An Econometric Analysis of the TOCOM Energy Futures: Volatility, Trading Activity & Market Microstructure

by

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Declaration

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Abstract

Japan is one of the largest importers of different types of energy commodities in the world due to the lack of domestic energy resources. Tokyo Commodity Exchange (TOCOM) plays an important role for participants in the energy markets in Japan, since it is one of the main commodity exchanges for energy futures. However, majority of studies on energy futures focus on NYMEX and ICE prices and there seems to be no systematic studies on TOCOM energy futures. Hence, we consider investigating the dynamics and the behaviour of TOCOM energy futures and its market microstructure. We study three most liquid energy futures contracts in TOCOM, namely gasoline, kerosene and crude oil, over six consecutive months with the aim to address three main questions. First, we analyse the dynamics of energy futures contracts by modelling the realised volatility with consideration of high- and low-volatility regimes. The in-sample results support that volatility of TOCOM energy futures is regime-dependent, while the results of out-of-sample are mixed. Next, we set up a framework to analyse the behaviour of TOCOM energy futures contracts by investigating the relation between trading volume and price volatility under different market conditions defined by the shape/slope of forward curve. Both contemporaneous and lead-lag relation between trading volume and volatility are found significantly positive, while the latter is weaker. The asymmetric effect of market conditions is different from commodities due to the use of underlying commodities. Kerosene futures participants are more sensitive when market is in contango while crude oil futures participants are more sensitive in backwardation. Finally, we study the market microstructure of TOCOM by analysing the determinants of bid-ask spread components, and examine the asymmetric impact of sell-initiated and negative-return trading volume on bid-ask spread. It is evident that trading volume and volatility are two important determinants of BAS, and sell-initiated transactions seem to happen with higher BAS. The findings of this thesis provide useful implications for risk management and trading strategy by offering dynamics of volatility and insights of market microstructure.

List of Abbreviations and Mathematical Symbols

ARFIMA-RV	Autoregressive Fractionally Integrated Moving Average Realised Volatility model
ARSV	logarithmic Autoregressive Stochastic Volatility
BAS	Bid-Ask Spread
bbl	barrel
CBOE	Chicago Board Options Exchange
CC	Conditional coverage test
CME	Chicago Mercantile Exchange
COMEX	Commodity Exchange
DAX	Deutscher Aktienindex (German Stock Index)
DJIA	Dow Jones Industrial Average
DM	Deutsche Mark
DM test	Diebold-Mariano test
DMX	Dubai Mercantile Exchange
EEX	European Energy Exchange
EIA	U.S. Energy Information Administration
FHS	Filtered Historical Simulation
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GMM	Generalised Method of Moment
HAR-RV	Heterogeneous Autoregressive Realised Volatility model
HAC	Heteroskedasticity and autocorrelation consistent
HS	Historical Simulation
ICE	Intercontinental Exchange
IDT	Information Driven Trade
IND	Independence test
IV	Implied Volatility
JPY	Japanese Yen
kl	Kilolitre
LDT	Liquidity Driven Trade
LNG	liquefied natural gas
LR	Log-likelihood ratio
MA (1)	Moving Average of order 1
MAE	Mean Absolute Error
mbd	million barrels per day
MDH	Mixture of Distribution Hypothesis
MDT	Motivation Driven Trade
MME(O)	Mean Mixed Error (Overpredict)
MME(U)	Mixed Mean Error (Underpredict)
MR	Mean Reversion
MRJD	Mean Reversion Jump Diffusion
MRS	Markov Regime Switching
MRS-HAR-RV	Markov Regime Switching Heterogeneous Autoregressive Realised Volatility model
MSE	Mean Squared Error
mtoe	million tonnes of oil equivalent
NYMEX	New York Mercantile Exchange

OTC	Over-The-Counter
PAJ	Petroleum Association of Japan
PF	Percentage proportion of failure
Qlike	Quasi likelihood function
R&D	Research and Development
RC	Realised Correlation
RV	Realised Volatility
SGF-DT	Singapore Exchange Derivatives Trading Limited
SGX	Singapore Exchange
SHFE	Shanghai Futures Exchange
SIAH	Sequential Information Arrival Hypothesis
SV	Stochastic Volatility
SVAR	Structural Vector autoregression
SVCJ	Stochastic Volatility model with Correlated Jumps
TAIFEX	Taiwan Futures Exchange
TOCOM	Tokyo Commodity Exchange
T-SVAR	Transition Structural Vector autoregression
UC	Unconditional coverage test
US$	United States dollar
VaR	Value at Risk
VAR	Vector autoregression
WTI	West Texas Intermediate

Ask_t	Ask price of energy futures
Bid_t	Bid price of energy futures
d_t	The difference in loss functions between two forecasting models
$\bar{d}$	the average of the difference in loss function
D_t^W	Dummy for the first transaction after the weekend or holidays
D_t^S	Dummy of sell-initiated transactions
D_t^N	Dummy of negative-return transactions
DTR_t	Days to rollover date
$E(e^2)$	The second moment of microstructure noise
$E(e^4)$	The forth moment of microstructure noise
$f(\cdot, \theta)$	Likelihood function
$F^{-1}(\alpha)$	The corresponding p-percentile (e.g. 0.5%, 1%, 5%) of assumed distribution
h	Fixed trading period (one day in this study)
h_t	Forecasts of realised variance
I_t	Indicator function for violation of VaR
$IV_t^{(d)}$	One-day integrated variance
$L(\theta)$	Log-ikelihood function
$L(h_t, RV_t)$	Loss function of realised variance forecast h_t
M	The number of intervals
M^*	The optimal number of intervals
Mid_t	Mid-quote of energy futures
N_0	Total number of no violation of VaR
N_1	Total number of violation of VaR
N_{ij}	The number of indicator being *i* followed by indictor being *j*
p_t	Logarithm of the instantaneous price of TOCOM energy

	futures
p_{12}	the probability of being in state 2 in the current period, given that you were in state 1 in the previous period
p_{21}	the probability of being in state 1 in the current period, given that you were in state 2 in the previous period
$\boldsymbol{P}$	Conditional probability matrix
P_t	Transaction price
P_b	The price 15 minutes before the transaction
P_a	The price 15 minutes after the transaction
$\Pr(\cdot)$	The probability of events
Q	Integrated quarticity of energy futures returns
$\hat{Q}$	Estimated integrated quarticity of energy futures returns
r	Return of energy futures
$RV_t^{(d)}$	One-day realised variance
$\mathrm{RV}_\mathrm{t}^{(\mathrm{w})}$	One-week realised variance
$\mathrm{RV}_\mathrm{t}^{(\mathrm{m})}$	One-month realised variance
st	State of regime
S_t	Indicator of market in backwardation
u	Tolerance level of VaR
$(1-u)$	Confidence level of VaR
V	Integrated variance of energy futures returns
$\hat{V}$	Estimated integrated variance of energy futures returns
w_t	Standard Brownian motion process
z_t	Slope of forward curve
α	Significant level of Chi-squared statistic
Δ^*	The optimal fixed interval frequency
θ	Vector of parameters (Chapter4)
μ_t	Time-varying drift term
v_t	Change in trading volume
π	Percentage proportion of failure
π_{ij}	The probability of indicator being *i* followed by indictor being *j*
σ_t	The instantaneous volatility of p_t
σ_t^2	Realised variance of futures returns (Chapter 5)
Σ	Volatility of residuals
Ω_t	Information given at time *t*

Chapter 1 Introduction to Energy Markets

1.1 Introduction

The global production, consumption and trade in energy commodities have been increasing in pace with world economic growth. Energy commodities play a crucial role in the world economy as input for production, manufacturing, transportation as well residential and commercial consumptions. Amongst primary sources of energy (petroleum, natural gas, coal, hydroelectricity, and renewable), petroleum and petroleum products have been the main source of energy for almost a century. The world consumption of petroleum and petroleum products averaged just over 95 million barrels per day (mbd) in 2015, and the largest proportion of world total primary energy consumption with approximately 33% share.[1] In addition, despite the increase in investment on renewable energy, discovery of new sources of energy closer to consumption areas such as shale gas, as well as uncertainty about the economic growth and environmental issues in the long run, it is estimated that global demand for

[1] BP Statistical Review of World Energy

petroleum and petroleum products will increase by an average of 1.1% per annual, to 121 mbd in 2040.[2]

Japan is the world third largest economy after US and China with a GDP of 4.383 trillion US$ in 2015, according to the World Bank statistics, and is one of the largest importers of different types of energy commodities. In fact, the lack of domestic energy resources has turned Japan into one of largest importers of energy in the world. Based on the EIA statistic in 2015, less than 4% of total energy consumed in Japan was domestically produced. Japan is the world's largest liquefied natural gas importer (4.0 billion cubic feet per year), third-largest coal importer (210 million tons per year), and third-largest crude oil importer (3.8 mbd). Given the energy intensity of the economy and the consumption of petroleum in Japan, Tokyo Commodity Exchange (TOCOM) introduced futures contracts on petroleum products (Kerosene and Gasoline) in 1999 and crude oil in 2001, to allow consumers and producers to hedge their exposure and traders to invest or speculate on energy prices.

The aim of this chapter is first to provide an overview of the world energy markets and trade. Second, we discuss the Japanese energy demand, market as well as the role of Tokyo Commodity Exchange (TOCOM) in providing petroleum and petroleum product futures for Japanese energy consumers and producers to hedge their exposure and traders to invest or speculate on prices. Finally, a number of areas are identified and discussed as topics for this thesis. These include using high frequency intraday data to estimate and forecast realised volatility, examining how the information disseminates into market, and investigating the determinants of bid-ask spread.

1.2 An Overview of Global Energy Market

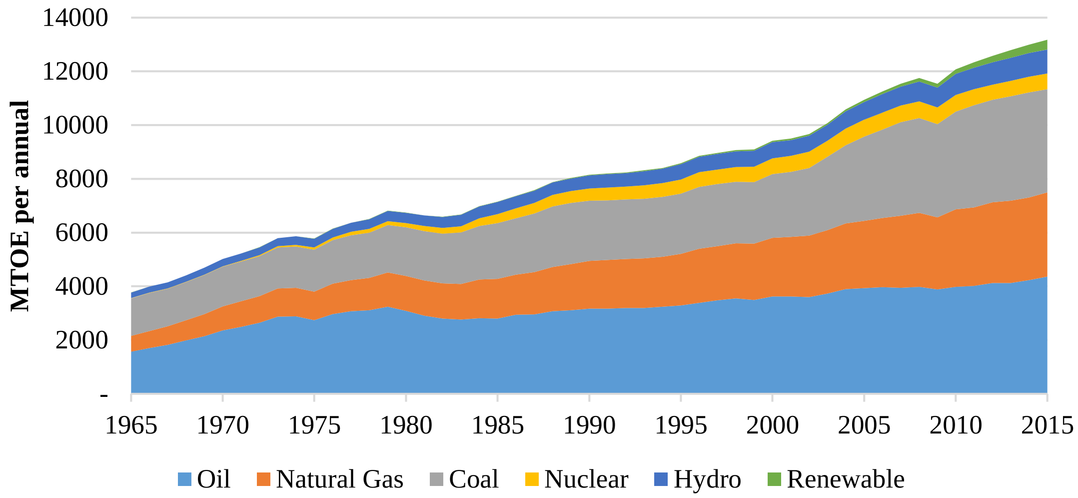
Energy markets and prices have been the topic of many studies over the years because energy commodities are essential for the economy. Energy commodities are used as inputs for manufacturing, transportation, construction, industrial production,

[2] EIA International energy outlook 2016

commercial and residential consumption, and almost all aspects of economic activities. The importance of energy commodities for the world economy has increased as we become more and more dependent on energy for our day to day life. In fact, the global demand and supply for energy commodities including crude oil and petroleum product, natural gas, coal, and electricity (hydro, nuclear, wind, renewable, amongst others) have been continuously increasing over the past 100 years. Figure 1-1 presents the historical evolution of world energy consumption by type from 1965 to 2015. Amongst different types of energy commodities, crude oil by far has the largest share in world energy consumption (4362 million tonnes of oil equivalent) in 2015, followed by coal (3840 mtoe), natural gas (3135 mtoe), hydroelectricity (893 mtoe), Nuclear (583 mtoe) and renewable energy sources (365 mtoe).

The global energy markets function with a unique structure of supply and demand mechanisms which introduces a great degree of complexity along with significant levels of uncertainty. In addition, weather and climate changes, technological advances, changes and geopolitical events, all influence both supply and demand for energy commodities. For instance, in 1973, crude oil prices soared from \$3/bbl to \$12/bbl due to the embargo against the U.S. imposed by Arab oil producer. In 1979, the Iranian revolution caused the severe decline in crude oil production in Iran, which drove crude oil prices up to another peak of over \$39/bbl. However, the increase in crude oil production in non-OPEC countries and the gradually decline in crude oil consumption led to the oil glut in the 1980s. In 1986, the crude oil sharply dropped to \$10.25/bbl, and followed by volatile fluctuations. Baumeister and Peersman (2013) argue that oil supply and demand in short-term has become less elastic since oil prices fell in 1986, so any small disturbance in either side can cause greater impact on prices. Thus, the volatility of crude oil has increased to a higher level, which in turn created the opportunity to producers, consumers, investors and energy market participants for large profits from speculation on oil and energy prices as well as large losses when investment strategies failed, and motivated more speculative trading. Büyükşahin et al. (2008) point out that the proportion of NYMEX crude oil speculative traders, defined by CFTC as a trader who does not hedge but trades with objective and of achieving profits through successful anticipation of price movements[3], increases from around 25% in 2000 to approximately 50% in 2008. According to the COT reports, the proportion in 2016 has increased to just over 70%.

Figure 1-1: World energy consumption by type



Source: BP Statistical Review of World Energy 2016

A major part of global demand for petroleum and refined products is from the OECD countries (See Figure 1-2).[4] However, the petroleum consumption in non-OECD countries has been growing fast, especially since mid-2000, and gradually becoming the main driver for the growth in global petroleum consumption. In fact, the consumption of crude and petroleum products in non-OECD countries reached the same level of consumption in OECD countries. The consumption of crude oil and products in OECD countries, on the other hand, has had a small growth until the end of 1990s, and then remains stable with a little decline in recent years, as a result of increase in use of alternative energy resource including nuclear and renewable energy. Furthermore, Figure 1-3 presents the growth in petroleum consumption in five largest consuming economies in 2014, namely the US (19.11 mbd), China (11.52 mbd), Japan (4.3 mbd), India (3.74 mbd) and Russia (3.70 mbd). It can be seen that while the US

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[3] http://www.cftc.gov/ConsumerProtection/EducationCenter/CFTCGlossary/glossary_s
[4] The data is according to the U.S. Energy Information Administration (EIA).

remains the largest consumer of petroleum in the world, the consumption in China has been growing at a fast rate and become the second largest petroleum consuming country ahead Japan, India and Russian Federation and other large European economies.

Figure 1-2: Development of World Petroleum Consumption

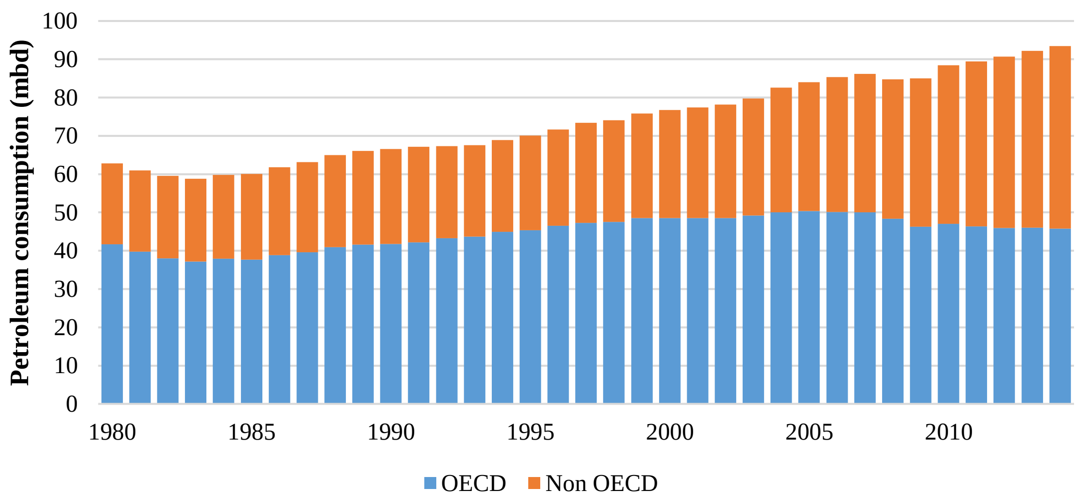
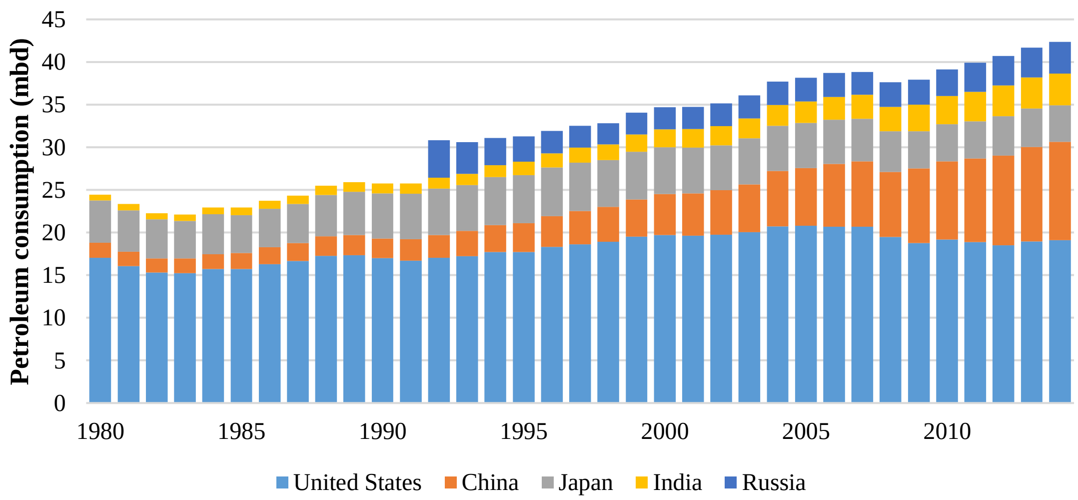


Figure 1-3: Historical petroleum consumption for top five consuming countries



With respect to the supply of petroleum and products, Figure 1-4 presents the historical production in OECD and non-OECD countries. It can be seen that the largest proportion of petroleum production belongs to the non-OECD countries with a steady growth to meet the increasing demand for petroleum. The OECD countries seem to produce around 24% of the world petroleum but their consumption share is around 50%. Finally, Figure 1-5 presents historical petroleum production for five largest petroleum procuring countries. It can be noted that the U.S. has become the largest petroleum producer by producing 14.13 mbd in 2014, while Saudi Arabia and Russia are second and third biggest producers by producing 11.62 and 10.85 mbd, respectively.

Figure 1-4: World petroleum production

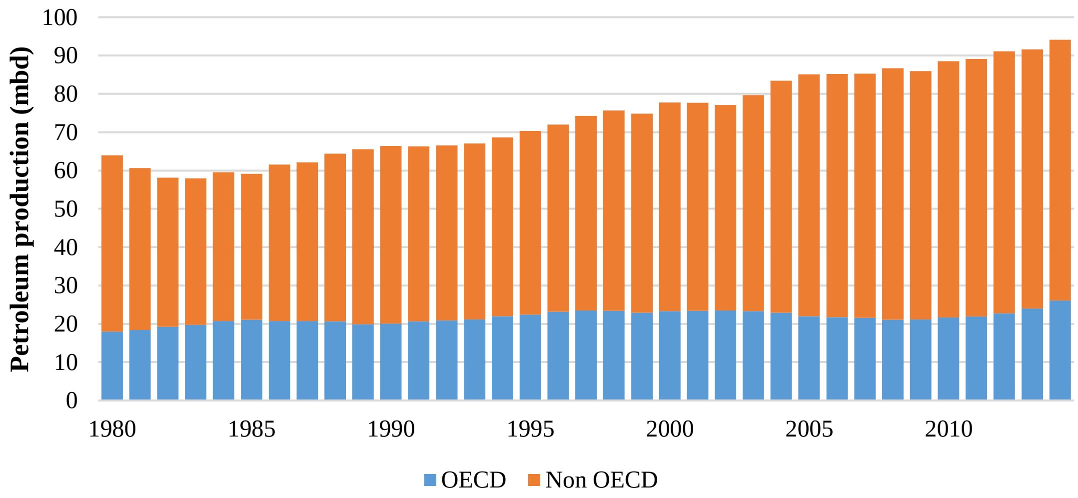


Figure 1-5: Historical Petroleum Production for the Top Five Producing Countries

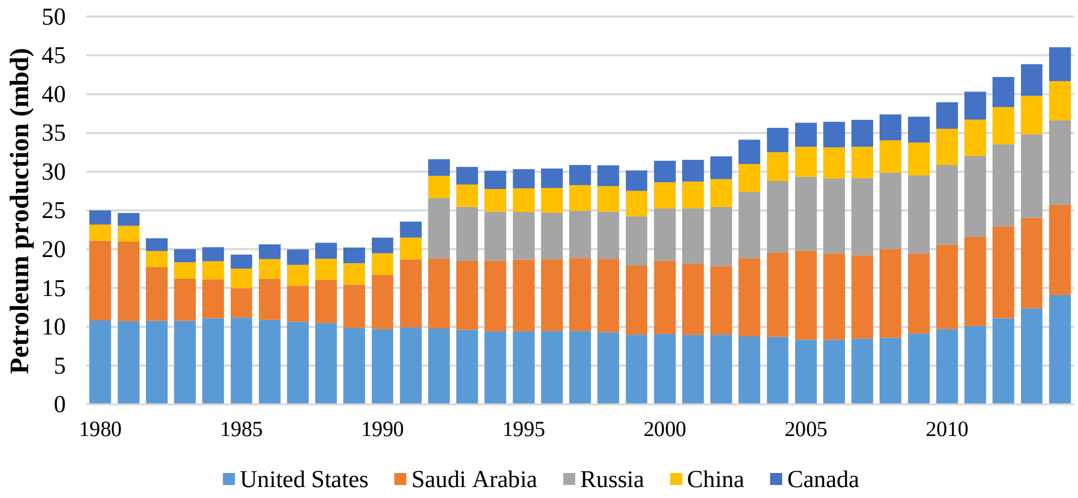
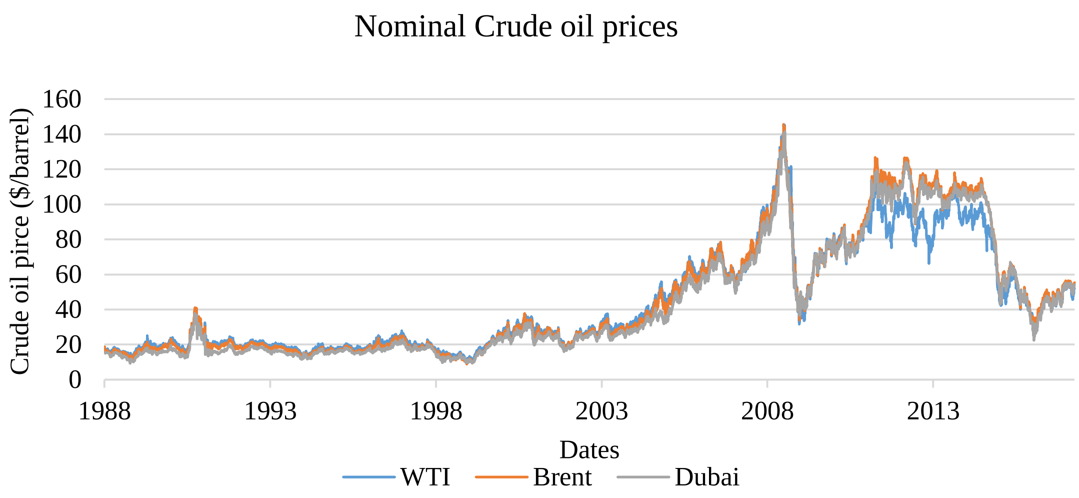
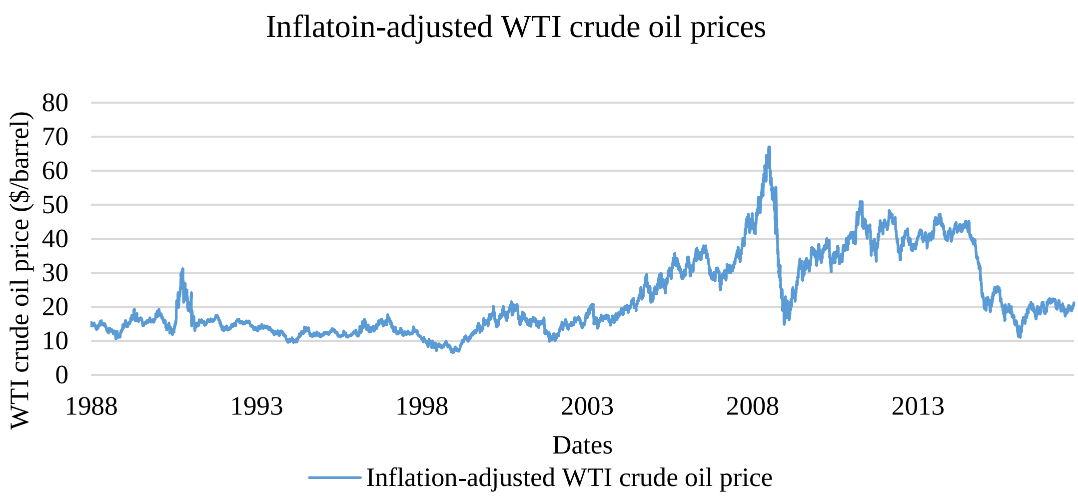


Figure 1-6: Historical Price Movement of WTI, Brent, Bonny and Dubai crude oil





The other noticeable trend in international crude oil market is the increase in price and price volatility over the years, and in particular, in the last 10 to 15 years. Figure 1-6 shows the historical nominal prices for three major crude oil benchmarks around the work, namely West Texas Intermediate (WTI) in the US, Brent Crude in the UK and Europe, and Dubai crude in the Middle East, and the real prices for WTI crude oil since 1988. As illustrated in Figure 1-6, crude oil prices exhibit an upward trend with increased fluctuations between 2000 and 2008, when they reached a peak of $147/bbl in May 2008. Following the global financial crisis, there was a significant decline in crude oil prices during the second half of 2008 when oil prices plunged to $35/bbl. Nevertheless, crude oil prices soon reverted back to more than $100/bbl in

2010 but they are still lower than the historical highest level of $147/bbl. Moreover, both graphs of nominal and real crude oil prices reveal that significant increase in fluctuation of the crude oil price after 2000.

Energy derivatives contracts and markets have been developed since the early 1970s to provide market participants with instruments to manage the risk exposure, trade energy commodities, speculate on energy prices or diversify their investment portfolios. Futures, Forwards, Swaps and Options are the main derivatives contracts used by traders and participants in the energy market. There are a number of exchanges offer energy futures and option contracts including CME (NYMEX) in New York, ICE in London, TOCOM in Tokyo, SGX in Singapore, DMX in Dubai, EEX in Leipzig, amongst others. Apart from energy derivatives traded in organised exchanges such, there is a very active OTC market for energy derivatives (e.g. forwards, swaps, swaptions, and other structured derivatives) for which the exact trading volume is not available.

The financialisation of energy commodities has also contributed to the growth of trade in energy derivatives as more and more investors, trading houses, hedge funds and financial institutions realised the potential of energy commodities as an asset class for both speculation and diversification (Irwin and Sanders, 2011; Basak and Pavlova, 2016). As a result, the global trade in energy derivatives has increased substantially over the last two decades which made this market the largest amongst all commodity derivatives (Agricultural, Metal, Livestock, etc.).

A forward contract is an agreement allowing two parties to trade a contracted amount of underlying asset (i.e. crude oil) in the future at a fixed price agreed on today. A futures contract is a derivative contract similar to a forward contract in providing the same function in terms of price exposure. However, the two contracts differ in two main aspects. Firstly, futures contracts are exchange traded standardised contracts in respect to the size, maturity, the underlying asset and settlement, whereas, forwards contracts are over-the-counter agreements, where the contract size, maturity, the underlying asset and settlement is determined through negotiation between the buyers and sellers. Even though, many of forward contracts in the energy market are nowadays standardised to facilitate the negotiation process and save time. The other difference between futures and forward contracts is that all futures contracts are cleared through a clearing process by a clearing house, which eliminates any counterparty risk default risks; whereas, forward contracts ate OTC and carry significant counterparty risk. Nevertheless, clearing houses begun offering clearing facilities for forward contracts in recent years so participants in forward market for energy commodities can also eliminate any counterparty risk.

One theory pricing futures or forward contracts is cost of carry model, firstly formalised by Kaldor (1939) and Working (1948, 1949), which formulates the forward price as the sum of the spot price and net cost of carry over a convenient yield. Net cost of carry is the amount of storage cost, interest expense, insurance expense over any dividend yield, and a convenient yield is the implied benefit of holding the physical asset between present time and the maturity. If cost of carry theory does not hold, an arbitrage opportunity may exist. For example, when the actual forward price is lower than the theoretical price, one can take a long position of the forward contract, and a short position of the spot asset. At the maturity of the forward contract, the risk-free profit is the spot price minus the dividend yield, the convenient yield and the forward price given no counterparty risk. In addition, the cost of carry theory also links the contracts for the same commodities across different maturities, because they are all related to spot price of the commodity. Nonetheless, the difference in the maturity also causes inconsistent cost of carry and convenient yields, so the theoretical price for the same commodity but different maturity contracts is still not identical.

Futures and forward contracts are most frequently used instruments for the purpose of hedging and speculation in energy market. Hedgers in energy markets utilise energy futures and forward contracts to reduce or eliminate their price risk exposure, by locking into a price in advance of the physical transactions. For example, if a refinery is expecting to produce and sell 1000 barrels of gasoline in two months, they can sell (take a short position) one gasoline futures in order to hedge against the potential decline in gasoline prices and guarantee the selling price of its product. However, this hedging strategy also eliminates the possibility of any gain should there be any increase in gasoline prices.

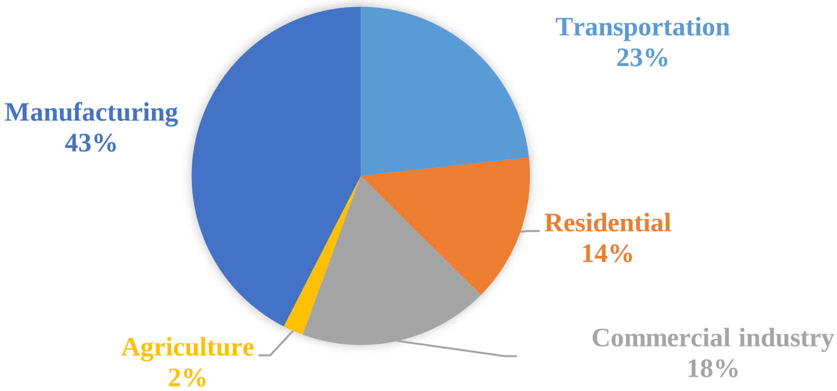
In contrast to hedgers, speculators trade energy futures and forward contracts in order to profit from changes in price of futures and forward contracts. In fact, futures and forward contracts provide a great opportunity for speculators to trade in energy markets without having any physical commitments. In addition, energy futures and forward contracts allow speculators to trade and profit from both rising and falling prices. Speculators take long or short positions based on their view and predication of future price movements. For instance, a speculator who expects a rise in gasoline prices will take a long position on gasoline futures. Through such a transaction she will be exposed to gasoline futures price, and the payoff of the trade is determined by the movement of the gasoline price over the holding period of the contract. If over the investment period the price of gasoline and consequently price of the futures contract increase, the speculator can earn a profit by closing the futures contract. However, if over the investment period the price gasoline and consequently price of the futures contract fall, the speculator will suffer a loss by closing the futures contract.

1.3 Japan's Energy Demand and Market

Japan is one of the largest importers of different types of energy commodities in the world. In fact, the lack of domestic energy resources has turned Japan into one of largest importers of energy in the world. Based on the EIA statistic in 2015, less than 4% of total energy consumed in Japan was domestically produced. Japan, as the largest liquefied natural gas (LNG) importer, imported 4.0 billion cubic feet of liquefied natural gas, which is equal to approximately 101.7 mtoe and accounts for over 99% natural gas consumption. Moreover, Japan is also the third largest coal and oil importer, importing 210 million metric tonnes of coal and 3.8 mbd of crude oil. The imported energy used in different sectors including transportation, electricity generation, industrial production as well as residential and commercial consumption as shown in Figure 1-7.

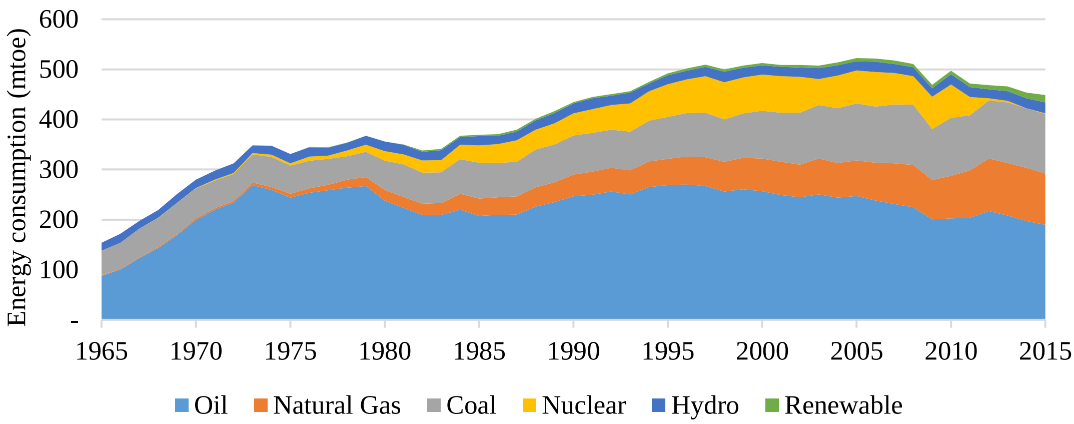
A large number of Japanese firms are also involved in exploration and production of energy resources overseas and provide capital, equipment and engineering expertise in different energy projects around the world. In addition, Japan is one of the main producers and exporters of the energy equipment and plants. Japanese government strongly supports and invests in research and development (R&D) in the energy sector through a programme which is dedicated to increase the energy security and energy efficiency to reduce the emission.

Figure 1-7: Japan's Energy Consumption by Sector in 2015



Source: Agency for Natural Resources and Energy, Japan

Figure 1-8: Japan's Energy consumption by energy type



Source: BP Statistical Review of World Energy 2016

Figure 1-8 shows historical consumption of different energy commodities in Japan's. Three main observations could be the change in energy mix over time towards a more diversified and balanced energy portfolio, the decline in overall energy consumption after the 2008 global financial crisis, and sharp reduction in nuclear energy consumption after Fukushima accident in 2011. However, petroleum remains the main source of energy in Japan with 44% share, followed by coal 27% and natural gas 22%. In addition, due to the fact that all fusil fuel energy sources are imported, prices for other commodities such as natural gas and to a certain extent coal are also linked to petroleum prices. Therefore, the analysis of TOCOM energy market and, in particular, crude oil futures contracts becomes more important since the Japanese economy can be significantly influenced by the dynamic of energy prices.

1.4 The Tokyo Commodity Exchange (TOCOM)

Tokyo Commodity Exchange (TOCOM) is established in 1984 when three exchanges, namely, Tokyo Textile Exchange, Tokyo Rubber Exchange and Tokyo Gold Exchange, merged and became the second Asian exchange offering energy futures after Singapore Exchange (SGX). In 5 July 1999, TOCOM listed Kerosene and Gasoline futures contract for the first time, and following the successful uptake of the two energy futures contracts, Crude oil futures were launched in 10 September 2001. Subsequently, in September 2003 TOCOM introduced Gasoil futures contract, however, this contract was delisted and reintroduced, but it did not take off as expected. Two other energy futures contracts launched on 12 October 2010 are Chukyo-gasoline and Chukyo-kerosene futures. These are in fact mini contracts with smaller quantities to allow traders to take smaller positions (see Chapter 3 for detail discussion on TOCOM energy futures contracts). Very recently, in March 2014, TOCOM has launched the intercommunity spread contracts to enable simultaneous execution of two legs of crack spread at one price, and is planning to introduce LNG and Electricity futures.

Among five futures contracts currently traded at TOCOM (excluding gasoil), only the crude oil futures are cash-settled, while other contracts are all physically delivered according to a specific process outlined by the exchange. All energy futures contracts listed on TOCOM are denominated in Japanese Yen (JPY), which offer Japanese companies and energy market participants a convenient set of instruments to hedge their exposure to energy prices, speculate in energy markets, or use energy futures as alternative asset for diversification and exposure to energy prices.

A feature of TOCOM energy market is that the exchange imposes the limitation of the number of futures contracts traded by commercial traders[5], investment trusts[6] and non-commercial traders. On average, a commercial customer or an investment trust is allowed to transact twice to five times more futures contracts than a non-commercial trader, which may largely decrease the proportion of speculators in TOCOM futures markets. Such limitation in trading position of market participants can have important consequences on price behaviour and efficiency of the market. Interestingly, despite of the difference in the limit of position does between commercial and non-commercial traders, non-commercial traders are still the majority of TOCOM energy futures trading. However, the position limit has been removed for crude oil futures since June 2015, and the crude oil futures was also renamed to Dubai crude oil futures. Even though the trading volume does not sharply increase immediately after the limit was removed, the historical record of trading volume for crude oil future was exceeded in December 2015 and continued to be broken in the next two months. The total trading volume for crude oil in 2015 was 3,651,528 contracts, which was 1 million more than the historical record in 2004, about 2,284,572 contracts[7].

The other feature of TOCOM futures market is that even though futures are traded in JPY, the foreign trades ratio is surprisingly high, about 50% during the first half of 2015. The foreign trades ratio increases gradually since TOCOM extended night trading session on 22 September 2010.

Figure 1-9 reveals that the foreign trade ratio has increased from 20% in 2011 to 50% currently. Table 1-1 exhibits the proportion of foreign trades and open interest on TOCOM energy futures. It seems that crude oil futures are the most foreign traded among three energy futures with 50% foreign trades, while the foreign trades ratios for gasoline and kerosene futures are very similar, around 25%. This may be because the underlying commodity of crude oil is the middle east crude oil, which was globally

[5] Commercial customers are defined by the Commodity Derivatives Act and Articles of Incorporation as "Those who, as their line of business, engage in the purchase, sales, intermediary of trades, brokerage or agency activity, production, processing or use of Listed Commodity Component Products."
[6] According to TOCOM's definition, investment trusts include entities using collective investment schemes, such as investment trusts, ETFs, and commodity funds, etc., that are led with the Financial Service Agency of Japan or an authority corresponding to the Financial Service Agency in a foreign jurisdiction.
[7] http://www.tocom.or.jp/historical/dekidaka.html, September 2016.

traded while the underlying commodities for gasoline and kerosene are domestic products. Another noticeable feature in Table 1-1 is that the proportion of foreign trades almost doubles that of foreign open interest. For example, the foreign trades ratio for crude oil is 50%, but the foreign open interest ratio is just below 25%. Intuitively, foreign traders have less motivation to hedge their petroleum assets with TOCOM energy futures since all TOCOM futures are traded in JPY. Hedging with TOCOM energy futures brings them a new risk exposure from the uncertainty of exchange rate, and they need take positions in currency derivatives, such as swaps, to minimise this exposure. Hence, they are more likely to trade TOCOM energy futures in short-term instead of holding them until settlement, which causes the difference between trading and open interest.

Figure 1-9: Foreign customer trades ratio of commodities in TOCOM

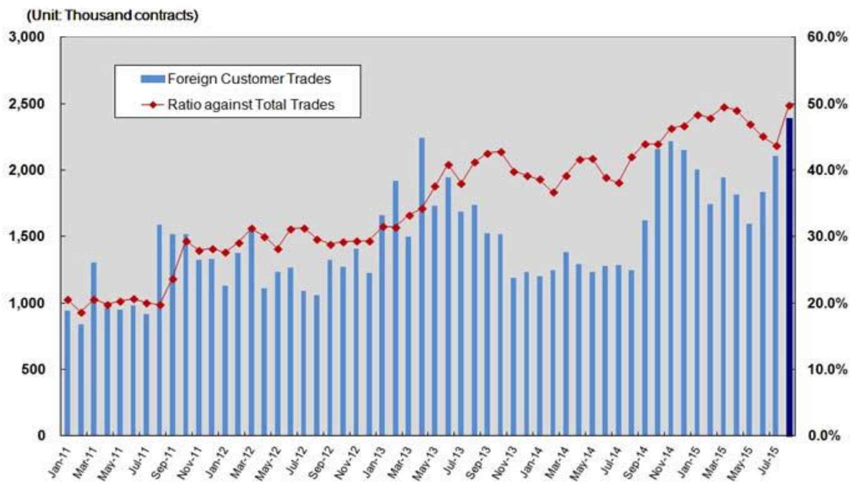


Table 1-1: Trades and open interest of TOCOM energy futures for September 2014

	Trades			Open interest		
	Oversea	Japan	Oversea%	Oversea	Japan	Oversea%
Gasoline	64,204	199,606	24.3%	6,816	38,922	14.9%
Kerosene	24,925	73,281	25.4%	5,521	32,889	14.4%
Crude oil	67,398	66,992	50.2%	7,814	23,538	24.9%

- Source: Tokyo Commodity Exchange (TOCOM) participation survey 2014

1.5 Aims, Objectives and Contributions of the Thesis

Our research is focused on TOCOM energy futures market, which is an important market for commodities influencing the Japanese economy and perhaps the global energy market. To the best of our knowledge there has not been any study on TOCOM energy markets. The only exception is Duong and Kalev (2008) study on the Samuelson Hypothesis on 20 different commodity futures including energy futures. They find that only volatility of the agriculture futures increases as contracts approach maturity. Majority of studies on energy derivatives concentrate on West Texas Intermediate (WTI) crude oil, New York Harbour gasoline and heating oil futures listed on New York Mercantile Exchange (NYMEX) and the Brent crude oil and European Gasoil listed in the Intercontinental Exchange (ICE). Therefore, this study is aimed to extend literature to energy futures contracts traded on TOCOM and investigate the behaviour and dynamics of their prices. In particular, we study the volatility and its relation with trading volume, as well as market microstructure of TOCOM energy futures.

The starting point of our research is the analysis of dynamics of crude oil, kerosene and gasoline futures returns in the form of modelling time-varying volatility using high frequency intraday data and estimating the realised volatility of the three energy futures contracts. Next, we model and forecast the realised volatilities and allow for changes in different state of the market using a regime wwitching approach. In addition, we evaluate the performance of different volatility models including non-parametric methods for risk management applications (VaR estimation).

Furthermore, we set up a framework to analyse the market microstructure of TOCOM energy futures contracts by investigating the relation between trading volume and realised volatility under different market conditions defined by the shape/slope of forward curve. To achieve this, we adapt a Transition Structural Vector Autoregressive (T-SVAR) model to measure the contemporaneous and lead-lag interaction between trading volume and the realised volatility. In addition, we take into account the roll-over effect by introducing day-to-rollover to capture the time effect of maturity and roll-over of contracts.

Finally, we examine the determinants of BAS components for TOCOM energy futures contracts using intraday data. Three types of components are considered in choosing the potential determinants, namely adverse-selection costs, inventory-hold costs, order processing costs. As it is not possible to obtain the information of number of market makers, the level of competition is not included here. Moreover, two asymmetric effects of sell-initiated and negative-return transactions are also considered in our model. In this respect, we examine the effect of trading volume, realised volatility and potential asymmetric impact of trading volume on bid-ask spread of energy futures contracts.

1.5.1 Modelling Volatility of Energy Futures Return

Modelling and estimation of volatility of asset prices has always been a key issue in financial econometrics because correct volatility estimates and forecasts are essential for risk management, pricing derivatives, trading strategies, as well as portfolio optimisation and asset allocation. Therefore, many studies have proposed and employed different techniques to estimate time-varying volatility of financial and commodity prices (see chapter 2 for detailed discussion on different approach for modelling volatility). Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models are the most commonly used methodologies to estimate the time-varying volatility of asset prices based on historical date. An alternative approach is the Stochastic Volatility (SV) model, which is based on the argument that both mean and variance of returns follow stochastic process. For those assets and commodities with active an options market, the volatility of the underlying asset (Implied Volatility, IV) can be derived by inverting an option pricing formula (e.g. Black and Scholes, 1973) for given traded option values model. These three volatility estimation approaches are usually used with low-frequency data, namely daily, weekly, and monthly. Nevertheless, the increase in the availability of intraday high-frequency financial data led to the development of a new concept for estimation of volatility, namely Realised Volatility (RV), which utilises information on intraday price movement. The daily RV is measured as the sum of the intraday squared returns (Andersen et al., 2001a and 2003), and has been argued to be more efficient for estimation volatility than daily squared returns (McAleer and Medeiros, 2008).

To further investigate the importance of market conditions on volatility of TOCOM energy futures, we employ a flexible regime switching approach to estimate the realised volatility of energy futures prices. We follow the Markov Regime Switching technique of Hamilton (1989) for estimation of Heterogeneous Autoregressive Realised Volatility (HAR-RV) model. The benchmark model is the simple (HAR-RV) model proposed by Corsi (2009), which has been argued to have best forecasts in WTI crude oil futures among several variation HAR-RV models (Sévi, 2014). However, Markov Regime Switching HAR-RV (MRS-HAR-RV) approach assumes that realised volatility is explained by the weighted average of historical volatility, and the weighting changes according the market conditions between current and lagged volatilities. Extending the HAR-RV approach to account for changes in market condition in estimating realised volatility is expected to produce more accurate volatility forecasts compared to alternative approaches such GARCH type or simple HAR-RV models.

1.5.2 Trading Volume and Volatility Relation

There is a large body of literature on the relation between trading activity and price behaviour in different financial and commodity markets. Many studies investigate the theoretical and empirical relation between trading volume as well as trading volume and price volatility using different econometric techniques, sample period and frequency. The theoretical foundations of these studies are based on three main theories proposed for the relation between trading activity and price behaviour. These are: The Mixture of Distribution Hypothesis (MDH) of Clark (1973), Sequential Information Arrival Hypothesis (SIAH) of Copeland (1976), and Motivation Driven Trade of Wang (1994).

The MDH postulates the existence of the contemporaneously positive relation between trading volume and price volatility, because it assumes that the trading volume and price changes follow a joint distribution and are driven by a single mixing variable which is arrival of information. On the other hand, the SIAH suggests a positive relation is a lead-lag relationship between trading volume and volatility. The SIAH argues that traders receive information gradually and adjust their holding positions based on the arrival of information over time. The gradual adjustment of portfolios creates a series of disequilibria and hence the market price evolves and reaches a new equilibrium only when the all traders in the market obtained the information and readjusted their portfolio. Hence, the speed of the change of market prices depends on the rate of the information arrival, and is usually later than the change of trading volume because of the existence of private information. Finally, the third theory on volume-volatility relation is the Motivation Driven Trade, which separates the types of trades into Liquidity Driven Trade (LDT) and Information Driven Trade (IDT). Under MDT hypothesis, Liquidity Driven Trades are likely to cause a reversal in consecutive returns, which increase the volatility of returns and induce a positive relation between volume and volatility. In the contrast to LDT, Information Driven Trades tend to create a momentum in consecutive returns, which reduces the volatility of returns and implies a negative volume-volatility relation.

In Chapter 5 we investigate the relation between trading activity and price behaviour of the three energy commodities traded in TOCOM. To achieve this, we use the realised volatility obtained using high frequency intraday data and a Structural Vector Autoregressive (SVAR) model to measure the contemporaneous and lead-lag interaction between trading volume and volatility. We modify the SVAR by including a dummy variable to capture the effect of market condition on volume-volatility relation, which allows the parameters of the SVAR to be dependent on the slope of forward curve, so called T-SVAR. In addition, we take into account the roll-over effect by introducing a dummy variable to capture the time effect of maturity and roll-over of contracts.

1.5.3 Components and Determinants of Bid-Ask Spread of TOCOM Energy Futures

Bid-Ask spread (BAS) has always been one of crucial topics in financial research because it is of concern to several participants in financial market. For market-makers, BAS is their potential profit as a compensation of providing liquidity to the market. From exchange’s point of view, BAS provides a clue for market design, such as whether they should assign a single market-makers, or increase the competition of different market-makers, and the determination of minimum tick size. It is also very important for regulators since it can be a tool to measure the fairness of market-makers' rent.

Four components of BAS have been identified, adverse-selection costs, inventory-hold costs, order-processing costs and level of competition (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Glosten and Harris, 1988; Stoll, 1989; Bollen et al., 2004). The adverse-selection component is due to the existence of informed traders. When market-makers and informed investors possess asymmetric information, informed investors can profit by trading on their private/superior information, while market-makers provide them liquidity on a loss. Therefore, market-makers tend to widen BAS in order to reduce the possibility of informed trading and increase the profit traded with other investors. The second component, inventory-hold costs, occurs when market-makers' funds are held to markets. This may include the opportunity cost of investing alternative assets and the risk of adverse movement of invested assets. The order-processing costs are directly related to providing liquidity, including exchange seats, floor space rent, computer costs, labour costs, and even the opportunity cost of market-makers' time. The last component, level of competition, is because increases in competition among market-makers reduce the profit of each market-maker and so does BAS.

To investigate the determinants of BAS components for TOCOM energy futures markets, we employ a time-series model which considers intraday information on three components, namely adverse-selection costs, inventory-hold costs, order processing costs. As it is not possible to obtain the information of number of market makers, the level of competition is not considered here. Two variables, realised volatility and trading volume are included. The former reflects inventory-hold costs, while the latter contains information of adverse-selection and order-processing costs. Moreover, this study also considers two different the asymmetric effects of trading volume on BAS, which are sell-initiated and negative-return transactions.

1.6 Summary and Conclusions

The aim of this study is to focus on a new market for energy derivatives with several distinctive characteristics. First, in contrast to NYMEX and ICE energy derivatives markets, TOCOM is a more domestic market where crude and products futures contracts are traded in Japanese yen. Second, the exchange regulations impose trade restriction and position limits for different participants depending on the nature of their trade (see Chapter 3 for details). Third, the trading pattern in TOCOM seems to be different from other energy and commodity derivatives markets since liquidity or trading volume appears to have a positive relation with contract maturity; that is, trading volume decreases as contract maturity reduces.

In terms of general contributions, this study extends the exiting literature on energy futures markets in several dimensions. First, we estimate and forecast realised volatility of TOCOM energy futures contracts by adapting a regime switching model which takes into account changes in the dynamic of estimated realised volatility. In addition, we evaluate the performance of the regime switching realised volatility models across maturity of futures contracts using a battery of tests as well as VaR metrics. Second, using a T-SVAR model, we investigate the trading activity and volatility relation of energy futures contacts and find that while volatility and trading volume are contemporaneously related, however, the strength of the relation can vary according to the market conditions as indicated by the slope of the forward curve. The main justification for such a change in trading activity and price volatility is explained using market structure and trading patterns of market participants. Third, the analysis of the determinants of components bid-ask spread of energy futures traded in TOCOM using high frequency data reveals important information on the impact of return volatility, trading volume and potential asymmetric impact of trading volume on bid-ask spread. In particular, we find that while volatility has appositive impact on bid-ask spread as suggested by the literature according to the inventory holding cost, the results revealed that trading volume has a negative impact on the BAS of energy futures. In addition, the asymmetric impact of sell-initiated transaction has been found positive, which indicates BAS is narrowed less when ta trade is sell-initiated.

The rest of this research is structured as follows. We begin with the review of relevant literature in Chapter 2, which explains the theories and past empirical studies in detail. Chapter 3 presents an introduction of TOCOM energy futures, descriptive statistics and a preliminary analysis of data. In Chapter 4, 5 and 6, we present three analyses, namely modelling realised volatility, volume-volatility relation, and determinants of bid-ask spread components. Chapter 7 concludes.

Chapter 2 Review of Literature

2.1 Introduction

There has been a significant increase in the number of studies on energy prices and markets in recent years due to the importance of the sector to national economies, international trade, world geopolitical landscape, and opportunities that energy commodities offer to investors. Over the years, researchers have examined different aspects of energy commodity prices and energy derivatives markets including the time series behaviour of prices, market efficiency and price discovery, risk management and hedging effectiveness, market microstructure and liquidly, pricing of derivatives contracts, as well as performance of forecasting and trading strategies.

Amongst different types of energy commodities, crude oil and petroleum products have been the focus of many studies as crude oil and petroleum products are essential commodities as input for production and manufacturing, fuel for transportation and shipping, as well as source of energy for commercial and residential use. In addition, crude oil and petroleum products are also used as investment commodities which allow investors to diversify their portfolios or benefit from trading these commodities in physical form or under derivatives contracts.

