U.S. Energy Futures Markets:

Liquidity and Optimal Speculative Position Limits

Peiran Cheng

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By: Peiran Cheng

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Signed by the final examining committee:

Dr. Mahesh C. Sharma ________________ Chair

Dr. Ravi Mateti ________________ Examiner

Dr. Gregory J. Lypny ________________ Examiner

Dr. Latha Shanker ________________ Supervisor

Approved by Dr. Thomas Walker ________________
Chair of Department or Graduate Program Director

Dr. Harjeet S. Bhabra ________________
Dean of Faculty

Date ________________

ABSTRACT

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U.S. energy prices have grown dramatically since the 2007 financial crisis. Speculators are blamed for market manipulation, and regulators seek additional tools to control the market. Given the growing roles of liquidity and position limits in finance along with recent Wall Street legislation changes made by the Dodd-Frank Act, we carry out studies to test how effectively price impact liquidity measures measure liquidity, whether position limits have impacts on market liquidity, and how optimal speculative position limits should be modeled, based on microstructure theories. Using the major New York Mercantile Exchange (NYMEX) energy futures data from Bloomberg, we compare low-frequency liquidity proxies with high-frequency liquidity benchmarks, run an event study on futures contracts' liquidity following the launching of the Dodd-Frank Act, and develop a theory-based position limits model. Our empirical results indicate that the new price impact liquidity proxy developed in this thesis is more effective in measuring liquidity than the Amihud (2002) proxy. Further, contrary to Grossman's (1993) finding, position limits on financial futures do not force traders to move to foreign substitute markets. Finally, position limits for single commodity derivatives should be based on corresponding underlying spot market factors, and strong fluctuations in optimal position limits over time suggest that exchanges should update position limits on a high-frequency basis.

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Chapter 1. Introduction

Liquidity and position limits have played important roles in the finance literature during the last decade, particularly since the 2007 financial crisis when dramatic increase in energy prices became a heated topic. Correspondingly, futures contracts also drew heavy attention because futures contracts are a common instrument used by speculators to trade for profits. Yet, there are only a handful of studies on whether liquidity proxies really measure liquidity and on how speculative position limit models should be constructed. Do position limits have impacts on the liquidity of corresponding markets? The launching of the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 along with its relevant rule-making proposals of position limits provides a perfect opportunity for us to study these issues for the U.S. energy futures market.

1.1 The importance of underlying issues

Speculators are often blamed for manipulating the spot markets so that commodity prices are driven away from their true values and are deemed to be "too high". Both market regulators and research scholars argue that market surveillance is not enough to regulate derivatives market speculation and that exchanges need position limits as an additional tool to discourage spot market manipulation for heavily traded commodities.

How does imposing speculative position limits on derivatives contracts discourage manipulation in the underlying spot markets? For example, a speculator could take a speculative position in the crude oil futures market and then manipulate the crude oil spot market, thus creating an artificial spot price that is driven away from its true value in order to gain benefits in the futures market. The profit is the difference between the benefits from the futures position and the costs that are incurred in trading crude oil in the spot market. Without a limit on the speculative position in the futures contract, the speculator would manipulate as much as he or she needs to in order to maximize his/her profits. However, imposing a position limit on the crude oil futures contract limits the maximum number of contracts that the speculator can hold and carry into the final settlement and thus the profits from manipulation, thereby limiting the speculator's incentive to manipulate the spot market price.

Thus, the issue becomes important as to how to choose the optimal speculative position limits for derivatives contracts for a single energy commodity so that corresponding spot market manipulation is effectively discouraged. During our research of position limit models, we found that liquidity, which refers to the degree to which a security can be bought or sold in the market without affecting its price, is a vital variable to construct position limits. Moreover, the level of position limits on derivatives contracts is positively related to the liquidity of the underlying spot market.

Consequently, how well liquidity proxies measure liquidity and which liquidity proxy we should employ for position limits models became extremely important issues. Furthermore, concerns from hearings of the Dodd-Frank Act make us recognize that it is important to investigate whether the launching of position limits has impacts on the liquidity of the futures contracts and whether traders would move to foreign or substitute markets due to this potential liquidity change.

1.2 Contribution to the literature

This thesis contributes to the literature in the following aspects: Firstly, this thesis develops a new low-frequency price impact liquidity proxy, and this proxy along with a widely employed price impact proxy is tested for its ability to capture liquidity. Secondly, an event study, one of the most common corporate finance research methodologies, is applied to the liquidity of the futures market with respect to the implementation of the Dodd-Frank Act as the event of interest. Lastly, a theory-based model of the optimal speculative position limits for a single commodity futures contract is developed, and levels of position limits for major energy commodities are computed under certain assumptions, using low-frequency historical data.

Our main findings are: The new price impact liquidity proxy developed in this thesis is more effective in measuring the magnitude of liquidity than the Amihud (2002) proxy. Moreover, position limits on financial futures do not force traders to move to foreign substitute markets, which does not support Grossman's (1993) finding. Lastly, optimal speculative position limits for single commodity derivatives contracts should be based on corresponding underlying spot market factors, and strong fluctuations in the level of position limits over time suggest that exchanges should update position limits on a high-frequency basis such as once per month.

1.3 Structure of the thesis

The thesis is organized as follows: Chapter 2 reviews the literature that is related to issues addressed in this thesis. In Chapter 3, we develop and list relevant models and theories. In Chapter 4, we present hypotheses and relevant methodologies of tests that we use to test the above models. The data are described in Chapter 5, and test results are discussed and interpreted in Chapter 6. Chapter 7 concludes the thesis.

Chapter 2. Related literature review

In this chapter, we review previous research and relevant components of the Dodd-Frank Act along three lines. First, we review liquidity proxies and how they are compared to liquidity benchmarks computed from transaction data. Then, we review the relevant timeline of the Dodd-Frank Act and the event study methodologies used in previous research. Last, we review the U.S. Commodity Futures Trading Commission's (CFTC) proposals of position limits rule-making for the U.S. energy market, the role of manipulation theory and the models of position limits proposed by previous researchers.

2.1 Liquidity

In the field of finance, the role of liquidity has grown rapidly over the last 15 years. Many studies propose different measures of liquidity. The majority of these studies focuses on proxies that measure the bid/ask spread, such as Roll (1984), Lesmond, Ogden, and Trzcinka (1999), Pastor and Stambaugh (2003), Hasbrouck (2004), and Holden (2009); meanwhile, a number of studies develop proxies that measure the price impact, such as Cooper, Groth, and Avera (1985), Berkman and Eleswarapu (1998), Amihud (2002), and Pastor and Stambaugh (2003).

Further, a handful of studies, Lesmond, Ogden, and Trzcinka (1999), Lesmond (2005), Hasbrouck (2009), and Goyenko, Holden, and Trzcinka (2009) test whether these proxies are related to liquidity benchmarks calculated from transaction costs. Specifically, Goyenko, Holden, and Trzcinka (2009) run horse races of widely employed proxies of liquidity in the literature against liquidity benchmarks calculated from intraday data, and find that the effective/realized spread measures developed by them win the majority of horse races of bid/ask spread and that the Amihud (2002) price impact proxy well measures price impact.

The Amihud (2002) price impact measure captures the "daily price response associated with one dollar of trading volume". Since the quality of the price impact liquidity proxy is vital for constructing our model of position limits, and intraday transaction data are largely unavailable and much more compute-intensive, we test how the Amihud (2002) model captures the size of liquidity benchmarks from intraday data along with a new price impact liquidity proxy proposed by this thesis. In addition, we question the method of comparison of low-frequency liquidity proxies and high-frequency liquidity benchmarks used by Goyenko, Holden, and Trzcinka (2009), towing to inconsistence in the units used by these measures.

2.2 Event Study

The Dodd-Frank Wall Street Reform and Consumer Protection Act caused a huge legislation change in the U.S. financial industry and affects many aspects of the field. The Act aims to provide solutions to problems that arose from the 2007-2010 financial crises, such as reducing risk, increasing transparency, and promoting market integrity within the financial system. Changes in legislation affect currency, hedge funds, insurance, banking, Wall Street transparency, supervision and regulation of the Securities, costumer protection, and mortgage reform. In this thesis, we only focus on relevant parts of the Dodd-Frank Act that are associated with position limits in energy derivatives markets.

