SPECULATION AND RETURN VOLATILITY: EVIDENCE FROM THE WTI CRUDE OIL MARKET

by

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ABSTRACT

Based on the data of the Commitments of Traders reports from 2000 to 2013, this paper investigates the impact of speculative futures trading on the return volatility of WTI crude oil.

The threshold GARCH specification associated with proxies and dummy variables is employed to measure the crude oil return volatility. The Granger-causality tests and impulse response analysis are used to estimate the influence of speculative futures trading on the spot return volatility of crude oil through Vector of Autoregression technique.

The results from the TGARCH model indicate that the onset of futures trading reduces the conditional volatility of oil returns by 30.6%. The results further indicate that there is a lead-lag relationship between speculators' positions change and the oil return volatility, but the Granger-causality does not exist for the opposite direction. The results also suggest that a sudden change in speculators' positions does not contribute a large shock on forecasting the future changes in oil spot return in an economic sense, followed by impulse response analysis.

LIST OF ABBREVIATIONS USED

ADF	Augmented Dickey Fuller test
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
BHHH	Berndt, Hall, Hall, and Hausman
CFTC	Commodity Futures Trading Commission
COT	Commitments of Traders
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GJR-GARCH	The GARCH model of Glosten, Jaganathan and Runkle
IRF	Impulse Response Function
MCI	Moody’s Commodity Index
ΔNetLong	Changes in non-commercials’ net long positions
NYMEX	New York Mercantile Exchange
OPEC	Organization of the Petroleum Exporting Countries
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
TOI	Total Open Interest
VAR	Vector Autoregression
WTI	West Texas Intermediate

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CHAPTER 1

INTRODUCTION

Since the 1970s, the crude oil market has grown into one of the world's largest commodity markets. In recent years, crude oil prices have presented remarkable gyrations—they have steadily increased from $10 per barrel in 1998 to over $145 per barrel in mid-2008; and in December 2008, the oil prices have fallen by more than 70% since the 2008 peak (see Figure 1.1). This surge in price has intensified a heated public debate about the drivers of the price of crude oil. It has been shown by several studies that the price dynamics of crude oil market could be influenced by many risk factors such as the short-term variation of stocks, interest rates, the monetary and political policies [Zhang (2013); Hatch and Lantz (2013); Gallo et al. (2010)]. There is some agreement among practitioners that this precipitous rise cannot be fully explained by the rudiments of fundamental supply and demand, but was caused by increased financialization of oil futures markets, which in turn acknowledged speculation as one of main determinants of the crude oil price [Masters (2008, 2010); Einloth (2009); Lombardi and Van Robays (2011); Fattouh et al. (2012)]. However, much of the academic debate, which centers on these allegations, shows little evidence of speculators having systematically driven up oil prices [Alquist and Kilian (2010); Fattouh et al. (2012)].

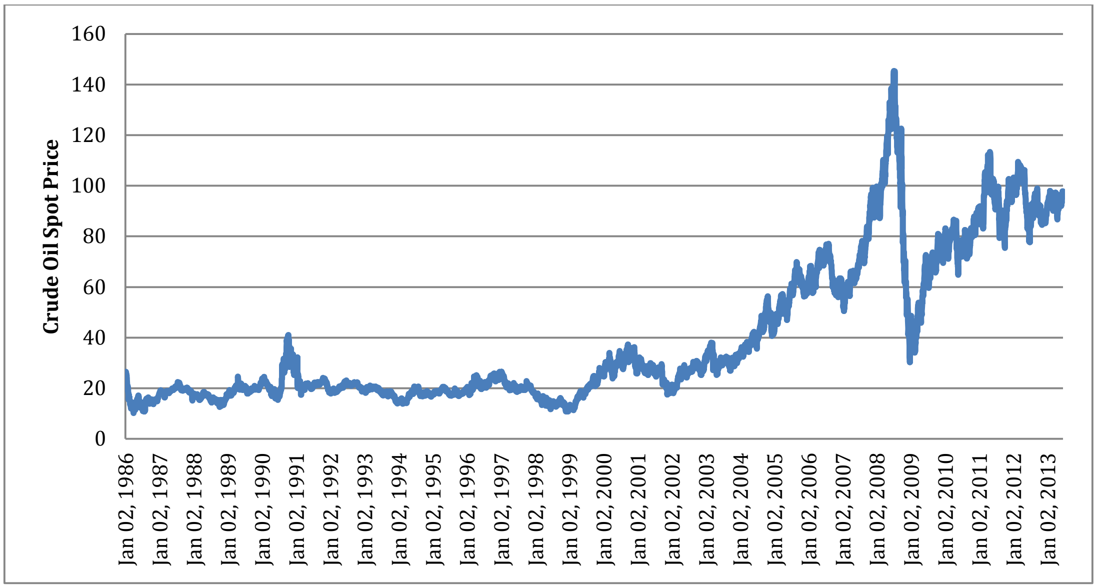

Figure 1.1 Crude oil spot price for West Texas Intermediate (WTI) from January 2, 1986 to January 2, 2013. Source: Energy Information Administration, US Department of Energy.

Several explanations have been put forward in discussing the recent crude oil price fluctuations. Amongst these is the influx of financial investors such as commodity index fund traders into crude oil markets. Non-academics such as Michael Masters (2008) contend that the continued growing capital liquidity and financial innovation attracted more market makers pour into the market[1]. They are interested only in riding a price trend and reaping price gains by trading futures contracts. Due to the price discovery mechanism, the

[1]According to Michael Masters, "Assets allocated to commodity index investment have increased from 13 billion dollars at the end of 2003 to 260 billion dollars as of March 2008" [Masters (2008), pg. 3].

crude oil futures price has been viewed as a determinant of the future spot price. More precisely, it used as a benchmark for the spot price. Hence, more participation by speculators in the oil futures market could cause higher futures prices, which in turn led to higher spot prices. In addition, by conducting a survey of 36 types of commodities, Citigroup finds that the largest non-commercials' positions in natural gas and crude oil is the main driver for rising commodity prices.[2] Indeed, the increased participation by non-commercial crude oil traders during 2003-2008 provided great fodder for causal connections with concurrent price spike [Masters (2008); Büyükşahin and Harris (2011); Zhang (2013)].

On the other hand, academics such as Fattouh et al. (2012) find that speculation plays a limited role in driving the oil price. For example, by using the Commitments of Traders (COT) data of the Commodity Futures Trading Commission (CFTC) for crude oil, Sanders et al. (2004) conclude that the oil futures returns and positions held by non-commercial traders are positively correlated, but changes of traders' net positions do not lead to market returns change in general, followed by Granger causality tests. Moreover, Weiner (2005) asserts that the unprecedented oil price volatility during the Gulf War (1990-1991) was caused by a combination of political events and market fundamentals, rather than speculative trading [Hacheand Lantz (2013); Sanders et al (2004); Weiner (2005); Zhang (2013)].

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[2]See Citigroup (2006). "Commodity Heap"
https://www.citigroupgeo.com/pdf/SZB180995.pdf

In addition, Krugman (2008) suggests, "the only way speculation can have a persistent effect on oil prices, then, is if it leads to physical hoarding". However, the oil inventories did not increase substantially throughout the alleged bubble period. This implies that the so-called "oil bubble" unsupported by speculation, but the consequence of fundamental factors, mainly due to the stagnant oil supply and the strong growth demand in Asian countries.[3] Moreover, analysis by CFTC (2008)[4] contends that fundamental demand and supply factors give the best explanation for the crude oil price surge until mid-2008. Apart from that, Lammerding et al. (2013) claim that speculation has not been a key driver of oil prices, because speculative behavior does not in advance of oil price movement but rather responds to them.

Besides, Brook et al. (2004) assert that it is hard to tell whether speculation has any impact on the average level of prices either higher or lower than would occur in its absence, because it is difficult to differentiate between a circumstance in which hedgers drive market prices and the opposite one, where speculators are behind price fluctuations. Further, according to Weiner (2002), "…even if speculators can raise by buying up futures contracts, they cannot unload these positions at the higher price without a change in market fundamentals. The very action of unwinding their large positions will cause prices to fall." Thus, there is little evidence showing that the size of non-commercials' positions is

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[3]See Krugman (2008). "The Oil Nonbubble". The New York Times (May 12, 2008). http://www.nytimes.com/2008/05/12/opinion/12krugman.html

[4]See CFTC, "Interim Report on Crude Oil. Interagency Task Force on Commodity Markets", (July 22, 2008).http://www.cftc.gov/PressRoom/PressReleases/pr5520-08

correlated to the profitability of such positions, nor whether speculators have any impact on market efficiency [Weiner (2002), pg. 392].

Although the existing literature provides a good reference to understand the role of speculation on the volatility of returns in the crude oil market, these controversial allegations warrant and motivate for further studies. This thesis employs more comprehensive approaches to explain whether speculative trading in oil futures markets significantly affect the return volatility in the spot market.

I begin the research using the threshold GARCH (TGARCH) framework associated with proxies and dummy variables to measure the spot return volatility of crude oil. The use of proxy variables in the mean equation of TGARCH model allows isolating the influence of general market changes on oil spot price. The dummy variable, which accounts for the onset of futures trading in the variance equation, measures the return volatility before and after the introduction of oil futures market. Furthermore, the Granger-causality tests are used to examine the lead-lag relations between speculative trading in the oil futures market and the spot return volatility. Finally, the impulse response analysis is employed to estimate the influence of a sudden change in speculative trading activity on the spot market volatility of crude oil through the Vector of Autoregression (VAR) technique.

The remainder of this paper is organized as follows. Chapter two offers a background of the U.S. crude oil market, followed by a survey of the existing literature on the impact of speculation on price volatility through the futures market. Chapter three describes the sample selection and the dataset employed. Chapter four presents the methodology and econometric modeling. Chapter five analyses and discusses the empirical results and Chapter six concludes the study and a brief summary of the major findings.

CHAPTER 2

BACKGROUND INFORMATION

Prior to discussing the existing economic literature of the impact of speculators' position change on the return volatility in the oil spot market, it is important to have a broad understanding of the crude oil futures market and its mechanisms in general.

The rollercoaster ride of oil prices has been remarkable in the last 40 years. However, the world oil prices stretching between 1874 and 1974 were relatively stable within a range from $10 to $20 per barrel in 2007 dollars[5], and this so-called "golden era" has ended after 1970 with changes in the international political climate. For example, in 1973, several OPEC (Organization of the Petroleum Exporting Countries) members implemented an embargo on oil exporting to the U.S. in response to their support to Israel during the Arab-Israeli war. This embargo policy caused oil price increased from $12 to $53 per barrel within four months. Before the end of the 1970s, the Iranian Revolution pushed oil prices to $95, and then, prices reached an all time low at $21 in 1986 due to over abundance of supplies. Later on, the oil prices soared to a new peak of $41 during 1990-

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[5]See BP. p.l.c. (June 2008). BP Statistical Review of World Energy.

