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 role in driving this salient empirical pattern. We identify oil shocks from a large dataset using a factor-augmented vector autoregressive (FAVAR) model. This method is motivated by the fact that a small scale VAR is 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 mainly explained by global demand 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 recent oil price increase is mainly driven by the strength of global demand but that the financialization process of commodity markets also played a role.

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"[...] 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)[1]

1 Introduction

The long-standing debate regarding the sources of oil price fluctuations recently intensified due to the dramatic rise in oil prices. 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 demand factors. Since this contribution, an impressive list of empirical studies have investigated the effects of different types of oil shocks, agreeing with Kilian's (2009) conclusion.[2]

While this finding has gained strong support, the developments in the oil market in the past ten years have been so dramatic that they took many market participants by surprise. In fact, some of them have suggested that the recent run-up in oil prices *"(...) has not been driven by supply and demand."*[3] Tang and Xiong (2011) suggest that a speculative component may be behind the recent boom in commodity prices. 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. Evidence suggests that commodities have become a recognized asset class within the investment portfolios of financial institutions as a means to diversify risks such as inflation or equity market weakness (see Geman, 2005, and 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

[1] 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).

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

[3] This comes from a 2006 interview of Lord Browne, Group Chief Executive of British Petroleoum, as reported in "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). We note that this report also contains testimonies from other CEOs along the same lines.

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) note 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. To this end, we assess the role of supply, demand and speculative shocks as drivers of oil prices. Shocks are identified by imposing economically meaningful sign restrictions on the impulse responses of a subset of variables. Supply shocks, which have historically been the center of attention in the oil literature (see Hamilton, 1985, 2003; Kilian, 2008a, and b), refer to changes in the current physical availability of crude oil. Global demand shocks, which are the focus of recent research (see footnote 2), reflect an increase in demand for all industrial commodities triggered by the state of the global business cycle. Speculative shocks have attracted the attention of a new strand of the literature, fueled by the oil market developments of the past decade.

In our analysis we consider two types of speculative shocks. The first one, which we call oil inventory demand shock, is proposed by Kilian and Murphy (2011a) and refers to a shock to the demand for oil inventories driven by shifts in expectations not otherwise captured by the demand and supply shocks. Specifically, this shock represents a shift of the demand curve along an upward sloping supply curve as a consequence of an increase in inventory demand. The second one, named speculative shock, is inspired by Hamilton (2009a), where he conjectures an alternative channel through which speculation can affect the physical side of the market. In particular, he describes how speculators can affect the incentives faced by producers by purchasing a large number of futures contracts and signalling higher expected spot prices. Producers, revising their expectations for the price of oil for future delivery, 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 oil at higher future prices. As Hamilton (2009a) describes, we could think that oil market participants were misled by the speculative purchases of oil futures contracts into reducing current production in response. Although this last type of shock may not be directly linked to fundamentals, because it affects future spot prices it influences the current behavior of oil market participants, modifying the incentives to accumulate (above and below ground) inventories. In fact, this corresponds to a contemporaneous shift in the demand for above and below ground inventories.[4] Kilian and Murphy (2011a) refer to such shocks as speculative supply shocks.

Although the latter speculative shock is motivated by the recent trend of investment in commod-

[4]In the presence of higher expected prices, we should expect an increase in the demand for inventories, as well as a reduction of oil supply (i.e. increase in the demand for below ground inventories). See Appendix E for more details.

ity markets, the same response on the producer's side can arise in the absence of futures markets. This will happen 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 profit at a future date. Davidson et al. (1974) find evidence supporting the existence of speculative activity before futures markets were developed. The presence of futures markets may exacerbate the role of shocks to the expectation of future oil prices, but clearly the concept of speculation that we identify is a general one.

In terms of methodology, we re-examine the role of speculation relative to supply and demand forces as drivers of oil prices using a factor-augmented vector autoregressive (FAVAR) model. Our paper is the first application of this method in the context of the oil market. Bernanke et al. (2005) provide an extensive description of the advantages of the FAVAR approach. In particular, they 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 (see also Giannone et al., 2005). We provide evidence that a small-scale VAR for the oil market, typically used in the literature, is not informationally 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. Evidence suggests that some of these factors summarize complementary measures of economic activity and financial variables, such as the exchange rate and the stock market.

The use of a FAVAR allows us to investigate the transmission of oil shocks to a large number of variables. Therefore, we can analyze the conditional correlations between oil prices and the price of other commodities. It turns out that global demand shocks are the main drivers of the comovement among commodity prices, 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, even though it is smaller in magnitude than the correlation given by global demand shocks. This is consistent with the results of Tang and Xiong (2011) and suggests 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 supply and inventory demand shocks, implying that they 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 Singleton, 2011, and Tang and Xiong, 2011), as well as anecdotal evidence (see, e.g., Masters, 2008).[5] 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.

Our paper is also related to a strand of the literature that studies the effects of speculation on the oil spot price using data on traders' positions in the futures market (see, for example, Haigh et al. 2007, Büyüksahin et al. 2008, and Büyüksahin and Harris, 2011). These studies find mixed evidence on the role of financial activity in oil spot prices. Using a different methodology, Lombardi and Van Robays (2011) provide evidence that financial investors caused oil prices to diverge from the level justified by fundamentals. In contrast to this literature, our aim is to reconcile the argument of speculation with what happens on the physical side of the market. In this way, we offer a complementary approach. Overall, we find evidence consistent with the fact that the main determinant of oil price fluctuations is global demand. Therefore, our results provide additional support to the demand driven explanations of the recent developments in the oil market. Nevertheless, speculation shocks are also relevant, suggesting that speculative activities, by affecting the expectation formation of market participants can affect the incentives faced by operators in the oil market.

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

2.1 The Model

Since 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

[5] 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 increase in the non-commercial spread position in the last part of the sample is unprecedented.

Hansen and Sargent, 1991, Lippi and Reichlin, 1993, 1994, and Fernandez-Villaverde et al., 2007). However, additional information available in other economic series excluded from the VAR may be relevant to the dynamic relation implied in the VAR model. 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 from a wider set of variables (see Forni et al., 2009). 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. For example, we can look at the comovement between oil prices and the price of other commodities.

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:

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

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 weakly 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, 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. In fact, low-dimensional VARs typically used to analyze the oil market include some proxy for global demand. However, any observable measure of this general concept is likely to be contaminated by measurement errors.[6]

The common component is a linear combination of a relatively small number of r (static) factors and is generally responsible for the bulk of the comovement between the variables in the dataset.[7] For example, in our case, they could reflect movements in global economic activity.

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 to be a single observable factor. We complement the existing empirical evidence by allowing the stochastic dimension of the large dataset of macroeconomic and financial 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.[8] The specification (2) highlights that the low-dimensional VARs will not be able to identify the structural shocks whenever they fail to incorporate all the relevant information embodied in the factors. This condition can be easily verified by looking at a Granger causality test of the low-dimensional VAR with respect to the information summarized by the factors (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.[9] This

[6] As Bernanke et al. (2005) describe, the concept of "economic activity" may not be accurately represented by an observable measure. A similar argument is also made in Giannone et al. (2005).

[7] 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).

[8] 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).

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

implies that the identified shocks need not be global shocks but does not rule out the possibility.[10] We pursue this approach due to contrasting evidence on the impact of oil shocks on the global business cycle. Some evidence suggests that oil shocks are global. For example, the seminal papers of Hamilton (1983, 1985) show that oil prices have been among the key driving forces behind most U.S. recessions. By contrast, Kilian (2008a,b) suggest that oil supply shocks played a minor role in the evolution of the US and other G7 economies since the 1970s, although they mattered for some historical episodes.

2.2 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 FAVAR model.[11] 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.[12]

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 $\mathbf{Q}'\mathbf{Q} = \mathbf{I}$. The structural shocks can be recovered as $\boldsymbol{\eta}_t = \mathbf{Q}\mathbf{u}_t$. The orthonormal matrices $\mathbf{Q}$ are found from the eigenvalue decomposition of a random $q \times q$ matrix (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

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

where the moving average representation of the ith variable in the dataset can be written as

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

[10] 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.

[11] 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.

[12] 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.

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 for estimation uncertainty, we adopt a non-overlapping block bootstrap technique. We partition the $T \times (N+3)$ matrix of data $\mathbf{Z} = [y_{it}\ x_{it}]\ \forall i, t$ into S sub-matrices $\mathbf{Z}_s$ (blocks), $s = 1, ..., S$, of dimension $\tau \times (N+3)$, where τ is an integer part of T/S. In the empirical Section we set $\tau = 20$ (equivalent to five year blocks). 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 $\mathbf{Z}^* = \left[\mathbf{Z}'_{h_1}, ..., \mathbf{Z}'_{h_S}\right]'$ of dimension $\tau S \times (N+3)$ and the corresponding impulse responses are estimated.

3 Empirical Analysis

3.1 Data

The estimation period runs from the second quarter of 1972 to the end of 2009. The dataset consists of 151 series which includes macroeconomic and financial variables of the G7 countries as well as oil market data, measures of global economic activity and a rich set of commodity prices. Appendix A provides a complete description of the data and sources. The panel is unbalanced and therefore the extraction of the factors makes use of the EM algorithm as discussed in Stock and Watson (2002b).

The set of macroeconomic and financial variables includes output, prices, labor market indicators, trade, interest rates, stock market price indices and exchange rates and is sourced from the 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 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.[13] The price of other commodities is from the IFS and considered in real terms after being deflated by the U.S. CPI. Two proxies of global economic activity are also included in the dataset. 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 as proposed by Kilian (2009).[14]

[13] Petroleum stocks sourced from the EIA include crude oil (including strategic reserves) as well as unfinished oils, natural gas plant liquids, and refined products. Following Kilian and Murphy (2011a) we treat the OECD data as a proxy for global petroleum inventories given that the EIA does not report data for non-OECD economies. Since consistent series for OECD petroleum stocks are not available not available prior to 1987.4, we follow Kilian and Murphy (2011a) and extrapolate the percent change in OECD inventories backwards at the rate of growth of U.S. petroleum inventories.

