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Does Speculation Affect Oil Price Volatility?

Coimbra, Outubro de 2017

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Does Speculation Affect Oil Price Volatility?

Dissertação submetida ao Instituto Superior de Contabilidade e Administração de Coimbra para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Análise Financeira, realizada sob a orientação da Professora Doutora Maria Elisabete Neves e coorientação da Professora Doutora Joana Jorge de Queiroz Leite.

Coimbra, Outubro de 2017

TERMO DE RESPONSABILIDADE

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Vítor Hugo Alves Oliveira

Mestrado em Análise Financeira

Coimbra, Outubro 2017

"An investment in knowledge pays the best interest."

Benjamin Franklin

Dedicatory

I dedicate the present dissertation to my parents, because without them none of this would have been possible. A special dedication goes out to my mom because she has always believed in my work and ambition, helping me be my best from day one.

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The first and most sincere thanks is for my parents because without their investment in my knowledge this dissertation would not have been possible. They have always given me the liberty and strength to get out of life everything I set my mind to. Special thanks go out to my mom, she always led me towards the path of knowledge, revealing its importance. She helped me conquer all of my objectives, knowing she didn't have the opportunity to do the same for herself.

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Resumo

O objetivo do presente estudo é tentar perceber se a atividade especulativa é o fator principal na repentina subida de preços do crude no spot market, especialmente no mais recente episódio especulativo que ocorreu entre 2003 e a primeira metade de 2008. A base do nosso estudo assenta num modelo já existente de vectores autoregressivos que foi proposto por Kilian e Murphy (2014); um modelo estrutural do mercado global do crude que permite uma análise de choques de procura e oferta e também choques especulativos. A originalidade do modelo apresentado nesta dissertação, relativamente ao daqueles autores, reside na introdução de um componente especulativo para medir os *spreads* usando contratos de futuros do crude. Com o *output* do modelo estrutural apresentado conseguimos excluir a teoria da especulação como fator na subida do preço do crude; no entanto, os nossos resultados sugerem que a subida se deve a um aumento na procura conduzido por um crescimento económico inesperado na economia global. As conclusões deste estudo permitem confirmar as de outras obras literárias da mesma natureza e revelam a importância dos futuros enquanto instrumentos preditivos.

Palavras-chave: *Procura; Oferta; Especulação; Inventários; Spreads; Futuros; Crude; Elasticidade; Mercados Globais*

Abstract

The objective of the present study is to understand if speculative activity is a main factor in the run-up of oil prices in the spot market, especially the most recent price bubble in the 2003-mid 2008 period. The basis of our model is set on an existing vector autoregressive model proposed by Kilian and Murphy (2014), a structural model of the global market for crude oil that allows for shocks to flow demand and flow supply as well as speculative demand shocks for oil. Our speculative component of the real price is set on the data of oil futures, which we used to construct our oil spread variable. From the output of our structural model we ruled out speculation as a factor of rising oil prices. Instead we found that rapid oil demand caused by an unexpected increase in the global business cycle is the most accurate culprit. The conclusions in this study confirm the findings of other authors in existing literature of the same nature and shed light on the predictive power of futures.

Keywords: *Demand; Supply; Speculation; Inventories; Spreads; Futures; Crude Oil; Elasticity; Global Markets*

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Acronyms and Abbreviations

CFTC – Commodity Futures Trading Commission

CME – Chicago Mercantile Exchange

CPI – Consumer Price Index

GAI – Global Activity Index

G7 – The Group of Seven

IEA – International Energy Agency

IRF – Impulse Response Functions

NYMEX – New York Mercantile Exchange

OECD - Organization for Economic Co-operation and Development

OPEC – Organization of Petroleum Exporting Countries

SVAR – Structural Vector Autoregressive

USA – United States of America

VAR – Vector Autoregressive

WTI – West Texas Intermediate

Introduction

The factor that motivated the carrying out of the present dissertation is imbedded in the need to quench the thirst of curiosity for the sporadic run-up of crude oil prices in the most recent crude oil price bubble in the 2003- mid 2008 period. This phenomenon of the price of oil has been debated by commentators, analysts and academic researchers. Some issues are still open and can be summarized in the following: Might the surge be due to speculative trading? Is it the reduction in oil supply caused by the OPEC (Organization for Economic Co-operation and Development)? These issues lead us to blame traders and investors on the one hand and to deduce that economic growth may have been the result of the rise in the real price of oil on the other, especially in emerging Asian markets.

Recent papers recognize that stock demand and flow demand for oil are an important aspect in modeling for the real price of oil. Some of the research papers that we have considered in our work are Hamilton (2009), Kilian (2009), Alquist and Kilian (2010) and Kilian and Murphy (2014), among others. For example, Kilian and Murphy (2014) added on to the Structural Vector Autoregressive (SVAR) model of Kilian (2009) by identifying the speculative component using speculative demand shocks as an extra restriction and using inventories as an additional variable.

This paper will use a structural Vector Autoregressive (VAR) model of the global market for crude oil that has the objective of explaining the underlying determinants of the real price of oil, quantifying the effects of demand and supply shocks. The original model proposed by Kilian and Murphy (2014) sought out to draw conclusions of the economic theory for storable commodities, drawing assumptions about the expected direction of the real price of oil and its fundamental determinants, driven by the force of supply and demand.

Studies on the commodity future prices are very frequent, they are usually criticized and seen as bad indicators of forecast power, future prices seem to do no better than random walk forecasts, Alquist and Kilian (2010). Therefore, one of the objectives of this work is to debunk this criticism by using Lutz Kilian's and Dan Murphy's model and to closely study their work by substituting crude oil inventories for futures spreads between the spot price and future price of oil.

It is important to put out that the purpose of the present work is not to take a stand on the social morality of speculative activity nor does it define unhealthy speculative behavior. There is no attempt in distinguishing normal speculation from excessive speculation.

Alquist and Kilian (2010) conclude that for short maturities the deviation of the future-spot relationship is small, meaning that even though futures might do no better than random walk models they are not completely excluded as a predictor of the real price of oil. Having that in mind, the spread theory used as a variable in our model is the same as Alquist and Kilian (2010).

Traditional VAR models construct their market expectations on past data of the variables. Having a forward-looking structure keeps flow demand and flow supply valid, because it assumes that not all traders base their prediction of future demand and supply on historical data, we consider that not all traders are chartists and that the fundamentals of future movements shouldn't only be based off of historical data. Open interest positions shift rapidly in response to news of oil discoveries, war or just trader's uncertainty about future oil supply and future global market consumption of said commodity.

Expectations of a shortfall of future oil supply, relative to demand not captured by the basic flow demand and flow supply shocks, altering the price of oil, is referred to as a speculative demand shock. It is these shocks that have policymakers and researchers attributing oil price volatility to speculative activity. These shocks cannot be directly observed and can only be identified within the model.

Who is a speculator? A speculator is a non-commercial agent with imperfect information regarding the evolution of oil price fundamentals that only enters the market on arbitrage to make money, Vansteenkiste (2011). Speculative purchasers reflect increased uncertainty about future supply and demand conditions, Alquist and Kilian (2010).

Section 2 explains Methodology and VAR Model Specifications based on Kilian and Murphy (2014) and present the variables used in the model and their sources. Section 3 gives an insight on the identification process based on sign restriction and the additional imposed boundaries. In section 4 we discuss the results and impacts of speculative activity in general and how it may or may not be responsible for oil price swings, especially the heavily debated 2003- mid 2008 period.

1. Literature Review

1.1. Insight on the NYMEX and Crude Oil Futures Market

The New York Mercantile Exchange (NYMEX) trading floors started off as a tight-knit circle of family farm businesses as an egg, cheese and butter market in 1872, this was before organized oil trading was in existence. New York dairy merchants would all gather to exchange goods, recording prices by hand with chalk on old large blackboards, working for only a few hours a day. Today there is only one remanence of that time, sticking to a farmer's market hours, some four and a half hours working days. As years passed, the market kept growing in a skyrocket fashion, trades went from million to billions. Merchants and Farmers that were able to keep up with the market started to bring in their sons and each new generation found itself willing to run more risk to protect their growing legacy and global fiefdom. Debt after debt and default after default, run in with the law and family feuds were not able to shake down this "dog eat dog market". After more than 130 years of failure after failure nobody would guess that it would become the biggest oil market on earth.

In fact, the oil market did not begin with the masterminds and wilder beasts of the trading floors but with a sour relationship between father and son. Michel Marks was the engineer of the modern oil market, the son of the well-known Francis Marks that at one time owned the most seats on the NYMEX floor due to his flourishing fruits and vegetables business, Paris Foods. When Michel first entered the pits the cash crop was the Maine potato, a major commodity at the time known for keeping the balance of world power. The Maine potato represented 80% of the NYMEX market but the prices were greatly manipulated by the older traders, breaking the market in an irreparable fashion. Not only traders but also corrupt farmers, corrupt market officials, and potatoes passing inspection in Maine but showing up spoiled at delivery date. Trains that were supposedly filled with potatoes would arrive empty, these inside jobs tinkering with supplies were meant to influence the prices and drive them from their fundamental values.

In 1976, potatoes were the third most traded commodity in the United Stated and in that same year prices soared from $5 a contract to $19 a contract. This era of fast and loose market regulations ended for the potato market when it caught the governments attention and it intervened in the potato crisis. The newly created Commodity Futures Trading

Commission (CFTC), the new market watchdog, banned the trading of potato futures for an indefinite time.

This move killed the most prosperous and thriving business on the NYMEX floor and it had lost the only legitimacy it had. NYMEX floor seats that were priced at $47.000 had now plunged to $5.000, leaving seat holders furious and seeking a new alternative to trade. Younger seat holders and traders wanted a new leader with a decent education and one that wasn't a potato trading freak like the older seat holders and traders. It was then in 1977 that Michel Marks saw himself become the youngest NYMEX chairman.

In 1983 Ronald Regan removed the final energy barrier, giving birth to the futures contracts on light, sweet crude oil. After submitting the proposal to the CFTC, and fighting with the commissions board to approve the NYMEX contracts before the Chicago Mercantile Exchange (CME), on the 30th of March of 1983 the first contracts on crude oil were traded. NYMEX debuted futures contracts on West Texas Intermediate (WTI) with delivery point Cushing, Oklahoma, and on the same day CME started trading futures contracts on Louisiana light, sweet crude oil, with delivery point in Parish, Louisiana. These contracts would be shaped and maintained with the help of Louis Guttmann, that would later come to assume the paper of chairman on the NYMEX board.

"No one had taught the traders how to build the world's first free oil market. And no one had left them with any idea of how to keep it from spinning out of control"

Leah McGrath Goodman, *The Asylum*, pg. 95

1.2. Using Oil Futures as an Indicator of Market Expectations

Kilian and Murphy (2014) claim that using oil inventories is the best measure to capture the market expectations, because most of the relevant information is already included in the inventory data.

Kilian and Murphy (2014) also don't use futures because they already use inventories making the use of futures redundant as well as disadvantageous due to the fact that crude oil futures only came into play in the 1980's, leaving most of their sample nonexistent.

Oil futures prices reflect the agreement between buyers and sellers at a given delivery month. These prices should be an indicator of the investors' expectations of the market's behavior for any given commodity.

Many authors state that a random walk model is as good if not better predictor of the future behavior of crude oil prices, and is used as a benchmark to prove or disprove the efficiency of the forecasting performance of other models. As studied by Reeve and Vigfusson (2011), futures constantly outperform the random walk model.