1991 Gulf War, and skidded to a bottom at $12 after 1997 when the Asian financial crisis set in. The erratic oil price trend has continued more recently, after a breathtaking ascent to over $145 per barrel in July 2008, oil price fell to almost $30 per barrel in early 2009 [Smith (2009); Zhang (2013)].

In fact, the crude oil market proves a rather complex system. Other than political circumstance, there are a plenty of fundamental market forces such as oil supply shocks driven by production disruption, OPEC, increases in oil demand result from global economic activities, and limited refinery capacities, have had their impacts on price dynamics. In the following, I explain the crude oil futures market, and then shed light on existing economic models on the role of speculative trading and how changing in speculative positions held by non-commercial traders influence financial markets and returns volatility in crude oil spot market [Lammerding et al. (2013); Jochen (2009); Zhang (2013)].

2.1 THE CRUDE OIL FUTURES MARKET

The futures market is a central financial exchange where standardized futures contracts are traded.[6] Moreover, the futures market was established for commodities prone to large variability and uncertainty about future spot prices. It is universally acknowledged that the

[6] A futures contract is a contractual agreement between two parties to buy and sell a specified quantity (1,000 barrels) of a commodity at an agreed upon certain date in the future, at a pre-determined price [Chang et al (2011)].

oil futures market has a crucial role to play in commodity pricing and transferring risk, which in turn considered price discovery mechanism and risk management as two major functions of a futures market. As for the oil market, price discovery is the general process of determining spot price through basic demand and supply factors related to the market, while transferring of risk or hedging function focuses on when and how to control costly exposures to the risk associated with spot price fluctuations by using oil futures contracts [Zhang and Wang (2013)].

Most oil futures contracts are traded on the New York Mercantile Exchange (NYMEX), a subsidiary of the Chicago Mercantile Exchange (CME), which is supervised by the CFTC—the U.S. Government Agency. According to NYMEX, the light, sweet crude oil (also known as West Taxes Intermediate) futures contract is the world's largest by volume trading[7]. The contract represents 1,000 barrels of WTI crude oil, deliverable at Cushing, Oklahoma. Due to its higher liquidity and lower transaction costs on the exchange, NYMEX has attracted a variety of crude oil futures traders into the market. The party to take delivery of the commodity in the futures is *long* in the position, whereas the one who is agreeing to deliver the commodity is in the *short* position. A speculative agent will benefit when s/he is long if the price goes up, short if the price goes down. For every short position, there is a long position. That is, all gains in a long position could be offset by

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[7] For more contract specifications and trading details, please refer to the NYMEX website.

losses in the opposing short position [Smith, (2009); Sharps et al. (2000); Goodman (2011) pp.68-91].

2.1.1 Market Players

The CFTC classifies market players into two categories—commercial and non-commercial. Commercial traders, such as hedgers, deal directly in the commodity, whereas those with no direct interest would be non-commercial traders such as speculators and arbitrageurs. Hedgers typically include producers and consumers of a commodity, or asset owners who attempt to offset exposure to adverse movements in the price. Unlike hedgers, speculators such as commodity index funds investors wish to make a profit from the inherently risky nature of the commodity market by betting on the price movement. Arbitrageurs, on the other hand, try to take advantage of discrepancies between prices in two markets. Thus, for arbitrageurs to be profitable, they would purchase the undervalued asset on one exchange and short the overvalued asset on another until both the spot and future prices converged [CFTC (2008); Gorton, Hayshi and Rouweuhorst (2008)].

Hedgers

Crude oil hedgers, such as producers and refineries, deal with futures contracts to make offsetting investments against the risk form adverse price movements, because futures contracts "lock in" a definite price to buy or sell underlying commodities for the foreseeable future. In this way, hedging by means of futures contracts secures more certain outcomes, even though it not necessarily with the highest returns [Sharps et al. (2000)].

Speculators

Speculators are to gamble on the oil price fluctuation in the near future for possible profit. For those market participants have to be willing to accept uncertainty. Normally, speculators enter into derivative contracts (either futures or options) taking the opposite position of commercial traders to hedge risk. Tilton et al. (2011) classified speculators into long-short and long-only speculators. Just as the label implies, long-short investors combine a long position in one security and a short position in another. For example, a speculator may not foresee whether the price of crude oil will appreciate or depreciate in the near future, but s/he believes that the price of crude oil will outperform the healthcare, then, s/he could take a long-position with a futures contract on oil and short the healthcare one. Thus s/he can benefit from both falling and rising commodity prices. Such speculators are more sensitive to price fluctuation and typically leveraged (they use borrowed money). Unlike long-short speculators, long-only investors commonly are index-related investors, they are generally unleveraged, and more likely insensitive to price movements [Tilton et al. (2011), pg.188].

Arbitrageurs

Arbitrage is a rather important activity in financial markets. Arbitrageurs profit from the difference in prices of the same commodity traded on different markets. For example, if the oil price is higher on the exchange in London than the one in New York, arbitrageurs will buy oil in New York and sell it in London, thus making a risk-free profit. As a consequence, this strategy would drive up the oil price in New York with increased demand and lower down the oil price in London with increased supply, leading the disappearance of arbitrage opportunity (Downes and Goodman, 1998).

2.1.2 The CFTC & COT Reports

The Commodity Futures Trading Commission (CFTC) mandates and regulates the U.S. commodity futures and option markets in order to ensure financial market integrity, and its primary mission is to guarantee the economic utility of the futures markets and to protect market traders from manipulation, price disruption and systemic risk related to derivatives that are subject to the Commodity Exchange Act (CEA)[8] (Sanders et al., 2004). The CFTC compiles position data for large commercial and non-commercial users of open interest across all futures and option contracts.[9] The commitments of traders (COT) is a subset data issued by CFTC, and COT report releases a breakdown of aggregate positions held by

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[8] The information was taken from publications on the CFTC website. Please see<http://www.cftc.gov> for details.

[9] The CFTC data under the U.S. CEA are required to report their open interest each day they hold a large position [See Weiner (2002), pg. 396].

traders for every Friday. The open interest[10] includes reporting and non-reporting traders, where reporting traders hold positions in excess of the CFTC reporting level[11]. Further, reporting traders can be divided into commercials (known as hedgers) and non-commercials (referred to large speculators), and the non-reporting traders are sometimes called small speculators who do not hold positions in excess of the CFTC reporting level [Weiner (2002); Sanders et al. (2004); Aulerich et al. (2013)].

To protect futures and options market from manipulation and price distortion, the CFTC uses the Large Trader Reporting System (LTRS), a surveillance program from CFTC, to "determine when a trader's position in a futures market becomes so large relative to other factors that it is capable of causing prices to no longer accurately reflect legitimated supply and demand conditions" [Sanders et al. (2004), pg.429]. The LTRS collects daily positions (from traders and/or brokers) if they meet or larger than the CFTC reporting level. For example, the current reporting level in the crude oil futures contract is 350 contracts.[12] The reporting level is on a futures equivalent or delta-adjusted basis.[13] Therefore, a trader

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[10] The number of contracts outstanding at the end of the trading session is called open interest.

[11] Sizes of positions set by the CFTC at or above which commodity traders or brokers who carry these accounts must make daily reports about the size of the position by commodity, by delivery month, and whether the position is controlled by a commercial or non-commercial traders. See the Large Trader Reporting System (LTRS). http://www.cftc.gov/consumerprotection/educationcenter/cftcglossary/glossary_qr

[12] Reporting levels can be referenced under the CFTC Part 15.03(b).

[13] Delta is the change in option price for a one percent change in the price of the underlying futures contract. Adjusting options positions by delta makes options positions comparable to futures positions in terms of price changes (See Aulerich et al., 2013, pg.10).

may hold contracts larger than the reporting level, but it is not a reportable position if the position is delta-neutral [Sanders et al. (2000), pg.429; Aulerich et al. (2013)].

The commitments of traders (COT) reports issued by the CFTC reflect the open interest in futures and option contracts, broken down by several categories of market participant, distinguishing hedgers from speculators. The COT data are released on every Friday for the open interest as of close of trading on the previous Tuesday. Therefore, the changes in flows of traders in their long, short, or spread positions can be identified by comparing week-to-week COT data (Jickling and Austin, 2011).

2.2 EXISTING LITERATURE

How speculative activities affect crude oil price is a hot topic but not a new one. The interactive mechanism between them has been a subject of many studies, but the findings do not appear consistent [Dale and Zyren (1996); Irwin and Sanders (2011)]. In this section, I begin by briefly highlighting the existing theories to explain the oil price, followed by a survey of literature on the role of speculation in crude oil markets.

2.2.1 Existing Theories

On the drivers of oil price and volatility, there are three approaches used: the non-structural models (Hotelling, 1931), the structural models (or the supply-demand framework) (Dées et al., 2007) and the informal approach (Fattouh, 2007).

The starting point for using non-structural model to explain the prices volatility of exhaustible resources has been the well-documented Hotelling (1931)'s model[14] (Slade and Thille, 2009). Hotelling indicates that the optimum extraction path would be the price of exhaustible resource (the crude oil price in our context) increases over time (at the interest rate r) and eventually the demand for this resource (or oil) will vanish at a very high price level (Fattouh, 2007). Pindyck (1999) adopts the non-structural model to investigate the long-term price behavior of oil. He found that the non-structural model is better used for explaining short-term price volatility rather than long-term forecasting for the reason that "oil prices revert to an unobservable trending long-run marginal cost with a fluctuating level and slope over time" (Fattouh, 2007; pg.131). Since the work of Hotelling (1931), further studies make the non-structural model more realistic, for example, allow for changes in cost of production or holding inventories [see, for instance, Slade (1982); Moazzami and Anderson (1994); Slade and Thille (2009); Fattouh (2007)]. Deaton and Laroque (1996) find that the theory of storage works well on predicting price changes of commodity by using first-order linear autoregression (AR) model, but it performs poorly when allows shocks (i.e. excess supplies) to AR process. As Fattouh (2007) asserts, "Hotelling's original model was not intended to and did not provide a framework for predicting prices or analyzing the time series properties of prices of exhaustible resource, aspects that the recent literature tends to emphasis" (pg.132).

[14]Hotelling (1931)'s model is mainly concerned with the question that "given demand and the initial stock of the non-renewable resource, how much of the resource should be extracted every period so as to maximize the profit of the owner of resource" (Fattouh, 2007, pg.130).

The structural model (known as the demand-supply framework) is the most widely used approach to modeling the crude oil market (Dées et al, 2007). The demand-supply model, as implied by its name, deals with the interaction between oil supply and demand to the price of oil, income and price elasticity of demand and reserves (Fattouh, 2007). Notwithstanding the structural model helps understanding the oil market in an insightful way, it fails to predict oil prices. Cashin et al. (1999) conclude the reasons why this model has very limit ability to predict oil prices as: 1) price prediction are highly sensitive to price and income price elasticity of demand, the price elasticity of supply and OPEC behavior; 2) the structural model fails to capture the impact of unexpected shocks[15]; and 3) this type of framework does not include the geopolitical factors and general market conditions (see, e.g., Fattouh, 2007).