[14] This measure is available from Lutz Kilian's website at monthly frequency. We use the last month of each quarter

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 a 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 informationally sufficient to identify the shocks. The method uses the Gelper and Croux (2007) multivariate extension of the out-of-sample Granger causality test. 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 principal components Granger-cause the variables of the VAR. If the null of no Granger causality is not rejected for any of the successive combinations of principal components, 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 proceed by augmenting the VAR with an additional factor and repeat the process until the alternative hypothesis is always rejected for any number of the remaining factors up to the specified maximum number of factors.

Table 1 reports the (bootstrapped) p-values of the Granger causality test for the VAR and VAR augmented with the factors. Two measures of global economic activity have been used in the literature. Therefore, we consider 2 variants of a 4-variable VAR, which include oil production, oil inventories, real oil price, and real economic activity. The first VAR (Panel A) measures real economic activity by an index of aggregate industrial production (as in e.g., Baumeister and Peersman, 2011). The second VAR (Panel B) includes a measure of global real economic activity based on dry cargo freight rates as proposed by Kilian (2009) and used in Kilian and Murphy (2011a). The first column of each panel presents the p-value for the null that the first six 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 until we fail to reject the null. For both specifications we are not able to reject the informational sufficiency of the FAVAR once 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

to obtain the quarterly index.

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 observable economic variables span the same information of the unobserved factors. Bai and Ng (2006) propose a test of this hypothesis based on the t-statistic

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

where $\widehat{z}_{jt} (= \widehat{\boldsymbol{\delta}}_j \widehat{\mathbf{f}}_t)$ is the least square projection of the variable z_{jt} on the estimated latent factors and the associate variance is constructed as detailed in Bai and Ng (2006). Two statistics can be used to test the null hypothesis that the observable variable can be considered an exact factor (i.e. $\widehat{z}_{jt}$ 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, and $M(j)$ is the maximum deviation of the statistic from zero. 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 factors 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 statistical measures of how good z_{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

$$NS(j) = \frac{\widehat{var}\left(z_{jt} - \widehat{z}_{jt}\right)}{\widehat{var}\left(\widehat{z}_{jt}\right)} \tag{4}$$

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

[15] Appendix B shows the impulse responses for different numbers of factors. Substantial differences exist with respect to the version with no factors (or only one factor). For example, movements in oil production in the FAVAR with more than one factor are transitory, whereas they remain persistent in the VAR and FAVAR with one factor. Similarly, the effects on oil prices seem to be smaller in the FAVAR with more than one factor. As a result, the response of real activity is also smaller, and tends to revert now to zero. In addition to these quantitative differences, it is important to note that the results of the information sufficiency test suggest that the differences across models are statistically significant. We also note that the results are unchanged when we include an additional factor specific to commodity prices.

If z_{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 z_{jt} from the latent factors. Similarly, the $R^2(j)$ would be unity if z_{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 proxy 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.[16] 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 a measure of aggregate demand, loading primarily on US real personal consumption. In addition, this factor also loads on some leading indicators, such as interest rate spreads, corroborating the conjecture by Kilian (2009) that this proxy of real economic activity is more forward looking than other direct measures of the global business cycle. [17]

[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). This is in line

[16] Looking at the fit of each economic variable in the dataset can help us to gauge the validity of our empirical strategy. We would expect some variables not to display a significant fit with the factors. For example, the price of iron ore, which was regulated until recently, loads weakly on the factors. By contrast, other variables which are particularly sensitive to global demand forces, such as copper prices, display a striking fit.

[17] 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 is that this measure of real economic activity is calculated from dry cargo bulk freight rates. The developments in the shipping industry in the past decade might have significantly affected this measure. It is worth mentioning that freight rates have become a relevant tradable 'commodity' for specialized financial institutions (see Geman, 2005). In fact, in the past decade their volatility has increased tremendously: They are now twice as volatile as commodity prices and four times as volatile as stock prices (see Alizadeh and Nomikos, 2011).

with Kilian and Park (2009) who analyze the interaction between oil shocks and the stock market, as well as the argument that fluctuations in the dollar can play a role in the determination of oil prices (see, for example, Frankel, 2008, and Akram, 2009).The results of the test of sufficient information in section 3.2 suggest that these forces are relevant for a correct identification of the oil shocks.

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, summarized in Table 3, builds on those of Baumeister and Peersman (2011) and Kilian and Murphy (2011a, b). 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. 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).

[**Table 3 about here**]

An oil inventory demand shock is "a shock to the demand of above ground oil inventories arising from forward looking behavior" (Kilian and Murphy, 2011a, page 7). Kilian and Murphy (2011a) refer to this shock as "speculative demand shock." We use a different name to distinguish it from the alternative speculative shock analyzed in the next section. An oil inventory demand shock arises from the possibility of a sudden shortage in future production or expectations of higher demand in the future. A similar 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 increase in the real price of oil provides an incentive for oil producers to increase production. In addition, 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 Kilian and Hicks, 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 follow Kilian and Murphy (2011b) and impose an upper bound of 0.0257 for the response of the impact elasticity of oil supply with respect to the real price jointly after both demand shocks. Annex 1 presents the results for different elasticity bounds.

3.5 VAR and FAVAR

In this subsection we estimate a VAR and a FAVAR with three shocks and compare their results.[18] Note that in the case of the FAVAR we impose sign restrictions on both measures of real economic activity given that the two of them have been used in the literature. The impulse responses obtained from the FAVAR and the VAR yield differences in terms of the magnitude and shape of the responses (see Appendix D). Table 4 presents the forecast error variance decomposition of the oil price to the three shocks using the VARs (with the two measures of economic activity) and the FAVAR. The variance decomposition in both VARs is dominated by global demand shocks at all horizons. The oil inventory demand shock also plays a significant role, accounting for about 10% to 30% of oil price fluctuations in the VARs. The sum of the three shocks accounts for around 85% of the oil price variation in both VARs, whereas in the FAVAR the three shocks explain only around 55% of oil price fluctuations. In particular, the share of oil price fluctuations explained by demand forces decreases significantly, whereas the share driven by supply shocks remains largely robust. Global demand shocks still account for the largest proportion of oil price fluctuations, although the share is smaller compared to the VAR. The oil inventory demand shock is the one most significantly affected, as it now explains between 4% to 13% of the variation in oil prices.

[**Table 4 about here**]

The most important result from this comparison is the decrease in the role of demand forces to explain oil price fluctuations. These quantitative differences are relevant given that since Kilian (2009) most of the recent literature points at demand forces as drivers of the oil price. The variance decomposition of the FAVAR contains a large unexplained component. We conjecture that part of this is due to speculation in the oil market. The next section addresses the identification of this component.

3.6 Orthogonality

Despite the rejection of the informational sufficiency of the VAR, some shocks can still be correctly identified from the low-dimensional VAR. This is true whenever the identified structural shocks

[18] The estimated VAR is not directly comparable with Kilian and Murphy (2011a). In particular, the authors use monthly data, a different stationarity transformation of the data, and impose additional restrictions. Our objective is not to make a direct comparison of our results to theirs but to illustrate the potential implications of expanding the VAR information set with factors.

from the VAR are orthogonal to any available information at time t (for example, lagged values of the factors). Otherwise, the identified shock cannot be considered structural (Forni and Gambetti, 2011).

The identification by sign restrictions does not identify a single model. Therefore, we investigate the orthogonality of the shocks over all sets of identified impulse responses. Table 5 shows the percentage of rejections of the F-test of orthogonality for each of the shocks identified from the VAR with sign restrictions.[19] Specifically, for each possible set of shocks we first test whether they are Granger-caused by lagged factors. We then report the number of rejected shocks (at the 10% level) over the total identified shocks. The results in the first row of the table imply that the first factor Granger-causes none or a very limited fraction of the shocks (see Section 3.3).[20] This result is consistent with the view that the first factor reflects the business cycle and, consequently, is captured by aggregate industrial production. The last row of Table 3 suggests that a linear combination of 4 factors Granger-causes less than 1% of all the identified oil supply shocks, 58% of all the identified global demand shocks, and about 86% of all the identified oil inventory demand shocks. These results underline the results from the previous section. The demand shocks identified from a small dimensional VAR are not orthogonal to the information of lagged factors and as a consequence their influence can be overstated. Overall, these results highlight the importance of augmenting the low-dimension VAR with the set of factors.

[Table 5 about here]

4 Augmented Model

In this section we extend the FAVAR model with three identified shocks as previously analyzed to include speculation shocks. In this section we discuss the identifying restrictions to pin down the speculative shock.

4.1 Identification of speculation shock

Hamilton (2009a) discusses how the "financialization" of the oil market may play a role in the determination of oil prices (along the lines of Masters, 2008). In particular, he explains how the role of speculative activities can be reconciled with what happens in the physical side of the

[19] We do the test only for the VAR with aggregate industrial production as the analysis in Section 3.3. suggests this as the preferred measure.

[20] 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.

oil market. In this spirit, Kilian and Murphy (2011a) identify a speculative shock in which oil inventories increase, oil prices go up and oil production increases. Essentially, this is a shift of the demand of inventories along an upward sloping supply curve. Appendix E presents a simple model that justifies these restrictions. However, Hamilton (2009a) also conjectures the possibility that financial speculation, by affecting the expected future spot prices ($E_t P_{t+1}$), can change the incentives faced by producers, and therefore have an impact on the supply side of the market.

Following Frankel and Rose (2010), among others, speculation can be defined as the purchase of commodities (either in physical form or financial contracts) in anticipation of a financial gain at the time of the resale. For example, a typical investment strategy for commodity traders consists of taking a long-position in a futures contract at price F_t, selling it before it expires at the higher price P_{t+1} and using the proceeds to take a long position in another futures contract. If the expectations are such that the expected future spot price $E_t P_{t+1}$ is higher than the futures price F_t ($E_t P_{t+1} > F_t$), more investment funds will take long positions in futures contracts. As the number of buys of futures contracts exceeds the number of sells of expiring ones, futures prices go up and with them the expected spot price.[21] In the physical side of the market, as producers expect a higher price of oil for future delivery ($E_t P_{t+1}$), 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, oil producers will not accommodate the upward trend in oil prices but rather decrease production (see also Jovanovich, 2007). As Hamilton (2009a) describes, we could think that oil-producing countries were misled by the speculative purchases of oil futures contracts into reducing current production.[22]

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, speculative shocks lead to inventory accumulation not because of a fear of production shortage (which would generate a need for 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 (below ground) inventory holding, causes the current spot oil price to rise. The same types of incentives can lead to an increase in the storage

[21] Ignoring the effect of risk premia, arbitrage would be such that $E_t\left(P_{t+1}\right) = \left(1 + r_t\right) F_t$. In this discussion we are implicitly holding the real interest rate fixed.

