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Speculation in the Oil Market*

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Abstract

The run-up in oil prices since 2004 coincided with growing investment in commodity markets and increased price comovement among different commodities. We assess 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. This method is motivated by the fact that the small scale VARs are not infomationally sufficient to identify the shocks. The main results are as follows: (i) While global demand shocks account for the largest share of oil price fluctuations, speculative shocks are the second most important driver. (ii) The comovement between oil prices and the prices of other commodities is explained by global demand and speculative shocks. (iii) The increase in oil prices over the last decade is mainly driven by the strength of global demand. However, 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
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"The increase in [oil] prices has not been driven by supply and demand." —Lord Browne, Group Chief Executive of British Petroleum (2006)[1]

"[...] 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 S. Bernanke (2004)[2]

1 Introduction

The long-standing debate regarding the sources of oil price fluctuations recently intensified due to the dramatic rise in oil prices. The seminal contribution by Kilian (2009) highlights that oil price shocks can 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.[3]

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

One striking characteristic of the oil market over the past decade is that large financial institutions, hedge funds, and other investment funds have invested billions of dollars in the futures market to take advantage of oil price changes.

[1] From "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 States Senate, June 2006, (available at http://www.hsgac.senate.gov/imo/media/doc/SenatePrint10965MarketSpecReportFINAL.pdf?attempt=2)

[2] From "Oil and the Economy," remarks by then-Governor Bernanke delivered at the Distinguished Lecture Series, Darton College, Albary, Georgia, on October 21, 2004 (available at www.federalreserve.gov/boarddocs/speeches/2004/20041021/default.htm).

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

In fact, evidence suggests that 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 (see Gorton and Rouwenhorst, 2006). It is estimated that assets allocated to commodity index trading strategies rose from $13 billion in 2004 to $260 billion as of March 2008. This increased 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. Tang and Xiong (2011) suggest 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. We analyze whether 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 is inspired by Hamilton (2009). He argues that speculators can affect the incentives faced by producers by purchasing a large number of futures contracts and generating higher expected spot prices. As producers expect a higher price of oil for future delivery, they will hold oil back from the market and accumulate inventories. As explained by Hotelling's (1931) principle, it would benefit oil producers to forgo current production so they can sell the oil at higher future prices.

This perspective on speculation is encompassed in Kilian and Murphy (2011a). In their model they identify a more general speculative demand shock for oil inventories arising from expected shortfalls of future oil supply relative to future oil demand as well as speculation by traders.[4] Our identification strategy disentangles the two of them.

In terms of methodology, 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. We provide evidence that the small scale VAR is not infomationally sufficient to identify the shocks. Therefore, we use a set of factors to summarize the bulk of aggregate fluctuations of a large dataset, which includes both macroeconomic and financial variables of the G7 countries and a rich set of commodity prices. The procedure suggested by Bai and Ng (2006) suggests that none of the

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

variables can be considered an observable factor of our dataset. However, looking at the fit of the regression of the individual series against each of the factors allows us to shed some light on the economic concepts behind the factors. Interestingly, the first two factors capture complementary measures of real activity, and the remaining two are associated with financial variables.

We identify oil supply, global demand, oil inventory demand, and speculation shocks by imposing economically meaningful sign restrictions on the impulse responses of a subset of variables in the FAVAR. Supply shocks, which until recently were the center of attention in the oil literature (see Hamilton, 2003; Kilian, 2008a, and b), 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 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.[5] A speculation shock arises as a result of a shift in the expected future spot price. This can reflect an increase in oil prices driven by trading activity in the oil futures market. Although this last type of shock may not be directly linked with fundamentals, because it affects future spot 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, speculation shocks are on average the second most important driver of oil price dynamics, suggesting that speculative activities can affect the incentives faced by operators in the oil market.

The use of a FAVAR allows us to investigate the transmission of oil shocks to 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. We find that (i) all the identified shocks generate comovement in commodity prices and (ii) global demand shocks are the main drivers 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 speculation shock is also associated with a positive comovement between oil and the price of other commodities. This is consistent with the results of Tang and Xiong (2011) and supports the idea that the speculation shock that we identify is picking up the effects of financialization driven

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

by the rapid growth of commodity index investment as emphasized, among others, by Singleton (2011).[6] The correlation between oil prices and the prices of other commodities is negative for the other shocks. This implies that the oil inventory demand shock cannot be responsible for the comovement in commodity prices.

Interpreting oil price fluctuations over the past decade under the lens of our model reveals that speculation shocks began to play a relevant role as drivers of oil price increases in 2004. Interestingly, this timing is consistent with other studies documenting the increase in investment flows into commodity markets in 2004 (see Tang and Xiong, 2011, and Singleton, 2011). Our results are also related to the findings of Lombardi and Van Robays (2011) who provide evidence that financial investors caused oil prices to diverge from the level justified by supply and demand forces. Although speculation played a significant role in driving oil price increases between 2004 and 2008, and their subsequent decline, the increase in oil prices over the last decade is due mainly 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 models. Section 4 incorporates speculation shocks into the FAVAR. Section 5 presents the main results, and Section 6 offers some concluding remarks.

2 Econometric Method

Since the seminal paper by 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 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 –that is, that the identified structure of the shocks is fundamental (see Hansen and Sargent, 1991, Lippi and Reichlin, 1993,1994, and Fernandez-Villaverde et al.,

[6] Alquist and Kilian (2007) show evidence of increased trader activity from 2004 to 2007. The authors 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 non-commercial spread position is unprecedented in their sample.

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. Excluding 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 to augment the information set of the VAR by including a small set of principal components (factors) that summarize the information of a wider set of variables. In this section, we provide a summary of the factor-augmented vector autoregressive (FAVAR) model approach that we use in the empirical section. For additional details, see Bernanke et al. (2005).

The use of the FAVAR model 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 model is obtaining 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 have a positive impact on 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).

Let x_{it} denote 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[7]:

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

where $\mathbf{f}_t$ represents r unobserved factors ($N \gg r$), $\boldsymbol{\lambda}_i$ is the r-dimensional vector of factor loadings, and ξ_{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 consider them as shocks that affect a single variable or a small group of variables. For example,

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

in the specific dataset under analysis the idiosyncratic components will incorporate shocks to a single country that are not large enough to affect 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. 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 are generally responsible for the bulk of the comovement between the variables in the dataset.[8]

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:

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

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

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.[9] The specification (2) highlights that the low-dimensional

[8] 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).

[9] 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).

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 real oil prices in $\mathbf{y}_t$, whereas the effect of global demand is accounted for by the unobservable factors. We do not impose the restriction that any of the oil variables must be an observable factor in the system.[10] This implies that the identified shocks are not necessarily global shocks but does not rule out that possibility.[11] 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 U.S. recessions. As suggested by Engemann et al. (2010), it is likely that other countries are also affected similarly by the oil shocks. 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 U.S. real stock returns and external balances.

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 by Stock and Watson (2002b). In the second step, we use the estimated factors along with the oil variables to estimate our VAR model.[12] Stock and Watson (2002a) prove the consistency of the principal components estimator in an approximate factor model when both cross-sectional 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 strong distributional assumptions.[13]

Since the unobserved factors are estimated and then included as regressors in the FAVAR model the two-step approach might suffer from the "generated regressor" problem. In order to account

[10] This specification is consistent with the results in Section 3.3 where we test whether any of the oil variable can be considered as an observable factor.

[11] 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 implicitly constraining the oil shocks to be global shocks.

[12] 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.

[13] 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.

for estimation uncertainty, we adopt a non-overlapping block bootstrap technique. We partition the $T \times N$ matrix of data $\mathbf{X} = [x_{it}]$ into S sub-matrices $\mathbf{X}_s$ (blocks), $s = 1, ..., S$, of dimension $\tau \times N$, where τ is an integer part of T/S.[14] An integer h_s between 1 and S is drawn randomly with reintroduction S times to obtain the sequence $h_1, ..., h_s$. We then generate an artificial sample $\mathbf{X}^* = \left[\mathbf{X}'_{h_1}, ..., \mathbf{X}'_{h_3}\right]'$ of dimension $\tau S \times N$ and the corresponding impulse responses are estimated.

We are interested in analyzing the impact of different types of oil shocks within the framework of a FAVAR model. To give a structural interpretation to the shocks we follow the approach based on sign restrictions proposed by Canova and De Nicoló (2002) and Uhlig (2005). We identify the shocks by imposing economically meaningful sign restrictions on the impulse responses of a subset of variables. Specifically, let $\mathbf{Q}$ denote an orthonormal matrix such that $\mathbf{Q\prime Q} = \mathbf{I}$. The structural shocks can be recovered as $\boldsymbol{\eta}_t = \mathbf{Qu}_t$. The orthonormal matrices $\mathbf{Q}$ are found from the eigenvalue decomposition of a random $q \times q$ matrix (where $q = 3 + r$) 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 ith variable in the dataset can be written 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 consist of 151 series which include macroeconomic and financial variables of the G7 countries as well as oil market data, measures of global economic activity and rich set of commodity prices. Appendix A provides a complete description of the data and sources.

The set of macroeconomic and financial variables composed by output, prices, labor market indicators, trade, interest rates, stock market price indices and exchange rates, is sourced from the

[14] We set $\tau = 20$ (equivalent to five year blocks).

International Financial Statistics (IFS) database of the International Monetary Fund (IMF) and the Organisation for Economic Co-operation and Development (OECD).

The real oil price is the average oil price taken from the IFS deflated by the U.S. CPI. World oil production is obtained from the U.S. Department of Energy (DOE). Given the lack of data on crude oil inventories for other countries, we follow Hamilton (2009) and Kilian and Murphy (2011a) in using the data for total U.S. crude oil inventories provided by the Energy Information Administration (EIA), scaled by the ratio of OECD petroleum stocks over U.S. petroleum stocks. The price of other commodities is from the IFS and considered in real terms after being deflated by the U.S. CPI. We consider two proxies of global economic activity. The first one is an IFS index of aggregate industrial production and the second is the measure of global real economic activity based on data for dry cargo bulk freight rates proposed in Kilian (2009). All data are transformed to reach stationarity (see Appendix A for details).

3.2 Sufficient Information and the Choice of Factors

A natural question at this stage is whether our large dataset contains valuable information with respect to the small-scale VAR typically used in the literature to characterize the effects of oil shocks. Therefore, we use the procedure described in Forni and Gambetti (2011) to test whether the small scale VAR is infomationally sufficient to identify the shocks. 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, information sufficiency is rejected and the set of variables under consideration does not contain enough information 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 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 global real economic activity by an index of aggregate industrial production, which is also used in the literature (see Van Robays and Peersman, 2009, 2010).

