"[...] 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 (2012) argue 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 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 (2012) 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, global demand, oil inventory 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 refer to changes in the current physical availability of crude oil (see Hamilton, 1985, 2003; Kilian, 2008a, b). Global demand shocks reflect an increase in demand for all industrial commodities triggered by the state of the global business cycle. An oil inventory demand shock arises from the possibility of a sudden shortage in future production or expectations of higher demand in the future. This shock represents a shift of the demand curve along an upward sloping supply curve as a consequence of an increase in the demand for inventories.

[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, among others, Baumeister and Peersman (2010), Kilian and Murphy (2011a, b), Kilian and Park (2009), Lombardi and Van Robays (2011), and Peersman and Van Robays (2009, 2010).

[3] This idea can be found in 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, (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.

Speculative shocks have attracted a great deal of attention in the literature, fueled by the oil market developments in the past decade. Our identification of this shock is inspired by Hamilton (2009a), where he describes a channel through which speculation can impact the physical side of the market. In particular, he illustrates 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.[4] 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 shock represents a contemporaneous shift in the demand for above and below ground inventories.[5]

In terms of methodology, we re-examine the role of speculation relative to supply and demand forces as drivers of oil prices using a dynamic factor model (DFM). Bernanke et al. (2005) and Giannone et al. (2005) argue that the small number of variables in a vector autoregression (VAR) may not span the information sets used by market participants, who are known to follow hundreds of data series. We provide evidence that the small-scale VARs for the oil market, typically used in the literature, are 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. We show that the information set plays an important role: (i) The shape of the impulse responses is different in the VAR compared to the DFM; and (ii) The DFM suggests that although global demand shocks account for the largest share of oil price fluctuations, their contribution is smaller than in VAR estimates. In addition, our results also show that speculative shocks are the second most important driver of oil price dynamics.

Interpreting oil price fluctuations over the past decade under the lens of our model reveals that speculative 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, 2012), as well as with the anecdotal evidence presented in Masters (2008). Although speculation played a significant role in driving oil price increases between 2004 and 2008, and their subsequent decline, the increase in oil prices over the last decade is due mainly to the strength of global demand, in line with Kilian (2009), and most of the literature thereafter.

The use of a DFM allows us to investigate the transmission of oil shocks to a large number of variables. Therefore, we can analyze the correlations between oil prices and the price of other commodities in response to each shock. We find that global demand shocks are the main drivers of the comovement between commodity prices, consistent with the narrative in Kilian (2009). However, the speculative shock is also associated with a positive comovement between oil and the price of other commodities, even though it is smaller in magnitude

[4] The description of the speculative shock is motivated by the recent trend of investment in commodity markets. However, 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 strengthen the role of shocks to the expectation of future oil prices, but clearly the concept of speculation that we identify is a general one. See online appendix for further details.

[5] 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 B for more details.

than the correlation given by global demand shocks. This is consistent with the results of Tang and Xiong (2012) and suggests that the speculative shock that we identify is picking up the effects of financialization driven by the rapid growth of commodity index investment as emphasized by Singleton (2011), among others. The correlation between oil prices and the prices of other commodities is negative for supply and oil inventory demand shocks, implying that they cannot be responsible for the comovement in commodity prices.

Our paper is 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, e.g., 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. Our study offers a complementary approach. 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, we show that speculative shocks are also relevant. This suggests that speculative activities can alter the incentives faced by operators in the oil market since they affect the expectation formation of market participants .

The rest of the paper is organized as follows. Section 2 presents the econometric method. Section 3 describes the data and the identification strategy. Section 4 discusses the empirical results and Section 5 offers some concluding remarks.

2 Econometric Method

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 into their lagged values. This implies that all the relevant information for the identification of the shocks is included in the small set of variables in the VAR – that is, that the identified structure of the shocks is fundamental (see Hansen and Sargent, 1991; Lippi and Reichlin, 1993, 1994; and Fernandez-Villaverde et al., 2007).[6] 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 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 DFM approach that we use in the empirical section.

Let x_{it} denote a generic variable of a panel of N stationary time series, where both the N and T dimensions are very large. In a 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 and r is much smaller than N, $\boldsymbol{\lambda}_i$ 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.

[6] For a review about fundamentalness in VAR models see Alessi et al. (2011).

The idiosyncratic components also include a measurement error that is uncorrelated across variables. Allowing for a measurement error is particularly useful in our context. As an example, 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. 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).

As for the oil market variables, let $\mathbf{y}_t$ denote the 3×1 vector including the change in oil production, the change in the real oil price and the change in oil inventories. We assume that these variables can be decomposed into a common ($\mathbf{f}_t^{oil}$) and idiosyncratic ($\boldsymbol{\xi}_t^{oil}$) components as follows:

$$\mathbf{y}_t = \mathbf{f}_t^{oil} + \boldsymbol{\xi}_t^{oil}. \tag{2}$$

This specification ensures that most of the dynamics of the oil variables is picked up by "specialized" common factors, so that we can safely identify the structural shocks from the innovation to the transition equation for the factors, as discussed below.[7]

The last block of the model consists of the transition equation for the dynamics of the unobservable factors. We assume that the factors follow a stationary VAR process of order p, represented as follows:

$$\begin{bmatrix} \mathbf{f}_t^{oil} \\ \mathbf{f}_t \end{bmatrix} = \boldsymbol{\Phi}(L) \begin{bmatrix} \mathbf{f}_{t-1}^{oil} \\ \mathbf{f}_{t-1} \end{bmatrix} + \mathbf{u}_t, \tag{3}$$

where $\boldsymbol{\Phi}(L)$ is the lag polynomial in the lag operator L, and $\mathbf{u}_t$ is the error term with mean zero and (an unrestricted) variance-covariance matrix $\boldsymbol{\Sigma}$. Note that the block diagonal restriction on the loadings of the measurement equations, (1)-(2), ensures that the oil factors capture a large part of the variation in the oil variables, yet the specification for the transition equation ensures that the oil factors can still be influenced by the other factors (and vice versa). In the empirical section we also impose the restriction that oil prices are measured without error.[8] With these restrictions, our model is a special case of DFM, which nests the Factor Augmented VAR (FAVAR), allowing for measurement error in oil production and oil inventories.

