Round number effects in WTI Crude Oil Futures Market

Victor (Ro) Cho

Abstract

Round number effects predict excess buying just below a round number ($X.99) and excess selling just above a round number ($X.01). Using 148 million trade observations for West Texas (WTI) crude oil futures market for the period from January 01, 1996 to October 31, 2015, we find excess buying just below a round number and excess selling just above a round number in both pre- and post-electronic periods, confirming the existence of round number effects in WTI crude oil futures market. Further, this paper provides evidence that hedgers, who are less informed traders, influence round number effects. Earlier research into round number effects focuses on US stock markets only and does not address what type of traders influences round number effects. We also examine 24-hour trade return based on round number effects. Previous literature documents evidence that round number effects is a major determinant of 24-hour positive trade return in US stock markets. By contrast, we find round number effects is not a determinant of 24-hour positive trade return in WTI crude oil futures market and the average 24-hour trade return based on round number effects is negative 0.0014 percent. Additionally, we document evidence that the impact of the net position held by hedgers is greater than that of speculators on market liquidity and volatility in WTI crude oil futures market. We find negative relation between excess selling by hedgers and market liquidity and positive relation between excess buying by hedgers and market liquidity. We also find positive relation between excess selling by hedgers and market volatility but we find no evidence that trading activity of speculators affect market volatility.

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1. Introduction

A recent research by Bhattacharya, Holden and Jacobsen (2012) provide evidence that stock market traders use a round number as cognitive reference point for value. Bhattacharya, Holden and Jacobsen (2012) find excess buying just below a round number ($X.99) and excess selling just above a round number ($X.01) by liquidity demanders in U.S common stock markets and they term it round number effects. Their finding is most consistent with psychological pricing effect around a round number as discussed in research in cognitive psychology and marketing (Rosch, 1975; Thomas and Morwitz, 2005). Bhattacharya, Holden and Jacobsen (2012) discuss three different kinds of round number effects – (1) left-digit effect, (2) threshold trigger effect, and (3) the cluster undercutting effect – to explain the excess buying just below a round number ($X.99) and excess selling just above a round number ($X.01). Bhattacharya, Holden and Jacobsen (2012) further document that round number effects is a major determinant of 24-hour positive trade return.

A large literature documents the association between trading activity and price clustering at a round number (Niederhoffer, 1965; Niederhoffer, 1966; Harris 1991; Grossman, Miller, Cone, Fischel and Ross, 1997; Ikenberry and Weston 2003; Chung, Van Ness and Van Ness, 2004; Davis, Van Ness and Van Ness, 2014). Most studies document investors have a preference for a round number because of its high accessibility as discussed in cognitive psychology and marketing research (Rosch, 1975;Thomas and Morwitz, 2005). The key difference between the analysis of price clustering and round number effects is that the direction of trades only matters when analysing round number effects. While, in most existing studies, trading activity is measured by volume, we measure trading activity by order imbalance. Order imbalance, defined as the proportion of net buyer-initiated[1], is a measure of trading activity that is suggested as more informative than volume (Chordia, Roll and Subrahmanyam, 2002). Motivated by findings of Bhattacharya, Holden and Jacobsen, we extend this line of the literature by exploring the existence of round number effects in West Texas (WTI) crude

[1] The net buyer-initiated is defined as the difference between buyer-initiated and seller-initiated trades

oil futures market. The commodity futures markets are different from stock markets in several ways. One of the major differences is that while stocks are investment assets, commodity futures assets are consumption assets. Therefore, commodity futures markets are for hedging and speculating. U.S commodity futures trading commission (CFTC) publish weekly commitment of traders (COT) report that contains long and short positions held by hedgers and speculators. This special feature helps us to separate speculators from hedgers. This enables us to examine whether trading activity of hedgers or speculators influences round number effects. Since WTI crude oil futures is one of the largest commodity futures markets, the features of WTI crude oil futures should represent the general features of commodity futures markets.

In this paper, using 152 million trade observations over the period from January 01, 1996 to October 31, 2015, we explore the existence of round number effects in WTI crude oil futures market. We divide the sample period into two sub-sample periods: pre and post-electronic period to examine whether there is any change in round number effects. Following Bhattacharya, Holden and Jacobsen (2012), we also compute buy-sell ratio in three different ways: the proportion of the net buyer-initiated trades, the proportion of the net volume of buyer-initiated futures contact and the proportion of the net buyer-initiated dollar volume. For all three regressions, we find excess buying just below a round number and excess selling just above a round number during both pre and post-electronic periods. Thus, we confirm the existence of round number effects exist in WTI Crude oil futures market. We also examine which of three round number effects is more prevalent than the other two. Using nickel as a benchmark, we conducted four conditional buy-sell imbalance: ask falls below a round number", "ask falls to a round number", "bid rises to a round number", "bid rises above a round number" and their corresponding "ask falls below a nickel", "ask falls to a nickel", "bid rises to a nickel", "bid rises above a nickel". Inconsistent with Bhattacharya, Holden and Jacobsen (2012) who document that cluster undercutting effect is the dominant round number effects in US stock markets, we find that threshold trigger effect is more prevalent than the other two in WTI crude oil futures market. Having explored the existence of round number effects WTI crude oil futures market, we examine whether round number effects is a major determinant of 24-hour trade return as documented in Bhattacharya, Holden and Jacobsen (2012). However, we further find conflicting finding to that of Bhattacharya, Holden and Jacobsen (2012). We find no evidence that round number effects is a determinant of 24-hour positive trade return and the average 24-hour trade return based on round number effects is negative 0.0014 percent in WTI crude oil futures market. As a robustness check, we include two market variables – market liquidity and volatility measured by the relative bid-ask spread and standard deviation of price return respectively. Controlling for market liquidity and volatility separately, we find that round number remain persistent.

We make several new contributions to the literature on round number effects. First, we are the first study to provide evidence that round number effects exist in commodity futures markets. Second, we explore the trader type that influences round number effects. Previously, Johnson and Shanthikumar (2007) examine whether uninformed traders influence stock-price clustering in US stock markets but they find no evidence. Using COT, we are able to separate speculators from hedgers and find that hedgers, who are less informed, influences round number effects. To our knowledge, we are the first study to provide evidence that uninformed traders influences round number effects. Additionally, we examine the interaction between trading activity of hedgers and speculators and market liquidity. We find that net position of hedgers has an asymmetric effect on market liquidity. We provide evidence that there is negative relation between excess selling and market liquidity (i.e. wider bid-ask spread) and positive relation between excess buying and market liquidity (i.e. narrower bid-ask spread). We also examine the interaction between trading activity of hedgers and speculators and market volatility. We find that net position of hedgers has an asymmetric effect on market volatility. We provide evidence that excess selling by hedgers affect market volatility. However, we find no evidence that trading activity of speculators affect market volatility.

The rest of the paper is organised as follows. Section 2 discusses the literature review and hypothesis development. Section 3 explains the data source and the selection of sample data. Section 4 presents the methodology. Section 5 presents empirical evidence on left-digit effect in commodity futures market. Section 6 concludes.

2. Background, Prior Literature and Hypotheses Development

2.1. Hypothesis 1: Round number effects

Our first hypothesis is that there is excess buying just below a round number ($X.99) and excess selling just above a round number ($X.01). Round number effects predict excess buying just below a round number and excess selling just above a round number because stock traders use a round number as cognitive reference point for value. Thus, the theory tells us stock traders are motivated to buy just below a round number and motivated to sell just above a round number. Bhattacharya, Holden and Jacobsen (2012) are the first to test whether there is excess buying just below a round number and excess selling just above a round number in US stock markets, which they term round number effects. Using 100 million stock transactions, Bhattacharya, Holden and Jacobsen (2012) find excess buying just below a round number and excess selling just above a round number by liquidity demanders in US stock markets, providing evidence of the existence of round number effects in US stock markets.
As discussed above, excess buying just below a round number and excess selling just above a round number is an implication of round number effects. This gives us our first hypothesis.

Hypothesis 1 (H1). *Buy trades should outnumber sell trades just below a round number (e.g. $X.99) and sell trades should outnumber buy trades just above a round number (e.g. $X.01)*

Bhattacharya, Holden and Jacobsen discuss three different kinds of round number effects hypotheses for buy-sell imbalance pattern below and above a round number – (1) the left-digit effect, (2) threshold trigger effect and (3) the cluster undercutting effect.

2.1.1 Left-digit effects

First, one view that holds excess buying just below a round number and excess selling just above a round number is left-digit effect. Left-digit effect is the observation that leftmost price disproportionately affects our perception of price. This perception is more likely to occur when introducing a nine ending in the price. However, it is the change in the leftmost digit, rather than one cent drop, that affects the magnitude of perception. For example, the psychological difference between $3.00 and $2.99 is greater than the difference between $2.70 and $2.69 because consumers pay a lot more attention to the leftmost digit than right-hand digits. To consider evidence, we consider the marketing literature. Using 1,415 advertised retail prices from newspapers, Schindler and Kirby (1997) document evidence that 9-ending price is the most common practice by retailers. Stiving and Winer (1997) document evidence that consumers do not always process all of the numerical information contained in the price. Using the data for two frequently purchased products, tuna and yogurt, Stiving and Winer (1997) find that consumers process prices from left-to-right, beginning with leftmost digits and frequently ignore right-hand digits. Schindler and Wiman (1989) document evidence that 9-ending prices are less likely to be recalled accurately and the price will be underestimated when it is recalled. Thomas and Morwitz (2005) find that consumers perceive 9-ending price substantially lower than a 0-ending price only when the leftmost digit changes. Drawing on the over-representation of 9-ending in advertised retail prices by retailers, Brenner and Brenner (1982) conclude we have only a limited amount of memory and a limited capacity for storing directly accessible information. In other words, people have processing limitation and there is a limit on how much information a human being can deal with at once or within a limited period. Hinrichs, Yurko and Hu (1981) document that left-to-right reading causes people to make decision simply on the basis of the value of the leftmost digit – the most accessible number and storing only the leftmost digit of a number is a very simple operation. In line with studies on nine-ending price, a number of retail pricing studies provide evidence that the use of 9-ending price increase demand in retail sales (Anderson, and Simester, 2003; Schindler and Kibarian,1996).

2.1.2. Threshold trigger effect

The second round number effect is threshold trigger effect. The threshold trigger effect is defined as when a security price reaches or cross a round number, a wave of buying or selling is triggered. The key idea is investors have a preference for round numbers, where the hierarchy of roundness from the most round to the least round is whole dollars, half-dollars, quarters, dimes, nickels, and pennies. For example, if the security price falls to (or crosses below) a round number, it will trigger buy trades whereas if the price rises to (or crosses above) a round number, it will trigger sell trades. Research in cognitive psychology documents evidence that people employ heuristic to reduce judgements to simpler one when faced with the difficult task of judging the probability of event (Tversky and Kahneman, 1973). One heuristic that Rosch (1975) documents is that people use cognitive reference points as comparison standards to form judgment against other stimuli (Rosch 1975). In the context of numbers, Rosch (1975) documents that round numbers are cognitive reference points because round numbers have high cognitive accessibility as they are easier to recall and work with than non-round numbers. Schindler and Kirby (1997) show that round numbers have high cognitive accessibility and the high cognitive accessibility of round numbers account for the overrepresentation of 0- and 5-ending prices (the midpoint of 10) in retail markets. There is a large finance literature on price clustering at round numbers in financial markets. Price clustering is a phenomenon where transactions cluster at round numbers. Consistent with the threshold trigger effects, a number of studies provide evidence of the price clustering at round numbers in US stock markets. Using 1,854 NYSE and AMEX (pre-decimalization) transaction dataset during the week of September 28, 1987, Harris (1991) document evidence that whole-dollar prices are more common than half-dollar prices, and half-dollar prices are more common than odd quarters, confirming that price clustering is pervasive in US stock markets. Harris (1991) finds that clustering increases with volatility. Using post- decimalization trade price and quote dataset of NYSE and NASDAQ for May 2001, Chung, Van Ness and Van Ness (2004) provide evidence that price clustering persists even after the move to decimalization, with price clustering on zero-ending prices ($X.X0). Price clustering at round numbers is also reported in international equity markets (Aitken, Brown, Buckland, Izan and Walter, 1996; Grossman, Miller, Cone, Fischel and Ross, 1997; Cai, Cai and Keasey 2007; Guo, 2013). Aitken, Brown, Buckland, Izan and Walter (1996) find price clustering on Australian Stock Exchange and also find that price clustering increases volatility. Cai, Cai and Keasey (2007) find price clustering on both stock markets (the SHSE and SZSE) in China. Other financial markets such as IPO auction (Kandel, Sarig,and Wohl , 2001), currency (Goodhart and Curcio, 1990; Osler (2003)), gold (Aggarwal and Lucey, 2005) also report price clustering at round numbers. A recent research by Davis, Van Ness and Van Ness (2014) finds price clustering even in a sample that contains high-frequency trading firm's transactions. Using the database contains the trading activity of 26 high-frequency trading firms in 120 stocks on NASDAQ for the year 2009, Davis, Van Ness and Van Ness (2014) document evidence that price clustering increases with volatility when a non-high frequency trading firms provides liquidity. However, when a high-frequency trading firm provides liquidity, the variable is not significant.

