WP/14/218

IMF Working Paper

Oil Price Volatility and the Role of Speculation

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INTERNATIONAL MONETARY FUND

 WP/14/218

IMF Working Paper

Research Department

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December 2014

Abstract

How much does speculation contribute to oil price volatility? We revisit this contentious question by estimating a sign-restricted structural vector autoregression (SVAR). First, using a simple storage model, we show that revisions to expectations regarding oil market fundamentals and the effect of mispricing in oil derivative markets can be observationally equivalent in a SVAR model of the world oil market à la Kilian and Murphy (2013), since both imply a positive co-movement of oil prices and inventories. Second, we impose additional restrictions on the set of admissible models embodying the assumption that the impact from noise trading shocks in oil derivative markets is temporary. Our additional restrictions effectively put a bound on the contribution of speculation to short-term oil price volatility (lying between 3 and 22 percent). This estimated short-run impact is smaller than that of flow demand shocks but possibly larger than that of flow supply shocks.

JEL Classification Numbers: E32, D84, F02, Q41, Q43, Q48

Keywords: oil and the business cycle; crude oil speculation and inventories; demand and supply shocks; oil price volatility; vector autoregression (VAR)

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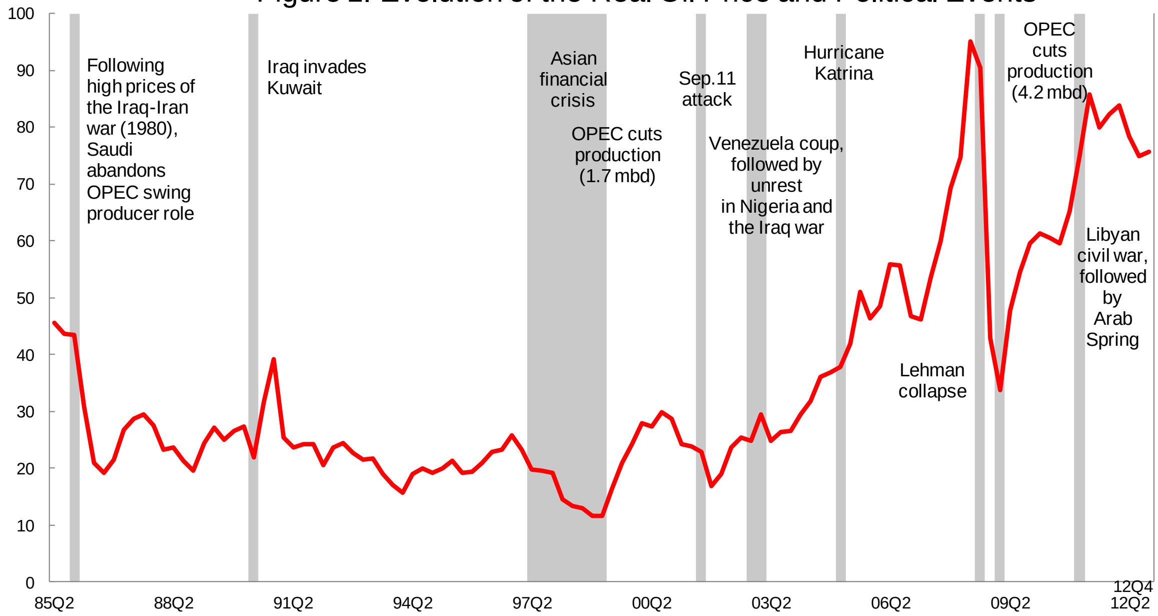
I. Introduction[1]

In a seminal contribution, Kilian (2009) broke with the tradition of assuming most oil price changes reflect exogenous supply shocks, emphasizing that fluctuations in global crude oil spot prices also reflect global economic conditions (Figure 1).[2] Using a structural vector auto regression (SVAR), he showed that global *flow* supply shocks have actually contributed very little to oil price movements when compared to global *flow* demand shocks, especially in the last decade. A question that naturally arises, though, is whether flow oil production and flow demand alone can span the entire spectrum of factors that can drive the real price of oil.

Figure 1. Evolution of the Real Oil Price and Political Events



Sources: IMF, Primary Commodity Price System; IMF Global Data Source. Note: The nominal price is deflated by the US CPI, 2010=100.

If storing oil were prohibitively expensive (both above and below ground) then the answer to the above question would be yes, since the only forces able to determine the oil price would in that case be captured by current demand and production conditions. However, since it is possible to store oil, changes in oil inventories are possibly a third driver behind oil price fluctuations. Of particular interest are changes in the demand for inventories arising

[1] We thank Christiane Baumeister, Olivier Blanchard, Olivier Coibion, Jörg Decressin, Thomas Helbling, and Lutz Kilian (for suggestions on an earlier draft); Daniel Rivera Greenwood and Marina Rousset (for research assistance); Michael Harrup and Anduriña Espinoza-Wasil (for editorial and administrative assistance, respectively); and RES seminar participants (for helpful discussions). Without implication, we are grateful for oil-market insights from: Fatih Birol, John Brunton, Bassam Fattouh, David Fyfe, Fabio Gabrieli, Antione Halff, Daniel Jaeggi, Olivier Jakob, Giles Jones, Jason Lejonvarn, Benoit Lioud, Donal O'Shea, Amrita Sen, and Joerg Spitzy. The usual disclaimer applies.

[2] In a theoretical context, Backus and Crucini (2000) and Nakov and Pescatori (2010) also highlighted the importance of distinguishing the source of shocks behind oil price movements.

from speculative motives, that is, changes driven by expectations of future price changes.[3] Indeed, Kilian and Murphy (2013) have extended the Kilian (2009) model, identifying speculative demand shocks and including oil inventories as an additional variable.

In a rational expectations world, speculation reflects the forward-looking nature of economic agents who manage inventories to smooth their oil consumption and production over time—paying attention to the expected future path of the oil price. Moreover, in a rational expectations world, such speculation helps to stabilize spot prices when there are temporary demand or supply shocks. For example, if spot prices rise (fall) because flow production (demand) temporarily drops due to a supply (demand) shock, inventory holders can realize profits by selling (buying) stocks, which they can replenish (sell) later at a lower (higher) price. This release (stocking up) of inventories will increase (decrease) the effective supply in the market, which in turn will dampen (push up) the spot price response to the supply (demand) shock.

From this vantage point, speculative demand simply represents rational decisions of adjusting above-the-ground holdings of oil inventories in anticipation of price movements as new information arrives on future market conditions. In other words, economic agents manage inventories to smooth their oil consumption and production over time, given the expected future path of the oil price. Changes in speculative demand are therefore a response to expected changes in *oil market fundamentals*—also known as *news shocks* (à la Jaimovich and Rebelo, 2009), such as oil discoveries, expectations of production disruptions, backstop technologies, and changes in world real interest rates or in global demand growth.[4]

In recent years, however, there have been strong concerns that the emergence of commodity derivatives as an asset class has led to destabilizing speculation. In the Kilian and Murphy (2013) model, this concern would manifest itself in destabilizing shocks to inventory demand. In other words, the claim would be that inventory demand has responded to changes in oil futures prices that are not firmly grounded in new information about future oil market fundamentals, including changes in economic activity. Or differently put, oil futures prices, similar to other commodity futures prices, have reflected a greater incidence of noise trading or other anomalies (à la Fama, 1998; and Singleton, 2011). Such concerns about destabilizing speculation have been a constant refrain in recent years despite the lack of conclusive supporting evidence (IMF, 2011b; Fattouh, Killian and Mahadeva, 2012; Büyükşahin and Robe, 2012; Knittel and Pindyck, 2013; and Kilian and Lee, 2013).

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[3] In addition to speculation, oil-specific demand shocks may affect oil prices. Even though these shocks are captured in our framework, they will not be at the center of our discussion.

[4] It is important to clarify that "news" has been used in the finance literature to mean the difference between expectations and outcomes. For example, Kilian and Vega (2011) test whether oil prices react to macroeconomic news from U.S. data releases, where macroeconomic news is defined as the difference between ex ante survey expectations and the subsequently announced realizations of macroeconomic aggregates.

In this paper, we attempt to explore the short-term effects of speculative oil demand shocks studied by Kilian and Murphy (2013) (henceforth KM) in greater detail. Using their framework, we cannot distinguish between speculative demand shocks driven by *news about fundamentals* and those driven by *noise trading*. However, we further narrow the set of admissible models by limiting the contribution of speculative demand shocks to the long-run oil price forecast error variance (in addition to the restrictions used in KM). In other words, we seek to identify a range for the response of oil prices (i.e., oil price volatility) to speculative demand shocks by imposing restrictions on the time horizon in which noise trading and other factors affect oil markets.