On July 21st, 2010, President Obama signed the Dodd-Frank Act, hereinafter referred to as the Act. Before the launch of the Act, a long period of hearings was held in the United States since 2009. During these hearings, concerns about introducing position limits in energy derivatives markets were expressed by different groups of interests. Major questions that were raised included whether speculators should be blamed for manipulating commodity prices, whether the liquidity of energy derivatives market would shrink due to the introduction of position limits and whether traders would move to foreign derivatives exchanges such as the Intercontinental Exchange (ICE) in London, U.K., whether position limits should be set on a monthly/yearly basis or intraday basis, how position limits should be set, and how the model should reflect the seasonal nature of some of the commodities underlying the derivatives.

With regard to the setting of level of position limits in the energy derivatives markets, the Commodity Futures Trading Commission (CFTC) has proposed different rules three times. The first proposal extends from January 26th, 2011 to March 28th, 2011; the interim proposal extends from November 18th, 2011 to January 17th, 2012; while the final proposal which extends from May 30th, 2012 to June 29th, 2012 has been accepted.

Some scholars do not agree on imposing position limits to control derivatives markets. Gastineau (1992) and Telser (1993) argue that market surveillance should be the primary tool to regulate manipulation. Grossman (1993) argues that position limits on financial futures can force traders to move their trades to foreign or substitute markets. We question Grossman's argument, and we employ an event study methodology to provide an answer.

Event study methodology is one of the most commonly used methodologies in the literature of corporate finance. It is widely used on stock returns data, such as those provided by the Center for Research in Security Prices (CRSP), which is a provider of historical stock market data and part of Booth School of Business at the University of Chicago. There are many studies on how to test the significance of abnormal returns around event dates. These tests fall into two categories: parametric tests and non-parametric tests. The main parametric tests include those of Patell's (1976) standardized residual test, Brown and Warner's (1980, 1985) methods with and without crude independence adjustment, and Boehmer, Musumeci and Poulsen's (1991) standardized cross-sectional test; whereas the main non-parametric tests include those of Sanger and McConnell's (1986) and Cowen and Sergeant's (1996) generalized sign test.

Event studies investigate how a particular event affects the value of a firm. The assumption is that the changed value of the company will be translated into an abnormal return on the stock of the firm. The key theory behind this is that information should be readily impounded into prices. Most of the previous papers deal with returns, whereas a few papers work with volume.

In this thesis, we use event study methodology to find out whether the launch of the Dodd-Frank Act and relevant legislation changes affect the liquidity of U.S. energy futures market, as well as the direction of the change in liquidity, if any.

2.3 Position limits

In its final proposal on rule making, the CFTC published in the Federal Register final rules which establish a position limits regime for 28 exempt and agricultural commodity futures and options contracts ("Core Referenced Futures Contracts" including four heavily traded energy contracts) and physical commodity swaps that are economically equivalent to such contracts. This notice proposes certain modifications to the Commission's policy for aggregation under the position limits regime in CFTC regulations.

There are three major components of the CFTC position limits regime: (1) the level of the limits, which set a threshold that restricts the number of speculative positions that a person may hold in the spot-month, individual month, and all months combined. (2) An exemption for positions that constitute bona fide hedging transactions. (3) Rules to determine which accounts and positions a person must aggregate for the purpose of determining compliance with the position limit levels. With regard to the purpose of this thesis, we only focus on the first component – the setting of the level of position limits.

The four energy contracts include the: (1) NYMEX Henry Hub Natural Gas (NG); (2) NYMEX light Sweet Crude Oil (CL); (3) NYMEX New York Harbor Gasoline Blendstock (RB); and (4) NYMEX New York Harbor Heating Oil (HO). These contracts are subject to two types of speculative limits: spot-month position limits and non-spot-month position limits. Spot-month position limits apply in the period immediately before delivery obligations are incurred for physical delivery contracts or a period immediately before contracts are liquidated by the clearinghouse based on a reference price for cash-settled contracts. The spot-month period is specific to each commodity contract, need not correspond to a month-long period, and may extend through the period when delivery obligations are incurred.

Generally, spot-month position limits for Referenced Contracts will be set at 25% of estimated deliverable supply. These limits will be applied separately for position in the physical-delivery and all cash-settled Referenced Contracts combined. However, the cash-settled NYMEX Henry Hub Natural Gas contracts will be subject to a cash-settled spot-month position limit and an aggregate limit set at five-times the limit that applies to the physical-delivery NYMEX Henry Hub Natural Gas contract. To the best of our knowledge, we have no information from the CFTC website and its three proposals on how the CFTC estimates deliverable supply. Information on deliverable supply is also unavailable from the website of the U.S. Energy Information Administration (EIA). Thus we are unable to test whether spot-month position limits set by the CFTC are consistent with the optimal position limits recommended by our model.

The non-spot-month position limits apply to positions that a trader may have in all contract months combined or in a single contract month. For each Referenced Contract, these limits will be set at 10 percent of open interest in the first 25,000 contracts and 2.5 percent thereafter. Open interest used in determining non-spot-month position limits will be based on the futures open interest, cleared swaps open interest, and uncleared swaps open interest. Generally, initial non-spot-month position limits will be set by the CFTC order using one year of open interest data and biennially thereafter.

As evidenced by the lack of academic interest in position limits, theoretical problems that arise from potential market manipulation have been considered as minor until the recent 2007-2010 financial crisis. Although researchers still argue whether speculators should be blamed for manipulating commodity prices, undoubtedly, manipulation theory, which was first proposed by Stephen Craig Pirrong in the 1990s, has played a very important role in the relevant literature as well as in legislation for exchanges and provided strong theoretical support for most position limit models.

Pirrong (1993) discusses manipulation of the commodity futures market delivery process. His analysis of the futures market delivery indicates necessary and sufficient conditions for long and short traders to manipulate prices at contract expiration. He further derives empirical and welfare implications of manipulation, and argues that manipulation is mostly likely to occur in markets in which economic frictions make it inefficient to return excessive deliveries to their original owners. Such consumption distortions induce price changes that favor manipulators. Later, Pirrong (1995) disagrees with the theoretical arguments that government regulation of manipulative practices in financial markets is unnecessary because exchanges have incentives to take nearly first-best precautions against the exercise of market power. After examining the history of self-regulation at 10 exchanges, he suggests that self-regulation is an inefficient means to reduce monopoly power in financial markets.

The literature only provides a few papers on modeling manipulation and position limits. Kyle (1984) develops a theoretical model of futures-market manipulation and suggests that effective position limits can reduce manipulation. Kumat and Seppi (1992) agree with this argument by their two-period asymmetric information model. However, both articles note that cash settlement simply transfers manipulation problems to the cash market. Dutt and Harris (2005) develop a microstructure theory based model that regulators can use to set position limits. They argue that these limits on positions that traders can carry into final settlement can mitigate associated economic inefficiencies when surveillance is insufficient. We employ their theory to build our position limits model, but we question the use of their price elasticity measure ε and the constant values they set for the price tolerance over elasticity ratio k/ε. k/ε is an important component of the Dutt and Harris (2005) position limits model. k is the tolerance of percentage price change from its true value for the underlying commodity; ε is the elasticity of price with respect to fraction of all outstanding shares traded by the manipulator. Nevertheless, we agree with Dutt and Harris (2005) in this thesis on the argument that models of position limits in derivatives markets should relate exclusively to underlying commodity spot market factors as opposed to factors in derivatives markets themselves.

Chapter 3. Theory and Model

In this chapter, we list all of the models that we use in this paper with the theories on which they are based. First, we list models of intraday liquidity benchmarks and daily liquidity proxies. Then, we explain our event study model. Last, we derive optimal speculative position limits based on manipulation theory and price tolerance criteria.

3.1 Liquidity

We use six high-frequency liquidity benchmarks and four low-frequency liquidity proxies. In this thesis, we use liquidity benchmarks as terms for all high-frequency (intraday) liquidity measures, and liquidity proxies as terms for all low-frequency (daily, monthly, or yearly) liquidity measures. Because our database – Bloomberg – only provide intraday transaction data by minute, not tick by tick, we make an assumption that all transaction occurred in the same minute have the same price and are treated as a single trade in order to indentify the direction of a transaction. Our first benchmark is the effective spread from Goyenko, Holden, and Trzcinka (2009). Specifically, for a given contract, the effective spread for the kth minute is defined as

$$\text{Effective Spread}_k = 2\cdot |\ln(P_k) - \ln(M_k)|, \tag{1}$$

where P_k is the price at the kth minute and M_k is the midpoint of the consolidated BBO prevailing at the time of the kth minute. BBO means the best bid and offer, which is the highest bid and lowest ask available for a given security at a moment in time.

