Determinants of the crude oil futures curve: Inventory, consumption and volatility

Christina Sklibosios Nikitopoulos[a], Matthew Squires[a], Susan Thorp[b], Danny Yeung[a]

[a] *University of Technology Sydney, Finance Discipline Group, UTS Business School, PO Box 123 Broadway NSW 2007, Australia*
[b] *The University of Sydney, Discipline of Finance, The University of Sydney Business School, NSW 2006, Australia*

Abstract

Since 2008, the usually negative crude oil futures spread has been positive for extended periods, raising doubts about conventional explanations. We re-examine the dynamics of the futures spread using monthly VARs on the CME WTI oil futures spread, OECD and U.S. oil and petroleum inventories and consumption, and historical and implied volatility. When we model the spread as one continuous series, results confirm bi-directional causation between inventory and the futures spread, as predicted by the theory of storage. However results show that excess inventory is not adequately modelled as deviations from a secular trend: consumption has a separate causal relation with de-trended inventory. When negative and positive spread regimes are modelled separately, we find that shocks to OECD petroleum consumption directly widen negative spreads. Further, increases in volatility make positive spreads more steeply positive but are not related to negative spreads, consistent with inelastic supply of crude oil.

Keywords: Oil futures curve, Inventory, Consumption, Implied volatility, VAR
JEL: Q40, C58

Email addresses: christina.nikitopoulos@uts.edu.au (Christina Sklibosios Nikitopoulos), matt.squires@me.com (Matthew Squires), susan.thorp@sydney.edu.au (Susan Thorp), danny.yeung-1@uts.edu.au (Danny Yeung)

1. Introduction

Since 2008, crude oil futures prices have exceeded spot prices for extended periods, sometimes by as much as 40%. Historically, the oil futures curve has usually been inverted, with future prices consistently lower than spot. The inverted futures curve rewards holders of crude oil inventories with a convenience yield, according to the theory of storage. However over the past decade, new production techniques, weak macroeconomic growth and slowing (or even declining) consumption of petroleum products have altered crude oil market conditions, reversing the usual price relatives.[1] The extended period of positive oil futures-spot spreads experienced since 2008 has revived a debate about whether a conventional empirical approach, focusing on inventory alone, is a sufficient explanation for the dynamics of the oil futures curve, or if other factors need to be considered. To address this question, we study the role of physical inventory, petroleum consumption and a new measure of implied volatility to explain the shape of the futures curve in the crude oil market from 1992 to 2015.

Conventional storage theory explains the shape of commodity futures curve using the concept of convenience yield, where holders of physical inventories can profit by "conveniently" supplying unexpectedly higher demand or taking advantage of a stock out (Kaldor (1939); Working (1948); Brennan (1958); Telser (1958); Williams and Wright (1991)). An inverted oil futures curve indicates high convenience yields and pressure on current oil inventories. Conversely, upward (normal) sloped curves mean plentiful current inventories or an expected future shortage. The theory of storage has had varying degrees of empirical support across a range of commodity markets, and although many studies have assumed that the slope of the futures curve, measured by the futures-spot spread, is a valid proxy for inventory pressures, more recent literature has modelled actual inventory data (Fama and French (1987); Ng and Pirrong (1994); Dincerler, Khokher, and Simin (2005); Geman and Ohana (2009)).

To provide a comprehensive and rigorous analysis of the dynamics of the oil futures curve, we estimate unrestricted VAR models at a monthly frequency from a 23-year sample of futures prices, inventories, consumption and volatility. We include inventory and consumption data on both OECD petroleum and U.S. crude oil and petroleum products. The OECD series measure global market conditions while the U.S. series connect more closely with the CME WTI futures data from which we compute the spread. We separately compare the relationship between volatility and inventory, and between volatility and the interest adjusted spread, so that we are able to verify whether the assumption that the spread is a proxy for inventory is sound or whether there may be additional factors that influence volatility. We also construct new variables that separate negative from positive futures spreads. We then estimate general models allowing different relations between the endogenous variables depending on whether the futures curve slope is positive (normal) or negative (inverted).

We make two main contributions to understanding the dynamics of the oil futures curve. First, few studies have investigated how oil options-implied volatility relates to the futures curve. The benefit of analyzing implied volatility is that it is determined by the market

[1] We use the following terms in our discussion: a curve is normal and the market is in contango when futures prices trade higher that spot prices, thus displaying an upward-sloping futures curve or positive spread; conversely, a curve is inverted and the market is in backwardation when futures prices trade below spot prices, thus exhibiting a downward-sloping futures curve or negative spread.

prices of options and provides a forecast of expected volatility, rather than simply a measure of past price variation. Implied volatility is not a statistical estimate therefore is not prone to sampling error or model specification error. It is also a relevant volatility measure, in the sense that the futures spread and implied volatility are both computed by using current futures and options prices, reflecting current nominal price variation. Furthermore, implied volatility changes contain more information than historical measures about innovations in expected volatility (Dennis, Mayhew, and Stivers (2006); Angolucci (2009)).

We show that implied volatility is a significant predictor of the futures spread, a relation that is more pronounced at longer maturities. Impulse response analysis further demonstrates that positive shocks to implied volatility raise futures prices relative to spot. This finding is consistent with an increase in precautionary demand for oil encouraging traders to hold more inventory in anticipation of future turbulence (Anzuini, Pagano, and Pisani (2015); Alquist and Kilian (2010)) or with inelastic supply (Carlson, Khokher, and Titman (2007); Kogan, Livdan, and Yaron (2009)).

Second, by separately modelling negative and positive spreads, we identify 1) a weakened relation between positive spreads and U.S. inventory when spreads are positive and 2) a direct transmission path from petroleum consumption shocks to the futures-spot spread. When we restrict the spread to be one continuous variable we find bi-directional causality between inventory and the interest adjusted spread. However when we estimate a separate series for negative and positive spreads, we find that positive spreads do not induce reductions in the U.S. crude oil and petroleum inventory as theory predicts. We associate this disconnection with frictions in the U.S. distribution chain during the shale oil boom and with declining consumption of petroleum products.

We also find evidence that shocks to OECD petroleum consumption are directly transmitted to the spread in inverted markets. In other words, stronger OECD consumption raises spot oil prices relative to future prices in backwardated markets, both directly, and indirectly through pressure on inventory levels. On the other hand, when the futures curve is upwardly sloped, shocks to U.S. petroleum consumption cause a small initial rise in spot relative to future prices that is later reversed. These results suggest a direct role for petroleum consumption as a signal of future oil market conditions, in addition to the immediate impact of higher consumption on inventories and convenience yields.

We add to recent studies that have underscored the important part macroeconomic demand and supply shocks have played in explaining crude oil price variation, providing strong evidence for considering consumption (as a measure of the interaction between oil demand and supply) in empirical studies of oil prices (Kilian (2009); Morana (2013); Kilian and Murphy (2014); Anzuini et al. (2015); Aastveit, Bjørnland, and Thorsrud (2015)).[2] Less attention has been given to the part such shocks have played in setting the slope of the futures curve, with the exceptions of Alquist and Kilian (2010) and Anzuini et al. (2015), who show how precautionary demand shocks are related to crude oil futures spreads, and Geman and Smith (2013) who include consumption into their empirical investigation of the theory of storage in the metals market.

[2]Other papers have explored the role of financial shocks and speculation. See D'Ecclesia, Magrini, Montalbano, and Triulzi (2014) and citations therein.

Our study also adds to the extensive literature on the theory of storage, confirming the fundamental relation between inventory and the futures spread and adding to understanding of the relation between volatility and the spread. In periods of high inventory, there can be large inventory responses to demand shocks without impacting the convenience yield, and, as a consequence, the interest adjusted spread remains relatively stable. Conversely in periods of scarcity, the convenience yield rises rapidly if inventory is used to meet a demand shock, having a large impact on the spot price and decreasing the spread. It follows that when inventories are low, spot prices will be more volatile than futures prices (Fama and French (1988)). Ng and Pirrong (1994) use the implication of the theory of storage, that fundamental supply and demand conditions determine the spread, to test whether these fundamentals also determine volatility in metals markets. They confirm that spot returns become relatively more volatile than futures returns as the adjusted spread becomes more negative. Most studies, including Geman and Ohana (2009) and Geman and Smith (2013), provide evidence of a significant negative correlation between volatility and inventory (where inventory is typically treated as a proxy for the slope of the futures curve) especially over periods of scarcity for oil and several metals. Our analysis shows that implied volatility predicts the futures-spot spread but that the spread, inventory and consumption do not generally predict volatility, either historical or implied. In addition, consistent with Kogan et al. (2009) and Haugom, Langeland, Molnár, and Westgaard (2014), we find evidence for high volatility associated with steeply positive spreads. In our sample volatility is more significantly related to positive than to negative spreads. This is evidence in favor of inelastic supply conditions.

The remainder of the paper is organised as follows. A description of the data for inventory, consumption, volatility and the shape of the crude oil futures curve is included in Section 2 and the method used to analyze their relation in Section 3. Section 4 provides a detailed discussion of the causality tests and impulse response functions that determine the shape of the crude oil futures curve. Section 5 concludes.

2. Data and Preliminary Analysis

We study WTI crude oil futures spreads, historical and implied volatility of futures returns, and related measures of petroleum inventory and consumption, from January 1992 to March 2015. The sample begins after the first Gulf War and ends before the ban on exports of crude oil from the U.S. was lifted. Recent divergence between WTI oil prices and the global price of crude oil, as measured by Brent prices, raise some questions about this choice of benchmark. However WTI markets are highly liquid, Brent and WTI prices are very highly correlated over our sample and the alternative Brent series has its own drawbacks Kilian (2016b).[3]

[3]Sun and Shi (2015) study the WTI oil *price* series finding breaks in August 1999, June 2002 and October 2008. In preliminary analysis, we searched a longer sample of the series in our study for sudden or gradual breaks using PcGive. Somewhat surprisingly, this process indicated important breaks associated with the first Gulf War, but no significant structural changes in the DGP for the system we estimate between 1992 and early 2015.

2.1. Interest Adjusted Spread

We construct monthly observations on the crude oil futures interest-adjusted spread (IAS) at a range of maturities from daily data on WTI oil futures. We collect daily observations of CME Light Sweet Crude Oil (WTI) futures prices for the nearest (first), fourth, seventh and thirteenth monthly contract expiry dates, from CME Group. A crude oil futures contract represents 1000bbl to be delivered at Cushing, Oklahoma. Each futures contract expires on the third business day prior to the 25^{th} calendar day of the month preceding the delivery month.[4] After a contract expires, the 1-month contract for the remainder of that calendar month is the contract for the second following month. Table 1 reports descriptive statistics for the daily futures price returns sample.

