Essays in Quantitative Investments

Thesis submitted in accordance with the requirements of the University of Liverpool
for the degree of Doctor in Philosophy by

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May 2018

Abstract

This thesis studies the characteristics of Chinese futures markets and the quantitative investment strategies. The main objective of this thesis is to provide a comprehensive analysis on the performance of quantitative investment strategies in the Chinese market. Furthermore, with an econometric analysis, the stylised facts of the Chinese futures markets are documented. Extensive backtesting results on the performance of momentum, reversal and pairs trading type strategies are provided. In the case of pairs trading type strategies, risk and return relationship is characterised by the length of the maximum holding periods, and thus reflected in the maximum drawdown risk. In line with the increasing holding periods, the profitability of pairs trading increases over longer holding periods. Therefore, the abnormal returns from pairs trading in the Chinese futures market do not necessarily reflect market inefficiency.

Momentum and reversal strategies are compared by employing both high- and low-frequency time series with precise estimation of transaction costs. The comparison of momentum and reversal investment strategies at the intra- and inter-day scales displays that the portfolio rebalancing frequency significantly impacts the profitability of such strategies. Complementarily, the excess returns of inter-day momentum trading with the inclusion of precise estimates of transaction costs reflect that quantitative investment strategies consistently produce abnormal profits in the Chinese commodity futures markets. However, from a risk-adjusted view, the returns are obtained only by bearing additional drawdown risks. Finally, this thesis suggests that investor should choose quantitative trading strategies according to the investment horizon, tolerance for maximum drawdown and portfolio rebalancing costs.

Acknowledgements

First, I would like to thank my supervisors, as both of them have helped me a lot. I thank Dr. Ahmet Göncü for believing in me even before I believed in myself and for always considering my interests. I thank Dr. Athanasios Pantelous for wisely guiding me through the early research life. I thank my colleagues in the Department of Mathematical Sciences; they have always provided support for me with respect to learning, teaching and researching issues. Moreover, I would like to express my gratitude to the examiners, Dr. Hefei Wang and Dr. Dejun Xie, both of them provide valuable suggestions for the revision. I also thank my parents. They gave me the chance to pursue my passions without worrying about anything. It is not just about pushing my limits; it is about overcoming challenges and living my dreams. Last, I thank my girlfriend. Her bravery always makes me stronger.

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Chapter 1

Preliminaries

By some financial engineering or econometric tools, quantitative or algorithmic investments now play a significant role in the global financial market. In this area, there are innumerable books or articles on the advanced mathematics and strategies employed by investors. However, most of the existing studies on quantitative investments focus on a few developed countries. Among the limited amount of literature on the emerging market, a vast majority of it analyses the stock market. Therefore, to our best knowledge, it still lacks comprehensive analysis of quantitative investments on the emerging futures market.

Investments in futures have raised their popularity for risk-hedging purposes. Bodie and Rosansky (1980) claims that the investor could reduce the return variability significantly without sacrificing any of the returns by allocating some funds to futures from an all-stock portfolio. Complementarily, the commodity futures proved to be a very qualified candidate for hedging the inflation risks. Therefore, commodity futures markets are increasingly in the focus of investors, and China is no exception to this trend. After several years' development, China's financial market has become an important constituent of the global economy.[1] With its rapidly growing economy, China has some of the world's most highly traded commodity futures, including the contracts on copper, gold, iron ore and palm oil. Comparing with stock trading,

[1] See (Hua and Chen, 2007; Fung and Tse, 2010; Li and Hayes, 2017; Lucey et al., 2018).

futures offer lower transaction costs, more flexibility for taking short positions and particularly the intra-day trading opportunity in China.[2] Additionally, numerous studies document that a variety of futures investment strategies can produce superior returns in comparison to the stock markets.

Given these preambles, this thesis provides a complete investigation of the entire Chinese futures market and makes some practical suggestions about trading strategies. The rest of this thesis focuses on the econometric analysis of market properties and empirical implementations of well-documented strategies, while hoping that many of the results would be useful for both individual and institutional investors. The thesis is composed of three chapters. Next, the comments on individual chapters are discussed separately.

Chapter 2, co-authored with Ahmet Göncü, examines the fundamental empirical characteristics of the Chinese futures markets, which include all the liquid financial and commodity futures traded in mainland China, and are determined at different time scales. The comprehensive results for the whole range of products provide valuable insight for the market practitioners, academics, and regulators for futures studies. Stylized facts from the stock markets such as serial correlation, volatility clustering, non-normality, gain/loss asymmetry, cointegration, risk characteristics and structural dependences are characterized. Futures returns in the Chinese futures markets display certain similarities and differences from the stock markets with respect to these properties stylized facts. Furthermore, these empirical observations from the futures markets contribute to the strategy selected for the following study.

Chapter 3, co-authored with Ahmet Göncü and Athanasios Pantelous, studies one popular market-neutral investment strategy, pairs trading. It is a sort of statistical arbitrage strategy based on the cointegration relationship, whose existence is verified in the Chinese futures market (See Chapter 2 for details). In this chapter, the profitability of different pairs selection and spread trading methods are compared using the complete dataset of commodity futures[3] from Dalian Commodity Exchange

[2] In the Chinese mainland, the $T+1$ rule is imposed on the stock market, i.e., the investor cannot sell the stock on the same day when it is bought; instead, the investor has to wait for the next trading day to sell the holding.

[3] The empirical analysis of this thesis focuses on the commodity futures due to the short history

(DCE), Shanghai Futures Exchange (SHFE) and Zhengzhou Commodity Exchange (CZCE). Pairs trading methods that are already known in the literature are compared in terms of the risk-adjusted returns via in-sample and out-of-sample backtesting and bootstrapping for robustness. The empirical results show that pairs trading in the Chinese commodity futures market offers high returns, whereas, the profitability of these strategies primarily depends on the identification of suitable pairs. The observed high returns are a compensation for the spread divergence risk during the potentially longer holding periods, which implies that the maximum drawdown is more crucial compared to the other risk-adjusted return measures such as the Sharpe ratio. Complementary to the existing literature, for the Chinese market, it is shown that if shorter maximum holding periods are introduced for the spread positions, then the pairs trading profits decrease. Therefore, the returns do not necessarily imply market inefficiency when the higher maximum drawdown associated with the holding period of the spread position is taken into account.

Chapter 4, co-authored with Ahmet Göncü and Athanasios Pantelous, investigates the momentum and reversal strategies. In this chapter, a wide range of momentum and reversal strategies at different trading frequencies are tested for the Chinese commodity futures markets. Accurate estimates of transaction costs for each commodity and the minute-level futures prices are utilized to obtain the most realistic out-of-sample backtesting results. Contrary to the existing literature, this dataset does not suffer from liquidity problems since the intra-day data is constructed from the most actively traded contracts for each commodity. Overall, there are three main findings of this chapter. First, momentum and reversal trading strategies can generate robust and consistent returns over time; however, the intra-day momentum and reversal strategies cannot generate sufficiently high excess returns to cover the excessive costs due to the higher frequency of trading. Second, at lower trading frequencies and longer holding periods momentum and reversal strategies can generate excess returns, but with higher maximum drawdown risk. Finally, double-sort strategies statistically improve the profitability of momentum and reversal strategies.

Chapter 5 presents the conclusion produced by the comprehensive analysis of the

of financial futures and the trading limitation imposed recently in China.

Chinese futures market.One objective of this thesis is making practical suggestions on trading for investors. Therefore, this chapter summarises the statistical characteristics of the Chinese futures markets and the performance of two representative strategies, namely pairs trading and momentum trading. Complementarily, this chapter discusses the relationship between the profitability of pairs trading and market efficiency, and the momentum life cycle framework in the Chinese futures market. Finally, some future research directions are pointed out.

Chapter 2

Anatomy of Chinese Futures Markets

2.1 Introduction

Chinese futures markets provide a broad range of products on commodities, stock market indices, and treasury bonds. As of 2017, there are four exchanges including Shanghai Futures Exchange (SHFE), Dalian Commodity Exchange (DCE), Zhengzhou Commodity Exchange (CZCE) and China Financial Futures Exchange (CFFEX), which provide fifty-two futures products for investors in the Chinese futures markets. Within the universe of Chinese futures products, excluding the short-history and low-liquidity products, there are 37 products (32 commodities and 5 financials) remaining with sufficiently long historical data series, i.e., with longer than three years of history. The modern Chinese futures markets originated in the 1990s when the first commodity futures exchange was established in Zhengzhou for the trade of grains and developed when the financial indices futures were included. The market expanded in 2014 when the risk management and assets management functions were promoted. Nowadays, the Chinese futures market is the largest globally in terms of trading volume for several commodity futures such as copper, iron ore, soybean and soybean oil[1]. However, the stock index futures are restricted since the aftermath of the Chinese stock market slump during 2015. The Chinese futures markets can be described as highly speculative (CTAs from hedge funds are significant active) and highly liquid (at least for some products). Relatively, different from the stock markets, where around 80% of the account owners are individual investors, futures markets in China are mainly dominated by the hedge funds, futures companies, and large commercial corporations[2].

The stock market collapse started on 12 June, 2015 when the Shanghai composite index decreased by one-third of its value within one month. Since stock index futures are considered to accelerate the fall in the stock market, new restrictions on the trading of the stock index futures were issued immediately after the stock collapse. The new regulation limits each account to hold a maximum of ten index futures contracts and increases the margin requirement and transaction cost for the trading of index futures. Comparatively, the position-holding cost for index futures is much higher than other futures products in China. Therefore, index futures have an obviously different structural relationship with commodity futures. The observation in this study demonstrates that index futures are distinctive with respect to their statistical properties in comparison to commodity futures. Meanwhile, the dependences and correlations among futures markets are documented at different time levels using the principle components analysis. Finally, the diversification benefits are investigated across sectors of futures products depending on the investment horizon.

Exploring stylized facts of a financial market is crucial for both the practitioners and academias since it is useful for investigating the price theory from the theoretical view or even developing profitable trading strategies. The objective of this chapter is to explore the main empirical characteristics of futures returns and their implications for investment and risk management in China. The literature on Chinese futures

[1]See 2015 WFE/IOMA Derivatives Market Survey reported by World Federation of Exchanges (WFE) and IOMA,"*The commodity options and futures traded in Shanghai and Dalian accounting for 50% of the volume traded in 2015 in terms of the number of contracts*" (published, 2 April, 2015).

[2]More than two thousand funds are reporting their weekly returns in the hedge fund database of the China Hedge Fund Research Center at the Shanghai Advanced Institute of Finance (SAIF).

markets is not sufficient to understand the comprehensive features of this market and we aim to fill this gap in the academic literature.

The stylized facts in the stock returns are substantially investigated. Pagan (1996) and Cont (2001) provide a collection of these features and techniques applied for identifying the stylized facts. There are several characteristics of stock returns widely documented such as leptokurtic and fat-tail distribution, co-integration relationship, volatility clustering, long memory and leverage effect (Bollerslev, 1987; Baillie and Myers, 1991; Alexander and Dimitriu, 2005a; Yang et al., 2017; Engle, 1982; Ding and Granger, 1996; Ding et al., 1996). Bouchaud and Potters (2001) study the downside correlations and leverage effect in the financial market, while the dependence between the stock and commodity markets is investigated via copula techniques. Furthermore, Ryden et al. (2010) describe the temporal dependence in a return series by a hidden Markov model.

Despite the fact that there is extensive literature on stylized facts of stock returns, the number of studies focusing on the Chinese futures markets is limited. Additionally, none of these studies analyse the fundamental features or empirical characteristics across the whole Chinese futures market. Chan et al. (2004) explore the volatility dynamics with respect to four commodity futures in China. The paper illustrates the asymmetric effects of returns on the volatility; negative returns have a more significant effect than positive returns. Furthermore, trading volume and the extent of large-volume traders' participation are positively related to the volatility, while the open interest is negatively related to the volatility. Moreover, the relationship between Chinese and international futures prices of aluminium, copper, soybean, and wheat is analysed in Hua and Chen (2007) via several statistical techniques such as the error correction model, impulse response analysis, the Granger causality test and the Johansens cointegration test. To sum up, existing literature on the Chinese futures markets only considers few products and low-frequency returns.

In this chapter, the whole universe of futures products traded in China is explored in terms of high- and low-frequency returns, and the objective is providing major statistical properties across various products. Meanwhile, the Chinese futures returns are investigated with a number of statistical tests for co-integration, leverage effects, serial correlation and volatility clustering. Our goal is providing the fundamental research on empirical analysis of trading strategies in the Chinese futures market. Moreover, the dependence structures across the whole universe and different sectors are characterized by principle components analysis. It is crucial for understanding potential factors that drive the Chinese futures market. This chapter provides a variety of fundamental analysis on the Chinese futures markets, which is useful for future investigations of trading strategies such as statistical arbitrage or momentum investments.

2.2 Data

Due to the co-existence of different maturity contracts being traded simultaneously on the markets, working with a futures prices is a delicate issue compared with the stock prices. The selection of underlying contracts and consideration of roll-over returns are crucial for the study on the futures markets. Since this chapter is fundamental for following research on practical strategies, the empirical analysis of stylized facts should be based on a times series that can reflect the actual trading phenomenon. The liquidity issues should be considered as well. The basic economic theory demonstrates that the most actively traded (liquid) contract represents the market behaviour best in comparison to the contracts with low liquidity, which can be measured by trading volume or open interests on the futures markets.

As a market activity, the switching dates for the highest liquidity contracts (roll-over dates) are not settled in advance, and the liquidity of one contract generally decreases before the expiry date approaches. Meanwhile, the quantity of roll-overs is not a constant over years for one product or across products. For example, the most active contract for futures traded in March can be the August contract for one product, while it might be the September contract for another product. Therefore, this chapter does not implement the data construction technique documented in literature, which normally selects the nearest or the next nearest futures contract(Miffre and Rallis, 2007; Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Fuertes, Miffre, and Perez, 2015). In this study, the price series of the most actively traded contract of each commodity or financial futures is applied to construct the dataset[3]. This approach is consistent with the practice of the hedge funds or commodity trading advisers (CTAs) operating in the Chinese futures markets.

The detailed demonstration of futures contracts maturities and trading liquidity is included in the Appendix A. It is shown that the nearest or second-nearest to maturity contract is always low-liquidity in the Chinese futures market, i.e., the trading volume is less than 100. The transaction costs to open long/short positions on the illiquid contracts are significantly high, and even the orders cannot be executed in some cases. Therefore, the backtesting based on the data of the nearest or second-nearest to maturity contract is not realistic due to liquidity issue. Furthermore, it is rational to employ the most actively traded contract for analysing the Chinese futures market.

The dataset in this study covers the recent period between 2015-05-22 and 2017-08-09 at the daily and minute level prices, which have 543 trading days of observations for the universe of 37 futures products that have a sufficiently long history. The dataset is constructed with 32 different commodities and 5 financial futures[4] . Figure 2.1 displays the normalized prices (i.e. starting with one) of all the futures contracts categorised into 6 sectors. The figure demonstrates the significant dependence among the products in the same sector.

The dataset construction technique is alternative in comparison to existing literature. Current studies implement the "immediate roll" (Miffre and Rallis, 2007; Shen et al., 2007) or the "gradual roll" (Wang and Yu, 2004; Marshall et al., 2008) methodology to construct the dataset, which are based on the assumption of that the liquidity switches near the expiration date in the uniform way across all products. However, the market's choice of the contract is not fixed, and there are sudden changes in the liquidity of futures contracts. Therefore, the trading volume and open interest are observed at the beginning of every trading day, and the "main" contract

[3]The main contract is identified by the trading volume and open interest after the market closed every day, if the contract with the maximum trading volume is same as the one with the maximum open interest, the underlying contract will be the main contract for the next trading day, otherwise, the contract with the further maturity month will be the main contract.

[4]The data is obtained from JYB-Capital, which is a Chinese hedge fund focusing on quantitative trading.

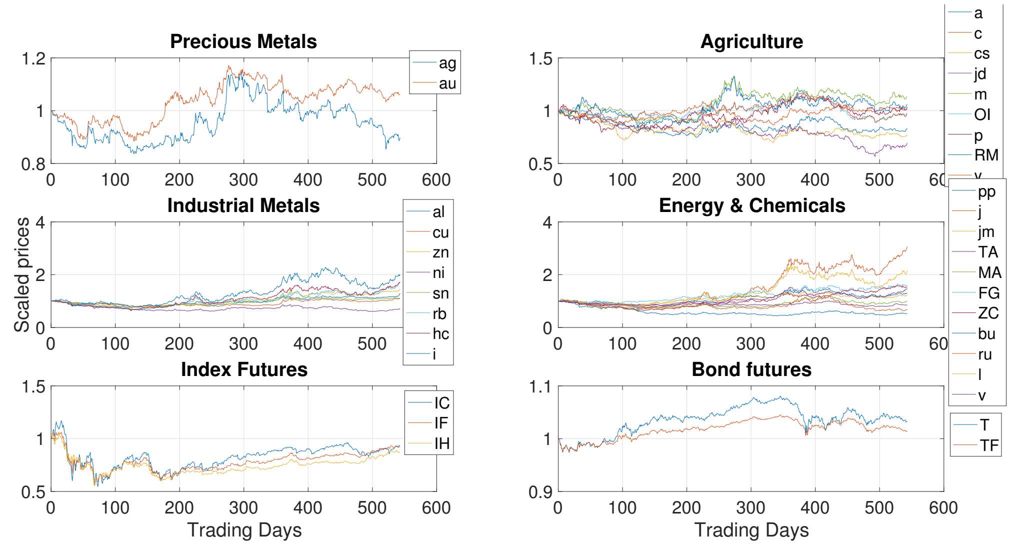

Figure 2.1: Plot of the scaled futures prices

Notes: The initial price is set as 1 for the thirty-seven actively traded futures contracts in China for the period from 2015-05-22 to 2017-08-09 containing 543 trading days.

is selected and utilized to construct the time series in this study.

For the consideration of roll-over returns, the daily log-returns are calculated from the close to pre-close prices when there is no roll-over between contracts, whereas if there is a roll-over happening, the return is obtained from the close to open price. The intuition behind this technique is that the holding positions would switch to the new active contract at the market open time. Additionally, the movement between the old and new active contracts occur regularly because most traders and CTAs appreciate short investment horizons (i.e. daily or few days) in the futures markets. This confirms that the financial industry does not pay much attention to the fixed roll-over rules, which is generally applied in the academic papers.

Normally, the quantity of roll-over per year is from three to five depending on the products and periods. The log-returns using the close prices at the 1, 5, 15 and 30-minute intervals are calculated for the high-frequency analysis. Since the roll-over happens between trading days, it is not considered in the construction of high-frequency dataset. Table 2.1 presents the futures contracts information with details such as the exchange tickers, IDs, commission fees, trading hours, launch dates of products and the maturity dates of contracts. Due to the difference between trading hours (i.e. night trading), the number of high-frequency observations per day varies from 225 to 555 across products.

The descriptive statistics for futures returns considered in this study are displayed in Table 2.2. Due to the limit of space, the normality test results are not included, but it can be emphasized that the normality assumption is rejected for all the contracts at the 5% significance level via the Jarque-Bera and Anderson-Darling tests. Table 2.2 demonstrates that high kurtosis and fat tails are exhibited across all products, while the unusual positive skewness appears sometimes in comparison to the stock markets. By checking the descriptive statistics at different sub-sample periods, the positive skewness is presented in many sub-periods. It can be simply stated that the negative skewness is not a common feature in the Chinese futures markets. This phenomenon is able to impact the extent of kurtosis, Value-at-Risk (VaR), and expected shortfall values.

There are two main differences between the Chinese futures markets and stock markets with respect to the regulation. Due to the general availability of leverage in futures markets, the price limits are set as 5% in the futures rather than 10% as in the stock markets. On the other side, the cost of short sales are much lower in the futures compared to that of the stock markets. From the view of our observations, commodity futures do not exhibit significant dependence in terms of one single market factor. In the futures markets, the dependence is shown with respect to the sector of products. This issue to decompose the futures returns is investigated more comprehensively in the principle component analysis section. Furthermore, the Value-at-Risk (VaR) and expected shortfall values for the holding positions do not illustrate the existence of a "gain/loss asymmetry", which is one stylized fact of stock returns documented in Cont (2001). The ease of short sale and the flexibility to use leverage are possible attributions for the absence of "systematic gain/loss asymmetry. Since the main objective is to document the empirical facts and provide possible insight that might lead to futures research, the comprehensive analysis of reasons behind these facts is not included in this study.

Table 2.1: Market information for the Chinese futures products

Commodity	Symbol	Exchange	Contract unit	Tick size	Commission Fee	Maturity months	Night trading	Last trading day	Start date
Copper	CU	SHFE	5T/H	10RMB/T	0.5%%	FGHJKMNQUVXZ	21:00-01:00	15th trading day	1993-03-01
Aluminium	AL	SHFE	5T/H	5RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	1992-05-28
Zinc	ZN	SHFE	5T/H	5RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2007-03-26
Nickel	NI	SHFE	1T/H	10RMB/T	6RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2015-03-27
Tin	SN	SHFE	1T/H	10RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2015-03-27
Gold	AU	SHFE	1KG/H	0.05RMB/G	10RMB	FGHJKMNQUVXZ	21:00-02:30	15th trading day	2008-01-09
Silver	AG	SHFE	15KG/H	1RMB/KG	0.5%%	FGHJKMNQUVXZ	21:00-02:30	15th trading day	2012-05-10
Screw Steel	RB	SHFE	10T/H	1RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2009-03-27
Hot Rolled Coil	HC	SHFE	10T/H	1RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2014-03-21
Petroleum Asphalt	BU	SHFE	10T/H	2RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2013-10-09
Rubber	RU	SHFE	10T/H	5RMB/T	0.45%%	FHJKMNQUVX	21:00-23:00	15th trading day	1993-11-01
Corn	C	DCE	10T/H	1RMB/T	1.2RMB	FHKNUX	N/A	10th trading day	2004-09-22
Corn Starch	CS	DCE	10T/H	1RMB/T	1.5RMB	FHKNUX	N/A	10th trading day	2004-12-19
Soybean 1	A	DCE	10T/H	1RMB/T	2RMB	FHKNUX	21:00-23:30	10th trading day	2002-03-15
Soybean Meal	M	DCE	10T/H	1RMB/T	1.5RMB	FHKNQUXZ	21:00-23:30	10th trading day	2000-07-17
Soybean Oil	Y	DCE	10T/H	2RMB/T	2.5RMB	FHKNQUXZ	21:00-23:30	10th trading day	2006-01-09
Palm Oil	P	DCE	10T/H	2RMB/T	2.5RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2007-10-29
Egg	JD	DCE	5T/H	1RMB/500KG	1.5RMB	FGHJKMUVXZ	N/A	10th trading day	2013-11-08
Polythene	L	DCE	5T/H	5RMB/T	2RMB	FGHJKMNQUVXZ	N/A	10th trading day	2007-07-21
Polyvinyl Chloride	V	DCE	5T/H	5RMB/T	5RMB	FGHJKMNQUVXZ	N/A	10th trading day	2009-05-25
Polypropylene	PP	DCE	5T/H	1RMB/T	0.6%%	FGHJKMNQUVXZ	N/A	10th trading day	2014-02-28
Coke	J	DCE	100T/H	0.5RMB/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2011-04-15
Coal	JM	DCE	60T/H	0.5R/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2013-03-22
Iron Ore	I	DCE	100T/H	0.5R/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2013-10-18
Cotton	CF	CZCE	5T/H	5RMB/T	6RMB	FHKNUX	21:00-23:30	10th trading day	2004-06-01
Sugar	SR	CZCE	10T/H	1RMB/T	3RMB	FHKNUX	21:00-23:30	10th trading day	2006-01-06
PTA	TA	CZCE	5T/H	2RMB/T	3RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2006-12-18
Canola Oil	RO	CZCE	5T/H	2RMB	N/A	FHKNUX	N/A	10th trading day	2007-06-08
	OI	CZCE	10T/H	2RMB/T	2.5RMB	FHKNUX	N/A	10th trading day	2015-05-15
Methyl Alcohol	ME	CZCE	50T/H	1RMB	N/A	FGHJKMNQUVXZ	N/A	10th trading day	2011-10-28
	MA	CZCE	10T/H	1RMB/T	1.4RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2015-05-15
Glass	FG	CZCE	20T/H	1RMB/T	3RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2012-12-03
Rapeseed Dregs	RM	CZCE	10T/H	1RMB/T	1.5RMB	FHKNQUX	21:00-23:30	10th trading day	2012-12-28
Steam Coal	ZC	CZCE	100T/H	0.2RMB/T	4RMB	FGHJKMNQUVXZ	N/A	10th trading day	2013-09-26
CSI300 index futures	IF	CFFEX	300RMB/P	0.2P	0.25%%	FGHJKMNQUVXZ	N/A	3rd Friday	2010-04-16
CSI500 index futures	IC	CFFEX	200RMB/P	0.2P	0.25%%	FGHJKMNQUVXZ	N/A	3rd Friday	2015-04-16
SSE50 index futures	IH	CFFEX	300RMB/P	0.2P	0.25%%	FGHJKMNQUVXZ	N/A	3rd Friday	2015-04-16
5-year t-bond futures	TF	CFFEX	10000RMB/P	0.005RMB	3RMB	HMUZ	N/A	3 trading day after 2rd Friday	2013-09-06
10-year t-bond futures	T	CFFEX	10000RMB/P	0.005RMB	3RMB	HMUZ	N/A	3 trading day after 2rd Friday	2015-03-20

Notes: The letter codes are F (January), G (February), H (March), J (April), K (May), M (June), N (July), Q (August), U (September), V (October), X (November) and Z (December). All commodity futures are traded in a general day trading period of 9:00-10:15, 10:30-11:30 and 13:30-15:00. All index futures are traded in a general day trading period of 9:30-11:30 and 13:00-15:00. All bond futures are traded in a general day trading period of 9:15-11:30 and 13:00-15:15. Gold futures are traded with maturity in three nearest months and even months within 12 nearest months. Petroleum asphalt is traded with maturity in 6 nearest months and season contract within 24 nearest months. All index futures are traded with maturity in two nearest natural months and two nearest season months. All bond futures are traded with maturity in three nearest season months (three consecutive months among March, June, September and December).