The rationale for our additional restrictions is as follows: while we cannot a priori exclude noise trading and other anomalies in oil futures markets in times of rapid structural change, we can plausibly assume that such anomalies will not last. Arbitrage by fundamental traders should ensure that prices are in line with fundamentals. Specifically, our null hypothesis is that only oil market *fundamentals* (or news about them) can induce low-frequency movements in oil prices. To be more concrete, oil discoveries (which have long lags before coming on stream) or revisions to potential growth of major economies (e.g., China, Japan, or the United States) must have a very *persistent* effect on the oil price. Under the null hypothesis, mispricing in the futures market (i.e., noise trading by financial speculators) is a temporary anomaly that does not contribute to low-frequency price movements. Therefore, it is possible to set a bound on its contribution to oil price volatility by restricting our attention to the admissible model that minimizes the oil price forecast error variance contribution of speculative shocks at long horizons (i.e., 20 years). Furthermore, even though other fundamental shocks may have only temporary effects on oil prices (for example, an anticipated *temporary* production shortfall), we would still be able to interpret our results as a short-run upper bound to the role played by financial and non-financial speculative shocks.[5] Indeed, given that we employ data on crude oil inventories to estimate this upper bound, it is actually an upper bound for the oil price response to *any speculative demand shock*, regardless of its motive.

The paper's contribution is mainly twofold. First, we show that news shocks on oil market fundamentals, mispricing in the oil futures market, and global real interest rate shocks can manifest themselves as speculative demand shocks under the KM identification strategy. Second, we propose a novel manner for putting a plausible bound on the contribution of financial speculation to short-term oil price volatility.

Our key findings are as follows. First, we find that typical speculative demand shocks in the crude oil market may increase or decrease the real oil price on impact between 10 and 35 percent, contributing to short-run oil price volatility. This estimated short-run impact is

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[5] As a corollary, for a *temporary* demand weakness, we would find a short-run *lower* bound to the role played by financial and non-financial speculative shocks.

smaller than that of flow demand shocks, but importantly larger than that of flow supply shocks. Second, we find that it matters what type of speculative demand is identified (from an *economic* rather than *statistical* point of view) for the historical decomposition. When speculative demand is confined to be short in duration, with small long-run effects on the real oil price, the run up in oil prices during 2003–08 can be attributed initially to flow oil demand shocks. But this is joined by speculative demand shocks after 2005—with the same drivers re-emerging again during 2011–12. Third, when we allow for speculative demand shocks to have larger effects in the short and long run, flow oil demand shocks lose explanatory power. In this case, we estimate speculative demand shocks to have contributed over 22 and 13 percent to the short- and long-run real oil price forecast error variance, respectively.

The remainder of this paper is organized as follows: Section II provides a selected literature overview; Section III develops a simple oil storage model of speculation; Section IV describes the data, VAR model methodology, identification issues and results. We conclude in Section V by drawing out the substantive implications of our analysis.

II. Literature Review

KM is the first paper that generalizes the structural oil market models pioneered by Kilian (2009), Kilian and Murphy (2012), and Baumeister and Peersman (2012), using data on oil inventories to identify the speculative demand component of the real oil price. The KM identification strategy rests on the assumption that unobservable shifts in expectations about future oil prices must be reflected in shifts in the demand for above-ground crude oil inventories (we confirm the theoretical validity of this assumption in the next section). The main finding of KM is that speculative demand played only a modest role in the real oil price buildup of 2003–08.[6] This result was later confirmed by Kilian and Lee (2013). Juvenal and Petrella (2011) instead have found a substantial role for financial speculation.[7]

Knittel and Pindyck (2013), using a reduced-form approach, assess whether speculation in (mainly) oil futures markets, as a driver of price changes, is consistent with the data on production, consumption, inventory changes, and spot and futures oil prices (given reasonable assumptions about elasticities of supply and demand).[8] They show that although they cannot rule out the possibility that speculation had any effect on oil prices, speculation as an explanation for the sharp changes in prices can be ruled out for the period since 2004.

[6] KM (2013) defines a speculator, from an economic point of view, as “anyone buying crude oil not for current consumption, but for future use.”

[7] Results in Juvenal and Petrella (2011) have been questioned by L. Kilian, see http://www.econbrowser.com/archives/2012/07/guest_contribut_21.html.

[8] They define speculation as “the purchase (or sale) of an oil-related asset with the expectation that the price of the asset will rise (or fall) to create the opportunity for a capital gain.”

They argue that, unless one believes that the price elasticities of both oil supply and demand are close to zero (a conjecture initially put forward by Hamilton, 2009), the behavior of inventories and futures-spot spreads are simply inconsistent with the view that speculation was a significant driver of spot prices over that period. Across their sample, speculation decreased prices on average or left them essentially unchanged and reduced peak prices by roughly 5 percent.

A common feature of the above papers is that their definition of speculation does not distinguish whether it is related to fundamentals or not—or, more generally, what induces speculative demand shocks.

Another strand of the literature has instead focused on a narrower definition of speculation which is mainly related to the possible malfunctioning of commodity financial derivative markets (à la Fama, 1998). Masters (2008) blames the oil price spike of 2007–08 on the actions of investors who bought oil futures not as a commodity to use but as a financial asset. He argues that by March 2008, commodity index trading funds (ITFs) holding a quarter of a trillion U.S. dollars' worth of futures contracts were able to push the spot price up dramatically—however, no coherent testable model is provided. Alquist and Kilian (2010), Liu and Tang (2010), and Tang and Xiong (2010) find a structural break in the spot oil price post-2004. The latter attribute it to institutional investors entering the futures market, which then led the spot price to rise higher, moving more closely with the "risk premium" of the stock market.

To rationalize deviations from fundamentals, Singleton (2011) evokes the beauty contest of Keynes, stressing that participants in oil futures markets may form expectations not only in terms of expected fundamentals, but also in anticipation of other market participants' actions.[9] He explores the impact of "active" investor flows and financial market conditions on returns in crude oil futures markets. Singleton (2011) shows how financial and informational frictions and the associated speculative activity induce prices to drift away from "fundamentals" and thus show increased volatility. He finds significant empirical support that financial activities are likely to drive the spot oil price away from fundamental values, primarily through investor flows influencing excess returns from holding oil futures contracts of different maturities. Various micro studies using confidential data of the Commodities Future Trading Commission, however, have struggled to find evidence that

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[9] This builds on earlier studies that showed that heterogeneity of expectations leads investors to overweigh public opinion and this, in turn, exacerbates volatility in financial markets. In addition to excessive volatility, differences of opinion can give rise to drifts in commodity prices and momentum-like trading (herding) in response to public announcements. Likewise, there is a concern that some market participants may overreact to or misinterpret public information or signals that do not reflect large changes in underlying fundamentals. This concern seems particularly pertinent when new market participants lack the expertise to understand oil market developments.

non-commercial players have been able to influence oil (or more generally, commodity) price movements (e.g., Büyükşahin and Robe, 2012).

III. A Storage Model of Speculation

In this section we present a simple storage model of the oil market, in the spirit of Scheinkman and Schechtman (1983), to guide our identification strategy.

Assume refiners need oil to produce a final good, Y, (e.g., gasoline) that can be sold in a competitive market at a price, P_y. To produce Y refiners can use a linear production technology that requires oil, X, as an input, $Y = AX$, where A is a productivity shifter. Oil is sold competitively in the spot market at a price P_o and, after being purchased, it can be stored as inventory, S, at a cost, $\kappa(S) \geq 0$, that is paid up front—where $\kappa: [0, \infty] \to [0, \infty]$ is a twice-differentiable function with $\kappa(0) = 0$ and $\kappa'(S) \geq 0$.

Inventories have the benefit of reducing the risk of stockouts, which is captured, following the literature, by introducing a convenience yield $c(S) \geq 0$—where S is the stock of inventories at the beginning of the period and $c: [0, \infty] \to [0, \infty]$ is a twice-differentiable function with $c(S) = 0$, $c'(S) \geq 0$, and $c''(S) \leq 0$ (Working, 1934; Kaldor, 1939; Brennan, 1958; and Telser, 1958).[10] We express the convenience yield in terms of final output, $P_{y,t}$.[11]

Assuming that refiners discount future profits through the pricing kernel $\beta M_{t,t+1}$ and that the flow of oil production is Z, we have

$$\max \;\; E_0 \sum_{t=0}^{\infty} \beta^t M_{t,t+1}\left[P_{y,t} A X_t - P_{o,t} Z_t + P_{y,t} c(S_{t-1}) - \kappa(S_t)\right]$$

$$s.t. \;\; \Delta S_t = Z_t - X_t \tag{1}$$

where E_t is the rational expectation operator based on time t information.

Setting A = 1, without loss of generality, necessary conditions for optimality imply

$$P_{y,t} = P_{o,t} \tag{2}$$

and, exploiting equation (2), we obtain

$$P_{o,t} + \kappa'(S_t) = \beta[1 + c'(S_t)] E_t M_{t,t+1} P_{o,t+1} \, . \tag{3}$$

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[10] The convenience yield is the flow of services that accrues to an owner of the physical commodity but not to the owner of a contract for future delivery of the commodity.

[11] This assumption, which seems natural in this framework, has also the benefit of simplifying the algebra.

Equation (2) equates the oil price (in terms of final output) to its marginal productivity, which is a necessary condition for an interior solution, while equation (3) is an inter- temporal Euler equation that equates the marginal cost of storing an additional unit of oil inventory to its discounted expected marginal benefit.

