2020

Three essays on financial markets

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by

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A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University

Ames, Iowa

2020

DEDICATION

To my family

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ACKNOWLEDGMENTS

I would like to take this opportunity to thank my co-major professors Dr. Sergio Lence and Dr. Oleksandr Zhylyevskyy for their invaluable help and guidance of conducting research and writing this dissertation. Their patience and support have inspired me to finish my graduation education. I am also deeply indebted to the rest of my committee, Dr. Chad Hart, Dr. Dermot Hayes, and Dr. Cindy Yu for their constructive comments and advice to this work. Lastly, I would like to thank my friends, colleagues, the department faculty and staff for their help in my graduate school career.

ABSTRACT

This dissertation focuses on the financial markets including stock markets, commodity futures and options markets.

Chapter 2 studies the trading activity in commodity futures and options markets. Little is known about trading activity in commodity options market. We study the information content of commodity futures and options trading volume. Time-series tests indicate that futures contracts in a portfolio with the lowest options-to-futures volume ratio (O/F) outperform those in a portfolio with the highest ratio by 0.3% per week. Cross-sectional tests show that O/F has higher predictive power for futures returns than such traditional risk factors as the carry, momentum, and liquidity factors. O/F has longer predictive horizon for post-announcement returns than the information contained in the monthly World Agricultural Supply and Demand Estimates (WASDE) reports. The analysis of the weekly Commitments of Traders (COT) reports indicates that commercials (hedgers) provide liquidity to non-commercials (speculators) in short-term in commodity options market.

Chapter 3 explores what kinds of information can explain the USDA forecast errors in crop ending stocks. In the empirical analysis using Markov Chain Monte Carlo (MCMC) method, we find that the futures basis, level of monthly ending stocks, and level of planted area are significant to explain the forecast errors. The out of sample test is employed and the adjusted forecasts improve the forecast accuracy of crop ending stocks.

Chapter 4 investigates the liquidity effect in Chinese stock market using an asset pricing model. The empirical results show that liquidity has a significant effect on stock returns and the liquidity premium exists in Chinese stock market. However, neither CAPM nor Fama-French three-factor model can explain the liquidity premium. We propose a new two-factor (market and liquidity) model in which the liquidity factor captures two dimensions of liquidity. The two-factor model

performs well in explaining the liquidity premium. Furthermore, unlike CAPM and Fama-French three-factor model, the two-factor model is able to explain the size effect in Chinese stock market.

CHAPTER 1. GENERAL INTRODUCTION

In the modern economy, financial markets play a vital role in facilitating the smooth operation of economies by allocating resources and creating liquidity for businesses and entrepreneurs. Buyers and sellers can trade their financial holdings through the financial markets. My dissertation makes a unique contribution to help us have a deeper understanding of financial markets.

Traditionally, commodity markets have been treated as traditional markets where producers short hedge their price risk and speculators provide the insurance so they can receive the risk premium. However, recent studies show that commercials (producers) not only hedge the price risk, but they also do speculation based on the private information they have. The information structure of commodity markets can affects equilibrium asset returns because investors demand compensation for bearing the risk of information-based trading. Different from commodity futures, commodity options have been received much less attention. Because commodity futures and options have different features, informed traders would choose between futures and options when they receive private information. Chapter 2 explores the information content in the trading volumes of futures and options, there is a significant negative relationship between the options-to-futures volume ratio (O/F) and expected returns on commodity markets. O/F has relatively longlived predictive power comparing with the predictive ability of the information contained in WASDE report. The question about who provide the short-term liquidity in commodity options markets has been answered in Chapter 2. The non-commercials demand for liquidity and commercials are compensated by providing liquidity on the short-term horizon.

Commodity markets have been largely affected by the release of USDA WASDE reports in every month. However, commodity markets contain information that can improve the accuracy of USDA forecasts. Previous studies have confirmed that the USDA forecasts are not efficient. USDA forecasts follow the balance sheet approach for the estimation on both supply and demand sides, but the forecasts may ignore the information in the futures markets. The empirical results in Chapter 3 show that the futures basis, level of monthly ending stocks, and planted area are significant to explain the forecast error in crop ending stocks. The adjusted forecasts can improve the accuracy of USDA forecasts in crop ending stocks.

An important feature of financial markets is to provide liquidity for both buyers and sellers. Chapter 4 focuses on the liquidity effect in Chinese stock market, which has been mostly ignored in the literature. In the recent years, Chinese stock markets have been among the most important markets in the world. We use two measures of liquidity and confirm the existence of liquidity premium in Chinese stock markets. A new two-factor (market and liquidity) model is proposed in which the liquidity factor captures two dimensions of liquidity. The two-factor model is capable of explaining the liquidity premium. What's more, the new model can explain the size effect in Chinese stock markets that CAPM and Fama-French three-factor model cannot.

CHAPTER 2. TRADING ACTIVITY IN COMMODITY FUTURES AND OPTIONS MARKETS

2.1 Introduction

According to Keynes (1930), the commodity futures market was previously treated as a traditional market, where commodity producers short hedged to lock in revenue, and speculative investors sought to make a profit and receive a risk premium for providing insurance to commodity producers. However, the market has fundamentally changed recently due to the phenomenon of "financialization" (Tang and Xiong, 2012). Commodity futures have become popular among financial investors and inflows into the futures market have increased from an estimated \$15 billion in 2003 to at least \$200 billion in mid-2008 (Tang and Xiong, 2012). A large fraction of this growing inflow of investments is attributed to institutional investors, who did not participate in commodity futures trading previously (Domanski and Heath, 2007).

Speculation in commodity markets is traditionally defined as trading in excess of what would be required to satisfy hedging demand. Based on this definition, many academic studies split market participants into "hedgers" and "speculators". The trading by hedgers is then treated as hedging and trading by speculators as speculation. The research on the role of speculators is pioneered by Working (1960), who creates Working's speculation index, a ratio of the position held by speculators to that of hedgers. When speculation is excessive, the value or volatility of the index is typically high. The theory underlying the speculation index assumes that the level of hedgers' positions is determined by exogenous hedging demand, while the speculation index itself is mainly driven by trading by speculators.

However, commercial hedgers have recently had other motives to trade. The volatility of commercial hedgers' positions is quite high and much larger than the volatility of output and revisions to the output forecasts (Cheng et al., 2014). In fact, price changes have a higher explanatory power compared to changes in the output forecasts when explaining the short-term changes in hedgers' positions. Kang et al. (2019) analyze weekly COT data and find that hedgers tend to sell commodities when prices are high and buy back when prices are low. Commercial hedgers may attempt to use their informational advantages over speculators by trading against the latter. For instance, commercial firms might have better knowledge of local physical market conditions. In general, hedgers need not trade only to hedge risks for their business.

In commodity markets, risk sharing is critical, but the boundary between speculation and hedging is occasionally blurred. If commercial hedgers are involved in trading to earn profits, their actions can resemble speculation. Thus, instead of classifying traders as commercial and non-commercial investors, we will focus on trading activities of informed investors.

Commodity market participants face severe information frictions (Sockin and Xiong, 2015). In particular, they are exposed to information frictions from the global supply, demand, and inventory of commodities. In a commodity market, information risk arises due to an asymmetry between informed and uninformed investors. Easley et al. (2002) argue that the information structure affects equilibrium asset returns because investors demand compensation for bearing the risk of information-based trading.

This paper focuses on informed trading in commodity futures and commodity options markets. To date, there has been much research into commodity futures markets such as Goldstein and Yang (2019) and Kang et al. (2019). However, commodity options markets have received much less attention.

A commodity options contract is written with a particular futures contract as the underlying security. One important difference between commodity options and equity options is that a commodity option is a derivative security of a derivative for a physical commodity. As the popularity of commodity markets increases among investors, equity options traders migrate to commodity options. We are specifically interested in the information content of trading volumes of commodity futures and options contracts. Trading volumes are important in financial markets because order imbalances can reflect private information.

We make four main contributions to the literature. First, we analyze the role of information risk in commodity markets. In the existing literature, the effect of informed trading in commodity futures markets has been analyzed using theoretical models only (Goldstein and Yang, 2019; Sockin and Xiong, 2015). To the best of our knowledge, we are the first to use commodity *options* to analyze the effect of information risk on commodity futures markets empirically. We find that there is a significant negative relationship between the options-to-futures volume ratio (O/F) and expected futures returns. Previous studies have focused on the theory of storage, normal backwardation theory, hedging pressure hypothesis, and momentum strategy to analyze expected returns. Our paper provides an alternative and new approach, which is based on the information risk, to analyze expected returns in commodity markets.

Second, we extend the growing literature on options contracts by considering commodity options. Examples of option and stocks in equity markets are Roll et al. (2010), Johnson and So (2012), An et al. (2014), Hu (2014), Ge et al. (2016), Stilger et al. (2016), Johnson and So (2017), Chan et al. (2015), Cremers and Weinbaum (2010), and Kacperczyk and Pagnotta (2019), among others.

Third, our study confirms the WASDE announcement effect. The surprise of forecast in ending stocks can predict post-announcement returns in short-term. O/F has relatively long-lived predictive power comparing with the predictive ability of the information contained in WASDE reports. It takes several weeks for the information in O/F to be fully reflected in futures prices.

Fourth, our paper answers the question about who demand the short-term liquidity in commodity options markets. The non-commercials demand for liquidity from commercials, who are compensated by providing liquidity on the short-term horizon.

The remainder of the paper proceeds as follows. In Section 2.2, we discuss the phenomenon of "financialization" and review the literature. Section 2.3 provides an empirical analysis, which includes time-series and cross-sectional tests. Section 2.4 presents additional evidence and discuss that the ability of O/F to predict post-WASDE announcement returns. Section 2.5 presents the findings of an analysis of COT report. Section 2.6 contains robustness checks. Section 2.7 concludes.

2.2 Related literature

2.2.1 Commodity financialization

In recent decades, commodity index traders have become a significant big player in the commodity futures market. Two significant effects of commodity financialization are that the longstanding hedging pressure theory have been mitigated and the financialization improves risk sharing in commodity futures market (Tang and Xiong, 2012). The limits of financial investors to financial arbitrage can generate limits to hedging by producers. Hence, the risks from other financial markets affect equilibrium commodity supply and prices (Acharya et al., 2013). The participation of financial institutions leads to a change in the allocation of risk, so that the hedgers hold more risk than before (Cheng et al., 2014).

Commodity financialization may also influence the microstructure of information in futures markets. The information frictions and speculative activity from investor flows may affect the expected returns of commodity futures and result in price booms and busts (Singleton, 2013). Sockin and Xiong (2015) highlight the feedback effects of informational noise on commodity demand and spot prices. The key information friction after financialization is that producers cannot differentiate between the reasons that cause the movement of futures prices, namely financial investors trading versus changes in global economic fundamentals. Goldstein and Yang (2019) emphasize that price informativeness in the futures market can either increase or decrease with commodity financialization. However, financialization can generally improve liquidity in the futures market and the commodity-equity market comovement goes up. Some papers use theoretical models to analyze how commodity financialization affects commodity prices. Basak and Pavlova (2016) build a model including institutional investors entering commodity futures markets. According to their model, all commodity futures prices, volatilities, and correlations go up with financialization. The model from Baker (2014) implies that financialization reduces the futures risk premium, and the correlation between futures open interest and the spot price level increases.

Our paper provides supportive evidence to confirm the financialization of commodity markets by comparing futures and options trading volume in Figure 2.2 and 2.3. There is a sharp increase of the futures trading volume since 2005, while the options trading volume has not changed too much. The results are consistent with the findings in the literature that commodity index traders mainly invest in commodity futures markets. Further, the empirical results are similar in before and after the start of the financialization sub-samples in robustness checks in Section A.2.

2.2.2 Options and their underlying assets

One important measure of information trading in the stock market is the options to stock trading volume ratio (O/S) proposed by Roll et al. (2010). They find O/S is related to many determinants such as delta and trading costs and O/S is higher around earnings announcements. Johnson and So (2012) further examine the information content of option and equity volumes when trade direction is unobserved. The empirical results show that firms in the lowest decile of O/S outperform the highest decile by 0.34% per week. What's more, O/S is a strong signal when short-sale costs are high or option leverage is low. Ge et al. (2016) try to explain why O/S predicts stock returns. Their results indicate that the role of options in providing embedded leverage is the most important channel why options trading predicts stock returns. Another new measure of multimarket information asymmetry (MIA) is created by Johnson and So (2017). The measure is based on the intuition that informed traders are more likely than uninformed traders to generate abnormal volume in options or stock markets.

Many papers study the equity option's characteristics in stock market. Cremers and Weinbaum (2010) find that deviations from put-call parity contain information about future stock returns. They use the difference in implied volatility between pairs of call and put options to measure these deviations. An et al. (2014) show that stocks with large increases in call implied volatilities over the previous month tend to have high future returns, while stocks with large increases in put implied volatilities over the previous month tend to have low future returns. Stilger et al. (2016) document a positive relationship between the option-implied risk-neutral skewness (RNS) of individual stock returns' distribution and future realized stock returns during the period 1996–2012.

To our knowledge, our paper is the first to use commodity options and the underlying assets commodity futures to analyze informed trading the commodity markets. Similar with Roll et al. (2010) and Johnson and So (2012), we construct the options-to-futures volume ratio O/F, after the time-series and cross-sectional tests, the results show there is a negative and significant relationship between O/F and expected futures return and the results maintain after the robustness checks in Section 2.6.2, 2.6.3, and 2.6.4. The analysis of COT reports shows that commercials provide liquidity to non-commercials in short-term horizon in commodity options markets

2.2.3 Asset pricing framework in commodity futures market

The previous literature includes many papers trying to use asset pricing models to price the cross-section of commodity futures. Jagannathan (1985) shows that the consumption-based intertemporal capital asset pricing model (CCAPM) fails to price commodity futures over monthly horizons. Yang (2013) identifies a factor that captures the different return between high and low basis portfolio, which can explain the cross-section of commodity futures returns. Hong and Yogo (2012) find that movements in open interest are highly pro-cyclical, correlated with both macroeconomic activity and movements in asset prices. Also, movements in commodity market open interest can predict commodity returns. Bakshi et al. (2017) show that a model that contains an average commodity factor, a carry factor, and a momentum factor is capable of describing the cross-sectional commodity returns. Idiosyncratic volatility is not priced when including commodity specific factors, such as the fundamental backwardation and contango cycle of commodity futures markets (Fernandez-Perez et al., 2016). Basu and Miffre (2013) construct long–short factor mimicking portfolios, and find that these portfolios are priced in the cross-sectional returns of commodity futures. Daskalaki et al. (2014) explore whether there are common factors in the cross-section of individual commodity futures returns. They test the asset pricing models including the models for equities markets and commodity theory motivated models. The results show that none of the employed factors prices the cross-section of commodity futures returns. Szymanowska et al. (2014) identify two types of risk premia in commodity futures returns: spot premia related to the risk in the underlying commodity, and term premia related to changes in the basis. The cross-section of spot premia can be explained by the single factor, which is the high-minus-low portfolio sorted by basis. Two additional basis factors are needed to explain the term premia.

In this paper, different from other papers in the literature, we construct the factor options-to-futures volume ratio (O/F) based on the dimension of informed trading. The results show that O/F has better predictive power for futures returns than the commonly used factors such as carry, momentum, and liquidity factors. Our paper makes an unique contribution to the asset pricing framework in commodity futures market.

2.3 Empirical analysis

2.3.1 Data and variable definitions

Our main data for this study come from Bloomberg and comprise individual futures contract for 25 commodities. The data include the comprehensive record of daily futures prices, open interest, volume, call volume, put volume and options implied volatility. We try our best to work with the broadest set of commodities with enough liquidity to be efficiently traded [1]. The sample period of our data is March 1994 to December 2018. We categorize all commodities into four broad sectors: Agriculture, Energy, Livestock, and Metals.

Each commodity has many futures contracts with many maturities. Multiple futures contracts trade simultaneously for each commodity that share the features except for the specified delivery period. The price series for contracts with adjacent and near-adjacent maturity date can overlap for a period of time. In this way, the cross-sectional dimension of different futures contracts offers more information than a single futures price series (Smith, 2005).

For each futures contract of each commodity, we restrict data sample according to its options expiration date. The options expiration date is usually in the prior month of the corresponding

[1] For example, we exclude commodities such as Butter, Palladium and Platinum to avoid problems of low liquidity.

futures expiration date. We subset the sample from the Tuesday on the week before expiration to 65 calendar days earlier by the option expiration date [2]. Figure 2.1 presents the procedure to obtain the selected sample. We eliminate futures contracts with less than one week of data. We also require futures contacts in each week to have at least two observations. The commodity-weeks with 0.3% highest and lowest value of O/F are excluded from the sample to avoid problems of liquidity [3]. After imposing these data restrictions, our data sample contains 32555 commodity-weeks corresponding to 1293 calendar weeks and 4283 individual futures contracts.

The option volume for one futures contract in each day is the total volume of option contracts across all strike prices. For the contract with maturity T of commodity i in each week t, we calculate total option and futures volumes. We denote option and futures volumes as $OVOL_{i,t,T}$ and $FVOL_{i,t,T}$. Next, we define the weekly option-to-futures volume ratio as

$$O/F_{i,t,T} = \frac{OVOL_{i,t,T}}{FVOL_{i,t,T}}$$

Similar to Yang (2013) and Gorton et al. (2012), we define the futures excess return as the fully collateralized return of longing a futures contract. At the time of signing a futures contract, the buyer has to deposit enough amount of money that at least equals the present value of the futures contract to eliminate counterparty risk. For commodity i, the futures price with maturity T at time t is denoted as $F_{i,t,T}$. To be consistent with the weekly report of COT about the positions from CFTC, the weekly futures excess return is calculated from the close of markets on Tuesday to the close of markets on Tuesday in the next week as

$$R_{i,t+1,T} = log(\frac{F_{i,t+1,T}}{F_{i,t,T}})$$

When there are trading holidays, we use the futures prices of the nearest day of that trading holiday. The option expiration dates are often in the month preceding the futures contract month. Also, the time of last observation we choose for one contract is the previous Tuesday before the option expiration date. In summary, we don't need to worry about the futures prices that are close to the

[2]We exclude data corresponding to the week of option expiration to avoid the trading volume problem that the investors roll over from the expiring option to the options with the next expiration date.

[3]The commodity options are overall less liquid than the equity options. We also find that excluding 0.3% highest and lowest intervals can delete the observable outliers

futures contract maturity because these futures prices are not purely financial, and the commodity has to be delivered after the contract maturity.

Table 2.1 reports the summary statistics of commodity futures for every individual commodity in the sample. Coffee futures have the highest O/F value, which means the coffee market is the most active in trading options comparing trading futures in our sample. In general, agriculture markets are more active in trading options than energy, livestock, and metals markets.

Table 2.2 includes the descriptive statistics of $O/F_{i,t,T}$ (hereafter referred to O/F) in each year in our sample. The number of commodities appear in each year is not 25 until year 2006, since the commodity Gasoline enters our sample in year 2006 [4]. The total number of contracts of all commodities increases from 139 in year 1994 to 195 in year 2018. The total number of weekly observations of all available commodities also goes up from 988 in year 1995 to 1438 in the year 2018. Figure 2.2 shows the average annual value of options and futures trading volume between 1994 to 2018. As we see in Figure 2.3, there is a significant decline in the value of O/F after 2006. To address the concern that the phenomenon may be caused by the introduction of Gasoline into data sample in 2006, we present the average annual value of O/F excluding Gasoline futures and options between 1994 and 2018 in Figure 2.4. The phenomenon still exists when excluding Gasoline from data sample. It's an interesting fact since the evidence suggests financialization of commodities starts around the early 2000s and commodities are considered as a new asset class since billions of investment dollars flowed into commodity markets from financial institution, insurance companies, hedge funds and wealth individuals (Tang and Xiong, 2012). We believe the main reason is that commodity index trader began to hold a larger portion of open interest in commodity futures markets. The index traders don't participate in informed trading, their trading is guided by their trading rules, which are determined and publicly disseminated well prior to the trades being executed (Brunetti and Reiffen, 2014). The sample mean of O/F is 0.220, which means the number of futures contracts traded are around 5 times of options contracts traded. Since there is a high concentration of relative option volume in a small set of commodities, O/F is positively

[4] Beginning October 2005, NYMEX began trading a futures contract for delivery of Reformulated Blendstock for Oxygenate Blending (RBOB).

skewed in all the sample sub-periods, which is very similar to the option-to-stock volume ratio in stock market (Johnson and So, 2012).

Table 2.3 presents the characteristics of groups sorted by O/F for all weekly observations. Group 1 has the lowest value of O/F and group 8 has the highest value of O/F. The groups from 3 to 7 include all of the 25 commodities in the sample. The groups with lower and higher O/F contain fewer number of commodities, but each group has at least 20 kinds of commodities. The commodities distribute evenly in all 8 groups. VLC and VLP indicate the trading volume of call and put contracts of the underlying asset in a given week. For all the groups, the number of call contracts traded is larger than the number of put contracts traded, which indicates that the call contracts are more liquid than the put contracts in the commodity options. This result is consistent with the finding in the equity options (Johnson and So, 2012). In general, higher O/F groups have higher level of option volume except for group 8. The option volume of group 8 is the second highest in all 8 groups and just lower than group 7. For the futures volume, there is no significant difference between the first 7 groups. However, the futures volume in group 8 is much lower than the other 7 groups. The last column r_{t+1} is the weekly average return of one group in the following week after the given week t. As we see in the table, the group 1 with the lowest level of O/F has the highest return in the following week. The group 8 with the highest level of O/F has the lowest return in the following week. Overall, there is a clear trend of declining return from group 1 to group 8, which indicates a negative relationship between relative option trading volume and the return in the following week. One possible reason is that when the informed investors obtain bad news, they prefer to short sale in the commodity option market than in the commodity futures market. Also, when good news happens, the informed investors are more willing to invest in futures than options. This result is also similar with the results in stocks and stock options (Johnson and So, 2012).

Figure 2.5 provides the scatter plot of the average futures return for individual commodity and the responding value of O/F. From this figure, there is a clear downward trend between the average return and the average value of O/F.

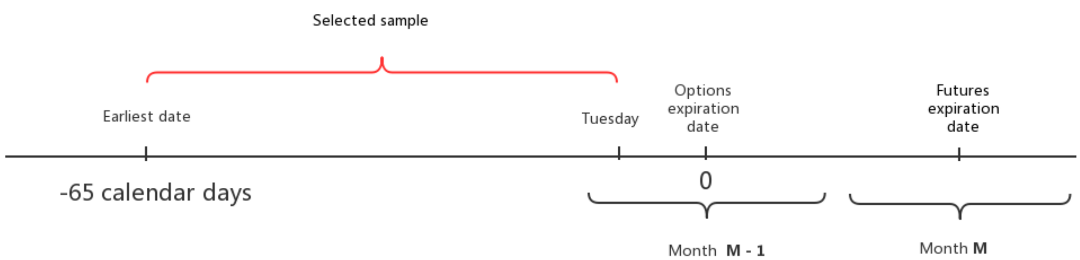

Figure 2.1 Procedure to select sample

2.3.2 Time-series tests

The baseline commodity pricing model we use to do time-series tests is from Bakshi et al. (2017). They construct three systematic risk factors and show that the three-factor model is capable of describing commodity futures returns. AVG is the average excess return of a long position in all available commodity futures. The commodity carry factor, denoted by $CARRY$, is constructed as the return on a portfolio that is long in the commodities that are most backwardated and short the ones that are most in contango. The momentum factor, denoted by MOM, is constructed as the return on a portfolio that is long in the commodities with the highest returns over the past 8 weeks and short in the ones with the lowest return over the past 8 weeks.

