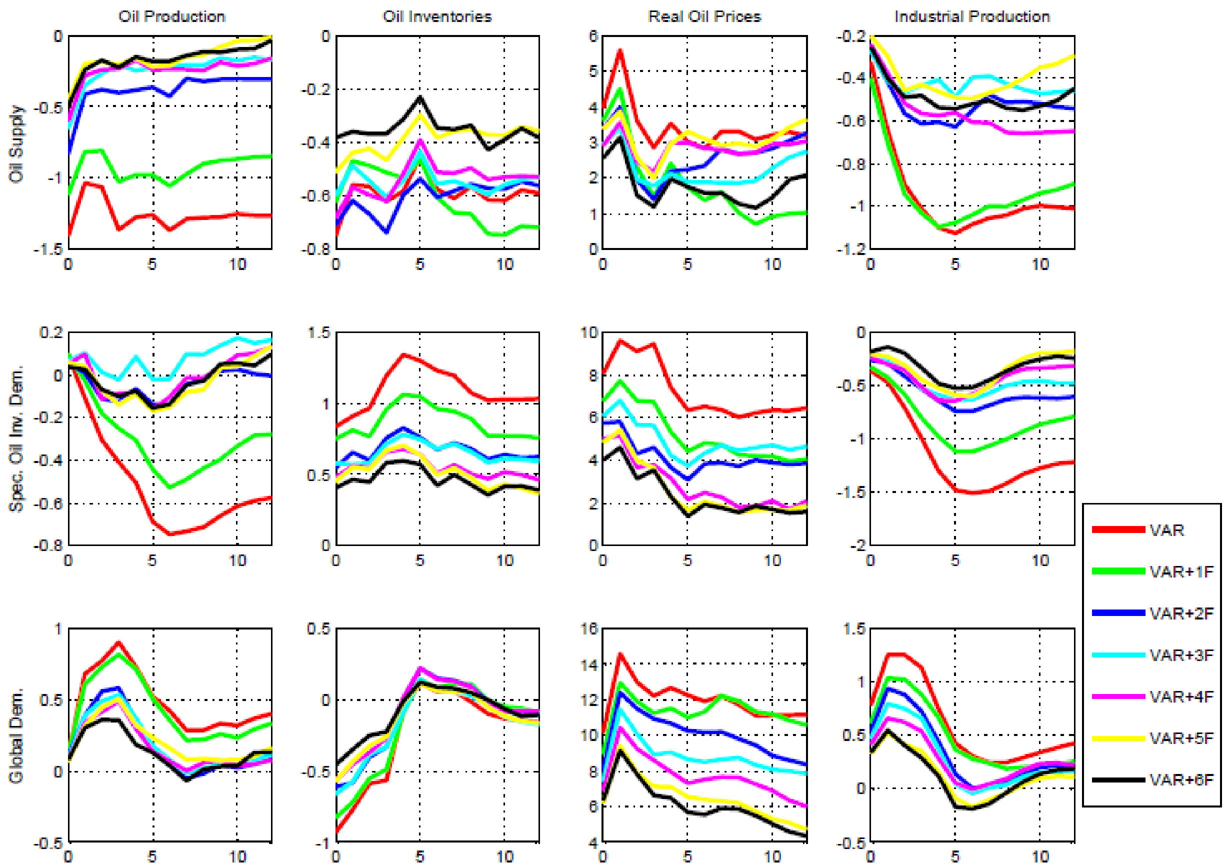
Notes: (1) denotes level, (2) denotes first difference, (3) denotes log, (4) denotes log difference, and (6) denotes first difference of annual growth rates.