Our second benchmark is the realized spread from Huang and Stoll (1996), which is the temporary component of the effective spread. Specifically, for a given contract, the realized spread for the kth minute is defined as

$$\text{Realized Spread}_k$$

$$= \begin{cases} 2\cdot(\ln(P_k) - \ln(P_{k+5})) & \textit{when the kth minute trade is a buy} \\ 2\cdot(\ln(P_{k+5}) - \ln(P_k)) & \textit{when the kth minute trade is a sell} \end{cases}, \tag{2}$$

where P_k is the price at the kth minute and P_{k+5} is the price of trades five minutes after the kth minute. We follow the Lee and Ready (1991) algorithm to identify buy and sell transactions. Lee and Ready (1991) develops an algorithm to indentify the direction (buy or sell) of a trade based on price information. They call it the “Tick test”, which compares the trade price to the price of the preceding trade. The methodology is stated as follows: if the price of a trade increases from the last trade, it is classified as an uptick. If the price decreases from the last trade, it is classified as a downtick. If the price change is zero, a trade with an uptick preceding trade is tagged as a zero-uptick, and a trade with a downtick preceding trade is tagged as a zero-downtick. All of the uptick and zero-uptick trades are indentified as buy, and the rest as sell.

Our third benchmark from Goyenko, Holden, and Trzcinka (2009) focuses on the change in quote midpoint after a signed trade. Price impact is commonly defined as the increase (decrease) in the midpoint over a five-minute interval beginning at the time of the buyer (seller) initiated transaction. This is the permanent price change of a given transaction, or equivalently, the permanent component of the effective spread. Specifically, for a given contract, the five-minute price impact is

$$5-\text{Minute Price Impact}_k$$

$$=\begin{cases} 2\cdot(\ln(M_{k+5})-\ln(M_k)) & \textit{when the kth minute trade is a buy} \\ 2\cdot(\ln(M_k)-\ln(M_{k+5})) & \textit{when the kth minute trade is a sell}' \end{cases} \tag{3}$$

where M_k is the midpoint of the consolidated BBO prevailing at the time of the kth minute and M_{k+5} is the midpoint of the consolidated BBO at the k+5th minute. We also follow the Lee and Ready (1991) algorithm to identify buy and sell transactions here.

In addition, we construct three new price impact benchmarks which produce numerical results. These benchmarks are defined as the ratio of the above benchmarks measurement (1), (2), and (3) over the dollar amount of trading volume respectively. We name our fourth, fifth, and sixth price impact benchmarks as Effective spread (Cheng), Realized Spread (Cheng), and 5-minute price impact (Cheng) respectively.

We compare the magnitude of intraday liquidity benchmarks to daily proxies by aggregating intraday per minute benchmarks on a daily basis, and pair these daily measures according to the variable date. Aggregating over a time interval i (a day or a month/year), a contract's illiquidity benchmarks are the dollar-volume-weighted average of our six per minute benchmarks computed over all minutes in time interval i respectively.

Our first low-frequency price impact proxy is the Amihud (2002) proxy. It is a price impact measure that captures the "daily price response associated with one dollar of trading volume." Specifically, for a given contract, Amihud uses the ratio

$$\text{Illiquidity}_A = \text{Average}\left(\frac{|r_t|}{Volume_t}\right), \tag{4}$$

where r_t is the return on day t, and $Volume_t$ is the dollar volume on day t;

For a futures contract, it is useful to express equation (4) as

$$\text{Illiquidity}_A = \text{Average}\left(\frac{|P_t - P_{t-1}|}{Volume_t}\right), \tag{5}$$

where P_t is the last price of day t, P_{t-1} is the price of day t-1, and $Volume_t$ is the dollar volume on day t.

Our second proxy comes from the position limits model developed in this thesis. It captures how much the price has been driven away from its true value due to one dollar of trading volume. Specifically, the ratio is:

$$\text{Illiquidity}_C = \text{Average}\left(\frac{|P_t - V_t|}{Volume_t}\right), \tag{6}$$

where P_t is the last price of day t, V_t is the fair market value of the contract on day t, and $Volume_t$ is the dollar volume on day t.

Additionally, we also construct measures as follows in order to test whether they perform better than proxies (5) and (6),

$$\text{Illiquidity}_A{}' = \text{Average}\left(\frac{|\ln(P_t) - \ln(P_{t-1})|}{Volume_t}\right), \tag{7}$$

and

$$\text{Illiquidity}_C{}' = \text{Average}\left(\frac{|\ln(P_t) - \ln(V_t)|}{Volume_t}\right), \tag{8}$$

where the natural logarithm of prices are used instead of prices alone as in equation (5) and (6) respectively.

In the above low-frequency proxy equations, the average is calculated over all non-zero volume days, since the ratio is undefined for zero-volume days.

3.2 Event study

Our model is designed as follows: when an event occurs, market participants revise their beliefs causing a shift in the contract's return generating process and trading volume, and thus a shift in its liquidity. For a given contract, in non-event periods,

$$\lambda_t = \alpha_t B + e_t, \tag{9}$$

while in event periods

$$\lambda_t = \alpha_t B + \beta D + e_t, \tag{10}$$

where λ_t is the illiquidity of the contract at time t; α_t is a vector of independent variables at time t, specifically a benchmark; B is a parameter vector for the independent variables in α_t; β is a row vector of the contract influencing the impact of the event on liquidity, and it is set to unity for convenience. D is a parameter vector measuring the effect of β, and e_t is a mean zero disturbance term possibly differing in event and non-event periods.

3.3 Position limits

According to Dutt and Harris (2005), a position limits model is constructed from market microstructure theory and price tolerance criteria. A market manipulator seeks to maximize profit (the difference between benefit and cost) from his or her manipulation. The benefit is the profit that a manipulator earns in the derivatives contract; the cost is the transaction cost that the manipulator incurs in trading the underlying commodity. The optimal aggregate size of the trade in the spot market is determined by maximizing this profit. This aggregate size of the trade in turn determines the change in the price due to manipulation. Given an assumed price change tolerance of the regulator, position limits for the given derivative contract are obtained.

For a given futures contract, the notional value Z of a trader's contract position is

$$Z = \theta m P_F, \tag{11}$$

where θ is the number of futures contracts that the trader holds, m is the contract multiplier, and P_F is the futures price of the contract.

A linear function is assumed for the price function based on widely accepted market microstructure theory. Therefore, the market price of the underlying commodity P_S is assumed to deviate from its true value V_S in proportion to Q_S, the aggregate quantity that the manipulator trades in the spot market according to the following function:

$$P_S = V_S + \lambda_S Q_S, \tag{12}$$

where λ_S is a measure of the illiquidity of the spot market.

It is assumed that the manipulator trades in opening auctions in the spot market and that the price will immediately revert to V_S following the manipulation. Thus, assuming a per unit commission rate of c, the total cost of the manipulation is

$$C = P_S Q_S + cQ_S - V_S Q_S = (V_S + \lambda_S Q_S) Q_S + cQ_S - V_S Q_S = \lambda_S Q_S^2 + cQ_S. \tag{13}$$

At the delivery date, the futures price is deemed to equal the corresponding spot price, thus combining (11), (12) and (13) gives the net profit from manipulation:

$$\pi = Z - C = -\lambda_S Q_S^2 + \left(\theta m \lambda_S - c\right) Q_S + \theta m V_S. \tag{14}$$

Maximizing this expression with respect to Q_S yields

$$Q_S = \frac{\theta m \lambda_S - c}{2\lambda_S}. \tag{15}$$

Substituting expression (15) into (12) gives the percentage price change due to the manipulation:

$$\frac{P_S - V_S}{V_S} = \frac{\lambda_S Q_S}{V_S} = \frac{\theta m \lambda_S - c}{2V_S}. \tag{16}$$

The price tolerance criterion will define the level of the speculative position limits, and it requires the absolute percentage price change to be no more than k for a given futures contract. Ignoring the absolute-value sign, the criterion requires

$$\frac{P_S - V_S}{V_S} = \frac{\theta m \lambda_S - c}{2V_S} < k. \tag{17}$$

Thus the level of the optimal speculative position limits is given by:

$$\theta < \frac{2kV_S}{m\lambda_S} + \frac{c}{m\lambda_S}. \tag{18}$$

Because commission c is generally small relative to V_S, the second term, in practice, does not matter much. Thus, the position limit for a given commodity can be calculated as

$$\theta < \frac{2kV_S}{m\lambda_S}. \quad (19)$$

We will apply this model to our empirical tests to determine the optimal speculative position limit for four major U.S. energy futures.