In this paper, we use weekly data instead of monthly data used in Bakshi et al. (2017). At the end of each week, we sort all the commodities of the available futures contracts into 8 groups based on the level O/F. The weekly return for each group is calculated as the equal-weighted return for

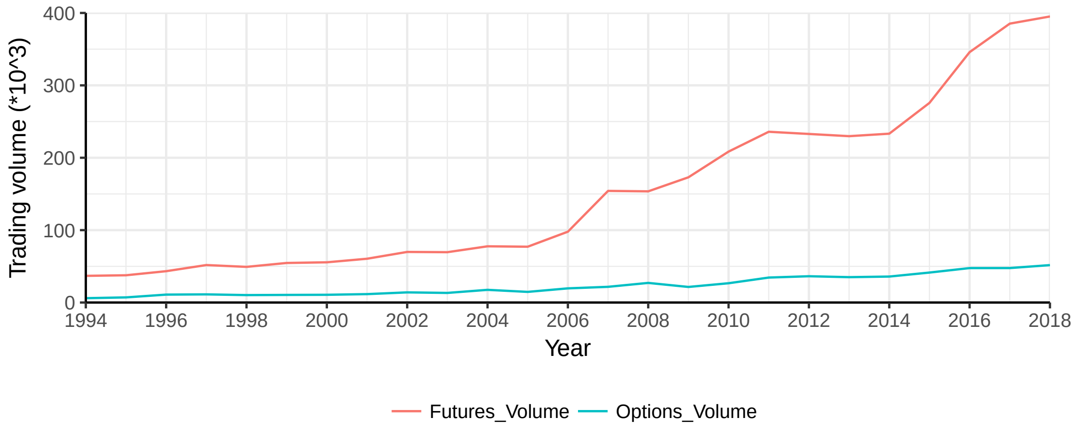

Figure 2.2 Options and futures volume by year from 1994 to 2018

a portfolio of all commodities in that group in the following week. We compute the weekly return from the close of markets on Tuesday to the close of markets on Tuesday in the next week.

The baseline three-factor asset pricing model of expected return representation for each group $i = 1, 2, ..., 8$:

$$r_{i,t+1} = \alpha_i + \beta_1 AVG_{i,t+1} + \beta_2 CARRY_{i,t+1} + \beta_3 MOM_{i,t+1} + \epsilon_{i,t+1}$$

implying that the expected excess return are a function of exposure to three factors.

For each commodity, for a given week t, let $F_t^{(0)}$ be the price of front-month futures contract, and let $F_t^{(1)}$ be the price of the next maturity futures contract. We define the weekly basis for commodity i on a given week t as the log difference between the front-month futures price and the next maturity futures price as:

$$Basis_{i,t} = log(\frac{F_t^{(1)}}{F_t^{(0)}})$$

A commodity is in backwardation if its futures curve is downward sloping (the basis is positive). Otherwise, the commodity is in contango.

To construct $CARRY$ factor, we first sort available commodities by basis at the end of week t and split them into 4 portfolios. In the following week $t+1$, the futures contracts of these commodities are one week closer to their maturities. Then we compute the weekly return of these futures contracts in week $t+1$. In each portfolio, we use equal weights to compute the average weekly excess return of a portfolio in week $t+1$. The $CARRY$ factor is constructed using the strategy of longing the highest basis portfolio and shorting the lowest basis portfolio.

To construct MOM factor, at the end of week t, we focus on equal weights and ranking of a commodity is determined by a commodity's past 8 weeks performance:

$$\overline{r}_t = (\prod_{j=0}^{7}(1 + r_{t-j}))^{\frac{1}{8}} - 1$$

The weekly return of a commodity is calculated as the average weekly return of all available futures contracts for that commodity. We first sort available commodities by past performance at the end of week t and split them into 6 portfolios. In the following week $t+1$, the futures contracts of these commodities are one week closer to their maturities. Then we compute the average weekly return of these futures contracts in week $t+1$. In each portfolio, we use equal weights to compute the weekly excess return of a portfolio in week $t+1$. The MOM factor is computed as the strategy of longing the best performance portfolio and shorting the worst performance portfolios.

To construct the AVG factor, we aggregate the excess returns of all available futures contracts using equal weights to calculate the average market return for each week t.

Table 2.4 presents the time-series factor regression for each group using three regressions. The first regression we use is the commodity CAPM, the intercept for each group tends to decrease with O/F. We find that the commodity portfolio with lowest O/F has the highest alpha of 0.001 (t-statistic = 2.732). And the portfolio of commodity with highest O/F has the lowest alpha of -0.001 (t-statistic = -2.275). The "1-8" column takes a statistical test for the difference of lowest between highest portfolios, the results show that there is a positive and significant difference (t-statistic = 3.144). The "(1+2)-(7+8)" takes a statistical test for the difference of two lowest and two highest O/F portfolios, we find that there is a positive and significant difference (t-statistic = 2.244).

The second regression employed is commodity AVG and $CARRY$. The third regression contains all three factors. In these two regressions, the lowest O/F portfolio has the highest statistically significant alpha and the highest O/F portfolio has the lowest statistically significant alpha. For the columns "1-8" and "(1+2)-(7+8)", the results are similar in both magnitude and statistical with commodity CAPM.

In summary, with the time-series tests, we find that low O/F can indicate high expected returns. A portfolio of commodities with lowest O/F has significantly positive alpha in the next week after portfolio formation. Also, high O/F indicates low expected returns, as the portfolio of commodities with highest O/F has significantly negative alpha in the next week after portfolio formation.

From Table 2.4, we also find that the strategies of "1-8" and "(1+2)-(7+8)" have a significantly positive loading on the market (AVG) factor. These results indicate that low O/F commodities have more market exposure than high O/F commodities, which is the opposite of the result in stock market that high option to stock volume ratio companies have more market exposure Johnson and So (2012).

2.3.3 Cross-sectional tests

The cross-sectional tests can be more powerful than traditional time-series tests since the variation in O/F across different commodities at a point in time may be more informative than the variation in O/F.

One potential concern when using the Fama-MacBeth approach is the independence in the time dimension. The average first-order autocorrelation of weekly time-series return of all 25 commodity futures markets is only 0.003. Based on this low autocorrelation of time series returns, we can be confident that the independence in the time dimension is a plausible assumption.

In addition to time-series tests, we also apply the Fama-MacBeth two-stage regression method (Cochrane, 2009). Fama and MacBeth (1973) suggest a computationally simple procedure for running cross-sectional regressions, and for producing standard errors and test statistics.

The Fama-MacBeth two-stage regression method tests the hypothesis that cross-sectional differences in asset returns are due to cross-sectional differences in asset risk exposure. The Fama-MacBeth regression has two steps. First, we regress the time-series of the excess return of commodity i on factors to estimate the vector of risk exposure (β_i) as

$$R_{i,t+1} = a_i + \beta_i^{'} f_t + \epsilon_{i,t}, \quad t = 1, 2, ..., T$$

where f_t is a set of risk factors. Second, we run the cross-sectional regression at each time period t as

$$R_{i,t+1} = \gamma_t + \beta_i^{'} \lambda_t + \alpha_{i,t}, \quad i = 1, 2, ..., N$$

We estimate λ as the average of the cross-sectional regression estimates as

$$\hat{\lambda} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t$$

In the Fama-MacBeth regressions, we include 7 factors to explain the dependent variable RET(1): $\log(O/F)$, CAR, MOM, AMI, $RET(0)$, $\log(FVOL)$, $\log(OPVOL)$.

RET(1) is the dependent variable indicating the return of commodity i in week $t+1$ after observing O/F at the end of week t.

$\log(O/F)$ is the log value of O/F for commodity i in week t. CAR equals the basis of commodity i at the end of week t. MOM is the cumulative returns measures over the past 8 weeks and adjusted by market return. $RET(0)$ is the contemporaneous return of commodity i in week t. $\log(FVOL)$ and $\log(OPVOL)$ equal the log value of futures and options trading volume of commodity i in week t.

We also include the liquidity factor AMI. According to Marshall et al. (2011), the Amihud (2002) liquidity factor is the best low-frequency liquidity measure for commodity futures. In this paper, we use this measure for the individual futures contract liquidity. The proxy measures absolute price changes per futures contract volume:

$$AMI = \frac{|r_t|}{Volume_t}$$

where r_t is the return on day t and $Volume_t$ is the futures volume on day t.

Estimation results of the Fama-MacBeth regressions are reported in Table 2.5. Column 1 contains the results of regressing $RET(1)$ on CAR and MOM. The coefficient of MOM is positive but not significant. The positive momentum effect doesn't exists in the commodity futures market for weekly data. Also, the CAR coefficient is positive but not significant, indicating that the carry effect is not significant in the commodity market of weekly observations.

Column 2 contains one more factor AMI than column 1. Results show that liquidity does not play an important role in predicting the weekly returns in commodity futures markets.

Columns 3 and 4 contain the results of regressing $RET(1)$ on futures volume and options volume after controlling for carry, momentum and liquidity factors. We find that neither futures volume nor options volume are significant in predicting futures returns, although the coefficients of futures volume and options volume are positive and negative.

Column 5 has the result of regressing $RET(1)$ on $\log(O/F)$ after controlling for carry, momentum. The result shows that $\log(O/F)$ is negative and statistically significant at the 5% percent level.

In column 6, we also use liquidity factor besides carry and momentum as the control variable. The variable $\log(O/F)$ is still negative and significant (t-statistics = -2.542).

Finally, in column 7, we include the contemporaneous return in the portfolio formation week, $RET(0)$, to control for the possibility of weekly return reversals. Although the coefficient of $RET(0)$ is positive, this factor is not statistically significant. Also, $\log(O/F)$ is still negatively significant in this regression.

In conclusion, Table 2.5 show that the negative relation between O/F and $RET(1)$ is robust after controlling for the other 4 variables.

2.4 WASDE announcement analysis

In every month, the United States Department of Agriculture (USDA) publishes the monthly WASDE (World Agricultural Supply and Demand Estimates) reports to announce current and expected market conditions for several agricultural commodities to participants in commodity markets. One important forecast from WASDE is the expected ending stock at the end of each marketing year. Ending stocks, also referred as carryout, are the amount of a commodity left over after all demand has been satisfied and enters the supply side of the market in the following marketing year. Low ending stocks can lead to high prices of the commodity since it is a signal for less supply of commodity.

In the previous literature, many papers have found the commodity futures react to WASDE announcements. For instance, Adjemian (2012) analyzes the absolute value of overnight return before and after the announcement date and confirms that the WASDE announcement effect persists across contract positions.

This section, however, focuses on a different dimension of the WASDE announcement effect. We study the link between the activities in futures and options markets and post-announcement returns. The commodities we analyze in this section are Soybean Oil, Corn, Cotton, Soybeans, Sugar, Soybean Meal, and Wheat.

2.4.1 Post-announcement returns

Our paper examines the predictive power of O/F for cumulative returns following the announcement. We use four return windows: CUM(+0,+5), CUM(+0,+10), CUM(+0,+15), CUM(+0,+20). CUM(X,Y) equals the cumulative return for each commodity from X trading days to Y trading days after the announcement date.

The forecast of ending stock from the WASDE report for commodity i in month m is defined as $ES_{i,m}$. To capture the news released at the announcement, the surprise of the forecast in ending stocks comparing with that in the last month is constructed as:

$$\Delta ES_{i,m} = \frac{ES_{i,m} - ES_{i,m-1}}{ES_{i,m-1}}$$

The pre-announcement returns may have a significant effect on the post-announcement returns since the informed traders can obtain private information before the announcement and start to trade in the same direction with the results from the announcement reports. Motivated by this rationale, we construct two more variables: pre-CUM denotes cumulative return over the pre-announcement window (days -5 to -1); abs(pre-CUM) denotes absolute value of cumulative return over the pre-announcement window (days -5 to -1). In the empirical method, the control variables are CAR and AMI that are the basis and measure for illiquidity for commodity over the pre-announcement window (days -5 to -1). To correct for cross-sectional correlation, the standard errors are clustered (by time), refer to Petersen (2009).

Table 2.6 presents the results about the predictive power of O/F on the cumulative returns after announcement. In the column of CUM(+0,+5), the coefficient on ΔES is significantly negative (t-statistic = -4.01). Higher prediction of ending stocks for a commodity i is a negative signal for futures price. The reason is that higher ending stocks means the supply is higher than expected, which would cause the futures price going down. After the WASDE report is released, the participants in the commodity market obtain the new information about the predicted ending stocks and change their trading behaviors, which will cause the decrease of futures prices [5]. So the negative relation between the change in forecasts of ending stocks and post-announcement returns is not surprising. However, when the horizon for cumulative returns is longer than CUM(+0,+5) such as CUM(+0,+10), CUM(+0,+15) and CUM(+0,+20), ΔES does not have enough predictive power for cumulative post-announcement returns. So after 5 days post-announcement windows (day 0 to day +5), the information of ending stocks from the WASDE report is not a reliable factor to predict the futures prices over a long time period. New information will come to investors several days after the WASDE report is released, they will make investment decisions based on the new information, which will affect the predictive power of ΔES.

From Table 2.6, we find that O/F has predictive power over a longer horizon than ΔES does. Consistent with the results in the previous section, the coefficient of O/F is strongly negative (t-statistics = -3.276) in the column of CUM(+0,+5). When the informed traders obtain the private information before the announcement, they will make decisions about investment before the report is released, which cause the significant change in options and futures trading volume. What's more, the coefficients of O/F are significant negative (t-statistics = -3.171, -3.822, -3.778) for other three columns of CUM(+0,+10), CUM(+0,+15), and CUM(+0,+20). Since the trading volume of options and futures in pre-announcement (day -5 to day -1) not only contains the information

[5] See Appendix A.1 for details

about the WASDE report, but also includes news that is farther away than post-announcement window (day 0 to day +5). So O/F has predictive power over a longer horizon than the change of predictions in ending stocks ΔES. The variable pre-CUM is positive and significant (t-statistics = 2.090, 1.814, 1.693) in the columns of CUM(+0,+5), CUM(+0,+10), and CUM(+0,+15). This indicates the momentum effect exists in before and after the announcement. The momentum effect fades away as the time horizon becomes longer.

2.5 COT report analysis

2.5.1 Basic information about COT reports

A database commonly used in the studies of commodity market is the weekly Commitments of Traders (COT) reports published by Commodity Futures Trading Commission (CFTC). The COT reports include the aggregate long and short positions of commodity futures market participants by trader type: commercials, non-commercials, and non-reportables. The COT reports provide a breakdown of each Tuesday's open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC. The weekly reports for Futures-Only Commitments of Traders and for Futures-and-Options-Combined Commitments of Traders are released every Friday.

For the Futures-and-Options-Combined report, the option open interest and traders' option positions are computed on a futures-equivalent basis using delta factors supplied by the exchanges. Long-call and short-put open interest are converted to long futures-equivalent open interest. Likewise, short-call and long-put open interest are converted to short futures-equivalent open interest. For example, if an investor holds a long call position of 100 contracts with the value of delta being 0.5, this trader is considered to be holding 50 contracts of long futures equivalent positions. A trader's long and short futures-equivalent positions are added to the trader's long and short futures positions to give "combined-long" and "combined-short" positions.

Each individual trader is distinguished by CFTC about whether she has a commercial interest in each commodity. If a trader uses futures contracts in a particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z), this trader is classified as commercial. The commercials are often considered to have long positions in the physical product, such as corn producers, trying to reduce the risk by taking short positions in the futures market. The non-commercials, sometimes called speculators, have no innate position in the physical commodity, and seek to earn a profit in the futures market by taking long or short positions to take advantage of what they view as favorable prices.

Since the COT reports only include the commodities that are traded on four American exchanges (NYMEX, NYBOT, CBOT, and CME), we exclude Cocoa futures from ICE London and Crude oil Brent futures from ICE Europe. In this section, the data sample includes 23 commodities and the sample period is from April 1995 to December 2018. Then we merge the COT reports with the data of futures contracts for individual commodities.

2.5.2 Baseline model

In the previous section, we have shown that there is a negative relation between the option-to-futures volume ratio and futures returns in the next week. The results indicate that the informed traders tend to trade in commodity option markets instead of futures market when hear bad news. Since the main participants in commodity markets are commercials and non-commercials (speculators), it is meaningful to investigate the behaviors of these two type traders.

Kang et al. (2019) also use weekly data (futures returns are constructed as Tuesday-Tuesday) to study the dynamic interaction between the net positions and risk premiums in commodity futures markets. For the short-term horizon (weekly level), the position changes are mainly driven by the liquidity demands of non-commercial traders. Also, we calculate the weekly return for each futures contract with different maturity for each commodity. However, Kang et al. (2019) compute the weekly excess return using the front-month contract. Since the open interest of COT reports is the total of all futures and option contracts for each commodity, our data sample is more consistent with the data in the COT reports.

We use the main model from Kang et al. (2019) as our baseline model. In their paper, they construct three variables to characterize the positions and trading behavior of participants in futures markets: hedging pressure (HP), net trading (Q), and the propensity to trade (PT).

Hedging pressure (HP) is defined as the number of contracts that the commercial traders are short minus the number of contracts that are long, divided by the total open interest. For commodity i in week t:

$$HP_{i,t} = \frac{\text{commercial netshort positions}_{i,t}}{OI_{i,t}}$$

$\overline{HP}_{i,t}$ is calculated as trailing 52-week moving average of the net short positions of commercials from week $t-51$ to week t scaled by the open interest in week t. Kang et al. (2019) show that $\overline{HP}_{i,t}$ captures sources of variation in risk premiums and significantly predicts expected returns.

For commercials and non-commercials, the net trading measure (Q) is defined as the net purchase of futures contracts, calculated as the change in their long position for commodity i from week $t-1$ to week t, normalized by the open interest at the beginning of the week:

$$Q_{i,t} = \frac{\text{netlong position}_{i,t} - \text{netlong position}_{i,t-1}}{OI_{i,t-1}}$$

Column 1 in Table 2.7 shows the results of the baseline model for commercials and confirms the findings by Kang et al. (2019). The commodities that are bought by the commercials in week t earn significant higher returns in week $t+1$ than the commodities sold by them. The coefficient of $\overline{HP}$ is also positive and similar with Kang et al. (2019), although not statistical significant. The results of the baseline model for non-commercials are in column 3 of Table 2.7. The results in column 3 also replicate the results from Kang et al. (2019). The variable $\overline{HP}$ is significant to predict commodity risk premium in the multivariate regression.

One concern is whether the relationship between O/F and the expected returns still hold in this baseline model. Table 2.7 helps to address this concern. In the regressions for commercials and non-commercials in columns 2 and 4, the coefficients of $\log(O/F)$ remain significant at 1% level (t-statistics = -2.614 and -3.142). These estimates indicate strong support for the findings in the previous section.

2.5.3 Liquidity supply and demand in commodity options market

An intuitive extension of Kang et al. (2019) is to explore the liquidity supply and demand in commodity options markets. Our empirical strategy in this section parallels the empirical method in Kang et al. (2019) for commodity futures markets. In commodity options markets, we construct net trading measure (NT) as the net purchase of options contracts for commercials and non-commercials, calculated as the change in their net long position in options contracts for commodity i from week $t-1$ to week t, normalized by the open interest at the beginning of the week:

$$NT_{i,t} = \frac{\text{netlong position}_{i,t} - \text{netlong position}_{i,t-1}}{OI_{i,t-1}}$$

where $OI_{i,t-1}$ is the total open interest (including futures and options) at week $t-1$.

We first explore the relationship between the net trading measure (NT) in options and contemporaneous or past returns. The average first-order autocorrelation of weekly time-series NT of all 23 commodity futures markets for commercials and non-commercials are only -0.056 and -0.036. Based on this low autocorrelation of time series NT, we can be confident to employ the Fama-MacBeth regression. Table 2.8 presents the time series average of the slope coefficients and the corresponding t-statistics. For both commercials and non-commercials, the net trading measure (NT) is significantly correlated to the contemporaneous and lagged commodity futures returns. However, the correlations between net trading measure (NT) in options with returns have opposite signs for commercials (negative) and non-commercials (positive). Actually, the commercials are contrarians and non-commercials are momentum traders in commodity options market. These results are consistent with the findings in Kang et al. (2019) in commodity futures market, as well as the results in Rouwenhorst and Tang (2012).

Motivated by the models in Campbell et al. (1993), Grossman and Miller (1988), Kaniel et al. (2008) and Kang et al. (2019), we hypothesize that the market makers typically trade against price trends and are compensated for providing liquidity by the price reversal subsequently. To determine the direction of liquidity provision, we conduct the analysis about the impact of net trading measure (NT) in options on the subsequent commodity futures returns. We run the predictive Fama-MacBeth regressions of cumulative commodity futures returns from week t to weeks $t+1$, $t+2$, and $t+3$ on the net trading measure (NT) in options with the control variables to capture variation in expected futures returns:

$$RET_i^{(t,t+j)} = \alpha_i + \beta_1 NT_{i,t} + \beta_2 CAR_{i,t} + \beta_3 r_{i,t} + \beta_4 Q_{i,t} + \beta_5 \overline{HP}_{i,t} + \epsilon_{i,t+j}, \quad j = 1, 2, 3$$

where $RET_i^{(t,t+j)}$ is the cumulative return of commodity i from week t to $t+j$. $CAR_{i,t}$ is the log of basis for commodity i in week t, $\overline{HP}_{i,t}$ is the moving average of hedging pressure for commodity i in week t.

From Table 2.9, we find that the commodities bought by the commercials in week t has significantly higher cumulative returns in the subsequent three weeks than the commodities sold by the commercials after controlling other variables. However, from Table 2.10, the commodities bought by the non-commercials in week t has significant lower cumulative returns in the subsequent three weeks than the commodities sold by the non-commercials.

One concern is that the commercials have the private information, so the prices of commodities they buy have higher chance to increase in the subsequent time periods. The commercials have the information advantage in the underlying physical commodities markets that is about the the fundamentals in the commodity markets, which the non-commercials may not be able to observe. If the commercial traders have the private information in commodity market, the price of commodities purchased by the commercials should simultaneously increase (Kang et al., 2019). However, in Table 2.8, the commercials are buying losers and sell winner before the release of the COT report, which is consistent with the theory of liquidity provision.

Overall, we find the clear answer for the question which participant provide the liquidity in commodity options markets. The empirical results show that, in the commodity options market, the commercials buy losers, sell winners, employ the contrarian strategy and provide the liquidity to satisfy the trading demand of non-commercial traders.

2.6 Robustness checks

2.6.1 Before and after the start of financialization

In the most recent decade, commodity index traders have become a significant big player in the commodity market. This fundamental change is called the financialization of commodity markets. Referring to Figure 2.3, there is a sharp decline of O/F since year 2005, which confirms the existence of financialization in commodity markets. Because commodity index traders mainly invest in the futures market, O/F fell sharply since year 2005. So it has great importance to investigate whether the empirical results would change before and after the start of financializtion in commodity market. We divide the whole sample interval into two sub-periods. Sub-period 1 include the time period before year 2005 (including 2005); sub-period 2 is the time period after year 2005.