Kilian (2009) highlights the importance of global demand forces in the determination of oil prices. In fact, after his contribution all the low dimensional VARs of the oil market always include a proxy for global economic activity among the relevant variables for identifying the structural shocks. In a way, the low-dimensional VARs can be considered a specific version of (3), where the proxy for global economic activity is considered to be a single observable factor. In this respect, we complement the existing empirical evidence by allowing the stochastic dimension of the large dataset of macroeconomic and financial variables (i.e., the world economy) to be larger than 1. This will be true whenever the global economy is affected by more than one source of common shocks.[9] Therefore, specification (3) 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.[10] In

[7] We restrict the factor loadings to be the identity matrix. This assumption is not restrictive, as we can always rotate the factors, yet it has the advantage of allowing us to interpret each of the factors as the signal embodied in each of the variables. Therefore, the idiosyncratic component can be thought of as the noise or measurement error in the oil variables.

[8] This restriction implies that (controlling for the identified shocks) oil prices are insensitive to non-global shocks or measurement errors in the oil variables. This assumption is justified by the highly integrated global market for oil and its derivatives. A similar approach has been pursued by Luciani (2012) in a different context. Note that the results are qualitatively similar if we were to include an idiosyncratic component in oil prices. The results from this estimation are not presented here to preserve space but are available upon request.

[9] This is a realistic assumption that holds even if one is not willing to postulate 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).

[10] This condition can be easily verified by looking at a Granger causality test of the low-dimensional VAR with respect to the

addition, allowing for measurement error in oil production and oil inventory data allows us to deal with the difficulty of constructing precise measures of these variables (see, e.g., Kilian and Lee, 2013).

The model in (1)-(3) can be formulated in a state space representation. Assuming that $\mathbf{u}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma})$ and the idiosyncratic components $\left[\boldsymbol{\xi}_t^{oil\prime}, \boldsymbol{\xi}_t^{\prime}\right]^{\prime} \sim N(\mathbf{0}, \mathbf{R})$, where $\mathbf{R}$ is a diagonal matrix, Doz et al. (2012) show that it can be consistently estimated by (Quasi) Maximum Likelihood under different sources of misspecification of the cross-sectional and serial correlation of the idiosyncratic components. Since the factors are unobserved, the maximum likelihood estimators of the parameters of model, $\{\boldsymbol{\Lambda}, \mathbf{R}, \boldsymbol{\Phi}, \boldsymbol{\Sigma}\}$, are generally not available in closed form. In addition, direct maximization of the likelihood is computationally demanding due to the large number of parameters. Therefore, we adopt the EM algorithm described in Banbura and Modugno (2012), which also allows us to handle the unbalancedness of the data.[11]

We are interested in analyzing the impact of different types of oil shocks within the framework of a DFM. 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

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

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

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

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 Data and Identification

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.

information summarized by the factors (see Giannone and Reichlin, 2006). We describe this test in Section 4 and report further details in Appendix C.

[11] We initialize the algorithm using the estimates from a FAVAR model, where the oil variables are assumed to be measured without error and a number of principal components are estimated from the balanced part of the dataset (following Stock and Watson, 2002). When it comes to the variance of the idiosyncratic components of the oil variables, which the FAVAR assumes to be equal to 0, we initialize it to be a small number, κ. The results are not affected by the particular choice of κ.

The set of macroeconomic and financial variables includes output, prices, labor market indicators, the trade balance, interest rates, stock market price indices as well as 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.[12] 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).[13]

3.2 Identification

We identify oil supply, global demand, oil inventory demand, and speculative shocks using the sign restrictions summarized in Table 1. The first three shocks have been the focus of the recent literature and their identification builds on Baumeister and Peersman (2011) and Kilian and Murphy (2011a, b). The identification of the speculative shock is inspired by Hamilton (2009a). In what follows we describe the identification of each shock in detail.

[Table 1 about here]

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.

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, leading to an increase in the level of inventories and real oil prices. 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 and also leads to a decline in real activity.[14]

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 while oil production increases to satisfy the higher

[12] 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 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.

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

[14] Kilian and Murphy (2011a) refer to this shock as "speculative demand shock," and define it as "a shock to the demand of above ground oil inventories arising from forward looking behavior" (Kilian and Murphy, 2011a).

demand. In turn, 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. The results are robust to the use of different elasticity bounds.

3.2.1 Identification of Speculative Shocks

We identify a speculative shock inspired by Hamilton (2009a), where he 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 oil market. Hamilton (2009a) describes 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.

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 (see Frankel and Rose, 2010). 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.[15] 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 Jovanovic, 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.[16]

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 type of incentives can lead to an increase in the storage of above ground inventories.[17] A summary of the sign restrictions consistent with

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

[16] 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 speculative 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 counteract the effect of the shift in demand. See Appendix B for more details).