[22] The equilibrium in the physical side of the market implies that inventories accumulate whenever production (Q_t) exceeds current consumption (X_t), i.e. $I_{t+1} - I_t = Q_t - X_t$. Therefore, when imposing our sign restriction for the speculation shock we are implicitly assuming that the price elasticity of production is smaller than the price elasticity of consumption; i.e the shift in supply is large enough to conteract the effect of the shift in demand. See Appendix E for more details.

of above ground inventories.[23] A summary of the sign restrictions used to identify the speculative component of the oil market is presented in the last row of Table 3. The intuition behind these restrictions can be found in a simple model presented in Appendix E.

This set of sign restrictions is also consistent with Bernanke (2004), who describes how speculation may drive oil prices up. He emphasizes that:

"(...) speculative traders who expect oil to be in increasingly short supply and oil prices to rise in the future can back their hunches with their money by purchasing oil futures contracts on the commodity exchange. Oil futures contracts represent claims to oil to be delivered at a specified price and at a specified date and location in the future. If the price of oil rises as the traders expect–more precisely, if the future oil price rises above the price specified in the contract–they will be able to re-sell their claims to oil at a profit.

If many speculators share the view that oil shortages will worsen and prices will rise, 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.[24] This reduction in the amount of oil available for current use will in turn cause today's price of oil to rise, an increase that can be interpreted as the speculative premium in the oil price."

We do not impose a sign restriction on the response of real economic activity as there are two forces that operate in opposite directions. The oil price increase would have a contractionary effect on demand. We are not comfortable imposing such a restriction in this case, because we do not want to rule out the possibility that increase of financial speculation is triggered by low real interest rates as suggested by Frankel (1986 and 2008). As he explains, low interest rates may have a number of effects on commodity markets. On the financial side, lower real rates reduce the cost of "carry trade" in the commodity markets, amplifying the effect of a mismatch between expected

[23] Let us illustrate with a simple example. Assume the existence of a NYMEX futures contract that consists of delivering 1,000 barrels of light sweet crude oil in one month to a buyer at Cushing, Oklahoma. The link between futures price and the cash price at Cushing can be described as follows. A producer of crude oil is offered $80 per barrel for 1,000 barrels of oil today. The same producer sees that the futures contract for delivery next month is trading at $85 dollars. Instead of selling at $80 to the refiner today, the producer could sell a futures contract for delivery next month at $85, store the 1,000 barrels for a month and be $5000 better off less the cost of a month storage. The refiner needing the 1,000 barrels of crude today is then in the position that he must offer the producer something closer to the $85 NYMEX price to obtain the crude oil. This implies that producers themselves may end up holding a higher level of above ground inventories. Notice that if the refiners also share the expectations of higher future prices, they would want to increase their holding of inventories too. This allows them to cover for expected higher prices of the input and to increase their future share of revenues. We implicitly assume that the market is not completely vertically integrated. If it was, we would not observe a change in above ground inventories.

[24] Inventories in this case stand for below ground inventories. However, as explained above, we expect that above ground inventories also increase, unless the market is perfectly vertically integrated.

future spot prices and futures prices. In the physical side of the market, real rates represent the opportunity cost of holding inventories both above and below ground. This channel is consistent with our identifying restrictions and would imply a positive effect on real activity (see Frankel and Rose, 2010).

The perspective on speculation that we describe in this Section is referred to as speculation by oil producers in Kilian and Murphy (2011a). In fact, this is one of the components of their supply shock, which we can disentangle from the standard supply shock only by imposing the additional negative restriction on oil inventories following an oil supply shock. Specifically, this restriction imposes a production-smoothing rationale for holding inventories in the presence of supply shocks. Kilian and Murphy (2011a) report evidence supporting this type of inventory behavior, so this restriction seems reasonable.[25]

4.1.1 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 markets. 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 how 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 foster the role of expectations of futures prices (through price discovery) 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.[26]

[25] Note that the sign restrictions imposed to identify the speculative shock could be consistent with a supply disruption in which consumers expect the disruption to get worst and therefore inventory accumulation increases. This would be consistent with a deliberate decision by oil producers to reduce current oil production (see, e.g., Hamilton, 2009b, p.188). However, this type of "oil supply" shock would manifest in a persistent upward trend in the oil price. This is at odds with the results that we will present in Section 5.4.

[26] 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.

5 Empirical Results from Augmented Model

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 decompositions to evaluate how much of the variation in oil market variables is accounted for by each of the shocks, and further examine the cumulative effect of the sequence of historical shocks on the historical path of the real 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, the real price of oil, real economic activity, and industrial production to oil supply, oil inventory demand, global demand, and speculative shocks.[27] 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. The initial increase is reversed within five quarters. Inventories exhibit a persistent increase as in Kilian and Murphy (2011a) and oil production increases. The effects on aggregate industrial production and real economic activity are negative and small.

A positive global demand shock is associated with a large increase in aggregate industrial production and real economic activity. As a consequence of high-demand pressures triggered by rapid growth, real oil prices exhibit a large persistent increase with a peak after two quarters and a very gradual decline. Oil production also rises, but only temporarily, and oil inventories decline to satisfy the higher demand.

[27] Inoue and Kilian (2011) criticize the use of median impulse responses. We note that the results using the mean impulse responses are almost identical. In addition, quantitatively similar results are found picking impulse responses using the Fry and Pagan (2011) "median solution".

A positive speculative shock is associated with a persistent increase in oil prices. Oil production exhibits a significant decline because producers hold oil back from the market in anticipation of higher prices in the future. The effects on real economic activity and industrial production are positive, small and temporary.

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 on 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. Barberis and Schleifer (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 aluminium 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 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.

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

Figure 3 shows the correlation of the real price of oil with four portfolios of commodity indexes, calculated as an equal-weighted real price index for each commodity sector, as well as an aggregate of all of them (Annex 2 presents the cross-sectional average pairwise correlation of all commodity prices in response to the shocks identified).[28] 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 even though this correlation is smaller than the one given by the global demand shock. By contrast, 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. This result shows that the type of speculative shock that we are capturing seems to be more in line with the type of behavior that would result from the financialization of commodity markets. Pindyck and Rotemberg (1990) were the first to emphasize that comovement in commodity markets can be related to the behavior of speculators who are long in several commodities at the same time. This is becoming the focus of study of a growing literature in finance (see Singleton, 2011 and Tang and Xiong, 2011). We note, however, that the correlation in the case of the speculative shock is smaller than for the global demand shock. This finding is in line with Tang and Xiong (2011). Third, there is not a large heterogeneity in the correlations between oil and each commodity sector.

[Figure 3 about here]

These results should be interpreted with care since they are an average result. The pattern of comovement among commodities changes across time. Our results imply that comovement will be stronger in periods in which global demand and/or speculation play a key role.

[28] The four porfolios are: Industrial metals, softs, grains, and precious metals. Industrial metals include copper, aluminium, nickel, iron ore, and zinc. The soft sector is composed of cotton, tobacco, sugar, coffee, and cacao. Grains are sunflower oil, palm oil, soybeans, wheat, rice and maize. Finally, precious metals include gold and silver. See Geman (2005) for a description of these commodity sectors and distribution of the global supply and demand of each of the commodities.

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 4. 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 9% of the variation in oil prices at all horizons.

[**Table 6 about here**]

Our results confirm Kilian's (2009) conclusion that global demand shocks are the main drivers of oil price fluctuations. 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 12% of inventory fluctuations. The global demand shock contributes up to 16% 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 perceived 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. The large effect of speculative shocks on oil production can be attributed to the fact that the speculative shock resembles a “managed supply” shock in the presence of higher expected prices. By contrast, the supply shock is a disruption, and therefore, it is large on impact but it slowly reverts. The fact that the speculative shock accounts for a larger share of the variance decomposition of oil production than oil inventory demand emphasizes that the channel of adjustment through below ground inventories is playing an important role. This is not surprising given that below ground inventories are generally less costly than above ground inventories.

[**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 4 presents the results.

[**Figure 4 about here**]

Figure 4 shows that global demand, and therefore real forces, were the main drivers of oil price increases. We also observe that speculation was responsible for a large proportion of the oil price increase between 2004 and 2007. 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 is that the contribution of speculative shocks to oil price increases becomes flatter from 2007 until 2008. This highlights that the gains from speculation decrease as the oil price goes up.[29]

[29] Let us illustrate this claim with a simple example that 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

We note that the period in which speculation plays a key role in oil price fluctuations (2004-2007) coincides with contango in the futures market (as documented, for example, in Singleton 2011). During this period the term structure of oil future contracts has a positive slope, suggesting that prices are expected to be higher. Hamilton (2009b) analyzes the contango and backwardation periods in the oil market and illustrates that in 2008 speculation did not play a role in the oil price increase. Our results are in line with his analysis given that the contribution of speculative shocks to oil fluctuations becomes flat in 2008, coincidentally in the period in which the market enters backwardation.

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.

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.

The historical decomposition also helps to explain the developments in the physical side of the oil market in the last decade. For example, Hamilton (2009b) observes that the growing demand of the past ten years was linked to a stagnant supply. Our model suggests that the reason for more stable oil production can be found in rising expectations of future spot prices, which undermined the incentives of producers to accommodate demand.

Some observers of the oil market have tended to disregard the idea that speculation played an important role in the last decade by pointing out that the level of inventories did not rise over this period (see Irwin and Sanders, 2010). With respect to this, we underline that, in the absence of any speculative reason for raising inventories, the strong increase in global demand over the past decade (coupled with stagnant supply) would have implied a reduction in the level of stocks. Again, we reconcile this pattern with global demand driving inventories down but speculation leading to an increase in storage. Therefore, our model offers a consistent explanation of the developments in the physical side of the market.

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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.

5.5 Robustness

The oil market has witnessed substantial changes over the sample period. Baumeister and Peersman (2010) 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 because we want to understand the role of speculation in driving oil prices, and the interaction between traders and producers that we describe accords better with a subperiod in which investment in futures markets 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 pre-1973 levels, and it also captures the great moderation and the development in futures markets. Peersman and VanRobays (2010) chose a comparable sample split.