Many studies [see, e.g., Masters (2008, 2010); Einloth (2009); Lombardi and Van Robays (2011); Fattouh et al. (2012)] agree that the surge in oil prices and price volatility could not be fully explained by non-structural or structural model. Economists have therefore attempted to identify other drivers that could influence oil price (known as the informal model mentioned above), such as unexpectedly strong demand, erosion of spare capacity, OPEC supply shocks, an increasing role of speculation etc. (Fattouh, 2007). Among these factors, the role of speculation in crude oil has drawn a huge attention from the public, it will be discussed in details in the next section.

[15]Please refer to Cashin et al. (1999, pg.39), "How Persistent Are Shocks to World Commodity Price?" for more information about the persistent shocks.

2.2.2 The Role of Speculation

The definition of speculation is rather unclear. Kilian and Murphy (2013) describe speculative buying in physical oil market as: if anyone buying crude oil not for current consumption, but for future use. In general, speculative trading will occur if the buyers predicting increasing oil prices. Speculative purchasing could be buying crude oil for physical storage leading to an accumulation inventories, or buying oil futures contracts from the futures market, either of these situations lets one to take a position on the expected change in the oil price (Fattouh et al., 2012).

Actually, speculation may make perfect economic sense and is a necessary part of the futures market. Friedman (1953) contends that there is no reason to believe speculation leading to price volatility in the physical market, since speculators buy when prices are low (low demand and high supply) and sell when prices are high (high demand and low supply). These speculative activities push prices going up when they are low and going down when they are high (Friedman, 1953). Moreover, without speculative traders, the futures market cannot fulfill the function of providing liquidity and discovering price [Büyükşahin and Harris (2011)].

The term speculation, however, always has a negative implication in the public debate because speculation is viewed as excessive. Fattouh et al. (2012) define excessive speculation as "the speculation that is beneficial from a private point of view, but would not be beneficial from a social planner's point of view" (pg.3). Nevertheless, measuring the excessive level of speculation is difficult.

A traditional approach to quantify speculation, the Working's speculative T index, was firstly proposed by Working (1960). It measures the percentage of speculation in excess of what is the minimal level to balance the hedging positions held by commercial traders in commodity futures markets (Büyükşahin and Harris, 2011). The Working's T index is better used as a relative measure, because the benchmark of the index is the historical value of the same index for other commodity markets. We need to compare these numbers, and then conclude whether excessive speculation exists. A high Working's speculative index number does not necessarily imply excessive speculation [Büyükşahin and Harris (2011); Fattouh et al. (2012)].

Another way to detect excessive speculation is to look at the relative size or trading volume of the futures market and spot market. According to Fattouh et al. (2012), the daily trading volume in the oil futures market is three times higher than physical oil production, drawing attention that speculators are dominating the oil market. Considering the number of days to delivery for the oil futures contracts, Ripple (2008) concludes that the ratio is misleading due to the comparison of a stock in the numerator to a flow in the denominator. The ratio is only a fraction of about one half of daily U.S. oil usage (Ripple, 2008). Up to now, the definition of speculation still remains vague, and none of literatures to date the speculation process has been quantified (Fattouh et al, 2012).

Many studies argue that speculation has very limited impact on the crude oil price [see, e.g., Sanders et al. (2004); Hamilton (2009b); Smith (2009); Krugman (2008)]. Others, such as Kaufmann and Ullman (2009), Kaufmann (2011), Cifarelli and Paladino (2010) and Eckaus (2008), on the other hand, claim that there is no reason to believe the current oil price has been justified based on current and expected market fundamentals, thus the oil price can be affected by speculations.

Masters (2008) suggests in the Testimony for the U.S. Senate that the speculative bubble of the oil price is primarily based on the increasing financialization[16] in the oil futures market reflected by the dramatic rise in index commodity funds starting in 2003 [Masters (2008); Lammerding et al (2013); Fattouh et al. (2012)]. Evidence is clear [see, e.g., Alquist and Kilian (2007); Büyükşahin et al. (2009)]. Büyükşahin and Robe (2010) find that if the overall share of hedge funds in energy futures has increased by 1%, ceteris paribus, the dynamic correlation between energy and equity returns increase in 5%. Similar conclusions are given by Silvennoinen and Thorp (2010) and Tang and Xiong (2012) when they examine the influence of the entry of index funds on the price co-movement between crude oil and non-energy commodities. Other studies such as Büyükşahin et al. (2009), however, assert that financialization makes derivatives pricing methods more efficient, and helps spot (or physical) market more integrity (Fattouh et al., 2012).

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[16]While the definition of financialization is vague, it captures the increasing acceptance of oil derivatives as a financial asset by a wide range of market participants including hedge funds, pension funds, insurance companies, and retail investors (Fattouh et al, 2012; pg.7).

Another strand of the studies has focused on the oil price-inventory relationship [see, e.g., Kilian and Murphy (2013); Pirrong (2008)]. The building up of inventories is often viewed as a sign of speculative bubble in the crude oil market. Alquist and Kilian (2010) test the relationship between crude oil inventories and the real price volatility of crude oil driven by demand shocks. They find that the increased uncertainty about future oil supply shortage may lead the oil price to overshoot in very short-run with no response from inventories [Fattouh et al. (2012); Büyükşahin and Harris (2011)]. Moreover, Kilian and Murphy (2013), for the first time, identify the impact of speculative demand shocks (viewed as endogenous variable) on the spot price of oil by using Structural Vector of Autoregressive (SVAR) models. They find that a positive shock to speculative demand is associated with increases in both oil inventories and the spot price. Therefore, changes in oil inventories tell us nothing about the absence of speculation [Kilian (2012); Fattouh et al. (2012) Büyükşahin and Harris (2011)].

Other studies [see, for instance, Lombardi and Van Robays (2011); Juvenal and Petrella (2011)] challenge Kilian-Murphy model (2013) may be misleading, as the model does not allow for "financial speculation" (Fattouh et al, 2012). Followed Lombardi and Van Robays (2011)'s work, Kilian and Murphy (2013) test an increment sample period from 1991 by using SVAR process identified with sign restrictions. They introduce a destabilizing financial speculation shock (or nonfundamental financial shock which defined as change in oil futures spread and the oil futures price) into the model, and leave other impact responses unrestricted. They find that market fundamentals are the main drivers of oil price movements, but financial activities indeed destabilize oil spot price in the short run, particularly in 2007 to 2009 (Lombard and Van Robays, 2011).

Another recent research related SVAR process is given by Juvenal and Petrella (2011). The major hypothesis of their study is that the speculative supply shock has negative impact on above-ground oil inventories in oil importing countries. Based on Kilian-Murphy model, Juvenal and Petrella (2011) allow an additional shock to capture speculative supply from oil producers, while maintaining the speculative demand shock in their model. Additionally, they impose a sign restriction on the inventory response to flow supply shocks, in order to maintain two speculative shocks (i.e. supply and demand shocks) in the model. But surprisingly, they find that the increased oil price volatility after 2003 is caused by demand shocks that conforms Kilian and Murphy (2013)'s finding (Fattouh et al., 2012).

Do speculative futures trading drive up the price and/or return volatility of crude oil, and why they are considered harmful to the economy? The existing evidence is not supportive about the quantitative importance of the role that speculation plays in the oil market. In the view of these unknowns, solid statistical inference about the impact of speculative behaviors on oil return (and price) volatility appears to be desirable.

For the purpose of modeling the changes in spot return volatility before and after the introduction of futures trading, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models by Bollerslev (1986) are the most frequently used. This is partly due to the demand for modeling time varying volatility in financial market, and partly due to the fact that these models are easy to implement, and provide more accurate estimates (Andersen and Bollerslev, 1998). In addition, GARCH models are quite successful in capturing the stylized facts of financial returns [Pagan (1996), Bollerslev et al. (1994), Palm (1996), Chang (2012), and Alberg et al. (2008)]. The first stylized fact is that the volatility of returns exhibit to be clustered[17] and provide a high level of volatility persistence [Mandelbrot (1963); Pagan (1996); Alizadeh et al. (2008)]. The second stylized fact is that the return is often fat-tailed with excess kurtosis or leptokurtosis, implying that the extreme returns have higher probability than expected under a normal distribution. The third stylized fact is that negative returns result in higher volatility than positive returns of the same size [Black, (1976); Alberg et al. (2008); Sopipan et al. (2012)].

However, normalizing the returns by conditional variances using GARCH models could not fully eliminate volatility clustering and leptokurtosis (Rabemananjara and Zakoian, 1993). Several authors [see, for example, Black (1976); Nelson (1991) Rabemananjara and Zakoian (1993)] have pointed out that the volatility of financial returns is usually affected asymmetrically from positive and negative shocks (i.e. the bad news have greater impacts on volatility than the good news). Since the distributions of GARCH models are symmetric, they fail to capture the asymmetric effect. To address this problem, many nonlinear extensions of GARCH models have been proposed, such as the exponential GARCH (EGARCH) by Nelson (1991), the GJR-GARCH by Glosten, Jagannathan, and

[17]As noted by Mandelbrot (1963), one way say volatility clustering that "large changes tend to be followed by large changes-of either sign-and small changes tend to be followed by small changes."

Runkle (1993) and the threshold GARCH (TGARCH) by Zakoian (1994). In this thesis the asymmetric GARCH model will be adopted to measure the oil return volatility prior and after the onset of futures trading. The standard GARCH and the asymmetric GARCH specifications will be discussed in depth in Chapter 4.

To fully understand whether speculative futures trading drive up the price and/or return volatility, many studies such as Pok and Poshakwale (2004) use the Granger-causality tests associated with appropriate speculative proxies[18] to examine the effect of changes in speculative positions on price and/or return volatility (which they modeled using GARCH models). Pok and Poshakwale (2004) find that the impact of the previous day's futures trading on volatility is positive but very short (only one day). In addition, based on CFTC data, Sanders et al. (2004) report a positive correlation between crude oil returns and positions held by noncommercial traders, followed by the Granger-causality tests. On the other hand, ITF (2008) finds that oil futures position changes of any classifications of traders do not Granger-cause oil price. Sanders and Irwin (2010) also conclude that there is no causal links between the positions of the two large ETFs (exchange-traded fund) and return volatility in crude oil market.

This thesis is motivated by allegations that speculative activity in the futures market is responsible for the return volatility of crude oil. The investigations have been focused on analyzing the spot return volatility before and after the introduction of futures market.

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[18] Different speculative measurements will be discussed in detail in Chapter 3.

Recent studies have been focused on how and to what extent of speculative futures trading affect return volatility of crude oil. In this thesis, both theories will be examined in the following chapters.

CHAPTER 3

DATA

This chapter presents a general sample selection, including the measurement of position size in crude oil futures market, followed by the descriptive statistics of data.

3.1 SAMPLE SELECTION

One time series data used in this study are the crude oil futures position weekly data (COT) as of Tuesday's close which span over January 4, 2000 to May 28, 2013 resulting 700 observations in total. The source of COT data are available on CFTC website.