[17] Let us illustrate this 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

this narrative and used to identify the speculative shock is presented in the last row of Table 1. The intuition behind these restrictions can be found in a simple model presented in Appendix B.

Note that 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 in principle have a contractionary effect on demand. However, we are not comfortable imposing such a restriction because we do not want to rule out alternative transmission channels. One of them refers to the possibility that the increase in financial speculation is triggered by low real interest rates, as suggested by Frankel (1986 and 2008). As he explains, lower real rates reduce the cost of "carry trade" in the commodity markets, amplifying the effect of a mismatch between expected 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 other channel is emphasized in Sockin and Xiong (2013), who propose a model in which an increase in commodity futures prices driven by non-fundamental factors may induce agents with imperfect information to believe this as a signal of strong global economic growth, and may therefore be associated with an increase in economic activity.

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.[18] In contrast to our identification strategy, Kilian and Murphy (2011a) identify a speculative shock in which oil inventories increase, oil prices go up, and oil production increases. This is what we refer to as oil inventory demand shocks, which essentially represents a shift of the demand of inventories along an upward sloping supply curve. Appendix B presents a simple model that justifies the restrictions for the oil inventory and speculative shocks.

The role of speculation in driving oil prices has been very active in the policy debate. In this regard, it is interesting to note that the set of sign restrictions that we use for identification are consistent with Bernanke (2004) description on how speculative activities can affect oil prices. The online appendix summarizes his perspective.

4 Empirical Results

4.1 The Role of the Information Set: VAR and DFM with 3 Shocks

As a first step we evaluate 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 by implementing the procedure introduced by Giannone and Reichlin (2006) and discussed in Forni and Gambetti (2011). The test results

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 higher expected input prices 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.

[18] 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 4.2.3.

imply that a small-scale VAR is not informationally sufficient to identify the shocks and suggest that 4 factors are added to the VAR (the test is presented in Appendix C).[19]

In what follows, we estimate two VARs and a DFM with the three shocks typically identified in the literature and compare their results. The two 4-variable VARs differ in the measure of economic activity used. The first one, named VAR-KM, includes the Kilian measure of global economic activity; and the second, named VAR-AIP, includes aggregate industrial production. Note that in the case of the DFM we impose sign restrictions on both measures of real economic activity given that the two of them have been used in VAR analysis of the oil market.[20]

Figure 1 shows the impulse responses. The black bold lines denote the median impulse responses from the estimated DFM and the shaded areas represent the 16th and 84th percentile bootstrapped error bands. The pink and blue lines represent the median impulse responses and error bands from the VAR-KM, and the VAR-AIP, respectively. The impulse responses obtained using the DFM are different both in terms of shape and magnitude compared to the VARs. In particular, the response of the oil price after a demand shock is substantially smaller in the DFM than in the VARs. In addition, the response of oil prices is smaller after an oil inventory demand shock and supply shocks. Although our main focus is on oil prices, there is a sharp contrast in the response of other variables. For example, the response of both measures of economic activity is higher and more persistent in the VARs than the DFM for all shocks.

[**Figure 1 about here**]

The contrast between the two methods is further assessed by analyzing the forecast error variance decomposition of the oil price presented in Table 2. The Table shows the variance decomposition for the DFM, and for the 4-variable VARs constructed using the two alternative measures of global economic activity.

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. The sum of the three shocks accounts for around 85% of the oil price variation in both VARs. By contrast, the variance decomposition from the DFM gives a different picture. First, the three shocks explain only around 65% of oil price fluctuations. Second, the share of oil price fluctuations explained by demand forces decreases significantly, while the share driven by supply shocks remains largely unchanged. Although global demand shocks still account for the largest proportion of oil price fluctuations, their contribution is smaller compared to the VARs. The oil inventory demand shock is also significantly affected, as using the DFM it only explains between 7% to 19% of the variation in oil prices.

[**Table 2 about here**]

The comparison between the DFM and the VARs yields a number of interesting results. First, the information set plays an important role. This is illustrated by the fact that the shape and magnitude of the impulse responses are significantly different. Second, the DFM suggests a smaller role of global 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. Third, the variance decomposition of the DFM contains a large unexplained component. We conjecture that part of this is due to speculation in the oil market which we incorporate in the next section.

[19] Implementing an orthogonality test reifnorces the results from information sufficiency test. The shocks identified from a low-dimensional VAR are not orthogonal to the information of lagged factors. See Appendix C for details.

[20] 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.

4.2 Baseline Model: DFM with 4 Shocks

In this section we extend the DFM model with three identified shocks as previously analyzed to include the speculative shock. We show impulse responses and variance decompositions to evaluate how much of the variation in oil market variables is accounted for by each of the shocks. We also examine the cumulative effect of the sequence of historical shocks on the path of the real oil price by looking at the historical decomposition and analyze the effects of each shock on the comovement between commodity prices.

4.2.1 Impulse responses

Figure 2 presents the median impulse responses (bold lines) 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 using a DFM. The figure also shows, for comparison purposes, the impulse responses using a DFM with 3 shocks (blue lines).

[**Figure 2 about here**]

Focusing on the estimation of the DFM, a negative oil supply shock is associated with a temporary drop in production. Oil inventories decrease in an effort to smooth production and this effect is persistent. The real oil price rises on impact, exhibiting a transitory effect. 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 an increase in aggregate industrial production and real economic activity. As a consequence of high-demand pressures triggered by rapid growth, real oil prices exhibit a persistent increase 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.