Wu and McCallum (2005) used a "future-spot spread" model and concluded that the standard deviation prediction errors range anywhere from 10% (1-month maturity) of the spot price to 30% (12-month horizon). They concur that predicting oil price movements in near term (short contract dates), up to 4 months, is a better indicator than a random walk. An observation worth noting is that future prices are more useful in forecasting near-term oil price movement and future contracts with small maturities are much more liquid in the futures market. As referred by Alquist and Kilian (2010), the sizes of open positions for short maturity contracts, 1-3 months, is of large volume and are much more accurate when compared to long maturity contracts, because those become more vulnerable to shocks that are not related to oil price movements in the future.

1.2.1 Why Data on Oil Inventories is Poor

Following the assumption of Khan (2009), oil inventories are notoriously poor because many important non-Organization for Economic Co-operation and Development countries (OECD) do not report any data at all. Most of these non-OECD countries, that make up half of the demand for crude oil, including many large consumers such as China, do not report any data on oil inventories. Oil stored in tankers, "oil at sea", is also not reported in the data for crude oil inventories, distorting the data used for many studies using such variable. Singleton (2010) states that most arguments supporting a historical linkage between supply/demand and inventory accumulations are wrong. A view held by many authors of the subject states that speculative trading tends to distort the prices of crude oil and is accompanied by an increase in inventory levels. These facts are partially true for historical data before the 2002-mid 2008 period, except in the occurrence of other oil "Boom/Bust" phenomenon, where the relationship of supply/demand-inventory levels makes little sense and many times has a negative relationship.

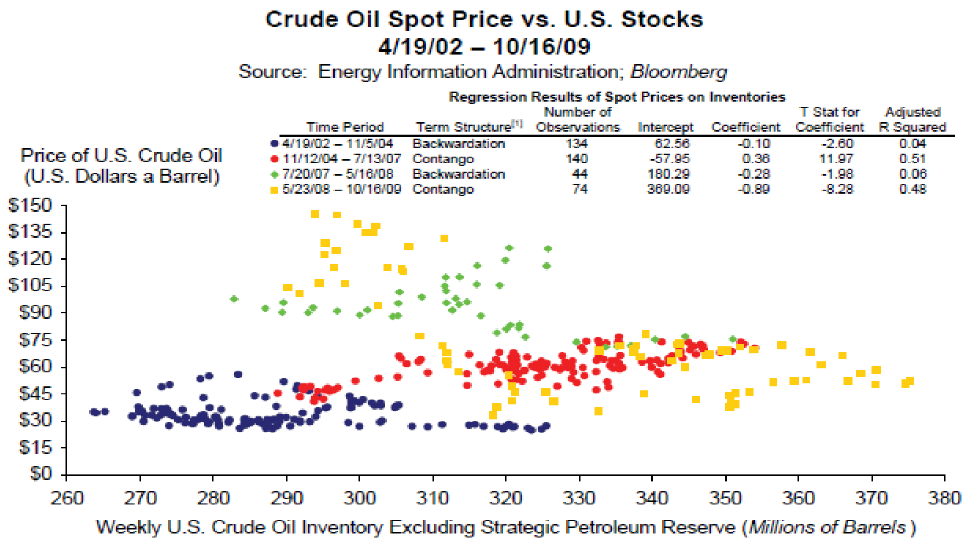

Figure 1- Commercial inventories of crude oil plotted against the spot price of oil

Note: Contango[1] and Backwardation[2] are defined using spot price and the three-month futures prices.

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[1] *Cotango* - refers to a situation where the future spot price is below the current price, and people are willing to pay more for a commodity at some point in the future than the actual expected price of the commodity.

[2] *Backwardation* - As the contract approaches expiration, the futures contract trades at a higher price compared to when the contract was further away from expiration

Singleton (2010) used data from the Energy Information Administration (EIA) to construct Figure 1 (above). It illustrates the inventory (millions of barrels) - price relationship that has been heavily debated by fundamentalists and speculators. The EIA (2008) claims that if speculation drives up prices then an imbalance in the form of higher stocks should be apparent. Some speculators claim that they did not find evidence of inventory hording on behalf of refiners (e.g, Hamilton (2009)), others argue that there was a visible rise in the 2004 to 2006 period and it serves as an evidence for speculation (e.g, U.S. Senate Permanent Subcommittee on Investigations (2006)).

From figure 1, prior to 2003, we can deduce that the oil price-inventory relationship was strongly negative. Said relationship then turned significantly positive from 2004 to 2007, as can be seen by the large rise in the adjusted R squared value, revealing some level of significance between the oil price-inventory relationship. Looking at the 2007 period, there is a weakening in the relationship, being largely negative with only a slight positive gain in the first half of 2008. The problem with studying this relationship is the omitted stockpiling of strategic reserves from major emerging economies, a problem noted in the above text by Khan (2009). This is only a small portion of the oil price-inventory relationship due to the fact of lacking data on reserves from major emerging economies. Data from G7 is bad enough in terms of reliability, and it's the best there is, taking away data from large consumers like China only makes the price-inventory relationship studying even harder.

Pirrong (2009) points out that there is no stable relationship between the price of oil and inventory data, and the relationship that might exist is just a consequence of increased supply/demand uncertainty. There is no theoretical reasoning to backup this theory of changes in prices having correlation with oil inventories. Another factor to keep in mind is that speculation plays a true role in defining oil prices, inventory adjustments depend mainly on what one assumes to be the nature of supply/demand, even if it is all just pure speculation.

1.2.2 Problems with Futures Data as an Indicator of Speculative Activity

Using oil futures as an indicator of speculative activity has its ups and downs. For one, there is no way in isolating the speculative component in net open positions, unless one separates commercial from non-commercial positions. This is so because non-commercial traders are foreseen as the speculators in the market, commercial traders are related to hedging positions to protect their demand for oil. Isabel Vansteenkiste (2011) estimates that 20% of traders at NYMEX are non-commercial, they are not in the market to hedge prices for consumption or selling, basically they just bet on the direction of prices. Future prices should equal their spot counterpart plus the price of carry[3] and the convenience yield[4]. Most of these non-commercial traders have an imperfect knowledge of the determinants of oil prices and the evolution of fundamentals that make up these prices. They do not take into account fundamentals and base their expectations of prices and trading strategies upon observed historical patterns in past prices, Vansteenkiste (2011). Benefit of entry for these traders increases with expected deviation of oil prices from their fundamentals, the further the future prices deviate from underlying fundamentals, the more non-commercial fundamental traders are willing to enter the market. The factors that drive the oil futures prices at each moment in time will depend on the share of non-commercial traders present in the futures market, Vansteenkiste (2011).

Many authors have commented on the use of futures, such as Hamilton (2009), Alquist and Kilian (2010), and Kilian and Murphy (2014). They claim that there is an arbitrage condition that links real oil prices in the spot market to their future market counterpart. Kilian and Murphy (2014) use oil inventories because they argue that speculation drives up the price of oil in the futures market, thus arbitrage will imply that traders buy inventory in the spot market to hedge/profit in the futures market. This way, they can quantify speculation using inventory volatility in the spot market, studying its behavior to different economic shocks. In their defense, oil inventories are easier to read and use in modeling consumption of said commodity, and futures only came around in the early

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[3] *Price of carry* - The sum of the cost of storage plus the interest rate.

[4] *Convenience yield* - the benefit from holding spot oil which accrues to the owner of the spot commodity.

eighties, which would make most of their study redundant. Modeling using oil future spreads can become invalid in when the arbitrage between spot and futures markets is less than perfect, making the data invalid. A hard task of using oil spreads is imposing identifying information about price elasticity of oil demand, Kilian and Murphy (2014). Nonetheless it has not been proven impossible and we believe it is possible to overcome this task.

1.2.3 Open Interest Positions

In the light of the above, one question arises: What is a rise in open interest positions[5]? The rising share of non-commercial traders in all open interest positions tend to increase during the period of rising oil prices, 2003-mid 2008. This is a result of oil becoming a popular asset because of the troubles with the housing market worldwide and the beginning of the financial crisis, driving investors to the alternative commodities market. During this time frame, the habitual commodities traders were joined by pension funds and commodity index fund in the speculative game.

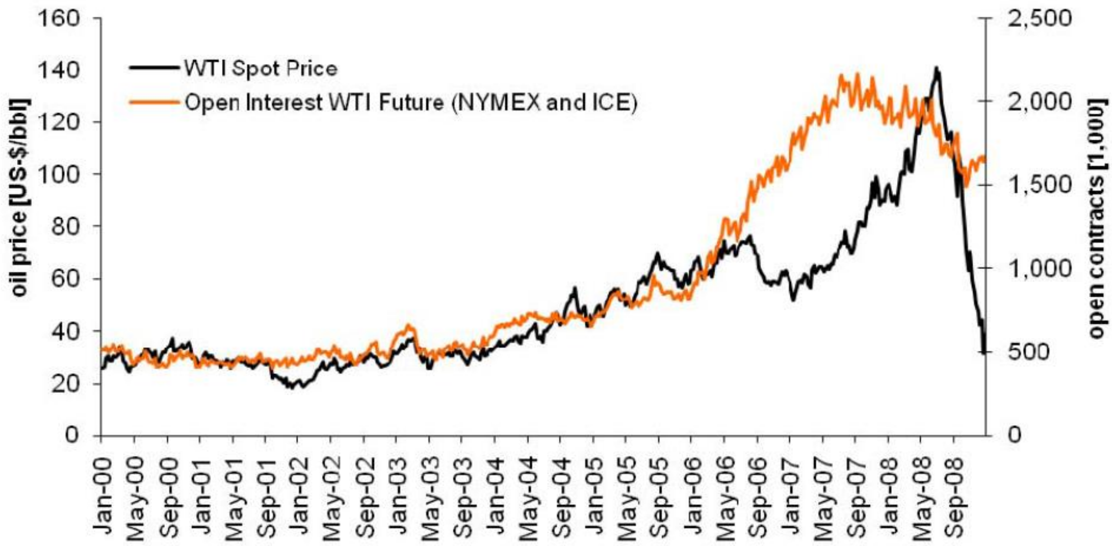

Figure 2- Open interest in future contracts

[5] *Open interest positions* - the total number of open or outstanding, not closed or delivered positions, in the options and futures contracts that exist on a given day and are delivered on a particular day.

Non-commercial traders are a key factor in providing the necessary liquidity for the buyers and sellers in the market, so the entry of speculative capital in the crude oil future market will in general improve the functioning of the market. It may seem that speculators are to blame for the increase in oil prices because their activities influence the spot price by pushing up future prices, assuming that a higher oil future price feeds back the tendency into the spot price. The figure below is a description of open net-long positions, betting on rising prices, against open short positions, betting on falling prices. In the time frame being analyzed it is easy to spot the offset of open long positions by the non-commercial traders all through the price surge of 2003-mid 2008 period. From analyzing the data below we can deduce that net-long positions increase after prices increase, meaning that speculation may follow movements in the spot price.