Table 1 reports the (bootstrapped) p-values of the Granger causality test for the VAR and VAR augmented with the factors. Panel A shows the results for the VAR with the Kilian (2009) measure of economic activity and Panel B includes the results with aggregate industrial production. The first row of each panel 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.[15]

3.3 Empirical Factors

Before proceeding to describe our identification method it is interesting to consider to what extent some observable economic variable span the same information of the unobserved factors. Bai and Ng (2006) propose a test of this hypothesis based on the t-statistic

$$\tau_t(j) = \frac{\widehat{x}_{jt} - x_{jt}}{\sqrt{\widehat{var}\left(\widehat{x}_{jt}\right)}}, \tag{3}$$

where $\widehat{x}_{jt}(= \widehat{\boldsymbol{\delta}}_j' \widehat{\mathbf{f}}_t)$ is the least square projection of the variable x_{jt} on the estimated latent factors and the associate variance is constructed as detailed in Bai and Ng (2006). Two statistics can be

[15] When we estimate the FAVAR with a different number of factors 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, the results do not change when we include more than 3 factors. Appendix B shows the impulse responses for different numbers of factors. We also note that the results are virtually unchanged when we include an additional factor specific to commodity prices.

used to test the null hypothesis that the observable variable can be considered an exact factor (i.e. $\widehat{x}_{jt}$ is an exact linear combination of $\mathbf{f}_t$): $A(j)$ is the frequency that the t-statistic, $|\tau_t(j)|$, exceeds the 5% asymptotic critical value, whereas $M(j)$ is the value of the test and is equal to the maximum deviation of the statistic from 0. Given our sample size, the associated 5% critical value is 3.6. The first two columns of Table 2 show the results of these statistics for the oil variables included in $\mathbf{y}_t$ and the two measures of economic activity. Appendix C presents the statistics for all the variables of the dataset. From Table 2 it follows that none of the variables can be considered an observable factor of our dataset.

[Table 2 about here]

Requiring that an observable factor is an exact linear combination of the latent factor is a rather strong assumption. Indeed, it could be the case that an observable series is not an exact factor in the mathematical sense but still matches the variation of the latent factors very closely. The last two columns report statistic measures of how good x_{jt} is as a proxy for the factors. The $NS(j)$ statistic, i.e. the noise-to-signal ratio, and the coefficient of determination $R^2(j)$, are defined as

$$NS(j) = \frac{\widehat{var}\left(x_{jt} - \widehat{\boldsymbol{\delta}}_j' \widehat{\mathbf{f}}_t\right)}{\widehat{var}\left(\widehat{x}_{jt}\right)} \tag{4}$$

$$R^2(j) = \frac{\widehat{var}\left(\widehat{x}_{jt}\right)}{\widehat{var}\left(x_{jt}\right)}. \tag{5}$$

If x_{jt} is an exact factor, the population value of $NS(j)$ is zero. Therefore, a large $NS(j)$ indicates that there is an important departure of x_{jt} from the latent factors. Similarly, the $R^2(j)$ would be unity if x_{jt} is an exact factor, and zero if the observed variable is irrelevant. Table 2 shows that aggregate industrial production, a widely used indicator of aggregate economic activity, has the highest $R^2(j)$ and the lowest $NS(j)$, suggesting a strong relation with the latent factors. Not surprisingly, the Kilian measure of economic activity also has a strong relation with the latent factors, although considerably weaker than the one of aggregate industrial production. For the oil variables the association with the factors is generally weak.

Since the factors are identified only up to an orthogonal transformation, a detailed discussion of the individual factors is unwarranted. However, looking at the fit of the regression of the individual series in our dataset against each of the factors can still give an idea of the economic concepts behind the factors.

Figure 1 plots each measure of economic activity together with the projection of the variable on the factor with the highest explanatory power and the projection of the variable on all four latent factors. The results are quite interesting. While the first factor primarily loads on aggregate industrial production, the second factor has the highest explanatory power for the Kilian measure of economic activity. This suggests that these two factors summarize complementary economic concepts. In fact, the analysis suggests that the first factor summarizes a more general measure of the aggregate business cycle, explaining the main bulk of comovement among the main macroeconomic variables. By contrast, the second factor seems to be more of a measure of aggregate demand, loading primarily on US real personal consumption.[16]

[Figure 1 about here]

While the first two factors are associated with real economic concepts, the last two capture financial variables, such as exchange rates and the stock market (see Appendix C). The results of the test of sufficiency information in section 3.2 suggest that these forces are relevant for a correct identification of the oil shocks. This is in line with Kilian and Park (2009) who analyze the interaction between oil shocks and the stock market, as well as to the argument that fluctuations in the dollar can play a role for the determination of oil prices (see, for example, Frankel, 2008, and Akram, 2009).

From this analysis we conclude that the main variables used in our model cannot be considered as observable factors. This motivates the use of a FAVAR model. The factors are, however, a good proxy of a number of economic variables.

3.4 Identification

In this subsection we discuss the sign restrictions imposed to estimate oil supply, global demand, and oil inventory demand shocks, which are the focus of the recent literature. We incorporate the speculation shock in the next section. Our identification strategy, summarized in Table 3, builds on

[16] We note that the fit of the second factor to the measure of real economic activity becomes less strong in the last part of the sample. A potential explanation for this has to do with the fact that this measure of real economic activity is calculated from dry cargo bulk freight rates. The development in the shipping industry in the past decade might have significantly affected this measure. It is worth mentioning that freight rates became a relevant tradable 'commodity' for specialized financial institutions. In fact, in the past decade their volatility has increased tremendously: They are now twice more volatile than commodity prices and four times more volatile than stock prices.

those of Kilian and Murphy (2011a, b) and Peersman and Van Robays (2010). An oil supply shock is defined 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 to disentangle this shock from the speculative shock (see Section 4).[17]

[**Table 3 about here**]

An oil inventory demand shock arises from the possibility of a sudden shortage in production or expectations of higher demand in the future. Therefore, it is associated with expected shortfalls of the future oil supply relative to future oil demand. Such situation can occur in the presence of uncertainty about future oil supplies, driven, for example, by political instability in key oil-producing countries such as Nigeria, Iraq, Venezuela, or Libya. A positive oil inventory demand shock raises demand for inventories, causing the level of inventories and real oil prices to increase. Inventories of crude oil increase so that supply can 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. The increase in the real oil price causes a decline in real activity.

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 other emerging economies (see Hicks and Kilian, 2009). This increase in the demand for oil will drive up its real price. Oil production increases to satisfy the higher demand. 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; this bound is consistent with that used by Kilian and Murphy (2011b). This bound is imposed for all shocks except the supply shock.

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

3.5 Orthogonality

Despite the rejection of the information sufficiency of the VAR, some shocks can still be correctly identified from the low-dimensional VAR. This is true 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 4 shows 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 first test whether each is Granger-caused by lagged factors. We then report the number of rejected shocks over the total identified shocks. The results in the first row of the table 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 row of Table 3 suggests that a linear combination of 4 factors Granger-causes 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.[18]

[Table 4 about here]

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.

3.6 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

[18] 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 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.

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 (see Appendix D). However, some differences between the two methods emerge when we analyze the variance decomposition. Table 5 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 global demand shocks at all step horizons. The oil inventory demand shock also plays a significant role, accounting for about 25% to 35% of oil price fluctuations in the VARs. The sum of the three shocks account for around 80% of the oil price variation in both VARs.

[Table 5 about here]

The FAVAR offers a contrasting picture. While global demand shocks explain the largest share of oil price fluctuations, the oil inventory demand shock plays a smaller role compared to the VARs. They account for 4% to 13% of the variation in oil prices. 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 around 55% of oil price fluctuations.

The oil supply shock is the least affected by the inclusion of the factors. This is consistent with the results in the previous subsection. Specifically, among the 3 shocks, oil supply has 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 emphasize the potential benefits of identifying the shocks with a FAVAR. The FAVAR allows us to rely on more information, which can be useful in correctly identifying the shocks and recovering their fundamental structure. From the previous results we observe that a substantial unexplained component plays an important role. We conjecture that one of these components is speculation in the oil market. The next section addresses the identification of this component.

4 Augmented Model

In this section we extend the FAVAR model with 3 identified shocks as previously analyzed to include speculation shocks. We first describe the main characteristics of speculation in the oil market and then 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 invested 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 nonmarket 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 them the spot prices.

Commodities have become a recognized asset class within investment portfolios of financial institutions used 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 on both 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 as a vehicle for financial diversification substantially after 2004.

This financialization of commodities might give rise (and many believe it did) to a speculative bubble in the price of oil.[19] Singleton (2011) presents evidence of 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 induce 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. In a related study, Lombardi and Van Robays (2011) provide evidence that financial investors caused oil prices to diverge from the levels justified by fundamentals.

In addition to technical studies, there is also anecdotal evidence that speculation has significantly increased oil prices. Most recently, this idea attracted extensive media coverage after the CFTC filed lawsuits against traders for manipulating the price of oil.[20] In the next subsection we propose an identification strategy to disentangle the speculative shock and analyze its role as a driver of oil prices.

4.2 Identification of speculation shock

For the reasons explained previously, oil can be considered 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 Hamilton (2009). He argues that speculators can affect the incentives faced by producers by pushing up the expected future spot price (E_tP_{t+1}). As he explains, the typical strategy consists on taking a long-position in a futures contract at price F_t, sell it before it expires at a higher price P_{t+1} and use the proceeds to take a long position in another futures contract. If the expectations are such that the expected future spot price E_tP_{t+1} is higher than the futures price F_t ($E_tP_{t+1} > F_t$), more investment funds would take long positions

[19]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.

[20]See Chazan (2011) and Bowley (2011).

in futures contracts. As the number of buys of futures contracts exceeds the number of sells of expiring ones, futures prices would go up and with it the spot price. As producers expect a higher price of oil for future delivery (E_tP_{t+1}), 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 Hotelling's (1931) principle, it would benefit oil producers to forgo current production so they can 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. In contrast to an oil inventory demand shock, in a speculation shock inventories accumulate not because of a fear of production shortage (which would 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, causes the current spot oil price to rise.

This set of sign restrictions are also consistent with Bernanke (2004), who describes how speculation may drive oil prices up. He emphasizes that because 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 on a specified date at a specified price 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 resell 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 causes 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.

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 that 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 a speculation shock by traders. In this way, Kilian and Murphy (2011a) allow for our speculation shock but do not separately identify it. In our paper, we identify the oil inventory demand shock, which includes (i) and (ii) and speculation, which includes (iii).

We note that in order to disentangle oil supply shocks from speculation shocks in our framework we need to impose a negative restriction on oil inventories following an oil supply shock. This implicitly imposes a consumption-smoothing rationale for holding inventories in the face of supply shocks. Kilian and Murphy (2011a) report evidence supporting this type of inventory behavior, so this restriction seems reasonable.