| Variable | Unit | Source | Start Date | End Date | Seasonally Adjusted | Stationarity Transformation |
|---|---|---|---|---|---|---|
| **M1** | | | | | | |
| US | (Real, deflated by CPI, Bil. USD) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| UK | (Real, deflated by CPI, Bil. GBP) | OECD MEI/BIS | 1971 Q4 | 2009 Q4 | Y | 4 |
| France | (Real, deflated by CPI, Bil. FRA) | IFS/BIS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Germany | (Real, deflated by CPI, Bil. DEM) | IFS/BIS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Italy | (Real, deflated by CPI, Bil. ITL) | IFS/BIS | 1974 Q4 | 2009 Q4 | Y | 4 |
| Canada | (Real, deflated by CPI, Bil. CAD) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| Japan | (Real, deflated by CPI, Bil. JPY) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| **M2** | | | | | | |
| US | (Real, deflated by CPI, Bil. USD) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| UK | (Real, deflated by CPI, Bil. GBP) | OECD MEI | 1982Q3 | 2009 Q4 | Y | 4 |
| France | (Real, deflated by CPI, Bil. FRA) | IFS/BIS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Germany | (Real, deflated by CPI, Bil. DEM) | IFS/BIS | 1971 Q1 | 2009 Q4 | Y | 4 |
| Italy | (Real, deflated by CPI, Bil. ITL) | IFS/BIS | 1974Q4 | 2009 Q4 | Y | 4 |
| Canada | (Real, deflated by CPI, Bil. CAD) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| Japan | (Real, deflated by CPI, Bil. JPY) | OECD MEI | 1971 Q1 | 2009 Q4 | Y | 4 |
| **Trade Balance** | | | | | | |
| US | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| UK | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| France | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| Germany | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| Italy | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| Canada | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| Japan | %GDP | OECD MEI/IFS | 1971 Q1 | 2009 Q4 | Y | 2 |
| **Stock Market Price Index** | | | | | | |
| US | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| UK | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| France | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| Germany | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| Italy | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| Canada | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| Japan | Index (2005=100) | OECD MEI | 1971 Q1 | 2009 Q4 | N | 4 |
| **REER** | | | | | | |
| US | Index (2000=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| UK | Index (2000=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| France | Index (1990=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Germany | Index (1990=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Italy | Index (1990=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Canada | Index (2000=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Japan | Index (2000=100) | JP Morgan (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| **Foreign Exchange Rate with Dollar** | | | | | | |
| UK | GBP/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| France | EUR/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Germany | EUR/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Italy | EUR/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Canada | CAD/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| Japan | JPY/USD | Federal Reserve Board (via Haver) | 1971 Q1 | 2009 Q4 | N | 4 |
| | | | 1971 Q1 | | | |
| **Spread 3m / Overnight rate** | | | | | | |
| US | % | IFS | 1971 Q1 | 2009 Q4 | N | 1 |
| UK | % | IFS | 1972 Q1 | 2009 Q4 | N | 1 |
| France | % | IFS | 1971 Q1 | 2009 Q4 | N | 1 |
| Germany | % | OECD MEI | 1971 Q1 | 2009 Q4 | N | 1 |
| Italy | % | IFS | 1971 Q1 | 2009 Q4 | N | 1 |
| Canada | % | IFS | 1971 Q1 | 2009 Q4 | N | 1 |
| Japan | % | IFS | 1971 Q1 | 2009 Q4 | N | 1 |
| **Spread 10y / Overnight rate** | | | | | | |
| US | % | See 10Y and 1D interest rate sources. | 1971 Q1 | 2009 Q4 | N | 1 |
| UK | % | See 10Y and 1D interest rate sources. | 1972 Q1 | 2009 Q4 | N | 1 |
| France | % | See 10Y and 1D interest rate sources. | 1971 Q1 | 2009 Q4 | N | 1 |
| Germany | % | See 10Y and 1D interest rate sources. | 1971 Q1 | 2009 Q4 | N | 1 |
| Italy | % | See 10Y and 1D interest rate sources. | 1987 Q4 | 2009 Q4 | N | 1 |
| Canada | % | See 10Y and 1D interest rate sources. | 1971 Q1 | 2009 Q4 | N | 1 |
| Japan | % | See 10Y and 1D interest rate sources. | 1989 Q1 | 2009 Q4 | N | 1 |

Notes: (1) denotes level, (2) denotes first difference, (3) denotes log, (4) denotes log difference, and (6) denotes first difference of annual growth rates.