Crude oil spot prices vary with the grade and physical location of the oil being traded. Futures are priced for a standard grade and delivery location, making futures prices easier to observe and interpret than spot prices. Accordingly, we follow the convention of treating the 1-month futures price as a proxy for the oil spot price. We also expect to find different relations between fundamental determinants of the spread at different maturities. We therefore compute the 3-month, 6-month and 12-month daily IAS at date t as

$$(n-1)\text{-month IAS}_t = \frac{F(t,n) - F(t,1)[1 + r(t,n-1)(n-1)/12]}{F(t,1)}, \tag{1}$$

for $n = 4, 7, 13$ where $F(t,n)$ is the n^{th}-month nearest futures price at date t, $F(t,1)$ is the 1^{st}-month nearest futures price at date t, $r(t,n-1)$ is the $(n-1)$-month LIBOR rate at date t from Bloomberg. We take the mean daily interest adjusted spread observed during a given calendar month for the monthly observations. Taking the mean of daily spreads over the month ensures that the spread series is consistent with inventory series.

Figure 1 graphs the 3-month, 6-month, and 12-month IAS, from January 1992 to March 2015, showing the regime changes that we investigate in detail in the econometric analysis to follow. Prior to 2008, the crude oil futures curve was usually inverted and the IAS was negative. For some periods in the 1990s and more often during the past decade, the oil futures curve has been normally sloped and the IAS has been positive. The graph also shows that longer duration spreads typically have steeper slopes, with the 12-month IAS further from zero than the 3-month and 6-month IAS. We also separate the IAS by the sign of the slope, creating two series:

$$IAS_{+t} = max(IAS_t, 0), \tag{2}$$
$$IAS_{-t} = min(IAS_t, 0). \tag{3}$$

These variables allow us to investigate the v-shaped relation between the slope of the futures curve and price volatility, established by Carlson et al. (2007) and Kogan et al. (2009) and tested by Haugom et al. (2014). The classical relation associates low inventory and a backwardated spread to high volatility (Litzenberger and Rabinowitz (1995a)): the option value of keeping the resource in the ground increases with price volatility, so spot prices

[4] If the 25^{th} day of the month is not a business day, trading ceases on the third business day prior to the business day preceding the 25^{th} calendar day.

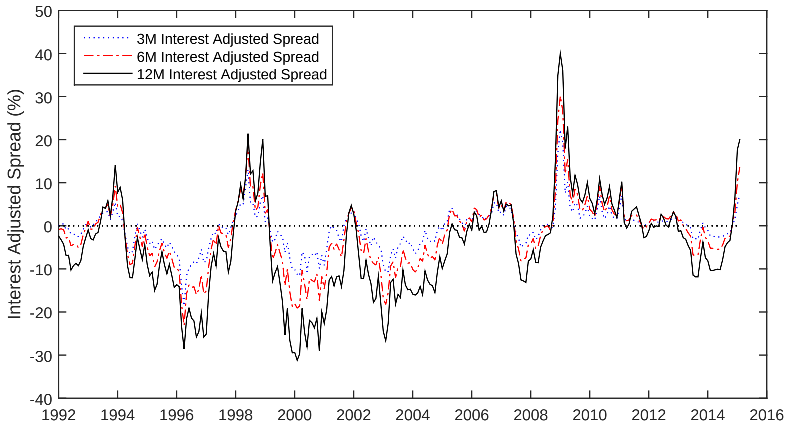


Figure 1: **3-month, 6-month, and 12-month Interest Adjusted Spreads**
The plot displays the 3-month, 6-month, and 12-month mean daily interest adjusted spreads computed by using daily WTI futures prices, during a given month, from January 1993 and March 2015.

must rise and the slope become more negative to ensure supply. Carlson et al. (2007) and Kogan et al. (2009) expand this argument to allow for inelastic supply due to irreversible investments by producers, or high adjustment costs. An implication of these models is that future prices at longer maturities are less affected by supply inelasticity than are spot prices, hence the positive spread can be related to high volatility. Together, these theories predict increasing volatility as the spread becomes steeper in either a positive or negative direction.

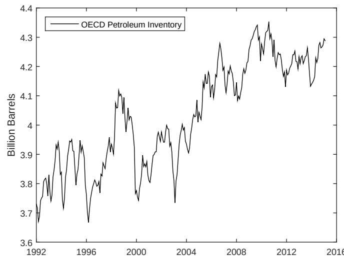
2.2. Inventory

We use two measures of inventory in order to capture different features of the petroleum and crude oil markets. The first inventory measure relates to global market conditions: the total inventory of petroleum products in the Organisation for Economic Cooperation and Development's (OECD) member countries, compiled from the U.S. Energy Information Administration's (EIA) Total Energy Reviews. Figure 2.a graphs monthly OECD petroleum inventory from January 1992 to March 2015. Although the futures contract prices we use relate to physical WTI oil for delivery at Cushing, Oklahoma, it is plausible that the size and liquidity of this market attracts participants hedging the price risk associated with other petroleum products or delivery locations.[5] In addition Geman and Ohana (2009) find that OECD petroleum inventory, by covering most industrialized countries, reflects global market conditions and determines the average shape of the oil forward curve over longer periods.

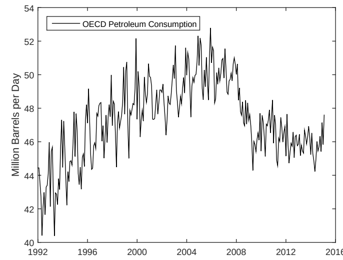
However, OECD inventory is less correlated with short-run U.S. crude oil prices. WTI prices are more affected by immediately available inventory (Geman and Ohana (2009)). Hence the second inventory measure we model is the EIA monthly series on primary stocks of U.S. crude oil and petroleum inventory, graphed in Figure 2.c.[6] The composition of

[5]http://www.eia.gov/totalenergy/data/monthly/

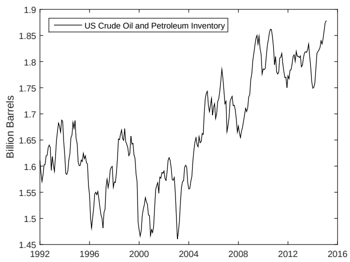
[6]We use the EIA series for U.S. ending stocks of crude oil and petroleum products. The EIA definition is



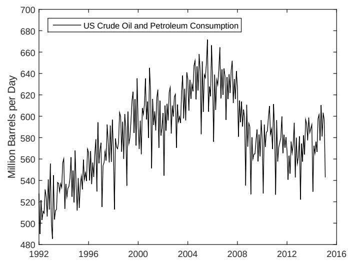
2.a: OECD Petroleum Inventory



2.b: OECD Petroleum Consumption



2.c: U.S. Crude Oil and Petroleum Inventory



2.d: U.S. Crude Oil and Petroleum Consumption

Figure 2: **U.S. and OECD Inventory and Consumption**
The plot displays the monthly OECD petroleum inventory/consumption and the monthly U.S. crude oil and petroleum inventory/consumtion, from January 1992 to March 2015.

global, and especially of U.S., oil supply has changed since the early 2000s. Improvements to exploration and drilling methods have brought supplies of "tight" or "shale" oil to global markets, reversing a trend decline in U.S. crude oil output. Relatively low WTI prices between 2011 and 2015 were caused partly by a persistent glut of oil at the U.S. hub in Cushing, Oklahoma, that, because of pipeline restrictions, could not be dispersed quickly (Kilian (2016b)), we can better estimate the influence of inventories by separating U.S. from OECD measures.

2.3. Consumption

The theory of storage is based on the notion of excess inventory, that is, the size of inventory relative to market pressure. A common approach to measuring relative abundance or scarcity of inventory in the oil market is to assume that demand for crude oil and petroleum products is linearly increasing over time. Abundance or shortage is thus measured by the deviations of inventory from a linear trend.

"Primary stocks include crude oil or petroleum products held in storage at (or in) leases, refineries, natural gas processing plants, pipelines, tank farms, and bulk terminals that can store at least 50,000 barrels of petroleum products or that can receive petroleum products by tanker, barge, or pipeline. Crude oil that is in-transit by water from Alaska or that is stored on Federal leases or in the Strategic Petroleum Reserve is included. Primary stocks exclude stocks of foreign origin that are held in bonded warehouse storage."

For much of the post-war period, it has been reasonable to assume that demand for petroleum products follows a linear trend because consumption of petroleum products has kept pace with, or risen somewhat slower than, growth in GDP (CEA (2015)). Surprisingly, however, this assumption has been contradicted since the early 2000s. Instead of growing at the EIA projected rate of 1.8% p.a., U.S. petroleum consumption has declined over the past decade, and was actually lower in 2014 than in 2003 (CEA (2015)). Europe and Japan also experienced declines in consumption of petroleum. Causes of the U.S. consumption decline include falls in vehicle miles traveled associated with slow income growth and population aging, and by increasing fuel economy, in other words, long term changes in transportation technology and usage patterns (CEA (2015)). Unexpected turning points in trend consumption of petroleum in the U.S. and OECD mean that linear detrending will dramatically understate excess inventory in recent years.

To avoid potential mis-measurement of excess inventory arising from secular detrending, we directly model monthly consumption, or "petroleum products supplied" in the OECD and the U.S.[7] We use monthly petroleum consumption data from the U.S. Energy Information Administration's Total Energy Reviews. We collect observations from January 1992 to March 2015 for OECD petroleum consumption and U.S. crude oil and petroleum consumption. Figure 2.b and Figure 2.d graph these series. In Section 4.2 we analyze the dynamics of the interaction between consumption and inventory, and its effect on the shape of the futures curve.

2.4. Historical and Implied Volatility

Other studies show that both backward and forward looking futures returns volatility can be useful in modeling WTI futures (Haugom et al. (2014); Martens and Zein (2004); Wang, Wu, and Yang (2008)). We calculate historical and implied volatility. Historical monthly volatility is the annualized standard deviation of daily log returns to the nearest futures contract over a given calendar month.

We compute implied volatility using daily observations of at-the-money call and put CME Group Light Sweet Crude Oil futures options from January 1992 to March 2015 for the first and second nearest expiring contracts.[8] We apply the algorithm of Kutner (1998) to invert the Barone-Adesi and Whaley (1987) quadratic approximation method for pricing American options, which gives implied volatilities specific to the residual time to maturity of the option contracts. We then interpolate the 30-day implied volatility using the VIX weighting method CBOE (2009). (Appendix B describes our method for calculating the implied volatility series.) Monthly implied volatility is the mean 30-day implied volatility observed for a given calendar month. We use the mean 30 day implied volatility, instead of longer maturities, so we can compare results with estimates for the monthly historical

[7]Consumption of petroleum by the OECD countries is "petroleum product supplied", defined in the glossary of the EIA Petroleum Supply Monthly. We note that this measure includes some products derived from natural gas and renewable fuels, as well as those refined from crude oil.

[8]These contracts cease trading three business days before the termination of trading in the underlying futures contract, that is, they expire on the 6^{th} business day prior to the 25^{th} calendar day of the month preceding the delivery month. As with the futures contracts, after a contract expires the nearest contract for the remainder of that calendar month is that of the second following month.