4.2.1 Speculation in the absence of futures markets

Given that futures markets were not developed until the 1980s, it is natural to ask whether speculation would have the same characteristics in the absence of futures market. We refer to speculation in the oil market as speculation motivated by the recent trend of investment in commodity markets. However, the same pattern can arise in the absence of developed futures markets if the oil price is expected to increase relative to production costs and current production is reduced as producers withhold some energy resources to sell at a greater "discounted" profit at a future date (see Davidson et al., 1974). In fact, there is evidence supporting the presence of speculative activity in the absence of futures markets. Davidson et al. (1974) describe 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. This suggests an explicit decision by producers to restrict available production flows.

The only role that futures markets are playing now is to fuel the expectations of higher futures prices but the same general idea applies previous to their development. Therefore, our sign restrictions to identify the speculative shock are valid for a broad concept of speculation, also arising in the absence of futures markets.[21]

5 Empirical Results

This section presents the results of the augmented model with four shocks. We show the impulse responses, and examine the effects of each shock on the comovement between commodity prices. We also present the variance decomposition to evaluate how much of the variation in oil market variables is accounted by each of the shocks, and further examine the transmission of shocks to the oil price by looking at the historical decomposition. As a final step, we check the sensitivity of our results to a subsample starting in 1986.

5.1 Impulse responses

Figure 2 presents the median impulse responses of oil production, oil inventories, real economic activity, and industrial production to oil supply, oil inventory demand, global demand, and speculative shocks. The impulse responses, estimated using a FAVAR with the sign restrictions from Table 3, have been accumulated and are shown in levels.

[Figure 2 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 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

[21] In the next section we check the sensitivity of our results to a subsample starting in 1986, when futures markets were developed. They remain robust.

oil prices exhibit a persistent increase. Oil production also rises temporarily, and oil inventories decline to satisfy the higher demand.

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

5.2 Other commodity prices

The FAVAR model allows us to include a large number of variables such as the prices 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 importance since it allows 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 prices 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 other commodity prices also allows 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 over 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 iron ore will rise because these commodities are used as inputs in production. At the same time, demand for nonindustrial commodities is likely to rise as a result of increases in income. Demand pressures would be associated with an increase in the price of all commodities.

In what follows we examine 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 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 allows us to understand which shocks are responsible for the increased correlation in commodity prices.

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

$$COR(v_t, z_t; K, s) = \frac{\sum_{k=1}^{K} v_k^{imp,s} z_k^{imp,s}}{SD(v_t; K) SD(z_t; K)}. \tag{6}$$

In Equation 6, $v_k^{imp,s}$ and $z_k^{imp,s}$ are the Kth-period responses of v and z to a 1-standard deviation innovation of the sth structural shock, and SD denotes the total standard deviation of the Kth-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, the correlations are positive for all shocks. The largest response on impact occurs for 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 quite similar.[22]

[Figure 3 about here]

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

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

commodity indexes, calculated as an equal-weighted real price index for each commodity sector. Figure 4 presents the correlations.

[Figure 4 about here]

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 speculation shock is associated with a positive correlation between oil prices 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). In a related study, Pindyck and Rotemberg (1990) highlight that comovement in commodity markets can be related to the behavior of speculators who are long in several commodities at the same time. Third, the correlations between oil prices and the prices of other commodities are negative in the case of oil supply and oil inventory demand shocks. This implies that the oil inventory demand shock cannot be responsible for the comovement in commodity prices. The correlation in the case of the speculative shock is smaller than for the global demand shock. This result should be interpreted with care since it is an average result. Speculation can still be an important driver of the increased correlation in periods when it played a more relevant role.

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. The variance decomposition for oil prices is shown in Table 6. The first point to note is that the results are quite stable with respect to the FAVAR with three shocks shown in Table 5. It is generally suggested that identifying more shocks tends 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. As before, global demand shocks are the most important driver of oil prices, accounting for up to 45% of oil price fluctuations. Speculative shocks are the second most important driver, explaining up to 13% of oil price movements. The oil inventory demand shock is particularly important on impact (13%) but decreases to 4% at longer horizons. The oil supply shock is the least relevant driver, explaining less than 8% of the variation in oil prices at all horizons.

[**Table 6 about here**]

Our results confirm that Kilian's (2009) conclusion that global demand shocks as the main drivers of oil fluctuations remains robust. In addition, we show that 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 informative to show their variance decomposition, presented in Table 7. In the short run, 22% of the variation in oil inventories is driven by oil supply shocks, consistent with production smoothing in response to a supply shock. Interestingly, oil inventory demand explains up to 14% of inventory fluctuations. The global demand shock contributes up to 15% of inventory movements. In turn, 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 32%. The explanatory power of oil inventory demand and speculative shocks is similar to the short-run case. These results suggest that fluctuations in oil inventories are due to oil inventory demand motives as well as production smoothing in response to oil supply shocks. In this way, our findings are consistent with those of Kilian and Murphy (2011a).

[**Table 7 about here**]

Table 8 presents the variance decomposition of oil production. On impact, oil supply shocks explain around 35% of oil production fluctuations. The speculative shock affects the incentives faced by producers, who lower oil production in anticipation of predictable increases in the price of oil. Therefore, it is expected that speculative shocks play a role as a driver of oil production. In fact, they explain around 20% of oil production fluctuations.

[**Table 8 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 shock. We note here that this is an average measure for the entire 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 possibility, 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 speculation contributed around 15% to oil price increases in this period. It is interesting that the speculative shock begins to play a relevant role as a driver of oil price increases in 2004, which is when significant index investment started to flow into commodities markets (see Tang and Xiong, 2011). This finding confirms that we are picking up the form of speculative shock resulting 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 feature of interest refers to the fact that the contribution of speculative shocks to oil price increases becomes flatter from 2006 until 2008. This highlights that the gains from speculation decrease as the oil price goes up.[23]

Another aspect to emphasize is that 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 recent recession is due to oil inventory demand shocks.

[23] Let us illustrate this claim with a simple example which applies to contango periods like the one observed in 2004-2007. Suppose that the spot price is 30 USD, the 1 year forward price is 60 USD, the interest rate is 10%, and there are no storage costs. An investor would borrow 30 USD, buy oil, wait for delivery and sell it for 60 USD. The total cost for the investor is 33, and the revenue is 27. Now assume that the forward curve shifts upwards, so that the spot price is 100 USD and the forward price is 130 USD. In this case the total cost for the investor is 110 USD, and the revenue is 20 USD.

The V-shaped decline in the real price of oil in late 2008 is driven mainly by the recession associated with the global financial crisis, and reflected by the global demand shock. However, the speculation 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.

5.5 Robustness

The oil market has witnessed substantial changes over the sample period. Baumeister and Peersman (2011) document that oil supply shocks are characterized by a much smaller impact on world oil production and a greater effect on the real price of crude oil since the second half of the 1980s. In addition, futures markets were not developed until the 1980s. This feature is of relevance to us since we want to understand the role of speculation in driving oil prices, and the interaction between traders and producers that we describe accommodates better in a subperiod where investment in futures market play a role. We also note that the period starting with the great-moderation may involve different structural characteristics that may affect the transmission of shocks.

It is natural to ask whether these changes affected the way oil shocks affect the economy. Therefore, we estimate the FAVAR for a subsample starting in 1986. We chose 1986 as the date to split our sample because this is the year in which oil prices stabilize and go back to the pre-1973 levels, and also is a period that includes the great moderation and the development in futures markets.

Appendix E compares the impulse responses and historical decomposition for the benchmark results and the subperiod starting in 1986. Some results are of interest. The comparison of the impulse responses for the two periods reveals that the transmission of shocks remains very stable. The historical decomposition is very robust to the subsample analysis, with the speculative shock playing a slightly more important role from 2004 to 2008.

6 Conclusion

The increase in oil prices in 2004 coincided with a large flow of investment in commodity markets and an increased price comovement between different commodities. 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 use a FAVAR model to identify oil shocks from a large dataset, including both macroeconomic and financial variables of the G7 countries and a rich set of commodity prices. This method is motivated by showing that the small scale VAR is not infomationally sufficient to identify the shocks. Therefore, a set of factors summarizes a bulk of aggregate fluctuations in our data. In particular, the first two factors capture complementary measures of real activity, and the remaining two are associated with financial variables.

The FAVAR model allows us to investigate the transmission of the oil shocks to a many 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 prices of other commodities, we find that the largest correlations are in response to global demand shocks, consistent with Kilian (2009). Interestingly, the speculative shock is also associated with a positive comovement between oil prices and prices of other commodities. This finding is consistent with the results of Tang and Xiong (2011) and further supports the idea that the speculation 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 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, speculation shocks are the second most important driver.

We find that the increase in oil prices over the past decade is due mainly to the strength of global demand, consistent with previous studies. However, 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 when significant investment started to flow into commodity markets. We find that the decline in the real price of oil in late 2008 is driven mainly by the negative global demand shock associated with the recession after the financial crisis. However, we note that the speculative shock also played a significant role in the decline as the financial crisis eroded the balance sheets of many financial institutions, which in turn affected their demand for commodity assets in their portfolio, consequently pushing prices down.

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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. Evaluating Latent and Observed Factors

	$A(j)$	$M(j)$	$NS\,(j)$	$R^2\,(j)$
Oil production	0.793	38.776	6.112	0.140 (0.039-0.242)
Real oil prices	0.767	25.572	2.081	0.324 (0.203-0.445)
Oil inventories	0.916	83.424	28.093	0.034 (0.000-0.090)
Aggregate industrial production	0.567	9.495	0.289	0.775 (0.713-0.937)
Kilian measure of economic activity	0.709	15.752	1.101	0.475 (0.362-0.589)

Notes: The table reports Bai and Ng (2006)'s statistics to evaluate the extent to which observed factors differ from latent factors. $A(j)$ is the frequency that the t-statistic $|\tau_t(j)|$ exceed the 5% asymptotic critical value. $M(j)$ is the value of the test (given the sample size the associated 5% critical value is 3.6). $NS\,(j)$ is defined in Equation (4) and $R^2\,(j)$ is defined in Equation (5).