One particular aspect of a group of studies in the literature has been the modelling and forecasting volatility of energy prices as such information can be used for different purposes including risk management, asset allocation and investment, and derivatives pricing and trading, to name a few. In addition, a number of studies are also devoted to examining the market microstructure and in particular the relation between trading activities and volatility of energy commodities in futures markets to explain the behaviour of investors and their impact on prices. In this chapter, we begin by presenting the relevant literature on market microstructure and some application in energy market. Afterwards, we discuss different approaches used in the literature for modelling volatility of energy prices and returns and their findings. Next, we investigate the studies on the return-volume and volatility-volume relations in energy markets. Majority of the studies are concentrated in investigating the volatility of energy futures markets in the US (NYMEX) and UK (ICE) as the two mature and established energy futures exchanges. Finally, the relevant literature on components and determinants of BAS is presented.

2.2 Market microstructure and energy market

Market microstructure provides the insight of the behaviour of market makers and other participants. Two main theories are discussed by the literature, namely inventory model and information model. Both of them focuses on how market makers set bid and ask prices to provide liquidity and meanwhile prevent themselves from failure. In the following, theoretical models of inventory effect and information effect are presented. Then, the empirical literature for examining two models and the discussion in energy market are discussed.

2.2.1 Inventory model

Market makers play an important role in the literature of market microstructure, who adjust bid and ask prices based on the change in market condition and mainly earn the bid-ask spread as the return for providing liquidity to markets. Demsetz (1968) argues that the bid-ask spread is determined by waiting cost and level of competition in addition to other direct costs such as transaction fee and commission to brokers. Waiting cost is defined as the cost incurs for waiting to trade with any immediate incoming orders. Thus, any trader demands a quick trading have to pay higher price as the compensation to those who stand ready and wait to trade.

Earlier studies explaining the intraday variation in bid-ask spread mainly focus on the role of inventory, such as Smidt (1971) and Garman (1976). Smidt (1971) suggests that market makers reduce the bid prices to accumulate their inventory when there is an excess of supply, while increase the ask prices to dispose of their inventory when there is an excess of demand. Garman (1976) proposes the theoretical model of market microstructure based on the relation between the market maker's inventory and quotes. The model is set to be a one single monopolistic market maker who processes all trading, and sets the bid and ask prices. The market maker has finite cash and stock inventory, and fails to provide service by either cash or stock depletion. Garman's model suggests that given the inventory is assumed as a random walk with zero drift, the market maker will eventually fail, and the probability of failure and the length to failure are both related to the market maker's inventory level. This implies the importance of the market maker's inventory, so the market maker will reluctantly change inventory unless the price significantly declines.

Amihud and Mendelson (1980) extend Garman's model by introducing the states of the market maker's stock inventory level, meaning the market maker can only take limited short or long position. This model shows that the price policy of market maker is to maintain a preferred inventory position by adjusts his quoted prices If the inventory level is away from the preferred inventory position, the market maker quotes prices to draw his inventory level back to the preferred one. Another extension of the inventory model is proposed by Madhavan and Smidt (1993). In the setting of Madhavan and Smidt's model, the market maker is both a dealer who provides liquidity to the market and an investor who invests for his own account. Moreover, their model incorporates both inventory effect and information effect, and allows the preferred inventory level to change over time. Their empirical evidence shows that allowing time-varying preferred inventory level improves the goodness of fit from 2%

to 18% on average, and produce the more reasonable inventory half-life from 49.7 trading days to 7.3 trading days. Hence, instead of targeting an unchanged long-term inventory level, the market maker tends to quote prices that leads his inventory to a time-varying preferred level.

2.2.2 Information model

More recently studies pay attention to the behaviour of different types market participants in response to the arrival and dissemination of information under an imperfection market. Bagehot (1971) firstly distinguish market traders into three different categories, namely informed, uninformed and noise traders, based on their motivation for trading. Informed traders possess private information, while uninformed traders possess information that they believe it is private but, in fact, is not. Noise traders transact due to liquidity need such as adjustment of their portfolio. As market makers are responsible to provide liquidity to the market, they always lose money trading with informed traders. As a result, market makers need to set up a positive spread that covers the informational component, which is also called adverse-selection component in Section 2.5, in order to regain the profit from the other two types (Copeland and Galai, 1983).

Glosten and Milgrom (1985) develop the information model in a dealership market with informed traders and uninformed traders, defined as purely liquidity traders here. In their model, the expectation value from the market maker and informed traders will eventually fully converge, because the market maker learns the correct price by observing the order flow. In addition, the bid-ask spread is widened when the ratio of informed traders to uninformed traders increases since the rise in the ratio indicates higher probability of adverse selection. Easley and O'Hara (1987) extend Glosten and Milgrom’s model by considering the market maker’s pricing policy in response to the trade size. In particular, since informed traders compete with each other, they are more likely to trade in large size in order to maximise their profit. Therefore, the market maker can set higher spread to the large quantity of trades than to the small one.

On the contrast to Easley and O'Hara's model, Kyle (1985) proposes a model with a single trader who possesses the monopolistic private information and trade on it in order to maximise his profit. Similar to other information models, the market maker updates his belief of the price by observing the order flow from informed and uninformed traders, and the market price eventually reflect all available information. Moreover, Kyle's model suggests that the trading activity of the inform trader becomes more aggressive when the liquidity from uninformed traders are larger, since the market maker can regain more profit from the larger quantity of uninformed trading. Admati and Pfleiderer (1988) expand Kyle's model by allowing discretionary uninformed traders, who can choose the trading time of the day and the competition between informed traders. Their model suggests that discretionary liquidity trading tends to be concentrated, especially in the period closer to the realisation of their demand. In addition, it is consistent with Kyle's model that informed trading is more active when liquidity trading is in concentration.

2.2.3 Empirical evidence

Both inventory and information effect are examined by several empirical studies. French and Roll (1986) investigate the daily returns of all common stocks on the New York and American Stock Exchange, and find the variance of returns during trading hours is much higher than that during non-trading hours. They examine three possible causes of this phenomenon: 1) the high variance during trading hours is caused by public information because public information is observed during business hours; 2) the high variance during trading hours is caused by private information because private information only affects prices through informed trading; 3) the high variance during trading hour is caused by trading process (mispricing) itself. By comparing weekday holidays returns with single-calendar-day returns, they distinguish public information from private information. Since public information is still available in other markets during weekday holidays, the variance of weekday holidays returns is expected to approximately double that of single-calendar-day returns if the variance is mainly driven by the public information. Their result shows that the variance of weekday holidays returns is only 14.5% higher than that of single-calendar-day returns, which implies that the variance of returns is mainly caused by the flow of private information.

Hasbrouck (1988) studies quotes and trades data on NYSE to examine the inventory and information effects. His result suggests that trades are negatively autocorrelated for low-volume stocks but not for high-volume stocks, which indicates the inventory effect does not always exist. In addition, the impact of trades on quotes revision seems insignificant. With respect to the information effect, their evidence shows that the persistence impact of trade quotes is strong, and more information is conveyed by large trades. Hasbrouck (1991a) further uses a vector autoregressive system to investigate the interaction between trades and quotes revision. The empirical result supports the existence of information effect and inventory control effect, and shows that large trades usually widen the bid-ask spread, which also increases price impacts. Moreover, Hasbrouck (1991b) decomposes the variance of efficient price into public information component and private information component, so called trade-uncorrelated and trade-correlated component. By studying firms listed on New York and American Stock Exchange, he finds that the trade informativeness, defined as the efficient price variance attributable to trades, is larger for smaller capitalisation stocks, and 34 percent of efficient variance attributes to trades.

Engle (2000) incorporate durations, defined as the waiting time between the arrival of two successive transactions and modelled by the ACD model (Engle and Russell, 1998), into a GARCH framework to investigate the impact of trade timing on price volatility. This study investigates 52,144 IBM stock transactions, and finds that both expected and observed duration is negatively related to the price volatility because the long duration indicates no news comes to markets. In addition, the evidence also suggests the greater bid-ask spread and trading volume indicates the rise in the price volatility. Moreover, Dufour and Engle (2000) investigate the impact of duration under Harbrouck’s VAR framework for 144 stocks on NYSE. Their findings show that the shorter the duration is, the higher the quotes revision and the autocorrelation of trades are, which indicates the high trading activity implies the great price impact and the concentrated trades. In the connection to the results of Hasbrouck (1991a), high trading activity (low duration), wider bid-ask spreads, large price impact and large trade size are bound together. Therefore, the duration and trade size may provide other market participants, such as uninformed traders and market makers, a hint of the presence of informed trading. More recently, Manganelli (2005) analyses 10 stocks on NYSE to examine three hypotheses: 1) the trading volume is in cluster;

2) the greater trading activity coincides with a high number of informed traders; 3) the price variance of high trading activity stocks converges to long-run equilibrium faster than that of low trading ones. His results show that the trades clustering exists for all stocks, and autocorrelation in trading volume is stronger for more frequently trading stocks. In addition, the duration is negatively related to the price variance, while the trading volume is positively related to the price variance. Because the positive relation between volume and variance indicates trading is information driven, the low duration (high trading activity) coincides a high proportion of informed trading. With regards to the last hypothesis, the average time taken to absorb shocks for low duration stocks is less than that for high duration stocks, which confirms the hypothesis.

2.2.4 Microstructure in energy futures market

One major difference between financial futures and commodity futures is the underlying assets. The underlying of financial futures are financial assets, such as stocks, bonds, interest rates or currency whereas that of commodity futures are physical assets, such as petroleum, agriculture products and metals. The prices of physical assets are determined by the supply and demand function of both the cash market, which is for instant purchases or sales, and storage market, which is for the inventory held by producers and consumers (Pindyck, 2001). Nonetheless, for most financial assets, the impact of storage costs can be negligible. Pindyck (2001) also points out that the existence of the storage market may also smooth the fluctuations of commodity prices. For example, if there is an excess of demand, the producers can use their inventory to fulfil the (expected) increase in consumptions so that the fluctuations in the market can be reduced.

Even though the theory of storage can explain the dynamics of storable commodities spot and futures prices, the impact of storage on the microstructure is limited because futures are still more related to financial assets. However, Vansteenkiste (2011) investigates WTI futures prices by two aspects, namely fundamental, which is implied by cost-of-carry theory, and market microstructure. The results show that if the fundamental volatility is high, only commercial traders would enter the market. However, if oil demand volatility decreases or unexpected oil shocks happens, non-commercial traders would participate the market. This is consistent to the main motivation for trading of commercial and non-commercial traders, since commercial traders hedge especially when the underlying market is volatile while non-commercial traders earn profit thorough trading on information. This study implies that even though the theory of cost-of-carry does not directly affect the market microstructure, it still has indirect impact on market microstructure, such as the component of the participants. Moreover, the information effect in energy market is also examined by analysing the relation between volume and volatility. In section 2.4.4, literature discussing the volume-volatility relation in both daily and intraday frequency analyses are presented in detail.

2.3 Modelling Volatility of Energy Futures Return

The issue of modelling the dynamics of volatility of energy prices and returns has been of interest to researchers for many years. This is because variation in energy prices can have significant effect on income of producers, costs and expenses of consumers, as well as investment portfolios of traders in energy markets. Therefore, different approaches have been proposed and employed to capture the dynamics of volatility of energy prices and returns. In what follows we classify and present the studies on modelling volatility of energy prices according to the approach used, and discuss their findings and the pros and cons of each method.

2.3.1 Autoregressive Conditional Heteroscedasticity models

Following the pioneering study of Engle (1982) on modelling the dynamics of the second moment of a time series using Autoregressive Conditional Heteroscedasticity (ARCH), a large number of studies are devoted to examine and model the time varying conditional volatility of economic and financial series including stock returns, commodity futures prices, exchange rates, inflation, interest rates and other financial and economic variables (see Bera and Higgins, 1992, Bollerslev et al., 1992, Engle and Ng, 1993, and Teräsvirta, 2006 for detailed reviews of applications and extensions of ARCH-type models).

At the same time, a number of the studies focus on the specification of these models in capturing the stylised facts of asset prices and returns including leverage effect, non-normality, time-varying skewness and kurtosis, and structural breaks and regime shifts. For instance, Engle and Ng (1993) argue that the impact of shocks on volatility can vary depending on their sign and magnitude. In this respect, they propose a series of diagnostic tests for volatility models, which examine the effects of shocks on volatility.[8] To account for asymmetric effects of shocks on volatility, Glosten et al. (1993) and Nelson (1991) propose the Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH) specifications, respectively, to capture asymmetric response of volatility to positive and negative shocks.

Different specifications of GARCH model have also been widely employed to model and forecast volatility of energy prices as it has been shown that GARCH specification is able to capture the long memory property in crude oil market. Apart from the standard GARCH model, Asymmetric GARCH (AGARCH) and Integrated GARCH (IGARCH) are also applied to model volatility of crude oil and petroleum prices. For instance, Sadorsky (2006) examines the forecasting performance of GARCH and Threshold GARCH (TGARCH) type models in predicting volatility of daily oil prices concludes that no one model is the best predictor. Narayan and Narayan (2007) found the evidence supporting the asymmetric effect of shocks on the volatility by EGARCH. They argue that this approach is more appropriate as it can address deviations from normality. Hou and Suardi (2012) show that nonparametric GARCH models can produce better forecasts of crude oil futures return volatility compared to parametric GARCH models. This is expected because of the deviation of the oil price distribution from normality and the existence of excess kurtosis as observed by Chan et al. (2007). Fan et al. (2008) propose a Generalised Error Distribution (GED) GARCH approach to estimate Value-at-Risk of WTI and Brent crude oil prices, while Giot and Laurent (2003) employ a APARCH model with skewed Student-t distribution to model the conditional variance, and then to estimate the VaR for metal, energy and

[8] These tests are the sign bias, size bias, and the joint test. The sign bias tests the asymmetry response of volatility to shocks with different signs, whereas the size bias tests the response of volatility to shock with different magnitude, and the joint test is used to investigate the existence of both effects.

agricultural commodities.

Moreover, Cheong (2009) and Kang et al. (2009) discuss modelling and forecasting volatility in three crude oil markets (Brent, Dubai, and West Texas Intermediate, WTI) using different types of GARCH models. For instance, Kang et al. (2009) find that the CGARCH and FIGARCH models are better equipped to capture persistence in volatility and provide superior performance in out-of-sample volatility forecasts compared to the GARCH and IGARCH models. Mohammadi and Su (2010) also investigate the out-of-sample performance of different GARCH specifications (GARCH, EGARCH, APARCH and FIGARCH) in forecasting volatility of spot prices for eleven international crude varieties. They report that the forecasting performances of the models are mixed, but APARCH model seem to marginally perform better. Moreover, Wei et al. (2010) employ the Superior Predictive Ability (SPA) test to compare different specifications of GARCH models, and conclude that no particular GARCH model outperforms other models and researchers should find the optimal model depending on the purpose of the modelling exercise. For instance, linear GARCH models are suitable for forecasting short-run volatility (less than 1 year) whereas non-linear models can produce better forecasts for long-term (more than 1 year).

In a recent study Chkili et al. (2014) find that in-sample and out-of-sample volatility of commodity returns (including NYMEX WTI crude oil and Natural Gas futures) can be better described by nonlinear volatility models such as FIAPARCH which accommodates the long memory and asymmetry features of commodity price volatility. They also report that the FIAPARCH model performs better in estimating the VaR forecasts for both short and long trading positions. Furthermore, the bivariate GARCH models have also been developed to forecast variance and covariance of spot and futures prices for determination of hedge ratios. For instance, Chang et al. (2010), Chang et al. (2010), Wang and Wu (2012) and Efimova and Serletis (2014) provide evidence that multivariate GARCH model can forecast crude oil return volatility better than univariate models.

In another extension of GARCH models, Fong and See (2002) highlight the importance of market condition or regimes in dynamics of volatility of energy prices. By employing a Regime Switching GARCH model, Fong and See (2002) show that regime shifts are present in the crude oil price volatility and dominate GARCH effects. Based on the same argument, Alizadeh et al. (2008) employ Bivariate Regime Switching GARCH (MRS-GARCH) models to examine the hedging effectiveness of WTI Crude Oil, Heating Oil, and Gasoline futures contracts traded in NYMEX. Using in- and out-of-sample tests, Alizadeh et al. (2008) report that regime switching hedge ratios are generally perform better than other dynamic hedge ratios including multivariate GARCH models.

Alizadeh and Talley (2009) and Nomikos and Pouliasis (2011) also argue that the dynamics of volatility can be different depending on prevailing market conditions. Alizadeh and Talley (2009) use the slope of forward curve as proxy for market condition and report that the dynamics of volatility of four NYMEX energy futures (WTI crude oil, Gasoline, Heating oil and Natural Gas) can vary under conango and backwardation states. They also report a quadratic relation between the slope of forward curve and the volatility of energy futures prices. Nomikos and Pouliasis (2011) use different GARCH specifications including a Markov Regime Switching GARCH (MRS-GARCH) model and a Mix-GARCH[9] model to examine the volatility of four energy futures (NYMEX WTI crude oil, and Heating oil, and ICE Brent crude and Gasoil). They report that a two state regime MRS-GARCH and Mix-GARCH models explain the in-sample volatility of energy futures better than alternative GARCH specifications, however, their out-of-sample forecast are somehow mixed.

2.3.2 Implied Volatility

Although GARCH type models are able to capture the long memory property of volatility, the lack of forecast accuracy of GARCH models has been pointed out in several studies including Figlewski (1997) and Poon and Granger (2003). Cabedo and Moya (2003) and Sadeghi and Shavvalpour (2006) point out that because of high persistence in GARCH models, they tend to overestimate the variance which in turn results in inaccurate forecast of variance and inefficient VaR estimates. An alternative

[9] The Mix-GARCH model proposed by Vlaar and Palm (1993) differs from the MRS-GARCH model in the definition of regime probabilities. In the Mix-GARCH the overall regime probability over the total sample is considered.

approach to estimate the volatility of financial assets is to use the Implied Volatility based on traded option values proposed by Latane and Rendleman (1976) and Beckers (1981). Implied Volatility (IV) estimates are obtained by inverting a closed form option pricing formula such as Black and Scholes (1973) using traded option premia on the underlying asset.

Day and Lewis (1993) compare the forecasting performance of GARCH and EGARCH models with the IV of option prices on NYMEX WTI crude oil futures over the period November 1986 to March 1991. They report that volatility forecasts based on IV outperform the forecast produced by complicated GARCH models. Jorion (1995) and Fleming et al. (1995) also find evidence suggesting that IV is a better predictor of volatility in currency and stock markets, respectively. Szakmary et al. (2003) examine 35 options on futures, and reports that implied volatilities perform marginally better than historical and GARCH type volatilities in predicting volatility of futures prices.

Despite the extensive empirical evidence in favour of implied volatility across different markets (Christensen and Prabhala, 1998, Ederington and Guan, 2002, Giot, 2003, and Pong et al. 2004), a few studies argue that implied volatility is an inefficient and biased estimate of realised volatility. For instance, Lamoureux and Lastrapes (1993) and Canina and Figlewski (1993) studies on stock market, find that implied volatility is a biased estimate of volatility. For instance, Canina and Figlewski (1993) examine the performance of IV of options on S&P 500 index futures contract and argue that that along with investors' perception of future volatility, an option's market price also reflects the net effect of many other factors that influence option supply and demand but are not in the closed form option pricing model. In addition, liquidity considerations, interaction between the OEX option (options on S&P100 index) and the (occasionally mispriced) S&P 500 index futures contract, and investors' preferences for particular payoff patterns could also contribute to inaccuracy of implied volatilities derived from market traded option values. Engle and Rosenberg (2000) point out that the methodological issues such as sample selection bias could be a reason for the implied volatility to be a biased estimator of volatility. However, Neely (2009) provides evidence to reject such an argument for IV in foreign exchange market, and argues that IV is the conditional expectation of RV (that is, unbiased predictor of future volatility) only under fairly stringent assumptions and the IV bias exist because it is not economically significant to be arbitraged away.

Furthermore, Agnolucci (2009) points out that although the GARCH estimate outperforms the implied volatility in NYMEX crude oil options on futures, however, there is still value in the implied volatility as the information contained in the IV forecasts is not contained in those obtained by using time series models. In a recent paper, Haugom et al. (2014) also argue that including the Crude Oil Implied Volatility Index (OVX), reported by CBOE, in models based on realised volatility measures can significantly improve the predictive power of daily and weekly volatility forecasts.

2.3.3 Realised Volatility Models

A number of recent studies suggest that high-frequency data are useful for estimating and predicting future volatility as intraday movements in prices is less subject to measurement error compared to price observations at lower frequency, Andersen and Bollerslev (1998). In this approach, an unbiased estimator of volatility, known as realised volatility (RV), can be estimated using the squared values of intraday returns. Therefore, considering the intraday returns series, $r_{i,t}$, can be constructed by dividing each day into *M* equidistant intraday periods, then the realised volatility of day *t* for a portfolio of assets can be measured as $\mathrm{RV}_t = \sqrt{\sum_{i=1}^{M} r_{i,t}^2}$ (see 4.3.1 for detailed explanation on RV). Under the assumption that returns are independent with a zero mean, RV_t^2 is an unbiased estimator of the true variance. Andersen et al. (2001a) and Andersen et al. (2003) propose different time-series models for estimation realised volatility with high-frequency data. Barndorff-Nielsen and Shephard (2004), Andersen et al. (2007), and Barndorff-Nielsen and Shephard (2007) further argue the importance of accounting for jumps in estimation of realised volatility. Andersen et al. (2006) and McAleer and Medeiros (2008) provide a thorough survey of studies on the estimation and applications of realised volatility.

In the energy sector, the first study employing the realised volatility approach to estimate the volatility of sweet crude oil is Martens and Zein (2004), and followed by Wang et al. (2008) investigating NYMEX crude oil and natural gas futures prices. They suggest that RV is an appropriate measure of volatility in both crude oil and natural gas market as well the Realised Correlation between the futures prices of the two commodities. Wei (2012) examines the crude oil futures traded in Shanghai Futures Exchange (SHFE), and argues that the RV and the stochastic volatility (SV) models are able to produce more accurate volatility forecasts compared to GARCH models.

In a recent study, Sévi (2014) employs intraday data to forecast the volatility of WTI crude oil futures for 1- to 66-day horizon using a variety of models based on the decomposition of realized variance into its positive or negative part (semivariances) and its continuous or discontinuous part (jumps). Considering eleven Heterogenous Autoregressive (HAR) models proposed in the literature (Andersen et al. 2007, Corsi, 2009, Chen and Ghysels, 2010, and Patton and Sheppard 2015), Sévi (2014) reports that the model with independent squared jump has best forecast in-sample, but does not improve significantly the out-of-sample forecast. Haugom et al. (2014) also analyse the realised volatility of WTI crude oil futures, and employ an augmented HAR-RV model of Corsi (2009) which incorporates implied volatility (CBOE Crude Oil Volatility Index as a proxy) and other market variables including trading volume, open interest, daily returns, bid-ask spread and the slope of the futures curve. Their forecasting results reveal that incorporating the IV (Crude Oil ETF Volatility Index, OVX) can significantly improve the short term (daily and weekly) volatility forecasts, while including the other market variables improves the long term (monthly) volatility forecasts.

2.3.4 Stochastic Volatility Models

A recent approach in modelling and estimating volatility is based on the concept that volatility of asset prices can behave stochastically. This led to the introduction of the family of stochastic volatility models where the variance is decomposed into deterministic and stochastic parts. For instance, Taylor (2008) proposes a basic logarithmic Autoregressive Stochastic Volatility (ARSV). However, a model which has been used and discussed extensively in the literature especially for derivatives pricing is Heston's (1993) stochastic volatility model where the volatility is assumed to follow a mean-reverting process. [10] While different processes can be used to explain the mean, for instance mean-reversion (MR) or mean-reversion jump diffusion (MRJD) processes, most studies in the literature assume a MR type process for volatility to ensure variance process remain stationary.

The empirical application of stochastic volatility models has been limited mainly due to the difficulties involved in their estimation. The major problem is that the likelihood function is hard to evaluate, despite the introduction of several new estimation methods in the literature in recent years (see Broto and Ruiz (2004) for a detailed survey and discussion of stochastic volatility estimation methods). However, the stochastic volatility models tend to exhibit a lower degree of persistence compared to the GARCH model which can result in better volatility predations.

Larsson and Nossman (2011) use four affine jump diffusion stochastic volatility models (namely Jump Diffusion, Stochastic Volatility, Stochastic Volatility with Jumps, and Stochastic Volatility with Correlated Jumps) to study WTI crude oil spot price dynamics during the period May 1989 to May 2009. Their results provide support for a stochastic volatility model with correlated jumps in both prices and volatility (SVCJ) as the SVCJ model outperforms the others in terms of a superior fit to data. In a recent paper, Chiarella et al. (2013) propose a multifactor stochastic volatility model within the Heath et al. (1992) framework which captures the main characteristics of the volatility structure of NYMEX crude oil futures including the hump shape in the term structure of volatility. They report evidence on the existence of three volatility factors, two of which tend to exhibit a hump. Finally, using hedge ratios implied by their proposed unspanned hump-shaped stochastic volatility model, they report that hedging performance of the proposed model is better than a model with only exponential decaying volatility term structure.

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[10] Heston's (1993) stochastic volatility model has the following specification $dV = \alpha(\bar{V} - V)dt + \xi\sqrt{V}dw$, where dt is an infinitesimal fraction of time, *V* is volatility (variance), *dw* is a random variables, $\bar{V}$ is the long term variance, ξ is a coefficient which determines the fluctuation in the variance (the standard deviation of the variance). The absolute volatility of the variance is $\xi\sqrt{V}$.

2.4 Trading Volume and Volatility Relation

The relationship between trading volume, price change and volatility has been widely investigated in many financial and economic studies. There are a number of reasons for such an interest in discovering the true nature of the relationship both in theoretical and practical terms. A large number of studies have been devoted to examine the trading volume and price relationship in different markets, using different sample period and functional forms. The general consensus is that there is a positive relationship between trading volume and price change in financial and commodity markets. A number of theoretical frameworks have been proposed to explain the positive relation between trading activity and price change including Mixture of Distribution Hypothesis (MDH) by Clark (1973), the Sequential Information Arrival Hypothesis (SIAH) by Copeland (1976), Motivation Driven Trades by Wang (1994) and Llorente et al. (2002). In addition, the relation between trading volume and price volatility has been the subject of many studies and the overall empirical evidence suggests that there is a positive relation between trading activity and market volatility in different markets (e.g. Lamoureux and Lastrapes, 1990, Najand and Yung, 1991, Bessembinder and Seguin, 1993, Foster, 1995, Moosa and Silvapulle, 2000, Moosa et al., 2003, Chevallier and Sevi, 2012, Halova, 2012, and among others).

2.4.1 Mixture of Distribution Hypothesis

The Mixture of Distribution Hypothesis of Clark (1973) postulates that price change and trading volume follow a joint probability distribution; hence, price change and trading volume are positively correlated as they jointly depend on a common underlying variable, which is normally interpreted as the random flow of information to the market. The MDH also assumes that all traders receive and react (e.g. trades) to the information simultaneously. Evidence in support of MDH is provided by Epps and Epps (1976) who examine 20 stocks on the New York Stock Exchange (NYSE). They prove MDH by using transaction volume as the mixing variable. Tauchen and Pitts (1983) model the joint distribution of volume and squared price change for 90-day T-bills futures and report consistent results with MDH. Other studies utilise the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model by

Engle (1982) and Bollerslev (1986) to investigate the volume-volatility relation as the return distribution of financial assets is usually time-varying. For instance, Lamoureux and Lastrapes (1990) find a positive contemporaneous relationship between trading volumes and return variance in 20 S&P500 stocks, which is in line with MDH. Moreover, Najand and Yung (1991) and Rahman et al. (2002) report a positive volume-volatility relationship in both the Treasury-bond futures market and the NASDAQ 100 index. More interestingly, Lamoureux and Lastrapes (1990) find that the persistence of lagged square residual becomes much weaker when trading volume is included in the variance equation.

However, including trading volume as a variable in the GARCH model is argued to be inappropriate by Fleming et al. (2006), since volume should be endogenous to volatility according to MDH. Therefore, simultaneity bias may incur if the GARCH model is estimated. To overcome the problem of simultaneity, studies employ the Generalised Method of Moment (GMM) to analyse the volume-volatility relationship. For instance, Foster (1995) on the Brent and WTI crude oil market, Wang and Yau (2000) on the S&P500 index, Deutsche Mark, and silver and gold futures, and Lee and Rui (2002) on the US, UK, and Japanese stock markets, all provide evidence of contemporaneously positive volume-volatility relationships. More recently, Hussain (2011) investigated the volume-volatility relationship for the DAX 30 stock index considering the effect of expected and unexpected trading volume on the volatility of the index. He finds a positive relationship between unexpected trading volume and return volatility with certain asymmetric effect; that is, a positive change in trading volume can increase return volatility more than a negative change in volume can.

2.4.2 Sequential Information Arrival Hypothesis

Sequential Information Arrival Hypothesis (SIAH), proposed by Copeland (1976) and discussed further in Jennings et al. (1981), explains the positive relationship between price changes and volume as a consequence of random arrival but gradual dissemination of information in the market. Therefore, informed traders who receive the information first, rebalance their portfolios accordingly, which results in shifts in supply and demand in the market and a series of transitory equilibria. Once the information is fully absorbed by all traders, informed and uninformed, then the new equilibrium is reached. This sequential dissemination of information initiates transactions at different price levels during the day, the number of which increases with the rate of information flow to the market. Consequently, both trading volume and movement in price increase as the rate of arrival of information to the market increases which implies the existence of a positive relationship between the trading activity and price variability.

SIAH implies a lead-lag relationship between trading volume and price volatility, and several empirical papers provide evidence in support of such a relationship in different financial and commodity markets. Smirlock and Starks (1988) study 300 S&P 500 companies, and find the existence of a lead-lag relation between absolute price change and trading volume. Using 5-minute intraday data and an EGARCH specification, Darrat et al. (2003) investigate the volume-volatility relation in the Dow Jones Industrial Average (DJIA) index. Their results reveal a weak contemporaneous relationship but a strong lead-lag relationship between the volume and volatility of DJIA, which is in line with SIAH. Darrat et al. (2007) argue that SIAH can be tested only in periods when the news is public. They examine the dynamic relation between intraday trading volume and the return volatility of large and small NYSE stocks using two partitioned samples, with and without identifiable public news. Their results reveal a bi-directional Granger-causality between volume and volatility when information is public, as hypothesized by SIAH. However, in periods when there is no public news, only trading volume Granger-causes volatility. Darrat et al. (2007) relate the latter to behavioural models like the overconfidence and biased self-attribution model by Daniel et al. (1998).

Generally speaking, the MDH and the SIAH both suggest existence of a positive relation between trading volume and price volatility. Nevertheless, they differ in the symmetry of the flow of information to the market. The MDH assumes all traders and market participants receive the random information simultaneously, so the volume-volatility relation is contemporaneous. On the other hand, the SIAH assume that the information arrives randomly but reaches different traders sequentially. As a result, changes in trading volume precede price movements. In other words, the trading volume is supposed to lead the price change and volatility under the SIAH hypothesis.

Strangely enough, these two hypotheses do not seem to be mutually exclusive. The literature providing evidence in support of MDH also reveals lead-lag relationship between volume and volatility. Foster (1995), Wang and Yau (2000) and Hussain (2011) find that the lagged trading volume also explains the contemporaneous return or price volatility using a VAR setting and the GMM estimation technique, even though the sign of coefficient is not always positive. Lee and Rui (2002) shows the positive feedback effect in the trading volume and volatility relation in US, UK and Japan stock markets, while trading volume in the US even Granger-causes UK and Japan financial markets.

2.4.3 Trader Types and Volume-Volatility Relation

Wang (1994) and Llorente et al. (2002) argue that volume and return dynamics depend on the motivation behind the trade. For instance, Wang (1994) discusses two different hypotheses, namely Liquidity Driven Trade (LDT) and Information Driven Trade (IDT) hypotheses. Under the LDT hypothesis, a reversal in consecutive returns is likely if the trading by informed traders is driven by changes of investment opportunities outside the market. In this case, trading volume will contribute positively to the subsequent volatility. Under the IDT hypothesis, it is argued that the momentum in consecutive returns is a consequence of the informed investors' trade due to better private information. This is because when a subset of informed investors sells (buys) because they have unfavourable (favourable) private information; the asset price decreases (increases), reflecting the negative (positive) private information about its payoff. Since this information is usually only partially incorporated into the price at the beginning, the negative (positive) return in the current period will be followed by another negative (positive) return in the next period. Thus, this trading volume leads to lower subsequent volatility since these two period returns tend to be of the same sign, which means that high trading volume will be followed by a low volatility; that is, trading volume and subsequent volatility are negatively related. Llorente et al (2002) also show that "hedging trades", which are liquidity-driven trades, generate negatively auto-correlated returns, while "speculative trades", which are information-driven trades, generate positively auto-correlated returns.

2.4.4 Evidence from energy markets

Serletis (1992) studies the relation between trading volume and the volatility of crude oil futures contracts traded in NYMEX during the period from January 1987 to July 1990, allowing for maturity effect. Although he finds that crude oil futures prices become more volatile and trading volume increases as futures contracts approach, the results of causality tests reveal that just as volatility does not affect trading volume, trading volume has little effect on volatility. Herbert (1995) examines the relation between the trading volume and price volatility of natural gas futures contracts considering the time to maturity, and reports that a) the volume of trade rather than maturity explains the variance of the volatility, and b) that of trading volume can explain price volatility but price volatility has much less of an influence on trading activity. Moosa et al. (2003) present empirical evidence of temporal asymmetry in the price-volume relationship in the crude oil futures market. They use 3- and 6-month futures prices and trading volumes, and find that the price-volume relationship is bidirectional and asymmetric, since the effect of negative price and volume changes is stronger than that of positive price and volume changes.

More recently and with the availability of intraday data, a number of studies investigate the volume and volatility relationship using high frequency observations. For instance, Ripple and Moosa (2009) use a range-based volatility measure and examine the effect of intra-day trading volume and open interest on crude futures contracts. They report the positive and significant role for trading volume in the determination of volatility as well as the importance of the open interest, which has a significant negative effect. Chevallier and Sévi (2012) investigate the relationship between trading volume and price volatility in the crude oil and natural gas futures markets using various measures of realized volatility. They report existence of a contemporaneous and largely positive relationship between trading volume and price change. They also argue that the volatility-volume relationship is symmetric in relation to positive and negative realized semivariance, in the sense that the information content of negative realized semivariance is higher than for positive realized semivariance. Halova (2012) also examines the intraday volume and volatility relationship in the crude oil and natural gas futures markets using high frequency data. Based on a series of Granger-causality tests using conditional and absolute volatility measures, she reports that trading volume seems to drive volatility, which supports the SIAH.

In the electricity market, Gianfreda and Renò (2012) investigate the trading volume and spot price volatility relation in four European markets. They employ both GARCH model and realised volatility estimate and report that there is limited interaction between volume volatility of spot electricity prices when price spikes are accounted for. They argue that the lack of trading based on superior information since there is limited speculative trade in the spot electricity market.

Overall, the results of the previous literature point to the existence of a positive relationship between price volatility and trading volume in different financial and commodity markets. Additionally, there is evidence that a causal relationship exists between trading volume and price changes although the direction of causality seems to differ depending on the period and the market under investigation. One reason for such discrepancy in reported results could be that the relation between trading activity and price change can be dependent on market condition and trading behaviour of agents. Therefore, this study aims to fill this gap by investigating the trading activity, price change and volatility relationship in the TOCOM energy complex (crude oil, gasoline and kerosene) under different market conditions as indicated by the slope of forward curve. In particular, we use volatility estimates based on RV and a SVAR framework to examine whether there is any asymmetry in the volume-price relation under different market conditions. We also investigate whether market conditions in the form of the slope of forward curve can explain the trading behaviour of market participants.

2.4.5 Structural Vector Autoregressive model (SVAR)

As discussed in section 2.4.1, utilising GARCH to investigate the contemporaneous relation between trading volume and volatility may result in the simultaneity issue

(Fleming et al., 2006). Literature (Foster, 1995; Wang and Yau (2000); Lee and Rui (2002), and among others) employs GMM as a solution to avoid possible problems due to the simultaneity bias, such as inconsistent estimator and heteroskedasticity in covariance matrix, when analysing the contemporaneous volume-volatility relation. An alternative to GMM is structural Vector autoregressive model (SVAR) proposed by Sims (1980). Under Vector Autoregressive model (VAR) system, all variables are treated as endogenous and modelled by the equations in the system.

One crucial issue of the estimation of SVAR is the identification because the parameters of a SVAR is hardly identified without restrictions on structural parameters. Rothenberg (1971) provides the necessary number of restrictions for a SVAR to be identified, which is equal to $n\times(n-1)/2$, where n is the number of endogenous variables. Two classes of restrictions are utilised in the literature. The first one is linear restrictions on the parameters of both contemporaneous and lagged variables. This kind identification scheme can be triangular or non-triangular restrictions. The triangular linear restriction, also known as recursive or Choleski identification scheme, usually has a lower triangular matrix of contemporaneous parameters. For example, let us consider a simultaneous system with three endogenous variables, x_t , y_t and z_t, there are nine contemporaneous coefficients to estimate without restrictions, shown as below.

$$\begin{bmatrix} e_x \\ e_y \\ e_z \end{bmatrix} = \begin{bmatrix} a_{xx} & a_{xy} & a_{xz} \\ a_{yx} & a_{yy} & a_{yz} \\ a_{zx} & a_{zy} & a_{zz} \end{bmatrix} \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \\ \varepsilon_z \end{bmatrix},$$

where e_x, e_y and e_z are the structural disturbance, and ε_x, ε_y and ε_z are the residuals in the reduced form VAR. A triangular restriction reduces the number of contemporaneous parameters from nine to six, which can be expressed as

$$\begin{bmatrix} e_x \\ e_y \\ e_z \end{bmatrix} = \begin{bmatrix} a_{xx} & 0 & 0 \\ a_{yx} & a_{yy} & 0 \\ a_{zx} & a_{zy} & a_{zz} \end{bmatrix} \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \\ \varepsilon_z \end{bmatrix}.$$

The restrictions imply that the variable x_t is not affected by the innovations of the variable y_t and z_t, and the variable y_t is not affected by the innovation of the variable z_t. Moreover, it is clear that the order of variables in the SVAR with the triangular restriction is importance since it decides whether the innovations have impact on the variables. Christiano et al. (1996) employ a recursive SVAR to investigate the impact of the monetary policy shocks on the U.S. economy, and assume that the monetary policy is affected by the shocks of real GDP, the GDP deflator, and an index of sensitive commodity prices. Kilian (2009) differentiates the shocks in crude oil market into three types, namely supply shock, aggregate demand shock, and oil-market specific demand shock, and investigate the impact of global crude oil market shocks on US economy. He provides evidence in support of the response of real GDP growth and CPI inflation to crude oil supply and aggregate demand shocks. However, the assumptions for the recursive identification scheme can be controversial, so Sims (1986), Bernanke (1986) and Blanchard and Watson (1986) suggest an alternative to the recursive restrictions, which is so called the non-triangular identification. Even though the contemporaneous parameters matrix of non-triangular identification scheme can have non-recursive restrictions, the minimum number of restriction still need to address the requirement of $n \times (n-1)/2$.

The second type of restrictions is a non-linear restriction, which includes the restriction on contemporaneous parameters and short-run or long-run impulse function. As the impulse function is non-linear transformation of the contemporaneous parameters, the restrictions on the impulse function naturally result in non-linear restrictions on contemporaneous parameters. Blanchard and Quah (1989) investigate the causes of the unemployment level and GNP dynamics by a SVAR with non-linear restrictions, which prevent any long-run effect from demand disturbances to both unemployment and GNP. They find that the impact of demand disturbances on unemployment and GNP is a hump-shaped curve, which disappears in two to three years. However, the effect of supply disturbances on GNP peaks at the second year and levels off after the fifth year. Clarida and Gali (1994) investigate the impact of supply, demand and money shocks on relative output, real exchange rate and national price level through a SVAR with long run restrictions. They find that the majority of the variance of exchange rate fluctuations is explained by the shocks of demand for real money balance, while the shocks of supply only explain little.

2.5 Components and Determinants of Bid-Ask Spread of TOCOM Energy Futures

Bid-Ask spread (BAS) has always been one of crucial topics in financial research because it is of concern to several participants in financial market. For market-makers, BAS is their potential profit as a compensation of providing liquidity to the market. From exchange's point of view, BAS provides a clue for market design, such as whether they should assign a single market-makers, or increase the competition of different market-makers, and the determination of minimum tick size. It is also very important for regulators since it can be a tool to measure the fairness of market-makers' rent.

The components of BAS are firstly classified by literature into two different types (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Glosten and Harris, 1988), adverse-selection and transitory. The adverse-selection component caused by asymmetric information between market-makers and informed investors. This cost happens when informed investors trade on their private information, and market-makers provide them liquidity on a loss. The transitory component, as suggested by the name, it is the costs unrelated to price changes, such as inventory-hold costs, clearing costs, and/or monopoly profit. Stoll (1989) further decomposes BAS into three components, adverse-selection, inventory-hold and order processing costs. He finds that the order processing costs account for the largest part of BAS, and followed by adverse-selection and inventory-hold costs sequentially. More recently, Bollen et al. (2004) add level of competition as an additional component since the increase in competition of market-makers reduces the profit of each market-maker and so does BAS.

2.5.1 Adverse-selection costs

Market-makers bear adverse-selection costs when trading with informed investors who have better information about the price movement of petroleum than themselves. In equilibrium, the loss from trading with informed traders is assumed to be the same size of the gain from trading with uninformed traders. The expected loss from trading with informed traders are viewed as adverse-selection costs for market-makers. Different proxies for adverse-selection costs have been. For example, Branch and Freed (1977) use the number of securities in which a dealer makes a market, because the dealer with larger the number of securities is less informed about an individual stock. Glosten and Harris (1988) use the concentration of ownership by insiders. A corporation with higher concentration has greater probability to trade on their prior information, and then results in higher adverse-selection costs. The market value of shares outstanding is used by Harris (1994), since the information of a larger firm should be more well-known and public, which reduce the probability of adverse-selection. Easley et al. (1996) use the volume of trading. When the trading volume is higher, it implied that the proportion of uninformed traders may be higher than when the trading volume is lower. Therefore, the adverse-selection costs are lower.

2.5.2 Inventory-hold costs

Inventory-hold costs occur when market-makers hold the inventory that they intend to supply traders in the market. There are two obvious costs according to holding the inventory. The first one is the opportunity costs of fund. Because the fund of market-makers is held to the inventory, they lose the opportunity to trade on other assets. The second cost is the risk of adverse movement. This cost incurs when price moves differently to marker-makers' expectation before they can provide liquidity to other investors. Several proxies have been used in literature for inventory-hold costs. For example, volatility is the most obvious proxy for the second kind of inventory-hold costs, such as Tinic (1972) utilises the standard deviation of price to measure the inventory-hold costs, Stoll (1978) uses the logarithm of the return variance, and Harris (1994) uses return standard deviation. Trade frequency and the number of shareholders are employed by Demsetz (1968) since both of them are viewed to represent transaction rate. When transaction rate is higher, market-makers are less likely to bear loss from both opportunity cost and risk of adverse movement.

2.5.3 Order processing costs

Order-processing costs are, as the name suggests, the costs directly related to liquidity providing, including exchange seat, floor space rent, computer costs, labour costs, and even the opportunity costs of market makers' time. Because they are mostly fixed costs, they should be lower when trading volume is higher. As market-makers usually provide liquidity for more than one security, the order-processing costs can be reduced to a very small amount. In a highly competitive market, BAS may not cover order-processing costs, and equal to the marginal costs of providing liquidity. Hence, literature mainly utilises trading volume, number of transaction or the inverse and logarithm of them as proxy of order-processing costs (Tinic, 1972; Tinic and West, 1972; Tinic and West, 1974; Branch and Freed, 1997; Stoll, 1978; Harris, 1994).

2.5.4 Determinants of BAS

Two fundamental determinants of BAS have been identified by literature, which are trading volume and volatility. In most studies, increases in trading volume usually reduce BAS while increases in volatility rise BAS. Wang and Yau (2000) investigate S&P 500 index, Deutsche Mark, silver and gold futures, and find a positive relation between BAS and price volatility but a negative relation between BAS and trading volume. Huang (2004) studies stock index futures on Taiwan Futures Exchange (TAIFEX) and Singapore Exchange Derivatives Trading Limited (SGX-DT), and finds price level and volatility are two main determinants of BAS components. Price level is positively related to both asymmetric information cost and order processing cost, and volatility is the same. More recently, Wang et al. (2013) also found similar relation between BAS, daily standard deviation of mid-quote and trading volume on corn futures on CME.

However, the direction of impact from trading volume and volatility on BAS is not consistent among literature. Chordia et al. (2001) investigate NYSE stocks, and find absolute return is negatively related to quoted and effective spread. Brock and Kleidon (1992) argue that during the high demand period, such as opening and closing, market makers may charge higher price to transact, which leads to a negative relation between volume and spread, which is also suggested by Easley and O'Hara (1992). Easley and O'Hara (1992) argue that low trading volume may imply less information arrival, so market makers trade with safer investors with lower spread when volume reduces. Nonetheless, Johnson (2008) finds no effect of volume on spread but the variance of spread in NYSE stocks and US government bond markets. More recently, Narayan et al. (2014) studies 734 US stocks listed on NYSE, and their evidences show a negative relation between BAS and volatility but a positive relation between BAS and trading volume.

2.6 Summary and conclusions

Generally speaking, the price and return volatility of energy and energy derivatives have been modelling by four different approaches. The first one is GARCH type models which can capture the property of long memory in energy market, such as FIGARCH (Cheong, 2009, and Kang et al., 2009), MRS-GARCH (Fong and See, 2002, Alizadeh et al., 2008, and Nomikos and Pouliasis, 2011), FIAPAGCH (Wei et al., 2010 and Chkili et al., 2014). Due to the advent of energy options, the implied volatility is utilised (Agnolucci, 2009). With the availability of high-frequency data, the realised volatility in the form of the sum of intraday squared returns provides researchers an alternative way to model volatility (Wang et al., 2008, Sévi, 2014). Finally, Larsson and Nossman (2011) and Chiarella et al. (2013) model the volatility with stochastic process. The first empirical chapter of this thesis proposes a model which take into account changes in market condition in the persistence and dynamics of realised volatility of TOCOM energy futures contracts. The proposed model extends the Heterogeneous Autoregressive model of Realised Volatility (HAR-RV) with a Markov Regime Switching approach (MRS). Out-of-sample analyses are also performed to assess the performance of volatility prediction and VaR estimation of the MRS-HAR-RV model with alternative approaches.

With respect to volume-volatility relation, three theories are proposed to explain the market microstructure, namely Clark's (1973) MDH, Copeland's (1976) SIAH, and Wang's (1994) MDT. Several empirical studies on energy market also examine the relation between trading volume and volatility. For instance, Herbert (1995) and

Moosa et al. (2003) provide significant evidence supporting the strong relation between trading volume and volatility, and Ripple and Moosa (2009) and Chevallier and Sévi (2012) utilise the realised volatility to examine the relation between trading volume and volatility. We extend the literature in this area by investigating the trading activity and volatility relation under different market condition utilising the three energy futures contracts traded in TOCOM.

Four components of BAS have been identified, adverse-selection costs, inventory-hold costs, order-processing costs and level of competition (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Glosten and Harris, 1988; Stoll, 1989; Bollen et al., 2004). The last empirical chapter of this thesis focuses on determinants of the BAS in TOCOM energy futures. Due to the lack of detailed information of market-makers, we employ select variables in a time-series model, which reflect only three types of BAS components (adverse-selection costs, inventory-hold and order processing costs). In addition, we consider possible asymmetric effect of sell-initiated and negative-return transactions.

Chapter 3 Data and Sample Selection

3.1 Introduction

The aim of this chapter is to provide a detailed description of the main energy futures contracts traded on TOCOM, namely gasoline, kerosene, crude oil, gasoil, Chukyo-gasoline and Chukyo-kerosene. The characteristics of these contracts, including underlying assets, settlement type, contract month and size, trading hours, delivery process, and position limitations of TOCOM energy futures, are presented in detail. In addition, comparisons are drawn on contract specifications, position limits and trading activities across the energy futures contracts. After reviewing the specifications of TOCOM energy futures contracts, we describe our sample selection, variables and periodicity. For the purpose of analysis, we utilise two sample sets, one with daily frequency and one with intraday or high frequency. We then perform preliminary statistical tests to establish the univariate behaviour of prices for TOCOM energy futures contracts, including normality, unit root, autocorrelation and heteroscedasticity.

3.2 Energy Futures on the Tokyo Commodity Exchange (TOCOM)

The first two energy contracts listed on TOCOM on 5 July 1999 were gasoline and kerosene futures. This was a milestone for TOCOM, as the largest Asian commodity exchange. Two years later, on 10 September 2001, TOCOM introduced crude oil futures, before gasoil futures were introduced on 8 September 2003. This was followed by Chukyo-gasoline futures and Chukyo-kerosene futures in 2010. Overall, with the exception of gasoil, which is delisted, there are five energy futures contracts currently traded on TOCOM. A comparison of the contract specifications and a summary of trading rules are presented in Table 3-1.

Gasoline and kerosene futures are mainly physically delivered contracts. The underlying asset of gasoline futures is defined as the regular gasoline of JIS 2202 Grade in the Tokyo Bay area, while that of kerosene futures is kerosene of JIS K2203 Grade 1 in the Tokyo Bay area. In addition, both underlying gasoline and kerosene cargoes must be refined within Japan or cleared through customs. Both futures contracts have the same contract month, trading session, contract size and delivery rules, as well as position limits for traders as described below.

Gasoline and kerosene futures contracts are traded based on six consecutive contract months starting from the second month after the month in which the new contract is initiated. In other words, the maturity of gasoline and kerosene futures contracts are from one month to six months forward from the trading month. For example, if today is 4 August, there would be futures contracts ready for delivery in September, October, November, December, January, and February. Regarding trading hours, TOCOM has two trading sessions – classified as day and night sessions. The day session lasts from 8:40 a.m. to 3:15 p.m. Japanese Standard Time (JST), and the night session runs from 4:30 p.m. to 5:30 a.m. (JST). The last trading session (day) for both gasoline and kerosene futures contracts is the day session on the 25th before the current contract month, and the following night session on the same day is the first trading day for the new gasoline and kerosene futures contracts. For example, the last trading day for the September contract is the day session on 25 August, and the first trading day for the March contract is the night session on 25 August. In respect of contract size, the deliverable volume per contract is 50 kilolitres (kl), and every delivery must involve at least two contracts, with a 2% tolerance limit volume of delivery.

Over the settlement period, both gasoline and kerosene futures contracts are delivered by barges in different locations depending on the seller's choice. The seller has the option to choose refineries or oil tanks which accommodate barges and are approved by TOCOM in Tokyo, Kanagawa or Chiba, while the buyer can set the delivery date within the contract month. In addition, the buyer must pay gasoline tax when taking delivery of gasoline, which is excluded from the contract price, whereas delivery cost is included in the contract price. The circuit breaker trigger level is decided at the beginning of each clearing period and is based on the settlement price of the previous clearing period, which is 5 p.m. of the night session. If it is a new month contract, the trigger level depends on the settlement price of the preceding contract month. In addition, TOCOM has different position limits for commercial traders, investment trusts and non-commercials. Commercial traders are able to trade up to 2,000, 3,000 and 5,000 contracts for the 1-month, 2-month and each other maturity, respectively, and limits for short and long positions are separate. Non-commercial customers can only enter into each short or long position for 250, 500, and 1,500 contracts of the 1-month, 2-month and each other maturity, respectively. For instance, if today is 4 August, a commercial trader can trade at most 5,000 contracts to be delivered in November while a non-commercial trader can only trade a maximum of 1,500 lots for the November contract.