Table 2.2: Descriptive statistics for the Chinese futures returns

ID	Mean	Std	Skew	Kurt	Min	Max	VaR Left	ES Left	VaR Right	ES Right
a	-0.0003	0.0113	0.1162	5.622	-0.0512	0.0474	-0.0184	-0.0256	0.0184	0.0266
ag	-0.0001	0.0128	-0.3406	8.9788	-0.0718	0.0518	-0.0181	-0.0306	0.0195	0.0308
al	0.0005	0.0112	0.1090	4.7176	-0.0405	0.0493	-0.0184	-0.0248	0.0183	0.0267
au	0.0001	0.0086	0.5337	6.7461	-0.0404	0.0453	-0.0123	-0.0171	0.0145	0.021
bu	-0.001	0.0202	-0.3895	4.0211	-0.0758	0.0666	-0.0395	-0.049	0.0298	0.0395
c	0.0001	0.0098	-0.0238	5.2623	-0.0355	0.0364	-0.015	-0.0233	0.0153	0.0229
CF	0.0003	0.0136	0.0663	6.069	-0.068	0.0542	-0.0203	-0.0307	0.0234	0.0341
cs	-0.0004	0.0120	0.0992	4.1505	-0.0497	0.0411	-0.0203	-0.0262	0.0198	0.0269
cu	0.0003	0.0128	0.4080	6.8967	-0.0577	0.0616	-0.018	-0.0276	0.0203	0.0311
FG	0.001	0.0158	0.1243	4.3144	-0.0521	0.0565	-0.0268	-0.0347	0.0274	0.0383
hc	0.0012	0.0205	-0.2090	4.983	-0.079	0.0824	-0.0314	-0.0475	0.038	0.0463
i	0.0016	0.0254	-0.1142	3.7018	-0.0763	0.0736	-0.043	-0.0564	0.0445	0.0566
IC	0.0003	0.0273	-0.6555	7.6112	-0.1082	0.0975	-0.0495	-0.0783	0.0383	0.0634
IF	0.0001	0.0209	-0.7313	9.9247	-0.1051	0.0954	-0.0347	-0.0594	0.0288	0.049
IH	-0.0001	0.0188	-0.9307	12.719	-0.1043	0.0957	-0.0262	-0.0524	0.0264	0.0434
j	0.0023	0.0233	-0.2224	5.4516	-0.0989	0.0914	-0.0357	-0.0546	0.0446	0.0563
jd	-0.0006	0.0141	0.2166	5.1642	-0.0531	0.0606	-0.0229	-0.0313	0.0236	0.0341
jm	0.0017	0.0234	-0.1334	4.6255	-0.0867	0.0913	-0.04	-0.0532	0.0418	0.0531
l	0.0005	0.0147	0.0811	4.7419	-0.0554	0.0685	-0.0229	-0.033	0.0244	0.0336
m	0.0003	0.0132	0.2254	4.4081	-0.0466	0.0519	-0.0212	-0.0283	0.0227	0.0317
MA	0.0001	0.0165	-0.0172	3.8377	-0.059	0.053	-0.0263	-0.036	0.0287	0.0361
ni	-0.0005	0.0159	-0.3304	4.4157	-0.0684	0.0575	-0.029	-0.0386	0.0238	0.0319
OI	0	0.0106	-0.0595	4.5672	-0.0417	0.0381	-0.0163	-0.0237	0.0191	0.024
p	0.0001	0.0134	-0.1093	3.4672	-0.0546	0.0381	-0.0216	-0.0284	0.0243	0.0282
pp	0.0006	0.0155	0.1483	3.7077	-0.0558	0.0521	-0.0259	-0.032	0.0291	0.036
rb	0.0012	0.0213	-0.0368	4.6485	-0.079	0.0665	-0.0342	-0.048	0.0382	0.0503
RM	0.0002	0.0158	-0.0399	4.2647	-0.0609	0.0562	-0.0245	-0.0357	0.0263	0.0358
ru	-0.0004	0.0216	-0.3589	4.529	-0.0755	0.0606	-0.0395	-0.0548	0.0347	0.0458
sn	0.0003	0.0133	-0.0086	4.0644	-0.0453	0.0453	-0.0227	-0.0299	0.0235	0.0297
SR	0	0.0089	0.2006	6.3912	-0.0428	0.0417	-0.0133	-0.0189	0.0141	0.0209
T	0.0001	0.0031	-0.0927	7.5619	-0.018	0.0157	-0.0047	-0.0071	0.0045	0.0072
TA	-0.0002	0.0130	-0.3537	7.1047	-0.0801	0.0501	-0.0211	-0.0306	0.02	0.0284
TF	0	0.0021	-0.0168	8.1985	-0.0117	0.0109	-0.0032	-0.005	0.0031	0.0049
v	0.0008	0.0133	0.1471	4.3812	-0.0487	0.0473	-0.0194	-0.0281	0.0257	0.0323
y	0	0.0106	-0.1854	3.9582	-0.0414	0.0369	-0.0168	-0.0231	0.0168	0.0214
ZC	0.0009	0.0155	-0.1103	4.3739	-0.0576	0.0448	-0.0252	-0.035	0.0282	0.0356
zn	0.0008	0.0153	-0.0270	4.7273	-0.0709	0.0575	-0.0232	-0.0325	0.0258	0.0349

Notes: For all the products the normality of daily returns is rejected at the 95% confidence level via the Jarque-Bera and Anderson-Darling normality tests.

2.3 Empirical Stylized Facts in the Chinese Futures Markets

There are significant differences between the stock and futures markets in China in terms of the return analysis. This difference leads several future researchers to investigate the reasons behind the distinctive characteristics. One of the fundamental dimensions is the investor behavior and investment horizon. The Chinese stock market is famous for its retail feature, while the futures markets are dominated by the institutional investors (i.e. hedge funds or futures companies.). Normally, the hedge funds/CTAs trade the futures contracts in short investment horizons[5]. The economic reason behind this phenomenon is widely explained that the invested futures contracts are lacking cash-flow generation. Hence, the hedge funds/CTAs focus on short-term investment strategies, which dominate the futures markets in China.

2.3.1 Serial Correlation

Cont (2001) claims that (linear) auto-correlation is normally statistically insignificant in asset returns, whereas it is significant for quite high-frequency (below a 20-minute interval) data when micro-structure effects are considered. Generally, the serial correlation is insignificant in the stock markets; otherwise, the assumption of the efficient market would be repudiated. If the existence of the serial correlation for an asset is raised significantly, the implementable predictability can yield the conclusion of inefficiency in the market. These parts explore the serial correlation in the Chinese futures returns, and it is found that the significant serial correlations for the vast majority of the products cannot be judged as statistically significant via the Ljung-Box test.

Table 2.3 shows the Ljung-Box test result for the mean subtracted log-returns

[5] According to the information received from various hedge funds (i.e. JinYiBao Ltd.) and the Hedge Fund Research Center at SAIF, there are variations in the investment horizon of different funds due to the high leverage in the industry, while intra-day or a few days' (1-5 days) holding period is the most typical investment horizon in the Chinese futures markets.

and squared returns[6] in terms of the p-value. The results demonstrate that the serial correlation assumption is rejected at the 95% confidence level for most of the commodity products with very few exceptions. The interesting fact is that in the Chinese market the serial correlation problem is more severe for the futures on stock market indices. The possible reason behind this phenomenon is the specific restriction implemented on index futures trading since the 2015 stock market turmoil in China. For the Chinese futures products except for the index ones, serial correlations are weak for the daily horizon, while they are strong for the high-frequency data (i.e. 1-5 minutes interval) in which the micro-structure effects are considered. When the data of 15-30 minute interval returns is considered, almost all of the products show significant serial correlation with the last one lag. The interpretation of this phenomenon can be the wide implementation of trend-following strategies by the intra-day traders. Therefore, the existence of serial correlation in the Chinese futures markets is more pronounced at the high-frequency level data due to investor behavior. For the data with higher frequencies than the five-minute level, the micro-structure effect is revealed; specifically, the "bid-ask bounce" causes the significant negative serial correlation for the first lag of the returns.

Table 2.3: Serial correlation tests for the Chinese futures markets

ID	a	ag	al	au	bu	c	CF	cs	cu	FG	hc	i	IC	IF	IH	j	jd	jm	l
r_t	0.09	0.38	0.54	0.72	0.58	0.65	0.49	0.51	0.02	0.50	0.39	0.09	0.00	0.00	0.00	0.60	0.29	0.19	0.12
$\|r_t\|$	0.05	0.65	0.02	0.49	0.45	0.13	0.00	0.02	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.27

ID	m	MA	ni	OI	p	pp	rb	RM	ru	sn	SR	T	TA	TF	v	y	ZC	zn
r_t	0.57	0.68	0.27	0.55	0.33	0.46	0.55	0.51	0.94	0.23	0.26	0.27	0.45	0.22	0.61	0.35	0.07	0.09
$\|r_t\|$	0.00	0.01	0.00	0.00	0.25	0.71	0.00	0.00	0.05	0.00	0.15	0.00	0.00	0.00	0.00	0.01	0.00	0.00

Notes: This table illustrates the Ljung-Box serial correlation test results with the log-returns and squared log-returns with the p-values of the test results presented. P-values less then 5% level indicates the rejection of the null hypothesis of "no serial correlation".

Figure 2.2 displays the sample partial auto-correlation function for the stock

[6] Last five lag values are used for testing the serial correlation. The results with different lags are similar and the lags that are within the last five trading days are normally more significant than the previous ones.

index futures (i.e. IH, IF and IC) returns and for the corresponding absolute values. Additional to the partial auto-correlation of returns, the absolute value of these returns are implemented to check the volatility clustering. The result illustrates that the index futures exhibit stronger serial correlation both in the returns and corresponding absolute values than the commodity and bond futures in the market. Similarly, Figures 2.3 and 2.4 demonstrate the sample partial auto-correlation function for the bond futures (i.e. T and TF), respectively. In the comparison of index futures, bond futures show the insignificant serial correlation in the returns. However, the bond futures show significant serial correlation for the corresponding absolute value, which is consistent with the index futures in terms of the volatility clustering effect. The serial correlation shown in the index futures returns can be interpreted by the regulations on the trading of index futures. Hence, it implies the existence of inefficiencies in the price discovery function of these products.

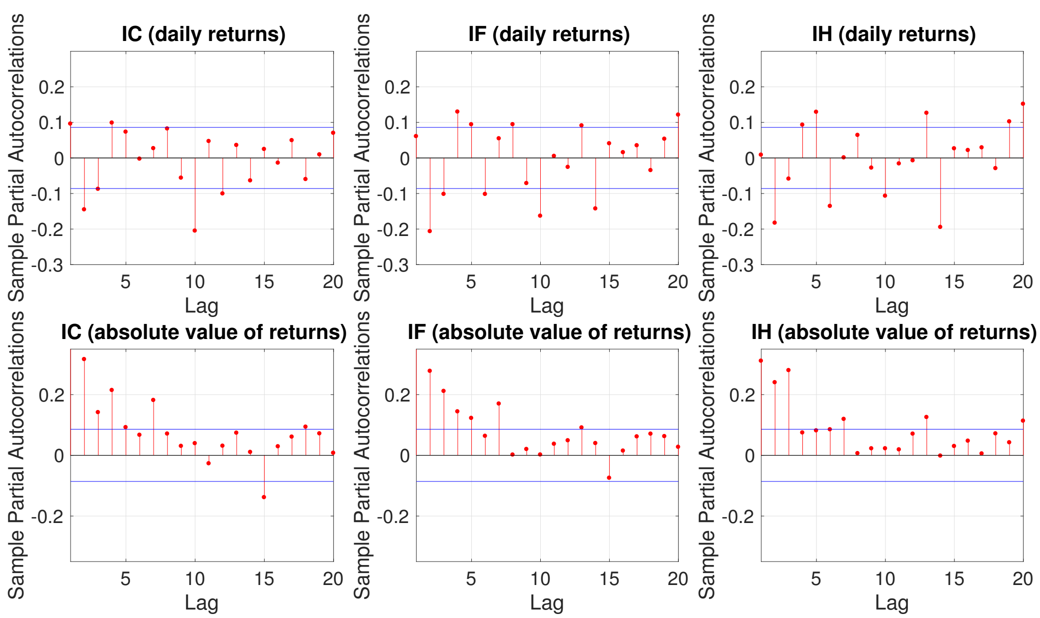

Figure 2.2: Partial autocorrelations of stock index futures returns.

Additionally, the strong serial correlation is illustrated for the high-frequency returns (i.e. 1, 5, 15 and 30-minute intervals.) because of the micro-structure effect.

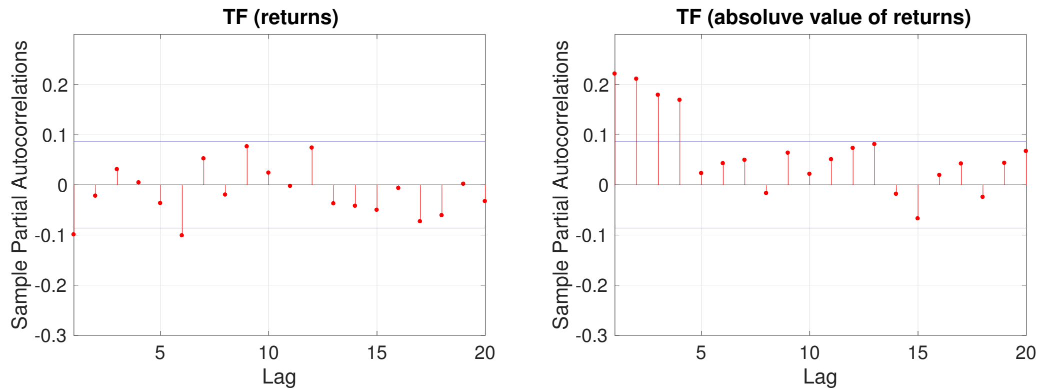

Figure 2.3: Partial autocorrelations of 5-year bond futures returns.

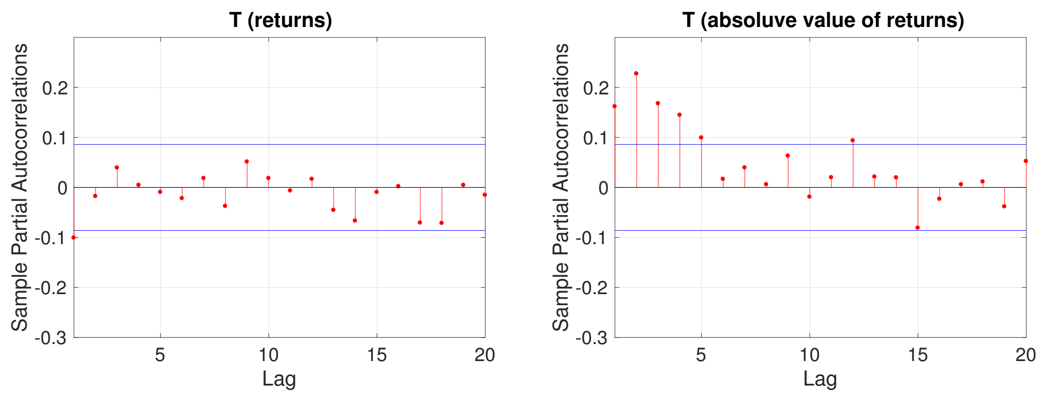

Figure 2.4: Partial autocorrelations of 10-year bond futures returns.

The bid-ask bounce normally leads to the negative serial correlation in the first lag for all products. This observation confirms the proposed stylized fact of equity markets in Cont (2001). The minute-level partial auto-correlation function for the soybean futures is plotted in Figure 2.5, and there is stronger volatility clustering effect verified in the high-frequency returns via the plot of the partial autocorrelation function. Similar results occur for all the futures returns series, but they are not presented for saving spaces. Overall, the more pronounced serial correlation of index futures compared to other products can be explained by the additional restrictions on trading activities, and it is illustrated that the full satisfaction of the market's price expectation is essential for the market efficiency.

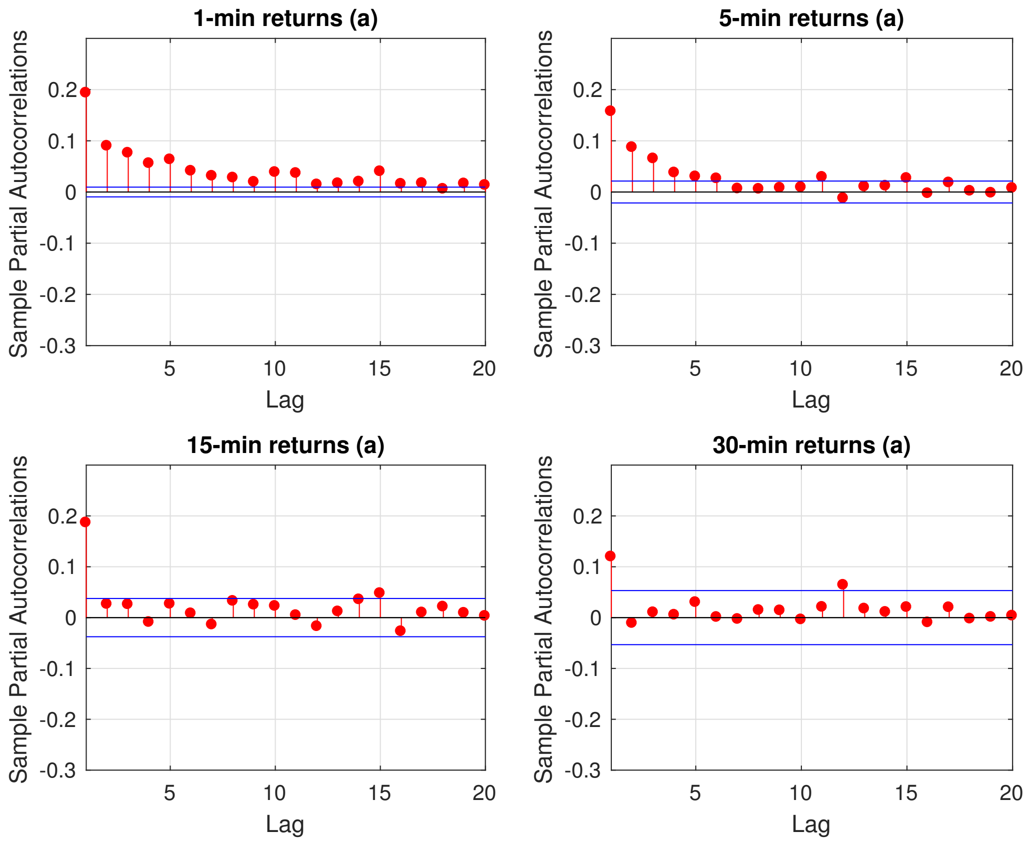

Figure 2.5: Partial autocorrelations of soybean futures returns.

On the other side, volatility clustering is one characteristic of the daily stock returns in several markets including the Chinese stock markets[7]. This phenomenon is observed in both high- and low-frequency returns[8]. Tsay (2005) inspects the volatility clustering effect visually via the partial correlation function of the squared/absolute returns, while the Ljung-Box serial correlation test for absolute returns is implemented in this study. The statistical analysis (Table 2.3) on the PACF and ACF of the futures returns confirms that the financial futures returns exhibit stronger serial correlation compared to the commodity futures. Therefore, various GARCH specifications are

[7]See Daal et al. (2007) and Friedmann and Kohle (2002) for details.
[8]See Jacobsen and Dannenburg (2003) for details.

applied for exploring the volatility clustering behavior in the following parts.

In fact, both the stock index futures (i.e. IF, IH and IC) and the bond futures (i.e. T and TF) display significant volatility clustering effects in the first few lags of return time series that can be observed in Figures 2.2, 2.3 and 2.4. However, the commodity futures demonstrate insignificant volatility clustering relative to the financial futures. Table 2.3 presents the Ljung-Box test result of the (squared) residuals in order to check the significance of serial correlation and ARCH/GARCH effects in the return series. Hence, the volatility clustering effects can be verified for a few commodity futures in terms of the significant serial correlation of the absolute return series.

2.3.2 Conditional Heteroskedasticity

The volatility clustering effect is a well-documented phenomenon in the stock return series. Engle (1982) and Bollerslev (1986) introduce the autoregressive conditional heteroskedastic (ARCH) and generalized autoregressive conditional heteroskedastic (GARCH) models to capture this characteristic, and some extensive literature followed these studies. For instance, Akgiray (1989) proposes a GARCH(1,1) process to fit American stock returns. The conditional volatility and asymmetric behavior of Asian daily stock data are discussed in Chiang and Doong (2001). Additional to the volatility clustering, "leverage effect" is another stylized fact for stock returns that can be captured in asymmetric GARCH models. The leverage effect denotes the existence of the negative correlation between asset returns and its changes of volatility. Nelson (1990) and Glosten et al. (1993) introduce some widely applied models for describing such behavior in asset returns (i.e. the exponential GARCH and the GJR model). Therefore, the existence of the leverage effect in futures returns is discussed by exploring the GARCH model, the exponential GARCH (EGARCH) model and the GJR model of Glosten et al. (1993). The GARCH model is nested within the GJR model, and the likelihood ratio test can be implemented to verify the significance of parameters that capture the asymmetry in the volatility equation. Furthermore, the EGARCH model is presented to confirm the direction of the asymmetry between a futures return and its volatility.

The benchmark GARCH(1,1) model is given by

$$
\begin{aligned}
y_t &= \mu + \sigma_t z_t, && (2.1)\\
\sigma_t^2 &= \kappa + \gamma\sigma_{t-1}^2 + \alpha\epsilon_{t-1}^2, && (2.2)
\end{aligned}
$$

where the innovation z_t follows a Gaussian distribution and

$$\kappa > 0, \gamma \geq 0, \alpha \geq 0, \gamma + \alpha < 1 \tag{2.3}$$

needs to be satisfied for stationarity and positivity of the volatility. To extend the traditional GARCH model, the logarithm of the conditional volatility process is included in the EGARCH model. With the additional logarithm term, the EGARCH model is capable of capturing the asymmetry in the volatility clustering. The volatility in the EGARCH(1,1) model is formulated as

$$\log\sigma_t^2 = \kappa_e + \gamma_e \log\sigma_{t-1}^2 + \alpha_e\Big[\frac{|\epsilon_{t-1}|}{\sigma_{t-1}} - \mathbb{E}\big[\frac{|\epsilon_{t-1}|}{\sigma_{t-1}}\big]\Big] + \xi_e(\frac{\epsilon_{t-1}}{\sigma_{t-1}}). \tag{2.4}$$

For Gaussian distribution,

$$\mathbb{E}\big[\frac{|\epsilon_{t-1}|}{\sigma_{t-1}}\big] = \mathbb{E}[|z_{t-1}|] = \sqrt{\frac{2}{\pi}}. \tag{2.5}$$

The GJR model provides an alternative formulation for capturing the asymmetric volatility clustering in terms of the threshold between positive and negative lagged innovations. In the GJR(1,1) model, the volatility is given by

$$\sigma_t^2 = \kappa_g + \gamma_g\sigma_{t-1}^2 + \alpha_g\epsilon_{t-1}^2 + \xi_g I[\epsilon_{t-1} < 0]\epsilon_{t-1}^2, \tag{2.6}$$

where the indicator function $I[\epsilon_{t-1} < 0] = 1$ for $\epsilon_{t-1} < 0$; otherwise, $I[\epsilon_{t-1} < 0] = 0$. Additionally, the GJR(1,1) model has the following constraints similar to the GARCH(1,1) model:

$$\kappa_g > 0, \gamma_g \geq 0, \alpha_g \geq 0, \alpha_g + \xi_g \geq 0, \gamma_g + \alpha_g + \frac{1}{2}\xi_g < 1. \tag{2.7}$$

Table 2.4 demonstrates the estimation results for fitting the conditional variance models under different assumptions. The results are in agreement with the past studies for the stock markets, and the futures data provides strong evidence of time-varying volatility (Koutmos, 1998; Lee et al., 2001). The table illustrates that the traditional GARCH(1,1) model is rejected in favor of the GJR(1,1) model for 14 out of 37 products with respect to the log-likelihood test at the 0.05 significance level, while the restricted model cannot be rejected for other products. Meanwhile, the leverage coefficient estimate, i.e. ξ_g in Table 2.4, provides evidence in favor of the "leverage effect" for 17 out of 37 products by the t-test. Note that in most of the products we have a negative value for ξ_g, which shows that positive shocks are correlated with a higher volatility in the futures products. This is opposite to what is often observed in the stock markets, where negative returns are correlated with higher volatility. Furthermore, the mixed signs of the leverage coefficient in the GJR(1,1) model demonstrate that in futures markets during bullish periods for a particular product a positive return is likely to be correlated with the volatility. During bearish times negative returns might be correlated with the higher volatility, which is consistent with the findings of Chan et al. (2004). Additionally, the opposite sign of the leverage coefficient in the EGARCH(1,1) model confirms that both a negative and positive leverage effect can be observed depending on the specific futures products.

2.3.3 Unit Root

The trending behavior or non-stationarity in the mean is often exhibited in the financial times series. It is an important mission for the financial econometrician to describe the data by appropriate trend properties. Two common trend removal techniques can be applied to the data with trending terms, differencing and cointegration regression. The differencing is normally implemented for handling unit-root nonstationary, which is discussed in this part. Additionally, the co-integration is explored in the rest of this chapter. According to Tsay (2005), the autoregressive integrated moving-average (ARIMA) model is specifying the AR polynomial to have 1 as a characteristic root in

Table 2.4: Summary of the estimation results for the conditional variance models.

Products	EGARCH(1,1)				GJR(1,1)				
	κ_e	γ_e	α_e	ξ_e	κ_g	γ_g	α_g	ξ_g	P-value^l
a	-0.2548	0.9709*	0.1073*	0.0178	0.0000	0.9214*	0.0598*	-0.0335*	0.1656
ag	-14.2286*	-0.6303*	0.0873*	0.0503*	0.0000*	0.7182*	0.1037*	-0.0881*	0.0214
al	-0.5287*	0.9401*	0.2056*	0.0681*	0.0000*	0.8636*	0.1446*	-0.0915*	0.0119
au	-0.8840*	0.9062*	0.1533*	0.0613*	0.0000*	0.8318*	0.1278*	-0.1278*	0.2124
bu	-0.6623	0.9150*	0.0187	0.0567*	0.0004	0.1046	0.0051	-	1.0000
c	-0.5264	0.9425*	0.0874*	0.0498*	0.0000	0.9000*	0.0500*	-	1.0000
CF	-0.2040*	0.9770*	0.0145	0.1645*	0.0000*	0.9387*	0.0956*	-0.0956*	0.0000
cs	-0.2956	0.9663*	0.1140*	0.0124	0.0000	0.9264*	0.0585*	-0.0228	0.3672
cu	-0.7004*	0.9192*	0.2379*	0.0414*	0.0000*	0.8031*	0.1166*	-0.0261	0.4708
FG	-0.0285*	0.9972*	-0.0385*	0.1089*	0.0000*	0.9000*	0.0500*	-	1.0000
hc	-0.1120*	0.9851*	0.0865*	0.0460*	0.0000	0.9530*	0.0730*	-0.0624*	0.0006
i	-0.0273	0.9962*	0.0210	0.0572*	0.0000	0.9570*	0.0686*	-0.0588*	0.0046
IC	-0.0410*	0.9953*	0.0365*	-0.1072*	0.0000*	0.9513*	0.0672*	-	0.0005
IF	-0.0578*	0.9928*	0.0821*	-0.0706*	0.0000*	0.9497*	0.0008	0.0702*	0.0035
IH	-0.0702*	0.9908*	0.1212*	-0.0496*	0.0000	0.9337*	0.0379*	0.0344	0.1896
j	-0.1037*	0.9858*	0.0535*	0.0654*	0.0000*	0.9484*	0.0934*	-0.0934*	0.0000
jd	-14.1888*	-0.6620*	-0.0740	-0.0474	0.0000*	0.9000*	0.0500*	-	1.0000
jm	-0.0710*	0.9904*	0.0541*	0.0803*	0.0000	0.9522*	0.0881*	-0.0881*	0.0000
l	-2.9312	0.6532*	-0.0035	-0.0885*	0.0002	0.2106	0.0897	-	0.0687
m	-0.4119*	0.9526*	0.0952*	0.0784*	0.0000*	0.9003*	0.1042*	-0.1042*	0.0008
MA	-1.5226	0.8142*	0.1818*	-0.0199	0.0001	0.7355*	0.0753	0.0087	0.8814
ni	-1.9247	0.7670*	0.1468*	0.0102	0.0001	0.6421*	0.0998	-0.0345	0.5134
OI	-15.7914*	-0.7362*	-0.0878	-0.0221	0.0000	0.9614*	0.0466*	-0.0369*	0.1141
p	-0.1688	0.9804*	0.0503	0.0010	0.0000	0.9000*	0.0500	-	1.0000
pp	-0.4796	0.9421*	0.0757	0.0077	0.0000	0.9039*	0.0428	-0.0132	0.5903
rb	-0.0808*	0.9894*	0.0220	0.0663*	0.0000	0.9330*	0.0945*	-0.0660*	0.0007
RM	-0.4667*	0.9435*	0.1393*	0.0288	0.0000*	0.8886*	0.0870*	-0.0548	0.1360
ru	-0.0235*	0.9974*	-0.0367*	0.0662*	0.0000	0.9847*	0.0306*	-0.0306*	0.0001
sn	-0.6272*	0.9270*	0.1680*	0.0292	0.0000*	0.8574*	0.1029*	-0.0547	0.0769
SR	-0.3468	0.9628*	0.0923*	0.0015	0.0000	0.9000*	0.0500*	-	1.0000
T	-0.3422*	0.9706*	0.1821*	-0.0720*	0.0000	0.8892*	0.0471*	0.0775*	0.0002
TA	-4.4251*	0.4927*	0.3802*	0.0163	0.0001*	0.1492	0.2469*	0.0073	0.9467
TF	-0.2516*	0.9799*	0.1356*	-0.1074*	0.0000	0.7037*	0.1491*	0.2160*	1.0000
v	-0.3888*	0.9541*	0.1784*	0.0064	0.0000*	0.8762*	0.0898*	-0.0042	0.8935
y	-0.6036	0.9335*	0.1270*	0.0023	0.0000	0.9000*	0.0500	-	1.0000
ZC	-0.2588*	0.9684*	0.0818*	0.0460*	0.0000	0.9397*	0.0749*	-0.0703*	0.0051
zn	-0.5910*	0.9290*	0.1479*	-0.0504	0.0000*	0.9000*	0.0500*	-	1.0000

Notes: This table displays the summary of the estimation results for the conditional variance models, namely EGARCH(1,1) and GJR(1,1) models. The likelihood ratio test results for the GJR model and the GARCH model are represented by p-values. - represents that the leverage term is close to zero (reduced) in the estimation by Econometrics toolbox in MATLAB. * represents that the coefficient is statistically significant at the 0.05 level.

an ARMA model. In the ARIMA model, the coefficients of its MA representation do not decay to zero over time; therefore, it presents the unit-root nonstationary. Hence, the unit root test is applied to determine if the Chinese futures log-price series should be first differenced in this study.