Table 3. Sign Restrictions

Shock	Oil production	Oil inventories	Real oil prices	Real activity
Oil supply	−	−	+	−
Oil Inventory demand	+	+	+	−
Global Demand	+		+	+
Speculative	−	+	+	

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 4. Orthogonality Test

	Oil supply	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 5. Variance Decomposition of the Real Oil Price

Horizon		Supply	Oil Inventory Demand	Global Demand
1	VAR (KM)	0.0446	0.3526	0.4231
	VAR (AIP)	0.0700	0.3533	0.4027
	FAVAR	0.0641	0.1286	0.3698
2	VAR (KM)	0.0396	0.2777	0.4843
	VAR (AIP)	0.0811	0.2915	0.4464
	FAVAR	0.0460	0.0730	0.4178
3	VAR (KM)	0.0147	0.1998	0.5626
	VAR (AIP)	0.0518	0.2596	0.4896
	FAVAR	0.0297	0.0475	0.4420
4	VAR (KM)	0.0120	0.1450	0.6037
	VAR (AIP)	0.0412	0.2587	0.4926
	FAVAR	0.0265	0.0390	0.4429
8	VAR (KM)	0.0102	0.1232	0.6095
	VAR (AIP)	0.0460	0.2845	0.4943
	FAVAR	0.0532	0.0475	0.3836
12	VAR (KM)	0.0108	0.1339	0.6057
	VAR (AIP)	0.0545	0.2651	0.4965
	FAVAR	0.0916	0.0687	0.3339

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 6. Variance Decomposition of the Oil Price (FAVAR)

Horizon	Oil Supply	Oil Inventory Demand	Aggregate Demand	Speculative
1	0.0638	0.1315	0.3924	0.0900
2	0.0459	0.0742	0.4378	0.0984
3	0.0289	0.0475	0.4596	0.1095
4	0.0253	0.0388	0.4555	0.1269
8	0.0484	0.0464	0.4078	0.1043
12	0.0842	0.0677	0.3595	0.0924

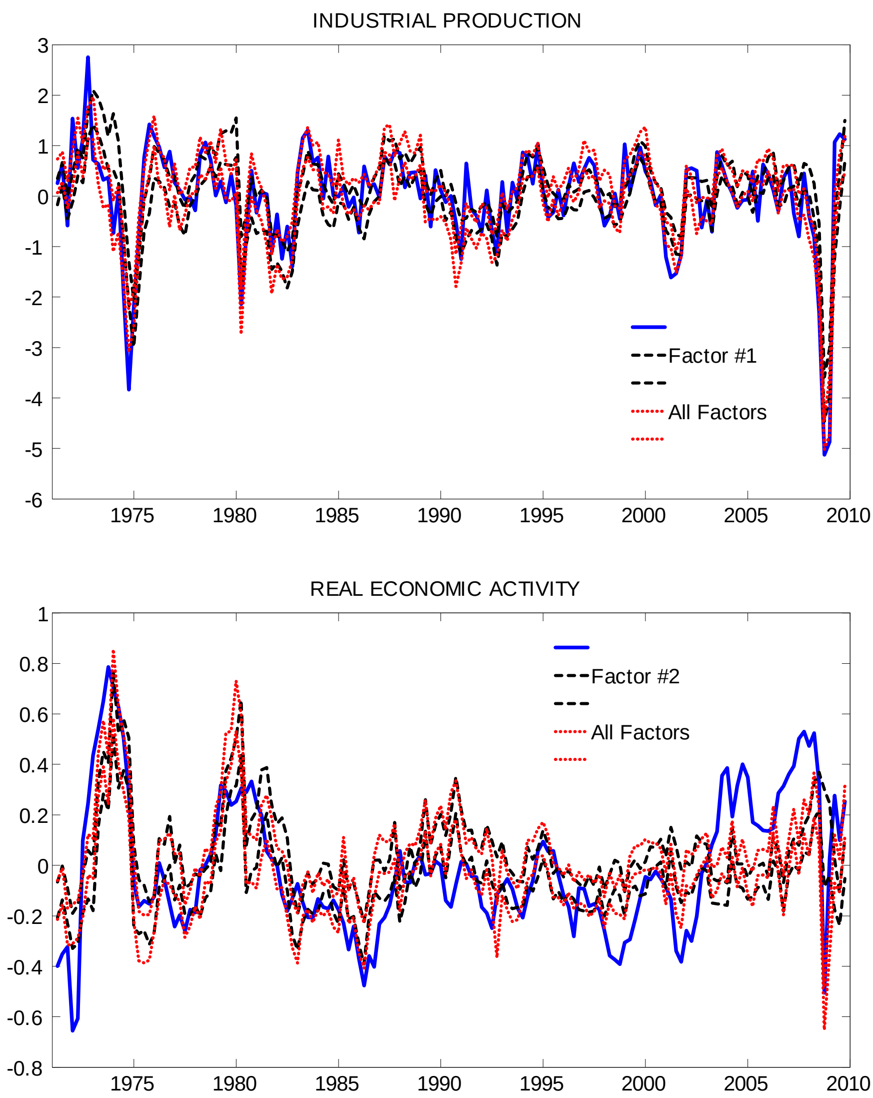
Table 7. Variance Decomposition of Inventories (FAVAR)

Horizon	Oil Supply	Oil Inventory Demand	Aggregate Demand	Speculative
1	0.2196	0.1230	0.1612	0.0858
2	0.2241	0.1456	0.1289	0.1012
3	0.2538	0.1407	0.1069	0.0978
4	0.3031	0.1436	0.0897	0.0778
8	0.3228	0.0992	0.1166	0.0958
12	0.3162	0.1281	0.0866	0.0828

Table 8. Variance Decomposition of Oil Production (FAVAR)

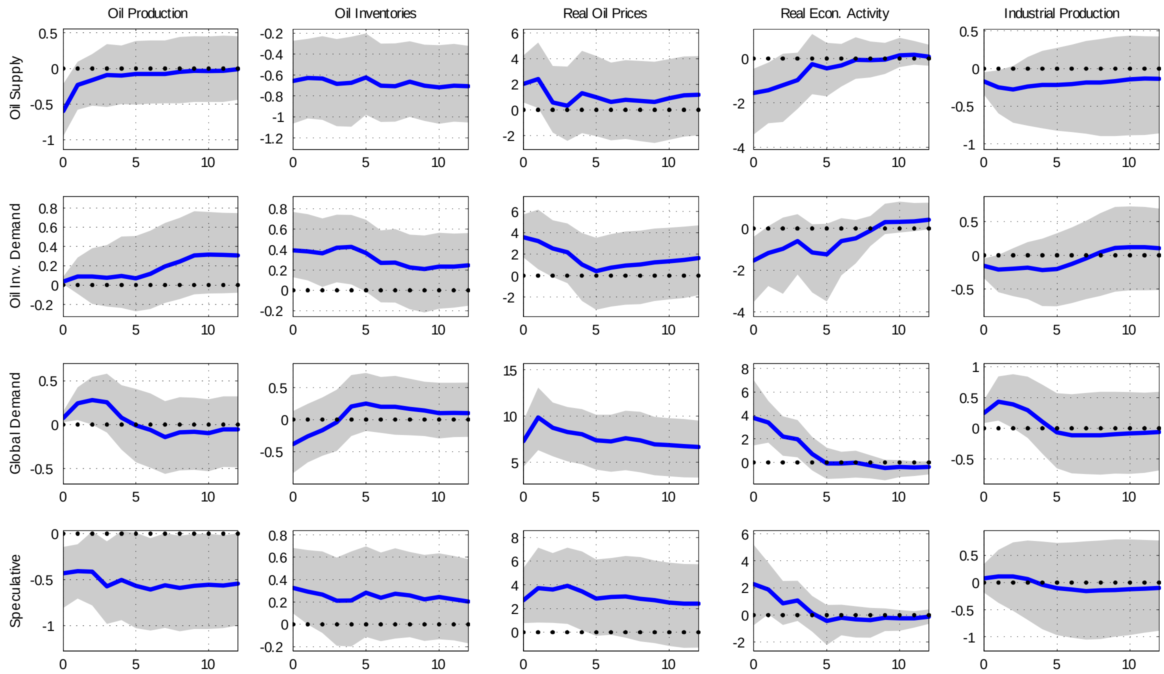
Horizon	Oil Supply	Oil Inventory Demand	Aggregate Demand	Speculative
1	0.3500	0.0023	0.0064	0.1885
2	0.1913	0.0294	0.0914	0.2009
3	0.1273	0.0467	0.1153	0.2112
4	0.1200	0.0400	0.0929	0.2487
8	0.0834	0.1360	0.0924	0.2367
12	0.0956	0.1635	0.0741	0.2169

Figure 1. Factors Fit for Measures of Real Economic Activity



Notes: The figure shows each measure of economic activity together with the projection of the variable on the factor with the highest explanatory power and the projection of the variable on all four latent factors.

Figure 2. Impulse Responses: Main Variables



Notes: The figure shows the impulse responses to oil supply, oil inventory demand, global demand, and speculative 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