Crude oil futures contracts have been listed on TOCOM since 10 September 2003. There are some notable differences between crude oil and gasoline (or kerosene) futures contracts. Firstly, crude oil futures contracts are cash-settled, which means there is no physical delivery of cargo. The underlying asset was first introduced as the average of Dubai and Oman crude delivered in Japan, and was changed to Dubai crude only in June 2015. In addition, both Dubai and Oman crude oil are quoted in US dollar per barrel (US$/bbl), while TOCOM crude oil futures contracts are traded in Japanese Yen per kilolitre (JPY/kl). Hence, TOCOM uses the following formula for calculation of the reference price for spot crude oil (before June 2015), which uses the spot Dollar-Yen exchange rate.

$$S = \frac{(P_D + P_O)\times 0.5\times FOREX}{0.1590}, \quad (3.1)$$

where S is the spot reference price, P_D and P_O are the prices of Dubai and Oman crude oil provided by Platts, $FOREX$ is the foreign exchange rate (JPY/US$) quoted by the Bank of Tokyo-Mitsubishi UFJ, Ltd., and 0.1590 is the conversion rate of barrel to kilolitre (1 bbl = 0.1590 kl). Although TOCOM discontinued providing the spot reference price after 18 August 2009 because of a license agreement with its data provider, final settlement prices are now the monthly average of the spot reference price. (See equation (3.1))

Secondly, crude oil futures also include six consecutive contract months, but the contract months start from the nearby month and continue up to five months ahead contract. For instance, if today is 4 August 2014, there would be six tradable contracts with maturities in August 2014, September 2014, and up to December 2014. This also indicates that the first and the last session of trading are different from those of gasoline and kerosene futures. The last trading session of the current contract month is the day session of the last business day in the contract month, and the first trading day of the new contract month is the night session on the same day. For example, the last trading day for the August 2014 contract is the day session on 31 August 2014, and the February 2014 contract starts to be traded in the night session on 31 August 2014. However, there is an exception at the end of the year. If the last trading day of the current month is 31 December, the new contract month begins in the day session of the business day immediately following the last trading day. The final difference between crude oil and product futures contracts relates to position limits. Generally, customers can trade more contracts in crude oil futures than gasoline or kerosene futures. Commercial traders and investment trusts can hold up to 12,800 crude oil futures in each of the contract months for each long and short position, while non-commercial customers have a traded limit of a maximum of 2,400 contracts. Nonetheless, the position limits have been abandoned since June 2015.

Following crude oil futures, the fourth energy future listed on TOCOM is for gasoil futures introduced on 8 September 2003. However, gasoil futures were suspended during the period from February 2006 to May 2010 because of quiet trading activity. With an increase in the volatility of the gasoil market, demand for hedging with futures also arose. Therefore, TOCOM reopened transactions of gasoil futures on 6 May 2010, but trading activity continues to be very limited.

Two relatively new contracts launched by TOCOM on 12 October 2010 are Chukyo-gasoline and Chukyo-kerosene futures. They are also mainly physically delivered contracts, with underlying assets being the regular gasoline of JIS K2202 Grade 2 (excluding E3-gasoline, gasoline with 3% ethanol content) and kerosene of JIS K2203 Grade 1 in the Aichi area. As with gasoline and kerosene futures, the underlying products must be refined within Japan or cleared through customs. The contract months and trading sessions of Chukyo-gasoline and Chukyo-kerosene futures are exactly the same as those of gasoline and kerosene futures, but the contract size, delivery rules and position limits are different. For instance, every Chukyo-gasoline/kerosene futures contract contains 10 kl gasoline/kerosene, and every delivery involves one contract: namely 10 kl per delivery with a 2% tolerance limit in delivered volume. The delivery process of Chukyo-gasoline and Chukyo-kerosene is by tanker trucks. The seller has the right to choose any oil tank appointed by TOCOM within Shiomi-cho, Minato-ku, Nagoya, Aichi and Tobishima-mura, Ama-gun, and Aichi as delivery points. On the other hand, the buyer can decide the transaction date. In addition, the buyer of Chukyo-gasoline futures must pay gasoline tax when delivery is taken, because it is not included in the contract price. In terms of position limits, there are relatively fewer restrictions in trading Chukyo-gasoline and Chukyo-kerosene. For both futures, non-commercial traders can take long or short positions up to a maximum of 300 contracts for the current contract month: 600 contracts for the second contract month and 3,600 contracts for each of the future contract months. On the other hand, commercial traders and investment trusts can trade up to 1,500, 3,000 and 6,000 contracts for the current, second, and each of the other contract months, respectively.

Overall, only one out of six energy futures traded on TOCOM is of a cash-settled type, crude oil futures, while the others are physically delivered. Hence, the contract month, the first and last trading day of crude oil futures, is also different from other energy futures. In addition, although discrimination in the limitation of holding positions for commercial and non-commercial customers may be designed to protect TOCOM from the disturbance of potential speculative traders, non-commercial traders are still the majority of TOCOM energy market participants. Thus, the prevention of speculator’s distortion may be limited.

Table 3-1: Comparison of six TOCOM energy commodities

Specification	Gasoline	Kerosene	Gasoil	Chukyo-gasoline	Chukyo-kerosene	Crude oil
First listed day	July 5, 1999	July 5, 1999	September 8, 2003	October 12, 2010	October 12, 2010	September 10, 2001
Transaction type	Physical delivery	Physical delivery	Physical delivery	Physical delivery	Physical delivery	Cash settled
Underlying/ Standard	Regular gasoline of JIS K2202 Grade 2 (Tokyo Bay area)	Kerosene of JIS K2203 Grade 1 (Tokyo Bay area)	Gasoil JIS K2204 (three qualities)	Regular gasoline of JIS K2202 Grade 2 (Aichi area)[a]	Kerosene of JIS K2203 Grade 1 (Aichi area)	Middle East crude oil (the average of Dubai and Oman)
Contract unit	50 kl	50 kl	50 kl	10 kl	10 kl	50 kl
Delivery unit	100 kl	100 kl	100 kl	10 kl	10 kl	N/A
Contract month	6 consecutive months (from second month)	6 consecutive months (from second month)	6 consecutive months (from second month)	6 consecutive months (from second month)	6 consecutive months (from second month)	6 consecutive months (from current month)
Last trading day	Day session on 25th	Day session on 25th	Day session on 25th	Day session on 25th	Day session on 25th	Day session on the last business day
First trading day	Night session on 25th	Night session on 25th	Night session on 25th	Night session on 25th	Night session on 25th	Night session on the last business day [b]
Limitation position: commercials [c]	Contract month: 2,000 contracts 2nd contract month: 3,000 contracts Other contract months (each): 5,000 contracts			Current contract month: 1,500 contracts 2nd contract month: 3,000 contracts Other contract months (each): 6,000 contracts		Each contract month: 12,800 contracts
Limitation position: non-commercials	Contract month: 250 contracts 2nd contract month: 500 contracts Other contract months (each): 1,500 contracts			Current contract month: 300 contracts 2nd contract month: 600 contracts Other contract months (each): 3,600 contracts		Each contract month: 2,400 contracts

[a] E3, 3% ethanol gasoline, is exclusive.
[b] If the last business day is the end of the year, the first trading day is the day session of the first business day of the next year.
[c] This includes investment trusts.

3.3 Sample Selection, Descriptive Statistics and Preliminary Analysis

Considering that the series of gasoil futures is discontinuous between 2006 and 2010, and given the very low trading activities of Chukyo-gasoline and Chukyo-kerosene, we concentrate analysis on gasoline, kerosene and crude oil futures only, which have a relatively long and continuous sample size and higher trading activities. Moreover, in this study, we utilise both daily and intraday data. Daily observations are mainly used for analysing Value at Risk (VaR) in Chapter 4, whereas intraday data is used to estimate realised volatility, investigate the relation between return volatility and trading volume, and to analyse determinants of bid-ask spread (BAS).

3.3.1 Daily Data

Our daily sample data begins on 22 September 2010 and continues until 30 October 2015, which totals approximately 1253 daily observations. Although data are available from January 1999 for gasoline and kerosene futures, and from 3 December 2001 for crude oil futures, the beginning date of the sample is chosen to be 22 September 2010 for two reasons. Firstly, the night trading session was extended from 6 hours (17:00-23:00) to 11 hours (17:00-4:00) on 22 September 2010 in order to attract more foreign trades to TOCOM. Therefore, the potential participation of a new type of investor may have changed the market structure. Secondly, energy markets experienced a sharp rise and drop around 2008 due to the financial crisis. Choosing the beginning date as 22 September 2010 can also avoid possible structural changes in the TOCOM energy futures market. Data is acquired from the TOCOM website (http://www.tocom.or.jp). In order to compare the results across the term structure, six maturities futures are included in the sample, namely 1- to 6-month gasoline and kerosene futures and nearby- to 5-month crude oil futures, which is a total of 18 futures.

Figure 3-1 presents the historical prices for gasoline, kerosene and crude oil futures over the sample period. It is evident that all of the three futures prices across different contract months move closely, and exhibit similar dynamics to those of spot prices for crude oil (Figure 1-6 in Chapter 1). The spot and futures prices for oil and energy commodities peaked at the end of 2012 and remained stable for about two years until sharply dropping at the end of 2014. Even though they recovered to relatively high levels at the beginning of 2015, prices declined again in the second half of 2015.

The other noticeable characteristic of TOCOM energy futures contracts is the difference in the volume of trading across different contact months. Surprisingly, it seems that trading volume is positively related to contracts maturity (see Figure 3-2 and Panel A of Table 3-3), which is in contrast to what is observed in other energy futures markets, where trading volume increases as maturity approaches. For example, the descriptive statistics of nearby- to 5-month WTI futures on NYMEX (Table 3-4) shows a positive relation between trading volume and maturity. The main reason for this paradox is because the limits in trading contracts with longer than 5 or 6 month maturities. Therefore, hedgers who need to hedge their exposure for longer than 5 or 6 months, adapt a stack and roll strategy using futures contracts with 5 or 6 month to maturity. Other traders also trade on the longest contracts because of their higher liquidly, which result in build-up of liquidity in the longer-term contracts.

Another feature shown in Figure 3-2 is that the trading volume of crude oil futures has constantly increased since the fourth quarter of 2014. There are two possible reasons. Firstly, the oil prices sharply declined since the mid of 2014, which may increase the demand of hedging from oil producer and exploration companies. Based on Figure 1-9 and Table 1-1, the foreign trades ratio increased to over 50% after September 2014, which may also indicate the possibility of the increase in foreign hedgers. Secondly, the limit on the position of trading crude oil futures has been removed since June 2015, which provides motivation for both hedgers and speculators to engage in TOCOM market.

The descriptive statistics reported in Table 3-2 reveal that TOCOM energy futures prices generally have negative skewness and low coefficients of kurtosis, and that there is not much difference between contracts with different maturity. However, TOCOM energy futures returns exhibit different statistical properties, being negatively skewed but with excess kurtosis. This implies that negative and extreme returns are more likely to be observed than positive and normal cases. The results of the augmented Dickey-Fuller (ADF) unit root tests reported in Table 3-2 cannot reject the null hypothesis of the existence of unit root for all three TOCOM energy futures prices. However, the results of the ADF test support that the TOCOM energy futures return is all stationary series. Hence, we can conclude that TOCOM energy futures prices are all non-stationary and integrated of order one, I(1). Furthermore, Ljung and Box (1978)'s Q statistic is performed to examine the autocorrelation function for the first 22 lags. The number of lags for Q statistic is chosen as 22 because it provides a potential comparison of the persistence between returns and volatility. Corsi (2009) indicates that realised volatility is highly persistent, and can be explained by at least up to 1-month lagged realised volatility. Therefore, choosing 22 as the number of lags for Q statistic may allow us to test the difference in the persistence between return and realised volatility. The results in Table 3-2 show the significance in the Q statistic on the first 22 lags of the autocorrelation function in both energy futures prices and returns, which suggests that both series are autocorrelated.

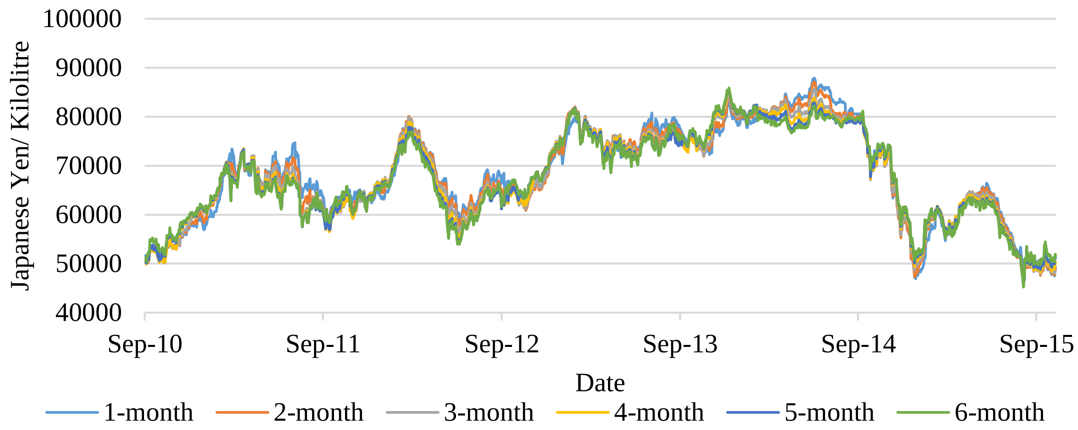
Table 3-3 reveals the descriptive statistics of daily trading volume and the number of transactions. Comparing the mean of trading volume and number of transactions, it is clear that the trading volume per transaction is quite small. For example, for 5-month crude oil futures, it is only 1.6 contracts per transaction. In addition, by dividing trading hours per day by the number of transactions per day, the frequency between trades can also be calculated. Based on the given day and night trading session, the trading hours are 63900 seconds per day, so the average frequency of transaction is 15.46 seconds for the most frequently traded contract, 6-month gasoline futures. This implies that the choice of sampling frequency may be lower for TOCOM energy futures than for futures on other energy exchanges (see discussion in Section 3.3.2).

Moreover, there is differences in the levels of kurtosis of trading volume across maturities. The magnitude of kurtosis increases as contract maturity decreases. For example, the kurtosis of 6-month gasoline futures is 5.5755, whereas that of 1-month ones is 36.9432. This indicates that for shorter maturity contracts, the trading activity is relatively quiet, but the volume per transaction is much more extreme. This pattern is confirmed by the figures shown in Panel A and Panel B of Table 3-3. For instance, the average trading volume per transaction is 1.6 for 5-month crude oil futures, but 2 for nearby-month crude oil futures[11]. Nonetheless, with respect to autocorrelation and the existence of unit root, the trading volume and the number of transactions show the similar pattern. It is evident that both trading volume and the number of transactions are highly autocorrelated based on Q statistics with 22 lags. However, the results of ADF test suggest that the trading volume and the number of transactions are not stationary for some kerosene and crude oil futures. Hence, there is a potential concern of spurious regression when the relation between trading volume and realised is analysed, and more details are discussed in Section 5.4.

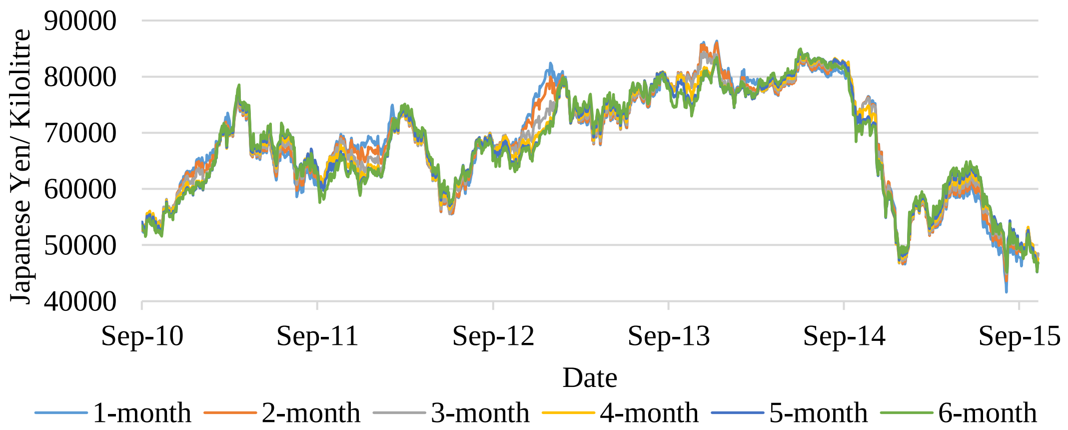
[11] The kurtosis of trading volume for WTI futures shown in Table 3-4 also confirm that the kurtosis is higher for less liquid contracts.

Figure 3-1: Historical daily futures prices of three TOCOM energy futures

Gasoline



Kerosene



Crude oil

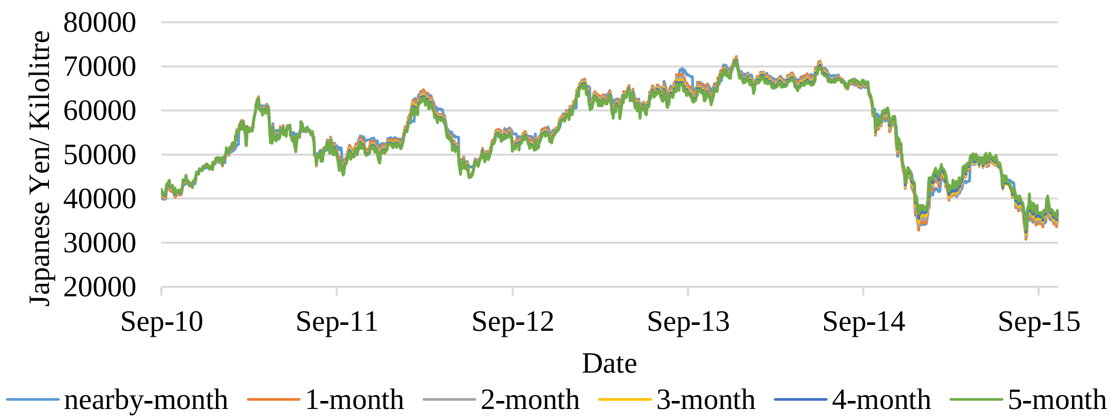


Figure 3-2: Historical daily trading volume of three TOCOM energy futures

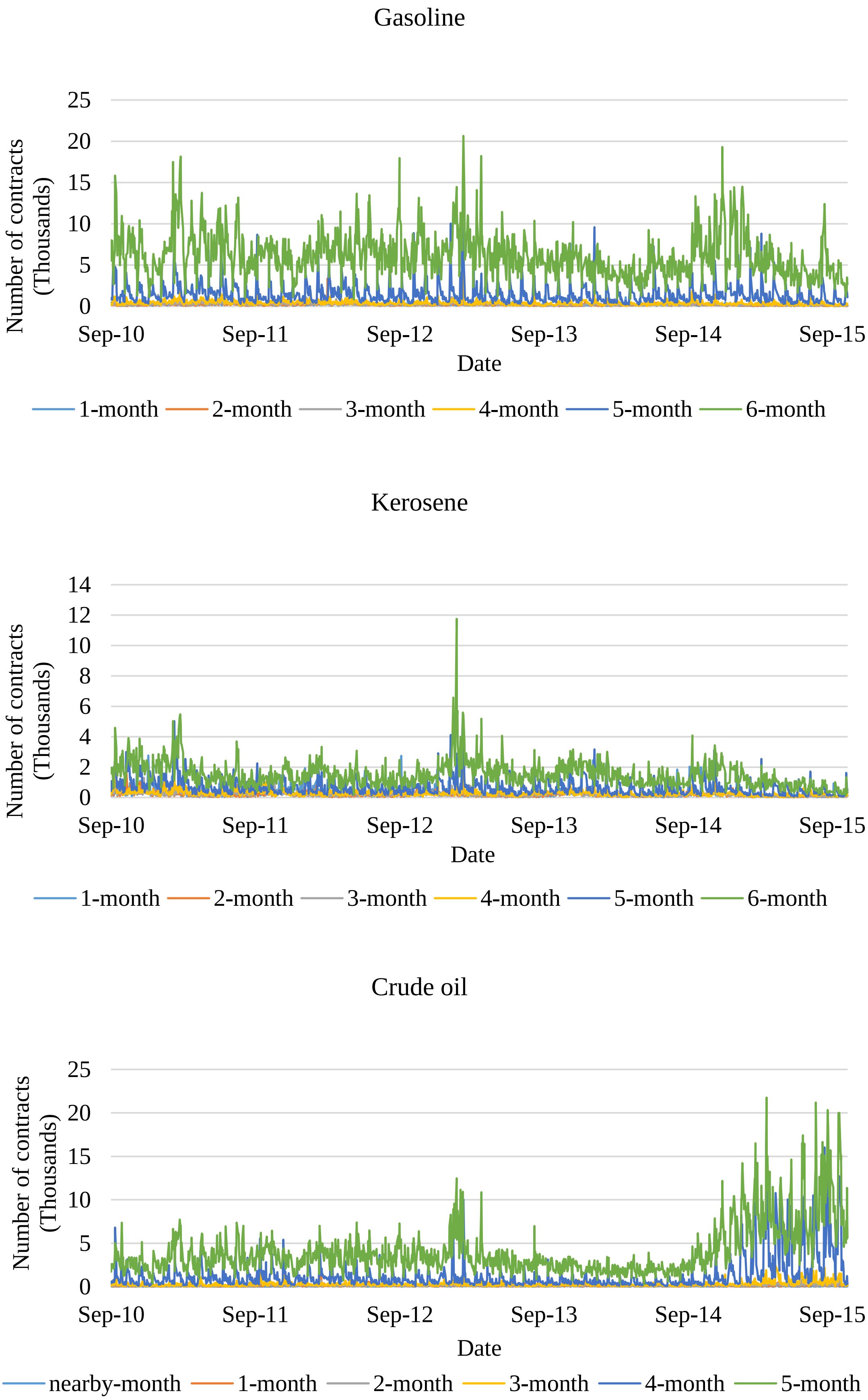


Table 3-2: Descriptive statistics and preliminary tests for prices and returns

			Gasoline			
	1-month	2-month	3-month	4-month	5-month	6-month
			Panel A: Price			
Mean	68426.0	68136.3	67843.0	67630.5	67523.2	67513.4
Std.	9708.2	9638.3	9513.6	9341.1	9156.0	8990.6
Skewness	-0.1795	-0.1728	-0.1559	-0.1444	-0.1203	-0.0929
Kurtosis	2.1980	2.1360	2.0539	2.0116	1.9709	1.9422
Q(22)	23197.4 [a]	23204.7 [a]	23170.2 [a]	23199.8 [a]	23200.7 [a]	23244.5 [a]
ADF	-1.9337	-1.9177	-1.7918	-1.8028	-1.7447	-1.7178
KW	0.2616	0.2303	0.2245	0.2183	0.2166	0.2117
			Panel B: Return (annualised)			
Mean	-1.13%	-0.78%	-0.58%	-0.20%	0.15%	0.18%
Std.	0.2270	0.2286	0.2286	0.2286	0.2302	0.2302
Skewness	-0.5506	-0.4537	-0.5134	-0.4907	-0.4533	-0.4131
Kurtosis	6.8994	6.2788	6.6244	6.5178	6.5040	6.4346
Q(22)	42.4111 [a]	45.5585 [a]	40.5444 [a]	33.3127 [a]	27.1030 [a]	26.5008 [a]
ADF	-6.4899 [a]	-6.5061 [a]	-6.8552 [a]	-6.8969 [a]	-6.9981 [a]	-7.0970 [a]
KW	13.1815 [b]	12.5082 [b]	9.9383 [b]	9.0218	7.2439	5.8408
			Kerosene			
	1-month	2-month	3-month	4-month	5-month	6-month
			Panel A: Price			
Mean	68165.0	68158.9	68108.2	68022.6	67953.9	67913.4
Std.	9849.5	9606.2	9407.4	9294.9	9281.2	9323.8
Skewness	-0.3548	-0.2985	-0.2517	-0.2251	-0.2130	-0.2315
Kurtosis	2.1925	2.1804	2.1708	2.1510	2.1567	2.1679
Q(22)	23492.1 [a]	23405.7 [a]	23277.4 [a]	23174.0 [a]	23001.6 [a]	22854.0 [a]
ADF	-1.8075	-1.7101	-1.6454	-1.5867	-1.5922	-1.6437
KW	0.2204	0.2495	0.2311	0.2446	0.2100	0.1940
			Panel B: Return (annualised)			
Mean	-1.81%	-1.84%	-2.02%	-2.55%	-2.92%	-2.65%
Std.	0.2254	0.2270	0.2302	0.2318	0.2365	0.2413
Skewness	-0.4723	-0.5613	-0.5382	-0.5090	-0.4960	-0.4727
Kurtosis	8.1421	8.0342	8.0072	8.0045	7.8825	8.1462
Q(22)	39.7738 [a]	42.8056 [a]	43.6274 [a]	45.0068 [a]	46.8630 [a]	46.5762 [a]
ADF	-6.7955 [a]	-6.9604	-7.1098 [a]	-7.0791 [a]	-7.0581 [a]	-7.0420 [a]
KW	6.6494	9.7124 [b]	9.7734 [b]	12.4988 [b]	10.4946 [b]	4.4839
			Crude oil			
	nearby-m.	1-month	2-month	3-month	4-month	5-month
			Panel A: Price			
Mean	55495.4	55272.4	55146.4	55067.2	55012.8	54981.9
Std.	9618.5	9561.4	9363.8	9162.3	8955.3	8748.7
Skewness	-0.3696	-0.3525	-0.3205	-0.2904	-0.2581	-0.2268
Kurtosis	2.2075	2.2308	2.1857	2.1494	2.1131	2.0825
Q(22)	23886.1 [a]	23460.1 [a]	23434.9 [a]	23405.7 [a]	23384.9 [a]	23324.6 [a]
ADF	-1.6489	-1.5492	-1.5507	-1.5374	-1.5368	-1.5304
KW	0.1718	0.2003	0.1987	0.2001	0.1938	0.2016
			Panel B: Return (annualised)			
Mean	-3.02%	-3.38%	-3.07%	-2.95%	-2.77%	-2.60%
Std.	0.2476	0.3000	0.2969	0.2921	0.2889	0.2857
Skewness	-1.3702	-0.4192	-0.4131	-0.4470	-0.4610	-0.4344
Kurtosis	19.8075	8.8096	8.6320	8.6275	8.5339	8.3298
Q(22)	61.5804 [a]	56.1335 [a]	65.8989 [a]	58.6773 [a]	61.9948 [a]	60.7493 [a]
ADF	-6.4992 [a]	-7.1554 [a]	-7.1290 [a]	-7.1493 [a]	-7.1011 [a]	-7.1382 [a]
KW	8.9103	6.6706	5.4759	5.2433	5.1530	4.8786

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015. KW is the Kruskal-Wallis statistic, which follows χ^2_4.

Table 3-3: Descriptive statistics and preliminary tests for daily trading volume and the number of transactions

			Gasoline			
	1-month	2-month	3-month	4-month	5-month	6-month
			Panel A: Trading volume			
Mean	265.862	205.051	258.757	405.626	1524.745	6211.321
Std.	260.389	172.996	192.295	299.628	1328.784	2697.353
Skewness	4.578	6.789	3.493	4.388	2.671	1.172
Kurtosis	36.959	100.793	26.511	44.499	12.701	5.587
Q(22)	299.652 [a]	1048.847 [a]	1337.937 [a]	1210.215 [a]	1167.047 [a]	2236.680 [a]
ADF	-4.180 [a]	-4.502 [a]	-4.699 [a]	-4.858 [a]	-4.484 [a]	-4.327 [a]
KW	10.8283 [a]	17.5892 [a]	7.7404	1.8884	1.9172	9.3888
			Panel B: Number of transactions			
Mean	116.46	146.39	206.62	330.53	1096.55	4132.65
Std.	61.80	81.33	121.76	200.20	882.57	1784.86
Skewness	1.4889	1.4259	1.9976	2.5507	2.6886	1.2909
Kurtosis	6.5111	6.2202	10.9215	18.8992	13.0613	5.8810
Q(22)	742.30 [a]	1687.16 [a]	1671.20 [a]	1123.98 [a]	1066.06 [a]	2452.07 [a]
ADF	-4.9835 [a]	-3.8886 [a]	-4.2950 [a]	-4.7311 [a]	-4.2145 [a]	-4.0877 [a]
KW	18.6666 [a]	9.9262 [b]	10.8702 [b]	2.0817	2.0199	9.4477
			Kerosene			
	1-month	2-month	3-month	4-month	5-month	6-month
			Panel A: Trading volume			
Mean	292.280	192.476	207.956	279.471	685.609	1510.005
Std.	336.346	165.814	173.547	222.193	576.501	857.977
Skewness	3.265	3.064	3.676	4.623	2.546	2.637
Kurtosis	16.897	22.281	31.725	51.332	13.424	22.071
Q(22)	1252.777 [a]	3059.868 [a]	1881.688 [a]	1384.745 [a]	2106.877 [a]	4771.246 [a]
ADF	-2.720	-3.104	-4.969 [a]	-5.369 [a]	-3.637 [b]	-3.697 [b]
KW	3.7835	6.4737	12.8288 [a]	2.8457	1.0560	5.5717
			Panel B: Number of transactions			
Mean	110.00	128.08	156.18	221.80	497.20	1088.05
Std.	65.47	83.63	95.68	138.74	366.67	545.27
Skewness	1.3186	1.4726	1.4189	2.2287	2.3031	1.7971
Kurtosis	6.0603	6.0731	6.5753	15.1809	11.0347	10.7561
Q(22)	3238.37 [a]	3348.19 [a]	2500.69 [a]	1376.11 [a]	1775.05 [a]	4050.27 [a]
ADF	-3.2778	-3.3928	-4.0735 [a]	-4.8360 [a]	-3.6669 [b]	-3.6155 [b]
KW	1.8283	8.2766	11.3851 [a]	2.9437	1.2187	7.6181
			Crude oil			
	nearby-m.	1-month	2-month	3-month	4-month	5-month
			Panel A: Trading volume			
Mean	61.089	113.265	164.186	290.953	1340.777	4059.605
Std.	83.378	105.965	149.644	288.330	1991.702	2945.363
Skewness	5.593	3.386	2.833	2.925	3.699	2.410
Kurtosis	54.024	25.080	16.308	13.965	19.147	10.312
Q(22)	161.954 [a]	354.202 [a]	590.865 [a]	2040.016 [a]	4818.851 [a]	9499.131 [a]
ADF	-5.045 [a]	-5.243 [a]	-4.508 [a]	-3.252	-1.428	-1.742
KW	1.9740	5.8465	8.7236	5.5047	0.8976	13.4031 [a]
			Panel B: Number of transactions			
Mean	29.08	76.12	113.15	200.61	717.03	2444.16
Std.	30.04	59.61	93.35	183.13	880.63	1606.34
Skewness	2.4286	1.9607	2.9154	3.0134	3.9517	1.9641
Kurtosis	12.7845	8.6050	18.1243	15.2057	25.2731	7.4058
Q(22)	763.53 [a]	778.41 [a]	1098.59 [a]	2797.34 [a]	3282.31 [a]	10918.48 [a]
ADF	-5.4376 [a]	-5.0636 [a]	-4.6767 [a]	-3.1590	-2.0517	-2.3751
KW	0.5544	7.9112	8.1902	7.1998	0.9825	11.6321 [b]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015. KW is the Kruskal-Wallis statistic, which follows χ^2_4.

Table 3-4: Descriptive statistics and preliminary tests for daily trading volume of WTI futures

	nearby-m.	1-month	2-month	3-month	4-month	5-month
Mean	275485.4	134731.4	57819.5	35645.8	24987.0	17782.8
Std.	111091.3	81900.0	27728.7	22054.7	18040.4	15272.6
Skewness	0.2478	1.4691	1.2864	1.9091	2.5071	2.2666
Kurtosis	3.9124	5.8101	5.8552	7.7156	12.7021	8.9764
Q(22)	2478.56 [a]	2408.97 [a]	3011.24 [a]	4152.85 [a]	3560.46 [a]	4175.14 [a]
ADF	-5.6037 [a]	-7.8257 [a]	-6.0609 [a]	-6.5949 [a]	-7.1013 [a]	-7.5957 [a]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015.

3.3.2 High-frequency Data

With the availability of tick data for TOCOM energy futures, this research will use high-frequency data to measure the daily realised volatility of energy futures prices. It is argued that high-frequency data may have disturbance because of microstructure features, such as price discreteness (see Harris, 1990, 1991), a periodical volatility pattern, nonsynchronous trading, etc., which may affect the measure of realised volatility based on intraday data (Andersen and Bollerslev, 1998). To overcome this issue, most studies on energy prices resample high-frequency data into a 5-minute horizon. For instance, Wang et al. (2008) measure the realised volatility of NYMEX light, sweet crude oil, and Henry-Hub natural gas futures with 5-minute frequency returns. In addition, Chevallier and Sévi (2012) choose to resample data into 5-minute frequency, and measure the realised volatility of WTI front-month futures returns. They find that the use of 5-minute frequency data eliminates microstructure noise, and still preserves the information in intraday data.

However, the TOCOM market is less liquid compared with other markets as discussed in Section 3.3.1. Therefore, extra care must be taken when deciding the optimal sample intervals. This study employs two approaches to find the optimal sampling frequency. First, Bandi and Russell (2008) propose an approximation to determine the optimal number of intervals per day (M^*) and then the optimal fixed interval frequency (Δ^*). The optimal number of intervals is defined as

$$M^* = \{\frac{hQ}{[E(e^2)]^2}\}^{1/3}, \tag{3.2}$$

where h is the fixed trading period (one day here), Q is integrated quarticity of returns, and $E(e^2)$ is the second moment of microstructure noise. An estimator of integrated quarticity provided by Barndorff-Nielsen and Shephard (2002a) is $\hat{Q} = \frac{M}{3h}\sum_{j=1}^{M} r_j^4$, which is consistent with an absence of microstructure noise. However, microstructure noise is inevitable, so an estimate of integrated quarticity is arrived at via 15-minute interval samples to minimise the bias between Q and $\hat{Q}$, as suggested by Bandi and Russell (2008). The second moment of microstructure noise is estimated by $E(e^2) = \frac{1}{M}\sum_{j=1}^{M} r_j^2$ using 1-minute interval samples, since $\frac{1}{M}\sum_{j=1}^{M} r_j^2$ converges in probability to the population moment for large M. Moreover, they also offer an estimator for MSE of realised volatility with MA(1) microstructure noise across different sampling frequencies shown as below.

$$MSE_{MA} = \frac{2h}{M}Q + Mb + M^2a + c, \tag{3.3}$$

$$a = [E(e^2)]^2,$$

$$b = E(e^4) + 2E(e^2e_{-1}^2) - 3[E(e^2)]^2,$$

$$c = 4E(e^2)V - 2E(e^2e_{-1}^2) + 2[E(e^2)]^2.$$

where V is integrated variance, $\hat{V} = \sum_{j=1}^{M} r_j^2$, estimated by realised variance using a 15-minute interval sample, and the fourth moments of microstructure noise are estimated by $E(e^4) = \frac{1}{M}\sum_{j=1}^{M} r_j^4$ using 1-minute interval samples. The second approach is volatility signature plot, which illustrates averages of realised volatility against different corresponding sampling frequency. The optimal frequency is chosen as after which average of realised volatility becomes stable, which indicates microstructure noise is reduced to a certain level.

Table 3-5 shows that 2-minute and 5-minute interval yield the lowest MSE, and are supposed to be the optimal sampling frequency according to Bandi and Russell (2008)'s approximation. However, the signature plots (Figure 3-3) reveal that both 2-minute and 5-minute sampling realised volatility are still unstable, which may be because the assumption that unobserved microstructure noise is MA (1) process does not hold for TOCOM energy futures market. Therefore, instead of using 2- or 5-minute sampling frequency, our high-frequency data is sampled with 15-minute interval, since realised volatility seems stabilised from 15-minute sampling frequency for most futures. This might seem a lower frequency than other studies which use a 5-minute interval; however, given the transaction volume and frequency of trading in TOCOM energy futures, it is a reasonable sampling interval. In addition, Liu et al. (2015) also suggest that while 5-minute sampling interval is used for moderately liquid assets, it is more appropriate to use 15-minute to one-hour interval for less liquid assets. Hence, realised volatility for TOCOM energy futures estimated by 15-minute interval should be the optimal frequency. Figure 3-4 presents the prices of tick-by-tick and 15-minute frequency samples for 5-month crude oil futures on 1 Aug 2014. It is evident that the price of 15-minute samples moves very closely with that of tick-by-tick samples, and is smoother at the beginning of the market; as a result, we believe that the realised volatility measured with 15-minute interval samples should be able to maintain the stylised facts of energy futures, reflect market information, and eliminate microstructure noise.

Table 3-6 presents the descriptive statistic of annualised realised volatility, sampled in 15-minute intervals and measured as the sum of intraday squared returns. According to the literature (Andersen et al., 2001a; Andersen et al., 2003; Andersen et al., 2006; McAleer and Medeiros, 2008; among others), the realised volatility has been characterised by higher persistence and long-memory process. It is of our interest to investigate the autocorrelation of realised volatility on TOCOM energy futures. The autocorrelation function with 1, 5 and 22 lags (ACF_1, ACF_5 and ACF_{22}) shows a couple interesting features of TOCOM energy futures. Firstly, the speed of the decline in autocorrelation is faster than implied by literature. For instant, Fuertes and Olmo (2013) study stocks, exchange rates, bonds and gold markets, and find the autocorrelation only slightly reduces after 5 periods. Secondly, Despite the quick speed of autocorrelation reducing, the values of ACF_5 still indicate the rejection of non-autocorrelation, while those of ACF_{22} does not. For gasoline and kerosene, only the realised volatility of highly liquid futures has significant 22-lag ACF. However, except nearby-month and 3-month maturity, the ACF of the realised volatility is significant for crude oils futures. Even though this may generate the doubt of employing Corsi's HAR-RV to model the realised volatility of TOCOM energy futures, the significant values of Q statistic with 22 lags still suggest that the realised volatility is highly autocorrelated up to 1 month for all TOCOM energy futures.

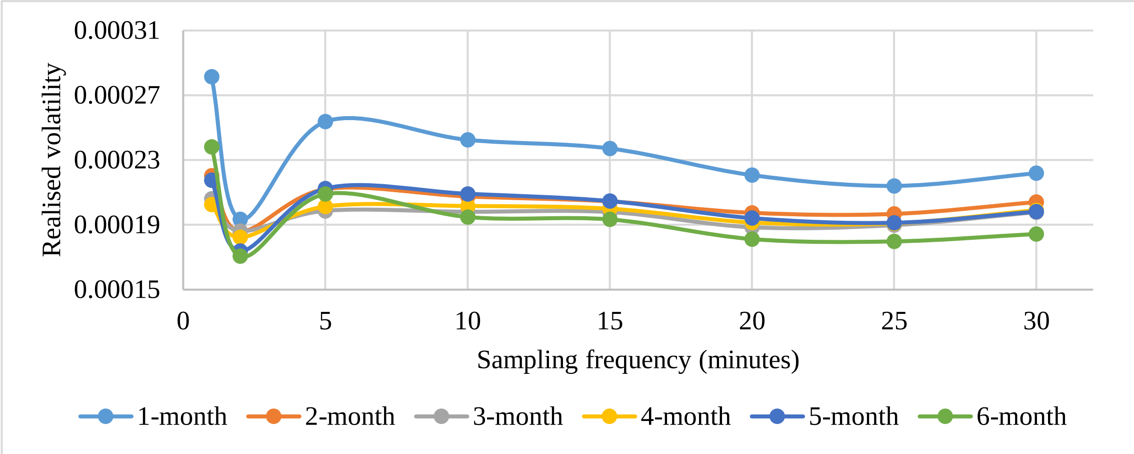
Table 3-5: Comparison of MSE of realised volatility for different sampling frequency

	Gasoline					
	1-month	2-month	3-month	4-month	5-month	6-month
1-minute	5.75E-07	4.59E-07	3.97E-07	3.51E-07	3.57E-07	4.75E-07
2-minute	**3.90E-07**	**3.85E-07**	3.63E-07	3.35E-07	3.17E-07	**3.20E-07**
5-minute	4.56E-07	4.27E-07	**3.27E-07**	**3.06E-07**	**3.12E-07**	4.80E-07
10-minute	4.41E-07	4.37E-07	3.49E-07	3.28E-07	3.28E-07	3.37E-07
15-minute	4.32E-07	4.06E-07	3.68E-07	3.35E-07	3.28E-07	5.27E-07
20-minute	4.50E-07	4.66E-07	3.63E-07	3.41E-07	3.43E-07	3.87E-07
25-minute	4.35E-07	4.71E-07	3.87E-07	3.50E-07	3.40E-07	4.02E-07
30-minute	4.76E-07	4.85E-07	4.22E-07	3.82E-07	3.77E-07	4.48E-07
	Kerosene					
	1-month	2-month	3-month	4-month	5-month	6-month
1-minute	8.73E-07	4.89E-07	5.16E-07	4.55E-07	4.31E-07	4.27E-07
2-minute	**7.18E-07**	**4.12E-07**	**4.50E-07**	**3.84E-07**	**3.93E-07**	**4.16E-07**
5-minute	7.45E-07	4.71E-07	4.76E-07	4.45E-07	4.34E-07	4.21E-07
10-minute	7.50E-07	4.95E-07	5.01E-07	4.62E-07	4.59E-07	4.41E-07
15-minute	7.52E-07	4.95E-07	4.99E-07	4.37E-07	4.75E-07	4.64E-07
20-minute	8.02E-07	5.23E-07	5.11E-07	4.81E-07	4.91E-07	4.75E-07
25-minute	7.97E-07	5.25E-07	5.54E-07	4.72E-07	5.38E-07	5.03E-07
30-minute	8.35E-07	5.58E-07	5.60E-07	5.04E-07	5.54E-07	5.28E-07
	Crude oil					
	nearby-m.	1-month	2-month	3-month	4-month	5-month
1-minute	1.99E-06	**1.16E-06**	**1.23E-06**	1.40E-06	1.11E-06	1.14E-06
2-minute	**1.47E-06**	1.24E-06	1.27E-06	**1.26E-06**	**9.56E-07**	**9.40E-07**
5-minute	2.00E-06	1.22E-06	1.29E-06	1.34E-06	1.01E-06	1.01E-06
10-minute	2.03E-06	1.38E-06	1.42E-06	1.40E-06	1.07E-06	1.05E-06
15-minute	2.18E-06	1.37E-06	1.44E-06	1.31E-06	1.05E-06	1.03E-06
20-minute	2.33E-06	1.55E-06	1.54E-06	1.53E-06	1.16E-06	1.13E-06
25-minute	2.44E-06	1.56E-06	1.54E-06	1.45E-06	1.13E-06	1.10E-06
30-minute	2.55E-06	1.61E-06	1.64E-06	1.56E-06	1.21E-06	1.18E-06

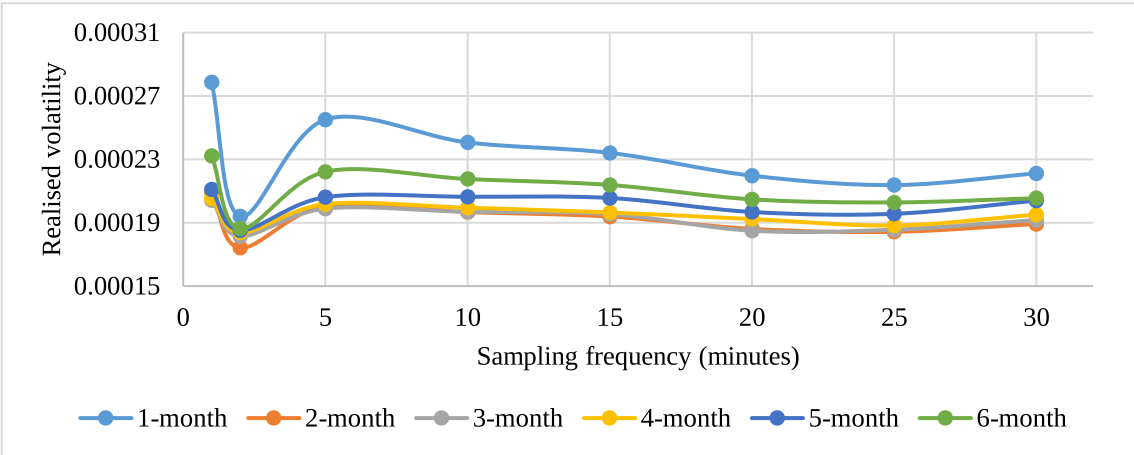
- nearby-m. denotes nearby-month contract. MSE of estimated realised volatility is calculated by (3.3). The lowest MSE of realised volatility is in bold.

Figure 3-3: Realised volatility under different sampling frequency for three TOCOM energy futures

Gasoline



Kerosene



Crude oil

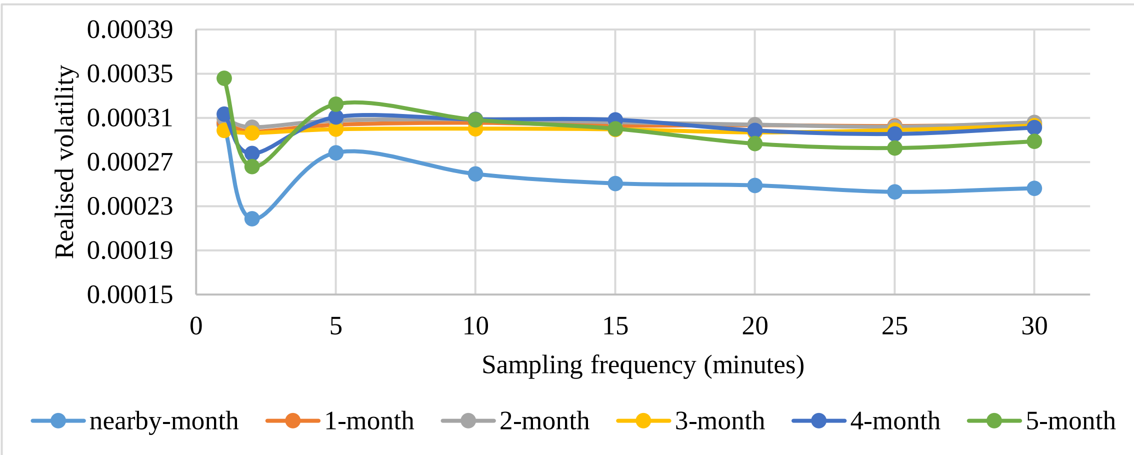


Figure 3-4: The tick-by-tick and 15-minute sampling price of crude oil futures

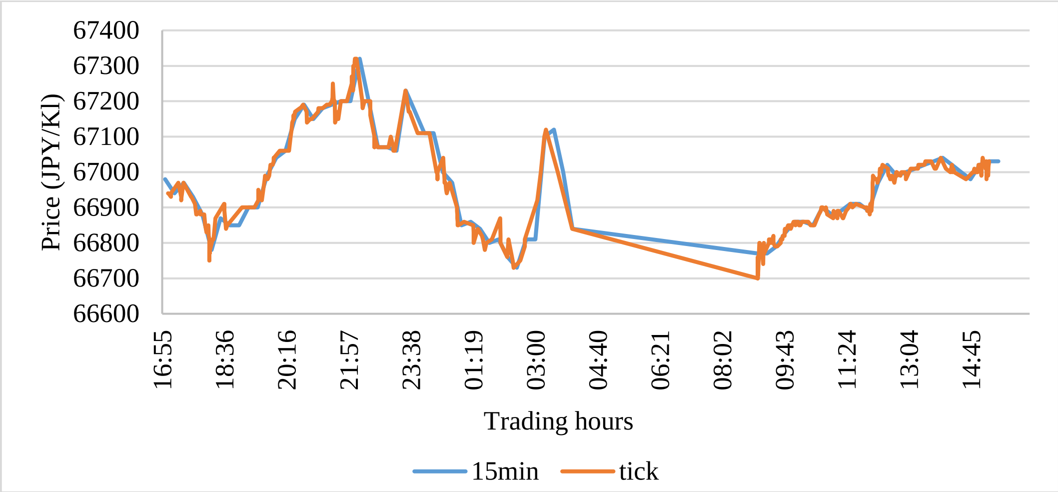


Table 3-6: Descriptive statistics and preliminary tests for daily realised volatility

	1-month	2-month	3-month	4-month	5-month	6-month
Gasoline						
Mean	0.0592	0.0512	0.0495	0.0500	0.0512	0.0484
Std.	0.0889	0.0865	0.0842	0.0797	0.0793	0.0990
Skewness	4.9216	10.5160	11.2357	12.5324	13.6389	21.9423
Kurtosis	37.8911	198.2678	217.3890	268.3630	307.2535	639.4619
ACF_1	0.2508	0.2983	0.2790	0.2952	0.3071	0.7136
ACF_5	0.1561	0.0939	0.1132	0.1216	0.1560	0.3875
ACF_{22}	0.0424	0.0322	0.0437	0.0530	0.0693	0.2236
Q(22)	413.7169 [a]	484.2097 [a]	521.1716 [a]	528.0508 [a]	699.8308 [a]	231.9596 [a]
ADF	-4.9741 [a]	-5.2210 [a]	-5.4466 [a]	-5.1155 [a]	-5.0418 [a]	-5.4065 [a]
KW	3.8762	5.5321	4.2410	6.0885	2.4609	2.6041
Kerosene						
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	0.0586	0.0485	0.0489	0.0492	0.0514	0.0535
Std.	0.1262	0.0950	0.0951	0.0893	0.0928	0.0922
Skewness	14.3429	12.4605	14.9452	15.9391	18.1506	16.0226
Kurtosis	284.1241	254.8750	346.0088	393.0574	483.0959	394.4081
ACF_1	0.1980	0.1888	0.3006	0.2279	0.2068	0.2658
ACF_5	0.1281	0.0953	0.1028	0.1049	0.1034	0.1430
ACF_{22}	0.0165	0.0352	0.0343	0.0403	0.0463	0.0679
Q(22)	256.1135 [a]	321.3244 [a]	389.8241 [a]	450.4213 [a]	416.6683 [a]	596.0530 [a]
ADF	-5.4460 [a]	-5.2532 [a]	-5.3402 [a]	-5.0615 [a]	-4.8775 [a]	-4.8682 [a]
KW	6.9305	3.1638	0.9244	2.5814	4.7067	3.1922
Crude oil						
	nearby-m.	1-month	2-month	3-month	4-month	5-month
Mean	0.0637	0.0759	0.0766	0.0750	0.0771	0.0751
Std.	0.1987	0.1542	0.1634	0.1564	0.1417	0.1400
Skewness	11.2731	13.5571	12.7545	17.4678	16.6099	16.9713
Kurtosis	186.2509	298.2578	250.0441	450.7457	416.1393	429.1186
ACF_1	0.1744	0.4377	0.4012	0.2198	0.2686	0.2547
ACF_5	0.0406	0.1876	0.2836	0.0819	0.1620	0.1546
ACF_{22}	0.0534	0.1038	0.1197	0.0428	0.0772	0.0679
Q(22)	137.5266 [a]	417.8199 [a]	487.8208 [a]	437.1057 [a]	623.2719 [a]	540.4901 [a]
ADF	-5.1707 [a]	-4.7753 [a]	-5.0058 [a]	-4.8888 [a]	-4.7563 [a]	-4.9112 [a]
KW	2.8630	2.6712	1.2938	1.3589	4.2200	3.0522

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. ACF_i is the autocorrelation function with i lags, and the 95% confidence interval is [-0.0565,0.0565]. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015. KW is the Kruskal-Wallis statistic, which follows χ^2_4.

3.3.3 Daily and Intraday Seasonality

The seasonality is also an important issue on the discussion of petroleum market. Ewing et al. (2006) analyse three US petroleum futures and spot prices, namely crude oil, heating oil and gasoline, and find that heating oil and gasoline display daily seasonal behaviour but crude oil does not. Auer (2014) investigates daily seasonality on returns and volatility for Brent crude oil, and suggests that the volatility is higher on Monday than on the other weekdays, but returns are lower on Monday. Therefore, it is crucial to check whether the seasonality exists in TOCOM energy futures.

Kruskal-Wallis test is employed to examine the potential daily seasonality in TOCOM energy futures. The test is implemented by firstly dividing the sample into five groups, namely Monday, Tuesday, Wednesday, Thursday and Friday, and then testing whether the median of each group is equal. The last row of each panel in Table 3-2, 3-3 and 3-6 shows the result of Kruskal-Wallis (KW) test for daily prices, returns, trading volume, the number of transactions and realised volatility. The KW statistics indicate that there is no seasonality in futures prices, while the returns of three gasoline and four kerosene contracts show significantly daily seasonality. Figure 3-5 presents the average level of returns on weekdays. It is clear that the returns are negative on Monday and Tuesday, positive on Wednesday and Thursday, and slightly decrease on Friday. This finding is similar to the evidence reported in Auer (2014) that suggests lower return on Monday.

Moving to the seasonality of trading volume, according to Figure 3-2, it seems like the seasonality in trading volume exists. Surprisingly, the results of KW test are only significant for two gasoline, one kerosene and one crude oil futures. Figure 3-6 presents the average trading volume on each weekday. Due to the dramatic difference in the magnitude of trading volume, only two contracts are presented in the figures for a convenient comparison. One contract shows significant seasonality (orange line) whereas the other one does not (green line). It appears that, for the seasonal one, the trading volume is more like to increase on Thursday and decrease to approximately the level on the other weekdays. However, the trend of trading volume for the non-seasonal one is rather smooth, except the 4-month crude oil. The results of KW tests for the number of transactions is similar to trading volumes, which is expected since these two variables are highly correlated. Given the existence of the seasonality in trading volume for some contracts, one may expect to see the same trend in realised volatility. Nonetheless, the results of KW tests show no significance for the realised volatility of all TOCOM energy futures, which suggests no evidence to support the daily seasonality on the realised volatility. Figure 3-7reveals the average realised volatility from Monday to Friday. Compared with the pattern of returns across weekday, the trend of realised volatility is much stable with no dramatic movements. However, it is noticeable that a slight increase in the realised volatility occurs on Friday across all commodities and maturities. In addition, the realised volatility of shortest maturity futures seems to move in a slightly seasonal pattern; that is, it increases on Tuesday and decreases to an even lower on Wednesday. However, the difference may be too small to be significant.