Three different specifications of the augmented Dickey-Fuller test[9] are utilized for determining the unit roots in the time-series of daily log-prices. The results show that the unit root hypothesis can be rejected in some cases, and the rejection relies on the assumption of the alternative hypothesis.

According to Tsay (2005), the auto-regressive model variant (AR) of the unit-root investigation procedure is testing the null model

$$y_t = y_{t-1} + \epsilon_t \tag{2.8}$$

against the alternative model

$$y_t = \varphi y_{t-1} + \epsilon_t, \tag{2.9}$$

with AR(1) coefficient, $\varphi < 1$. This is the original unit root test for a random walk without any drift term. However, this model is too simple to represent the real economic or financial data which often includes a trend term.

Therefore, the auto-regressive model with drift variant (denoted as ARD) proposes a test of the null model

$$y_t = y_{t-1} + \epsilon_t \tag{2.10}$$

against the alternative model

$$y_t = c + \varphi y_{t-1} + \epsilon_t, \tag{2.11}$$

with drift coefficient c, and the AR(1) coefficient, $\varphi < 1$. This model is first given by Nelson and Plosser (1982), who claim that the macroeconomic time series usually presents a unit root phenomenon with a stochastic trend. The first difference of these time series is stationary; hence this characteristic is described as "difference

[9]The augmented Dickey-Fuller test is implemented using the "adftest(.)" function in MATLAB with the null hypothesis of the existence of a unit root.

stationary" (DS).

Furthermore, Perron (1989) argues that the acceptance of structural changes in the trend term establishes a "trend stationary" (TS) model for many macroeconomic time series. In Perron's paper, the test is given by

$$y_t = c + y_{t-1} + \epsilon_t \tag{2.12}$$

against the alternative model

$$y_t = c + \delta t + \varphi y_{t-1} + \epsilon_t, \tag{2.13}$$

with drift coefficient c, deterministic trend coefficient δ and AR(1) coefficient, $\varphi < 1$. This study employs all of the three specifications of unit roots tests. The test results for the universal 37 products in the Chinese futures markets are displayed in Table 2.5 as a p-values format. There are several rejections that depend on the products and models, specifically that the CSI500 index futures (IC) shows the rejection in the AR model assumption; corn starch (cs) and PTA (TA) illustrate rejection in the ARD model assumption; and glass (FG), CSI500 index futures (IC) and CSI300 index futures (IF) demonstrate rejection in the TS model assumption.

Overall, the random walk hypothesis is rejected for some commodities given the three model specifications implemented for the log-price time series. However, it is well-known that market efficiency is a concept that is not directly testable due to the joint hypothesis problem[10]. Fama (1998) proposes that most long-term anomalies are sensitive to the statistical methodology utilized. It is shown that at least for a few products, the unit root, which is a pre-requisite for the random walk hypothesis, can be rejected. Therefore, potential inefficiencies in the market might be exploitable via trading strategies to generate statistical arbitrage profits. Hogan et al. (2004) discuss the market efficiency and statistical arbitrage strategies, which also provides a potential research direction for the Chinese futures markets.

[10]See Fama (1998) for details.

Table 2.5: Unit root tests for the Chinese futures log-prices.

Products	TS	AR	ARD	Products	TS	AR	ARD
a	0.30	0.50	0.08	ag	0.51	0.10	0.40
al	0.25	0.51	0.92	au	0.59	0.30	0.59
bu	0.50	0.67	0.05	c	0.06	0.07	0.33
CF	0.64	0.41	0.74	cs	0.15	0.57	0.04*
cu	0.26	0.27	0.72	FG	0.03*	0.88	0.88
hc	0.23	0.73	0.95	i	0.50	0.81	0.89
IC	0.05*	0.04*	0.24	IF	0.03*	0.19	0.26
IH	0.06	0.32	0.12	j	0.46	0.97	0.98
jd	0.29	0.70	0.45	jm	0.48	0.89	0.93
l	0.38	0.50	0.73	m	0.59	0.40	0.58
MA	0.39	0.26	0.64	ni	0.31	0.60	0.06
OI	0.62	0.06	0.36	p	0.36	0.15	0.56
pp	0.66	0.61	0.87	rb	0.17	0.69	0.95
RM	0.44	0.14	0.36	ru	0.66	0.34	0.42
sn	0.19	0.39	0.87	SR	0.40	0.10	0.46
T	0.75	0.45	0.41	TA	0.08	0.23	0.02*
TF	0.66	0.35	0.47	v	0.45	0.74	0.94
y	0.69	0.09	0.40	ZC	0.28	0.88	0.99
zn	0.22	0.71	0.95				

Notes: This table displays the unit root test results for daily returns in terms of the p-value. * represents significance at the 5% level.

2.3.4 Distributional Properties

The violation of normality is well-documented in previous analysis of stock market returns. This stylized fact can be observed from three aspects. First of all, the distribution of stock returns generally exhibits the aggregational Gaussianity. Secondly, the stock returns approach to normal distribution in low-frequency level data (i.e. weekly or monthly), whereas the lepto-kurtosis is dominantly displayed in the high-frequency level data (i.e. 1- or 5-minute interval). Finally, the negative skewness shown on the stock return distributions implies that the probability of large negative returns is higher than large positive returns[11].

This part analyses the futures returns with respect to the distributional properties. Firstly, the normality assumption is tested for the universe of futures products at the low-frequency level (i.e. daily and weekly). The Anderson-Darling test, Jarque-Bera test, and the chi-squared goodness-of-fit test are considered for the normality checking. The results show that the normality assumption is rejected for almost all of the products at the low-frequency level data[12].

Alternatively, t-location scale distribution is utilized to fit the futures returns as documented in Table 2.6. Peiro (2010), Bollerslev (1987) and Baillie and Myers (1991) propose that the Student's t distribution is suitable for fitting the futures returns with high peak and fat tails. Therefore, the t-location scale distribution is applied as an alternative assumption, which is well-documented to provide a better fit for the stock returns compared to the normal distribution.

In this study, the chi-squared goodness-of-fit test[13] is implemented with the daily and weekly log-returns of the universal futures products in China. The log-return series is created by removing the roll-over returns as discussed in the data section. Table 2.6 presents the test results in terms of p-values. A p-value less than 0.05 implies the rejection of the null hypothesis, which is the assumed distributions of normal and t-location scale distributions, respectively. Although the results for Anderson-Darling

[11] See Cont (2001) for details.

[12] For brevity, only the chi-squared goodness-of-fit test returns are presented, and others are available upon request.

[13] This test is implemented using the "chisquare(.)" goodness-of-fit function in MATLAB, and similar built-in functions exist in other statistical software.

Table 2.6: Chi-square tests results.

Frequency	Daily Returns		Weekly Returns	
Distribution	Normal	t Location-Scale	Normal	t Location-Scale
a	0.00*	0.49	0.34	0.19
ag	0.00*	0.24	0.11	0.17
al	0.00*	0.16	0.12	0.43
au	0.00*	0.07	0.08	0.04*
bu	0.00*	0.00*	0.46	0.31
c	0.00*	0.32	0.65	0.68
CF	0.00*	0.58	0.00*	0.51
cs	0.00*	0.65	0.12	0.06
cu	0.00*	0.90	0.10	0.05
FG	0.00*	0.09	0.44	0.28
hc	0.00*	0.00*	0.29	0.77
i	0.00*	0.12	0.04*	0.01*
IC	0.00*	0.02*	0.00*	0.05*
IF	0.00*	0.18	0.03*	0.26
IH	0.00*	0.29	0.01*	0.27
j	0.00*	0.33	0.02*	NaN
jd	0.00*	0.14	0.40	0.27
jm	0.00*	0.00*	0.23	0.14
l	0.00*	0.06	0.17	0.10
m	0.00*	0.24	0.53	0.36
MA	0.17	0.98	0.19	0.10
ni	0.00*	0.00*	0.02*	0.01*
OI	0.00*	0.75	0.16	0.09
p	0.58	0.68	0.40	0.25
pp	0.00*	0.06	0.75	0.63
rb	0.00*	0.02*	0.03*	NaN
RM	0.00*	0.38	0.19	0.12
ru	0.00*	0.17	0.91	0.84
sn	0.00*	0.13	0.93	0.85
SR	0.01*	0.31	0.16	0.15
T	0.00*	0.40	0.15	0.49
TA	0.00*	0.41	0.48	0.35
TF	0.00*	0.77	0.00*	NaN
v	0.00*	0.01*	0.05*	0.02*
y	0.24	0.22	0.13	0.07
ZC	0.00*	0.00*	0.20	0.10
zn	0.01*	0.47	0.40	0.26

Notes: This table displays the chi-squared test results for normal and t Location-Scale distribution for daily and weekly returns in terms of p-value.
* represents significance at the 5% level, and NaN represents that the p-value approaches 1.

Table 2.7: Parameter estimates for the t-Location-Scale distribution.

	Daily Returns			Weekly Returns		
ID	μ	σ	ν	μ	σ	ν
a	-0.0006	0.0077	3.3517	-0.0032	0.0213	>20
ag	-0.0003	0.0069	2.3158	-0.0038	0.0227	3.9259
al	0.0004	0.0084	4.1956	-0.0001	0.0181	4.8928
au	-0.0002	0.0063	4.1074	0.0013	0.0219	>20
bu	0.0001	0.0157	4.6105	-0.0111	0.0418	>20
c	0.0001	0.0067	3.3306	-0.0017	0.0171	7.1093
CF	0.0001	0.0084	2.7567	-0.0005	0.0148	1.8196
cs	-0.0005	0.0099	6.0903	-0.0049	0.0244	8.7613
cu	0.0000	0.0088	3.5875	-0.0020	0.0227	>20
FG	0.0008	0.0115	3.7022	0.0033	0.0259	>20
hc	0.0011	0.0143	3.3928	0.0037	0.0302	4.1174
i	0.0018	0.0210	5.9956	0.0055	0.0473	8.2634
IC	0.0017	0.0091	1.3545	0.0116	0.0402	2.5970
IF	0.0009	0.0071	1.4277	0.0040	0.0274	2.2909
IH	0.0004	0.0066	1.5542	0.0044	0.0265	2.5786
j	0.0022	0.0143	2.6207	0.0049	0.0305	2.5921
jd	-0.0009	0.0096	3.3120	-0.0033	0.0271	>20
jm	0.0018	0.0168	3.6576	0.0085	0.0290	4.1474
l	0.0003	0.0111	4.2849	0.0033	0.0283	>20
m	0.0000	0.0103	4.6629	0.0019	0.0259	>20
MA	0.0001	0.0139	6.7253	-0.0014	0.0304	>20
ni	0.0001	0.0128	5.3109	-0.0040	0.0282	>20
OI	-0.0001	0.0084	4.9719	0.0009	0.0208	>20
p	0.0002	0.0124	14.5904	0.0003	0.0308	>20
pp	0.0003	0.0131	6.7445	0.0031	0.0319	>20
rb	0.0008	0.0142	2.9974	0.0035	0.0287	3.4465
RM	0.0002	0.0124	4.8491	0.0010	0.0293	>20
ru	0.0002	0.0153	3.5597	-0.0019	0.0376	>20
sn	0.0001	0.0104	4.8154	0.0000	0.0281	>20
SR	-0.0001	0.0066	4.3876	0.0011	0.0155	4.3281
T	0.0001	0.0022	3.6540	0.0011	0.0040	4.2569
TA	-0.0002	0.0091	3.6482	-0.0019	0.0220	>20
TF	0.0000	0.0013	3.0636	0.0009	0.0023	2.2150
v	0.0003	0.0099	4.0383	0.0031	0.0235	>20
y	0.0001	0.0094	9.5186	0.0010	0.0216	>20
ZC	0.0005	0.0104	2.9739	0.0022	0.0307	>20
zn	0.0007	0.0123	5.6513	0.0009	0.0278	>20

Notes: This table displays the parameter estimates for the t-Location-Scale distribution for the for daily and weekly futures returns.

and Jarque-Bera test statistics are not presented due to the limit of space, the results from different techniques are consistent, and only three products with tickers “MA, p and y” do not reject the normality for the daily return series. However, the rejection of normality decreases (p-value increases) for the weekly returns, which indicates that the aggregational Gaussianity is observed as the stock markets. Table 2.6 notes that the t-location scale distribution provides a better fitting since it can be rejected for only 8 of total 37 products, namely “bu, hc, IC, jm, ni, rb, v and ZC”.

Figure 2.6 provides a visual exploration of the goodness-of-fit for the daily log-returns, and the empirical histogram is plotted together with the fitted normal and t-location scale distributions. It is consistent with the exhibited excess kurtosis and fat tails. Figure 2.6 demonstrates that the t-location scale distribution fits the data better than the normal distribution. Table 2.7 confirms the existence of fat tails in terms of the estimated degrees of freedom parameter νin the t-location scale distribution. Furthermore, the large estimated values in the weekly case illustrate the tendency for aggregational Gaussianity and weakening of the fat tails over longer time horizons. The results show that the t-location scale distribution assumption can be rejected in only a few products. As a result of non-uniform skewness behavior across different products, value-at-risk (VaR) estimates for both sides of the tails are usually close. Generally, there is no evidence supporting that the VaR values for the left tail are larger than that of the right tail as the observation in Table 2.2. Therefore, the negative skewness is difficult to be considered as a stylized fact of futures returns. The skewness behavior is closely related to the momentum trading, which indicates that positive skewness is common during bullish periods, while negative skewness is common during the bearish periods.

Overall, the three well-documented stylized facts of the stock returns are analysed with the Chinese futures return data in this study. The violation of normality and aggregational Gaussianity properties are verified in the futures return series. However, the negative skewness commonly observed in stock returns is not a general property for the case of futures returns, which exhibit positive/negative skewness depending on the particular trend and sub-period. Moreover, the t-location scale distribution fits the futures return series better than the normal distribution, and this phenomenon is

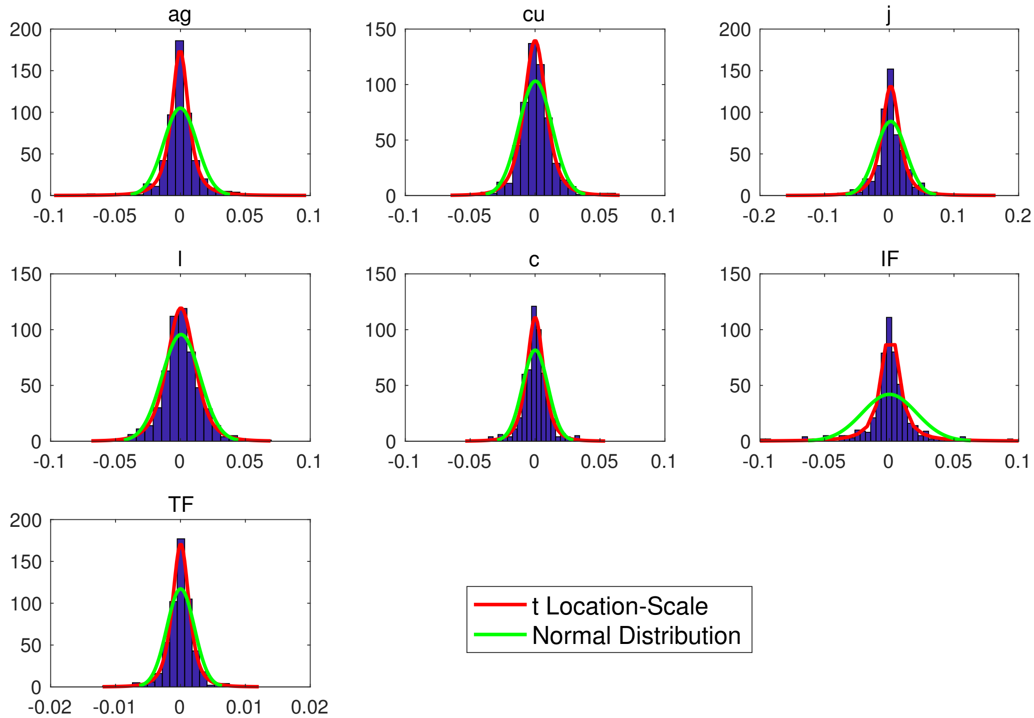

Figure 2.6: Normal and t-Location-Scale distribution fitting plots.
Notes: This figure displays the normal and t Location-Scale distribution fitting for daily returns.

consistent with the observation in the stock returns.

2.3.5 Principle component analysis

The factor model is widely applied to explain the returns of stock portfolios. Fama and French (1993) decompose the stock portfolio returns into three terms, namely the market risk, size and value factors. In the futures markets, which dominantly consist of commodity futures, such risk factors are not readily available or at least do not explain the behavior across different sectors of products well. Therefore, it is worthy to find the factors to explain the risk premia in futures returns. Principle component analysis is considered as a technique to investigate whether there is common behavior or a factor that is driving the futures returns at different time scales. Principle component analysis is used to explore at what time scales the common factors can be significant or how many factors would be needed for explaining the correlation structure of futures returns.

First, the principle component analysis is implemented with the correlation matrix of daily returns for futures. Figure 2.7 displays the correlation matrix for the universe of 37 futures products in terms of the heat map. It shows that the financial futures are not significantly correlated with the commodity futures, whereas the financial futures have high correlation with each other. Meanwhile, it illustrates that futures products within the same sector tend to have high correlation coefficients. These observations support that the investment in the commodity futures provides diversification possibilities.

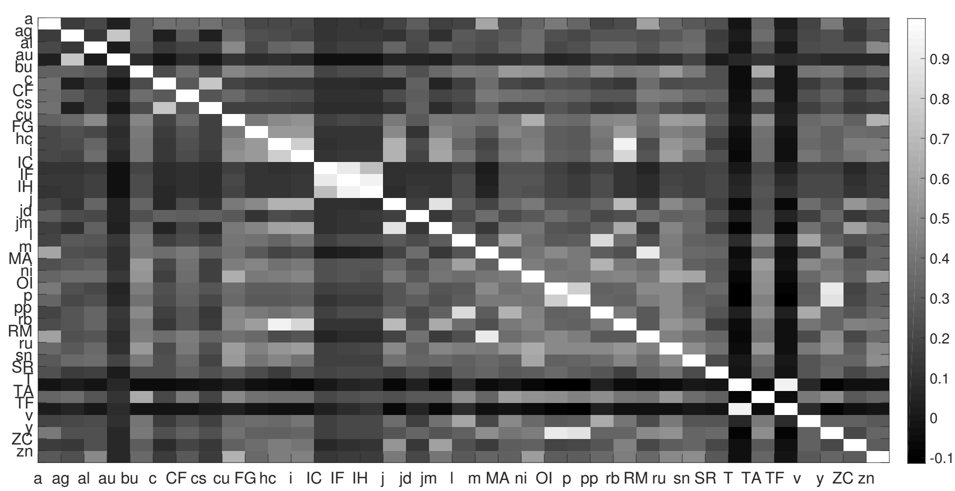

Figure 2.7: Correlations of close-to-close futures returns.

Tsay (2005) proposes that principle component analysis (PCA) is one useful statistical methodology to reduce the dimension of a multivariate time series. The separation between the stock returns and commodity futures returns reveals itself in the principle component analysis. For instance, the result of PCA applied to

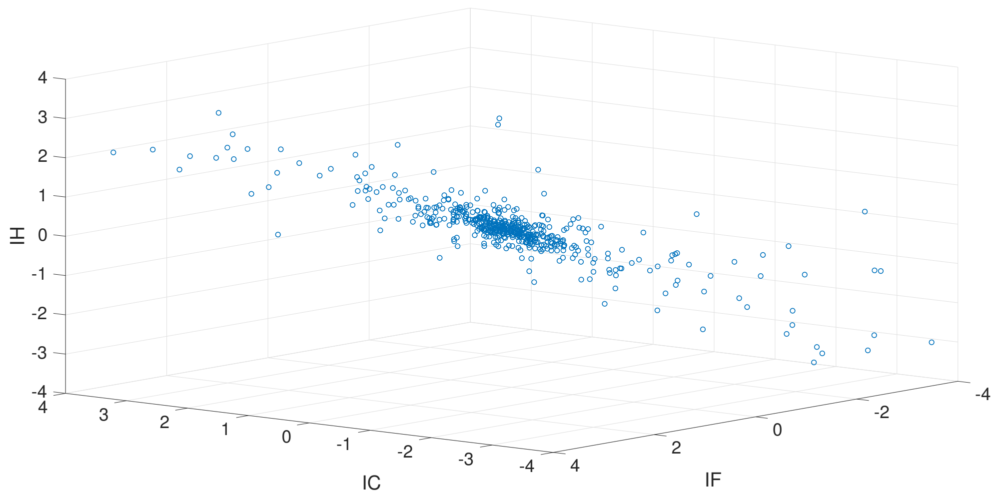

Figure 2.8: Scatter plot for the z-scores of the daily log-returns on index futures.

the Chinese index futures (i.e. IF, IH and IC) indicates that the index futures are dominantly driven by a single factor. Figure 2.8 provides the joint scatter plot for normalized returns (i.e. the z-scores) for Chinese index futures. Table 2.8 implies that 90% of the variation of the daily returns of the index futures can be explained by one a single factor. Similarly, the bond futures (i.e. T and TF) are driven by a common factor that accounts for 97% of the variation. Furthermore, Table 2.8 demonstrates that two common factors can be utilized to explain all the financial futures in the Chinese market. The first factor accounts for 88% and the second factor explains the remaining 10% of the variation in the financial futures.

When the whole set of 37 futures products are considered simultaneously, the first factor can only explain about 30% of the source of variations. Moreover, even if the financial futures are removed, the first component cannot explain a high percentage of the correlation structure across the remaining 32 products. Hence, it is difficult to construct a single factor model that can capture the risk premia of the whole futures markets in China. The universe of 37 futures products in China is sorted into financial, precious metals, industrial metal, agriculture, energy and chemicals by the traditional grouping technique. Therefore, detailed analysis shows that among these

Table 2.8: Principle component analysis results (daily returns).

	Percentage of the variation explained by the first k-number of principle components of futures returns.					
Principle Component	Precious M. (2)	Industrial M. (8)	Energy&Chemicals (11)	Agriculture (9)	Financial (5)	All (37)
1	89%	63%	43%	37%	88%	31%
2	100%	77%	59%	58%	98%	44%
3		85%	71%	75%	99%	52%
4		90%	78%	85%	100%	57%
5		93%	84%	93%		62%
6		96%	88%	96%		65%
7		98%	91%	98%		69%
8		100%	94%	99%		72%
9			97%	100%		75%
10			99%			77%
11			100%			79%
⋮						⋮
18						90%

Notes: This table illustrates the percentages explained by the first k-number of principle components for different industries of futures product daily returns in China. The number of products for the precious metals, industrial metals, energy and chemicals, agriculture and financial futures are given in the parentheses.

groups of futures, financials and precious metals can be explained in a single factor setting, whereas industrial metals can be explained with two factors (i.e. more than 80% as the threshold). Energy and chemicals, together with agriculture, show the existence of at least four factors in order to explain nearly 80% of the variation in these return series.

On the other side, the principle component analysis is implemented with the weekly (i.e. five trading days interval) futures returns[14]. Generally, the use of weekly returns tends to slightly increase the proportions explained by the first few factors due to the smoothing effect at this return horizon. The certain short-term deviations between co-moving futures products are reduced by the use of weekly returns, and it improves the proportions explained by the first few factors. Hence, the behavior of the dependence at different investment horizons tends to show variations to some extent. One drawback that avoids a comprehensive robustness check on the stability over time is the limited length of the futures dataset in China since many of the products

[14]The result is not presented for brevity.

have recent launch dates. Nevertheless, this drawback is handled by considering the high-frequency returns additional to the daily and weekly futures returns.

Regarding high-frequency data, the 5-minute returns are considered since at the 1-minute level the log-returns are heavily affected by the micro-structure effects (i.e. bid-ask bounce). Meanwhile, only the high-frequency data at the day-time trading hours are included since not all products have night trading.

In Figure 2.9, for each trading day the principle component analysis is implemented using the intra-day correlation matrix obtained from the 5-minute level returns. y-axis displays the percentage of variation explained with the first few factors. For instance, the first plot of Figure 2.9 demonstrates that the first factor explains a high percentage of the intra-day correlation matrix of the index futures returns. However, the percentage explained by the first factor is quite volatile. A significant drop in the first factor indicates that index futures returns deviate from each other significantly and are not driven by the common factor during those days. Overall, the results are comparable with the principle component analysis in Table 2.8. For instance, Table 2.8 implies that daily agricultural returns can be explained about 37% with the first factor, while Figure 2.9 displays that the 5-minute agricultural returns can be explained with a percentage ranging from 30% to 85% with the first factor. This observation demonstrates that each trading day provides a different degree of co-movement with respect to the common factor for the high-frequency futures returns. Hence, high-frequency trading within a dynamic trading strategy yields significant diversification benefits when the percentage explained with the first factor goes down. Since the 5-minute returns often deviate from the common factor, the dynamic CTA trading strategies provide qualified diversification benefits for Chinese stock market investors.

The variation of the dependence structure at different timescales of returns has important implications for investors in terms of diversification and exposure to common sources of risk for different products. For instance, industrial metals have a stronger dependence on the first factor compared to agricultural futures at the daily level. Therefore, the investment in different agricultural futures products provides less exposure to the common risk factor that drives the industrial metals. Similarly,

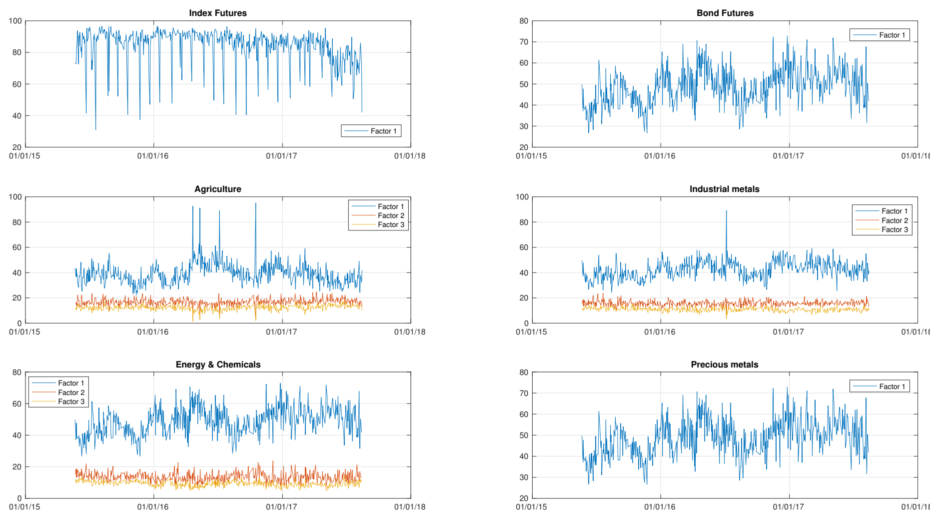

Figure 2.9: Principle component analysis results (five-minute returns).
Notes: This figure displays the principle component analysis results applied using the five-minute returns for the different groups of futures contracts in the Chinese market. The y-axis displays the proportion of variation explained by the first few principle components obtained from the intra-day correlation matrix, i.e., the correlation matrix is estimated for each day using the minute-level returns in the day-trading hours.

the investor can build an asset allocation system based on the exposure of common risk factors. This provides possibilities to decompose sector-based futures returns and investigate potential benefits from diversification.