2.1.3 Cluster undercutting effect

The last round number effect is the cluster undercutting effect. Undercutting occurs when a new limit sell (buy) is submitted at a penny lower (higher) than the existing ask (bid) at a round number. For example, a market 'buy' hits the new ask price at $2.99 and thus, buy trades are frequently recorded below round numbers. Conversely, a market 'sell' hits the new bid price at $3.01 and thus, sell trades are frequently recorded above round numbers. The cluster undercutting effect predicts excess buying below round numbers and excess selling above round numbers. Bhattacharya, Holden and Jacobsen document that the cluster undercutting is the most pervasive round number effects.

2.2. Hypothesis 2: Impacts of Trading activity of Speculators and hedgers on round number

Our second hypothesis is that the net position of the trader type that influences round number effects is long position below a round number and short position above a round number. Excess buying below a round number and excess selling above a round number is driven by behavioural bias and therefore, is not associated with information motivated trading. A number of studies documents that unspecialised traders have no information analysing skills and therefore, their trades are more likely to be motivated by behavioural bias whereas specialised traders have better analysing skills and information and trade on information (Nofsinger and Sias, 1999; Kamesaka, Nofsinger and Kawakita, 2003). Research on futures market shows that speculators are better trained and have better resources than hedgers. (Schwarz, 2012; Dewally, Ederington and Fernando, 2013; Chen and Chang,2015).
Earlier research on price clustering finds no evidence of what trader type influences price clustering at round numbers. In the previous literature, Bhattacharya, Holden and Jacobsen (2012) do not discuss what trader type influences round number effects. Johnson and Shanthikumar (2007) examine whether uninformed traders influences stock-price clustering in US stock markets but they find no evidence. Davis, Van Ness, and Van Ness (2014) document evidence that better-informed high-frequency traders exhibit less price clustering in their transactions than non-high frequency traders. However, Davis, Van Ness, and Van Ness (2014) only suggest that price clustering is a result of human bias and provide no evidence that non-high frequency traders influences price clustering.

In this paper, we want to determine and test what trader type influences round number effects in WTI crude oil futures market. This gives our second hypothesis:

Hypothesis 2 (H2). *The net position of the trader type that influences round number effects is long position just below a round number (e.g. $X.99) and short position just above a round number (e.g. $X.01)*

2.3. Hypothesis 3: the determinant of 24-hour trade return

Bhattacharya, Holden and Jacobsen (2012) document evidence that round number effects is a major determinant of 24-hour positive trade return and a trading strategy based on round number effects generate $59.8 million per year in US stock markets. However, earlier research on behaviour-based trade shows that specialised traders, who are better informed and have better analysing skills, trade for information because their net position is positively related to their trade return whereas unspecialised traders' trading is motivated by behavioural bias because their net position is negatively related to their trade return (Nofsinger and Sias, 1999; Kamesaka, Nofsinger and Kawakita, 2003). Using data during 1977 to 1996 for US stock markets, Nofsinger and Sias (1999) document trading that earns high returns indicates that the trading was motivated by information whereas trading that results in a low return indicates a behavioural-based motivation. Kamesaka, Nofsinger and Kawakita (2003) also document strong evidence that trading with high returns indicate that the trading is motivated by information whereas trading with low returns indicate that the trading is motivated by behavioural bias using data during 1980 to 1997 for Tokyo Stock Exchange.

In futures market, speculators are specialised traders because their net position is positively related to their trade return whereas hedgers are unspecialised traders because their net position is negatively related to their trade return (Schwarz, 2012; Dewally, Ederington and Fernando, 2013; Chen and Chang,2015). Using data during 1993–1997 for energy futures market, Dewally, Ederington and Fernando (2013) document evidence that mean hedger profits are negative whereas speculator profits are positive and conclude that traders who hold net positions opposite sign to hedgers have higher profits than traders whose net positions align with hedgers.

We examine whether round number effects is a major determinant of 24-hour positive trade return as documented in Bhattacharya, Holden and Jacobsen (2012) in WTI crude oil futures market. This gives us our third hypothesis.

Hypothesis 3 (H4). *Round number effects is a major determinant of 24-hour positive trade return*

2.4. Impacts of different traders' position on price volatility

Additionally, we examine the impacts of trading activity of hedgers and speculators on market liquidity and volatility in WTI crude oil futures market.

The boom and bust in commodity prices during 2006 – 2008 accompanied by substantial increase in trading activity of speculators and commodity investing (i.e. financialization of commodity markets) has led to a renewed interest in the potential effect of commodity futures trading. There is ongoing debate as to whether the trading activity of speculators has a destabilizing role by increasing volatility in commodity market. Thus, we particularly focus on the impacts of speculation activity on WTI crude oil futures market.

The evidence is mixed. Sanders, Irwin and Merrin (2010) and Till (2009) find that speculation rises merely as a response to a rise in hedging demand and speculation is not to be blamed for the boom and bust of 2008 in commodity futures price. Buyuksahin and Harris (2011) test whether speculators has destabilizing effect on commodity futures market and find little evidence that speculation has harmful impact. However, the perception of the general public and policy makers is that there was actually excessive speculation in the commodity futures markets which had a destabilizing effect on price during the boom and bust of 2008. According to Chang, Chen, Chou, and Gau (2013), in 2009, the Commodity Futures Trading Commission (CFTC) imposed position limits in an attempt to control excessive speculation and stabilize price movements in some futures markets including Crude oil futures.

3. Data

We use tick history data for West Texas light (WTI) crude oil futures market for the period from January 01, 1996 to October 31, 2015 from Thomson Reuters Tick History (TRTH). TRTH database began in 1996, so this is the starting point. We collect tick data on quote and trade price, trade volume, and the bid and ask quotes at a millisecond frequency. We use one-hundred twenty WTI futures contracts. Our quote and transaction data cover both open-outcry and electronic trading.

3.1. Roll over

In order to avoid thin trading and expiration effects, we follow De Ville de Goyet, Dhaene, and Sercu (2008) to construct continuing series of the most actively traded contracts. Following De Ville de Goyet, Dhaene, and Sercu (2008), we replace a contract that expires in month m with the next nearest-to-maturity contract on the last day of month m – 1. For example, March contract (CLH) expires in February (month m) but its most actively traded period is January (month m – 1). Thus, we only consider quotes and trades from January (month m – 1) for the March contract. Specifically, on the last day of month m – 1, the last trade price is the last observation of the expiring contract whereas on the first day of month m, the first trade price is the first observation of the new contract. This ensures that at roll-over. In total, we have over one-hundred fifty-two million trade observations across one-hundred twenty active WTI crude oil futures contracts.

3.2. Pre and Post-electronic period

Prior to September 3rd, 2006, trading on U.S futures market was entirely in the open-outcry market. Now, trading is largely on the electronic platform and intermediated largely by electronic market makers.

We divide our sample data into two subsample periods – pre and post-electronic periods – to explore the existence of round number effects and to examine whether there was any change in round number effects.

The data sample for the pre-electronic period is based on all trades and quotes over the period from January 1, 1996 to September 2nd, 2006, containing a total of over 3.9 million trade observations. We begin our post-electronic sample period on September 3rd, 2006. The post-electronic sample period is based on all trades and quotes over the period from September 3rd, 2006 to October 31, 2015, containing a total of over 148 million trade observations.

3.3. Buy-sell imbalances

We follow the algorithm presented in Lee and Ready (1991) to assign a trade direction to each trade. We assign a buy if the transaction price is above the bid-ask midpoint and a sell if the transaction price is below the bid-ask midpoint. The midpoint is defined as the average of the best bid and best ask prices. Trades executed exactly at the midpoint are classified as neither buyer nor seller initiated and considered as no trade. For each .XX price point, we aggregate all buys and all sells (for example, at $39.99, $40.99, $41.99, etc are aggregated at the .99 price point) for each day (or each week) and compute the buy-sell ratio. For each day (or each week) interval, we define the buy-sell ratio as

$$Buy - sell\ Ratio_{t,i} = \frac{Buy_{t,i} - Sell_{t,i}}{Buy_{t,i} + Sell_{t,i}} \tag{1}$$

where $Buy_{t,i}$ is the number of buys at .XX price point i on day t and $Sell_{i,t}$ is the number of sells at .XX price point i on day t.

Bhattacharya, Holden and Jacobsen (2012) compute the buy-sell ratio in three different ways as the number of buyer- less the number of seller-initiated trades, the number of buyer-initiated shares purchased less the number of seller-initiated shares sold and the dollars paid by buyer-initiators less the dollars received by seller–initiators. For all three buy-sell ratio measures, Bhattacharya, Holden and Jacobsen (2012) find excess buying just below a round number and excess selling just above a round number.

We also compute buy-sell ratio in three different ways. For each day (or each week) interval we compute the following:

$\mathrm{OIB\#}_{t,i}$: the proportion of the net buyer-initiated trades at .XX price point i on day t;[2]
$\mathrm{OIBvol}_{t,i}$: the proportion of the net volume of buyer-initiated futures contact at .XX price point i on day t;[3]
$\mathrm{OIB\$}_{t,i}$: the proportion of the net buyer-initiated dollar volume at .XX price point i on day t;[4]

3.4. Hedger and speculator positions

U.S Commodity Futures Trading Commission (CFTC) collects data on traders' positions in futures market. CFTC collect the position of commercial (commonly referred to as hedgers) and non-commercial traders (commonly referred to as speculators) and aggregates these data into commitment of traders (COT) report every Tuesday and publish it in the following Friday. Thus, the COT reflects positions as of the preceding Tuesdays. The COT report categorises positions into hedgers and speculators. Hedgers has some physical dealings or commercial interaction with the underlying commodity and therefore face price risks in the cash market that they seek to offset or hedge in futures market. Speculators hold positions opposite those of hedgers, thereby providing liquidity to the market without necessarily suffering any physical risk exposure that needs to be offset.

The information in the COT reports allows us to separate speculators from hedgers. This enables us to examine whether trading activity of hedging or speculating influences round number effects. We use the weekly COT for the post-electronic period from September 7, 2006 to 31 October 2015.

[2] The net buyer-initiated is defined as number of buyer-initiated trades less the number of seller-initiated trades
[3] The net volume of buyer-initiated futures contact is defined as the volume of buyer-initiated futures contact less the volume of seller-initiated futures
[4] The net buyer-initiated dollar volume is defined as the buyer-initiated dollar volume less seller-initiated dollar volume

For each week interval, we compute the net position to proxy for the trading activity of hedgers and speculators. The net position of for each category of traders is defined as

$$T_{t,i}^{j} = \frac{Long_{t,i} - Short_{t,i}}{Long_{t,i} + Short_{t,i}} \tag{2}$$

where $Long_{i,t}$ and $Short_{i,t}$ is long and short position of trader type j at .XX price points i in week t and $T_{t,i}^{j}$ is the net position of trader type j at .XX price points i in week t and defined as the proportion of net long position (i.e. net buy-initiated trades) at price points i in week t

To examine the relation between net positions (i.e. order flow) of different traders and buy-sell ratios, we aggregate all buys and all sells for each week instead of each day for each .XX price point and compute buy-sell ratio.

3.5. Liquidity and volatility

For each week interval, we compute the following measures of liquidity and volatility:
We use is the relative bid-ask spread to proxy for the liquidity. We calculate the relative bid-ask spread by taking the difference between bid price and ask price and then divide it by the average of the bid and ask price (i.e. midpoint price). For each .XX price point, we take the average bid-ask spread for each week during the post-electronic period.
$Spread_{t,i}$: the relative bid-ask spread at .XX price points i in week t

We use the standard deviation of price return to proxy for the volatility. We measure prices in natural logs and calculate returns using the percentage change in the last traded price. For each .XX price point, we calculate the standard deviation of price return for each week during the post-electronic period.
$retvol_{t,i}$: the volatility at .XX price points i in week t

4. Methodology

Our first hypothesis is to test whether round number effects exist in WTI Crude oil futures market. Excess buying just below a round number ($X.99) and excess selling just above a round number ($X.01) is the implication of round number effects. We formally test the existence of round number effects in WIT Crude oil market for both pre and post-electronic periods by running the regression of buy-sell ratio on price points, with particular focus on just below a round number and just above a round number. We implement three-regressions based on three versions of the buy-sell ratios: OIB#, OIBvol and OIB$. A positive coefficient on just below a round number indicates excess buying and a negative coefficient on just above a round number indicates excess selling. The following model tests the first hypothesis:

$$Buysell_{t,i} = \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \varepsilon_{t,i} \tag{3}$$

where the dependent variable $Buysell_{t,i}$ is the buy-sell ratio at .XX price points i on day t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 on day t.