Let us assume an isoelastic demand function for gasoline with an elasticity parameter $\eta \geq 0$. Two types of shocks can shift the demand schedule: a shock known at time *t*, $\varepsilon_{x,t}$, and a shock known *k* periods in advance, $\nu_{x,t-k}$. We will refer to the latter as a news shock—consistent with the business cycle literature, à la Jaimovich and Rebelo (2009). Equating demand and supply of Y we derive an oil demand equation (using lowercase letters for logs)

$$x_t = -\eta_x p_{o,t} + \varepsilon_{x,t} + \nu_{x,t-k}. \tag{4}$$

For simplicity, we assume an inelastic oil production function (also expressed in logs)

$$z_t = \eta_z p_{o,t} + \varepsilon_{z,t} + \nu_{z,t-k} \tag{5}$$

where oil production shifters $\varepsilon_{z,t}$ and $\nu_{z,t-k}$ are known at time *t* and *k* periods in advance, respectively.[12]

We now introduce explicitly the futures (or forward) commodity market, where refiners can buy (sell) commodity futures contracts for delivery in the next period: we define $F_{t,t+1}$ as the futures price agreed at time t to be paid for delivery of a commodity at $t+1$. This means that the expected marginal benefit of buying (selling) oil tomorrow in the refiners' inter-temporal Euler equation can be evaluated by using the futures price (known and fixed at time *t*) instead of a future spot price not yet known at time *t*. Hence, analogous to equation (3) where $P_{o,t}$ is now replaced by $F_{t,t+1}$ holds

$$P_{o,t} + \kappa'(S_t) = \beta[1 + c'(S_t)]F_{t,t+1}E_t M_{t,t+1}. \tag{6}$$

Combining equation (3) and equation (6) yields a standard relation between the future spot and forward oil price:

[12] Hamilton (2009) notices that if the elasticities of both demand and production are zero (i.e., $\eta = 0$ and $Z_{p,t} = 0$), the marginal cost of holding additional inventories is negligible, $\kappa' = 0$, and the marginal convenience yield is constant, $c' = \bar{c}$, then the system described by equations (1), (2), (4), and (5) pins down quantities and relative prices such that equation (3) becomes redundant. More precisely, equation (3) is defined up to a constant, which means that the oil price level is undetermined. Clearly, the assumptions required to have indeterminacy are extreme. However, it is conceivable that in the short run those conditions (especially the near zero price elasticity of production and demand of oil) may be a satisfactory approximation of the oil market, at least locally. In this case, mispricing in the oil futures market could play a role in affecting the spot price and "it might conceivably take some time before mispricing arising from the futures markets would be recognized and corrected" (Hamilton 2009).

$$F_{t,t+1} = \frac{E_t M_{t,t+1} P_{o,t+1}}{E_t M_{t,t+1}} = E_t P_{o,t+1} + \frac{\text{Cov}(M_{t,t+1}, P_{o,t+1})}{E_t M_{t,t+1}}. \qquad (7)$$

Equation (7) suggests that the futures price is equal to the expected future spot price plus a risk premium. Futures prices are, thus, determined residually from the rest of the system, that is, equations (1)–(5), through equation (6) (or, equivalently, equation (7)). In other words, causality does not run from futures to spot prices but runs in the opposite direction. Loosely speaking, in this case futures prices are determined by *fundamentals*—that is, there is no "mispricing." We will refer to the system (1)–(6) as a *fundamental system* and its associated variables as fundamental values which will be denoted by an asterisk, for example, $F^*_{t,t+1}$.

To introduce the possibility of deviations from fundamentals (i.e., *mispricing*) in the futures market we postulate the following simple equation:

$$\log(F_{t,t+1}) = \log(F^*_{t,t+1}) + \omega_t, \qquad (7')$$

where ω_t is a stationary process that represents a shock that makes the actual futures price deviate from its fundamental value $F^*_{t,t+1}$.[13] Contrary to equation (7), equation (7′) is not a combination of equations (3) and (6). Thus the system given by equations (1)–(6), and (7′) is over-identified: to have a well-identified system, we need to drop one equation. It is reasonable to drop equation (3), which is the inter-temporal equation describing the optimality condition of refiners. The new system, given by equations (1), (2), (4), (5), (6), and (7′), can no longer be split into two blocks where the futures price is determined residually from the rest of the system.[14] Loosely speaking, the no-arbitrage condition that links the futures market to the cash market, equation (6), now describes how futures prices can affect spot prices and inventories. When $\omega_t \equiv 0$, the non-fundamental system becomes or collapses to the fundamental system described above. This also means that the non-fundamental system is oscillating around the fundamental system's steady state.

[13] The economic literature has highlighted various reasons that may limit arbitrage. For example, arbitrage conditions can break down in the presence of some transaction costs or credit frictions that would ultimately induce some forms of market segmentation (Gromb and Vayanos, 2010). In this context, market segmentation may, on the one hand, prevent investors in the futures market from operating in the cash market, and, on the other hand, may prevent investors in the cash market (e.g., refiners)—possibly because of liquidity constraints or risk aversion—from arbitraging away the futures market.

[14] More precisely, the overall system is formed by equations (1), (2), (4), (5), (6), and (7′) and by the fundamental system, equations (1)–(6), necessary to determine fundamental values, such as ${F^*}_{t,t+1}$; hence, the overall system is 12 equations in 12 unknowns.

Interestingly, we can also write a new version of equation (3) where the spot oil price depends on the future expected spot price plus a "*wedge*", $w_{t,t+1}$. This wedge is meant to reflect the deviation of actual expectations of future spot prices from expectations based only on fundamentals:

$$P_{o,t} + \kappa'(S_t) = \beta[1 + c'(S_t)]\left[E_t M_{t,t+1} P_{o,t+1} - w_{t,t+1}\right], \qquad (3')$$

where $w_{t,t+1} = E_t M_{t,t+1}(P_{o,t+1} - P^*_{o,t+1})$ and $P^*_{o,t+1}$ is the fundamental oil price.

First, we focus on the fundamental system by setting $\omega_t \equiv 0$. The (linearized) rational expectation equilibrium can be summarized by two equations (see appendix for details):

$$\begin{cases} s_t^* = \dfrac{\lambda_1}{1+\gamma} s_{t-1}^* - (1+\gamma)^{-1} \displaystyle\sum_{j=0}^{\infty} \lambda_1^{j+1} E_t[\mu_{t+j+1} - \mu_{t+j}] \\ p_{ot}^* = \eta^{-1}(\Delta s_t^* - \mu_t) \end{cases}$$

where $\eta = \eta_z + \eta_x$, while $\lambda_1$is a function of model's parameters satisfying $0 < \lambda_1 \leq 1$ and $\mu_t = \varepsilon_t + \nu_{t-k}$ with $\varepsilon_t \equiv \varepsilon_{z,t} - \varepsilon_{x,t}$ and $\nu_{t-k} \equiv \nu_{z,t-k} - \nu_{x,t-k}$.

It is now possible to summarize the model's predictions in terms of fundamental shocks:

Flow supply shocks. A negative oil production shock ε_z has an unambiguous positive effect on the oil price since $\lambda_1 \leq 1$. The smaller the oil price elasticity, the higher the price impact of the flow supply shock. The impact on inventories is unambiguously negative in case of either *i.i.d*. or persistent but mean-reverting shocks: inventories will be brought down initially to cushion the reduction in production and then, slowly, will reverse back to their steady-state level.[15] Global oil demand unambiguously falls since its price elasticity is strictly positive.

Flow demand shocks. A positive oil demand shock ε_x has an unambiguous positive effect on the oil price for the same reason as the flow supply shocks. Indeed, as before, the impact on inventories is also unambiguously negative. Finally, global oil production unambiguously rises as far as its price elasticity is strictly positive.

Expectations shifts linked to fundamentals (news shocks). The effect of news shocks is quite similar whether they relate to demand or production. Hence, let us assume that at time *t* (today) there is some negative news on oil production in the k^{th} period ahead.

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[15] In the case of autocorrelated shocks, the sign might reverse. Autocorrelation in the exogenous processes has similar, though not identical, features to endogenous autocorrelation in demand and supply (which is what we have in the VAR).

Forecasting excess demand in the k^{th} period ahead has a positive effect on inventories today, hence, contrary to the flow supply shock, inventories unambiguously rise. The increase in oil demand driven by storage motives can take place if oil consumption decrease or oil production increase, hence the spot oil price has to rise. The smaller the elasticity the higher the price increase. Regardless of whether the news is realized or not after the k^{th} period has elapsed, the higher *level* of inventories will put downward pressure on the oil price, overall implying additional volatility.

Joint behavior of oil prices and inventories. Finally, when inventories are above their long-run level, they exert downward pressure on prices. This means that when a shock pushes both the real oil price and inventories higher, we should expect both of them to monotonically decline toward their long-term levels.

Next, we turn to the financial speculation shock, captured by ω_t, which by construction makes the futures price deviates from its fundamental value. It is useful to write the non-fundamental system in deviation from the fundamental system analyzed above. Denoting variables in deviation form from their fundamental value with a tilde (e.g., $\tilde{x}$) we have (see the appendix)

$$\begin{cases} \tilde{s}_t = \dfrac{\tilde{s}_{t-1}}{1+\eta\vartheta} + \eta \dfrac{\tilde{f}_{t,t+1}}{1+\eta\vartheta} \\ \tilde{p}_{ot} = -\vartheta \dfrac{\tilde{s}_{t-1}}{1+\eta\vartheta} + \dfrac{1+\gamma}{1+\eta\vartheta} \tilde{f}_{t,t+1} \\ \tilde{f}_{t,t+1} = \omega_t \end{cases}$$

where $\vartheta = k''(S) - c''(S) \geq 0$.