Chapter 4. Hypothesis and Methodology

In this chapter, we present all of our hypotheses along with the methodologies we employ to test them. First, we provide the hypothesis and test methodology for the comparison between intraday liquidity benchmarks and daily liquidity proxies. Then, we examine the hypotheses of abnormal liquidity associated with the event study and both parametric test and non-parametric test methodologies. Finally, we present the hypothesis of high coherence in demand and supply relationships between the spot market and futures market for the same underlying commodity. We use this relationship as a base to compute optimal speculative position limits under certain assumptions. Because the fair market value of the underlying commodity and the trading volume in the spot market are unobservable to us, we employ futures market data to compute optimal speculative position limits under certain assumptions. Note that although we employ futures market factors in the calculation, position limits should be constructed using spot market variables.

4.1 Liquidity

We first calculate daily illiquidity measures from both intraday benchmarks and daily proxies (ten in total) as presented in Section 3.1. Then we compare these daily proxies with intraday benchmarks via descriptive analysis of the samples, and we choose possible matches from these measurements to conduct paired t-tests between daily proxies and intraday benchmarks. The t-test examines the significance of the difference between the mean liquidity measures calculated from the low-frequency data and from the high-frequency data. Correlation and covariance are also tested between these measurements in order to provide a consolidated result of the comparison.

Thus, our first null hypothesis is as follows:

H_1: The difference between the mean price impact liquidity proxies calculated from daily data and price impact liquidity benchmarks calculated from intraday data is not significantly different from zero.

4.2 Event study

For the event study, each of the four major energy futures contracts traded on the NYMEX is paired with a benchmark futures contract traded on the ICE in the U.K. in order to estimate the expected liquidity of the NYMEX contracts in the event periods. A timeline for this event study is displayed in Figure 1.

As Figure 1 indicates, the illiquidity of a NYMEX contract is regressed on the illiquidity of its benchmark ICE contract using equation (9). This will give us the value of parameter vector B. With coefficient B and the illiquidity of the benchmark ICE contract in the event periods, we are able to estimate the expected illiquidity of the corresponding NYMEX contract during the event periods. Further, we calculate the difference between the actual illiquidity and the expected illiquidity of these NYMEX contracts to estimate the abnormal illiquidity. The abnormal illiquidity stands for the row vector D in equation (10).

Thereafter, we test whether the cumulative value of the abnormal illiquidity during event periods is significant different from zero using a Student's t-test. We also test whether it is positive or negative by a sign test. Consequently, our second and third null hypotheses are as follows:

H_2: The cumulative abnormal illiquidity of the major NYMEX energy futures contracts during the event periods that relate to the Dodd-Frank Act is not significantly different from zero.

H_3: The Dodd-Frank Act and its relevant rule-making proposals of position limits on the NYMEX energy futures markets have a negative impact on the liquidity of the corresponding contracts, in other words, a positive impact on the illiquidity of these contracts.

4.3 Position limits

In order to compute the optimal speculative position limit for a given commodity futures contract from equation (19), we need to know the contract multiplier m, price tolerance criterion k, the true value of the underlying commodity V_S, and the illiquidity of the underlying commodity market λ_S. Unfortunately, except for the contract multiplier, all of the other three factors are unobservable to us.

We know that futures prices reflect market participants' expectations of the underlying commodity prices in the future. Therefore, future prices should move in high coherence with spot prices, and there should not be much difference between their daily price changes. If this is true, under the assumption the true value of a security can be observed as the mean-revision of it price, the fair market value of the futures contract, which measures the true value of the contract, should also be a good proxy for the true value of the underlying commodity.

Let's assume that hedgers and speculators only trade in the futures market to hedge and earn profits, respectively. Under this assumption, it is assumed that there is a constant relationship between the trading volume in futures market and the trading volume in the spot market within the same time interval. This relation could be expressed as:

$$\gamma Q_S = mQ_F, \tag{20}$$

where m is the contract multiplier, γ is a constant number which measure the assumed constant relationship between the trading volume in futures market and the spot market within the same time interval, Q_S aggregates all buys and sells of the commodity in the spot market, and Q_F aggregates all buy and sell of the contract in the futures market. With these contracts, traders in the futures market hold the rights to buy and sell the underlying commodity in the spot market at a predetermined futures price. Let's assume γ equals 2 for calculation convenience.

Note that in order to incorporate the illiquidity measure within our position limit model, we need to change the Amihud (2002) price impact illiquidity proxy to

$$\lambda_F = \text{Average}\left(\frac{|P_{F,t} - P_{F,t-1}|}{Q_{F,t}}\right), \tag{21}$$

combining (21) and (20) with $\gamma = 2$,

$$m\lambda_S = m \text{ Average}\left(\frac{|P_{F,t} - P_{F,t-1}|}{\frac{m}{2} Q_{F,t}}\right) = 2\lambda_F, \tag{22}$$

Thus, our position limit model is restated as:

$$\theta < \frac{2kV_S}{m\lambda_S} \approx \frac{kV_F}{\lambda_F}. \tag{23}$$

The premise of the above derivation is that the daily price change in the futures market does not differ much from the daily price change in the spot market for the same underlying commodity. This gives us a fourth null hypothesis:

H_4: The difference between the mean daily price change in the futures market and the mean daily price change in the spot market for the same underlying commodity is not significantly different from zero.

We use a paired t-test to test whether this null hypothesis is rejected or not.

Chapter 5. Data

In this chapter, we detail our data collection process from Bloomberg and related calculations of all the variables. The details are in Section 5.1, Section 5.2, and Section 5.3 for liquidity, the event study, and position limits respectively.

5.1 Liquidity

In order to calculate and compare daily liquidity proxies to intraday liquidity benchmarks, both daily data and intraday data are obtained from Bloomberg for the period December 16, 2011 to June 16, 2012 (Bloomberg only provides about 6 months of historical intraday data). These data are obtained for the NYMEX Henry Hub Natural Gas futures, NYMEX Light Sweet Crude Oil futures, NYMEX New York Harbor Gasoline Blendstock futures, and NYMEX New York Harbor Heating Oil futures respectively.

For daily proxies, we collect daily variables including the last price of the day, closing price one day ago, fair market value of the futures contract of the day, trading volume of the day, and high and low price of the day. Because the value weighted average price is not available, we use the average of the daily high and low prices as a proxy. This along with trading volume gives us the dollar amount of trading volume. We use these variables to calculate the four daily liquidity proxies we need. After cleaning the data sample, 125 days of illiquidity measures are obtained for each proxy for each contract.

For intraday benchmarks, we collect transaction data for each minute. The variables include the last trade price, the dollar amount of the trading volume, highest bid price, and lowest ask price. First, we use the highest bid price and lowest ask price to calculate the midpoint of the consolidated BBO for each minute. Then, we match the trade sample with the bid sample along with the ask sample. The Lee and Ready (1991) algorithm is applied to obtain the direction of the transaction for each minute. Based on the direction, each benchmark measure with respect to each contract is calculated for the six intraday benchmarks. After cleaning and matching, we have 162,429 minutes of observations for the crude oil contract, 88,960 minutes of observations for the heating oil contract, 75,850 minutes of observations for the gasoline contract, and 110,420 minutes of observations for the natural gas contract.

Each benchmark measure for each contract is then aggregated on a daily basis using the weighted average method with the dollar-volume being the weight. Absolute values of the measure are then paired with daily proxies for each contract for each day. In this way, we have a set of ten columns of 125-day paired liquidity measures for each of the four contracts. Further, we also create a sample containing ten columns of 500-day paired liquidity measures for the whole energy market by consolidating all of the subsamples together.