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

By comparing the DFM with 3 and 4 shocks we note that estimating an additional shock does not affect the shape and magnitude of the impulse responses identified with 3 shocks only.[21]

4.2.2 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 3. The first point to note is that the results are quite stable with respect to

[21] In the online appendix we compare the impulse responses of the 4-variable VARs with 3 and 4 shocks against our DFM baseline (with 4 shocks) to assess whether the incorporating an additional shock affects the results. Very small differences arise (although the differences are more pronounced than the ones we observe from comparing the DFM with 3 and 4 shocks). We conclude that the identification of the additional shock does not severely affect the results in the VARs. However, we emphasize that the differences between the DFM and the VARs are large, reinforcing the idea that the information set matters for identification.

the DFM with three shocks shown in Table 2. 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 43% of oil price fluctuations. Speculative shocks are the second most important driver, explaining up to 14% of oil price movements. The oil inventory demand shock is particularly important on impact (10%) and then decreases after 2 quarters and regains importance at longer horizons. The oil supply shock is the least relevant driver, explaining less than 8% of the variation in oil prices at all horizons.

[**Table 3 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 4. In the short run, 20% 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 while global demand shock contributes up to 22% of inventory movements. In turn, speculative shocks explain only 11% of the fluctuations in oil inventories. At longer horizons, the share of global demand declines to 7%, while the share of oil supply increases to 28%. 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 4 about here**]

Table 5 presents the variance decomposition of oil production. On impact, oil supply shocks explain around 33% 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 would 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 holding below ground inventories is generally less costly than holding above ground inventories.

[**Table 5 about here**]

4.2.3 Speculation and oil prices in the past decade

In Table 2 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 3 presents the results.

[Figure 3 about here]

Figure 3 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 mid-2006. 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, 2012). This finding confirms that we are picking up the form of speculative shock resulting from the financialization of commodity markets. The upward 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, 2012). 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.[22]

We note that the period in which speculation plays a key role in oil price fluctuations (2004-2006) coincides with contango in the futures market (as documented, e.g., 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.

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 speculative 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, 2012), consequently pushing prices down. 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.

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 there are two contrasting forces pushing oil inventories in opposite directions. On the one hand, the strong increase in global demand over the past decade (coupled with stagnant supply) would have implied a reduction in the level of stocks. On the other hand, speculative forces would be accompanied by an increase in inventories. Therefore, it is not surprising that, as a result of these two effects, oil inventories do not show large changes. Our model offers a consistent explanation of these developments in the physical side of the market.

[22] 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 there are no storage costs. An investor would borrow 30 USD, buy oil, wait for delivery and sell it for 60 USD. The total cost for the investor is 33, and the revenue is 27. Now assume that the forward curve shifts upwards, so that the spot price is 100 USD and the forward price is 130 USD. In this case the total cost for the investor is 110 USD, and the revenue is 20 USD.

The oil market has witnessed substantial changes over the sample period analyzed. It is therefore natural to ask whether these changes affected the way oil shocks affect the economy. We estimate the DFM for a subsample starting in 1986 and our results remain robust.[23]

4.2.4 Comovement in Commodity Prices

One of the advantages of the DFM is that it allows us to include a large number of variables such as the prices of different commodities. Therefore, we can assess what is the impact of each shock on the price of other commodities. This question is of particular importance since it allows us to check whether commodity prices co-move after a speculative shock, as suggested by Pindyck and Rotemberg (1990). 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 Kilian and Hicks, 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.

To illustrate comovement between commodity prices we decompose the correlation between the real oil price and a commodity portfolio into the contributions of the structural shocks of the DFM following the methodology by Den Haan and Sterk (2011). Figure 4 shows the correlation between the real oil price and 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.[24] 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 speculative 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. Third, the correlations between oil prices and the prices of other commodities are negative in the case of oil supply and oil inventory demand shocks. This implies that the oil inventory demand shock cannot be responsible for the comovement in commodity prices. 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, 2012). 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 (2012). Overall, there is not a large heterogeneity in the correlations between oil prices and the prices for each commodity sector.

[Figure 4 about here]

[23] The results are not presented here to preserve space but are available upon request.

[24] 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 the distribution of global supply and demand for each of these commodities.

5 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 DFM 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 small scale VARs are not informationally sufficient to identify the shocks. Therefore, we use a set of factors to summarize the bulk of aggregate fluctuations in our data. We show that the inclusion of a large information set matters. The DFM 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 (2012) and further supports the idea that the speculative 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, suggesting that they may not be 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. 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 (in the DFM).

Table 2. 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
	DFM	0.0814	0.1943	0.4160
2	VAR-KM	0.0732	0.1997	0.6259
	VAR-AIP	0.1162	0.2379	0.5212
	DFM	0.0641	0.1245	0.4733
3	VAR-KM	0.0351	0.1623	0.6920
	VAR-AIP	0.0784	0.2528	0.5439
	DFM	0.0349	0.1002	0.5228
4	VAR-KM	0.0280	0.1361	0.7128
	VAR-AIP	0.0655	0.2805	0.5327
	DFM	0.0281	0.0848	0.5520
8	VAR-KM	0.0306	0.0687	0.7766
	VAR-AIP	0.0868	0.1846	0.5993
	DFM	0.0384	0.0702	0.5672
12	VAR-KM	0.0307	0.0837	0.7613
	VAR-AIP	0.0879	0.2019	0.5814
	DFM	0.0477	0.1072	0.5354

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 3. Variance Decomposition of the Real Oil Price (DFM)