# B Appendix: Choice of Factors

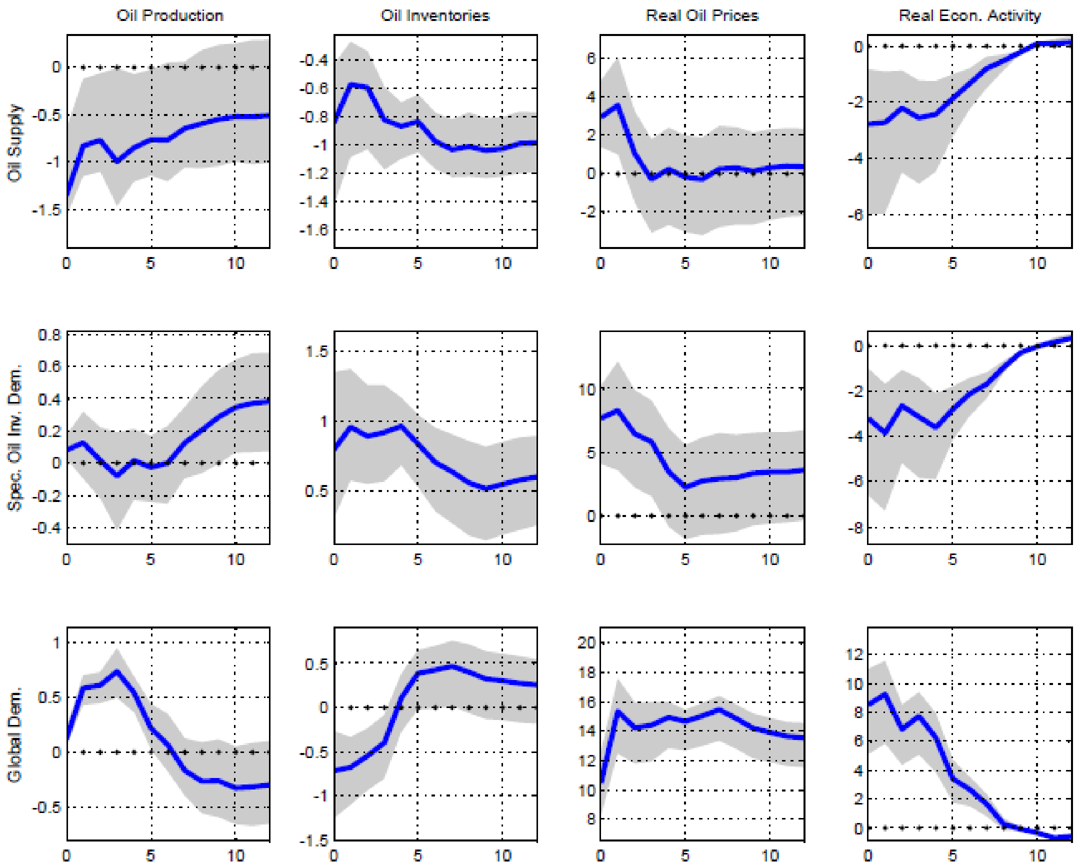
**Figure B1. Impulse Responses for Different Choice of Factors**




**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, and global demand shocks estimated using sign restrictions for a different choice of factors.

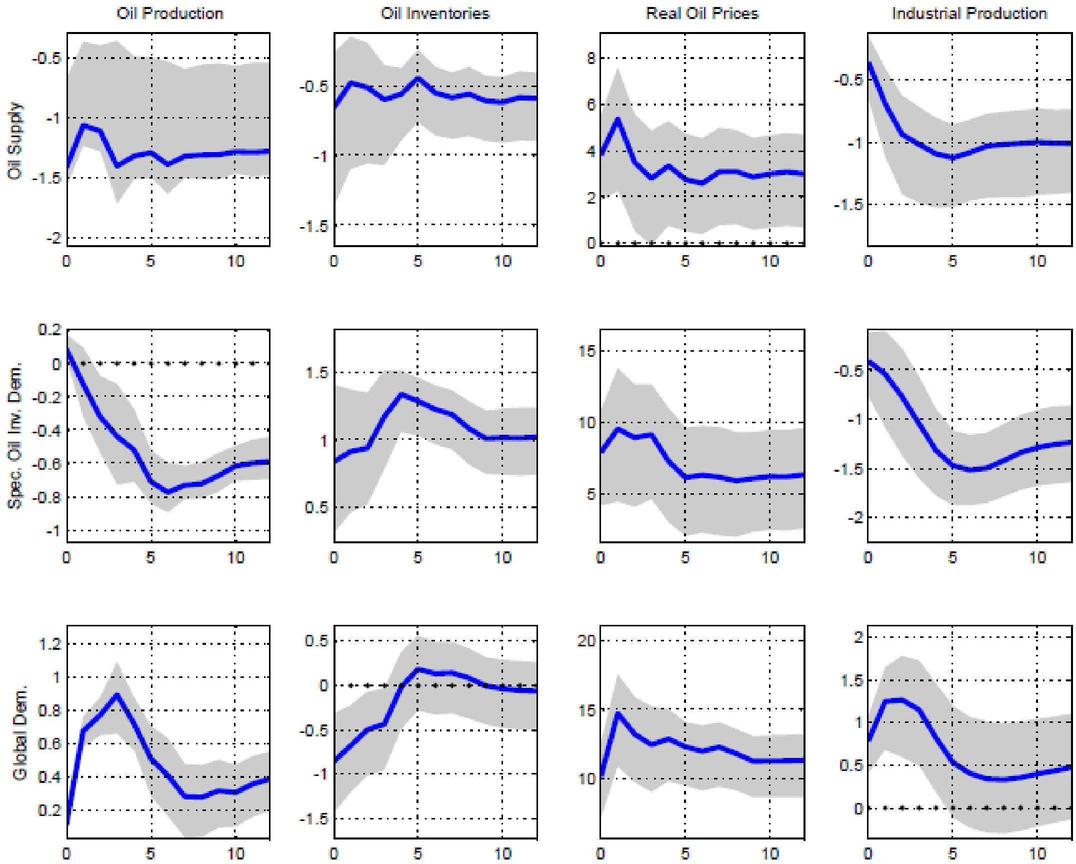
# C Appendix: Impulse Responses VAR and FAVAR