In conditional buy-sell imbalance test, we explore which of three round number effects dominate in WTI crude oil futures market. Following, Bhattacharya, Holden and Jacobsen (2012), we test whether buy trades outnumber sell trades after ask prices fall just below a round number and sells outnumber their buys after bid prices rise just above a round number. We use “nickel” as a benchmark to “round number”. We conduct four conditional buy-sell imbalance: “ask falls below round number”, “ask falls to round number”, “bid rises to round number”, “bid rises above round number” samples and their corresponding “ask falls below nickel”, “ask falls to nickel”, “bid rises to nickel”, “bid rises above nickel” samples. We use *t*-statistic to assess the significance. *t*-statistic is computed as follow

$$tstat = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}}$$

(4)

where $\bar{x}_1$ is either median or mean buy-sell ratios, σ_1 is the standard deviation, and n_1 is the number of observation for round numbers and $\bar{x}_2$ is either median or mean buy-sell ratios, σ_2 is the standard deviation, and n_2 is the number of observation for nick benchmarks

Our second hypothesis is to explore what type of traders influences round number effects. Using COT data, we want to determine what kind of traders (i.e. hedgers or speculators) influences round number effects in futures market. We use the net position defined in equation (2) to proxy for the trading activity of different types of traders. We expand the regression model in equation (3) to include interaction variables that captures the trading activity of hedgers and speculators at price points $X.01, $X.49, $X.51 and $X.99 to test for the second hypothesis. Since COT provides weekly data, for each .XX price point, we aggregate all buys and all sells (for example, at $39.99, $40.99, $41.99, etc are aggregated at the .99 price point) for each week and compute the buy-sell ratio. We then implement three-regressions based on three versions of the buy-sell ratios as in the following model:

$$\begin{aligned} Buysell_{t,i} = {} & \alpha + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01} T^j_{t,01} + \alpha_2 X_{t,49} T^j_{t,49} \\ & + \alpha_3 X_{t,51} T^j_{t,51} + \alpha_4 X_{t,99} T^j_{t,99} + \beta_5 T^j_{t,i} + \varepsilon \end{aligned} \tag{5}$$

where the dependent variable $Buysell_t$ is the buy-sell ratio at .XX price points i in week t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 in week t. $T^j_{t,i}$ is the net position of trader type j at .XX price points i in week t and $X_{t,01}T^j_{t,01}$, $X_{t,49}T^j_{t,49}$, $X_{t,51}T^j_{t,51}$, $X_{t,99}T^j_{t,99}$ are the net position held by trader type j at price points $X.01, $X.49, $X.51 and $X.99 in week t.

The net position of the trader type that influences round number effects just below a round number is long position and just above a round number is short position. A positive coefficient on interaction term for just below a round number indicates long position and a negative coefficient on interaction term for just above a round number indicates short position.

Our third hypothesis tests whether round number effects is a major determinant of 24-hour positive trade return in WTI crude oil futures market as documented in Bhattacharya, Holden and Jacobsen (2012). If traders use a round number as reference point for value, a potential profitable strategy is sell above a round number and buy below a round number. We compute 24-hour trade return as follow. For every buy trade observation just below a round number (X.99), we buy at the actual trade price below a round number and sell at the bid price 24 hours later to close the position and compute 24-hour trade return. For example, if there is a buy at 11:00 a.m. on day t, we sell at the bid price at 11:00 a.m. on the next day $t+1$. Similarly, for every sell trade observation above a round number (X.X01), we sell at the actual trade price above a round number and buy at the ask price 24 hours later to close the position and compute 24-hour trade return. For each .XX price point, we end up with two return categories: (1) the 24-hour trade return to buy, (2) the 24-hour trade return to sell. We take the median 24-hour trade return by taking the difference between median 24-hour trade return to buy and median 24-hour trade return to sell.

We then run the regression of 24-hour trade return on price points as in the following model:

$$24hour\ trade\ return_{t,i} = \alpha_{i,t} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \varepsilon_{i,t} \tag{6}$$

where the dependent variable is 24-hour trade return at .XX price points i on day t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for \$X.01, \$X.49, \$X.51 and \$X.99 on day t

A positive coefficient on intercept indicates that average 24-hour trade return is positive. Next, as a robustness check, we control for liquidity and volatility. First, we test whether round number effects persist after controlling for the liquidity. We use is the relative bid-ask spread to proxy for liquidity. We calculate the relative bid-ask spread by taking the difference between bid price and ask price and then divide it by the average of the bid and ask price (i.e. midpoint price). For each .XX price point, we take the average bid-ask spread for each week during the post-electronic period. A high bid-ask spread indicates low liquidity. A positive coefficient implies wider bid-ask spread (i.e. larger trading costs) and lower market liquidity conditions whereas a negative coefficient implies narrower bid-ask spread (i.e. smaller trading costs) and higher market liquidity conditions in commodity futures market. We also include interaction variables that captures impacts of net positions held by different trader types at price points $X.01, $X.49, $X.51 and $X.99 on liquidity. We estimate the following regression to test whether round number effects persist after controlling for liquidity:

$$
\begin{aligned}
Buysell_{t,i} = {} & \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01} T^j_{t,01} + \alpha_2 X_{t,49} T^j_{t,49} \\
& + \alpha_3 X_{t,51} T^j_{t,51} + \alpha_4 X_{t,99} T^j_{t,99} + \beta_5 T^j_{t,i} + \alpha_5 X_{t,01} T^j_{t,01} Spread_{t,01} \\
& + \alpha_6 X_{t,49} T^j_{t,49} Spread_{t,49} + \alpha_7 X_{t,51} T^j_{t,51} Spread_{t,51} + \alpha_8 X_{t,99} T^j_{t,99}\, Spread_{t,99} \\
& + \beta_6 Spread_{t,i} + \varepsilon_{t,i}
\end{aligned} \tag{7}
$$

where the dependent variable $Buysell_{t,i}$ is the buy-sell ratio at .XX price points i in week t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 in week t, $T^j_{t,i}$ is the net position of trader type j at .XX price points i in week t and $X_{t,01}T^j_{t,01}$, $X_{t,49}T^j_{t,49}$, $X_{t,51}T^j_{t,51}$, $X_{t,99}T^j_{t,99}$ are the net position held by trader type j at price points $X.01, $X.49, $X.51 and $X.99 in week t. $Spread_{t,i}$ is the relative bid-ask spread at .XX price points i in week t and $X_{t,01}T^j_{t,01}Spread_{t,01}$, $X_{t,49}T^j_{t,49}Spread_{t,49}$, $X_{t,51}T^j_{t,51}Spread_{t,51}$, $X_{t,99}T^j_{t,99}\, Spread_{t,99}$ are interaction variables that capture the impact of the net position held by trader type j on liquidity at price points $X.01, $X.49, $X.51 and $X.99 in week t.

Next, we test whether round number effects persist after controlling for volatility. We use the standard deviation of price return to proxy for the volatility. We measure prices in natural logs and calculate returns using the percentage change in the last traded price.

For each .XX price point, we calculate the standard deviation of price return for each week during the post-electronic period. We include interaction variables that captures impacts of net positions held by different trader types at price points \$X.01, \$X.49, \$X.51 and \$X.99 on volatility. Additionally, we also examine impacts of net positions of hedgers and speculators on volatility. We estimate the following regression to test whether round number effects persist after controlling for volatility:

$$\begin{aligned} Buysell_{t,i} = {} & \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01} T^j_{t,01} + \alpha_2 X_{t,49} T^j_{t,49} \\ & + \alpha_3 X_{t,51} T^j_{t,51} + \alpha_4 X_{t,99} T^j_{t,99} + \beta_5 T^j_{t,i} + \alpha_5 X_{t,01} T^j_{t,01} retvol_{t,01} \\ & + \alpha_6 X_{t,49} T^j_{t,49} retvol_{t,49} + \alpha_7 X_{t,51} T^j_{t,51} retvol_{t,51} + \alpha_8 X_{t,99} T^j_{t,99}\, retvol_{t,99} \\ & + \beta_6 retvol_{t,i} + \varepsilon_{t,i} \end{aligned} \quad (8)$$

where the dependent variable $Buysell_t$ is the buy-sell ratio at .XX price points i in week t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for \$X.01, \$X.49, \$X.51 and \$X.99 in week t. $T^j_{t,i}$ is the net position of trader type j at .XX price points i in week t and $X_{t,01}T^j_{t,01}$, $X_{t,49}T^j_{t,49}$, $X_{t,51}T^j_{t,51}$, $X_{t,99}T^j_{t,99}$ are the net position held by trader type j at price points \$X.01, \$X.49, \$X.51 and \$X.99 in week t. $retvol_{t,i}$ is volatility at .XX price points i in week t and $X_{t,01}T^j_{t,01}retvol_{t,01}$, $X_{t,49}T^j_{t,49}retvol_{t,49}$, $X_{t,51}T^j_{t,51}retvol_{t,51}$, $X_{t,99}T^j_{t,99}\, retvol_{t,99}$ are interaction variables that capture the impact of the net position held by trader type j on volatility at price points \$X.01, \$X.49, \$X.51 and \$X.99 in week t

5. Empirical results

5.1. Summary statistics during pre-electronic Period

To obtain a preliminary view of the existence of round number effects, we present descriptive statistics for the median buy-sell ratio for each day at price points from X.01 to X.99 during the pre-electronic period (January 1, 1996 to September 2nd, 2006) in Figures 1 - 4. The buy-sell ratio patterns at price points in Figures 1-3 resembles that of documented in Bhattacharya, Holden and Jacobsen (2012). The sample includes total of over 3.9 million trade observations. Figure 1 shows the median proportion of the net buyer-initiated trades by .XX price point, Figure 2 shows the median proportion of the net volume of buyer-initiated futures contact by .XX price point and Figure 3 shows the median proportion of the net buyer-initiated dollar volume by .XX price point. These median buy-sell ratio figures show a regular pattern every ten cents. All three figures show that at trade price ending in X.X9 buy trades exceeds sell trades whereas at trade price ending in X.X1 sell trades exceeds buy trades. The main message emerging from Figures 1 – 4 is that round number effects exist in WTI crude oil futures market. Figures 1 – 3 are the evidence in favour of Threshold trigger effect as X.X0 and X.X5 are round numbers in decreasing order of roundness. As the left-digit changes around X.X0, Figures 1 – 3 are also evidence in favour of left-digit effect.