We can summarize the testable implications as follows:

Financial speculation shock. Movements in futures prices not justified by fundamentals affect oil prices, inventories, and production in the same direction, while oil demand moves in the opposite direction. The speculation shock has an effect on spot oil prices and inventories that resembles that of news shocks, even though, by construction, the deviation is temporary and the system reverts back to its fundamental values.[16]

In sum, we allow speculation in futures markets to generate volatility in physical crude oil inventories and, in turn, spot oil price volatility. Our null hypothesis, however, is that anomalies and bubbles in financial markets are only temporary; thus we expect the

[16] A further difference between news shocks and speculation shocks is that (low) demand or supply oil price elasticities do not directly magnify these types of shocks compared to news and flow shocks previously analyzed.

effects of financial speculation shocks to diminish beyond the short or medium run—contributing little to low-frequency oil price movements. We will evoke this *null hypothesis* in Section IV.D when we add further restrictions to uniquely identify the model's responses to a speculative shock.

IV. An Estimated VAR Model of the Global Oil Market

In this section, we describe the data set, explain our identification and estimation approach, and report our main results. The model is an adaptation of KM, estimated on quarterly data over the sample period of 1983:Q1–2012:Q4.

A. Data

Data on global crude oil production are available from the monthly database of the International Energy Agency (IEA). These data also include lease condensates but exclude natural gas liquids. Oil production is expressed in log-differences in the model. The log of the real price of oil is defined as the U.S. refiners' acquisition cost for imported crude oil, as reported by the U.S. Energy Information Agency (EIA), deflated by the U.S. consumer price index and demeaned.[17]

There are two commonly used proxies for global oil demand, both with shortcomings, albeit different in nature. The first is the Global Activity Index (GAI) introduced by Kilian (2009) and the second is the log-difference of the global industrial production (IP) index (Giese, Nixon, and Tudela, 2010; Baumeister and Peersman, 2012; and Aastveit Bjørnland, and Thosrud, 2012).[18] This paper's choice rests on the second, while being cognizant of its shortcomings.[19]

Conceptually, the GAI is essentially a price index that is used to proxy real activity (quantity). Moreover, not only do the GAI and IP diverge at times, but there is concern that changes in oil prices may affect the GAI contemporaneously—since bunker fuel prices (used

[17] We also employ the log of the IMF average petroleum spot price (APSP), an index of a simple average of UK Brent, West Texas Intermediate (WTI) and Dubai Fateh, which is also demeaned, with similar results, as well as each of UK Brent and WTI oil varieties. For more details see IMF (2013).

[18] The Kilian (2009) index is based on the average deviation of dry cargo ocean freight rates from their trend path across multiple routes and obtained from http://www-personal.umich.edu/~lkilian/reaupdate.txt.

[19] The global industrial production index is available from the online World Economic Outlook database and IMF (2012); the index originates from the Netherlands Bureau for Economic Policy Analysis (CPB) (http://www.cpb.nl/en) and is available for 1991 to the present. As in IMF (2012), the series is spliced with OECD industrial production prior to 1990 to obtain a series going back to the start of the sample period. Splicing per se may not present too much difficulty given that the advanced economies would have accounted for the bulk of world industry prior to 1990. Note that the Baumeister and Peersman (2012) global industrial production index was discontinued in 2008.

for cargo freight shipping in the GAI) and the oil price are correlated. [20] However, Baumeister and Kilian (2013) have compared the forecasting power of the OECD industrial production index and the GAI for the real oil price and have shown that the GAI outperforms the OECD IP index. At the same time, Beckers and Beidas-Strom (forthcoming), employ this paper's IP index in a reduced-form VAR for forecasting purposes to show that it consistently outperforms the futures curve, random-walk models and the same VAR when the GAI is employed, amongst others.[21]

We use total OECD crude inventories provided by the IEA database as a proxy for global inventories and hence speculative demand for oil.[22,23] We transform the crude inventories data by taking level changes, since our model is stationary. Preliminary tests provide no evidence of co-integration between oil production and crude inventories. Moreover, contrary to the findings of Dvir and Rogoff (2013) for the United States, we find no evidence of a trend in the rate of crude oil inventory accumulation in recent years.

B. Model Specification

Our setup is a four-variable, four-lags VAR estimated on quarterly data from 1983:Q1 to 2012:Q4. Variables are as follows: $\Delta prod_t$, is the log-difference in global crude oil production (flow oil production above the ground); $\Delta log\ ip_t$ is the log-difference of the global industrial production index, which captures flow demand for crude oil; $log\ rpo_t$ is the log of the demeaned real price of oil; and $\Delta crinv$ is the level change in OECD crude oil inventories introduced to help identify speculative shocks.[24]

It may seem that our global oil spot market model is incomplete in that it excludes the

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[20] See the appendix for more details on: visual differences between the Global Activity Index and Global Industrial Production Index; visual co-movement between bunker fuels and the oil price; and results of contemporaneous correlations between the GAI and fuel/oil.

[21] Beckers and Beidas-Strom (forthcoming 2013) also *add* interest rates, spreads, and an exchange rate for the USD weighted against currencies of major oil consumers; and *disaggregate* global IP (by emerging and advanced economies) and oil production and demand by regions (OPEC, North America, and the largest oil consuming advanced and emerging economies); and *add* non-commercial futures positions in crude oil as a ratio of total open interest.

[22] The OECD data start in 1983, hence the start of our sample. While data on non-OECD crude oil inventories is not available, some partial individual country data is available, which seems to indicate a coverage of forward demand of well-below OECD levels, at about 40 days. See recent issues of the IEA Monthly Oil Report and Petroleum Intelligence Weekly (available to subscribers). There are also crude inventories held by commodity trading houses and in transit. The fact that our dataset for crude oil inventories is incomplete will likely show up in the residual demand shock of the historical decomposition.

[23] This is a departure from Kilian and Murphy (2012) and (2013), who use data for total U.S. crude oil inventories provided by the EIA, scaled by the ratio of OECD petroleum stocks over U.S. petroleum stocks, also obtained from the EIA. Kilian and Lee (2013) access a *global* inventories database compiled from proprietary data from the Energy Intelligence Group (EIG), a private sector company. Despite the complete dataset, they find the results of KM (2013) largely unaltered.

[24] See the appendix for more details on the model description.

price of oil futures contracts, which is commonly viewed as an indicator of market expectations about future oil prices. As mentioned in section III, this is not the case since, as suggested by Alquist and Kilian (2010) and KM, most of the relevant information is included in the inventory data. This is also consistent with the fact that the oil futures spread does not Granger-cause the variables in our model.

C. Estimation Methodology and Identification

The reduced-form VAR model is consistently estimated by least-squares. We initially partially identify the model using sign restrictions combined with additional empirically plausible bounds on the magnitude of the short-run oil supply elasticity and on the response of global demand.[25]

Initial Specification: Dynamic Sign Restrictions and Elasticities Bounds

Below we summarize the economic intuition behind the imposed sign restriction scheme:

- An unexpected *flow supply shock* is associated with a negative response of oil production (for at least four quarters), a positive response of the real oil price, and lower global activity on impact. Hence, a negative oil supply shock shifts the oil supply curve to the left, lowering the quantity of oil supplied to the market and raising the real oil price, and therefore lowering global economic activity. We do not restrict the response of inventories.
- A *global flow demand shock* induces an increase in real activity (for at least four quarters), shifting the contemporaneous oil demand curve to the right along the oil supply curve, raising the real oil price and stimulating oil production on impact. We do not restrict the response of inventories once again.
- A *speculative demand shock*, whatever its motive, embodies a shift in crude oil inventory demand, and thus is associated with an increase in crude oil inventories and the real price of oil. The accumulation of inventories requires oil production to increase and oil consumption (and hence real activity) to decline.
- Finally, we impose the cross-restriction that over the long term (defined here to be 20 years), declining oil prices have to be associated with no increase in the level of inventories.

The model also includes a *residual oil demand shock* designed to capture idiosyncratic oil-specific demand shocks driven by reasons that cannot be classified as any one of the first three structural shocks (such as changes in inventory technology or preferences, or politically motivated releases of the U.S. Strategic Petroleum Reserve).

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[25] See the appendix for the procedure used to implement the identification.

The admissible models thus take the form—with missing signs denoting that no restrictions are applied:

$$e_t = A\varepsilon_t.$$

That is,

$$\begin{bmatrix} e_t^{\Delta prod} \\ e_t^{\Delta log\ ip} \\ e_t^{\Delta crinv} \\ e_t^{log\ rpo} \end{bmatrix} = \begin{bmatrix} + & + & + & x \\ + & + & - & x \\ x & x & + & x \\ - & + & + & x \end{bmatrix} \begin{bmatrix} \varepsilon_t^{flow\ oil\ supply\ shock} \\ \varepsilon_t^{flow\ demand\ shock} \\ \varepsilon_t^{speculative\ demand\ shock} \\ \varepsilon_t^{residual\ demand\ shock} \end{bmatrix}.$$

Boundary restrictions

In addition to these sign restrictions, following Kilian and Murphy (2012), the model imposes an upper bound on the impact price elasticity of oil supply so as not to generate unrealistically large oil supply responses to demand in the short run and restricts the impact price elasticity of oil demand to be negative and smaller in magnitude than the long-run price elasticity of oil demand. The latter ranges between 0.1 and 0.6 (IMF, 2011a). The price elasticity of oil supply and the price response to flow demand with respect to the speculative demand shock can be expressed as

- $\max_{i \neq 1}({}^{a_{1i}}/{}_{a_{3i}}) < 0.0258 * 3$ —price elasticity of oil supply.[26]
- $-0.1 * std(flow\ demand) < a_{23} < 0.$

Overall, the restrictions imposed narrow the admissible models to about 1,100 from 5 million candidates.