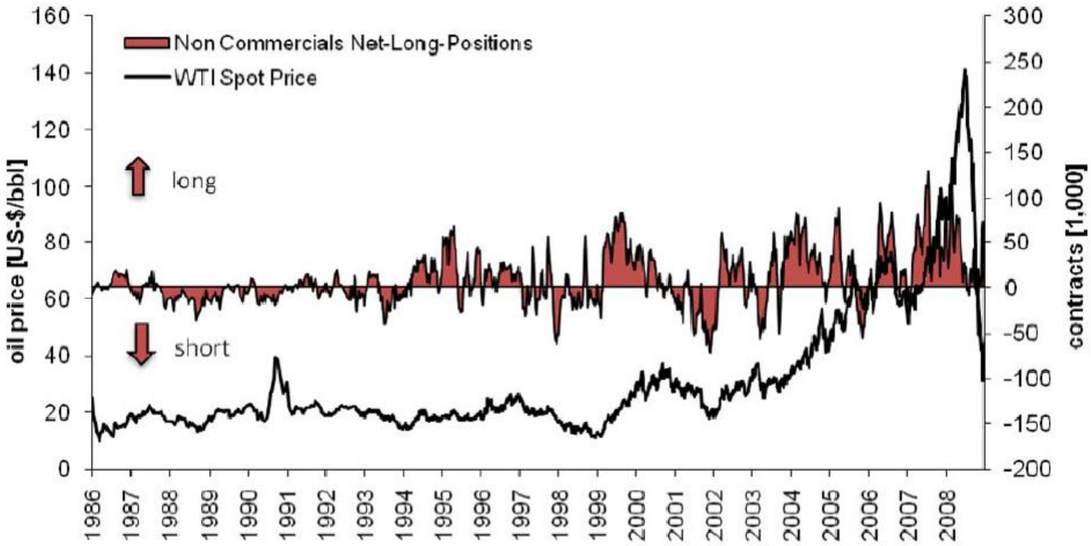

Figure 3- Net long positions of non-commercial traders

In conclusion, for near term contracts, future prices contain important information of future oil movements. With these facts in hand, the substitution of oil inventories for short term futures, in the indicated time frame, could be considered as a good indicator to capture market expectations.

2. Methodology and VAR Model Specifications

2.1. Data/Variables

The data on the global crude oil production ($\Delta Prod_t$) was made available by the EIA in the Monthly Energy Review, the data is available from the monthly database. It includes lease condensates but exclude natural gas liquids. In the model, the data on oil production is expressed in log-differences.

Real price of oil ($\Delta Log\ RPO_t$) is the log of the real price of oil defined as the United States (U.S.) refiners acquisition cost for imported crude oil. This data was found as reported by the U.S. EIA and deflated by the U.S. consumer price index (CPI) and demeaned. As referred by Kilian and Murphy (2014), the refiners acquisition cost for crude oil is a better proxy because the U.S. price of domestic crude oil was regulated during the 1970s and early 1980s, making refiners acquisition cost a better price for crude oil markets. CPI is used to deflate the real price of oil and was made available by the U.S. Bureau of Labor Statistics, seasonally adjusted and monthly reported.

Oil demand can be commonly found in two different proxies, first is the Global Activity Index (GAI), used by Kilian (2009), the second is the log-difference of the global production index ($\Delta Log\ RA_t$), used by Kilian and Murphy (2014) and by Beidas-Strom and Pescatori (2014). Since this thesis rests on the work of Kilian and Murphy (2014), the latter was used as the variable for oil demand in the model.

Futures prices were taken from the Journal of Applied Econometrics, where Alquist and Kilian (2010) published their work on *What We Learn from The Price of Crude Oil Futures*. Their commercial provider was Price-Data.com. CPI is used to deflate the future price of oil and was made available by the U.S. Bureau of Labor Statistics, seasonally adjusted and monthly reported. They constructed their data for various maturities by identifying the h-month futures contracts trading closest to the last trading day of the month and used the price associated with that contract as the end-of-month value. Since the model in study uses only 1- month futures contracts, the continuous monthly time series is based on a backward-looking window of at most three days. This approach has the objective of computing in consistent matter end-of-month time series for oil future prices, allowing for the closest match possible of future prices and spot prices. The variable created with this data is similar to the futures spread ($\Delta Log\ Sprd_t$) used in the published work of Alquist and Kilian (2010). It is a different approach that uses the spread between spot prices and future prices as an indicator of the volatility direction of the price of oil. In the occasion of the future price equaling the spot price, the spread will be an indicator of the expected change in said spot prices.

$$Sprd_t = 1 + LN\left(\frac{F_t^{(h)}}{S_t}\right) \tag{1}$$

$Ft^{(h)}$ is the price of the future price of oil of maturity (h), be it 1-month or 3-month future and so on. St is the real price of oil for a given period in time. Both the future and spot prices are multiplied by the CPI to adjust prices to inflation.

This model is an adaptation of the Kilian Murphy (2014) model, estimated on monthly data over the sample period of April 1983-December 2008. The data for all variables starts in April of 1983 because it was on the 30^{th} of March 1983 that crude oil futures were first traded on the NYMEX floors. All of the variables were taken from the Journal of Applied Econometrics, where Kilian and Murphy (2014) and Alquist and Kilian (2010) published their work and data. It was then used as a reference and manipulated to fit the needs of the model used in this dissertation.

2.2. VAR Model for the Market of Crude Oil

Our model is based on Kilian and Murphy (2014) and consists of a four-variable model and its reduced form allows for two years' worth of lags. Hamilton and Herrera (2004) argue that a lag length of 24 months (2 years) is sufficient to capture the dynamics in the data modeling business cycles of commodity markets. The importance of long lags was also cited by Killian (2009), claiming they allow for a long delay in the effects of oil prices and for a sufficient number of lags to remove serial correlation. Long lags are equally important in structural models of the world oil market to account for low frequency co-movement between the real rice of oil and global economic activity. Kanga, Rattib and Yoo (2014) find that anticipated reduction in crude oil production is closely associated with an increase in implied co-variance of return and volatility that extends for up to 24 months.

The demand indicator of the model will be the log-difference of the global industrial production index, capturing the demand for crude oil. To exemplify the supply indicator the log-difference in global crude oil production will be used, this will consist of above ground production only.

The standard VAR, corresponding to the structural model of the global oil market, is written as follows:

$$\beta_0 y_t = \sum_{i=1}^{24} \beta_i y_{t-i} + \varepsilon_t \qquad (2)$$

This model is the same one used by Kilian and Murphy (2014). In this case ε_t is the representation of a (4x1) vector of uncorrelated structural innovations. The β_i, i=0, …24 (*l*), is the impact on the coefficient matrices at the i-th lag where the demand and supply elasticities are found.

Vector ε_t consists of four structural shocks. The first shock is the flow supply shock that is associated to a negative response of the price for crude oil and a numbing down of the global production index business cycle. These shocks incorporate supply disruptions that are associated with political events linked to oil producing countries, and unexpected supply decisions by OPEC members and other flow supply shocks. A negative flow supply shock triggers a predictable increase in the real price of oil, meaning that the expected future price can be above or below the spot price of oil when the futures contact maturity comes to terms, as can be seen below (3).

$$\left(\frac{F_t^{(h)}}{S_t}\right) = 1 \text{ or } \left(\frac{F_t^{(h)}}{S_t}\right) > 1 \text{ or } \left(\frac{F_t^{(h)}}{S_t}\right) < 1 \qquad (3)$$

This gap of uncertainty between future and spot price reaction to the negative flow supply shock makes it hard to imply sign restrictions, much like the behavior of inventories that Kilian and Murphy (2014) cite in their work. Positive flow supply shock, shifts to the right of the contemporaneous oil demand curve along the oil supply curve, raise prices and stimulate oil production. Like the situation of a negative flow supply shock, it is hard to tell how it will impact the futures spread.

A flow demand shock induces an increase in real activity, shifting the contemporaneous oil demand curve to the right along the supply curve. This will raise by consequence the price of oil, which should in effect increase or stimulate the production of crude oil on impact to foment the increased demand caused by unexpected fluctuations in the business cycle.

The third shock is the speculative demand shock, it captures the use of our oil spreads arising from a forward-looking behavior not otherwise captured by the model. A positive speculative demand shock will shift demand for oil, causing traders to raise expected future prices and causing the real price of oil to increase on impact. The effect of rising prices will in turn stimulate production and reduce oil consumption (real activity). Both flow demand shocks and flow supply shocks have the expected behavior, but differ because flow demand shocks involve an increase in demand, whereas speculative demand shocks do not. Speculative shocks are fed by traders' perception of what other traders think evolves or simply beliefs not related to fundamentals. The present econometric model does not specify how expectations should be formed and that gives a new insight on the flexibility of the crude oil market.

Finally, there is a residual oil demand shock that is designed to capture idiosyncratic oil demand shocks driven by reasons not explained by any of the anterior structural shocks. Non-accounted shocks can be caused by various factors with no direct economic interpretation such as changes in inventory, technology, political reasons, and or Petroleum Reserve releases that may be politically derived.

The admissible model takes shape and is represented below (4), the matrix has the applied structural sign restriction that will be explained in section 3.1 of the present work. It is important to mention that missing signs denote that no restrictions were applied. This matrix differs from table 1 because it includes residual demand shocks, the fourth innovation. Given the difficulty of economically identifying the conglomerate of idiosyncratic residual demand shocks, the results will not be interpreted. Kilian and Murphy (2014) claim that they are too weak to be true determinants of the real price of oil.

$$\begin{pmatrix} e\Delta_t^{Prod} \\ e\Delta_t^{Log\ RA} \\ e\Delta_t^{Log\ RPO} \\ e\Delta_t^{Log\ Sprd} \end{pmatrix} = \begin{pmatrix} - & + & + & x \\ - & + & - & x \\ + & + & + & x \\ x & x & + & x \end{pmatrix} \begin{pmatrix} \varepsilon^f_t Flow\ oil\ supply\ shock \\ \varepsilon^f_t Flow\ demand\ shock \\ \varepsilon^f_t Speculative\ demand\ shock \\ \varepsilon^f_t Residual\ demand\ shock \end{pmatrix} \tag{4}$$

3. Identification

The VAR model is consistently estimated by least-squares and based on various combinations of sign restriction. To these restrictions are added additional plausible bounds on the magnitude of supply and demand elasticities. Restrictions can be implied by economic theory or they can be extrinsic, belonging to no proper explanation or economic theory. Identifying restrictions are used and will be discussed in the following sections.

3.1. Identification Based on Sign Restrictions

Table 1 registers the sign restrictions on the impact responses of futures, real activity, oil production and the real price of oil. The restrictions in the table below directly follow the model for the market of crude oil explained in the anterior section. These restrictions also identify residual innovation but since the results of residuals are extrinsic it is hard to interpret them economically. Not being an important determinant of the real price of oil, the results are not reported. Sign restriction were also not applied to the flow supply shock and flow demand shock because they are hard to economically quantify as outlined in section 2.2.

	Flow Supply Shock	*Flow Demand Shock*	*Speculative Demand Shock*
Oil Production	–	+	+
Real Activity	–	+	–
Real Price of Oil	+	+	+
Oil Future Spread			+

Table 1- Sign restrictions on impact responses in the vector autoregressive model

Note: The absence of entries in the Oil future spread flow supply shock and flow demand shock mean that no sign restrictions were imposed.