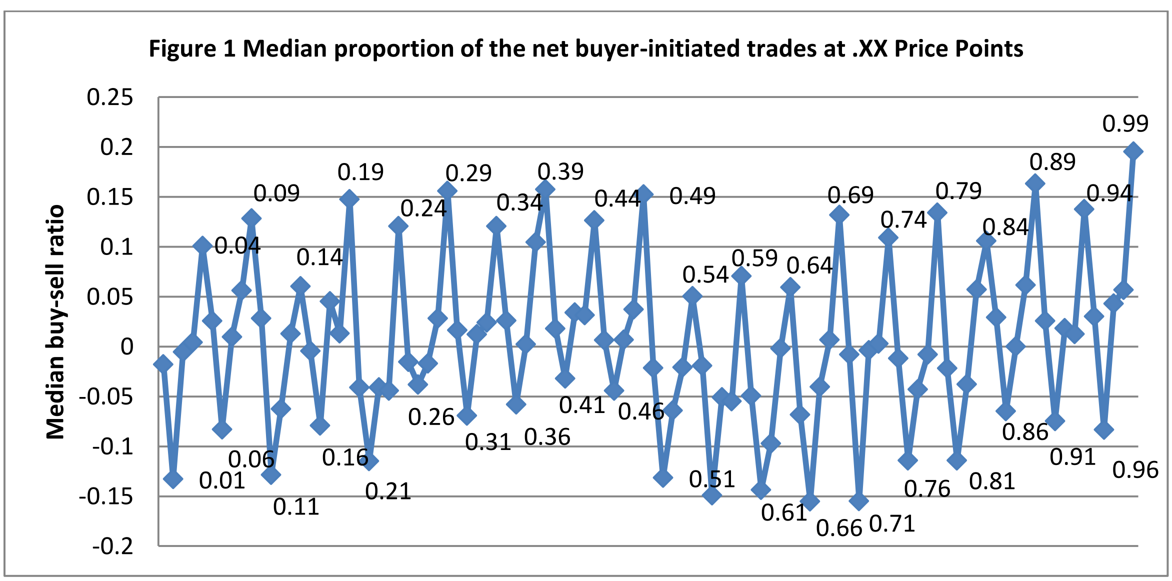

Figure 1 Median proportion of the net buyer-initiated trades at .XX Price Points

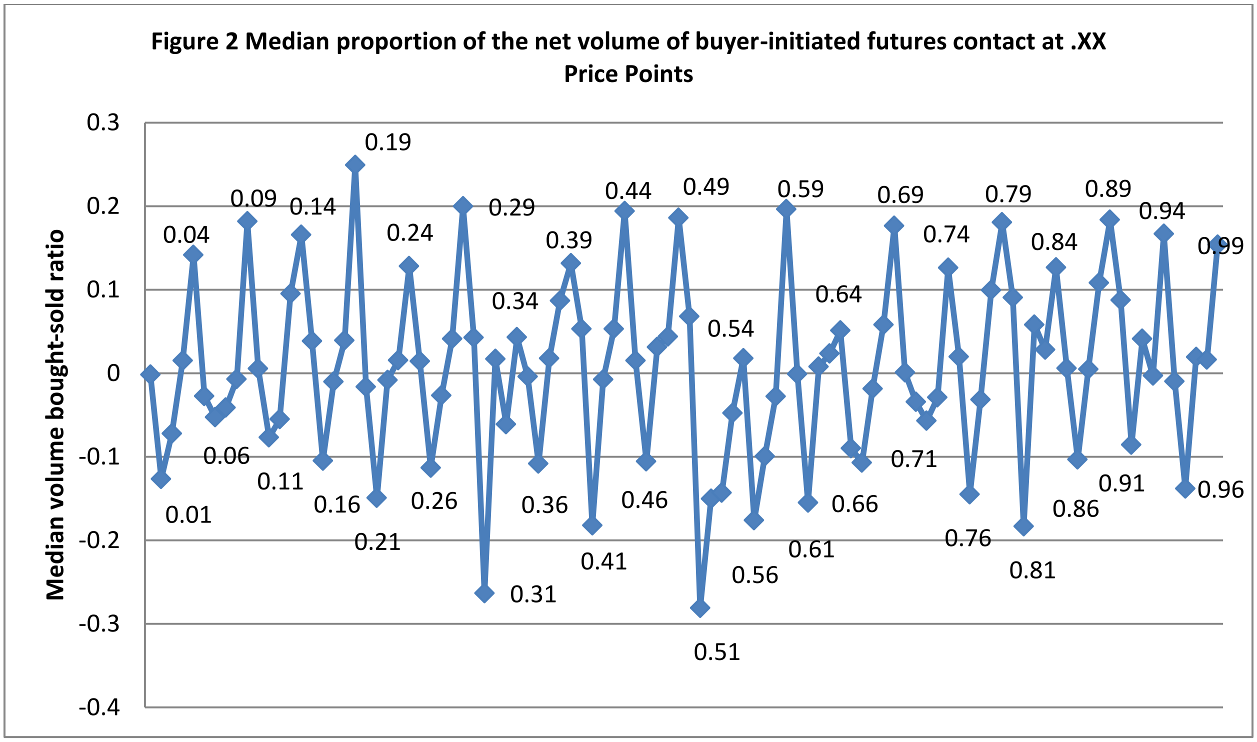

Figure 2 Median proportion of the net volume of buyer-initiated futures contact at .XX Price Points

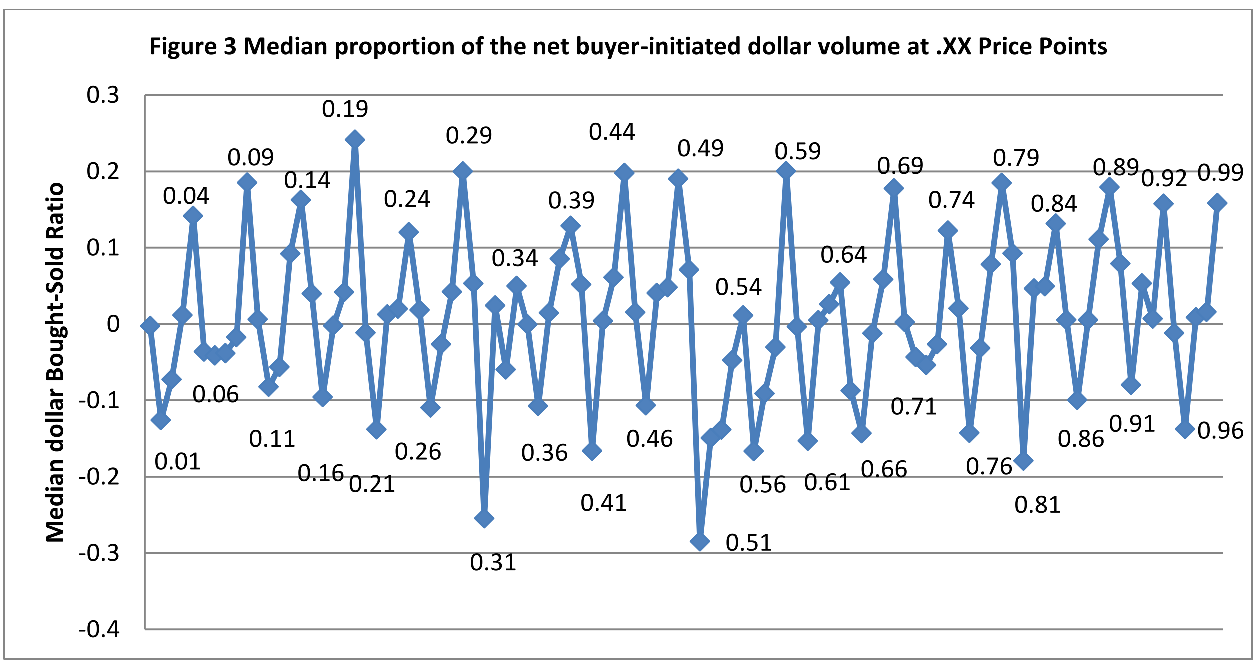

Figure 3 Median proportion of the net buyer-initiated dollar volume at .XX Price Points

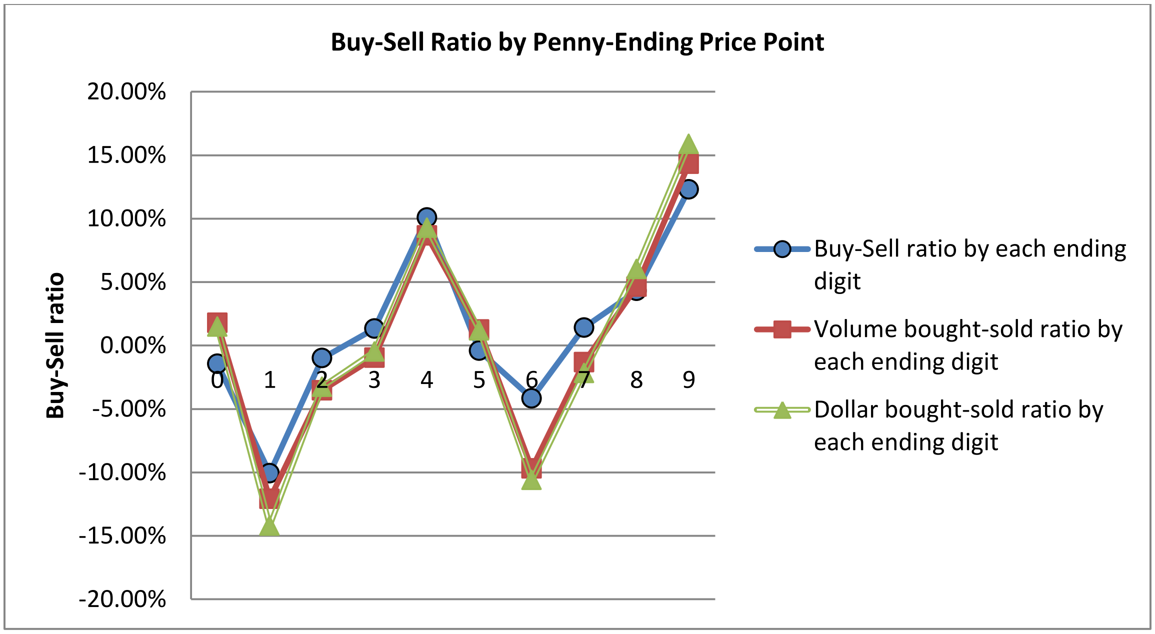

Figure 4 Buy-sell Ratio by Penny-Ending Price Points

Figure 4 explores this further by showing the median buy-sell ratios by penny-ending price points: X0, .X1, …, .X9. Interestingly, the pattern of buy-sell ratios by penny-ending price points is nearly identical for all three buy-sell ratio measures and all three buy-sell ratios show that the highest ratios of buy-sell occurs trade prices ending in .X9, and the lowest ratio of buy-sell occurs at trades ending in .X1. Similarly, the second highest ratios of buy-sell occurs trade prices ending in .X4, and the second lowest ratio of buy-sell occurs at trades ending in .X6. In other words, the largest imbalances occur at the price points surrounding X.X0 and the next largest imbalances occur at the price points surrounding X.X5. Figure 4 is the evidence in favour of Threshold trigger effect as dollars and half-dollars in decreasing order of roundness. As the left-digit changes around X.00 and X.X0, Figure 4 is also in favour of left-digit effect. Finally, Figures 1 – 4 are also evidence in favour of the clustering undercutting effect as this effect occurs around X.00 and X.X0. Limit orders clustered on X.X0 are undercut by limit sells at .X9 to yield excess buying at .X9, and undercut by limit buys at .X1 to yield excess selling at .X1. Figures 1 – 4 suggest that buying and selling at each price point is not uniformly distributed and the buy-sell imbalance patterns at each price point share the same limitation: they are based on static prices.

The above observations lead us to examine the existence of round number effects in commodity futures market. We formalize these observations in the next section by estimating the regression as specified in equation (5).

5.2. Hypothesis 1: existence of round number effects during pre-electronic period

In this section, we examine evidence of existence of round number effects during the pre-electronic period. Here, the objective is to explore whether round number effects exist in WTI crude oil futures market. In Table 1, we present test results of hypothesis 1 as specified in equation (4) for three regressions based on three versions of buy-sell ratios.

Results in Table 1 show that for all three regressions, the coefficients on just below a round number (X.99) are all positive and statistically significant at 1 percent level, indicating excess buying just below a round number. The results support the marketing research by Thomas and Morwitz (2005) who find 9-ending price is perceived to be substantially lower than a 0-ending price when the leftmost digit changes. The results show that the opposite is true for the coefficients just above a round number (X.01). The coefficients on just above a round number are all negative and statistically significant at 1 percent level, indicating excess selling just above a round number. These results are consistent with the prediction of round number effects and we confirm the existence of round number effects in WTI crude oil futures market. The finding of excess buying just below a round number (X.99) and excess selling just above a round number (X.01) is consistent with previous research (Bhattacharya, Holden and Jacobsen, 2012). In addition, the results in Table 1 also show that for all three regressions, the coefficients on just below a half-dollar are all positive and statistically significant at 1 percent level and the coefficients on just above a half-dollar are all negative and statistically significant at 1 percent level. The results are consistent with threshold trigger effect that investors have a preference for round numbers where the hierarchy of roundness from the most round to the least round is whole dollars, half-dollars (i.e. the midpoint of round number), quarters, dimes, nickels and pennies.

Overall, we find evidence that round number effects exist during the pre-electronic period.

Table 1

Three regressions based on three versions of buy-sell ratios on price points $X.01, $X.49, $X.51 and $X.99

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	0.0141	0.0000	***	0.0063	0.1409	***	0.0070	0.1029	***
$X_{t,01}$	-0.1142	0.0001	***	-0.1624	0.0001	***	-0.1619	0.0001	***
$X_{t,49}$	0.1158	0.0001	***	0.1518	0.0003	***	0.1524	0.0003	***
$X_{t,51}$	-0.1248	0.0000	***	-0.2290	0.0000	***	-0.2294	0.0000	***
$X_{t,99}$	0.1552	0.0000	***	0.1572	0.0002	***	0.1589	0.0002	***

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$Buysell_{t,i} = \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \varepsilon_{t,i} \tag{4}$$

where the dependent variable $Buysell_{t,i}$is the buy-sell ratio at .XX price points i on day t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 on day t. The data sample for the pre-electronic period is based on all trades and quotes over the period from January 1, 1996 to September 2nd, 2006, containing a total of over 3.9 million trade observations.

5.3. Summary statistics during post-electronic period

We continue exploring the existence of round number effects for the post-electronic period.