Admissible Set of Impulse Responses

We now turn to reporting the overall behavior of the estimated models across our sample by examining 30 randomly selected models from the full set of admissible impulse response functions (IRFs) (Figure 2).[27] As customary in the literature, the shocks are one standard deviation.

In response to an unexpected negative oil supply shock (Figure 2, top row), there is a persistent reduction in oil production, up to 5 percent, and in global industrial production,

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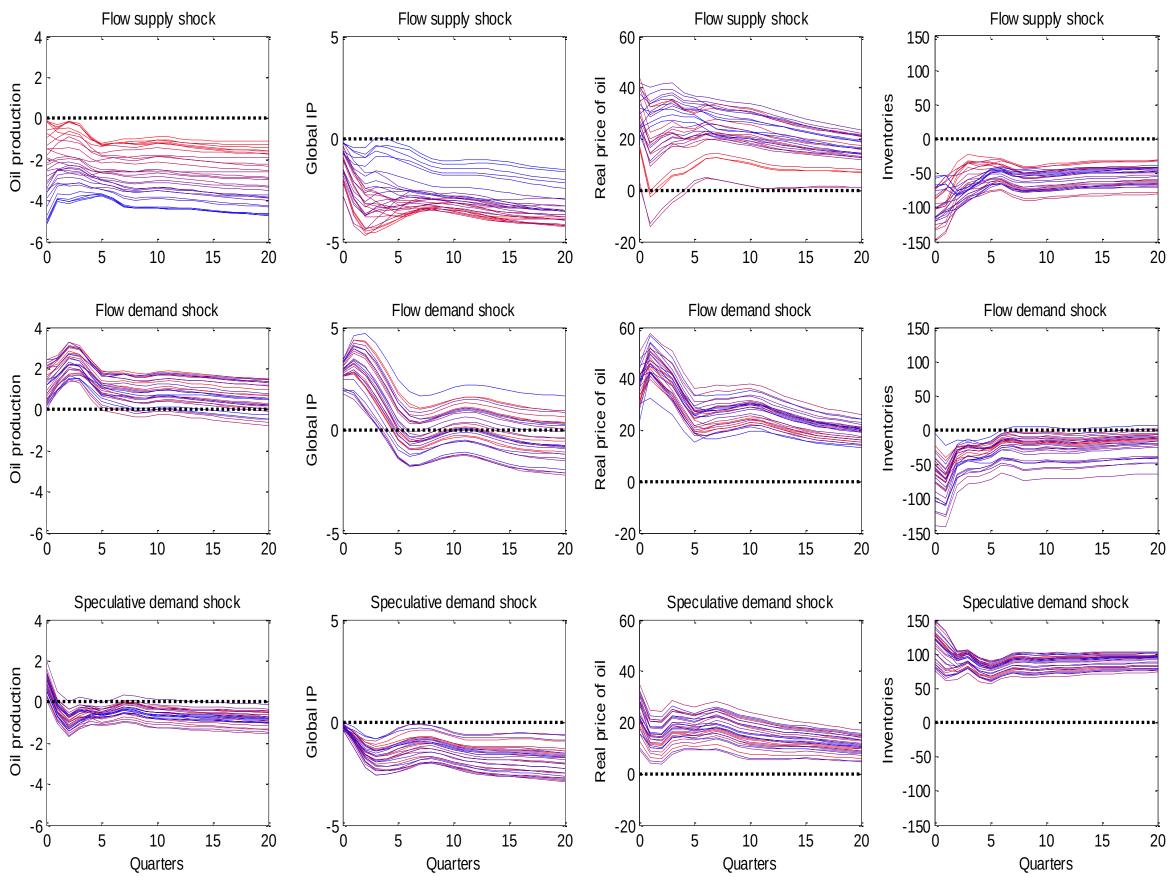
[26] The bound adopted by Kilian and Murphy (2012), 0.0258, seems to be a conservative upper bound and hence is used in our paper but multiplied by three since we have quarterly data, rather than monthly.

[27] See the appendix for the maximum and minimum impulse responses generated by the estimation.

while the oil price increase is not necessarily very persistent.[28] The negative supply shock induces an inventory drawdown, to bring more oil to the market allowing consumption smoothing to satisfy demand. This result shows that despite being agnostic on this point, almost all the identified models show a negative reaction of inventories. A flow demand shock (Figure 2, middle row) implies a somewhat persistent rise in industrial production between 2 and 5 percent. The increase in real oil prices is large and particularly persistent, with prices rising sharply initially—anywhere between 20 and 50 percent—but then falling. In both cases, the negative supply and positive demand shocks are each associated with sizeable upward pressure on the real oil price and a drawdown of crude oil inventories.

Figure 2. Admissible Estimated Models—Impulse Response Functions



[28] Some of the admissible models (vivid red in the graph) show an unrealistic response of global activity to a relatively small supply shock. The same models often show a reduction in the real oil price after a quarter. We would put little weight on those models.

Finally, the speculative demand shock: demand for physical inventories temporarily pushes up the spot real oil price by anywhere between 10 and 35 percent (Figure 2, bottom row), but then the price gradually declines. Interestingly, oil production—restricted to rise at impact—eventually declines under all the admissible models, bringing down also global industrial production in a manner similar to the flow supply shock.

D. When Does Speculative Demand Matter?

Under the null hypothesis that anomalies in futures markets are temporary, the expectation is that financial speculation can increase the short-run oil price volatility (through shifts in the demand for oil inventories), but it should contribute little to low-frequency fluctuations. To shed some light on the role of financial speculation shocks, we use two strategies; each one imposes an additional restriction on the set of admissible models:

i. Interpreting strictly the null hypothesis, we select the model that has the lowest contribution of the speculative demand shock to the real oil price forecast error variance (MFEV, for short) at 20 years (intended to indicate the long run), while being agnostic about the short-term effects.

Given that this restriction may look too conservative, effectively "minimizing" the oil price volatility, we also use a less stringent interpretation of our null hypothesis:

ii. We select the model that maximizes the difference between the short- and long-run oil price reaction to a speculative shock—in other words, the impulse response function with the largest slope (the Max Ratio, for short).

With these two restrictions, we will be able to determine the range of impact from speculation, whereby mispricing in the futures market has an estimated minimum and maximum in terms of its effect on short-run oil prices—which is manifest in shifts in inventory demand. Our proposed additional restrictions outlined above rest on economic theory (rather than statistical methods). In other words, we do not compute cumbersome posterior distributions of outcomes. Nor do we adopt the simpler approach of picking the median impulse response function from the set of admissible models since each model/IRF would be equally consistent with the observed data and underlying restrictions (as shown in Fry and Pagan, 2011).

Our results are shown in Figure 3. The first results shown are the MFEV (solid black lines). With this restriction, however, other shocks such as risk premium shocks and news shocks related to events that are expected to be temporary are also captured. Even so, the total contribution of this type of speculative shock is very modest. Indeed, while a temporary speculative demand shock implies a large quest for physical inventories (as predicted by theory) the real spot oil price moves little, by at most 10 percent (Figure 3, bottom row).[29]