Kilian (2009) imposes identifying restrictions on the slope of the short-run oil supply. Noting that the short-run oil supply curve is vertical, leaves the assumption that global oil production does not respond to oil demand shocks as they happen and are usually lagged by a month. The reason for such behavior might be due to the elevated costs and repercussions of adjusting production, this method is in line with the OPEC production decisions. Sign restrictions on the VAR response functions arise naturally in the context of structural models of the oil market. Table 1 is the baseline of sign restrictions, the same restrictions used in related works such as Kilian (2009), Baumeister and Peersman (2012); Kilian and Murphy (2012); Beidas-Strom and Pescatori (2014) and Kilian and Murphy (2014). A number of set restrictions imposed in table 1 are based on a unique response pattern caused by each structural shock, referred and explained in section 2.2.

3.2. Bound on Price Elasticity of Oil Supply

Using the equation model (2), an estimate of the impact price elasticity can be deducted. The ratio of the impact responses of oil production and real price of oil to sporadic increase in speculative demand or in demand. There is a need for boundary restrictions, in addition to the sign restrictions, because it will allow for better candidates when selecting admissible models. This sets a boundary on unrealistic oil supply responses, from other literary works such as Hamilton (2009), it can be concluded that in the absence of significant excess production capacity, the short-run price elasticity of oil supply is low if not effectively zero. Kilian (2009) suggests that changing production is costly so even in the presence of space capacity; the response of oil supply might not be directly in line with the price signals. In the case of our work, using oil futures, we will see if production responds to future price changes. Kellogg (2011) suggests that in his study he found no response of oil production to oil future price change.

Kilian and Murphy (2014), impose a bound of 0.025 on the impact price elasticity of oil supply, for this study the same will be kept.

$$\mathrm{Max}_{i\neq 1}\ {a1_i}/{a3_i} < 0.025 - \text{price elasticity of oil supply} \qquad (5)$$

These restrictions narrow down the admissible models, Beidas-Strom and Pescatori (2011) and Kilian and Murphy (2014) use 5 million candidates. The model in this thesis only uses 500000, this is because tests were run for more candidates and the results were the same. Having less computational power it made it possible to run the model more times using fewer rotations.

3.3 Bound on Price Elasticity of Oil Demand

Using the equation model (2), an estimate of the impact price elasticity of oil demand can be deducted. The ratio of the impact responses of oil production and real price of oil to unexpected increase in speculative demand or in demand. To Kilian and Murphy (2014), the relevant measure is the sum of oil production flow and the consumption of oil held in inventory triggered by an oil supply shock. Much like them, this model uses the same method except it uses oil spreads instead of oil inventories, using the movement of the spread price the same way they use oil inventory depletion. The construction of the price elasticity of oil demand in use is as follows:

$$\Delta_{U_t} = \Delta_{Q_t} - \Delta^2{}_{Sprd_t} \tag{6}$$

The oil in use is denoted as Δ_{U_t},for a given t period, and is equal to the quantity of oil produced Δ_{Q_t} minus the spread $\Delta^2{}_{Sprd_t}$.

$$n_t^{Use} = \frac{\%\Delta_{U_t}}{\%\Delta_{RPO_t}} \tag{7}$$

The price elasticity of oil in use is defined as n_t^{Use}, where $\%\Delta$ represents a percentage change to an oil supply shock at a given period t and $\%\Delta_{RPO_t}$ is the real price of oil. It refers to the resulting elasticity measured as oil demand elasticity in production. The elasticity can be estimated as a ratio of the impact response of oil production to an oil supply shock, relative to the impact response of the real price of oil. Percentage change in oil demand $\%\Delta_{U_t}$ is calculated as follows:

$$\%\Delta_{U_t} = \frac{\Delta Q_t - \Delta^2_{Sprd_t}}{Q_{t-1} - \Delta_{Sprd_{t-1}}} \tag{8}$$

Construction of the price elasticity of oil in use depends on the historical data of oil production Q_{t-1}, which means it will be time varying, while demand elasticity in production is not. Therefore, the oil demand elasticity reported is an average made over the sample period.

4. Results

Identification restrictions described in the anterior section are not know-all for structural impulse responses. The *jmax* value in Kilian and Murphy (2014) generate 5 million rotations based on the reduced-form VAR estimate, and to replicate their study using oil future spreads we imposed a reduced number of rotations of only 500000. Of these candidate models that were yielded, the selection was down to the candidate models that satisfied all of the identification restriction.

4.1. Oil Supply/Demand Shocks Results

The figures in section 4.1.1 plot the results of each variable in the model to the supply/demand shocks with the 68% posterior error bands obtained by drawing from the reduced-form posterior distribution. Figure 4 and figure 5 illustrate the roles of inventory storage and oil future spreads, and the way they differ depending on the nature of the shocks in question. Shocks have been normalized as they imply an increase in the real price of oil. The objective of the following section is to compare the results using inventories, Kilian and Murphy (2014), with our assumption of crude oil future spreads. The Kilian and Murphy (2014) time series was reduced to match the beginning of market traded crude oil futures that only came into existence in 1983.

4.1.1 Crude Oil Inventories and Oil Future Spreads (1983.4-2008.12)

Figure 4 is a plot of structural impulse responses to three distinct supply/demand shocks and how they have an impact on oil inventories in the mentioned time frame. Much like the assumptions of Beidas-Strom and Pescatori (2014) and Kilian and Murphy (2014), the changing of the time series does not seem to affect the plot of the responses to certain structural shocks. Flow supply shocks seem to draw down inventory levels to smooth the production of crude oil, shocks much similar to the sign restriction table mentioned in anterior sections.

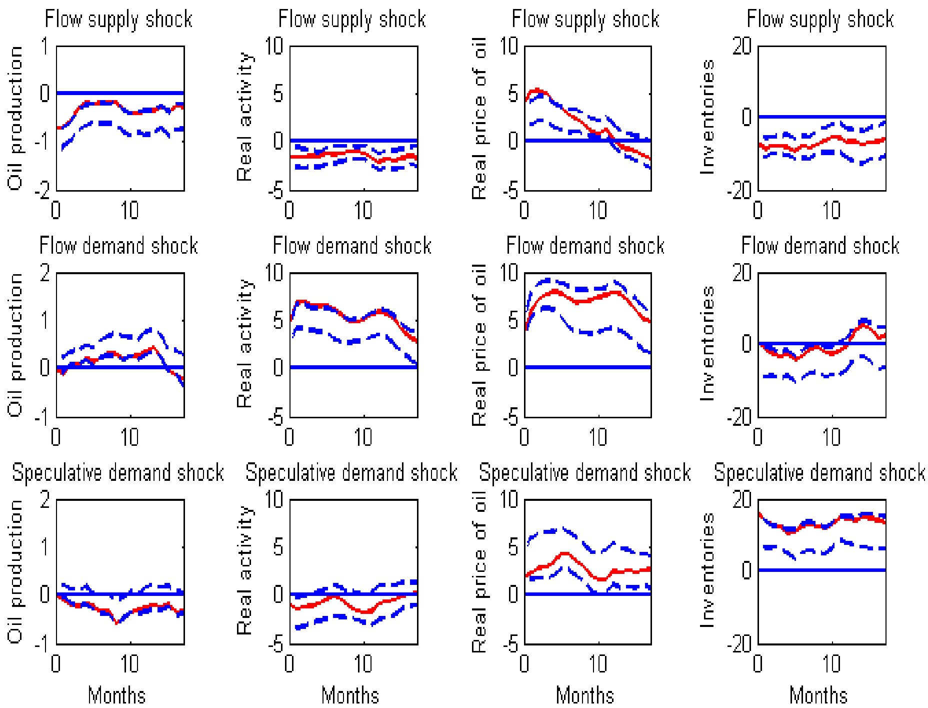

Figure 4- Structural impulse responses (1983.4-2008.12) - Inventories

Global real activity is reduced when faced with negative flow supply shocks, and the same happens with the production of oil at an initial stage, but within a couple of months the behavior is reduced and normalized. In this situation, the real price of oil rises at an initial stage and falls back to normal levels, as global activity keeps falling so does the price of oil. At the one-year mark it falls below its starting value.

Positive flow demand shocks keep oil inventories close to the zero-base line, with little to no drop in the following months. After a year or so the inventories rise above their initial level, but all in all this type of shock seems to have little to no effect on the inventory levels. In contrast to what happens with flow supply shocks, the global activity rises initially a par with the real price of oil, both peaking close to year end and dropping from there onward. Oil production sees a slight rise with a similar peak at year end which is followed in a descending matter from there onward.

Shocks of speculative nature cause a constant rise in the levels of oil inventories and an immediate rise in the real price of oil that gradually settles at the 10-month mark. The oil production and real activity are barely affected by the speculative shock, although negative all through the sample, it is small. Even though the sample period in study differs from that of Kilian and Murphy (2014), the structural impulse responses of all three shocks seem largely unmodified, leaving us with the assumption that there is economic reasoning behind this theory.

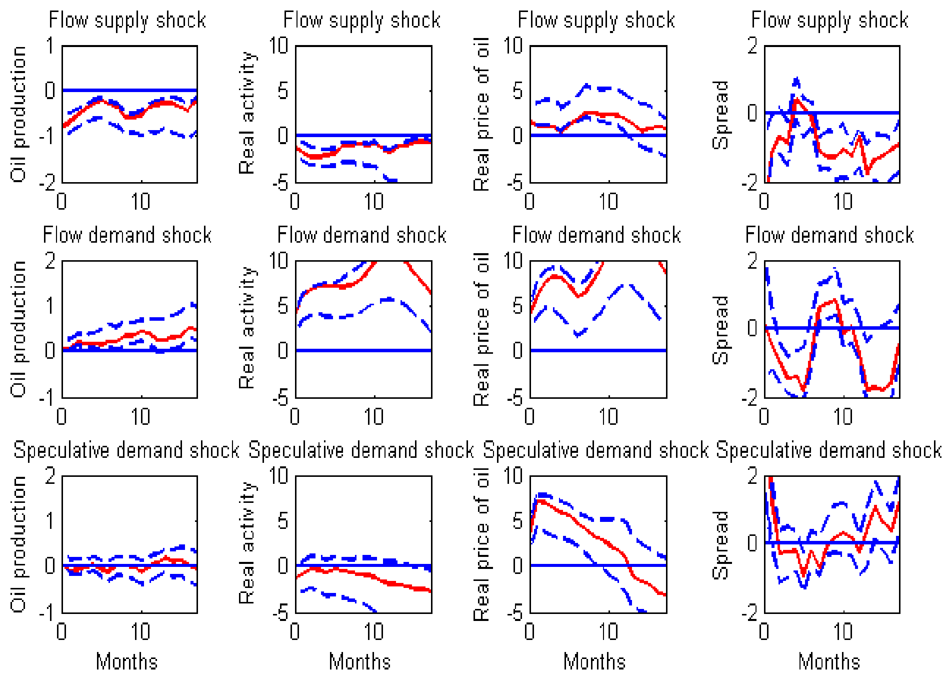

Figure 5- Structural impulse responses (1983.4-2008.12) - Oil Spreads

Figure 5 is a plot of structural impulse responses of three distinct supply/demand shocks and how they have an impact on oil future spreads in the mentioned time frame, along with other factor variables in the model. Flow supply shocks cause spreads to fall, having only a small peak within the first three months, but then resumes to fall. This can be explained with the rise of the real price of oil in the first few months, to the end it seems that spread values seem to rise as the real price of oil drops below its starting value, but the volatile nature of the spread output makes it hard to fully analyze. Real activity drops along with oil production, this explains the rise in the real price of oil. The behavior that affect these variables is similar to that of the flow supply shock with inventories, Kilian and Murphy (2014).