First, we employ time-series tests for these two sub-periods. The baseline model is the same as that in Section 2.3.2. The results for the time-series tests are in Table A.1 and Table A.2. For sub-period 1, the "1-8" and "(1+2)-(7+8)" columns show positive significant alpha for one, two, three factor models. Column 1 also presents positive significant alpha (t-statistics = 2.277, 2.451, 2.331) for all three models. For sub-period 2, all the alphas are positive significant in column 1 and "1-8" for all the models. In summary, the results in two sub-periods pass the time-series tests.

Next, the cross-sectional tests are conducted for both sub-periods as in Section 2.3.3. From Table A.3, the coefficients of O/F are negative and significant in both models for the two sub-periods.

2.6.2 Commodity sector analysis

Do our results hold in different sectors, or are they mainly driven by one sector of commodities that have high expected returns with low O/F or low expected returns with high O/F? We sort our sample commodities into 4 sectors: Agriculture, Energy, Livestock, and Metals. For each sector, the cross-sectional tests are employed. In Table A.4, we report the results for each sector. The predictive power of O/F still exists and negatively significant in Agriculture, Energy, and Livestock sectors. An interesting finding is that the impact of CAR, MOM and AMI is different from Table 2.5, which is based on the whole sample. CAR and MOM have opposite significant impact in predicting prices, then it is not surprised that these two variables are not significant in the cross-sectional results based on the whole sample.

2.6.3 Monthly analysis

In the previous sections of our paper, we use the weekly data to do the analysis. In the literature, many papers use monthly data such as Yang (2013), Bakshi et al. (2017), and Hong and Yogo (2012). An intuitive question is to ask whether the empirical results only hold in the weekly data. In this section, we assess whether we can get similar results in monthly data.

The results of monthly analysis are reported in Table A.5. The coefficient of O/F remains positively significant after controlling different variables, which indicates O/F has good predictive power even on a longer long time period.

2.6.4 Alternative measure $\Delta O/F$

The last robustness check is to utilize an alternative measure of O/F. Similar to the stock market, one potential concern with our empirical results is that some commodities could have consistently higher O/F and lower average returns for some reasons (Johnson and So, 2012). To address this concern, we construct an alternative measure $\Delta O/F$ as the change in O/F relative to a rolling average of past O/F in prior 8 weeks for each commodity. $\Delta O/F$ is defined as:

$$\Delta O/F_{i,t} = \frac{O/F_{i,t} - \overline{O/F_i}}{\overline{O/F_i}}$$

where $\overline{O/F_i}$ is the average $O/F_{i,t}$ for commodity i over the prior 8 weeks.

The results in Table A.6 show that the coefficient estimates of $\Delta O/F$ are negative and significant, which is consistent with our expectation. We can address the concern that some commodities have consistently high O/F with low average returns or low O/F with high average returns.

2.7 Conclusion

In this paper, we examine the information content in commodity futures and options volume. In the previous literature, commodity options markets have received much less attention than commodity futures markets. However, the trading activities in options markets can have great effect on the underlying futures markets. We are the first to study the option-to-futures volume ratio in an empirical asset pricing framework.

After the time-series tests and cross-sectional tests, we confirm the return predictability of O/F. Our results are robust across a variety of specifications. Our paper makes an unique contribution to confirm WASDE announcement effect. Comparing with the predictive ability of the information contained in the WASDE report, O/F has relatively long-lived predictive power, which suggests that it takes multiple weeks for the information in O/F to become fully reflected in futures prices. In the analysis of COT reports, we find that the non-commercial traders in commodity options markets demand short-term liquidity from the commercial traders. Non-commercials pay a premium by buying the underperformance commodities and sell outperformance commodities.

Our work suggests many areas of further research. First, given the data of commodity options, an interesting topic is to explore the determinants of volatility in commodity futures prices since the investors often refer to implied volatility to make investment decisions on options market. Second, the volume differences across calls and puts could be examined to predict commodity futures returns skewness, which can be a good complement to Fernandez-Perez et al. (2018). Finally, a critically important topic is to find more empirical evidence to explain why there is a negative and significant relationship between O/F and expected futures returns. These and other issues are left for future research.

Table 2.1 Summary statistics of commodity futures for every individual commodity in the sample.

Sector	Commodity	Symbol	N	O/F	E[R](%)	$\sigma[R]$	Sharpe ratio
Agriculture	Soybean oil	BO	1641	0.091	-0.131	0.033	-4.021
	Corn	C	988	0.300	-0.125	0.037	-3.354
	Cocoa (ICE-US)	CC	1035	0.154	-0.024	0.039	-0.622
	Cotton	CT	1015	0.400	-0.082	0.035	-2.323
	Orange juice	JO	1232	0.291	-0.080	0.044	-1.825
	Coffee	KC	1032	0.415	-0.121	0.051	-2.397
	Lumber	LB	1196	0.074	-0.211	0.042	-5.033
	Oats	O	908	0.075	0.023	0.046	0.495
	Cocoa (ICE-London)	QC	777	0.156	-0.193	0.036	-5.310
	Rough rice	RR	1215	0.085	-0.220	0.035	-6.339
	Soybeans	S	1414	0.341	-0.011	0.032	-0.330
	Sugar	SB	840	0.249	-0.221	0.043	-5.112
	Soybean meal	SM	1633	0.106	0.112	0.036	3.076
	Wheat	W	988	0.255	-0.223	0.041	-5.499
Energy	Crude oil (WTI)	CL	2548	0.196	0.025	0.047	0.532
	Crude oil (Brent)	CO	1958	0.057	0.249	0.043	5.843
	Heating oil	HO	2415	0.029	0.077	0.044	1.740
	Natural gas	NG	2460	0.080	-0.411	0.062	-6.608
	Gasoline	XB	1193	0.013	-0.071	0.047	-1.512
Livestock	Feeder cattle	FC	1687	0.132	0.031	0.020	1.550
	Live cattle	LC	1176	0.199	0.040	0.021	1.856
	Lean hogs	LH	1504	0.154	-0.063	0.036	-1.769
Metals	Gold	GC	1233	0.135	0.032	0.023	1.425
	Copper	HG	1840	0.008	0.045	0.034	1.307
	Silver	SI	1032	0.090	0.052	0.039	1.332

Note: The sample include the average weekly close quotes of individual futures contract of 25 commodities from March 1994 to December 2018. The column N is the number of weekly observations available for a commodity. The column O/F reports the historical average weekly ratio of options-to-futures trading volumes. The columns E[R](%) and $\sigma[R]$ are the historical average and standard deviation of weekly futures excess returns of individual commodities with different maturities.

Table 2.2 Descriptive statistics of O/F by year.

Year	Commodities	Contracts	N	MEAN	P25	MEDIAN	P75	SKEW
1994	23	139	988	0.207	0.058	0.107	0.209	9.768
1995	24	193	1434	0.276	0.066	0.136	0.256	15.193
1996	24	176	1295	0.259	0.083	0.163	0.303	7.938
1997	24	191	1376	0.254	0.078	0.165	0.282	14.479
1998	24	197	1448	0.248	0.079	0.175	0.298	5.561
1999	24	199	1484	0.251	0.080	0.158	0.267	13.686
2000	24	197	1432	0.326	0.066	0.149	0.266	9.644
2001	23	173	1249	0.291	0.073	0.168	0.301	6.810
2002	24	188	1332	0.318	0.057	0.152	0.310	13.694
2003	24	196	1393	0.309	0.055	0.139	0.278	13.410
2004	24	191	1334	0.286	0.061	0.166	0.339	8.571
2005	24	180	1210	0.312	0.065	0.139	0.272	13.514
2006	25	195	1365	0.225	0.045	0.130	0.267	24.946
2007	25	197	1442	0.158	0.030	0.075	0.178	12.895
2008	25	208	1456	0.169	0.034	0.079	0.194	10.030
2009	25	209	1428	0.158	0.021	0.064	0.165	19.023
2010	25	214	1472	0.138	0.020	0.067	0.175	5.615
2011	25	213	1511	0.158	0.020	0.070	0.213	4.087
2012	25	202	1477	0.205	0.029	0.079	0.223	20.220
2013	25	211	1497	0.170	0.043	0.095	0.220	23.924
2014	25	211	1486	0.174	0.038	0.109	0.236	11.847
2015	25	213	1499	0.171	0.040	0.110	0.228	7.650
2016	25	206	1457	0.164	0.041	0.105	0.225	4.492
2017	25	207	1457	0.160	0.036	0.100	0.214	8.008
2018	25	195	1438	0.165	0.030	0.104	0.204	12.095
ALL	25	4281	34960	0.220	0.044	0.119	0.246	19.670

Note: This table provides the sample size information and descriptive of $O/F_{i,t,T}$, where $O/F_{i,t,T}$ is the ratio of option volume to futures volume of the contract with maturity T of commodity i in each week t from March 1994 to December 2018. The column Commodities is the number of commodities that appear in each year. The column Contracts is the total number of contracts of all commodities in each year. The column N is the total number of weekly observations of all commodities available in a year. The last 5 columns are the mean, 25th percentile, median, 75th percentile and skewness of $O/F_{i,t,T}$ for each year.

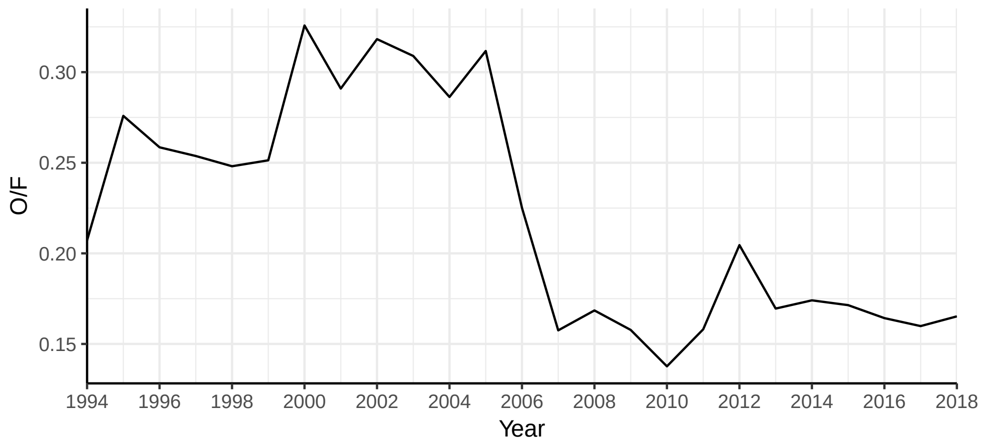

Figure 2.3 Average annual value of O/F between 1994 to 2018

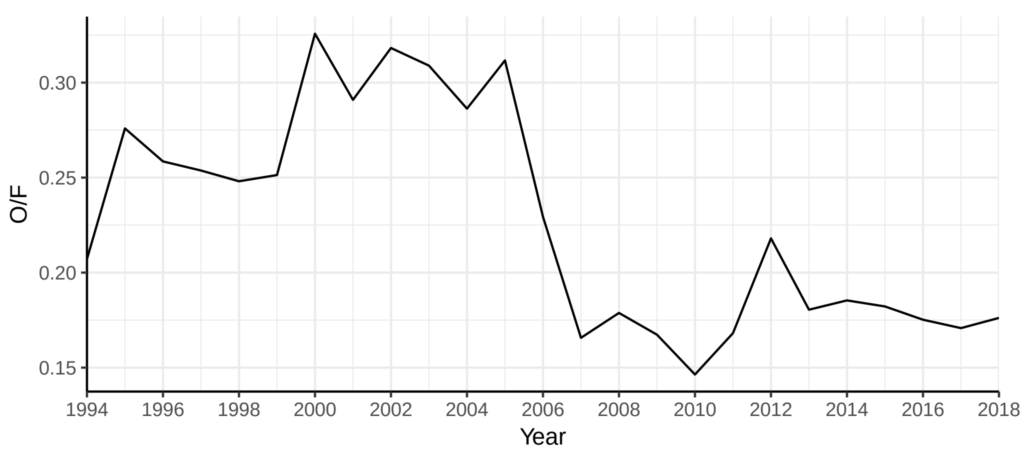

Figure 2.4 Average annual value of O/F excluding gasoline futures and options between 1994 to 2018

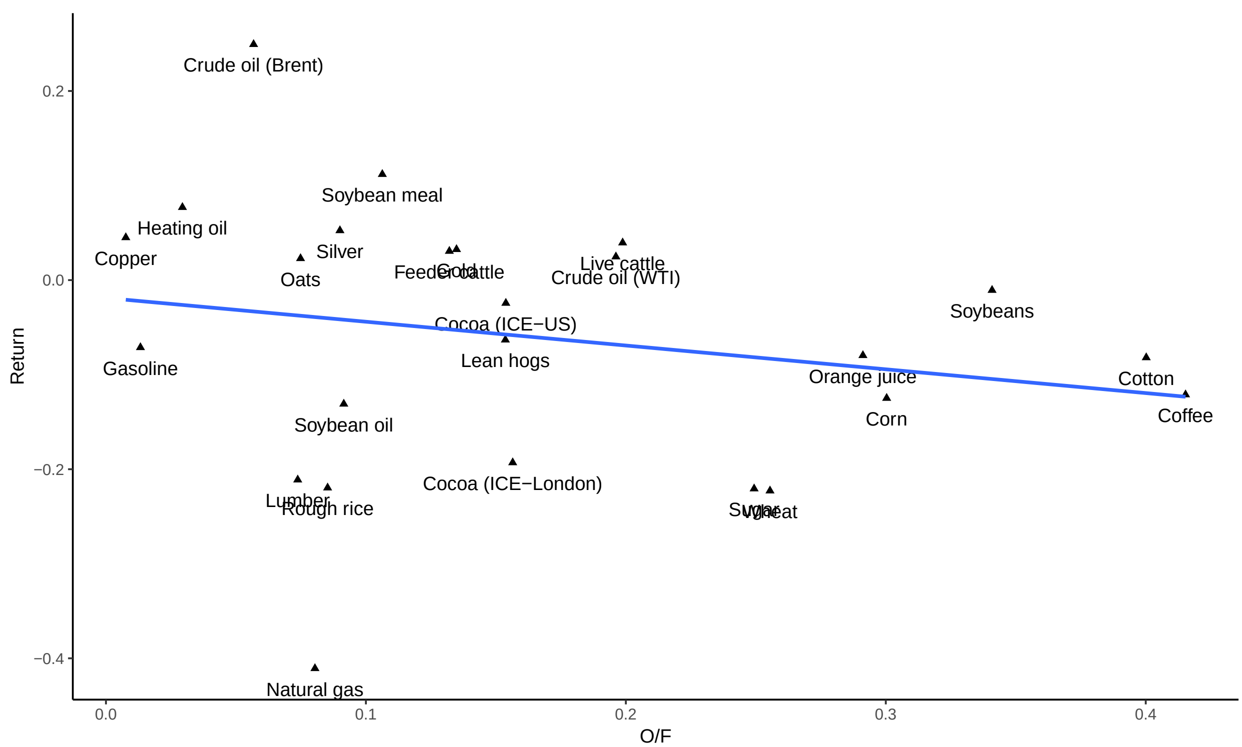

Figure 2.5 Cross-sectional of average futures return and average value of O/F.

Table 2.3 Group characteristics sorted by O/F.

Group	Commodities	Contracts	VLC	VLP	OPVOL	FVOL	O/F	r_{t+1}
1	21	1147	660.648	571.822	1232.470	158066.472	0.008	0.054
2	23	1666	2443.777	2209.608	4653.385	147130.722	0.031	0.015
3	25	1852	4710.775	4302.299	9013.074	150986.305	0.060	-0.013
4	25	2022	8005.445	7323.093	15328.538	156346.984	0.097	-0.112
5	25	2097	14934.845	14631.800	29566.645	204271.365	0.145	0.018
6	25	1985	20693.111	19690.694	40383.805	195293.307	0.207	-0.038
7	25	1791	25686.789	23791.294	49478.082	165071.331	0.303	-0.101
8	24	1369	22782.214	19535.015	42317.229	77647.619	0.909	-0.220

Note: This table provides the characteristics of groups sort by O/F for all weekly observations. The date range of the sample is from March 1994 to December 2018. We divide the sample data into 8 groups with the same number of commodity-weeks data. Group 1 is with the lowest value of O/F. Group 8 has the highest value of O/F. The column Commodities and Contracts are the total number of commodities and contracts in each group. VLC and VLP are the average call and put contracts trading volume in each group. OPVOL and FVOL are the average options and futures trading volume in each group. The column O/F is historical average value of O/F for each group. r_{t+1} is the weekly average return of a group in the next week after the given week t.

Table 2.4 Time-series tests results of groups sorted by O/F

	1 (Low)	2	3	4	5	6	7	8 (High)	1-8	(1+2)-(7+8)
					Commodity CAPM					
Alpha	0.001	-0.0002	0.0004	-0.001	-0.001	0.0003	-0.0002	-0.001	0.003	0.003
	(2.732)	(-0.343)	(0.702)	(-1.438)	(-1.063)	(0.540)	(-0.361)	(-2.275)	(3.144)	(2.244)
AVG	1.137	0.862	0.831	0.739	0.728	0.905	0.951	0.875	0.263	0.173
	(42.188)	(28.158)	(26.196)	(24.978)	(22.547)	(27.928)	(29.173)	(26.336)	(5.530)	(2.583)
R^2	0.580	0.381	0.347	0.326	0.283	0.377	0.398	0.350	0.022	0.004
					Commodity *AVG* and *CARRY*					
Alpha	0.001	-0.0001	0.001	-0.001	-0.001	0.0003	-0.0003	-0.001	0.003	0.003
	(2.809)	(-0.170)	(0.820)	(-1.542)	(-1.061)	(0.544)	(-0.400)	(-2.246)	(3.164)	(2.360)
AVG	1.141	0.869	0.835	0.735	0.728	0.905	0.951	0.876	0.264	0.182
	(42.228)	(28.446)	(26.286)	(24.812)	(22.473)	(27.913)	(29.116)	(26.299)	(5.546)	(2.713)
CARRY	-0.036	-0.055	-0.014	0.030	-0.007	-0.030	-0.006	-0.014	-0.022	-0.071
	(-2.043)	(-2.794)	(-0.666)	(1.599)	(-0.332)	(-1.423)	(-0.291)	(-0.633)	(-0.716)	(-1.637)
R^2	0.581	0.386	0.349	0.326	0.282	0.377	0.397	0.349	0.022	0.006
					Commodity *AVG*, *CARRY* and *MOM*					
Alpha	0.002	-0.0001	0.0005	-0.001	-0.001	0.0004	-0.0002	-0.002	0.003	0.003
	(2.869)	(-0.164)	(0.742)	(-1.647)	(-1.106)	(0.661)	(-0.377)	(-2.341)	(3.267)	(2.423)
AVG	1.138	0.869	0.838	0.740	0.731	0.899	0.950	0.881	0.256	0.175
	(41.996)	(28.331)	(26.334)	(24.925)	(22.471)	(27.680)	(28.975)	(26.388)	(5.371)	(2.602)
CARRY	-0.033	-0.055	-0.018	0.025	-0.009	-0.023	-0.005	-0.019	-0.014	-0.063
	(-1.862)	(-2.751)	(-0.861)	(1.315)	(-0.450)	(-1.111)	(-0.231)	(-0.876)	(-0.444)	(-1.454)
MOM	-0.021	-0.002	0.030	0.038	0.018	-0.046	-0.009	0.039	-0.059	-0.053
	(-1.220)	(-0.128)	(1.500)	(2.033)	(0.901)	(-2.257)	(-0.434)	(1.859)	(-1.994)	(-1.259)
R^2	0.581	0.386	0.350	0.328	0.281	0.379	0.397	0.351	0.024	0.006

Note: The groups are sorted by $O/F_{i,t}$, where $O/F_{i,t}$ is the ratio of option volume to futures volume of commodity i in week t. Group 1 has the lowest value of O/F, where group 8 is with highest O/F. The return of each group is the weekly return in week $t+1$. We include three contemporaneous risk factors of week $t+1$ in the regressions: AVG, $CARRY$, MOM. The three regressions have part or full of these three risk factors. The t-statistics are shown in parenthesis.