5.2 Event study

Because Bloomberg only provides information on the fair market value since June 2010, we use the Amihud (2002) price impact proxy to calculate the measure of illiquidity for the event study. The same daily variables as described in Section 5.1 are collected for both the NYMEX energy contracts and the ICE energy contracts from January 1, 2003 to June 16, 2012. Specifically, the ICE energy futures are the Brent crude oil (benchmark for the WTI Light Sweet Crude Oil), natural gas (benchmark for the Henry Hub Natural Gas), and gasoil (benchmark for both heating oil and gasoline as they are all refined products made from crude oil).

The Amihud (2002) proxy is calculated for contracts on both exchanges and matched one on one for each date in order to perform a paired t-test. After matching, the crude oil sample has 2,364 days of observations, the heating oil sample has 2,347 days of observations, the gasoline sample has 2,306 days of observations and the natural gas sample has 2,335 days of observations. We use data in the estimation period to estimate the parameter vector B in order to estimate the expected illiquidity for the four NYMEX energy contracts during the event period.

Abnormal illiquidity is studied separately for each single event period for each contract. Furthermore, two new samples are created by aggregating data in the event periods. One of the new samples aggregates data from different contracts in order to study how the energy market as a whole reacts in different event periods; the other new sample aggregates data from different event periods in order to study how each contract reacts to the whole event.

5.3 Position limits

First, we collect daily price change data for the four NYMEX energy futures contracts and their respective underlying spot commodities from May 16, 1990 to June 16, 2012. Then, we matched the futures and spot price data for each date for each contract. After matching, there are 5,233 days of observations for crude oil, 5,119 days of observations for heating oil, 1,838 days of observations for gasoline, and 3,652 days of observations for natural gas. These four samples are used to determine the coherence of the price movement between the futures market and the spot market for the same commodity.

To construct position limits according to equation (23), we use the unmatched daily data of Section 5.2 for the four NYMEX contracts, and we calculate illiquidity using equation (21). The optimal level of position limits is computed for June 2010 to June 16, 2012, because Bloomberg only provides the fair market value for futures contract since June 2010. Note that we need the trading volume expressed in the number of contracts, rather than the dollar-volume amount which was required, to calculate the illiquidity measure in our model. Data is aggregated for each month to calculate the position limits on a monthly basis.

Chapter 6. Results and Interpretations

In this chapter, we present the results of our empirical tests and discuss the results with appropriate interpretations. Associated results, tables and figures are listed and interpreted in Section 6.1, Section 6.2, and Section 6.3 for liquidity, the event study, and position limits respectively.

6.1 Liquidity

Before testing whether low-frequency liquidity proxies are good estimates of high-frequency liquidity benchmarks, we show descriptive statistics of the ten sets of daily illiquidity samples for each contract and for all contracts combined in Table 1. Possible matches based on the mean and median from these samples are highlighted in squares for both intraday liquidity benchmarks and daily liquidity proxies.

The results of Table 1 indicate that the daily liquidity measures aggregated using the Goyenko, Holden, and Trzcinka (2009) intraday liquidity benchmarks are not consistent with those calculated using daily liquidity proxies; neither do the measures based on the daily natural logarithm liquidity proxies consistent with the measures of liquidity from intraday transaction data. These measures, equation (1), (2), (3), (7) and (8), will not be used in the following tests. For the rest of the measures, the price impact liquidity proxy developed in this thesis is generally consistent with the liquidity measures from intraday data better than the Amihud (2002) price impact proxy for crude oil and the two refined products made from it. Neither of the two proxies seems to be consistent with liquidity measures aggregated from intraday data for natural gas. In addition, the Amihud (2002) proxy improves whereas the proxy developed in this thesis fails for the combination of all four contracts.

Table 2 provides results of paired t-tests of differences between the mean illiquidity calculated from daily proxies and the mean illiquidity calculated from intraday benchmarks, as well as the correlation and covariance between these measures. Significant P values from t-tests are highlighted as well as high correlations and covariances in the table. T-test results are consistent with the descriptive analysis of Table 1.

The results of Table 2 indicate that, our first hypothesis is strongly rejected for Amihud's (2002) proxy with respect to crude oil and its refined products; the hypothesis is rejected for both proxies with respect to the natural gas contract; and the hypothesis is rejected for our new developed proxy, equation (6), for all contracts combined, while is accepted for the Amihud (2002) proxy using a 99% confident interval. In addition, correlation between the measures is high and the covariance is very low in general.

In other words, the daily price impact liquidity proxies are consistent with those estimated from transaction data. Only our proxy (equation (6)) is a good measure of liquidity from transaction data for crude oil and its refined products. Neither of the two proxies works for natural gas. However, when we combine all contracts together, our proxy loses power for the natural gas sample, whereas the performance of the Amihud (2002) proxy improves dramatically.

6.2 Event study

Table 3 lists results from both a parametric test (Student t-test) and a non-parametric test (sign test), which test the significance and direction of abnormal illiquidity during the event periods. Significant P values for the Student t-tests are highlighted in squares; and the probabilities of having a positive abnormal illiquidity during event periods are also indicated with sign tests.

Our second hypothesis is rejected with insignificant P values for the Student t-tests. Specifically, for crude oil, abnormal illiquidity is significant around the effective date of the Dodd-Frank Act and during the interim rule-making proposal from CFTC, insignificant during the rest of the event periods; for heating oil, abnormal illiquidity is significant around the effective date and during the first proposal, insignificant for the following periods; for gasoline and natural gas, abnormal illiquidity is significant around the effective date and during the first and interim proposals, insignificant for the final proposal.

Throughout the whole event, abnormal illiquidity is significant for crude oil, gasoline and natural gas, and insignificant for the heating oil contract. In addition, for the whole energy market, abnormal illiquidity is significant around the effective date and during the first and interim proposals, and is insignificant for the final proposal.

Our third hypothesis is strongly rejected for all sign tests because the probabilities of having a positive sign are very low (far below 50%) in general. Thus, the Dodd-Frank Act and its relevant rule-making proposals from the CFTC have negative impacts on illiquidity for all NYMEX energy futures contracts, and consequently positive impacts on liquidity of these contracts.

As summarized above, market participants in NYMEX actually have significant and positive expectations of launching position limits on the energy market. Quite contrary to expressions of concerns during the hearings, market liquidity actually grows compared to a foreign substitute market in which there were no such changes of rules for benchmark contracts. Therefore, traders perceive the NYMEX as more competitive and will not shift to foreign markets.

In addition, the size of abnormal liquidity is large and statistically significant around the effective date of the Act, gradually reduces throughout the event periods, and becomes small and insignificant when the CFTC final rule-making proposal is accepted. This could be interpreted as: the final proposal does not meet market participants' expectations, and traders recognize the new position limit as ineffective and potentially harmful to the liquidity and competitiveness of the U.S. energy futures market.

6.3 Position limits

Prior to computing position limits using the methodology in Section 4.3, we test whether the premise (our fourth hypothesis) is met. Table 4 shows the results of paired t-test of the mean daily price change on the spot and futures markets for the same underlying commodity. As highlighted in the table, correlations between the spot and futures prices and the P values of the t-tests are both very high for all commodities. These results are consistent with acceptance of our fourth hypothesis, which in turns allow us to calculate position limits using the assumptions described in Section 4.3.

Using equation (23) with the price tolerance k set to a value of 5%, we calculate optimal monthly speculative position limits from June 2010 to June 2012 and list our results for each energy contract in Table 5. The results from Table 5 are also plotted in Figure 2. In addition, daily position limits for each contract are drawn in Figure 3.

We observe strong fluctuations in position limits over time in both figures. This is mainly due to high fluctuations in liquidity over time. Minor fluctuations of fair market value also contribute to this volatility. Figure 2 shows a clear relationship between the optimal position limits for the four energy contracts. Consequently, the CFTC should set the position limit for crude oil much higher than for the other three contracts. Position limits on heating oil and gasoline should be set on a similar level, and the position limits on natural gas should be about double the size of position limits on the two refined products from crude oil.

Chapter 7. Conclusion

In this thesis, we carry out three different studies to solve three aspects of issues associated with the U.S. energy futures market. The first study tests whether liquidity proxies calculated from low-frequency data capture liquidity benchmarks computed from high-frequency transaction data. The second study tests the significance and direction of unexpected liquidity of four energy futures contracts following the Dodd-Frank Act and its relevant CFTC rule-making proposals on the energy market. The last study estimates the optimal speculative position limits based on the model of Dutt and Harris. Based on our empirical results, we conclude the following:

Both the Amihud (2002) price impact liquidity proxy and the new price impact liquidity proxy (Cheng) developed in this thesis are consistent with liquidity measure estimated from intraday transaction data. However, the liquidity proxy developed in this thesis does a better job at measuring the size of liquidity benchmarks than the Amihud (2002) proxy.