Appendix F 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 while the impact of the other shocks is almost identical. The fact that the speculative shock exerts a larger influence in the 1986 subsample suggests that, if anything, we might be understating the importance of speculation over the last decade.

6 Conclusion

The increase in oil prices in 2004 coincided with a large flow of investment into commodity markets and an increased price comovement between different commodities. One of the objectives of this paper is to analyze 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 informationally sufficient to identify the shocks. Therefore, we use a set of factors to summarize the bulk of aggregate fluctuations in our data. The first two factors capture complementary measures of real activity, and the remaining two are associated with financial variables. The inclusion of a large information set matters. The

FAVAR model proposed in this paper implies a smaller role for global demand shocks in explaining fluctuations in the real price of oil than VAR estimates.

Consistent with previous studies, we find that oil prices have been historically driven by the strength of global demand. However, speculation contributed to the oil price increase between 2004 and 2008. Our analysis pins down the start of speculative forces driving oil prices to 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. 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.

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. The correlation between oil prices and the prices of other commodities is negative for the other shocks; this implies that it is unlikely that they are responsible for the comovement in commodity prices.

Our results highlight a major challenge faced by policymakers in the medium to long-run: Although speculation played a significant role, the high oil prices witnessed in the past decade are mainly due to demand pressures, which are likely to resurge with the recovery of the world economy.

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Table 1. Test for Sufficient Information

Panel A. 4 variable-VAR with aggregate industrial production

	VAR	VAR+1F	VAR+2F	VAR+3F	VAR+4F
1F	0.0233	—	—	—	—
2F	0.0100	0.1133	—	—	—
3F	0.0033	0.2333	0.4433	—	—
4F	0.0067	0.0167	0.0233	0.0000	—
5F	0.0200	0.0200	0.0033	0.0000	0.1433
6F	0.0300	0.0167	0.0000	0.0000	0.1200

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

	VAR	VAR+1F	VAR+2F	VAR+3F	VAR+4F
1F	0.0400	—	—	—	—
2F	0.0033	0.0133	—	—	—
3F	0.0033	0.0033	0.0733	—	—
4F	0.0000	0.0000	0.0000	0.0067	—
5F	0.0000	0.0000	0.0200	0.0133	0.1333
6F	0.0033	0.0300	0.1600	0.0100	0.3500

Notes: Bootstrapped p-values of the Granger causality test for the VAR and VAR augmented with factors. Based on the Gelper and Croux (2007) multivariate extension of the out-of-sample Granger-causality test. Corresponds to one-step-ahead forecasting and the forecasting evaluation period includes the last 15 years.

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 $|\tau_t(j)|$ exceeds the 5% asymptotic critical value. $M(j)$ is the maximum deviation of the statistic from zero (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[a]
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.

[a] Sign restrictions for real activity are imposed jointly on aggregate industrial production and the Kilian measure of economic activity.

Table 4. Variance Decomposition of the Real Oil Price

Horizon		Oil supply	Oil inventory demand	Global demand
1	VAR (KM)	0.0865	0.2850	0.5415
	VAR (AIP)	0.1171	0.2937	0.4758
	FAVAR	0.0609	0.1254	0.3769
2	VAR (KM)	0.0732	0.1997	0.6259
	VAR (AIP)	0.1162	0.2379	0.5212
	FAVAR	0.0443	0.0712	0.4242
3	VAR (KM)	0.0351	0.1623	0.6920
	VAR (AIP)	0.0784	0.2528	0.5439
	FAVAR	0.0297	0.0469	0.4461
4	VAR (KM)	0.0280	0.1361	0.7128
	VAR (AIP)	0.0655	0.2805	0.5327
	FAVAR	0.0272	0.0384	0.4449
8	VAR (KM)	0.0306	0.0687	0.7766
	VAR (AIP)	0.0868	0.1846	0.5993
	FAVAR	0.0573	0.0467	0.3834
12	VAR (KM)	0.0307	0.0837	0.7613
	VAR (AIP)	0.0879	0.2019	0.5814
	FAVAR	0.0951	0.0696	0.3372

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

Table 5. Orthogonality Test

# of factors	Oil supply	Oil inventory demand	Global demand
1	0.0000	0.0180	0.0020
2	0.3470	0.1710	0.4440
3	0.3590	0.3870	0.2240
4	0.0010	0.8600	0.5860

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

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

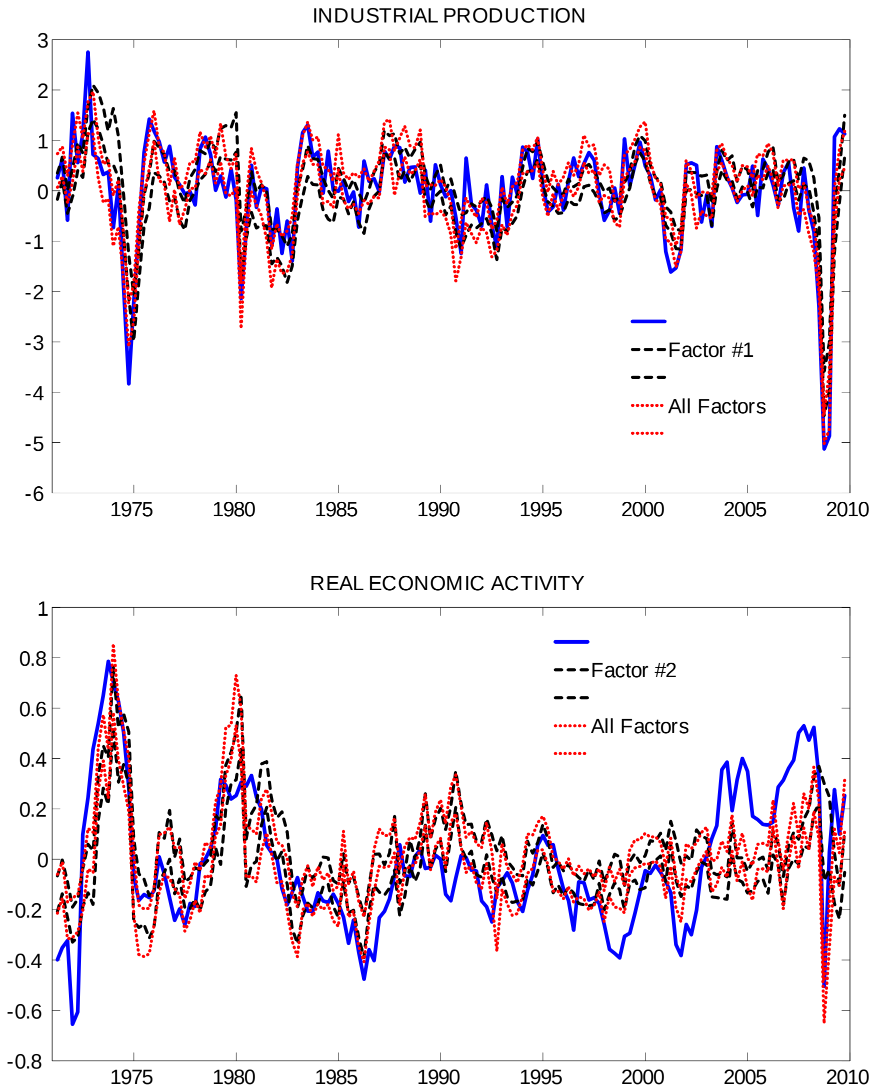
Table 7. Variance Decomposition of Inventories (FAVAR)

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)

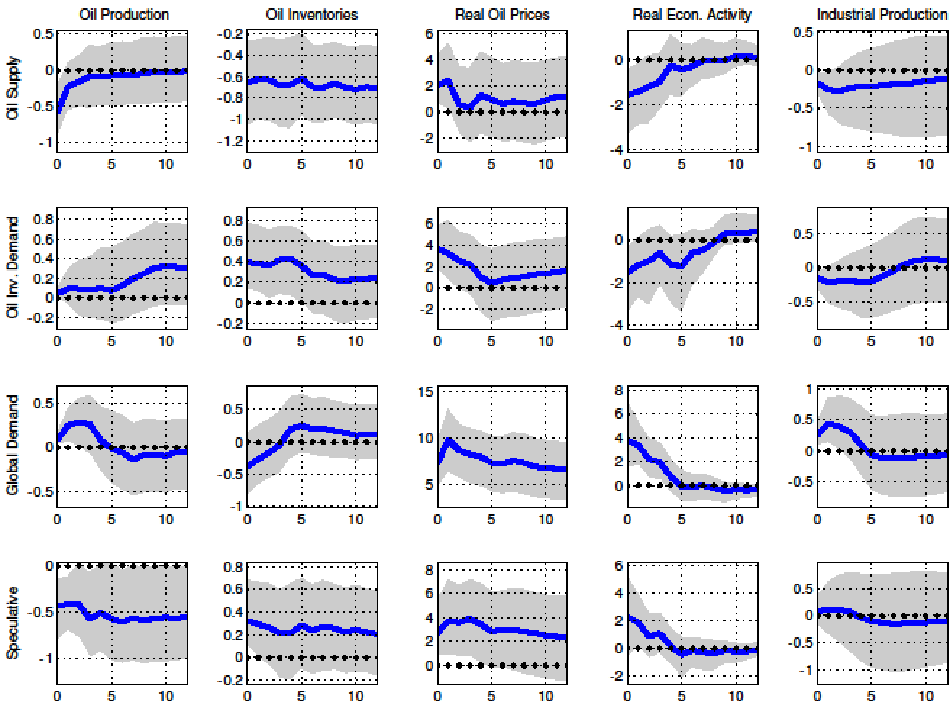
Horizon	Oil Supply	Oil inventory demand	Aggregate demand	Speculative
1	0.3500	0.0023	0.0064	0.1885
2	0.1913	0.0294	0.0914	0.2009
3	0.1273	0.0467	0.1153	0.2112
4	0.1200	0.0400	0.0929	0.2487
8	0.0834	0.1360	0.0924	0.2367
12	0.0956	0.1635	0.0741	0.2169