Horizon	Oil Supply	Oil Inventory Demand	Global Demand	Speculative
1	0.0737	0.0944	0.3208	0.1158
2	0.0532	0.0410	0.3492	0.1441
3	0.0338	0.0293	0.3867	0.1383
4	0.0276	0.0266	0.4290	0.1153
8	0.0539	0.0595	0.4037	0.0622
12	0.0723	0.1155	0.3496	0.0627

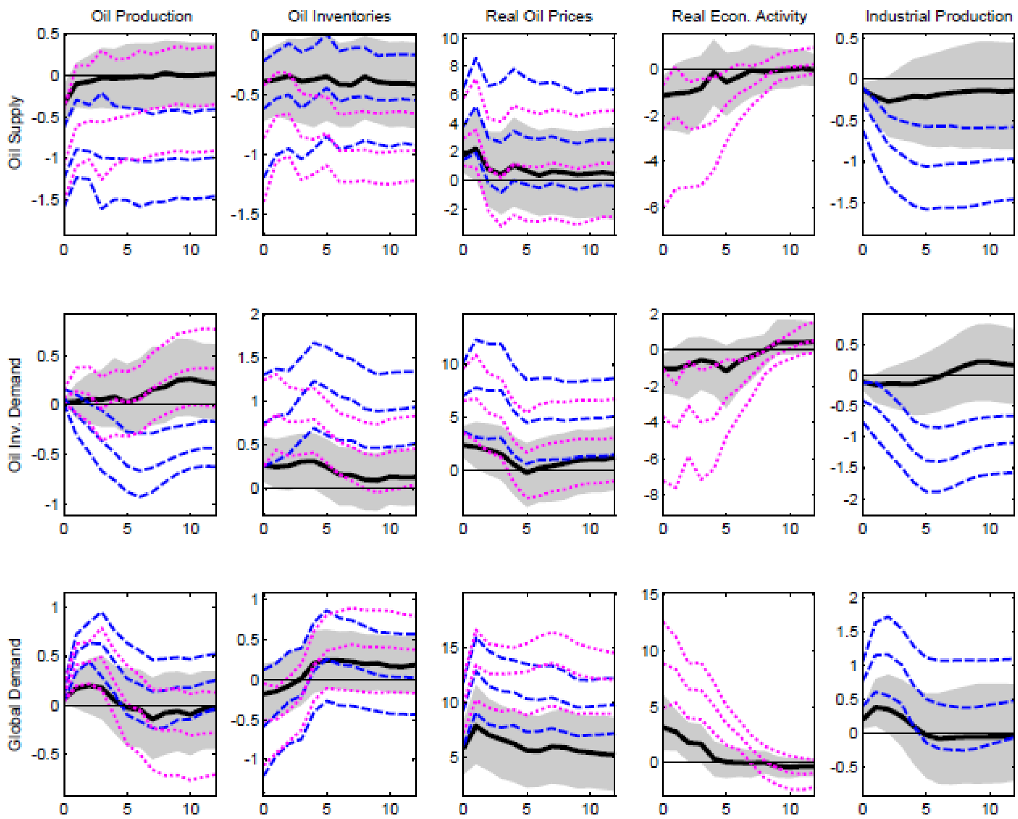
Table 4. Variance Decomposition of Oil Inventories (DFM)

Horizon	Oil Supply	Oil Inventory Demand	Global Demand	Speculative
1	0.1971	0.1375	0.1568	0.0993
2	0.1971	0.1344	0.1681	0.0893
3	0.1430	0.1976	0.1432	0.1052
4	0.1855	0.2241	0.1107	0.1092
8	0.3553	0.0506	0.1685	0.0941
12	0.2831	0.1955	0.0660	0.0539

Table 5. Variance Decomposition of Oil Production (DFM)

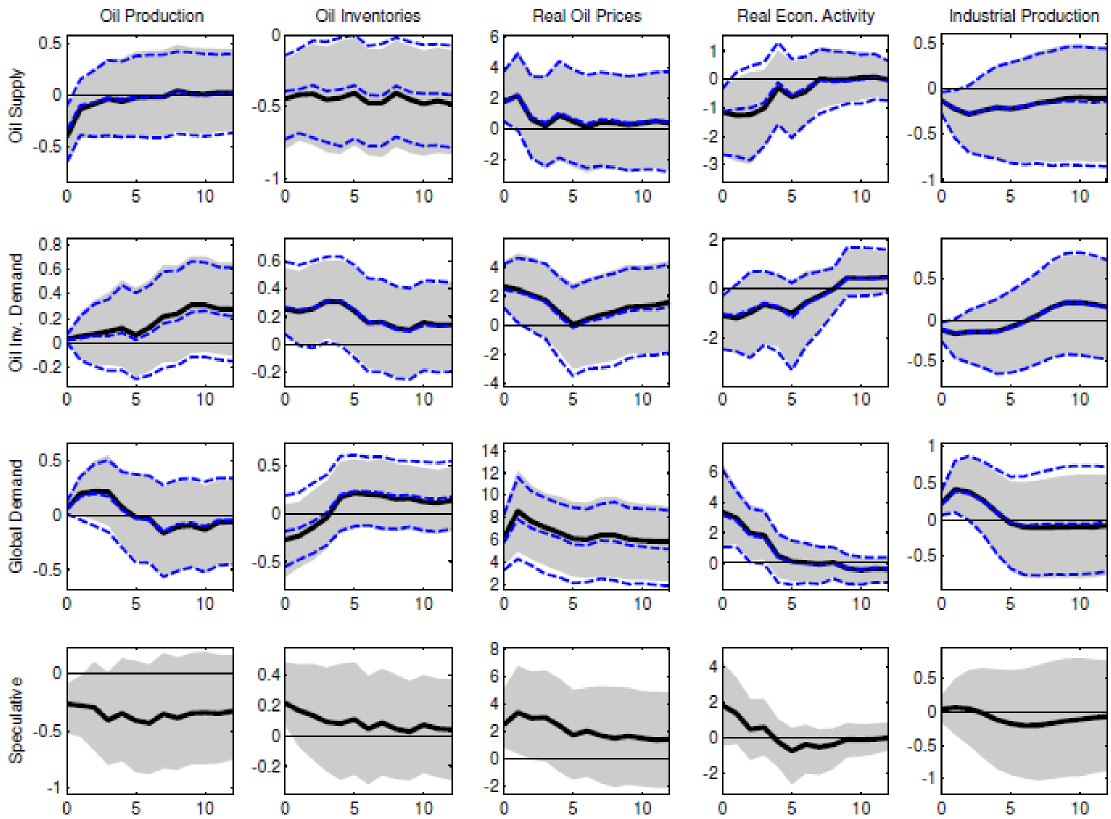
Horizon	Oil Supply	Oil Inventory Demand	Global Demand	Speculative
1	0.3269	0.0036	0.0117	0.1929
2	0.0836	0.0617	0.2053	0.1989
3	0.0855	0.0805	0.1852	0.1702
4	0.0835	0.0632	0.1981	0.1852
8	0.1827	0.1357	0.1109	0.1621
12	0.2352	0.1587	0.0943	0.1349