According to Sanders et al. (2004), there are two indicators to measure the position size. The first is the percent of the total open interest (TOI) held by each CFTC trader classification. This measure is the sum of the long and short positions held by the trader class divided by twice the market's *TOI* [Sanders et al. (2004), pp.431-432; Zhang (2013); pg.396].

(3.1) $$PNC_t = \frac{NCL_t + NCS_t + 2(NCSP_t)}{2(TOI_t)} * 100$$

where PNC_t is the reporting non-commercials' percent of TOI_t, NCL is the non-commercial long position, NCS is the non-commercial short position, $NCSP$ is the non-commercial spread position, CL is the commercial long position and CS is the commercial short position.

$$(3.2) \quad PC_t = \frac{CL_t + CS_t}{2(TOI_t)} * 100$$

where PC_t is the reporting commercials' percent of TOI_t. Other variables are defined same as previously.

The second indicator measures the net position of the average trader in a CFTC classification. The percent net long (PNL) position is calculated at the long position minus the short position divided by their sum [Sanders et al. (2004); De Roon et al. (2002); Zhang (2013)].

$$(3.3) \quad PNL_t^N = \frac{NCL_t - NCS_t}{NCL_t + NCS_t + 2(NCSP_t)} * 100$$

where PNL_t^N, which is known as "speculative pressure", represents the percent of net long position held by non-commercial traders. Other variables are defined same as previously. The difference between long and short positions is the net long position.

$$(3.4) \quad PNL_t^C = \frac{CL_t - CS_t}{CL_t + CS_t} * 100$$

where PNL_t^C, which is known as "hedging pressure", represents the percent of net long position held by commercial traders. Other variables are defined same as previously.

The weekly data of the spot prices in the U.S. dollar per barrel of WTI crude oil from January 2000 to May 2013 are retrieved from the Energy Information Administration (EIA) of the U.S. Energy. Trading details of the contract are provided in Table 3.1.

Table 3.1 Contract specification: light, sweet crude oil futures traded at NYMEX.

Product Symbol	CL
Contract Unit	1,000 barrels
Price Quotation	U.S. Dollars and cents per barrel
Minimum Fluctuation	$0.01 per barrel
Termination of Trading	Trading in the current delivery month ceases on the third business day prior to the 25th calendar day of the month proceeding the delivery month. If the 25th calendar of the month is a non-business day, trading ends on the third business day prior to the last business day proceeding the 25th calendar day.
Listed Contracts	Crude oil futures are listed nine years forward as following schedule: consecutive months are listed for the current your and the next five years; in addition, the June and December contract months are listed beyond the sixth year.
Settlement Type	Physical

Source: CME Group
http://www.cmegroup.com/trading/energy/crude-oil/light-sweet-crude_contract_specifications.html

Because the traders' position data in the COT reports are those as of Tuesday's close, a matching set of crude oil futures and spot prices should be constructed.[19] I extracted weekly data by the following way. From 3361 daily observations of futures contracts, I firstly select a Tuesday's closing price. If Tuesday observation is not available for a specific

[19]Also, the crude oil spot returns $R_t = 100 * \ln(P_t / P_{t-1})$ is calculated for nearby WTI crude oil futures, using the Tuesday-to-Tuesday closing price P_t.

week, then I take for the Monday's closing price just before that Tuesday. If Monday observation is not available either, I take the Wednesday's closing price, and then Thursday and Friday. Among 700 weekly observations, there are 690 Tuesday observations, 6 Monday observations and 4 Wednesday observations. By the same method, I obtain 700 weekly spot price observations, including 693 observations from Tuesday, 4 Monday observations and 3 Wednesday observations.

In addition, weekly prices of Moody's Commodity Index and Gold Bullion (from the London Bullion Market) are used as proxy variables for investigating crude oil return volatility. All of these data (700 observations for each) are retrieved from Datastream and then converted into a Tuesday-to-Tuesday data.

3.2 DATA DESCRIPTION

First, I examine the properties of the data. Figure 3.1 presents the percentage of the total open interest (TOI) held by each CFTC trader classification. By using the same definition in previous section, PC is the percentage of TOI held by commercial traders, and PNC denotes the percentage of TOI held by non-commercial traders. It is clear that the PC of TOI (with average value 60.48%) is higher than PNC (with average value of 32.18%) over the sample period. This indicates that the commercial traders dominate the crude oil futures market as the position volume is concerned, but the percentage of TOI held by non-commercial traders has steadily increased over time.

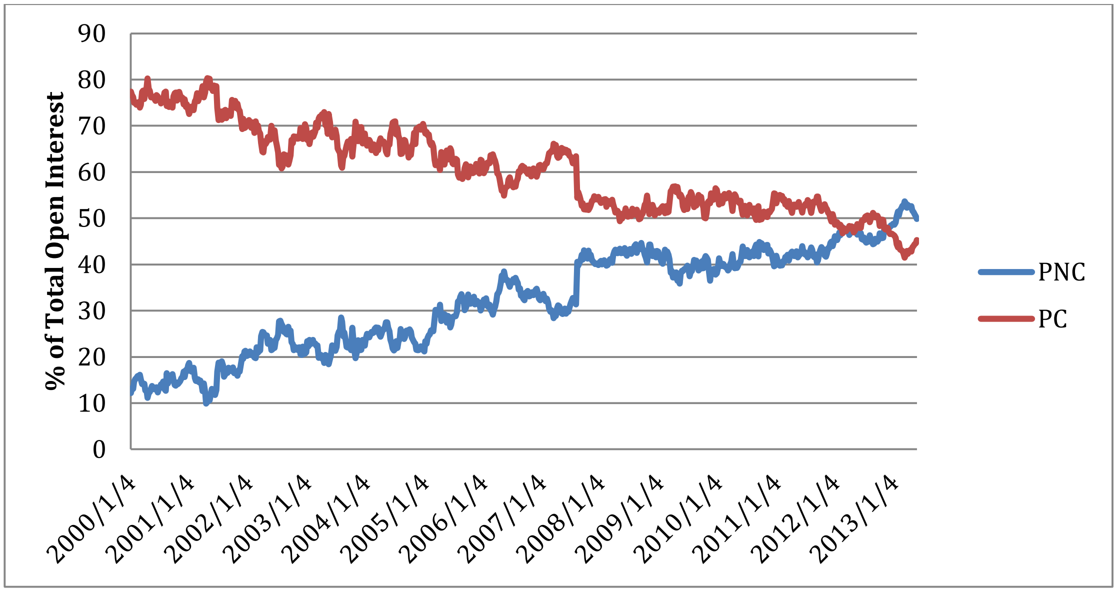

Figure 3.1 The percentage of the total open interest (TOI) held by each CFTC trader classification of WTI oil futures market. Source: CFTC, US

Note: 1. PC is the percentage of TOI held by commercial traders

2. PNC is the percentage of TOI held by non-commercial traders

This paper investigates whether speculative trading in crude oil futures markets affect the spot market volatility, a proxy of speculation—changes in non-commercials' net long positions—was constructed based on Zhang (2013)'s study. According to Zhang (2013, pg. 397):

$$\Delta NetLong_t = (NCL_t - NCS_t) - (NCL_{t-1} - NCS_{t-1}) \tag{3.2.1}$$

where *NCL* and *NCS* denote the non-commercials' long position and non-commercials' short position, respectively.

Having constructed continuous time-series for prices, for the WTI spot price, London Bullion Gold prices and MCI prices, I then transform them into returns by using the log-difference. The summary statistics of the returns series over the sample period are presented in Table 3.2. The negative excess skewness of all variables on returns level indicate that the distribution has a longer left tail (extreme losses) than right tail (extreme gains). The kurtosis of all returns are significantly higher than 3 except the WTI spot log-price, which indicate a fat-tailed distribution. The Jarque-Bera normality tests for all returns indicate significant departures from the normality. It would be expected that the GARCH-type model could feature these properties such as sharply peaked and leptokurtosis.

Table 3.2 Summary statistics of WTI crude oil, London Bullion Gold and Moody's Commodity Index

	WTI Spot Return	**WTI Spot Log-Price**	**Gold Spot Return**	**MCI Return**	**∆NetLong**
Maximum	0.2188	4.9485	0.1477	0.0673	63969
Minimum	-0.2514	2.8948	-0.1326	-0.0837	-77779
Mean	0.0019	3.9883	0.0023	0.0023	340.9040
Variance	0.0029	0.2593	0.0006	0.0003	242353980
Std. Dev.	0.0540	0.5093	0.0250	0.0182	15567.72
Skewness	-0.6622	-0.2468	-0.1674	-0.4718	-0.0551
Kurtosis	5.1798	1.7537	6.2142	4.7813	4.7476
JB test	189.4763	52.2588	304.1660	118.3404	89.1836

Note: 1. The sample period is from January 4, 2000 to May 28, 2013.
2. The returns are calculated by $R_t = 100^* \ln(P_t / P_{t-1})$.
3. JB test is the Bera and Jarque (1980) tests for normality. The test follows a Chi-square distribution with 2 degrees of freedom.
4. Data source: EIA, US Department of Energy and Datastream.

I then check the return series for unit root, since the GARCH and the VAR models are based on stationary processes. When a time-series is non-stationary, the shocks to the series are persistent and would not decay over time. I first conduct the Augmented Dickey and Fuller (1979) unit root test (ADF test hereafter) for the stationarity of the return series. Considering that the ADF test may have low power against stationary near unit root series[20], I also use the Phillips and Perron (1988) test (PP test hereafter). The PP test complements the ADF test. Any concern regarding the power of either test could be addressed by comparing the significance of statistics from both tests. As shown in Table 3.3, the unit root tests on the returns and their first differences indicate that the first difference of oil spot prices, gold price and MCI prices are stationary at the 1% significance level, and can be analyzed by GARCH and VAR models.

Table 3.3 Augmented Dickey-Fuller and Phillips and Perron unit root test results over the period

	ADF Unit Root Test		**PP Unit Root Test**	
	Test Statistics	p-value	Test Statistics	p-value
WTI Spot Return	**-7.7193**	0.01	**-24.3270**	0.01
WTI Spot Log-Price[5]	-3.0072	0.15	-16.3504	0.20
Gold Price Return	**-9.9251**	0.01	**-26.5687**	0.01
MCI Price Return	**-7.0619**	0.01	**-24.5316**	0.01
ΔNetLong	**-9.6571**	0.01	**-23.6526**	0.01

Note: 1. The sample period is from January 4, 2000 to May 28, 2013.
2. The null hypothesis of ADF and PP tests is that a time series has a unit root against a stationary alternative.
3. The critical values of ADF test are -4.015 (1%), -3.440 (5%) and -3.140(10%), respectively, and the critical values of PP test are -3.4388 (1%), -2.8652 (5%) and 2.5682 (10%), respectively.
4. Bold values indicate rejection of the unit root hypothesis at 5% level.
5. The ADF and PP unit root tests on the first difference of oil spot price (in log) for are -7.7075 (p-value=0.01) and -766.545 (p-value=0.01), respectively.