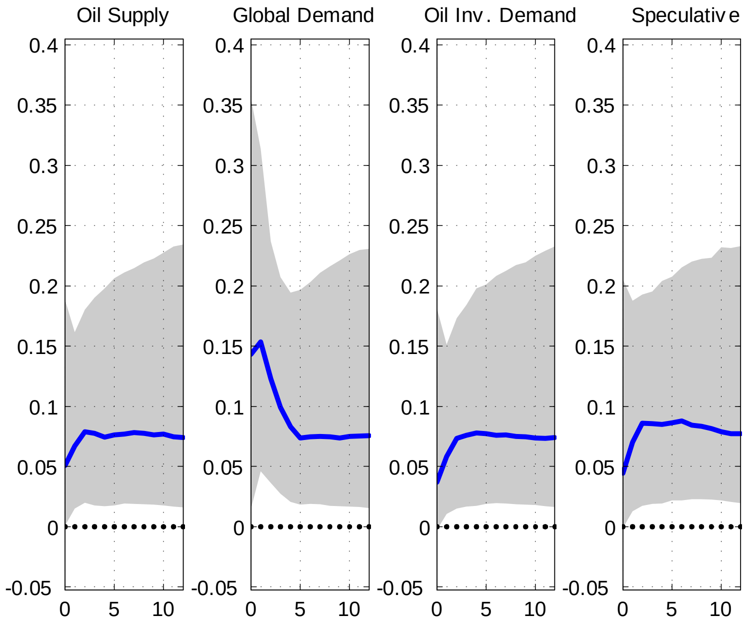
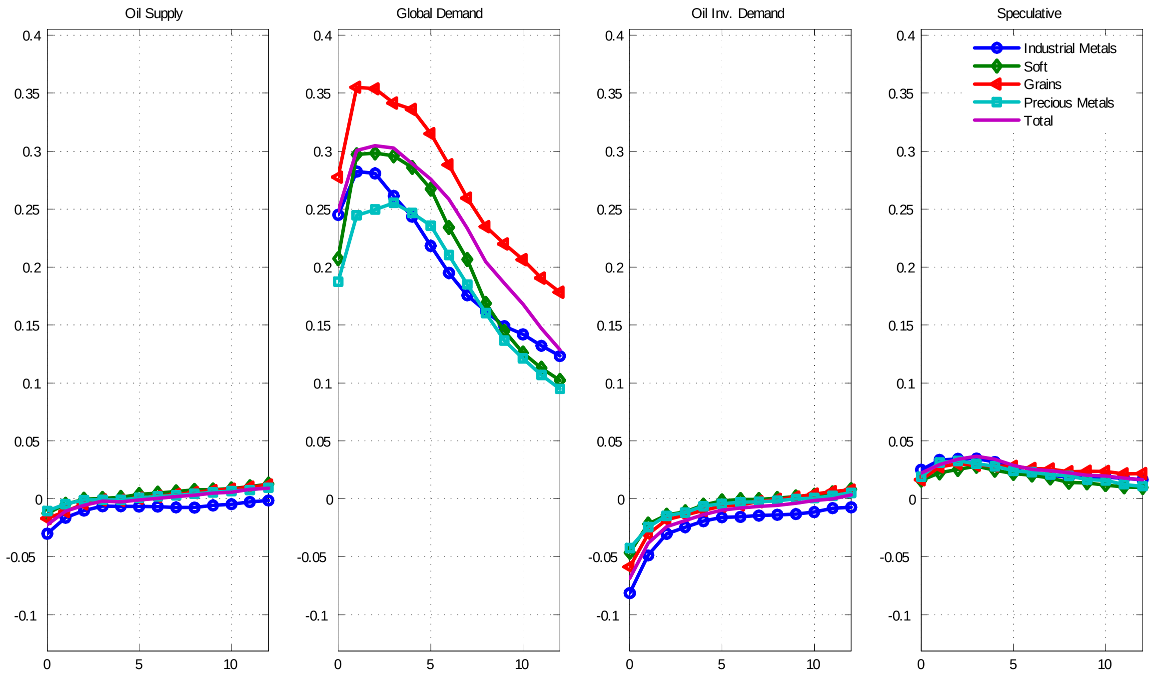
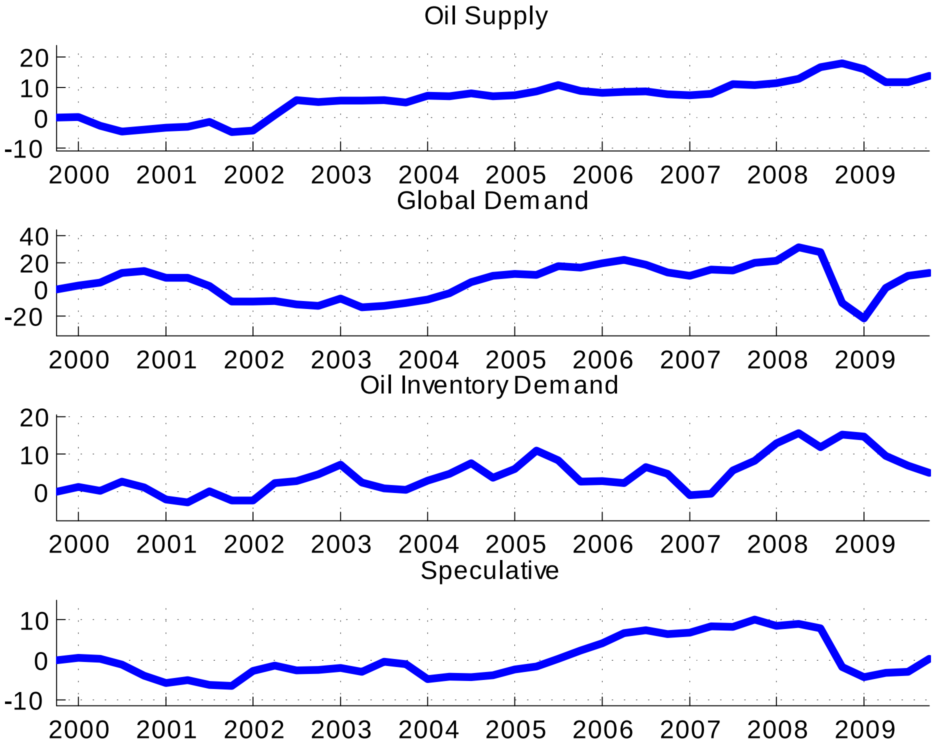


Figure 4. Conditional Correlations



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, soft, 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

Variables	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						
U.S.	MILL, USD	OECD	1971 Q1	2009 Q4	Y	4
U.K.	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						
U.S.	Bil. USD	IFS	1971 Q1	2009 Q4	Y	4
U.K.	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						
U.S.	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	4
U.K.	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.

Variables	Unit	Source	Start Date	End Date	Seasonally Adjusted	Stationarity Transformation
Employment						
U.S.	%	OECD Economic Outlook	1971 Q1	2009 Q4	Y	2
U.K.	%	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						
U.S.	%	OECD Economic Outlook	1971 Q1	2009 Q4	Y	2
U.K.	%	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						
U.S.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	6
U.K.	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						
U.S.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	6
U.K.	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						
U.S.	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	6
U.K.	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						
U.S.	%	IFS	1971 Q1	2009 Q4	N	2
U.K.	%	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						
U.S.	%	OECD MEI	1971 Q1	2009 Q4	N	2
U.K.	%	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

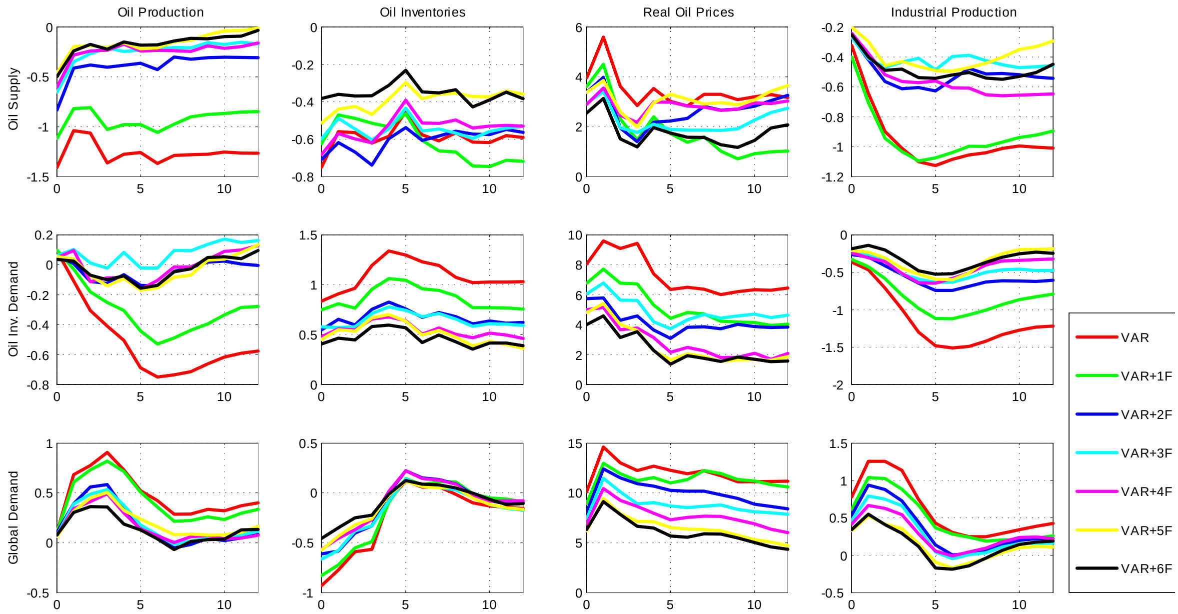
Notes: (1) denotes level, (2) denotes first difference, (3) denotes log, (4) denotes log difference, and (6) denotes first difference of annual growth rates.

Variables	Unit	Source	Start Date	End Date	Seasonally Adjusted	Stationarity Transformation
M1						
U.S.	(Real, deflated by CPI, Bil. USD)	OECD MEI	1971 Q1	2009 Q4	Y	4
U.K.	(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						
U.S.	(Real, deflated by CPI, Bil. USD)	OECD MEI	1971 Q1	2009 Q4	Y	4
U.K.	(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						
U.S.	%GDP	OECD MEI/IFS	1971 Q1	2009 Q4	Y	2
U.K.	%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						
U.S.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	N	4
U.K.	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						
U.S.	Index (2000=100)	JP Morgan (via Haver)	1971 Q1	2009 Q4	N	4
U.K.	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
Exchange Rate with Dollar						
U.K.	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						
U.S.	%	IFS	1971 Q1	2009 Q4	N	1
U.K.	%	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						
U.S.	%	See 10Y and 1D interest rate sources.	1971 Q1	2009 Q4	N	1
U.K.	%	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, oil inventory demand, and global demand shocks estimated using sign restrictions for a different choice of factors.