On September 3, 2006, U.S. commodity futures market introduced the electronic platform and since then there has been a substantial increase in trading activity of speculators and commodity investing in commodity futures market as shown in Figure 5 and 6. In our data, while we only observe the total of 3.9 million trade observations during the pre-electronic period, we observe the total of 148 million trade observations in the post-electronic period and that is nearly 38 times more trade observations than that of post-electronic period. During the boom and bust of commodity price in 2008, investors held their biggest position on record in the commodity futures market.

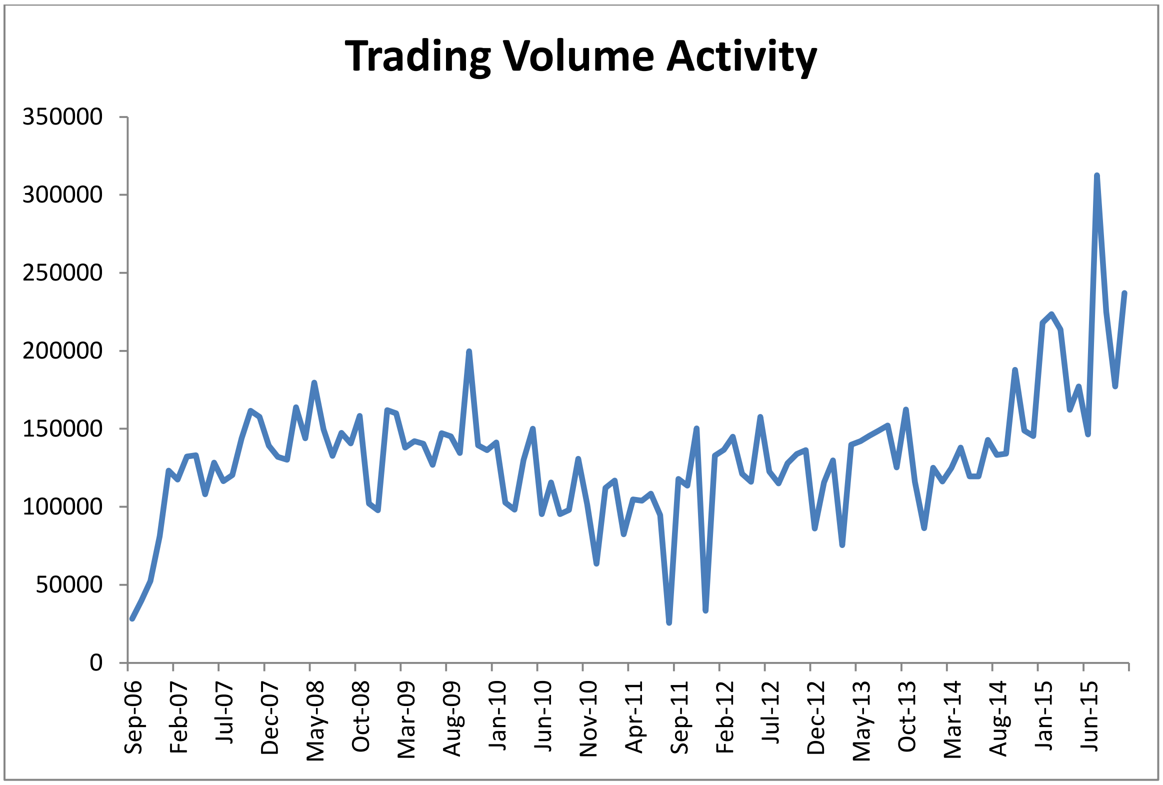

Figure 5 shows the Crude oil futures daily average trading volume (in contracts) from September 03, 2006 to October 31, 2015

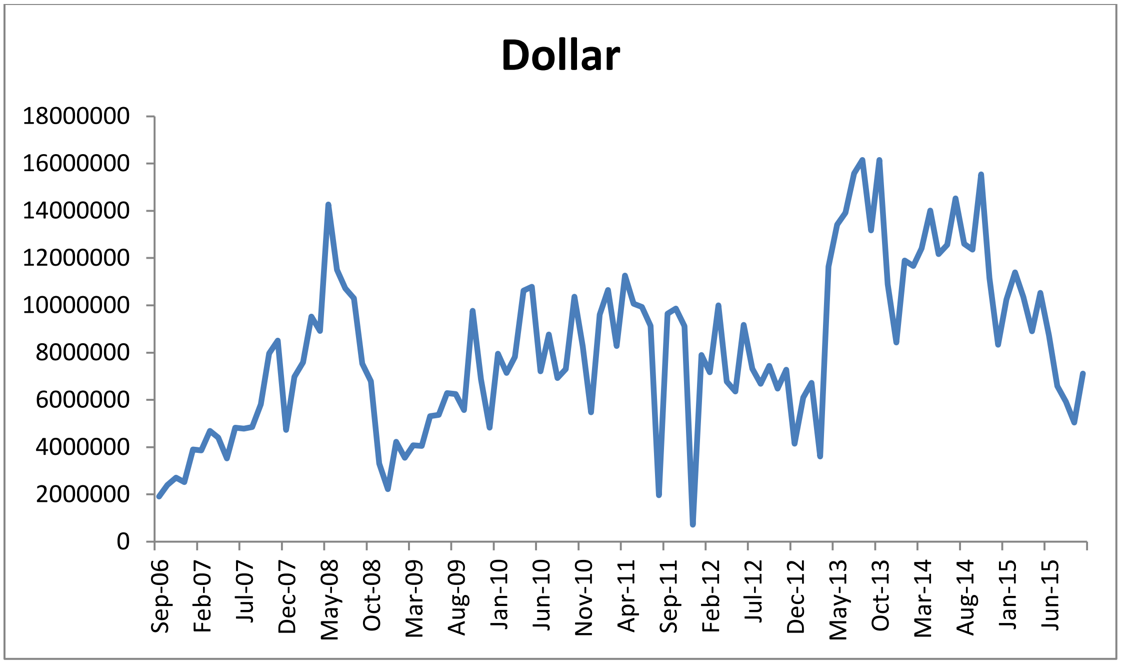

Figure 6 shows the WTI daily average dollar trading from September 2006 to October 2015

To obtain a preliminary view of the existence of round number effects in the post-electronic period (September 3rd, 2006 to October 31, 2015), we present descriptive statistics for median buy-sell ratio for each day at price points from X.01 to X.99 during the post-electronic period in Figures 7 - 10. Figure 7 shows the median proportion of the net buyer-initiated trades by .XX price point, Figure 8 shows the median proportion of the net volume of buyer-initiated futures contact by .XX price point and Figure 9 shows the median proportion of the net buyer-initiated dollar volume by .XX price point. Figures 7 – 9 show similar buy-sell ratio patterns to that of pre-electronic period. All three figures show that at trade price ending just below dollars, half-dollars, quarters, dimes and nickels (i.e. X.99, X.49, X.24, X.09, X.04) buy trades exceeds sell trades whereas at trade price ending just above dollars, half-dollars, quarters, dimes and nickels (i.e. X.01, X.51, X.26, X.11, X.06) sell trades exceeds buy trades. Figures 7 – 9 are the evidence in favour of Threshold trigger effect as dollars, half-dollars, quarters, dimes and nickels are round numbers in decreasing order of roundness. As the left-digit changes around X.X0, Figures 7 – 9 are also evidence in favour of left-digit effect.

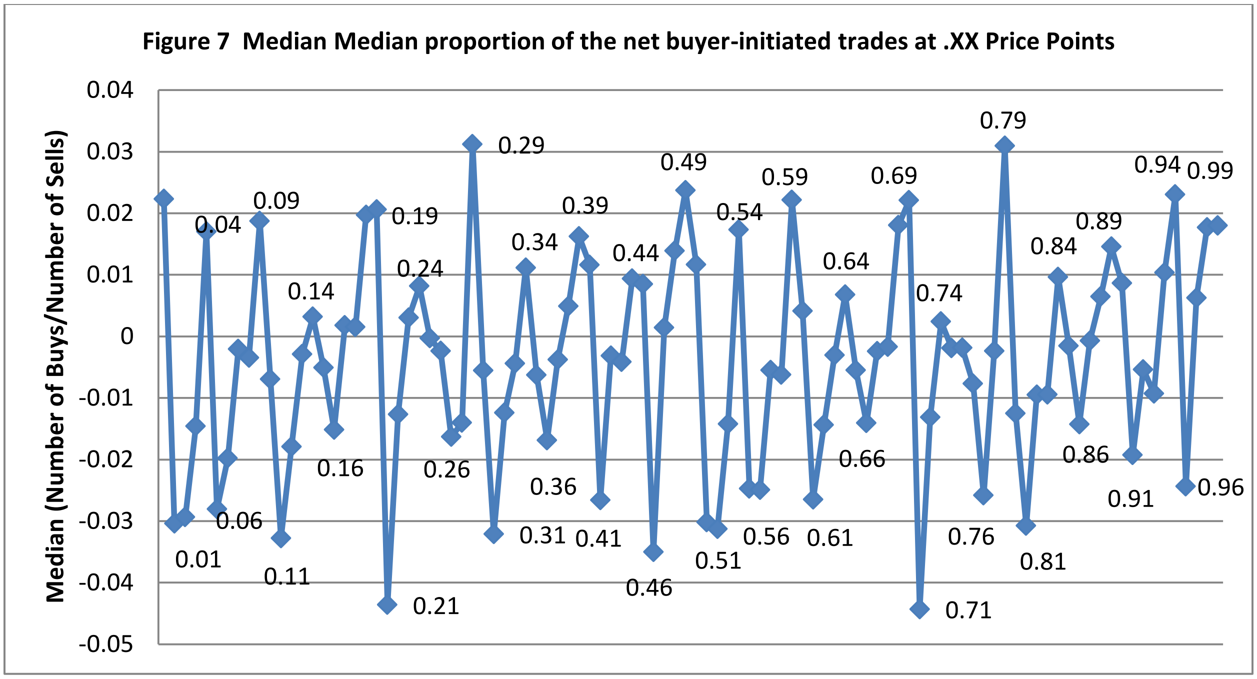

Figure 7 Median proportion of the net buyer-initiated trades at .XX Price Points

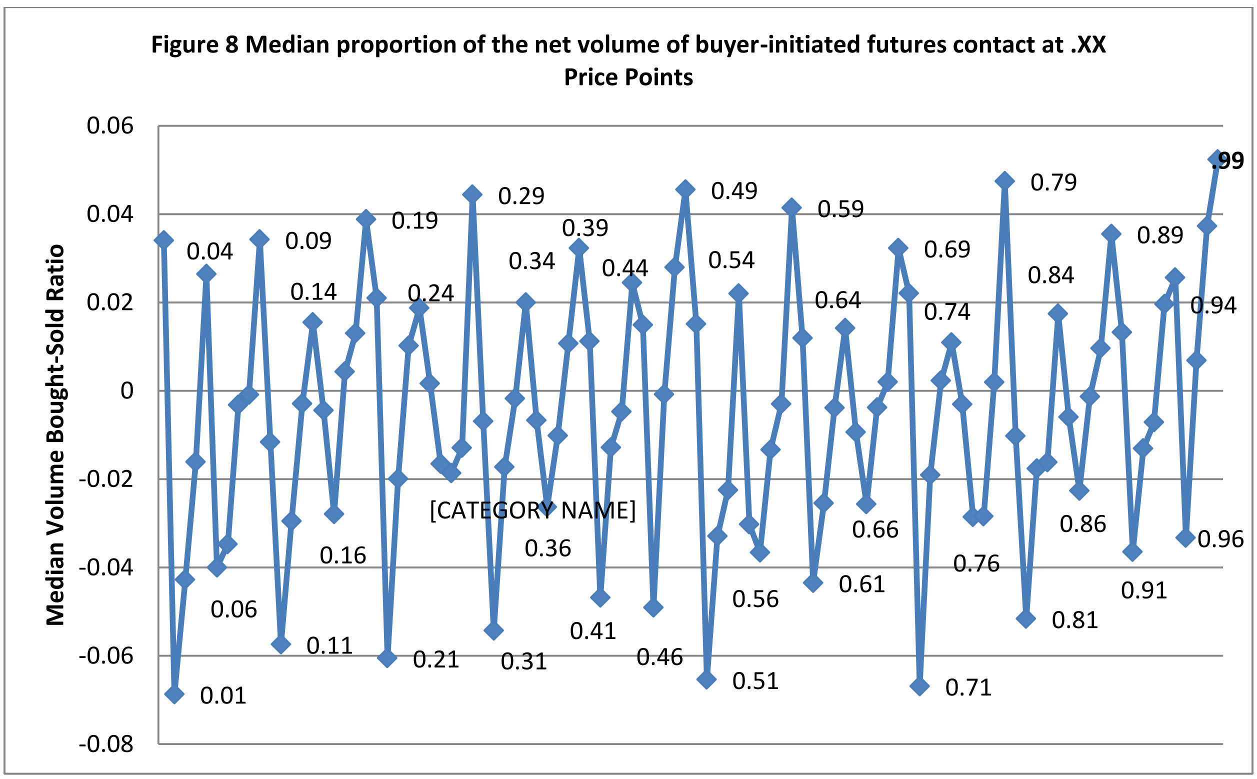

Figure 8 Median proportion of the net volume of buyer-initiated futures contact at .XX Price Points