[20]See Dickey and Fuller (1979) and Kasman and Kasman (2008).

In order to test the impact of speculative trading in the oil futures market on spot market volatility, I split the full sample into two sub samples. The first sub sample is form January 4, 2000 to October 25, 2005, and the second is from November 2, 2005 to May 28, 2013. These two sub sample fall pre and post the introduction of futures trading and are of equal in the number of observations. The summary statistics results for pre-futures trading and post-futures trading are shown in Table 3.4a and Table 3.4b, respectively. It is interesting that the variance and the standard deviation of WTI spot return in Table 3.4a do not increase after the introduction of futures trading (see Table 3.4b). This indicates that the unconditional volatility of the oil returns in the spot market do not change significantly pre and post the futures listing.

Table 3.4a Summary statistics for subperiod : January 4, 2000 to October 25, 2005

	Pre-futures trading			
	WTI Spot Return	**WTI Spot Log-Price**	**Gold Spot Return**	**MCI Return**
Maximum	0.1508	4.3349	0.0574	0.0354
Minimum	-0.2392	2.8948	-0.0832	-0.0590
Mean	0.0026	3.5872	0.0021	0.0022
Variance	0.0029	0.1299	0.0005	0.0002
Std.Dev.	0.0541	0.3604	0.0213	0.0133
Skewness	-0.7756	0.5093	-0.2366	-0.5374
Kurtosis	1.2939	2.1910	3.8338	4.4614
JB test	60.5804	24.6039	13.3662	47.8540
ADF test	**-7.9368**	-2.0216[6]	**-7.9048**	**-5.8959**
	(0.01)	(0.567)	(0.01)	(0.01)
PP test	**-21.7053**	-2.3249[6]	**-17.5941**	**-18.5557**
	(0.01)	(0.439)	(0.01)	(0.01)

Note: 1. The returns are calculated by $R_t = 100^* \ln (P_t / P_{t-1})$.

2. JB test is the Bera and Jarque (1980) test for normality. The test follows a Chi-square distribution with 2 degrees of freedom.
3. The null hypothesis of ADF and PP tests is that a time series has a unit root against a

stationary alternative.

4. The critical values of ADF test are -4.015 (1%), -3.440 (5%) and -3.140(10%), respectively, and the critical values of PP test are -3.4388 (1%), -2.8652 (5%) and 2.5682 (10%), respectively.
5. Bold values indicate rejection of the unit root hypothesis at 5% level.
6. The ADF and PP unit root tests on the first differences oil spot price (in log) for are -8.0489 (p-value=0.01) and -21.8099 (p-value=0.01), respectively.
7. Data source: EIA, US Department of Energy and Datastream.

Table 3.4b Summary statistics for subperiod : November 2, 2005 to May 28, 2013

	Post-futures trading				
	WTI Spot Return	**WTI Spot Log-Price[6]**	**Gold Spot Return**	**MCI Return**	**∆NetLong**
Maximum	0.2189	4.9485	0.1477	0.0673	63969
Minimum	-0.2514	3.5258	-0.1326	-0.0837	-77779
Mean	0.0012	4.3890	0.0025	0.0023	708.1782
Variance	0.0029	0.0670	0.0008	0.0005	331417045
Std.Dev.	0.0540	0.2588	0.0282	0.0221	18204.86
Skewness	-0.5465	-0.7598	-0.1337	-0.4211	-0.1044
Kurtosis	6.0534	3.7105	6.4784	3.8401	4.3788
JB test	152.9492	40.8060	176.4750	20.5155	28.1994
ADF test	**-5.027**	-2.5446	**-7.9964**	**-5.1621**	**-7.3689**
	(0.01)	(0.347)	(0.01)	(0.01)	(0.01)
PP test	**-19.3187**	-2.2070	**-19.407**	**-16.8473**	**-16.5234**
	(0.01)	(0.489)	(0.01)	(0.01)	(0.01)

Note: 1. The returns are calculated by $R_t = 100 * \ln (P_t / P_{t-1})$.

2. JB test is the Bera and Jarque (1980) test for normality. The test follows a Chi-square distribution with 2 degrees of freedom.
3. The null hypothesis of ADF and PP tests is that a time series has a unit root against a stationary alternative.
4. The critical values of ADF test are -4.015 (1%), -3.440 (5%) and -3.140(10%), respectively, and the critical values of PP test are -3.4388 (1%), -2.8652 (5%) and 2.5682 (10%), respectively.
5. Bold values indicate rejection of the unit root hypothesis at 5% level.
6. The ADF and PP unit root tests on the first differences oil spot price (in log) for are -5.0121 (p-value=0.01) and -19.2504 (p-value=0.01), respectively.
7. Data source: EIA, US Department of Energy and Datastream.

Table 3.5 shows the Ljung-Box Q statistics on the first 20 lags of the sample autocorrelation function. The results reject the null hypothesis that there is no serial correlation in the returns. Bollerslev's GARCH model is appropriate, as the Ljung-Box Q tests implies the existence of heteroscedasticity [Pok and Poshakwale (2004); Kasman and Kasman (2008); Alizadeh et al. (2008)].

Table 3.5 The Ljung-Box Q test for returns over the period: January 4, 2000 to May 28, 2013

	WTI Spot Return	**WTI Spot Log-Price**	**Gold Spot Return**	**MCI Return**
Lag 1	5.965 (0.015)	5.939 (0.015)	0.017 (0.894)	3.976 (0.046)
Lag 2	7.590 (0.022)	7.575 (0.023)	1.428 (0.489)	5.194 (0.074)
Lag 3	12.896 (0.005)	12.825 (0.005)	1.539 (0.673)	6.095 (0.107)
Lag 4	13.016 (0.011)	12.945 (0.012)	1.562 (0.815)	6.276 (0.179)
Lag 5	3.185 (0.021)	13.127 (0.022)	2.960 (0.706)	6.637 (0.249)
Lag 10	24.727 (0.005)	24.629 (0.068)	12.796 (0.235)	22.093 (0.014)
Lag 20	39.361 (0.006)	27.095 (0.006)	23.081 (0.163)	32.926 (0.032)

Note: 1. The figure in the parenthesis is p-value.
2. Data source: EIA, US Department of Energy and Datastream.

CHAPTER 4

EMPIRICAL METHODOLOGY

This chapter presents the methodology employed to test the theory that was discussed in chapter 2. First and foremost, I examine the impact of speculative trading in the oil futures market on spot market volatility of WTI crude oil. The volatility test is conducted using the GARCH (p, q)-class framework[21] to identify the conditional volatility of returns before and after the introduction of the speculative trading in the futures market. After that, the Granger causality test and impulse response analysis will be used to capture and measure if any causality relation between speculative positions and oil return volatility. Many of the attributes of this model are inherited from Antoniou and Foster (1992), Longin (1997), Pok and Poshakwale (2004), Kasman and Kasman (2008) and Zhang (2013).

[21]GARCH (p, q) model is a linear function of squared errors in previous p periods and conditional variances in previous q periods (Bollerslev, 1986).

4.1 THRESHOLD GARCH STATISTICAL MODEL

Bollerslev (1986) extends Engle (1982)'s Autoregressive Conditional Heteroscedasticity framework by developing a technique that allows the conditional variance to be an ARMA process. A GARCH (p, q) model therefore has the following form:

(4.1.1) $$Y_t = c_0 + \sum_{i=1}^{p} c_i Y_{t-i} + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N\ (0,\ h_t)$$

(4.1.2) $$\varepsilon_t = v_t \sqrt{h_t}, \ \ v_t \sim N\ (0, 1)$$

(4.1.3) $$h_t = \ \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

where v_t are independent and identically distributed random variable with $E[v_t] = 0$, $Var[v_t] = 1, \alpha_0 > 0,\ \alpha_i > 0\ for\ i > 0,\ \beta_j \geq 0\ for\ j > 0$ and $\sum_{i=1}^{max(p,q)} (\ \alpha_i + \beta_i) < 1$.

Intuitively, Y_t is the asset return over time t. c_i is the coefficient on the asset returns at t-i. The error term ε_t has a zero mean and a conditional variance h_t, and collects and conveys information depending on Ω_{t-1} (the information set form last period). The conditional variance may not be constant over time, due to the persistence of shocks. The GARCH model, as shown in equation (4.1.3), makes this persistence effect more clear. That is, the error variance depends upon past information h_{t-j} (or the persistence of shocks) and new information ε_{t-i}^2 (or exogenous shocks) as well. β_j indicates that shocks from the last time period has a less persistent impact on current price fluctuations, and the coefficient α_i absorbs new exogenous shocks more rapidly. These properties make the GARCH model applicable to the analysis of oil price volatility. The reason is that if the oil price volatility increased after introduction of the futures market, then the level of persistence effect of past shock is high (and resulting a lager value of h_{t-j}) in the market, which in turn indicated the futures market fails to fulfill the role of convey information nor price discovery (Holmes, 1996).

Nevertheless, normalizing the returns by the conditional variances using GARCH models does not fully eliminate volatility clustering and fat tails, and GARCH models contain several important limitations (Rabemananjara and Zakoian, 1993). For example, GARCH models require the parameters non-negativity. This constraint rules out random oscillatory behaviors in the conditional variance process. Another shortcoming of GARCH models is the high persistence of large volatility after a shock. According to Poterba and Summers (1986), if shocks persist indefinitely, the whole term structure of risk premia might be changed, and is therefore to have a significant impact on investment decision (Nelson, 1991). The third drawback of the standard GARCH model concerns the way of transmitting information. Antoniou et al. (1998) argue that futures trading may cause market volatility in terms of the way that volatility is transmitted and how information is incorporated into prices. It is often observed in financial markets that a downward volatility in the market tends to rise in response to bad news. This is described as asymmetric news impact.[22] GARCH models, on the other hand, assume that only the magnitude but not the

[22]The asymmetric effect or threshold effect means that negative returns result in higher volatility than positive returns of the same magnitude (Alberg et al., 2008).

sign of unanticipated excess returns, as their distributions are symmetric [Rabemananjara and Zakoian (1993); Nelson (1991); and Glosten et al. (1993)].

Many alternative parameterizations have been proposed to overcome these challenges. The most widely used are the asymmetric GARCH models. Nelson (1991) proposes an exponential GARCH (EGARCH) approach by specifying the logarithm of the conditional variance ($\ln h_t$). The main advantage of EGARCH is that it avoids the non-negativity constraints on parameters in GARCH model, hence cyclical behavior is allowed, as the variances can be of any sign. Glosten, Jaganathan and Runkle (1993) (GJR-GARCH) and Zakoian (1994) (TGARCH) incorporate a dummy variable as a threshold into the GARCH model in capturing the effect of the size on expected volatility as well as the positivity or negativity of unanticipated excess returns. The difference between GJR-GARCH and TGARCH is that the TGARCH specification is the one on conditional standard deviation instead of conditional variance.