Appendix C. Empirical Factors

VARIABLES	TEST ON FIT					FIT OF FACTORS (R^2)			
	A(j)	M(j)	NS(j)	R^2	Confidence Interval	F1	F2	F3	F4
Oil and Aggreggate Variables									
World oil production	0.794	38.777	6.113	**0.141**	[0.039; 0.242]	0.081	0.038	0.001	0.020
Aggregate industrial production	0.568	9.495	0.290	**0.775**	[0.713; 0.838]	**0.597**	**0.133**	0.025	0.020
Average world price of oil	0.768	25.573	2.081	**0.325**	[0.203; 0.446]	**0.207**	0.069	0.020	0.028
Inventories of oil	0.916	83.424	28.094	0.034	[0.000; 0.091]	0.006	0.022	0.002	0.005
Oil price spot-future spread	0.879	29.794	5.860	**0.146**	[0.022; 0.269]	0.080	0.020	0.035	0.001
Index of global economic activity	0.710	15.753	1.101	**0.476**	[0.362; 0.590]	0.081	**0.354**	0.016	0.024
Commodity Prices									
Gold	0.735	13.700	1.759	**0.362**	[0.242; 0.483]	0.067	0.021	**0.263**	0.010
Silver	0.735	28.865	3.393	**0.228**	[0.112; 0.344]	**0.112**	0.001	**0.112**	0.003
Copper	0.677	15.090	1.035	**0.492**	[0.379; 0.604]	**0.326**	0.021	**0.100**	0.044
Aluminium	0.684	15.152	1.453	**0.408**	[0.289; 0.527]	**0.228**	0.029	0.090	0.060
Nickel	0.735	23.451	2.388	**0.295**	[0.175; 0.416]	**0.147**	0.034	0.012	0.102
Iron Ore	0.742	88.444	9.441	0.096	[0.008; 0.184]	0.069	0.001	0.016	0.010
Zinc	0.787	28.644	2.604	**0.277**	[0.158; 0.397]	**0.206**	0.034	0.006	0.031
Rubber	0.748	18.953	1.443	**0.409**	[0.290; 0.528]	**0.288**	0.013	0.099	0.009
Timber	0.781	40.907	9.537	0.095	[0.007; 0.183]	0.015	0.001	0.014	0.066
Cotton	0.916	49.970	5.916	**0.145**	[0.042; 0.247]	**0.136**	0.001	0.007	0.001
Tobacco	0.910	97.210	33.891	0.029	[0.000; 0.080]	0.013	0.015	0.000	0.000
Sunflower oil	0.897	57.433	6.553	**0.132**	[0.033; 0.232]	0.081	0.026	0.011	0.014
Palm oil	0.858	39.784	3.752	**0.210**	[0.096; 0.324]	**0.194**	0.002	0.008	0.006
Sugar	0.839	29.999	4.475	**0.183**	[0.073; 0.293]	0.056	0.047	0.076	0.004
Soybeans	0.884	63.522	7.845	**0.113**	[0.019; 0.207]	0.088	0.003	0.014	0.008
Wheat	0.868	50.020	9.601	0.094	[0.006; 0.183]	0.062	0.006	0.026	0.000
Rice	0.806	39.579	4.763	**0.174**	[0.065; 0.282]	0.097	0.029	0.032	0.016
Maize	0.897	69.928	8.444	**0.106**	[0.014; 0.197]	0.092	0.002	0.011	0.000
Coffee	0.910	91.429	18.811	0.050	[0.000; 0.118]	0.033	0.015	0.003	0.000
Cacao	0.742	20.356	4.607	**0.178**	[0.069; 0.288]	0.059	0.001	0.046	0.072
Real GDP									
U.S.	0.684	14.458	0.721	**0.581**	[0.481; 0.682]	**0.244**	**0.255**	0.073	0.009
U.K.	0.632	23.474	1.729	**0.366**	[0.246; 0.487]	**0.183**	**0.177**	0.002	0.004
France	0.806	12.514	0.828	**0.547**	[0.442; 0.653]	**0.521**	0.009	0.014	0.004
Germany	0.839	33.166	2.767	**0.265**	[0.146; 0.385]	**0.243**	0.020	0.002	0.000
Italy	0.813	14.257	1.095	**0.477**	[0.364; 0.591]	**0.439**	0.000	0.031	0.007
Canada	0.690	15.977	1.094	**0.478**	[0.364; 0.591]	**0.317**	0.080	0.068	0.012
Japan	0.787	21.725	2.477	**0.288**	[0.167; 0.408]	**0.159**	0.074	0.011	0.043
Personal Consumption									
U.S.	0.665	9.934	0.725	**0.580**	[0.479; 0.680]	0.009	**0.523**	0.018	0.030
U.K.	0.781	29.041	3.854	**0.206**	[0.093; 0.320]	0.063	**0.124**	0.008	0.010
France	0.897	32.081	4.467	**0.183**	[0.073; 0.293]	0.090	0.027	0.011	0.054
Germany	0.935	406.505	116.236	0.009	[0.000; 0.037]	0.001	0.002	0.002	0.003
Italy	0.800	24.488	2.578	**0.279**	[0.160; 0.399]	**0.251**	0.000	0.027	0.001
Canada	0.819	30.780	4.039	**0.198**	[0.086; 0.311]	0.085	0.096	0.000	0.017
Japan	0.858	46.249	7.517	**0.117**	[0.022; 0.213]	0.005	**0.107**	0.005	0.000
Industrial Production									
U.S.	0.542	8.530	0.343	**0.745**	[0.675; 0.814]	**0.473**	**0.136**	**0.105**	0.030
U.K.	0.755	33.602	2.786	**0.264**	[0.145; 0.383]	**0.183**	0.072	0.010	0.000
France	0.690	15.116	0.789	**0.559**	[0.455; 0.633]	**0.511**	0.036	0.011	0.001
Germany	0.735	19.140	1.077	**0.481**	[0.368; 0.595]	**0.426**	0.038	0.000	0.018
Italy	0.768	28.662	1.334	**0.428**	[0.311; 0.546]	**0.412**	0.002	0.015	0.000
Canada	0.613	17.939	0.948	**0.513**	[0.404; 0.623]	**0.309**	0.084	0.067	0.054
Japan	0.561	14.802	0.705	**0.587**	[0.487; 0.686]	**0.519**	0.029	0.005	0.034

Notes: This table reports the Bai and Ng (2006) statistics to evaluate the extent to which observed factors differ from latent factors. Bold numbers indicate an $R^2 > 0.100$.

VARIABLES	TEST ON FIT					FIT OF FACTORS (R^2)			
	A(j)	M(j)	NS(j)	R^2	Confidence Interval	F1	F2	F3	F4
Employment									
U.S.	0.581	12.607	0.591	**0.629**	[0.536; 0.721]	**0.376**	0.096	0.107	0.049
U.K.	0.832	19.379	1.849	**0.351**	[0.230; 0.472]	**0.257**	0.042	0.016	0.036
France	0.929	80.159	24.609	**0.039**	[0.000; 0.099]	0.015	0.005	0.011	0.007
Germany	0.819	41.188	6.660	**0.131**	[0.032; 0.229]	0.072	0.010	0.046	0.002
Italy	0.910	39.624	7.209	**0.122**	[0.025; 0.218]	0.041	0.027	0.049	0.005
Canada	0.684	16.768	1.137	**0.468**	[0.353; 0.583]	**0.379**	0.020	0.043	0.025
Japan	0.961	61.572	26.965	0.036	[0.000; 0.093]	0.013	0.009	0.003	0.010
Unemployment									
U.S.	0.561	8.957	0.347	**0.742**	[0.673; 0.812]	**0.434**	**0.152**	0.110	0.046
U.K.	0.755	16.039	1.706	**0.370**	[0.249; 0.490]	**0.253**	0.052	0.041	0.024
France	0.845	39.282	5.020	**0.166**	[0.059; 0.273]	**0.161**	0.000	0.001	0.004
Germany	0.897	50.549	5.166	**0.162**	[0.056; 0.268]	**0.132**	0.000	0.012	0.018
Italy	0.942	52.812	12.647	0.073	[0.000; 0.152]	0.026	0.042	0.000	0.005
Canada	0.781	20.277	1.229	**0.449**	[0.332; 0.565]	**0.377**	0.038	0.013	0.021
Japan	0.865	43.727	3.799	**0.208**	[0.095; 0.322]	**0.195**	0.007	0.005	0.002
Employee Earnings									
U.S.	0.935	54.904	23.846	0.040	[0.000; 0.101]	0.006	0.018	0.015	0.002
U.K.	0.801	27.695	8.190	**0.109**	[0.015; 0.203]	0.000	0.016	0.070	0.021
France	0.709	29.413	2.424	**0.292**	[0.170; 0.414]	**0.117**	**0.160**	0.000	0.020
Germany	0.839	38.143	11.013	0.083	[0.000; 0.167]	0.009	0.017	0.056	0.001
Italy	0.921	83.645	23.708	0.040	[0.000; 0.102]	0.007	0.025	0.008	0.001
Canada	0.819	33.615	6.832	**0.128**	[0.030; 0.226]	0.033	0.018	0.001	0.075
Japan	0.887	94.312	11.297	0.081	[0.000; 0.165]	0.074	0.004	0.003	0.003
CPI									
U.S.	0.690	12.563	0.763	**0.567**	[0.464; 0.670]	**0.403**	**0.125**	0.039	0.000
U.K.	0.710	31.445	4.441	**0.184**	[0.074; 0.294]	0.017	**0.141**	0.012	0.014
France	0.658	14.076	0.821	**0.549**	[0.444; 0.654]	**0.241**	**0.304**	0.004	0.001
Germany	0.748	29.889	2.989	**0.251**	[0.133; 0.369]	**0.150**	0.067	0.002	0.032
Italy	0.690	16.418	1.440	**0.410**	[0.291; 0.529]	**0.106**	0.273	0.028	0.003
Canada	0.897	41.454	5.251	**0.160**	[0.054; 0.266]	0.075	0.085	0.000	0.000
Japan	0.710	15.577	1.182	**0.458**	[0.343; 0.574]	**0.216**	**0.181**	0.006	0.055
PPI									
U.S.	0.677	21.144	1.145	**0.466**	[0.351; 0.581]	**0.406**	0.021	0.038	0.002
U.K.	0.677	30.471	5.724	**0.149**	[0.045; 0.252]	0.000	0.003	0.048	0.097
France	0.556	13.865	0.412	**0.708**	[0.587; 0.829]	**0.561**	0.016	0.002	0.016
Germany	0.606	11.138	0.442	**0.694**	[0.613; 0.774]	**0.554**	**0.125**	0.005	0.009
Italy	0.667	16.040	0.985	**0.504**	[0.373; 0.635]	**0.410**	0.045	0.007	0.030
Canada	0.774	27.251	1.807	**0.356**	[0.235; 0.477]	**0.220**	0.066	0.000	0.070
Japan	0.632	11.313	0.857	**0.539**	[0.432; 0.645]	**0.412**	0.056	0.005	0.066
Overnight Rates									
U.S.	0.671	22.989	1.632	**0.380**	[0.260; 0.500]	**0.267**	0.004	**0.105**	0.004
U.K.	0.836	60.518	8.680	**0.103**	[0.012; 0.195]	0.071	0.022	0.000	0.010
France	0.645	19.267	1.368	**0.422**	[0.304; 0.541]	**0.194**	**0.169**	0.044	0.015
Germany	0.755	29.385	2.554	**0.281**	[0.161; 0.401]	**0.176**	0.067	0.034	0.003
Italy	0.755	38.823	3.166	**0.240**	[0.123; 0.357]	**0.107**	**0.114**	0.006	0.013
Canada	0.710	27.927	3.338	**0.231**	[0.114; 0.347]	0.050	0.053	0.124	0.004
Japan	0.665	16.381	1.388	**0.419**	[0.300; 0.537]	0.052	**0.309**	0.057	0.000
10-Year Rates									
U.S.	0.742	18.109	2.413	**0.293**	[0.172; 0.413]	**0.133**	0.021	**0.111**	0.028
U.K.	0.774	21.782	2.424	**0.292**	[0.172; 0.412]	**0.146**	0.094	0.035	0.017
France	0.768	15.938	1.295	**0.436**	[0.318; 0.553]	**0.154**	0.240	0.036	0.006
Germany	0.735	13.854	1.132	**0.469**	[0.354; 0.583]	**0.296**	0.089	0.076	0.009
Italy	0.665	23.100	2.175	**0.315**	[0.194; 0.436]	0.020	0.262	0.029	0.004
Canada	0.703	16.983	1.851	**0.351**	[0.230; 0.472]	**0.116**	0.059	0.170	0.005
Japan	0.903	74.418	9.741	0.093	[0.006; 0.180]	0.088	0.005	0.000	0.000