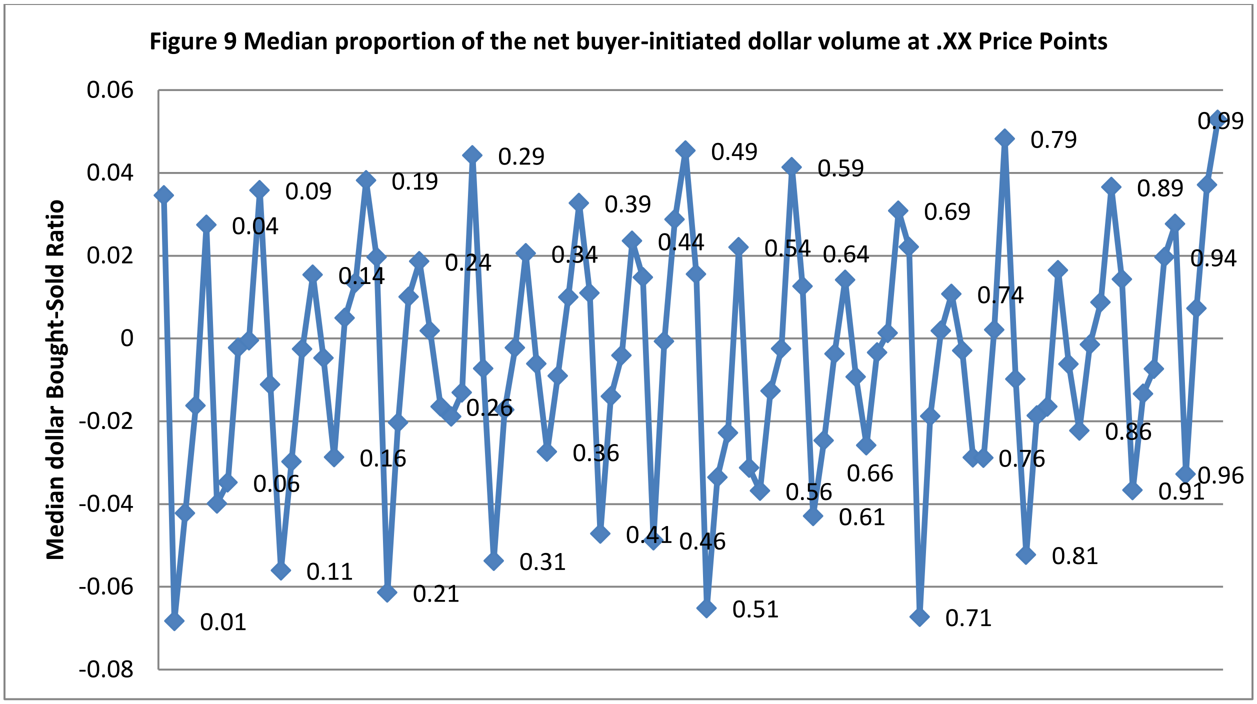

Figure 9 Median proportion of the net buyer-initiated dollar volume at .XX Price Points

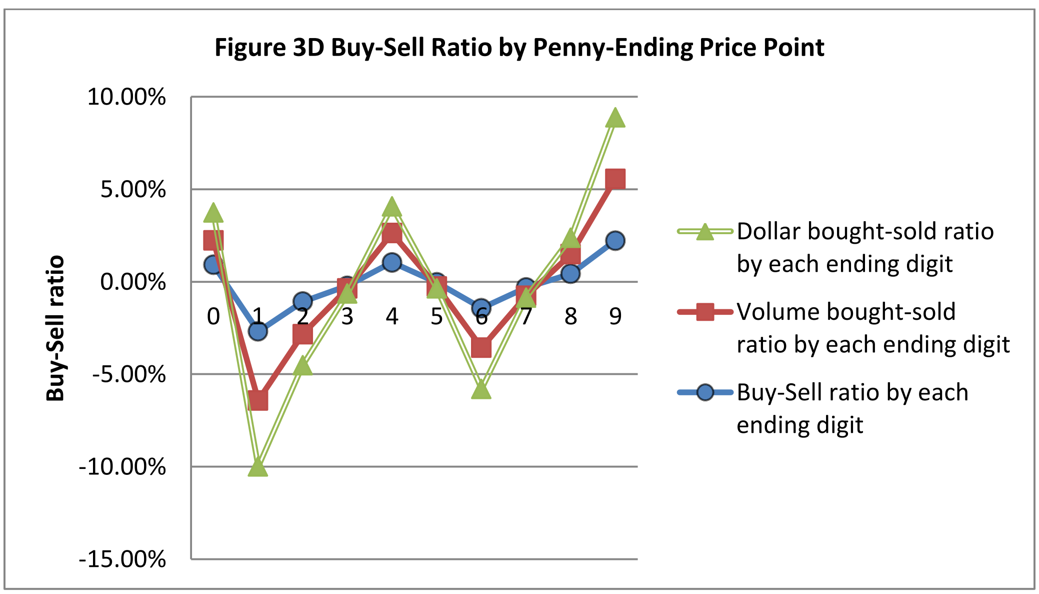

Figure 10 Buy-sell Ratio by Penny-Ending Price Point

Figure 10 explores this further by showing the median buy-sell ratios by penny-ending price points: X0, .X1, …, .X9. Similar to that of pre-electronic period, the pattern of buy-sell ratios by penny-ending price points is nearly identical for all three buy-sell ratio measures and all three buy-sell ratios show that the highest ratios of buy-sell occurs trade prices ending in X.X9, and the lowest ratio of buy-sell occurs at trades ending in X.X1. The next highest ratios of buy-sell occurs trade prices ending in X.X4, and the second lowest ratio of buy-sell occurs at trades ending in X.X6. Figure 10 is the evidence in favour of Threshold trigger effect as X.X0 and nickel (X.X5) are in decreasing order of roundness. As the left-digit changes around X.00 and X.X0, Figure 10 is also in favour of left-digit effect. Finally, Figures 7 – 10 are also evidence in favour of the clustering undercutting effect as this effect is around round numbers. Limit orders clustered on X.X0 are undercut by limit sells at X.X9 to yield excess buying at X.X9, and undercut by limit buys at X.X1 to yield excess selling at X.X1. Figures 7 – 10 show that buying and selling at each price point is still not uniformly distributed even with the electronic platform, with the largest imbalances occur at the price points surrounding X.X0 and the next largest imbalances occur at the price points surrounding X.X5 (nickels).

The above observations lead us to examine the existence of round number effects during the post-electronic period. We formalize these observations in the next section by estimating the regression as specified in equation (5).

5.4. Hypothesis 1: existence of round number effects during post-electronic period

In this section, we examine evidence of existence of round number effects during the post-electronic period. Here, the objective is to explore whether round number effects exist after the introduction of the electronic platform to WTI crude oil futures market. In Table 2, we present test results of hypothesis 1 as specified in equation (3) for three regressions based on three versions of buy-sell ratios.

Results in Table 2 show that for all three regressions, the coefficients on just below a round number (X.99) are all positive and statistically significant at 1 percent level, indicating excess buying just below a round number. The results show that the opposite is true for the coefficients just above a round number (X.01). The coefficients on just above a round number are all negative and statistically significant at 1 percent level, indicating excess selling just above a round number. These results are consistent with the prediction of round number effects as specified in equation (3) and we confirm the existence of round number effects even after the adoption of the electronic platform to WTI crude oil futures market. The finding of excess buying just below a round number (X.99) and excess selling just above a round number (X.01). In addition, the results in

Table 2 also show that for all three regressions, the coefficients on just below a half-dollar are all positive and statistically significant at 1 percent level and the coefficients on just above a half-dollar are all negative and statistically significant at 1 percent level. The results are consistent with threshold trigger effect that investors have a preference for round numbers where the hierarchy of roundness from the most round to the least round is whole dollars, half-dollars (i.e. the midpoint of round number), quarters, dimes, nickels and pennies.

Overall, we find evidence that round number effects exist during the post-electronic period.

Table 2
Three regressions based on three versions of buy-sell ratios on price points $X.01, $X.49, $X.51 and $X.99

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0033	0.0000	***	-0.0029	0.0000	***	-0.0027	0.0000	***
$X_{t,01}$	-0.0416	0.0000	***	-0.0505	0.0000	***	-0.0505	0.0000	***
$X_{t,49}$	0.0254	0.0000	***	0.0306	0.0000	***	0.0306	0.0000	***
$X_{t,51}$	-0.0347	0.0000	***	-0.0471	0.0000	***	-0.0471	0.0000	***
$X_{t,99}$	0.0236	0.0000	***	0.0344	0.0000	***	0.0344	0.0000	***

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$Buysell_{t,i} = \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \varepsilon_{t,i} \quad (4)$$

where the dependent variable $Buysell_{t,i}$is the buy-sell ratio at .XX price points i on day t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 on day t.The post-electronic sample period is based on all trades and quotes over the period from September 3rd, 2006 to October 31, 2015, containing a total of over 148 million trade observations

5.5. Conditional Buy-sell Imbalance Tests

Since both pre and post-electronic periods produce virtually the same evidence for the existence of round number effects, we are now interested in determining which of three round number effects is more prevalent than the other two. We use “nickel” as a benchmark to “round number”. We examine four conditional buy-sell imbalance: “ask falls below a round number”, “ask falls to a round number”, “bid rises to a round number”, “bid rises above a round number” samples and their corresponding “ask falls below a nickel”, “ask falls to a nickel”, “bid rises to a nickel”, “bid rises above a nickel” samples. We use *t*-statistic to assess the significance. Table 3 present the main conditional results.

Panel A contains the difference in median (mean) buy–sell ratio between the “ask falls below a round number” sample and the “ask falls below a nickel” benchmark. For all six regressions, the coefficient is negative and one of them is statistically significant at 5 percent. The results indicate that there is greater excess buying just below a nickel than that of just a round number. Thus, the results provide no evidence in favour of round number effects here.

Panel B contains the difference in median (mean) buy–sell ratio between the “ask falls to a round number” sample and the “ask falls to a nickel” benchmark. For all six regressions, the coefficient is positive and one of them is statistically significant at 10 percent. The results indicate that there is greater excess buying when ask price falls to a round number than that of a nickel. Thus, the results provide evidence in favour of round number effects here. The evidence is in favour of the threshold trigger but the results cannot be explained by the left-digit and the clustering undercutting effect.

Panel C contains the difference in median (mean) buy–sell ratio between the “bid rises to integer” sample and the “bid rises to a nickel” benchmark. For all six regressions, the coefficient is negative and two of them is statistically significant at 5 percent. The results indicate that there is greater excess selling when bid price rises to a round number than that of a nickel. Thus, the results provide evidence in favour of round number effects here. The evidence is in favour of the left-digit effect and threshold trigger effect but the results cannot be explained by the clustering undercutting effect.

The Panel D contains the difference in median (mean) buy–sell ratio between the “bid rises above a round number” sample and the “bid rises above a nickel” benchmark. For all six regressions, the coefficient is positive and two of them are statistically significant at 5 percent. The results indicate that there is greater excess selling when bid price rises to a nickel than that of a round number. Thus, the results provide no evidence in favour of round number effects here.

Overall, we find excess buying when ask price falls to a round number and excess selling when bid price rises to a round number. Thus, the evidence is in favour of the threshold trigger effect.