Figure 1. Factor Fit for Measures of Real Economic Activity



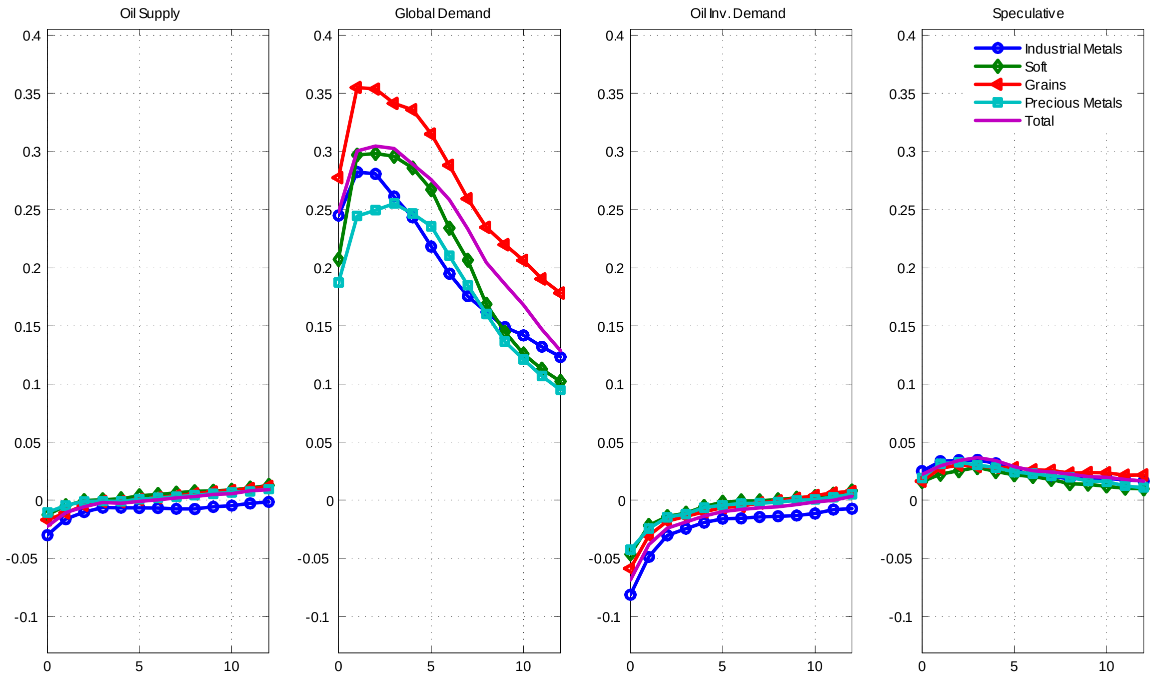
Notes: The figure shows each measure of economic activity together with the projection of the variable on the factor with the highest explanatory power and the projection of the variable on all four latent factors.

Figure 2. Impulse Responses: Main Variables



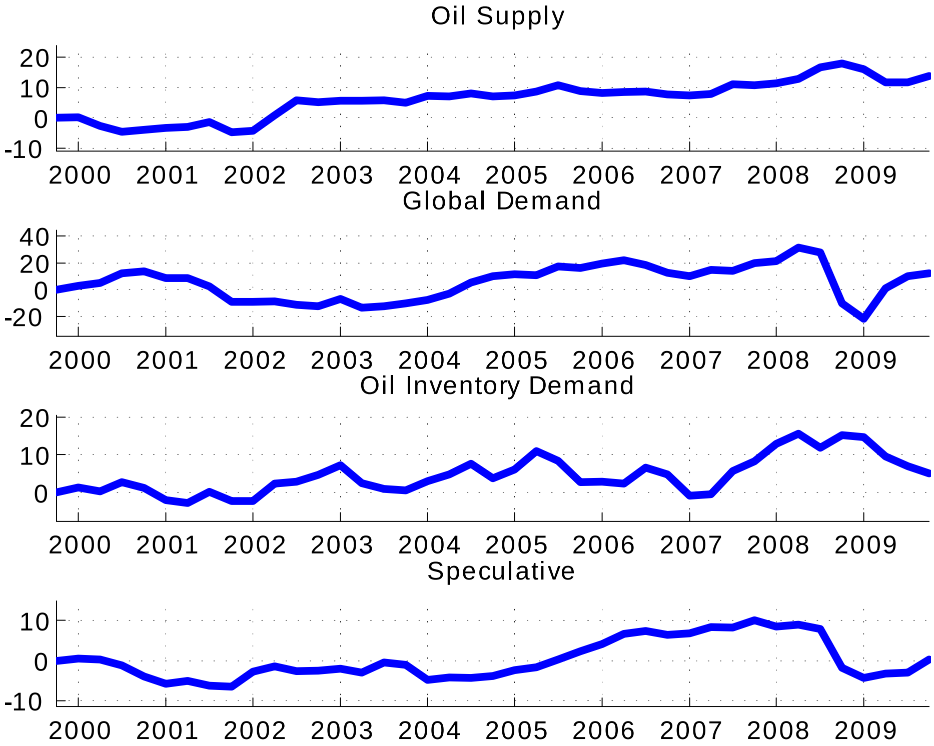
Notes: The figure shows the impulse responses to oil supply, oil inventory demand, global demand, and speculative shocks using a FAVAR with sign restrictions. The solid lines are the median impulse responses and the shaded areas represent the 16th and 84th percentile bootstrapped error bands.

Figure 3. Conditional Correlations



Notes: The figure shows the correlation of 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 4. 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	MILL, 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	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 (5) 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	5
U.K.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
France	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Germany	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Italy	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Canada	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Japan	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
CPI						
U.S.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
U.K.	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
France	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Germany	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Italy	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Canada	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Japan	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
PPI						
U.S.	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	5
U.K.	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	5
France	Index (2005=100)	IFS	1993Q1	2009 Q4	Y	5
Germany	Index (2005=100)	OECD MEI	1971 Q1	2009 Q4	Y	5
Italy	Index (2005=100)	IFS	1981Q1	2009 Q4	Y	5
Canada	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	5
Japan	Index (2005=100)	IFS	1971 Q1	2009 Q4	Y	5
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 (5) denotes first difference of annual growth rates.

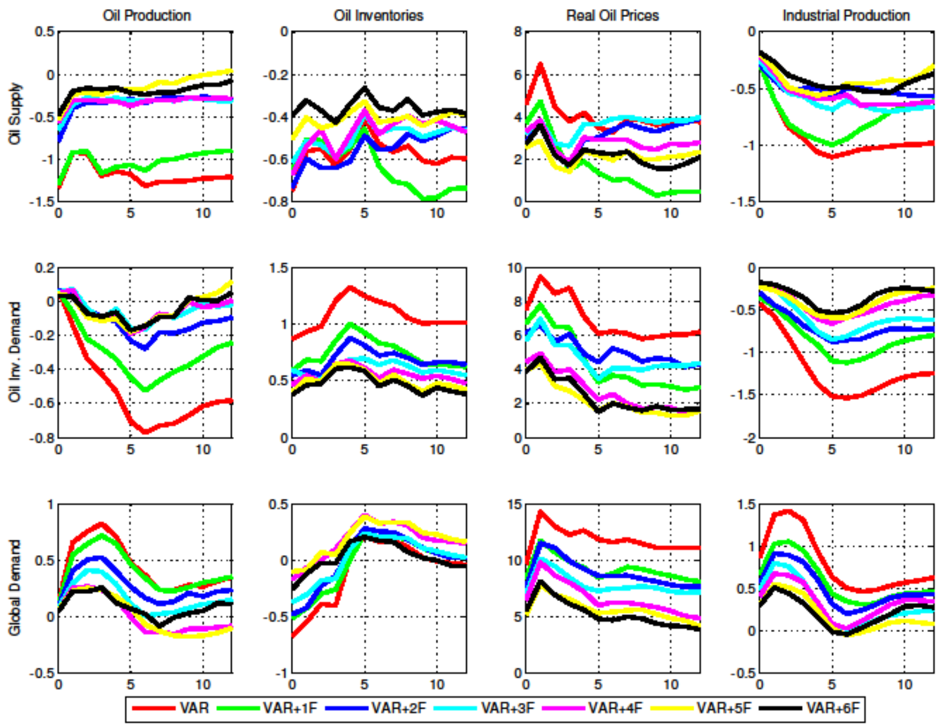
Variables	Unit	Source	Start Date	End Date	Seasonally Adjusted	Stationarity Transformation
M1						
U.S.	(Real, deflated by CPI, Bil. USD)	OECD MEI	1971 Q1	2009 Q4	Y	4
U.K.	(Real, deflated by CPI, Bil. GBP)	OECD MEI/BIS	1971 Q4	2009 Q4	Y	4
France	(Real, deflated by CPI, Bil. FRA)	IFS/BIS	1971 Q1	2009 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 (5) denotes first difference of annual growth rates.

B Appendix: Choice of Factors

In this appendix we show the 4-variable VAR specification with aggregate industrial production. The results from the information sufficiency test reported in Section 3.2. suggest that the differences across models are statistically significant.

Figure B1. Impulse Responses for Different Choices 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 Aggregate 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

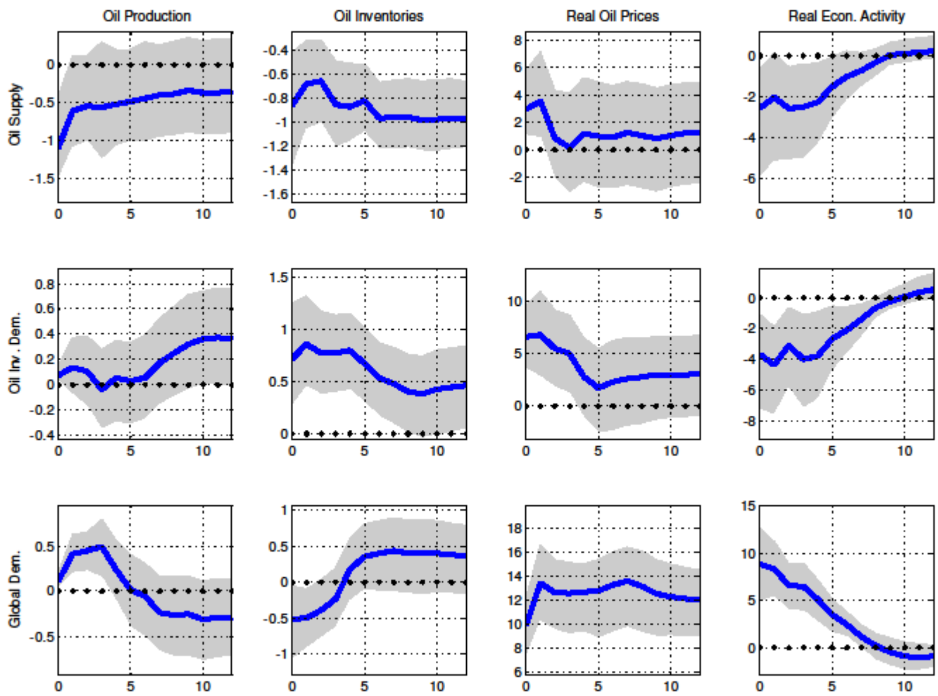
Notes: This table reports the Bai and Ng (2006) statistics to evaluate the extent to which observed factors differ from latent factors. Bold numbers indicate an $R^2 > 0.100$.