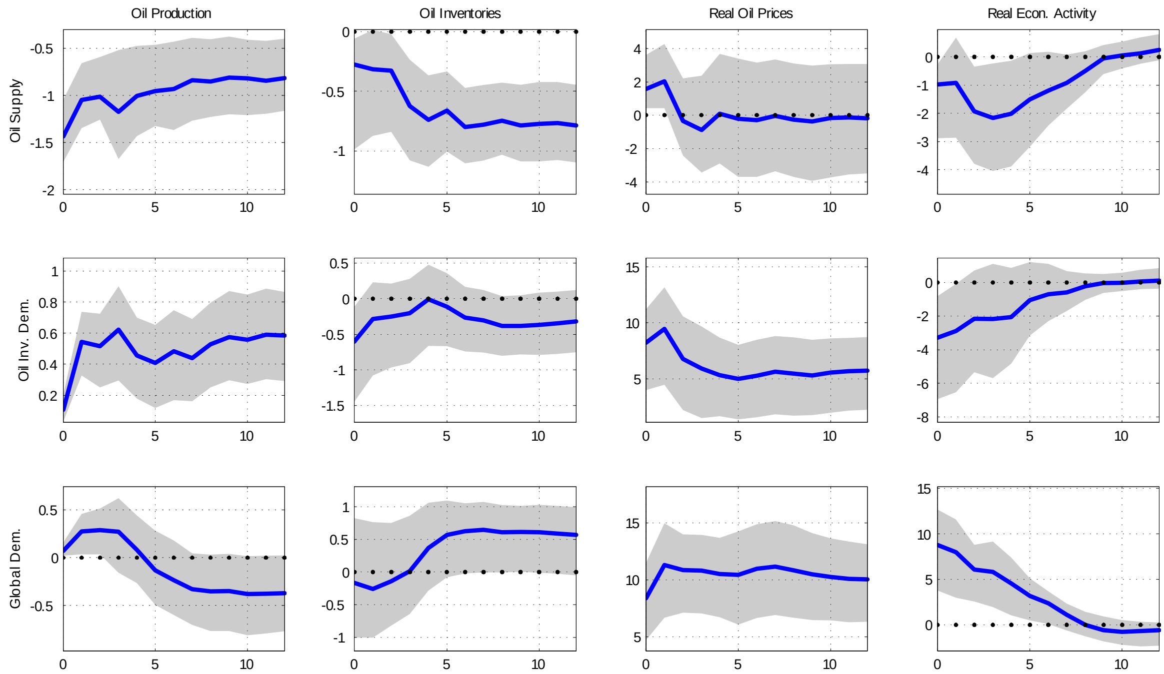
Notes: This table reports the Bai and Ng (2006) statistics to evaluate the extent to which observed factors differ from latent factors. Bold numbers indicate an $R^2 > 0.100$.

VARIABLES	TEST ON FIT					FIT OF FACTORS (R^2)			
	A(j)	M(j)	NS(j)	R^2	Confidence Interval	F1	F2	F3	F4
M1									
U.S.	0.684	17.338	1.648	**0.378**	[0.257; 0.498]	**0.133**	**0.122**	0.011	**0.112**
U.K.	0.737	22.497	2.051	**0.328**	[0.205; 0.450]	0.000	**0.282**	0.002	0.041
France	0.871	39.495	5.873	**0.145**	[0.043; 0.248]	0.007	**0.122**	0.002	0.015
Germany	0.761	37.812	3.558	**0.219**	[0.104; 0.335]	0.034	**0.142**	0.041	0.002
Italy	0.821	35.215	9.553	**0.095**	[0.002; 0.187]	0.000	0.062	0.008	0.025
Canada	0.748	17.242	2.184	**0.314**	[0.193; 0.435]	0.015	**0.209**	0.081	0.009
Japan	0.853	51.049	6.365	**0.136**	[0.031; 0.240]	0.011	**0.119**	0.000	0.012
M2									
U.S.	0.665	10.918	0.799	**0.556**	[0.452; 0.660]	**0.128**	**0.258**	0.000	**0.170**
U.K.	0.743	20.987	4.288	**0.189**	[0.057; 0.321]	0.003	**0.135**	0.004	0.013
France	0.877	25.122	4.463	**0.183**	[0.073; 0.293]	0.000	**0.112**	0.000	0.070
Germany	0.819	43.046	8.980	**0.100**	[0.011; 0.190]	0.009	0.001	0.023	0.067
Italy	0.850	55.847	10.135	**0.090**	[0.000; 0.180]	0.006	0.059	0.015	0.011
Canada	0.839	24.440	7.887	**0.113**	[0.019; 0.206]	0.001	0.004	0.007	**0.100**
Japan	0.787	21.012	2.581	**0.279**	[0.159; 0.399]	0.006	**0.245**	0.014	0.014
Trade Balance									
U.S.	0.858	28.889	3.842	**0.207**	[0.093; 0.320]	**0.174**	0.003	0.008	0.022
U.K.	0.768	29.006	4.373	**0.186**	[0.076; 0.297]	0.049	0.002	0.004	**0.130**
France	0.935	37.572	5.628	**0.151**	[0.047; 0.255]	0.096	0.046	0.008	0.000
Germany	0.916	76.160	27.234	0.035	[0.000; 0.093]	0.022	0.001	0.005	0.007
Italy	0.910	49.178	9.349	0.097	[0.008; 0.185]	0.057	0.008	0.001	0.031
Canada	0.923	58.799	15.444	0.061	[0.000; 0.134]	0.044	0.000	0.002	0.015
Japan	0.787	20.731	4.093	**0.196**	[0.084; 0.308]	0.043	0.063	0.011	0.079
Stock Market Price Index									
U.S.	0.484	6.996	0.562	**0.640**	[0.550; 0.731]	0.022	**0.265**	0.013	**0.340**
U.K.	0.555	8.662	0.700	**0.588**	[0.489; 0.688]	0.001	**0.340**	0.000	**0.247**
France	0.658	10.153	1.020	**0.495**	[0.383; 0.607]	0.040	**0.232**	0.000	**0.223**
Germany	0.574	10.162	1.047	**0.489**	[0.376; 0.601]	0.014	**0.155**	0.007	**0.313**
Italy	0.671	15.597	2.024	**0.331**	[0.209; 0.452]	0.062	0.091	0.012	**0.166**
Canada	0.529	11.637	0.894	**0.528**	[0.420; 0.636]	0.072	**0.156**	0.036	**0.264**
Japan	0.677	15.474	1.352	**0.425**	[0.307; 0.543]	0.076	**0.193**	0.007	**0.149**
REER									
U.S.	0.452	7.005	0.371	**0.730**	[0.657; 0.802]	**0.228**	0.015	**0.483**	0.004
U.K.	0.755	13.089	2.549	**0.282**	[0.162; 0.402]	0.019	0.000	0.027	0.236
France	0.766	17.916	4.443	**0.184**	[0.062; 0.305]	0.005	0.000	0.093	0.110
Germany	0.555	11.199	1.282	**0.438**	[0.309; 0.567]	0.000	0.000	0.300	**0.176**
Italy	0.836	47.557	21.546	0.044	[0.000; 0.144]	0.006	0.000	0.028	0.000
Canada	0.716	11.323	1.537	**0.394**	[0.274; 0.514]	0.097	0.012	0.001	**0.284**
Japan	0.716	15.758	2.773	**0.265**	[0.146; 0.384]	0.010	0.019	0.006	**0.230**
Exchange Rate with Dollar									
U.K.	0.587	8.131	0.829	**0.547**	[0.441; 0.652]	0.097	0.009	**0.391**	0.050
France	0.529	6.218	0.603	**0.624**	[0.530; 0.717]	0.025	0.012	**0.579**	0.008
Germany	0.600	6.687	0.606	**0.623**	[0.529; 0.716]	0.039	0.002	**0.561**	0.021
Italy	0.535	7.712	0.644	**0.608**	[0.512; 0.704]	0.022	0.021	**0.565**	0.001
Canada	0.594	10.633	1.030	**0.493**	[0.381; 0.605]	**0.139**	0.005	**0.130**	**0.218**
Japan	0.735	13.162	2.255	**0.307**	[0.186; 0.428]	0.000	0.047	**0.145**	**0.115**
Spread 3m / Overnight rate									
U.S.	0.697	10.918	1.154	**0.464**	[0.349; 0.579]	0.001	**0.400**	0.049	0.014
U.K.	0.855	29.481	4.606	**0.178**	[0.068; 0.289]	0.051	0.097	0.010	0.020
France	0.741	32.633	2.645	**0.274**	[0.134; 0.415]	**0.249**	0.009	0.021	0.014
Germany	0.761	25.370	2.959	**0.253**	[0.134; 0.371]	0.039	**0.171**	0.017	0.026
Italy	0.910	23.706	7.179	**0.122**	[0.026; 0.219]	0.006	**0.014**	0.082	0.020
Canada	0.858	67.328	6.101	**0.141**	[0.039; 0.242]	**0.135**	0.002	0.004	0.000
Japan	0.800	19.070	2.465	**0.289**	[0.168; 0.409]	0.034	**0.163**	0.008	0.083
Spread 10y / Overnight rate									
U.S.	0.748	12.714	1.164	**0.462**	[0.347; 0.577]	0.027	**0.328**	0.086	0.022
U.K.	0.868	44.622	14.521	0.064	[0.000; 0.140]	0.013	0.013	0.022	0.017
France	0.759	20.000	1.686	**0.372**	[0.230; 0.514]	0.053	**0.249**	0.030	0.002
Germany	0.800	17.998	2.487	**0.287**	[0.166; 0.407]	0.045	**0.240**	0.002	0.000
Italy	0.831	37.367	8.004	**0.111**	[0.000; 0.234]	0.013	0.009	0.037	0.048
Canada	0.839	21.683	4.482	**0.182**	[0.072; 0.292]	0.016	**0.123**	0.023	0.020
Japan	0.821	15.292	4.909	**0.169**	[0.023; 0.315]	0.003	**0.117**	0.017	0.001

Notes: This table reports the Bai and Ng (2006) statistics to evaluate the extent to which observed factors differ from latent factors. Bold numbers indicate an $R^2 > 0.100$.