In evaluating the performance of alternative asymmetric models of conditional volatility, I find that the asymmetric GARCH model proposed in Zakoian (1994) (TGARCH) outperforms others to give the highest log-likelihood value. Moreover, the first-order TGARCH (1, 1) model is the most appropriate among others for this study given the lowest Akaike information criterion (AIC) level. This confirms Bollerslve, Chou and Kroner (1992)'s finding when the authors review the empirical evidence of the ARCH-family modeling in finance. They conclude that the GARCH (1, 1) model is found to be the most appropriate representation in most financial series [Bollerslve et al. (1992); and Pok and Poshakwale (2004)].

The TGARCH (1, 1) model allows for different reactions of volatility to the sign of past shocks, based on the quadratic equation (4.1.3):

$$\text{(4.1.4)} \qquad \sigma_t = \alpha_0 + \alpha_1^+ \varepsilon_{t-1}^+ + \alpha_1^- \varepsilon_{t-1}^- + \beta_1 \sigma_{t-1}$$

where σ_t is conditional standard deviation of the error (ε_t) process. $\varepsilon_t^+ = \max(\varepsilon_{t-1}, 0)$, $\varepsilon_t^- = \min(\varepsilon_{t-1}, 0)$.Alternatively, $\varepsilon_{t-1}^+ = \varepsilon_{t-1}$ if $\varepsilon_{t-1} > 0$, and $\varepsilon_{t-1}^+ = 0$ if $\varepsilon_{t-1} \leq 0$. Likewise $\varepsilon_{t-1}^- = \varepsilon_{t-1}$if $\varepsilon_{t-1} \leq 0$, and $\varepsilon_{t-1}^- = 0$ if$\varepsilon_{t-1} > 0$. ε_{t-1} serves as a threshold. If the distribution is symmetric, the effect of a shock ε_{t-1} on the present volatility is $\alpha_1^+ - \alpha_1^-$. If $\alpha_1^+ < \alpha_1^-$, then negative shocks increase volatility more than positive innovations for the same magnitude [Rabemananjara and Zakoian (1993); Zakoian (1994)].

Studies of index futures, which concerned with the changes in price volatility before and after the futures listing, have concluded that there are many factors affect market volatility, and it is difficult to separate out the impacts of the onset of index futures trading and general changes in market conditions (McKenzie et al., 2001). In order to investigate the relationship between speculative trading in the oil futures markets and oil market volatility of returns more objectively, both a proxies and dummy variables are employed in this study. The proxy variables are used to isolate the general market fluctuations in addition to the dummy variable that captures the effect of introduction of futures trading.

As indicated by Antoniou and Foster (1992), the proxy variables should be commodities for which there is no futures trading or the price of which is not affected by the introduction of the crude oil futures market. Therefore, the returns of Bullion Gold and the Moody's Commodity Index (MCI) are used[23, 24] [Antoniou and Foster (1992); Antoniou and Holmes (1995); Pok and Poshakwale (2004)]. Following Antoniou and Foster (1992), the conditional mean takes the following form:

(4.1.5) $$R_t^O = c_0 + c_1 MCI_t + c_2 P_t^G + \varepsilon_t$$

where R_t^O is the log return of spot price for crude oil at time *t*, MCI_t is the weekly change in log return for the Moody's Commodity Index, P_t^G is the log return of gold price [i.e. R_t= 100* ln(P_t/ P_{t-1})]. Both MCI_t and P_t^G are proxy variables.

As discussed above, the volatility of the entire returns series is estimated with a dummy variable in the TGARCH (1, 1) model to account for the onset of futures trading in crude oil market. Eventually, following Longin and Slonik (1995) and Longin (1997), the conditional variance of the disturbance term ε_t in equation (4.1.5) can be estimated using TGARCH (1, 1) model as:

(4.1.6) $$\sigma_t^s = \alpha_0 + \alpha_1^+ \varepsilon_{t-1}^+ + \alpha_1^- \varepsilon_{t-1}^- + \beta_1 \sigma_{t-1} + \gamma P_t^O + \delta DFUT_t$$

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[23]The connection between gold and oil has been noted by Melvin and Sultan (1990).

[24]The Moody's Commodity Index is made up of 15 commodities (cocoa, coffee, cotton, copper, hides, hogs, lead, maize, silver, silk, steel scrap, sugar, rubber, wheat, and wool), weighted by the level of U.S. production or consumption.

The Brendt et al. (1974) (BHHH) algorithm is used to obtain parameter estimates that maximize the likelihood (ML) function. P_t^O is the first difference of crude oil price (in log) to control for the level effect, due to the oil price volatility is strongly correlated to the changes in real oil price. For example, according to Reilly et al. (1978) and others, there is less volatility at higher price level (Ferderer, 1996). $DFUT_t$ is the dummy variable, which measures introduction of speculative futures trading, where $DFUT_t$=0 response to pre-futures, and 1 otherwise. The coefficient δ can be viewed as a measure of the incremental information that the onset of futures leads to changes in the conditional variance of return. Then, the estimation of the statistical significance of δ tests the hypothesis that $DFUT_t$ significantly related to the volatility of returns in the spot market.

According to Rabemanamjara and Zakoian (1993, pg.44), there are five possibilities to check if any asymmetric effects:

Set 1: $\alpha_1^+ = \alpha_1^- > 0$

Set 2: $\alpha_1^- > \alpha_1^+ > 0$

Set 3: $\alpha_1^+ < 0 \; and \; |\alpha_1^+| < \alpha_1^-$

Set 4: $\alpha_1^+ < 0 \; and \; |\alpha_1^+| > \alpha_1^-$

Set 5: $\alpha_1^+ < 0 \; and \; |\alpha_1^+| = \alpha_1^-$

where set 1 denotes the symmetric distribution. Set 2 corresponds to the asymmetric effect, where bad news generates larger effects on volatility than good news, and the impact is increasing with the size in that case. Set 3 has a similar interpretation regarding asymmetric effect, but the volatility is at a positive value of the shock. For sets 4 and 5, the impacts on volatility of good and bad news of equal magnitude depend on the size—small negative shocks generate more volatility than small positive ones. Set 5 shows that large positive innovations, on the other hand, increase volatility more than negative shocks, or it is indifferently to positive and negative shocks [Rabemanamjara and Zakoian (1993), pg.44].

To check the performance of the TGARCH model specified in equation (4.1.5) and (4.1.6), diagnostics test such as the Ljung-Box portmanteau statistics (Ljung-Box Q test hereafter)[25] on the standardized residuals are conducted. The standardized residuals are the ordinary residuals from the mean equation of TGARCH (1, 1) model given in equation (4.1.5) divided by their estimated conditional standard deviation (see Figure 4.1). The standardized residuals should be used for model checking. If the mean and variance equations are appropriately defined, then the standardized residuals should not exhibit serial correlation (i.e. the Ljung-Box Q statistics should statistically insignificant). Moreover, Engle's (1982) ARCH test, carried out as the Ljung-Box Q statistic on the standardized squared residuals should reject the null hypothesis of no ARCH errors [Bollerslev, et al. (1992), Antoniou et al. (1998); Pok and Poshakwalw (2004); Alizadeh et al. (2008)].

[25] Ljung-Box portmanteau test, an asymptotically equivalent test, is to subject the residual (from the TGARCH mean equation) to standard tests for serial correlation based on the autocorrelation structure (Ljung and Box, 1978).

Table 4.1 Ljung and Box Portmanteau statistics for standardized residuals

Lag	Autocorrelation	Partial correlation	Ljung-Box (Q)
1	0.0504	0.0504	1.7806 (0.182)
2	-0.0090	-0.0116	1.8378 (0.399)
3	0.0276	0.0288	2.3730 (0.499)
4	-0.0080	-0.0111	2.4182 (0.659)
5	-0.0137	-0.0126	2.5498 (0.769)
10	0.0116	0.0092	4.9487 (0.895)
15	0.0066	-0.0059	11.3820 (0.725)
20	0.0091	-0.0081	17.1980 (0.640)

Note: 1. The sample period is from January 4, 2000 to May 28, 2013.
2. The figure in the parenthesis is the p-value.

Table 4.2 Ljung and Box Portmanteau statistics for standardized squared residuals

Lag	Autocorrelation	Partial correlation	Ljung-Box (Q)
1	-0.0974	-0.0974	6.6354 (0.010)
2	-0.0568	-0.0669	8.8931 (0.012)
3	0.0831	0.0716	13.7450 (0.003)
4	-0.0245	-0.0126	14.1680 (0.007)
5	0.0017	0.0070	14.1700 (0.015)
10	-0.0554	-0.0228	28.6920 (0.001)
15	-0.0631	-0.0475	34.4400 (0.003)
20	-0.0244	-0.0293	38.6840 (0.007)

Note: 1. The sample period is from January 2000 to May 2013.
2. The figure in the parenthesis is the p-value.

Table 4.1 reports the Ljung-Box portmanteau statistics for the first 20 autocorrelations of the standardized residuals. The results indicate no evidence of autocorrelation in the standardized residuals. Table 4.2 illustrates the Ljung-Box portmanteau statistics for the first 20 autocorrelations of the standardized squared residuals. It is clear that the results are statistically significant, indicating that the volatility of the oil returns follow the ARCH-type model (i.e. the TGARCH (1, 1) model is well behaved to capture the ARCH effects).

4.2 GRANGER CAUSALITY TEST

Although there are many studies suggest the lead-lag relations between volatility of returns and trading volume, much less effort has been paid to searching the relationship between speculative trading in the oil futures market and the volatility of returns in the oil spot market (Pok and Poshakwale, 2004). In this section, I estimate the level of any lead-lag relationship between speculative trading and oil spot market volatility by using Granger causality test through the technique of VAR.

The general idea is that the Granger-causal relationship between variable X and variable Y can be established by an F-test of the null hypothesis η_i=0 for $\forall i$ in the regression model:

(4.2.1) $$Y_t = z_0 + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \eta_i X_{t-i}$$

If the F-test statistics indicates that we cannot reject the null hypothesis, it means that variable X does not Granger-cause variable Y.

In this study, it is interesting to understand whether changes in non-commercial traders' positions are useful in forecasting market volatility of returns. To this end, we need to check whether the series $\Delta NetLong_t$ leads to the spot return volatility σ_t^s, using Granger-causality tests:

$$(4.2.2) \qquad \sigma_t^s = z_0 + \sum_{i=1}^{p} \varphi_i \sigma_{t-i}^s + \sum_{j=1}^{q} \eta_j \Delta NetLong_{t-i} + u_t$$

where the net long position change $\Delta NetLong_t$ is the change of net long positions from time *t-1* to time t (Zhang, 2013). The null hypothesis that $\Delta NetLong_t$ does not Granger-cause σ_t^s (i.e. H_0: η_j=0 $\forall j$) is tested with Wald chi-square test.