Our result does not support Grossman's (1993) finding: the Dodd-Frank Act and its relevant CFTC rule-making proposals have a positive and significant impact on the liquidity of the U.S. energy futures market. Thus, position limits on financial futures should not force trading to move to foreign or substitute markets.

The results of application of the model to estimate the optimal position limits for energy futures contracts show strong fluctuations in position limits over time. The results also suggest that heating oil and gasoline position limits should be set at a similar level, the natural gas position limit should be approximately double that amount, while the crude oil position limit should be set to a much higher level.

We have a number of suggestions for future research. First, we could test a variety of liquidity proxies and liquidity benchmarks with yearly, monthly, daily and intraday tick data from a longer range. We could also come up with better algorithm to deal with the sign of illiquidity in calculations. Second, we could test the abnormal liquidity for post event periods when data becomes available.

Lastly, for the position limits model, we could use relevant variables from the underlying spot market when data becomes available. We could also test the position limits model with other types of commodities for different exchanges with better estimates of true value and liquidity proxies. The price tolerance criterion should also change over time due to the seasonal nature of some commodities. We should be able to compare the position limits computed from our model to those required by the CFTC once data availability allows us to do so. In this way, we should be able to test the consistency of the CFTC rules on position limit levels and whether their model takes manipulation theory into account. It is noticeable that our model cannot forecast position limits for a future time, and it only works with real-time data to produce real-time limits. In the future, we should be able to forecast liquidity and the true value of the underlying commodity in order to predict optimal speculative position limits.

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Position Limits – CFTC website. http://www.cftc.gov/LawRegulation/DoddFrankAct/Rulemakings/DF_26_PosLimits/index.htm

Figure 1

Estimation and event periods

This figure shows the timeline of the event study related to the Dodd-Frank Act. The estimation period is from 2003 to 2006, which is before the 2007 financial crisis. The hold out period is from 2007 till the effective date of the Dodd-Frank Act, which includes the hearings of the Act. In this period, people starts to expect changes in the legislations and rules. The event periods are 4 separated periods around the effective date of Dodd Frank Act and days that cover the three CFTC rule-making proposals. Windows of periods are showed below:

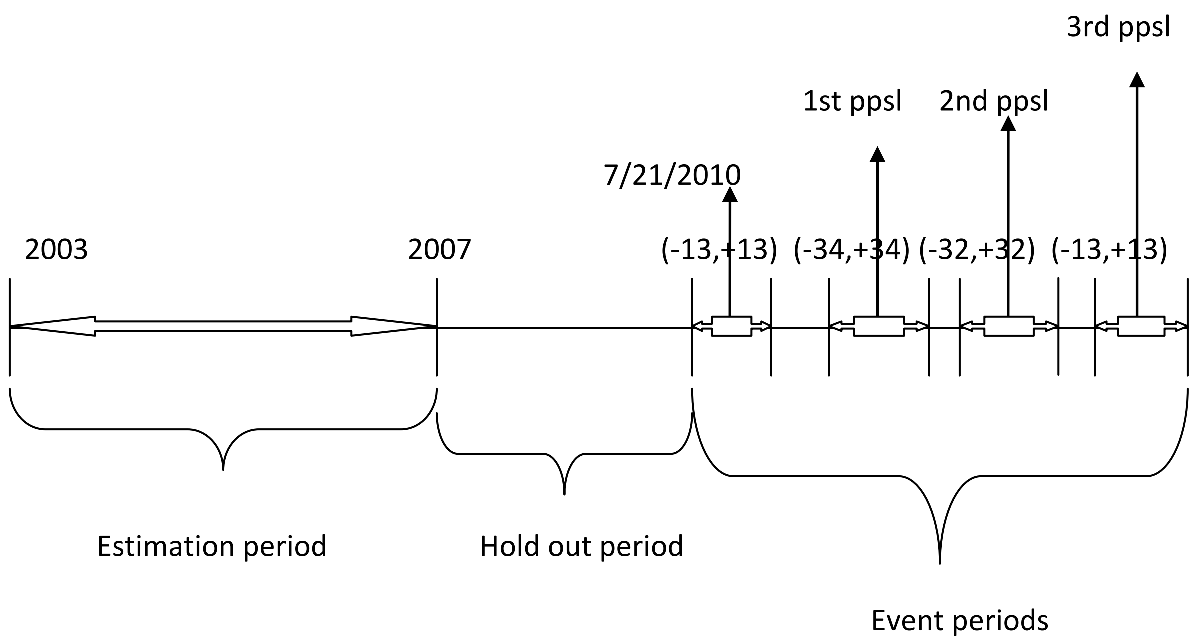

Figure 2

Monthly Position limits

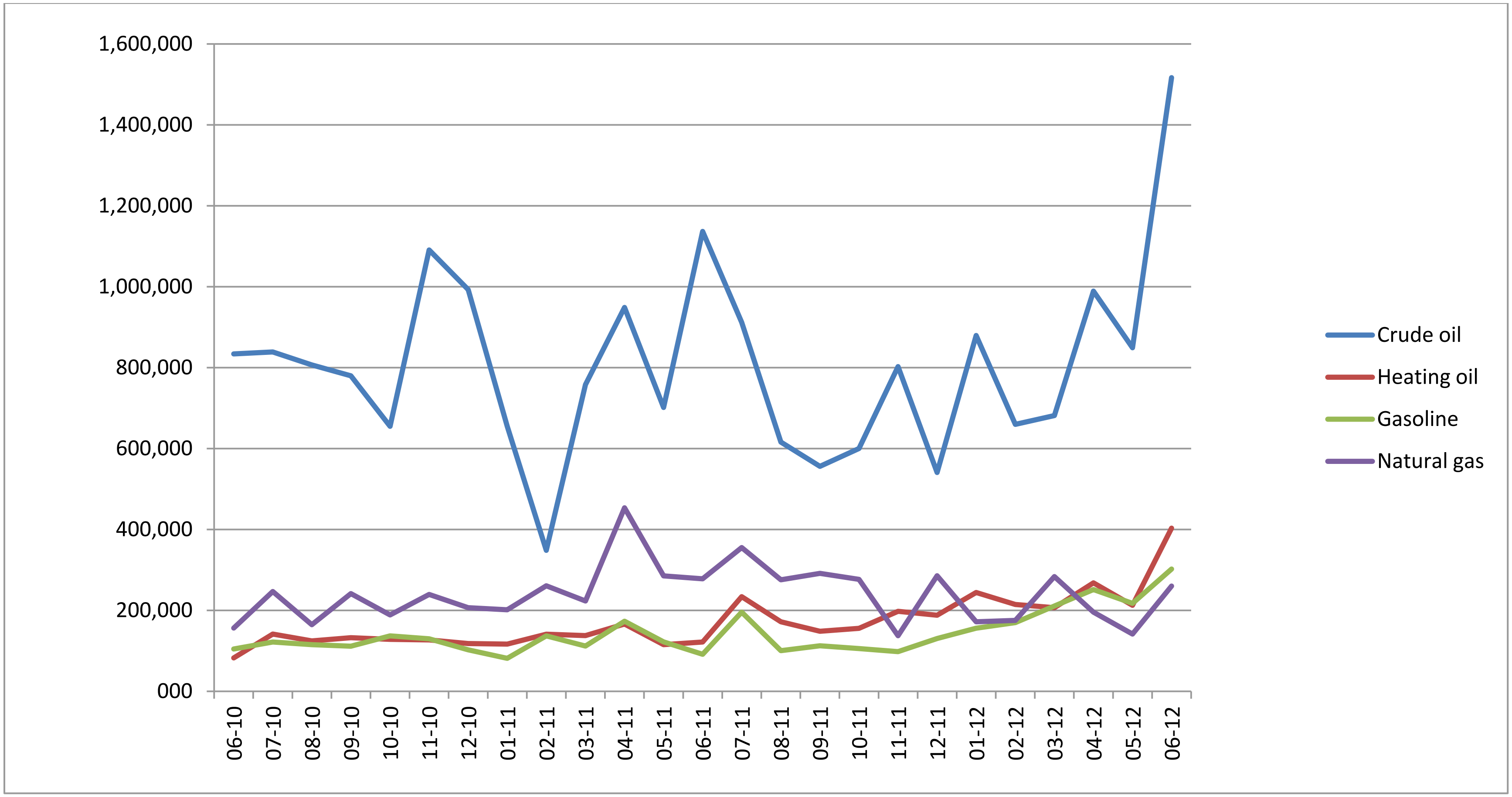

Figure 3

Daily Position Limits

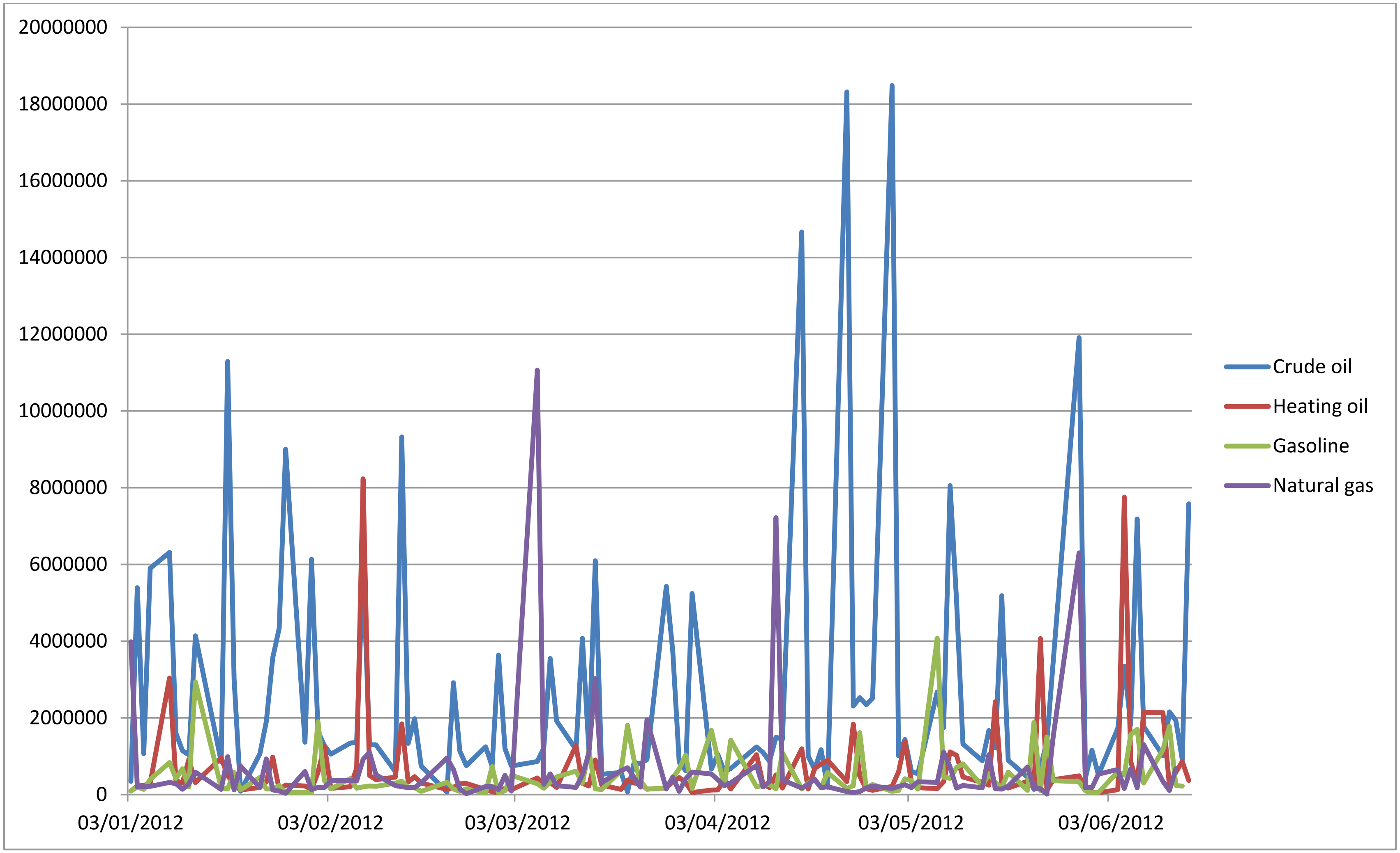

Table 1

Descriptive statistics for paired daily liquidity measures

	Intraday liquidity benchmarks						Daily liquidity proxies			
	Goyenko, Holden, and Trzcinka (2009)			Cheng (benchmarks developed in this thesis)						
	Effective Spread	Realized Spread	5-min Price Impact	Effective Spread	Realized Spread	5-min Price Impact	$Illiquidity_A$	$Illiquidity_A{}'$	$Illiquidity_C$	$Illiquidity_C{}'$
Panel A: Crude oil										
Mean	6.0644E-04	1.6355E-04	4.6987E-04	3.1600E-08	6.2421E-09	2.1419E-08	6.7281E-08	6.7478E-10	4.8088E-09	4.8525E-11
Std dev	1.8071E-04	1.8128E-04	2.7729E-04	3.9028E-08	1.0603E-08	2.4850E-08	1.3544E-07	1.3551E-09	1.8619E-08	1.8578E-10
Min	3.5890E-04	6.3464E-07	6.0023E-05	1.0083E-08	9.7000E-11	4.8505E-09	7.9117E-10	7.4142E-12	0.0000E+00	0.0000E+00
Median	5.8430E-04	1.2162E-04	4.3395E-04	1.9797E-08	3.5126E-09	1.3396E-08	3.8473E-08	3.8755E-10	1.0739E-09	1.0956E-11
Max	1.9028E-03	1.5405E-03	2.2354E-03	2.2569E-07	6.6465E-08	1.4432E-07	9.7277E-07	1.0182E-08	1.6379E-07	1.5856E-09
Panel B: Heating oil										
Mean	5.1733E-04	2.0990E-04	3.9184E-04	5.2487E-08	1.7368E-08	3.6529E-08	2.2360E-07	7.3694E-10	2.5038E-08	8.2617E-11
Std dev	1.6296E-04	2.3736E-04	2.9595E-04	3.3972E-08	3.6981E-08	4.8363E-08	2.0037E-07	6.7506E-10	9.0279E-08	2.9951E-10
Min	3.0692E-04	9.4558E-09	1.6860E-05	1.8059E-08	2.8048E-10	5.9925E-09	6.0851E-09	1.9074E-11	0.0000E+00	0.0000E+00
Median	4.9854E-04	1.5289E-04	3.3450E-04	3.6210E-08	7.3433E-09	2.5061E-08	1.6923E-07	5.3472E-10	7.6252E-09	2.5582E-11
Max	1.7891E-03	1.9624E-03	1.8214E-03	1.7589E-07	3.2183E-07	4.1909E-07	1.0534E-06	3.7916E-09	7.8009E-07	2.6655E-09
Panel C: Gasoline										
Mean	5.9373E-04	2.1677E-04	4.4743E-04	6.8912E-08	2.2368E-08	4.1005E-08	2.6272E-07	8.9007E-10	3.4129E-08	1.1798E-10
Std dev	1.4467E-04	2.0456E-04	3.1064E-04	4.1986E-08	2.8094E-08	3.2879E-08	2.6634E-07	9.2986E-10	1.1689E-07	4.0836E-10
Min	1.7540E-04	4.8638E-07	6.8893E-06	1.4330E-08	1.1556E-10	4.5433E-09	1.1892E-09	4.4287E-12	0.0000E+00	0.0000E+00
Median	5.6963E-04	1.5908E-04	3.9088E-04	5.4812E-08	1.1814E-08	3.2088E-08	1.9107E-07	6.0019E-10	8.0574E-09	2.6187E-11
Max	1.1091E-03	9.8688E-04	1.6769E-03	2.0776E-07	1.7544E-07	2.4517E-07	1.4103E-06	4.6346E-09	8.6849E-07	2.9146E-09