Figure 3-5: The average level of returns across weekdays

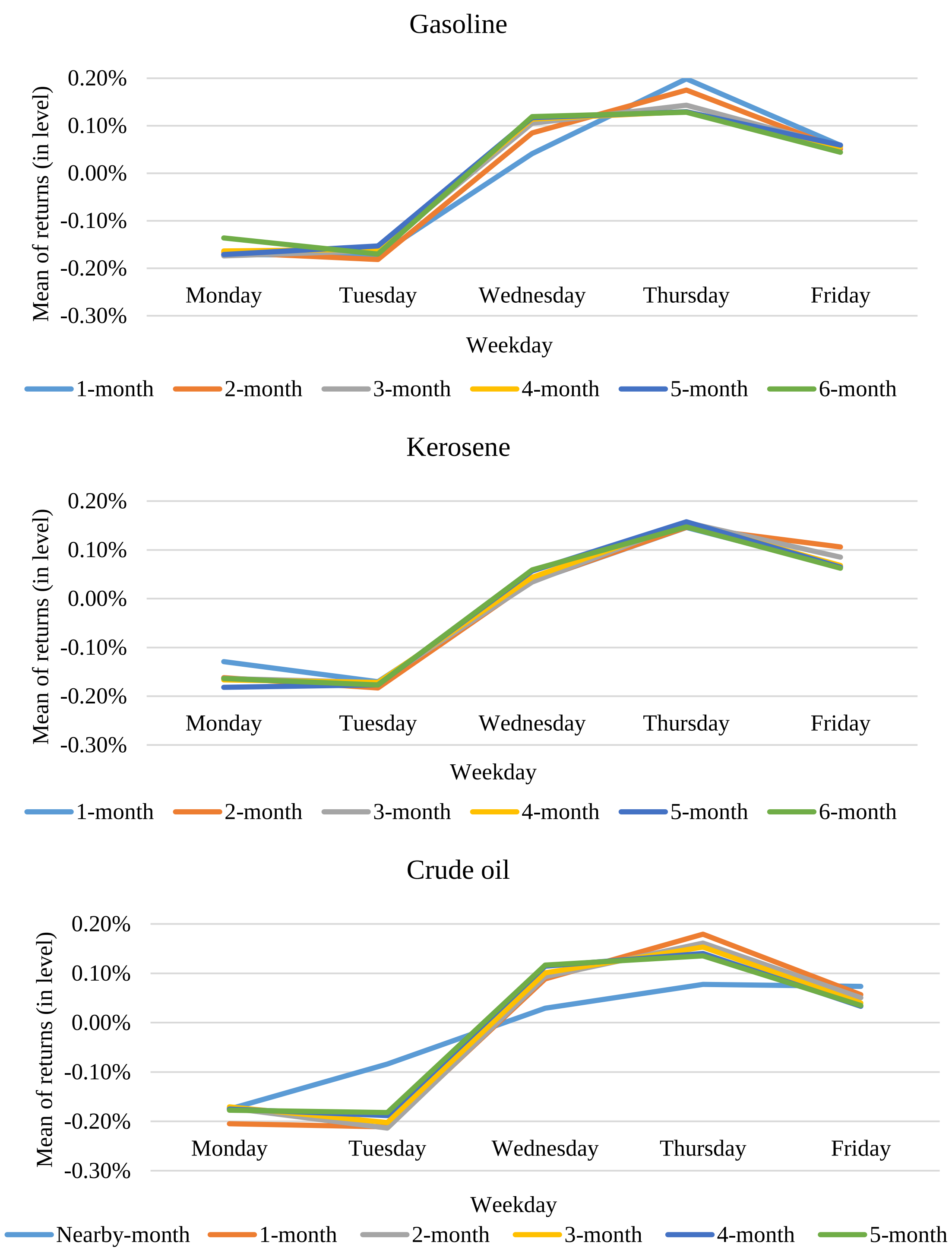
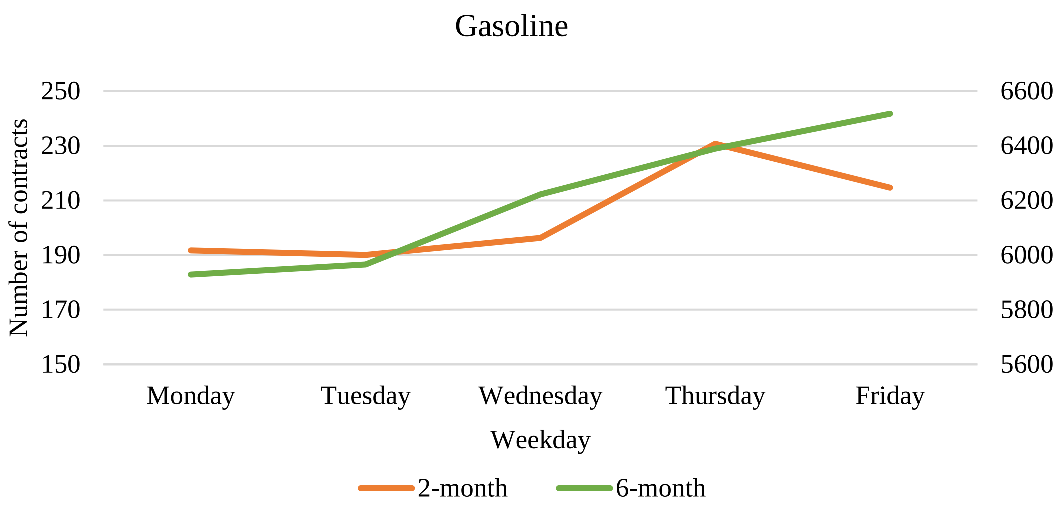
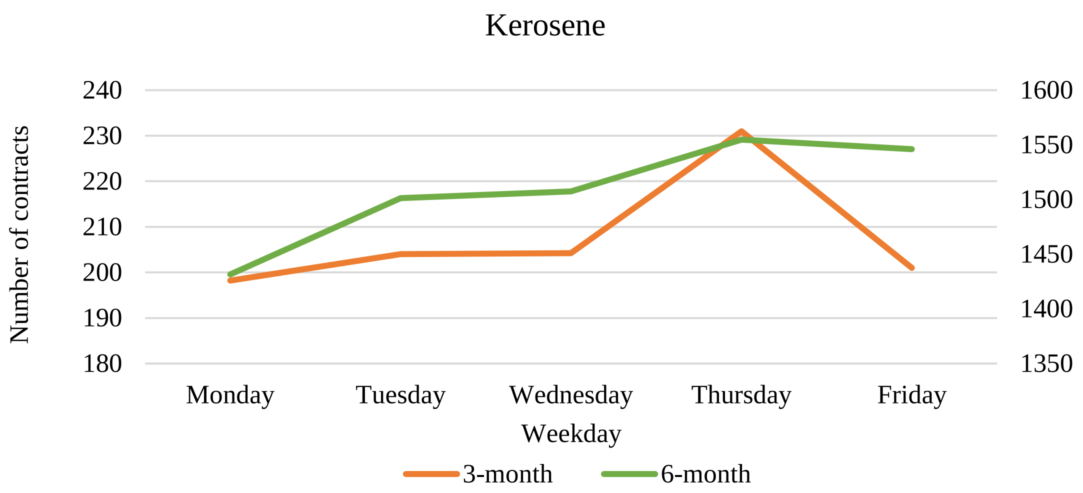


Figure 3-6: The average level of trading volume across weekdays





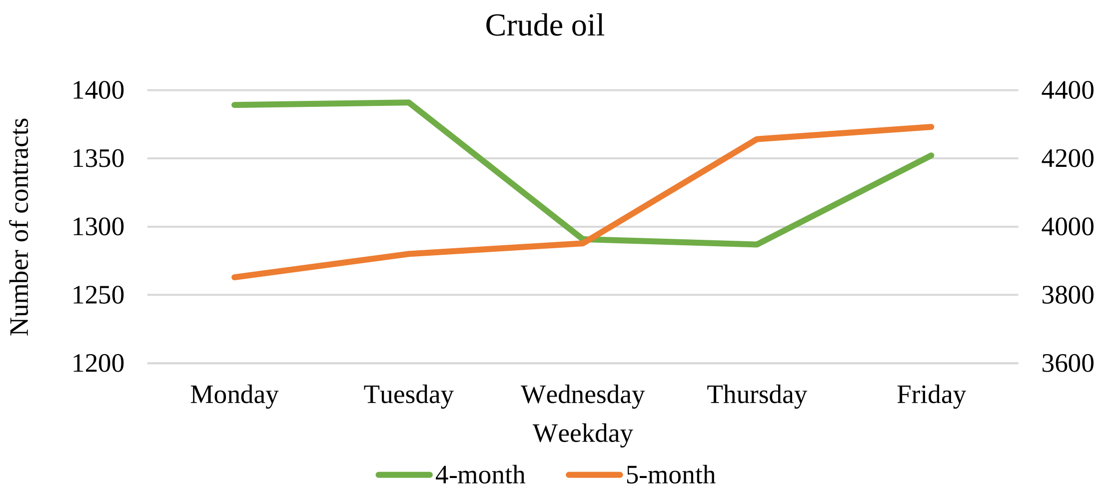
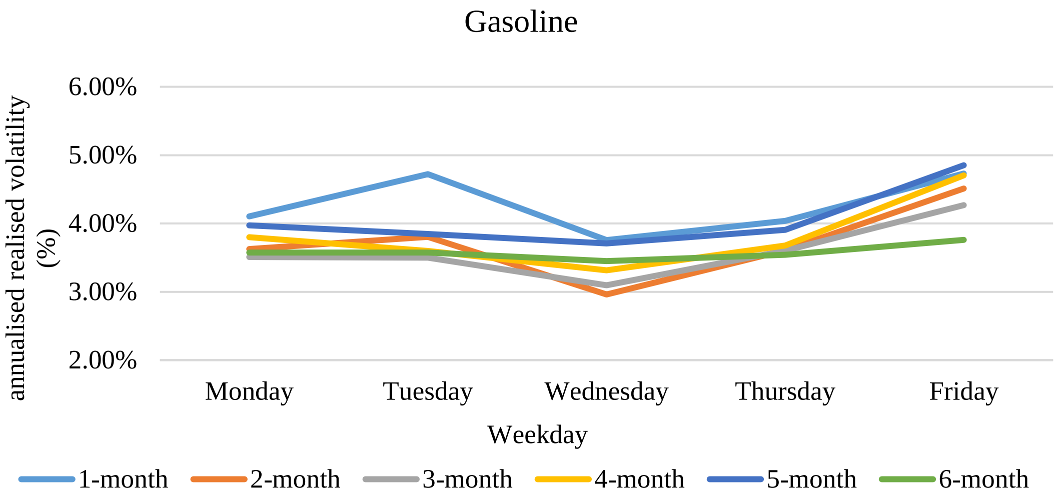
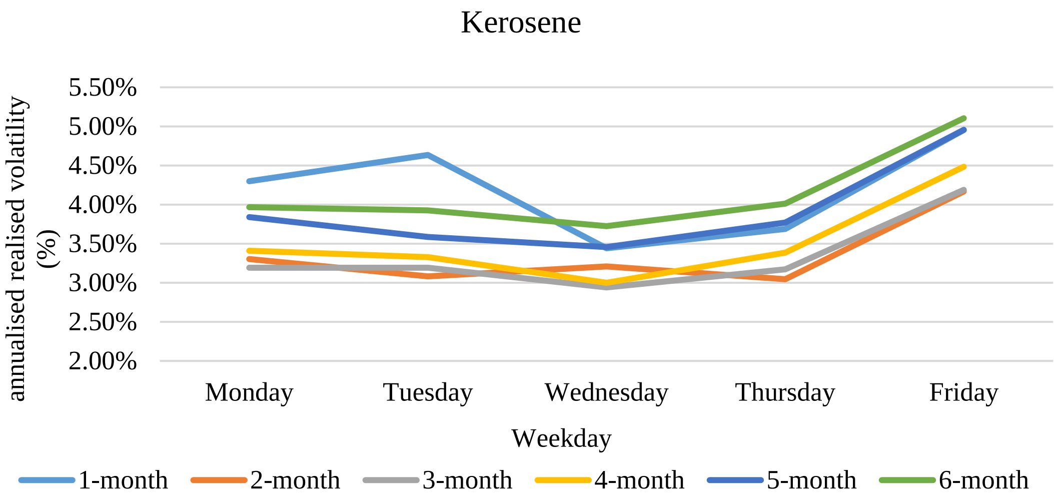
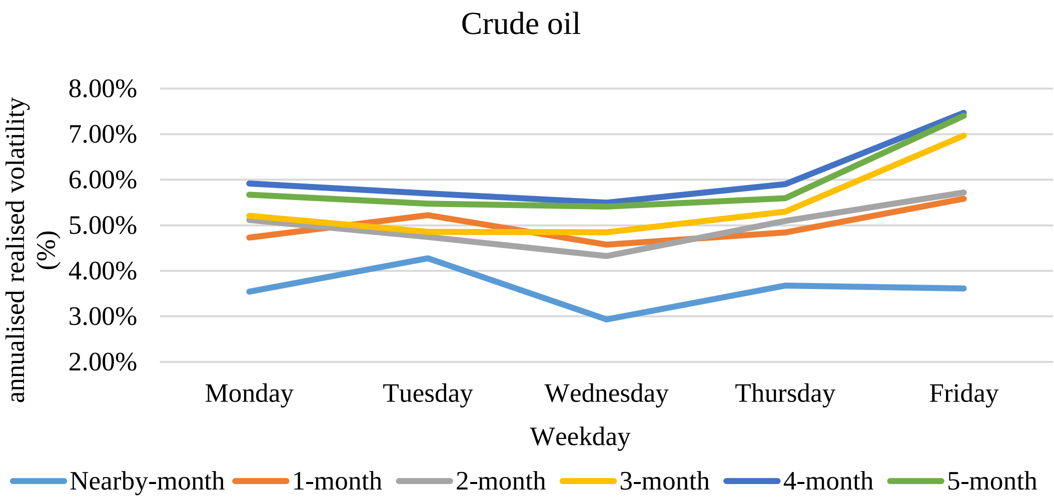


Figure 3-7: The average level of realised volatility across weekdays







Having discussed daily seasonality, the intraday seasonality should also be considered because realised volatility is estimated based on intraday data and the intraday relation between BAS and determinants is analysed in Chapter 6. Wood et al. (1985) investigate the minute-by-minute data on NYSE stocks, and find that the returns and standard deviation are much higher at the first 30 minutes after the opening and at the end of trading hours. Harris (1986) analyses all available transactions of common stocks on NYSE to investigate the intraday pattern, and obtains the similar result as Wood et al. (1985) do. The returns increase within the first 45 minutes and remain stable until the rise at the last 20 minutes before closing.

Kruskal-Wallis test is performed to examine the intraday seasonality of six different variables, price, returns, trading volume, the number of transactions, realised volatility and effective bid-ask spread (BAS). The effective BAS is estimated by the twice absolute difference between the logarithm of price and mid-quote, shown as below.

$$\mathrm{BAS}_t = 2|\ln(P_t) - \ln(Mid_t)|, \tag{3.4}$$

where P_t is the transaction price and Mid_t is the average of bid and ask prices, so called mid-quote. The BAS in this study is estimated by high-frequency data, and the descriptive statistic of effective bid-ask spread is presented in Table 3-7. By comparing the mean of effective BAS across maturities, it is found that the magnitude of effective BAS is much higher for lower maturity contracts than for higher maturity contracts. It is reasonable since BAS has been associated to liquidity and utilised as a measure of liquidity in the literature. (Amihud and Mendelson, 1986; Eleswarapu and Reinganum, 1993; Chordia et al., 2000). Therefore, as the liquidity of futures increases, the BAS is expected to reduce. Moreover, across all commodities and maturities, the results of 22^{nd} order Q statistics and ADF test suggest that BAS is highly autocorrelated and a stationary process.

With regard to the intraday seasonality, the results of KW test suggest no intraday seasonality on the prices whereas the significant intraday seasonality is found on other five variables, namely returns, trading volume, the number of transactions, realised volatility and effective BAS (see Table 3-8). Figure 3-8 to 3-11 shows the intraday dynamics of returns, trading volume, realised volatility and effective BAS.

Table 3-7: Descriptive statistics and preliminary tests for effective bid-ask spreads

			Gasoline			
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	0.2544%	0.1316%	0.0937%	0.0659%	0.0520%	0.0411%
Std.	0.3343%	0.1293%	0.0861%	0.0607%	0.0385%	0.0320%
Skewness	5.5435	6.8083	10.7977	30.5807	3.2162	3.0668
Kurtosis	73.1500	206.4553	605.1400	3588.3096	42.6714	23.0504
Q(22)	565780.8 [a]	360443.3 [a]	246973.3 [a]	84182.6 [a]	65327.0 [a]	66928.2 [a]
ADF	-61.6345 [a]	-68.1101 [a]	-74.1302 [a]	-106.9390 [a]	-98.1402 [a]	-106.9040 [a]
			Kerosene			
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	0.2636%	0.1605%	0.1188%	0.0899%	0.0784%	0.0702%
Std.	0.4246%	0.1557%	0.1030%	0.0806%	0.0719%	0.0627%
Skewness	15.6004	7.1029	2.2758	2.8595	6.3699	2.7711
Kurtosis	500.7587	378.9934	15.3865	25.7424	254.5107	18.1441
Q(22)	618362.1 [a]	437287.0 [a]	382819.7 [a]	332494.6 [a]	176750.4 [a]	153093.8 [a]
ADF	-53.3770 [a]	-64.0338 [a]	-57.9529 [a]	-66.4464 [a]	-87.2499 [a]	-95.2180 [a]
			Crude oil			
	nearby-m.	1-month	2-month	3-month	4-month	5-month
Mean	0.2986%	0.1119%	0.0811%	0.0653%	0.0590%	0.0507%
Std.	0.4521%	0.1422%	0.0723%	0.0630%	0.0492%	0.0459%
Skewness	5.4182	26.1674	2.5955	17.3464	5.0679	4.0133
Kurtosis	52.9679	1726.9011	16.7093	1265.5967	93.9342	34.4219
Q(22)	873131.9 [a]	392929.2 [a]	466071.4 [a]	202234.2 [a]	175422.2 [a]	125407.7 [a]
ADF	-40.9197 [a]	-59.1149 [a]	-57.4187 [a]	-85.7747 [a]	-85.9552 [a]	-104.9075 [a]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015.

Beginning with returns, the pattern of day session (9:00 to 15:30) and night session (17:00 to 04:00) is distinctive. The intraday returns in day session are higher at both opening and closing, which displays a U-shape as suggested by Wood et al. (1985) and Harris (1986). However, the intraday returns in night session start to increase in the second hour after the opening, and remain stable but with fluctuations. At the closing of night session, it appears that the trends of returns are inconsistent across commodities and maturities. In addition, the pattern of intraday crude oil futures returns is slightly different from that of gasoline and crude oil. For instance, in day session, the increase in intraday returns at the beginning is greater than that at the closing for crude oil, but it is the opposite for gasoline and kerosene. In night session, the fluctuation is more volatile for crude oil, but smoother for the other two commodities. Due to the huge difference in the number of trading volumes between maturities, only the intraday trading volume of the most liquid contracts is reported. The intraday trading volume at day session is also a U-shape curve, which is similar to the intraday returns. However, a W-shape curve is observed in the pattern of intraday trading volume at night session, which may be due to the difference in time zones. In particular, 5 p.m. JST is 9 a.m. Central European Time (CET), and 22 p.m. JST is 9 a.m. Eastern Time (ET). Therefore, the foreign trading may explain the increase in intraday trading volume at 5 p.m. and 22 p.m.

Intraday realised volatility exhibits similar dynamics of intraday trading volume, but with a few differences. In day session, the realised volatility is dramatically higher at the opening than in the rest of the day, while only slightly increases at the closing. The pattern of intraday realised volatility is more similar to a L-shape curve rather than a U-shape. In night session, the increase in the intraday realised volatility at closing is not as huge as it is at opening, but there is still a slight hump in the middle of trading hours and a small rise at the closing. Compared to the dynamic of intraday trading volume at night session, the intraday realised volatility exhibits a flatter W-shape curve. Regarding the pattern of intraday effective BAS, the difference between day and night session is still found. Due to the difference in the level of intraday effective BAS, only the most liquid contracts are shown in Figure 3-11. The U-shape curve is also observed in the pattern of intraday effective BAS at day session, but the increases in the intraday effective BAS at the opening and closing are much lower than those in intraday trading volume. Surprisingly, at night session, the dynamic of intraday effective BAS exhibits a mirror reflection of the pattern of intraday realised volatility. There appears no increase in intraday effective BAS at the opening of night session, and the level of intraday BAS remains stable until it rises at the trading hours around the closing. In consistent with the pattern of realised volatility and trading volume, there is also no hump in the middle of night trading hours.

Table 3-8: The results of Kruskal-Wallis tests of six different variables

	Gasoline					
	1-month	2-month	3-month	4-month	5-month	6-month
Price	0.4820	0.1062	0.0790	0.0781	0.0976	0.1256
Return	289.01 [a]	154.49 [a]	66.83 [a]	42.12 [a]	36.15 [a]	41.55 [a]
TV	30243.80 [a]	28901.03 [a]	28896.27 [a]	27042.88 [a]	21812.15 [a]	17307.00 [a]
NT	25502.37 [a]	25835.46 [a]	26736.75 [a]	26510.61 [a]	21420.17 [a]	16947.36 [a]
RV	20049.99 [a]	17109.49 [a]	14179.41 [a]	8662.07 [a]	2111.48 [a]	2470.77 [a]
BAS	2645.45 [a]	3090.35 [a]	2895.06 [a]	2700.02 [a]	4839.52 [a]	6493.79 [a]
	Kerosene					
	1-month	2-month	3-month	4-month	5-month	6-month
Price	0.1912	0.0474	0.0306	0.0687	0.0959	0.1341
Return	74.15 [a]	88.77 [a]	48.88 [a]	21.23	30.87 [b]	29.30 [b]
TV	28107.69 [a]	27241.15 [a]	27653.95 [a]	27889.36 [a]	27812.21 [a]	28600.90 [a]
NT	23881.92 [a]	23238.05 [a]	24601.36 [a]	26026.47 [a]	27441.39 [a]	28314.05 [a]
RV	20054.31 [a]	18239.81 [a]	16667.16 [a]	14078.84 [a]	6357.09 [a]	1622.85 [a]
BAS	3943.22 [a]	5382.02 [a]	5595.20 [a]	5099.10 [a]	7522.54 [a]	9295.73 [a]
	Crude oil					
	nearby-m.	1-month	2-month	3-month	4-month	5-month
Price	0.0664	0.2208	0.2537	0.1914	0.1186	0.1093
Return	27.38	47.95 [a]	58.91 [a]	71.35 [a]	43.68 [a]	48.82 [a]
TV	11747.32 [a]	15711.46 [a]	16160.89 [a]	16756.86 [a]	14228.02 [a]	16496.69 [a]
NT	7958.09 [a]	12474.63 [a]	13320.74 [a]	14670.87 [a]	13093.68 [a]	13573.06 [a]
RV	8972.86 [a]	11715.77 [a]	11128.80 [a]	9480.83 [a]	3358.94 [a]	5271.58 [a]
BAS	630.83 [a]	302.62 [a]	444.31 [a]	1023.40 [a]	3267.53 [a]	5289.20 [a]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. TV is trading volume, NT is the number of transactions, RV is realised volatility and BAS is the effective bid-ask spread. Kruskal-Wallis statistic follows χ^2_{18}. The sample period is from 22 September 2010 to 30 October 2015.

Figure 3-8: The average level of 15-minute returns across intraday trading hours

Figure 3-9: The average level of returns across intraday trading hours

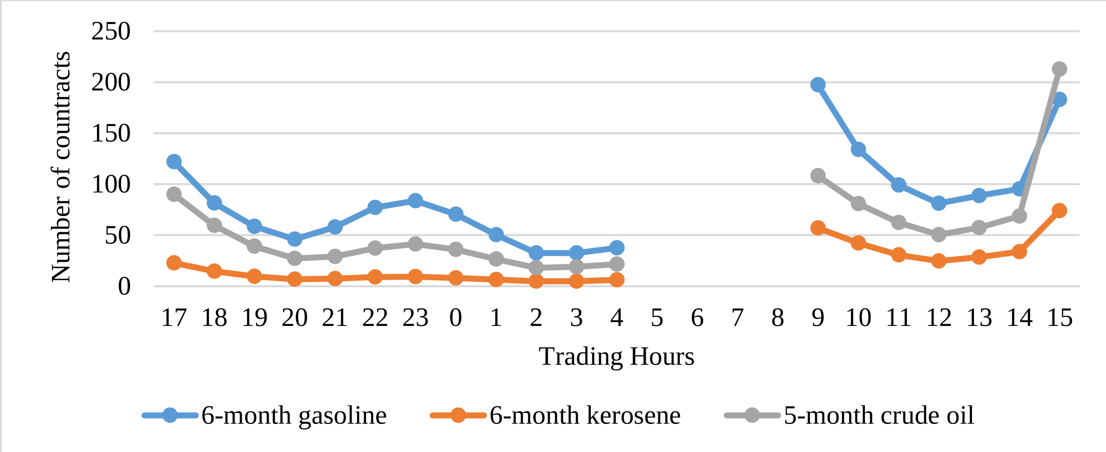
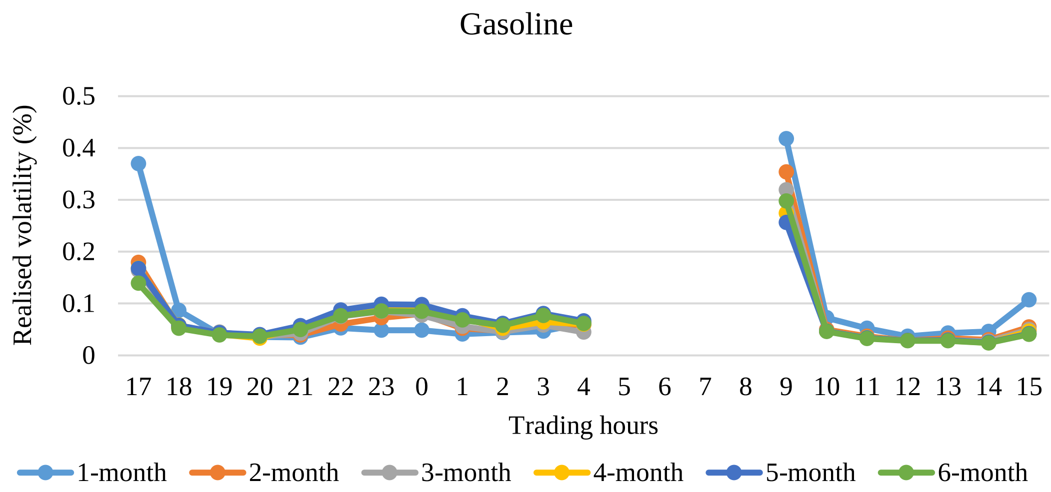


Figure 3-10: The average level of realised volatility across intraday trading hours



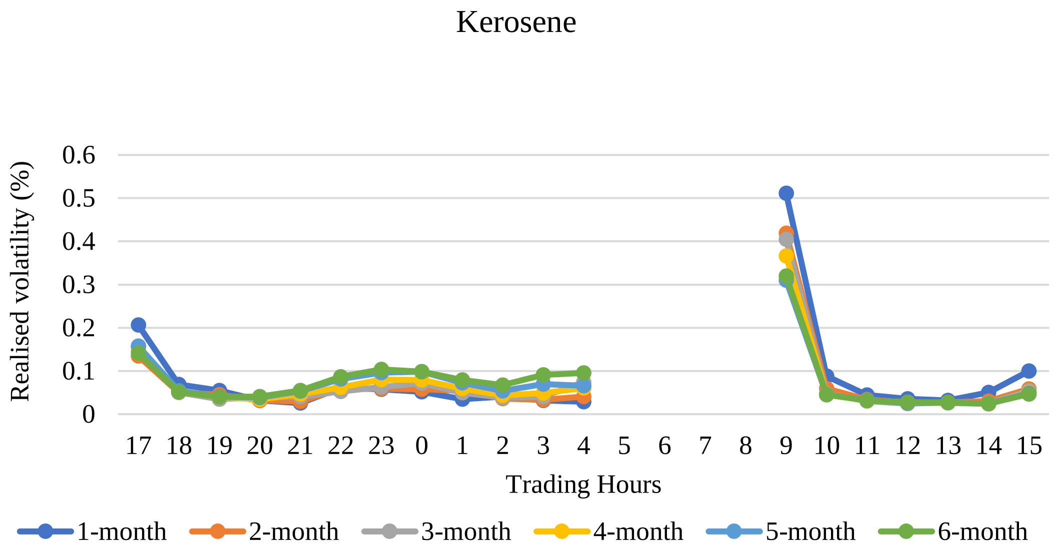


Figure 3-10 (Continued): The average level of realised volatility across intraday trading hours

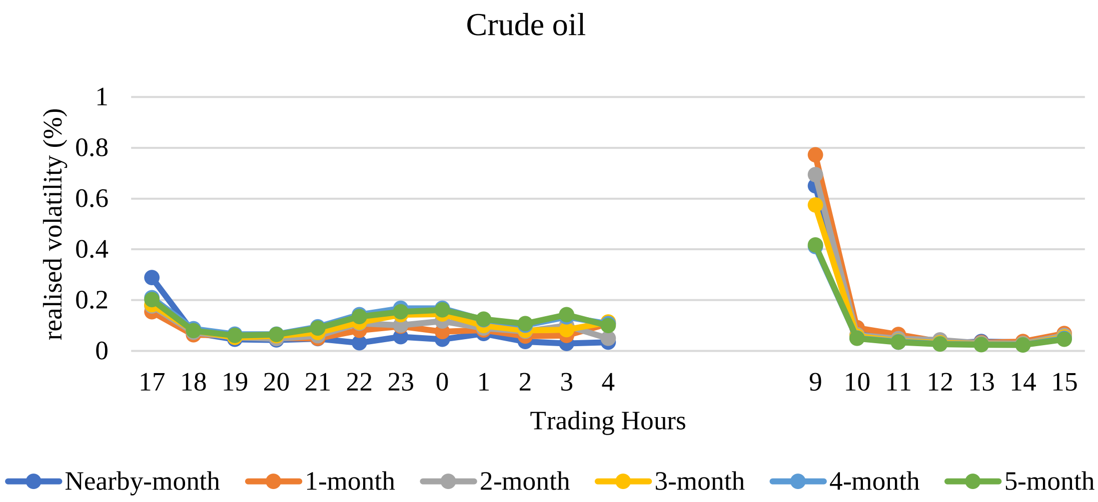
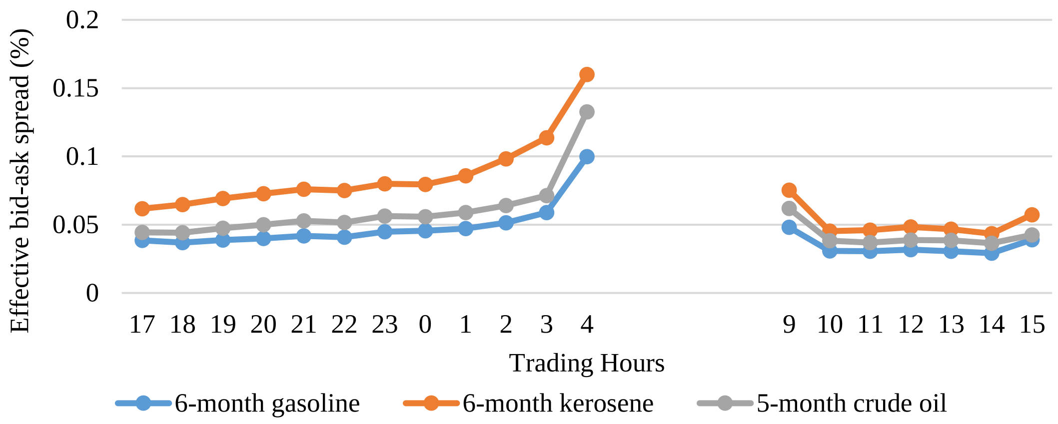


Figure 3-11: The average level of effective bid-ask spread across intraday trading hours



Overall, for all TOCOM energy futures, the dynamics of daily returns and trading volume are seasonal, and the daily seasonality of returns is consistent with the literature. However, no daily seasonality is found for daily realised volatility. The intraday data exhibits strong seasonality except the prices. The pattern of intraday seasonality at day session is consistent with literature (e.g. U-shape intraday returns, trading volume, and bid-ask spread), while, at night session, the movements are different. The difference in the working hours between different time zones may explain the distinctive pattern between day and night session.

Chapter 4 Modelling the Volatility of TOCOM Energy Futures Returns

4.1 Introduction

Modelling and estimating the volatility of asset prices has always been a key issue in financial econometrics because correct volatility estimates and forecasts are essential for risk management, pricing derivatives, trading strategies, as well as portfolio optimisation and asset allocation. The increase in the availability of intraday financial data has led to the development of a new concept for estimation of volatility, namely realised volatility (RV_t), which utilises intraday price movement information. In the present study, we consider the impact of different types of market participants on the persistence of realised volatility, and incorporate a Markov Regime Switching (MRS) technique with a Heterogeneous Autoregressive Model of Realised Volatility (HAR-RV) to produce one-day ahead forecasts for three Tokyo Commodity Exchange (TOCOM) energy futures. The in-sample estimation results suggest MRS-HAR-RV can better explain the dynamic of volatility, but seems to improve forecasting accuracy only for highly liquid contracts.

TOCOM energy futures play an important role in Japan and around the world. Firstly, a lack of domestic energy resources has turned Japan into one of the largest importers of energy in the world. TOCOM energy futures provide Japanese energy participants the most convenient way to hedge their cost or revenue. In addition, the trend towards the financialisation of energy commodities has inspired domestic investors, trading houses, hedge funds and financial institutions to utilise TOCOM energy futures as an asset class for both speculation and diversification[12] (Irwin and Sanders, 2011, and Basak and Pavlova, 2013). Finally, given the significant increase in global trade in energy derivatives over the last two decades, TOCOM energy futures are also a potential choice for foreign traders wanting to manage their investment portfolio. For all these three different participants, volatility is the most crucial parameter because it is involved in planning and implementing all hedging activities, speculation, or investment strategies.

Volatility in energy markets has been characterised as a heterogeneous and autoregressive process, so the General Autoregressive Conditional Heteroscedasticity (GARCH) and the Heterogeneous Autoregressive Model of Realised Volatility (HAR-RV) type models are commonly employed to model and forecast volatility. The other noticeable property of the volatility of energy commodities is the persistence of lagged observations, which points to the use of several long-memory models, such as Fractionally Integrated GARCH (FIGARCH), Corsi (2009)'s HAR-RV, and the Heston model of stochastic volatility. Although GARCH type models are able to capture the long memory property of volatility, the lack of GARCH models' forecasting accuracy has been pointed out in several studies, including by Figlewski (1997), Poon and Granger (2003), Cabedo and Moya (2003) and Sadeghi and Shavvalpour (2006). In addition, Liu and Wan (2012) and Wei et al. (2010) provide evidence that autoregressive type models of realised volatility outperform GARCH type models in forecasting volatility. Thus, this paper focuses on a discussion of realised volatility models and extends these models to allow for changes in their

[12] On the 8th of December 2015, TOCOM announced that the trading volume of crude oil futures is 55,388 contracts, which is 1.4 of the historical record. In addition, the open interest reached the highest record at 58,741 contracts on the 4th of December 2015. http://www.tocom.or.jp/news/2015/20151208.html

structure using a regime switching approach.

The motivation of this chapter is based on the influence of order imbalance (net buy-initiated or net sell-initiated transactions) on volatility. Theoretical microstructure models (e.g. Kyle, 1985; Admati and Pfleiderer, 1988) suggest that net order flow causes price movements. Market-makers are assumed to only observe trading activities on the market, and to not be able to distinguish information traders from liquidity traders. Therefore, when they observe excess buy (sell) order imbalance, they increase (decrease) their prices of orders. Several empirical studies (Glosten and Harris, 1988; Madhavan et al., 1997; Huang and Stoll, 1997) also find that the indicator of buy-initiated or sell-initiated trades can explain the intra-daily movements of price and quotes. Moreover, Chan and Fong (2000) study NYSE and Nasdaq stocks, and find that their volume-volatility relation becomes weaker following the impact of order imbalance. Chordia et al. (2002) have found evidence that both contemporaneous and lagged order imbalance have a significant effect on returns, while only contemporaneous order imbalance affects volatility (absolute return). Given that the storage cost is one of the linkages between spot and futures markets for storable commodities, a proportion of order imbalance is associated with the storage market. For example, higher storage costs imply a shortage in the supply of inventory, and the producers potentially loose one tool to hedge the risk of receiving revenue in the future. Therefore, futures are the only mean for them to hedge, and the order imbalance can be expanded by their taking position of futures. By contrast, when the storage cost is low, the producer has less motivation to use futures as hedging tools, and the order imbalance is less likely to increase. Nonetheless, as market makers are not able to distinguish liquidity traders and information traders, the volatility always increases when a high level of order imbalance appears.

The design of Corsi (2009)'s HAR-RV intends to capture the long-memory property of volatility in a RV setting. However, as stated in the last paragraph, the persistence of volatility does not always remain, so Corsi (2009)'s HAR-RV model may not be the optimal model with which to capture the dynamics of volatility. This paper aims first to introduce a Markov Regime Switching HAR-RV (MRS-HAR-RV) model, capturing dynamics in high- and low-volatility regimes. We expect to see that long-memory property exists in a low-volatility regime where the order imbalance is lower, whereas persistence vanishes in a high-volatility regime where the order imbalance is greater. Following the estimation of MRS-HAR-RV, we examine the accuracy of volatility forecasts produced by MRS-HAR-RV in comparison with alternative approaches, including Corsi (2009)'s HAR-RV.

This chapter contributes to the literature in several aspects. First, this is the first paper modelling and forecasting of the realised volatility of TOCOM energy futures, and all maturity contracts are included in our sample, which allows us to study the term structure of TOCOM energy futures. Second, we incorporate a HAR-RV and MRS approach to investigate different dynamics of realised volatility in different regimes. Third, we find high- and low-volatility regimes of realised volatility of TOCOM energy futures based on the average level of realised volatility in each regime, as well as the persistence of volatility. Finally, after identifying high- and low-volatility regimes, we investigate the performance of the regime switching HAR-RV model in predicting and estimating VaR in comparison with simple HAR-RV, a GARCH (1,1) model, MRS-GARCH (1,1) and Historical Simulation VaR estimates. The results suggest that incorporating the state of the market through a regime switching approach can improve the predictability of upside volatility forecasts but not downside volatility forecasts.

4.2 Literature Review

A number of recent studies suggest that high-frequency data are useful for estimating and predicting future volatility as intraday movements in prices are less subject to measurement error than price observations at a lower frequency (Andersen and Bollerslev, 1998). In this approach, an unbiased estimator of volatility, known as realised volatility (RV), can be arrived at using the squared values of intraday returns. For instance, daily realised volatility ($RV_t^{(d)}$) is defined as the sum of intraday squared returns (Andersen et al., 2001a and 2003), and has been argued to be a more efficient estimate of volatility than daily squared returns (McAleer and Medeiros, 2008). Under the assumption that returns are independent with a zero mean, RV is also an unbiased estimator of true variance. Barndorff-Nielsen and Shephard (2004), Andersen et al.

(2007), and Barndorff-Nielsen and Shephard (2007) further argue the importance of accounting for jumps in the estimation of realised volatility. Andersen et al. (2006) and McAleer and Medeiros (2008) provide a thorough survey of studies on the estimation and application of realised volatility.

The first study to employ a realised volatility approach to estimate the volatility of energy commodity prices (sweet crude oil) was by Martens and Zein (2004). This was followed by Wang et al. (2008), who investigated NYMEX crude oil and natural gas futures prices. They suggest that RV is an appropriate measure of volatility in both the crude oil and natural gas markets, as well as the realised correlation (RC) between the futures prices of the two commodities. Wei (2012) compares the accuracy of different volatility models, including six GARCH type models, ARFIMA-RV (Autoregressive Fractionally Integrated Moving Average Realised Volatility model) and Stochastic Volatility, in forecasting the volatility of fuel oil futures on the Shanghai Futures Exchange (SHFE).

In a recent study, Sévi (2014) employed intraday data to forecast the volatility of WTI crude oil futures for a 1- to 66-day horizon using different models based on the decomposition of realized variance into its positive or negative part (semivariances) and its continuous or discontinuous part (jumps). Considering eleven heterogenous autoregressive (HAR) models proposed in the literature (Andersen et al. 2007, Corsi, 2009, Chen and Ghysels, 2010, and Patton and Sheppard 2011), Sévi (2014) reports that the model with independent squared jump has best forecast in-sample, but does not significantly improve the out-of-sample forecast. Haugom et al. (2014) also analyse the realised volatility of WTI crude oil futures, and employ Corsi (2009)'s augmented HAR-RV model, which incorporates implied volatility (with the CBOE Crude Oil Volatility Index as a proxy) and other market variables, including trading volume, open interest, daily returns, bid-ask spread and the slope of the forward curve. Their results suggest that incorporating implied volatility (OVX) can significantly improve short term (daily and weekly) volatility forecasts, while including other market variables improves long term (monthly) volatility forecasts.

Another branch of literature focuses on changes in the dynamics of price volatility under different market conditions. The main approach proposed for taking into account market conditions when estimating the time-varying volatility of asset prices is the Markov Regime Switching (MRS) model (Hamilton, 1989). The MRS approach has been extended to GARCH models, namely MRS-GARCH, to incorporate the effect of regime changes on the dynamics of volatility in GARCH models under different regimes (market conditions). For example, Marcucci (2005) compares the volatility forecasting performance of several standard GARCH and MRS-GARCH models on the S&P100 Index, and finds that MRS-GARCH models outperform GARCH models at short horizon (one day to one week). Lee and Yoder (2007) apply the MRS-GARCH model to the corn and nickel futures markets and report higher, yet insignificant, variance reduction when compared to OLS and single regime GARCH hedging strategies; while Alizadeh, et al. (2008) analyse three sets of energy commodities data, crude oil, gasoline and heating oil, and also find that the use of a MRS-MGARCH model improves hedging performance.

Given the importance of market conditions and the behaviour of price volatility, as well as the benefits of using high frequency intraday data in estimations of volatility, we propose a regime switching model which allows for changes in the dynamics of RV according to market conditions. In particular, we utilise the MRS-HAR-RV model to examine if the realised volatility of TOCOM energy futures is regime-dependent and to determine whether the MRS-HAR-RV model produces superior forecasts compared to Corsi (2009)'s single regime HAR-RV.

4.3 Methodology

In this section, we discuss the estimation of the realised volatility of energy futures prices using high frequency intraday data, and present two forecasting models of realised volatility, namely Corsi's Heterogeneous Autoregressive RV (HAR-RV) and its regime switching extension, MRS-HAR-RV.

4.3.1 Estimating Volatility with High-frequency Data

We begin the discussion with a continuous-time Geometric Brownian process

$$dp_t = \mu_t dt + \sigma_t dw_t \,, \tag{4.1}$$

where p_t is the logarithm of the instantaneous price of TOCOM energy futures, μ_t is the time-varying drift term, σ_t is the diffusion parameter and also known as the instantaneous volatility of p_t, and w_t is the standard Brownian motion process. The integrated variance of TOCOM energy futures can then be defined as the integral of instantaneous variance (σ_t^2). For instance, the one-day integrated variance, our primary variation of interest, can be expressed as

$$IV_t^{(d)} = \int_{t-1d}^{t} \sigma_s^2 dw_s. \tag{4.2}$$

However, the integrated variance, defined by equation (4.2), is by nature a latent variable, so we need to find an observable variable in order to estimate volatility.

With the availability of intraday data, the sum of intraday squared returns, known as realised variance, has been utilised as the most common approximation of integrated variance. Plenty of literature (Andersen et al., 2001a, 2001b, 2003; Barndorff-Nielsen and Shephard, 2002a, 2002b) has shown that the realised variance converges to the integrated variance in probability. Hence, this paper follows the same approach in estimating realised variance. For instance, the realised variance for a one-day window$[t-1d, t]$, divided by M Δ-frequency intervals, is estimated by

$$RV_t^{(d)} = \sum_{j=0}^{M-1} r_{t-j\times\Delta}^2. \tag{4.3}$$

$RV_t^{(d)}$ is one-day realised variance, $\Delta = 1d/M$ is the frequency of intervals, $r_{t-j\times\Delta}^2$ is the intraday return at Δ-frequency interval, and M is the number of intervals in one day.

4.3.2 The Heterogeneous Autoregressive Realised Volatility Model

The simple HAR-RV is utilised as the benchmark model in this paper because Sévi (2014) suggests that the simple HAR-RV outperforms other alternative models that include jumps in terms of forecasting volatility. Corsi (2009) proposes a HAR-RV to forecast realised volatility, which considers the property of long memory in volatility and can be simply estimated using OLS. The HAR-RV model forecasts realised volatility with lagged realised volatility over different time horizons, namely one-day, one-week and one-month RV, shown as equation (4.4)

$$\mathrm{RV}_{t+1d}^{(d)}=\beta_0+\beta^{(d)}\mathrm{RV}_t^{(d)}+\beta^{(w)}\mathrm{RV}_t^{(w)}+\beta^{(m)}\mathrm{RV}_t^{(m)}+\varepsilon_{t+1d}^{(d)}, \tag{4.4}$$

$$\varepsilon_{t+1d}^{(d)}\sim N(0,\Sigma\quad),$$

where $\mathrm{RV}_{t+1d}^{(d)}$ is one-day ahead predicted realised volatility, and $\varepsilon_{t+1d}^{(d)}$ is the unpredicted error term following a normal distribution with zero mean and Σ volatility. Daily realised volatility ($RV_t^{(d)}$) is measured as equation (4.3), whilst weekly and monthly realised volatility ($\mathrm{RV}_t^{(w)}$ and $\mathrm{RV}_t^{(m)}$) are calculated as the average of the aggregate daily realised volatility as equation (4.5).

$$RV_t^{(m,w)}=\frac{1}{M}\sum_{i=0}^{M-1}RV_{t-i}^{(d)},$$

$$\text{where}\begin{cases}\text{M=5 for weekly RV}(\mathrm{RV}_t^{(w)})\\ \text{M=22 for monthly RV}(\mathrm{RV}_t^{(m)})\end{cases}. \tag{4.5}$$

Nonetheless, our benchmark modifies Corsi (2009)'s HAR-RV in two aspects. First, following Sévi (2014)'s modification, we avoid the overlapping of realised volatility over three different horizons. That is, weekly realised volatility is measured as the average of daily realised volatility between $t-1$ and $\mathrm{t}-5$, and monthly realised volatility is measured as the average of daily realised volatility between $t-6$ and $t-22$, shown as equation (4.6).

$$\mathrm{RV}_{\mathrm{t}}^{(\mathrm{w})} = \frac{1}{4}\sum_{i=1}^{4} \mathrm{RV}_{\text{t-i}}^{(\mathrm{d})}$$

$$\mathrm{RV}_{\mathrm{t}}^{(\mathrm{m})} = \frac{1}{17}\sum_{i=6}^{22} \mathrm{RV}_{\text{t-i}}^{(\mathrm{d})} \tag{4.6}$$

Second, according to the Samuelson Hypothesis (Samuelson, 1965), futures volatility increases when contracts approach maturity. The days-to-rollover is included in Corsi (2009)'s HAR-RV, which is shown below.

$$RV_{t+1d}^{(d)} = \beta_0 + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \beta^{(DTR)} DTR_t + \varepsilon_{t+1d}^{(d)}, \tag{4.7}$$

$$\varepsilon_{t+1d}^{(d)} \sim N(0, \Sigma \quad),$$

where $\mathrm{DTR}_{\mathrm{t}}$ is the days to rollover date. If the Samuelson Hypothesis holds, the volatility rises with a decrease in days-to-rollover, and $\beta^{(\mathrm{dtr})}$ is then expected to be negative and significant.

4.3.3 The Regime Switching HAR-RV

Considering the type of market participants, we modified the simple HAR-RV by incorporating a Markov Regime Switching technique proposed by Hamilton (1989). As described in Section 1, the persistence of realised volatility is expected to be higher if the market is in high level of order imbalance, but lower if the market is in low level of order imbalance. Hence, the coefficient stating the persistence of realised volatility should vary based on the states/regimes (st), shown as

$$RV_{t+1d}^{(d)} = \beta_{0,st} + \beta_{st}^{(d)} RV_t^{(d)} + \beta_{st}^{(w)} RV_t^{(w)} + \beta_{st}^{(m)} RV_t^{(m)} + \beta_{st}^{(DTR)} DTR_t + \varepsilon_{t+1d,st}^{(d)}, \tag{4.8}$$

$$\varepsilon_{t+1d,st}^{(d)} \sim N(0, \Sigma_{st}),$$

where st = {1,2} as we introduce a two-state MRS model, and all parameters (α_{st}, $\beta_{st}^{(d)}$, $\beta_{st}^{(w)}$, $\beta_{st}^{(m)}$ and Σ_{st}) are now state-dependent. The shift of regimes depends on the conditional probability matrix in that

$$\boldsymbol{P} = \begin{pmatrix} \Pr(st_t = 1|st_{t-1} = 1) = p_{11} & \Pr(st_t = 1|st_{t-1} = 2) = p_{21} \\ \Pr(st_t = 2|st_{t-1} = 1) = p_{12} & \Pr(st_t = 2|st_{t-1} = 2) = p_{22} \end{pmatrix} = \begin{pmatrix} 1-p_{12} & p_{21} \\ p_{12} & 1-p_{21} \end{pmatrix}. \quad (4.9)$$

where p_{12} measures the probability of being in state 2 in the current period, given that you were in state 1 in the previous period, while p_{21} is exactly the opposite transition. Based on the conditional transition probability (p_{12} and p_{21}), we can calculate the unconditional regime probability as

$$\Pr(st_t = 1) = p_{1,t} = \frac{p_{21}}{p_{12}+p_{21}};\ \Pr(st_t = 2) = p_{2,t} = \frac{p_{12}}{p_{12}+p_{21}}. \quad (4.10)$$

Moreover, we can now specifically rewrite the MRS-HAR-RV from the equation (4.8) to the following

$$RV_{t+1d}^{(d)} = p_{1,t}\left(\beta_{0,1} + \beta_1^{(d)} RV_t^{(d)} + \beta_1^{(w)} RV_t^{(w)} + \beta_1^{(m)} RV_t^{(m)} + \beta_1^{(dtr)} dtr_t + \varepsilon_{t+1d,1}^{(d)}\right) + \quad (4.11)$$

$$(1-p_{1,t})(\beta_{0,2} + \beta_2^{(d)} RV_t^{(d)} + \beta_2^{(w)} RV_t^{(w)} + \beta_2^{(m)} RV_t^{(m)} + \beta_2^{(dtr)} dtr_t + \varepsilon_{t+1d,2}^{(d)}),$$

$$\varepsilon_{t+1d,1}^{(d)} \sim N(0, \Sigma_1),\ \varepsilon_{t+1d,2}^{(d)} \sim N(0, \Sigma_2).$$

Finally, assuming that the state-dependent residuals follow a normal distribution, with mean zero and constant volatility, Σ_1 and Σ_2 for the two states respectively, the likelihood function for the entire sample is formed as a mixture of the probability distribution of the state variable, where:

$$f\left(RV_t^{(d)}, \theta\right) = \frac{p_{1,t}}{\sqrt{2\pi}\Sigma_1}\exp\left(-\frac{{\varepsilon_{t,1}^{(d)}}^2}{2\Sigma_1^2}\right) + \frac{p_{2,t}}{\sqrt{2\pi}\Sigma_2}\exp\left(-\frac{{\varepsilon_{t,2}^{(d)}}^2}{2\Sigma_2^2}\right) \quad (4.12)$$

with the log-likelihood function as

$$L(\theta) = \sum_{t=1}^{T} log f\left(RV_t^{(d)}, \theta\right), \quad (4.13)$$

where θ is the vector of parameters to be estimated. The log-likelihood function $L(\theta)$ is maximised using the BFGS estimation method subject to the constraint that $p_{1,t} + p_{2,t} = 0$ and $0 \leq p_{1,t}, p_{2,t} \leq 1$.