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 $R^2 > 0.100$.

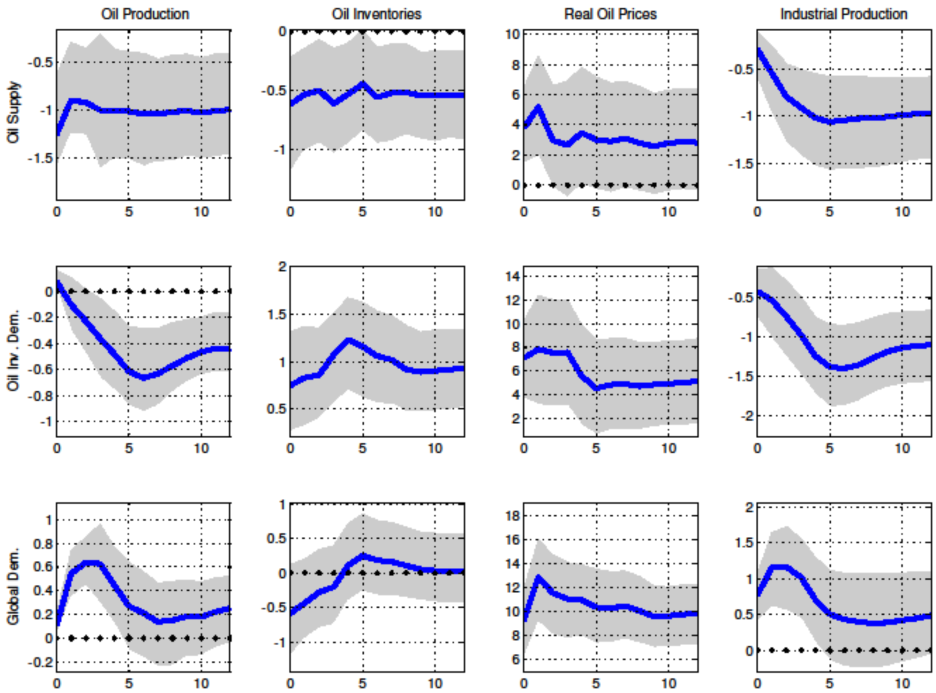
D Appendix: Impulse Responses VAR and FAVAR

Figure D1. Impulse Responses: VAR (with real economic activity)



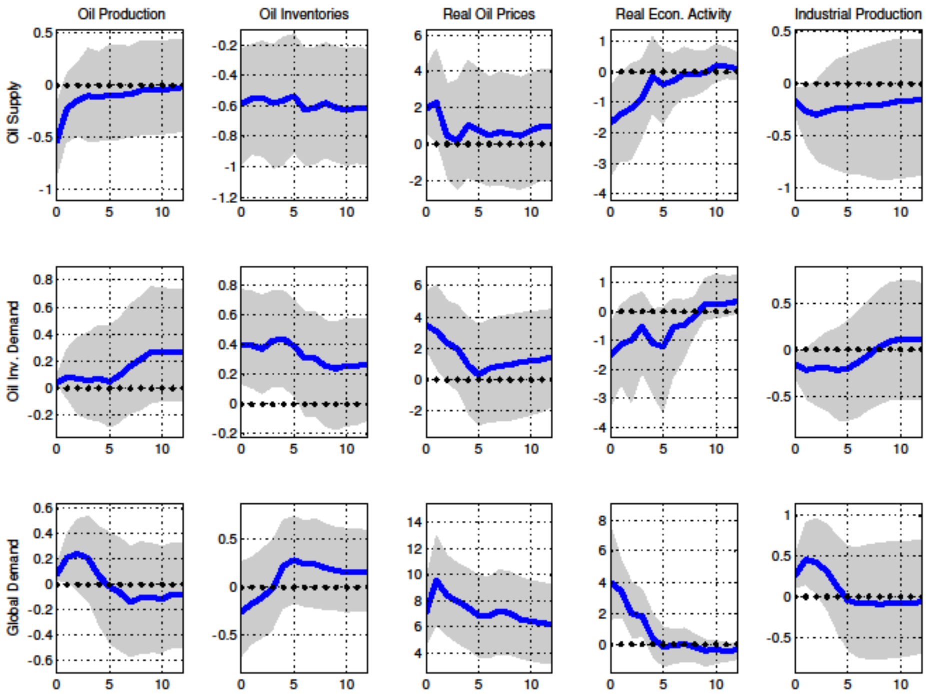
Notes: The figure shows the impulse responses to oil supply, oil inventory demand, and global demand shocks using a VAR with sign restrictions. The solid lines are the median impulse responses and the shaded areas represent the 16th and 84th percentile bootstrapped error bands.

Figure D2. Impulse Responses: VAR (with aggregate industrial production)



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 areas represent the 16th and 84th percentile bootstrapped 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 areas represent the 16th and 84th percentile bootstrapped error bands.

E Appendix: A Simplified Model of the Oil Market

This appendix presents a very stylized model of the oil market that provides insights about the propagation of the shocks identified in our paper.

The Demand for Oil

In what follows we summarize the main equations that determine the demand for oil. Detailed derivations can be found in Hamilton (2009a). The demand for oil originates from the demand of gasoline retailers. In fact, oil (X_t) is used as an intermediate input for the production of gasoline, whose real price is G_t. $F(X_t, I_t)$ is the production function and depends on the current level of inventories, I_t.[1] The first order conditions of the retailers' problem are:

$$F'_X(X_t, I_t) = \frac{P_t}{G_t}. \tag{1}$$

Equation (1) is the optimal demand schedule for crude oil by gasoline retailers. It states that the marginal productivity of oil has to be equal to the relative price (with respect to gasoline). This is nothing more than the usual result that under perfect competition marginal productivity is equal to marginal costs. Optimal inventory management implies that:

$$P_t + \mathbb{C}'(I_{t+1}) = \frac{G_{t+1}F'_I(X_{t+1}, I_{t+1}) + P_{t+1}}{1 + r_t}. \tag{2}$$

From Equation (2) it follows that if firms buy one more unit of oil today to store as inventory, incurring a (marginal) cost of $P_t + \mathbb{C}'(I_{t+1})$, this will lower next period's cost by $G_{t+1}F'_I(X_{t+1}, I_{t+1}) + P_{t+1}$.

Therefore, current oil production is either consumed for the production of gasoline or stored as inventories (for future production of gasoline). This implies that mismatches between time-t production (Q_t) and consumption (X_t) of oil are reflected in changes in the stock of inventories:

$$\Delta I_{t+1} = Q_t - X_t. \tag{3}$$

To close the model we assume the following demand for gasoline[2]

$$F(X_t, I_t) = \frac{\exp(\gamma_t)}{G_t^{\beta}}, \tag{4}$$

where γ_t is capturing the systematic (inelastic) demand for gasoline, as well as a random component that can be interpreted as an aggregate demand shock.

The inverse demand function for crude oil can be found from the intersection of (1) with (4):

$$P_t = \left[\frac{\exp(\gamma_t)}{F(X_t, I_t)}\right]^{\frac{1}{\beta}} F'_X(X_t, I_t). \tag{5}$$

[1] Including inventories as a state variable in the production function is a short-cut to produce positive convenience yields and therefore positive holding of inventories in every period.

[2] The demand for gasoline can be easily derived from a utility maximization where gasoline is a final good that produces utility to the households (see, e.g., Nakov and Nuno, 2011).

Note that (for $\beta > 0$) this is downward sloping, with crude oil prices inversely related to total crude consumed in the same period. In addition, this relation depends also on the current stock of inventories.

The inverse demand function of inventories can be found from (2) as

$$P_t = \frac{G_{t+1} F'_I\left(X_{t+1}, I_{t+1}\right) + P_{t+1}}{1 + r_t} - \mathbb{C}'\left(I_{t+1}\right),$$

therefore implying a downward sloping demand $I_{t+1} = D_{Inv}\left(P_t, P_{t+1}, G_{t+1}, X_{t+1}, r_t\right)$, where P_{t+1} acts as a forward shifter of the curve (i.e. $D'_{Inv,P_{t+1}} > 0$). Similarly, (5) also implies a downward sloping demand curve, $X_t = D_{Cons}\left(P_t, \gamma_t, I_t\right)$, however this does not depend on the future price level.

The total demand function for oil can be found substituting (5) and (2) into (3), which gives a relation that is a function of prices (P_t and P_{t+1}) and quantity produced (Q_t) (depending also on the accumulated stock of inventories):

$$Q_t = D_{Inv}\left(P_t, P_{t+1}, G_{t+1}, X_{t+1}, r_t\right) - I_t + D_{Cons}\left(P_t, \gamma_t, I_t\right). \tag{6}$$

This shows that a shift in the future oil price manifests itself into a shift in demand, specifically into an increase in the demand for inventories (Hamilton, 2009a, and Kilian and Murphy, 2011a).[3]

Modeling Oil Extraction

In this section we discuss the producer problem and derive optimal oil extraction.[4]

Denote with Q_t the production or extraction of oil in period t, and define with $\mathbb{Q}_t$ the cumulative extraction at the end of period t, so that: $\mathbb{Q}_t = \sum_{\tau=0}^{t} Q_\tau$. Let $\Re_t$ be the amount of proven reserves so that the total amount of the resources exploitable at time t is $R_t = \Re_t - \mathbb{Q}_t$.[5] Consider a typical competitive owner of an exhaustible resource who can obtain the market price, P_t, for the resource at time t. Her optimal extraction profile, $\{Q_\tau, R_\tau\}_{\tau=t}^{T}$, is obtained by maximizing the discounted stream of profits over the life of the field:

$$\Pi_t = \sum_{\tau=t}^{T} \frac{1}{\prod_{s=t}^{\tau}\left(1 + r_s\right)} \left[P_\tau Q_\tau - C\left(Q_\tau, \mathbb{Q}_\tau\right)\right], \tag{7}$$

given the resource constraint

$$R_t = R_{t-1} - Q_t + e_t, \tag{8}$$

where $e_t = \Re_t - \Re_{t-1}$ allows for the possibility that the total amount of proven reserves may vary over time, either due to data revisions or because of new resource discoveries. In this way, e_t can be considered as an exogenous flow supply shock.