Figure 3. Narrowing the Admissible Estimated Models—IRFs

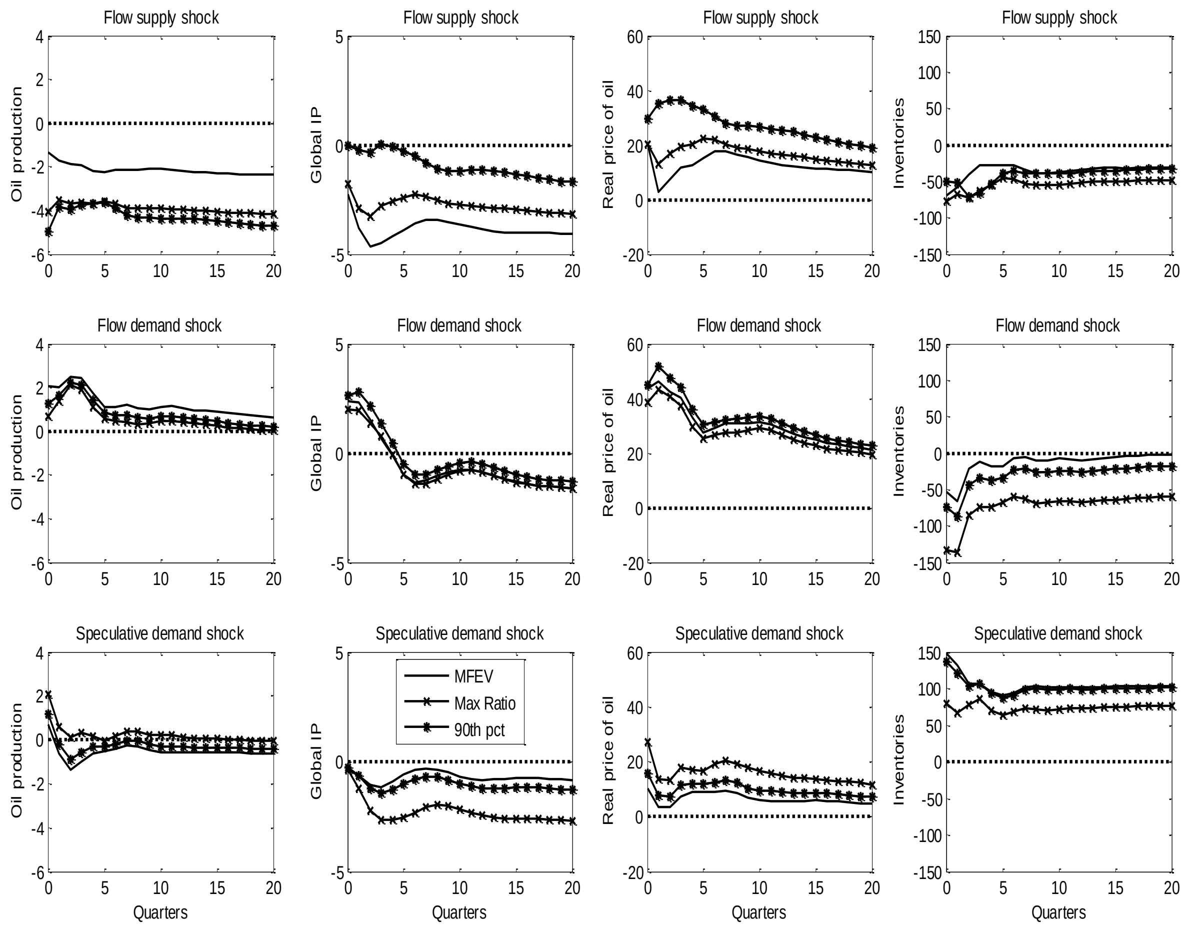


Figure 3 and Table 1's upper panel confirm that only 3 percent of the oil price forecast error variance (FEV) is explained by speculative demand shocks at short horizons. In other words, imposing that a speculative demand shock cannot explain much of the real oil price variance at long horizons implies that it will not explain much of it also at *short horizons*. Moreover, the residual demand shock now explains a larger amount of the real oil price variance, corroborating that what we have identified does not include fundamental oil market drivers (Table 1, upper panel, last column).

[29] To exclude the selection of an extreme case among admissible models, we bind the oil price impact at not below 10 percent. Relaxing this floor would imply even lower contributions to oil price volatility.

Now to give temporary speculative demand shocks the best chance of affecting the short-run oil price through a shift in demand for inventories (i.e., to obtain a plausible maximum), we choose the IRF with the steepest slope after impact (the Max Ratio).

Table 1. Real Oil Price Variance Decomposition (1984:1-2012:12)

	Flow oil supply shock	Flow demand shock	Speculative demand shock	Residual shock
		MFEV model		
Horizon				
1 quarter	13	58	3	27
20 years	8	49	2	41
		Max Ratio Model		
Horizon				
1 quarter	13	45	22	21
20 years	14	41	13	31

The response of the oil price under the Max Ratio restriction is almost three times greater than that under the MFEV restriction (Figure 3, bottom row, third column). The variance contribution of the speculative shock in the short term substantially increases to 22 percent, while the residual demand shock explains less of the variance (Figure 3 and Table 1, lower panel). The contribution at longer horizons, however, at 13 percent, becomes no longer negligible! This number is actually not far from the median contribution across all admissible models.[30] In other words, it no longer looks like the effect of short-run speculative demand; rather it seems now to be "contaminated" by reactions of market participants to "news shocks."

Overall, our findings suggest that the impact response of the oil price to speculative demand shocks driven by temporary motives in explaining the short-run real oil price volatility lie between 10 to 35 percent—second to those of flow demand (between 40 to 45 percent) but conceivably larger than that of flow supply (at 20 percent). This means that news on temporary supply disruptions or movements in risk premiums or perhaps financial speculation have played a nonnegligible role in moving oil prices in the short run. Moreover, those shocks explain a large part of inventory volatility, confirming the helpful role inventories play in stabilizing oil prices through increasing effective supply (Figure 3).

Finally, we have shown in section III that news on future shifts in oil demand and production schedules can show up as speculative demand shocks. However, in this case there

[30] Within the admissible set of identified models, the maximum contribution to the oil price forecast error variance is 47 percent at the one-quarter horizon and 35 percent at the 20 year horizon.

is no reason to believe that such speculative demand shocks would have no long-run effect on prices. In this case, we find the effects on prices could be substantial. Figure 3 shows the IRFs of the 90th percentile (on the oil price impact). This type of shock has the smallest impact on inventories but the highest on prices, showing that in general news shocks contribute substantially to short-run oil price volatility—pushing the price up (or down) by 35 percent. Moreover, since oil production eventually declines (even if constrained to rise on impact), it suggests that most of those news shocks are related in some way to expectation shifts in future production possibilities.

Historical decomposition

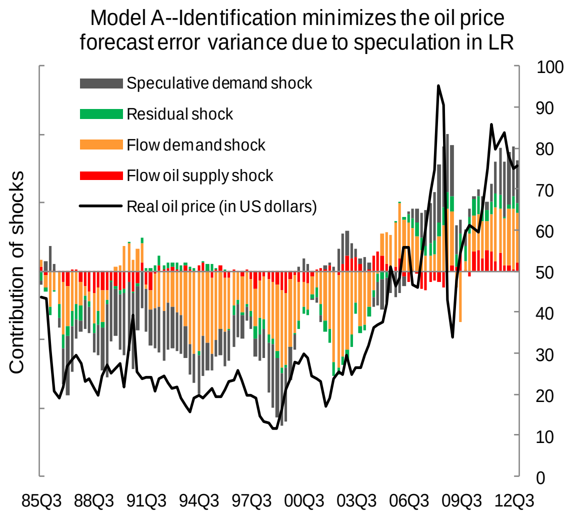
The historical decomposition focuses on the cumulative effects at each point in time of the flow supply shock, flow demand shock, speculative demand shock, and residual demand shock. Unlike KM, whose choice of historical decomposition relied on statistical methods,[31] our contribution is that we rest on economic theory—which has allowed us to build a model (without need for data on oil futures) wherein shocks to above-the-ground holdings of oil inventories, that is, speculative demand shocks, can cause temporary mispricing of oil futures and spill over to short-run spot prices.

Figure 4 shows how the *demeaned* real oil price would have evolved if all structural shocks barring the one in question had been turned off. So, for example, a bar that is increasing over time means that the shock the bar refers to is exerting upward pressure on the real oil price. The left panel displays the results from the restriction that minimized the long run oil price forecast error variance (MFEV). It highlights the dominance of flow demand shocks across the full sample even though speculative demand shocks played a role in the recent period. Interestingly, the run-up of oil prices during 2003–08 can be seen to be driven initially and solely by flow demand, but importantly since 2005 onward, flow demand is joined by speculative demand shocks—this occurring at the exact time when indexed-fund investors (hedge and pension funds) entered commodity markets, along with commodity trading houses which began to hedge (increasing) physical assets with financial instruments. Following the global financial crisis (i.e. during 2011–12), the 2005 drivers re-emerge and oil supply takes a more subdued role.

The right panel displays the results of the restriction that maximizes the ratio of the short-run oil price forecast error variance to that of the long run (Max Ratio). In this setting, flow demand loses some importance but, interestingly, speculative demand (due to the forward-looking behavior of oil market players) and the residual demand shock play the dominant role. In addition, oil supply picks up power.

[31] KM uniquely identify speculative demand with Bayesian priors and select the mode of the distribution. This choice of identification has important implications for the estimated impact of speculative demand shocks on the real oil price (or lack thereof).