4.4 Description of Data and Preliminary analysis

We include all contracts of maturity in this chapter, namely 1- to 6-month contracts for gasoline and kerosene futures and front- to 5-month contracts for crude oil futures, which allows comparison across the term structure. This is very important for investigating TOCOM energy futures, because the pattern of TOCOM trading volume regarding maturity is surprisingly different from futures exchange.

Figure 4-1 to 4-6 show the daily log return and realised volatility of gasoline, kerosene and crude oil futures across maturities over our sample period. We can clearly observe several clusters of log returns in Figure 4-1 to 4-3, which proves the heteroscedasticity of the realised volatility. In addition, the clusters in returns also match the corresponding high or low level volatility clusters in Figure 4-4 to 4-6. Excepting the clusters, several noticeable spikes are also seen in Figure 4-4 to 4-6. The most distinct spike occurred on 6 May 2011 when the oil price dropped sharply by 10% at 11 a.m. ET on 5 May 2011 (12 a.m. JST on 6 May 2011), known as the intraday flash crash in oil markets. The other spike took place on 7 May 2012, right after the against-austerity party won the legislative election in Greece. Hence, dummies of these two events are introduced to control their unexpected and significant effects, and the relevant equations (4.7) and (4.8) are then changed into the equations shown below

$$RV_{t+1d}^{(d)} = \beta_0 + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \beta^{(DTR)} DTR_t + \beta^{(D1)} D1_t + \beta^{(D2)} D2_t + \varepsilon_{t+1d}^{(d)}, \tag{4.14}$$

$$\varepsilon_{t+1d}^{(d)} \sim N(0, \Sigma \quad),$$

$$RV_{t+1d}^{(d)} = \beta_{0,st} + \beta_{st}^{(d)} RV_t^{(d)} + \beta_{st}^{(w)} RV_t^{(w)} + \beta_{st}^{(m)} RV_t^{(m)} + \beta_{st}^{(DTR)} DTR_t + \beta_{st}^{(D1)} D1_t + \beta_{st}^{(D2)} d2_t + \varepsilon_{t+1d,st}^{(d)}, \tag{4.15}$$

$$\varepsilon_{t+1d,st}^{(d)} \sim N(0, \Sigma_{st}),$$

where $D1_t$ and $D2_t$ are dummy variables for spikes on 6 May 2011 and 7 May 2012, respectively. Moreover, to examine whether the spikes cause structural change in the realised volatility, the unit root test with break point is performed. The idea of unit root with structural break was firstly proposed by Perron (1989) who argues the importance between unit root test and structural changes. In particular, a unit root test not allowing the structural change caused by unique economic events may be biased, and reduce the probability to reject the null hypothesis. Table 4-1 presents the results of the unit root test with structural breaks. It is evident that the realised volatility of all TOCOM energy futures is a stationary series.

Table 3-6 exhibits the autocorrelation function of the first 1, 5 and 22 lags. The level of the first and fifth order ACF is high across all contracts, but the 22nd order ACF is only significant for highly liquid contracts[13]. The lack of significance of 22nd order ACF may be caused by potential regime switching in the realised volatility since the persistence in the high-volatility regime is expected to be lower. However, the significance of Ljung and Box (1978)'s Q statistics for the first 22 lags of the autocorrelation function indicates that RV of all energy futures are still highly autocorrelated at least up to 1 month and confirms the long-memory property of realised volatility.

Table 4-1: The results of unit root with structural breaks for realised volatility across three TOCOM energy futures

Gasoline	1-month	2-month	3-month	4-month	5-month	6-month
	-19.1187 [a]	-19.7509 [a]	-19.8363 [a]	-24.4254 [a]	-17.9797 [a]	-25.5932 [a]
Kerosene	1-month	2-month	3-month	4-month	5-month	6-month
	-27.9097 [a]	-21.2141 [a]	-25.0793 [a]	-26.0246 [a]	-26.7835 [a]	-18.9187 [a]
Crude oil	nearby-m.	1-month	2-month	3-month	4-month	5-month
	-24.7068 [a]	-19.3949 [a]	-26.0456 [a]	-26.5545 [a]	-25.0362 [a]	-25.0108 [a]

- [a] indicates rejection at the 1% significance level. nearby-m. denotes nearby-month. The sample period is from 22 September 2010 to 30 October 2015.

[13] Haugom et al. (2014) and Sévi (2014) investigate WTI crude oil futures on NYMEX, and both find that the realised volatility of WTI crude oil futures is highly autocorrelated. Haugom et al. (2014) presents Q-statistic to demonstrate that the realised volatility is autocorrelated at least up to 10 lags. Sévi (2014) reports a graph of autocorrelation function, which shows the autocorrelation exists at least until 35th lag.

Figure 4-1: Daily log-return of gasoline futures

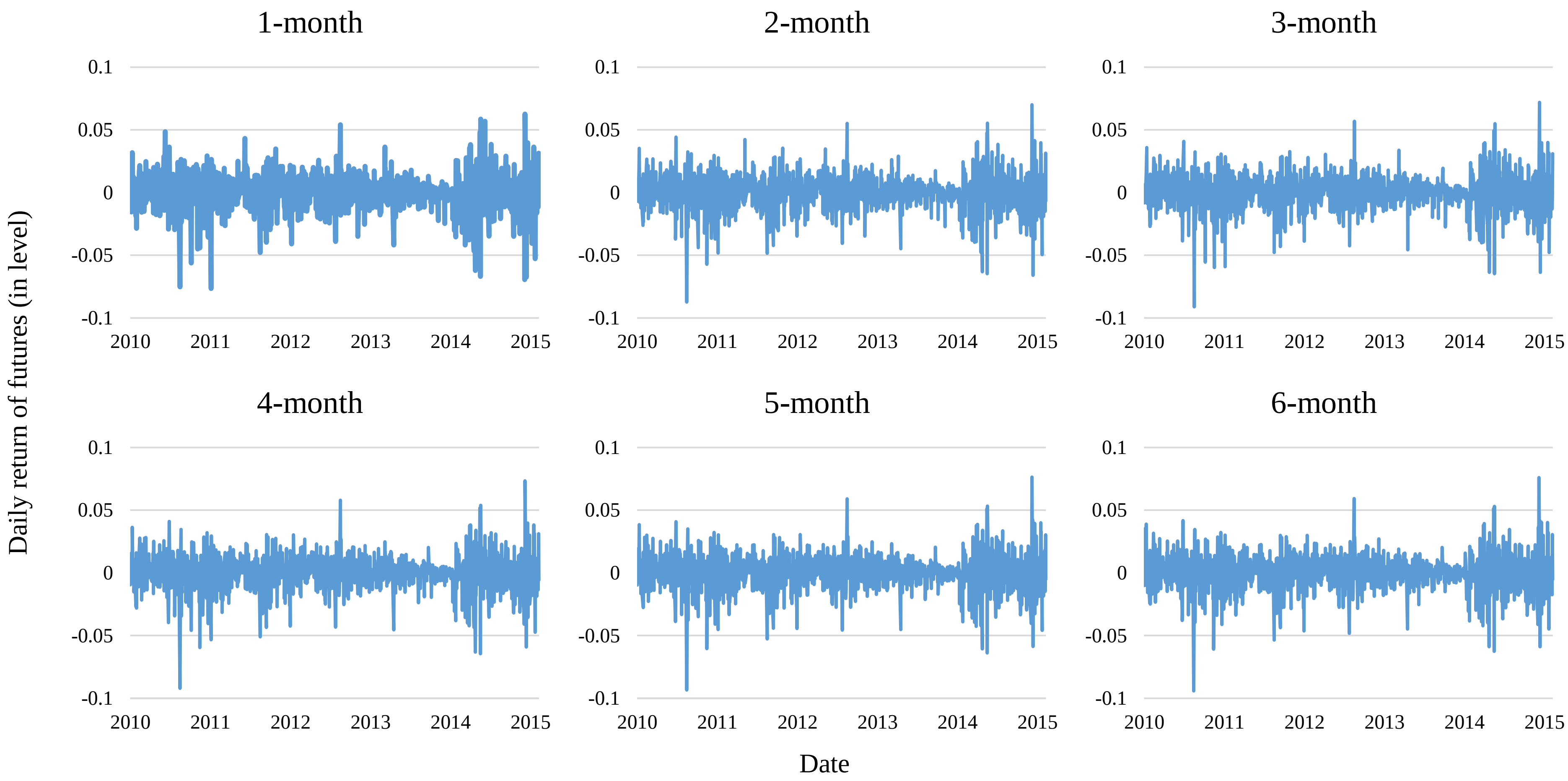


Figure 4-2: Daily log-return of kerosene futures

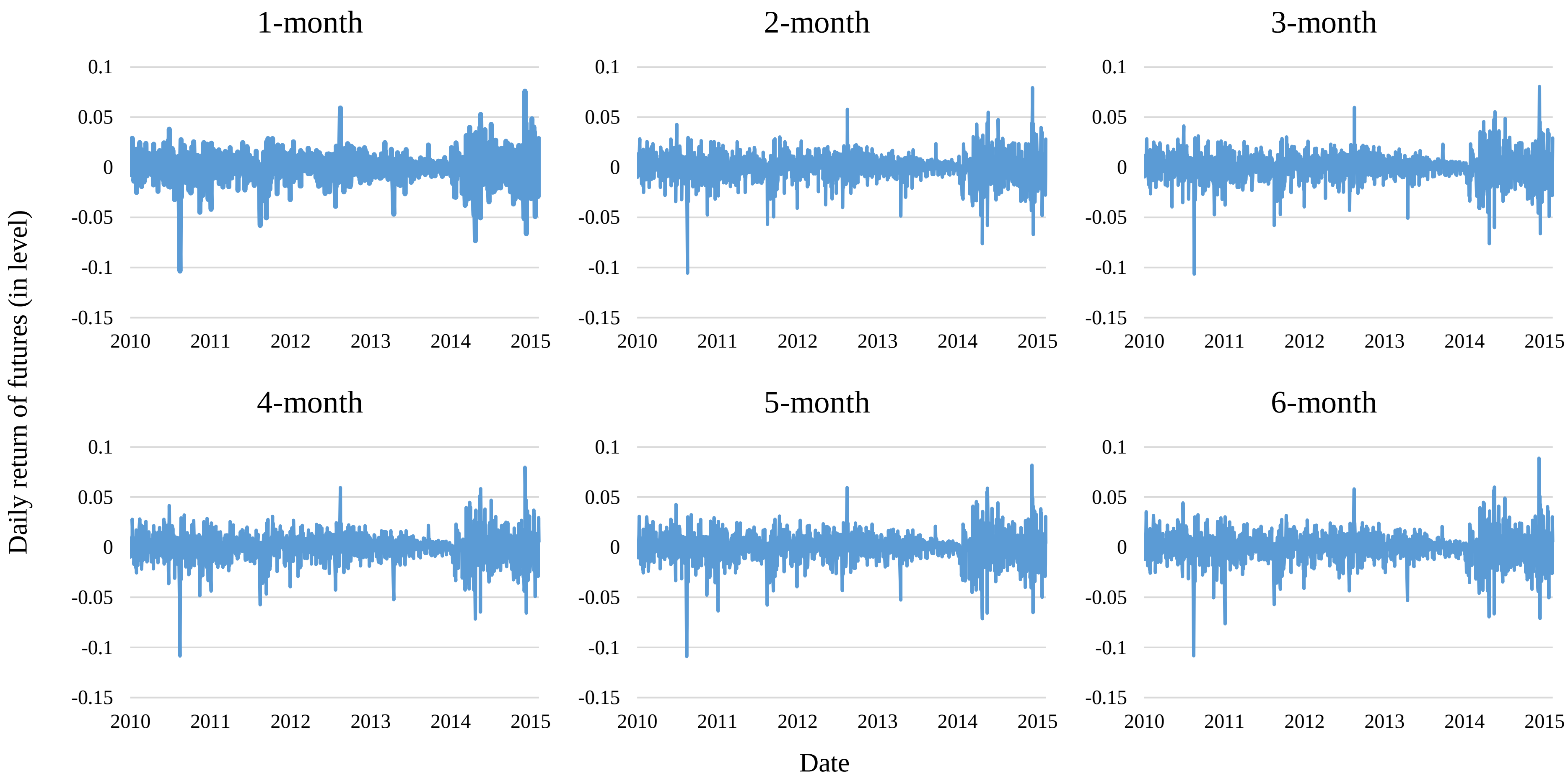


Figure 4-3: Daily log-return of crude oil futures

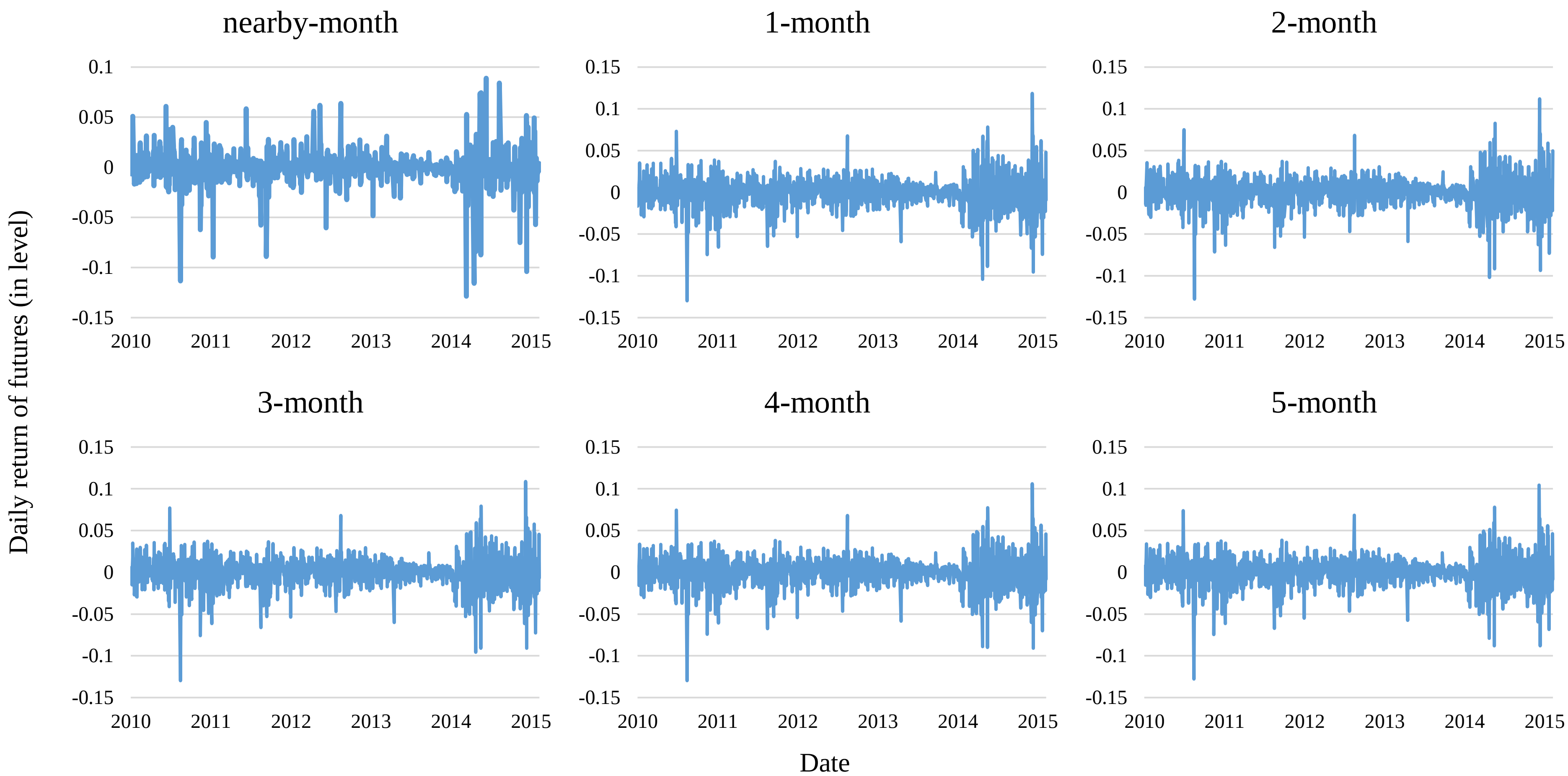


Figure 4-4: Daily realised volatility of gasoline futures

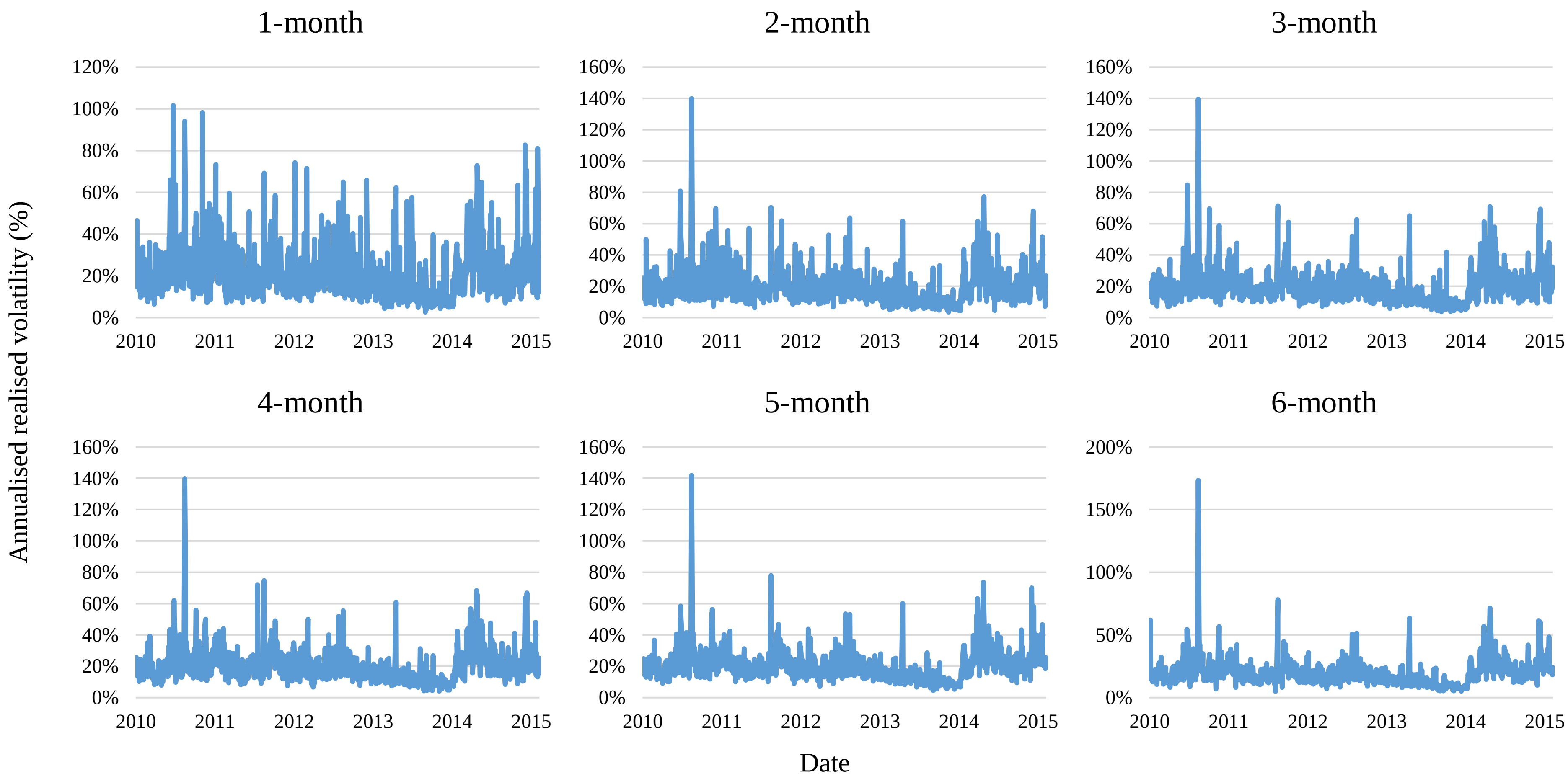


Figure 4-5: Daily realised volatility of kerosene futures

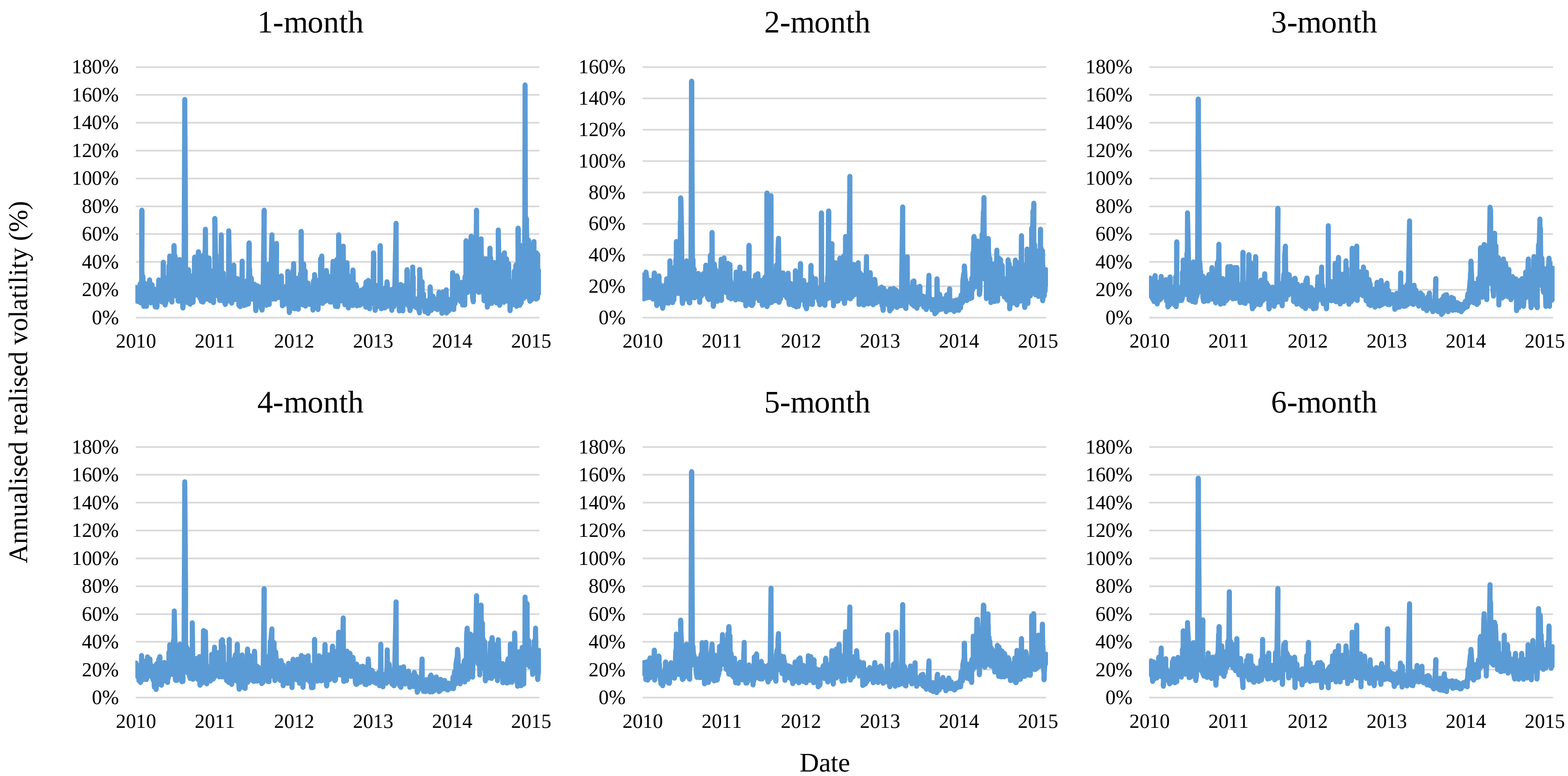
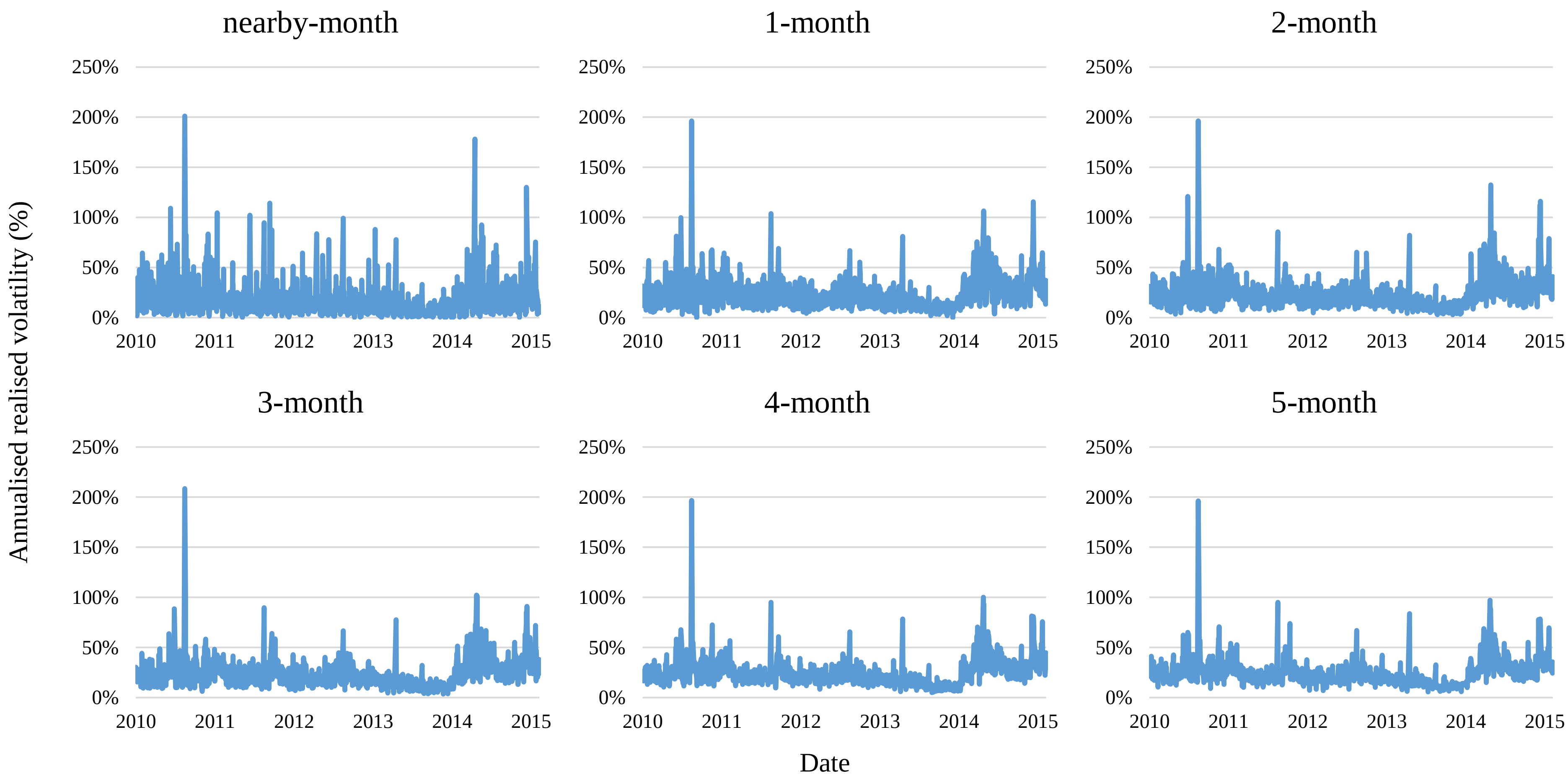


Figure 4-6: Daily realised volatility of crude oil futures



4.5 Empirical Results

The estimation results of the proposed realised volatility models in- and out-of-sample, as well as the relation between order-imbalance and RV over the sample period examined, are presented in the following subsections. The in-sample analysis is performed over the period from 22 September 2010 to 30 October 2015.

4.5.1 In-sample Analysis

The benchmark model, HAR-RV, is estimated by the Ordinary Least Square (OLS) method for three TOCOM energy futures across six different maturities. The left column of Table 4-2 to 4-4 exhibit that realised volatility is significantly affected by all one-day, one-week and one-month lagged observations. This indicates the existence of the long-memory property of realised volatility, and that the persistence of realised volatility can last for at least one month. For most futures, the impacts of one-day and one-month lagged realised volatility are greater than that of one-week when looking at the magnitude of coefficients. For example, for 5-month crude oil futures, the coefficients of one-day and one-month lagged realised volatility are 0.2608 and 0.1547, which are approximately double that of the one-week one, 0.1114. In addition, results show that days-to-rollover does not explain changes in realised volatility for gasoline and kerosene, since the coefficients are insignificant for most gasoline and kerosene futures. Two exceptions are 1-month gasoline and kerosene futures. The coefficients for these are negative and significant, which is consistent with the Samuelson Hypothesis. However, for crude oil futures, there is an effect of days-to-rollover on realised volatility, although it is opposite to the Samuelson Hypothesis. For the majority of crude oil contracts, the coefficients of days-to-rollover are positive and significant, which implies that when time approaches the rollover date (days-to-rollover decreases), the level of realised volatility reduces. This finding is in line with evidence from Chen et al. (1999) on Nikkei-225 index futures.

Moving onto the result of MRS-HAR-RV reported in the right column of Table 4-2 to 4-4, the different sizes and significances of coefficients confirm that the dynamics of the realised volatility of TOCOM energy futures switch between two

Table 4-2: Estimation results of simple HAR-RV and MRS-HAR-RV for gasoline futures

HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,1} + \beta_1^{(d)} RV_t^{(d)} + \beta_1^{(w)} RV_t^{(w)} + \beta_1^{(m)} RV_t^{(m)} + \beta_1^{(DTR)} DTR_t + \beta_1^{(D1)} D1_t + \beta_1^{(D2)} D2_t + \varepsilon_{t+1d,1}^{(d)}, \quad \varepsilon_{t+1d,1}^{(d)} \sim N(0, \Sigma_1)$											
MRS-HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,st} + \beta_{st}^{(d)} RV_t^{(d)} + \beta_{st}^{(w)} RV_t^{(w)} + \beta_{st}^{(m)} RV_t^{(m)} + \beta_{st}^{(DTR)} DTR_t + \beta_{st}^{(D1)} D1_t + \beta_{st}^{(D2)} D2_t + \varepsilon_{t+1d,st}^{(d)}, \quad st = \{1,2\}, \varepsilon_{t+1d,st}^{(d)} \sim N(0, \Sigma_{st})$											
	1-month		2-month		3-month		4-month		5-month		6-month	
	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR
$\beta_{0,1}$	0.0001***	5.41E-5***	4.28E-5**	0.0002***	5.21E-5***	0.0003***	5.04E-5***	0.0003***	5.74E-5***	0.0003***	7.84E-5***	0.0003***
	(2.56E-5)	(1.59E-5)	(1.67E-5)	(7.23E-5)	(1.51E-5)	(7.20E-5)	(1.33E-5)	(1.78E-5)	(1.09E-5)	(1.68E-5)	(1.03E-5)	(1.33E-5)
$\beta_1^{(d)}$	0.1687***	0.0826**	0.2783***	0.2800***	0.3125***	0.3246**	0.2726***	0.2075***	0.2938***	0.2115***	0.1286***	0.0864***
	(0.0295)	(0.0334)	(0.0199)	(0.0356)	(0.0188)	(0.1590)	(0.0169)	(0.0223)	(0.0142)	(0.0196)	(0.0104)	(0.0135)
$\beta_1^{(w)}$	0.2157***	0.0852	0.1196***	-0.0549	0.1184***	-0.0374	0.1192***	-0.0460	0.1338***	0.0262	0.1515***	0.0623*
	(0.0509)	(0.0597)	(0.0315)	(0.0583)	(0.0292)	(0.0679)	(0.0275)	(0.0824)	(0.0227)	(0.0363)	(0.0183)	(0.0347)
$\beta_1^{(m)}$	0.2465***	0.2298*	0.1765***	0.0758	0.1428***	-0.0601	0.1851***	-0.0549	0.1743***	-0.0755	0.1643***	-0.1307***
	(0.0764)	(0.1193)	(0.0502)	(0.1705)	(0.0459)	(0.1271)	(0.0433)	(0.0407)	(0.0346)	(0.0734)	(0.0303)	(0.0355)
$\beta_1^{(DTR)}$	-2.2612**	21.0914***	1.5037**	7.8172***	0.7392	0.8735	0.8328	1.5072	0.1136	-0.5228	-0.0914	-2.1827
	(1.1052)	(1.5830)	(0.7488)	(2.8736)	(0.6845)	(3.9618)	(0.5877)	(1.2814)	(0.4882)	(0.9360)	(0.4815)	(1.4709)
$\beta_{0,2}$		-4.07E-6***		4.81E-5***		3.51E-5***		3.42E-5***		3.00E-5***		2.24E-5***
		(3.69E-7)		(5.23E-6)		(1.46E-6)		(2.20E-6)		(1.67E-6)		(1.43E-7)
$\beta_2^{(d)}$		0.0005		0.0334***		0.2269***		0.1725***		0.2732***		0.3108***
		(0.0024)		(0.0123)		(0.0038)		(0.0115)		(0.0100)		(0.0084)
$\beta_2^{(w)}$		0.0176***		0.1610***		0.1451***		0.1434***		0.1896***		0.1145***
		(0.0034)		(0.0155)		(0.0276)		(0.0112)		(0.0084)		(0.0234)
$\beta_2^{(m)}$		0.0265***		0.1269***		0.1156***		0.1476***		0.1137***		0.2163***
		(0.0062)		(0.0142)		(0.0225)		(0.0059)		(0.0075)		(0.0171)
$\beta_2^{(DTR)}$		2.7709***		0.2167		0.2296		0.4337***		0.0502		0.0743
		(0.2395)		(0.2208)		(0.2412)		(0.1666)		(0.0921)		(0.1212)
Σ_i	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2
	0.0008***	3.88E-5***	0.0004***	5.80E-5***	0.0004***	5.61E-5***	0.0003***	5.24E-5***	0.0002***	4.28E-5***	0.0002***	4.29E-5***
p_{ij}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}
	0.5964	0.1911	0.4728	0.1058	0.4464	0.0928	0.4329	0.1005	0.3778	0.1086	0.3564	0.0889
$\bar{R}^2$	19.07%	45.84%	63.80%	76.46%	68.04%	78.93%	73.61%	81.56%	81.22%	84.38%	89.21%	91.43%
SBIC	6544.279	7221.092	6911.427	7506.899	6997.52	7587.82	7145.681	7648.697	7322.469	7772.782	7321.122	7833.976
Q(22)	24.659	32.920*	59.729***	71.427***	79.276***	34.307**	49.683***	33.247*	127.912***	64.849***	290.452***	70.794***
LR	1486.19***		1255.79***		1273.49***		1114.72***		1022.87***		1115.05***	

- Sample period used for estimation is from 21 September 2010 to 22 October 2014. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 4-3: Estimation results of simple HAR-RV and MRS-HAR-RV for kerosene futures

HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,1} + \beta_1^{(d)} RV_t^{(d)} + \beta_1^{(w)} RV_t^{(w)} + \beta_1^{(m)} RV_t^{(m)} + \beta_1^{(DTR)} DTR_t + \beta_1^{(D1)} D1_t + \beta_1^{(D2)} D2_t + \varepsilon_{t+1d,1}^{(d)}, \quad \varepsilon_{t+1d,1}^{(d)} \sim N(0, \Sigma_1)$
MRS-HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,st} + \beta_{st}^{(d)} RV_t^{(d)} + \beta_{st}^{(w)} RV_t^{(w)} + \beta_{st}^{(m)} RV_t^{(m)} + \beta_{st}^{(DTR)} DTR_t + \beta_{st}^{(D1)} D1_t + \beta_{st}^{(D2)} D2_t + \varepsilon_{t+1d,st}^{(d)}, \quad st = \{1,2\}, \varepsilon_{t+1d,st}^{(d)} \sim N(0, \Sigma_{st})$

	1-month		2-month		3-month		4-month		5-month		6-month	
	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR-
$\beta_{0,1}$	0.0001***	0.0005***	6.68E-5***	0.0004***	6.04E-5***	0.0003***	5.97E-5***	0.0003***	6.65E-5***	0.0003***	6.15E-5***	0.0003***
	(1.69E-5)	(2.18E-5)	(1.77E-5)	(3.33E-5)	(1.36E-5)	(4.37E-5)	(1.18E-5)	(1.73E-5)	(1.15E-5)	(2.28E-5)	(1.21E-5)	(9.38E-5)
$\beta_1^{(d)}$	0.1606***	0.1156**	0.2374***	0.0626	0.3028***	0.3158***	0.2411***	0.0118	0.1980***	-0.0491	0.2384***	0.1963***
	(0.0172)	(0.0455)	(0.0191)	(0.0964)	(0.0148)	(0.0241)	(0.0135)	(0.0323)	(0.0123)	(0.0496)	(0.0135)	(0.0267)
$\beta_1^{(w)}$	0.1188***	0.0812	0.0921***	0.0770	0.0666***	-0.1401**	0.0800***	0.0642	0.0982***	0.0019	0.1336***	0.0561*
	(0.0302)	(0.0769)	(0.0315)	(0.0582)	(0.0240)	(0.0702)	(0.0225)	(0.0584)	(0.0211)	(0.0744)	(0.0224)	(0.0286)
$\beta_1^{(m)}$	0.2199***	-0.1545*	0.1275**	-0.0486	0.1122***	-0.2330***	0.1558***	0.0428	0.1837***	0.4151***	0.1763***	-0.0880*
	(0.0503)	(0.0830)	(0.0540)	(0.2401)	(0.0405)	(0.0214)	(0.0377)	(0.0805)	6.65E-5***	(0.0994)	(0.0352)	(0.0518)
$\beta_1^{(DTR)}$	-3.2435***	-6.1435***	0.5564	0.7506	0.7478	3.3479***	0.7814	-0.3068	0.5476	1.7790	0.3686	0.9196
	(0.7467)	(1.3820)	(0.8152)	(4.6440)	(0.6300)	(0.3063)	(0.5361)	(0.9237)	(0.5201)	(1.1954)	(0.5527)	(5.0647)
$\beta_{0,2}$		5.83E-5***		4.54E-5***		2.84E-5***		3.62E-5***		3.93E-5***		3.21E-5***
		(2.20E-6)		(3.31E-6)		(5.13E-6)		(1.51E-6)		(1.87E-6)		(2.67E-6)
$\beta_2^{(d)}$		0.0289***		0.2368***		0.0428***		0.2572***		0.2017***		0.1947***
		(0.0077)		(0.0052)		(0.0095)		(0.0080)		(0.0078)		(0.0383)
$\beta_2^{(w)}$		0.0904***		0.0143		0.1460***		0.0789***		0.1219***		0.1213***
		(0.0069)		(0.0140)		(0.0062)		(0.0091)		(0.0082)		(0.0090)
$\beta_2^{(m)}$		0.1580***		0.1079***		0.2600***		0.0782***		0.1184***		0.2536***
		(0.0094)		(0.0051)		(0.0262)		(0.0075)		(0.0064)		(0.0190)
$\beta_2^{(DTR)}$		-0.7074***		0.2713***		0.2644		0.2626***		0.6054***		-0.1407
		(0.1242)		(0.0340)		(0.1739)		(0.0977)		(0.0975)		(0.1217)
Σ_i	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2
	0.0003***	5.43E-5***	0.0005***	5.65E-5***	0.0003***	4.90E-5***	0.0002***	4.38E-5***	0.0003***	5.12E-5***	0.0003***	4.16E-5***
p_{ij}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}	p_{12}	p_{21}
	0.4206	0.1435	0.5254	0.0856	0.4546	0.1155	0.4826	0.1460	0.3781	0.0749	0.3201	0.0943
$\bar{R}^2$	70.09%	80.34%	65.41%	74.01%	79.06%	86.89%	82.45%	89.52%	85.21%	88.27%	82.68%	85.33%
SBIC	6891.60	7385.36	6825.26	7573.75	7074.29	7645.14	7230.00	7684.98	7255.82	7747.40	7199.88	7762.27
Q(22)	46.254***	21.140	47.950***	36.457**	36.697**	30.394	42.948***	18.556	97.377***	31.773*	43.258***	11.127
LR	1125.23***		1639.56***		1240.42***		1048.55***		1092.75***		1247.28***	

- Sample period used for estimation is from 21 September 2010 to 22 October 2014. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 4-4: Estimation results of simple HAR-RV and MRS-HAR-RV for crude oil futures

HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,1} + \beta_1^{(d)} RV_t^{(d)} + \beta_1^{(w)} RV_t^{(w)} + \beta_1^{(m)} RV_t^{(m)} + \beta_1^{(DTR)} DTR_t + \beta_1^{(D1)} D1_t + \beta_1^{(D2)} D2_t + \varepsilon_{t+1d,1}^{(d)}, \quad \varepsilon_{t+1d,1}^{(d)} \sim N(0, \Sigma_1)$
MRS-HAR-RV	$RV_{t+1d}^{(d)} = \beta_{0,st} + \beta_{st}^{(d)} RV_t^{(d)} + \beta_{st}^{(w)} RV_t^{(w)} + \beta_{st}^{(m)} RV_t^{(m)} + \beta_{st}^{(DTR)} DTR_t + \beta_{st}^{(D1)} D1_t + \beta_{st}^{(D2)} D2_t + \varepsilon_{t+1d,st}^{(d)}, \quad st = \{1,2\}, \varepsilon_{t+1d,st}^{(d)} \sim N(0, \Sigma_{st})$

	nearby-month		1-month		2-month		3-month		4-month		5-month	
	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR	HAR-RV	MRS-HAR
$\beta_{0,1}$	-0.0001***	5.41E-5***	7.21E-5***	0.0004***	7.21E-5***	0.0005***	7.21E-5***	0.0004***	6.26E-5***	0.0004***	6.94E-5***	0.0003***
	(3.39E-5)	(1.59E-5)	(2.25E-5)	(7.69E-5)	(2.18E-5)	(0.0002)	(1.71E-5)	(2.44E-5)	(1.51E-5)	(7.76E-5)	(1.59E-5)	(2.39E-5)
$\beta_1^{(d)}$	0.0724***	0.0826**	0.1433***	0.1282***	0.2032***	0.0708	0.2210***	0.2076***	0.2606***	0.1113**	0.2608***	0.2255***
	(0.0207)	(0.0334)	(0.0156)	(0.0112)	(0.0156)	(0.0959)	(0.0116)	(0.0365)	(0.0113)	(0.0455)	(0.0118)	(0.0125)
$\beta_1^{(w)}$	0.0885**	0.0852	0.1172***	0.1105**	0.0854***	-0.0168	0.0756***	0.0049	0.1129***	0.0641*	0.1114***	0.0528*
	(0.0373)	(0.0597)	(0.0273)	(0.0529)	(0.0264)	(0.0561)	(0.0197)	(0.0468)	(0.0184)	(0.0334)	(0.0194)	(0.0272)
$\beta_1^{(m)}$	0.1950***	0.2298*	0.1850***	0.0475	0.1776***	-0.0565	0.1465***	-0.1467**	0.1541***	-0.0790	0.1547***	-0.1007
	(0.0666)	(0.1193)	(0.0472)	(0.2689)	(0.0455)	(0.1066)	(0.0341)	(0.0697)	(0.0302)	(0.1539)	(0.0319)	(0.0707)
$\beta_1^{(DTR)}$	14.0343***	21.0914***	2.3447**	-0.4638	1.9100*	1.0779	2.1797***	3.9491***	1.9675***	1.8648	1.5408**	1.9333*
	(1.6612)	(1.5830)	(1.0208)	(4.6667)	(1.0082)	(3.6245)	(0.8014)	(1.2789)	(0.6978)	(1.2547)	(0.7347)	(0.9925)
$\beta_{0,2}$		-4.07E-6***		4.78E-5***		3.52E-5***		1.90E-5***		1.41E-5***		3.54E-5***
		(3.69E-7)		(7.96E-6)		(1.30E-5)		(2.61E-6)		(5.47E-6)		(2.08E-6)
$\beta_2^{(d)}$		0.0005		0.0246		0.2035***		0.0127		0.2656***		0.2240***
		(0.0024)		(0.0156)		(0.0066)		(0.0081)		(0.0009)		(0.0095)
$\beta_2^{(w)}$		0.0176***		0.0502***		0.0945***		0.0980***		0.2680***		0.0894***
		(0.0034)		(0.0106)		(0.0205)		(0.0046)		(0.0096)		(0.0073)
$\beta_2^{(m)}$		0.0265***		0.0804*		0.1020***		0.2992***		0.0947***		0.2733***
		(0.0062)		(0.0481)		(0.0392)		(0.0089)		(0.0264)		(0.0079)
$\beta_2^{(DTR)}$		2.7709***		1.3677***		1.4789***		1.7384***		1.4438***		0.1631
		(0.2395)		(0.3796)		(0.4014)		(0.1394)		(0.2889)		(0.1092)
Σ_i	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2	Σ_1	Σ_2
	0.0008***	3.88E-5***	0.0004***	6.26E-5***	0.0005***	8.23E-5***	0.0003***	6.55E-5***	0.0003***	6.20E-5***	0.0004***	5.26E-5***
p_{ij}	p_{12}	p_{21}										
	0.5964	0.1911	0.4300	0.1832	0.4294	0.1003	0.3334	0.1111	0.2897	0.0849	0.2868	0.0923
$\bar{R}^2$	59.55%	71.17%	76.72%	83.81%	76.89%	81.29%	86.96%	91.39%	88.01%	90.04%	86.75%	89.21%
SBIC	6157.396	7386.73	6605.319	7119.792	6615.692	7178.596	6838.313	7324.865	6975.095	7446.656	6923.484	7503.817
Q(22)	34.730**	27.613	73.655***	74.793***	38.566**	21.880	89.609***	41.866***	98.562***	48.907***	88.463***	29.787***
LR	2502.36***		1162.83***		1221.59***		1038.27***		1046.34***		1267.85***	

- Sample period used for estimation is from 21 September 2010 to 22 October 2014. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

regimes. In general, the coefficients of one-day lagged realised volatility are significant in both regime 1 and 2, while the coefficients of one-week and one-month realised volatility are not always significant in regime 1. This implies that realised volatility is less persistent in regime 1 than in regime 2. Hence, we can infer that regime 1 is the high-volatility regime, whereas regime 2 is the low-volatility regime. Moreover, we can look at the conditional transition probability and unconditional regime probability to further identify the two regimes and their existence. First, based on the estimated conditional transition probability (p_{12} and p_{21}) in Table 4-2 to 4-4, the p_{12} (the probability of regime 1 transiting to 2) is generally higher than 0.35 but p_{21} (the probability of a low-volatility regime transiting to a high one) is only between 0.1 and 0.2. In other words, the switching of regime 1 to regime 2 occurs much more frequently than that of regime 2 to regime 1, which indicates that the persistence of regime 1 is weaker than that of regime 2. In addition, Table 4-5 shows that the number of days when the unconditional regime 1 probability is greater than 0.5 is much lower than that when the unconditional regime 2 probability is greater than 0.5, which matches the results of the condition transition probability. Based on the different levels of persistence in the regimes, we can conjecture that regime 1 is a high-volatility regime and regime 2 is a low-volatility regime. This is because the high-volatility regime results from large order imbalance between sell- and buy-initiated trades, which is a rare case in the market, so the persistence of a high-volatility regime is expected to be low. In order to further confirm the identity of regimes, we further compare the average level of realised volatility when unconditional regime 1 probability is greater than 0.5 ($p_{1,t} > 0.5$) with that when unconditional regime 2 probability is greater than 0.5 ($p_{1,t} \leq 0.5$). According to Table 4-5, the average realised volatility in regime 1 ($p_{1,t} > 0.5$) is about double that in regime 2 ($p_{1,t} \leq 0.5$), which is consistent with our previous conjecture. Therefore, based on the properties of regimes, we can now surely confirm the existence of high- and low-volatility regimes and identify regime 1 as a high-volatility regime and regime 2 as a low-volatility one.

Interestingly, the coefficients of days-to-rollover are very different in the magnitude between the two regimes, although their signs are mostly consistent with the results of a single regime. The magnitude of coefficients in high-volatility regimes is much higher than that in low-volatility regimes, which may be intuitively due to the level of volatility being much greater in high-volatility regimes. The results of 22nd order Q-statistic show that the residuals are highly autocorrelated for all contracts, even though some residuals of MRS-HAR-RV are not significantly autocorrelated. However, the standard errors reported in Table 4-2 to 4-4 are heteroscedasticity and autocorrelation consistent estimators, so the significance of autocorrelation has only limited impact on the interpretation of the results. Regarding the value of adjusted R-squared and SBIC, we can find that MRS-HAR-RV has a higher adjusted R-squared and better SBIC than HAR-RV does. Furthermore, the results of log-likelihood ratio tests confirm the significance of the difference in log-likelihood values between HAR-RV and MRS-HAR-RV. The in-sample results suggest that MRS-HAR-RV has a better ability to capture and explain the dynamic of realised volatility than HAR-RV for all three energy futures.

Table 4-5: The average level of volatility in high- and low-volatility regimes in in-sample

	Gasoline					
	1-month	2-month	3-month	4-month	5-month	6-month
$\overline{RV_1}$	40.84%	33.70%	35.60%	33.06%	30.56%	30.29%
$\overline{RV_2}$	17.72%	16.95%	17.15%	17.41%	18.07%	18.05%
N_1	157	193	142	168	182	145
N_2	824	788	839	813	799	836
	Kerosene					
	1-month	2-month	3-month	4-month	5-month	6-month
$\overline{RV_1}$	35.25%	37.42%	32.16%	31.19%	31.53%	31.26%
$\overline{RV_2}$	16.93%	16.78%	16.69%	17.21%	18.21%	18.25%
N_1	192	108	173	159	141	168
N_2	789	873	808	822	840	813
	Crude oil					
	nearby-m.	1-month	2-month	3-month	4-month	5-month
$\overline{RV_1}$	40.89%	37.51%	39.07%	36.82%	38.55%	35.05%
$\overline{RV_2}$	13.34%	18.68%	20.09%	19.86%	20.35%	21.46%
N_1	222	226	148	189	176	183
N_2	759	755	833	792	805	798

- Regime 1 (high-volatility regime) is defined as the regime with the estimated unconditional regime probability greater than 0.5, and regime 2 (low-volatility regime) is defined as the regime with the estimated unconditional regime probability less than or equal to 0.5. $\overline{RV_1}$ and $\overline{RV_2}$ are the average realised volatility of regime 1 and 2 (high- and low-volatility regimes), respectively. N_1 and N_2 are the numbers of observations in high- and low-volatility regimes, respectively.

4.5.2 Out-of-sample Forecasting and Evaluation

The following MRS-HAR-RV identifies and captures regime switching in the in-sample estimation. It is in our interest to see whether MRS-HAR-RV can also produce a better forecast than the alternative models, namely HAR-RV, GARCH and MRS-GARCH. The comparison between realised volatility model (MRS-HAR-RV and HAR-RV) and conditional volatility model (GARCH and MRS-GARCH) may rise the concern of overnight return, since realised volatility is estimated based on open-to-close data and the overnight return is missed. The difference in the variance during trading and non-trading hours has been found by French and Roll (1986), Lockwood and Linn (1990), Lockwood and McInish (1990), Masulis and Ng (1995), Gallo (2001), and among others. Their evidence shows that the volatility in trading hours is greater than in non-trading hours. Several approaches have been used to deal with the ignored overnight returns. The first approach calculates the overnight return as the difference between close and open price, and adds the squared overnight return to the sum of intraday squared returns (Blair et al., 2001; Fong and Martens 2002; Becker et al., 2007 and Bollerslev et al., 2009). The other solution is to scale up level of the realised volatility in order to cover the 24-hour period (Koopman et al., 2005). Finally, Hansen and Lunde (2005) propose an optimal weights for the overnight and the sum of intraday squared returns. However, there is also literature that simply ignores the overnight return, such as Andersen et al. (2001a), Thomakos and Wang (2003), Brownlees and Gallo (2009), Sevi (2014), and among others. This study does not consider the impact of overnight returns for two reasons. Firstly, the trading hours in TOCOM are 17.5 hours, while the trading hours in the stock exchanges, e.g. NYSE, are only 6.5 hours. Therefore, the non-trading time on TOCOM is relatively short, only 3.5 hours, which reduces the frequency of information arriving during non-trading time. Next, the trading session of TOCOM also covers the trading session of EU and US exchanges, so most information can still reflect on prices during the trading hours of TOCOM. As a result, the impact of overnight return may be not so significant, and comparing RV models with GARCH models is plausible.