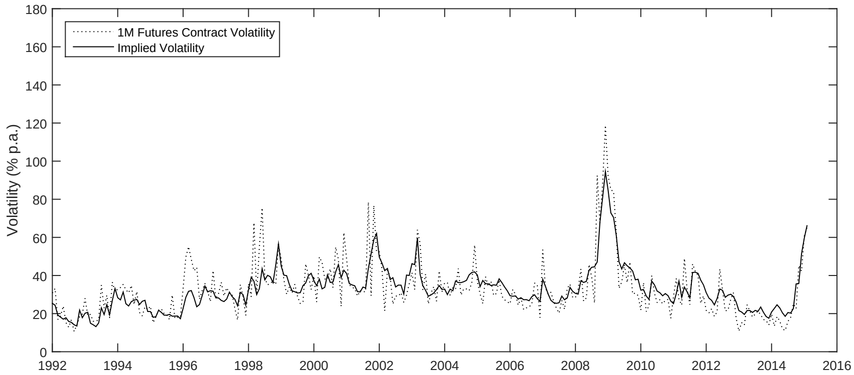


Figure 3: **1^{st} Nearest Month Futures Volatility and 30-Day At-The-Money Implied Volatility**
The plot displays the annualized standard deviation of daily log-returns over a given month and the mean 30-day implied volatility observed in a given month, between January 1992 to March 2015.

volatility series and for consistency with other data series.

Figure 3 graphs both volatility series. The 30-day implied volatility averaged 32.79% p.a. over our sample, very similar to average historical volatility for the nearest futures contract return (32.86% p.a.). There are several distinct periods of extremely high volatility evident in both series, including the Asian Financial Crisis in 1998, the September 11 terrorist attacks in 2001, the U.S. invasion of Iraq in 2003, the oil price boom and slump in 2008-9 associated with the credit crunch crisis and the fracking boom, and the marked price decline in 2014-15 related to slowing global demand for oil (Kilian (2016a)). There are also noticeable differences between the two volatility series: historical volatility exhibits higher peaks and more variation than the implied volatility series, and in the last five years of the sample, implied volatility is higher than historical volatility for a majority of months. We investigate these similarities and differences in the econometric models discussed below.

Table 1 reports descriptive statistics for all series used in estimation. Mean monthly oil spot returns are close to zero, exhibit excess kurtosis and negative skewness. The mean spread is negative over the sample at each of the 3-, 6- and 12- month maturities, consistent with the typically inverted oil forward curve.

3. Econometric Method

We want to identify the determinants of the oil forward curve, and explore their influence on its shape, by investigating the dynamic relationships between inventory, the interest adjusted spread, petroleum consumption and volatility using Vector Autoregression (VAR) models. Atheoretical VAR models are well suited to modeling short-run relationships between endogenous variables. We are not primarily interested in testing a theoretical structure, so we estimate unrestricted models and apply standard Granger-causality tests and compute impulse response functions.

3.1. Detrending

We begin by conducting stationarity tests of the series to be modeled. Table 2 reports the results of Augmented Dickey-Fuller (Dickey and Fuller (1979); Said and Dickey (1984)) unit root tests where the alternative hypothesis is that the series is a stationary process in deviations around a linear time trend. We reject the null hypothesis of the presence of a unit root with 95% confidence for the 3-month, 6-month, and 12-month IAS, OECD petroleum inventory and U.S. crude oil and petroleum inventory, and for historical and implied volatility. However, we cannot reject the null hypothesis of a unit root for the OECD and U.S. consumption series.

For estimation, we manage non-stationarity by including first differences of the OECD and U.S. petroleum consumption series. Other endogenous variables enter in levels, along with a time trend and (monthly) seasonal dummies to model the secular and seasonal components of the system. We select lag length in the VAR models using the conventional Akaike information criteria.[9]

3.2. VAR Model

Our primary interest is in explaining the sign of the crude oil IAS and the unusual changes in regime observed over recent periods. We include IAS firstly as a single series, then in a further refinement, we allow for different states of crude oil market conditions (normal and inverted) by introducing the two separate IAS measures. The *positive* interest adjusted spread (IAS_+) associated with an upward-sloping (normal) futures curve ($F_t > S_t$), and the *negative* interest adjusted spread (IAS_-) associated with a downward-sloping (inverted) futures curve ($F_t < S_t$).

We estimate

$$\boldsymbol{Y}_t = \sum_{i=1}^{p} \boldsymbol{\gamma_i}^T \boldsymbol{Y}_{t-i} + \boldsymbol{\delta_1}^T \boldsymbol{X} + \boldsymbol{\epsilon_t}. \tag{4}$$

where $\boldsymbol{Y}_t$ is a vector of endogenous variables including IAS_t = average interest adjusted spread, month t; or IAS_{+t} indicator variable for positive IAS and IAS_{-t} indicator variable for negative IAS; I_t = OECD or U.S. inventory, month t; ΔC_t = change in OECD or U.S. consumption, month t; V_t = annualized monthly historical volatility of the return on the nearest futures contract or 30-day options implied volatility. $\boldsymbol{X}$ is a vector of exogenous factors consisting of a time trend and centered seasonal dummies and $\boldsymbol{\epsilon_t}$ is a vector of i.i.d errors. In total we estimate 36 VAR models: for each of the 3, 6 and 12 month IAS, and OECD inventory and consumption series, we estimate models with no volatility series, historical or implied volatility series (9 models), and then re-estimate allowing the IAS series to condition on sign (another 9 models). We repeat this for U.S. inventory and consumption series.

Earlier studies testing how market conditions influence volatility have often assumed that the interest adjusted spread is a valid proxy for inventory. Here we separately compare

[9] To save space, we do not report the complete estimation results. These are available from the authors on request.

the relationship between volatility and inventory, and between volatility and the interest adjusted spread. This approach allows us to verify whether the assumption that the spread is a proxy for inventory is sound or whether there may be additional factors that influence volatility, such as speculative trading or herd behavior (Pindyck (2004)).

We also compare the impact of the historical volatility and implied volatility on these causal relationships. Since both implied volatility and the IAS are forward looking, we hypothesize that implied volatility will exhibit stronger relations than historical volatility measures, which only reflect past price variation.

In addition, by conditioning on the sign of the spread, we can test the non-monotonic correlation between spreads and volatility found in earlier studies. However we go further by estimating the influence of consumption on historical and implied volatility in normal and inverted markets. The recent decline in global petroleum consumption occurring around the same time as the fracking boom and associated divergence between U.S. and global oil prices justifies modeling consumption and inventories separately, and the U.S. and OECD separately.

3.3. Granger Causality Tests

Table A.1 and Table A.3 report the p-values of Granger causality tests between inventory, IAS, consumption and volatility for OECD petroleum products and for U.S. crude oil and petroleum products. Each table compares three models; model 1 without volatility, model 2 with historical volatility and model 3 with implied volatility.

Table A.2 and Table A.4 report the p-values of Granger causality tests between inventory, negative IAS denoted as IAS_{-}, positive IAS denoted as IAS_{+}, consumption and volatility for OECD petroleum products and U.S. crude oil and petroleum product market, respectively. In these models, we allow the relationships to depend on whether the market is normal (a positive IAS) or inverted (a negative IAS). Discussion of these results follows in Section 4.

4. The Crude Oil Futures Curve and its Determinants

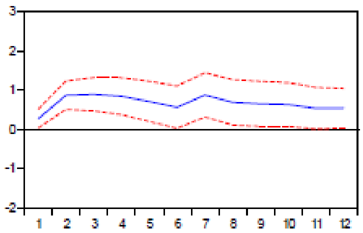
In this section we consider the relation between inventory and the IAS, then discuss the effects of changes in petroleum consumption and volatility on the IAS. We then review the sensitivity of these findings to separately modelling negative and positive IAS.

4.1. Inventory and IAS

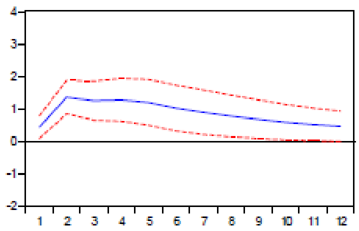
A large number of studies have assessed the ability of the interest adjusted spread to proxy for commodity inventory. The theory of storage (Kaldor (1939) and Working (1949)) says that low inventories mean a high convenience yield[10] causing the interest adjusted spread to decline (or even become negative). Conversely, a low interest adjusted spread can stimulate reverse cash-and-carry trading strategies, where shorting spot crude oil and buying futures leads to higher current and lower future inventories.

Data on interest adjusted spreads are readily available for all exchange traded commodities whereas reliable inventory data series are not always available. As a result, studies such

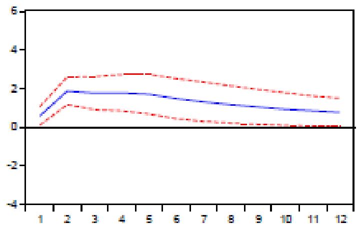
[10]The convenience yield is the return accruing to to owners of the physical commodity over a long futures position in the commodity.



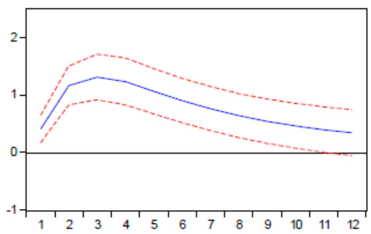
4.a: 3-month IAS to OECD inventory shocks



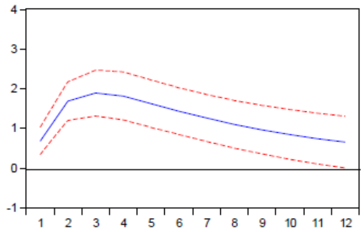
4.b: 6-month IAS to OECD inventory shocks



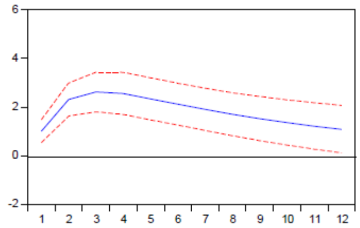
4.c: 12-month IAS to OECD inventory shocks



4.d: 3-month IAS to U.S. inventory shocks



4.e: 6-month IAS to U.S. inventory shocks



4.f: 12-month IAS to U.S. inventory shocks

Figure 4: **Response of IAS to Shocks in OECD Inventory and U.S. Inventory**
The LHS panel graphs the impact of a Cholesky one standard deviation shock to inventory on the 3−month IAS; the middle panel graphs the impact on the 6−month IAS and RHS panel on the 12−month IAS. Dotted lines show two standard error bounds.

as Fama and French (1987), Ng and Pirrong (1994) and Geman and Ohana (2009) have used the interest adjusted spreads as a proxy for inventory.[11] In models that use actual inventory data (when available), interest adjusted spread series usually become redundant. Indeed, futures prices often become redundant as well: Kilian and Murphy (2014) have shown that oil futures spreads do not hold additional information over and above the information carried by inventory data for spreads up to 12 months.[12]

Estimation results from models where the IAS is not conditioned on sign confirm a bi-directional relation between the WTI interest adjusted spread and inventory that supports theories of storage. Bi-directional causality is significant for both OECD and U.S. inventory series. (See rows 1 and 2 in Table A.1 and Table A.3.) Impulse response functions confirm that the IAS responds positively to shocks to OECD and U.S. inventory. The impact is stronger at longer maturities. In other words, abundant petroleum inventory is associated with low spot prices relative to future prices, see Figure 4.[13]

Estimates of causality between the IAS and inventory do not materially change when we include volatility in the vector of endogenous variables (see Pindyck (2004)). Overall, these results imply that the IAS is a good proxy for inventory, so that modelers can alternate

[11] Anzuini et al. (2015) used the spread as a proxy for precautionary demand.