Figure 4. Historical Decomposition of the Drivers of the Real Oil Price



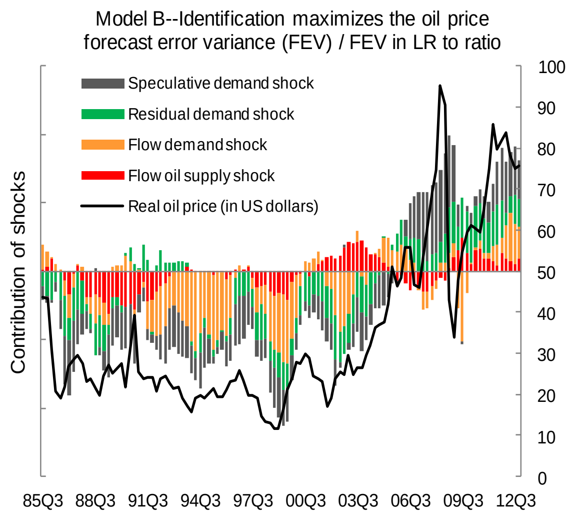
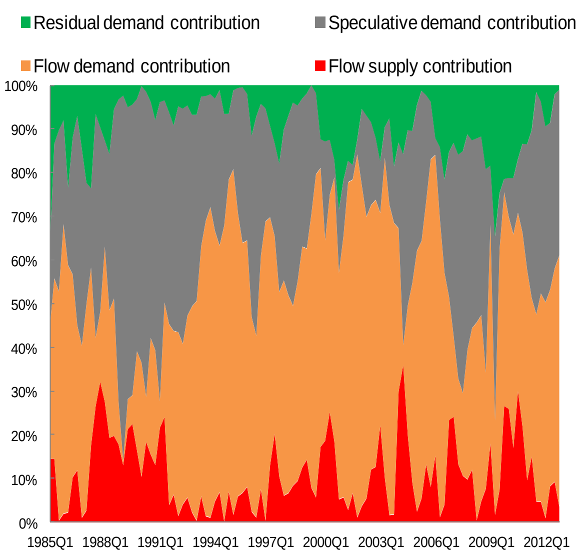
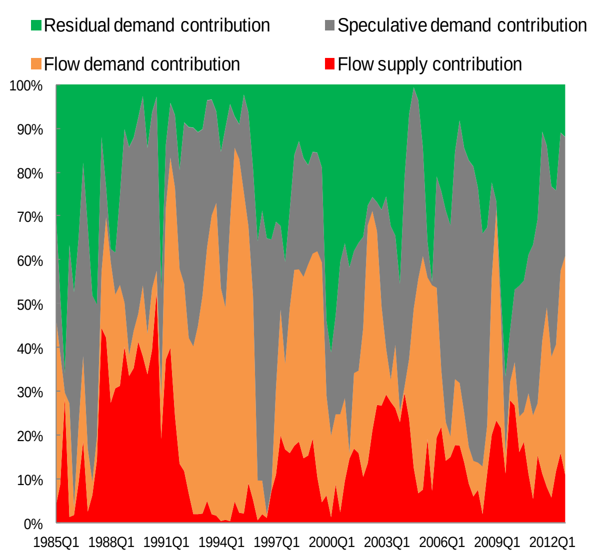


Figure 5. Absolute Drivers of the Real Oil Price

Model A—Identification minimizes the oil price forecast error variance due to speculation in the Long Run (MFEV)



Model B—Identification maximizes the oil price forecast error variance (FEV)/ Long Run FEV (Max Ratio)



Perhaps an even simpler approach to gauging the relative role of shocks is to examine their absolute contribution over time, to abstract from negative and positive movements. Figure 5 confirms that when using the MFEV restriction (left panel), flow demand is most prominent across the sample, with some downplay of the relative size of supply disruptions, (e.g., the 1990 Iraq invasion of Kuwait). On the other hand, when the Max Ratio restriction is used (right panel), speculative demand shocks induce inventory demand shifts. Thus, our results confirm that the identification and set of restrcitions matter appreciably when deciding on the relative importance of various shocks on the real oil price. Overall, we conclude that all four types of shocks (flow demand, speculative demand, supply and residual demand) have influenced the real oil price**.**

V. Conclusion

We have attempted in this paper to explore the short-term effects of speculative oil demand. In the Kilian and Murphy (2013) SVAR framework, one cannot distinguish between speculative demand shocks driven by *news about fundamentals* and those driven by *noise trading*. While we use this framework, we have proposed additional restrictions to estimate a range for the short-term impact of speculative demand shocks, regardless of their motive (destabilizing or not). These additional restrictions are on the contribution of speculative demand shocks to the long-run oil price forecast error variance—i.e., by imposing restrictions on the time horizon during which noise trading and other factors affect oil markets. They have allowed us to estimate the range (a minimum and a maximum) of the real oil price response to speculative demand shocks.

We have imposed these additional restrictions using economic theory: specifically that arbitrage by fundamental traders should ensure that oil prices are in line with fundamentals in the long run. With this in mind, our null hypothesis is that only oil market *fundamentals* (or news about them) can induce low-frequency movements in oil prices. Under the null hypothesis, mispricing in the futures market (i.e., noise trading by financial speculators) is a temporary anomaly that does not contribute to low-frequency price movements. Therefore it is possible to narrow its contribution to short-run oil price volatility by restricting our attention to the admissible model that minimizes the oil price forecast error variance's contribution of speculative shocks at long horizons (e.g., 20 years).

We have shown that news shocks on oil market fundamentals, mispricing in the oil futures market, and global real interest rate shocks can manifest themselves as speculative demand shocks (shifts in inventory demand) under the Kilian and Murphy (2013) identification strategy. Hence, we have proposed a novel manner to put a plausible bound on the contribution of financial speculation to short-term oil price volatility (which lies between 3 and 22 percent). We find the impact response of the oil price to a speculative shock to be smaller (between 10 to 35 percent) than that of a shock to flow demand (between 40 to 45 percent) but conceivably larger than that of a shock to flow supply (at 20 percent).

We find that the type of speculative demand identified through our restrictions matters for the historical decomposition in terms of the factors that have contributed to oil price fluctuations. Specifically, we find that when speculative demand is confined to be short in duration, with small long-run effects on the real oil price, the run-up in oil prices during 2003–08 can be attributed initially to flow oil demand shocks. Speculative demand shocks also contributed but only marginally after 2005—with the same drivers re-emerging again during 2011–12. However, when we allow speculative demand shocks to have larger effects in the short and long run (i.e. using our maximum), flow oil demand shocks have contributed less.

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APPENDIX

1. *Analytical Solution of the System of Equations (1) to (8)*

The non-linear system has been log-linearized around the deterministic steady state. Since we assume no trend growth in oil production, the existence of a steady state requires inventories to be constant; hence, it must be $X = Z$. Using equations (4) and (5) we can find the steady-state oil price that equilibrates oil demand and supply, $P_o = 1$. Finally, equation (3) determines the level of inventories as a function of the convenience yield and storage costs:

$$\beta[1 + c'(S)] - 1 - k'(S) = 0.$$

It is useful to first solve the fundamental system (variables are denoted with an astrisk), which is the system where there is no mispricing shock. Combining equations (1), (3) and (4) we have (lowercase letters denote log-deviations from steady state for prices and simple deviations for inventories)

$$\Delta s_t^* = \eta p_{o,t}^* + \mu_t,$$

where $\mu_t \equiv \varepsilon_{z,t} - \varepsilon_{x,t} + \nu_{z,t-k} - \nu_{x,t-k}$ summarizes the exogenous processes and $\eta = \eta_z + \eta_x$. Since what matters is the difference between demand and production shocks we can write $\mu_t = \varepsilon_t + \nu_{t-k}$ where $\varepsilon_t \equiv \varepsilon_{z,t} - \varepsilon_{x,t}$ and $\nu_{t-k} \equiv \nu_{z,t-k} - \nu_{x,t-k}$.

The inter-temporal equation takes the following form

$$p_{o,t}^* = (1 + \gamma)E_t p_{o,t+1}^* - \vartheta s_t^*,$$

where $\gamma = k'(S)$ and $\vartheta = k''(S) - c''(S) \geq 0$ depends on steady-state inventories. The linear system has been reduced to one endogenous state, inventories, and a jump variable, the oil price. The rational expectation equilibrium is characterized by the following equations

$$\begin{cases} s_t^* = \dfrac{\lambda_1}{1+\gamma} s_{t-1}^* - (1+\gamma)^{-1} \sum_{j=0}^{\infty} \lambda_1^{j+1} E_t[\mu_{t+j+1} - \mu_{t+j}] \\ p_{ot}^* = \eta^{-1}(\Delta s_t^* - \mu_t) \end{cases},$$

while it is possible to prove that under our assumptions $0 \leq \lambda_1 \leq 1$ given that[32]

$$\lambda_1 + \lambda_2 = 2 + \gamma + \eta\vartheta$$
$$\lambda_1 \lambda_2 = 1 + \gamma.$$

[32] To prove the assertion it is sufficient to note that all parameters are positive and $\lambda_1 + \lambda_2 - \lambda_1\lambda_2 > 1$.

Finally, the log-linear futures price is simply determined by log-linearizing equation (7): $f_{t,t+1}^{*} = E_t p_{o,t+1}^{*}$.

We now turn to the determination of the actual system where futures prices can deviate from fundamentals, which can be written as

$$\begin{cases} \Delta s_t = \eta\, p_{ot} + \mu_t \\ p_{ot} = (1+\gamma)\, f_{t,t+1} - \vartheta s_t \\ f_{t,t+1} = f_{t,t+1}^{*} + \omega_t \end{cases}.$$

Since the steady state is the same as in the fundamental system and, in absence of shocks, the two systems are by construction the same, it is possible to describe the non-fundamental system as deviations from the fundamental system (variables are denoted with a tilde: e.g., $\tilde{x}$)