[3] The demand function (6) sheds light into the propagation of other shocks. In fact, a flow demand shock incorporated into γ_t implies an upward shift of the demand curve (specifically a shift of current consumpion D_{Cons}). Moreover, any shift of the convenience yield, such as the ones modelled in Alquist and Kilian (2010), also implies an increase in total demand (specifically the precautionary demand of oil D_{Inv}). Neither of these two shocks implies a contemporaneous shift of the supply curve, as it will be clear from the next section.

[4] In this Appendix we refer to marginal changes in production for current wells in operation. Modeling the investment decision of developing a new well is out of the scope of the current paper, and it is likely to depend on medium to long run expectations of the oil price, which are longer than the typical length of a futures contract.

[5] Dating proven reserves at time t allows for the possibility that its total amont may vary over time, either due to data revisions or because of new resource discoveries.

Following Farzin (1992), the total extraction cost at time t is given by a twice continuously differentiable function $C_t = C(Q_t, \mathbb{Q}_t)$. It follows that the total extraction cost increases both with the current extraction rate (i.e. $C'_Q > 0$) and the cumulative extraction up to date (i.e. $C'_{\mathbb{Q}} > 0$).[6] In view of geological and engineering knowledge about exploitation of depletable resources, one expects the marginal extraction cost C'_Q to have the following properties: (i) *diminishing returns* to extraction rate that cause the marginal extraction cost to rise as the extraction rate increases ($C''_{QQ} > 0$); (ii) *depletion effect* that raises the marginal cost of maintaining a given rate of extraction as increasing amounts of resource are depleted ($C''_{Q\mathbb{Q}} > 0$). It is also usually postulated that the incremental cost due to cumulative extraction rises not only with the extraction rate ($C''_{\mathbb{Q}Q} > 0$), but also with the amount already extracted ($C''_{\mathbb{Q}\mathbb{Q}} > 0$) (see, e.g. Pindyck 1978).

The first order conditions from the above optimization problem imply

$$-\lambda_t = P_t - C'_Q(Q_t, \mathbb{Q}_t),$$

and

$$C'_{\mathbb{Q}}(Q_t, \mathbb{Q}_t) + \lambda_t - \frac{\lambda_{t+1}}{1+r_t} = 0.$$

The lagrangian multiplier λ_t (< 0) is the shadow cost associated with the cumulative extraction up to t. In equilibrium, it has to be equal to the discounted sum of the incremental costs that an additional unit of resource extracted at time t brings about in that period and also spills over into all future periods by raising cumulative extraction levels $\mathbb{Q}_t$ so that

$$\lambda_t = -\sum_{\tau=t}^{T} \frac{C'_{\mathbb{Q}}(Q_\tau, \mathbb{Q}_\tau)}{\prod_{s=t}^{\tau}(1+r_s)}.$$

Eliminating the multiplier yields

$$P_t - C'_Q(Q_t, \mathbb{Q}_t) - C'_{\mathbb{Q}}(Q_t, \mathbb{Q}_t) = \frac{P_{t+1} - C'_Q(Q_{t+1}, \mathbb{Q}_{t+1})}{1+r_t}, \tag{9}$$

which is the optimality condition for the extraction rate, i.e. the condition required for optimal below ground-inventory management. Note that if $C'_{\mathbb{Q}} = 0$, then the relation above is the Hotelling Principle: The price of the resource net of marginal extraction cost is expected to rise with the discount rate, r.

Clearly, if the firm were to face an increase in price ($P_{t+1} > P_t$), with all other prices remaining constant, it would respond by decreasing the amount of current production, until the condition given in equation (9) was restored.[7]

[6] For example, abstracting from technology developments, Favero and Pesaran (1994) show that an extraction cost function quadratic in the rate of extraction (Q_t) and linear in the level of remaining reserves ($\Re_t - R_t$), with the latter term capturing the importance of pressure dynamics in the determination of extraction costs $[C(Q_t, R_t) = \frac{A}{2}Q_t^2 + B(\Re_t - R_t)]$, is the best-performing specification using North Sea data.

[7] The optimal supply schedule also shows that a decrease in e_t (an unexpected decrease in total available/exploitable reserves), which might be caused by a war for instance, will increase the current marginal costs and therefore shift supply down.

The Impact Effect of a Speculative Shock

The equilibrium is given by the intersection of the demand function, (6), with the supply function, (9). We can think of a speculative shock as an unexpected increase in future prices, P_{t+1}, with respect to current prices, P_t, where this may result from traders' activity. If the retailers were to face an increase in price ($P_{t+1} > P_t$), with all other prices remaining constant, the demand for inventory would increase (2), which would result in an upward shift of the demand curve. The increase in the demand for inventories will create pressure to increase production, which is the standard effect of shift in demand along an upward sloping supply curve. This case is depicted in Figure E1.[8] At the same time, if oil producers were to be misled by the increase in prices, it would clearly be optimal response for them to hold production underground to increase it in the future. Facing an increase in price ($P_{t+1} > P_t$), with all other prices remaining constant, the supply curve shifts left, as producers respond by decreasing the amount of current production until the condition given in equation (9) is restored.

A priori it is not clear whether the impact on oil production is positive or negative. This will depend on the relative shift of the demand and supply curves, as well as the elasticities. In fact, the effect of the supply shift should dominate the effect of a demand shift (for the sign of production) whenever the supply curve is very steep.[9] Clearly, the opposite movements of demand and supply will, in any case, imply a large jump in the current oil price. Figure E2 shows the case when the response of production is dominated by the incentives of producers to increase future revenues, as opposed to current revenues.

In the paper we have assumed that the speculative shock is associated with a decrease in production. This is actually not clear a priori, and that is the reason why we refer to this case as a 'conjecture' by Hamilton (2009a). The model helps us understand what conditions are necessary for this to happen. However, it could be the case that part of the speculative component is captured by the oil inventory demand shock (as in Kilian and Murphy, 2011a). The fact that the implied path of the speculative shock moves in line with anecdotal evidence on the role of speculation in the past decade (in terms of timing, for instance) builds our confidence that the speculation shock is in fact capturing the effect of exogenous shifts in expectations of futures prices. The fact that oil inventory demand captures shifts in prices around well known episodes of increased uncertainty (such as the Iranian Revolution or the first Persian Gulf war) suggests that this shock is dominated by the precautionary demand motive (i.e. a shift in demand not counteracted enough by a downward shift of supply, see Kilian and Murphy, 2011a).

[8] This is the case considered in Kilian and Murphy (2011a). However, it must be emphasized that a similar picture would emerge as a result of a precautionary demand shock such as the one considered in Alquist and Kilian (2010), as well as a result of an expeced shortfall in production (see 2 and 6).

[9] This would be true in the extreme case of a vertical supply.

Figure E1. Oil Inventory Demand Shock

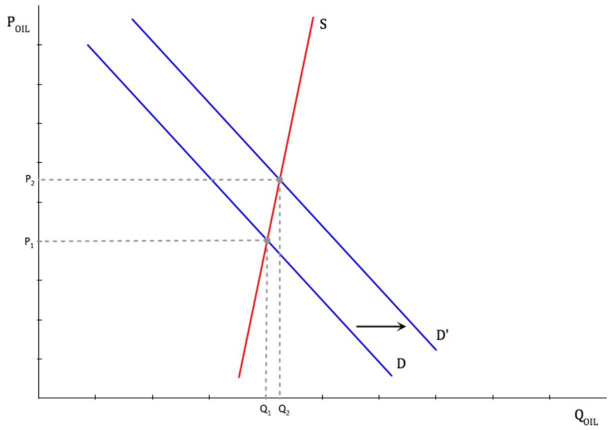
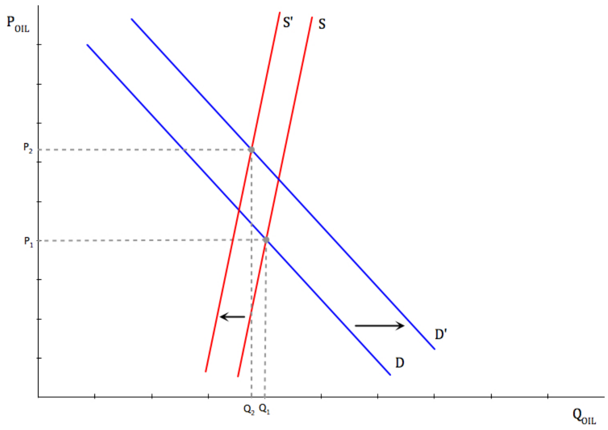
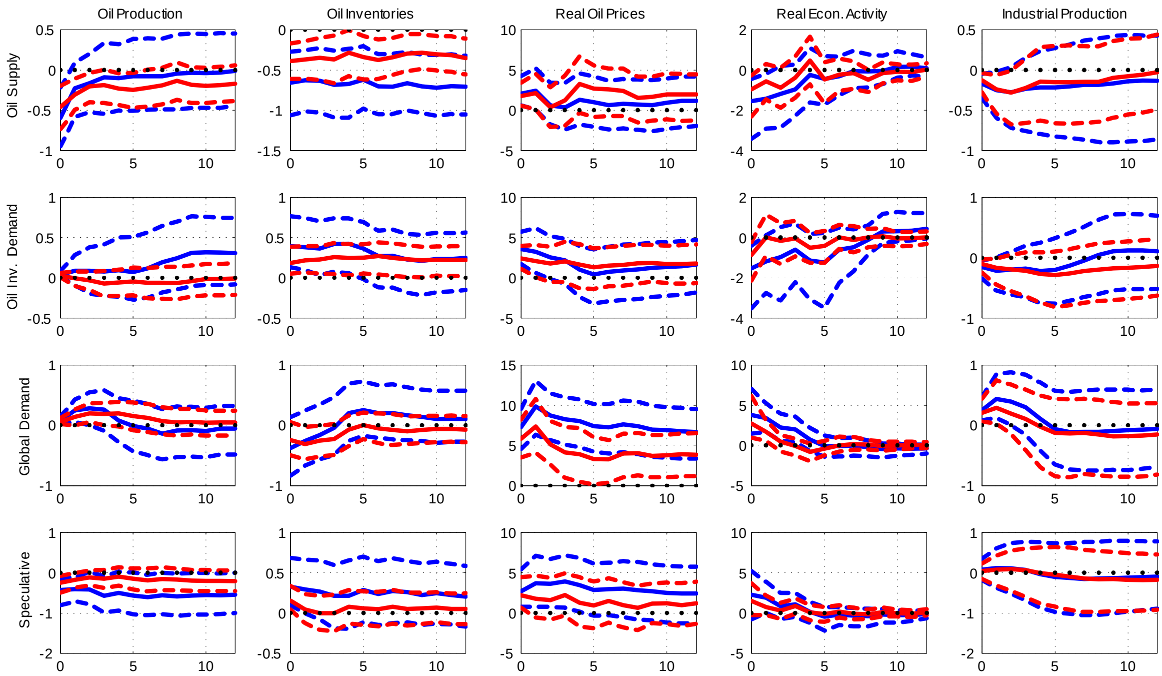