Figure 1. Impulse Responses: VARs and DFM (3 shocks)



Notes: The figure shows the impulse responses to oil supply, oil inventory demand, and global demand shocks using a DFM and VAR with sign restrictions. The black bold lines denote the median impulse responses from the DFM and the shaded areas represent the 16th and 84th percentile bootstrapped error bands. The pink lines represent the median impulse responses and 16th and 84th percentile bootstrapped error bands from the VAR-KM. The blue lines are the impulse responses and 16th and 84th percentile bootstrapped error bands for the VAR-AIP.

Figure 2. Impulse Responses: DFM



Notes: The figure shows the impulse responses to oil supply, oil inventory demand, global demand, and speculative shocks using a DFM with sign restrictions. The black bold lines denote the median impulse responses from the DFM and the shaded areas represent the 16th and 84th percentile bootstrapped error bands. The blue lines represent the median impulse responses and 16th and 84th percentile bootstrapped error bands for the DFM with 3 shocks (oil supply, oil inventory demand, and global demand shocks).

Figure 3. Historical Decomposition of the Oil Price for the Last Decade

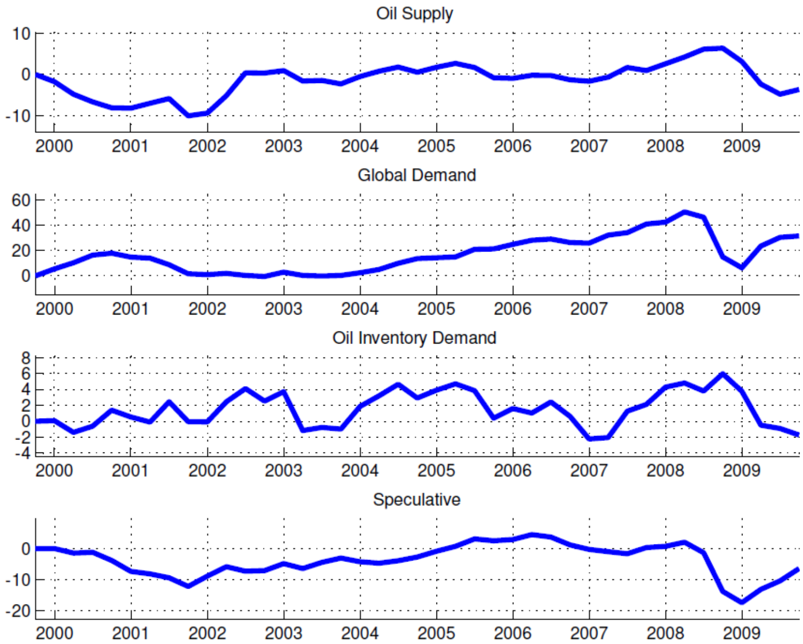
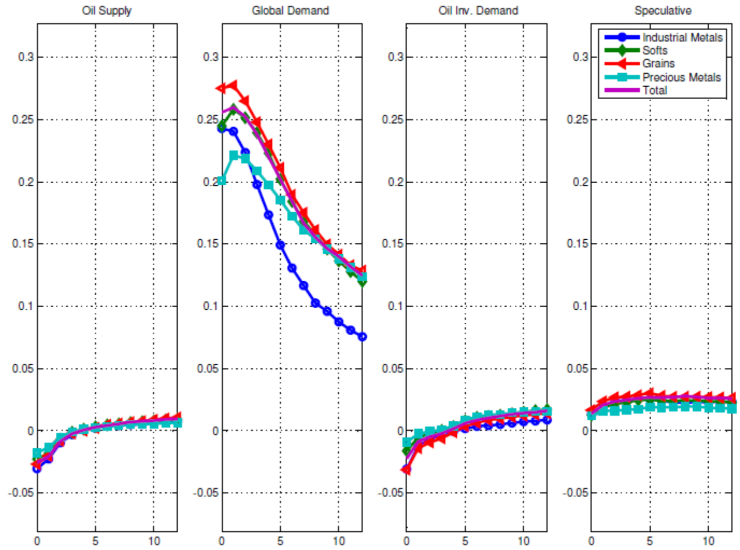


Figure 4. Conditional Correlations



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, softs, grains, and precious metals. Industrial metals include copper, aluminium, nickel, iron ore, and zinc; softs are composed of cotton, tobacco, sugar, coffee, and cacao; grains are sunflower oil, palm oil, soybeans, wheat, rice, and maize; precious metals include gold and silver.