Table 1 Continued

	Intraday liquidity benchmarks						Daily liquidity proxies			
	Goyenko, Holden, and Trzcinka (2009)			Cheng (benchmarks developed in this thesis)						
	Effective Spread	Realized Spread	5-min Price Impact	Effective Spread	Realized Spread	5-min Price Impact	$Illiquidity_A$	$Illiquidity_A{}'$	$Illiquidity_C$	$Illiquidity_C{}'$
Panel D: Natural gas										
Mean	1.5016E-03	4.9153E-04	1.0409E-03	4.2703E-06	1.0985E-06	2.5022E-06	2.5346E-07	1.0380E-07	2.9501E-08	1.2805E-08
Std dev	5.0119E-04	4.3240E-04	7.4564E-04	3.9633E-06	1.4265E-06	2.9925E-06	4.0617E-07	1.6376E-07	9.7397E-08	4.5364E-08
Min	1.5620E-07	2.1144E-07	1.5605E-07	1.5127E-08	1.2941E-08	1.5111E-08	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00
Median	1.3915E-03	3.9797E-04	8.2488E-04	3.2915E-06	8.0620E-07	1.9390E-06	1.7974E-07	6.9975E-08	9.6425E-09	3.6263E-09
Max	3.3512E-03	2.7395E-03	3.8689E-03	2.6490E-05	1.3944E-05	2.4872E-05	3.6676E-06	1.4683E-06	7.2387E-07	3.5783E-07
Panel E: All combined										
Mean	8.0477E-04	2.7044E-04	5.8751E-04	1.1058E-06	2.8613E-07	6.5030E-07	2.0177E-07	2.6525E-08	2.3369E-08	3.2634E-09
Std dev	4.9565E-04	3.0947E-04	5.2199E-04	2.6924E-06	8.5249E-07	1.8363E-06	2.8180E-07	9.3056E-08	8.9384E-08	2.3278E-08
Min	1.5620E-07	9.4558E-09	1.5605E-07	1.0083E-08	9.7000E-11	4.5433E-09	0.0000E+00	0.0000E+00	0.0000E+00	0.0000E+00
Median	6.0450E-04	1.7621E-04	4.5089E-04	5.0697E-08	1.0239E-08	3.0772E-08	1.2270E-07	7.2399E-10	4.9089E-09	3.2375E-11
Max	3.3512E-03	2.7395E-03	3.8689E-03	2.6490E-05	1.3944E-05	2.4872E-05	3.6676E-06	1.4683E-06	8.6849E-07	3.5783E-07

Table 2

Daily liquidity proxies compared to intraday benchmarks

	Intraday liquidity benchmarks (developed in this thesis)		
	Effective Spread	**Realized Spread**	**5-min Price Impact**
Panel A: Crude oil			
Amihud (2002)			
t-test P value	3.2244E-04	4.5762E-07	3.6672E-05
correlation	7.7983E-01	7.0745E-01	6.8720E-01
covariance	4.0891E-15	1.0079E-15	2.2944E-15
Cheng (developed in this thesis)			
t-test P value	1.5171E-16	3.2347E-01	4.6783E-17
correlation	6.1029E-01	5.0083E-01	6.5120E-01
covariance	4.3993E-16	9.8086E-17	2.9889E-16
Panel B: Heating oil			
Amihud (2002)			
t-test P value	1.3420E-18	5.2563E-24	2.5306E-22
correlation	5.4869E-01	5.5077E-01	6.0648E-01
covariance	3.7050E-15	4.0484E-15	5.8300E-15
Cheng (developed in this thesis)			
t-test P value	1.4806E-04	1.6410E-01	7.0610E-02
correlation	5.1532E-01	8.6340E-01	6.3282E-01
covariance	1.5678E-15	2.8595E-15	2.7408E-15
Panel C: Gasoline			
Amihud (2002)			
t-test P value	3.6739E-14	7.9379E-19	3.0633E-16
correlation	3.8442E-01	4.1143E-01	1.6480E-01
covariance	4.2645E-15	3.0540E-15	1.4317E-15
Cheng (developed in this thesis)			
t-test P value	3.1289E-04	2.0197E-01	4.4753E-01
correlation	4.5136E-01	6.0078E-01	5.9381E-01
covariance	2.1974E-15	1.9572E-15	2.2639E-15
Panel D: Natural gas			
Amihud (2002)			
t-test P value	1.0184E-22	1.3874E-10	2.3418E-15
correlation	6.4644E-01	3.2857E-01	5.8404E-01
covariance	1.0323E-12	1.8886E-13	7.0421E-13
Cheng (developed in this thesis)			
t-test P value	4.6116E-23	3.1430E-14	2.3780E-16
correlation	9.0614E-01	3.8583E-01	7.6944E-01
covariance	3.4698E-13	5.3179E-14	2.2247E-13
Panel E: All combined			
Amihud (2002)			
t-test P value	3.3201E-14	2.2435E-02	1.4477E-08
correlation	4.1805E-01	2.6555E-01	4.0836E-01
covariance	3.1655E-13	6.3664E-14	2.1088E-13
Cheng (developed in this thesis)			
t-test P value	2.0856E-18	7.6893E-12	4.6174E-14
correlation	3.9306E-01	2.1363E-01	3.7121E-01
covariance	9.4404E-14	1.6246E-14	6.0805E-14

Table 3

Event study Student t-test and sign test for cumulative abnormal illiquidity during event periods

	Crude oil	Heating oil	Gasoline	Natural gas	All contracts combined
Panel A: Dodd-Frank Effective Date					
student t-test P value	3.0370E-05	6.8750E-04	5.1063E-03	1.3025E-04	3.0113E-09
sign test P value	4.9233E-05	5.9246E-03	1.9157E-02	1.9157E-02	1.5198E-09
Panel B: CFTC first rule-making proposal					
student t-test P value	7.8326E-02	1.5748E-05	2.5755E-03	1.9674E-03	5.9597E-10
sign test P value	9.0951E-06	6.9219E-07	7.6205E-03	9.0951E-06	2.2911E-17
Panel C: CFTC interim rule-making proposal					
student t-test P value	7.5731E-04	8.5598E-02	4.7808E-06	9.1634E-11	2.8874E-04
sign test P value	2.7862E-07	2.0492E-09	4.2213E-04	3.5422E-09	1.4801E-25
Panel D: CFTC final rule-making proposal					
student t-test P value	1.4473E-01	3.1202E-01	3.0130E-02	1.7407E-02	3.0021E-01
sign test P value	2.8959E-02	2.4939E-03	1.0490E-05	1.4633E-02	4.2948E-10
Panel E: All event periods combined					
student t-test P value	7.0525E-05	2.9458E-01	1.7614E-06	6.2338E-15	
sign test P value	6.1235E-17	3.1586E-19	1.0119E-10	3.9734E-16	

Table 4

Paired t-test for daily price change between futures and spot markets for the same underlying commodity

	Crude oil	Heating oil	Gasoline	Natural gas
Mean from spot market	0.0109	0.0375	0.0894	0.0002
Mean from futures market	0.0110	0.0333	0.0743	0.0002
degree of freedom	5232	5198	1837	3651
Correlation	0.9648	0.9336	0.9006	0.3579
t-test P value	0.9833	0.7957	0.7978	0.9980

Table 5

Monthly Optimal Speculative Position limits estimated from our model

Month-Year	Crude oil	Heating oil	Gasoline	Natural gas
06-10	833,847	82,567	104,466	156,319
07-10	838,975	141,351	121,713	246,649
08-10	806,678	124,680	115,187	164,528
09-10	779,788	132,477	111,402	241,511
10-10	655,133	128,576	137,169	188,676
11-10	1,090,787	127,000	129,960	239,465
12-10	993,079	117,928	102,524	206,855
01-11	655,001	116,800	81,524	201,678
02-11	348,499	141,043	137,100	260,685
03-11	758,170	137,790	111,763	223,092
04-11	948,818	166,175	173,156	453,447
05-11	701,426	115,414	122,083	285,420
06-11	1,136,745	121,954	91,356	277,952
07-11	912,007	234,014	195,615	355,389
08-11	616,090	171,919	100,576	275,603
09-11	555,878	148,343	112,617	291,537
10-11	600,050	155,509	105,674	276,806
11-11	802,640	197,798	98,117	137,301
12-11	541,023	188,026	130,315	285,651
01-12	879,581	244,309	155,995	171,874
02-12	659,872	214,565	169,684	175,201
03-12	681,654	206,822	210,862	283,568
04-12	989,269	268,131	251,681	195,658
05-12	849,135	212,426	217,214	141,587
06-12	1,516,641	403,365	302,210	260,035