[12] Our models offer new evidence on the effect of oil consumption on the relation between the spread and inventory in Section 4.2.

[13] All impulse responses functions graph a Cholesky one standard deviation shock and dotted lines show two standard error bounds.

between spreads and inventory depending on the question at hand and data suitability. However, as we will discuss next, consumption is an important third component in the inventory-IAS connection and should be included in empirical applications of the theory of storage.

4.2. Consumption, Inventory and IAS

Monthly OECD and U.S. consumption data measures actual petroleum products supplied. Consumption, like price, responds to both oil demand and supply shocks (Kilian (2009); Morana (2013); and Kilian and Murphy (2014)). Kilian (2016a) proposes a classification of shocks that lists standard flow supply and flow demand shocks, as well as shocks to speculative oil demand, where uncertainty about future supply causes traders to add to inventories. Alquist and Kilian (2010) demonstrate that the crude oil futures spread can be treated as an indicator of price variation caused by precautionary or speculative demand shocks. Exogenous increases in uncertainty about oil supply, such as happened during the Gulf Wars, initially raise the convenience yield, the demand for inventory, and consequently the spot price of oil. Since inventory can't be built immediately, the spot price tends to overshoot. A high spot price leads to a decline in the spread that is gradually reversed as supplies are added to future inventory. These studies highlight the critical connection between the futures spread and consumption dynamics.

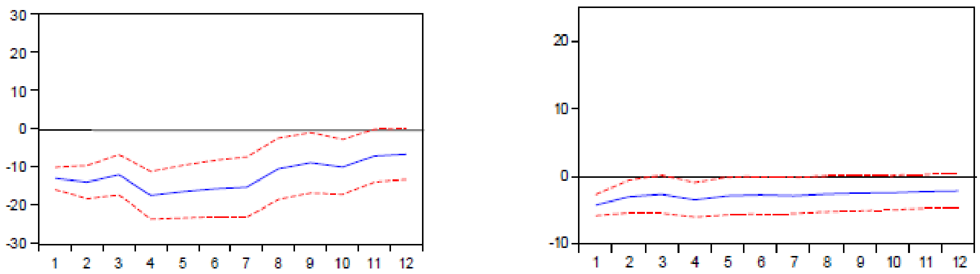
Our empirical analysis shows that changes in consumption and inventory are strongly related. We find a significant bi-directional causality relation between consumption and inventory of OECD petroleum products. The same relation is still significant, although marginally weaker, for U.S. petroleum products. (See rows 3 and 4 in Table A.1 and Table A.4.) Impulse response functions graphed in Figure 5 illustrate how positive shocks to consumption are smoothed by decreased inventories for over one year. These results are also unchanged when we include historical or implied volatility in the VAR model.

The bi-directional causality between consumption and inventory is significant even though we have included an exogenous secular trend term in the VAR models. Consequently these results show that linear detrending of inventories alone will not adequately model the effects of changes in the rate and direction of petroleum consumption on the oil futures curve.

When estimation does not condition on the sign of the IAS, we find that petroleum consumption shocks are not directly transmitted to the spread; the effect comes through changes in inventory. With the exception of one test, we consistently find no significant causality in either direction between changes in consumption and the IAS, at the 1% significance level. (See rows 5 and 6 in Table A.1 and Table A.3.) This is consistent with the finding of Alquist and Kilian (2010), who argued that all information in the crude oil futures spreads is already included in inventory data.[14]

We conclude that while the IAS is a reliable empirical proxy for oil inventory, and modelers might choose one or the other depending on their purpose, a complete description of oil

[14]Mis-measurement could also contribute to this result. Consumption and inventory data are compiled from the crude oil physical market, while the interest adjusted spreads are computed using data from exchange traded futures contracts on crude oil. Thus IAS are liable to mis-specifications from arbitrage imperfections between futures and spot prices, and might not always accurately reflect the impact of physical market variables.



5.a: OECD inventory to consumption shocks

5.b: U.S. inventory to consumption shocks

Figure 5: **Response of Inventory to Consumption Shocks**
The panel on the left (right) shows the response of OECD (U.S.) inventory to a Cholesky one standard deviation shock to OECD (U.S.) petroleum consumption. Dotted lines show two standard error bounds.

market conditions will also need a measure of consumption. Shocks to consumption transmit to inventory and then to the IAS.

Naturally, spreads are related to price volatility in the crude oil market (and in commodity markets in general) (Pindyck (2001); Litzenberger and Rabinowitz (1995a); Carlson et al. (2007); Kogan et al. (2009); and Alquist and Kilian (2010)). In the next section, we investigate the relation between volatility, inventory and the shape of the futures curve.

4.3. Historical and Implied Volatility

Pindyck (2001) and Pindyck (2004) investigated the volatility of commodity prices, reasoning that volatile price conditions will increase the convenience yield. Higher price volatility increases the "option premium" on the depletable resource (Litzenberger and Rabinowitz (1995a)), possibly delaying production and reducing supply in the short term. A higher spot relative to future price promotes supply and allows inventories to be replenished. However if oil production entails making irreversible investments or incurring adjustment costs, supply will be inelastic and volatility will be non-monotonically related to the spread. High volatility will be related to both very negative and very positive spreads (Carlson et al. (2007); Kogan et al. (2009)).

Our results show that the short run dynamic relation between volatility and the shape of the futures curve has some interesting features (Table A.1 and Table A.3). When we do not condition on the sign of the IAS, we find that in general, lagged levels of inventories, changes in consumption and the interest adjusted spread do not predict volatility (historical or implied), consistent with Pindyck (2004).

The U.S. petroleum inventory appears to be the only exception, where lagged changes in U.S. inventory explain current levels of historical volatility, whilst the equivalent OECD inventory measure does not.[15] These results align with the empirical results of Geman and

[15]Bu (2014) has shown that inventory information shocks (defined as the difference between reported inventory changes by EIA and forecast values from the Reuters' survey) affect the conditional mean of crude oil returns but not the conditional variance of crude oil returns. This happens because the announcement

Ohana (2009) who find that inventories of U.S. crude oil are more closely related to the historical volatility of crude oil prices than OECD inventory. Taking inventories as a proxy for interest adjusted spreads, this stronger correlation between U.S. crude oil inventories and volatility further implies that variation in the crude oil futures curve in the short run is more dependent on U.S. petroleum inventories than global inventories. Structural restrictions on the distribution and refining of U.S. crude oil related to the shale oil boom, along with the ban on crude oil exports from the U.S. (removed in December 2015) have probably made this dependence temporarily stronger.

Since implied volatilities are inferred from the option prices of crude oil futures, they contain expectations of the volatility of crude oil futures prices.[16] As such, implied volatility is not judged to be a good representation of uncertainty associated with shocks to precautionary oil demand (Alquist and Kilian (2010); Anzuini et al. (2015)), and its explanatory power for real oil prices is likely to be limited. However, when market conditions are modelled using futures spread (instead of inventories, e.g., Kilian and Murphy (2014)) then implied volatility becomes more relevant: both IAS and implied volatilities are derived from traded crude oil derivatives that are forward-looking, nominally-priced securities.

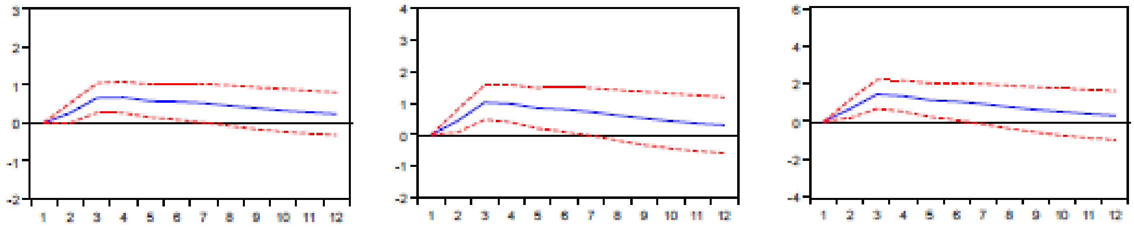
The new result that emerges from our analysis is that lags of implied volatility are significant predictors of the current IAS, a relation that is more pronounced with increasing IAS maturity, see Figure 6.a – Figure 6.c. Figure 6 highlights the fact that the 12-month IAS is more responsive to implied volatility shocks than the shorter durations. This result aligns with the work of Dempster, Medova, and Tang (2012), who demonstrate that trading variables and financial variables are primarily linked to the medium-term and long-term influences on oil convenience yields, while physical market variables have the biggest impact in the short term. Implied volatility, by construction, would better reflect variation from trading and financial variables rather than physical market variables, which are more durable. Then again, historical volatility displays no significant causal relation. (See rows 7 and 8 in Table A.1 and Table A.3. Both tables show very similar results.) We also find that changes in volatility impact the market more strongly through the convenience yield (or IAS in our analysis) than through inventories, which aligns with the findings of Pindyck (2004).

4.4. Determinants of Normal/Inverted Markets

"Normal" market conditions are associated with an upward sloping futures curve, but commodities typically exhibit inverted conditions, where the slope of the futures curve is negative (downward sloping futures curves). A high convenience yield where the value of holding the physical commodity is high will be reflected in an inverted market (Pindyck (2001); Routledge, Seppi, and Spatt (2000)). Indeed, during periods of high volatility, convenience yields and the demand for storage are expected to be high (Ng and Pirrong (1994); Litzenberger and Rabinowitz (1995b)). However since 2008, the crude oil market has experienced extended periods where the futures curve has been upward sloping, even though

effect of inventory on volatility deteriorates with time.

[16]Implied volatility changes contain more information than historical volatility about innovations in expected volatility, see the empirical studies of Dennis et al. (2006) and Angolucci (2009) in equity markets.



6.a: 3-month IAS to IV shocks 6.b: 6-month IAS to IV shocks 6.c: 12-month IAS to IV shocks

Figure 6: **Response of IAS to Shocks in Implied Volatility**
The LHS panel shows the response of the 3-month IAS to a Cholesky one standard deviation shock to implied volatility. The middle panels shows the response of the 6-month IAS and the RHS panel shows the response the 12 month IAS. Dotted lines show two standard error bounds.

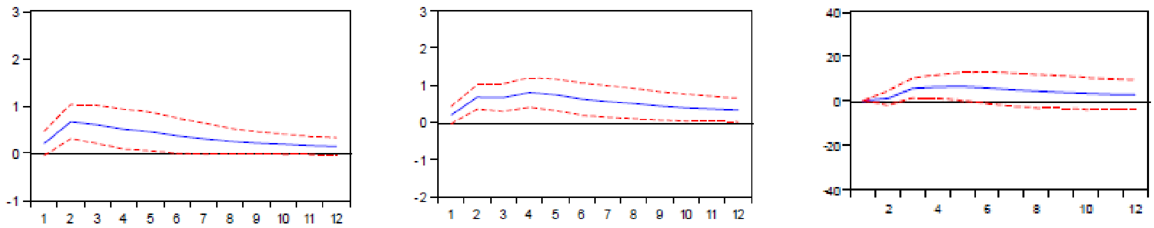
historically it has been predominantly inverted, as Figure 1 displays.[17] Consequently, we treat normal and inverted market conditions separately in an attempt to understand which variables may determine these two regimes.