As with most literature on volatility forecasting, we choose the Diebold-Mariano (DM) test developed by Diebold and Mariano (1995) to examine the forecast accuracy of MRS-HAR-RV and the alternatives in out-of-sample. This test requires a loss function that measures the difference between realised volatility and the forecast value. In terms of volatility forecast, Qlike loss function is utilised in most studies, and Patton (2011) proves Qlike loss function is robust even if realised volatility is an imperfect proxy for true volatility. The Qlike loss function is defined as

$$L(h_t, RV_t) = log(h_t) + \frac{RV_t}{h_t}, \tag{4.16}$$

where h_t is the forecasting value, and RV_t is the realised variance at time t. Before implementing the DM test, we need to calculate the difference in Qlike loss function between two models as

$$d_t = L_{MRS-HAR-RV}(h_t, RV_t) - L_{AL-RV}(h_t, RV_t), \tag{4.17}$$

where $L_{MRS-HAR-RV}(h_t, RV_t)$ is the Qlike loss function for the MRS-HAR-RV model, and $L_{AL-RV}(h_t, RV_t)$ is for the comparing alternative model. If d_t is negative, it indicates that MRS-HAR-RV has better forecasting ability than the alternative model, and vice versa. The DM statistic is then defined as:

$$DM\ statistic = \frac{\bar{d}}{\sqrt{Var(\bar{d})}}, \tag{4.18}$$

where $\bar{d}$ is the average of the difference in Qlike loss function, and $\sqrt{Var(\bar{d})}$ is the estimator of the corresponding standard deviation of $\bar{d}$. The DM statistic follows a standard normal distribution, so it is also convenient to implement this test. Furthermore, the hypothesis is

$$\mathrm{H}_0: \bar{d} = 0;\ \mathrm{H}_1: \bar{d} \neq 0. \tag{4.19}$$

Hence, if the result rejects the null hypothesis, it means MRS-HAR-RV has better predictive ability than the comparing alternative model, given that $\bar{d}$ is negative.

The results of difference in QLike loss function (percentage of MRS-HAR-RV lower than alternatives) and DM test are reported in Table 4-6. MRS-HAR-RV seems to generally have better performance than GARCH and MRS-GARCH, while the comparison with HAR-RV is mixed across three different energy futures and six different maturities. Let us begin with gasoline futures. MRS-HAR-RV produces

Table 4-6: Results of the Diebold-Mariano test for the comparison of QLike between MRS-HAR-RV and three alternative models

	HAR		GARCH		MRS-GARCH	
Panel A: Gasoline						
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	0.07%	0.7592	0.85%	0.1712	1.48%	**0.0571**
2-month	-0.11%	0.4035	1.22%	**0.0339**	0.26%	0.5583
3-month	-0.05%	0.7356	1.01%	**0.0354**	1.26%	0.1571
4-month	-0.02%	0.8319	1.19%	**0.0176**	0.61%	**0.0674**
5-month	0.21%	0.1027	1.19%	**0.0012**	0.85%	**0.0063**
6-month	0.64%	**0.0167**	1.26%	**0.0024**	0.44%	**0.0731**
Panel B: Kerosene						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	0.03%	0.9249	1.44%	0.1397	0.96%	0.1181
2-month	-0.19%	0.2937	0.66%	0.2822	-0.47%	0.1385
3-month	-0.06%	0.5960	1.24%	**0.0361**	0.40%	0.2906
4-month	-0.07%	0.6991	0.83%	0.1191	-0.05%	0.8914
5-month	-0.01%	0.9644	0.90%	**0.0319**	-0.15%	0.5288
6-month	0.07%	0.4504	1.13%	**0.0168**	0.19%	0.3725
Panel C: Crude oil						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
nearby-m.	8.74%	**0.0000**	6.44%	**0.0047**	8.97%	**0.0621**
1-month	-0.50%	0.0476	1.06%	0.2164	0.19%	0.7913
2-month	-0.62%	0.0987	0.36%	0.6820	-0.96%	0.1114
3-month	0.04%	0.8379	1.07%	**0.0826**	0.01%	0.9844
4-month	0.17%	0.2643	1.30%	**0.0018**	0.36%	0.2406
5-month	0.18%	0.1822	1.56%	**0.0007**	0.69%	**0.0330**

- The out-of-sample is from 23 October 2014 to 30 October 2015.
- Percentage change is the difference in QLike loss function, and positive value means MRS-HAR-RV outperforms the alternative model.

significantly superior forecasting for 6-month gasoline futures, but does not for other maturity contracts. Even though values of loss function of MRS-HAR-RV are higher than that of HAR-RV for 2- to 4-month gasoline futures, the difference is not significant. Regarding kerosene futures, MRS-HAR-RV only have lower value of loss function for 1- and 6-month kerosene futures, while differences for all maturities are not significant. Therefore, MRS-HAR-RV seems to have no better predictability for kerosene futures but also not outperformed by HAR-RV. Finally, the difference in loss function between MRS-HAR-RV and HAR-RV for nearby-month crude oil futures is positive and significant, whilst that is positive but insignificant for 3- to 5-month futures. In addition, the difference is negative for 1- and 2-month crude oil futures. In general, we find that MRS-HAR-RV can produce better but not significant forecasts for most longer maturity (highly liquid) contracts, yet is mostly outperformed by HAR-RV for contracts that expire in a shorter time in terms of predictability. The possible reason for this may be related to liquidity of contracts. For a lowly liquid contract, a small amount of order imbalance may have a higher opportunity to impact largely on volatility and trigger the switching of regimes because of a relatively low trading volume. As a result, it is more difficult to forecast the probability of changing in regimes, because new coming information tends to unexpectedly increase the order imbalance, and then increase the switching probability to a high-volatility regime. Therefore, the forecast of regime probability is more likely to be inaccurate, and leads to inaccurate forecasts for low liquidity contracts.

In order to further investigate the difference in the predictability of MRS-HAR-RV and three alternatives, two loss functions are employed, namely Mean Absolute Error (MAE) and Mixed Mean Error (MME), defined as follows

$$MAE = |RV_t - h_t|, \tag{4.20}$$

$$MME(O) = 1_{RV_t - h_t < 0}|RV_t - h_t| + 1_{RV_t - h_t > 0}\sqrt{|RV_t - h_t|}, \tag{4.21}$$

$$MME(U) = 1_{RV_t - h_t < 0}\sqrt{|RV_t - h_t|} + 1_{RV_t - h_t > 0}|RV_t - h_t|, \tag{4.22}$$

where $1_{RV_t - h_t < 0}$ is the indicator for under-predicted realised variance, and $1_{RV_t - h_t > 0}$ is the indicator for over-predicted realised variance. According to the specification, it is obvious that MAE is a symmetric loss function, while MME(O) more penalises over-prediction and MME(U) more penalises under-prediction. The results of these two loss functions are reported in Table 4-7 to 4-9. In general, the results of MAE are very similar to those of QLike, except for minor changes. For example, MRS-HAR-RV significantly outperforms HAR-RV for 1-month gasoline futures based on MAE comparison, but does not based on QLike comparison. Interestingly, the results of MME(O) and MME(U) are quite different, and inconsistent with those of QLike and MAE. The comparison of MME(O) and MME(U) between MRS-HAR-RV, GARCH and MRS-GARCH is distinct. MRS-HAR-RV outperforms the other two based on MME(O), but is outperformed by them based on MME(U). Turning to the comparison of MME(O) between MRS-HAR-RV and HAR-RV, MRS-HAR-RV has better performance than HAR-RV for most gasoline futures, except 6-month ones. However, if we compare MME(U), the results are completely opposite, although they lack significance. For kerosene futures, despite the fact that the differences are not as significant as we find for gasoline ones, they are mostly negative. For crude oil futures, the results are slightly different. MRS-HAR-RV seems to have better performance than HAR-RV for most crude oil futures, even though the differences are not always significant. Overall, it appears that HAR-RV, GARCH and MRS-GARCH tends to over-predict realised variance while MRS-HAR-RV tends to under-predict it. This may be related to the accuracy of forecasting regime switching probability. It seems that the probability of switching to a high-volatility regime tends to be underestimated. As mentioned in the discussion of QLike comparison, this may be the consequence of low liquidity, since for some higher liquid contracts, such as 6-month gasoline and 5-month crude oil futures, MRS-HAR-RV does not under-predict compared with HAR-RV. However, MRS-HAR-RV significantly under-predicts for most lowly liquid futures, such as 2-month gasoline, 1-month kerosene, and 1- and 2-month crude oil futures.

Table 4-7: Results of the Diebold-Mariano test for the comparison of MAE between MRS-HAR-RV and three alternative models

	HAR		GARCH		MRS-GARCH	
Panel A: Gasoline						
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	3.99%	**0.0500**	32.56%	**0.0014**	13.74%	**0.0726**
2-month	-1.44%	0.4384	48.47%	**0.0006**	20.90%	**0.0064**
3-month	-1.94%	0.2088	43.78%	**0.0003**	15.78%	**0.0056**
4-month	0.24%	0.9135	53.30%	**0.0002**	22.40%	**0.0009**
5-month	4.72%	**0.0180**	57.55%	**0.0002**	31.73%	**0.0005**
6-month	7.00%	**0.0452**	67.77%	**0.0006**	27.70%	**0.0040**
Panel B: Kerosene						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	-2.65%	0.4853	20.29%	**0.0058**	1.83%	0.5896
2-month	-1.38%	0.3147	44.59%	**0.0009**	-0.02%	0.9961
3-month	-1.66%	0.2652	53.06%	**0.0001**	10.04%	**0.0512**
4-month	-0.55%	0.7011	54.10%	**0.0003**	28.40%	0.2176
5-month	-3.84%	0.1697	57.17%	**0.0002**	4.42%	0.4463
6-month	-0.63%	0.6991	69.05%	**0.0006**	11.34%	**0.0988**
Panel C: Crude oil						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
nearby-m.	-3.59%	**0.0927**	19.53%	**0.0003**	2.24%	0.6408
1-month	-1.52%	0.4078	66.93%	**0.0001**	33.71%	**0.0044**
2-month	-3.52%	0.1592	46.18%	**0.0028**	12.69%	0.1781
3-month	1.00%	0.5529	60.63%	**0.0005**	27.99%	**0.0483**
4-month	1.08%	0.6578	74.49%	**0.0002**	38.86%	**0.0079**
5-month	2.77%	0.1929	88.06%	**0.0001**	40.58%	**0.0049**

- The out-of-sample is from 23 October 2014 to 30 October 2015.
- Percentage change is the difference in MAE loss function, and positive value means MRS-HAR-RV outperforms the alternative model.

Table 4-8: Results of the Diebold-Mariano test for the comparison of MME(O) between MRS-HAR-RV and three alternative models

	HAR		GARCH		MRS-GARCH	
Panel A: Gasoline						
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	6.85%	**0.0796**	47.83%	**0.0003**	10.28%	0.3453
2-month	6.45%	**0.0398**	90.90%	**0.0000**	51.79%	**0.0001**
3-month	1.33%	0.6412	92.06%	**0.0000**	34.41%	**0.0000**
4-month	5.77%	**0.0833**	97.65%	**0.0000**	49.27%	**0.0000**
5-month	11.28%	**0.0395**	109.26%	**0.0000**	52.02%	**0.0008**
6-month	-0.02%	0.9968	140.35%	**0.0000**	65.71%	**0.0000**
Panel B: Kerosene						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	4.63%	0.2372	66.31%	**0.0000**	-0.88%	0.9170
2-month	-0.26%	0.9440	112.78%	**0.0000**	13.88%	0.1536
3-month	-2.34%	0.4794	113.02%	**0.0000**	26.74%	**0.0021**
4-month	4.74%	0.1263	137.37%	**0.0000**	37.28%	**0.0023**
5-month	-11.08%	**0.0105**	119.02%	**0.0000**	17.35%	**0.0903**
6-month	5.68%	0.2424	162.08%	**0.0000**	39.26%	**0.0079**
Panel C: Crude oil						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
nearby-m.	-55.34%	**0.0000**	36.61%	**0.0000**	9.78%	0.2135
1-month	7.31%	**0.0982**	143.32%	**0.0000**	89.76%	**0.0000**
2-month	7.26%	0.1815	117.54%	**0.0000**	53.24%	**0.0006**
3-month	3.04%	0.5043	137.18%	**0.0000**	85.72%	**0.0000**
4-month	-6.05%	0.1311	137.86%	**0.0000**	74.68%	**0.0005**
5-month	3.47%	0.5500	172.22%	**0.0000**	91.81%	**0.0001**

- The out-of-sample is from 23 October 2014 to 30 October 2015.
- Percentage change is the difference in MME(O) loss function, and positive value means MRS-HAR-RV outperforms the alternative model.

Table 4-9: Results of the Diebold-Mariano test for the comparison of MME(U) between MRS-HAR-RV and three alternative models

Panel A: Gasoline						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	-1.02%	0.6095	-12.52%	**0.0233**	2.98%	0.6537
2-month	-7.76%	**0.0052**	-28.17%	**0.0000**	-18.41%	**0.0004**
3-month	-3.70%	0.1517	-33.37%	**0.0000**	-13.27%	**0.0303**
4-month	-2.11%	0.4318	-26.92%	**0.0000**	-12.72%	**0.0483**
5-month	-0.62%	0.8515	-24.73%	**0.0002**	-4.59%	0.4855
6-month	6.79%	0.1355	-32.98%	**0.0000**	-14.65%	**0.0058**
Panel B: Kerosene						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
1-month	-5.33%	0.0068	-30.94%	**0.0000**	1.52%	0.7809
2-month	-1.35%	0.6202	-37.91%	**0.0000**	-9.06%	**0.0706**
3-month	-1.14%	0.5975	-37.94%	**0.0000**	-10.66%	**0.0110**
4-month	-3.74%	**0.0955**	-43.21%	**0.0000**	-13.19%	**0.0045**
5-month	4.77%	0.1827	-42.56%	**0.0000**	-8.04%	0.2192
6-month	-5.04%	0.1040	-41.43%	**0.0000**	-10.71%	**0.0458**
Panel C: Crude oil						
	HAR		GARCH		MRS-GARCH	
	Change (%)	p-value	Change (%)	p-value	Change (%)	p-value
nearby-m.	33.59%	**0.0000**	-5.44%	0.2399	-6.10%	0.2991
1-month	-5.76%	**0.0067**	-40.39%	**0.0000**	-30.33%	**0.0000**
2-month	-7.71%	**0.0094**	-36.46%	**0.0000**	-23.44%	**0.0000**
3-month	0.45%	0.8459	-38.09%	**0.0000**	-31.97%	**0.0000**
4-month	5.74%	**0.0993**	-29.01%	**0.0000**	-15.43%	**0.0063**
5-month	0.69%	0.8361	-32.71%	**0.0000**	-20.03%	**0.0035**

- The out-of-sample is from 23 October 2014 to 30 October 2015.
- Percentage change is the difference in MME(U) loss function, and positive value means MRS-HAR-RV outperforms the alternative model.

4.5.3 Application: Value at Risk (VaR) Estimation

Forecasts of realised volatility can provide insights for market participants seeking to understand future market conditions, as well as can be used to quantify market risk and make trading decisions. One of the most popular approaches to quantifying market risk is VaR, which is the maximum loss for a portfolio given confidence level $(1 - u)$ over a fixed time horizon (k). Therefore, VaR can be defined as

$$\Pr\left(r_{t+1} < VaR_{u,t+1} \middle| \Omega_t\right) = u, \tag{4.23}$$

where Ω_t is the information given at time t. A direct approach to calculating VaR is Historical Simulation (HS) that directly estimates VaR by the percentile of historical returns. An alternative estimation of VaR is the product of the u-percentile of assumed distribution of returns and the forecasting volatility (standard deviation), and can be shown as below

$$VaR_{u,t+1} = F^{-1}(u)h_{t+1}, \tag{4.24}$$

where $F^{-1}(u)$ is the corresponding u-percentile (e.g. 0.5%, 1%, 5%) of assumed distribution, and h_{t+1} is the predicted volatility (squared root of variance) produced by one of the proposed models (e.g. HAR-RV, MRS-HAR-RV, GARCH and MRS-GARCH).

In our study, we calculate VaR at 99% confidence level (u=1%) since it has been employed in most literature, and four approaches are utilised, namely HS, GARCH, HAR-RV and MRS-HAR-RV. HS is estimated by a sample period of 250 days (1 year) of observations, since the percentile tends to be smoothed and VaR may be underestimated if the sample period is too long. GARCH approaches are based on the forecasts from GARCH (1,1), and the standard normal percentile is used for the estimation of $F^{-1}(u)$ due to the normality assumption of the GARCH model. Both HAR-RV and MRS-HAR-RV approaches employ the forecasts produced in out-of-sample analysis. However, instead of using standard normal percentile, we use Filtered Historical Simulation (FHS) to estimate the corresponding percentile because the realised volatility does not match normality assumption and the distribution of returns is non-normal (see Table 3-6). FHS is similar to historical simulation, but the percentile is calculated based on filtered historical returns. There are two steps to perform FHS, namely creating the filtered historical returns and calculating the percentile. The first step of FHS is to generate the filtered historical returns by dividing returns by historical standard deviation. Then, the percentile of the filtered historical returns is calculated and employed to calculate VaR for the HAR-RV and MRS-HAR-RV approaches.

In order to evaluate the accuracy of VaR, a backtesting test must be implemented. According to Christoffersen (2012), VaR models passing both unconditional coverage (UC) and conditional coverage (CC) log-likelihood ratio (LR) tests are considered to be adequate for risk management. The first step of both tests is to calculate the percentage proportion of failure (PF), which is the proportion of actual returns that exceed the estimated VaR or so-called hit. Therefore, an indicator function is defined as follows

$$\mathrm{I}_{t+1} = \begin{cases} 1, if\ r_{t+1} < VaR_{u,t+1}|\Omega_t \\ 0, if\ r_{t+1} \geq VaR_{u,t+1}|\Omega_t \end{cases}, \tag{4.25}$$

where I_{t+1} is the indicator function for violation of VaR. The sum of the indicator function over the out-of-sample is counted as total hit numbers, and the proportion of hit numbers to total number of out-of-sample represents PF. The VaR estimate is considered to be efficient if the following condition is satisfied

$$E[\mathrm{I}_{t+1}|\Omega_t] = u, \tag{4.26}$$

that is, on average, (1-PF) is equal to the nominal confidence level. The unconditional coverage (UC) test developed by Kupiec (1995), and the independence (IND), and conditional coverage tests (CC) proposed by Christoffersen (2012) are designed to examine whether PF is indifferent to the tolerance level p. We first denote π as PF calculated as

$$\pi = \frac{N_1}{N_0 + N_1}, \tag{4.27}$$

where N_0 is the total number of indicator being *0* (no violation of VaR), and N_1 is the total number of indicator being *1* (violation of VaR). Then, the null hypothesis for the unconditional coverage test can be expressed as

$$H_0: \pi = u, \tag{4.28}$$

and the LR statistic for the UC test ($LR_{(UC)}$) can be defined as

$$LR_{(UC)} = 2\{\ln[(1-\pi)^{N_0}\pi^{N_1}] - \ln[(1-u)^{N_0}u^{N_1}]\} \sim \chi_{1-\alpha,1}, \tag{4.29}$$

where $LR_{(UC)}$ follows a chi-square distribution with degree of freedom 1 under given significant level α. If $LR_{(UC)} > \chi_{\alpha,1}$, H_0 is rejected, this implies that the VaR estimate is not efficient. However, an unconditional coverage test only examines whether the total PF exceeds nominal tolerance level on average, but does not consider the cluster of violation (consecutive violation). An independent test is designed to examine the dependence of consecutive violation, and the LR statistic for independent test $LR_{(IND)}$ can be expressed as

$$LR_{(IND)} = 2\{\ln[(1-\pi_{01})^{N_{00}}\pi_{01}{}^{N_{01}}(1-\pi_{11})^{N_{10}}\pi_{11}{}^{N_{11}}] - \ln[(1-u)^{N_0}u^{N_1}]\} \sim \chi_{1-\alpha,1}, \tag{4.30}$$

$$\pi_{01} = \frac{N_{01}}{N_{00}+N_{01}} = \frac{N_{01}}{N_0}, \pi_{11} = \frac{N_{11}}{N_{10}+N_{11}} = \frac{N_{11}}{N_1}$$

where N_{ij} for *i,j = 0,1* is the number of indicator being *i* followed by indictor being *j*, andπ_{ij} is the corresponding probability. If *i = j = 1*, it indicates the occurrence of consecutive violation. $LR_{(IND)}$ also follows a chi-square distribution with degree of freedom 1 under given significant level α. Finally, the LR statistic for conditional coverage test $LR_{(CC)}$ is defined as the sum of $LR_{(UC)}$ and $LR_{(IND)}$, shown as

$$LR_{(CC)} = LR_{(UC)} + LR_{(IND)} \sim \chi_{1-\alpha,2}. \tag{4.31}$$

Similarly, $LR_{(CC)}$ follows a chi-square distribution but with degree of freedom 2 under given significant level α.

The VaR estimates and backtesting tests are reported in Figure 4-7 to 4-12 and Table 4-10 to 4-13. According to the figures, it seems that the VaR from the HS approach is smoother and underestimated compared with the other four approaches. Regarding the GARCH and MRS-GARCH approaches, the VaR estimates sometimes appear to be overestimated when comparing their distance from actual return. The VaR estimates from HAR-RV and MRS-HAR-RV are in between those from HS and GARCH, and are relatively close to each other.

Table 4-10: Value at Risk (VaR) for gasoline

	1-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
MRS-HAR	1.20%	0.0949	0.0973	0.1923	0.40%	1.1765	0.0161	1.1926
GARCH	4.80%	**19.0162**	**6.2668**	**25.2830**	1.60%	0.7691	0.1629	0.9320
MRS-G.	5.20%	**22.3170**	2.0889	**24.4059**	2.00%	1.9568	0.2453	2.2021
HS	4.80%	**19.0162**	**6.2668**	**25.2830**	2.00%	1.9568	0.2453	2.2021
	2-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	1.20%	0.0949	0.0973	0.1923	0.40%	1.1765	0.0161	1.1926
MRS-HAR	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
GARCH	4.00%	12.9555	8.5340	21.4895	0.40%	1.1765	0.0161	1.1926
MRS-G.	3.60%	10.2290	4.6934	14.9225	1.60%	0.7691	0.1629	0.9320
HS	4.40%	15.8906	7.3228	23.2134	2.40%	3.5554	2.4718	6.0271
	3-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	1.20%	0.0949	0.0973	0.1923	0.40%	1.1765	0.0161	1.1926
MRS-HAR	1.20%	0.0949	0.0973	0.1923	0.40%	1.1765	0.0161	1.1926
GARCH	4.40%	**15.8906**	**7.3228**	**23.2134**	0.40%	1.1765	0.0161	1.1926
MRS-G.	5.20%	**22.3170**	0.2567	**22.5737**	1.60%	0.7691	0.1629	0.9320
HS	4.40%	**15.8906**	**7.3228**	**23.2134**	2.00%	1.9568	**3.1944**	**5.1512**
	4-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	0.80%	0.1084	0.0485	0.1569	0.40%	1.1765	0.0161	1.1926
MRS-HAR	0.80%	0.1084	0.0485	0.1569	0.80%	0.1084	0.0485	0.1569
GARCH	3.60%	**10.2290**	**9.9356**	**20.1647**	0.80%	0.1084	0.0485	0.1569
MRS-G.	5.20%	**22.3170**	**5.3407**	**27.6577**	0.80%	0.1084	0.0485	0.1569
HS	3.60%	**10.2290**	1.0797	**11.3087**	1.60%	0.7691	**4.1393**	**4.9084**
	5-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	0.00%	N/A	N/A	N/A	0.40%	1.1765	0.0161	1.1926
MRS-HAR	0.00%	N/A	N/A	N/A	0.40%	1.1765	0.0161	1.1926
GARCH	3.60%	**10.2290**	**9.9356**	**20.1647**	0.80%	0.1084	0.0485	0.1569
MRS-G.	4.40%	**15.8906**	0.5575	**16.4481**	1.60%	0.7691	0.1629	0.9320
HS	3.20%	**7.7336**	0.5963	**8.3298**	1.60%	0.7691	**4.1393**	**4.9084**
	6-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	LR
HAR-RV	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
MRS-HAR	0.80%	0.1084	0.0485	0.1569	0.80%	0.1084	0.0485	0.1569
GARCH	3.60%	**10.2290**	**9.9356**	**20.1647**	0.80%	0.1084	0.0485	0.1569
MRS-G.	3.20%	**7.7336**	1.4460	**9.1795**	0.40%	1.1765	0.0161	1.1926
HS	3.20%	**7.7336**	0.5963	**8.3298**	2.40%	**3.5554**	2.4718	**6.0271**

- MRS-HAR denotes MRS-HAR-RV, and MRS-G. denotes MRS-GARCH. VaR is calculated based on 250 observations in out-of-sample from 23 October 2014 to 30 October 2015. PF is the probability of failures (violations). The LR statistic in bold denotes rejection of each test. The critical value for the unconditional coverage and independent test ($LR_{(UC)}$ and $LR_{(UC)}$) is 2.7055, and that for the conditional coverage likelihood ratio test $LR_{(CC)}$ is 4.6052.

Table 4-11: Value at Risk (VaR) for kerosene

	1-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
MRS-HAR	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
GARCH	2.00%	1.9568	**3.1944**	**5.1512**	0.40%	1.1765	0.0161	1.1926
MRS-G.	1.20%	0.0949	0.0973	0.1923	1.20%	0.0949	0.0973	0.1923
HS	3.60%	**10.2290**	**9.9356**	**20.1647**	1.60%	0.7691	0.1629	0.9320
	2-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	3.20%	**7.7336**	1.4460	**9.1795**	0.80%	0.1084	0.0485	0.1569
MRS-HAR	2.80%	**5.4970**	0.4618	**5.9588**	0.80%	0.1084	0.0485	0.1569
GARCH	1.20%	0.0949	**5.4494**	**5.5443**	0.40%	1.1765	0.0161	1.1926
MRS-G.	1.20%	0.0949	0.0973	0.1923	0.80%	0.1084	0.0485	0.1569
HS	2.80%	**5.4970**	**6.7930**	**12.2900**	2.40%	**3.5554**	2.4718	**6.0271**
	3-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.80%	**5.4970**	**6.7930**	**12.2900**	0.80%	0.1084	0.0485	0.1569
MRS-HAR	1.60%	0.7691	0.1629	0.9320	0.80%	0.1084	0.0485	0.1569
GARCH	1.60%	0.7691	**12.2557**	**13.0248**	0.40%	1.1765	0.0161	1.1926
MRS-G.	3.20%	**7.7336**	0.5963	**8.3298**	1.20%	0.0949	0.0973	0.1923
HS	4.00%	**12.9555**	**8.5340**	**21.4895**	2.40%	**3.5554**	2.4718	**6.0271**
	4-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	3.20%	**7.7336**	**5.6503**	**13.3838**	0.80%	0.1084	0.0485	0.1569
MRS-HAR	2.40%	**3.5554**	0.3449	3.9003	1.20%	0.0949	0.0973	0.1923
GARCH	1.20%	0.0949	**15.6753**	**15.7702**	0.40%	1.1765	0.0161	1.1926
MRS-G.	2.00%	1.9568	0.2453	2.2021	1.20%	0.0949	0.0973	0.1923
HS	4.40%	**15.8906**	**7.3228**	**23.2134**	2.80%	**5.4970**	1.9020	**7.3990**
	5-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.40%	**3.5554**	2.4718	**6.0271**	0.80%	0.1084	0.0485	0.1569
MRS-HAR	2.40%	**3.5554**	0.3449	3.9003	0.80%	0.1084	0.0485	0.1569
GARCH	0.80%	0.1084	**7.5099**	**7.6183**	0.40%	1.1765	0.0161	1.1926
MRS-G.	1.20%	0.0949	0.0973	0.1923	1.20%	0.0949	0.0973	0.1923
HS	4.40%	**15.8906**	**3.1898**	**19.0805**	3.60%	**10.2290**	1.0797	**11.3087**
	6-month							
	VaR for long position				VaR for short position			
	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.40%	**3.5554**	0.3449	3.9003	1.20%	0.0949	0.0973	0.1923
MRS-HAR	2.80%	**5.4970**	0.4618	**5.9588**	1.20%	0.0949	0.0973	0.1923
GARCH	1.20%	0.0949	**5.4494**	**5.5443**	0.40%	1.1765	0.0161	1.1926
MRS-G.	1.60%	0.7691	0.1629	0.9320	1.20%	0.0949	0.0973	0.1923
HS	4.00%	**12.9555**	**3.8824**	**16.8378**	3.60%	**10.2290**	1.0797	**11.3087**

- MRS-HAR denotes MRS-HAR-RV, and MRS-G. denotes MRS-GARCH. VaR is calculated based on 250 observations in out-of-sample from 23 October 2014 to 30 October 2015. PF is the probability of failures (violations). The LR statistic in bold denotes rejection of each test. The critical value for the unconditional coverage and independent test ($LR_{(UC)}$ and $LR_{(UC)}$) is 2.7055, and that for the conditional coverage likelihood ratio test $LR_{(CC)}$ is 4.6052.

Table 4-12: Value at Risk (VaR) for crude oil

	VaR for long position				VaR for short position			
nearby-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	5.20%	**22.3170**	**24.4059**	**46.7230**	3.60%	**10.2290**	**11.3087**	**21.5378**
MRS-HAR	3.60%	**10.2290**	**11.3087**	**21.5378**	2.00%	1.9568	2.2021	4.1590
GARCH	3.60%	**10.2290**	**14.9225**	**25.1515**	3.20%	**7.7336**	**9.1795**	**16.9131**
MRS-G.	3.60%	**10.2290**	**10.9775**	**21.2065**	2.40%	**3.5554**	**6.0271**	**9.5825**
HS	3.20%	**7.7336**	**9.1795**	**16.9131**	0.80%	0.1084	0.1569	0.2653
1-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.80%	**5.4970**	**5.9588**	**11.4558**	0.80%	0.1084	0.1569	0.2653
MRS-HAR	4.40%	**15.8906**	**16.9978**	**32.8884**	2.40%	**3.5554**	**3.9003**	**7.4556**
GARCH	2.00%	1.9568	2.2021	4.1590	0.40%	1.1765	1.1926	2.3691
MRS-G.	2.00%	1.9568	2.2021	4.1590	1.20%	0.0949	0.1923	0.2872
HS	3.60%	**10.2290**	**10.9775**	**21.2065**	4.00%	**12.9555**	**16.8378**	**29.7933**
2-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.00%	1.9568	2.2021	4.1590	0.40%	1.1765	1.1926	2.3691
MRS-HAR	3.20%	**7.7336**	**8.3298**	**16.0634**	1.20%	0.0949	0.1923	0.2872
GARCH	2.40%	**3.5554**	**6.0271**	**9.5825**	0.40%	1.1765	1.1926	2.3691
MRS-G.	2.00%	1.9568	2.2021	4.1590	0.80%	0.1084	0.1569	0.2653
HS	4.00%	**12.9555**	**13.7427**	**26.6982**	3.60%	**10.2290**	**14.9225**	**25.1515**
3-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.00%	1.9568	2.2021	4.1590	0.40%	1.1765	1.1926	2.3691
MRS-HAR	2.00%	1.9568	2.2021	4.1590	0.80%	0.1084	0.1569	0.2653
GARCH	2.40%	**3.5554**	**6.0271**	**9.5825**	0.40%	1.1765	1.1926	2.3691
MRS-G.	2.40%	**3.5554**	**6.0271**	**9.5825**	0.40%	1.1765	1.1926	2.3691
HS	4.00%	**12.9555**	**13.7427**	**26.6982**	3.60%	**10.2290**	**14.9225**	**25.1515**
4-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	2.00%	1.9568	2.2021	4.1590	0.40%	1.1765	1.1926	2.3691
MRS-HAR	0.40%	1.1765	1.1926	2.3691	0.40%	1.1765	1.1926	2.3691
GARCH	2.40%	**3.5554**	**6.0271**	**9.5825**	0.40%	1.1765	1.1926	2.3691
MRS-G.	2.00%	1.9568	2.2021	4.1590	0.40%	1.1765	1.1926	2.3691
HS	3.60%	**10.2290**	**10.9775**	**21.2065**	3.20%	**7.7336**	**9.1795**	**16.9131**
5-month	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$	PF	$LR_{(UC)}$	$LR_{(IND)}$	$LR_{(CC)}$
HAR-RV	1.60%	0.7691	0.9320	1.7012	0.40%	1.1765	1.1926	2.3691
MRS-HAR	1.60%	0.7691	0.9320	1.7012	0.40%	1.1765	1.1926	2.3691
GARCH	2.40%	**3.5554**	**6.0271**	**9.5825**	0.40%	1.1765	1.1926	2.3691
MRS-G.	2.00%	1.9568	2.2021	4.1590	0.80%	0.1084	0.1569	0.2653
HS	4.00%	**12.9555**	**13.7427**	**26.6982**	3.60%	**10.2290**	**14.9225**	**25.1515**

- MRS-HAR denotes MRS-HAR-RV, and MRS-G. denotes MRS-GARCH. VaR is calculated based on 250 observations in out-of-sample from 23 October 2014 to 30 October 2015. PF is the probability of failures (violations). The LR statistic in bold denotes rejection of each test. The critical value for the unconditional coverage and independent test ($LR_{(UC)}$ and $LR_{(UC)}$) is 2.7055, and that for the conditional coverage likelihood ratio test $LR_{(CC)}$ is 4.6052.

In order to more carefully examine the accuracy of VaR estimates, we need to further check the backtesting results in Table 4-10 to 4-13. For gasoline futures, all GARCH, MRS-GARCH and HS approaches fail to pass at least one of the backtesting tests, while both HAR-RV and MRS-HAR-RV approaches, by contrast, produce efficient VaR for all maturity contracts. Interestingly, for 5-month gasoline futures, it seems that both HAR-RV and MRS-HAR-RV may overestimate the value of VaR since the PFs are both 0.00%. Moving to kerosene futures, HS and GARCH approaches again fail to pass backtesting tests, while, surprisingly, HAR-RV and MRS-HAR-RV approaches do not pass the tests for five and four futures, respectively. MRS-GARCH performs the best among all models. Finally, for crude oil futures, the HS approach fails to pass backtesting tests for gasoline and kerosene, while the GARCH approach passes for two contracts, the 1-month and 5-month ones. The rest three models perform almost evenly by passing backtesting test for four and three (MRS-HAR-RV) contracts

To sum up, comparing the accuracy of VaR estimates reveals that both HAR-RV and MRS-HAR-RV can produce more accurate estimates than HS and GARCH approaches across commodities and maturities. Nonetheless, even though HAR-RV and MRS-HAR-RV approaches can both produce efficient VaR estimates for gasoline futures, MRS-GARCH seems to perform better for kerosene futures.

Figure 4-7: Value at Risk (1%) of 6-month gasoline futures

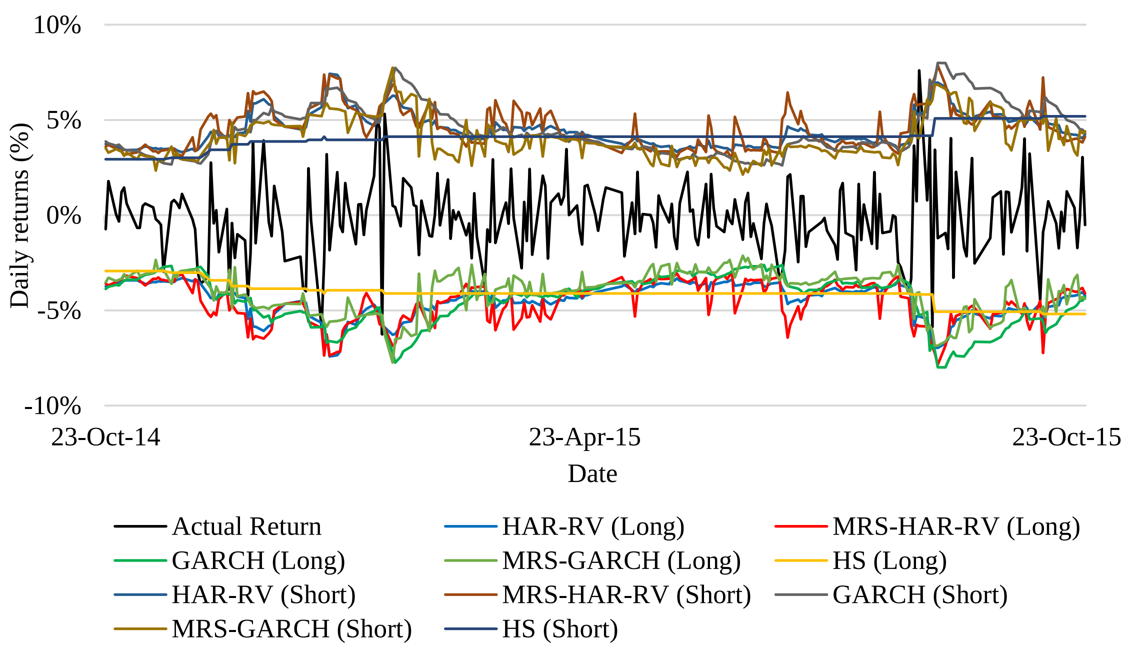


Figure 4-8: Value at Risk (1%) of 6-month kerosene futures

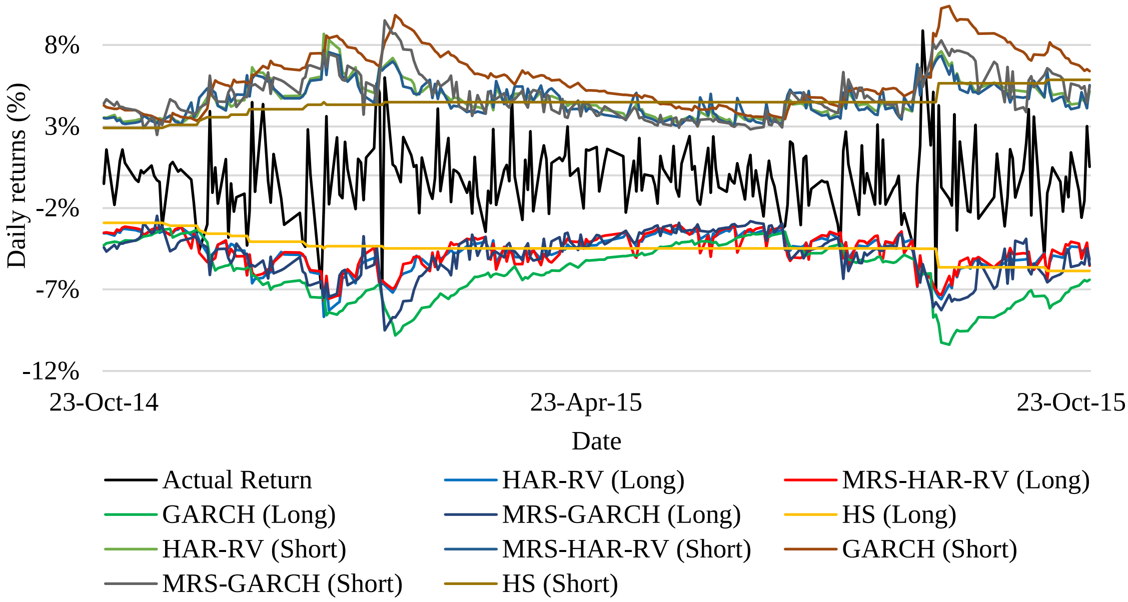
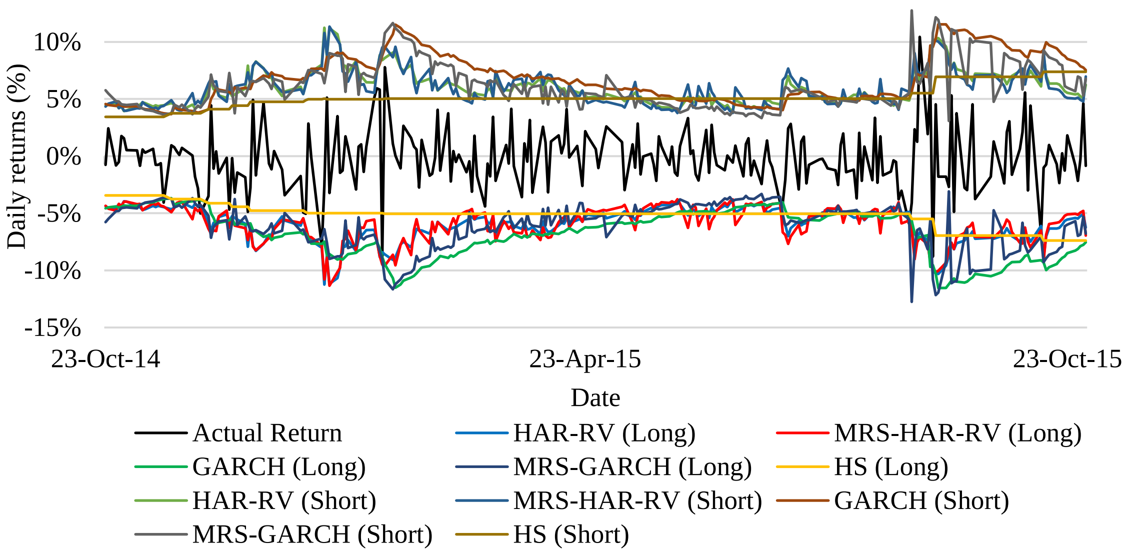


Figure 4-9: Value at Risk (1%) of 6-month crude oil futures



4.6 Conclusion

This paper investigates the dynamics of realised volatility for TOCOM gasoline, kerosene and crude oil futures. By modelling with HAR-RV, we find that realised volatility is a long-memory process. Nonetheless, by incorporating the MRS approach, we find that the persistence and average level of realised volatility switches in two different regimes, namely a high- and low-volatility regime. In the low-volatility regime, all one-day, one-week and one-month lagged realised volatility individually last for most energy futures. By contrast, the impact of one-week and one-month lags disappears for some contracts in the high-volatility regime. Moreover, the MRS-HAR-RV model can capture the dynamics of realised volatility better than HAR-RV, and has better goodness-of-fit regarding adjusted R-square and SBIC.

In out-of-sample, MRS-HAR-RV outperforms GARCH and MRS-GARCH for most TOCOM energy futures, while only has better forecast than HAR-RV for longer maturity futures, but not for shorter maturity futures regarding the QLike loss function. We conjecture that the lack of liquidity for shorter maturity contracts increases the impact of order imbalance on volatility and then also the probability of regime switching. Hence, any unexpected increase in order imbalance may lower the precision of forecasts of unconditional regime probability, leading to less accurate forecasts of realised volatility. We further compare the difference in MAE, MME(O) and MME(U), and find MRS-HAR-RV tends to under-predict realised variance, while alternative models tend to over-predict.

In the application of VaR estimation and valuation, both HAR-RV and MRS-HAR-RV outperform HS and GARCH approaches for all three commodities and across six maturities. However, MRS-GARCH seems to perform better for kerosene futures, while HAR-RV and MRS-HAR-RV perform better for gasoline futures.

Chapter 5 The Relation between Trading Volume and Realised Volatility

5.1 Introduction

Many studies investigate the theoretical and empirical relation between trading volume and price volatility using different econometric techniques, sample periods and frequencies. The theoretical foundations of these studies are based on three main theories proposed to explain the relation between trading activity and price behaviour. These are the Mixture of Distribution Hypothesis (MDH) by Clark (1973), the Sequential Information Arrival Hypothesis (SIAH) by Copeland (1976), and Motivation Driven Trade by Wang (1994).

MDH postulates the existence of a contemporaneously positive relation between trading volume and price volatility, because it assumes that trading volume and price changes follow a joint distribution and are driven by a single mixing variable which is arrival of information. On the other hand, SIAH suggests a positive relation to be a lead-lag relationship between trading volume and volatility. SIAH argues that traders receive information gradually and adjust their holding positions based on the arrival of information over time. The gradual adjustment of portfolios creates a series of disequilibria and hence the market price evolves and reaches a new equilibrium only when all traders in the market have obtained information and readjusted their portfolio. Hence, the speed of the change of market prices depends on the rate of information arrival, and is usually later than changes in trading volume because of the existence of private information. Finally, the third theory on the volume-volatility relation is Motivation Driven Trade, which separates types of trades into Liquidity Driven Trade (LDT) and Information Driven Trade (IDT). Under the LDT hypothesis, Liquidity Driven Trades are likely to cause a reversal in consecutive returns, which increases the volatility of returns and induces a positive relation between volume and volatility. In contrast to LDT, Information Driven Trades tend to create momentum in consecutive returns, which reduces the volatility of returns and implies a negative volume-volatility relation.

Generally speaking, MDH and SIAH both suggest the existence of a positive relation between trading volume and price volatility. Nevertheless, they differ in the symmetry of the flow of information to the market. MDH assumes all traders and market participants receive random information simultaneously, so the volume-volatility relation is contemporaneous. On the other hand, SIAH assumes that information arrives randomly but reaches different traders sequentially. As a result, changes in trading volume precede price movements. In other words, the trading volume is supposed to lead price change and volatility under the SIAH hypothesis.

We study the trading activity and price behaviour of the three energy commodities traded on TOCOM. To achieve this, we use two approaches. First, we utilise a Structural Vector Autoregressive (SVAR) model to measure the contemporaneous as well as lead-lag interaction between trading volume and volatility. In addition, we take into account the roll-over effect by introducing day-to-rollover to capture the time effect of maturity and the roll-over of contracts. Second, a Transition Structural Vector Autoregressive (T-SVAR) model is developed by introducing a dummy variable of backwardation into SVAR. The use of the dummy variable allows us to measure the asymmetric effect of market condition (backwardation and contango) on the relation between trading volume and volatility.

This chapter contributes to the literature in three aspects. First, this is the first paper discussing the volatility-volume relation for TOCOM energy futures. The distinctive characteristics of TOCOM energy futures, including the domestic nature of the market, lower liquidity compared to other energy futures markets, stricter trading limits, types of participants, as well as being the only energy futures market in Asia, makes it an interesting testing ground. Second, we examine the contemporaneous and lead-lag volume-volatility relation across the term structure of futures contracts for kerosene, gasoline and crude oil. Third, we examine the role of market conditions as defined by the slope of the forward curve in the volume-volatility relations.

5.2 Literature Review

Evidence in support of MDH is provided by Epps and Epps (1976) who examine 20 stocks on the New York Stock Exchange (NYSE). They prove MDH by using transaction volume as the mixing variable. Tauchen and Pitts (1983) model the joint distribution of volume and squared price change for 90-day T-bills futures and report consistent results with MDH. Other studies utilise the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model by Engle (1982) and Bollerslev (1986) to investigate the volume-volatility relation as the return distribution of financial assets is usually time-varying. For instance, Lamoureux and Lastrapes (1990) find a positive contemporaneous relationship between trading volumes and return variance in 20 S&P500 stocks, which is in line with MDH. Moreover, Najand and Yung (1991) and Rahman et al. (2002) report a positive volume-volatility relationship in both the Treasury-bond futures market and the NASDAQ 100 index. More interestingly, Lamoureux and Lastrapes (1990) find that the persistence of lagged square residual becomes much weaker when trading volume is included in the variance equation.

However, including trading volume as a variable in the GARCH model is argued to be inappropriate by Fleming et al. (2006), since volume should be endogenous to volatility according to MDH. Therefore, simultaneity bias may incur if the GARCH model is estimated. To overcome the problem of simultaneity, studies employ the Generalised Method of Moment (GMM) to analyse the volume-volatility relationship.

For instance, Foster (1995) on the Brent and WTI crude oil market, Wang and Yau (2000) on the S&P500 index, Deutsche Mark, and silver and gold futures, and Lee and Rui (2002) on the US, UK, and Japanese stock markets, all provide evidence of contemporaneously positive volume-volatility relationships. More recently, Hussain (2011) investigates the volume-volatility relationship for the DAX 30 stock index considering the effect of expected and unexpected trading volume on the volatility of the index. He finds a positive relationship between unexpected trading volume and return volatility with certain asymmetric effect; that is, a positive change in trading volume can increase return volatility more than a negative change in volume can.

SIAH implies a lead-lag relationship between trading volume and price volatility, and several empirical papers provide evidence in support of such a relationship in different financial and commodity markets. Smirlock and Starks (1988) study 300 S&P 500 companies, and find the existence of a lead-lag relation between absolute price change and trading volume. Using 5-minute intraday data and an EGARCH specification, Darrat et al. (2003) investigate the volume-volatility relation in the Dow Jones Industrial Average (DJIA) index. Their results reveal a weak contemporaneous relationship but a strong lead-lag relationship between the volume and volatility of DJIA, which is in line with SIAH. Darrat et al. (2007) argue that SIAH can be tested only in periods when the news is public. They examine the dynamic relation between intraday trading volume and the return volatility of large and small NYSE stocks using two partitioned samples, with and without identifiable public news. Their results reveal a bi-directional Granger-causality between volume and volatility when information is public, as hypothesized by SIAH. However, in periods when there is no public news, only trading volume Granger-causes volatility. Darrat et al. (2007) relate the latter to behavioural models like the overconfidence and biased self-attribution model by Daniel et al. (1998).

The volatility-volume relation has also been discussed in energy literature. Serletis (1992) studies the relation between trading volume and the volatility of crude oil futures contracts traded in NYMEX during the period from January 1987 to July 1990, allowing for maturity effect. Although he finds that crude oil futures prices become more volatile and trading volume increases as futures contracts approach, the results of causality tests reveal that just as volatility does not affect trading volume, trading volume has little effect on volatility. Herbert (1995) examines the relation between the trading volume and price volatility of natural gas futures contracts considering the time to maturity, and reports that a) the volume of trade rather than maturity explains the variance of the volatility, and b) that of trading volume can explain price volatility but price volatility has much less of an influence on trading activity. Moosa et al. (2003) present empirical evidence of temporal asymmetry in the price-volume relationship in the crude oil futures market. They use 3- and 6-month futures prices and trading volumes, and find that the price-volume relationship is bidirectional and asymmetric, since the effect of negative price and volume changes is stronger than that of positive price and volume changes.

5.3 Methodology

For the purpose of analysing the volatility of TOCOM energy futures, this paper employs the Structural VAR (SVAR) model to investigate the relation between volatility and change in volume. In contrast to reduced-from VAR, the SVAR model allows for discussion of contemporaneous relations. Furthermore, we include an indicator capturing the transition of market conditions to SVAR to investigate the asymmetric effect of market conditions on volume-volatility relations, the so-called T-SVAR model.

5.3.1 The Structural Vector Autoregressive (SVAR) Approach

The SVAR model is utilised to investigate the volume-volatility relation due to two concerns, the potential simultaneity issue of GARCH-type models and the limitation of reduced-form VAR. Analysing the volume-volatility relation under GARCH-type models treats conditional volatility as the dependent variable and trading volume as the independent variable, so there is an econometrics issue if trading volume is actually endogenous. However, VAR-type models treat all variables as exogenous and generate endogenously by the system of equations, providing flexibility for the analysis of economic time series in multivariate setting (Sims ,1980). In addition, reduced-form VAR, including only lags of variables, can only be used to discuss a lead-lag relation between volume and volatility, whilst SVAR, adding the contemporaneous variables into the equation, can be used to investigate whether MDH holds.

A bivariate SVAR (1) model with realised volatility and change in volume is utilised in this paper, shown as

$$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t} \tag{5.1}$$
$$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t} \,.$$

$\varepsilon_{\sigma^2,t}$and $\varepsilon_{\Delta v,t}$ are disturbance terms with zero covariance, $\mathrm{E}\left[\varepsilon_{v,t}\varepsilon_{\sigma^2,t}\right] = 0$, σ_t^2 is the realised variance of futures returns at time *t*, v_t is change in trading volume at time *t* (see Section 5.4 for further discussion), DTR_t is the day-to-rollover at time *t*, and z_t^2 is the squared slope of forward curve. Moreover, a_0 and b_0 are constant terms for each equation, a_1, a_2, b_1, and b_2 are the coefficients of lagged variables, and a_3 is the coefficient of contemporaneous trading volume in the realised volatility equation. In particular, a_2 measures the lead-lag relation between change in volume and volatility, while a_3 measures the contemporaneous relation between change in volume and volatility.

To identify the structural coefficients, at least 1 restriction needs to be imposed on the structural elements (see Section 2.4.5). Therefore, we restrict the coefficient of the contemporaneous realised volatility in change in trading volume equation to 0; in other words, only the change in volume contemporaneous impacts the realised volatility, but not the opposite direction. There are two reasons for this restriction. Firstly, according to the information model, market makers change their prices based on the order flow observed in the market, which carries the information from traders. If the information model holds, the change in prices is a result of the trading activity happening to the market. Therefore, the impact direction is expected to be from trading volume to realised volatility. Secondly, this chapter aims to investigate the dissemination of information into market, so the influence of trading volume on realised volatility is the focus. In addition, φ_{σ^2} and φ_v are the coefficients capturing the effect of rollover, and θ_{σ^2} and θ_v measure the impact of the magnitude of the forward curve slope. According to the Samuelson Hypothesis, volatility increases when maturity approaches (days to maturity/rollover decreases), so φ_{σ^2} is expected to be negative. z_t^2 measures the steepness of backwardation or contango. Carlson et al. (2007) argue that the relation between the slope of forward curve and volatility is a U-shape, which means the volatility increases when the forward curve is either positively or negatively steeper. Therefore, θ_{σ^2} is expected to be positive, which indicates a positive relation between the steepness of forward curve and the realised volatility.