The Granger-causality tests can be used to investigate if non-commercial traders change their positions based on past price fluctuation. According to Sanders et al. (2004, pg. 435), the traders who buy following price increases or sell following price decreases may be positive feedback traders (or known as trend followers). In contrast, traders buy following price decreases may be negative feedback traders (or known as contrarians). In either way, it would be valuable to understand how traders' positions respond to past market returns. Again, the Granger-causality is used:

$$(4.2.3) \qquad \Delta NetLong_t = \omega_0 + \sum_{i=1}^{p} \eta_i \Delta NetLong_{t-i} + \sum_{j=1}^{q} \varphi_j \sigma_{t-i}^s + \xi_t$$

The null hypothesis that σ_t^s does not Granger-cause $\Delta NetLong_t$ (i.e. H_0: π_j=0 $\forall j$) is tested with the Wald chi-square test.

Once determining the appropriate variables in the model, the optimal lag length for the VAR must be defined based on the AIC. The number of lags associated with the minimum AIC value will be used in the VAR model.

(4.2.4) $$AIC = -2\,ln(L) + 2T$$

where *T* is the number of parameters in the model. *2T* is a penalty as an increasing function of the number of tested parameters. *L*, the maximized value of the likelihood function for the estimated model. The model is then tested for serial correlation with a Lagrange multiplier test and for heteroscedasticity with White's test.

4.3 IMPULSE RESPONSE FUNCTION

The impulse response function (IRF) traces out the response of the dependent variable in the VAR system to shocks in the error terms. If the system of equation is stable any shock should decline to zero, and an unstable system would produce an explosive time path. In this study, I use the recursive form of VAR to propose an IRF analysis.

(4.3.1) $$\sigma_t^s = V_0 + \sum_{i=1}^{p} \varphi_i \sigma_{t-i}^s + \sum_{j=1}^{q} \eta_j \Delta NetLong_{t-j} + u_t$$

(4.3.2) $$\Delta NetLong_t = U_0 + \sum_{i=1}^{p} \eta_i \Delta NetLong_{t-i} + \sum_{j=1}^{q} \varphi_j \sigma_{t-i}^s + \tau \sigma_t^s + \xi_t$$

where σ_t^s, the standard deviation, denotes the crude oil spot return volatility. Other variables are defined same as previously. Here error terms u_t and ξ_t are uncorrelated. The idea of using IRF is to detect and measure any causality relations between speculative trading in the oil futures market and the volatility of returns in the oil spot market. In this case, changing ξ_t by one unit and keep u_t constant can capture the change in current values of oil futures price volatility. That is, the effect of the disturbance from ξ_t on the current value of volatility σ_t^s only comes from the shocks to $\Delta NetLong_t$.

CHAPTER 5

EMPIRICAL RESULTS

This chapter presents and analyzes the empirical results of objectives have been discussed in Chapter 4.

Based on the WTI crude oil weekly data, the TGARCH (1, 1) model with and without futures speculative trading dummy (δ) is estimated. The choice of the TGARCH model is motivated by the fact that this model captures the asymmetric effect of the size on expected return volatility in a more efficient way and intuitively appealing.

To test for the presence of an asymmetric effect of return volatility to past innovations, Zakoian (1994)'s TGARCH (1, 1) process has been adopted. Inspired by Antoniou and Foster (1992) and Longin (1997), the TGARCH (1, 1) model incorporates with a dummy variable (see equation (4.1.5) and (4.1.6)) is expected to capture the asymmetry response of conditional return volatility to shocks. The estimation results are reported in Table 5.1 and 5.2. In the mean equation (4.1.5), the results suggest that weekly return on Moody's Commodity Index (MCI) has a positive and statistically significant coefficient over the entire period and its subperiods. In a similar vein, the coefficient on the London Bullion Gold return is statistically significant for all time periods indicating that wider market events do have a significant impact on the WTI crude oil return.

Table 5.1
Mean equation: $R_t^O = c_0 + c_1 MCI_t + c_2 P_t^G + \epsilon_t$

	Entire period	**Pre-futures**	**Post-futures**
c_0	0.0138	0.0247	0.0085
	(0.000)	**(0.000)**	**(0.000)**
c_1	0.5534	0.3260	0.6545
	(0.000)	**(0.032)**	**(0.000)**
c_2	0.3144	0.1812	0.3343
	(0.000)	**(0.046)**	**(0.000)**

Note: 1. The whole sample period is from January 4, 2000 to May 28, 2013. The pre-futures period is from January 4, 2000 to October 25, 2005. The post-futures period is from November 2, 2005 to May 28, 2013.
2. The figure in the parenthesis is the p-value.
3. Bold values indicate rejection of the unit root hypothesis at the 5% significance level.

The variance equation results are shown in Table 5.2. The coefficient δ (-0.3062) is statistically significant, which supports the hypothesis that the onset of speculative trading has an impact on the volatility of return in the oil spot market. The negative coefficient estimate implies that trading in futures market has reduced return volatility by 30.62% (see Figure 5.2 and Figure 5.3).

The central feature can be observed from the variance equation is the asymmetry in all series data. The results indicate that negative shocks have greater influence on the market than the positive shocks of the same magnitude (i.e. $\alpha_1^- > \alpha_1^+$) for the entire sample period. The asymmetric impact also exhibits for subperiods: small negative shocks introduce more volatility than small positive ones, but large positive innovations increase volatility more than negative ones, as$\alpha_1^+ < 0 \; and \; |\alpha_1^+| > \alpha_1^-$, and $\alpha_1^- < 0 \; and \; |\alpha_1^-| < \alpha_1^+$ over the period before and after the introduction of futures trading, respectively.

The results also confirm the dependency of volatility on its past behavior, as β_1 are statistically significant over the entire period and its subperiods. The GARCH coefficient (β_1) normally indicates persistence of volatility and ARCH parameter (α_1) indicates less persistent and more peaks. The sum of α_1+β_1 = 0.8134 indicates the change in the response function of shocks to volatility over the entire period. In this case, the volatility shows a reasonable level of persistent at 0.8134. Because the persistence indicator is smaller than one, the volatility process is co-variance stationary and mean reverting. It is notable that when the level of persistent is compared between the pre-futures and post-futures trading periods, $\alpha_1$has increased and β_1 has decreased. α_1 measures the impact of market price changes from previous period to current period, a higher α_1 indicates that the introduction of futures trading makes a greater impact on price changes in this case. In addition, coefficient β_1 measures the persistence of volatility and is reduced from 0.6815 to 0.6041 (i.e. 7.7% reduction). This result indicates that the degree of persistence has lowered or absorbed by new information arrivals.

The coefficient γ are negative and statistically significant over the entire period and its two subperiods indicating that an increase in price reduces the crude oil spot return volatility, and this result confirms Reilly et al. (1987)'s finding.

Table 5.2 Variance equation: $\sigma_t^s = \alpha_0 + \alpha_1^+ \varepsilon_{t-1}^+ + \alpha_1^- \varepsilon_{t-1}^- + \beta_1 \sigma_{t-1} + \gamma P_t^O + \delta DFUT_t$

	Entire period	**Pre-futures**	**Post-futures**
α_0	-7.3541	-6.9184	-7.8912
	(0.000)	**(0.000)**	**(0.000)**
α_1^+	0.0367	-0.1512	0.2001
	(0.391)	(0.097)	**(0.003)**
α_1^-	0.1181	0.1107	-0.0144
	(0.094)	(0.413)	(0.883)
β_1	0.6586	0.6815	0.6041
	(0.000)	**(0.000)**	**(0.000)**
γ	-21.2081	-20.5830	-21.8246
	(0.000)	**(0.000)**	**(0.000)**
δ	-0.3062		
	(0.043)		
Log-likelihood	1230.0901	591.7379	651.7374

Note: 1. The entire period is from January 4, 2000 to May 28, 2013. The pre-futures period is from January 4, 2000 to October 25, 2005. The post-futures period is from November 2, 2005 to May 28, 2013.
2. The figure in the parenthesis is the p-value.
3. Bold values indicate rejection of the unit root hypothesis at the 5% significance level.

Table 5.3 reports the results of the Granger-causality tests on equation (4.2.2) and (4.2.3). The causality relations indicate that, in general, changes in non-commercials' net long positions lead to change in the conditional spot return volatility, and the causality does not exist for the opposite direction. The results are statistically significant with a p-values less than 5% for most of the cases. In the Table 5.3, "YES" means rejection of the null hypothesis that $\eta_j = 0 \; \forall j$ at the 95% confidence level, and "NO" denotes the failure in rejecting the null hypothesis, i.e. lack of any Granger-causality.

Table 5.3 Speculative futures trading versus conditional return volatility: Granger-causality

	$\Delta NetLong \rightarrow \sigma_t^s$		$\sigma_t^s \rightarrow \Delta NetLong$	
Lag 1	NO	(0.098)	NO	(0.731)
Lag 2	YES*	(0.017)	NO	(0.373)
Lag 3	NO	(0.063)	NO	(0.305)
Lag 4	YES***	(0.000)	NO	(0.560)
Lag 5	NO	(0.118)	NO	(0.100)
Lag 6	YES***	(0.004)	NO	(0.106)
Lag 7	YES***	(0.000)	NO	(0.127)
Lag 8	YES***	(0.000)	NO	(0.134)
Lag 9	YES***	(0.000)	NO	(0.192)
Lag 10	YES***	(0.000)	NO	(0.131)

Note: 1.Asterisks denote significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).
2. The figure in the parenthesis is p-value.
3. The numbers of optimum lags determined according to the Akaike Information criteria (AIC).
4. Sample period is from November 2, 2005 to May 28, 2013.

As shown in Table 5.4, the results of the impulse response analysis indicate that an error in estimating the sudden change in non-commercials' net long position does not contribute a large shock on forecasting the future changes in oil spot price. One unit increase in error of estimating the change in $\Delta NetLong$ causes to 0.068% increase in standard deviation of the spot return. The step-ahead prediction (0.039%) also not reveals a significant (in an economic sense) impact, as shown in Table 5.4 (see Figure 5.3 and Figure 5.4).

Table 5.4 Impact of speculative trading on spot return volatility of crude oil: IRF analysis

Step	Orthogonal IR	Lower	Upper
1	-0.00068	-0.00139	0.00003
2	0.00039	-0.00041	0.00121
3	0.00025	-0.00030	0.00079
4	0.00015	-0.00023	0.00040
5	0.00011	-0.00017	0.00029
99	0.00000	0.00000	0.00000
100	0.00000	0.00000	0.00000

Note: 1. The sample period is from November 2, 2005 to May 28, 2013.