Flow demand shocks cause an uncertain effect on oil spreads, they start with a large decline in value and at the five-month mark reach a peak similar to the starting value, followed again by a small drop and a rise towards the end. This behavior seems to be a bit in line with that of the real price of oil and real activity, they all seem to have a peak around the 10-month period and begin to drop from there onward until the end of the sample, much in line with the results obtained by Kilian and Murphy (2014). The initial drop in the spread value might have to do with a more rapid rise in the real price of oil than initially predicted by the futures values which causes a drop in the spread value calculation as can be analyzed in figure 5. Oil production rises slightly and slowly until the end of the sample period.

Speculative shocks have a very volatile effect on oil spreads, both oil spreads and oil prices are subject to an initial immediate rise, over time the real price of oil tends to decline, much like the behavior observed by Kilian and Murphy (2014). Oil spreads seem to not have a rational behavior, being in a constant rise and fall through the whole sample. One thing that can be analyzed is that at the ten-month mark oil spreads do begin to rise at a significant speed and the real price of oil falls. This can mean one of two thigs, either future prices maintain a steady value as the real price of oil drops or futures prices rise, creating a larger gap between the real price of oil and future prices. All other variables, oil production and real activity, suffer little to no alterations.

4.1.2. Was Speculation the Culprit of the 2003-2008 Oil Price Shock?

Large and sporadic increases in oil prices between 2003 and mid 2008 are attributed to speculation caused by a large influx of financial investors in the oil futures market. This phenomenon can be observed in section 1.2.3, where open interest positions are explained and how a rise in non-commercial traders might be correlated with a rise in oil prices. A large influx in the futures market drove up oil futures prices, that rise was viewed by the spot market participants as an indicator of an increase in expected oil prices.

Speculative shocks in the VAR model should be able to explain this sporadic surge in the real price of oil after 2003. Looking at the cumulative effects of speculative demand shock on the real price of oil in figure 6, it shows that for the use of inventories (right) there is no upward movement in the price of oil after 2003 associated with speculative demand shocks.

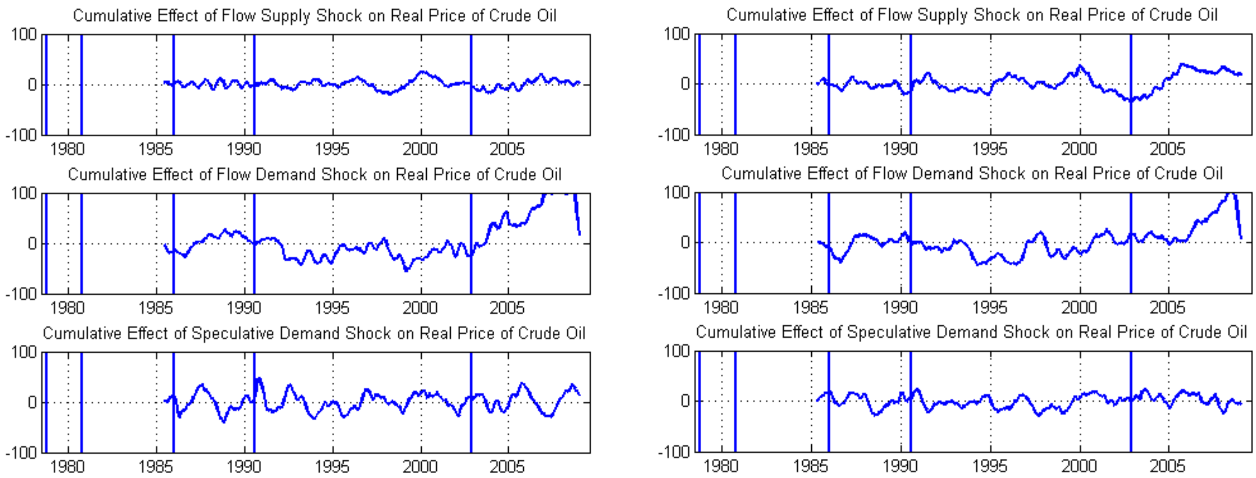

Figure 6- Historical decomposition for (1983.4-2008.12)

Note: The vertical bars signal other events in the crude oil markets much like the one in 2003-2008. It is an illustration of the cumulative effect of flow supply/demand/speculative shocks on the price of oil. On the left side figure 6 displays the use of spreads and on the right, it displays the use of oil spreads.

To the left is the output obtained using oil spreads, and much like with inventories, there is no upward movement in the price of oil after 2003 that can rule in favor of a speculative demand shock. From these results it can be concluded that the large influx of non-commercial investors and traders entering the oil market has not driven up future prices. Fattouh (2013) suggest that there is an operational distinction between what is excessive or normal (fundamental) when it comes to speculative activity. From the image on the right, Kilian and Murphy (2014) find no evidence of any type of speculation and suggest that the lack of speculation in the physical market represents a lack of speculation in its financial counterpart. There cannot be speculation under any definition if it does not apply to both. From using spreads (left) it is easy to concur with their hypothesis because there is a lack of speculation regarding future-spot spreads, as there is lack of speculation in the physical market.

If not speculation, was OPEC to blame? They held back production after 2001 in anticipation of even higher oil prices and used oil below the ground as inventories.

A way to observe this is analyzing the cumulative effects of flow supply shock on the real price of oil. The economic effect of OPEC withholding production is a negative flow supply shock. Figure 6 provides no evidence of a negative supply shock, be it with the Kilian and Murphy (2014) (right) or the one proposed in this work (left). This rules out speculative supply shocks as a valid hypothesis.

The last theory is based on the global production boom that peaked at around 2006. For this theory to be valid there would need to have been a negative supply shock before 2005, but as explained in the last hypothesis, the cumulative effect of flow supply shock on the real price of oil is pretty limited in explaining any theory. The peak oil theory is also ruled out as a hypothesis.

Surge in the real price of oil was mainly due to change in the flow demand for crude oil, associated with a boom in the business cycle. Even professional forecasters were shy on predicting this highly underestimated global growth during the 2003-mid 2008 period, especially the Asian markets such as China. This thriving rise in the price of oil can be observed in the cumulative effect of the flow demand shock on the real price of oil. There is a sharp rise in the demand shock during the 2003-mid 2008 period followed by a significant drop, start of the financial crisis, and this can be observed in work of Kilian and Murphy (2014) (right) and the present model in this work (left). In the annex, there is a descriptive analysis of all variables in the model and data with the evolution of said variables over the course of the study. If you carefully analyze the real price of oil and the real activity (pg.48-50), the dip in the real price of oil in mid-2008 coincides in direction with the global real activity.

With this analysis the consensus is that there are economic fundamentals on the demand side of the oil market that can explain the sharp rise of the real price of oil in the last couple of years. In this particular case it is easy to rule out speculation as a factor, and this finding is particularly exciting because no amount of regulation in the oil markets would have made a difference. Kilian and Murphy (2014) claim that an increase of U.S. oil production alone would have had no effect on the real price of oil at a global scale, while a full recovery of the global economy would raise the price of oil by as much as $50.

4.2. Short – Run Elasticity of Oil Demand

Short-Run price elasticity of oil demand has important implications for theoretical models of speculative demand. Hamilton (2009) suggests that even without an increase of oil inventories it is possible for speculation in the oil futures market to drive up the real price of oil via speculation. This can happen when refiners pass on to their consumers exogenous increases in the price of oil driven by speculation. For this to result the demand for gasoline would need to be price-inelastic.

This work, and the work of many others, does not give much evidence on the price elasticity of oil supply, but from what can be seen it is near zero in the short run. The conclusion sought out by Hamilton (2009) are hard to disprove or rule out because of elasticity being close to zero.

4.2.1 Short-Run Price Elasticity of Oil Demand in Production

The structural model is used to obtain direct estimates of the short-run price elasticity of oil demand in production and in use. Elasticity in production can be estimated from model (2) and is a ratio of the response of oil production to flow supply shocks, relative to an impact response on the real price of oil. In other literature it is evident that short-run price of elasticity in oil demand in production is very low.

Oil Inventories, (1983.4-2008.12)

		$\boldsymbol{n^{o,Production}}$	$\boldsymbol{n^{o,Use}}$
$\boldsymbol{n_t^{Supply}} \leq 0.025$	16th percentile	-0.5717	-0.4762
	50th percentile	-0.3444	-0.2313
	84th percentile	-0.1971	-0.0750

Table 2- Posterior distribution of the short-run price elasticity of demand for crude oil – Oil Inventories

Note: The data in table two was the output product of Impulse response functions (IRF)[6] process that can be found in the annex of this work in MATLAB Code for Oil Inventories Adapted to Time Frame - (1983.4 -2008.12); Main.

[6] *IRF* - dynamic response of the system to a single impulse, or innovation shock, of unit size. This impulse response is sometimes called the forecast error impulse response, because the innovations, ε_t, can be interpreted as the one-step-ahead forecast errors.

Spreads, (1983.4-2008.12)

		$\boldsymbol{n^{o,Production}}$	$\boldsymbol{n^{o,Use}}$
$\boldsymbol{n_t^{Supply}} \leq 0.025$	16th percentile	-0.6610	-0.6159
	50th percentile	-0.4341	-0.3914
	84th percentile	-0.2294	-0.1802

Table 3- Posterior distribution of the short-run price elasticity of demand for crude oil

Hamilton (2009) calculates an elasticity of -0.06, it is very low and close to zero. In table 2 Kilian and Murphy (2014), using oil inventories for the period stipulated to fit the needs of the present model, calculated a median (50th percentile) elasticity of -0.3444, a much larger estimate than other literature. Using oil spreads, the median (50th percentile) elasticity estimate is of -0.4342, very close to that of oil inventories. The difference between the results obtained in this model from other works is the estimation of a structural model and reduced form model. The standard econometric estimates of the crude oil demand elasticity fail to take into account the endogeneity of oil prices. When predicting the quantity demanded in equilibrium prices are endogenous because producers change their prices in response to demand, and consumers change their demand in response to the prices. This lack of attention to detail by other investigators lead to biased estimates of elasticity that float towards zero.

Using full structural econometric models allow the results to be unbiased. Baumeister and Peersman (2009) use a quarterly time-varying structural VAR model and obtain an estimate of oil demand elasticity rounding -0.38. The elasticity estimate is close to ours, but differs in variable choice, sample period and the data frequency. Like Kilian and Murphy (2014) suggest, the choice of rotations and seed used in the MATLAB VAR model will affect the output results. They use 5 million rotations and this study used only 500000, apart from the sample period and rotations, the seed is the same and for that the results are very close to the ones estimated in the original work.

The substantial probability mass to values are between -0.1971 and -0.5717 for oil inventories (1983.4-2008.12), and between -0.2294 and -0.6610 for spreads (1983.4-2008.12). Standard deviation for the 68% error band for impulse responses is of 0.1887 and 0.2159, respectively.