5.3.2 The Transition Structural Vector Autoregressive (TSVAR) Approach

The market condition of futures can be distinguished as either backwardation or contango based on the relationship between spot price and futures price. Backwardation implies that the market is currently in shortage of supply and less stable than contango, which may lead to a stronger volume-volatility relation. Therefore, it is in our interest to investigate the relation between volatility and volume change under different states of markets. By incorporating equation (5.1) with the indicator of market being in backwardation, S_t, the TSVAR(1) is specified as

$$\begin{aligned}
\sigma_t^2 &= a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 \\
&\quad + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t} \\
v_t &= b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 \\
&\quad + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t} \\
S_t &= \begin{cases} 1, & z_t > 0 \\ 0, & otherwise \end{cases}.
\end{aligned} \tag{5.2}$$

The contemporaneous (lead-lag) volume-volatility relation in contango is measured by $a_3(a_2,)$, while a_3+δ_3 (a_2+δ_2) stands for the relation in backwardation. Particularly, δ_2 and δ_3 measure the transition effect of market conditions on the lead-lag and the contemporaneous relation between volatility and change in volume, respectively. The significance of these two coefficients implies the existence of differences in volume-volatility relations under different states of markets, which is to be expected.

5.4 Data

The sample data consists of all TOCOM energy futures across commodities and maturities, and the sample period is from 22 September 2014 to 30 October 2015. Table 3-3 and Table 3-6 present descriptive statistics and preliminary tests for trading volume and realised volatility. Due to the mixed ADF test results, the unit root tests with structural breaks are performed to examine the stationarity of trading volume. Table 5-1 presents the unit root tests with structural breaks for trading volume. The results suggest that the trading volume is stationary for almost all futures after the structural breaks are considered. This may indicate that structural breaks exist in the trading volume and may be the cause of failing to reject the null hypothesis of ADF test shown in Table 3-3. However, this chapter still uses change in trading volume to investigate the volume-volatility relation instead of raw trading volume for three reasons. Firstly, the results of the unit root test with structural breaks still suggest that 1-month kerosene futures are not stationary, so, statistically, change in trading volume is also a more suitable variable to use for the analysis of TOCOM energy futures. Secondly, change in trading volume can capture the strength in information between two periods. For example, an increase in trading volume means the information today is much stronger than yesterday and tends to have more impact on price movements or volatility. Finally, due to the high autocorrelation of trading volume, changes in trading volume can be viewed as a measure of unexpected trading volume, which captures new information in the market. Therefore, change in volume is used to discuss the volume-volatility relation in this study[14].

Table 5-1: The results of unit root with structural breaks for trading volume across three TOCOM energy futures

Gasoline	1-month	2-month	3-month	4-month	5-month	6-month
	-31.4623 [a]	-14.6107 [a]	-15.8235 [a]	-20.6452 [a]	-4.99375 [a]	-12.2893 [a]
Kerosene	1-month	2-month	3-month	4-month	5-month	6-month
	-3.69905	-6.52732 [a]	-12.4984 [a]	-22.5639 [a]	-17.8077 [a]	-8.41739 [a]
Crude oil	nearby-m.	1-month	2-month	3-month	4-month	5-month
	-21.8849 [a]	-20.058 [a]	-25.9514 [a]	-24.4375 [a]	-5.74109 [a]	-13.9752 [a]

- [a] indicates rejection at the 1% significance level. nearby-m. denotes nearby-month. The sample period is from 22 September 2010 to 30 October 2015.

[14] Alizadeh and Tamvakis (2016) also use change in volume to discuss the volume-volatility relation of four oil futures on NYMEX.

Table 5-2: Descriptive statistics and preliminary tests for daily change in trading volume

			Gasoline			
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	-0.2149	-0.1278	-0.0815	-0.0168	0.0631	-4.3251
Std.	312.4046	188.0132	205.5372	283.0687	1341.3979	2313.1926
Skewness	-0.9443	1.9041	0.9632	-0.3735	2.3139	-0.1261
Kurtosis	27.4158	68.7155	23.9945	36.2685	16.8577	5.8265
ACF_1	-0.3837	-0.3873	-0.3777	-0.3057	-0.2781	-0.2921
ACF_5	0.0042	0.0897	0.1035	0.0385	-0.0199	-0.0181
ACF_{22}	-0.0532	-0.0534	-0.0095	-0.0036	0.0619	0.0195
Q(22)	269.3137	226.8248	245.1324	181.9245	136.8723	144.0369
ADF	-52.9753	-53.1967	-52.6084	-48.4829	-47.0403	-47.7632
KW	20.2603 [a]	15.7035 [a]	16.6907 [a]	3.6957	7.4383	20.6540 [a]
			Kerosene			
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	-0.4880	-0.2093	-0.3355	-0.4097	-0.4888	-1.3219
Std.	370.2537	166.3585	179.9694	215.3702	485.5380	718.4511
Skewness	-0.6790	-0.1034	0.5612	-1.6250	1.1623	1.2039
Kurtosis	16.8991	20.5579	23.2425	46.6787	14.9272	36.8060
ACF_1	-0.4570	-0.4263	-0.3947	-0.3017	-0.2433	-0.3653
ACF_5	0.0273	0.0400	-0.0126	0.0284	0.0339	0.0573
ACF_{22}	-0.0148	-0.0951	0.0544	0.0630	0.0879	-0.0071
Q(22)	316.2682	289.6501	223.3786	175.3948	134.8345	219.8618
ADF	-57.9164	-55.7885	-53.7100	-48.3101	-45.3392	-51.8555
KW	5.9132	9.8712 [b]	17.2834 [a]	3.1853	4.7302	10.3223 [b]
			Crude oil			
	nearby-m.	1-month	2-month	3-month	4-month	5-month
Mean	-0.0088	0.1318	0.0823	0.0176	-0.2157	2.2284
Std.	106.3994	122.7532	171.3809	287.7755	1412.2971	1839.6882
Skewness	0.0859	0.0071	-0.0228	0.1421	1.1190	0.1674
Kurtosis	43.0152	19.9331	11.7339	10.4777	22.1020	7.9401
ACF_1	-0.4785	-0.4140	-0.4065	-0.3383	-0.1525	-0.3001
ACF_5	0.0082	-0.0342	-0.0025	-0.0102	0.0004	-0.1367
ACF_{22}	-0.0067	0.0322	0.0788	0.0519	0.2076	0.0605
Q(22)	344.0524	240.7526	243.5733	214.7071	239.3035	203.2752
ADF	-59.5334	-54.9185	-54.4001	-50.2535	-41.2241	-48.1060
KW	3.7521	4.1582	13.8025 [a]	6.2497	2.2009	30.8312 [a]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. ACF_i is the autocorrelation function with i lags, and the 95% confidence interval is [-0.0565,0.0565]. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015. KW is the Kruskal-Wallis statistic, which follows χ^2_4.

Table 5-2 reports the descriptive statistics for daily change in trading volume. The daily average of change in trading volume is around zero for most contracts, but away from zero for highly liquid contracts. With regard to kurtosis, the change in trading volume is leptokurtotic for all contracts, which is similar to the property of trading volume. Even though the kurtosis also decreases as the maturity increases, the pattern seems a bit inconsistent. For example, the kurtosis of 1-month kerosene is 16.89 while that of 6-month kerosene is 36.81. Regarding the autocorrelation, the first order ACF is significantly from zero, but the results of 5th and 22nd order ACF are mixed. Nonetheless, the result of 22nd order Q-statistic shows that change in volume is highly autocorrelated at least up to 22 lags. Moreover, the stationarity of change in trading volume is confirmed by the result of ADF test. In terms of daily seasonality, the result of KW test for change in trading volume shows that only 8 out 18 contracts exhibit daily seasonal behaviour, which is similar to that for raw trading volume.

5.5 Empirical Results

5.5.1 Estimation of Structural Vector Autoregressive (SVAR)

The estimation results of SVAR for gasoline, kerosene and crude oil futures are shown in the left column of Table 5-3 to 5-5. Firstly, we observe the coefficient a_3 in measuring the relation between volatility and contemporaneous change in volume. The coefficients for most contracts are positive and significant, except for 1- and 3-month kerosene and 3-month crude oil futures. This implies that realised volatility increases with the rise in change in volume, and that MDH may hold in TOCOM energy futures markets. Then, we look at the coefficients a_2 in measuring the relation between volatility and lagged change in volume. Interestingly, for just more than a half of energy futures, the coefficients a_2 are also positive and significant, which implies the existence of a link between volatility and lagged change in volume. Nonetheless, it seems that the lead-lag relation is weaker than the contemporaneous one because the magnitude of coefficients a_2 is relatively smaller than coefficients a_3, except in the case of some lowly liquid futures, such as 1-month gasoline and kerosene futures. Therefore, it appears that there are two elements affecting realised volatility, namely contemporaneous and lagged change in trading volume, and that the former has a more significant impact. This result is also in line with the findings of Foster (1995), Wang and Yau (2000) and Hussain (2011), who suggest positive and significant coefficients of both contemporaneous and lagged volumes. Overall, our results suggest the existence of both MDH and SIAH.

Turning to the relation between volatility and day-to-rollover (φ_{σ^2}), the results are different for three energy commodities. For gasoline and kerosene futures, the coefficients φ_{σ^2} are generally positive but insignificant. This is consistent with Duong and Kalev (2008), who find that there exists no relation between volatility and days to maturity for most commodities, except agriculture. However, the coefficients φ_{σ^2} are negative and significant for 1-month contracts, but positive and significant for 2- and 3-month contracts. This implies that the Samuelson Hypothesis only holds for 1-month contracts, but that the opposite case occurs for 2- and 3-month contracts. The results of crude oil futures are different from that of gasoline and kerosene. For all maturity contracts, the coefficients φ_{σ^2} are positive and significant, which implies that realised volatility decreases when maturity/rollover date approaches.

Finally, the relation between volatility and squared slope of forward curve is discussed. Interestingly, the coefficients θ_{σ^2} of gasoline and crude oil futures are similar, while those of kerosene ones are different. The coefficients θ_{σ^2} are all positive and significant across all maturity contracts for gasoline and crude oil futures, although the magnitudes of the coefficients of crude oil are greater than those of gasoline. This indicates that realised volatility increases when the slope of the forward curve becomes steeper, which means the market is in deeper backwardation or contango.

5.5.2 Estimation of Transition Structural Vector Autoregressive (TSVAR)

Having discussed the relation between volatility and change in volume, we then discuss the impact of the market being in backwardation on the volume-volatility relation. However, before the discussion of the asymmetric effect, we notice that the significance of a_3 seems have a pattern across maturities based on the results of both SVAR and TSVAR. For instance, the coefficients for 3-month kerosene and 2-month crude oil futures are insignificant, and that for 3-month gasoline futures is less significant (only at 5%) than that for other maturities. Nonetheless, based on the descriptive statistics of realised volatility, trading volume and change in trading volume, there is no significant difference between 3-month futures and other maturity futures. The explanation of this pattern remains a mystery.

Regarding the volume-volatility in different market conditions, we firstly look at the coefficient δ_3 in measuring the difference in the volume-volatility relation under backwardation and contango. For gasoline futures, the coefficients δ_3 are only significant for 1-month and 2-month contracts, and are all negative. This indicates that the volume-volatility relation only becomes weak for 1-month and 2-month gasoline futures when the market is in backwardation, but has no change for gasoline futures of other maturity periods. The result of kerosene futures is slightly different, the coefficients δ_3 are negative and significant for most contracts, except 3-month and 5-month ones. Therefore, the relation between volatility and change in volume under backwardation is weaker than that under contango for most kerosene futures. The opposite situation is found in the results of crude oil futures. Except nearby-month crude oil futures, coefficients δ_3 are generally positive but only significant for 2-, 3- and 5-month contracts. As a result, the contemporaneous volume-volatility relation enhances when the market is in backwardation.

The types of energy market participants may explain the difference in the impact of backwardation on the volume-volatility for kerosene and crude oil futures. Based on statistics from PAJ (Petroleum Association of Japan), more than 90% of crude oil is used for refining purposes, and more than 80% of petroleum products are sold to domestic energy consumers. Therefore, in Japan, refineries are the major participants importing crude oil and selling products to domestic energy consumers. As TOCOM energy futures are the most convenient vehicles with which Japanese refineries can hedge, the behaviour of refineries plays an important role in the activities of TOCOM energy futures markets. Refineries can take a long position in crude oil futures to avoid increases in the costs of purchasing crude oil, while taking a short position in gasoline/kerosene futures to prevent a drop in the revenue of selling products. This indicates that refineries tend to pay more attention to the rise of crude oil rather than the decline of gasoline/kerosene futures. As a result, the volume-volatility relation of crude oil futures is expected to be stronger in backwardation, while that of kerosene ones is likely to be stronger in contango.

The other crucial coefficient deserving our attention is δ_2, which measures the difference in the lead-lag relation between volatility and change in volume in backwardation. Results show that the coefficients δ_2 are generally insignificant for all three commodities futures, which may indicate that the market condition does not change the lead-lag volume-volatility relation. Two possible reasons may explain this result. Firstly, the lead-lag relation is already not as strong as the contemporaneous relation according to the result of SVAR, so a significant transition on weaker lead-lag relation is not expected. This may be due to the fact that the transition is based on current market conditions instead of previous market conditions. As a result, if private information is inaccurate or market conditions change in the current period, the lead-lag relation may be weak. The other reason is related to the cause of lead-lag relation, SIAH, which finds that some investors hold and trade on private information before the market reflects it, so trading volume is ahead of volatility. Such information-driven trading is usually conducted by speculators who can flexibly change the direction of their position based on market conditions, so they do not give extra attention to either backwardation or contango. As a result, the transition of lead-lag relation is very weak.

With respect to diagnostic tests, the results of 22nd order Q-statistic reveal that the autocorrelation of residuals in realised volatility and change in volume equation is very strong. However, HAC estimators are used for the estimation of standard errors, so the interpretation of the results is still valid. Regarding the SBIC, the value of SBIC for SVAR is slightly higher than that for TSVAR. It seems like TSVAR does not perform better to capture the dynamics of realised volatility and change in volume according to the comparison of SBIC, which is in line with the significance of the transition coefficients. Except the transition coefficient of contemporaneous change in trading volume in realised volatility equation (δ_3), the rest transition coefficients are insignificant. However, the results of the LR test suggest that the increase in log-likelihood function value from SVAR to TSVAR is significant.

Table 5-3: Estimation results for SVAR(1) and T-SVAR(1) for gasoline

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel A: Realised Volatility Equation (σ_t^2)

	1-month		2-month		3-month		4-month		5-month		6-month	
a_0	0.0073***	0.0074***	0.0051***	0.0052***	0.0047***	0.0049***	0.0047***	0.0047***	0.0042***	0.0040***	0.0043***	0.0039***
	(0.0009)	(0.0009)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0011)	(0.0009)
a_1	0.4235***	0.4372***	0.4784***	0.4995***	0.5353***	0.5454***	0.5587***	0.5823***	0.6378***	0.6705***	0.6041***	0.6583***
	(0.0472)	(0.0636)	(0.0567)	(0.0720)	(0.0471)	(0.0567)	(0.0453)	(0.0552)	(0.0476)	(0.0488)	(0.0901)	(0.0740)
a_2	0.0483***	0.0717***	0.0108*	-0.0020	0.0060	0.0035	0.0072	-0.0050	-0.0008	-0.0009	0.0025***	0.0027***
	(0.0116)	(0.0130)	(0.0062)	(0.0142)	(0.0078)	(0.0081)	(0.0055)	(0.0059)	(0.0007)	(0.0009)	(0.0005)	(0.0007)
a_3	0.0250***	0.0680***	0.0344**	0.0701***	0.0282***	0.0179**	0.0278***	0.0288***	0.0059***	0.0051***	0.0066***	0.0073***
	(0.0097)	(0.0173)	(0.0160)	(0.0212)	(0.0094)	(0.0090)	(0.0062)	(0.0080)	(0.0011)	(0.0017)	(0.0010)	(0.0014)
φ_{σ^2}	-0.1580	-0.0318	0.4793***	0.4945***	0.2688*	0.2878*	0.2110	0.2327	0.0359	0.0508	0.1216	0.1367
	(0.2470)	(0.2473)	(0.1590)	(0.1554)	(0.1621)	(0.1619)	(0.1497)	(0.1488)	(0.1278)	(0.1274)	(0.1185)	(0.1172)
θ_{σ^2}	0.2726**	0.3377***	0.2700**	0.3122***	0.2817***	0.3184***	0.2216**	0.2524***	0.1886**	0.2176**	0.1872**	0.2135**
	(0.1205)	(0.1205)	(0.1226)	(0.1211)	(0.1032)	(0.1018)	(0.0931)	(0.0941)	(0.0860)	(0.0880)	(0.0847)	(0.0864)
δ_0		-0.0006		-0.0003		-0.0004		-2.74E-5		0.0002		0.0005
		(0.0009)		(0.0008)		(0.0007)		(0.0007)		(0.0007)		(0.0010)
δ_1		-0.0367		-0.0405		-0.0215		-0.0452		-0.0596		-0.0929
		(0.0681)		(0.0789)		(0.0650)		(0.0570)		(0.0577)		(0.0946)
δ_2		-0.0285*		0.0171		0.0044		0.0186**		0.0002		-0.0003
		(0.0162)		(0.0158)		(0.0142)		(0.0078)		(0.0014)		(0.0010)
δ_3		-0.0523***		-0.0488*		0.0182		-0.0024		0.0014		-0.0014
		(0.0179)		(0.0254)		(0.0158)		(0.0107)		(0.0023)		(0.0017)
Q(22)	238.696***	214.098***	314.975***	254.166***	302.214***	231.288***	333.453***	263.211***	385.730***	251.150***	344.804***	324.137***
SBIC	7213.408	7204.351	7939.247	7923.657	7941.072	7920.174	7598.606	7578.838	5793.826	5775.413	5168.148	5151.371
LR	31.8000***		18.7480***		8.1300		10.3920		13.1020*		16.3736**	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 5-3 (Continued): Estimation results for SVAR(1) and T-SVAR(1) for gasoline

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel B: Volume Equation (v_t)

	1-month		2-month		3-month		4-month		5-month		6-month	
b_0	0.0302***	0.0276***	0.0028**	0.0013	0.0023**	0.0021	0.0012	0.0006	-0.0083	-0.0107	0.0610**	0.0669**
	(0.0034)	(0.0030)	(0.0013)	(0.0014)	(0.0011)	(0.0014)	(0.0017)	(0.0025)	(0.0079)	(0.0162)	(0.0259)	(0.0261)
b_1	-0.5810***	-0.3505***	-0.1013*	0.0142	-0.2537***	-0.2244***	-0.4729***	-0.3981**	-1.6935***	-1.4861	-5.4968***	-5.6655***
	(0.1363)	(0.1128)	(0.0576)	(0.0721)	(0.0671)	(0.0822)	(0.1377)	(0.1666)	(0.5604)	(1.2291)	(1.9747)	(1.8145)
b_2	-0.4649***	-0.5880***	-0.3860***	-0.4505***	-0.3710***	-0.4042***	-0.3011***	-0.3408***	-0.2798***	-0.3348***	-0.2660***	-0.2538***
	(0.0308)	(0.0624)	(0.0352)	(0.0410)	(0.0360)	(0.0433)	(0.0524)	(0.0626)	(0.0244)	(0.0349)	(0.0299)	(0.0366)
φ_v	-14.250***	-14.193***	-0.9167	-0.8688	0.4700	0.4870	2.7948***	2.8325***	17.7665***	17.6083***	1.2222	2.5045
	(1.3514)	(1.3365)	(0.6204)	(0.6138)	(0.4200)	(0.4147)	(0.6868)	(0.6849)	(3.2416)	(3.2591)	(2.2326)	(5.6431)
θ_v	0.1995	0.2260	-0.0484	-0.0377	0.0207	0.0537	0.1024	0.1441	0.6924	0.7580	2.3025	1.6713
	(0.2988)	(0.3081)	(0.0896)	(0.1039)	(0.1154)	(0.1229)	(0.1972)	(0.2139)	(0.9727)	(0.9969)	(5.6503)	(2.3651)
π_0		0.0039		0.0022*		0.0002		0.0008		0.0048		-0.0110
		(0.0024)		(0.0012)		(0.0014)		(0.0035)		(0.0235)		(0.0295)
π_1		-0.3747**		-0.1864*		-0.0578		-0.1325		-0.4104		0.2123
		(0.1803)		(0.0995)		(0.1056)		(0.2871)		(1.8383)		(2.5486)
π_2		0.1518*		0.0860		0.0610		0.0614		0.1059**		-0.0221
		(0.0792)		(0.0591)		(0.0631)		(0.0848)		(0.0494)		(0.0561)
Q(22)	174.497***	156.457***	151.971***	151.056***	159.995***	182.499***	147.601***	110.380***	153.692***	148.871***	131.311***	82.360***
SBIC	7213.408	7204.351	7939.247	7923.657	7941.072	7920.174	7598.606	7578.838	5793.826	5775.413	5168.148	5151.371
LR	31.8000***		18.7480***		8.1300		10.3920		13.1020*		16.3736**	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 5-4: Estimation results for SVAR(1) and T-SVAR(1) for kerosene

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel A: Realised Volatility Equation (σ_t^2)

	1-month		2-month		3-month		4-month		5-month		6-month	
a_0	0.0084***	0.0082***	0.0059***	0.0060***	0.0054***	0.0051***	0.0053***	0.0053***	0.0052***	0.0049***	0.0050***	0.0048***
	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0007)	(0.0009)
a_1	0.4398***	0.4634***	0.4600***	0.4588***	0.5118***	0.5442***	0.5358***	0.5543***	0.5699***	0.5964***	0.6157***	0.6386***
	(0.0523)	(0.0627)	(0.0577)	(0.0597)	(0.0454)	(0.0491)	(0.0462)	(0.0527)	(0.0556)	(0.0694)	(0.0535)	(0.0685)
a_2	0.0140***	0.0138	0.0189*	0.0289	0.0135*	0.0210	0.0037	0.0027	-0.0023	-0.0089**	0.0058***	0.0061**
	(0.0045)	(0.0087)	(0.0101)	(0.0198)	(0.0079)	(0.0176)	(0.0065)	(0.0109)	(0.0023)	(0.0040)	(0.0016)	(0.0027)
a_3	0.0109	0.0331***	0.0242*	0.0567**	0.0140	0.0249	0.0234***	0.0484***	0.0103***	0.0144***	0.0169***	0.0243***
	(0.0068)	(0.0110)	(0.0124)	(0.0274)	(0.0090)	(0.0205)	(0.0075)	(0.0160)	(0.0026)	(0.0055)	(0.0023)	(0.0040)
φ_{σ^2}	-0.8163***	-0.7791***	0.2854*	0.2897*	0.2873*	0.2748	0.1836	0.1740	0.1641	0.1611	-0.0074	-0.0142
	(0.2784)	(0.2853)	(0.1518)	(0.1495)	(0.1676)	(0.1688)	(0.1568)	(0.1575)	(0.1453)	(0.1460)	(0.1361)	(0.1335)
θ_{σ^2}	0.0605	0.0782	0.0067	0.0230	0.0170	0.0301	0.0071	0.0199	-0.0179	-0.0216	-0.0144	-0.0123
	(0.0902)	(0.0964)	(0.0548)	(0.0539)	(0.0460)	(0.0484)	(0.0450)	(0.0472)	(0.0402)	(0.0417)	(0.0397)	(0.0428)
δ_0		0.0003		-0.0004		0.0009		0.0003		0.0009		0.0006
		(0.0009)		(0.0012)		(0.0010)		(0.0009)		(0.0010)		(0.0012)
δ_1		-0.0735		0.0040		-0.1096		-0.0624		-0.0802		-0.0635
		(0.0719)		(0.1065)		(0.0890)		(0.0795)		(0.0867)		(0.0941)
δ_2		0.0001		-0.0123		-0.0116		0.0021		0.0104**		-0.0011
		(0.0097)		(0.0216)		(0.0193)		(0.0132)		(0.0047)		(0.0033)
δ_3		-0.0308**		-0.0423*		-0.0173		-0.0369**		-0.0074		-0.0119***
		(0.0127)		(0.0255)		(0.0222)		(0.0179)		(0.0066)		(0.0045)
Q(22)	224.677***	225.721***	267.726***	305.586***	241.640***	286.432***	273.590***	326.064***	261.224***	383.590***	347.390***	335.856***
SBIC	6992.992	6974.861	8062.349	8044.231	8062.197	8046.397	7875.406	7861.353	6935.199	6918.439	6534.392	6517.298
LR	13.6000*		13.6920*		18.3280**		21.8200***		16.4060**		15.7397**	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 5-4 (Continued): Estimation results for SVAR(1) and T-SVAR(1) for kerosene

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel B: Volume Equation (v_t)

	1-month		2-month		3-month		4-month		5-month		6-month	
b_0	0.0320***	0.0319***	0.0030***	0.0022**	0.0004	-0.0004	-0.0011	-0.0024*	-0.0064**	-0.0084**	0.0142**	0.0126*
	(0.0030)	(0.0032)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0011)	(0.0013)	(0.0028)	(0.0033)	(0.0064)	(0.0071)
b_1	-0.1734*	-0.1595	-0.1602***	-0.0919**	-0.1037**	-0.0214	-0.1815**	-0.0648	-0.4940**	-0.2652	-1.3650***	-1.1860**
	(0.1032)	(0.1143)	(0.0486)	(0.0464)	(0.0520)	(0.0573)	(0.0853)	(0.0822)	(0.2013)	(0.2242)	(0.4181)	(0.4820)
b_2	-0.5087***	-0.5416***	-0.4229***	-0.5399***	-0.3922***	-0.4805***	-0.3049***	-0.4105***	-0.2514***	-0.2121***	-0.3520***	-0.3005***
	(0.0206)	(0.0413)	(0.0404)	(0.0994)	(0.0297)	(0.0528)	(0.0586)	(0.0495)	(0.0526)	(0.0822)	(0.0474)	(0.0343)
φ_v	-18.381***	-18.407***	-0.6674*	-0.6583*	0.5101	0.5263	1.9601***	1.9842***	7.6713***	7.5729***	0.1114	1.8067
	(1.5944)	(1.5806)	(0.3816)	(0.3749)	(0.3538)	(0.3554)	(0.4075)	(0.4217)	(1.1963)	(1.2027)	(0.2908)	(1.5499)
θ_v	-0.0861	-0.0892	-0.0036	-0.0124	-0.0040	0.0029	0.0681	0.0584	0.1268	0.1097	1.9469	0.0739
	(0.1971)	(0.2138)	(0.0602)	(0.0607)	(0.0585)	(0.0712)	(0.0983)	(0.1120)	(0.3288)	(0.3476)	(1.5642)	(0.3413)
π_0		0.0003		0.0019		0.0026		0.0039		0.0082		0.0073
		(0.0037)		(0.0013)		(0.0020)		(0.0039)		(0.0066)		(0.0104)
π_1		-0.0283		-0.1886*		-0.2640		-0.3734		-0.7979		-0.6525
		(0.2685)		(0.1116)		(0.1761)		(0.3291)		(0.4945)		(0.8371)
π_2		0.0467		0.1549		0.1283*		0.1498		-0.0704		-0.0822
		(0.0581)		(0.1080)		(0.0740)		(0.1063)		(0.0962)		(0.0650)
Q(22)	163.196***	173.454***	150.625***	154.718***	180.466***	160.124***	109.625***	136.588***	148.398***	151.380***	82.315***	129.209***
SBIC	6992.992	6974.861	8062.349	8044.231	8062.197	8046.397	7875.406	7861.353	6935.199	6918.439	6534.392	6517.298
LR	13.6000*		13.6920*		18.3280**		21.8200***		16.4060**		15.7397**	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 5-5: Estimation results for SVAR(1) and T-SVAR(1) for crude oil

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel A: Realised Volatility Equation (σ_t^2)

	nearby-month		1-month		2-month		3-month		4-month		5-month	
a_0	-0.0006	4.58E-5	0.0057***	0.0062***	0.0056***	0.0065***	0.0050***	0.0058***	0.0046***	0.0049***	0.0048***	0.0052***
	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0006)	(0.0008)	(0.0005)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
a_1	0.1563***	0.2297***	0.3874***	0.4239***	0.4272***	0.4415***	0.4739***	0.4804***	0.5575***	0.5847***	0.5710***	0.5947***
	(0.0421)	(0.0686)	(0.0513)	(0.0590)	(0.0443)	(0.0674)	(0.0443)	(0.0588)	(0.0456)	(0.0452)	(0.0527)	(0.0469)
a_2	0.0704***	0.1314**	0.0212	0.0146	0.0274*	0.0594**	0.0019	0.0022	0.0016	0.0023*	0.0041***	0.0042***
	(0.0257)	(0.0558)	(0.0145)	(0.0268)	(0.0149)	(0.0291)	(0.0061)	(0.0093)	(0.0010)	(0.0013)	(0.0008)	(0.0010)
a_3	0.1484***	0.2393***	0.0548***	0.0316	0.0171	-0.0325	0.0221***	0.0066	0.0031**	0.0022	0.0065***	0.0047***
	(0.0449)	(0.0619)	(0.0208)	(0.0316)	(0.0182)	(0.0282)	(0.0078)	(0.0092)	(0.0013)	(0.0016)	(0.0012)	(0.0013)
φ_{σ^2}	5.1565***	5.2039***	1.1234***	1.1188***	0.8790***	0.8747***	0.9456***	0.9582***	0.6758***	0.6640***	0.4592***	0.4594***
	(0.4452)	(0.4549)	(0.2490)	(0.2465)	(0.2553)	(0.2591)	(0.2182)	(0.2160)	(0.1871)	(0.1782)	(0.1645)	(0.1563)
θ_{σ^2}	1.0783***	0.8893***	1.1064***	0.9938***	1.0950***	1.0003***	1.0257***	0.9497***	0.8824***	0.7948***	0.7779***	0.6980***
	(0.2491)	(0.2367)	(0.1316)	(0.1349)	(0.1767)	(0.1809)	(0.1702)	(0.1727)	(0.1480)	(0.1400)	(0.1450)	(0.1326)
δ_0		-0.0006		-0.0004		-0.0011		-0.0010		-0.0002		-0.0003
		(0.0009)		(0.0008)		(0.0008)		(0.0008)		(0.0007)		(0.0007)
δ_1		-0.1327*		-0.0712		-0.0221		-0.0176		-0.0470		-0.0405
		(0.0768)		(0.0534)		(0.0566)		(0.0517)		(0.0452)		(0.0495)
δ_2		-0.0975*		0.0136		-0.0546		0.0012		-0.0025		0.0002
		(0.0586)		(0.0290)		(0.0334)		(0.0128)		(0.0021)		(0.0016)
δ_3		-0.1452*		0.0347		0.0836**		0.0310**		0.0028		0.0042*
		(0.0766)		(0.0427)		(0.0344)		(0.0149)		(0.0028)		(0.0024)
Q(22)	128.589***	101.155***	185.593***	158.695***	199.454***	147.062***	214.697***	163.618***	229.634***	190.628***	235.171***	199.902***
SBIC	8108.223	8097.488	8116.587	8097.946	7774.953	7767.928	7265.318	7252.444	5414.851	5399.156	5190.554	5178.641
LR	28.6000***		12.6440*		35.8780***		24.1780***		18.5360***		26.0997***	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

Table 5-5(Continued): Estimation results for SVAR(1) and T-SVAR(1) for crude oil

SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_v DTR_t + \theta_v z_t^2 + \varepsilon_{v,t}$
T-SVAR (1)	RV equation:	$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 v_{t-1} + a_3 v_t + \varphi_{\sigma^2} DTR_t + \theta_{\sigma^2} z_t^2 + S_t(\delta_0 + \delta_1\sigma_{t-1}^2 + \delta_2 v_{t-1} + \delta_3 v_t) + \varepsilon_{\sigma^2,t}$
	Volume equation:	$v_t = b_0 + b_1\sigma_{t-1}^2 + b_2 v_{t-1} + \varphi_{\hat{v}} DTR_t + \theta_v z_t^2 + S_t(\pi_0 + \pi_1\sigma_{t-1}^2 + \pi_2 v_{t-1}) + \varepsilon_{v,t}$

Panel B: Volume Equation (v_t)

	nearby-month		1-month		2-month		3-month		4-month		5-month	
b_0	0.0001	8.36E-5	8.52E-5	0.0002	0.0004	0.0008	-0.0013	-0.0009	-0.0112	-0.0028	0.0138	0.0137
	(0.0005)	(0.0006)	(0.0005)	(0.0008)	(0.0008)	(0.0011)	(0.0014)	(0.0022)	(0.0086)	(0.0131)	(0.0148)	(0.0204)
b_1	-0.0473*	-0.0207	-0.0969***	-0.1129**	-0.1592***	-0.1313	-0.3791***	-0.2839*	-1.6961***	-1.8741*	-2.9494***	-2.7616*
	(0.0267)	(0.0388)	(0.0318)	(0.0477)	(0.0526)	(0.0840)	(0.0875)	(0.1646)	(0.4862)	(1.0297)	(1.0780)	(1.4113)
b_2	-0.4686***	-0.4856***	-0.4147***	-0.3947***	-0.4143***	-0.4177***	-0.3423***	-0.2937***	-0.1643***	-0.1331**	-0.2835***	-0.2191***
	(0.0396)	(0.0553)	(0.0355)	(0.0390)	(0.0312)	(0.0436)	(0.0328)	(0.0458)	(0.0425)	(0.0539)	(0.0358)	(0.0552)
φ_v	0.2472	0.2477	0.7254***	0.7388***	1.0070***	0.9997***	3.4681***	3.3988***	20.4405***	20.8706***	7.6181**	13.6319***
	(0.2994)	(0.3005)	(0.2477)	(0.2477)	(0.3452)	(0.3474)	(0.7037)	(0.7160)	(3.6952)	(3.7569)	(3.3486)	(5.0031)
θ_v	-0.0327	-0.0776	0.1186	0.1431	0.2348	0.1418	0.9999***	0.7528**	3.3518*	3.0997	13.8749***	7.1979**
	(0.0944)	(0.0956)	(0.1379)	(0.1567)	(0.1811)	(0.2127)	(0.3060)	(0.3706)	(1.8430)	(2.0848)	(5.0560)	(3.3698)
π_0		0.0002		-0.0003		-0.0003		3.60E-5		-0.0117		-0.0002
		(0.0006)		(0.0009)		(0.0011)		(0.0023)		(0.0137)		(0.0233)
π_1		-0.0453		0.0283		-0.0595		-0.1548		0.1702		-0.1734
		(0.0449)		(0.0535)		(0.0858)		(0.1540)		(0.9733)		(1.5591)
π_2		0.0259		-0.0296		0.0078		-0.0970		-0.1156*		-0.1491**
		(0.0792)		(0.0613)		(0.0606)		(0.0628)		(0.0669)		(0.0666)
Q(22)	195.659***	195.288***	126.305***	126.410***	133.603***	132.868***	160.865***	161.799***	286.822***	284.738***	126.869***	128.757***
SBIC	8108.223	8097.488	8116.587	8097.946	7774.953	7767.928	7265.318	7252.444	5414.851	5399.156	5190.554	5178.641
LR	28.6000***		12.6440*		35.8780***		24.1780***		18.5360***		26.0997***	

- Sample period used for estimation is from 21 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. The figure in parentheses is the standard error of coefficient. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test.

5.6 Conclusion

This chapter first analyses the relation between realised volatility and both current and lagged change in volume for three different TOCOM energy futures, gasoline, kerosene and crude oil. Among all three energy futures, the relation between change in trading volume and realised volatility is very similar but with minor differences. In general, the contemporaneous relation is positive and significant between realised volatility and contemporaneous change in trading volume, which is consistent with most literature. Moreover, the existence of lead-lag relation is also found, so our study supports both MDH and SIAH. However, the lead-lag relation is less strong than the contemporaneous one.

Following this, the difference in the volume-volatility between backwardation and contango is investigated. After considering the asymmetric effect of market conditions, we find that the contemporaneous relation becomes weak for gasoline and kerosene, but strong for crude oil. This may be explained by the fact that refineries, as the main hedgers on TOCOM, purchase crude oil and sell products, so they are more sensitive when crude oil prices go up while product prices fall. Regarding the lead-lag relation, it appears that there is no significant difference in the volume-volatility relation under different market conditions.

In addition, the relation between realised volatility and days to rollover appears weak for gasoline and kerosene futures. However, the empirical result shows that volatility decreases when the date to rollover approaches for crude oil futures, which is opposed to the Samuelson Hypothesis. The pattern of trading volume may be the reason, because trading volume usually decreases with days to rollover. Moreover, realised volatility seems to increase when the forward curve is less flat, namely when there is more backwardation or contango.

Chapter 6 Determinants of Bid-Ask Spread of TOCOM energy futures

6.1 Introduction

Bid-ask spread (BAS) has always been a crucial topic in financial research because it is of concern to several participants in the financial market. For market-makers, BAS represents potential profit as a compensation for providing liquidity to the market. From the point of view of the Stock or Commodities Exchange, BAS provides clues for market design, such as whether single market-makers should be assigned, or competition between different market-makers should be increased, and in the determination of minimum tick size. It is also very important for regulators since it can be a tool for measuring the fairness of market-makers' rent.

Early studies classify the components of BAS into two main types, adverse-selection and transitory components (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Glosten and Harris, 1988). The adverse-selection component is due to the existence of informed traders. When market-makers and informed investors possess asymmetric information, informed investors can profit by trading on their private/superior information, while market-makers provide them liquidity on a loss. Therefore, market-makers tend to widen BAS in order to reduce the possibility of informed trading and increase the profit traded with other investors. The second component, transitory costs, contains inventory-hold costs, clearing costs and/or monopoly profit that are less related to changes in underlying value. Stoll (1989) further decomposes BAS into three components, namely adverse-selection, inventory-hold and order processing costs. He finds that order processing costs account for the largest part of BAS, followed by adverse-selection and inventory-hold costs in turn. More recently, Bollen et al. (2004) have added level of competition as an additional component, since increases in competition among market-makers reduces the profit of each market-maker and so does BAS.

Studies into BAS components are usually implemented by cross-sectional analysis, but there is also literature analysing BAS via time-series models. Wang and Yau (2000) investigate S&P 500 index futures, Deutsche Mark (DM) futures, gold futures and silver futures traded in the Chicago Mercantile Exchange (CME) and the Commodity Exchange (COMEX), and find a positive relation between BAS and price volatility, and a negative relation between BAS and trading volume. Moreover, Huang (2004) analyses the determinants of BAS components in the Taiwan Futures Exchange (TAIFEX) and Singapore Exchange Derivatives Trading Limited (SGF-DT) under an intra-day framework, and suggests that volatility and information are major determinants of components, while number of trades is not.

This chapter employs a time-series approach to investigate the determinants of BAS components for TOCOM energy futures markets, instead of investigating the components of BAS. This is due to the fact that this research only focuses on TOCOM energy futures, so the number of observations (six contracts) is not enough for a cross-sectional analysis. However, the variables chosen still reflect/contain the determinants of three types of components, namely adverse-selection costs, inventory-hold costs, and order processing costs. The fourth component, level of competition, is excluded since it is not possible to obtain detailed information about market-makers.

In addition, this study considers two different asymmetric effects of trading volume on BAS, which are sell-initiated transactions and negative-return transactions.

Prior literature shows that the trading pattern and behaviour of sellers and buyers are different. Kraus and Stoll (1972) and Gemmill (1996) suggest that buy blocks (plus ticks) have a bigger price impact on average than sell blocks on the New York Stock Exchange (NYSE) and the London Stock Exchange. Chan and Lakonishok (1993, 1995) also find that the block of purchase for a sample of 37 large institutions has a much greater price impact than that of sales on the NYSE and the American Stock Exchange (AMEX), and that the price impact of sales block is much smaller than that indicated by the findings of Kraus and Stoll (1972). More recently, Frino et al. (2008) investigate futures on CME, and find large buy trades have a higher permanent price impact (information effect), whereas temporary price impact (liquidity effect) is found for large sell trades. Therefore, it seems most literature suggests that sell-initiated block trading causes a lower and temporary price impact than buy-initiated block trading. Consequently, we expected that BAS is lower for sell-initiated trades, as it has a lower price impact and lower possibility of being subject to informed trading.

The dummy of negative-return transactions measures the attitude of market participants towards different market conditions, namely upside and downside market conditions. Adams and Montesi (1995) show that corporate managers are mostly concerned about downside risk. Earlier, Petty and Scott (1981) found that many Fortune 500 firms identified risk as the probability of falling below a target return. If market-makers are more sensitive to downside market conditions, BAS should be widened when a negative-return transaction occurs, and vice versa. However, if market-makers are indifferent to upside and downside market conditions, an asymmetric effect may not exist.

This study contributes to the literature in three aspects. First, this is the first research to analyse the pattern of bid-ask spread in TOCOM energy markets. Second, we consider the potential asymmetric impact of transaction initiation sides (buy- or sell-initiated). Finally, the investigation of positive- and negative-return transactions allows us to understand market-makers' preferences for upside and downside risks.

6.2 Market-making Costs

BAS is the payoff earned by market-makers, so should consist of all the possible costs incurred when market-makers provide liquidity to the market. According to Bollen et al. (2004), there are four main components of BAS, adverse-selection, inventory-hold, order processing and competition costs. However, due to lack of information about the competition level, this study only considers the first three components.

6.2.1 Adverse-selection Costs

Market-makers bear adverse-selection costs when trading with informed investors who have private information about the price movement of petroleum. In equilibrium, the loss from trading with informed traders is assumed to be the same size of the gain from trading with uninformed traders. The expected loss from trading with informed traders is viewed as adverse-selection costs for market-makers. Different proxies for adverse-selection costs have been utilised by literature. For example, Branch and Freed (1977) use the number of securities in which a dealer makes a market, because a dealer with a larger number of securities is less informed about individual stock. Glosten and Harris (1988) use the concentration of ownership among insiders. A corporation with a higher concentration has a greater probability of trading on their prior information, which then results in higher adverse-selection costs. The market value of shares outstanding is used by Harris (1994), since information from a larger firm tends to be more well-known and public, which reduces the probability of adverse-selection. Easley et al. (1996) use the volume of trading as the proxy for adverse-selection cost. They argue that the information for highly traded securities is more well-known, so traders are less likely to possess private information that they can trade on. By contrast, the less frequently traded security is analysed only by a few investors and specialists, so the informed trading has higher probability to happen. Hence, high trading volume indicates that the high possibility of uninformed trading and low cost of adverse selection, and market makers would require less compensation by narrowing the bid-ask spread.

6.2.2 Inventory-hold Costs

Inventory-hold costs occur when market-makers hold the inventory that they intend to supply to traders in the market. There are two obvious costs associated with holding the inventory. The first is the opportunity cost of funds. If the funds of market-makers are held to the inventory, they lose the opportunity to trade on other assets. The second cost is the risk of adverse movement. This cost is incurred when price moves differently to market-makers' expectations and before they can provide liquidity to other investors. Several proxies have been used in literature for inventory-hold costs. For example, volatility is the most obvious proxy for the second kind of inventory-hold costs. Along this line, Tinic (1972) utilises the standard deviation of price to measure inventory-hold costs, Stoll (1978) uses the logarithm of the return variance, and Harris (1994) uses return standard deviation. Trade frequency and the number of shareholders are employed by Demsetz (1968), since both are viewed to represent the transaction rate. When the transaction rate is higher, market-makers are less likely to bear losses from either opportunity cost or the risk of adverse movement.

6.2.3 Order-processing Costs

Order-processing costs are, as the name suggests, the costs directly related to providing liquidity, including exchange seats, floor space rent, computer costs, labour costs, and even the opportunity cost of market-makers' time. Because they are mostly fixed costs, they tend to be lower when trading volume is high. As market-makers usually provide liquidity for more than one security, order-processing costs can be reduced to a very small amount. Hence, the literature mainly utilises trading volume, number of transactions, or the inverses and logarithms of these as proxies of order-processing costs (Tinic, 1972; Tinic and West, 1972; Tinic and West, 1974; Branch and Freed, 1997; Stoll, 1978; Harris, 1994). In a highly competitive market, BAS may not cover order-processing costs, and be equal to the marginal costs of providing liquidity. Klock and McCormich (1999) investigate the bid-ask spread of NASDAQ stocks, and find negative relation between the number of market makers and the bid-ask spread. According to the information from TOCOM, the number of designated market makers is five in 2011[15], but without further information, such as the number of futures for each market maker and the market maker's share for each contract, it is difficult to conclude whether TOCOM is a competitive market between market makers.

6.3 Methodology

In this section, two models are introduced. The first one, used as a benchmark model, includes the two possible determinants of the traditional three components mentioned in the previous section, trading volume and realised volatility, and a dummy capturing weekend effect. The other model adds two more intersection of dummies, sell-initiated transactions and negative-return transactions, and trading volume. According to the discussion in Chapter 5, the endogeneity problem may exist for BAS, realised volatility and trading volume. Therefore, a three-equation simultaneous system is employed in this chapter, namely BAS, realised volatility and trading volume equations.

6.3.1 Model 1: Benchmark Model

The benchmark model considers possible determinants of BAS components. Firstly, we consider adverse-selection costs. Due to the lack of market information and the difference between the financial market and energy market, several variables mentioned in the last section are unobtainable, such as the number of securities (futures here) to which market-makers provide liquidity, the concentration of ownership, and the market capitalisation of securities. Therefore, the most suitable variable is trading volume, as suggested by Easley et al. (1996). Next, the order-processing cost is also captured by trading volume in this chapter, because it is normally a fixed number and the marginal order-processing costs can be minimised when the trading volumes is greater. In addition, literature (Tinic, 1972; Tinic and

[15] TOCOM refused to provide further information of designated market makers since it is confidential.

West, 1972; Tinic and West, 1974; Branch and Freed, 1997, and among others) also uses trading volume as the measure of order-processing costs. Finally, two possible variables reflecting inventory-hold costs are considered, namely volatility and traded frequency. Volatility measures the possibility of assets held by market makers moving reversely. When volatility increases, maker makers have higher probability of losing money from holding assets. Trade frequency is defined as the average time of each trade arriving, and estimated by dividing the trading time per day by the number of transactions per day. Demsetz (1968) points out that the opportunity cost for market makers is lower when the trade happens more frequently because high trade frequency let market makers quickly disposal of their inventory. However, because trade frequency is similar to the inverse of the number of transactions, it is highly correlated with trading volume. Therefore, this chapter only considers using return realised volatility as the determinant of inventory-hold costs.

Due to the potential endogeneity issue between BAS, realised volatility and trading volume, a three-equation simultaneous system is employed, namely a trivariate SVAR. As discussed in Chapter 5, we have to impose at least 3 restrictions ($\frac{3(3-1)}{2}$) on the structural elements. The first restriction is on the impact of realised volatility on trading volume, which is also imposed in Chapter 5. The other two restrictions are imposed on the impact of contemporaneous BAS on realised volatility and trading volume respectively. Beginning with the relation between realised volatility, when realised volatility increases, market makers need to widen BAS in order to compensate the potential loss from the rise in the probability of prices reversely moving. However, when BAS is widened, it does not necessarily increase the BAS since it may be the result of the shocks from other components. Therefore, the contemporaneous influence of BAS shocks on realised volatility is restricted to zero. Next, with respect to trading volume, Kyle (1985) suggests that market makers adjust BAS after observing the arrive of order flows, so trading volume is expected to contemporaneously impact BAS instead of the opposite.

In general, in addition to the lag terms, our model includes two main variables as independent variables, realised volatility and trading volume. Realised volatility is treated as the determinant of inventory-hold costs, and trading volume is treated as the determinant of both adverse-selection costs and order-processing costs. As a result, the benchmark model (Model 1) is presented as

$$\begin{aligned}
\mathrm{BAS}_t &= \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{\mathrm{S},t} \\
\sigma_t &= \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t} \\
V_t &= \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t},
\end{aligned} \tag{6.1}$$

where BAS_t is bid-ask spread at time t, σ_t is realised volatility of returns at time t, V_t is the trading volume of the transaction at time t, and D_t^W is the dummy for the first transaction after the weekend or holidays. $\varepsilon_{\mathrm{S},t}$, $\varepsilon_{\sigma,t}$, and $\varepsilon_{V,t}$ are the residuals of BAS, realised volatility and trading volume equations respectively, and follow normal distribution. The weekend dummy is added because we find the first 15-minute realised volatility usually increases right after weekends[16], which may reflect the large amount of information that is generated during weekends. The model is estimated by OLS with heteroskedasticity and autocorrelation consistent standard error since slight serial correlation and serious heteroscedasticity issues are found.

6.3.2 Model 2: The Asymmetric Effect of Sell-driven and Negative-return Transactions on BAS

Model 2 follows the specifications of Model 1 but considers the symmetric impact of sell-driven and negative-return transactions. Two dummy variables for sell-initiated and negative-return transactions are included in the equation, shown as

$$\begin{aligned}
\mathrm{BAS}_t &= \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \\
&\qquad \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{\mathrm{S},t} \\
\sigma_t &= \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t} \\
V_t &= \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t},
\end{aligned} \tag{6.2}$$

$$D_t^S = \begin{cases} 1, & \text{sell initiated transaction} \\ 0, & \text{otherwise} \end{cases},$$

$$D_t^N = \begin{cases} 1, & \text{negative return transaction} \\ 0, & \text{otherwise} \end{cases},$$

[16] The increase in the realised volatility is only found in the first 15-minute interval. With regard to the average level of realised volatility after weekend, there is no significant increase as suggested by Table 3-6.

where D_t^S is the indicator of sell-initiated transaction at time *t*, and D_t^N is the indicator of negative-return transaction at time *t*. Because the main focus of this chapter is BAS, the intersection of dummies and trading volume is not considered in other two equations, namely realised volatility and trading volume. The classification of buy- or sell-initiated transactions is based on Lee and Ready (1991). Two different cases are considered. First, when the transaction prices are between bid and ask prices, we compare the transaction price with prevailing bid and ask prices between current and previous transactions.[17] If the transaction price is above or at ask price, it is classified as a buy-initiated transaction. If the transaction price is below or at bid price, it is classified as a sell-initiated transaction. Second, if the transaction price is within the range of bid and ask prices and different from the previous transaction price, this transaction is classified as buy (sell)-initiated trade when it is higher (lower) than the previous transaction price, which is also called up/plus (down/minus) tick. If the transaction price is exactly the same as the previous transaction price, called a zero tick, it is then classified as the same type of trade as the previous one.

In equation (6.2), α_S measures the difference in the impact of trading volume on BAS between sell- and buy-initiated transactions. Since the expected sign of α_2 is negative, positive α_S indicates that an increase in trading volume reduces market-makers' costs to a lower extent when the transaction is sell-initiated. According to Frino et al. (2008), one expects that α_S is negative because sell-initiated trades tend to have a lower price impact and are more likely to be uninformed trading, which reduces the market-makers' costs. As a result, market-makers require less compensation for sell-initiated transactions than buy-initiated ones. Besides that, α_N measures the impact of negative-return transactions. The sign and significance of α_N is uncertain and dependent on market-makers' risk preferences. If market-makers are sensitive to downside risk, α_N is expected to be positive as it implies they require more compensation (widen BAS) for downside risk, and vice versa. However, if market-makers are indifferent to risk on both sides, α_N is expected to be insignificant.

[17] Lee and Ready (1999) compare the transaction price with prevailing bid and ask prices within the last five seconds in order to confirm the validity of bid and ask prices. However, liquidity in TOCOM is relatively lower than NYSE stocks, so we compare the transaction price only with the bid and ask prices of current and previous trades. The appendix gives examples of the identification procedure in detail.

6.4 Data

6.4.1 Description of Data

Our sample data consists of intraday bid, ask and transaction prices of TOCOM energy futures for the period from 22 September 2010 to 30 October 2015, acquired from Tomson Reuter Tick History. The main reason for using 15-minute samples instead of daily samples is that the aggregate of buy/sell-initiated transactions may contain less information about trade sides, as the size of net trading volume (sell-initiated over buy-initiated volume) is ignored when a dummy is used. For example, a low positive net trading volume is also recognised as a sell-initiated transaction, but actually has much less impact on BAS, which may lower the impact of sell-initiated transactions. When the aggregation interval is shortened, i.e. there is a higher-frequency sample, this issue can be reduced.

In this chapter, only the most liquid two contracts of each commodity are included, namely 5- to 6-month contracts for gasoline and kerosene futures and 4- to 5-month contracts for crude oil futures. The lack of valid observations for other lowly liquid contracts is the main reason for the sample selection. The most liquid two futures have at least two-third valid observations of the total sample, while the other contracts do not.