Table 2.5 Cross-sectional tests results

Fama-MacBeth regressions of RET(1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAR	-0.982	-0.915	-0.582	-0.933	-0.530	-0.410	-0.479
	(-0.977)	(-0.894)	(-0.556)	(-0.890)	(-0.522)	(-0.396)	(-0.424)
MOM	0.299	0.363	0.322	0.360	0.293	0.371	0.415
	(0.637)	(0.758)	(0.672)	(0.749)	(0.624)	(0.779)	(0.789)
AMI		2.339	7.077	0.630		1.729	2.818
		(0.416)	(0.883)	(0.089)		(0.299)	(0.410)
$\log(FVOL)$			0.027				
			(1.161)				
$\log(OPVOL)$				-0.016			
				(-1.189)			
$\log(O/F)$					-0.040**	-0.049**	-0.067***
					(-2.161)	(-2.542)	(-3.307)
$RET(0)$							1.003
							(0.866)
Constant	0.952	0.882	0.280	1.054	0.406	0.267	0.307
	(0.937)	(0.854)	(0.257)	(0.993)	(0.395)	(0.255)	(0.268)
Observations	27,024	27,024	27,024	27,024	27,024	27,024	25,729
R^2	0.268	0.313	0.344	0.323	0.273	0.320	0.387

Note: This table presents Fama-MacBeth regression results from regressing $RET(1)$ on risk factors. $RET(1)$ is the dependent variable indicates the return of commodity i in week t+1 after observing O/F at the end of week t. CAR equals the basis of commodity i at the end of week t. MOM is the cumulative returns measures over the past 8 weeks and adjusted by market return. AMI is the Amihud illiquidity of commodity i in week t. $RET(0)$ is the contemporaneous return of commodity i in week t. $FVOL$ equals the futures volume of commodity i in week t. $OPVOL$ equals the options volume of commodity i in week t. The t-statistics are shown in parenthesis. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table 2.6 Results for post-announcement cumulative returns analysis

Dep. variable:	CUM(+0,+5)	CUM(+0,+10)	CUM(+0,+15)	CUM(+0,+20)
ΔES	−3.992***	0.122	0.039	0.021
	(−4.007)	(1.093)	(0.399)	(0.267)
log(O/F)	−0.280***	−0.040***	−0.043***	−0.036***
	(−3.276)	(−3.171)	(−3.822)	(−3.778)
pre-CUM	0.080**	0.010*	0.009*	0.007
	(2.090)	(1.814)	(1.693)	(1.566)
abs(pre-CUM)	−0.080	−0.007	−0.003	−0.004
	(−1.515)	(−0.944)	(−0.386)	(−0.800)
CAR	7.122*	0.707	1.006**	0.578*
	(1.938)	(1.504)	(2.225)	(1.652)
AMI	−204.298	108.648	84.806*	38.321
	(−0.346)	(1.376)	(1.862)	(0.645)
Constant	−7.632**	−0.798*	−1.102**	−0.651*
	(−2.032)	(−1.649)	(−2.375)	(−1.810)
Observations	2,190	2,090	2,090	2,090
R^2	0.026	0.013	0.017	0.014

Note: This table presents the results about the predictive power of O/F on the cumulative returns after the announcement. ΔES is the change of forecast in ending stock from last month to current month, scaled by the forecast in the last month. pre-CUM denotes cumulative return over the pre-announcement window (days -5 to -1); abs(pre-CUM) denotes absolute value ofcumulative return over the pre-announcement window (days -5 to -1). CAR and AMI are the basis and measure for illiquidity for commodity over the pre-announcement window. The standard errors are clusterd (by time). The t-statistics are shown in parentheses. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table 2.7 Results for Commercials and Non-Commercials

Fama-MacBeth regressions of RET(1)				
	Commercials		Non-Commercials	
	(1)	(2)	(3)	(4)
CAR	-0.737	-0.382	-0.977	-0.696
	(-0.625)	(-0.311)	(-0.821)	(-0.567)
$RET(0)$	3.053**	2.209	2.883**	2.134
	(2.185)	(1.514)	(2.095)	(1.503)
Q	5.460***	4.610***	-6.009***	-5.297***
	(5.048)	(3.916)	(-5.134)	(-4.217)
$\overline{HP}$	0.280	0.281	0.381*	0.389*
	(1.443)	(1.400)	(1.940)	(1.935)
$\log(O/F)$		-0.076***		-0.085***
		(-2.614)		(-3.142)
Constant	0.694	0.170	0.913	0.444
	(0.582)	(0.136)	(0.758)	(0.356)
Observations	21,548	21,548	21,548	21,548
R^2	0.294	0.310	0.291	0.306

Note: This table presents Fama-MacBeth regression results from regressing $RET(1)$ on risk factors for commercials and non-commercials. $RET(1)$ is the dependent variable indicates the return of commodity i in week $t+1$ after observing O/F at the week t. $RET(0)$ is the return of commodity i in week t. CAR equals the basis of commodity i at the end of week t. Q is the net trading measure of commercials and non-commercials for commodity i in week t. $\overline{HP}$ is the smoothed hedging pressure for commodity i in week t. The t-statistics are shown in parenthesis. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table 2.8 Relationship of NT with contemporaneous and lagged returns

Dependent Variable: NT(0)				
	Commercial		Non-Commercial	
	(1)	(2)	(3)	(4)
$RET(0)$	-0.095***		0.067***	
	(-32.235)		(26.070)	
$RET(-1)$		-0.007**		0.013***
		(-2.454)		(4.800)
$NT(-1)$		-0.003		0.023*
		(-0.205)		(1.680)
Constant	-0.0001**	-0.0001	0.0001**	0.0001*
	(-2.000)	(-1.426)	(2.034)	(1.671)
Observations	22,416	22,396	22,416	22,396
R^2	0.218	0.170	0.142	0.149

Note: This table presents the Fama-MacBeth regression results from regressing $NT(0)$ on risk factors for commercials. $RET(0)$ is the contemporaneous return of commodity i in week t. $RET(-1)$ is one lag return of commodity i in week $t-1$. $NT(-1)$ is one lag net trading measure (NT) of commodity i in week $t-1$. The t-statistics are shown in parenthesis. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table 2.9 Return predictability of NT for Commercials

Return predictability for Commercials			
	RET(+0,+1)	RET(+0,+2)	RET(+0,+3)
CAR	-0.828	-2.250	-1.522
	(-0.663)	(-1.248)	(-0.690)
$RET(0)$	3.492**	6.608***	8.843***
	(2.280)	(3.062)	(3.327)
$\overline{HP}$	0.252	0.499*	0.876**
	(1.244)	(1.701)	(2.391)
Q	5.730***	8.604***	10.226***
	(4.775)	(4.815)	(4.699)
NT	9.815*	23.416***	23.863**
	(1.647)	(2.902)	(2.361)
Constant	0.801	2.193	1.392
	(0.634)	(1.202)	(0.624)
Observations	21,548	21,528	21,507
R^2	0.317	0.311	0.313

Note: This table presents the Fama-MacBeth regression results from regressing $RET(1)$ on risk factors for commercials. $RET(1)$ is the dependent variable indicates the return of commodity i in week $t+1$. The control variables are CAR, $RET(0)$, $\overline{HP}$, and Q. The t-statistics are shown in parenthesis. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table 2.10 Return predictability of NT for Non-Commercials

Return predictability for Non-Commercials			
	RET(+0,+1)	RET(+0,+2)	RET(+0,+3)
CAR	-1.002	-2.709	-2.575
	(-0.801)	(-1.485)	(-1.148)
$RET(0)$	3.797**	6.062***	8.054***
	(2.457)	(2.855)	(3.121)
$\overline{HP}$	0.370*	0.635**	0.871**
	(1.782)	(2.170)	(2.345)
Q	-6.403***	-9.279***	-9.930***
	(-4.946)	(-4.861)	(-4.299)
NT	-12.113**	-26.478***	-29.717***
	(-2.142)	(-3.330)	(-3.060)
Constant	0.949	2.623	2.440
	(0.750)	(1.420)	(1.074)
Observations	21,548	21,528	21,507
R^2	0.313	0.306	0.304

Note: This table presents the Fama-MacBeth regression results from regressing $RET(1)$ on risk factors for non-commercials. $RET(1)$ is the dependent variable indicates the return of commodity i in week $t+1$ after observing O/F at the week t. The control variables are CAR, $RET(0)$, Q and $\overline{HP}$. The t-statistics are shown in parenthesis. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

CHAPTER 3. HOW WELL CAN USDA FORECAST ERROR OF CROP ENDING STOCKS BE EXPLAINED?

3.1 Introduction

The United States Department of Agriculture (USDA) publishes the monthly World Agricultural Supply and Demand Estimates (WASDE) reports for the participants in the commodity markets. The WASDE reports provide the forecasts in many aspects of the agriculture markets such as price, production, imports, exports, and ending stocks. Given the critical role of public information in commodity markets, it is not surprising that the information of WASDE reports is must-read for producers, traders, and policy makers in agriculture markets. The USDA WASDE reports follow the balance sheet approach for the estimation on both supply and demand sides (Vogel and Bange, 1999). The total supply for a crop includes beginning stocks, imports, and prospective production. While the toal demand side reflects domestic use, exports, and ending stocks. Specifically, ending stocks are estimated as the difference between total supply and total consumption (Botto et al., 2006; Isengildina-Massa et al., 2013).

Given the importance of the USDA forecasts, previous studies have confirmed that the markets would react after the release of USDA reports in each month. Isengildina et al. (2006b) investigate six major USDA reports in hog and cattle markets. They find the USDA reports have large effects on these two markets by increasing conditional standard deviation. The release of USDA forecasts have been found to be associated with 7 times higher futures returns volatility than normal futures returns for corn and soybean (Isengildina-Massa et al., 2008a). Also, WASDE reports could resolve the market uncertainty and lead a significant decrease of implied volatility in corn and soybean options markets (Isengildina-Massa et al., 2008b). Adjemian (2012) shows that the publication of WASDE reports is followed by the immediate reaction in the opening futures prices for cotton, soybeans and hard winter wheat. Zhang (2019) analyzes 7 agricultural commodities and finds that

USDA forecasts of ending stocks can predict the futures returns in the subsequent time periods after the announcement.

However, literature in this area seems to find that the USDA forecasts lack accuracy and efficiency. Most papers focus on USDA price and production forecasts (Von Bailey and Brorsen, 1998; Isengildina et al., 2004, 2006a; Sanders and Manfredo, 2002, 2003). But the USDA forecasts for ending stocks have received much less attention.

Ending stocks also referred as carryout are the amount of a commodity left over after all demand has been satisfied and enters the supply side of the market in the following marketing year. Low ending stocks can lead to high prices of the commodity. The USDA forecast is one major resource of crop ending stock forecast. Besides the USDA forecasts, a great number of private analysts has started to provide the crop ending stocks forecasts recently. The resources they use for the ending stocks forecast are from crop-production related surveys of farmers and some common information such as satellite maps or macroeconomic conditions (Xiao, 2015).

Ending stocks are very important in agricultural markets since the magnitude of marketing year ending stocks may be the single most important factor that summarizes the price implications and the commodity prices react to the ending stocks forecasts (Good and Irwin, 2014; Zhang, 2019).

As a major issuer of the crop ending stock forecast, the predictive efficiency and accuracy of USDA forecasts have been extensively studied. Literature in this area seems to find that the USDA forecasts of crop ending stocks inefficient. Botto et al. (2006) present the results that the soybean ending stocks are overestimated over the marketing years 1980/81 to 2003/04. Another finding is that there is a significant downward trend in the variance of the forecast errors for the shorter forecast horizon. Isengildina-Massa et al. (2013) analyze how the behavioral and macroeconomics factors affect the USDA forecast errors from 1987/88 to 2009/10 marketing years. The results suggest the multiple cases of inefficiency with respect to these two factors on the ending stocks forecasts. They also find USDA ending stock forecast suffers from behavioral bias. Xiao et al. (2017) propose an efficiency test on the crop ending stocks forecasts errors that are decomposed into unforecastable shocks and idiosyncratic residuals. They find that the USDA forecasts are inefficient and can be improved based on existing information. Also, the USDA is conservative in the crop ending stocks forecasts. For the crop ending stocks forecasts from private analysts, the forecasts are inefficient all three commodities of corn, soybean and wheat (Xiao, 2015).

An intuitive question is to ask what factors can cause the USDA forecast errors. Previous studies have proposed some hypothesis about where the errors come from. Isengildina-Massa et al. (2013) investigate the sources of the USDA forecast errors. For the macroeconomic factor, they find the largest increase in the size of USDA forecast errors was associated with structural changes in commodity markets. During the periods of economic growth and changes in exchange rates, corn, soybean and wheat forecast errors increased. For the behavioral factor, there exists leniency and pessimism in USDA forecasts across different categories. WASDE forecasts may be improved using the findings from their study. Isengildina et al. (2006a) focus on the USDA forecast revisions on corn and soybean production forecasts. Not all information available was incorporated in the forecasts and part of the loss in forecast accuracy is due to the "smoothed" forecast. Sanders and Manfredo (2002) show that USDA forecasts do not fully incorporate the information in the past forecasts and encompassing simple time-series models is necessary.

To the best of our knowledge, little has been proposed regarding what kinds of information influence the magnitude of the USDA forecast error in ending stocks. Isengildina-Massa et al. (2013) find that the lagged percentage forecast errors and post-2006 dummy variables are correlated with the percentage forecast errors. Based on the rational storage model, this paper finds that futures prices contain information about the ending stocks.

Although many studies focus on the efficiency of USDA forecasts, very few papers have investigated how to improve the USDA forecasts. Sanders and Manfredo (2003) analyze USDA livestock price forecasts, and suggest that a composite forecasts include both USDA and a time-series alternatives can improve the forecast accuracy. Hoffman et al. (2015) study the season-average price projections from WASDE. They find that the composite forecasts based on futures adjusted forecasts and WASDE projection can reduce the RMSEs for all forecast periods.

We analyze the USDA forecast error in ending stocks and try to find whether the error is dependent on information in the market that is not completely utilized. Out of sample test is used to find that the adjusted forecast can improve the efficiency of USDA forecast.

The remainder of the study is organized as follows. In Section 3.2, we provide the economics background about why futures contracts contain the information in ending stocks. Section 3.3 introduces the data and variables we choose in this paper. Section 3.4 presents the empirical specifications and proposed model. Section 3.5 discusses the main results. Section 3.6 shows the out of sample tests. Section 3.7 concludes.

3.2 Economic background

To determine the variables in the model, the economic rationale is from the rational storage model. In the rational storage model, theoretically, the amount of crop to be stored to the following period shall be compensated by the carry in the futures markets:

$$E_t[p_T(z_T + c_T)] - p_t = g(c_T|c_t) \tag{3.1}$$

where p_T is the harvest price of corn in year T, p_t is the spot price, z_T and c_T are the new production and remaining carryout at harvest, the carryout from the last marketing year is c_t. Denote the cost of carry, $g(c_T|c_t)$, as the cost of storing c_T amount of corn from time t to the harvest time, T , conditional on the initial carryout available, c_t.

If we assume that there is no risk premium:

$$E_t[p_T(z_T + c_T)] = f_{t,T} \tag{3.2}$$

If the inverse of the cost of carry function g exists, we can express the carryout available at this year's harvest as:

$$c_T = g^{-1}(c_t, p_t - f_{t,T}) \tag{3.3}$$

Thus the ending stocks can be expressed as a function of the carryout in the previous time period, and the futures basis.

Besides the rational storage model, other variables may also influence the ending stocks in the end of the marketing year. The planted area is revealed in April in each year and can reflect the information of harvest that starts in September. When the planted area in that year is open to public, it will impact people's expectation of output in that year. Then it can change the expectation of the ending stocks at the end of August. The yield realization in the previous year can also impact the level of ending stocks in August this year. The past yield realization influences the producers' decisions about how much to plant and the harvest size will be impacted.

3.3 Data

For corn, the U.S. marketing year begins at September 1 and ends on August 31 in the following calendar year. USDA starts the ending stocks forecast for a marketing year over a year before the final estimation are determined. In May before the marketing year begins, the first forecast is released. The last forecast is in September when the marketing year ends and before the ending stocks for the marketing year is determined. For the ending stocks in each marketing year, there are total 16 monthly forecasts from USDA. The USDA monthly forecast is obtained from WASDE (World Agricultural Supply and Demand Estimates). The Data used for analysis are over the marketing years 1980/81 to 2016/17.

3.3.1 Definition of the USDA forecast error

We define $\ln(S_t)$ as the logarithm of the realization of the ending stocks for corn at the end of marketing year t, $\ln(F_{t,n})$ is the logarithm of n-month ahead USDA forecast of ending stocks for marketing year t. In this paper, we consider the month which can be January to August in calendar year t or June to December in calendar year $t-1$. In this paper, $n = 1, 2, 3, \ldots, 15$. Figure 3.1 illustrates the forecast horizons of USDA forecast.

The difference $\ln(S_t) - \ln(F_{t,n}) = e_{t,n}$ represents the n-month ahead forecast error of USDA forecast in marketing year t.

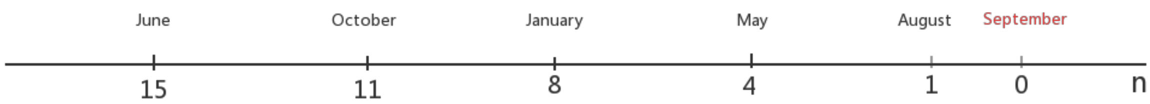

Figure 3.1 Forecast horizons

3.3.2 Ending stocks

The quarterly data of ending stocks for United States is retrieved from Grain Stocks Report organized by NASS. The quarterly data is in early March, June, September and December. To obtain the monthly data of ending stocks between the December in the previous year to September in this year, we use the method of linear interpolation. Since we have got the quarterly data, the monthly data can be approximated for the time period which is between December in the previous year to September this year. During this time period, the harvest in that marketing year has finished and the new production has released, it is reasonable to get the monthly data by the method of linear interpolation. From Figure 3.2 of historical quarterly data of ending stocks, we can find the similar pattern in the same marketing year.

We define $i_{t,n}$ as the ending stocks in n-month ahead USDA forecast for marketing year t. The logarithm change of ending stocks in this month from the ending stocks in the previous month is:

$$di_{t,n} = \ln(i_{t,n}) - \ln(i_{t,n+1})$$

3.3.3 Futures basis

The corn futures contract price data are from Chicago Mercantile Exchange (CME). In each month, we utilize the data from futures contract before the date that the USDA forecast is released.

We use two types of futures basis in this paper. One measure of the futures basis is the difference between the futures prices for September and December deliveries:

$$basis_{t,n} = \ln(f_{t,n,Sep}) - \ln(f_{t,n,Dec})$$

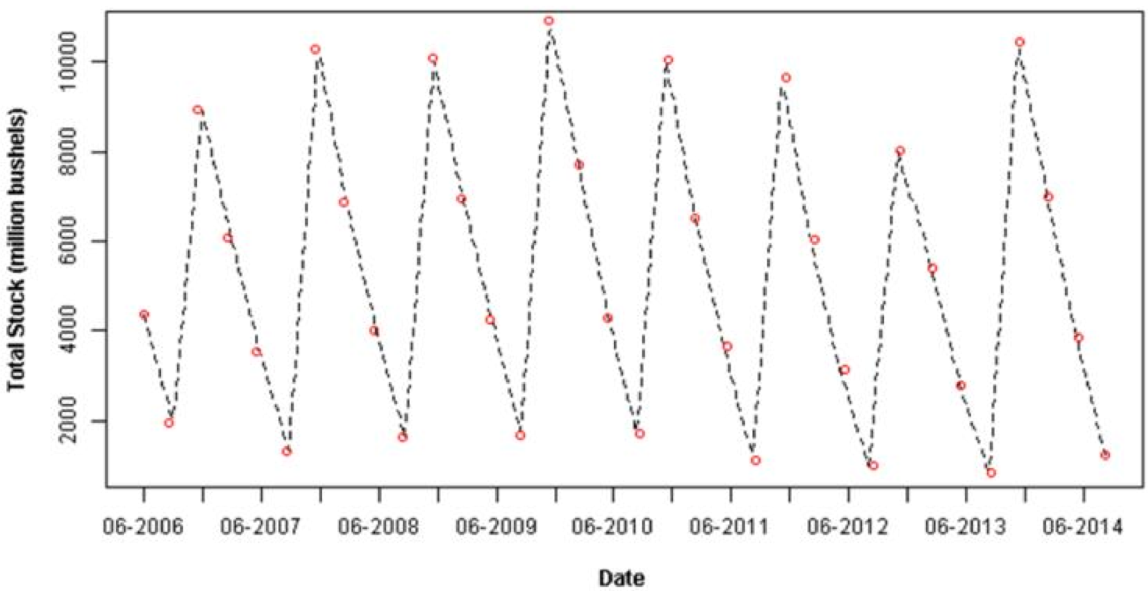

Figure 3.2 Quarterly data of ending stocks

Another measure of the futures basis is the difference between the futures price of September delivery and the cash price in that particular month:

$$basis_{t,n} = \ln(f_{t,n,Sep}) - \ln(p_{t,n})$$

We approximate the cash prices using the continuous nearby futures price that is constructed by rolling into the next nearby futures contract month on the last trading day of the expiring contract.

3.3.4 Past yield realization

The data of yield realization are from National Agricultural Statistics Service (NASS).

Denoting y_t as the corn yield realization in year t, we define the level of the yield realization as the logarithm change of this year's corn yield from a trend yield of past 5 years:

$$dy_t = \ln(y_t) - \ln(\frac{\sum_{i=t-5}^{t-1} y_t}{5})$$

3.3.5 Planted area

The data of planted area are from National Agricultural Statistics Service (NASS).

Denote s_t as the planted area of corn in year t. Similar with the yield realization, we define the level of the planted area as the logarithm change of this year's planted area of corn from a trend planted area of past 5 years:

$$ds_t = \ln(s_t) - \ln(\frac{\sum_{i=t-5}^{t-1} s_t}{5})$$

3.4 Empirical specification

3.4.1 Sub-periods

USDA ending stocks forecasts are made for a specific target which is the crop stocks being held at the end of the market year in September, so the forecasts are fixed-event forecasts. However, there are different forecast horizons. In different forecast horizons, the past and available information to be taken into account is also different. In order to analyze the forecast error in different forecast horizons, we divide the whole forecast horizons into four sub-periods. The sub-periods are as

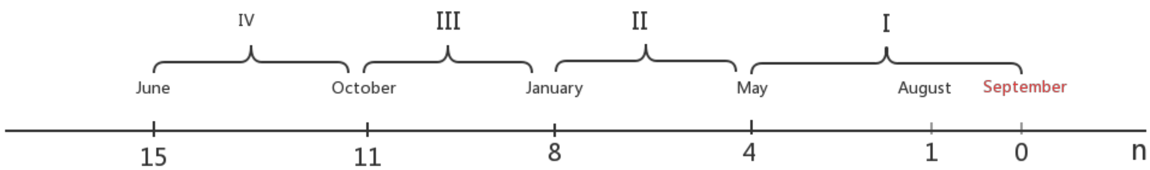

Figure 3.3 Sub-periods

follows: (i) pre-harvest and the planted area of the marketing year t has been determined; (ii) post-harvest and the yield in the previous year has been determined; (iii) the harvest time in the previous year; (iv) from the beginning of USDA forecast to the harvest time in the previous year. Figure 3.3 illustrates the timeline of these sub-periods.

Sub-period I is for forecast horizons that are $n = 1, 2, 3, 4$. For corn, this sub-period covers May to August. In this sub-period, the planted area in year t has been determined. The futures basis is the difference between the futures prices for September and December deliveries. The explanatory variables are $basis_{t,n}$, $di_{t,n}$, ds_t, and dy_{t-1}.

Sub-period II is for forecast horizons that are $n = 5, 6, 7, 8$. For corn, this sub-period covers January to April. The difference between sub-period II with sub-period I is that the planted area in year t is unknown in sub-period II. The futures basis is the difference between the futures prices for September and December deliveries. The explanatory variables are $basis_{t,n}$, $di_{t,n}$, and dy_{t-1}.

Sub-period III is for forecast horizons that are $n = 9, 10, 11$. For corn, this sub-period covers October to December in the previous calendar year. In this sub-period, the corn yield in year $t-1$ is unknown. However, the planted area in year $t-1$ has been determined. The futures basis is the difference between the futures prices for September and December deliveries. The explanatory variables are $basis_{t,n}$ and ds_{t-1}.

Sub-period IV is for forecast horizons that are $n = 12, 13, 14, 15$. For corn, this sub-period covers June to September in the previous calendar year. In this sub-period, the information of planted area in year $t-1$ has been released. Since the December futures contracts are not actively traders in this time period. The futures basis in sub-period IV is the difference between the futures price of September delivery and the cash price. The explanatory variables are $basis_{t,n}$, $di_{t,n}$, and ds_{t-1}.

3.4.2 Proposed model

In appendices, we have checked the heteroscedasticity and autocorrelation in the ordinary least squares model. There are serious problems about heteroscedasticity and autocorrelation.

In order to deal with the problems of autocorrelation and heteroscedasticity, we follow the model of efficiency test in Xiao et al. (2017). In the proposed model, we introduce the forecast innovation ($\ln F_{t,N-1} - \ln F_{t,N}$), which contains the past information between two nearby forecasts. The proposed model is as following system of equations:

$$\begin{cases} \ln S_t - \ln F_{t,1} = \alpha + \delta(\ln F_{t,1} - \ln F_{t,2}) + \boldsymbol{\beta}(\boldsymbol{\Delta x}_{t,1}) + k_{t,1} + \epsilon_{t,1}, \\ \\ \ln F_{t,1} - \ln F_{t,2} = \alpha + \delta(\ln F_{t,2} - \ln F_{t,3}) + \boldsymbol{\beta}(\boldsymbol{\Delta x}_{t,2}) + k_{t,2} - \epsilon_{t,1} + \epsilon_{t,2}, \\ \\ \vdots \\ \\ \ln F_{t,N-2} - \ln F_{t,N-1} = \alpha + \delta(\ln F_{t,N-1} - \ln F_{t,N}) + \boldsymbol{\beta}(\boldsymbol{\Delta x}_{t,N-1}) + k_{t,N-1} - \epsilon_{t,N-2} + \epsilon_{t,N-1} \end{cases}$$

N is the maximum forecasting horizon for a marketing year. $\boldsymbol{X}_{t,N}$ consists the existing information in the n-ahead forecast horizon.

$k_{t,n}$ is the unforecastable error where

$$k_{t,n} \sim N(0, \sigma_n^2)$$

So $k_{t,n}$ follows normal distribution with different variance for different forecast horizon n. In this way, the proposed model allows for heteroscedasticity in the model.