Figure E2. Speculative Shock



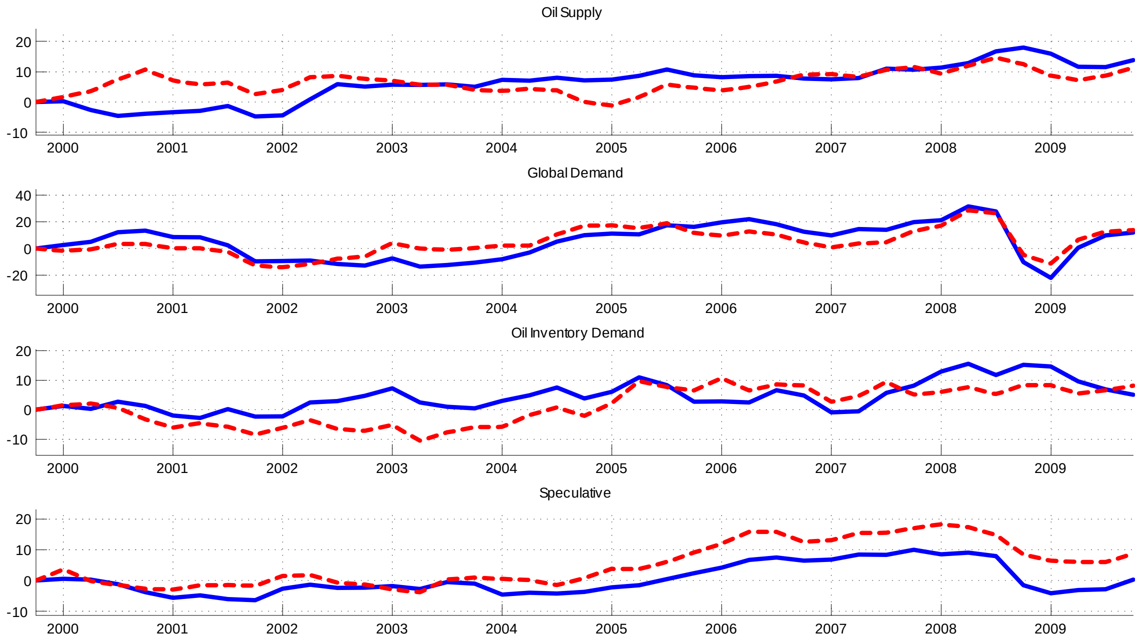
F Appendix: Subsample Analysis

Figure F1. Impulse Responses: Benchmark and Subsample



Notes: The figure compares the impulse responses to oil supply, oil inventory demand, global demand, and speculative 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 dashed lines represent the 16th and 84th percentile bootstrapped error bands.

Figure F2. Historical Decomposition of the Oil Price: Benchmark and Subsample

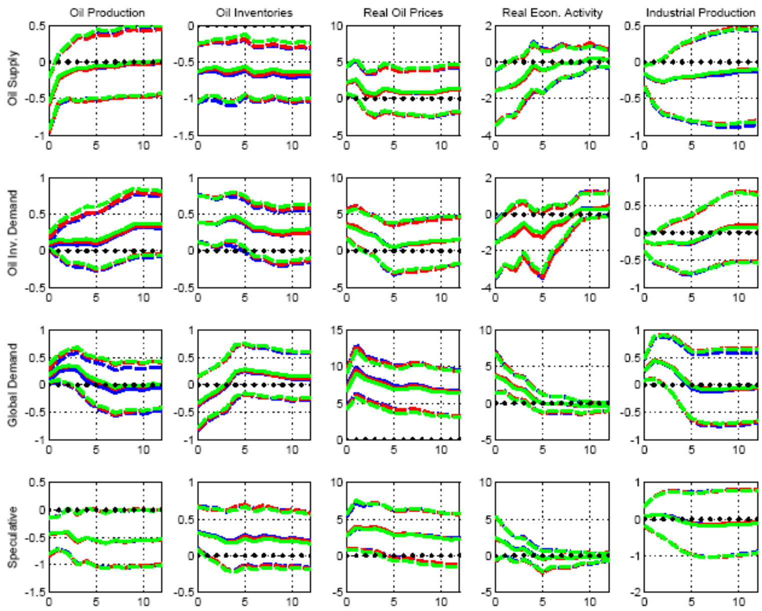


Notes: The figure compares the historical decomposition of the oil price for the benchmark FAVAR shown in Figure 4 (blue lines) and the FAVAR estimated for a subsample starting in 1986 (red lines).

Annex 1: Elasticity Bounds

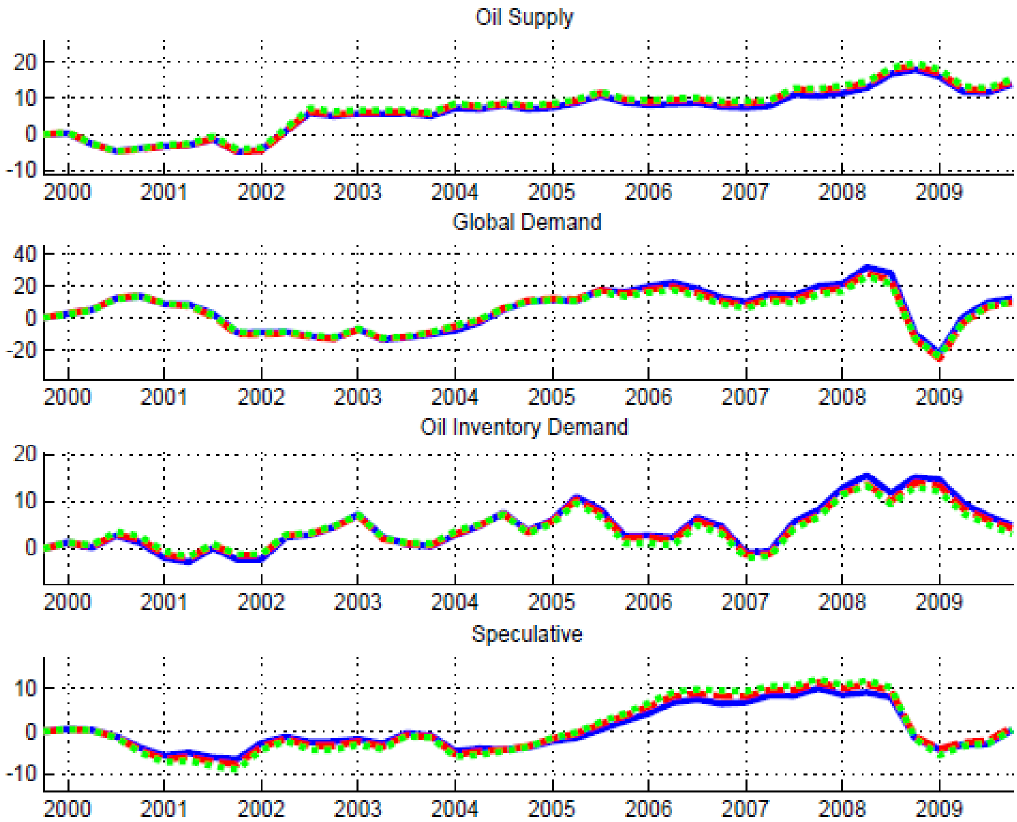
As we explain in Section 3.4., we impose an upper bound of 0.0257 for the response of the impact elasticity of oil supply with respect to the real price jointly after both demand shocks. This bound is proposed by Kilian and Murphy (2011b) and is designed for a monthly model. Since we have quarterly data it is not clear whether the same restriction should be applied. Therefore, we check the robustness of our results to a an elasticity bound of two and three times the Kilian and Murphy (2011b) value. The impulse responses and historical decomposition are presented below.

Figure 1. Impulse Responses for Different Elasticity Bounds



Notes: The figure shows the impulse responses to oil supply, oil inventory demand, global demand, and speculative shocks using a FAVAR with sign restrictions. Blue lines show our benchmark identification as in Figure 2, red lines show the results for the Kilian and Murphy (2011b) elasticity bound multiplied by 2 and green lines show the results for the Kilian and Murphy (2011b) elasiticy bound multiplied by 3. The solid lines are the median impulse responses and the shaded area represents the 16th and 84th bootstrapped error bands.

Figure 2. Historical Decomposition for Different Elasticity Bounds



Notes: Blue lines show our benchmark identification as in Figure 4. Red lines and green lines show, respectively, the results for the Kilian and Murphy (2011b) elasticity bound multiplied by 2 and 3.

Annex 2: Pairwise correlations

Figure 1 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 from an increase in demand for all commodities. The results using only industrial commodities are quite similar.

Figure 1. Pariwise Correlation: All Commodities