4.2.2 Short-Run Price Elasticity of Oil Demand in Use

In section 3.2.2 of the present work, Bound on Price Elasticity of Oil Demand, the estimation theory for the price elasticity of oil demand in use is explained. The short-run price elasticity of oil demand in use for oil inventories has a median (50^{th} percentile) estimate of -0.2313, while the estimate for production is of -0.3444. Short-run price elasticity of oil demand in use for spreads has a median (50^{th} percentile) estimate of -0.3914 while the same estimate for production has an output value of -0.4341. The results are very similar for both variables with the original identification based on sign restriction in section 3.1. For flow demand the impact is negative[7] as predicted for both inventories and spreads. These elasticity estimates are far larger than the conventional estimates, and in line with economic fundamentals. Kilian and Murphy (2014) conclude, using oil inventories, that the surge of oil prices after 2003 is a product of economic fundamentals that can be observed with larger than usual elasticity estimates. High short-run price elasticity of oil demand nullifies the theory of speculation being the culprit for the run-up of oil prices in the 2003-mid 2008 period. From the results obtained, using oil spreads, the conclusions drawn are in line with those of Kilian and Murphy (2014). They also tested for upper bounds of 0.05 and 0.1 and found elasticity output to be very similar, so no time was waisted in running our model for such upper bounds.

[7] Over the short term, demand is more likely to be inelastic because of the limited options to compensate to changes in price. Oil is inelastic over the short term, so when the OPEC countries decide to decrease supply, from Q1 to Q2, the price increased dramatically, rising from P1to P2.

Conclusion

In this work we adapted the structural model to include shocks to demand through oil future spreads, reflecting expectation of future oil supply and demand that cannot be captured through the traditional flow supply and flow demand shocks. Traditional VAR models tend to focus on shocks to the flow supply and demand for oil, leaving out the speculative shocks. Kilian and Murphy (2014) execute this method using crude oil inventories as speculative demand shocks that are represented as shifts to the oil demand curve, rather than its supply counterpart. Our contribution lies on the substitution of oil inventories for oil spreads, from existing literature such as Singleton (2011) it is clear that inventories have their limitations. With that mindset we decided to see the effect of oil spreads in the same structural model. The structural model present in this dissertation includes oil spreads that allow for the identification of three distinct types of shocks (supply/demand/speculative) based on historical data that dates back to March 1983 up until December of 2008. The adaptation of a different time period is due to the fact that oil futures on came into existence in March of 1983.

Taking into consideration recent policy debates on the run-up of oil prices in the 2003-mid 2008 period, we thought it would be an interesting theme to dissect. Many popular views were debated on this matter, and through this work we try to find the explanation that fits best. Our results show evidence disproving the most popular view of a real price driven increase via speculation. There is also no evidence for the peak oil theory or that it had much effect in the run-up of the real price of oil. Much like the results of Kilian and Murphy (2014), ours reflect the same view. The driver of the real price of oil is primarily associated with business cycle fluctuations affecting the flow demand for oil. An unexpected boom in the business cycle of the world market, especially Asian markets, is the underlying fundamental factor that drove up the real price of oil. Comparing the evolution of isolated variables, real activity (flow demand) and the real price of oil, we can deduce that they rise in similar fashion and both see a sharp fall in the mid 2008 period onward.

Another observation to point out is that including the endogeneity of the real price of oil allows the present model to estimate traditional oil demand elasticity in production and oil supply elasticity in spread movements. This makes our short-run elasticity higher than estimates in other literatures cited throughout this work, casting doubt on models with perfect price-inelastic output for crude oil.

Taking note on recent information, the price of oil is making a comeback with the recuperation of the global economy after the financial crisis. As the economy recovers and prices rise again, the policy dilemma will come back into play. In underlying economic factors are to blame, then extra regulations on the oil markets will have no effect in keeping the price of oil under control, nor will sporadic increases in production ease the rising prices. The solution to this dilemma might be found in the use of alternative energy sources to foment the rising economy or restriction on consumption.

This work isn't short on limitation, oil spreads were only calculated for a 1-month maturity period and it would have been beneficial to run the model for various maturities to see the effects of expected future prices in the long run. Lack of computational power limited our model runs because it took too long to run each model and would have been almost impossible to run the model for various maturities.

The present study may assist academics and policy makers alike. Academics can pick up on the limitations and make the alterations necessary to run the model more times and for different maturity horizons. It is a great launching point for studying the behavior of other commodities and possibly other financial products bought and sold in the financial markets. Policy makers can use the conclusions drawn to draft up new alternatives to control the rising prices of oil since sanctioning the global market for crude oil will not help with the volatile prices. With speculation out of way, from what we and other academics were able to conclude, new alternatives could be drafted, but we will leave that to other experts.

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Appendix

MATLAB Code Adapted to Oil Future Spreads - (1983.4 - 2008.12)

The following code is an adaption of Kilian and Murphy (2014). It was made available by the Journal of Applied Econometrics where the authors published their work.

Bays Draws

```
%Bayes draws for reduced form parameters of the VAR.


close all;
clc;
clear;

global xmax

load kmData

load worldprod
ProdMBPM=worldprod(2:end)*30/1000;
OECDCrudeDif=kmData(:,4);

xmax=17;     %horizon
jmax=1000000;  %number of draws for sign restrictions
rdraws=50;    %posterior draws

randn('state',1112)% seed

tic;
[IRFposs
]=BAYESsign(kmData,xmax,4,24,rdraws,jmax,ProdMBPM,OECDCrudeDif);
%save IRFpossBayes IRFposs
%load IRFpossBayes
toc;

%saving for constructing error bands
IRMposs=IRFposs;
save BayesPosterior IRMposs
%for use in Main.m (Figure 1)

[j k l] = size(IRFposs);

elasuse=zeros(1,l);
elasprod=zeros(1,1);
for i=1:l;
    IRprod=IRFposs(1,1,i); IRinv=IRFposs(4,1,i);
IRprice=IRFposs(3,1,i);
    FlowNew=ProdMBPM*(1+IRprod/100)-mean(OECDCrudeDif)-IRinv;
    Flow=ProdMBPM-mean(OECDCrudeDif);
    PctChange=100*(FlowNew-Flow)./Flow;
    ElasUseSeries=PctChange/IRprice;
    elasuse(i)=mean(ElasUseSeries);
```

```
    elasprod(i)=IRFposs(1,1,i)./IRFposs(3,1,i);
end;

%obtain the median elasticity in use
 medelasuse=median(elasuse)
    save medelasuse medelasuse; %called by Main.m

elasusepctile=prctile(elasuse,[16 50 84])
elasprodpctile=prctile(elasprod,[16 50 84])

std(elasusepctile)
std(elasprodpctile)
```

Main

```
lose all;
clc;
clear;

global xmax

load kmData
% percent change in global oil production, real activity index from
Kilian(AER 2009), the log real price of oil, and changes in OECD crude
oil spreads

[BETAnc,B,X, SIGMA, U, V]=lsvarcSA(kmData,24);

xmax=17;
jmax=500000;
randn('state',316)
[IRFaer, K]=VARirf(BETAnc,SIGMA,xmax);


[IRFposs]=IRFsign(BETAnc,SIGMA,xmax,jmax);


[j k l] = size(IRFposs);

load worldprod
ProdMBPM=worldprod(2:end)*30/1000;
OECDCrudeDif=kmData(:,4);


%imposing additional restrictions

index=1;
IRFelas=zeros(4^2,xmax+1);  %will be populated with the admissible
IRFs
elasticity=IRFposs(9,1,:)./IRFposs(11,1,:);  %supply elasticity in
response to speculative demand shock
ADelas=IRFposs(5,1,:)./IRFposs(7,1,:);  %supply elasticity in response
to flow demand shock
elasuse=0;
format short
for i=1:l;
```

```
    %%elas in use
    IRprod=IRFposs(1,1,i); IRinv=IRFposs(4,1,i);
IRprice=IRFposs(3,1,i);
    FlowNew=ProdMBPM*(1+IRprod/100)-mean(OECDCrudeDif)-IRinv;
    Flow=ProdMBPM-mean(OECDCrudeDif);
    PctChange=100*(FlowNew-Flow)./Flow;
    ElasUseSeries=PctChange/IRprice;
    if elasticity(i)<=.0258 && ADelas(i)<=.0258  &&
mean(ElasUseSeries)<=0    && min(cumsum(IRFposs(1,1:12,i)))>=0 &&
min(IRFposs(2,1:12,i))>=0 && max(IRFposs(3,1:12,i))<=0 ;
        IRFelas(:,:,index)=IRFposs(:,:,i); %admissible IRFs
        elasuse(index)=mean(ElasUseSeries);  %elasticity in use
        index=index+1;
    end;

end;

load medelasuse
%median of posterior is -.26
distance=abs(elasuse-medelasuse);
%find index of IRF with elasuse closest to -.26
[mindist, findex]=min(distance)

%Figure 1
Figure1

%Figure 2
Figure2

%Figures 3 through 7
Figures3to7;

%Table 2
Btilda=reshape(IRFelas(:,1,findex),4,4);  %recovering identification
matrix
%variance decomp
VDC=zeros(15,4);
VDCrpoil=zeros(15,4);
  for h=1:15;
      [VC, K]=VARdecomp(BETAnc,Btilda,h);
      %inventory change is fourth variable
      VDC(h,:)=VC(4,:);
      VDCrpoil(h,:)=VC(3,:);
  end;

  [VC, K]=VARdecomp(BETAnc,Btilda,600);
  VDCinf=VC(4,:)
  VDCinfrpoil=VC(3,:)
```

Figure 1

```
%obtain relevant IRF
IRF=IRFelas(:,:,findex);
%obtain IRFs from the Posterior draws
load BayesPosterior;
```

```
time=(0:1:xmax);
CI=prctile(IRMposs,[16 84],3);
CI1458912=prctile(cumsum(IRMposs,2),[16 84],3);
CI([1 4 5 8 9 12],:)=CI1458912([1 4 5 8 9 12],:);

CI5=prctile(IRMposs,[2.5 97.5],3);
CI5_1458912=prctile(cumsum(IRMposs,2),[2.5 97.5],3);
CI5([1 4 5 8 9 12],:)=CI5_1458912([1 4 5 8 9 12],:);


figure;
set(gcf,'name',['Figure 1'])
set(gcf,'NumberTitle','off')

subplot(3,4,1); %row 1
plot(time,-cumsum(IRF(1,:)),'r',time,-(CI(1,:,1)),'b--',time,-
(CI(1,:,2)),'b--','linewidth',2);
title('Flow supply shock')
ylabel('Oil production')
line([0 xmax], [0 0],'linewidth',2)
axis([0 xmax -2 1])
hold off;

subplot(3,4,2);
    plot(time,-IRF(2,:),'r',time,-(CI(2,:,1)),'b--',time,-
(CI(2,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Real activity')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

subplot(3,4,3);
    plot(time,-IRF(3,:),'r',time,-(CI(3,:,1)),'b--',time,-
(CI(3,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Real price of oil')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

subplot(3,4,4);
    plot(time,-cumsum(IRF(4,:)),'r',time,-(CI(4,:,1)),'b--',time,-
(CI(4,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Inventories')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;

 subplot(3,4,5);
    plot(time,cumsum(IRF(5,:)),'r',time,(CI(5,:,1)),'b--
',time,(CI(5,:,2)),'b--','linewidth',2);
    title('Flow demand shock')
    ylabel('Oil production')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -1 2]);
```

```
    hold off;

 subplot(3,4,6);
    plot(time,IRF(6,:),'r',time,(CI(6,:,1)),'b--',time,(CI(6,:,2)),'b-
-','linewidth',2);
    title('Flow demand shock')
    ylabel('Real activity')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

subplot(3,4,7);
    plot(time,IRF(7,:),'r',time,(CI(7,:,1)),'b--',time,(CI(7,:,2)),'b-
-','linewidth',2);
    title('Flow demand shock')
    ylabel('Real price of oil')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

 subplot(3,4,8);
    plot(time,cumsum(IRF(8,:)),'r',time,(CI(8,:,1)),'b--
',time,(CI(8,:,2)),'b--','linewidth',2);
    title('Flow demand shock')
    ylabel('Inventories')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;

 subplot(3,4,9);
    plot(time,cumsum(IRF(9,:)),'r',time,(CI(9,:,1)),'b--
',time,(CI(9,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Oil production')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -1 2]);
    hold off;

subplot(3,4,10);
    plot(time,IRF(10,:),'r',time,(CI(10,:,1)),'b--
',time,(CI(10,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Real activity')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

 subplot(3,4,11);
   plot(time,IRF(11,:),'r',time,(CI(11,:,1)),'b--
',time,(CI(11,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Real price of oil')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;
```

```
  subplot(3,4,12);
   plot(time,cumsum(IRF(12,:)),'r',time,(CI(12,:,1)),'b--
',time,(CI(12,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Inventories')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;
```