$\epsilon_{t,n}$ is the idiosyncratic residuals where

$$\epsilon_{t,n} \sim N(0, \sigma^2)$$

$\epsilon_{t,n}$ follows normal distribution with the same variance for different t and n. As we can see in the proposed model, the model allows for autocorrelation.

Within one single market year t, the covariance matrix is matrix A.

$$\boldsymbol{A} = \begin{bmatrix} \sigma_1^2+\sigma^2 & -\sigma^2 & 0 & \dots & 0 \\ -\sigma^2 & \sigma_2^2+2\sigma^2 & -\sigma^2 & \dots & 0 \\ 0 & -\sigma^2 & \sigma_3^2+2\sigma^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & -\sigma^2 \\ 0 & 0 & 0 & \dots & \sigma_{N-1}^2+2\sigma^2 \end{bmatrix}$$

3.4.3 MCMC method

3.4.3.1 Introduction

Markov Chain Monte Carlo (MCMC) is a computer–driven sampling method. It allows one to characterize a distribution without knowing all of the distribution's mathematical properties by randomly sampling values out of the distribution. By constructing a Markov Chain that has the desired distribution as its equilibrium distribution, one can obtain a sample of the desired distribution by observing the chain after a number of steps.

One advantage is that the MCMC method can help to deal with the problems of heteroscedasticity and autocorrelation. By setting the structure of the proposed model with allowing for heteroscedasticity and autocorrelation, MCMC method can help us to obtain the results. Another advantage is that it yields full posterior distributions for the parameters of interest. Sometimes, the researcher may have interest in the characteristics of the parameters such as skewness.

3.4.3.2 Model

The system of regressions can be written as:

$$y_{t,n} = \boldsymbol{z}_{t,n}\boldsymbol{\delta} + \boldsymbol{x}_{t,n}\boldsymbol{\beta} + k_{t,n} - \epsilon_{t,n-1} + \epsilon_{t,n}$$

where $\boldsymbol{z}_{t,n} \equiv [1\ (\ln F_{t,n} - \ln F_{t,n+1})]$, $\boldsymbol{\delta} \equiv [\alpha\ \delta]^T$.

$$y_{t,n} \equiv \begin{cases} \ln S_t - \ln F_{t,1} & n = 1 \\ \ln F_{t,n-1} - \ln F_{t,n} & n \neq 1 \end{cases}$$

$$\boldsymbol{x}_{t,n} \equiv \begin{cases} [basis_{t,n} \quad di_{t,n} \quad ds_t \quad dy_{t-1}] & n = 1,2,3,4 \\ [basis_{t,n} \quad di_{t,n} \quad dy_{t-1}] & n = 5,6,7,8 \\ [basis_{t,n} \quad ds_{t-1}] & n = 9,10,11 \\ [basis_{t,n} \quad di_{t,n} \quad dst-1] & n = 12,13,14,15 \end{cases}$$

We can rewrite the regression system of panel for marketing year t in matrix form as:

$$\boldsymbol{y}_t = \boldsymbol{z}_t\boldsymbol{\delta} + \boldsymbol{x}_t\boldsymbol{\beta} + \boldsymbol{k}_t + \boldsymbol{g}\boldsymbol{\epsilon}_t$$

where $\boldsymbol{y}_t \equiv [y_{t,1}, ..., y_{t,N-1}]^T$, $\boldsymbol{z}_t \equiv [\boldsymbol{z}_{t,1}, ..., \boldsymbol{z}_{t,N-1}]^T$, $\boldsymbol{x}_t \equiv [\boldsymbol{x}_{t,1}, ..., \boldsymbol{x}_{t,N-1}]^T$, $\boldsymbol{k}_t \equiv [k_{t,1}, ..., k_{t,N-1}]^T$, $\boldsymbol{\epsilon}_t \equiv [\epsilon_{t,1}, ..., \epsilon_{t,N-1}]^T$. $\boldsymbol{g}$ is the matrix that indicates the corresponding elements of $\boldsymbol{\epsilon}_t$.

When we combine the annual panels, the system of regression can be rewritten as:

$$\boldsymbol{Y} = \boldsymbol{Z}\boldsymbol{\delta} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{K} + \boldsymbol{G}\boldsymbol{e}$$

3.4.3.3 Posterior density

If we estimate the proposed model using ordinary least squares, you do not have to bother about the probabilistic formulation. The reason is that you are searching for optimal values of parameters by minimizing the squared errors of fitted values to predicted values.

In Bayesian approach instead of ordinary least squares, we would assume prior distributions for the estimated parameters and use Bayes theorem:

$$\text{posterior} \propto \text{likelihood} \times \text{prior}$$

Let Θ be the set of estimated parameters in the proposed model:

$$\Theta \equiv \left\{ \boldsymbol{\delta}, \boldsymbol{\beta}, \sigma^2, \{\sigma_n^2\}_{n=1}^{N-1} \right\}$$

By Bayes theorem, the posterior distribution can be expressed as:

$$\underbrace{\rho(\Theta|\boldsymbol{Y},\boldsymbol{Z},\boldsymbol{X})}_{\text{posterior}} \propto \underbrace{\rho(\boldsymbol{Y}|\boldsymbol{\delta},\boldsymbol{\beta},\boldsymbol{K},\sigma^2\boldsymbol{\Omega})}_{\text{likelihood}} \underbrace{\rho(\boldsymbol{\delta})\rho(\boldsymbol{\beta})\rho(\boldsymbol{K})\rho(\sigma^2)\prod_{n=1}^{N-1}\rho(\sigma_n^2)}_{\text{priors}}$$

where

$$\boldsymbol{Y}|\boldsymbol{\delta},\boldsymbol{\beta},\boldsymbol{K},\sigma^2\boldsymbol{\Omega} \sim MVN(\boldsymbol{Z\delta}+\boldsymbol{X\beta}+\boldsymbol{WK},\sigma^2\boldsymbol{\Omega})$$

We know

$$\boldsymbol{\Omega} = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & 0 \\ 0 & -1 & 2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & -1 \\ 0 & 0 & 0 & \dots & 2 \end{bmatrix}$$

3.4.3.4 Prior density

A prior distribution of a parameter is the probability distribution that represents the uncertainty about the parameter before the current data are examined. Multiplying the prior distribution and the likelihood function together leads to the posterior distribution of the parameter. We need to choose the priors if it has minimal impact on the posterior distribution of the estimated parameters. So the noninformative priors that appear to be more objective are expected.

Gelman et al. (2006) suggests using the half-t family distribution prior for variance parameters in hierarchical models. So we choose the priors for the standard deviation σ and σ_n are

$$\sigma, \sigma_n \sim Uniform(0,\infty)$$

where $Uniform(0,\infty)$ can be interpreted as a limit of the half-t family.

For the coefficient vector $\boldsymbol{\delta}$ and $\boldsymbol{\beta}$, we use the conjugate priors. If the posterior distributions are in the same probability distribution family as the prior probability distribution, the prior and posterior are then called conjugate distributions, and the prior is called a conjugate prior for the likelihood function. In this paper, the priors of $\boldsymbol{\delta}$ and $\boldsymbol{\beta}$ are

$$\boldsymbol{\delta} \sim MVN(\mathbf{0}, \mathbf{\Lambda_1})$$

$$\boldsymbol{\beta} \sim MVN(\mathbf{0}, \mathbf{\Lambda_2})$$

where $\mathbf{\Lambda_1}$ and $\mathbf{\Lambda_2}$ are identity matrices that the value of diagonal element is very large.

3.4.3.5 Procedures

To implement MCMC method more efficiently, we use software Stan to help us obtain the results. Stan is a state-of-the-art platform for statistical modeling and high-performance statistical computation. The Interface we use is the R package Rstan.

We set three Markov Chains, each has 3000 iterations. The first 1000 iteration of each chain is discarded as the warm-up period. The values of $\hat{R}$ is close to 1, which means the Markov Chains converge.

3.5 Results and discussion

Estimation results are for the marketing year over 1980/81 to 2016/17 of Sub-period I, II, III and IV.

The results of sub-period I are in Table 3.1, this table displays the means and standard deviations for the estimated parameters. The coefficients of futures basis, the level of monthly ending stocks and the level of planted area are statistically significant. Also, the forecast innovation variable and intercept are not statistically significant, which means the proposed model explain the USDA forecast error pretty well.

The results of sub-period II are in Table 3.2, this table displays the means and standard deviations for the estimated parameters. The difference between sub-period I and II is that the level of planted area variable is not included in sub-period II. The futures basis variable is statistically significant at the 1% level. Also, the monthly ending stocks is statistically significant in sub-period II.

Table 3.1 Sub-period I

	Mean	(St. Dev.)
$\Delta basis_{t,n}$	0.765***	(0.233)
$\Delta di_{t,n}$	-0.110***	(0.039)
Δds_t	0.252*	(0.125)
Δdy_{t-1}	-0.082	(0.089)
δ	0.030	(0.062)
Intercept	0.011**	(0.005)

Note: *,**, ***: 10%, 5%, 1% level of significance

Table 3.2 Sub-period II

	Mean	**(St. Dev.)**
$\Delta basis_{t,n}$	2.867***	(0.497)
$\Delta di_{t,n}$	-0.482***	(0.135)
Δdy_{t-1}	0.096	(0.165)
δ	0.073	(0.094)
Intercept	0.005	0.009

Note: *,**, ***: 10%, 5%, 1% level of significance

Table 3.3 Sub-period III

	Mean	**(St. Dev.)**
$\Delta basis_{t,n}$	2.925***	(0.830)
Δds_{t-1}	0.099	(0.351)
δ	0.236*	(0.132)
Intercept	0.014	(0.014)

Note: *,**, ***: 10%, 5%, 1% level of significance

Table 3.4 Sub-period IV

	Mean	(St. Dev.)
$\Delta basis_{t,n}$	0.267	(0.297)
$\Delta di_{t,n}$	-0.179	(0.103)
Δds_{t-1}	0.805	(0.673)
δ	0.223^{*}	(0.121)
Intercept	-0.012	(0.024)

Note: *,**, ***: 10%, 5%, 1% level of significance

The results show that the proposed model can explain a part of forecast error but the performance is not as good as that in sub-period I.

The results of sub-period III are in Table 3.3, this table displays the means and standard deviations for the estimated parameters. According to the empirical design, there are only two explanatory variables in sub-period II. The futures basis is still statistically significant at 1% level. Also, the forecast innovation variable is statistically significant, which means the forecast innovation can explain a part of the forecast errors.

The results of sub-period IV are in Table 3.4, this table displays the means and standard deviations for the estimated parameters. In sub-period IV, the proposed model can explain some part of the forecast error but the performance is not as good as that in the first three sub-periods.

Next, we analyze the performance of each explanatory variable.

In sub-periods I, II, and III, futures basis is significant to explain the forecast errors. In these sub-periods, the futures basis is the difference between the futures prices for September and December deliveries. The futures basis would always reflect the cost of carry between September and December, based on expectations about the size of the new crop and ending stocks at the end of August. Since the futures basis contains information about the size of ending stocks at the end of August, it is reasonable that the futures basis can explain part of the forecast error. The USDA predictors may ignore the information from the futures market, which is one reason of the forecast error.

The level of planted area is significant in sub-period I. The planted area is revealed in April and can reflect the information of harvest that starts in September. When the planted area in that year is open to public, it will impact people's expectation of yield in that year. Then it can change the expectation of the ending stocks at the end of August.

In sub-periods I and II, the level of monthly ending stocks variables are significant. Since there is only the report of quarterly ending stocks, the estimation of monthly ending stocks maybe ignored by the USDA predictors.

As the forecast horizon lengthens, the model has less explanatory power. When the forecast horizon is longer, the random unforecastable shock is more significant to influence the forecast.

3.6 Out of sample performance

The adjusted forecast is $\hat{e}_{t,n} = \ln F_{t,n} + \widetilde{e}_{t,n}$, where $\widetilde{e}_{t,n}$ is the estimated forecast error.

The MSPE ratio is the ratio between the mean square error of the adjusted forecast and the mean square error of the unadjusted forecast error. We use the data from 1981 to 2017 as our forecast evaluation period and calculate the initial estimates based on data from 1981 to 2007. Then we calculate the one-step forward recursive estimations of MSPE ratio.

In order to compare two different forecasts, Clark and West (2007) propose a convenient way, which is to define:

$$\hat{f}_{t+n} = (y_{t+n} - \hat{y}_{1t,t+n})^2 - [(y_{t+n} - \hat{y}_{2t,t+n})^2 - (\hat{y}_{1t,t+n} - \hat{y}_{2t,t+n})^2]$$

where $\hat{y}_{1t,t+n}$ and $\hat{y}_{2t,t+n}$ are two competing n-step ahead forecasts.

Table 3.5 Out of sample performance

	I	II	III	IV
MSPE ratio	0.4633	0.3533	0.8285	1.4862
WC-test	3.068**	3.302**	2.356*	−0.822

To test for equal MSPE for two forecasts, we can regress $\hat{f}_{t+n}$ on a constant and using the resulting t-statistic for a zero coefficient. Reject the hypothesis that the MSPE for two forecasts are equal when the statistics is larger than 1.645 (for a one sided 0.05 test).

In Table 3.5, the MSPE ratio of adjusted forecasts of sub-period I, II, III and IV are presented in row 2. In row 3 is the Clark and West (2007) t-statistics. The MSPE ratio is less than 1 in sub-period I, II and III, which means the mean square error of the adjusted forecasts is less than the unadjusted forecasts. What's more, the Clark and West (2007) t-statistics are statistically significant in all the three sub-periods. There are significant differences between the mean square error of adjusted forecasts and unadjusted forecasts. So the adjusted forecasts can improve the forecast accuracy of crop ending stocks in sub-period I, II and III.

In sub-period IV, the MSPE ratio is larger than 1, which means the mean square error of the adjusted forecasts is larger than the unadjusted forecasts. Also, the Clark and West (2007) t-statistics is not statistically significant. As a whole, in sub-period IV, we cannot obtain the conclusion that the adjusted forecast is superior than the unadjusted forecasts.

3.7 Conclusion

USDA provides the must-read crop ending stocks forecasts to the participants in the agriculture market. But the literature in this area finds that the USDA forecasts of crop ending stocks inefficient. Our paper conducts research to find what kinds of information influence the magnitude of the USDA forecast error in corn ending stocks. In the empirical analysis using Markov Chain Monte Carlo (MCMC) method, we find that the futures basis, the level of monthly ending stocks, and the level of planted area are significant to explain the forecast errors. The out of sample performance shows that the adjusted forecasts can improve the forecast accuracy of corn ending stocks.

CHAPTER 4. LIQUIDITY AND ASSET PRICING: EVIDENCE FROM THE CHINESE STOCK MARKET

4.1 Introduction

Chinese stock markets are among the most important in the world. The Shanghai stock market is the largest in mainland China. The Shanghai stock market developed quite rapidly. Despite being established as recently as 1990, by February 2016 Shanghai had become the world's 5th largest stock market by capitalization, at US$3.5 trillion. As shown in Figure 4.1, the total number of companies listed in the Shanghai stock market increased almost every single year since its inception, but it grew at an especially fast pace between until 2004. Even though the growth rate slowed down noticeably after 2004, by 2015 there were about 1000 companies listed in Shanghai.

Given the high standing and growing relevance of Shanghai among the world's stock markets, and the lack of studies investigating whether liquidity has affected its returns, the present analysis aims at addressing this gap in the literature. In particular, our study attempts to determine whether liquidity has been an important pricing factor for stocks listed in Shanghai. Our results should also shed useful insights on the impact of liquidity in emerging stock markets in general. With few exceptions, such as Bekaert et al. (2007), research about liquidity effects on stock returns has mostly focused on U.S. and European markets. However, Bekaert et al. (2007) found that liquidity effects may be particularly strong in emerging markets, which contrasts with what is observed in developed markets. Hence, it is of interest to compare the results from the present study on an emerging market with the findings by Bekaert et al. (2007). Another reason why analyzing liquidity in the Shanghai stock market is of special interest is that, unlike most stock markets, and especially developed ones, the government plays an important role in it. Prominent examples of the outsize government role in the Shanghai market are the restrictions to trading by domestic and foreign investors, with domestic investors allowed to invest only in A shares and foreign investors allowed

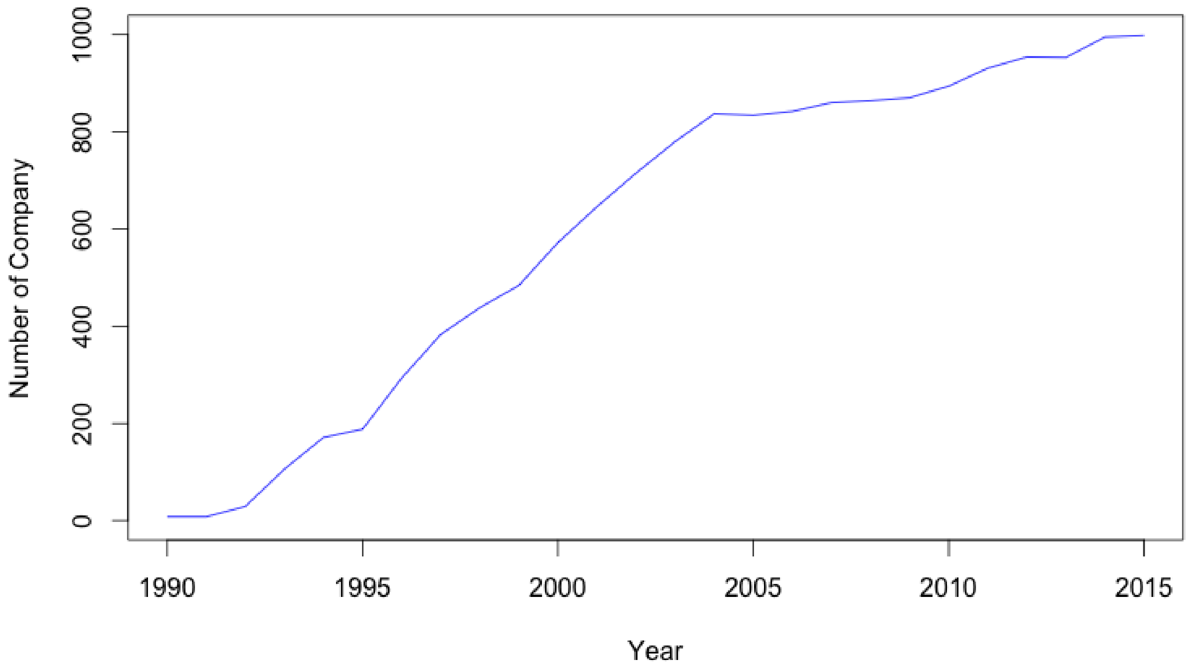

Figure 4.1 Number of companies listed in the Shanghai stock market

access only to B shares. In addition, there are rules that restrict the trading volume for specific traders, and there is a daily price up/down limit of 10% for stocks and mutual funds.

The remainder of the paper continues as follows. Section 4.2 provides a literature review of the measure of liquidity, liquidity in asset pricing and studies of liquidity in different markets. Section 4.3 describes the data and characteristics of liquidity measures. Section 4.4 shows the research design and empirical results. Section 4.5 concludes the paper.

4.2 Literature Review

4.2.1 Measures of Liquidity

Liquidity describes the ability to trade large quantities quickly at low cost and with little price impact. As such, liquidity plays a very important role in investment decisions. According to

Chollete et al. (2008), there are four dimensions of liquidity: trading cost, trading quantity, price impact, and trading speed. Interestingly, a variety of different methods have been proposed in the previous literature to measure liquidity, but there is no single measure that captures all four dimensions.

Following the dimensions proposed by Chollete et al. (2008), the trading cost dimension of liquidity is addressed by the bid-ask spread used by Amihud and Mendelson (1986). Assume each asset j generates a perpetual cash flow of $\$d_j$ per unit time and has a relative spread of S_j, reflecting its trading cost. If investors quote an ask price V_j for asset j, then the bid price is $V_j(1 - S_j)$. Since the size of the spread from one asset to another will differ mainly because of the differences in liquidity across assets, the bid-ask spreads measure the liquidity of the assets. Amihud and Mendelson (1986) find that expected asset returns are increasing in the relative bid-ask spread.

The trading quantity dimension of liquidity is the focus of the turnover measure advocated by Datar et al. (1998):

$$TOx = \frac{1}{D_x} \sum_{d=1}^{D_x} \frac{(\text{Number of shares traded})_d}{(\text{Number of shares outstanding})_d}.$$

The term D_x denotes the number of trading days over the prior x month. The turnover rate of a stock is defined as the number of shares traded divided by the number of shares outstanding of that stock. Hence, TOx is the average daily turnover rate of a stock over the prior x month. A larger value of TOx represents greater liquidity because it means that the stock is traded more frequently.

In regards to the price impact dimension of liquidity, one of the most commonly used methods is the one advocated by Amihud (2002). His measure is defined as the average ratio of daily absolute return to trading volume:

$$ILLIQx = \frac{1}{D_x} \sum_{d=1}^{D_x} \frac{|R_d|}{VOL_d}.$$

The term $|R_d|$ is the absolute value of return of stock on day d, and VOL_d is corresponding daily trading volume in monetary units. $ILLIQx$ reflects the impact of capital flow on the stock price. A greater value of $ILLIQx$ implies a greater price impact, and therefore less liquidity; i.e., $ILLIQx$ measures illiquidity.

Another measure corresponding to the price impact dimension is the one introduced by Pástor and Stambaugh (2003). They investigate whether market-wide liquidity is a state variable important for asset pricing, and focus on temporary price changes accompanying order flow. Their liquidity measure for stock i in month t is the estimate of coefficient $\gamma_{i,t}$ in the ordinary least squares regression

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} sign(r^e_{i,d,t}) \times v_{i,d,t} + \epsilon_{i,d+1,t},$$

where $r^e_{i,d,t} \equiv r_{i,d,t} - r_{m,d,t}$, $r_{i,d,t}$ is the return for stock i on day d of month t, $r_{m,d,t}$ is the return on the CRSP value-weighted market return on day d of month t, and $v_{i,d,t}$ is the dollar volume for stock i on day d of month t. The authors find that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity.

Finally, in the dimension of trading speed, Liu (2006) proposes a measure for individual stocks which captures multiple dimensions of liquidity (e.g., trading speed, trading quantity, and trading cost), but has particular emphasis on trading speed. Liu (2006) defines the liquidity measure of a security as the standardized turnover-adjusted number of zero daily trading volumes over the prior x months (x= 1, 6, 12):

$$\begin{aligned} LMx \quad = \quad & [\text{Number of zero daily volume in prior } x \text{ months} \\ & + \frac{1/(x - \text{month turnover})}{Deflator}] \times \frac{21x}{NoTD}. \end{aligned}$$

In the expression above, $x-$month turnover denotes turnover over the prior x months, calculated as the sum of daily turnover over the prior x months, where daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day. $Deflator$ is a value chosen such that $0 < \frac{1/(x-\text{month turnover})}{Deflator} < 1$, and $NoTD$ is the total number of trading days in the market over the prior x months.

4.2.2 Liquidity and Asset Pricing

Jacoby et al. (2000) develop a model based on the capital asset pricing model (CAPM) to show that, in the presence of liquidity costs, the true measure of system risk is based on the net (after bid-ask spread) returns. Under their CAPM framework, there is a positive relationship between the expected return and the future spread cost.