6.4.2 Estimation of Bid-ask Spread

Bid-ask spread is usually estimated by two approaches, quoted relative spread and effective relative spread. Quoted relative spread is the ratio of the difference in bid and ask price to mid quote, and can be expressed as

$$\mathrm{BAS}_t = \frac{Ask_t - Bid_t}{Mid_t}, \qquad Mid_t = \frac{Ask_t + Bid_t}{2}, \tag{6.3}$$

where Bid_t is the bid price at time *t*, Ask_t is the ask price at time *t*, and Mid_t is the mid quote at time *t*. Effective relative spread is proposed by Huang and Stoll (1994), which suggests the difference between price and mid quote is one-half of effective spread. Consequently, effective relative spread is calculated as

$$\mathrm{BAS}_t = 2|\ln(P_t) - \ln(Mid_t)|, \quad (6.4)$$

where P_t is the transaction price.

Glosten and Harris (1988) have shown the difference between quoted spread and effective spread to be the adverse-selection cost. Effective spread is the amount market-makers' can earn from informed investors while quoted spread is the amount earned from uninformed investors. The concept is based on an immediate buy/sell combination conducted by informed traders. Assume informed traders buy futures at time t and sell immediately at time t+1. The ask and bid prices should rise following the purchase (t+1) according to Stoll (1989), given that spread is determined by either inventory-hold costs or adverse-selection costs. The informed trader can then sell futures at a higher bid price at time t+1, which causes a lower rent to be earned by market-makers. In general, effective spread is usually lower or equal to quoted spread. This thesis only focuses on the determinants of effective spread for two reasons. Firstly, the major participants of TOCOM energy futures are non-commercial traders, who are potentially informed traders and more likely to conduct immediate buy/sell combinations. Secondly, compared with quoted spread, effective spread can represent the rent received by market-makers more precisely since both bid/ask prices may change following a purchase or sale of futures.

6.4.3 Descriptive Statistics

Descriptive statistics of effective BAS are reported in Table 3-7. In addition to the positive relation between maturity and effective BAS, it appears a pattern of effective BAS across commodities. The average effective BAS of kerosene is highest, followed by crude oil and gasoline in turn. One possible explanation for the difference in effective BAS among the three commodities is related to trading volume, since the effective BAS of higher liquid futures (higher trading volume) is expected to be lower than that of lower ones (lower trading volume). According to Table 3-3, the trading volume of gasoline futures is much higher than kerosene and crude oil, so the effective BAS of gasoline is expected to be lower than that of the other two commodities.

Table 6-1: The average level of five variables for intraday sell- and buy-initiated transactions

Panel A: Gasoline				
	5-month		6-month	
	Buy	Sell	Buy	Sell
Effective BAS	0.0504%	0.0505%	0.0399%	0.0401%
Realised volatility	0.1247%	0.1283%	0.1122%	0.1148%
Trading volume	24.4133	28.0291	90.8199	95.6839
The size of blocks	129.5891	133.9311	341.4410	347.5365
The number of blocks	47.72%	52.28%	48.45%	51.55%
Panel B: Kerosene				
	5-month		6-month	
	Buy	Sell	Buy	Sell
Effective BAS	0.0699%	0.0700%	0.0660%	0.0656%
Realised volatility	0.1392%	0.1377%	0.1259%	0.1254%
Trading volume	14.6085	15.8319	24.0306	26.6557
The size of blocks	82.5812	80.6542	120.2769	119.6170
The number of blocks	48.24%	51.76%	48.50%	51.50%
Panel C: Crude oil				
	4-month		5-month	
	Buy	Sell	Buy	Sell
Effective BAS	0.0567%	0.0567%	0.0487%	0.0491%
Realised volatility	0.1668%	0.1657%	0.1389%	0.1428%
Trading volume	25.6603	29.6464	58.5859	64.3703
The size of blocks	175.1726	177.8171	276.6321	292.0971
The number of blocks	45.95%	54.05%	49.00%	51.00%

- Effective BAS is the average effective bid-ask spread. Realised volatility is the average return realised volatility in each 15-minute interval. Trading volume is the average trading volume in each 15-minute interval. The definition of block trading is the trading volume that exceeds the 90th percentile of total trading volume. The size of blocks is the average trading volume of each block trading. The number of blocks is the ratio of the number of sell-/buy-initiated block transactions to the number of total block transactions.

Furthermore, it is of our interest to examine the difference in the dynamics of sell- and buy-initiated transaction. The comparison of five basic variables between intraday sell- and buy-initiated transactions is reported in Table 6-1, including average effective BAS, realised volatility, average trading volume, trading volume in each block trading, and the ratio of the number of block transactions to the total number of transactions. Several differences between intraday sell- and buy-initiated transactions can be noticed. Firstly, it seems that the average effective BAS is higher when the transaction is sell-initiated, apart from in the case of 6-month kerosene futures, although the magnitude of the difference is not large. Secondly, the average return realised volatility of sell-initiated transactions is greater than that of buy-initiated ones for 3 out of 6 contracts, namely 5-month and 4-month gasoline and 5-month crude oil futures. Next, the average trading volume of intraday sell-initiated transactions also seems to be greater than that of intraday buy-initiated ones. Finally, we compare the difference in the pattern of sell- and buy-initiated block trading. The block trading is defined as transactions with trading volumes over the 90^{th} percentile of total trading volumes. The results show that the average trading volume of sell-initiated block transactions is larger than that of buy-initiated ones, which may imply that the information carried by sell-initiated transactions is greater than by buy-initiated transactions. In addition, block trading is more likely to happen when the transaction is sell-initiated. For example, for 5-month crude oil futures, 51% of block transactions are sell-initiated while 49% are buy-initiated. Overall, compared with buy-initiated transactions, sell-initiated transactions are characterised by high effective BAS, high trading volume, and high possibility of block trading.

6.5 Empirical Results

6.5.1 Estimation results of the benchmark (Model 1)

The results of Models 1 to 2 are reported in Table 6-2 to 6-4. The first column of the result of each contract shows the estimated coefficients of Model 1. Regarding the BAS equation, it appears that all coefficients are significant for all futures. The coefficients of contemporaneous realised volatility (α_1) are positive for all futures, which is consistent with expectations because market-makers tend to widen BAS to avoid potential losses caused by increasing volatility. Regarding the coefficients of contemporaneous trading volume (α_2), the results are negative, which is also consistent with expectations. The coefficients are expected to be negative since 1) adverse-selection costs should be lower when volume is high because the increase in volume will increase the probability of uninformed trading; 2) order-processing costs should be amortised by a higher number of trading volumes. With regard to the lagged variables, the coefficients of lagged realised volatility and trading volume (α_3 and α_4) are all significant, and the direction of them is consistent with the contemporaneous coefficients. Interestingly, the coefficients of weekend dummy (α_W) are negative. Intuitively, one would expect the coefficient to be positive because there is a large amount of information that is not reflected in markets during weekends. However, as realised volatility is included in Model 1, the impact of increasing volatility caused by a large amount of information should also be controlled by α_1. Consequently, the negative α_W may be explained by other reasons. One explanation is the increase in demand of trading on Monday or the first trading day right after weekends or holidays. In order to adjust the holding position of futures responding to information during weekends and holidays, market participants tend to trade quickly at the opening of the market. Figure 6-1 shows average numbers of transactions for the first 15-minutes interval among 5 weekdays and the dates of our weekend dummy. It appears that the numbers of transactions for the first 15-minutes interval on Monday and weekend dummy being 1 are much higher than that on the other weekdays. Therefore, market makers are likely to lower BAS so that traders can be attracted to transact with them.

Move to the results of realised volatility and trading volume equation, it seems that the estimation results are not exactly similar to the findings in Chapter 5. Although the positive contemporaneous relation between realised volatility and trading volume is found, but the lead-lag impact of trading volume on realised volatility appears to be negative. However, Darrat et al. (2007) also find the negative intraday causality from trading volume to realised volatility. They provide the explanation that the increase in trading volume is a result of assets being mispriced and contemporaneously causes the rise in volatility, which leads to a sequential decrease in volatility after the price reverts the fundamental value. This may only be observed in high-frequency data, since the price should convert a rational value at the end of trading day to eliminate any arbitrage opportunities at the opening in the other day. Regarding the coefficients of lagged BAS on realised volatility and trading volume, the results are consistent with the inverse impacts. The increase in BAS sequentially increases the realised volatility but decreases the trading volume since the wider BAS can cause the greater price change and is less attractive for market participants. In addition, the coefficients of weekend dummy (β_W and γ_W) indicates that the realised volatility and trading volume of the first 15-minute interval are greater after a longer non-trading hours (Monday or after holidays). This finding is in line with the argument in the last paragraph. Due to the large information to digest after a long non-trading time, the trading activity sharply increases, which increases realised volatility but decreases bid-ask spread.

6.5.2 Estimation results of the asymmetric model (Model 2)

The second column reveals the results of Model 2, and the discussion only focuses on the BAS equation in this section since the intersection terms are only added to the BAS equation. The coefficients α_S, measuring the difference in the impact of volume on BAS between buy- and sell-initiated transactions, are mostly positive and significant as expected, except in the cases of 6-month kerosene futures. This indicates that market-makers require more compensation when sell-initiated transactions occur. Since trading volume reflects both adverse-selection and order-processing costs, we discuss the asymmetric effect of these two aspects, namely order-processing costs and adverse-selection costs. Beginning with order-processing costs, BAS should be narrowed when trading volume is greater because the transaction fee per trading volume is reduced. However, the marginal effect of an increase in trading volume reducing order-processing costs should diminish with increases in the trading volume. A comparison of trading volume between buy- and sell-initiated transactions shows that the trading volume of sell-initiated transactions is significantly higher than that of buy-initiated ones (see Table 6-1). Therefore, the marginal effect of sell-initiated trading volume amortising order-processing costs is lower than the buy-initiated one.

Turning to adverse-selection costs, a higher trading volume implies a potentially lower proportion of informed trading, as do adverse-selection costs and BAS. Nonetheless, the result of a positive α_S suggests that even though the sell-initiated trading volume is higher than the buy-initiated, adverse-selection costs increase. A possible explanation for this is that the sell-initiated trading volume is more likely to be information-driven rather than liquidity-driven trading, which is opposed to the argument of Frino et al. (2008). Holthausen et al. (1987) and Gemmill (1996) propose a procedure to measure the permanent effect of a transaction, which decomposes total price effect into permanent and liquidity effects, as shown below

$$\text{Total price effect} = |\ln(P_t) - \ln(P_b)|, \qquad (6.5)$$

$$\text{Temporary effect} = |\ln(P_t) - \ln(P_a)|,$$

$$\text{Permanent effect} = |\ln(P_a) - \ln(P_b)|,$$

where P_t is the transaction price, P_b is the price 15 minutes before the transaction and

P_a is the price 15 minutes after the transaction. Table 6-5 shows the results of permanent price impact between buy- and sell-initiated transactions. It is evident that the permanent price impact of sell-initiated trades is significantly higher than that of buy-initiated ones, except in the cases of 6-month gasoline and 5-month crude oil, although the differences in the values of sell-initiated over buy-initiated transactions are all positive. Consequently, sell-initiated trading may have a higher proportion of informed trading than buy-initiated, leading to higher adverse-selection costs for sell-initiated transactions.

The other asymmetric effect in Model 2 is the negative-return transaction, measured by the coefficients α_N. The estimated coefficients are only significant for 5-month gasoline and 6-month kerosene, although the sign for the former is negative, and that for the latter is positive. Insignificance may indicate that market makers are indifferent between upside and downside market conditions, so the impact of trading volume on BAS remains the same level for positive- and negative-turn. In terms of the autocorrelation of residuals, Ljung-Box test is performed with 22 lags. The results of 22nd order Q statistic suggest that the serial correlation is strong, so all the standard error is estimated by the HAC approach. Regarding the comparison of SBIC between Model 1 and Model 2, it seems like including two intersection terms does not provide more explanation to the model. This may be because, despite the significant asymmetric effect of sell-initiated volume on BAS, it is still included in the impact of trading volume, leading to a limited increase in SBIC. However, the results of LR test still suggest the importance of including these dummy variables, since most of them is significant under 5% level.

Table 6-2: Results of two SVAR models with effective BAS for gasoline futures

Model 1:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0444***	0.0445***	0.0481***	0.0482***
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
α_1	3.7865***	3.7861***	3.0753***	3.0743***
	(0.2669)	(0.2668)	(0.3267)	(0.3269)
α_2	-0.0025***	-0.0025***	-0.0031***	-0.0032***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
α_3	2.2423***	2.2421***	2.5237***	2.5242***
	(0.1614)	(0.1616)	(0.2356)	(0.2353)
α_4	-0.0022***	-0.0022***	-0.0027***	-0.0027***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
α_5	0.1870***	0.1870***	0.2221***	0.2222***
	(0.0096)	(0.0096)	(0.0086)	(0.0086)
α_W	-0.0329***	-0.0329***	-0.0329***	-0.0329***
	(0.0026)	(0.0026)	(0.0023)	(0.0023)
α_S		0.0002**		9.72E-5*
		(0.0001)		(5.75E-5)
α_N		-0.0002*		1.92E-5
		(0.0001)		(5.71E-5)
β_0	0.0005***	0.0005***	-0.0007***	-0.0007***
	(0.0133)	(0.0133)	(0.0173)	(0.0173)
β_1	0.0003***	0.0003***	0.0005***	0.0005***
	(3.7205)	(3.7205)	(2.7977)	(2.7977)
β_2	0.1754***	0.1754***	0.1427***	0.1427***
	(0.0049)	(0.0049)	(0.0040)	(0.0040)
β_3	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.1477)	(0.1477)	(0.1394)	(0.1394)
β_4	0.0072***	0.0072***	0.0086***	0.0086***
	(0.0668)	(0.0668)	(0.0512)	(0.0512)
β_W	0.0034***	0.0034***	0.0036***	0.0036***
	(2.09E-5)	(2.09E-5)	(3.58E-5)	(3.58E-5)
γ_0	1.1247***	1.1247***	1.5258***	1.5258***
	(7.11E-6)	(7.11E-6)	(9.81E-6)	(9.81E-6)
γ_1	-24.3544***	-24.3544***	4.6151*	4.6151*
	(0.0109)	(0.0109)	(0.0070)	(0.0070)
γ_2	0.5686***	0.5686***	0.6203***	0.6203***
	(6.47E-6)	(6.47E-6)	(7.23E-6)	(7.23E-6)
γ_3	-1.7650***	-1.7650***	-0.1628	-0.1628
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
γ_W	2.6691***	2.6691***	2.2337***	2.2337***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
$Q(22)_{EBAS}$	5498.54***	5503.88***	8054.85***	8055.77***
$Q(22)_{\sigma_t}$	5436.83***	5436.83***	4213.81***	4213.81***
$Q(22)_{V_t}$	5897.06***	5897.06***	4741.19***	4741.19***
SBIC	386778.46	386770.10	496228.37	496219.67
LR	5.566*		5.171*	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

Table 6-3: Results of two SVAR models with effective BAS for kerosene futures

Model 1:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0711***	0.0711***	0.0643***	0.0643***
	(0.0021)	(0.0021)	(0.0013)	(0.0013)
α_1	5.8488***	5.8584***	5.5418***	5.5407***
	(0.7397)	(0.7378)	(0.8214)	(0.8248)
α_2	-0.0082***	-0.0088***	-0.0082***	-0.0085***
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
α_3	2.6088***	2.6064***	2.4209***	2.4203***
	(0.3509)	(0.3470)	(0.2932)	(0.2909)
α_4	-0.0032***	-0.0032***	-0.0033***	-0.0033***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
α_5	0.2419***	0.2417***	0.2282***	0.2282***
	(0.0208)	(0.0207)	(0.0148)	(0.0148)
α_W	-0.0648***	-0.0643***	-0.0642***	-0.0640***
	(0.0074)	(0.0073)	(0.0062)	(0.0062)
α_S		0.0011***		8.25E-5
		(0.0004)		(0.0002)
α_N		0.0002		0.0005**
		(0.0004)		(0.0002)
β_0	0.0006***	0.0006***	0.0004***	0.0004***
	(0.0263)	(0.0263)	(0.0268)	(0.0268)
β_1	0.0002***	0.0002***	0.0003***	0.0003***
	(7.3488)	(7.3488)	(6.7203)	(6.7203)
β_2	0.1210***	0.1210***	0.1091***	0.1091***
	(0.0088)	(0.0088)	(0.0075)	(0.0075)
β_3	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.1996)	(0.1996)	(0.2371)	(0.2371)
β_4	0.0058***	0.0058***	0.0073***	0.0073***
	(0.1400)	(0.1400)	(0.1403)	(0.1403)
β_W	0.0050***	0.0050***	0.0057***	0.0057***
	(4.34E-5)	(4.34E-5)	(4.81E-5)	(4.81E-5)
γ_0	1.0940***	1.0940***	1.2660***	1.2660***
	(1.38E-5)	(1.38E-5)	(1.49E-5)	(1.49E-5)
γ_1	-15.8057**	-15.8057**	-15.7270**	-15.7270**
	(0.0228)	(0.0228)	(0.0240)	(0.0240)
γ_2	0.4898***	0.4898***	0.5516***	0.5516***
	(1.28E-5)	(1.28E-5)	(1.31E-5)	(1.31E-5)
γ_3	-1.6233***	-1.6233***	-2.2143***	-2.2143***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
γ_W	2.6626***	2.6626***	2.8380***	2.8380***
	(0.0013)	(0.0013)	(0.0014)	(0.0014)
$Q(22)_{EBAS}$	887.14***	888.27***	903.18***	904.67***
$Q(22)_{\sigma_t}$	296.67***	296.67***	512.93***	512.93***
$Q(22)_{V_t}$	956.63***	956.63***	1004.17***	1004.17***
SBIC	93014.18	93009.16	111637.59	111630.69
LR	9.711***		6.109**	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

Table 6-4: Results of two SVAR models with effective BAS for crude oil futures

Model 1:

$\text{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$\text{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

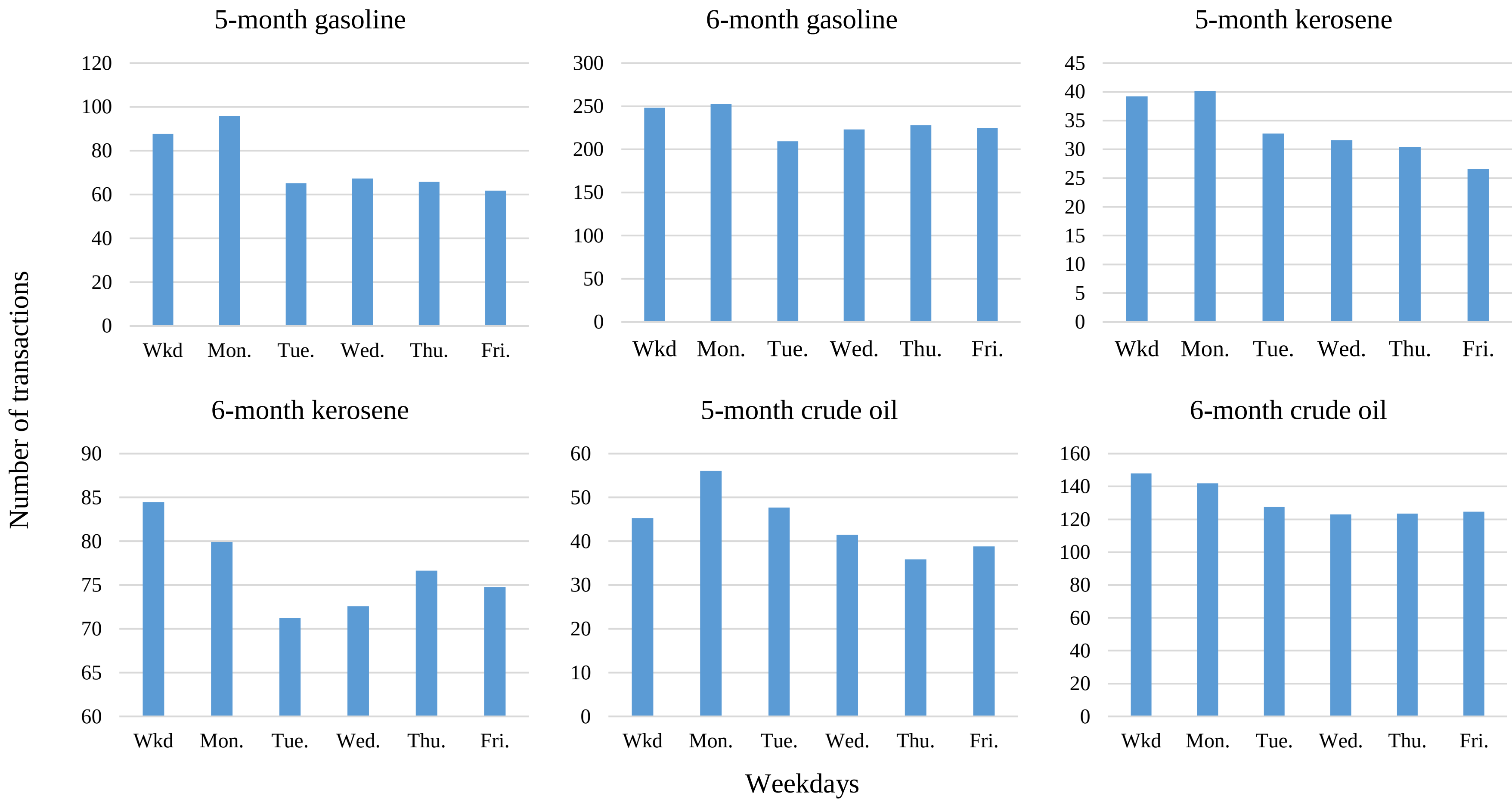
$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0442***	0.0443***	0.0336***	0.0336***
	(0.0009)	(0.0009)	(0.0008)	(0.0008)
α_1	2.4341***	2.4329***	0.3143***	0.3141***
	(0.2327)	(0.2334)	(0.0126)	(0.0126)
α_2	-0.0038***	-0.0041***	-0.0042***	-0.0043***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
α_3	1.5024***	1.5035***	0.2545***	0.2544***
	(0.1163)	(0.1159)	(0.0110)	(0.0110)
α_4	-0.0004**	-0.0004**	-0.0013***	-0.0013***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
α_5	0.2598***	0.2598***	0.3018***	0.3018***
	(0.0135)	(0.0135)	(0.0111)	(0.0111)
α_W	-0.0270***	-0.0270***	-0.0391***	-0.0391***
	(0.0031)	(0.0031)	(0.0030)	(0.0030)
α_S		0.0004***		0.0002**
		(0.0001)		(7.81E-5)
α_N		0.0002		0.0001
		(0.0001)		(7.87E-5)
β_0	0.0008***	0.0008***	0.0148***	0.0148***
	(0.0156)	(0.0156)	(0.0166)	(0.0166)
β_1	0.0002***	0.0002***	0.0040***	0.0040***
	(3.6692)	(3.6692)	(0.2499)	(0.2499)
β_2	0.1989***	0.1989***	0.2210***	0.2210***
	(0.0070)	(0.0070)	(0.0042)	(0.0042)
β_3	-0.0001***	-0.0001***	-0.0017***	-0.0017***
	(0.1382)	(0.1382)	(0.1271)	(0.1271)
β_4	0.0068***	0.0068***	0.0712***	0.0712***
	(0.0892)	(0.0892)	(0.0587)	(0.0587)
β_W	0.0047***	0.0047***	0.0235***	0.0235***
	(2.95E-5)	(2.95E-5)	(0.0003)	(0.0003)
γ_0	1.1057***	1.1057***	1.3507***	1.3507***
	(9.69E-6)	(9.69E-6)	(7.50E-5)	(7.50E-5)
γ_1	-16.0311***	-16.0311***	-1.0583***	-1.0583***
	(0.0163)	(0.0163)	(0.0052)	(0.0052)
γ_2	0.4852***	0.4852***	0.6012***	0.6012***
	(8.23E-6)	(8.23E-6)	(6.87E-5)	(6.87E-5)
γ_3	-0.2260	-0.2260	0.2898**	0.2898**
	(0.0004)	(0.0004)	(0.0020)	(0.0020)
γ_W	2.0134***	2.0134***	2.3966***	2.3966***
	(0.0007)	(0.0007)	(0.0027)	(0.0027)
$Q(22)_{EBAS}$	9991.67***	9986.74***	13124.91***	13130.84***
$Q(22)_{\sigma_t}$	3475.85***	3475.85***	8158.18***	8158.18***
$Q(22)_{V_t}$	6419.71***	6419.71***	6946.80***	6946.80***
SBIC	281565.67	281560.84	247357.63	247351.18
LR	12.247***		9.634***	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

Figure 6-1: Comparison of number of transactions at the first 15 minutes across weekdays for six futures



- Wkd denotes to the case that the dummy of weekend is 1, which includes all dates right after weekend and holidays. Mon., Tue., Wed., Thr., Fri. denote Monday, Tuesday, Wednesday, Thursday and Friday.

Table 6-5: Comparison of the permanent price impact of three futures for two maturities

	Panel A: Gasoline			
	5-month		6-month	
	Buy	Sell	Buy	Sell
Permanent price impact	0.065%	-0.070%	0.081%	-0.083%
T-Statistic	2.4973***		1.1945	
	Panel B: Kerosene			
	5-month		6-month	
	Buy	Sell	Buy	Sell
Permanent price impact	0.061%	-0.067%	0.066%	-0.071%
T-Statistic	2.2027***		2.5716***	
	Panel C: Crude oil			
	4-month		5-month	
	Buy	Sell	Buy	Sell
Permanent price impact	0.068%	-0.069%	0.072%	-0.076%
T-Statistic	0.5607		2.3407***	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. Permanent price impact is calculated as the log-return of price before and after trades.

6.5.3 Analysis with Quoted Bid-Ask Spread

To confirm the robustness of the analysis, we perform again the analysis with quoted BAS, defined as equation (6.3). The descriptive statistic of quoted BAS is reported in Table 6-6. One main difference between effective BAS (see Table 3-7) and quoted BAS is that the average effective BAS is slightly lower than the average quoted BAS. Because transaction prices are usually between bid and ask prices, the effective BAS, calculated as twice of the difference between price and mid-quote, is expected to be narrower than the quoted BAS, calculated as the difference between bid and ask prices. Regarding the autocorrelation and stationarity, the results of Q-statistic with 22 lags and ADF test suggest that quoted BAS is highly autocorrelated and stationary, which is similar to the properties of effective BAS.

The empirical results of two SVAR models, namely model 1 and model 2, are reported in Table 6-7 to 6-9. With regard to the benchmark model, even though we can still observe slightly difference in the magnitude, the significance and the sign of coefficients in the results with quoted BAS are the consistent with the effective BAS. This confirms the use of realised volatility and trading volume as the determinants of BAS, and the positive relation between realised volatility and BAS and the negative relation between trading volume and BAS. Move to the results of the asymmetric model, even though the coefficients of the sell-initiated intersection term are still positive except 6-month kerosene, but the significance and the magnitude drop for 6-month gasoline and crude oil compared with the results of effective BAS. The explanation is that effective BAS measures the rent received from informed traders while the quoted BAS measures the rent received from uninformed traders (Glosten and Harris, 1988). Therefore, the effective BAS is more sensitive to the increase in the probability of informed trading, while the quoted BAS is less sensitive. However, the coefficients of negative-return intersection term become positive and significant for 5-month kerosene and crude oil futures, which is consistent with the finding of Estrada (2007) who suggests that the market participants are more sensitive to downside risk measure rather than the overall risk measure.

In terms of the diagnostic tests, the 22^{nd} order Q statistic suggests the residuals of all contracts are highly correlated, which is consistent with the results of effective BAS. Therefore, all standard errors are still HAC estimators. The results of LR tests suggest the joint significance of both intersection terms, namely sell-initiated transactions and negative-return transactions. Overall, the empirical finding with quoted BAS are similar to effective BAS, but with slight difference in the significance of the asymmetric coefficients.

Table 6-6: Descriptive statistics and preliminary tests for quoted bid-ask spreads

	Gasoline					
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	0.2685%	0.1459%	0.1081%	0.0755%	0.0552%	0.0420%
Std.	0.3769%	0.1363%	0.0907%	0.0633%	0.0387%	0.0312%
Skewness	7.2125	6.5857	10.1433	33.4748	6.2636	3.5396
Kurtosis	108.6143	211.0780	534.2364	3985.2150	251.2490	41.7848
Q(22)	663837.0 [a]	383381.3 [a]	275656.0 [a]	93663.6 [a]	67758.7 [a]	69980.9 [a]
ADF	-56.6209 [a]	-64.5645 [a]	-67.7466 [a]	-99.3490 [a]	-94.6675 [a]	-102.6660 [a]
	Kerosene					
	1-month	2-month	3-month	4-month	5-month	6-month
Mean	0.2811%	0.1772%	0.1370%	0.1046%	0.0851%	0.0728%
Std.	0.4670%	0.1643%	0.1111%	0.0869%	0.0738%	0.0628%
Skewness	16.2084	6.5875	2.2897	2.9099	8.4958	2.8784
Kurtosis	484.8044	345.6907	19.2411	25.4043	493.6108	19.7851
Q(22)	640342.9 [a]	457031.5 [a]	412446.4 [a]	376354.2 [a]	193434.5 [a]	160516.4 [a]
ADF	-51.5495 [a]	-60.7393 [a]	-53.0654 [a]	-60.2469 [a]	-84.3190 [a]	-92.1419 [a]
	Crude oil					
	nearby-m.	1-month	2-month	3-month	4-month	5-month
Mean	0.3051%	0.1285%	0.0981%	0.0794%	0.0655%	0.0528%
Std.	0.4525%	0.1489%	0.0791%	0.0660%	0.0495%	0.0451%
Skewness	5.0565	25.0261	2.5304	20.7353	5.6443	3.9485
Kurtosis	46.3623	1601.8396	16.7432	1843.7884	116.0780	32.0555
Q(22)	876127.0 [a]	374912.4 [a]	500252.9 [a]	215295.7 [a]	177372.7 [a]	132059.3 [a]
ADF	-40.4521 [a]	-59.9093 [a]	-51.9935 [a]	-79.9660 [a]	-80.3987 [a]	-99.7827 [a]

- [a] and [b] indicate rejection at the 1% and 5% significance levels. nearby-m. stands for nearby-month contracts. Std. is the standard deviation. Q(22) is Q-statistic with 22 lags. ADF is the augmented Dickey-Fuller test statistic. The sample period is from 22 September 2010 to 30 October 2015.

Table 6-7: Results of two SVAR models with quoted BAS for gasoline futures

Model 1:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0457***	0.0458***	0.0480***	0.0481***
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
α_1	3.5322***	3.5309***	2.9555***	2.9543***
	(0.2636)	(0.2636)	(0.3174)	(0.3176)
α_2	-0.0019***	-0.0020***	-0.0031***	-0.0032***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
α_3	2.3172***	2.3169***	2.4344***	2.4344***
	(0.1518)	(0.1519)	(0.2225)	(0.2221)
α_4	-0.0024***	-0.0024***	-0.0026***	-0.0026***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
α_5	0.2029***	0.2029***	0.2366***	0.2367***
	(0.0102)	(0.0102)	(0.0091)	(0.0091)
α_W	-0.0321***	-0.0321***	-0.0332***	-0.0332***
	(0.0025)	(0.0025)	(0.0021)	(0.0021)
α_S		0.0002**		5.63E-5
		(0.0001)		(5.48E-5)
α_N		-0.0001		6.16E-5
		(0.0001)		(5.48E-5)
β_0	0.0004***	0.0004***	-0.0007***	-0.0007***
	(0.0139)	(0.0139)	(0.0175)	(0.0175)
β_1	0.0003***	0.0003***	0.0005***	0.0005***
	(3.6662)	(3.6662)	(2.7561)	(2.7561)
β_2	0.1733***	0.1733***	0.1411***	0.1411***
	(0.0049)	(0.0049)	(0.0040)	(0.0040)
β_3	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.1570)	(0.1570)	(0.1451)	(0.1451)
β_4	0.0078***	0.0078***	0.0090***	0.0090***
	(0.0670)	(0.0670)	(0.0511)	(0.0511)
β_W	0.0034***	0.0034***	0.0036***	0.0036***
	(2.20E-5)	(2.20E-5)	(3.69E-5)	(3.69E-5)
γ_0	1.1471***	1.1471***	1.5339***	1.5339***
	(7.13E-6)	(7.13E-6)	(9.82E-6)	(9.82E-6)
γ_1	-22.9080***	-22.9080***	5.2500*	5.2500*
	(0.0107)	(0.0107)	(0.0070)	(0.0070)
γ_2	0.5678***	0.5678***	0.6195***	0.6195***
	(6.42E-6)	(6.42E-6)	(7.23E-6)	(7.23E-6)
γ_3	-2.0804***	-2.0804***	-0.3027**	-0.3027**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
γ_W	2.6801***	2.6801***	2.2416***	2.2416***
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
$Q(22)_{EBAS}$	6247.17***	6254.11***	8487.72***	8487.19***
$Q(22)_{\sigma_t}$	5070.19***	5070.19***	3977.35***	3977.35***
$Q(22)_{V_t}$	5854.30***	5854.30***	4752.88***	4752.88***
SBIC	388901.83	388893.09	499294.87	499286.14
LR	4.802*		5.1*	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

Table 6-8: Results of two SVAR models with quoted BAS for kerosene futures

Model 1:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$\mathrm{BAS}_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0732***	0.0733***	0.0639***	0.0639***
	(0.0022)	(0.0022)	(0.0015)	(0.0015)
α_1	5.6865***	5.6916***	5.4338***	5.4325***
	(0.7246)	(0.7248)	(0.8156)	(0.8180)
α_2	-0.0073***	-0.0081***	-0.0080***	-0.0082***
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
α_3	2.6382***	2.6399***	2.3053***	2.3048***
	(0.3689)	(0.3642)	(0.2930)	(0.2913)
α_4	-0.0036***	-0.0036***	-0.0032***	-0.0032***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
α_5	0.2541***	0.2540***	0.2400***	0.2401***
	(0.0213)	(0.0212)	(0.0162)	(0.0163)
α_W	-0.0694***	-0.0687***	-0.0651***	-0.0649***
	(0.0076)	(0.0076)	(0.0064)	(0.0065)
α_S		0.0010***		-7.15E-5
		(0.0003)		(0.0002)
α_N		0.0006*		0.0005**
		(0.0004)		(0.0002)
β_0	0.0006***	0.0006***	0.0004***	0.0004***
	(0.0275)	(0.0275)	(0.0272)	(0.0272)
β_1	0.0002***	0.0002***	0.0003***	0.0003***
	(7.2062)	(7.2062)	(6.6910)	(6.6910)
β_2	0.1199***	0.1199***	0.1095***	0.1095***
	(0.0088)	(0.0088)	(0.0075)	(0.0075)
β_3	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.2065)	(0.2065)	(0.2408)	(0.2408)
β_4	0.0060***	0.0060***	0.0073***	0.0073***
	(0.1409)	(0.1409)	(0.1405)	(0.1405)
β_W	0.0050***	0.0050***	0.0057***	0.0057***
	(4.52E-5)	(4.52E-5)	(4.84E-5)	(4.84E-5)
γ_0	1.1146***	1.1146***	1.2741***	1.2741***
	(1.38E-5)	(1.38E-5)	(1.49E-5)	(1.49E-5)
γ_1	-14.6533**	-14.6533**	-15.2398**	-15.2398**
	(0.0226)	(0.0226)	(0.0240)	(0.0240)
γ_2	0.4890***	0.4890***	0.5509***	0.5509***
	(1.28E-5)	(1.28E-5)	(1.31E-5)	(1.31E-5)
γ_3	-1.7682***	-1.7682***	-2.2946***	-2.2946***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
γ_W	2.6748***	2.6748***	2.8464***	2.8464***
	(0.0013)	(0.0013)	(0.0014)	(0.0014)
$Q(22)_{EBAS}$	868.51***	871.28***	971.04***	971.87***
$Q(22)_{\sigma_t}$	270.95***	270.95***	511.52***	511.52***
$Q(22)_{V_t}$	945.79***	945.79***	1003.37***	1003.37***
SBIC	93265.27	93261.61	111734.63	111727.00
LR	12.424***		4.646*	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

Table 6-9: Results of two SVAR models with quoted BAS for crude oil futures

Model 1:

$BAS_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

Model 2:

$BAS_t = \alpha_0 + \alpha_1\sigma_t + \alpha_2 V_t + \alpha_3\sigma_{t-1} + \alpha_4 V_{t-1} + \alpha_5 BAS_{t-1} + \alpha_W D_t^W + \alpha_S V_t D_t^S + \alpha_N V_t D_t^N + \varepsilon_{S,t}$

$\sigma_t = \beta_0 + \beta_1 V_t + \beta_2\sigma_{t-1} + \beta_3 V_{t-1} + \beta_4 BAS_{t-1} + \beta_W D_t^W + \varepsilon_{\sigma,t}$

$V_t = \gamma_0 + \gamma_1\sigma_{t-1} + \gamma_2 V_{t-1} + \gamma_3 BAS_{t-1} + \gamma_W D_t^W + \varepsilon_{V,t}$

	5-month		6-month	
	Model 1	Model 2	Model 1	Model 2
α_0	0.0465***	0.0465***	0.0338***	0.0338***
	(0.0012)	(0.0012)	(0.0008)	(0.0008)
α_1	2.0949***	2.0938***	0.3007***	0.3005***
	(0.2349)	(0.2355)	(0.0125)	(0.0125)
α_2	-0.0020***	-0.0023***	-0.0038***	-0.0040***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
α_3	1.7428***	1.7435***	0.2477***	0.2476***
	(0.1216)	(0.1211)	(0.0106)	(0.0106)
α_4	-0.0010***	-0.0010***	-0.0013***	-0.0013***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
α_5	0.2655***	0.2656***	0.3173***	0.3174***
	(0.0164)	(0.0164)	(0.0106)	(0.0106)
α_W	-0.0275***	-0.0275***	-0.0407***	-0.0406***
	(0.0031)	(0.0031)	(0.0029)	(0.0029)
α_S		0.0003**		8.27E-5
		(0.0001)		(7.42E-5)
α_N		0.0002		0.0002***
		(0.0001)		(7.53E-5)
β_0	0.0007***	0.0007***	0.0145***	0.0145***
	(0.0173)	(0.0173)	(0.0168)	(0.0168)
β_1	0.0002***	0.0002***	0.0040***	0.0040***
	(3.5991)	(3.5991)	(0.2497)	(0.2497)
β_2	0.1960***	0.1960***	0.2197***	0.2197***
	(0.0070)	(0.0070)	(0.0043)	(0.0043)
β_3	-0.0001***	-0.0001***	-0.0017***	-0.0017***
	(0.1651)	(0.1651)	(0.1283)	(0.1283)
β_4	0.0079***	0.0079***	0.0743***	0.0743***
	(0.0898)	(0.0898)	(0.0587)	(0.0587)
β_W	0.0047***	0.0047***	0.0235***	0.0235***
	(4.50E-5)	(4.50E-5)	(0.0003)	(0.0003)
γ_0	1.1210***	1.1210***	1.3536***	1.3536***
	(9.61E-6)	(9.61E-6)	(7.48E-5)	(7.48E-5)
γ_1	-15.2345***	-15.2345***	-1.0204***	-1.0204***
	(0.0164)	(0.0164)	(0.0052)	(0.0052)
γ_2	0.4849***	0.4849***	0.6008***	0.6008***
	(8.01E-6)	(8.01E-6)	(6.86E-5)	(6.86E-5)
γ_3	-0.4544***	-0.4544***	0.2239*	0.2239*
	(0.0007)	(0.0007)	(0.0020)	(0.0020)
γ_W	2.0223***	2.0223***	2.4023***	2.4023***
	(0.0007)	(0.0007)	(0.0027)	(0.0027)
$Q(22)_{EBAS}$	9793.88***	9986.74***	13377.34***	13384.79***
$Q(22)_{\sigma_t}$	3167.17***	3475.85***	7978.44***	7978.44***
$Q(22)_{V_t}$	6454.08***	6419.71***	6949.67***	6949.67***
SBIC	281142.95	281136.01	249200.12	249194.56
LR	8.018**		11.419***	

- The sample period is from 22 September 2010 to 30 October 2015. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively. SBIC is calculated as the log-likelihood value minus the penalty parameters. Q(22) is Q-statistic with 22 lags. LR is the statistic of likelihood ratio test. Due to heteroskedasticity and serial correlation problem, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used here.

6.6 Conclusion

The components of BAS have been a very important issue in financial research. This study investigates the determinants of BAS components using two different SVAR models. Realised volatility is utilised as a determinant of inventory-hold costs, and trading volume is treated as a determinant of both adverse-selection and order-processing costs. We find that realised volatility is positively related to BAS, while trading volume is negatively related to BAS, which is consistent with expectations. In addition, the magnitude of BAS right after the weekend seems to be lower than at other transaction times, which may be due to increases in trading activity at opening.

This research further includes dummies of sell-initiated and negative-return transactions. The empirical results show that there is an asymmetric impact of trading volume on effective BAS. For sell-initiated transactions, increases in trading volume reduce effective BAS to a lesser extent, meaning market-makers require more compensation for sell-initiated transactions. This is due to the fact that sell-initiated transactions seem to have a higher permanent price impact (information effect), which indicates the proportion of informed trading for sell-initiated transactions is more likely to be higher. Therefore, the adverse-selection costs for market-makers increase, and the marginal impact of trading volume reducing effective BAS decreases. Moreover, results show that effective BAS is indifferent to positive-return and negative-return transactions. This may suggest that market-makers have no preference for sensitivity in either upside or downside market conditions. The analysis of quoted BAS provides is performed as sensitivity analysis, and its results are similar to effective BAS but with slight difference in the significance of the asymmetric effects.

APPENDIX 6.A Identification of buy- and sell- initiated transactions

Table 6-10 reports an example of the procedure for identifying buy- and sell-initiated transactions. The prices in bold are identified by comparing transaction price with prevailing bid and ask prices. For example, the transaction occurring at 03:06:53 on 20/2/2015 was traded at price JPY 45790, matching the prevailing ask price, so it is classified as a buy-initiated transaction. Generally, more than 80% of transactions can be identified by this approach, but some transactions still rely on the tick rule for identification. For instance, the price of the transaction at 03:06:54 on 20/2/2015 was JPY 45810, which is between the best bid and ask prices. As a result, comparing the price with prevailing bid and ask prices cannot classify the trading-side of this transaction. However, by applying the tick rule/test, one can identify this transaction as an uptick (plus tick), and so a buy-initiated transaction.

Table 6-10: Example of identifying buy- and sell-initiated transactions

Time	Bid	Ask	Price	Sell/Buy
20/02/2015 03:06:50	45750			
20/02/2015 03:06:50	45740			
20/02/2015 03:06:52	45750			
20/02/2015 03:06:52		45780		
20/02/2015 03:06:53	45760			
20/02/2015 03:06:53		**45790**		
20/02/2015 03:06:53			**45790**	Buy
20/02/2015 03:06:53			**45790**	Buy
20/02/2015 03:06:54	45800	**45820**		
20/02/2015 03:06:54			*45810*	Buy
20/02/2015 03:06:54			**45820**	Buy
20/02/2015 03:06:54	**45790**			
20/02/2015 03:06:54		45810		
20/02/2015 03:06:55			**45790**	Sell

Chapter 7 Concluding Remarks and Further Research

7.1 Summary and Conclusions

TOCOM, as the primary exchange of energy futures in Japan, is the major hedging tool for domestic refineries, crude oil exploration companies, and other petroleum consumers. In addition, it is also an alternative investment platform for domestic institutional and retail investors and international investment banks. The properties of TOCOM energy futures have been found to be different from petroleum futures traded on other exchanges. Chapters 1 and 3 illustrate the major differences, such as in terms of trading volume patterns across term structures, lower liquidities, lower sizes of trading volume in each transaction, and conflicts between the use of local currency and high foreign participation rates. All these natures of TOCOM show the importance of exploring this less investigated market, and providing both domestic and foreign TOCOM participants a means to design hedging and trading schemes.

With the fast development of high-frequency trading and the recent financialisation of commodities futures, the dynamic of petroleum futures not only depends on fundamental value itself, but also intraday trading behaviours. Therefore, analysis based on high-frequency data provides energy futures participants a tool with which to measure market volatility patterns and to understand the behaviour and preference of other participants and intraday trading patterns, in order to develop a more efficient risk management scheme and trading strategies. The following section reviews the main findings of this thesis. Next, a direction for potential research into futures is discussed.

7.1.1 Risk Management

With the availability of intraday data, the realised volatility (sum of intraday square returns) can be more accurately estimated and utilised to enhance the efficiency of risk management. Chapter 4 addresses the modelling of realised volatility by incorporating a regime switching technique and the HAR-RV model. Corsi (2009)'s HAR-RV model is one of the most popular realised volatility models, as it considers the long-memory property of realised volatility. However, when there appears a strong order imbalance (the difference in trading volume between sell and buy transactions) in the market, market-makers are forced to move their prices accordingly. As a result, prices tend to move volatilely, causing a high level of volatility, even though they may recover with shrinks in order imbalance. Given the existence of intraday price pressures on market-makers, RV is considered as regime-dependent in this paper, and a regime switching technique is applied to capture this regime-dependent property (MRS-HAR-RV).

The empirical results of in-sample suggest the existence of high- and low-volatility regimes. For a high-volatility regime, the persistence of RV is weaker and the occurrence of a high-volatility regime is less frequent. The opposite property of RV is found for a low-volatility regime. However, MRS-HAR-RV seems neither to outperform traditional HAR-RV in out-of-sample nor to be outperformed based on the symmetric loss function, QLike and MAE. In addition, the prediction of MRS-HAR-RV seems to be better for highly liquid futures. This may be because it requires a lower level of order imbalance to trigger the switching for lowly liquid futures than highly liquid ones. According to the results of comparison of asymmetric loss function, MME(O) and MME(U), it appears that MRS-HAR-RV tends to under-predict volatility, while alternative models (HAR-RV, GARCH, MRS-GARCH) over-predict volatility. Then, an application of VaR is conducted. The results of VaR are not consistent for three energy futures. MRS-HAR-RV performs the best for gasoline futures, but fails to outperform other models for kerosene and crude oil futures. In general, two different regimes are identified, suggesting that consideration of different regimes is necessary, although it may require some adjustment to the prediction of volatility using MRS-HAR-RV (discussed in Section 7.2).

7.1.2 Dissemination of Information to the Market

Having identified the regime-dependent property of realised volatility, Chapter 5 examines the relation between trading volume and realised volatility. The two most popular theories explaining the volume-volatility relation are MDH and SIAH. MDH supports a contemporaneously positive relation, while SIAH suggests a lead-lag positive relation. In order to avoid the possible simultaneity issue of the GARCH framework, the SVAR technique is applied in this thesis. Moreover, considering market participants' sensitivity to market information under different market conditions, backwardation and contango, a dummy variable is incorporated with SVAR, the so-called T-SVAR. Theoretically, energy participants are supposed to be more sensitive when the market is in backwardation, because backwardation implies a shortage of supply in the market and a higher possibility of a more volatile market.

Analysis of SVAR suggests both MDH and SIAH are held in the TOCOM energy futures market, whereas it seems that evidence supports the MDH being stronger than SIAH. This may indicate that even though most information is contemporaneously reflected into the market, there is still some information incorporated into price at a later time point. When the dummy of backwardation is included into SVAR, the results of SVAR show that kerosene futures participants are less sensitive, crude oil futures participants are more sensitive, and gasoline futures participants are indifferent. The principal consumer of petroleum in Japan being refineries may provide an explanation for the difference in the asymmetric effect of kerosene and crude oil futures. As a refinery, the cost is from the purchase of crude oil, while the revenue is the sales of product oil, such as kerosene. Therefore, they are likely to be more sensitive when crude oil price rises (crude oil market in backwardation) and when kerosene price declines (kerosene in contango), which causes the asymmetric effect shown in our empirical results. Overall, MDH and SIAH are found in TOCOM energy futures markets, while MDH seems to be the major way of dissemination. The volume-volatility relation is stronger under backwardation for crude oil futures but weaker for kerosene futures.

7.1.3 Determinants of Bid-ask Spread (BAS)

Chapter 6 discusses possible determinants of bid-ask spread (BAS) using relevant variables linking the three components of BAS, inventory-hold, adverse-selection and order-processing costs. Realised volatility and trading volume are two important variables in this analysis, because realised volatility reflects that the inventory-hold cost and trading volume is related to adverse-selection and order-processing costs. Furthermore, the asymmetric effect of sell-initiated and negative-return transactions is considered. Sell-initiated transactions tend to have a lower and temporary price impact than buy-initiated ones, so market-makers are likely to require less compensation for them, leading to a lower BAS. In addition, market-makers' preference for market conditions (up or down) can also affect the bid and ask prices set by them. If they are more sensitive to downside risk, they require more compensation for negative-return transactions by widening BAS, and vice versa. Analysis is implemented under a high-frequency framework, so only the two most liquid contacts are utilised because the valid sample of other maturities is not sufficient.

The evidence shows that realised volatility, trading volume and lagged BAS can partially explain the dynamic of BAS, even though there is still a large proportion not explained by these variables. Realised volatility is positively related to BAS, and trading volume is negatively related to BAS, which matches our assumption of their relation to these three components. Specifically, increases in realised volatility raise inventory-hold costs, while increases in trading volume lower both adverse-selection and order-processing costs. The asymmetric effect of sell-initiated transactions is found, but the sign is not as predicted by relevant literature. The reason for this is that the permanent price impact (information effect) of sell-initiated transactions is found to be higher than that of buy-initiated ones, implying that the proportion of informed trading is higher for sell-initiated transactions. Consequently, market-makers require more compensation for sell-initiated transactions, and the marginal effect of trading volume reducing BAS becomes less. Finally, the asymmetric effect of negative-return transactions is not found, indicating that market-makers may have no particular preference for upside or downside risk. Generally speaking, realised volatility and trading volume are determinants of intraday BAS, and the asymmetric impact of trading volume on BAS exists for sell-initiated transactions, since sell-initiated transactions are more likely to be informed trading.

7.2 Further Research

The three levels of analysis undertaken in this thesis reveal different asymmetric effects in TOCOM energy futures markets. Moreover, the last two chapters show that the properties of TOCOM are special and different from other futures markets, such as in terms of the strength of relation between volume and volatility across term structure, the asymmetric effect of backwardation for kerosene futures, and the higher permanent price impact for sell-initiated transactions. They all provide TOCOM participants a better understanding of the market patterns and components of traders. Further research should focus on 1) increasing the accuracy of predictions, 2) the potential impact of foreign exchange rates, 3) cointegration between the three energy futures and 4) the linkage between TOCOM energy futures and the Japanese equity market.

First of all, even though MRS-HAR-RV identifies two regimes, and has higher explanatory power than other models, it fails to outperform in forecasting. The Markov Regime Switching model has been criticised for a lack of predictive ability due to the instability of parameters across different samples. Boot and Pick (2014) propose an optimal forecasting approach for the Markov Regime Switching model, which uses weighted MRS parameters to produce predicted value. By using weighted optimal parameters, the influence of low quality parameters tends to be minimised, causing a better prediction.

Secondly, two reasons motivate the investigation of the impact of foreign exchanges. Regarding foreign trades, all futures traded in TOCOM are dominated by the local currency, Japanese Yen. However, it has a relatively high foreign trade ratio, especially for crude oil futures. Hence, it is in our interest to investigate whether exchange rates affect the behaviour of foreign trade and TOCOM markets, such as by including the realised volatility of foreign exchange rates into MRS-HAR-RV, and investigating the relation between the BAS of TOCOM energy futures and the realised volatility of exchange rates. Turning to domestic participants, even though most product oils are for domestic use, refineries still pay USD to import crude oil as a raw material. As a result, the exchange rate should also affect the decisions of domestic consumers. For example, if the exchange rate drops, the cost of importing crude also declines, and refineries may then lower their hedging position.

Thirdly, the cointegration of three TOCOM energy futures may exist, as both gasoline and kerosene are refined products of crude oil. However, it is not guaranteed that gasoline and kerosene are also cointegrated. The existence of cointegration between gasoline and kerosene may depend on the purpose of using and the time of using. For example, if they are substitutes, the cointegration may be weak, but if they are complementary, they may be strongly cointegrated. In addition, due to a high foreign trade ratio, cointegration may not fully depend on physical linkage between these commodities, but be influenced by the behaviours of overseas investors.

Finally, correlation between TOCOM energy futures and the Japanese stock market may be an issue worthy of investigation due to the increase in the financialisation of commodities futures. In addition, Japan’s economy relies heavily on the import of crude oil, which also suggests the possibility of linkage. In addition, several pieces of literature (Kilian and Park, 2009; Narayan and Sharma, 2011; Creti et al., 2013; Cunado and Grecia, 2014) have found linkage between stock and petroleum markets in different markets, such as the NYSE, S&P 500 and other European oil importing countries. It is interesting to compare the differences between Japan and other countries when it comes to the linkage between TOCOM energy futures markets and the Japanese equity market.

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