Figure 2

```
dentMat=reshape(IRFelas(:,1,findex),4,4);
Uhat=U;
p=24;
t=308; t=length(kmData)
[K, q]=size(IdentMat);
% Compute structural multipliers
A=  [BETAnc; eye(K*(p-1),K*(p-1)), zeros(K*(p-1),K)];
J=[eye(K,K) zeros(K,K*(p-1))];
IRF=reshape(J*A^0*J'*IdentMat,K^2,1);

for i=1:t-p-1
    IRF=([IRF reshape(J*A^i*J'*IdentMat,K^2,1)]);
end;




% Compute structural shocks Ehat from reduced form shocks Uhat
Ehat=inv(IdentMat)*Uhat(1:q,:);

% Cross-multiply the weights for the effect of a given shock on the
real
% oil price (given by the relevant row of IRF) with the structural
shock
% in question
yhat1=zeros(t-p,1); yhat2=zeros(t-p,1); yhat3=zeros(t-p,1);
yhat4=zeros(t-p,1);
for i=1:t-p
    yhat1(i,:)=dot(IRF(3,1:i),Ehat(1,i:-1:1));
    yhat2(i,:)=dot(IRF(7,1:i),Ehat(2,i:-1:1));
    yhat3(i,:)=dot(IRF(11,1:i),Ehat(3,i:-1:1));
    yhat4(i,:)=dot(IRF(15,1:i),Ehat(4,i:-1:1));
end;

time=(1983+5/12+1/12*p):1/12:2008+12/12; %starts at 1983.5


cumshock=yhat1+yhat2+yhat3+yhat4;


figure;
subplot(3,1,1)
plot(time,yhat1,'b-','linewidth',2);
title('Cumulative Effect of Flow Supply Shock on Real Price of Crude
Oil')
```

```
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on

subplot(3,1,2)
plot(time,yhat2,'b-','linewidth',2);
title('Cumulative Effect of Flow Demand Shock on Real Price of Crude
Oil')
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on

subplot(3,1,3)
plot(time,yhat3,'b-','linewidth',2);
title('Cumulative Effect of Speculative Demand Shock on Real Price of
Crude Oil')
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on
```

MATLAB Code for Oil Inventories Adapted to Time Frame - (1983.4 - 2008.12)

Bays Draws

```
%Bayes draws for reduced form parameters of the VAR.

close all;
clc;
clear;

global xmax

load kmData

load worldprod
ProdMBPM=worldprod(2:end)*30/1000;
OECDCrudeDif=kmData(:,4);

xmax=17;     %horizon
jmax=1000000;  %number of draws for sign restrictions
rdraws=50;    %posterior draws
```

```
randn('state',1112)% seed

tic;
[IRFposs
]=BAYESsign(kmData,xmax,4,24,rdraws,jmax,ProdMBPM,OECDCrudeDif);
%save IRFpossBayes IRFposs
%load IRFpossBayes
toc;

%saving for constructing error bands
IRMposs=IRFposs;
save BayesPosterior IRMposs
%for use in Main.m (Figure 1)

[j k l] = size(IRFposs);

elasuse=zeros(1,l);
elasprod=zeros(1,l);
for i=1:l;
    IRprod=IRFposs(1,1,i); IRinv=IRFposs(4,1,i);
IRprice=IRFposs(3,1,i);
    FlowNew=ProdMBPM*(1+IRprod/100)-mean(OECDCrudeDif)-IRinv;
    Flow=ProdMBPM-mean(OECDCrudeDif);
    PctChange=100*(FlowNew-Flow)./Flow;
    ElasUseSeries=PctChange/IRprice;
    elasuse(i)=mean(ElasUseSeries);
    elasprod(i)=IRFposs(1,1,i)./IRFposs(3,1,i);
end;

%obtain the median elasticity in use
 medelasuse=median(elasuse)
    save medelasuse medelasuse; %called by Main.m

elasusepctile=prctile(elasuse,[16 50 84])
elasprodpctile=prctile(elasprod,[16 50 84])

std(elasusepctile)
std(elasprodpctile)
```

Main

```
close all;
clc;
clear;

global xmax

load kmData
% percent change in global oil production, real activity index from
Kilian(AER 2009), the log real price of oil, and changes in OECD crude
oil inventories

[BETAnc,B,X, SIGMA, U, V]=lsvarcSA(kmData,24);

xmax=17;
```

```
jmax=500000;
randn('state',316)
[IRFaer, K]=VARirf(BETAnc,SIGMA,xmax);


[IRFposs]=IRFsign(BETAnc,SIGMA,xmax,jmax);


[j k l] = size(IRFposs);

load worldprod
ProdMBPM=worldprod(2:end)*30/1000;
OECDCrudeDif=kmData(:,4);


%imposing additional restrictions

index=1;
IRFelas=zeros(4^2,xmax+1);  %will be populated with the admissible
IRFs
elasticity=IRFposs(9,1,:)./IRFposs(11,1,:);  %supply elasticity in
response to speculative demand shock
ADelas=IRFposs(5,1,:)./IRFposs(7,1,:);  %supply elasticity in response
to flow demand shock
elasuse=0;
format short
for i=1:l;
    %%elas in use
    IRprod=IRFposs(1,1,i); IRinv=IRFposs(4,1,i);
IRprice=IRFposs(3,1,i);
    FlowNew=ProdMBPM*(1+IRprod/100)-mean(OECDCrudeDif)-IRinv;
    Flow=ProdMBPM-mean(OECDCrudeDif);
    PctChange=100*(FlowNew-Flow)./Flow;
    ElasUseSeries=PctChange/IRprice;
    if elasticity(i)<=.0258 && ADelas(i)<=.0258  &&
mean(ElasUseSeries)<=0    && min(cumsum(IRFposs(1,1:12,i)))>=0 &&
min(IRFposs(2,1:12,i))>=0 && max(IRFposs(3,1:12,i))<=0 ;
        IRFelas(:,:,index)=IRFposs(:,:,i); %admissible IRFs
        elasuse(index)=mean(ElasUseSeries);  %elasticity in use
        index=index+1;
    end;

end;

load medelasuse
%median of posterior is -.26
distance=abs(elasuse-medelasuse);
%find index of IRF with elasuse closest to -.26
[mindist, findex]=min(distance)

%Figure 1
Figure1

%Figure 2
Figure2

%Figures 3 through 7
Figures3to7;
```

```
%Table 2
Btilda=reshape(IRFelas(:,1,findex),4,4);  %recovering identification
matrix
%variance decomp
VDC=zeros(15,4);
VDCrpoil=zeros(15,4);
  for h=1:15;
      [VC, K]=VARdecomp(BETAnc,Btilda,h);
      %inventory change is fourth variable
      VDC(h,:)=VC(4,:);
      VDCrpoil(h,:)=VC(3,:);
  end;

  [VC, K]=VARdecomp(BETAnc,Btilda,600);
  VDCinf=VC(4,:)
  VDCinfrpoil=VC(3,:)
```

Figure 1

```
%obtain relevant IRF
IRF=IRFelas(:,:,findex);
%obtain IRFs from the Posterior draws
load BayesPosterior;

time=(0:1:xmax);
CI=prctile(IRMposs,[16 84],3);
CI1458912=prctile(cumsum(IRMposs,2),[16 84],3);
CI([1 4 5 8 9 12],:)=CI1458912([1 4 5 8 9 12],:);

CI5=prctile(IRMposs,[2.5 97.5],3);
CI5_1458912=prctile(cumsum(IRMposs,2),[2.5 97.5],3);
CI5([1 4 5 8 9 12],:)=CI5_1458912([1 4 5 8 9 12],:);


figure;
set(gcf,'name',['Figure 1'])
set(gcf,'NumberTitle','off')

subplot(3,4,1); %row 1
plot(time,-cumsum(IRF(1,:)),'r',time,-(CI(1,:,1)),'b--',time,-
(CI(1,:,2)),'b--','linewidth',2);
title('Flow supply shock')
ylabel('Oil production')
line([0 xmax], [0 0],'linewidth',2)
axis([0 xmax -2 1])
hold off;

subplot(3,4,2);
    plot(time,-IRF(2,:),'r',time,-(CI(2,:,1)),'b--',time,-
(CI(2,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Real activity')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;
```

```
subplot(3,4,3);
    plot(time,-IRF(3,:),'r',time,-(CI(3,:,1)),'b--',time,-
(CI(3,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Real price of oil')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

subplot(3,4,4);
    plot(time,-cumsum(IRF(4,:)),'r',time,-(CI(4,:,1)),'b--',time,-
(CI(4,:,2)),'b--','linewidth',2);
    title('Flow supply shock')
    ylabel('Inventories')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;

 subplot(3,4,5);
    plot(time,cumsum(IRF(5,:)),'r',time,(CI(5,:,1)),'b--
',time,(CI(5,:,2)),'b--','linewidth',2);
    title('Flow demand shock')
    ylabel('Oil production')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -1 2]);
    hold off;

 subplot(3,4,6);
    plot(time,IRF(6,:),'r',time,(CI(6,:,1)),'b--',time,(CI(6,:,2)),'b-
-','linewidth',2);
    title('Flow demand shock')
    ylabel('Real activity')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

subplot(3,4,7);
    plot(time,IRF(7,:),'r',time,(CI(7,:,1)),'b--',time,(CI(7,:,2)),'b-
-','linewidth',2);
    title('Flow demand shock')
    ylabel('Real price of oil')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

 subplot(3,4,8);
    plot(time,cumsum(IRF(8,:)),'r',time,(CI(8,:,1)),'b--
',time,(CI(8,:,2)),'b--','linewidth',2);
    title('Flow demand shock')
    ylabel('Inventories')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;

 subplot(3,4,9);
    plot(time,cumsum(IRF(9,:)),'r',time,(CI(9,:,1)),'b--
',time,(CI(9,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Oil production')
```

```
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -1 2]);
    hold off;

subplot(3,4,10);
    plot(time,IRF(10,:),'r',time,(CI(10,:,1)),'b--
',time,(CI(10,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Real activity')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

 subplot(3,4,11);
   plot(time,IRF(11,:),'r',time,(CI(11,:,1)),'b--
',time,(CI(11,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Real price of oil')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -5 10]);
    hold off;

  subplot(3,4,12);
   plot(time,cumsum(IRF(12,:)),'r',time,(CI(12,:,1)),'b--
',time,(CI(12,:,2)),'b--','linewidth',2);
    title('Speculative demand shock')
    ylabel('Inventories')
    xlabel('Months')
    line([0 xmax], [0 0],'linewidth',2)
    axis([0 xmax -20 20]);
    hold off;
```