Acharya and Pedersen (2005) propose a liquidity-adjusted CAPM: $E(r_t^p - r_t^p) = \alpha + \kappa E(c_t^p) + \lambda\beta^{net,p}$, where $\beta^{net,p} := \beta^{1p} + \beta^{2p} - \beta^{3p} - \beta^{4p}$, the paper sets $\kappa = 1$. The paper decomposes the liquidity beta into four components and finds the performance of the model is better than the traditional CAPM.

Keene and Peterson (2007) employ the Fama-French time-series regression approach to examine liquidity as a risk factor affecting stock returns. This paper finds that after the effects of market, size, book-to-market equity and momentum are considered, liquidity is an important factor affecting portfolio returns. So this can be taken as evidence in support of Amihud and Mendelson (1986).

Nguyen et al. (2007) uses a four-factor model based on the Fama-French three-factor model and Pastor-Stambaugh liquidity factor to examine the role of liquidity on stock returns. The findings suggest that the model cannot capture the liquidity premium nor do stock characteristics serve as proxies for liquidity.

Some papers in this field have shown that the market-wide liquidity is an important state variable for asset pricing. Holmström and Tirole (2001) propose a liquidity-based asset pricing model based on insights from the field of corporate finance. This paper develops an alternative approach to asset pricing based on corporations' desire to hoard liquidity. The authors find that a security's expected return is related to its sensitivity to aggregate liquidity. Pástor and Stambaugh (2003) find that stocks with higher sensitivity to the market-wide liquidity factor have higher required returns than stocks with low sensitivity.

4.2.3 Studies about different markets

To date, most studies are on the US stock market, which is arguably the most liquid market in the world. Amihud and Mendelson (1986) investigate the relationship between stock return, relative risk and spread using data over the period 1961-1980 in NYSE stocks. They find that there is a positive relation between expected return and illiquidity. Liu (2006) uses sample that comprises all NYSE/AMEX/NASDAQ ordinary stocks over the period January 1960 to December 2003. The paper proposes a new method to measure liquidity and shows the model can account for the book-to-market effect, which the Fama-French three-factor model fails to explain.

For the European stock markets, there are many research papers. In Europe, one of the most important stock markets is the London Stock Exchange. Foran et al. (2010) investigate the existence of liquidity risk in UK equities using daily data with the time period from 1986 to 2007. They use the liquidity measure based on Amihud (2002). Then the paper uses the CAPM and Fama-French three-factor model to find the evidence that liquidity risk is a determinant of returns in the UK equity market. Galariotis and Giouvris (2009) use the data from UK FTSE100 stocks. This paper uses the liquidity measure based on bid-ask spread and reports that systematic liquidity has an effect on stock pricing. In other markets in Europe, Martınez et al. (2005) analyze the Spanish stock market. They try to find whether stocks average return vary cross-sectionally with betas estimated relative to three competing liquidity risk factors. The empirical results show that systematic liquidity risk is significantly priced in the Spanish stock market.

For the emerging markets, Bekaert et al. (2007) focuses on 19 emerging equity markets. The main liquidity measure is a transformation of the proportion of zero daily firm returns, averaged over the month. The results show that local market liquidity is an important driver of expected returns in emerging markets. Lam and Tam (2011) construct nine liquidity proxies and use an asset pricing model to investigate the Hong Kong stock market. They build the portfolio based on the intersection between the size of companies, book-to-market ratio and liquidity proxies. They compare alternative factor models and find that the liquidity four-factor model (market excess return, size, book-to-market ratio, and liquidity) is the best model to explain stock returns in the

Hong Kong stock market. Chan and Faff (2005) investigate the role of liquidity in asset pricing in the Australian stock market. They use the turnover rate as the liquidity measure and find that liquidity is negatively related to stock returns. Moreover, the importance of turnover persists after controlling for book-to-market, size, stock beta and momentum.

4.2.4 Studies about the Chinese stock market

In the previous studies on the Chinese stock market, the main findings are that the liquidity and liquidity risk can influence the stock returns.

Some papers use different measure of liquidity to explain stock returns. Chi et al. (2005) select the turnover ratio to measure stock liquidity and show liquidity premium exist in the Shanghai stock market. Zhang and Liu (2006) find the negative relationship between turnovers and cross-sectional stock returns in the Chinese stock market cannot be completely explained by liquidity premium theory. Yang (2015) develops a new illiquidity measure which combines the price reaction to trading volume and the percentage of zero-return days. The paper estimates how the Nontradable Share Reform affects cross-sectional relations between liquidity and stock return autocorrelation. Ho and Chang (2015) employ four liquidity measures to confirm the presence of a liquidity risk premium and the pricing of liquidity risk.

Some studies focus on the liquidity-adjusted asset pricing model. Kong (2006) use data of Chinese stock market to test the liquidity-adjusted CAPM (LCAPM) and show LCAPM can fit the real data better than the CAPM in spite of the time period. Chen et al. (2011) implement the liquidity-adjusted three-moment CAPM and conclude the model is a better fit to the realized returns of various stock portfolios. Narayan and Zheng (2010) examine the cross-sectional stock return model with the market liquidity risk factor and test whether the model can capture financial market anomalies.

This paper offers several contributions to the literature. First, this paper proposes a new liquidity factor that captures two dimensions of liquidity that are in terms of trading quantity and price impact. Second, the results of the new two-factor model confirm the existence of liquidity premium in the Chinese stock market as in the previous literature. Third, the new two-factor model can explain the the size effect in the Chinese stock market.

4.3 Data and Liquidity Measures

4.3.1 Data

The data used in the present study are obtained from the China Stock Market and Accounting Research (CSMAR) database, which is one of the most complete databases for the Chinese stock market. The time period selected for the analysis covers January 2000 through December 2015. Data for years earlier than 2000 are not included because the number of companies listed in the Shanghai stock market was relatively small before the year 2000. In addition, in the 1990s the Chinese stock market earned a reputation as a casino manipulated by speculators and insiders (Carpenter et al., 2015).

The analysis focuses on 384 companies listed in the Shanghai stock market. This set of companies is chosen because they are traded in every month from 2000 through 2015. Importantly, the selected companies represent all major industry sectors in China, and have very large market capitalizations relative to the aggregate capitalization of firms listed in Shanghai. For each of the firms in the selected set, the database contains daily trading information, such as market value, trading volume, number of trading shares, and daily rate of return (including dividends). The database also has annual accounting information for each firm included in the analysys, such as book-to-market ratio.

4.3.2 Liquidity Measures

The analysis of liquidity conducted in this paper relies on the aforementioned turnover (TOx) and illiquidity ($ILLIQx$) measures proposed respectively by Datar et al. (1998) and Amihud (2002). We were unable to obtain bid-ask data for the Shanghai stock market, which prevented us from analyzing liquidity by means of the bid-ask spread, as advocated by Amihud and Mendelson (1986). This is consistent with the conclusions from Bekaert et al. (2007), who find that detailed transaction data such as bid-ask spreads are not widely available in emerging markets. As per the LMx liquidity measure advanced by Liu (2006), it is not used here because for the set of selected stocks there were too few days with zero trading volume to make it meaningful. In the previous literature, empirical results show that one-month holding period is limiting in describing stock liquidity since the liquidity measure fails to distinguish some illiquid stocks (Liu, 2006).

Table 4.1 Summary statistics for liquidity measures

	$TO12$ (in $1/10^3$)	$ILLIQ12$ (in $1/10^9$)	MV (RMB in 10^3)	B/M
Panel A: Descriptive statistics				
Mean	21.300	2.548	7,640,517	1.045
Median	18.630	1.582	6,471,881	1.048
Standard Deviation	11.674	2.693	4,649,896	0.416
Minimum	7.913	0.344	2,454,995	0.377
Maxmum	46.310	9.269	18,410,637	1.669
Panel B: Spearman rank correlations				
$TO12$	1.000			
$ILLIQ12$	-0.526	1.000		
MV	0.706	-0.712	1.000	
B/M	-0.142	0.073	0.078	1.000

The proposed liquidity measures were computed assuming both six- and twelve-month holding periods. The performance was very similar for the two holding periods. Therefore, to save space, only results for the measures involving a twelve-month holding period are presented and discussed in the remainder of the paper. Table 4.1 presents summary statistics for the liquidity measures, with $TO12$ denoting the average daily turnover rate over the prior 12 months, and $ILLIQ12$ representing the ratio of the absolute return on a particular day to the dollar trading volume on that day averaged over the prior 12 months. Table 4.1 also reports summary statistics for market value (MV) and book-to market value (B/M). In panel A, as we can see, there is a big difference between the minimum and maximum value of $ILLIQ12$.

Panel B shows that $TO12$ and $ILLIQ12$ are negatively related. This negative correlation is to be expected, as higher $TO12$ represents less liquidity, whereas higher $ILLIQ12$ means more liquidity. It can also be observed that $TO12$ is strongly and positively correlated with market value (correlation = 0.706), whereas $ILLIQ12$ is strongly and negatively correlated with market value (correlation = -0.712). These correlations indicate that market value could serve as a proxy for liquidity. The empirical results show that the illiquid stocks tend to be characterized by lower market values and higher book-to-market ratios. These findings are similar to the findings reported in previous studies for other stock markets.

4.4 Research Design and Empirical Results

Investors face higher liquidity risk when holding stocks that are less liquid. Hence, investors are expected to require a higher liquidity premium to compensate for the higher liquidity risk. To test for the existence of a liquidity premium, stocks can be sorted into separate portfolios according to the values of their respective liquidity measures. If the returns of the portfolios comprising less liquid stocks are larger than the returns of the portfolios involving more liquid stocks, one can arguably interpret it as evidence supporting the presence of a liquidity premium. Stronger evidence for the existence of a liquidity premium can be inferred by the failure of the CAPM or the Fama-French factor model to mimic the differential excess returns accruing to the portfolios sorted according to the alternative liquidity measures. This strategy to assess the existence of a liquidity premium is adopted here, by sorting portfolios according to $TO12$ in the next subsection, and according to $ILLIQ12$ in the following subsection. Since the results of this analysis suggest that the Shanghai stock market is characterized by the presence of a liquidity premium, two-factor models based on the advocated liquidity measures are then proposed, and their performance investigated.

4.4.1 Performance of Portfolios Sorted by $TO12$

For each month from January 2001 through December 2015, stocks were sorted into eight portfolios based on the liquidity measure $TO12$. For example, the portfolios corresponding to January 2001 are based on the $TO12$ measure calculated using the 12-month holding period from February 2000 through January 2001. Then, the monthly net rates of return corresponding to each

Table 4.2 Monthly net rate of returns for equally-weighted portfolios of stocks sorted by $TO12$

S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Monthly net rate of return (%)							
0.378	0.544	0.763	0.711	0.717	0.715	0.603	0.269
(0.468)	(0.683)	(0.983)	(0.936)	(0.957)	(1.013)	(0.865)	(0.440)

The numbers within parentheses are t-statistics.

portfolio were computed for the period January 2001 through December 2015. To this end, equally-weighted (as opposed to value-weighted) portfolios were constructed. Equally-weighted portfolios were used to avoid bias in the estimation of the liquidity premium, which may arise due to the strongly positive correlation between firm size and liquidity (see Table 4.1). That is, as found in the previous literature, illiquid stocks tend to correspond to smaller firms.

Table 4.2 shows the results of each portfolio, with S and B denoting the portfolios with the highest liquidity (i.e., the highest $TO12$) and the lowest liquidity (i.e., the lowest $TO12$). According to the table, the returns of the portfolios follow an inverted U-shape, with the lowest returns corresponding to the the portfolios that exhibit either the highest or the lowest liquidity. While the lower returns for the least liquid portfolios are inconsistent with the presence of a liquidity premium, the positive association between liquidity and returns for the most liquid portfolios suggests that a liquidity premium might exist when the stocks are sorted according $TO12$.

To further investigate the possible presence of a liquidity premium based on $TO12$, the CAPM is used to compute the expected excess returns of the sorted portfolios. This is achieved by fitting the CAPM regression

$$r_{it} - rf_t = \alpha_i + \beta_i(rm_t - rf_t) + \epsilon_{it},$$

where r_{it} is the net rate return of portfolio i in month t, rf_t is China's monthly risk-free net rate of return in Chinese Stock market, and rm_t is the monthly net rate of return in the Shanghai stock market. Results of the CAPM regressions for the $TO12$-based portfolios are reported in Table 4.3. This table shows that the CAPM cannot account for the inverted U-shape pattern that

Table 4.3 Performance of CAPM on portfolios of stocks sorted by $TO12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
CAPM performance								
$\hat{\alpha}$ (%)	-0.241	-0.075	0.154	0.110	0.120	0.141	0.035	-0.244
	(-1.339)	(-0.641)	(1.369)	(1.041)	(1.324)	(1.510)	(0.298)	(-1.283)
$\hat{\beta}$	1.085	1.086	1.058	1.036	1.024	0.964	0.947	0.800
	(58.678)	(90.064)	(91.423)	(95.601)	(109.867)	(100.220)	(78.099)	(40.892)
R^2	0.951	0.978	0.979	0.981	0.985	0.983	0.972	0.903

The numbers in parentheses are t-statistics.

characterizes the portfolio net rates of return reported in Table 4.2. First, the estimated intercepts ($\hat{\alpha}$) exhibit the same inverted-U as returns do in Table 4.3. This finding is in sharp contrast with the CAPM prediction that such intercepts should be around zero. Second, the estimated slopes ($\hat{\beta}$) decrease almost monotonically from the most liquid portfolio (S) to the least liquid portfolio (B). However, if the market beta captured the return behavior of the liquidity-sorted portfolios shown in Table 4.2, so that that CAPM could account for the inverted U-shaped returns, then the slope estimates ($\hat{\beta}$) should also exhibit an inverted-U shape. In short, the CAPM cannot explain the returns of the portfolios of stocks sorted according to $TO12$.

Turning to the performance of the Fama-French factor model to explain the pattern characterizing Table 4.2, the fitted regression is

$$r_{it} - rf_t = a_i + b_i(rm_t - rf_t) + s_i SMB_t + h_i HML_t + \epsilon_{it}.$$

Regressors SMB and HML were constructed in the manner proposed by Fama and French (1993). The famous studies show that a combination of firm size and book-to-market effect is better able to capture the cross-section of stock returns than the market beta alone (Fama and French, 1992, 1993, 1998). For each month from January 2001 to December 2015, stocks are ranked based on the corresponding market capitalizations and book-to-market ratios. Then, a 50 percent breakpoint for market capitalization is calculated so as to sort the stocks into two portfolios: Small and Big groups according to market capitalization. Similarly, breaking points for book-to-market ratios are computed to sort the stocks into three portfolios: Low, Medium and High groups according to book-to-market ratios. The Low (High) portfolio comprises the 30 percent of stocks with the lowest (highest) to book-to-market ratios. The Medium portfolio consists of the stocks whose book-to-market ratios belong in the middle 40 percent. Finally, stocks are grouped into six equal-weighted portfolios as the intersection of market capitalization and book-to-market ratio: Small Low (SL), Small Medium (SM), Small High (SH), Big Low (BL), Big Medium (BM), Big High (BH). The number of stocks in each of the six portfolios is different.

SMB is the equal-weighted average of the returns on the small stock portfolios minus the returns on the big stock portfolios. SMB is formed in the following way:

$$SMB = \frac{(SL + SM + SH) - (BL + BM + BH)}{3}$$

In a similar way, HML is the equal-weighted average of the returns on the value stock stock portfolios and growth stock portfolios. HML is formed in the following way:

$$HML = \frac{(SH + BH) - (SL + BL)}{2}$$

In Table 4.4, S denotes the most liquid portfolio (the highest $TO12$), B denotes the least liquid portfolio (the lowest $TO12$). Table 4.4 shows that the Fama-French three-factor model cannot account for the liquidity premium. The reason is that the market betas $\hat{\beta}$ are almost monotonically decreasing from the most liquid portfolio (S) to the least liquid portfolio (B). The coefficients of SMB and HML are not significant in the regressions of different portfolios. So the Fama-French three-factor model does not explain the return of stocks well.

4.4.2 Performance of portfolios sorted by $ILLIQ12$

4.4.2.1 Liquidity premium

$ILLIQ12$ means the holding time period is 12 months. For the portfolios in January 2001, the holding time period is from February 2000 to January 2001. For each month from January 2001 to December 2015, I sorted the stocks into eight portfolios based on the liquidity measure $ILLIQ12$.

Table 4.4 Performance of Fama-French three-factor model on portfolios of stocks sorted by $TO12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Fama-French three-factor-adjusted performance								
$\hat{a}$ (%)	-0.128	0.066	0.095	0.101	0.190	0.068	-0.041	-0.350
	(-0.580)	(0.463)	(0.683)	(0.775)	(1.700)	(0.592)	(-0.283)	(-1.495)
$\hat{b}$	1.087	1.089	1.056	1.036	1.026	0.963	0.945	0.797
	(57.879)	(89.487)	(89.682)	(93.790)	(108.321)	(98.634)	(76.644)	(40.044)
$\hat{s}$	-0.013	0.158	-0.059	0.014	0.071	-0.016	-0.048	-0.108
	(-0.085)	(1.674)	(-0.646)	(0.162)	(0.967)	(-0.210)	(-0.497)	(-0.701)
$\hat{h}$	0.177	-0.091	0.025	-0.037	-0.033	-0.072	-0.019	0.049
	(0.900)	(-0.716)	(0.205)	(-0.321)	(-0.330)	(-0.702)	(-0.145)	(0.237)
R^2	0.950	0.979	0.979	0.981	0.985	0.983	0.971	0.903

The numbers in parentheses are t-statistics.

Table 4.5 Monthly net rate of returns for equally-weighted portfolios of stocks sorted by $ILLIQ12$

S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Raw return of each portfolio (%)							
0.235	0.256	0.400	0.525	0.738	0.577	0.768	1.200
(0.351)	(0.355)	(0.553)	(0.703)	(0.990)	(0.755)	(1.008)	(1.511)

The numbers in parentheses are t-statistics.

Then I calculate the raw returns of each portfolio from the time period from January 2001 to December 2015. I calculate the equally-weighted portfolio returns, not value-weighted portfolio returns. Because according to the previous literature, the size of illiquid stocks tend to be small. So the value-weighted method can cause bias when estimate the liquidity premium. Table 4.5 shows the results of each portfolio.

From Table 4.5, we can see the portfolio return increases from the most to the least liquid portfolio. So the ILLIQ12 measure displays a significant liquidity premium.

Table 4.6 Performance of CAPM on portfolios sorted by $ILLIQ12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
CAPM performance								
$\hat{\alpha}$ (%)	-0.306	-0.322	-0.182	-0.070	0.143	-0.024	0.168	0.593
	(-1.429)	(-2.277)	(-1.588)	(-0.695)	(1.734)	(-0.185)	(1.287)	(2.698)
$\hat{\beta}$	0.876	0.974	0.984	1.021	1.021	1.036	1.035	1.052
	(39.756)	(67.008)	(83.626)	(98.662)	(120.411)	(76.635)	(77.165)	(46.503)
R^2	0.898	0.962	0.975	0.982	0.988	0.970	0.971	0.924

The numbers in parentheses are t-statistics.

4.4.2.2 Performance of CAPM on portfolios sorted by $ILLIQ12$

In Table 4.6, S denotes the most liquid portfolio (the lowest $ILLIQ12$), B denotes the least liquid portfolio (the highest $ILLIQ12$). From Table 4.6, for portfolio $D2$ and B, the abnormal returns $\hat{\alpha}$ are statistically significant different from zero, which mean this model does not perform well in explaining the return of $ILLIQ12$ sorted portfolios well.

4.4.2.3 Performance of Fama-French three-factor model sorted by $ILLIQ12$

In Table 4.7, S denotes the most liquid portfolio (the lowest $ILLIQ12$), B denotes the least liquid portfolio (the highest $ILLIQ12$). The coefficients of SMB and HML are not significant in this model, which means SMB and HML do not play an important role in the model. Also, for portfolio $D3$ and $D5$, the abnormal returns $\hat{a}$ are significant different from zero, which means this model does not explain asset returns well.

4.4.3 A two-factor model

In the empirical study above, the Fama-French three-factor model has little power to explain the variation in asset returns. In the pioneering paper by Pástor and Stambaugh (2003), they find evidence that liquidity risk is a state variable. As a motivation, Liu (2006) develops a liquidity-augmented two-factor model. Jang et al. (2012) construct a two-factor model that captures various aspects of liquidty risk including $TO6$, $ILLIQ6$, and $LM6$. In this paper, I use a similar but

Table 4.7 Performance of Fama-French three-factor model on portfolios of stocks sorted by $ILLIQ12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Fama-French three-factor-adjusted performance								
$\hat{a}$ (%)	-0.318	-0.245	-0.307	-0.022	0.215	0.064	0.118	0.496
	(-1.201)	(-1.410)	(-2.192)	(-0.176)	(2.122)	(0.393)	(0.731)	(1.826)
$\hat{b}$	0.876	0.975	0.982	1.023	1.023	1.038	1.035	1.049
	(38.971)	(66.037)	(82.474)	(97.131)	(118.940)	(75.490)	(75.766)	(45.554)
$\hat{s}$	-0.032	-0.020	-0.049	0.075	0.085	0.039	0.008	-0.106
	(-0.183)	(-0.178)	(-0.527)	(0.914)	(1.271)	(0.366)	(0.077)	(-0.592)
$\hat{h}$	0.042	0.142	-0.084	-0.069	-0.054	0.050	-0.084	0.057
	(0.177)	(0.920)	(-0.677)	(-0.623)	(-0.604)	(0.366)	(-0.587)	(0.238)
R^2	0.897	0.962	0.975	0.982	0.988	0.970	0.971	0.923

The numbers in parentheses are t-statistics.

different method to construct the liquidity factor. I construct a mimicking liquidity factor, LIQ, based on the liquidity measure $TO12$ or $ILLIQ12$ or both of them.

In the previous literature, there have been some applications of mimicking portfolios. Breeden (1979) finds that mimicking portfolios can replace the state variables in the asset pricing model. In Chen et al. (1986), the authors use the mimicking portfolios to construct the macroeconomic factor. The most famous application is Fama and French (1996), who use mimicking portfolios to construct SMB and HML to explain the return of stocks.

4.4.3.1 Liquidity factor based on $TO12$

The model is

$$r_{it} - rf_t = \alpha_i + \beta_{mi}(rm_t - rf_t) + \beta_{li}LIQ_t + \epsilon_{it}$$

where LIQ is constructed in the following way. I sort all stocks in descending order on $TO12$ for each month from January 2001 to December 2015. Based on $TO12$, I form two portfolios, low-liquidity (LL) with highest $TO12$ and high-liquidity (HL) with lowest $TO12$: LL contains the 30% lowest-liquidity stocks, HL contains the 30% highest-liquidity stocks. I then construct the

Table 4.8 Performance of two-factor model based TO12

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Panel A: Performance of portfolios sorted by $TO12$								
$\hat{\alpha}$ (%)	-0.219	-0.065	0.159	0.113	0.119	0.138	0.022	-0.268
	(-2.103)	(-0.690)	(1.486)	(1.082)	(1.315)	(1.518)	(0.275)	(-2.552)
$\hat{\beta_m}$	0.951	1.021	1.025	1.019	1.028	0.986	1.025	0.945
	(73.748)	(88.060)	(77.346)	(79.193)	(91.487)	(87.891)	(101.164)	(72.864)
$\hat{\beta}_l$	-0.693	-0.334	-0.166	-0.089	0.019	0.113	0.401	0.749
	(-18.807)	(-10.090)	(-4.390)	(-2.434)	(0.607)	(3.526)	(13.857)	(20.206)
R^2	0.983	0.986	0.981	0.981	0.985	0.984	0.986	0.971
Panel B: Performance of portfolios sorted by $ILLIQ12$								
$\hat{\alpha}$ (%)	-0.319	-0.326	-0.185	-0.068	0.145	-0.017	0.171	0.598
	(-1.612)	(-2.339)	(-1.636)	(-0.679)	(1.763)	(-0.137)	(1.325)	(2.741)
$\hat{\beta_m}$	0.954	0.998	1.003	1.008	1.012	0.988	1.016	1.022
	(38.996)	(57.919)	(71.754)	(81.561)	(99.678)	(66.013)	(63.594)	(37.867)
$\hat{\beta}_l$	0.397	0.124	0.096	-0.069	-0.051	-0.246	-0.100	-0.151
	(5.687)	(2.517)	(2.396)	(-1.961)	(-1.745)	(-5.764)	(-2.183)	(-1.959)
R^2	0.914	0.963	0.976	0.982	0.988	0.975	0.971	0.925

The numbers in parentheses are t-statistics.

liquidity factor LIQ as the monthly profits from buying one dollar of equally weighted LL and selling one dollar of equally weighted HL.