Table 3
The Difference in Median (Mean) Buy-Sell Ratios

	OIB#	*t*-stat		OIBVol	*t*-stat	OIB$	*t*-stat
	Panel A: Ask Falls Below a round number vs. Ask Falls Below a Nickel						
Difference in Median buy-sell ratios	-0.0012	-0.1962		-0.0016	-0.0010	-0.0016	-0.0011
Difference in Mean buy-sell ratios	-0.0141	-2.3111	**	-0.0094	-0.0056	-0.0095	-0.0067
	Panel B: Ask Falls to a round number vs. Ask Falls to a Nickel						
Difference in Median buy-sell ratios	0.0076	0.9697		0.0244	0.0142	0.0239	0.0169
Difference in Mean buy-sell ratios	0.0124	1.5910	*	0.0260	0.0151	0.0260	0.0184
	Panel C: Bid Rises to a round number vs. Bid Rises to a Nickel						
Difference in Median buy-sell ratios	-0.0244	-2.7385	**	-0.0259	-0.0154	-0.0259	-0.0183
Difference in Mean buy-sell ratios	-0.0441	-4.9406	**	-0.0551	-0.0328	0.0620	0.0439
	Panel D: Bid Rises Above a round number vs. Bid Rises Above a Nickel						
Difference in Median buy-sell ratios	0.0583	5.1825	**	0.0715	0.0435	0.0712	0.0503
Difference in Mean buy-sell	0.0537	4.7748	**	0.0620	0.0378	0.0620	0.0439

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$tstat = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{\sigma_1}{n_1} + \frac{\sigma_2}{n_2}}} \tag{3}$$

where $\bar{x}_1$ is either median or mean buy-sell ratios, σ_1 is the standard deviation, and n_1 is the number of observation for round numbers and $\bar{x}_2$ is either median or mean buy-sell ratios, σ_2 is the standard deviation, and n_2 is the number of observation for nick benchmarks. The post-electronic sample period is based on all trades and quotes over the period from September 3rd, 2006 to October 31, 2015, containing a total of over 148 million trade observations

5.6. Hypothesis 2: impacts of hedging and speculating on round number effects

Table 4 presents the test results of hypothesis 2 as specified in equation (5). Here, the objective is to explore what trader type – hedger or speculator – influences round number effects.

For all three regressions, Panel A shows that the coefficient on the interaction variables is negative when there is excess selling just above a round number and statistically significant at 1 percent. The opposite is true for the coefficient for hedgers when there is excess buying just above a round number. Panel A shows that the coefficient on the interaction variables is positive when there is excess buying just above a round number and statistically significant at 1 percent. The results indicate that the net position held by hedgers just above a round number is short position and net position held by hedgers just below a round number is long position which is consistent with the prediction of hypothesis 2.

Panel B shows opposite is true for speculators. For all three regressions, Panel B shows that the coefficient on the interaction variables is positive when there is excess selling just above a round number and statistically significant at 1 percent. The results indicate that the net position held by speculators is long position but the size of the long position is about twice smaller than that of short position held by hedgers just above a round number. Panel A also shows that the coefficient on the interaction variables is negative when there is excess buying just above a round number and statistically significant at 1 percent. The results indicate that the net position held by speculators is short position but the size of the short position is about twice smaller than that of long position held by hedgers just below a round number. The results indicate that the net position held by speculators just above a round number is long position and net position held by speculators just below a round number is short position which is inconsistent with the prediction of hypothesis 2. The results are consistent with thought that Speculators hold positions opposite those of hedgers, thereby providing liquidity to the market. The results also support the findings of Sanders, Irwin and Merrin (2010) and

Till (2009) who document evidence that speculation rises as a response to a rise in hedging demand.

Overall, when we divide commodity futures market traders into hedgers and speculators, we find that trading activity of hedgers influences round number effects.

Table 4
The impact of positions of commercial traders and non-commercial traders on buy-sell ratios above and below a round number

Panel A: the independent variable $T_{t,i}^{i}$ is hedger

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0114	0.0000	***	-0.0120	0.0000	***	-0.0118	0.0000	***
$X_{t,01}$	-0.0551	0.0000	***	-0.1121	0.0000	***	-0.1120	0.0000	***
$X_{t,49}$	0.0370	0.0000	***	0.0816	0.0000	***	0.0818	0.0000	***
$X_{t,51}$	-0.0480	0.0000	***	-0.1026	0.0000	***	-0.1025	0.0000	***
$X_{t,99}$	0.0395	0.0000	***	0.1041	0.0000	***	0.1041	0.0000	***
$X_{t,01}T_{t,01}^{i}$	-3.2820	0.0000	***	-8.4644	0.0000	***	-8.4403	0.0000	***
$X_{t,49}T_{t,49}^{i}$	2.4709	0.0001	***	6.5620	0.0000	***	6.5665	0.0000	***
$X_{t,51}T_{t,51}^{i}$	-2.7400	0.0000	***	-7.0606	0.0000	***	-7.0445	0.0000	***
$X_{t,99}T_{t,99}^{i}$	2.2004	0.0006	***	7.6158	0.0000	***	7.6234	0.0000	***
$T_{t,i}^{i}$	-1.0169	0.0000	***	-1.1450	0.0000	***	-1.1426	0.0000	***

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 4 (Continued)

Panel B: the independent variable $T_{t,i}^{i}$ is speculator

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0121	0.0000	***	-0.0128	0.0000	***	-0.0127	0.0000	***
$X_{t,01}$	-0.0601	0.0000	***	-0.1253	0.0000	***	-0.1253	0.0000	***
$X_{t,49}$	0.0474	0.0000	***	0.0960	0.0000	***	0.0962	0.0000	***
$X_{t,51}$	-0.0542	0.0000	***	-0.1157	0.0000	***	-0.1156	0.0000	***
$X_{t,99}$	0.0463	0.0000	***	0.1171	0.0000	***	0.1171	0.0000	***
$X_{t,01}T_{t,01}^{i}$	1.2814	0.0000	***	3.3139	0.0000	***	3.3077	0.0000	***
$X_{t,49}T_{t,49}^{i}$	-1.2057	0.0000	***	-2.7168	0.0000	***	-2.7198	0.0000	***
$X_{t,51}T_{t,51}^{i}$	1.1449	0.0000	***	2.8375	0.0000	***	2.8350	0.0000	***
$X_{t,99}T_{t,99}^{i}$	-0.9837	0.0000	***	-3.0210	0.0000	***	-3.0240	0.0000	***
$T_{t,i}^{i}$	0.3643	0.0000	***	0.4133	0.0000	***	0.4122	0.0000	***

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$Buysell_{t,i} = \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01} T_{t,01}^{j} + \alpha_2 X_{t,49} T_{t,49}^{j} + \alpha_3 X_{t,51} T_{t,51}^{j} + \alpha_4 X_{t,99} T_{t,99}^{j} + \beta_5 T_{t,i}^{j} + \varepsilon_{t,i} \quad (5)$$

where the dependent variable $Buysell_t$ is the buy-sell ratio at .XX price points i in week t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 in week t. $T_{t,i}^{j}$is the net position of trader type j at .XX price points i in week t and $X_{t,01}T_{t,01}^{j}$, $X_{t,49}T_{t,49}^{j}$, $X_{t,51}T_{t,51}^{j}$, $X_{t,99}T_{t,99}^{j}$ are the net position held by trader type j at price points $X.01, $X.49, $X.51 and $X.99 in week t. The post-electronic sample period is based on all trades and quotes over the period from September 3rd, 2006 to October 31, 2015, containing a total of over 148 million trade observations

5.7. Hypothesis 3: the determinants of 24-hour trade return

Having explored that trading activity of hedgers influences round number effects, we examine results for 24-hour trade return based on round number effects in this section. Table 5 present test results of hypothesis 3 as in equation (6). Here, the objective is to explore whether round number effects is a major determinant of 24-hour positive trade return as documented in Bhattacharya, Holden and Jacobsen (2012). In contrast to the finding of Bhattacharya, Holden and Jacobsen (2012), our results in Table 5 show that round number effects have no explanatory power in 24-hour positive trade return. The intercept in Table 5 has negative sign and statistically significant at 1 percent level. The intercept in Table 5 suggest that the average 24-hour trade return based on round number effects is negative return of 0.0014 percent. This finding contrasts with that for US stock markets. Furthermore, the 24-hour trade return decreases by 0.0007 for traders who buy just below a round number.

Table 5
Difference in Median 24-Hour Returns Regressed on Price Point Dummies

	Difference in median 24-hour trade price returns (median return to buying - median return to selling) (%)	*p*-value	
Intercept	-0.0014	0.0000	***
$X_{t,01}$	-0.0006	0.1589	
$X_{t,49}$	0.0002	0.6210	
$X_{t,51}$	0.0005	0.2651	
$X_{t,99}$	-0.0007	0.0842	*

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$24hour\ trade\ return_{t,i} = \alpha_{i,t} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \varepsilon_{i,t} \tag{6}$$

where the dependent variable is 24-hour trade return at .XX price points i on day t and $X_{t,01}$, $X_{t,49}$, $X_{t,51}$, $X_{t,99}$ are price points dummy variables for $X.01, $X.49, $X.51 and $X.99 on day t. The post-electronic sample period is based on all trades and quotes over the period from September 3rd, 2006 to October 31, 2015, containing a total of over 148 million trade observations

The negative mean 24-hour trade return is consistent with Sanders, Boris, and Manfredo (2004) who provide evidence that there is negative correlation between returns and net position held by hedgers in energy futures market. The results are also confirms the findings of Schwarz (2012) and Dewally, Ederington and Fernando (2013) who document that the net position of hedgers is negatively related to their trade return in commodity futures market. In addition, These results in Table 5 also support the findings of Nofsinger and Sias (1999) and Kamesaka, Nofsinger and Kawakita (2003) that behavioural biased trading generate low returns.

Overall, we find that round number effects have no explanatory power in 24-hour positive trade return and the mean 24-hour trade return based on round number effects is negative 0.0014 percent.

5.8 Robustness

To confirm our main results in Table 4 are robust, we conduct two robustness checks. We use two market quality variables – market liquidity (i.e. measured by the relative bid-ask spread) and market volatility (i.e. measured by standard deviation of price return) to test for the robustness of our main results in Table 4. Additionally, we examine the impact of trading activity of hedgers and speculators on the market liquidity and volatility.

5.8.1 Liquidity and trading activity

In this section, the objective is to examine whether round number effects remain robust after controlling for market liquidity. In Table 6, we present the results for the robustness check after controlling for market liquidity as specified in equation (7). The inclusion of market liquidity does not weaken our main results in Table 4. For all three regressions, the coefficient on just above and below a round number is still significant at the 1 percent level and thus, controlling for market liquidity, round number effects remain robust.

Additionally, we also examine the interaction between trading activity of different trader types and market liquidity. For all three regressions, Panel A shows that the coefficient on the interaction variables is positive and statistically significant at 1 percent when there is excess selling by hedgers just above a round number. The opposite is true when there is excess buying by hedgers just below a round number. For all three regressions, Panel A shows that the coefficient on the interaction variables is negative and statistically significant at 1 percent when there is excess buying by hedgers just below a round number. The results indicate that the bid-ask spread is wider (i.e. low liquidity) when there is excess selling and the bid-ask spread is narrower (i.e. high liquidity) when there is excess buying and consistent with Huang and Chou (2007). The opposite is true for speculators. For all three regressions, Panel B shows that the coefficient on the interaction variables is negative and statistically significant at 1 percent when there is excess selling by hedgers just above a round number. However, the impact is about four times smaller than that of hedgers. For all three regressions, Panel B shows that the coefficient on the interaction variables is positive and statistically significant at 1 percent when there is excess buying by hedgers just below a round number. However, the impact is about three times smaller than that of hedgers.

Overall, we find that net position of hedgers has an asymmetric effect on market liquidity. We find that there is negative relation between excess selling and market liquidity (i.e. wider bid-ask spread) and positive relation between excess buying and market liquidity (i.e. narrower bid-ask spread).