This subsection verifies the correlation between the major factor for each given industry of futures products. The result with respect to each industry provides the first factor that explains the highest proportion of the correlation matrix in the corresponding industry. Hence, the correlations between the major factor across industries can be explored, thus verifying if these factors driving the returns in different industries are also correlated with each other. Note that the first factor obtained from each industry provides a weighted average of the futures returns within that industry. In other words, it provides an index to represent that industry. Table 2.9 displays the correlation matrix of the first factors of each industry. It is observable

Table 2.9: Correlation matrix of the first factors of each industry obtained from the principle components analysis (daily returns).

	Index	Bonds	Precious Metals	Agriculture	Industrial M.	Energy & Chem.
Index	1.000					
Bonds	0.053	1.000				
Precious M.	0.060	0.061	1.000			
Agriculture	0.162	-0.075	0.198	1.000		
Industrial M.	0.203	-0.055	0.264	0.480	1.000	
Energy & Chem.	0.256	-0.037	0.267	0.539	0.786	1.000

that the major risk factor for the industrial metals versus energy & chemical have the highest correlations, while the energy & chemicals principle component is also highly correlated with the principle component of the agricultural futures. All the other factors are not significantly correlated with each other, which indicates that the investor can construct the principle component factors as a portfolio from different industries and enjoy the diversification benefits of the low correlation between these factor portfolios.

2.3.6 Co-integration

Principle component analysis provides insight regarding the common risk factors across various futures products. Co-integration analysis is able to capture another form of co-movement. Co-integration is a well-studied phenomenon for the case of stock markets, which often exhibit this feature. Co-integration is also closely related to the widely implemented statistical arbitrage strategies (i.e. pairs trading), which involves exploiting the long-term equilibrium relationship between two stocks or portfolios. There is a potential issue in the principle component analysis if the estimated correlation matrix is not robust. For instance, Alexander and Dimitriu (2005a) propose that the correlation analysis is not as robust as the co-integration analysis on asset returns. Alexakis (2010) discusses long-run relations among international stock market indices under a different market relationship. Chiu and Wong (2011) claims the existence of co-integration in asset prices. Several studies focus on the co-integration relationship between the Chinese markets and the international markets or between the spot markets and the futures markets (Yang et al., 2004; Hua and Chen, 2007; Fung and Tse, 2010; Liu and An, 2011). Additionally, many instances of pairs trading within the framework of co-integration can be found in Alexander and Dimitriu (2005a), Zeng and Lee (2014) and Göncü and Akyıldırım (2016a). A comprehensive analysis of the profitability of pairs trading in the Chinese futures markets can be found in Yang et al. (2017).

The Engle-Granger co-integration test technique is implemented to check the existence of co-integration in this study. All possible pairs of Chinese futures products are included, and the tested data is the scaled daily log-price (i.e. removing the roll-over returns). The result indicates significant co-integration relations in Chinese futures markets.

In existing pairs trading literatures, the spread of two assets is defined by the co-integration equation

$$\ln(S_t^i) = \alpha + \gamma \ln(S_t^j) + \epsilon_t, \quad \epsilon_t \text{ i.i.d. } \sim (0, \sigma_\epsilon^2), \tag{2.14}$$

where the regression estimate of $\hat{\gamma}$ is used to construct the spread between the log prices of assets i and j, which is given by

$$X_t = \ln(S_t^i) - \hat{\gamma} \ln(S_t^j). \tag{2.15}$$

Therefore, the existence of co-integration can be tested by the augmented Dickey-Fuller test for the spread of possible pairs of futures.

Figure 2.10 illustrates that the null hypothesis can be rejected in most cases at the 10% significance level. In the figure, the dark regions indicate the existence of co-integration for those pairs of futures contracts. Across the combinations of products, there are numbers of combinations with statistically significant co-integration. The result confirms the findings of Yang et al. (2017), which shows that the co-integration relationship in Chinese futures markets can be utilized in the framework of pairs trading strategies.

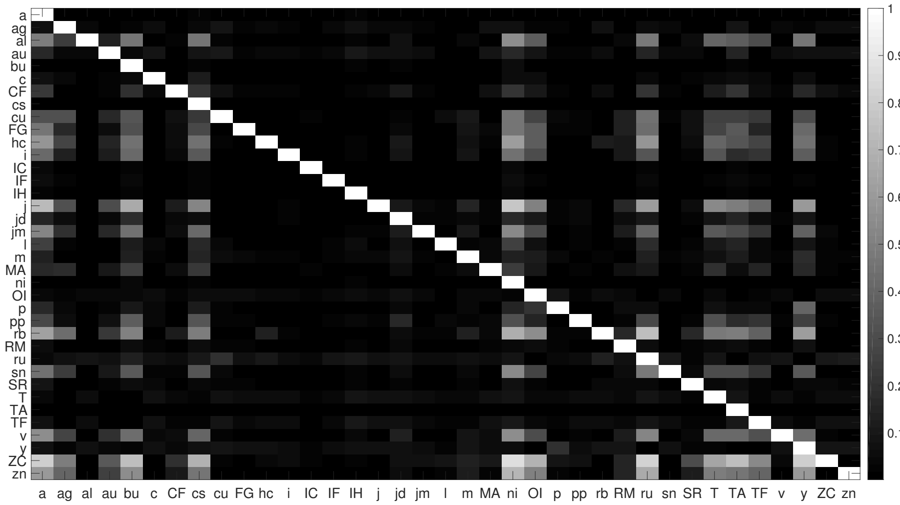

Figure 2.10: Augmented Dickey-Fuller test results.
Notes: This figure displays the augmented Dickey-Fuller test results for the co-integration Equation 2.15, the colour from black to white represents the p-Value from low to high in the augmented Dickey-Fuller test.

Table 2.10: Augmented Dickey-Fuller test results.

	a	ag	al	au	bu	c	CF	cs	cu	FG	hc	i	IC	IF	IH	j	jd	jm	l	m	MA	ni	OI	p	pp	rb	RM	ru	sn	SR	T	TA	TF	v	y	ZC	zn
a	-	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01
ag	0.07	-	0.04	0.01	0.03	0.06	0.00	0.04	0.09	0.03	0.04	0.02	0.01	0.04	0.07	0.04	0.05	0.03	0.01	0.00	0.07	0.07	0.02	0.02	0.01	0.06	0.00	0.06	0.05	0.01	0.01	0.08	0.00	0.04	0.02	0.06	0.06
al	0.49	0.24	-	0.13	0.45	0.01	0.02	0.46	0.02	0.00	0.00	0.00	0.01	0.01	0.03	0.00	0.06	0.00	0.01	0.04	0.02	0.55	0.37	0.01	0.00	0.00	0.05	0.48	0.00	0.06	0.40	0.37	0.31	0.00	0.46	0.00	0.00
au	0.16	0.03	0.04	-	0.04	0.08	0.01	0.09	0.10	0.02	0.04	0.04	0.02	0.04	0.11	0.07	0.07	0.05	0.01	0.01	0.09	0.17	0.09	0.03	0.03	0.06	0.01	0.15	0.04	0.04	0.01	0.15	0.00	0.06	0.07	0.07	0.06
bu	0.01	0.00	0.00	0.00	-	0.00	0.00	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.02	0.01	0.02	0.01	0.00	0.01	0.01	0.06	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
c	0.08	0.04	0.00	0.03	0.05	-	0.01	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.06	0.05	0.01	0.01	0.00	0.02	0.05	0.00	0.02	0.05	0.05	0.03	0.00	0.05	0.00	0.00
CF	0.23	0.00	0.01	0.02	0.19	0.05	-	0.21	0.07	0.03	0.03	0.03	0.00	0.01	0.03	0.05	0.10	0.03	0.01	0.00	0.07	0.22	0.11	0.02	0.01	0.05	0.00	0.21	0.02	0.01	0.12	0.21	0.06	0.03	0.16	0.06	0.04
cs	0.01	0.00	0.00	0.00	0.01	0.01	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
cu	0.32	0.32	0.01	0.16	0.33	0.00	0.08	0.23	-	0.01	0.01	0.00	0.03	0.01	0.01	0.00	0.02	0.01	0.05	0.09	0.00	0.46	0.27	0.04	0.02	0.01	0.13	0.45	0.02	0.06	0.26	0.26	0.22	0.01	0.31	0.01	0.00
FG	0.46	0.17	0.00	0.06	0.33	0.01	0.05	0.28	0.01	-	0.00	0.01	0.00	0.00	0.01	0.01	0.04	0.01	0.00	0.09	0.03	0.46	0.37	0.02	0.03	0.00	0.14	0.43	0.00	0.07	0.27	0.35	0.15	0.01	0.41	0.01	0.00
hc	0.58	0.27	0.00	0.15	0.45	0.01	0.05	0.44	0.03	0.00	-	0.01	0.00	0.00	0.02	0.00	0.10	0.00	0.00	0.08	0.02	0.62	0.36	0.00	0.00	0.12	0.10	0.59	0.00	0.06	0.39	0.33	0.28	0.00	0.44	0.02	0.00
i	0.42	0.14	0.00	0.11	0.42	0.01	0.04	0.34	0.00	0.01	0.00	-	0.00	0.00	0.02	0.01	0.09	0.00	0.01	0.09	0.01	0.44	0.30	0.01	0.01	0.02	0.10	0.34	0.00	0.02	0.34	0.18	0.21	0.00	0.36	0.02	0.00
IC	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.02	0.01	0.00	0.01	0.00	0.00
IF	0.05	0.02	0.00	0.01	0.03	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.03	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.02	0.04	0.02	0.00	0.03	0.00	0.00
IH	0.02	0.01	0.00	0.01	0.03	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.02	0.01	0.00	0.01	0.00	0.00
j	0.72	0.33	0.00	0.30	0.66	0.01	0.12	0.52	0.01	0.01	0.01	0.02	0.00	0.00	0.01	-	0.10	0.03	0.03	0.16	0.03	0.78	0.50	0.02	0.04	0.00	0.17	0.62	0.00	0.06	0.54	0.50	0.41	0.00	0.60	0.01	0.00
jd	0.14	0.06	0.01	0.04	0.18	0.01	0.03	0.06	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.01	-	0.02	0.03	0.05	0.02	0.16	0.10	0.03	0.03	0.01	0.06	0.10	0.01	0.02	0.08	0.15	0.06	0.02	0.09	0.01	0.01
jm	0.53	0.19	0.00	0.17	0.45	0.01	0.05	0.41	0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.03	0.12	-	0.00	0.10	0.01	0.54	0.31	0.00	0.02	0.01	0.12	0.41	0.00	0.01	0.36	0.31	0.22	0.00	0.38	0.04	0.00
l	0.26	0.03	0.01	0.01	0.12	0.04	0.01	0.16	0.04	0.00	0.00	0.00	0.01	0.02	0.05	0.01	0.08	0.00	-	0.02	0.04	0.26	0.07	0.00	0.02	0.01	0.03	0.17	0.00	0.02	0.11	0.14	0.04	0.01	0.08	0.02	0.01
m	0.13	0.00	0.01	0.01	0.13	0.03	0.00	0.15	0.05	0.03	0.02	0.03	0.01	0.02	0.04	0.03	0.08	0.03	0.01	-	0.05	0.13	0.12	0.05	0.01	0.03	0.00	0.14	0.02	0.05	0.08	0.12	0.04	0.02	0.18	0.02	0.03
MA	0.16	0.18	0.01	0.11	0.26	0.01	0.05	0.23	0.00	0.01	0.01	0.00	0.02	0.01	0.02	0.01	0.05	0.01	0.03	0.06	-	0.25	0.11	0.00	0.02	0.01	0.08	0.11	0.00	0.03	0.19	0.06	0.15	0.02	0.16	0.02	0.01
ni	0.00	0.00	0.01	0.01	0.04	0.01	0.00	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.02	0.00	0.01	0.00	0.00	0.00	0.01	-	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.00
OI	0.04	0.02	0.04	0.03	0.04	0.06	0.02	0.06	0.06	0.05	0.04	0.04	0.02	0.04	0.05	0.05	0.06	0.04	0.02	0.04	0.03	0.02	-	0.08	0.02	0.06	0.05	0.01	0.04	0.01	0.03	0.01	0.02	0.03	0.01	0.06	0.05
p	0.16	0.04	0.00	0.03	0.10	0.04	0.01	0.11	0.02	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.05	0.00	0.14	0.21	-	0.00	0.01	0.06	0.06	0.00	0.00	0.08	0.04	0.05	0.00	0.39	0.02	0.01
pp	0.29	0.06	0.00	0.07	0.36	0.04	0.01	0.34	0.03	0.03	0.00	0.01	0.01	0.02	0.04	0.02	0.16	0.01	0.04	0.02	0.04	0.32	0.15	0.00	-	0.02	0.02	0.30	0.00	0.03	0.32	0.18	0.21	0.02	0.26	0.03	0.01
rb	0.63	0.42	0.00	0.23	0.51	0.01	0.12	0.49	0.02	0.00	0.13	0.03	0.01	0.00	0.01	0.00	0.05	0.02	0.03	0.13	0.04	0.67	0.55	0.03	0.03	-	0.16	0.74	0.00	0.17	0.47	0.49	0.38	0.02	0.62	0.00	0.00
RM	0.05	0.00	0.01	0.01	0.05	0.02	0.00	0.06	0.03	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.01	0.01	0.00	0.02	0.05	0.05	0.03	0.00	0.02	-	0.06	0.01	0.02	0.03	0.05	0.02	0.01	0.07	0.01	0.01
ru	0.04	0.07	0.09	0.07	0.14	0.08	0.06	0.10	0.20	0.07	0.10	0.06	0.05	0.09	0.10	0.07	0.09	0.06	0.05	0.07	0.05	0.09	0.01	0.04	0.06	0.13	0.07	-	0.11	0.03	0.08	0.00	0.07	0.08	0.02	0.10	0.11
sn	0.44	0.24	0.00	0.10	0.34	0.03	0.03	0.34	0.03	0.00	0.00	0.00	0.01	0.01	0.03	0.00	0.05	0.00	0.00	0.05	0.01	0.54	0.28	0.00	0.00	0.00	0.06	0.47	-	0.04	0.30	0.30	0.21	0.00	0.36	0.00	0.00
SR	0.09	0.01	0.01	0.02	0.06	0.04	0.00	0.03	0.03	0.02	0.01	0.01	0.00	0.01	0.02	0.01	0.02	0.00	0.01	0.03	0.02	0.08	0.02	0.00	0.01	0.03	0.04	0.04	0.01	-	0.04	0.06	0.02	0.01	0.03	0.05	0.02
T	0.04	0.01	0.06	0.01	0.00	0.07	0.04	0.02	0.08	0.06	0.05	0.06	0.02	0.05	0.09	0.07	0.08	0.06	0.03	0.04	0.08	0.09	0.04	0.04	0.06	0.06	0.04	0.08	0.05	0.03	-	0.09	0.02	0.06	0.03	0.06	0.06
TA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00
TF	0.07	0.00	0.06	0.00	0.00	0.07	0.02	0.02	0.08	0.04	0.05	0.05	0.02	0.05	0.10	0.07	0.07	0.04	0.02	0.03	0.08	0.11	0.04	0.03	0.05	0.06	0.03	0.09	0.05	0.02	0.02	0.11	-	0.06	0.02	0.07	0.07
v	0.56	0.28	0.00	0.20	0.43	0.03	0.06	0.40	0.02	0.01	0.00	0.01	0.01	0.01	0.04	0.00	0.14	0.00	0.02	0.09	0.05	0.56	0.30	0.00	0.03	0.01	0.12	0.52	0.00	0.04	0.41	0.41	0.31	-	0.43	0.03	0.00
y	0.08	0.02	0.07	0.03	0.03	0.08	0.05	0.06	0.09	0.08	0.06	0.06	0.03	0.06	0.07	0.07	0.08	0.06	0.02	0.08	0.06	0.06	0.01	0.20	0.05	0.09	0.09	0.02	0.06	0.03	0.02	0.01	0.02	0.06	-	0.08	0.08
ZC	0.81	0.49	0.00	0.35	0.75	0.01	0.19	0.69	0.03	0.01	0.03	0.06	0.02	0.00	0.02	0.02	0.07	0.08	0.09	0.13	0.11	0.86	0.69	0.09	0.07	0.00	0.15	0.81	0.00	0.31	0.65	0.74	0.55	0.04	0.80	-	0.00
zn	0.61	0.40	0.00	0.26	0.55	0.01	0.10	0.46	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.06	0.00	0.03	0.12	0.02	0.70	0.50	0.03	0.01	0.00	0.15	0.66	0.00	0.12	0.50	0.46	0.40	0.00	0.61	0.00	-

Notes: This table documents the augmented Dickey-Fuller test results for the co-integration Equation 2.15, the result is reported in terms of p-Value as a numerical demonstration.

2.4 Summary

In this chapter, several stylized facts of the futures markets are investigated with using the low-frequency (i.e. daily and weekly) and high-frequency (i.e. minute level) data for the universe of 37 products in China. It is worth mentioning that the data processing methodology in this study follows the hedge fund industry practice of using the most active contract for each trading day instead of implementing a uniform contract roll-over methodology across different products. The main statistical and empirical features of the Chinese futures market can be summarized as follows.

- *Serial correlation:* The serial correlation in most of the futures returns are weak for the daily returns. However, there is one exception for the index futures, which is likely because of the artificial limitation on the trading (i.e. contract size limits by account). For the high-frequency data (i.e. minute-level futures returns), serial correlation is considerable for all the products and micro-structure effects come into play as in the case of stock returns.

- *Volatility clustering:* Financial futures, including the index and bond futures, show the strongest volatility clustering effect which reveals itself as high dependence or serial correlation with the previous few days' squared returns. For the commodity futures volatility clustering effect seems to be weaker and more than half of the products do not show significant volatility clustering effect.

- *Conditional heteroskedasticity:* Additional to the existence of volatility clustering, there is asymmetry in the correlation between a futures return and its volatility. Different from stock returns, a positive leverage effect is more common in the futures returns. In other words, the direction of asymmetry is not uniform across different products, which is likely to depend on the bullish or bearish investment periods as well.

- *Unit root and stationarity:* When employing the unit root tests with different specifications, only for a few cases can the unit root be rejected in the log-prices of futures returns, which shows that the random walk hypothesis can be rejected for these products. For most of the products such direct conclusion is not possible.

- *Distributional properties:* The non-normality of futures returns is consistent with the stylized facts of stock returns. Furthermore, the t-location scale is shown to be a suitable distribution for fitting the futures returns. Second, aggregational Gaussianity property can be observed in the futures returns similar to the stock markets. Third, negative skewness, which is often observed in stock return distributions, is not the case for most of the futures returns and the sign of skewness seems to depend on the bullish or bearish periods of products.

- *Principle components:* Principle components analysis (PCA) is employed to decompose the correlation across futures products. The percentage of variation explained by the first few factors is highest in the industrial metals sector of futures; in other words, within this group of futures contracts the first common factor can explain most of the correlations among futures contracts. Similarly, financial futures show high dependence and co-movement with the first factor, explaining a high ratio of the correlation matrix. PCA applied in the high-frequency returns shows that intra-day co-movement of futures returns and the correlation matrix can be explained by the first few factors as well. For specific industry groups of futures products, a high explanatory power for the first component indicates there are fewer diversification benefits from investment within that group of futures.

- *Co-integration:* There are many pairs of futures products that are co-integrated in the Chinese futures markets. Therefore, statistical arbitrage trading strategies, such as pairs trading, can be justified within this framework.

Overall, this chapter provides a comprehensive analysis of the fundamental statistical and empirical properties of the futures returns in China. It is worthy to mention that the stylized facts in stock markets cannot be simply generalized to the case of futures markets. The empirical properties of futures returns documented in this chapter can be considered as an input for various models of investment or risk management. For example, two empirical investment strategies, pairs trading and momentum trading, are explored in the following chapters. A standard analysis of statistical features for the Chinese futures market is fundamental for further research on the development of practical investment strategies, which is the main topic of this thesis.

Chapter 3

Pairs Trading with Commodity Futures

3.1 Introduction

The increasing popularity of futures trading has led to a tremendous evolution in the financial markets since the early 1980s. Currently, the attraction of commodity futures markets for both individual and institutional investors increases dramatically all over the world, and China is no exception to this trend.[1] With its swiftly growing economy, China has some of the world's most actively traded commodity futures such as copper, iron ore and palm oil. This chapter discusses the Chinese commodity futures because of China's significant global role with respect to trading volume.[2]

After the Chinese stock market collapse in the summer of 2015, the attraction of commodity futures trading exploded because of the following three main reasons: firstly the slowing down of the Chinese economy and the downward trend of commodity prices globally led the speculators to take short positions in the commodity futures

[1]See Financial Times article reported by Yang Yuan (Zhengzhou), Christian Shepherd, Wan Li and Lucy Hornby (Beijing) and written by Lucy Hornby and Neil Hume entitled: "*Chinese retail investors throw global commodities into a tailspin*" (published, 6 May, 2016 5:44 pm).

[2]See 2015 WFE/IOMA Derivatives Market Survey reported by World Federation of Exchanges (WFE) and IOMA,"*the commodity options and futures traded in Shanghai and Dalian accounting for 50% of the volume traded in 2015 in terms of number of contracts*" (published April 2016).

market for betting that the slowdown of the Chinese economy might continue coupled with the slow global growth; secondly, due to the low correlation between the commodity futures prices and the stock markets, while the Chinese stock market collapsed, the commodity futures produced important diversification benefits for the investors; and finally, the short selling restrictions in the Chinese stock market resulted in that the hedge funds consider commodity futures as a major alternative investment tool.

The growing existence of investment banks and hedge funds in the commodity futures markets has resulted in the enhanced implementation of quantitative trading strategies to produce statistical arbitrage profits. Current literature discusses the profitability of pairs trading by analysing its maximum drawdown with different maximum holding periods for the spread position, and the main contribution of this chapter is to provide evidence that at the longer maximum holding periods, the performance of pairs trading improves in the Chinese commodity futures markets. The maximum drawdown, which is widely applied in the hedge fund industry, is a measure of the decline from the historical peak over a specific time period. Complementarily, the relationship between the performance and the maximum holding period for spreads appears to be robust both in time and across the different pairs. The intuitive reason behind this phenomenon is that if the investor does not employ stop-loss barriers and can hold the spread position for longer periods of time, then a higher premium can be obtained from pairs trading, which definitely comes with the risk of a larger potential drawdown during this waiting time. Moreover, utilizing the comprehensive dataset of Chinese commodity futures prices from 2005 to 2016, the profitability of the major pairs trading models applied in the past studies is verified and compared.

This chapter is organised as follows. Section 3.2 briefly reviews the pairs trading and statistical arbitrage. Section 3.3 presents the dataset utilized in this study, while the spread model is presented together with the identification methods of potential pairs. Empirical performances are documented and investigated in Section 3.4, and finally Section 3.5 summarises the whole discussion.

3.2 Pairs Trading and Statistical Arbitrage

The intuition behind statistical arbitrage is related to the spread of expected returns of large portfolios and asset classes. Normally, statistical arbitrage strategies take the long position in the set of assets with the highest expected return and take the short position in the set of assets with the lowest expected return. Employing statistical arbitrage strategies to beat the market index returns have been popular in the hedge fund and asset management industry since the implementation of sophisticated statistical methods to develop high-tech pairs trading programs at Morgan Stanley in the mid-1980s by the team headed by the Wall Street quantitative analyst Nunzio Tartaglia. Since the pairs trading was originally proposed, it has become widely applied and increasingly attractive across different asset classes and markets. In contrast to the popularity of statistical arbitrage strategies in the financial industry, the academic literature has been slow to lay the theoretical foundations, and particularly, its definition.

After a long history of pairs trading, a significant gap exists between the academic studies and financial industry. Bondarenko (2003) proposes the definition of a statistical arbitrage in a finite time horizon economy. However, his concept assumes technical requirements on the pricing kernels, while Hogan et al. (2004) introduce the statistical arbitrage opportunity in a general probability space and in an infinite time economy instead. Meanwhile, the efficient market hypothesis is tested under the new infinite time framework by Hogan et al. (2004). Afterwards, Jarrow et al. (2012) slightly improve the test methodology by avoiding penalizing incremental profits with positive deviations. Hogan et al. (2004) are regarded as having the most popular mathematical definition for the statistical arbitrage currently that considers the asymptotic behaviour of an investment strategy.

From a brief standpoint, pairs trading is a market-neutral strategy to produce statistical arbitrage profits, and it seeks the temporary deviations of a pair of asset prices from the long-term equilibrium level. Nevertheless, even if perfect information on the model parameters of the spread is obtained, there is the risk that mean reversion of the long-term equilibrium level might take too long or never happen in practice. Therefore, the major risk in pairs trading is the possibility that the spread continues to diverge relative to the long-term mean level after a position is opened (Gatev et al., 2006). For instance, the limitations with respect to the duration of short-selling in the equity markets probably lead the positions are terminated forcefully by realizing a loss.

From a detailed view, the pairs trading strategy is implemented in two steps. First of all, the identification of suitable pairs is prerequisite for exploiting the pairs trading profits. The second one is to examine the proper time for entering and exiting the market, namely to determine the definite asset prices for opening/closing the long and short positions. This chapter discusses some well-documented approaches for identifying the potential pairs of assets, such as the profitability index based on cointegration, the minimum distance and the correlation method. Initially, Alexander (1999) and (Alexander and Dimitriu, 2005a,b) introduce the relationship of cointegration for identifying optimal pairs of assets for trading. Afterwards, a profitability based on the cointegration framework for the spread of two correlated assets is provided by Zeng and Lee (2014). Since the minimum distance method is widely applied by industry practitioners, Gatev et al. (2006) and Perlin (2009) consider the sum of squared deviations of two price time series and employ the indicator for constructing the pairs trading portfolio. Furthermore, Huck and Afawubo (2015) investigate the profitability of the pairs trading strategy by using various pair selection criteria with the data of S&P500 index components. Although it is difficult to propose a universally superior selection criterion, the empirical analysis in this chapter indicates that a qualified technique can be developed by considering these methods simultaneously.

Göncü (2015) and Göncü and Akyıldırım (2016a) provide the existence of statistical arbitrage opportunities in terms of Hogan et al. (2004)'s definition for the Black-Scholes and mean-reverting stochastic spread frameworks, respectively. Additionally, current literatures explore the performance of pairs trading strategies theoretically and empirically (Gatev et al., 2006; Baronyan et al., 2010; Cummins and Bucca, 2012; Do and Faff, 2010, 2012; Bowen and Hutchinson, 2014; Jacobs and Weber, 2015; Focardi et al., 2016). Specifically, Gatev et al. (2006) provide a detailed analysis and the evidence of abnormal returns for the pairs trading strategies. Do and Faff

(2010) illustrate that pairs trading performed strongly during periods of economic depression, including the 2008-2009 financial crisis. Meanwhile, the robustness of pairs trading is verified and a number of market-neutral strategies are discussed in Baronyan et al. (2010). By using the data of the US equity market over the period of 1963-2009, Do and Faff (2012) claim that pairs trading remains profitable when commissions, market impact and short selling fees are included. Furthermore, Bowen and Hutchinson (2014) comprehensively investigate the performance of pairs trading strategies in the UK market. Jacobs and Weber (2015) explore 34 international stock markets as well as the US market and display that trading pairs solely constructed from historical price information turn out to be consistently profitable. The recent empirical evidence that abnormal returns can be produced by applying the dynamic factor models with S&P500 data over the period of 1989-2011 is provided in Focardi et al. (2016).