In panel A of Table 4.8, S denotes the most liquid portfolio (the highest $TO12$), B denotes the least liquid portfolio (the lowest $TO12$). For portfolio S and B abnormal return $\hat{a}$ are significant different from zero. The liquidity beta $\hat{\beta}_l$ monotonically increases from S to B, meaning that the illiquid portfolio has higher liquidity risk with higher return, supporting evidence of liquidity premium.

In panel B of Table 4.8, S denotes the most liquid portfolio (the lowest $ILLIQ12$), B denotes the least liquid portfolio (the highest $ILLIQ12$). The liquidity beta $\hat{\beta}_l$ decreases from S to B. Also, for portfolio $D2$ and B, the abnormal return $\hat{a}$ are significant different from zero.

As a whole, the performance of the two-factor is not very good in this case.

Table 4.9 Performance of two-factor model based $ILLIQ12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Panel A: Performance of portfolios sorted by $TO12$								
$\hat{\alpha}$ (%)	-0.324	-0.111	0.101	0.115	0.075	0.134	0.127	-0.116
	(-1.806)	(-0.937)	(0.901)	(1.067)	(0.829)	(1.407)	(1.125)	(-0.628)
$\hat{\beta_m}$	1.072	1.080	1.049	1.037	1.017	0.963	0.962	0.821
	(56.717)	(86.687)	(88.833)	(91.812)	(107.158)	(96.090)	(80.891)	(42.100)
$\hat{\beta}_l$	0.130	0.056	0.083	-0.007	0.071	0.012	-0.144	-0.199
	(2.713)	(1.764)	(2.762)	(-0.259)	(2.944)	(0.453)	(-4.765)	(-4.037)
R^2	0.952	0.979	0.980	0.981	0.986	0.982	0.975	0.911
Panel B: Performance of portfolios sorted by $ILLIQ12$								
$\hat{\alpha}$ (%)	-0.319	-0.326	-0.185	-0.068	0.145	-0.017	0.171	0.598
	(-1.612)	(-2.339)	(-1.636)	(-0.679)	(1.763)	(-0.137)	(1.325)	(2.741)
$\hat{\beta_m}$	0.954	0.998	1.003	1.008	1.012	0.988	1.016	1.022
	(38.996)	(57.919)	(71.754)	(81.561)	(99.678)	(66.013)	(63.594)	(37.867)
$\hat{\beta}_l$	0.397	0.124	0.096	-0.069	-0.051	-0.246	-0.100	-0.151
	(5.687)	(2.517)	(2.396)	(-1.961)	(-1.745)	(-5.764)	(-2.183)	(-1.959)
R^2	0.914	0.963	0.976	0.982	0.988	0.975	0.971	0.925

The numbers in parentheses are t-statistics.

4.4.3.2 Liquidity factor based on $ILLIQ12$

The model is

$$r_{it} - rf_t = \alpha_i + \beta_{mi}(rm_t - rf_t) + \beta_{li}LIQ_t + \epsilon_{it}$$

where the LIQ is constructed in the following way. I sort all stocks in ascending order on $ILLIQ12$ for each month from January 2001 to December 2015. Based on $ILLIQ12$, I form two portfolios, low-liquidity (LL) with lowest $ILLIQ12$ and high-liquidity (HL) with highest $ILLIQ12$: LL contains the 30% lowest-liquidity stocks, HL contains the 30% highest-liquidity stocks. I then construct the liquidity factor LIQ as the monthly profits from buying one dollar of equally weighted LL and selling one dollar of equally weighted HL.

In panel A of Table 4.9, S denotes the most liquid portfolio (the highest $TO12$), B denotes the least liquid portfolio (the lowest $TO12$). We can see that no abnormal return obtains for any portfolio after adjusting for the two factors. But the liquidity factor $\hat{\beta}_l$ decreases from S to B. As a result, in this case, the model fails to account for the performance of the lowest-$TO12$ portfolio (B).

In panel B of Table 4.9, S denotes the most liquid portfolio (the lowest $ILLIQ12$), B denotes the least liquid portfolio (the highest $ILLIQ12$). We can see that in portfolio $D2$ and B, the abnormal returns $\hat{a}$ are significantly different from zero after adjusting for the two factors. Also, the liquidity factor $\hat{\beta}_l$ does not increase from S to B. So we cannot get the result that that low-liquidity stocks bear high liquidity risk. As a result, the model cannot explain the performance of highest-$ILLIQ12$ portfolio (B).

4.4.3.3 Liquidity factor based both on $TO12$ and $ILLIQ12$

In the above, there are two ways to construct LIQ that are based on $TO12$ or $ILLIQ12$. These two models individually cannot explain the returns of stocks in terms of liquidity well. So I use a new construction of LIQ based on both $TO12$ and $ILLIQ12$. So the liquidity factor captures two dimensions of liquidity that are in terms of trading quantity and price impact. The model is

$$r_{it} - rf_t = \alpha_i + \beta_{mi}(rm_t - rf_t) + \beta_{li}LIQ_t + \epsilon_{it}$$

where the LIQ is constructed in the following way. I sort all stocks in ascending order on $ILLIQ12$ and descending order on $TO12$ for each month from January 2001 to December 2015. Based on $TO12$, I form two portfolios, low-liquidity ($TO-L$) and high-liquidity ($TO-H$): $TO-L$ contains the 30% lowest-liquidity stocks, $TO-H$ contains the 30% highest-liquidity stocks. Based on $ILLIQ12$, I form two portfolios, low-liquidity ($ILL-L$) and high-liquidity ($ILL-H$): $ILL-L$ contains the 30% lowest-liquidity stocks, $ILL-H$ contains the 30% highest-liquidity stocks. Then I form two portfolios, low-liquidity (LL) and high-liquidity (HL): LL combines $TO-L$ and $ILL-L$,

Table 4.10 Performance of two-factor model based both on $TO12$ and $ILLIQ12$

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B
Panel A: Performance of portfolios sorted by $TO12$								
$\hat{\alpha}$ (%)	-0.082	0.005	0.159	0.148	0.072	0.090	-0.015	-0.376
	(-0.488)	(0.049)	(1.386)	(1.400)	(0.800)	(0.974)	(-0.130)	(-2.043)
$\hat{\beta_m}$	1.068	1.077	1.057	1.032	1.030	0.970	0.952	0.814
	(61.441)	(91.969)	(89698)	(94.667)	(111.456)	(101.912)	(78.479)	(42.894)
$\hat{\beta}_l$	-0.567	-0.289	-0.017	-0.138	0.173	0.183	0.180	0.473
	(-5.567)	(-4.211)	(-0.240)	(-2.154)	(3.194)	(3.293)	(2.537)	(4.260)
R^2	0.958	0.980	0.979	0.981	0.986	0.983	0.972	0.912
Panel B: Performance of portfolios sorted by $ILLIQ12$								
$\hat{\alpha}$ (%)	-0.036	-0.115	-0.084	-0.039	0.132	-0.108	-0.004	0.254
	(-0.199)	(-1.041)	(-0.778)	(-0.386)	(1.582)	(-0.841)	(-0.044)	(1.542)
$\hat{\beta_m}$	0.847	0.952	0.974	1.018	1.023	1.045	1.054	1.088
	(45.239)	(83.819)	(87.559)	(97.392)	(118.492)	(79.012)	(94.633)	(64.053)
$\hat{\beta}_l$	-0.966	-0.741	-0.350	-0.110	0.038	0.300	0.617	1.212
	(-8.811)	(-11.146)	(-5.371)	(-1.798)	(0.744)	(3.868)	(9.469)	(12.188)
R^2	0.929	0.977	0.978	0.982	0.988	0.973	0.981	0.958

The numbers in parentheses are t-statistics.

HL combines $TO-H$ and $ILL-H$. So I construct the liquidity factor LIQ as the monthly profits from buying one dollar of equally weighted LL and selling one dollar of equally weighted HL.

In panel A of Table 4.10, S denotes the most liquid portfolio (the highest $TO12$), B denotes the least liquid portfolio (the lowest $TO12$). We can see that almost no abnormal returns obtained for all these eight portfolios after adjusting the two factors except for portfolio B. Also, almost all the coefficients of liquidity factor are significant ($t - value \geq 1.96$), which means the liquidity factor has a good power to explain the excess return of stocks. The liquidity factor $\hat{\beta}_l$ increases monotonically from S to B, which means that the lower liquidity stocks have higher liquidity risk. In Table 4.3 and Table 4.4, the CAPM and Fama-French three factor models are poor to explain the stock returns in terms of liquidity when sorted by $TO12$. So we can conclude that our two factor model has a better performance in explaining the liquidity sorted portfolios.

In panel B of Table 4.10, S denotes the most liquid portfolio (the lowest $ILLIQ12$), B denotes the least liquid portfolio (the highest $ILLIQ12$). The results are similar to those in panel A. There is no abnormal return after adjusting for the two factors in all the portfolios. From the coefficients of liquidity factor, we can see that the higher-$ILLIQ12$ portfolio is more sensitive to the liquidity factor, which is consistent with expectations because of the existence of a liquidity premium. What's more, after controlling for liquidity risk, the least liquid portfolio (B) has the highest market factor coefficient $\hat{\beta_m}$, indicating that B is more sensitive to market movements than the average stock.

From the evidence above, we can argue that the statement that the two factor model in which LIQ depends both on $TO12$ and $ILLIQ12$ has good performance to describe the liquidity premium when the portfolios are sorted by different liquidity measures.

4.4.4 The two-factor model and CAPM-related anomalies

Similar with Liu (2006), in this section I test the performance of the two-factor model in which LIQ depends both on $TO12$ and $ILLIQ12$ on the portfolios formed by MV and B/M. The reason is that in the above tests we use the same characteristic to form the explanatory variable and different portfolios, so I want to test the model when the portfolios are formed by other measures.

4.4.4.1 Sorted by MV

For each month from January 2001 to December 2015, stocks are sorted by descending order by MV and then grouped into eight portfolios. The portfolios have been equally weighted and held for 12 months. S is the biggest MV portfolio and B is the smallest MV portfolio. $B-S$ is the difference between B and S.

Table 4.11 shows that on average the raw returns of small stocks are higher than big stocks by 0.890% ($t = 2.042$) per month. After the CAPM adjustment, the smallest-MV portfolio (B) still has a higher return than largest-MV portfolio (S) by 0.602% ($t = 1.457$) per month. Also, in portfolio $D2$ and B, there are significant abnormal returns. After controlling for the Fama-French

Table 4.11 Performance of asset pricing models on the portfolios sorted by MV

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B	$B-S$
MV- classified portfolios									
Raw (%)	0.233	0.261	0.395	0.574	0.674	0.607	0.832	1.123	0.890
	(0.358)	(0.368)	(0.536)	(0.779)	(0.907)	(0.766)	(0.832)	(1.428)	(2.042)
$\alpha_{C\hat{A}PM}$ (%)	-0.297	-0.309	-0.194	-0.016	0.080	-0.009	0.223	0.521	0.602
	(-1.338)	(-2.009)	(-1.769)	(-0.156)	(0.875)	(-0.068)	(1.464)	(2.349)	(1.457)
$\alpha_{F\hat{F}3F}$ (%)	-0.254	-0.421	-0.208	-0.030	0.134	(-0.004)	0.281	0.498	0.547
	(-0.928)	(-2.220)	(-1.539)	(-0.243)	(1.185)	(-0.003)	(1.505)	(1.822)	(1.072)
Two-factor (market and liquidity) model									
$\hat{\alpha}$ (%)	-0.117	-0.162	-0.096	0.012	0.073	-0.063	0.086	0.267	0.169
	(-0.554)	(-1.139)	(-0.932)	(0.121)	(0.785)	(-0.484)	(0.601)	(1.367)	(0.452)
$\hat{\beta_m}$	0.825	0.936	0.996	1.003	1.017	1.082	1.074	1.068	0.243
	(38.008)	(63.993)	(94.114)	(96.272)	(105.648)	(80.221)	(73.258)	(53.155)	(6.319)
$\hat{\beta}_l$	-0.643	-0.526	-0.352	-0.100	0.025	0.195	0.492	0.909	1.549
	(-5.055)	(-6.145)	(-5.686)	(-1.636)	(0.449)	(2.467)	(5.729)	(7.727)	(6.880)
R^2	0.899	0.961	0.981	0.982	0.985	0.974	0.968	0.940	0.287

The numbers in parentheses are t-statistics.

three factors, the smallest-MV portfolio (B) has a higher return than largest-MV portfolio (S) by 0.547% ($t = 1.072$) per month. However, after the two factors adjustment, the difference of return between B and S is only 0.169% ($t = 0.452$). As a result, the two-factor model can explain the size effect better than the CAPM and Fama-French three-factor model. Also, the market factor loading $\hat{\beta_m}$ and liquidity factor loading $\hat{\beta}_l$ both increase almost monotonically from the largest-MV portfolio (S) to smallest-MV portfolio (B), which means the small firms have more risk than big firms. So the small stocks are less liquid than big stocks.

4.4.4.2 Sorted by B/M

For each month from January 2001 to December 2015, stocks are sorted by descending order by B/M and then grouped into eight portfolios. The portfolios have been equally weighted and held for 12 months. S is the largest B/M portfolio and B is smallest B/M portfolio. $B - S$ is the difference between B and S. The numbers in parentheses are t-statistics.

Table 4.12 Performance of asset pricing models on the portfolios sorted by B/M

	S	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	B	$B-S$
B/M- classified portfolios									
Raw (%)	0.246	0.279	0.563	0.407	0.601	0.671	0.663	1.269	1.023
	(0.818)	(0.877)	(1.811)	(1.288)	(2.00)	(2.205)	(2.275)	(3.918)	(9.157)
$\alpha_{\hat{CAPM}}$ (%)	-0.032	-0.004	0.281	0.124	0.321	0.390	0.386	0.985	0.802
	(-0.117)	(-0.015)	(0.990)	(0.429)	(1.173)	(1.405)	(1.448)	(3.326)	(7.167)
$\alpha_{\hat{FF3F}}$ (%)	-0.782	-0.959	-0.643	-0.757	-0.520	-0.511	-0.524	0.089	0.666
	(-2.402)	(-2.874)	(-1.968)	(-2.268)	(-1.653)	(-1.596)	(-1.733)	(0.262)	(5.084)
Two factor model									
$\hat{\alpha}$ (%)	-0.122	-0.108	0.175	-0.005	0.199	0.274	0.269	0.848	0.755
	(-0.440)	(-0.371)	(0.616)	(0.019)	(0.730)	(0.988)	(1.010)	(2.874)	(6.749)
$\hat{\beta_m}$	0.181	0.194	0.192	0.197	0.187	0.189	0.182	0.201	0.021
	(6.333)	(6.456)	(6.562)	(6.621)	(6.660)	(6.591)	(6.634)	(6.620)	(1.778)
$\hat{\beta_l}$	0.322	0.371	0.377	0.422	0.436	0.414	0.419	0.490	0.167
	(1.918)	(2.111)	(2.198)	(2.426)	(2.644)	(6.591)	(2.611)	(2.755)	(2.468
R^2	0.178	0.185	0.191	0.195	0.199	0.194	0.198	0.199	0.032

The numbers in parentheses are t-statistics.

Table 4.12 shows that on average the raw return of smallest-B/M portfolio is higher than largest-B/M portfolio by 1.023% ($t = 9.157$) per month. After the CAPM adjustment, we find that there is an abnormal return in all the portfolios and the return of $B-S$ is 0.802% ($t = 7.167$). So the CAPM has little power to explain the value effect. The results are similar when controlling Fama-French three factors. For the two-factor model, it is also unable to explain the value effect. The smallest-B/M portfolio (B) still has a higher return than the largest-B/M portfolio (S) by 0.755% ($t = 6.749$) per month.

I think one reason of this result is that the I only have the annual accounting data of book-to-market ratio. So I don't have the data of book-to-market ratio in every month, a limitation of the data can have great effect in the results.

4.5 Conclusion

In the previous literature, the studies of liquidity effect on the return of stocks are mainly on developed markets. Much less research has been conducted on emerging and asian markets. So in this paper, I study whether liquidity has a significant effect on Chinese stock market. I focus on the time period from 2000 to 2015 because Chinese stock market was partially manipulated by speculators and insiders before 2000. $TO12$ and $ILLIQ12$ are the measures of liquidity I use in this paper.

The empirical results show that there is a liquidity premium in the Chinese stock market under different kinds of liquidity measures. It confirms that liquidity has a significant effect in explaining the cross-section of stock returns. But neither the CAPM nor Fama-French three-factor model can account for the liquidity premium in different measures of liquidity. I propose a new two-factor model in which LIQ depends on both $TO12$ and $ILLIQ12$. The two-factor model has good performance in describing the liquidity premium. What's more, the model can help explain the size effect in Chinese stock market that CAPM and Fama-French three-factor model cannot.

BIBLIOGRAPHY

Acharya, V. V., Lochstoer, L. A., and Ramadorai, T. (2013). Limits to arbitrage and hedging: Evidence from commodity markets. *Journal of Financial Economics*, 109(2):441–465.

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2):375–410.

Adjemian, M. K. (2012). Quantifying the wasde announcement effect. *American Journal of Agricultural Economics*, 94(1):238–256.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Amihud, Y. and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2):223–249.

An, B.-J., Ang, A., Bali, T. G., and Cakici, N. (2014). The joint cross section of stocks and options. *Journal of Finance*, 69(5):2279–2337.

Baker, S. D. (2014). The financialization of storable commodities. *Finance Down Under 2014 Building on the Best from the Cellars of Finance*.

Bakshi, G., Gao, X., and Rossi, A. G. (2017). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*.

Basak, S. and Pavlova, A. (2016). A model of financialization of commodities. *Journal of Finance*, 71(4):1511–1556.

Basu, D. and Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. *Journal of Banking and Finance*, 37(7):2652–2664.

Bekaert, G., Harvey, C. R., and Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies*, 20(6):1783–1831.

Botto, A. C., Isengildina, O., Irwin, S. H., and Good, D. L. (2006). Accuracy trends and sources of forecast errors in wasde balance sheet categories for corn and soybeans. Technical report.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Brunetti, C. and Reiffen, D. (2014). Commodity index trading and hedging costs. *Journal of Financial Markets*, 21:153–180.

Campbell, J. Y., Grossman, S. J., and Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics*, 108(4):905–939.

Carpenter, J. N., Lu, F., and Whitelaw, R. F. (2015). The real value of china's stock market. Technical report, National Bureau of Economic Research.

Chan, H. W. and Faff, R. W. (2005). Asset pricing and the illiquidity premium. *Financial Review*, 40(4):429–458.

Chan, K., Ge, L., and Lin, T.-C. (2015). Informational content of options trading on acquirer announcement return. *Journal of Financial and Quantitative Analysis*, 50(5):1057–1082.

Chen, L., Li, S., and Wang, J. (2011). Liquidity, skewness and stock returns: evidence from chinese stock market. *Asia-Pacific Financial Markets*, 18(4):405–427.

Chen, N.-F., Roll, R., and Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, pages 383–403.

Cheng, I.-H., Kirilenko, A., and Xiong, W. (2014). Convective risk flows in commodity futures markets. *Review of Finance*, 19(5):1733–1781.

Chi, X. et al. (2005). An empirical study of liquidity premium in shanghai stock market [j]. *Quantitative & Technica Economics*, 9.

Chollete, L., Næs, R., and Skjeltorp, J. A. (2008). The risk components of liquidity. In *EFA 2008 Athens Meetings Paper*.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1):291–311.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton university press.

Cremers, M. and Weinbaum, D. (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis*, 45(2):335–367.

Daskalaki, C., Kostakis, A., and Skiadopoulos, G. (2014). Are there common factors in individual commodity futures returns? *Journal of Banking and Finance*, 40:346–363.

Datar, V. T., Naik, N. Y., and Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2):203–219.

Domanski, D. and Heath, A. (2007). Financial investors and commodity markets. *BIS Quarterly Review*, page 53.

Easley, D., Hvidkjaer, S., and O'hara, M. (2002). Is information risk a determinant of asset returns? *Journal of Finance*, 57(5):2185–2221.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56.

Fama, E. F. and French, K. R. (1998). Value versus growth: The international evidence. *Journal of Finance*, 53(6):1975–1999.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., and Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking and Finance*, 86:143–158.

Fernandez-Perez, A., Fuertes, A.-M., and Miffre, J. (2016). Is idiosyncratic volatility priced in commodity futures markets? *International Review of Financial Analysis*, 46:219–226.

Foran, J., Hutchinson, M., and O'Sullivan, N. (2010). Testing for the presence and pricing of liquidity risk in the uk equity market using daily data. Technical report, Working Paper.

Galariotis, E. C. and Giouvris, E. (2009). Systematic liquidity and excess returns: evidence from the london stock exchange. *Review of Accounting and Finance*.

Ge, L., Lin, T.-C., and Pearson, N. D. (2016). Why does the option to stock volume ratio predict stock returns? *Journal of Financial Economics*, 120(3):601–622.

Gelman, A. et al. (2006). Prior distributions for variance parameters in hierarchical models (comment on article by browne and draper). *Bayesian Analysis*, 1(3):515–534.

Goldstein, I. and Yang, L. (2019). Commodity financialization and information transmission. *Available at SSRN: https://ssrn.com/abstract=2555996*.

Good, D. and Irwin, S. (2014). Accuracy of usda forecasts of corn ending stocks. *farmdoc daily*, 4.

Gorton, G. B., Hayashi, F., and Rouwenhorst, K. G. (2012). The fundamentals of commodity futures returns. *Review of Finance*, 17(1):35–105.

Grossman, S. J. and Miller, M. H. (1988). Liquidity and market structure. *Journal of Finance*, 43(3):617–633.

Ho, T.-w. and Chang, S.-H. (2015). The pricing of liquidity risk on the shanghai stock market. *International Review of Economics & Finance*, 38:112–130.

Hoffman, L. A., Etienne, X. L., Irwin, S. H., Colino, E. V., and Toasa, J. I. (2015). Forecast performance of wasde price projections for us corn. *Agricultural Economics*, 46(S1):157–171.

Holmström, B. and Tirole, J. (2001). Lapm: A liquidity-based asset pricing model. *Journal of Finance*, 56(5):1837–1867.

Hong, H. and Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105(3):473–490.