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.

Appendix B: 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:

$$F_X'(X_t, I_t) = \frac{P_t}{G_t}, \tag{B1}$$

$$P_t + \mathbb{C}'(I_{t+1}) = \frac{G_{t+1}F_I'(X_{t+1}, I_{t+1}) + P_{t+1}}{1+r_t}. \tag{B2}$$

Equation (B1) 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. Equation (B2) is implied by optimal inventory management. 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:

$$\Delta I_{t+1} = Q_t - X_t. \tag{B3}$$

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

$$F(X_t, I_t) = \frac{\exp(\gamma_t)}{G_t^{\beta}}, \tag{B4}$$

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 (B1) with (B4):

$$P_t = \left[\frac{\exp(\gamma_t)}{F(X_t, I_t)}\right]^{\frac{1}{\beta}} F_X'(X_t, I_t). \tag{B5}$$

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 (B2) as

$$P_t = \frac{G_{t+1}F_I'(X_{t+1}, I_{t+1}) + P_{t+1}}{1+r_t} - \mathbb{C}'(I_{t+1});$$

therefore implying a downward sloping demand, where $I_{t+1} = D_{Inv}(P_t, P_{t+1}, G_{t+1}, X_{t+1}, r_t)$, and P_{t+1} acts as a forward shifter of the curve (i.e. $D'_{Inv, P_{t+1}} > 0$). Similarly, (B5) also implies a downward sloping demand curve, $X_t = D_{Cons}(P_t, \gamma_t, I_t)$, however this does not depend on the future price level.

[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).

The total demand function for oil can be found substituting (B5) and (B2) into (B3), which gives the following relation:

$$Q_t = D_{Inv}\left(P_t, P_{t+1}, G_{t+1}, X_{t+1}, r_t\right) - I_t + D_{Cons}\left(P_t, \gamma_t, I_t\right). \tag{B6}$$

This shows that a change in the future oil price leads to a shift in demand, through 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:

$$\Pi_t = \sum_{\tau=t}^{T} \frac{1}{\prod_{s=t}^{T}\left(1+r_s\right)} \left[P_\tau Q_\tau - C\left(Q_\tau, \mathbb{Q}_\tau\right)\right], \tag{B7}$$

given the resource constraint

$$R_t = R_{t-1} - Q_t + e_t, \tag{B8}$$

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 supply shock.

Following Farzin (1992), the total extraction cost at time t is given by a twice continuously differentiable function $C_t = C\left(Q_t, \mathbb{Q}_t\right)$. 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 for the above optimization problem imply

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

and

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

[3] The demand function (B6) also illustrates propagation of other shocks. In fact, a global demand shock incorporated into γ_t implies an upward shift of the demand curve (specifically, a shift of current consumption D_{Cons}). Moreover, any shift of the convenience yield, such as the one modelled in Alquist and Kilian (2010), also implies an increase in total demand (this would be the precautionary demand for oil and will affect D_{Inv}). These shocks do not imply a contemporaneous shift of the supply curve, as it will be clear in 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 amount may vary over time, either due to data revisions or because of new resource discoveries.

[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 $[C\left(Q_t, R_t\right) = \frac{A}{2}Q_t^2 + B\left(\Re_t - R_t\right)]$, is the best-performing specification using North Sea data.

The Lagrange 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

$$P_t - C'_Q(Q_t, \mathbb{Q}_t) - C'_{\mathbb{Q}}(Q_t, \mathbb{Q}_t) = \frac{P_{t+1} - C'_Q(Q_{t+1}, \mathbb{Q}_{t+1})}{1+r_t}, \tag{B9}$$

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 (B9) was restored.[7]

The Impact Effect of a Speculative Shock

The equilibrium is given by the intersection of the demand function, (B6), with the supply function, (B9). 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 (as B2 suggests), resulting 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, depicted in Figure B1, represents what we refer to as the oil inventory demand shock.[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 (B9) 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, opposite movements of demand and supply will, in any case, imply a large jump in the current oil price. Figure B2 plots the speculative shock and 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. As we discussed, this is actually not clear a priori, and that is the reason why we take this case as a "conjecture" by Hamilton (2009a). The model helps us understand what conditions are necessary for this

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

[8] This is the case considered in Kilian and Murphy (2011a). However, we emphasize that a similar picture would emerge as a result of a precautionary demand shock such as the one considered in Alquist and Kilian (2010), and also as a result of an expected shortfall in production (see B2 and B6).

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

configuration 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).