**Figure C1. Impulse Responses: VAR**



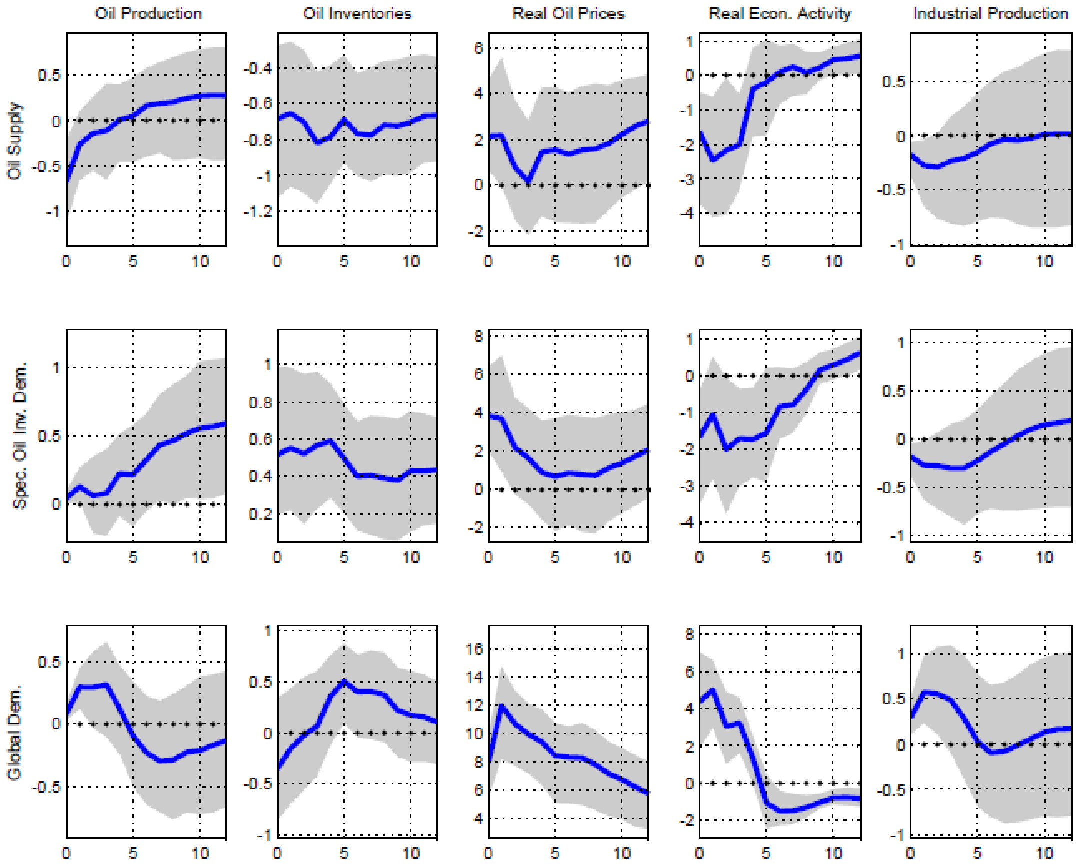

**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, and global demand shocks using a VAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

**Figure C2. Impulse Responses: VAR**




**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, and global demand shocks using a VAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

**Figure C3. Impulse Responses: FAVAR**




**Notes:** The figure shows the impulse responses to oil supply, speculative oil inventory demand, and global demand shocks using a VAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.