Gatev et al. (2006) highlight that the risk-adjusted returns are a compensation for a latent or dormant risk factor that has not been considered in pairs trading. Therefore, the vast majority of pairs trading literature focuses on equity markets, where the risk-adjustment of returns are discussed with well-documented factor models. Nevertheless, this chapter concentrates on the commodity futures market, where the different dynamics result in that most of the factor models widely applied in the stock markets are not valid (Focardi et al., 2016). Thus, the Chinese futures market offers a potential testing environment for the performance of pairs trading strategies.

The objective of this chapter is to verify that the abnormal returns of pairs trading in the commodity futures markets do not necessarily imply a market anomaly or inefficiency. The possible intuition behind this phenomenon can be explained in two aspects. Firstly, pairs trading often involves short-selling in the relatively over-priced asset, which is always assumed to be arbitrarily long term in the literature. Practically, the fact is ignored that high maximum drawdown might give rise to the liquidation of spread position with big losses; hence, proper risk adjustment can only be developed in terms of the average or maximum drawdown calculated over the holding period of each spread position.[3] Secondly, by controlling the spread position in terms of different maximum holding periods, it is displayed that the performance of pairs trading changes significantly. For instance, the risk-adjusted returns decrease drastically as shorter maximum holding periods are performed for each spread position. This is a potential reflection that the market participants associate the duration of spread positions with higher drawdown risk.

Essentially, the studies on pairs trading in equity markets attempt to seek risk factors for explaining the abnormal returns rather than considering the maximum drawdown in different trade horizons. In this chapter, the maximum drawdown is calculated in order to explain why some abnormal opportunities cannot be practically obtained in the existence of risk-controls, such as stop-loss barriers which are widely utilized in the hedge fund industry. Therefore, the consistent presence of abnormal returns and Sharpe ratios from pairs trading does not necessarily imply the market inefficiency. Moreover, three different criteria for selecting asset pairs are considered, namely, the profitability index, the empirical distance (the minimum distance) and the correlation coefficient by employing the dataset of Chinese commodity futures traded in Shanghai, Dalian and Zhengzhou Commodity Exchanges. After identifying the potential pairs, the trading strategies with definite spread thresholds are developed and compared according to past studies based on the first-passage time theory and the Kalman filter technique (Elliot et al., 2005; Gatev et al., 2006; Zeng and Lee, 2014; Göncü and Akyıldırım, 2016a).

3.3 Data and Models

This section introduces the data and models applied to explore the performance of pairs trading in the Chinese commodity futures market. Complementarily, the pairs

[3]Based on several discussions with senior managers on hedge funds operating in the Chinese commodity futures markets, it is highlighted that the industry considers the average or maximum drawdown to measure the performance of investment strategies. Additionally, a longer duration to hold the spread position and high maximum drawdown results in the position probably being liquidated before the pairs trading profit is realized due to stop-loss barriers that are commonly used as the risk management tool.

selection criteria and trading threshold calculation formulas are explained in detail. Furthermore, the solution for the data snooping issue and the discussion of futures contract maturity months and liquidity are provided as well.

3.3.1 Data

This study considers the historical data of the commodity futures traded in Shanghai Futures Exchange (SHFE), Dalian Commodity Exchange (DCE) and Zhengzhou Commodity Exchange (CZCE), which covers the period from 1 January, 2005 to 1 June, 2016 in terms of daily close prices.[4] In the empirical analysis, the commodity futures with more than 1,000 observations are included, which attains 9 products in SHFE, 9 in DCE and 7 in CZCE, totally 25 different commodities. Table 3.1 summarises the main information of the futures contracts with respect to tickers, maturities and launch dates. Due to that, the trading of the 25 product futures did not start simultaneously, and the length of observations are different. Additionally, 6 different maturities for each commodity are considered, which offers 150 potential contracts for pairs trading.

3.3.2 Models

This study implements pairs trading by identifying the potential pairs, utilizing the training sample and then trading these pairs with a 1-year length of out-of-sample periods. The choice of 1 year for trading intervals is consistent with the tenor of the futures contract in this dataset, and in this way, the problem of rolling over the next contract is avoided since the spread position is already closed at least 5 days prior to the maturity day of each futures contract.

Modelling the Spread Process

This chapter considers the difference in log-prices for modelling the stochastic spread process between two assets. This consideration has several advantages. At first,

[4]The data is obtained from WIND Information Co. Ltd. financial terminal.

Table 3.1: Main information on contracts with long history.

Commodity	Exchange	Wind Ticker	Launch Date	Maturity Months
Aluminium	SHFE	AL	May 1992	FGHJKMNQUVXZ
Gold	SHFE	AU	January 2008	FGHJKMNQUVXZ
Copper	SHFE	CU	May 1992	FGHJKMNQUVXZ
Fuel Oil	SHFE	FU	August 2004	FGHJKMNQUVXZ
Lead	SHFE	PB	March 2011	FGHJKMNQUVXZ
Screw Steel	SHFE	RB	March 2009	FGHJKMNQUVXZ
Zinc	SHFE	ZN	March 2007	FGHJKMNQUVXZ
Natural Rubber	SHFE	RU	January 1999	FHJKMNQUVX
Wire Material	SHFE	WR	March 2009	FGHJKMNQUVXZ
Soybean 1	DCE	A	March 2002	FHKNUX
Soybean 2	DCE	B	December 2004	FHKNUX
Bean Dreg	DCE	M	July 2000	FHKNQUXZ
Bean Oil	DCE	Y	January 2006	FHKNQUXZ
Corn	DCE	C	September 2004	FHKNUX
Palm Oil	DCE	P	October 2007	FGHJKMNQUVXZ
Polythene	DCE	L	July 2007	FGHJKMNQUVXZ
Polyvinyl Chloride	DCE	V	May 2009	FGHJKMNQUVXZ
Coke	DCE	J	April 2011	FGHJKMNQUVXZ
Cotton	CZCE	CF	June 2004	FHKNUX
Methyl Alcohol	CZCE	MA	October 2011	FGHJKMNQUVXZ
Strong Wheat	CZCE	WH	March 2003	FHKNUX
White Sugar	CZCE	SR	January 2006	FHKNUX
Pure Terephthalic Acid	CZCE	TA	December 2006	FGHJKMNQUVXZ
Colza Oil	CZCE	OI	June 2007	FHKNUX
Indica Rice	CZCE	RI	April 2009	FHKNUX

Note: This table is a summary of the main information on contracts traded in the Shanghai, Dalian and Zhengzhou commodity futures markets with more than 1,000 observations. The letter codes are F (January), G (February), H (March), J (April), K (May), M (June), N (July), Q (August), U (September), V (October), X (November) and Z (December).

the log-prices produce stochastic models that are valid to the use of the geometric Brownian motion process for the asset prices. Additionally, the differencing of time series allows the model to focus on the returns and avoids the scaling issues. Empirically, this consideration makes significant contribution to detecting the mean reversion property. Therefore, following Elliot et al. (2005), Avellaneda and Lee

(2010), Zeng and Lee (2014) and Göncü and Akyıldırım (2016a), the spread of two assets is defined by the cointegration equation

$$\ln(S_t^i) = \alpha + \gamma \ln(S_t^j) + \epsilon_t, \quad \epsilon_t \text{ i.i.d. } \sim (0, \sigma_\epsilon^2), \tag{3.1}$$

where the estimate of $\hat{\gamma}$ is used to construct the spread between assets i and j, and it is given by

$$X_t = \ln(S_t^i) - \hat{\gamma} \ln(S_t^j). \tag{3.2}$$

Additionally, the dynamics of the spread is often assumed to follow a mean reverting Ornstein-Uhlenbeck (OU) process[5], and it is given by

$$dX_t = -\rho(X_t - \mu)dt + \sigma dW_t, \tag{3.3}$$

where ρ is the speed of mean reversion, W_t is a standard Brownian motion (on some probability space) and μ is the long-term equilibrium level of the spread. The mean reverting OU process is commonly applied in the literature with respect to pairs trading (Elliot et al., 2005; Avellaneda and Lee, 2010; Bertram, 2010; Bogomolov, 2013; Zeng and Lee, 2014; Göncü and Akyıldırım, 2016a). Therefore, this study conducts the analysis based on the mean reverting OU process embedded within the cointegration theory (i.e., test in the Chapter 2) following the literature suggestion. The solution of Eq. 3.3 is provided by

$$X_t = X_0 e^{-\rho t} + \mu(1 - e^{-\rho t}) + \sigma \int_0^t e^{-\rho(t-s)} dW_s, \tag{3.4}$$

where X_t is normally distributed with $E[X_t] = X_0 e^{-\rho t} + \mu(1 - e^{-\rho t})$ and $V(X_t) = \frac{\sigma^2}{2\rho}(1 - e^{-2\rho t})$, respectively. The stationary mean and variance are given as μ and $\sigma^2/2\rho$ as $t \to \infty$, respectively.

It is known that the parameters of the OU process can be estimated by an AR(1)

[5]The Ornstein-Uhlenbeck (OU) process is widely applied to model (with modifications) interest rates, currency exchange rates, and commodity prices, specifically, the model describing the evolution of interest rates is commonly known as Vasicek model in finance.

representation for the discretization of Eq. 3.3, where the discretization error of the stochastic differential equation is $O(\Delta t)$. Let us denote the mean subtracted process $\tilde{X}_t := X_t - \mu$, and thus, the AR(1) process is written by

$$\tilde{X}_{t+1} = (1 - \rho\Delta t)\tilde{X}_t + \epsilon_t, \quad \epsilon_t \text{ i.i.d. } \sim (0, \sigma_\epsilon^2 \Delta t), \quad \rho > 0. \tag{3.5}$$

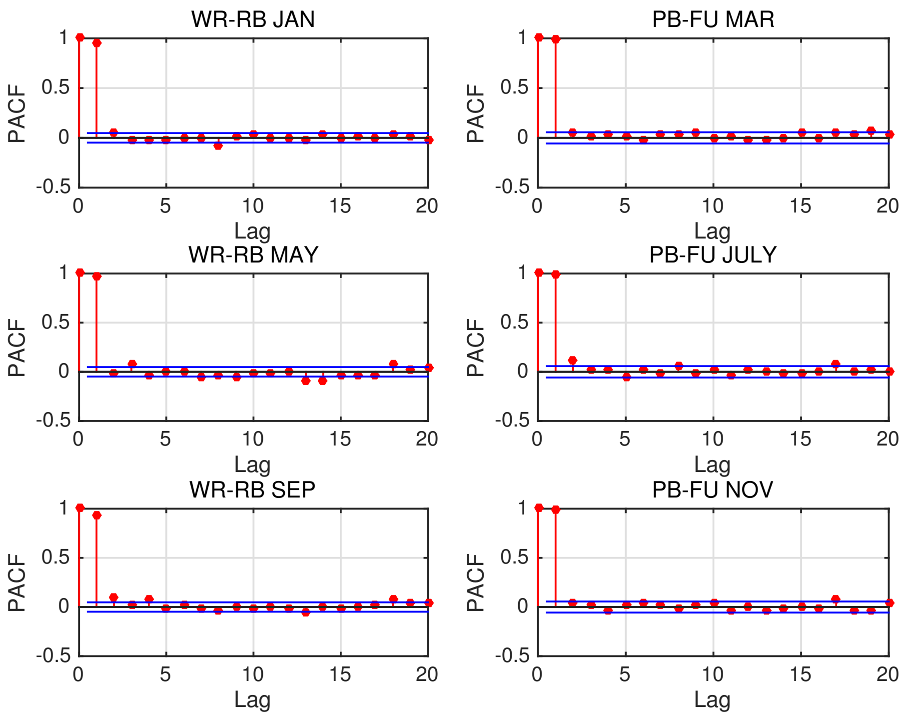

Figure 3.1: Partial autocorrelation functions for the spreads
Notes: This plot displays the partial autocorrelation functions for the spreads of the given pairs of futures contracts, where the AR(1) effect is demonstrated.

Our dataset for the spread of futures contracts consists of daily observations, thus by implementing Eq. 3.5, the daily parameter values of the model are obtained[6].

[6]The estimation of the model parameters can also be obtained from the maximum likelihood estimation of the AR(1) process; however the least-squares estimation of the discretized model is faster in most of the statistical software, and a comparison of computational times can be found in Göncü and Akyıldırım (2016a), Page 9 Table 1.

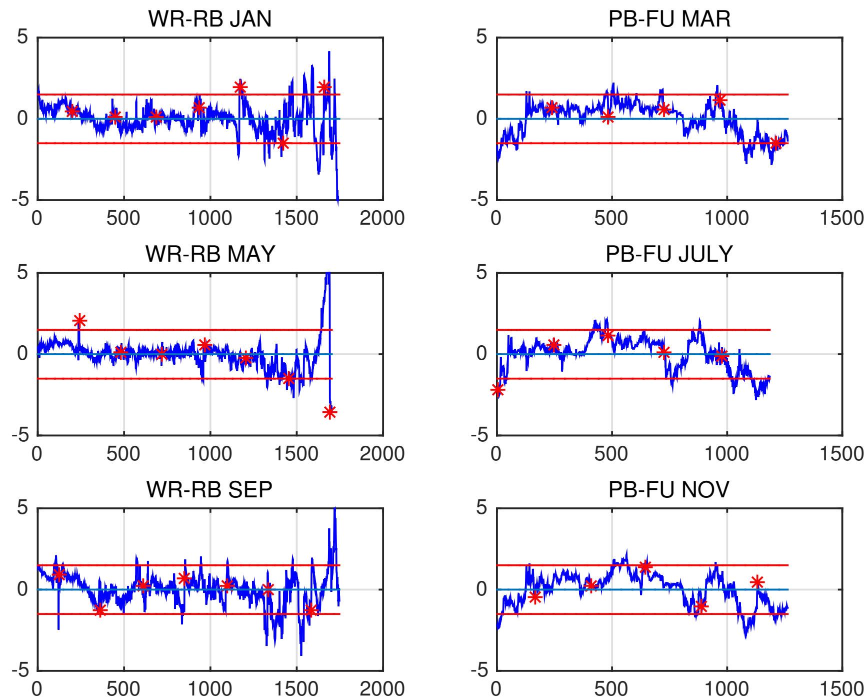

Figure 3.2: Historical spreads of the given pairs of futures contracts.
Notes: The figures illustrate the historical spreads of the give pairs of futures contracts. The stars represent the contract roll-over dates. In our backtesting, the portfolio positions are closed at least 5 days prior to the maturity date in order to avoid the artificial return from the roll-over effect and the illiquidity issues.

Additionally, the partial autocorrelation function for the spreads can be verified, as the AR(1) effect is reported. For instance, in Fig. 3.1, the plots of the partial autocorrelation function for the spread of WR-RB and PB-FU[7] pairs with different maturities are provided.[8] See also the plot of the spreads in Fig. 3.2 for the above-mentioned pairs as they are derived by Eq. 3.2. From this small sample of pairs that is demonstrated in Fig. 3.1 and 3.2, it is clear that the spreads have historically

[7]WR - RB stands for Wire Material and Screw Steel; PB - FU stands for Lead and Fuel Oil; see Table 3.1.

[8]The maturity for WR-RB pair is in January, May and September, and PB-FU pair is in March, July and November

strong mean reversion around the long-term mean. Therefore, they can be considered as potentially good candidates for pairs trading.

Formation of Pairs

This study covers 25 different kinds of commodities with more than 1,000 daily observations from the three commodity futures exchanges in the Chinese market. This major challenge is that each exchange specializes in different types of commodities with diverse rules and non-synchronized maturity dates, which is shown in Table 3.1. In this chapter, only pairs between contracts from the same exchange are considered, but there is also the possibility to create portfolios with pairs that are contained in different exchanges. In fact, this approach is considered as conservative, since the potential spread formation space is restricted within pairs from the same exchanges, however, the potential profitability increases significantly by relaxing this limitation.[9] In the backtesting analysis, each candidate pair is ranked in terms of the values of selection criteria by using the whole available history going backward. Although the best pairs rankings include the whole historical data series, out-of-sample backtesting does not employ any future information in the formation of pairs.

As selection criteria, the following indicators are considered. Firstly, the correlation coefficient between log-prices is calculated. Secondly, a profitability index calculated with respect to the volatility and mean reversion of the spread is calculated. Thirdly, the sum of squared deviations of two futures price series is computed. In addition to the simple historical correlation coefficient, the sum of squared differences (SSD) is calculated, which is used to pick potential pairs of assets as give by Gatev et al. (2006), Huck (2013) and Huck and Afawubo (2015). In order to rank the different pairs by comparable values, the average SSD is calculated in terms of the normalized prices give by

$$SSD_{i,j} = \frac{\sum_{t=1}^{T} (S_t^i/S_0^i - S_t^j/S_0^j)^2}{T}, \tag{3.6}$$

with S_t^i and S_t^j are the prices of the two assets. Complementarily, the profitability

[9]Mathematically, by expanding the set of possible pairs, it is more likely to have pairs that are more profitable than those that have already been considered in the conservative approach.

index measure is calculated following Zeng and Lee (2014), which is given with respect to the volatility σ and the mean-reversion parameter ρ by

$$\text{Profitability index } = \sigma\sqrt{\rho/2}. \tag{3.7}$$

The profitability of a spread improves if the spread of prices show high volatility and mean reversion at the same time.

Maturity Months and Trading Volume

As is the practice of the hedge fund industry, intra-day trading of commodity futures is usually based on the contract with the highest volume. Therefore, the liquidity risk is minimized by utilizing the most actively traded maturity month for the investor. Thus, this study considers the extra cost for rolling the futures over different contracts and maturity mismatches as the spread is traded over long time horizons with low frequency.

Consequently, 1-year fixed maturity contracts are employed; hence the spread position can be held until the end of the maturity without rolling over a different maturity contract. Additionally, the results obtained for all the 6 different maturity months traded in all the exchanges are presented in order to avoid data selection biases. The trading volume of these contracts fluctuates depending on the underlying commodity. For instance, soybean futures with maturities in January, May and September are more popular than those with maturities in March, July and November. Normally, the trading volume goes down prior to the last trading day. Therefore, this study enforces that the spread position is closed at least 5 trading days before the maturity to avoid liquidity and physical delivery issues.

Data Snooping

For minimizing potential data snooping biases, this study mainly implements out-of-sample backtesting without any future information. The out-of-sample backtesting is organised from two aspects, namely the pairs selection and the trading thresholds calculation. Furthermore, the backtesting is proceeded with different model training and trading periods, and it focuses on the model-free approach of the two-standard deviation (2-stdev) rule following Gatev et al. (2006), which is widely implemented in the hedge fund industry. In this trading rule, whenever the spreading process deviates by two historical standard deviations away from the long-term mean level, the short or long position in the spread portfolio is opened, and the position is closed when the spread dynamic returns to the long-term equilibrium. Due to the advantage of model-free assumption, Huck (2009), Do and Faff (2012), Huck (2013) and Huck and Afawubo (2015) implement and compare the performance of empirical standard deviation (sigma) rules.

Thresholds for Pairs Trading

For completeness and robustness, additional to the 2-stdev rule which is widely employed by the practitioner (Gatev et al., 2006), alternative trading models are considered and the results are reported. Thus, two well-documented pairs trading thresholds (triggers) based on the first passage time theory[10] existing in the literature are implemented with and without the Kalman filter technique of Elliot et al. (2005). Next, the main features of each trading method are discussed.

Elliot, Van Der Hoek and Malcolm's Kalman Filter (KF) method: Elliot et al. (2005) consider a mean-reverting Gaussian Markov chain model for the spread which is observed in Gaussian noise. Therefore, the Kalman filter technique is used to filter the noise and tried to obtain better estimates of the true mean-reverting OU process. Elliot et al. (2005) employ two EM algorithms for implementing the Kalman filter, which are given by Shumway and Stoffer (1982) and Elliot and Krishnamurthy (1999), respectively. The empirical analysis in this study implements the Shumway and Stoffer (1982) EM algorithm, which is amply discussed in Appendix D.

Zeng and Lee (ZL)-method: Zeng and Lee (2014) propose the optimal trading thresholds as functions of the parameters of the OU process, and the transaction

[10]The details are included in Appendix C.

cost. A polynomial expression for the expectation of the first-passage time of the OU process with two-side boundary is derived, and the analytic formula for optimal trading thresholds is obtained as the solution. Zeng and Lee (2014) produce the best threshold level that maximizes the expected return per unit time in order to initiate the pairs trading. If the trading threshold has narrow bands around the mean level, then the time it takes to return to the long-term mean is short, and hence is the profit per trade. On the other hand, if the threshold is far away from the long-term mean, the profit in each trade is larger, and hence on average, it takes longer to realize it. In the view of the realistic consideration, only the case with positive transaction cost is included in this study. The details on this method are included in Appendix E.

Göncü and Akyıldırım (GA) method: Recently, Göncü and Akyıldırım (2016a) derived an optimal threshold level that maximizes the probability of successful termination (mean-reversion probability) of the spread portfolio for a given investment horizon (i.e., 1-year). The details on this method are included in Appendix F.

Note that there is a significant difference between the trading rules of the 2-stdev, Zeng and Lee (2014) and Göncü and Akyıldırım (2016a) methods. In Zeng and Lee (2014) the trade cycles are longer since a trader that opens a spread position at the upper (lower) threshold closes it at the lower (upper) threshold instead of at the long-term mean level. In the 2-stdev and Göncü and Akyıldırım (2016a) methods, the trader closes the position whenever the long-term mean level is reached (which can be considered as the classical way of implementing pairs trading).

3.4 Empirical Results

3.4.1 Preliminary Analysis

This section compares the performance of different pairs selection and spread trading methods using the complete dataset for 25 commodities from the three Chinese commodity futures exchanges. Both in-sample and out-of-sample backtesting are employed to verify the profitability of the pairs trading strategies. However, in order to avoid physical delivery or a low liquidity issue towards the maturity of the futures contracts, the liquidation of the spread position is enforced at least five trading days before the maturity date. In that way, the problem of rolling over different futures contracts is avoided.

To check the robustness of the strategy with respect to parameter changes, sub-period analysis is considered that is performed by selecting different out-of-sample trading periods, and the pairs are selected at the beginning of each sub-period. Therefore, Subperiod 1 contains the last 1 year as the trading period, and all the previous history is included as the training sample, whereas Subperiod 2 starts the out-of-sample trading period by being shifted backwardly by 75 trading days, and thus, the interval for training period contains 75 fewer observations, and so on and so forth. By shifting the out-of-sample starting dates, nine different annual out-of-sample trading periods are obtained. Additionally, because the expanding window is applied for the training period, the size of the training period is largest for Subperiod 1. The rationale behind the choice of 75 trading days is related to the fact that a larger number leads to smaller number of sub-periods because some commodities in the Chinese futures market do not have a long history of trade. Meanwhile, a smaller number increases the overlap between different out-of-sample intervals which might cause higher autocorrelation between the out-of-sample returns obtained.

During the implementation of pairs trading, the model parameters are updated by utilizing an expanding window of daily observations. Every time a spread position is closed for any given pair in the portfolio, the parameters of that spread are re-estimated with the available, up-to-date information. For the sub-periods, as they have been designed and presented above, it is implied that Subperiod 1, which has the longest training period of forming pairs, utilizes the largest dataset both for the formation of pairs as well as the estimation of the model parameters.

For the formulation of portfolios of pairs, it is assumed that each pair has a committed capital proportional to the weight of that pair within the portfolio of pairs. Therefore, when the portfolios of pairs are formulated, two alternative return calculations, namely the committed capital and the fully invested return, can be implemented (Gatev et al., 2006). However, this study follows the most conservative approach and reports the committed capital return. Thus, it is assumed that even if a pair is not traded for the whole period of trading time, an equal amount of capital committed to this pair is still allocated, and the equally weighted average is calculated with the number of pairs. In this way, the opportunity cost of the investor to commit capital to each pair in the portfolio is taken into account even though all the pairs are not traded.

Table 3.2 documents the calculated returns[11] of the pairs trading for the 9 out-of-sample trading sub-periods with different starting dates using the 2-stdev trading rule as a benchmark. Panel A presents the annual returns obtained from the pairs trading when the spread positions are opened at the end of the day when the prices diverge and when they are closed at the end of the day when the prices converge. It is observed that in 5 out of 9 sub-periods, the returns are very high, which shows that potentially pairs trading might be very profitable. Lower returns are observed in sub-periods 7, 8 and 9 which is likely because a smaller size of the training sample as an expanding window for the subperiod analysis is used. Alternatively, Figure 3.3 demonstrates the growth of 1 money-unit allocated to the pairs trading with a portfolio of 1, 3 and 6 best pairs in 2013–2016 trading period. Different from the analysis in Table 3.2, Figure 3.3 assumes that the 1 money-unit position is traded annually over the 3-year period, and the best pairs are re-identified at the end of each annual trading cycle.

3.4.2 Transaction Costs

According to the contrarian nature of pairs trading strategies, the returns might be biased upward because of the bid-ask bounce (Conrad and Kaul, 1989; Jegadeesh, 1990; Jegadeesh and Titman, 1993, 1995), particularly when the assets that have done relatively well are sold and the ones that have done poorly are bought. Gatev

[11] The spread is constructed with ratio $\hat{\gamma}$ in Equation 3.2, which implies that for each contract in i, $\hat{\gamma}$ number of contracts for j should be held. Following Zeng and Lee (2014) the return realized from pairs trading is calculated as $\frac{P_{l1}-P_{l0}}{0.5(P_{l0}+P_{l1})} + \hat{\gamma}\frac{P_{s0}-P_{s1}}{0.5(P_{s0}+P_{s1})}$, where P_{l0}, P_{s0} are the prices when the long and short positions are opened, and P_{l1}, P_{s1} are prices of the same contracts when the long and short positions are closed, respectively. Consequently, the cost of capital in the margin account is ignored in the return calculation.

Table 3.2: Pairs trading returns with different numbers of pairs in a portfolio.

Periods/Portfolios	1 Pair	2 Pairs	3 Pairs	4 Pairs	5 Pairs	6 Pairs
Panel A: Returns (%) (no waiting)						
Subperiod 1	31.39	24.24	33.48	29.62	28.61	29.95
Subperiod 2	44.29	48.24	45.08	41.58	32.87	29.49
Subperiod 3	38.30	43.25	37.90	44.24	44.02	41.28
Subperiod 4	13.98	28.58	21.16	21.21	22.90	19.46
Subperiod 5	43.45	24.65	14.96	13.12	10.95	9.06
Subperiod 6	24.83	4.20	0.52	-1.23	3.47	3.28
Subperiod 7	4.42	5.80	4.95	4.63	5.85	3.78
Subperiod 8	10.50	9.59	6.94	3.96	3.88	4.18
Subperiod 9	5.26	9.63	6.64	5.04	5.67	6.59
Average Return	24.03	22.02	19.07	18.02	17.58	16.34
Stdev.	16.06	16.13	16.22	17.05	14.97	14.21
Panel B: Returns (%) (one day waiting)						
Subperiod 1	31.16	28.14	33.74	31.75	30.41	32.67
Subperiod 2	37.67	51.79	48.86	43.93	34.22	30.00
Subperiod 3	32.86	47.49	39.35	43.01	43.04	40.12
Subperiod 4	12.00	27.94	18.35	16.88	20.37	16.91
Subperiod 5	38.38	20.78	12.86	9.80	7.76	6.34
Subperiod 6	17.20	-0.07	-2.80	-2.50	2.38	1.91
Subperiod 7	4.43	3.82	3.14	2.71	3.44	1.71
Subperiod 8	12.58	9.20	4.99	2.54	2.32	2.28
Subperiod 9	0.47	5.61	4.06	2.80	3.42	3.90
Average Return	20.75	21.63	18.06	16.77	16.37	15.09
Stdev.	14.52	18.91	18.37	18.26	15.99	15.33
Panel C: Trading Statistics						
Avg. Number of Trades/Year	4	4.3	4.1	3.9	3.6	3.4
Average Trade Duration	35.2	37.8	39.1	38	43.3	44.1
Percentage of Negative Returns	0	6%	11%	14%	13%	15%

Notes: Best pairs are identified using the training sample by first filtering the pairs that have a correlation coefficient larger than 0.5 and choosing the top eight minimum SSD and largest profit index values. Annual returns are obtained with the annual trading period. We trade according to the rule that opens a position in a pair at the end of the day when the divergence of the spread exceeds the historical two standard deviations around the mean (Panel A). The results in Panel B correspond to a strategy that delays the opening of the spread position by one day for removing the bid-ask spread effect. Panel C presents the trading statistics. The trading threshold calculation is based on the historical standard deviation $(2-\sigma)$.