Table 6
Robustness check after controlling for market liquidity measured by the relative bid-ask spread

Panel A: the independent variable $T_{t,i}^{j}$ is hedger

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0047	0.0083	***	-0.007	0.009	***	-0.007	0.009	***
$X_{t,01}$	-0.0512	0.0000	***	-0.103	0.000	***	-0.103	0.000	***
$X_{t,49}$	0.0326	0.0000	***	0.073	0.000	***	0.073	0.000	***
$X_{t,51}$	-0.0431	0.0000	***	-0.094	0.000	***	-0.094	0.000	***
$X_{t,99}$	0.0334	0.0000	***	0.097	0.000	***	0.097	0.000	***
$X_{t,01}T_{t,01}^{i}$	-7.3338	0.0000	***	-17.261	0.000	***	-17.277	0.000	***
$X_{t,49}T_{t,49}^{i}$	6.5534	0.0000	***	14.487	0.000	***	14.483	0.000	***
$X_{t,51}T_{t,51}^{i}$	-7.3676	0.0000	***	-15.122	0.000	***	-15.160	0.000	***
$X_{t,99}T_{t,99}^{i}$	8.0681	0.0000	***	14.529	0.000	***	14.531	0.000	***
$T_{t,i}^{j}$	-0.8803	0.0000	***	-1.038	0.000	***	-1.040	0.000	***
$X_{t,01}T_{t,01}^{i}Spread_{t,01}$	27.1765	0.0003	***	59.051	0.000	***	59.325	0.000	***
$X_{t,49}T_{t,49}^{i}Spread_{t,49}$	-27.7025	0.0003	***	-53.812	0.000	***	-53.755	0.000	***
$X_{t,51}T_{t,51}^{i}Spread_{t,51}$	31.2386	0.0000	***	54.428	0.000	***	54.792	0.000	***
$X_{t,99}T_{t,99}^{i}\ Spread_{t,99}$	-39.7977	0.0000	***	-46.880	0.000	***	-46.846	0.000	***
$Spread_{t,i}$	-29.2537	0.0000	***	-22.879	0.023	**	-22.047	0.029	**

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 6 – (Continued)

Panel B: the independent variable $T_{t,i}^{j}$ is speculator

	OIB#	p-value		OIBVol	p-value		OIB$	p-value	
Intercept	-0.0075	0.0001	***	-0.011	0.000	***	-0.011	0.000	***
$X_{t,01}$	-0.0533	0.0000	***	-0.112	0.000	***	-0.112	0.000	***
$X_{t,49}$	0.0448	0.0000	***	0.088	0.000	***	0.088	0.000	***
$X_{t,51}$	-0.0460	0.0000	***	-0.103	0.000	***	-0.102	0.000	***
$X_{t,99}$	0.0337	0.0000	***	0.106	0.000	***	0.106	0.000	***
$X_{t,01}T_{t,01}^{i}$	2.3101	0.0000	***	5.247	0.000	***	5.256	0.000	***
$X_{t,49}T_{t,49}^{i}$	-1.5810	0.0004	***	-3.866	0.000	***	-3.865	0.000	***
$X_{t,51}T_{t,51}^{i}$	2.3360	0.0000	***	4.720	0.000	***	4.732	0.000	***
$X_{t,99}T_{t,99}^{i}$	-2.8395	0.0000	***	-4.661	0.000	***	-4.662	0.000	***
$T_{t,i}^{j}$	0.3273	0.0000	***	0.395	0.000	***	0.396	0.000	***
$X_{t,01}T_{t,01}^{i}Spread_{t,01}$	-7.8853	0.0099	***	-14.832	0.001	***	-14.949	0.001	***
$X_{t,49}T_{t,49}^{i}Spread_{t,49}$	2.9118	0.3315		8.931	0.040	**	8.893	0.040	**
$X_{t,51}T_{t,51}^{i}Spread_{t,51}$	-9.2101	0.0024	***	-14.558	0.001	***	-14.672	0.001	***
$X_{t,99}T_{t,99}^{i}\,Spread_{t,99}$	14.3852	0.0000	***	12.712	0.004	***	12.692	0.004	***
$Spread_{t,i}$	-18.9280	0.0102	**	-9.288	0.384		-8.441	0.429	

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$\begin{aligned} Buysell_{t,i} = {} & \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01}T_{t,01}^{j} + \alpha_2 X_{t,49}T_{t,49}^{j} + \alpha_3 X_{t,51}T_{t,51}^{j} + \alpha_4 X_{t,99}T_{t,99}^{j} + \beta_5 T_{t,i}^{j} \\ & + \alpha_5 X_{t,01}T_{t,01}^{j}Spread_{t,01} + \alpha_6 X_{t,49}T_{t,49}^{j}Spread_{t,49} + \alpha_7 X_{t,51}T_{t,51}^{j}Spread_{t,51} + \alpha_8 X_{t,99}T_{t,99}^{j}\,Spread_{t,99} \\ & + \beta_6 Spread_{t,i} + \varepsilon_{t,i} \end{aligned} \tag{7}$$

where the variables are as defined in Equation (6). The relative bid-ask spreads are multiplied by 1000.

The results also show that the coefficients on bid-ask interaction variable just above a round number and half-dollar are all positive and statistically significant at 1 percent level, indicating that commodity market is relatively illiquid when the net position of hedgers are short. Panel B shows the regression results from estimating equation (6) where the independent variable T_t^i is speculator. In Panel B, the coefficients for the bid-ask interaction just above a round number and half-dollar are all negative and statistically significant at 1 percent level, indicating that the trading activity of speculators reduces transaction costs when their net position is long.
In sum, round number effect remain persistent after controlling for market liquidity. Additionally, the coefficient on bid-ask spread for both hedgers and speculators are negative, indicating that greater participation of both type traders reduce transaction costs and improve liquidity.

5.8.2 Volatility and trading activity

In this section, the objective is to examine whether round number effects remain robust after controlling for market volatility. In Table 7, we present the results for the robustness check after controlling for market volatility as specified in equation (8). The inclusion of market volatility does not weaken our main results in Table 4. For all three regressions, the coefficient on just above and below a round number is still significant at the 1 percent level and thus, controlling for market volatility, round number effects remain robust.

Additionally, we also examine the interaction between trading activity of different trader types and market volatility. For all three regressions, Panel A shows that the coefficient on the interaction variables is positive and statistically significant at 5 percent when there is excess selling by hedgers just above a round number. For all three regressions, Panel A shows that the coefficient on the interaction variables is negative but is statistically insignificant when there is excess buying by hedgers just below a round number. The results indicate that excess selling by hedgers affects market volatility and are consistent with Brown, Walsh and Yuen (1997) who document evidence that the impact of excess sell orders is greater on market volatility than that of excess buy orders.

The opposite is true for speculators but the coefficients are statistically insignificant. For all three regressions, Panel B shows that the coefficient on the interaction variables is negative but statistically insignificant when there is excess selling by hedgers just above a round number. For all three regressions, Panel B shows that the coefficient on the interaction variables is positive but statistically insignificant when there is excess buying by hedgers just below a round number. The results indicate that trading activity of speculators does not affect market volatility. The results support the finding of Buyuksahin and Harris (2011) who find little evidence that speculation has harmful impact.

Overall, we find that net position of hedgers has an asymmetric effect on market volatility and find that excess selling by hedgers affect market volatility. However, we find no evidence that trading activity of speculators affect market volatility.

Table 7
Robustness check after controlling for market volatility measured by standard deviation of price return

Panel A: the independent variable $T^{j}_{t,i}$ is hedger

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0117	0.0000	***	-0.013	0.000	***	-0.013	0.000	***
$X_{t,01}$	-0.0539	0.0000	***	-0.110	0.000	***	-0.110	0.000	***
$X_{t,49}$	0.0367	0.0000	***	0.081	0.000	***	0.081	0.000	***
$X_{t,51}$	-0.0460	0.0000	***	-0.100	0.000	***	-0.100	0.000	***
$X_{t,99}$	0.0394	0.0000	***	0.104	0.000	***	0.104	0.000	***
$X_{t,01}T^{i}_{t,01}$	-4.2571	0.0000	***	-10.062	0.000	***	-10.059	0.000	***
$X_{t,49}T^{i}_{t,49}$	2.8706	0.0002	***	6.953	0.000	***	6.951	0.000	***
$X_{t,51}T^{i}_{t,51}$	-4.0297	0.0000	***	-8.873	0.000	***	-8.887	0.000	***
$X_{t,99}T^{i}_{t,99}$	2.3874	0.0004	***	7.916	0.000	***	7.911	0.000	***
T^{i}_{t}	-1.0231	0.0000	***	-1.151	0.000	***	-1.150	0.000	***
$X_{t,01}T^{i}_{t,01}retvol_{t,01}$	9.9782	0.0513	*	16.246	0.029	**	16.433	0.027	**
$X_{t,49}T^{i}_{t,49}retvol_{t,49}$	-3.7895	0.3411		-3.802	0.510		-3.772	0.513	
$X_{t,51}T^{i}_{t,51}retvol_{t,51}$	13.8987	0.0216	**	19.413	0.027	**	19.706	0.025	**
$X_{t,99}T^{i}_{t,99}\ retvol_{t,99}$	-1.5403	0.3783		-2.545	0.315		-2.442	0.335	
$retvol_{t,i}$	0.9746	0.0535	*	2.960	0.000	***	3.985	0.000	***

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 7 – (Continued)

Panel B: the independent variable $T_{t,i}^{j}$ is speculator

	OIB#	*p*-value		OIBVol	*p*-value		OIB$	*p*-value	
Intercept	-0.0123	0.0000	***	-0.013	0.000	***	-0.013	0.000	***
$X_{t,01}$	-0.0583	0.0000	***	-0.123	0.000	***	-0.123	0.000	***
$X_{t,49}$	0.0478	0.0000	***	0.097	0.000	***	0.097	0.000	***
$X_{t,51}$	-0.0519	0.0000	***	-0.114	0.000	***	-0.114	0.000	***
$X_{t,99}$	0.0458	0.0000	***	0.117	0.000	***	0.117	0.000	***
$X_{t,01}T_{t,01}^{i}$	1.5081	0.0000	***	3.556	0.000	***	3.556	0.000	***
$X_{t,49}T_{t,49}^{i}$	-1.1670	0.0000	***	-2.615	0.000	***	-2.615	0.000	***
$X_{t,51}T_{t,51}^{i}$	1.3825	0.0000	***	2.998	0.000	***	3.004	0.000	***
$X_{t,99}T_{t,99}^{i}$	-1.0521	0.0000	***	-3.078	0.000	***	-3.076	0.000	***
$T_{t,i}^{j}$	0.3663	0.0000	***	0.416	0.000	***	0.416	0.000	***
$X_{t,01}T_{t,01}^{i}retvol_{t,01}$	-2.6692	0.1252		-2.818	0.264		-2.878	0.254	
$X_{t,49}T_{t,49}^{i}retvol_{t,49}$	-0.4488	0.7713		-1.150	0.607		-1.167	0.602	
$X_{t,51}T_{t,51}^{i}retvol_{t,51}$	-2.9872	0.1944		-1.986	0.551		-2.070	0.535	
$X_{t,99}T_{t,99}^{i}\ retvol_{t,99}$	0.7349	0.3554		0.638	0.580		0.591	0.608	
$retvol_{t,i}$	1.0267	0.0419	**	3.020	0.000	***	4.045	0.000	

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

$$Buysell_{t,i} = \alpha_{t,i} + \beta_1 X_{t,01} + \beta_2 X_{t,49} + \beta_3 X_{t,51} + \beta_4 X_{t,99} + \alpha_1 X_{t,01}T_{t,01}^{j} + \alpha_2 X_{t,49}T_{t,49}^{j} + \alpha_3 X_{t,51}T_{t,51}^{j} + \alpha_4 X_{t,99}T_{t,99}^{j} + \beta_5 T_{t,i}^{j} + \alpha_5 X_{t,01}T_{t,01}^{j}retvol_{t,01} + \alpha_6 X_{t,49}T_{t,49}^{j}retvol_{t,49} + \alpha_7 X_{t,51}T_{t,51}^{j}retvol_{t,51} + \alpha_8 X_{t,99}T_{t,99}^{j}\ retvol_{t,99} + \beta_6 retvol_{t,i} + \varepsilon_{t,i} \quad (8)$$

where the variables are as defined in Equation (7). The volatility is multiplied by 1000.

6. Conclusion

In this paper, we document evidence that round number effects exist in WTI crude oil futures market during both pre and post-electronic periods. We extend the line of the literature on round number effects by exploring the existence of round number effects in West Texas (WTI) crude oil futures market. Consistent with Bhattacharya, Holden and Jacobsen (2012), we find excess buying just below a round number and excess selling just above a round number during both pre and post-electronic periods. Thus, we confirm the existence of round number effects in WTI crude oil futures market. Using nickel as a benchmark, we also examine which of three round number effects is more prevalent than the other two. Inconsistent with Bhattacharya, Holden and Jacobsen (2012) who document that cluster undercutting effect is the dominant round number effects in US stock markets, we find that threshold trigger effect is more prevalent than the other two in WTI crude oil futures market. Using COT, we explore what trader type – hedger or speculator – influences round number effects and find trading activity of hedgers, who are uninformed traders, influences round number effects. Having explored that trading activity of hedgers influences round number effects in WTI crude oil futures market, we examine whether round number effects is a major determinant of 24-hour trade return as documented in Bhattacharya, Holden and Jacobsen (2012). However, We find no evidence that round number effects is a determinant of 24-hour positive trade return and the average 24-hour trade return based on round number effects is negative 0.0014 percent in WTI crude oil futures market. As a robustness check, controlling for market liquidity and volatility separately, we find that round number remain persistent and confirm our main results. Additionally, we examine the interaction between trading activity of different trader type and market liquidity. We find that net position of hedgers has an asymmetric effect on market liquidity. We find that there is negative relation between excess selling and market liquidity (i.e. wider bid-ask spread) and positive relation between excess buying and market liquidity (i.e. narrower bid-ask spread). We also examine the interaction between trading activity of different trader types and market volatility. We find that net position of hedgers has an asymmetric effect on market volatility and find that excess selling by hedgers affect market volatility. However, we find no evidence that trading activity of speculators affect market volatility.

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