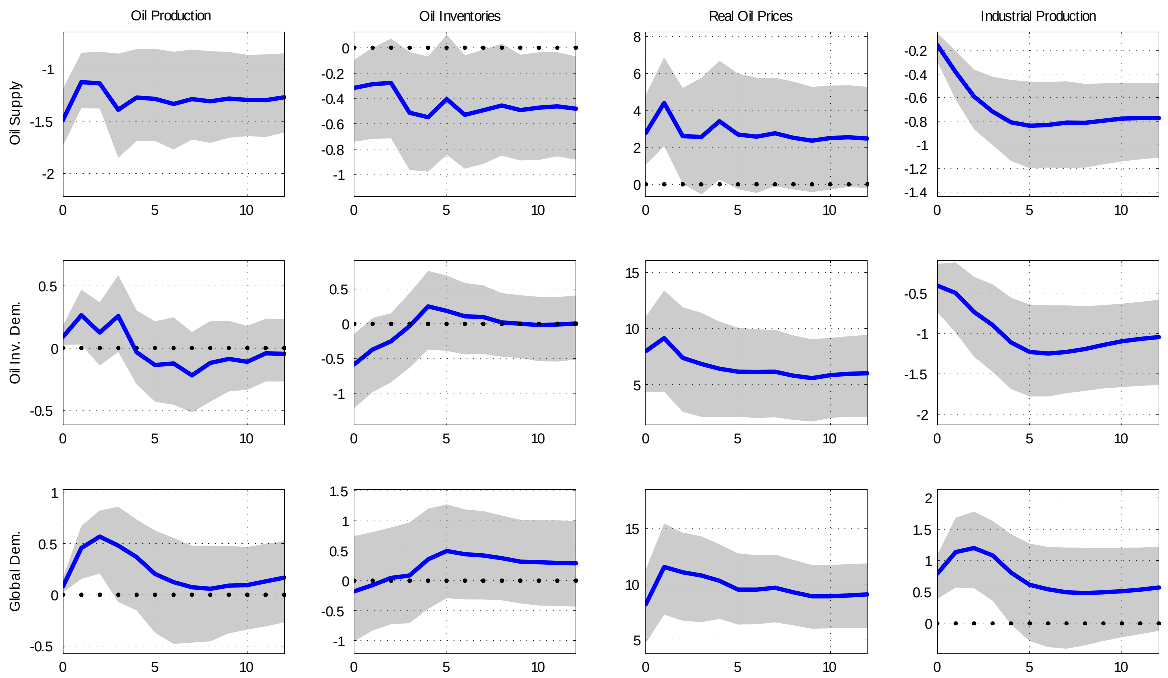
D Appendix: Impulse Responses VAR and FAVAR

Figure D1. Impulse Responses: VAR



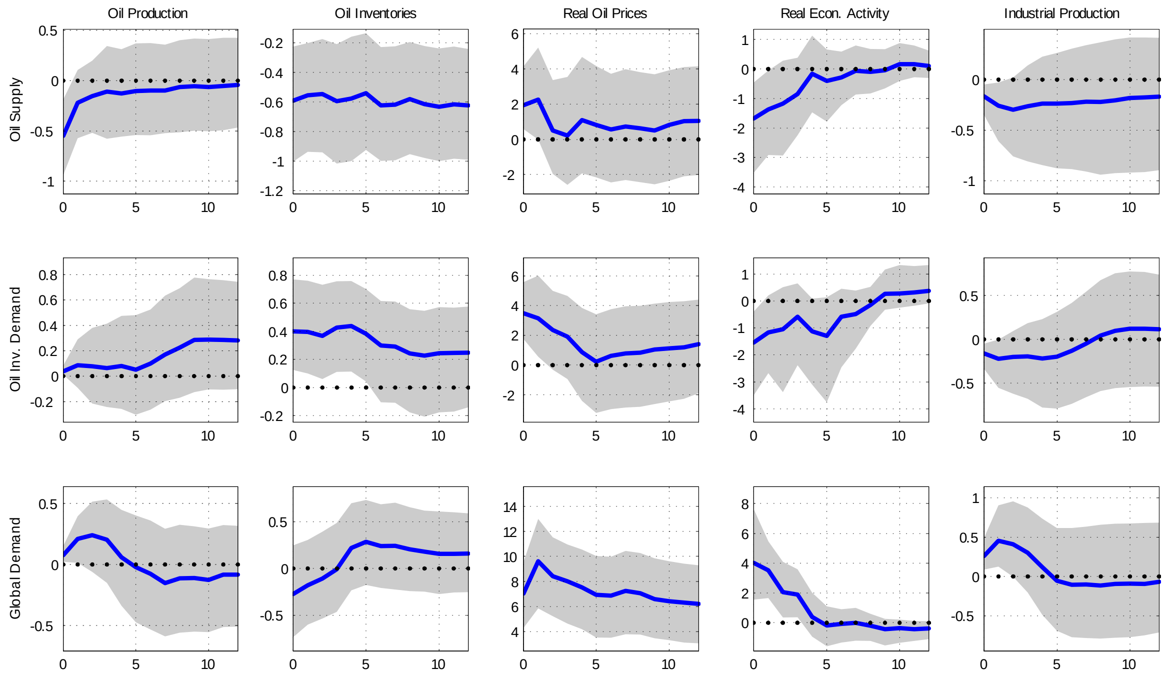
Notes: The figure shows the impulse responses to oil supply, oil inventory demand, and global demand shocks using a VAR with sign restrictions. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

Figure D2. Impulse Responses: VAR



Notes: The figure shows the impulse responses to oil supply, 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.

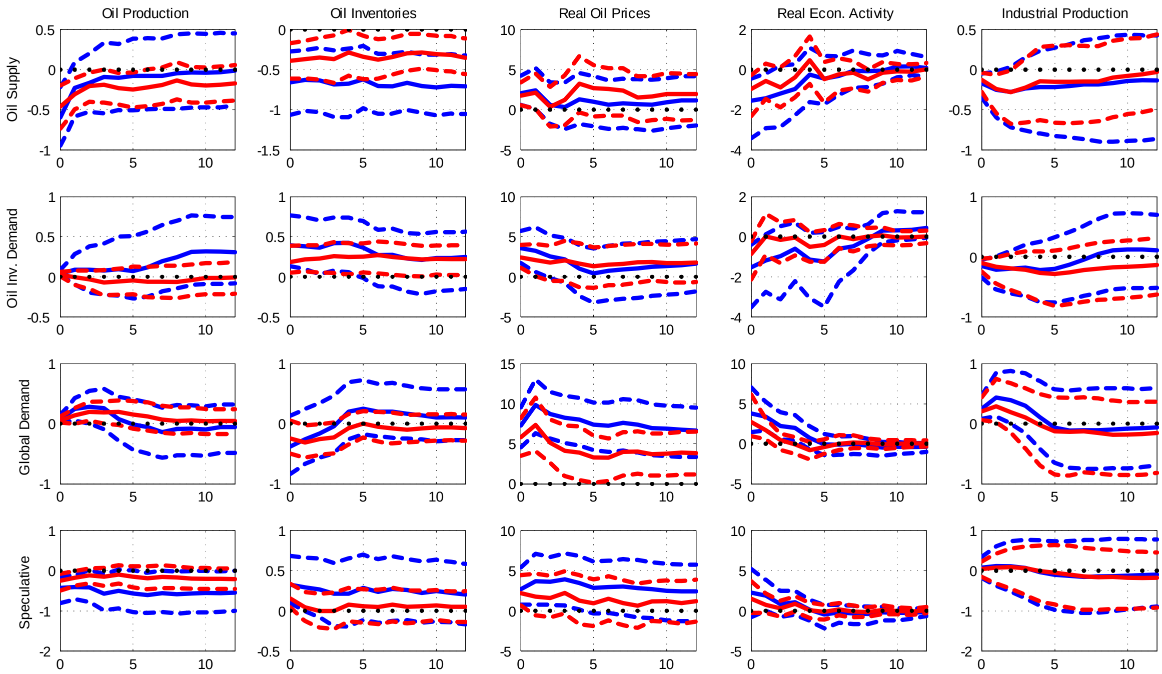
Figure D3. Impulse Responses: FAVAR



Notes: The figure shows the impulse responses to oil supply, oil inventory demand, and global 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.

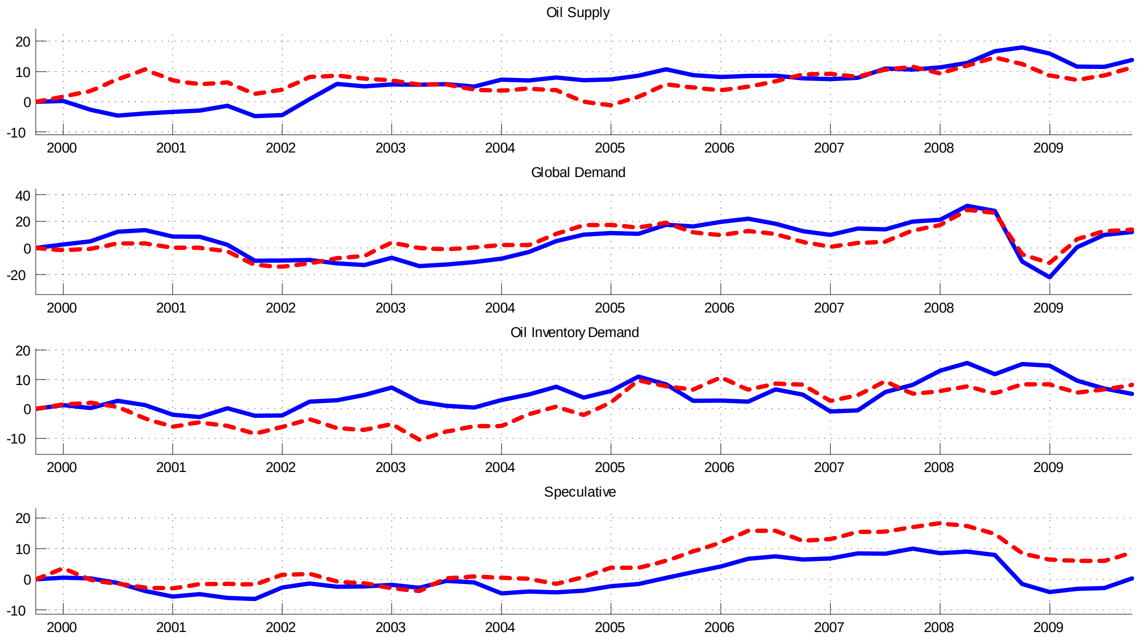
E Appendix: Subsample Analysis

Figure E1. Impulse Responses: Benchmark and Subsample



Notes: The figure compares the impulse responses to oil supply, oil inventory demand, and global demand shocks using the benchmark FAVAR with sign restrictions shown in Figure 2 (blue lines) and the FAVAR for a subsample starting in 1986 (red lines). The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstraped error bands.

Figure E2. Historical Decomposition of the Oil Price: Benchmark and Subsample



Notes: The figure compares the historical decomposition of the oil price for the benchmark FAVAR shown in Figure 5 (blue lines) and the FAVAR estimated for a subsample starting in 1986 (red lines).