The estimated models bring out three key findings. First, and as expected, inverted futures curves are related to current or upcoming inventory scarcity. The recent extended periods of normal futures curves are related to relatively abundant inventory. Second, changes in OECD and U.S. petroleum consumption are directly related to the IAS in different regimes, over and above the effects that are transmitted through inventory shocks. Third, separating positive and negative IAS shows the effect of both implied and historical volatility in futures curve dynamics.

Conditioning on the sign of the IAS highlights some interesting differences in bi-directional relation between the IAS and inventory. First, estimates show that OECD and U.S. inventory Granger-causes both negative and positive spreads (Table A.2 and Table A.4). Figure 7.a and Figure 7.b show that positive shocks to OECD inventory increase the IAS independent of its sign. Shocks to U.S. inventory also have a positive impact on the IAS that increases with maturity (Figure 8). Higher inventory relieves shortages so that inverted forward curves become less steep, and aggravates gluts so that normal forward curves become more positive, as the theory of storage affirms.

When we review the reverse causation relation, we see that negative spreads significantly cause both U.S. and OECD inventory, especially at longer maturities. By contrast, the causality from positive spreads to inventories is much smaller or insignificant. Positive spread shocks have a weak impact on OECD inventories (Figure 7.c) but no significant impact on U.S. inventories. Positive spreads have prevailed in the post-2008 period when supplies of shale oil have become abundant. In some instances, the U.S. has experienced gluts and shortages in different areas (Kilian (2016a)). In addition, U.S. petroleum consumption has been declining and OECD consumption has slowed (CEA (2015)). Although the theory of

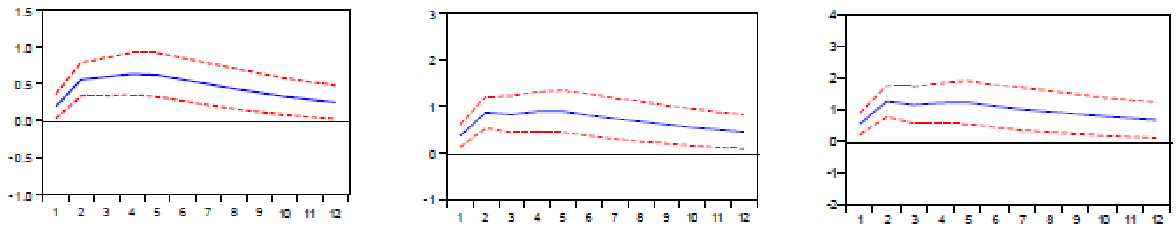
[17]Positive IAS is equivalent to the futures prices trading higher than spot prices and futures prices with longer maturities trade higher than futures prices with shorter maturities, resulting in an upward sloping futures curve.



7.a: IAS_+ to OECD inventory shocks 7.b: IAS_- to OECD inventory shocks 7.c: OECD Inventory to shocks in IAS_+

Figure 7: **Response of positive 6-month IAS/negative 6-month IAS to Shocks in OECD Inventory**

The right panel shows the response of positive IAS to a Cholesky one standard deviation shock to OECD inventory. The middle panel shows the response of negative IAS to shocks to OECD inventory. The left panel shows the response of OECD inventory to a Cholesky one standard deviation shock to positive IAS.



8.a: 3-month IAS_- to U.S. inventory shocks 8.b: 6-month IAS_- to U.S. inventory shocks 8.c: 12-month IAS_- to U.S. inventory shocks

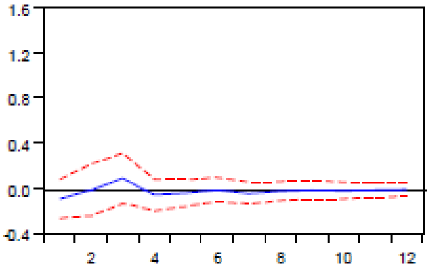
Figure 8: **Response of negative IAS to Shocks in U.S. Inventory**

The panels shows the response of the (3-month, 6-month and 12-month) negative IAS to a Cholesky one standard deviation shock to U.S. inventory. Dotted lines show two standard error boundaries.

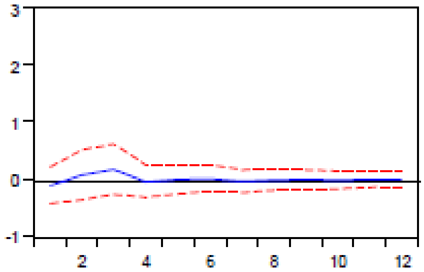
storage predicts that positive spreads would lead to reductions in inventory, the unusually high volume of oil available, structural frictions in the distribution and dispersal of U.S. oil, and weakening consumption may have prevented inventory levels adjusting.

In general, an unexpected increase in current consumption will lead to reduction of inventories, and consequently to a more negative IAS. However weak consumption driven by demographics, turbulent macroeconomic conditions, such as the sub-prime, credit crunch and sovereign debt crises, the increase in speculative trading in futures markets, and unusual supply conditions, drove the usually inverted crude oil market towards an extended period of positive spreads between 2008 and 2015 (Pindyck (1993); Kilian and Murphy (2014)).

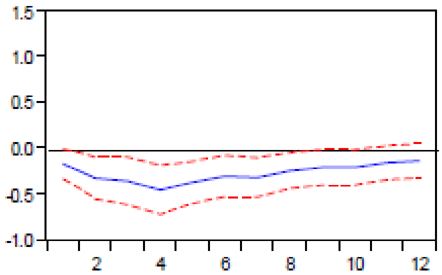
In the models discussed above (Section 4.2) where the IAS regimes were not separated, we found that consumption shocks were generally transmitted to the spread indirectly through inventory changes. When we separately model the positive (normal) and negative (inverted) IAS we find direct channels from consumption to the IAS in addition to the indirect effects via inventory. Lagged changes in OECD petroleum consumption Granger-cause negative spreads especially at longer durations (see row 8 of Table A.2). Lagged changes in U.S. petroleum consumption Granger-cause positive spreads (see row 10 of Table A.4). Impulse response



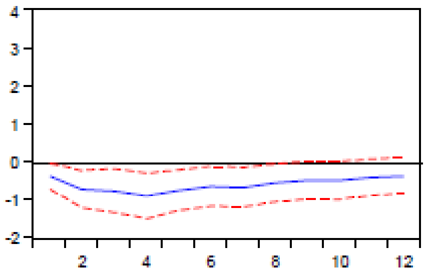
9.a: 3-month IAS_+ to U.S. consumption shocks



9.b: 12-month IAS_+ to U.S. consumption shocks



9.c: 3-month IAS_- to OECD consumption shocks

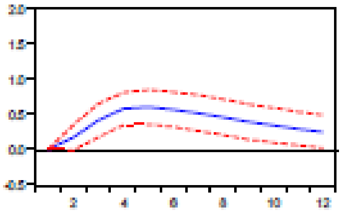


9.d: 12-month IAS_- to OECD consumption shocks

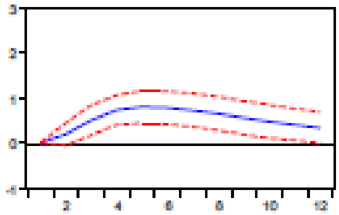
Figure 9: **Response of positive IAS to Shocks in U.S. Consumption and response of negative IAS to Shocks in OECD Consumption**
The top panels show the response of positive IAS to a Cholesky one standard deviation shock to U.S. petroleum consumption. The bottom panels show the response of negative IAS to OECD petroleum consumption.

analysis suggests that the impact of a positive shock in U.S. consumption is to initially decrease then increase the positive spread, although the response is small. A positive shock to OECD consumption is significant during inverted markets and consistent with increasingly negative spreads (Figure 9).

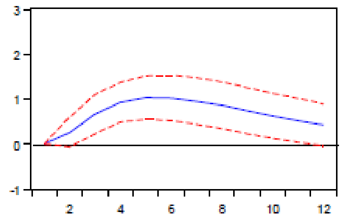
Turning to volatility, we again find that conditioning on the sign of the spread changes results. When positive spreads and negative spreads are modelled separately, lags of both historical and implied volatility predict the IAS. Specifically, we find that both historical and implied volatility Granger-cause the positive IAS but not the negative IAS. A positive shock to volatility leads to an increase in positive IAS, (see Figure 10.a–Figure 10.f). Thus as either the historical or implied volatility increases, the slope of an upward-sloping futures curve steepens, consistent with the predictions of Kogan et al. (2009). These results support the notion that supply inelasticity that suppresses the current spot price beyond the usual market fundamentals, but has less impact on futures prices, might have contributed to the shape of the crude oil futures curve (see also Morana (2013) and Kilian and Murphy (2014)).



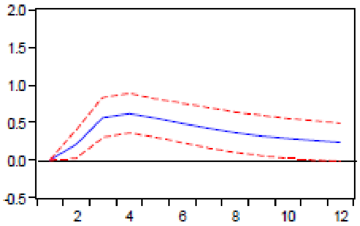
10.a: 3-month IAS_+ to HV shocks



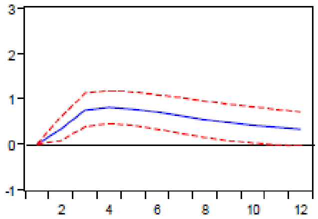
10.b: 6-month IAS_+ to HV shocks



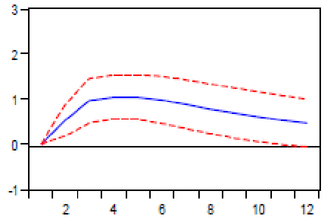
10.c: 12-month IAS_+ to HV shocks



10.d: 3-month IAS_+ to IV shocks



10.e: 6-month IAS_+ to IV shocks



10.f: 12-month IAS_+ to IV shocks

Figure 10: **Response of IAS_+ to Shocks in Volatility**
The top panels show the response of the (3-month, 6-month and 12-month) positive IAS to a Cholesky one standard deviation shock to historical volatility. The bottom panels show the response of the (3-month, 6-month and 12-month) positive IAS to a Cholesky one standard deviation shock to implied volatility. Dotted lines show two standard error bounds.

5. Conclusion

The turbulence in oil markets over the past two decades, culminating in the extended period of positive oil futures-spot spreads experienced since 2008, has raised questions about the adequacy of conventional inventory-based approaches to describing the dynamics of the spread. We address this question using unrestricted VAR estimations of monthly market data from 1992 to 2015. We include, along with the interest adjusted spread, both consumption and inventory of OECD and U.S. oil and petroleum products, and historical and implied volatility. In addition, we separate the negative and positive spread regimes to investigate if connections between variables differ when the spread changes sign.

The theory of storage relates the shape of the oil forward curve to abundant or scarce inventory of the physical commodity. Excess inventory has often been proxied by deviations in inventory levels from a secular trend, thus assuming that regular demand for and supply of oil will continue to grow steadily. In fact, global petroleum consumption has slowed since the early 2000s, and declined in the U.S. Our empirical analysis shows that changes in consumption and inventory are strongly related. We find a significant bi-directional causality relation between consumption and inventory of OECD and U.S. petroleum products. Our estimations show that linear detrending of inventories alone will not adequately model the effects of changes in rate and direction of petroleum consumption on the oil forward curve.