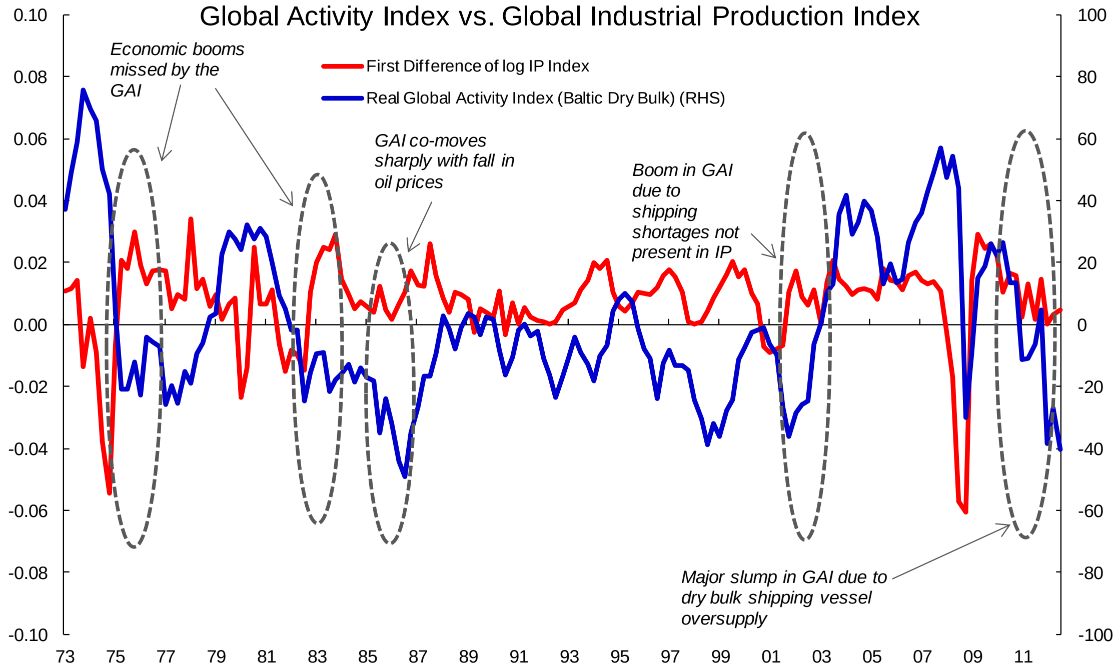
$$\begin{cases} \Delta \tilde{s}_t = \eta\, \tilde{p}_{ot} \\ \tilde{p}_{ot} = (1+\gamma)\omega_t - \vartheta \tilde{s}_t \end{cases}.$$

The system has a simple solution

$$\begin{cases} \tilde{s}_t = \dfrac{\tilde{s}_{t-1}}{1+\eta\vartheta} + \eta\,\dfrac{\omega_t}{1+\eta\vartheta} \\ \tilde{p}_{ot} = -\vartheta\,\dfrac{\tilde{s}_{t-1}}{1+\eta\vartheta} + \dfrac{1+\gamma}{1+\eta\vartheta}\,\omega_t \end{cases}.$$

2. Differences between the Global Activity Index and Global Industrial Production

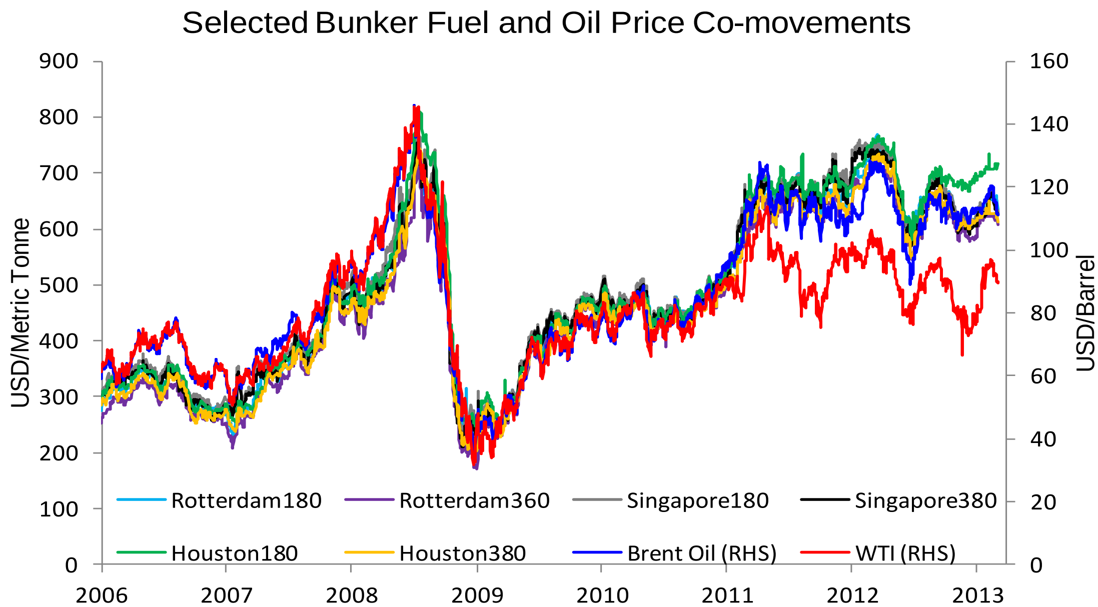
GAI and IP diverge at times, including at times of structural change in the shipping sector. For example, this has been the case in the period since 2011, when freight costs collapsed with the onset of large economies of scale in shipping—i.e., when Chinamax and cape vessels, triple or double the size of Panamax, came on stream (figure below, grey dashed circles).



Sources: IMF WEO database; Kilian's webpage: http://www-personal.umich.edu/~lkilian/reaupdate.txt.; and authors' estimates.

There is also concern that GAI and oil prices move contemporaneously—since the GAI incorporates bunker fuel prices (used for cargo freight shipping). This appears to be the case for the most commonly traded bunker fuel varieties shown along the major dry bulk shipping routes, indicating that the real oil price has a contemporaneous effect on the GAI at monthly and quarterly frequency.

We find the contemporaneous correlation between GAI and Brent or WTI to be mildly positive (about 0.3), while the contemporaneous correlation between GAI and the bunker fuel (figure above) is stronger: about 0.4.



Sources: Bloomberg, L.P.; and IMF, Primary Commodity Price System.

3. *Standard VAR(4) Model Representation*

Consider a 4-dimensional vector $\boldsymbol{y}_t$, l lags, and matrices of coefficients $\boldsymbol{\beta}$ and $\boldsymbol{B}_i$ such that

$$\boldsymbol{y}_t = \boldsymbol{\beta} + \sum_{i=1}^{l} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \boldsymbol{e}_t,$$

As explained by Hamilton (1994), since the structural disturbances are related to the VAR innovations, $\boldsymbol{e}_t$, we can represent them by:

$$\boldsymbol{e}_t = \boldsymbol{B}_0 \boldsymbol{\varepsilon}_t$$

If the structural VAR representation has the following form:

$$\boldsymbol{A}_0 \boldsymbol{y}_t = \boldsymbol{\alpha} + \sum_{i=1}^{l} \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t,,$$

where $\boldsymbol{\varepsilon}_t$ denotes the (4×1) vector of serially and mutually uncorrelated structural innovations, $\boldsymbol{\alpha}$ is a (4×1) vector of constants, and $\boldsymbol{A}_i$, $i = 0, \ldots, l$, denotes the impact or coefficient matrices at the l-th lag where the demand and supply elasticity are contained.

Then to have the orthogonalised innovations to coincide with the true structural disturbances we must have:

$$\boldsymbol{e}_t = \boldsymbol{A}_0^{-1} \boldsymbol{\varepsilon}_t = \boldsymbol{B}_0 \boldsymbol{\varepsilon}_t$$

4. *Implementation of the Identification Procedure*[33]

Consider the reduced-form VAR model $A(L)y_t = e_t$, where y_t is the N-dimensional vector of variables, $A(L)$ is a finite-order autoregressive lag polynomial, and e_t is the vector of white-noise reduced-form innovations with variance–covariance matrix Σ_e. Let ε_t denote the corresponding structural VAR model innovations. The construction of structural impulse response functions requires an estimate of the N × N matrix $\tilde{B}$ in $e_t = \tilde{B}\,\varepsilon_t$. Let $\Sigma_e = P \wedge P'$ and $B = P \wedge^{0.5}$ such that B satisfies $\Sigma_e = BB'$. Then $\tilde{B} = BD$ also satisfies $\tilde{B}\tilde{B}' = \Sigma_e$ for any orthogonal $N \times N$ matrix D. One can examine a wide range of possibilities for $\tilde{B}$ by repeatedly drawing at random from the set of orthogonal matrices D. We construct the set ˜B of admissible models by drawing from the set D of rotation matrices and discarding candidate solutions for $\tilde{B}$ that do not satisfy a set of a priori restrictions on the implied impulse response functions. The matlab procedure follows Uhlig (2005) and Kilian and Murphy (2012) and consists of the following steps:

- Draw an N × N matrix K of NID(0, 1) random variables. Derive the QR decomposition of K such that K = $Q \cdot$ R and $QQ' = I_N$.
- Let D = Q'. Compute impulse responses using the orthogonalization $\tilde{B} = BD$.
- If all implied impulse response functions satisfy the identifying restrictions, retain D. Otherwise discard D.
- Repeat the first two steps a large number of times, recording each D that satisfies the restrictions and storing the corresponding impulse response functions.

The resulting set $\tilde{\boldsymbol{B}}$ comprises the set of admissible structural VAR models. The estimation uncertainty underlying these structural impulse response estimates may be assessed by Bayesian methods. Here we follow the standard approach in the literature outlined in Uhlig (2005) and Kilian and Murphy (2012) of specifying the prior distribution for the reduced-form parameters and the distribution for the rotation matrix. The posterior distribution of the structural impulse responses is obtained by applying our identification procedure to each draw.

[33] This section closely follows Kilian and Murphy (2013).

5. ***Maximum and Minimum Impulse Responses Generated by the Estimation, Quarterly Frequency***