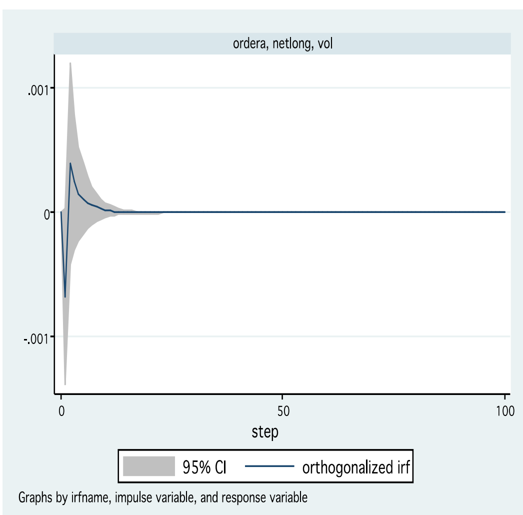

Figure 5.3 The IRF, impulse: $\Delta NetLong$, response: oil return volatility

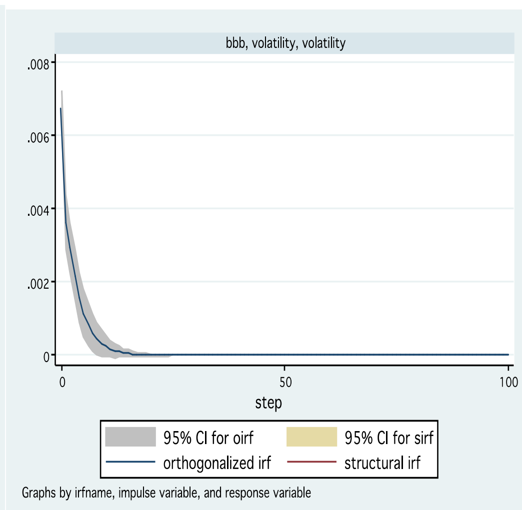

Figure 5.4 The IRF, impulse: oil return volatility, response: oil return volatility

CHAPTER 6

CONCLUSION

The impact of speculative trading on return volatility of WTI crude oil has drawn much attention from regulators and investors. The main argument against futures trading is that whether the introduction of futures trading increases oil return volatility, or such return volatility are inherent the nature of market fundamentals.

In order to understand the impact of futures trading and to investigate the interactive mechanism between speculative position change and oil return volatility in the U.S. crude oil market, in this thesis I employ the Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) framework associated with proxies and dummy variables to measure the conditional volatility of the crude oil return before and after the onset of futures trading. Furthermore, I analyze the relationship between changes in speculative positions and oil return volatility in the spot market using Vector Autoregressive (VAR) and the Granger causality tests.

In general, the results show that there has been a decrease in crude oil return volatility following the introduction of futures trading. In addition, the degree of persistence in return volatility has reduced about 7.7% after the introduction of futures trading, and this finding is in line with many studies such as Antoniou et al. (1998) and Kasman and Kasman (2008). Moreover, by using the TGARCH specification, the oil return volatility exhibits asymmetric effects, which indicates negative shocks have greater influence on this market than the positive shocks of the same magnitude.

I further investigate the level of any lead-lag relationship between speculative trading and oil return volatility by using Granger-causality tests. The results show that, in general, changes in non-commercials' net long positions Granger-cause the change in the conditional spot market volatility, and the Granger-causality does not exist for the opposite direction. Finally, the results of impulse response analysis indicate that sudden change in speculative trading positions does not contribute a large shock on forecasting the future changes in oil spot return in an economic sense.

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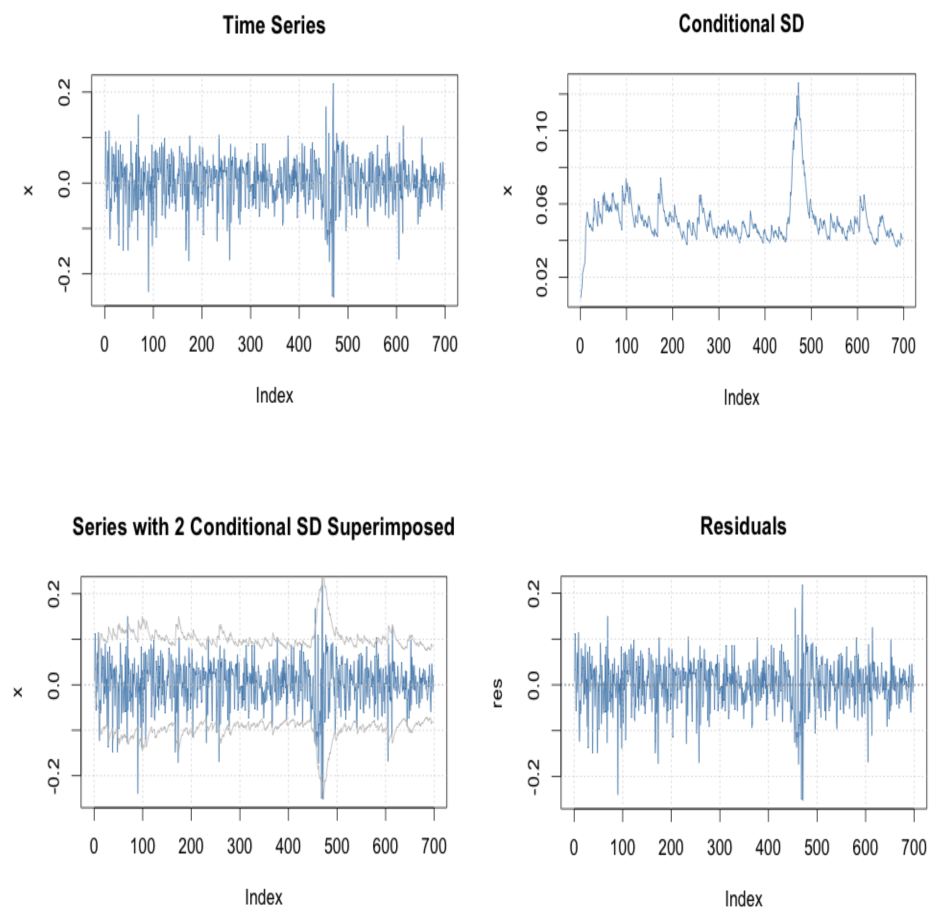
APPENDIX A

FIGURE FROM THE TEXT



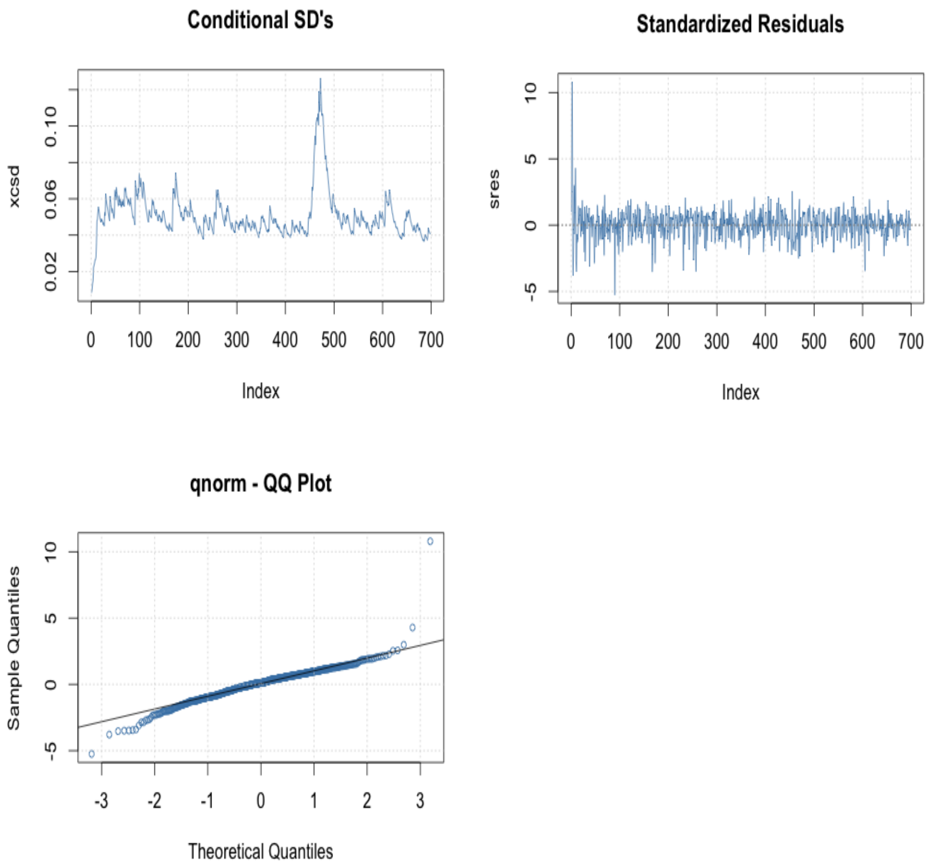


Figure 4.1 Returns, the distribution, the autocorrelation function and the Quantile-Quantile plot of the standardized residuals of volatility for the WTI crude oil over the period from January 2000 to May 2013.

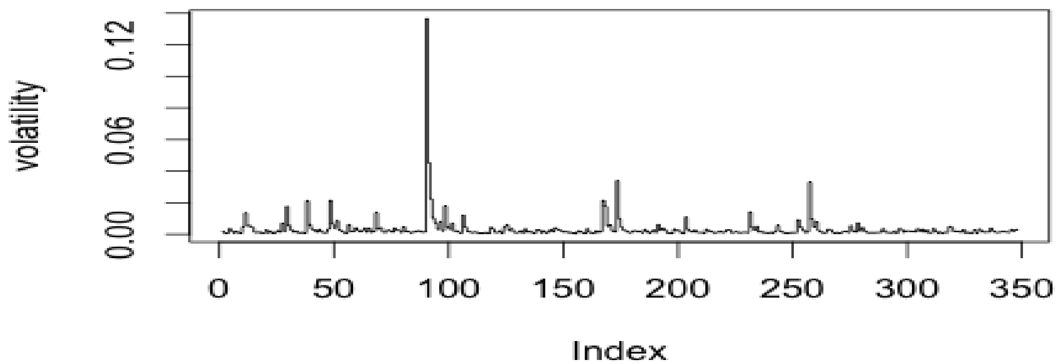


Figure 5.1 Weekly volatility of WTI crude spot price over the period from January 2000 to October 2005 (pre-futures).

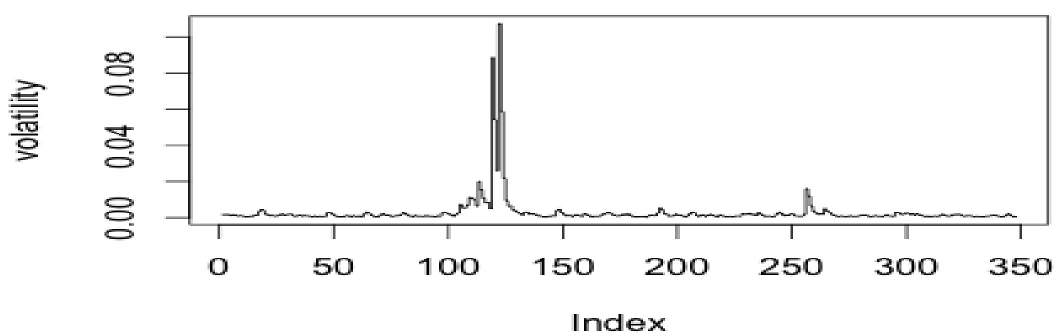


Figure 5.2 Weekly volatility of WTI crude spot price over the period from November 2005 to May 2013 (post-futures).