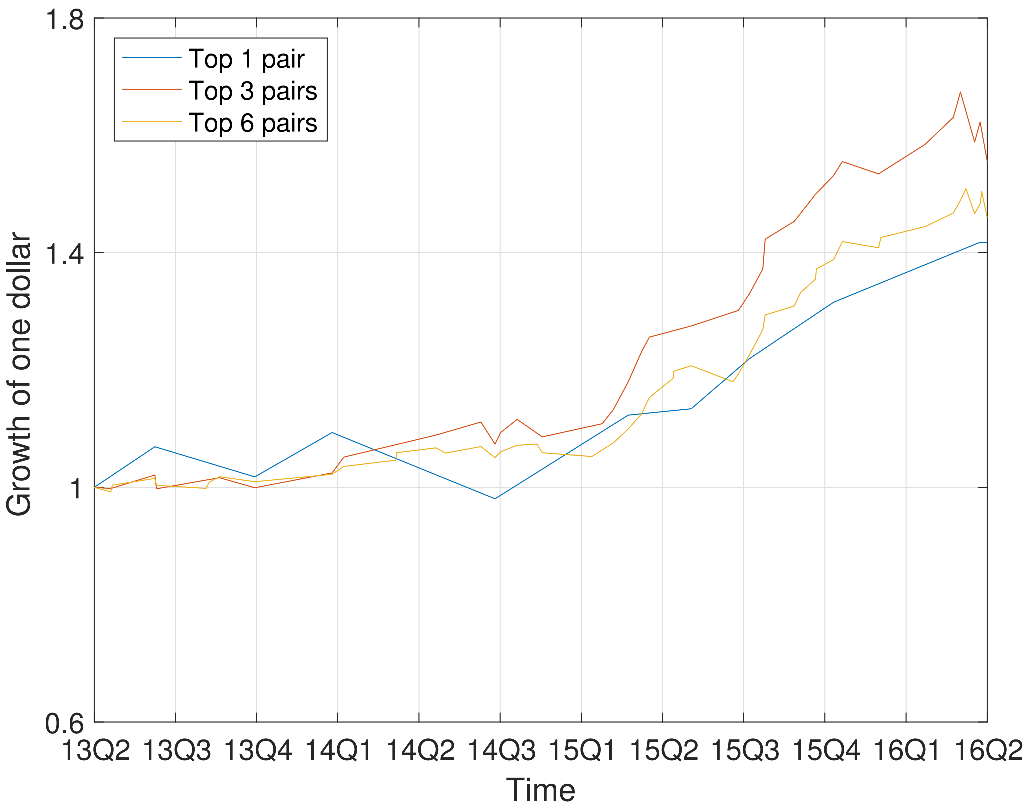

Figure 3.3: The growth of one dollar with pairs trading in three years. The trading threshold calculation is based on the historical standard deviation ($2-\sigma$).

et al. (2006) propose that the winner's price is more likely to be an ask quote and the loser's price is a bid quote, whereas the opposite is true at the second crossing when the spread converges to its long-term equilibrium level. To address this issue, Table 3.2 Panel B presents the result of pairs trading with a one-day gap between the divergence/crossing and the execution of trade following Gatev et al. (2006). As it is displayed in Table 3.2 Panel C, the average return can drop by $24.03 - 20.75 = 3.28\%$ with 4 average numbers of pairs trading cycles per year. Therefore, as a rather conservative estimate, this study assumes a 2% round-trip transaction cost per pairs trade, which is expected to be sufficient to cover market frictions, liquidity costs and commission fees.[12]

3.4.3 Testing alternative pairs trading models

Table 3.2 indicates that the pairs trading generates high returns even after the transaction costs are included. This section introduces the question as to whether an alternative pairs selection or trading models can significantly change the implied profitability. To our best knowledge, a comparison among the alternative theoretical approaches proposed by Zeng and Lee (2014) and Göncü and Akyıldırım (2016a) as well as with the practical 2-stdev approach used by Gatev et al. (2006) (and practitioners) with and without the Kalman filter technique of Elliot et al. (2005) has not been provided so far.[13] The historical standard deviation model (practical 2-stdev approach) is employed as a baseline model because of the model-free feature. Additionally, the time-dependent volatility model (i.e., GARCH) is considered as a potential candidate to be implemented in the backtesting analysis. However, the result shows a significant increasing of the time spend on the modelling due to that the estimation of GARCH model is more complex than the historical standard deviation model, but the performance is not apparently improved. The backtesting result and comparison of computing times are documented in Table B.2 and Table B.1 of Appendix B. The equivalent performance of model-free 2-stdev approach affirms that employing more general models does not necessarily improve the profitability of the pairs trading strategy. The argument exists on the robustness of the pairs trading under the different pairs selection and trading models that in terms of backtesting results derived from the three alternative approaches with and without the Kalman filter technique.

[12] Note that the difference in average returns is 3.28% with 4 average numbers of pairs. Roughly, for each trade the estimated cost is given by $3.28/4 = 0.82\%$ (i.e., 1.64% for a round-trip transaction cost). With a conservative assumption the transaction cost is rounded up as 2%.

[13] For instance, ZL-EL and ZL are the Zeng and Lee (2014) approach with or without the Kalman filter technique of Elliot et al. (2005), which is based on the EM-algorithm (Shumway and Stoffer, 1982).

In-sample backtesting

For the in-sample comparison, the best pairs are identified with respect to the three selection criteria presented in Section 3.3.2 using the whole dataset. The cointegration equation for the spread is also estimated from the whole sample until the end of the trading period. Using the last 252 observations for the formulation of the trading period, the annualized returns (after subtracting the transaction costs) are calculated for each pairs trading that is derived with the different methods.

The results of the in-sample backtesting are reported for the trading periods from 22 May, 2015 to 1 June, 2016 and 13 May, 2014 to 22 May, 2015 in Tables 3.3 and 3.4, respectively. Therefore, the following observations are worthy to be highlighted. The profitability index and the combination methods identify pairs that are more likely to produce high returns at least for the GA and 2-stdev rules. However, the Kalman filter fails to improve the performance of pairs trading. The potential explanation behind the failure is that the commodity futures prices exhibit large fluctuations and high volatility, where the Kalman filter tends to treat these fluctuations as the noise term, which in turn cause narrower trading thresholds and potentially lowering the profitability. Moreover, astonishingly, the simplest 2-stdev rule, which is widely applied by practitioners and free from model specification errors, seems to perform quite well compared with all the other theoretical methods with or without the Kalman filter.

Out-of-sample backtesting

The in-sample backtesting analysis provides the comparison with respect to the performance of different pairs selection and trading models. In the realistic consideration, the out-of-sample backtesting illustrates the performance of pairs trading when the model parameters are obtained without any future information. For the out-of-sample backtesting, the dataset is split into two parts called the training and out-of-sample backtesting periods.

The pairs are identified using the training period data, and the initial estimates of the model parameters are obtained with the expanding window of observations

Table 3.3: In-sample backtesting results of pairs trading - 1.

Criteria	Maturity	Pair	GA	GA-KF	ZL	ZL-KF	2-σ	2-σ-KF
Correlation	JAN	(WR-RB)	22.71%	43.01%	27.80%	20.78%	49.57%	20.53%
		SHFE	(16.8)	(20.3)	(33.7)	(33.9)	(19.9)	(19.9)
	MAR	(WR-RB)	23.38%	32.83%	37.89%	44.74%	32.95%	30.12%
		SHFE	(14.3)	(20.2)	(27.9)	(22.8)	(19.7)	(22.3)
	SEP	(WR-RB)	36.74%	36.98%	49.96%	39.30%	31.52%	32.60%
		SHFE	(32)	(32.3)	(31.4)	(31.4)	(34.7)	(30.3)
	Average	**Return**	**27.61%**	**37.61%**	**38.55%**	**34.94%**	**38.01%**	**27.75%**
		Hitting Days	(21)	(24.2)	(31)	(29.4)	(24.7)	(24.2)
Profitability Index	SEP	(WR-RB)	36.74%	36.98%	49.96%	39.30%	31.52%	32.60%
		SHFE	(32)	(32.3)	(31.4)	(31.4)	(34.7)	(30.3)
	JULY	(PB-FU)	66.23%	-31.10%	14.81%	-38.62%	48.50%	-31.10%
		SHFE	(43.5)	(122.5)	(76.7)	(83.7)	(51.5)	(122.5)
	NOV	(V-J)	0%	-33.24%	45.39%	-76.61%	0%	-33.24%
		DCE	(0)	(122.5)	(35.9)	(83.7)	(0)	(122.5)
	Average	**Return**	**33.67%**	**-9.12%**	**36.72%**	**-25.31%**	**26.00%**	**-10.58%**
		Hitting Days	(25.2)	(92.4)	(48)	(66.2)	(31.7)	(91.8)
SSD	MAY	(PB-AL)	17.87%	12.26%	17.47%	17.47%	13.52%	18.15%
		SHFE	(127)	(132)	(62.5)	(62.5)	(130)	(89)
	MAY	(WR-RB)	8.87%	8.87%	-4.73%	-11.39%	13.57%	-5.20%
		SHFE	(23)	(23)	(83.7)	(83.7)	(28.3)	(34.8)
	JULY	(PB-AL)	14.94%	12.42%	11.53%	9.93%	12.42%	16.98%
		SHFE	(127)	(130)	(105.5)	(105.5)	(130)	(72.5)
	Average	**Return**	**13.89%**	**11.18%**	**8.09%**	**6.34%**	**13.17%**	**9.98%**
		Hitting Days	(92.3)	(95)	(83.9)	(83.9)	(96.1)	(65.4)
Combination	SEP	(WR-RB)	36.74%	36.98%	49.96%	39.30%	31.52%	32.60%
		SHFE	(32)	(32.3)	(31.4)	(31.4)	(34.7)	(30.3)
	JULY	(PB-FU)	66.23%	-31.10%	14.81%	-38.62%	48.50%	-31.10%
		SHFE	(43.5)	(122.5)	(76.7)	(83.7)	(51.5)	(122.5)
	MAR	(PB-FU)	13.86%	-32.14%	11.27%	-28.48%	7.06%	-32.14%
		SHFE	(129)	(122.5)	(58.5)	(83.7)	(130)	(122.5)
	Average	**Return**	**38.95%**	**-8.75%**	**25.35%**	**-9.27%**	**29.02%**	**-10.21%**
		Hitting Days	(68.2)	(92.4)	(55.5)	(66.2)	(72.1)	(91.8)

Notes: This table displays the backtesting results (transaction costs included) in terms of annualized returns achieved from the in-sample data for the considered methods: Göncü and Akyildirim (GA), Zeng and Lee (ZL) and Kalman filter (KF) methods. The average number of days per spread position is given in parenthesis. The trading period is from 22 May, 2015 to 1 June, 2016, consisting of 252 trading days in total.

Table 3.4: In-sample backtesting results of pairs trading - 2.

Criteria	Maturity	Pair	GA	GA-KF	ZL	ZL-KF	2-σ	2-σ-KF
Correlation	MAY	(WR-RB)	37.01%	26.89%	34.64%	50.57%	29.32%	40.76%
		SHFE	(10.2)	(14.7)	(24.3)	(16.9)	(12.5)	(11.1)
	JAN	(WR-RB)	42.03%	37.99%	32.85%	29.01%	34.07%	44.53%
		SHFE	(16.6)	(22.2)	(34.1)	(35)	(17)	(16.7)
	MAR	(WR-RB)	11.49%	11.98%	44.00%	40.97%	12.85%	27.70%
		SHFE	(8.3)	(13.5)	(26.4)	(27.2)	(13)	(14.9)
	Average	**Return**	**30.18**%	**25.62**%	**37.17**%	**40.18**%	**25.31**%	**37.66**%
		Hitting Days	(11.7)	(16.8)	(28.3)	(26.3)	(14.2)	(14.2)
Profitability Index	SEP	(WR-RB)	18.70%	25.39%	8.40%	23.61%	14.20%	20.06%
		SHFE	(22)	(20.3)	(56.8)	(35.4)	(27.5)	(21)
	MAY	(WR-RB)	37.01%	26.89%	34.64%	50.57%	29.32%	40.76%
		SHFE	(10.2)	(14.7)	(24.3)	(16.9)	(12.58)	(11.1)
	JAN	(WR-RB)	42.03%	37.99%	32.85%	29.01%	34.07%	44.53%
		SHFE	(16.6)	(22.2)	(34.1)	(35)	(17)	(16.7)
	Average	**Return**	**32.58**%	**30.09**%	**25.30**%	**34.39**%	**25.86**%	**35.12**%
		Hitting Days	(16.3)	(19.1)	(38.4)	(29.1)	(19)	(16.3)
SSD	MAY	(PB-AL)	7.72%	10.92%	6.93%	6.15%	7.22%	7.64%
		SHFE	(25)	(14)	(41.8)	(41.8)	(13.5)	(18.8)
	MAY	(WR-RB)	37.01%	26.89%	34.64%	50.57%	29.32%	40.76%
		SHFE	(10.2)	(14.7)	(24.3)	(16.9)	(12.5)	(11.1)
	JULY	(WR-RB)	45.08%	43.80%	35.68%	32.93%	44.72%	44.34%
		SHFE	(17.8)	(21.2)	(35.7)	(31.3)	(21.2)	(22.3)
	Average	**Return**	**29.94**%	**27.20**%	**25.75**%	**29.88**%	**27.09**%	**30.91**%
		Hitting Days	(17.6)	(16.6)	(34)	(30)	(15.7)	(17.4)
Combination	SEP	(WR-RB)	18.70%	25.39%	8.40%	23.61%	14.20%	20.06%
		SHFE	(22)	(20.3)	(56.8)	(35.4)	(27.5)	(21)
	MAY	(WR-RB)	37.01%	26.89%	34.64%	50.57%	29.32%	40.76%
		SHFE	(10.2)	(14.7)	(24.3)	(16.9)	(12.5)	(11.1)
	JAN	(WR-RB)	42.03%	37.99%	32.85%	29.01%	34.07%	44.53%
		SHFE	(16.6)	(22.2)	(34.1)	(35)	(17)	(16.7)
	Average	**Return**	**32.58**%	**30.09**%	**25.30**%	**34.39**%	**25.86**%	**35.12**%
		Hitting Days	(16.3)	(19.1)	(38.4)	(29.1)	(19)	(16.3)

Notes: This table displays the backtesting results (transaction costs included) in terms of annualized returns achieved from the in-sample data for the considered methods: Göncü and Akyildirim (GA), Zeng and Lee (ZL) and Kalman filter (FL) methods. The average number of days per spread position is given in parenthesis. The trading period is from 13 May, 2014 to 22 May, 2015, 252 trading days in total.

(Elliot et al., 2005; Zeng and Lee, 2014; Göncü and Akyıldırım, 2016a). Similarly, the model-free 2-stdev method (Gatev et al., 2006) simply employs the sample means and standard deviations calculated from the expanding window of observations as well.

Using the least-squares regression, the spread parameter $\hat{\gamma}$ is estimated and updated regularly every time a spread position is closed. Backtesting is performed from the last data point in the training sub-sample and updates the thresholds to include new information in every trading day repeatedly. Moreover, by assuming that during the 1 year trading period the spread position is closed n-times, the annual return is calculated as $(1 + r_1) \cdots (1 + r_n)$, where each return from the pairs trading r_i is subtracted by the transaction cost. At the end of the out-of-sample period, this study enforces closing the position and realizing the profit or loss on the last trading day. In both in-sample and out-of-sample experiments, the GA method is implemented with the investment horizon of $T = 1$ year, which is consistent with the maturity of futures contracts. When the Elliot et al. (2005) method is implemented, the trading threshold is $\mu \pm \sigma/\sqrt{2\rho}$.

The out-of-sample backtesting results are provided in Tables 3.5 and 3.6. On a few occasions, pairs with no trade opportunity can be observed and thus a return of zero is recorded. Out-of-sample backtesting results are overall in line with the in-sample results in the sense that the 2-stdev rule offers consistently good performance, and the Kalman filter and ZL methods are not able to improve the profits considerably. Therefore, both results confirm that 2-stdev and GA methods perform well. Given the simplicity and the model-free nature of the 2-stdev rule, it is not out of the rationale that practitioners regard the 2-stdev rule as the first choice for implementing pairs trading.

3.4.4 Profitability and the maximum holding period for the spread positions

The in-sample and out-of-sample backtesting results demonstrate that pairs trading produces abnormal returns which are obtained for various contracts and commodity

Table 3.5: Out-of-sample backtesting results of pairs trading - 1.

Criteria	Maturity	Pair	GA	GA-KF	ZL	ZL-KF	2-σ	2-σ-KF
Correlation	MAY	(WR-RB)	13.11%	3.02%	1.70%	1.70%	5.09%	2.53%
		SHFE	(31)	(35.3)	(50.2)	(50.2)	(33.8)	(36)
	JAN	(WR-RB)	46.71%	38.58%	15.48%	15.48%	37.96%	17.87%
		SHFE	(17.7)	(21.4)	(33.9)	(33.9)	(22.4)	(20.2)
	MAR	(WR-RB)	29.55%	24.64%	39.22%	30.61%	24.64%	14.51%
		SHFE	(17)	(22.7)	(27.9)	(27.9)	(22.7)	(23.3)
	Average	**Return**	**29.79%**	**22.08%**	**18.80%**	**15.93%**	**22.56%**	**11.64%**
		Hitting Days	(21.9)	(26.5)	(37.3)	(37.3)	(26.3)	(26.5)
Profitability Index	SEP	(WR-RB)	32.26%	32.77%	8.43%	18.12%	25.39%	40.27%
		SHFE	(37)	(31.8)	(83.7)	(50.2)	(42)	(27.8)
	MAY	(WR-RB)	13.11%	3.02%	1.70%	1.70%	5.09%	2.53%
		SHFE	(31)	(35.3)	(50.2)	(50.2)	(33.8)	(36)
	JAN	(WR-RB)	46.71%	38.58%	15.48%	15.48%	37.96%	17.87%
		SHFE	(17.7)	(31.4)	(33.9)	(33.9)	(22.4)	(20.2)
	Average	**Return**	**30.69%**	**24.79%**	**8.54%**	**11.87%**	**22.81%**	**20.22%**
		Hitting Days	(28.6)	(32.8)	(55.9)	(44.8)	(32.7)	(28)
SSD	MAY	(PB-AL)	7.94%	4.82%	-4.71%	-6.34%	6.38%	4.82%
		SHFE	(140)	(173)	(72.7)	(72.7)	(163)	(173)
	MAY	(WR-RB)	13.11%	3.02%	1.70%	1.70%	5.09%	2.53%
		SHFE	(31)	(35.3)	(50.2)	(50.2)	(33.8)	(36)
	JULY	(WR-RB)	9.69%	6.09%	4.00%	3.18%	10.03%	7.49%
		SHFE	(36.2)	(39)	(62.3)	(62.8)	(35.3)	(42)
	Average	**Return**	**10.25%**	**4.64%**	**0.33%**	**-0.49%**	**7.17%**	**4.95%**
		Hitting Days	(69.1)	(82.4)	(61.7)	(61.9)	(77.4)	(83.7)
Combination	SEP	(WR-RB)	32.26%	32.77%	8.43%	18.12%	25.39%	40.27%
		SHFE	(37)	(31.8)	(83.7)	(50.2)	(42)	(27.8)
	MAY	(WR-RB)	13.11%	3.02%	1.70%	1.70%	5.09%	2.53%
		SHFE	(31)	(35.3)	(50.2)	(50.2)	(33.8)	(36)
	JAN	(WR-RB)	46.71%	38.58%	15.48%	15.48%	37.96%	17.87%
		SHFE	(17.7)	(21.4)	(33.9)	(33.9)	(22.4)	(20.2)
	Average	**Return**	**30.69%**	**24.79%**	**8.54%**	**11.87%**	**22.81%**	**20.22%**
		Hitting Days	(28.6)	(32.8)	(55.9)	(44.8)	(32.7)	(28)

Notes: This table displays the backtesting results (transaction costs included) in terms of annualized returns achieved in the out-of-sample backtesting with daily updated parameters for the considered methods: Goncu and Akyildirim (GA), Zeng and Lee (ZL) and Kalman filter (KF) methods. The average number of days per spread position is given in parenthesis. The out-of-sample period is from 22 May, 2015 to 2 June, 2016, totalling 252 trading days.

Table 3.6: Out-of-sample backtesting results of pairs trading - 2.

Criteria	Maturity	Pair	GA	GA-KF	ZL	ZL-KF	2-σ	2-σ-KF
Correlation	JAN	(WR-RB) SHFE	19.76% (60.3)	20.13% (48.5)	28.15% (35.7)	23.64% (35.7)	15.31% (64.7)	19.81% (37)
	MAY	(WR-RB) SHFE	17.85% (22)	39.86% (9.9)	18.33% (27.9)	17.49% (27.9)	34.28% (12.6)	29.23% (12)
	MAY	(Y-P) DCE	0% (0)	6.03% (5)	-11.32% (124)	-11.79% (125.5)	6.03% (5)	-4.52% (122.5)
	Average	**Return**	**12.54%**	**22.00%**	**11.72%**	**9.78%**	**18.54%**	**14.84%**
		Hitting Days	(27.4)	(21.1)	(62.5)	(63.0)	(27.4)	(57.2)
Profitability Index	SEP	(WR-RB) SHFE	5.41% (43)	8.24% (45)	-8.75% (62.5)	-8.75% (62.5)	1.05% (59.3)	16.03% (29.1)
	MAY	(WR-RB) SHFE	17.85% (22)	39.86% (9.9)	18.33% (27.9)	17.49% (27.9)	34.28% (12.6)	29.23% (12)
	NOV	(WR-RB) SHFE	10.14% (67)	21.77% (34)	19.03% (47.8)	19.03% (47.8)	15.59% (48.7)	27.03% (32)
	Average	**Return**	**11.13%**	**23.29%**	**9.54%**	**9.25%**	**16.97%**	**24.09%**
		Hitting Days	(44)	(29.6)	(46.1)	(46.1)	(40.2)	(24.3)
SSD	MAY	(WR-RB) SHFE	17.85% (22)	39.86% (9.9)	18.33% (27.9)	17.49% (27.9)	34.28% (12.6)	29.23% (12)
	JAN	(ZN-PB) SHFE	-12.99% (138)	-12.56% (109.5)	-17.16% (83.7)	-17.16% (83.7)	-13.33% (113)	-15.01% (122.5)
	NOV	(ZN-PB) SHFE	-12.97% (93)	-24.05% (118.5)	-27.33% (83.7)	-27.33% (83.7)	-22.60% (113.5)	-24.95% (122.5)
	Average	**Return**	**-2.70%**	**1.08%**	**-8.72%**	**-9.00%**	**-0.55%**	**-3.58%**
		Hitting Days	(84.3)	(79.3)	(65.1)	(65.1)	(79.7)	(85.7)
Combination	SEP	(WR-RB) SHFE	5.41% (43)	8.24% (45)	-8.75% (62.5)	-8.75% (62.5)	1.05% (59.3)	16.03% (29.1)
	MAY	(WR-RB) SHFE	17.85% (22)	39.86% (9.9)	18.33% (27.9)	17.49% (27.9)	35.71% (12.6)	30.62% (12)
	NOV	(WR-RB) SHFE	10.14% (67)	21.77% (34)	19.03% (47.8)	19.03% (47.8)	15.59% (48.7)	27.03% (32)
	Average	**Return**	**11.13%**	**23.29%**	**9.54%**	**9.25%**	**16.97%**	**24.09%**
		Hitting Days	(44)	(29.6)	(46.1)	(46.1)	(40.2)	(24.3)

Notes: The table displays the backtesting results (transaction costs included) in terms of annualized returns achieved in the out-of-sample backtesting with daily updated parameters for the considered methods: Goncu and Akyildirim (GA), Zeng and Lee (ZL) and Kalman filter (KF) methods. The average number of days per spread position is given in parenthesis. The out-of-sample period is from 13 May, 2014 to 22 May, 2015, totalling 252 trading days.

pairs.[14] Obviously, the simplest and model-free approach of the 2-stdev trading method can be considered safe as a very good first choice for the traders. To check the robustness, the out-of-sample backtesting is repeated with 9 blocks of sub-samples with 1-year trading periods.

Additionally, the relationship between the duration of the spread positions and the profitability of pairs trading is crucial. Therefore, in the presence of risk-controls, which is often the case in practice, the spread positions do not last for the whole maturity of futures contracts. For instance, if the pairs trading of two commodities has an average drawdown of 5%, this implies that on average for every spread position, the spread diverges 5% above the threshold that the position was opened. In the case that a stop-loss barrier of 3% exists, most of the time the stop-loss barrier is hit before realizing the mean-reversion and the profit. This drastically changes the profitability of pairs trading in practice. Furthermore, if the hedge funds are expected to act without risk-controls and they can exploit the so-called market inefficiency, this might not be a feasible expectation since a high leverage exists in the hedge fund industry and the highly possible maximum drawdown that they experience from the pairs trading might lead them to bankruptcy. Therefore, in order to test that argument, the out-of-backtesting is re-run with six different constraints on the maximum holding periods of each spread position with 10, 22, 44, 66, 126 and 252 trading days. By repeating the out-of-sample backtesting for the last trading year, the Sharpe ratio and the excess return/maximum drawdown are documented.

Figure 3.4 illustrates that the Sharpe ratio and the maximum drawdown normalized average returns obtained from pairs trading with 1, 2 and 3 best spread positions selected from the out-of-sample backtesting. It is displayed that the Sharpe ratio and maximum drawdown normalized returns decrease as the maximum holding periods are getting shorter. This affirms that if the spread position cannot be held for long periods of time, then the profitability decreases rapidly. Therefore, the high-profits that can be observed in the Chinese commodity futures market does not necessarily imply the inefficiency of the market.

[14] In backtesting analysis, there is no leveraged position assumed in line with the conservative approach followed in this study.

As a robustness check, the effect of different maximum holding positions for the spread trading is verified. In Table 3.7, the out-of-sample backtesting results for the last trading year are repeated for all the best six pairs from Table 3.5 with different maximum holding periods. Hence, the annual returns, the largest drawdown during each spread position and the maximum 1-year drawdown are calculated. The results in Table 3.7 confirm that as the maximum holding period of each spread position gets shorter, the profitability and annual return/average drawdown ratio are reduced. Overall, the same phenomenon is observed to occur in all the identified best pairs. Therefore, the relationship between the profitability and the maximum holding period for spreads is robust in time and across the different pairs that are considered.

Finally, the study constructs six different portfolios that consist of equally weighted investments in 1 to 6 different pairs that are identified from the combined criteria of correlation, SSD, and profit index ranking. The results in Table 3.8 are summarized as follows. The pairs that are identified as the best ones from the combined criteria of correlation, SSD and profit index indeed produce higher returns. In the case that the limitation of a shorter maximum duration is performed for each spread position, the profitability for pairs trading portfolios with a different number of pairs appears to have the same behavior in all cases. It can also be noted that the profitability of pairs trading in the Chinese commodity futures markets is at a similar level with the international markets. Studies such as Cummins and Bucca (2012) and Göncü and Akyıldırım (2016b) show that the pairs trading in international commodity markets can generate profits around 16% per year in the presence of transaction costs, and thus the Chinese market is an exception of the international markets in this sense.