When we model the interest adjusted spread as a continuous variable, our results confirm a regular bi-directional relation between the interest adjusted spread and inventory that supports theories of storage. In addition, in these models, shocks to consumption are transmitted to the spread only indirectly via inventory. However, separating negative from positive spreads reveals that the bi-directional relation breaks down during periods of positive spreads. Specifically, positive spreads do not Granger-cause changes in U.S. oil and petroleum inventory whereas negative spreads do. The theory of storage predicts that positive spreads induce reductions in inventory however unusually high volumes of oil, associated structural frictions in the distribution and dispersal of U.S. oil, and weakening consumption may have prevented inventory levels adjusting in the usual way.

We also find direct linkages from consumption shocks to the IAS. Shocks to OECD consumption amplify a negative spread by further raising spot prices relative to future prices in addition to the immediate impact of higher consumption on inventories and convenience yields.

We also analyze and compare the contribution of implied volatility to the dynamics of the oil spread. Options-implied volatility predicts changes to the IAS, in line with its character as a forward looking measure that better reflects financial and trading variables than historical spot price volatility. Further investigation shows that the impact of volatility on the spread is strongest when the IAS is positive, and leads to even higher relative future prices.

Acknowledgements

We thank Angelo Aspris, Anthony Hall, Boda Kang, and the participants of the Frontiers in Econometrics Workshop, Queensland University of Technology, Brisbane,2014, the Energy and Commodity Finance Conference, ESSEC Business School, 2016 and the UTS Finance Discipline Group internal research seminars for fruitful discussions and helpful suggestions. Nikitopoulos acknowledges financial support under ARC DP 1095177 and UTS Business Research Grant in 2014. Thorp acknowledges support under ARC DP120102239. Parts of this work was supported by the UTS Chair of Finance and Superannuation via the Sydney Financial Forum (Colonial First State Global Asset Management), the NSW Government, the Association of Superannuation Funds of Australia (ASFA), the Industry Superannuation Network (ISN) and the Paul Woolley Centre for the Study of Capital Market Dysfunctionality, UTS.

Appendix A. Granger Causality Tests

Table 1: **Descriptive Statistics**

The table reports the descriptive statistics - in levels and in percentage changes - of OECD petroleum inventory (in billion of barrels per day) and consumption (in millions of barrels per day), the percentage changes in the levels of the U.S. crude oil and petroleum inventory (in billions of barrels per day) and consumption (in millions of barrels per day). Monthly series are averages of daily observations. The table also reports the descriptive statistics of the three series of interest adjusted spreads with maturities 3 months, 6 months, and 12 months, the daily futures price returns (1−month, 4−month, 7−month and 13−month) and volatility (historical and implied). All data series run from January 1992 to March 2015. The data set includes 278 observations.

Series	Mean	Standard Deviation	Kurtosis	Skewness
1−month futures price returns	0.0153%	0.0226	4.4783	-0.1425
4−month futures price returns	0.0168%	0.0184	3.6506	-0.2160
7−month futures price returns	0.0175%	0.0166	3.8300	-0.2273
13−month futures price returns	0.0184%	0.0147	3.8774	-0.2322
OECD Petroleum				
Inventory	4.028	0.182	-1.2682	-0.0526
Inventory % Changes	0.0473%	0.0092	1.0630	-0.4116
Consumption	47.305	2.337	-0.1754	-0.1869
Consumption % Changes	0.0800%	0.0303	-0.1426	-0.1156
U.S. Crude Oil and Petroleum				
Inventory	1.666	0.107	-1.0437	0.1228
Inventory % Changes	0.0679%	0.0116	0.9180	-0.5834
Consumption	582.222	38.073	-0.5106	-0.1202
Consumption % Changes	0.1938%	0.05489	-0.4035	0.1385
Interest Adjusted Spread				
3-month Interest Adjusted Spread	-0.7411	4.8599	3.2356	0.3908
6-month Interest Adjusted Spread	-2.0537	7.7025	1.5520	0.3459
12-month Interest Adjusted Spread	-4.8760	11.5720	1.0327	0.3763
30-day Implied Volatility	32.79%	0.1162	5.3293	1.6920
1-month Futures Historical Volatility	32.86%	0.1507	6.1610	1.9940

Table 2: **Augmented Dickey-Fuller Unit-Root Tests**

The table reports the Augmented Dickey-Fuller t-statistic of the model $\Delta x_t = \mu + \alpha x_{t-1} + \sum_{i=1}^{p} \beta_i \Delta x_{t-i} + \gamma t + \epsilon_t$. The number of lagged changes p is selected based on the Akaike Information Criterion, testing up to a maximum of $p = 15$ lags. The symbols ***, **, and * indicate rejection of the unit-root null hypothesis at the 99%, 95%, and 90% confidence levels respectively, for which the critical values are -3.46, -2.87, and -2.57.

Series	Optimum Lags	Test Statistic	p-value
OECD Petroleum			
Inventory	12	-4.41***	0.00
Consumption	14	-1.79	0.71
US Crude Oil and Petroleum			
Inventory	12	-3.296***	0.07
Consumption	14	-1.867	0.67
Interest Adjusted Spread			
3-month Interest Adjusted Spread	1	-4.65***	0.00
6-month Interest Adjusted Spread	1	-4.00***	0.00
12-month Interest Adjusted Spread	1	-3.65**	0.03
30-day Implied Volatility	1	-3.61**	0.03
1-month Futures Historical Monthly Volatility	3	-4.57***	0.00

Table A.1: **Granger Causality Tests: IAS, OECD Inventory, OECD Consumption and Volatility**

This table reports the results of Granger causality tests on each of the series. A significant F-statistic indicates rejection of the null hypothesis that the particular series is not Granger-caused by the other. The number of lags p is chosen based on the Akaike Information Criterion.

	3-month IAS			6-month IAS			12-month IAS		
	No Vol.	Hist. Vol.	Impl. Vol.	No Vol.	Hist. Vol.	Impl. Vol.	No Vol.	Hist. Vol.	Impl. Vol.
Null hypothesis									
$I \nRightarrow IAS$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$IAS \nRightarrow I$	0.0300	0.0136	0.0930	0.0006	0.0032	0.0016	0.0006	0.0036	0.0020
$I \nRightarrow \Delta\ C$	0.0108	0.0001	0.0137	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001
$\Delta\ C \nRightarrow I$	0.0012	0.0022	0.0012	0.0019	0.0031	0.0000	0.0028	0.0046	0.0000
$IAS \nRightarrow \Delta\ C$	0.0566	0.3213	0.2071	0.0596	0.1596	0.1831	0.0747	0.2088	0.1625
$\Delta\ C \nRightarrow IAS$	0.2973	0.7219	0.1311	0.4483	0.5519	0.0524	0.3378	0.4557	0.0729
$IAS \nRightarrow V$		0.8494	0.6203		0.5863	0.8550		0.2789	0.6212
$V \nRightarrow IAS$		0.3836	0.0000		0.1783	0.0007		0.1387	0.0003
$I \nRightarrow V$		0.3975	0.4387		0.3423	0.7688		0.2734	0.6948
$V \nRightarrow I$		0.4396	0.3774		0.5065	0.6740		0.5413	0.7425
$\Delta\ C \nRightarrow V$		0.5606	0.5048		0.5270	0.8659		0.5057	0.8600
$V \nRightarrow \Delta\ C$		0.1623	0.5184		0.1660	0.5953		0.1780	0.6168

Table A.2: **Granger Causality Tests:** IAS_{+}, IAS_{-}, **OECD Inventory, OECD Consumption and Volatility**

This table reports the results of Granger causality tests on each of the series. A significant F-statistic indicates rejection of the null hypothesis that the particular series is not Granger-caused by the other. The number of lags p is chosen based on the Akaike Information Criterion.

	3-month IAS			6-month IAS			12-month IAS		
	No Vol.	Hist. Vol	Impl. Vol	No Vol.	Hist. Vol	Impl. Vol	No Vol.	Hist. Vol	Impl. Vol
Null hypothesis									
$I \nRightarrow IAS_{-}$	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001
$IAS_{-} \nRightarrow I$	0.1747	0.0685	0.0855	0.0193	0.0087	0.0120	0.0085	0.0034	0.0042
$I \nRightarrow IAS_{+}$	0.0021	0.0000	0.0001	0.0020	0.0002	0.0004	0.0038	0.0013	0.0016
$IAS_{+} \nRightarrow I$	0.0266	0.0823	0.1214	0.0075	0.0789	0.1408	0.0197	0.1543	0.2813
$I \nRightarrow \Delta\ C$	0.0001	0.0004	0.0003	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001
$\Delta\ C \nRightarrow I$	0.0021	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
$IAS_{-} \nRightarrow \Delta\ C$	0.6225	0.3844	0.5614	0.2000	0.0895	0.1447	0.1253	0.0437	0.0768
$\Delta\ C \nRightarrow IAS_{-}$	0.5856	0.0431	0.0367	0.0281	0.0310	0.0221	0.0826	0.0794	0.0573
$IAS_{+} \nRightarrow \Delta\ C$	0.2135	0.6887	0.7797	0.3196	0.8583	0.9558	0.4079	0.8899	0.9804
$\Delta\ C \nRightarrow IAS_{+}$	0.7806	0.7115	0.8139	0.8974	0.7107	0.8277	0.7730	0.5747	0.6994
$IAS_{-} \nRightarrow V$		0.2553	0.4976		0.6957	0.4856		0.9531	0.3972
$V \nRightarrow IAS_{-}$		0.8830	0.9344		0.9158	0.5508		0.7601	0.2410
$IAS_{+} \nRightarrow V$		0.0093	0.2920		0.0034	0.1619		0.0016	0.0973
$V \nRightarrow IAS_{+}$		0.0000	0.0000		0.0000	0.0000		0.0001	0.0001
$I \nRightarrow V$		0.5291	0.8169		0.5071	0.7513		0.4252	0.6299
$V \nRightarrow I$		0.4246	0.6064		0.3192	0.5865		0.2912	0.4895
$\Delta\ C \nRightarrow V$		0.6900	0.8899		0.7212	0.8654		0.7069	0.8627
$V \nRightarrow \Delta\ C$		0.1540	0.6643		0.1137	0.5208		0.0834	0.3869

Table A.3: **Granger Causality Tests: IAS, US Inventory, US Consumption and Volatility**

This table reports the results of Granger causality tests on each of the series. A significant F-statistic indicates rejection of the null hypothesis that the particular series is not Granger-caused by the other. The number of lags p is chosen based on the Akaike Information Criterion.