Figure 2

```
dentMat=reshape(IRFelas(:,1,findex),4,4);
Uhat=U;
p=24;
t=308; t=length(kmData)
[K, q]=size(IdentMat);
% Compute structural multipliers
A=  [BETAnc; eye(K*(p-1),K*(p-1)), zeros(K*(p-1),K)];
J=[eye(K,K) zeros(K,K*(p-1))];
IRF=reshape(J*A^0*J'*IdentMat,K^2,1);

for i=1:t-p-1
    IRF=([IRF reshape(J*A^i*J'*IdentMat,K^2,1)]);
end;



% Compute structural shocks Ehat from reduced form shocks Uhat
Ehat=inv(IdentMat)*Uhat(1:q,:);
```

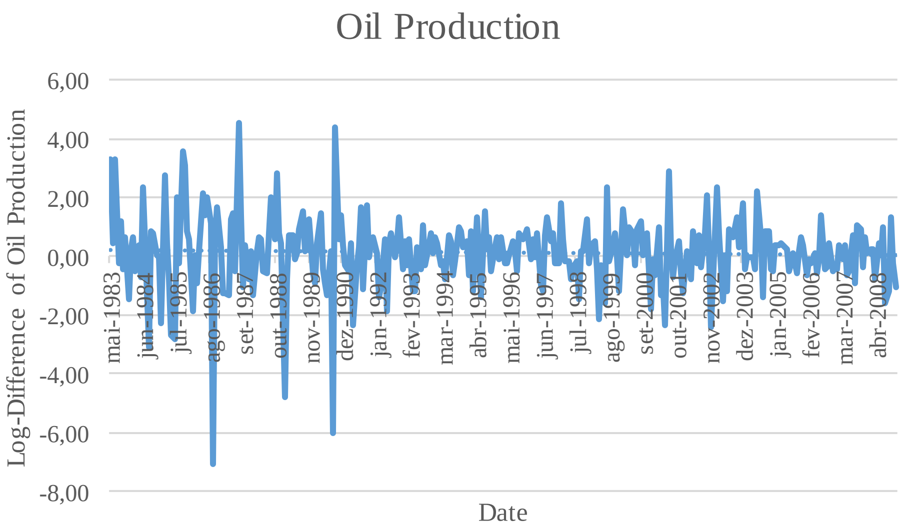
```
% Cross-multiply the weights for the effect of a given shock on the
real
% oil price (given by the relevant row of IRF) with the structural
shock
% in question
yhat1=zeros(t-p,1); yhat2=zeros(t-p,1); yhat3=zeros(t-p,1);
yhat4=zeros(t-p,1);
for i=1:t-p
    yhat1(i,:)=dot(IRF(3,1:i),Ehat(1,i:-1:1));
    yhat2(i,:)=dot(IRF(7,1:i),Ehat(2,i:-1:1));
    yhat3(i,:)=dot(IRF(11,1:i),Ehat(3,i:-1:1));
    yhat4(i,:)=dot(IRF(15,1:i),Ehat(4,i:-1:1));
end;

time=(1983+5/12+1/12*p):1/12:2008+12/12; %starts at 1983.5


cumshock=yhat1+yhat2+yhat3+yhat4;




figure;
subplot(3,1,1)
plot(time,yhat1,'b-','linewidth',2);
title('Cumulative Effect of Flow Supply Shock on Real Price of Crude
Oil')
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on

subplot(3,1,2)
plot(time,yhat2,'b-','linewidth',2);
title('Cumulative Effect of Flow Demand Shock on Real Price of Crude
Oil')
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on

subplot(3,1,3)
plot(time,yhat3,'b-','linewidth',2);
title('Cumulative Effect of Speculative Demand Shock on Real Price of
Crude Oil')
axis([1978+6/12 2009+8/12 -100 +100])
line([(1990+7/12) (1990+7/12)], [-100 100],'linewidth',2)
line([(1978+9/12) (1978+9/12)], [-100 100],'linewidth',2)
line([(1980+9/12) (1980+9/12)], [-100 100],'linewidth',2)
line([(2002+11/12) (2002+11/12)], [-100 100],'linewidth',2)
line([(1985+12/12) (1985+12/12)], [-100 100],'linewidth',2)
grid on
```

Annex

Descripetive Statistics

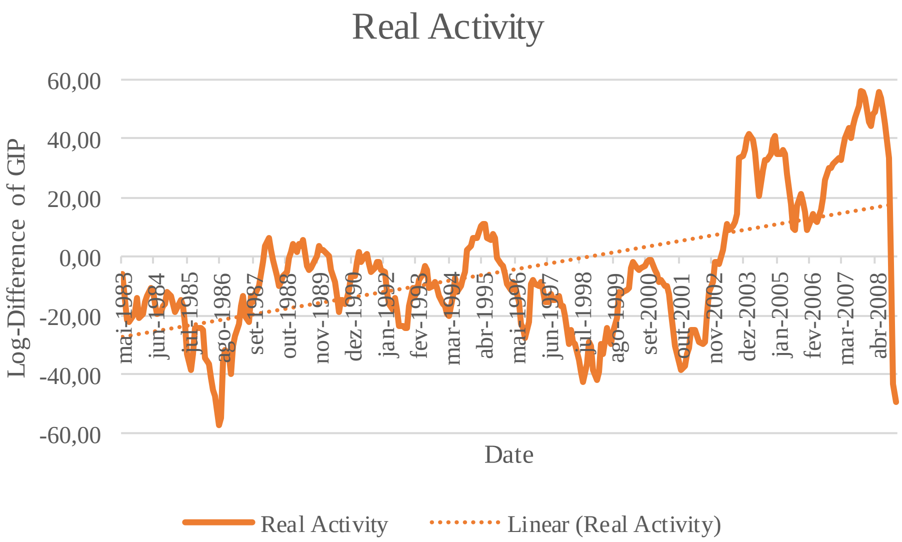
Oil Production

	Oil Production
Mean	0,1150
Standard Error	0,0713
Median	0,1399
Mode	
Standard Deviation	1,2511
Sample Variance	1,5652
Kurtosis	6,2577
Skewness	-0,8318
Range	11,6091
Minimum	-7,0825
Maximum	4,5266
Sum	35,4210
Count	308,0000
Largest(1)	4,5266
Smallest(1)	-7,0825
Confidence Level (95,0%)	0,1403



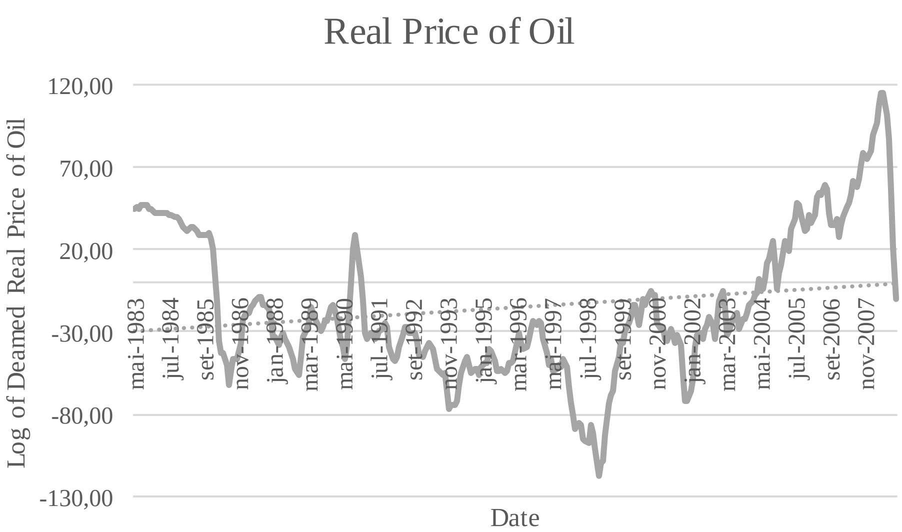
Real Activity

Real Activity	
Mean	-4,7287
Standard Error	1,3193
Median	-8,8944
Mode	
Standard Deviation	23,1531
Sample Variance	536,0646
Kurtosis	0,1641
Skewness	0,6979
Range	113,4625
Minimum	-57,2989
Maximum	56,1636
Sum	-1456,4537
Count	308,0000
Largest(1)	56,1636
Smallest(1)	-57,2989
Confidence Level (95,0%)	2,5960



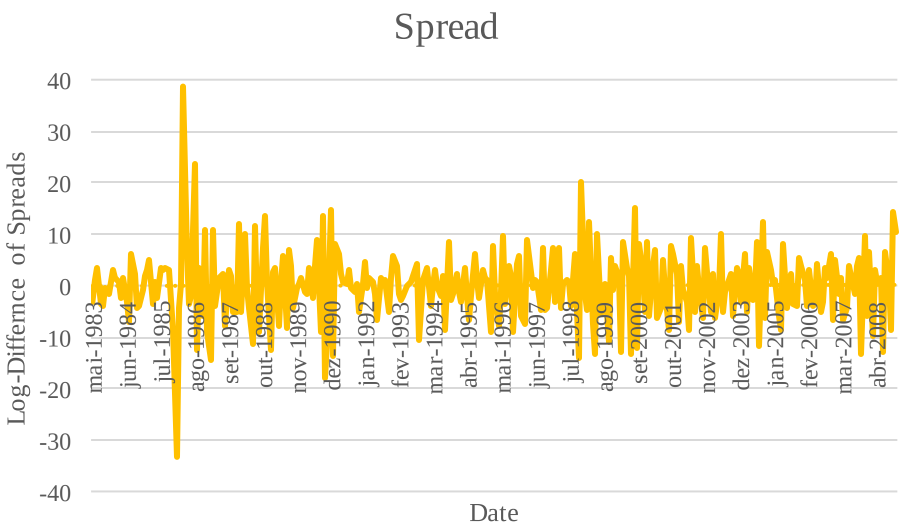
Real Price of Oil

Real Price of Oil	
Mean	-15,2146
Standard Error	2,4932
Median	-26,4604
Mode	
Standard Deviation	43,7551
Sample Variance	1914,5055
Kurtosis	0,0017
Skewness	0,5754
Range	232,5600
Minimum	-117,5350
Maximum	115,0250
Sum	-4686,1059
Count	308,0000
Largest(1)	115,0250
Smallest(1)	-117,5350
Confidence Level (95,0%)	4,9059



Spread

Spread	
Mean	0,03762
Standard Error	0,38961
Median	0,50896
Mode	
Standard Deviation	6,83762
Sample Variance	46,75300
Kurtosis	4,69461
Skewness	0,29541
Range	71,94331
Minimum	-33,27884
Maximum	38,66447
Sum	11,58766
Count	308,00000
Largest(1)	38,66447
Smallest(1)	-33,27884
Confidence Level (95,0%)	0,76664



Inventory

Inventory	
Mean	3,1113
Standard Error	1,3358
Median	2,0060
Mode	
Standard Deviation	23,4438
Sample Variance	549,6118
Kurtosis	0,1512
Skewness	0,2433
Range	138,7404
Minimum	-60,2651
Maximum	78,4753
Sum	958,2950
Count	308,0000
Largest(1)	78,4753
Smallest(1)	-60,2651
Confidence Level (95,0%)	2,6286