Table 3.7: Out-of-sample backtesting results with the different maturity contracts

Pair	Measures	22-days	44-days	66-days	126-days	252-days
(WR-RB)	Annual Return	38.09%	42.34%	37.96%	37.96%	37.96%
JAN	Avg. Drawdown	5.31%	6.61%	7.24%	7.24%	7.24%
SHFE	Max. Drawdown	21.43%	21.43%	21.43%	21.43%	21.43%
	Annual Return / Avg. Drawdown	7.17	6.40	5.24	5.24	5.24
(WR-RB)	Annual Return	10.94%	18.04%	24.64%	24.64%	24.64%
MAR	Avg. Drawdown	5.91%	6.14%	6.14%	6.14%	6.14%
SHFE	Max. Drawdown	12.84%	12.84%	12.84%	12.84%	12.84%
	Annual Return / Avg. Drawdown	1.85	2.94	4.01	4.01	4.01
(WR-RB)	Annual Return	-10.37%	2.10%	3.96%	5.09%	5.09%
MAY	Avg. Drawdown	5.99%	8.85%	9.34%	10.07%	10.07%
SHFE	Max. Drawdown	23.20%	23.80%	45.10%	45.10%	45.10%
	Annual Return / Avg. Drawdown	-1.73	0.24	0.42	0.51	0.51
(WR-RB)	Annual Return	-9.78%	8.46%	9.48%	10.03%	10.03%
JULY	Avg. Drawdown	8.74%	8.99%	11.24%	11.24%	11.24%
SHFE	Max. Drawdown	17.11%	24.50%	24.50%	24.50%	24.50%
	Annual Return / Avg. Drawdown	-1.12	0.94	0.84	0.89	0.89
(WR-RB)	Annual Return	9.49%	20.19%	25.39%	25.39%	25.39%
SEP	Avg. Drawdown	10.07%	9.31%	12.09%	12.09%	12.09%
SHFE	Max. Drawdown	17.54%	21.64%	21.64%	21.64%	21.64%
	Annual Return / Avg. Drawdown	0.94	2.17	2.10	2.10	2.10
(PB-AL)	Annual Return	-5.26%	-3.15%	-4.68%	2.51%	6.38%
NOV	Avg. Drawdown	3.67%	6.36%	7.16%	9.07%	16.51%
SHFE	Max. Drawdown	15.09%	16.51%	16.51%	16.51%	16.51%
	Annual Return / Avg. Drawdown	-1.43	-0.49	-0.65	0.28	0.39

Notes: This table displays the out-of-sample backtesting results with different maturity contracts using the 2-stdev rule in the last one year as the out-of-sample period. Annual returns and average/maximum drawdown are calculated with different maximum holding periods for the spread positions. Annual returns divided by average drawdown are also given. The trading threshold calculation is based on the historical standard deviation $(2 - \sigma)$.

Table 3.8: Profitability of portfolios with different numbers of pairs

Profitability	1 pair	2 pairs	3 pairs	4 pairs	5 pairs	6 pairs
Panel A: Termination T=22						
Average Return (%)	8.94	8.13	6.95	5.79	5.28	4.44
Standard Deviation (%)	13.62	10.79	10.93	11.46	10.19	9.19
Standard Error (Newey-West) (%)	6.94	6.78	6.63	6.42	5.79	5.07
Sharpe Ratio	0.44	0.48	0.36	0.24	0.22	0.16
Return /Avg. Max.Drawdown	0.99	0.92	0.74	0.62	0.61	0.53
t-Statistics	1.29	1.20	1.05	0.90	0.91	0.88
p-Value	0.12	0.13	0.16	0.20	0.19	0.20
Median (%)	9.49	1.33	8.72	6.86	2.72	2.51
Skewness	0.28	0.43	0.31	0.43	0.53	0.88
Kurtosis	1.82	1.43	1.94	1.86	1.84	2.63
Minimum (%)	-6.82	-2.79	-5.23	-6.59	-5.04	-3.96
Maximum (%)	31.91	23.04	25.83	22.91	22.31	22.79
Negative Return	33%	33%	33%	44%	44%	44%
Panel B: Termination T=44						
Average Return (%)	14.85	12.32	10.14	8.97	8.83	7.97
Standard Deviation (%)	15.05	14.92	14.58	14.96	12.40	11.53
Standard Error (Newey-West) (%)	11.11	10.14	9.19	8.93	7.99	7.26
Sharpe Ratio	0.79	0.62	0.49	0.40	0.47	0.43
Return /Avg. Max.Drawdown	1.48	1.31	1.01	0.85	0.92	0.85
t-Statistics	1.34	1.21	1.10	1.01	1.11	1.10
p-Value	0.11	0.13	0.15	0.17	0.15	0.15
Median (%)	10.93	11.15	9.37	7.40	5.98	2.78
Skewness	0.19	0.50	0.45	0.44	0.38	0.53
Kurtosis	1.61	1.82	1.87	1.78	1.68	1.82
Minimum (%)	-3.92	-3.30	-6.49	-8.59	-5.05	-4.15
Maximum (%)	36.19	36.24	35.21	32.17	29.01	27.95
Negative Return	22%	44%	44%	44%	44%	44%
Panel C: Termination T=66						
Average Return (%)	15.43	13.04	10.17	9.44	9.45	8.49
Standard Deviation (%)	14.53	13.91	13.69	14.52	12.49	11.36
Standard Error (Newey-West) (%)	11.00	10.09	8.75	8.82	8.18	7.35
Sharpe Ratio	0.86	0.72	0.52	0.44	0.52	0.48
Return /Avg Max.Drawdown	1.54	1.23	0.94	0.85	0.94	0.87
t-Statistics	1.40	1.29	1.16	1.07	1.16	1.15
p-Value	0.10	0.12	0.14	0.16	0.14	0.14
Median (%)	11.17	14.67	8.64	7.42	6.00	3.01
Skewness	0.14	0.50	0.52	0.53	0.62	0.63
Kurtosis	1.44	1.95	1.92	1.83	1.99	1.89
Minimum (%)	-2.98	-2.98	-6.27	-7.82	-4.00	-3.28
Maximum (%)	36.19	36.24	33.75	31.08	31.07	28.24
Negative Return	11%	11%	33%	44%	33%	33%
Panel D: Termination T=126						
Average Return (%)	16.03	13.35	10.92	10.24	10.56	9.50
Standard Deviation (%)	13.85	13.50	13.77	14.67	12.52	11.79
Standard Error (Newey-West) (%)	11.05	10.05	9.11	9.22	8.63	7.87
Sharpe Ratio	0.94	0.77	0.58	0.49	0.60	0.55
Return /Avg Max.Drawdown	1.60	1.23	0.99	0.91	1.03	0.95
t-Statistics	1.45	1.33	1.20	1.11	1.22	1.21
p-Value	0.09	0.11	0.13	0.15	0.13	0.13
Median (%)	12.83	14.65	6.96	6.12	4.95	2.48
Skewness	0.19	0.52	0.46	0.48	0.57	0.62
Kurtosis	1.40	2.10	1.87	1.84	1.90	1.88
Minimum (%)	0.42	-3.80	-6.82	-8.23	2.93	2.39
Maximum (%)	36.19	36.24	33.75	32.74	32.42	30.28
Negative Return	0%	11%	11%	33%	11%	11%
Panel E: Termination T=252						
Average Return (%)	16.03	13.35	10.92	10.24	10.38	9.45
Standard Deviation (%)	13.85	13.50	13.77	14.67	12.60	11.81
Standard Error (Newey-West) (%)	11.05	10.05	9.11	9.22	8.58	7.87
Sharpe Ratio	0.94	0.77	0.58	0.49	0.59	0.55
Return /Avg. Max.Drawdown	1.60	1.23	0.99	0.91	1.00	0.94
t-Statistics	1.45	1.33	1.20	1.11	1.21	1.20
p-Value	0.09	0.11	0.13	0.15	0.13	0.13
Median (%)	12.83	14.65	6.96	6.12	4.95	3.40
Skewness	0.19	0.52	0.46	0.48	0.56	0.61
Kurtosis	1.40	2.10	1.87	1.84	1.89	1.89
Minimum (%)	0.42	-3.80	-6.82	-8.23	-2.93	-2.39
Maximum (%)	36.19	36.24	33.75	32.74	32.42	30.28
Negative Return	0%	11%	11%	33%	22%	22%

Notes: This table presents average annualized returns, standard deviations of returns and the Sharpe ratios calculated with the risk-free rate assumed as 3%. The t-statistic of the mean is computed using Newey-West standard errors with two lags. The result is calculated by repeating the out-of-sample backtesting for the 9 trading subperiods with respect to different maximum holding period. The trading threshold calculation is based on the historical standard deviation $(2-\sigma)$.

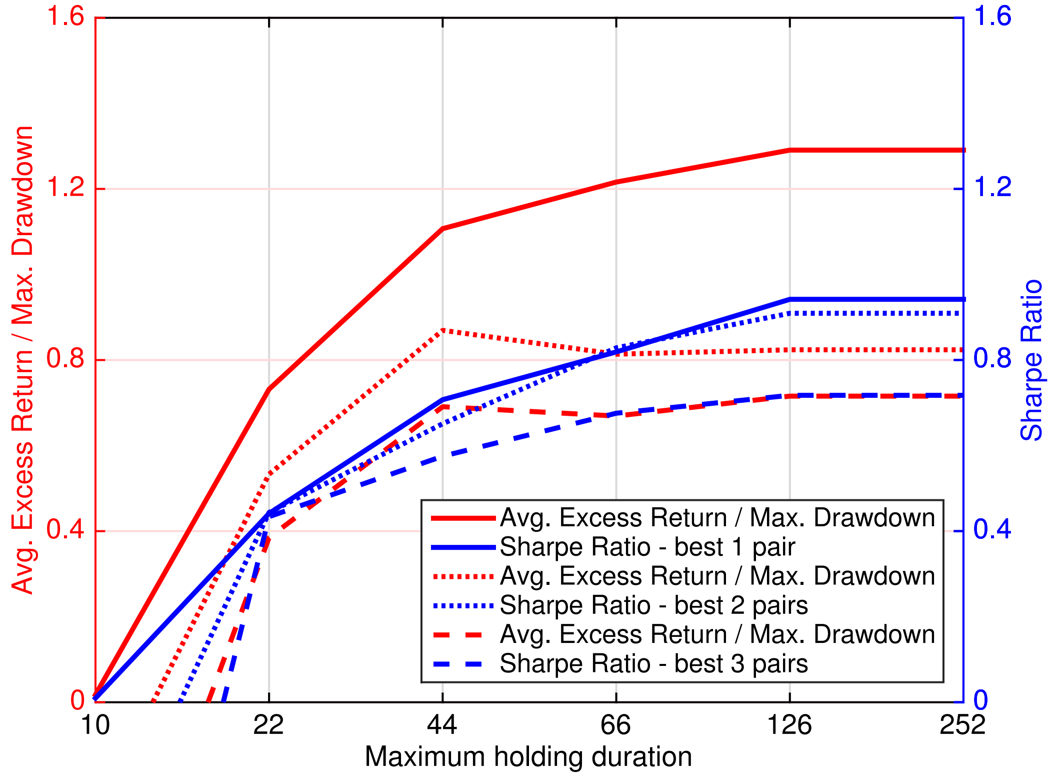

Figure 3.4: Risk-adjusted returns of pairs trading

Notes: This figure displays the risk-adjusted returns of pairs trading (assuming the risk-free rate as 3%) in terms of the Sharpe ratio and the average excess returns/maximum drawdown with respect to different numbers of pairs in the portfolio and maximum holding durations. The trading threshold calculation is based on the historical standard deviation ($2-\sigma$).

3.5 Summary

While the pairs trading strategy is well-documented for the stock markets (Gatev et al., 2006; Huck, 2009; Do and Faff, 2010), similar studies in commodity futures markets are rare. To the best of our knowledge, this study is the first one to connect the holding period and the maximum drawdown risk with the profitability of pairs trading strategies in the commodity futures markets. The superior pairs trading profits are generated when the investor does not have any stop-loss barriers, which enables him to hold the spread portfolio for long durations bearing the high-drawdown risk at the same period.

The results which are presented in this chapter verify the profitability of different pairs selection and pairs trading models for the Chinese commodity futures market. Several pairs trading models which have been suggested in the influential literature are compared in terms of the returns and risk-adjusted returns generated via in-sample and out-of-sample backtesting. There is evidence that the profitability of pairs trading decreases as shorter maximum holding periods are imposed for each spread position. Robustness of results is verified for different sub-periods and for considering a variety of portfolios of pairs. Pairs trading produces consistently high abnormal returns; however, at the same time there is high drawdown risk. Therefore, high pairs trading profits at least should not be taken for granted as a market anomaly or inefficiency. There exists a clear risk-return relationship when one accounts for the open positions in the spread trading and the potential drawdown during the holding period of the spread. If the trader is able to hold the spread position for very long periods of time withstanding high drawdown, then s/he can realize the pairs trading profits successfully. However, if the decrease in the value of the spread position during the long holding periods cannot be tolerated (for example, due to the stop-loss barriers), then the profitability of pairs trading decreases drastically, invalidating the market inefficiency arguments.

The result in this study is consistent with Gatev et al. (2006), which claim that the abnormal returns documented are a compensation for risk, in particular, the reward to arbitrageurs for enforcing the "Law of One Price". The rationale behind this theory is that if the two assets are statically correlated, any changes in the relationship are expected to be followed by a reversion to the long-term mean trend, creating a profit opportunity. Trading pairs is not a risk-free strategy, otherwise, the abnormal returns in pairs trading may imply the market inefficiency. Our findings have linked the profitability of pairs trading with a common factor (i.e., maximum holding period). The risk-adjusted return relationship is a significant complement to Gatev et al. (2006).

Theoretically speaking, the market activity increases the price of relatively undervalued assets and decreases the price of relatively overvalued assets, the pairs trading investors realize some excess returns in this process. However, the excess returns are not taken for granted as a market anomaly (i.e., risk-free), it is taken by bearing additional holding period risks. During the long holding periods, the investor needs to tolerate the risk of spread divergence (i.e., decreasing value of the spread position), the position may be closed forcefully by risk management tools (i.e., stop-loss barriers). Therefore, this study addressed, at least partially, the question raised in Gatev et al. (2006), there is a common factor can be linked to the profitability of pairs trading. Furthermore, it is demonstrated that the abnormal returns from statistical arbitrage (i.e., pairs trading) do not imply the market inefficiency.

Furthermore, the empirical comparison of pairs formation and trading models demonstrates that the 2-stdev rule performs quite well compared to the more sophisticated methods which are model-driven pairs trading. The identification of the best pairs is the primary determinant for the profitability of pairs trading, whereas the choice of the trade thresholds (triggers) can be based on simple rules based on the historical standard deviation of the spreading process.

Last but not least, this chapter verifies the practical value of the market analysis in the previous chapter, which shows that there are several pairs of futures products that are co-integrated in the Chinese futures market. The profitability of pairs trading affirms provides an empirical example for the cointegration feature. Moreover, the following chapter tests a wide range of momentum and reversal strategies. Meanwhile, accurate estimates of transaction costs and the high-frequency level data are utilized to provide the most realistic out-of-sample backtesting results.

Chapter 4

Momentum and Reversal Strategies with Commodity Futures

4.1 Introduction

Investment in futures is useful for asset allocation in terms of risk-hedging functions, the risk factors can be hedged by the futures market includes the inflation risk[1] and the systematic risk in stock or bond markets[2]. Meanwhile, futures markets provide lower transaction costs, more easily accessible for taking short positions and more flexibility in investment strategies than the stock markets[3]. Additionally, a number of studies document that investments in the futures markets can generate superior returns[4] in comparison to the equity markets. Normally, the dynamics of commodity markets

[1]See Bodie and Rosansky (1980), Bodie (1983), Bernard and Frecka (1987) and Rallis, Miffre, and Fuertes (2012) for details.

[2]See Gorton and Rouwenhorst (2006), Baur and McDermott (2010), Chong and Miffre (2010) and Daskalaki, Kostakis, and Skiadopoulos (2015) for details.

[3]There are several restrictions (i.e., maximum holding period) and much higher costs (i.e., commission fees) to take the short position in the stock market

[4]For instance, Shen et al. (2007), Miffre and Rallis (2007), Szakmary et al. (2010), Bianchi, Drew, and Fan (2015) and Fuertes, Miffre, and Perez (2015) report significant returns of the investment in the futures markets.

are significantly different from those of equity markets, which can be considered as a motivation for trading in this asset class as alternative investments (Gorton and Rouwenhorst, 2006; Daskalaki, Kostakis, and Skiadopoulos, 2015). Moreover, the empirical analysis in this study demonstrates that Chinese equity indices have no qualified explanatory power over the commodity futures returns.

The increasing popularity of global commodity markets cannot be explored independently from the rapidly expanding Chinese economy and its increasing demand for commodities. Currently, the Chinese commodity futures market consists of three exchanges in Shanghai, Dalian and Zhengzhou[5], and it has the largest volume around the world in the last years.[6] However, the vast majority of studies on the commodity futures markets and investment strategies focuses on the US and a few other developed countries. The existing literature reports that the long-short portfolios can capture the rates of returns as high as 20% per annum (depending on the sample period), which are based on various signals such as momentum, reversal, term-structure, hedging pressure and idiosyncratic.

Conrad and Kaul (1998) proposes that momentum and contrarian strategies are equally likely to be profitable in the financial markets. However, there is no consensus on whether the momentum returns may vanish when the transaction costs are considered (Lesmond, Schill, and Zhou, 2004; Korajcayk and Sadka, 2004). Locke and Venkatesh (1997) demonstrate that the transaction costs are lower relative to the minimum price changes in the futures market. Furthermore, Shen et al. (2007) and Szakmary et al. (2010) propose that momentum returns are statistically significant and large enough to cover transaction costs in commodity futures. Miffre and Rallis (2007) provide evidence to support the profitable of momentum strategies, while contrarian strategies do not work during that sample period. Moreover, Moskowitz, Ooi, and Pedersen (2012) illustrate that speculators profit from momentum at the expense of hedgers by determining the trading activities in multiple markets. Recently, Bianchi,

[5]More energy-related commodities will be traded in the Shanghai International Energy Exchange in the future.

[6]See 2015 WFE/IOMA Derivatives Market Survey reported by World Federation of Exchanges (WFE) and IOMA,"*the commodity options and futures traded in Shanghai and Dalian accounting for 50% of the volume traded in 2015 in terms of number of contracts*" (published, 2 April, 2015).

Drew, and Fan (2015) documented excess returns by implementing momentum and contrarian trading strategies simultaneously. Similarly, the superior performance of a novel triple-screening strategy based on the momentum, term-structure and idiosyncratic volatility signals is displayed in Fuertes, Miffre, and Perez (2015).

This study makes three contributions to the literature.

First of all, the vast majority of the existing studies focuses on the developed markets; however, it cannot be ignored that nowadays, China is not only the largest consumer of a wide range of commodities, but it also owns the commodity futures market with the largest volume globally in many products, such as aluminium, iron ore, soybean, sugar and so on. Therefore, the Chinese commodity futures market is worthy to be investigated due to its size, impact and future potential. To the best of our knowledge, this is the first study that utilizes the comprehensive Chinese futures data for exploring momentum and reversal strategies. Moreover, the complete and unique dataset for China includes the minute level high-frequency futures prices for all liquid contracts. There are many studies that consider high-frequency trading on equity markets (Carrion, 2013; Cartea and Jaimungal, 2013; Menkveld, 2013), whereas the high-frequency market data of commodity futures is not widely discussed so far. High frequency price data is often employed in the stock market micro-structure or in short-term stock return predictions. For example, the relationship between the first-half hour return and the last-half hour return is documented in (Heston, 2010; Bogousslavsky, 2016; Elaut et al., 2017), whereas Gao, Han, Li, and Zhou (2017) documents that the market timing strategy based on the correlation between the first and last half-hours returns can be exploited to generate consistent returns. However, in the commodity futures markets no other study provides a comprehensive analysis for the momentum and reversal type strategies utilizing both low and high frequency data.

Secondly, the data processing technique utilized in the literature has certain deviations from what it is utilized by the markets' practitioners, and it is not suitable for the Chinese futures markets. However, on contrary, the dataset of futures prices is constructed from the most actively traded contracts for each commodity in each trading day. Most of the literature, including (Miffre and Rallis, 2007; Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Szakmary et al., 2010; Basu and Miffre, 2013; Dewally, Ederington, and Fernando, 2013; Clare et al., 2014; Bianchi, Drew, and Fan, 2015; Fuertes, Miffre, and Perez, 2015), do not consider the fact that each commodity has its own characteristics in terms of the most preferred maturity months. In the existing literature, the first or the second nearest to maturity contract of the commodity futures exhibit the highest volume and open interests; therefore the literature rolls over positions in the current contract to the next nearest one to maintain a continuous exposure. Particularly, in the Chinese futures markets, the nearest to maturity contracts are not the most liquid ones; instead, there are few maturity month choices of the investors that are more distant in terms of the maturity date and rolls to another distant contract of the choice depending on the commodity.[7] Moreover, most of the academic literature ignores this phenomenon, and for convenience, the roll-over issue is handled uniformly across different commodities. Hence, different from existing literature, our out-of-sample backtesting results both at the inter- and intra-day trading are relatively free from this liquidity-related problem.[8]

On the other side, the transaction costs are accurately estimated one-by-one for each of the commodities traded in the Chinese commodity markets by considering the exact commission fees and the minimum tick changes of contracts. For instance, the minimum tick change may correspond to 5 basis points for one product, whereas it corresponds to 2 basis points in another product. The transaction costs are calculated by taking the summation of the minimum tick changes and the commission fees, which is in accordance with the industry's practice. The precise estimate of transaction costs demonstrates that the excess returns generated by high-intensive strategies vanish when the transaction cost is taken into account.[9] This is consistent with the

[7]For instance, in the Chinese commodity futures markets, "May" contracts are very active for many futures, such as iron ore or zinc, whereas towards April the most active contract for these commodities becomes the "September" contracts. On the other hand, in some commodities, it appears that in certain maturity months, their contracts are never the most active throughout the years. Therefore, the roll-over between different contracts changes the liquidity significantly.

[8]In accordance with the market practitioners, the best approach to constructing the futures prices in the backtesting analysis is to utilize the most active contract with respect to trading volume and open interest for each trading day.

[9]High-intensive strategies refer to multiple round-trip trades per day, which is called "high-frequency trading" as well.

earlier studies for stock markets (Lesmond, Schill, and Zhou, 2004; Korajcayk and Sadka, 2004) and index futures (Lee, 2015), while the excess profitability survives for the case of the low-frequency trading strategies that are often coupled with higher maximum drawdown during the longer holding periods.

Finally, existing studies on momentum and contrarian strategies normally focus on monthly or low-frequency intervals, while it is worthy to investigate these strategies on daily or high-frequency levels. Since futures are not general instruments for long-term buy-and-hold type strategies as it might be the case in the stock markets, momentum and contrarian type strategies in the futures markets are tested both at the inter- and intra-day time horizons in this chapter. Therefore, the performance of various long-short investment strategies based on the momentum and reversal signals both at the inter- and intra-day frequencies is explored, where the formation and holding periods can be in the order of days and minutes, respectively. Although the results display that the single- and double-sort momentum/reversal strategies generate excess returns, the profitability of different signals significantly vary with respect to the choice of formation and holding period. For the case of low-intensity trading strategies, our results illustrate the similar profitability as in Bianchi, Drew, and Fan (2015) and Fuertes, Miffre, and Perez (2015).

The remainder of this chapter is organised as follows. Section 4.2 introduces the dataset and data processing methodologies utilized in this study. Section 4.3 explains the various types of momentum and contrarian trading strategies and the backtesting results are documented in Section 4.4. In Section 4.5, various market factors are tested for potential explanatory power on the empirical performance of the trading strategies. In Section 4.6, the tests for the data snooping bias are presented, while the empirical performance is discussed in Section 4.7 when the transaction costs are considered. Finally, Section 4.8 summarizes the whole discussion.

4.2 Data

The dataset in this chapter includes the most recent history of the one-minute-level and daily open-close prices of main commodity futures contracts[10] traded in the *Dalian Commodity Exchange*(DCE), *Shanghai Futures Exchange*(SHFE), and *Zhengzhou Commodity Exchange*(CZCE) from May 3^{rd}, 2013 to September 26^{th}, 2017.[11] Trading time depends on each product and exchange, hence there are differences between commodities with respect to the data length for intra-day cases. For instance, some commodities have night trading and some others do not have, and the night trading hours for different products are not the same. For consistency, the dataset is constructed by the observations on the common trading hours among different products. Afterwards, the momentum/reversal strategies are implemented over the common trading hours. In fact, the common day trading hours are the same among different products, but there are three different night trading periods for SHFE, DCE, and CZCE. Table 4.1 and 4.2 present the key information about the commodity futures contracts included in this chapter. Table 4.1 summarises the market information for commodity futures contracts with high trading volume and Table 4.2 reports the descriptive statistics for the main contracts of each product. A few products are filtered out due to the low liquidity (trading volume), and the trading strategies are explored with the remaining 31 products.

[10] The main contract for each product is identified by the trading volume and open interest after the market closed every day. If the contract with the maximum trading volume is the same one with the maximum open interest, the underlying contract will be the main contract for the next trading day; otherwise, the contract with the further maturity month will be the main contract. The objective of this identification approach for main contract is to prevent the contract jump around during the roll-over periods.

[11] The data is obtained from JYB-Capital, which is a Chinese private fund company focusing on quantitative trading.

Table 4.1: Market information for high-liquidity commodity futures.

Commodity	Symbol	Exchange	Contract unit	Tick size	Commission Fee	Maturity months	Night trading	Last trading day	Start date
Copper	CU	SHFE	5T/H	10RMB/T	0.5%%	FGHJKMNQUVXZ	21:00-01:00	15th trading day	1993-03-01
Aluminium	AL	SHFE	5T/H	5RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	1992-05-28
Zinc	ZN	SHFE	5T/H	5RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2007-03-26
Nickel	NI	SHFE	1T/H	10RMB/T	6RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2015-03-27
Tin	SN	SHFE	1T/H	10RMB/T	3RMB	FGHJKMNQUVXZ	21:00-01:00	15th trading day	2015-03-27
Gold	AU	SHFE	1KG/H	0.05RMB/G	10RMB	FGHJKMNQUVXZ	21:00-02:30	15th trading day	2008-01-09
Silver	AG	SHFE	15KG/H	1RMB/KG	0.5%%	FGHJKMNQUVXZ	21:00-02:30	15th trading day	2012-05-10
Screw Steel	RB	SHFE	10T/H	1RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2009-03-27
Hot Rolled Coil	HC	SHFE	10T/H	1RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2014-03-21
Petroleum Asphalt	BU	SHFE	10T/H	2RMB/T	1%%	FGHJKMNQUVXZ	21:00-23:00	15th trading day	2013-10-09
Rubber	RU	SHFE	10T/H	5RMB/T	0.45%%	FHJKMNQUVX	21:00-23:00	15th trading day	1993-11-01
Corn	C	DCE	10T/H	1RMB/T	1.2RMB	FHKNUX	N/A	10th trading day	2004-09-22
Corn Starch	CS	DCE	10T/H	1RMB/T	1.5RMB	FHKNUX	N/A	10th trading day	2004-12-19
Soybean 1	A	DCE	10T/H	1RMB/T	2RMB	FHKNUX	21:00-23:30	10th trading day	2002-03-15
Soybean Meal	M	DCE	10T/H	1RMB/T	1.5RMB	FHKNQUXZ	21:00-23:30	10th trading day	2000-07-17
Soybean Oil	Y	DCE	10T/H	2RMB/T	2.5RMB	FHKNQUXZ	21:00-23:30	10th trading day	2006-01-09
Palm Oil	P	DCE	10T/H	2RMB/T	2.5RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2007-10-29
Egg	JD	DCE	5T/H	1RMB/500KG	1.5RMB	FGHJKMUVXZ	N/A	10th trading day	2013-11-08
Polythene	L	DCE	5T/H	5RMB/T	2RMB	FGHJKMNQUVXZ	N/A	10th trading day	2007-07-21
Polyvinyl Chloride	V	DCE	5T/H	5RMB/T	5RMB	FGHJKMNQUVXZ	N/A	10th trading day	2009-05-25
Polypropylene	PP	DCE	5T/H	1RMB/T	0.6%%	FGHJKMNQUVXZ	N/A	10th trading day	2014-02-28
Coke	J	DCE	100T/H	0.5RMB/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2011-04-15
Coal	JM	DCE	60T/H	0.5R/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2013-03-22
Iron Ore	I	DCE	100T/H	0.5R/T	0.6%%	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2013-10-18
Cotton	CF	CZCE	5T/H	5RMB/T	6RMB	FHKNUX	21:00-23:30	10th trading day	2004-06-01
Sugar	SR	CZCE	10T/H	1RMB/T	3RMB	FHKNUX	21:00-23:30	10th trading day	2006-01-06
PTA	TA	CZCE	5T/H	2RMB/T	3RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2006-12-18
Canola Oil	RO	CZCE	5T/H	2RMB	N/A	FHKNUX	N/A	10th trading day	2007-06-08
	OI	CZCE	10T/H	2RMB/T	2.5RMB	FHKNUX	N/A	10th trading day	2015-05-15
Methyl Alcohol	ME	CZCE	50T/H	1RMB	N/A	FGHJKMNQUVXZ	N/A	10th trading day	2011-10-28
	MA	CZCE	10T/H	1RMB/T	1.4RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2015-05-15
Glass	FG	CZCE	20T/H	1RMB/T	3RMB	FGHJKMNQUVXZ	21:00-23:30	10th trading day	2012-12-03
Rapeseed Dregs	RM	CZCE	10T/H	1RMB/T	1.5RMB	FHKNQUX	21:00-23:30	10th trading day	2012-12-28

Notes: The letter codes are F (January), G (February), H (March), J (April), K (May), M (June), N (July), Q (August), U (September), V (October), X (November) and Z (December). All commodity futures are traded in a general day trading period of 9:00-10:15, 10:30-11:30 and 1:30-15:00. Gold futures are traded with maturity in 3 nearest months and even months within 12 nearest months. Petroleum asphalt futures are traded with maturity in 6 nearest months and season contract within 24 nearest months.