	3-month IAS			6-month IAS			12-month IAS		
	No Vol.	Hist. Vol.	Impl. Vol.	No Vol.	Hist. Vol.	Impl. Vol.	No Vol.	Hist. Vol.	Impl. Vol.
Null hypothesis									
$I \nRightarrow IAS$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$IAS \nRightarrow I$	0.0144	0.0125	0.0583	0.0023	0.0125	0.0093	0.0010	0.0053	0.0033
$I \nRightarrow \Delta\ C$	0.0416	0.0275	0.0698	0.0200	0.0275	0.0382	0.0142	0.0178	0.0271
$\Delta\ C \nRightarrow I$	0.0071	0.0095	0.0069	0.0071	0.0095	0.0073	0.0083	0.0122	0.0090
$IAS \nRightarrow \Delta\ C$	0.4463	0.3074	0.8551	0.2003	0.3074	0.4504	0.1242	0.1634	0.2648
$\Delta\ C \nRightarrow IAS$	0.0967	0.1043	0.0805	0.1161	0.1043	0.1012	0.1782	0.1638	0.1558
$IAS \nRightarrow V$		0.3822	0.7969		0.3822	0.6463		0.1261	0.3678
$V \nRightarrow IAS$		0.2354	0.0091		0.2354	0.0144		0.3777	0.0146
$I \nRightarrow V$		0.0443	0.1961		0.0443	0.1878		0.0226	0.1572
$V \nRightarrow I$		0.5054	0.2796		0.5054	0.2735		0.4633	0.2080
$\Delta\ C \nRightarrow V$		0.3008	0.5097		0.3008	0.5057		0.3194	0.5133
$V \nRightarrow \Delta\ C$		0.5726	0.4376		0.5726	0.5083		0.4890	0.4788

Table A.4: **Granger Causality Tests:** IAS_{+}, IAS_{-}, **US Inventory, US Consumption and Volatility**

This table reports the results of Granger causality tests on each of the series. A significant F-statistic indicates rejection of the null hypothesis that the particular series is not Granger-caused by the other. The number of lags p is chosen based on the Akaike Information Criterion.

	3-month IAS			6-month IAS			12-month IAS		
	No Vol.	Hist. Vol	Impl. Vol	No Vol.	Hist. Vol	Impl. Vol	No Vol.	Hist. Vol	Impl. Vol
Null hypothesis									
$I \nRightarrow IAS_{-}$	0.0000	0.0000	0.0000	0.0001	0.0002	0.0002	0.0006	0.0010	0.0007
$IAS_{-} \nRightarrow I$	0.0311	0.0442	0.0480	0.0030	0.0031	0.0051	0.0013	0.0018	0.0022
$I \nRightarrow IAS_{+}$	0.0001	0.0000	0.0000	0.0002	0.0000	0.0000	0.0003	0.0002	0.0002
$IAS_{+} \nRightarrow I$	0.3372	0.0155	0.6479	0.4159	0.6448	0.4900	0.4155	0.6758	0.4478
$I \nRightarrow \Delta\ C$	0.0411	0.0590	0.0691	0.0154	0.0254	0.0320	0.0122	0.0176	0.0240
$\Delta\ C \nRightarrow I$	0.0089	0.0097	0.0080	0.0083	0.0093	0.0075	0.0094	0.0121	0.0093
$IAS_{-} \nRightarrow \Delta\ C$	0.5919	0.5834	0.6678	0.1825	0.1861	0.2421	0.1524	0.1551	0.2094
$\Delta\ C \nRightarrow IAS_{-}$	0.7741	0.6122	0.7795	0.8267	0.8193	0.8330	0.8911	0.8695	0.9014
$IAS_{+} \nRightarrow \Delta\ C$	0.8018	0.5348	0.7885	0.8559	0.8492	0.6859	0.7341	0.7713	0.6584
$\Delta\ C \nRightarrow IAS_{+}$	0.0299	0.0044	0.0170	0.0432	0.0216	0.0287	0.0413	0.0244	0.0283
$IAS_{-} \nRightarrow V$		0.1188	0.1896		0.1795	0.1386		0.2313	0.1354
$V \nRightarrow IAS_{-}$		0.8572	0.9739		0.8466	0.9554		0.8073	0.9005
$IAS_{+} \nRightarrow V$		0.0247	0.3659		0.0359	0.2730		0.0114	0.2206
$V \nRightarrow IAS_{+}$		0.0000	0.0000		0.0000	0.0000		0.0000	0.0000
$I \nRightarrow V$		0.4735	0.2273		0.0214	0.1990		0.0091	0.1673
$V \nRightarrow I$		0.0844	0.2630		0.2751	0.2150		0.4123	0.2195
$\Delta\ C \nRightarrow V$		0.4375	0.5141		0.2704	0.4938		0.3168	0.5257
$V \nRightarrow \Delta\ C$		0.1438	0.2847		0.4571	0.2837		0.5054	0.3286

Appendix B. Implied Volatility Computation

Barone-Adesi and Whaley (1987) derive a quadratic approximation method to value American options. At the specific commodity price S^* (S^{**}) for which the value of an American call (put) option with strike price X, time to maturity T, risk free rate r, cost of carry b [18], and implied volatility σ, becomes equal to its exercisable proceeds, the following conditions must hold,

$$S^* - X = c(S^*, T) + \{1 - e^{(b-r)T}\mathrm{N}[d_1(S^*)]\}S^*/q_2, \tag{B.1}$$

$$X - S^{**} = p(S^{**}, T) - \{1 - e^{(b-r)T}\mathrm{N}[-d_1(S^{**})]\}S^{**}/q_1. \tag{B.2}$$

At commodity prices where it is not optimal to early exercise an American call (put) option $S < S^*$, ($S > S^{**}$), Barone-Adesi and Whaley (1987) show the approximate value of an American call (put) option $C(S,T)$ ($P(S,T)$) should equal the value of the corresponding European call (put) option $c(S,T)$ ($p(S,T)$) plus an early exercise premium,

$$C(S,T) = c(S,T) + A_2(S/S^*)^{q_2}, \tag{B.3}$$

$$P(S,T) = p(S,T) + A_1(S/S^{**})^{q_1}. \tag{B.4}$$

Kutner (1998) presents a procedure that employs the Generalized Newton Method to numerically solve the two pairs of nonlinear simulations equations, equations (B.1) & (B.3) and equations (B.2) & (B.4).

Given we can observe the American option prices, their time to maturity, the price of the underlying futures contract, and the LIBOR rate, the above equations may be expressed as functions of only two unknown variables, the critical commodity price S^* or S^{**}, and the option's implied volatility σ,

$$\begin{array}{lcll} f(S^*, \sigma^2) & = & c(S^*, T) + \{1 - e^{(b-r)T}\mathrm{N}[d_1(S^*)]\}S^*/q_2 - (S^* - X) & = 0, \\ g(S^*, \sigma^2) & = & c(S,T) + A_2(S/S^*)^{q_2} - C(S,T) & = 0, \end{array} \tag{B.5}$$

$$\begin{array}{lcll} f(S^{**}, \sigma^2) & = & p(S^{**}, T) - \{1 - e^{(b-r)T}\mathrm{N}[-d_1(S^{**})]\}S^{**}/q_1 - (X - S^{**}) & = 0, \\ g(S^{**}, \sigma^2) & = & p(S,T) + A_1(S/S^{**})^{q_1} - P(S,T) & = 0, \end{array} \tag{B.6}$$

[18] $b = 0$ for options on futures (Barone-Adesi and Whaley (1987)).

where,

$$
\begin{aligned}
q_1 &= \frac{-(N-1)-\sqrt{(N-1)^2+4M/K}}{2},\\
q_2 &= \frac{-(N-1)+\sqrt{(N-1)^2+4M/K}}{2},\\
A_1 &= -(S^{**}/q_1)\{1-e^{(b-r)T}\mathrm{N}[-d_1(S^{**})]\},\\
A_2 &= (S^{*}/q_2)\{1-e^{(b-r)T}\mathrm{N}[d_1(S^{**})]\},\\
d_1(S) &= \frac{\ln(S/X)+(b+\frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}},\\
d_2(S) &= d_1(S)-\sigma\sqrt{T},\\
\mathrm{N}[\,\cdot\,] &= \text{standard cumulative normal distribution},\\
c(S,T) &= Se^{(b-r)T}\mathrm{N}[d_1(S)]-Xe^{-rT}\mathrm{N}[d_2(S)],\\
p(S,T) &= Xe^{-rT}\mathrm{N}[-d_2(S)]-Se^{(b-r)T}\mathrm{N}[-d_1(S)],\\
K &= 1-e^{-rT}, N=2b/\sigma^2, M=2r/\sigma^2.
\end{aligned}
$$

Under the procedure presented by Kutner (1998), for call options, values of S^* and σ^2 are chosen iteratively with starting values S_0^* and σ_0^2 as follows,

$$
\begin{bmatrix} S_{i+1}^* \\ \sigma_{i+1}^2 \end{bmatrix} = \begin{bmatrix} S_i^* \\ \sigma_i^2 \end{bmatrix} - \mathbf{J}^{-1}\begin{bmatrix} g(S_i^*,\sigma_i^2) \\ f(S_i^*,\sigma_i^2) \end{bmatrix}, \tag{B.7}
$$

where $\mathbf{J}^{-1}$ is the inverse of the Jacobian matrix $\mathbf{J}$,

$$
\mathbf{J} = \begin{bmatrix} \partial g/\partial S^* & \partial g/\partial\sigma^2 \\ \partial f/\partial S^* & \partial f/\partial \sigma^2 \end{bmatrix}, \tag{B.8}
$$

$$
\mathbf{J}^{-1} = \frac{1}{\det(\mathbf{J})}\begin{bmatrix} \partial f/\partial\sigma^2 & -\partial g/\partial\sigma^2 \\ -\partial f/\partial S^* & \partial g/\partial S^* \end{bmatrix}, \tag{B.9}
$$

where $\det(\mathbf{J}) = (\partial g/\partial S^*)(\partial f/\partial\sigma^2) - (\partial g/\partial\sigma^2)(\partial f/\partial S^*)$ is the Jacobian determinant. S^{**} and σ are computed analogously for put options by replacing S^* with S^{**} in the above procedure.