Figure B1. Oil Inventory Demand Shock

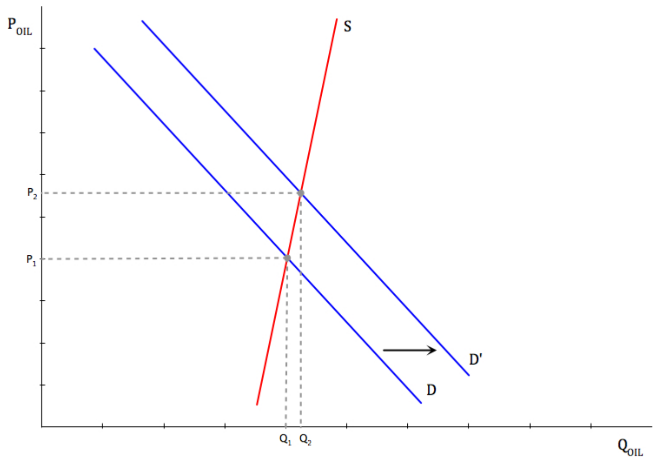
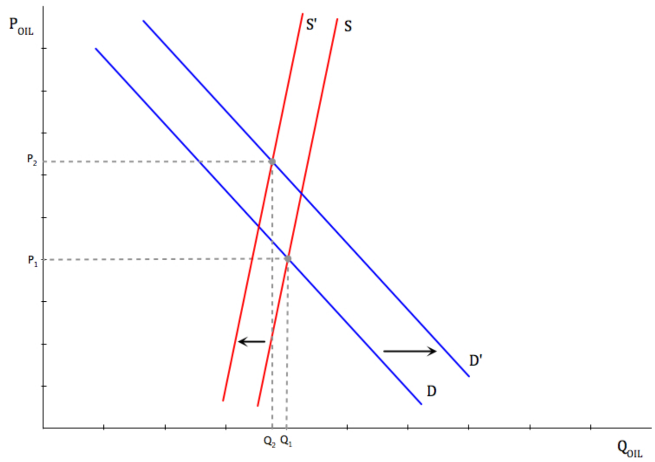


Figure B2. Speculative Shock



Appendix C: Sufficient Information and the Choice of Factors

We use the procedure introduced by Giannone and Reichlin (2006) and 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. We set the maximum number of factors to be $r = 6$ and extract the corresponding 6 factors.[1] Then, we test whether the factors Granger-cause the variables of the VAR. If the null of no Granger causality is not rejected for any of the successive combinations of the factors, 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 C1 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 two variants of a 4-variable VAR, which include oil production, oil inventories, the real oil price, and a proxy for real economic activity. The first column presents the p-value for the null that the first six factors 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 factors. This implies that the VAR is not informationally sufficient and motivates the use of a DFM to identify the shocks. Since the null is rejected, we proceed by augmenting the VAR with factors until we fail to reject the null. In the VAR-AIP, we are not able to reject the informational sufficiency of the DFM once 3 factors are added to the baseline VAR. By contrast, in the VAR-KM, we are not able to reject the informational sufficiency of the DFM once 5 factors are added to the baseline VAR. To reach a balance between the two specifications, our model includes 4 factors. However, our results are robust to the estimation of the DFM with 3 or 5 factors.

Despite the rejection of the informational sufficiency of the VAR, some shocks could still be correctly identified from the low-dimensional VAR. This is true whenever the identified structural shocks from the VAR are orthogonal to any available information at time t (for example, lagged values of the factors). Otherwise, the identified shock cannot be considered structural (Forni and Gambetti, 2011). In this subsection we further investigate the role played by the information set by implementing an orthogonality test for each of the shocks.

Given that the identification by sign restrictions does not identify a single model, we investigate the orthogonality of the shocks over all sets of identified impulse responses. Table C2 shows the percentage of rejections of the F-test of orthogonality for each of the shocks identified from the VARs with sign restrictions. 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 for the VAR-AIP suggest that a linear combination of 4 factors Granger-causes 92% of all the identified oil supply shocks, 97% of all the identified oil inventory demand shocks, and 95% of all the identified global demand shocks. Similarly, results for the VAR-KM show that a linear combination of 4 factors Granger-causes 91% of all the identified supply shocks, 69% of all oil inventory demand shocks and 48% of all identified global demand shocks. These results reinforce the results obtained using the information sufficiency test: The shocks identified from a low-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 a low-dimensional VAR with a set of factors.

[1] The factors are extracted from model (1)-(3) assuming that there are no measurement errors in (2). The results would be qualitatively similar if we had performmed the test using the first 6 principal components in the data, or including a measurement error in (2).

Table C1. Test for Sufficient Information

	VAR	VAR+1F	VAR+2F	VAR+3F	VAR+4F	VAR+5F
			VAR-AIP			
1F	0.0200	—	—	—	—	—
2F	0.0000	0.4500	—	—	—	—
3F	0.0000	0.2600	1.0000	—	—	—
4F	0.0000	0.0200	0.4733	0.9133	—	—
5F	0.0000	0.0333	0.2633	0.6500	1.0000	—
6F	0.0000	0.0000	0.0000	0.1533	0.9700	1.0000
			VAR-KM			
1F	0.0133	—	—	—	—	—
2F	0.1367	0.2767	—	—	—	—
3F	0.0167	0.3333	0.7433	—	—	—
4F	0.0100	0.0133	0.4400	0.9867	—	—
5F	0.0000	0.0000	0.0000	0.0033	0.0100	—
6F	0.0000	0.0000	0.0000	0.0000	0.0000	0.9933

Notes: Bootstrapped p-values of the Granger causality test for the VAR and VAR augmented with factors. AIP-VAR denotes that the VAR was estimated using aggregate industrial production. KM-VAR denotes that the VAR was estimated using the Kilian measure of real economic activity.

Table C2. Orthogonality Test

	Oil supply	Oil inventory demand	Global demand
		VAR-AIP	
4 Factors	0.9240	0.9700	0.9510
		VAR-KM	
4 Factors	0.9110	0.6980	0.4800

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. VAR-AIP denotes that the VAR was estimated using aggregate industrial production. VAR-KM denotes that the VAR was estimated using the Kilian measure of real economic activity.