Hu, J. (2014). Does option trading convey stock price information? *Journal of Financial Economics*, 111(3):625–645.

Isengildina, O., Irwin, S. H., and Good, D. L. (2004). Evaluation of usda interval forecasts of corn and soybean prices. *American Journal of Agricultural Economics*, 86(4):990–1004.

Isengildina, O., Irwin, S. H., and Good, D. L. (2006a). Are revisions to usda crop production forecasts smoothed? *American Journal of Agricultural Economics*, 88(4):1091–1104.

Isengildina, O., Irwin, S. H., and Good, D. L. (2006b). The value of usda situation and outlook information in hog and cattle markets. *Journal of Agricultural and Resource Economics*, pages 262–282.

Isengildina-Massa, O., Irwin, S. H., Good, D. L., and Gomez, J. K. (2008a). The impact of situation and outlook information in corn and soybean futures markets: Evidence from wasde reports. *Journal of Agricultural and Applied Economics*, 40(1):89–103.

Isengildina-Massa, O., Irwin, S. H., Good, D. L., and Gomez, J. K. (2008b). Impact of wasde reports on implied volatility in corn and soybean markets. *Agribusiness: An International Journal*, 24(4):473–490.

Isengildina-Massa, O., Karali, B., and Irwin, S. H. (2013). When do the usda forecasters make mistakes? *Applied Economics*, 45(36):5086–5103.

Jacoby, G., Fowler, D. J., and Gottesman, A. A. (2000). The capital asset pricing model and the liquidity effect: A theoretical approach. *Journal of Financial Markets*, 3(1):69–81.

Jagannathan, R. (1985). An investigation of commodity futures prices using the consumption-based intertemporal capital asset pricing model. *Journal of Finance*, 40(1):175–191.

Jang, J., Kang, J., and Lee, C. (2012). Liquidity risk and expected stock returns in korea: a new approach. *Asia-Pacific Journal of Financial Studies*, 41(6):704–738.

Johnson, T. L. and So, E. C. (2012). The option to stock volume ratio and future returns. *Journal of Financial Economics*, 106(2):262–286.

Johnson, T. L. and So, E. C. (2017). A simple multimarket measure of information asymmetry. *Management Science*, 64(3):1055–1080.

Kacperczyk, M. and Pagnotta, E. S. (2019). Chasing private information. *Review of Financial Studies*, 32(12):4997–5047.

Kang, W., Rouwenhorst, K. G., and Tang, K. (2019). A tale of two premiums: The role of hedgers and speculators in commodity futures markets. *Journal of Finance*.

Kaniel, R., Saar, G., and Titman, S. (2008). Individual investor trading and stock returns. *Journal of Finance*, 63(1):273–310.

Keene, M. A. and Peterson, D. R. (2007). The importance of liquidity as a factor in asset pricing. *Journal of Financial Research*, 30(1):91–109.

Keynes, J. M. (1930). *A treatise on money: in 2 volumes*. Macmillan & Company.

Kong, D. (2006). Asset pricing with liquidity risk: Evidence from chinese stock market [j]. *South China Journal of Economics*, 3(008).

Lam, K. S. and Tam, L. H. (2011). Liquidity and asset pricing: Evidence from the hong kong stock market. *Journal of Banking and Finance*, 35(9):2217–2230.

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3):631–671.

Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2011). Commodity liquidity measurement and transaction costs. *Review of Financial Studies*, 25(2):599–638.

Martınez, M. A., Nieto, B., Rubio, G., and Tapia, M. (2005). Asset pricing and systematic liquidity risk: An empirical investigation of the spanish stock market. *International Review of Economics & Finance*, 14(1):81–103.

Narayan, P. K. and Zheng, X. (2010). Market liquidity risk factor and financial market anomalies: Evidence from the chinese stock market. *Pacific-Basin Finance Journal*, 18(5):509–520.

Nguyen, D., Mishra, S., Prakash, A., and Ghosh, D. K. (2007). Liquidity and asset pricing under the three-moment capm paradigm. *Journal of Financial Research*, 30(3):379–398.

Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1):435–480.

Roll, R., Schwartz, E., and Subrahmanyam, A. (2010). O/s: The relative trading activity in options and stock. *Journal of Financial Economics*, 96(1):1–17.

Rouwenhorst, K. G. and Tang, K. (2012). Commodity investing. *Annual Review of Financial Economics*, 4(1):447–467.

Sanders, D. R. and Manfredo, M. R. (2002). Usda production forecasts for pork, beef, and broilers: an evaluation. *Journal of Agricultural and Resource Economics*, pages 114–127.

Sanders, D. R. and Manfredo, M. R. (2003). Usda livestock price forecasts: A comprehensive evaluation. *Journal of Agricultural and Resource Economics*, pages 316–334.

Singleton, K. J. (2013). Investor flows and the 2008 boom/bust in oil prices. *Management Science*, 60(2):300–318.

Smith, A. (2005). Partially overlapping time series: A new model for volatility dynamics in commodity futures. *Journal of Applied Econometrics*, 20(3):405–422.

Sockin, M. and Xiong, W. (2015). Informational frictions and commodity markets. *Journal of Finance*, 70(5):2063–2098.

Stilger, P. S., Kostakis, A., and Poon, S.-H. (2016). What does risk-neutral skewness tell us about future stock returns? *Management Science*, 63(6):1814–1834.

Szymanowska, M., De Roon, F., Nijman, T., and Van den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *Journal of Finance*, 69(1):453–482.

Tang, K. and Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(5):54–74.

Vogel, F. and Bange, G. (1999). Understanding usda crop forecasts. national agricultural statistics service (nass) and world agricultural outlook board (waob), office of the chief economist (oce). *US Department of Agriculture. Miscellaneous Publication*, (1554).

Von Bailey, D. and Brorsen, B. W. (1998). Trends in the accuracy of usda production forecasts for beef and pork. *Journal of Agricultural and Resource Economics*, pages 515–525.

Working, H. (1960). Speculation on hedging markets. *Food Research Institute Studies*, 1(1387-2016-116000):185.

Xiao, J. (2015). Essays on the forecasts of ending stocks. *Graduate Theses and Dissertations. 14895. https://lib.dr.iastate.edu/etd/14895.*

Xiao, J., Hart, C. E., and Lence, S. H. (2017). Usda forecasts of crop ending stocks: How well have they performed? *Applied Economic Perspectives and Policy*, 39(2):220–241.

Yang, C. (2015). An empirical study of liquidity and return autocorrelations in the chinese stock market. *Asia-Pacific Financial Markets*, 22(3):261–282.

Yang, F. (2013). Investment shocks and the commodity basis spread. *Journal of Financial Economics*, 110(1):164–184.

Zhang, T. (2019). Trading activity in commodity futures and options markets. *Available at SSRN: https://ssrn.com/abstract=3542967.*

Zhang, Z. and Liu, L. (2006). Turnovers and stock returns: Liquidity premium or speculative bubbles?[j]. *China Economic Quarterly*, 2.

APPENDIX A. APPENDIX TO CHAPTER 2

A.1 Model for ending stocks and futures prices

In the rational storage model, theoretically, the amount of crop to be stored to the following period shall be compensated by the carry in the futures markets:

$$E_t[p_T(z_T + c_T)] - p_t = g(c_T|c_t)$$

where p_T is the harvest price of crop in year T, p_t is the spot price, z_T and c_T are the new production and remaining carryout at harvest, the carryout from the last marketing year is c_t. Denote the cost of carry, $g(c_T|c_t)$, as the cost of storing c_T amount of crop from time t to the harvest time, T , conditional on the initial carryout available, c_t.

If we assume that there is the absence of a risk premium:

$$E_t[p_T(z_T + c_T)] = f_{t,T}$$

Since the price function p_T is decreasing in c_T, there is a negative relationship between c_T and $f_{t,T}$.

A.2 Robustness Checks

Table A.1 Time-series test for sub-period 1

	1 (Low)	2	3	4	5	6	7	8 (High)	1-8	(1+2)-(7+8)
					Commodity CAPM					
Alpha	0.002	0.0003	-0.001	0.0001	-0.002	-0.0003	-0.001	-0.002	0.003	0.005
	(2.277)	(0.385)	(-1.186)	(0.097)	(-2.212)	(-0.304)	(-1.304)	(-1.656)	(2.497)	(2.645)
AVG	1.011	0.749	0.760	0.726	0.792	0.929	0.926	0.905	0.106	-0.071
	(21.835)	(15.294)	(13.693)	(14.305)	(14.528)	(15.485)	(15.593)	(15.353)	(1.301)	(-0.631)
R^2	0.438	0.276	0.234	0.250	0.256	0.281	0.284	0.278	0.001	-0.001
					Commodity *AVG* and *CARRY*					
Alpha	0.002	0.0005	-0.001	-0.00005	-0.002	-0.0002	-0.001	-0.002	0.004	0.005
	(2.451)	(0.582)	(-0.939)	(-0.057)	(-2.107)	(-0.247)	(-1.363)	(-1.600)	(2.550)	(2.801)
AVG	1.027	0.765	0.781	0.711	0.803	0.938	0.925	0.912	0.115	-0.045
	(22.026)	(15.527)	(13.986)	(13.916)	(14.585)	(15.511)	(15.428)	(15.275)	(1.400)	(-0.395)
CARRY	-0.066	-0.039	-0.058	0.040	-0.051	-0.057	-0.004	-0.022	-0.044	-0.079
	(-2.676)	(-1.509)	(-1.968)	(1.477)	(-1.777)	(-1.796)	(-0.134)	(-0.686)	(-1.019)	(-1.314)
R^2	0.443	0.282	0.242	0.250	0.257	0.282	0.283	0.277	0.001	0.0001
					Commodity *AVG*, *CARRY* and *MOM*					
Alpha	0.002	0.001	-0.001	-0.0001	-0.002	-0.0001	-0.001	-0.002	0.003	0.005
	(2.331)	(0.635)	(-0.974)	(-0.155)	(-2.067)	(-0.106)	(-1.299)	(-1.582)	(2.468)	(2.731)
AVG	1.016	0.770	0.777	0.702	0.807	0.954	0.932	0.913	0.103	-0.059
	(21.712)	(15.527)	(13.820)	(13.661)	(14.551)	(15.737)	(15.444)	(15.191)	(1.243)	(-0.516)
CARRY	-0.072	-0.036	-0.060	0.034	-0.049	-0.048	-0.0002	-0.021	-0.051	-0.087
	(-2.916)	(-1.384)	(-2.029)	(1.263)	(-1.688)	(-1.493)	(-0.005)	(-0.652)	(-1.176)	(-1.440)
MOM	0.051	-0.024	0.019	0.045	-0.018	-0.077	-0.033	-0.007	0.058	0.067
	(2.331)	(0.635)	(-0.974)	(-0.155)	(-2.067)	(-0.106)	(-1.299)	(-1.582)	(2.468)	(2.731)
R^2	0.446	0.282	0.241	0.252	0.257	0.287	0.283	0.276	0.002	0.0004

Note: The groups are sorted by $O/F_{i,t}$, where $O/F_{i,t}$ is the ratio of option volume to futures volume of commodity i in week t. Group 1 has the lowest value of O/F, where group 8 is with highest O/F. The return of each group is the weekly return in week $t+1$. We include three contemporaneous risk factors in the regressions: AVG, $CARRY$, MOM. The three regressions have part or full of these three risk factors. The t-statistics are shown in parentheses.

Table A.2 Time-series test for sub-period 2

	1 (Low)	2	3	4	5	6	7	8 (High)	1-8	(1+2)-(7+8)
					Commodity CAPM					
Alpha	0.001	-0.001	0.002	-0.002	0.001	0.001	0.001	-0.001	0.003	0.001
	(1.764)	(-0.670)	(2.309)	(-2.098)	(0.577)	(1.149)	(0.943)	(-1.588)	(2.070)	(0.704)
AVG	1.205	0.922	0.874	0.744	0.697	0.893	0.968	0.859	0.347	0.301
	(36.863)	(23.295)	(23.101)	(20.542)	(17.435)	(24.565)	(25.926)	(21.857)	(5.973)	(3.625)
R^2	0.667	0.444	0.440	0.383	0.309	0.471	0.498	0.413	0.049	0.018
					Commodity *AVG* and *CARRY*					
Alpha	0.001	-0.001	0.002	-0.002	0.0005	0.001	0.001	-0.001	0.003	0.001
	(1.762)	(-0.664)	(2.306)	(-2.100)	(0.573)	(1.148)	(0.943)	(-1.586)	(2.068)	(0.707)
AVG	1.205	0.922	0.873	0.744	0.697	0.893	0.968	0.859	0.346	0.301
	(36.837)	(23.364)	(23.122)	(20.535)	(17.444)	(24.547)	(25.907)	(21.842)	(5.969)	(3.625)
CARRY	0.006	-0.066	0.043	0.020	0.040	-0.0003	-0.004	-0.007	0.013	-0.049
	(0.238)	(-2.221)	(1.509)	(0.736)	(1.326)	(-0.010)	(-0.136)	(-0.239)	(0.296)	(-0.789)
R^2	0.667	0.448	0.441	0.383	0.310	0.470	0.497	0.412	0.047	0.017
					Commodity *AVG*, *CARRY* and *MOM*					
Alpha	0.001	-0.001	0.002	-0.002	0.0004	0.001	0.001	-0.001	0.003	0.001
	(1.886)	(-0.705)	(2.237)	(-2.151)	(0.515)	(1.181)	(0.917)	(-1.699)	(2.221)	(0.795)
AVG	1.183	0.932	0.890	0.755	0.711	0.886	0.973	0.883	0.300	0.258
	(35.523)	(23.054)	(23.037)	(20.357)	(17.382)	(23.768)	(25.422)	(22.044)	(5.091)	(3.052)
CARRY	0.015	-0.070	0.036	0.016	0.034	0.003	-0.006	-0.017	0.032	-0.032
	(0.607)	(-2.339)	(1.268)	(0.565)	(1.131)	(0.098)	(-0.213)	(-0.579)	(0.737)	(-0.507)
MOM	-0.070	0.031	0.051	0.035	0.044	-0.023	0.017	0.078	-0.148	-0.134
	(-3.058)	(1.110)	(1.929)	(1.371)	(1.545)	(-0.893)	(0.648)	(2.820)	(-3.647)	(-2.301)
R^2	0.671	0.448	0.444	0.384	0.311	0.470	0.497	0.418	0.064	0.023

Note: The groups are sorted by $O/F_{i,t}$, where $O/F_{i,t}$ is the ratio of option volume to futures volume of commodity i in week t. Group 1 has the lowest value of O/F, where group 8 is with highest O/F. The return of each group is the weekly return in week $t+1$. We include three contemporaneous risk factors in the regressions: *AVG*, *CARRY*, *MOM*. The three regressions have part or full of these three risk factors. The t-statistics are shown in parentheses.

Table A.3 Cross-sectional tests for sub-periods

Fama-MacBeth regressions of RET(1)				
	Sub-period 1		Sub-period 2	
	(1)	(2)	(3)	(4)
log(O/F)	-0.057*	-0.091***	-0.042*	-0.045*
	(-1.855)	(-2.816)	(-1.739)	(-1.801)
CAR	-0.414	0.125	-0.407	-1.023
	(-0.281)	(0.076)	(-0.279)	(-0.658)
MOM	0.404	0.284	0.342	0.533
	(0.538)	(0.348)	(0.566)	(0.786)
AMI	1.125	2.428	2.274	3.169
	(0.143)	(0.281)	(0.270)	(0.302)
RET(0)		0.837		1.152
		(0.475)		(0.755)
Constant	0.330	-0.269	0.211	0.826
	(0.222)	(-0.162)	(0.142)	(0.522)
Observations	12,346	11,852	14,678	13,877
R^2	0.263	0.338	0.358	0.419

Note: This table presents Fama-MacBeth regression results from regressing RET(1) on risk factors. RET(1) is the dependent variable indicates the return of commodity i in week $t+1$ after observing O/F at the end of week t. CAR equals the basis of commodity i at the end of week t. MOM is the cumulative returns measures over the past 8 weeks and adjusted by market return. AMI is the Amihud illiquidity of commodity i in week t. RET(0) is the return of commodity i in week t. The t-statistics are shown in parentheses. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table A.4 Results of commodity sector analysis

Dependent variable: RET(1)	Agriculture		Energy		Livestock		Metals	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(O/F)	−0.064*	−0.072**	−0.076*	−0.088*	−0.034**	−0.035***	0.004	−0.001
	(−1.854)	(−2.089)	(−1.738)	(−1.757)	(−2.491)	(−5.834)	(0.481)	(−0.128)
CAR	−0.153	−0.299	−0.023	0.366	1.091***	1.089***	−14.465***	−14.249***
	(−0.135)	(−0.259)	(−0.008)	(0.135)	(2.766)	(3.353)	(−3.732)	(−2.971)
MOM	−0.786	−0.812	1.918***	1.809***	−0.146	−0.215	−0.636	−0.409
	(−1.572)	(−1.512)	(4.516)	(3.904)	(−0.369)	(−0.589)	(−0.348)	(−0.239)
AMI	−0.491	−1.666***	−19.370***	−19.587***	−10.398	−12.721	−0.243**	−0.191
	(−0.906)	(−5.636)	(−8.252)	(−8.009)	(−1.104)	(−1.277)	(−2.346)	(−1.601)
RET(0)		0.151		0.395		3.383		3.550***
		(0.180)		(0.296)		(0.982)		(9.651)
Constant	−0.067	0.064	−0.245	−0.671	−1.145***	−1.140***	14.582***	14.337***
	(−0.059)	(0.056)	(−0.082)	(−0.241)	(−2.790)	(−3.264)	(3.736)	(2.971)
Observations	14,667	13,735	5,576	5,530	3,414	3,254	3,367	3,210
R^2	0.001	0.001	0.003	0.003	0.002	0.003	0.002	0.003

Note: This table presents ordinary least squares regression results from regressing $RET(1)$ on risk factors. $RET(1)$ is the dependent variable indicates the return of commodity i in week $t+1$ after observing O/F at the end of week t. CAR equals the basis of commodity i at the end of week t. MOM is the cumulative returns measures over the past 8 weeks and adjusted by market return. AMI is the Amihud illiquidity of commodity i in week t. $RET(0)$ is the return of commodity i in week t. The standard errors are clusterd (by time). The t-statistics are shown in parentheses. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table A.5 Results of monthly analysis

Fama-MacBeth regressions of RET(1)	(1)	(2)	(3)	(4)	(5)
log(O/F)			-0.219**	-0.228**	-0.275***
			(-2.373)	(-2.386)	(-2.835)
CAR	-5.059	-5.773	-6.448	-7.388	-6.680
	(-1.199)	(-1.256)	(-1.530)	(-1.587)	(-1.384)
MOM	-0.036	-0.043	-0.035	-0.043	0.008
	(-0.662)	(-0.766)	(-0.649)	(-0.770)	(0.138)
AMI		904.383		-1,424.941	-1,934.951
		(0.132)		(-0.199)	(-0.258)
RET(0)					-0.001
					(-0.058)
Constant	4.916	5.658	5.886	6.840	5.922
	(1.145)	(1.214)	(1.366)	(1.441)	(1.209)
Observations	6,609	6,609	6,609	6,609	6,608
R^2	0.214	0.216	0.217	0.221	0.277

Note: This table presents Fama-MacBeth regression results from regressing RET(1) on risk factors. RET(1) is the dependent variable indicates the return of commodity i in month $t+1$ after observing O/F at the end of month t. CAR equals the basis of commodity i at the end of month t. MOM is the cumulative returns measures over the past 6 month and adjusted by market return. AMIHUD is the Amihud illiquidity of commodity i in month t. RET(0) is the return of commodity i in month t. The t-statistics are shown in parentheses. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Table A.6 Results of ΔOF

Fama-MacBeth regressions of RET(1)			
	(1)	(2)	(3)
$\Delta O/F$		-0.074*	-0.092**
		(-1.841)	(-2.147)
CAR	-0.915	-0.819	-0.627
	(-0.894)	(-0.768)	(-0.541)
MOM	0.363	0.298	0.359
	(0.758)	(0.607)	(0.667)
AMI	2.339	0.569	4.824
	(0.416)	(0.096)	(0.699)
RET(0)			0.980
			(0.813)
Constant	0.882	0.790	0.599
	(0.854)	(0.733)	(0.511)
Observations	27,024	26,824	25,559
R^2	0.313	0.317	0.385

Note: This table presents Fama-MacBeth regression results from regressing RET(1) on risk factors. RET(1) is the dependent variable indicates the return of commodity i in week $t+1$ after observing O/F at the end of week t. CAR equals the basis of commodity i at the end of week t. MOM is the cumulative returns measures over the past 8 weeks and adjusted by market return. AMIHUD is the Amihud illiquidity of commodity i in week t. RET(0) is the return of commodity i in week t. The t-statistics are shown in parentheses. The notations ***, **, * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

APPENDIX B. APPENDIX TO CHAPTER 3

B.1 Stationary process

As we know, the stationary process is a very important concept of the time series regression model. Non-stationary process could cause huge bias to the results of the time series regression. In this paper, I use Augmented Dickey–Fuller test and Phillips–Perron test to check whether the time series of variables in the regressions are stationary.

Table B.1 Stationary process

	Sub-period I	
	ADF Test	PP Test
$error_{t,n}$	-4.1089***	-52.037***
$basis_{t,n}$	-3.1528*	-39.973***
$di_{t,n}$	-3.805**	-122.09***
ds_t	-4.0116**	-38.811***
dy_{t-1}	-4.2783***	-46.485***

	Sub-period II	
	ADF Test	PP Test
$error_{t,n}$	-4.0254***	-43.493***
$basis_{t,n}$	-3.4353**	-37.72***
$di_{t,n}$	-3.8728**	-85.053***
dy_{t-1}	-4.2783***	-46.485***

	Sub-period III	
	ADF Test	PP Test
$error_{t,n}$	-4.0465***	-38.665***
$basis_{t,n}$	-3.7932**	-37.663***
ds_{t-1}	-4.3803***	-36.052***

	Sub-period IV	
	ADF Test	PP Test
$error_{t,n}$	-5.424***	-75.616***
$basis_{t,n}$	-3.3274*	-37.281***
di_t	-3.6477**	-97.342***
ds_{t-1}	-3.38*	-27.211***

Note: *p<0.1; **p<0.05; ***p<0.01

From the results in Table B.1, we can find that almost all the variables are statistically significant at 5% level, all the variables are statistically significant at 10% level. Then we can make sure the assumptions of stationary process for the regressions are satisfied.

B.2 Autocorrelation

The serial correlation in the error terms of a multiple time series regression model is a critical problem. Although the autocorrelation does not change the estimation in coefficients of the explanatory variables, it can greatly affect the standard deviation of the estimation. Thus, the serial correlation in the errors will cause the usual OLS statistics to be invalid for testing purposes. In this paper, I use Ljung–Box test to check the autorrelation and find there is strong autocorrelation of residuals in OLS regression in all four sub-periods.

B.3 Heteroscedasticity

The presence of heteroscedasticity, while not causing bias or inconsistency in the estimator of explanatory variables, does invalidate the standard deviation, t statistics and F statistics. We use Breusch–Pagan test to check the heteroscedasticity.

Table B.2 Heteroscedasticity

	I	II	III	IV
bp	20.823***	7.383**	12.464***	0.326

Note: *p<0.1; **p<0.05; ***p<0.01

From Table B.2, we can find that heteroscedasticity exists in Sub-period I, II, III.