Kutner's (1998) expressions for the elements of the Jacobian matrix $\mathbf{J}$ are presented below. Variables are as previously defined, and $\mathrm{n}[\,\cdot\,]$ is the standard normal probability density function. In the case of call options,

$$
\partial g/\partial S^* = (S/S^*)^{q_2}[(1/q_2)y_1 - (S^*/q_2)y_3y_2 - q_2A_2(1/S^*)], \tag{B.10}
$$

$$
\partial f/\partial S^* = y_3\mathrm{N}[d_1(S^*)] + (y_1/q_2) - (S^*/q_2)y_3y_2 - 1, \tag{B.11}
$$

$$
\partial g/\partial\sigma^2 = y_5 + (S/S^*)^{q_2}[A_2\ln(S/S^*)y_4 - (S^*/q_2)y_3y_6\mathrm{n}[d_1(S^*)] - y_1y_4(S^*/q_2^2)], \tag{B.12}
$$

$$
\partial f/\partial\sigma^2 = y_7 - y_1y_4(S^*/q_2^2) - (S^*/q_2)y_3y_6\mathrm{n}[d_1(S^*)]. \tag{B.13}
$$

In the case of put options,

$$
\begin{aligned}
\partial g/\partial S^{**} &= (S/S^{**})^{q_1}[(S^{**}/q_1)z_2 - (1/q_1)z_1 - q_1 A_1(1/S^{**})], && \text{(B.14)}\\
\partial f/\partial S^{**} &= z_1(1-1/q_1) + (S^{**}/q_1)z_2, && \text{(B.15)}\\
\partial g/\partial \sigma^2 &= \mathrm{n}[-d_2(S)]X\sqrt{T}e^{-rT}/2\sigma + (S/S^{**})^{q_1}[A_1\ln(S/S^{**})z_4 + z_5], && \text{(B.16)}\\
\partial f/\partial \sigma^2 &= \mathrm{n}[-d_2(S^{**})]X\sqrt{T}e^{-rT}/2\sigma + (S^{**}/q_1)e^{(b-r)T}\mathrm{n}[-d_1(S^{**})]z_3 + (S^{**}/q_1^2)z_1z_4. && \text{(B.17)}
\end{aligned}
$$

where,

$$
\begin{aligned}
y_1 &= 1 - e^{(b-r)T}\mathrm{N}[d_1(S^*)], & z_1 &= 1 - e^{(b-r)T}\mathrm{N}[-d_1(S^{**})],\\
y_2 &= \mathrm{n}[d_1(S^*)]/(S^*\sigma\sqrt{T}), & z_2 &= -\mathrm{n}[-d_1(S^{**})]e^{(b-r)T}/(S^{**}\sigma\sqrt{T}),\\
y_3 &= e^{(b-r)T}, & z_3 &= [\ln(S^{**}/X) + bT]/(2\sigma^3\sqrt{T}) - \sqrt{T}/4\sigma,\\
y_4 &= b/\sigma^4 - \tfrac{(N-1)b+2r/K}{\sigma^4\sqrt{(N-1)^2+4M/K}}, & z_4 &= b/\sigma^4 + \tfrac{(N-1)b+2r/K}{\sigma^4\sqrt{(N-1)^2+4M/K}},\\
y_5 &= X\sqrt{T}e^{-rT}\mathrm{n}[d_2(S)]/2\sigma, & z_5 &= (S^{**}/q_1)(e^{(b-r)T}\mathrm{n}[-d_1(S^{**})]z_3) + (S^{**}/q_1^2)z_1z_4,\\
y_6 &= -2[\ln(S^*/X) + bT]/(\sigma^2\sqrt{T}), & &\\
y_7 &= X\sqrt{T}e^{e-rT}\mathrm{n}[d_2(S^*)]/2\sigma. & &
\end{aligned}
$$

We arbitrarily select for out initial values $S_0^* = S + 10$, $S_0^{**} = S - 10$, and $\sigma_0 = 10\%$ where S is the price of the underlying futures contract. We repeat the procedure until $|f| < 0.00001$ and $|g| < 0.0001$. Consistent with the claims of Kutner (1998), we find the procedure generally converges within 6 iterations.

The implied volatilities obtained from this procedure span the period from the current date until the option's expiry. As time progresses and options approach maturity the period over which the implied volatility is calculated diminishes. We accordingly interpolate the 30-day implied volatility from the first and second nearest option contracts using the weighting method prescribed by the Chicago Board Option Exchange in their VIX white paper (CBOE (2009)),

$$
\sigma_{\text{30-day}} = \sqrt{\left\{T_1\sigma_1^2\left[\frac{T_2 - T_{30}}{T_2 - T_1}\right] + T_2\sigma_2^2\left[\frac{T_{30} - T_1}{T_2 - T_1}\right]\right\} \times \frac{365}{30}}, \tag{B.18}
$$

where $\sigma_{1,2}$ is the implied volatility of first and second nearest option contracts, $T_{1,2}$ is the number of trading days until expiry of the first and second nearest option contracts, and $T_{30} = 30 \times \frac{252}{365}$ is the number of trading days in 30 calendar days.

In most circumstances the nearest month options have less than 30 calendar days to expiration and the second month options have more than 30 days to expiration. Accordingly the 30-day implied volatility $\sigma_{\text{30-day}}$ is an interpolation of σ_1 and σ_2. When the contracts roll over each month it is possible for both the first and second nearest contracts to have more than 30 days to expiration. Consistent with the VIX calculation, the same formula in (B.18) is used but the nearest contract's weight is greater than 1 and the second nearest contract's weight is negative, resulting in an extrapolation of the 30-day implied volatility (CBOE (2009)).

We compute the 30-day at-the-money implied volatility separately for the call and put options and rank these series according to the difference between the call and put implied volatilities. We remove spurious results by winsorising the data at the 1st and 99th percentiles, -1.1409% and 1.2349% respectively. We then take a simple average of the two series and average this by calendar month to obtain our final implied volatility data series, as depicted in Figure 3.

References

Aastveit, K. A., Bjørnland, H. C., Thorsrud, L. A., 2015. What drives oil prices? emerging versus developed economies. Journal of Applied Econometrics 30 (7), 1013–1028.

Alquist, R., Kilian, L., 2010. What do we learn from the price of crude oil futures? Journal of Applied Econometrics 25 (4), 539–573.

Angolucci, P., 2009. Volatility in crude oil futures: A comparison of the predictive ability of garch and implied volatility models. Energy Economics 31, 316–321.

Anzuini, A., Pagano, P., Pisani, M., 2015. Macroeconomic effects of precautionary demand for oil. Journal of Applied Econometrics 30 (6), 968–986.

Barone-Adesi, G., Whaley, R. E., 06 1987. Efficient analytic approximation of American option values. The Journal of Finance 42 (2), 301–320.

Brennan, M. J., 03 1958. The supply of storage. The American Economic Review 48 (1), 50–72.

Bu, H., 2014. Effect of inventory announcements in crude oil price volatility. Energy Economics 46, 485–494.

Carlson, M., Khokher, Z., Titman, S., 2007. Equilibrium exhaustible resource price dynamics. The Journal of Finance 62 (4), 1663–1703.
URL http://dx.doi.org/10.1111/j.1540-6261.2007.01254.x

CBOE, 2009. The CBOE Volatility Index - VIX. White paper, The Chicago Board Options Exchange.

CEA, 2015. Explaining the U.S. petroleum consumption surprise. Council of Economic Advisors: Washington D.C.
URL https://www.whitehouse.gov/sites/default/files/docs/

D'Ecclesia, R. L., Magrini, E., Montalbano, P., Triulzi, U., 2014. Understanding recent oil price dynamics: A novel empirical approach. Energy Economics 46, S11–S17.

Dempster, M. A. H., Medova, E., Tang, K., 2012. Determinants of oil futures prices and convenience yields. Quantitative Finance 12 (12), 1795–1809.

Dennis, P., Mayhew, S., Stivers, C., 2006. Stock returns, implied volatility innovations, and the asymmetric volatility phenomenon. Journal of Financial and Quantitative Analysis 41 (2), 381–406.

Dickey, D. A., Fuller, W. A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74 (366a), 427–431.

Dincerler, C., Khokher, Z. I., Simin, T. T., 2005. An empirical analysis of commodity convenience yields, working paper, The Pennsylvania State University.

Fama, E. F., French, K. R., 01 1987. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. The Journal of Business 60 (1), 55–73.

Fama, E. F., French, K. R., 12 1988. Business cycles and the behavior of metals prices. The Journal of Finance 43 (5), 1075–1093.

Geman, H., Ohana, S., 2009. Forward curves, scarcity and price volatility in oil and natural gas markets. Energy Economics 7 (4), 576–585.

Geman, H., Smith, W. O., 2013. Theory of storage, inventory and volatility in the lme base metals. Resources Policy 38 (1), 18–28.

Haugom, E., Langeland, H., Molnár, P., Westgaard, S., 2014. Forecasting volatility of the U.S. oil market. Journal of Banking and Finance 47, 1–14.

Kaldor, N., 10 1939. Speculation and economic stability. The Review of Economic Studies 7 (1), 1–27.

Kilian, L., 2009. Not all price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review 99 (3), 1053–1069.

Kilian, L., 2016a. The impact of the fracking boom on arab oil producers. Tech. rep., CEPR Discussion Paper No. DP11107.

Kilian, L., 2016b. The impact of the shale oil revolution on U.S. oil and gasoline prices. Review of Environmental Economics and PolicyForthcoming.

Kilian, L., Murphy, D. P., 2014. The role of inventories and speculative trading in the global market for crude oil. Journal of Applied Econometrics 29 (3), 454–478, dOI: 10.1002/jae.2322.

Kogan, L., Livdan, D., Yaron, A., 2009. Oil futures prices in a production economy with investment constraints. The Journal of Finance 64 (3), 1345–1375.
URL http://dx.doi.org/10.1111/j.1540-6261.2009.01466.x

Kutner, G. W., 1998. Determining the implied volatility for American options using the QAM. Financial Review 33 (1), 119–130.

Litzenberger, R. H., Rabinowitz, N., 1995a. Backwardation in oil futures markets: Theory and empirical evidence. The Journal of Finance 50 (5), 1517–1545.
URL http://dx.doi.org/10.1111/j.1540-6261.1995.tb05187.x

Litzenberger, R. H., Rabinowitz, N., 1995b. Backwardation in oil futures markets: Theory and empirical evidence. The Journal of Finance 50, 1517–1545.

Martens, M., Zein, J., 2004. Predicting financial volatility: High-frequency time-series forecasts vis-a-vis implied volatility. Journal of Futures Markets 24 (11), 1005–1028.
URL http://dx.doi.org/10.1002/fut.20126

Morana, C., 2013. Oil price dynamics, macro-finance interactions and the role of financial speculation. Journal of Banking and Finance 37, 206–226.

Ng, V. K., Pirrong, C. S., 1994. Fundamentals and volatility: Storage, spreads, and the dynamics of metals prices. The Journal of Business 67 (2), 203–230.

Pindyck, R. S., 05 1993. The present value model of rational commodity pricing. The Economic Journal 103 (418), 511–530.

Pindyck, R. S., 07 2001. The dynamics of commodity spot and futures markets: A primer. Energy Journal 22 (3), 1–29.

Pindyck, R. S., 2004. Volatility and commodity price dynamics. Journal of Futures Markets 24 (11), 1029–1047.

Routledge, B. R., Seppi, D. J., Spatt, C. S., 2000. Equilibrium forward curves for commodities. The Journal of Finance 55 (3), 1297–1338.

Said, S. E., Dickey, D. A., 12 1984. Testing for unit roots in autoregressive-moving average models of unknown order. Biometrika 71 (3), 599–607.

Sun, J., Shi, W., 2015. Breaks, trends, and unit roots in spot prices for crude oil and petroleum products. Energy Economics 50, 169 – 177.
URL http://www.sciencedirect.com/science/article/pii/S014098831500153X

Telser, L. G., 06 1958. Futures trading and the storage of cotton and wheat. Journal of Political Economy 66 (3), 233–255.

Wang, T., Wu, J., Yang, J., 2008. Realized volatility and correlation in energy futures markets. Journal of Futures Markets 28 (10), 993–1011.
URL http://dx.doi.org/10.1002/fut.20347

Williams, J. C., Wright, B. D., 1991. Storage and Commodity Markets. Cambridge University Press, Cambridge, England.

Working, H., 02 1948. Theory of the inverse carrying charge in futures markets. Journal of Farm Economics 30 (1), 1–28.

Working, H., 1949. The theory of price of storage. The American Economic Review 39 (6), 1254–1262.