Table 4.2: Summary statistics and transaction costs for commodity futures.

Sector	Symbol	Average price	Daily returns on long positions				Average trading value	Transaction Cost	
			Mean	Std. dev.	Skewness	Kurtosis	(RMB billions)	Tick size	Commission
Precious metals	AU	258.8601	-0.0001	0.0093	0.4755	5.5572	53.6726	0.0002	0.0000
	AG	3920.3371	-0.0003	0.0140	-0.0131	7.3669	65.8297	0.0003	0.0001
Industrial metals	CU	44655.4342	0.0001	0.0115	0.1940	7.0335	79.2388	0.0002	0.0001
	AL	13210.5784	0.0002	0.0093	0.2939	6.1828	8.9525	0.0004	0.0000
	ZN	16890.4673	0.0006	0.0124	-0.0495	6.2366	25.2109	0.0003	0.0000
	NI	81126.0855	-0.0005	0.0167	-0.1185	4.5260	50.3179	0.0001	0.0001
	SN	122022.8192	0.0002	0.0133	0.0467	4.0400	2.0167	0.0001	0.0000
	RB	2815.4062	0.0000	0.0167	0.1133	6.5141	118.7303	0.0004	0.0001
	HC	2781.6832	0.0004	0.0176	-0.0874	6.1317	6.5878	0.0004	0.0001
	I	534.3819	0.0000	0.0219	0.0120	4.2832	87.5495	0.0009	0.0001
Energy & Chemical	BU	2930.5451	-0.0011	0.0174	-0.4636	5.0852	16.7871	0.0007	0.0001
	RU	14562.2969	-0.0008	0.0195	-0.2342	4.5354	88.1007	0.0003	0.0000
	L	9659.9206	0.0005	0.0130	0.0371	4.9803	29.8671	0.0005	0.0000
	V	5908.8260	0.0002	0.0112	0.2165	5.7874	1.8101	0.0008	0.0002
	PP	8347.2027	0.0004	0.0144	0.0725	4.1113	24.4096	0.0001	0.0001
	J	1245.1891	0.0005	0.0191	0.0374	7.1051	46.8899	0.0004	0.0001
	JM	893.2435	0.0001	0.0193	-0.0221	5.9522	14.8655	0.0006	0.0001
	TA	5656.8430	-0.0004	0.0122	-0.3141	6.5694	30.4645	0.0004	0.0001
	MA	2321.1313	-0.0001	0.0158	-0.0128	4.2138	29.2722	0.0004	0.0001
	FG	1121.0560	0.0003	0.0137	0.1289	4.8585	11.6400	0.0009	0.0001
Agriculture	C	2032.8413	0.0001	0.0074	-0.0530	8.4764	8.0562	0.0005	0.0001
	CS	2192.2452	-0.0002	0.0113	0.0454	4.4317	7.0739	0.0005	0.0001
	A	4148.2099	-0.0002	0.0096	0.0574	6.8923	6.5052	0.0002	0.0000
	M	2957.9673	0.0003	0.0118	0.1771	4.6403	49.4562	0.0003	0.0001
	Y	6279.8710	-0.0003	0.0099	-0.0586	4.2288	35.2377	0.0003	0.0000
	P	5418.6461	-0.0001	0.0120	-0.0156	3.7701	37.3653	0.0004	0.0000
	JD	3999.2622	-0.0004	0.0129	0.0282	5.4563	7.1763	0.0003	0.0000
	CF	14972.7498	0.0000	0.0112	0.1099	7.5037	17.7454	0.0003	0.0001
	SR	5507.0720	0.0000	0.0092	0.3701	5.6606	40.5236	0.0002	0.0001
	OI	6582.5901	-0.0004	0.0099	-0.1205	5.0202	7.8476	0.0003	0.0000
	RM	2318.9524	0.0003	0.0139	-0.0841	4.4768	34.9451	0.0004	0.0001

Notes: Returns reported in this table are gross returns with one trading day interval from 2015-05-03 to 2017-09-26. No allowance is made for transaction costs associated with rolling over contracts. All commodities' daily returns indicate statistical significance at the 1% level in Jarque-Bera tests, which tests the null hypothesis that the returns are normally distributed. Trading value is the notional value of main contracts on an average minute, defined as the total number of contracts trade×futures price×contract units.

4.2.1 Data processing

In this study, trading strategies are explored both at the intra- and inter-day investment horizons. For the inter-day trading, the daily log returns[12] are calculated from the close to pre-close prices when there is no roll-over between contracts, whereas if there is a roll-over to another contract then the return is obtained from the open to close prices for those few roll-over days.[13] Normally, there are four roll-overs per annum for each product. This technique excludes the artificial roll-over returns in the backtesting of trading strategies, and it implies the most realistic situation for practitioners. Moreover, the illiquid commodity futures[14] with less than 200 trades on its main contract per day are filtered out.[15] In the high-frequency dataset, the intersection of trading times with all products is taken to construct the common timeline. Therefore, the log-returns for every minute is calculated from the minute-by-minute close prices, and the high-frequency data is free of roll-over effects.

The dataset construction technique utilized in this study provides a significant advantage over the current literature. In the previous studies, the date series are compiled by the "immediate roll" (Miffre and Rallis, 2007; Shen et al., 2007) or the "gradual roll" (Wang and Yu, 2004; Marshall et al., 2008) approaches. However, all these roll-over approaches are based on the strong assumption of liquidity, and they are decreased by the expiration date in the same way. Therefore, a potential problem raised is that the contracts actively traded in the market are not necessarily those that are used in the out-of-sample backtesting. Our technique avoids this problem by determining the trading volume and open interest at the end of each trading day, then the most actively traded contracts are selected in the out-of-sample backtesting, which provides the most realistic results. Finally, since the only official commodity futures index in China is recently launched (22 May, 2015), the benchmark is constructed by

[12] The log returns are considered to be consistent with previous studies such as (Shen et al., 2007; Szakmary et al., 2010), among others.

[13] This calculation technique is considered because the positions are closed by the end of the trading day and reopen at the next market open in the roll-over period.

[14] The threshold for filtering is not often exceeded, except for one or two commodities out of thirty-one

[15] The inclusion of illiquid products would create a distortion in the empirical results since the transaction costs estimated would not imply the reality for such products.

averaging the log returns of available commodities in each trading day in this study.

4.3 Trading Strategies

4.3.1 Single-sort strategies

A momentum strategy is a trading rule that buys the past winners and sells the past losers, whereby the justification is obtained from the historical data. On the other side, a reversal (contrarian) strategy buys the worst and sells the best performers again based on a historical ranking. Jegadeesh and Titman (1993) claim that the momentum trading is profitable in US stock markets although there is dependence on the setting of the formation and holding periods. This argument is supported by some of the following studies as well.[16]

In the existing momentum trading literature, all products are ranked based on their log-returns during the formation period, from the highest to the lowest ones (hereafter referred to as “winners”, “middle” and “losers” with respect to three terciles of historical performance). With the opposite direction, the portfolio is constructed by taking long positions on the winners (losers), whereas there is short selling of the losers (winners) in the momentum (reversal) strategies. In previous studies, the number of products included in the momentum/reversal portfolios was not uniform. For instance, Jegadeesh and Titman (1993) apply the quartiles and Bianchi, Drew, and Fan (2015) use one-sixth of the available products for the long and short positions, respectively. In this study, the first decile of the best and worst performers are selected from the sorted list of products[17], which yields three products each for the long and short side with a total of six futures in the portfolio.

As the commencement of each K “holding period”[18], all available products are ranked according to their performances in previous J intervals, i.e., during the

[16]See Asness et al. (2013) and Bianchi, Drew, and Fan (2015) for details.

[17]Generally, the performance of the strategy is approaching the market trend as increasing the number of commodities included in the portfolio.

[18]At the beginning of the holding period, the portfolio is constructed using the historical information and the same portfolio is held until the end of the holding period.

"formation period". The equal-weighted portfolio is constructed by the ranking criteria (momentum/reversal) and held until the new portfolio is formed at the end of the underlying holding period. The procedures from ranking to holding the products are repeated up to the termination of the backtesting period. In our backtesting, there are no skipped observations between the formation and holding periods for consistency with other studies.[19]

4.3.2 Double-sort strategies

This study implements a kind of double-screen technique to test the combing momentum and reversal strategies. In the double-sort strategies, products are ranked by a combination of various signals such as momentum, reversal, trading volume and so on. At the beginning, all products are ranked into three groups (i.e., winners, middle and losers) with respect to the first ranking criteria; then the commodities within each group are ranked again by the second criteria. Afterwards, the portfolio is constructed based on the final result of taking a long (short) position on the top (bottom) percentiles. In the existing literature, the double-sort strategies based on momentum/reversal signals combined with others are widely investigated. Lee and Swaminathan (2000) claim that the combing momentum and trading volume strategy performs well in the equity markets, while Bianchi, Drew, and Fan (2015) propose that combing the ranking on momentum and reversal as a double-sort strategy is profitable in the commodity futures markets. Fuertes, Miffre, and Perez (2015) show that idiosyncratic volatility can provide significant improvement for momentum trading. This study demonstrates a double-sort strategy by considering the momentum (reversal) as the first ranking criteria, and the reversal (momentum), trading volume and idiosyncratic volatility as the second sorting criteria.

At the beginning of each K holding period, all products are sorted into three groups according to their log-returns during the previous J formation periods.[20] Within each group, the products are ranked again based on the indicators in the

[19]See Bianchi, Drew, and Fan (2015) and the references therein for details.

[20]Ranking from highest to the lowest for the momentum-based strategies and from lowest to the highest for the reversal-based strategies.

previous I formation period based on the second signal, where these signals are briefly introduced as follows.

- *Reversal signal*: the commodities are sorted by their log-returns of a longer formation period. Therefore, the portfolio is constructed by taking long positions in short-term winners that are long-term losers and short positions in short-term losers that are long-term winners (Bianchi, Drew, and Fan, 2015). The profitability of reversal strategies are widely explored in the equity markets (Barberis et al., 1998; Daniel et al., 1998; Conrad and Kaul, 1998). However, few studies have investigated the excess return of contrarian strategies in the commodity futures literature, and most of them focus on the low-frequency (i.e. monthly) data (Shen et al., 2007; Bianchi, Drew, and Fan, 2015). This section of our study provides a comprehensive analysis of reversal signals both at inter- and intra-day level data.

- *Trading volume signal*: the commodities are sorted by their turnover ratios in the same period as single-sort momentum trading. Following Lee and Swaminathan (2000), the portfolio is constructed by taking long positions in the momentum winners with the low volume and short positions in the momentum losers with the high volume.[21] Lee and Swaminathan (2000) propose a momentum life cycle (MLC) framework to display the interaction between price momentum, reversals and trading volume in the stock market. This study attempts to validate the MLC framework in the Chinese commodity futures markets with low- and high-frequency data.

- *Idiosyncratic volatility signal*: the idiosyncratic volatility signal is defined following Fuertes, Miffre, and Perez (2015) as

$$r_{i,t} = \alpha_i + \beta_i B_t + \epsilon_{i,t}, \tag{4.1}$$

[21] Trading volume is defined as the average turnover during the portfolio formation period, where turnover is the ratio of the number of contracts traded each time interval to the close open interest of that commodity contract.

where $r_{i,t}$ is the return of the i^{th} commodity futures contract at time t, B_t is the benchmark index to denote the systematic risk premium, $\epsilon_{i,t}$ is the residual term, and (α_i, β_i) are parameters estimated by the least-squares regression repeatedly over the formation periods spanned by the rolling window.[22] Accordingly, the portfolio is constructed by taking long (short) positions in momentum winners (losers) with the lowest (highest) volatility, which is calculated as the residual standard deviation from the above time-series model. The idiosyncratic volatility signal, originated by Ang et al. (2006) and Ang et al. (2009), buying the stocks with low volatility and selling the stocks with high volatility. Fuertes, Miffre, and Perez (2015) propose that the triple-screening of signals including volatility are better able to diversify equity risk than the benchmark S&P-GSCI portfolio. Similarly, existing studies only consider the low-frequency data. Therefore, this study compensates the gap between the international and Chinese markets and the lack of high-frequency analysis.

The portfolio is constructed and held during the K holding period, which is similar to the single-sort strategies. Then the same procedure is repeated until the termination of the out-of-sample period.

4.4 Empirical Performance of Trading Strategies

Futures have frequent contract switch cycles due to expiration dates and liquidity. As mentioned in Section 4.2, lots of futures traders focus on the intra-day trade and clear positions by the end of each trading day in order to avoid the roll-over issue or overnight risk. Therefore, the profitability of trading strategies both at the intra- and inter-day trading horizons is explored for the first time in the commodities literature. This study documents a complete suite of performance that includes both the inter-

[22] The benchmark is constructed by the equal-weighted return of the actively traded commodity futures with the most liquid contracts. Furthermore, for the idiosyncratic volatility method we also considered the construction of the benchmark return by sectors, however, the results are similar and available upon request. For simplicity, we only present the result with the benchmark constructed from the equally weighted average return of all the commodity futures

and intra-day trading results for investigating the impact of the investment horizon.[23]

For the intra-day trading, two versions of the same strategies are investigated. Originally, the products are ranked based on the previous night's trading performance, and new positions are opened based on the next day's opening values. Alternatively, the total formation period of the first x minutes of the opening trading session is implemented for ranking the products. Afterwards, the investment portfolios are constructed by the rankings obtained from these two techniques with and without the overnight information. This methodology is implemented to determine whether the inclusion of overnight information together with the market opening values changes the performance of the trading strategies.

Table 4.3 demonstrates the profitability of eight single-sort momentum strategies with respect to different formation and holding periods. Panels A and B report the results of long- and short-side portfolios respectively, and Panel C records the long-short portfolio performances based on the momentum strategy. Additionally, Panel C displays that all single-sort momentum strategies generate positive returns and some are statistically significant. The long-short portfolios earn an average return of 0.62% per month (i.e., 7.44% per annum), over the 2013-2017 sample period, and the passive long-only benchmark that equally weights all commodities over the same periods returns 0.03% per month. Panels A and B demonstrate that the short portfolios earn on average a insignificant return of 0.30% per month. (i.e., 3.6% per annum), while the long sides capture an insignificant return of 0.93% per month. This observation illustrates the consistency with past studies on the commodity investment in other countries, as momentum returns are captured dominantly by the long position in China (Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Bianchi, Drew, and Fan, 2015). However, the skewness of returns in Panel C of Table 4.3 displays a major difference with Daniel and Moskowitz (2016). The momentum strategy exhibits positive skewness in the Chinese commodity futures markets, while other markets usually show negative skewness because of the so-called "momentum crashes" effect. Moreover, the momentum profits can be considered as the opposite

[23] Natural differences exist on the formation and holding period lengths for the intra- and inter-day trading, whereas the rest of the methodology is the same.

Table 4.3: Performance of inter-day trading with single-sort momentum strategies.

	$J = 5d$		$J = 10d$		$J = 15d$		$J = 20d$		Benchmark
	$K = 1d$	$K = 5d$	$K = 1d$	$K = 10d$	$K = 1d$	$K = 15d$	$K = 1d$	$K = 20d$	
Panel A: long portfolio									
Monthly Return	0.0020	-0.0014	0.0145	0.0064	0.0278	0.0061	0.0191	-0.0001	0.0003
t-Statistics	0.2323	-0.1541	1.3979	0.6981	1.5338	0.6855	1.3357	-0.0080	0.0476
Monthly Volatility	0.0582	0.0615	0.0717	0.0634	0.1257	0.0610	0.0982	0.0857	0.0448
Monthly Downside Volatility	0.0248	0.0273	0.0311	0.0299	0.0246	0.0281	0.0313	0.0515	0.0222
Reward/Risk Ratio	0.0335	-0.0222	0.2018	0.1008	0.2214	0.1000	0.1948	-0.0012	0.0069
Sortino ratio	0.0788	-0.0501	0.4658	0.2140	1.1312	0.2169	0.6113	-0.0020	0.0140
Skewness	0.6361	0.9028	1.3690	1.5267	4.3073	0.6933	1.9713	0.6672	0.5019
Kurtosis	2.8672	3.8631	5.9597	7.3149	25.2176	2.7490	7.7402	6.0156	3.2153
95% VaR	-0.0179	-0.0177	-0.0180	-0.0179	-0.0187	-0.0186	-0.0194	-0.0196	-0.0102
99% VaR(Cornish-Fisher)	-0.0254	-0.0271	-0.0277	-0.0268	-0.0297	-0.0289	-0.0296	-0.0280	-0.0151
% of positive days	0.4972	0.4953	0.5152	0.5047	0.5085	0.5077	0.5193	0.4874	0.4961
Maximum Drawdown	0.1335	0.1328	0.1774	0.1882	0.1389	0.1997	0.1788	0.2544	0.0938
Max month rolling return	0.2738	0.3027	0.3441	0.3535	0.8821	0.2758	1.1579	0.3719	0.1547
Min month rolling return	-0.1855	-0.1990	-0.1786	-0.2309	-0.1527	-0.2065	-0.1603	-0.2524	-0.1064
Panel B: short portfolio									
Monthly Return	-0.0015	-0.0021	-0.0018	0.0097	0.0013	0.0018	0.0099	0.0067	0.0003
t-Statistics	-0.1614	-0.2334	-0.1802	1.3513	0.1465	0.2341	1.0963	0.8188	0.0476
Monthly Volatility	0.0639	0.0613	0.0689	0.0500	0.0613	0.0531	0.0621	0.0552	0.0448
Monthly Downside Volatility	0.0483	0.0471	0.0711	0.0276	0.0439	0.0362	0.0365	0.0388	0.0222
Reward/Risk Ratio	-0.0233	-0.0337	-0.0260	0.1950	0.0212	0.0341	0.1599	0.1207	0.0069
Sortino ratio	-0.0308	-0.0439	-0.0252	0.3537	0.0295	0.0502	0.2718	0.1715	0.0140
Skewness	-0.6193	-0.5292	-2.1051	-0.4201	-0.3629	-0.1946	-0.0926	-0.2193	0.5019
Kurtosis	4.8037	4.4717	9.9447	2.3049	3.8295	3.3049	2.8343	3.7497	3.2153
95% VaR	-0.0169	-0.0175	-0.0166	-0.0180	-0.0163	-0.0170	-0.0167	-0.0176	-0.0102
99% VaR(Cornish-Fisher)	-0.0265	-0.0280	-0.0281	-0.0282	-0.0266	-0.0281	-0.0287	-0.0306	-0.0151
% of positive days	0.4801	0.4830	0.4896	0.5085	0.4763	0.4942	0.5000	0.5010	0.4961
Maximum Drawdown	0.2585	0.2533	0.3369	0.1404	0.2188	0.1488	0.1546	0.1686	0.0938
Max month rolling return	0.1824	0.1789	0.1486	0.1486	0.1510	0.1766	0.1607	0.1639	0.1547
Min month rolling return	-0.2809	-0.2855	-0.3659	-0.1522	-0.2673	-0.1723	-0.1749	-0.1729	-0.1064
Panel C: total portfolio									
Monthly Return	0.0002	-0.0017	0.0063	0.0081	0.0146	0.0040	0.0145	0.0033	0.0003
t-Statistics	0.0628	-0.3466	1.3975	1.8947	1.8145	0.9137	2.4486	0.6146	0.0476
Monthly Volatility	0.0257	0.0343	0.0314	0.0295	0.0556	0.0297	0.0407	0.0362	0.0448
Monthly Downside Volatility	0.0132	0.0260	0.0179	0.0167	0.0256	0.0185	0.0116	0.0255	0.0222
Reward/Risk Ratio	0.0091	-0.0500	0.2017	0.2735	0.2619	0.1333	0.3572	0.0906	0.0069
Sortino ratio	0.0176	-0.0661	0.3550	0.4841	0.5689	0.2135	1.2548	0.1287	0.0140
Skewness	0.0351	-0.5602	-0.0965	0.0403	2.3084	-0.1129	1.6677	-0.2790	0.5019
Kurtosis	2.4636	3.5668	3.1441	3.1622	14.0716	2.5462	6.7971	3.7645	3.2153
95% VaR	-0.0106	-0.0103	-0.0105	-0.0104	-0.0105	-0.0111	-0.0106	-0.0107	-0.0102
99% VaR(Cornish-Fisher)	-0.0158	-0.0158	-0.0150	-0.0158	-0.0159	-0.0161	-0.0172	-0.0170	-0.0151
% of positive days	0.5095	0.5000	0.5417	0.5256	0.5464	0.5126	0.5338	0.5116	0.4961
Maximum Drawdown	0.0756	0.1392	0.0832	0.0949	0.1078	0.0894	0.0776	0.1213	0.0938
Max month rolling return	0.1013	0.0944	0.1087	0.1279	0.3220	0.0848	0.5086	0.1211	0.1547
Min month rolling return	-0.1014	-0.1514	-0.1258	-0.0801	-0.1105	-0.0872	-0.1103	-0.0891	-0.1064

Notes: This table illustrates the performance of eight single-sort momentum strategies. Panel A reports a long (winners) portfolio, Panel B shows the short (loser) portfolio and Panel C summarizes the long-short (winners-losers) portfolio. J and K denote formation and holding periods, respectively. The Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

sign of the reversal returns. The results also demonstrate that the reversal signal cannot generate excess returns in the combination of different formation and holding periods. Therefore, the momentum strategy is applied as the basic signal in the double-sort strategies for the inter-day trading.

Table 4.4 illustrates the performance of double-sort strategies in contrast to the single-sort strategies. Panels A, B and C display the portfolio profits in the corresponding formation and holding periods, accordingly. The result suggests that all the double-sort strategies based on momentum and trading volume earn higher profits than the passive benchmark. The double-sort momentum-volume strategies, on average, capture a 0.53% p.mo. (i.e., 0.09% lower than the single-sort momentum). From the view of risk-adjusted returns, the average reward/risk ratio is higher than the single-sort strategy. Apparently, the trading volume as a second ranking signal improves the single-sort momentum strategy.

The double-sort momentum with trading volume strategies apparently exceeds the passive benchmark based on most of the reported risk measurements. Furthermore, this does not come at a cost of bearing additional risks. It is worth mentioning that in Panel C of Table 4.4, active strategies exhibit an average standard deviation of 3.17% p.mo. while that is 4.48% for the benchmark. In other words, active strategies can reduce risk and generate a higher return in comparison to the benchmark of average market returns. Moreover, the active strategies provide a lower 95% value-at-risk (VaR) of 0.88% compared to 1.02% with the benchmark based on the normality assumption, and 99% Cornish-Fisher VaR t 1.44% versus 1.51% when skewness and kurtosis are incorporated. The average reward/risk and Sortino ratios of active strategies are also superior compared to the passive benchmark.

Tables 4.5 and 4.6 display the performance of double-sort momentum strategies based on the reversal and idiosyncratic volatility as the second signal, accordingly. Table 4.5 records that the profit from inter-day momentum with reversal trading does not consistently improve the risk-adjusted returns compared to the single-sort.[24] For instance, the average long-short portfolio returns in the case of inter-day trading is

[24]For robustness reasons, 45 and 60 days are utilized as the formation periods of reversal signals as well, and the results are consistent and available upon request.

Table 4.4: Performance of inter-day trading for double-sort momentum and volume strategies.

	$J = 5d$		$J = 10d$		$J = 15d$		$J = 20d$		Benchmark
	$K = 1d$	$K = 5d$	$K = 1d$	$K = 10d$	$K = 1d$	$K = 15d$	$K = 1d$	$K = 20d$	
Panel A: long portfolio									
Monthly Return	0.0080	0.0011	0.0048	0.0025	0.0139	-0.0008	0.0046	0.0042	0.0003
t-Statistics	0.9954	0.1702	0.7544	0.3740	1.1817	-0.1189	0.4741	0.6336	0.0476
Monthly Volatility	0.0556	0.0431	0.0440	0.0455	0.0813	0.0443	0.0669	0.0452	0.0448
Monthly Downside Volatility	0.0198	0.0229	0.0242	0.0176	0.0214	0.0212	0.0279	0.0205	0.0222
Reward/Risk Ratio	0.1437	0.0246	0.1089	0.0540	0.1706	-0.0173	0.0692	0.0924	0.0069
Sortino ratio	0.4038	0.0462	0.1982	0.1394	0.6486	-0.0362	0.1656	0.2035	0.0140
Skewness	1.9024	1.0519	0.8372	1.5079	3.9720	0.6391	2.2047	0.6719	0.5019
Kurtosis	7.9109	5.4706	4.3236	6.0663	23.3124	3.7286	10.6733	3.2592	3.2153
95% VaR	-0.0105	-0.0118	-0.0118	-0.0119	-0.0122	-0.0120	-0.0128	-0.0125	-0.0102
99% VaR(Cornish-Fisher)	-0.0208	-0.0191	-0.0186	-0.0197	-0.0198	-0.0196	-0.0197	-0.0186	-0.0151
% of positive days	0.4896	0.4934	0.4962	0.4915	0.4981	0.4720	0.5000	0.4923	0.4961
Maximum Drawdown	0.1045	0.0986	0.0923	0.1046	0.1087	0.1329	0.1012	0.0939	0.0938
Max month rolling return	0.2667	0.2401	0.2509	0.2500	0.5484	0.1821	0.8634	0.1664	0.1547
Min month rolling return	-0.0985	-0.1221	-0.1123	-0.0881	-0.1500	-0.1140	-0.1083	-0.1012	-0.1064
Panel B: short portfolio									
Monthly Return	0.0033	0.0037	0.0000	0.0115	0.0030	0.0090	0.0025	0.0135	0.0003
t-Statistics	0.3062	0.3519	0.0019	1.4226	0.3055	0.9905	0.2268	1.2340	0.0476
Monthly Volatility	0.0743	0.0724	0.0815	0.0562	0.0677	0.0622	0.0742	0.0753	0.0448
Monthly Downside Volatility	0.0633	0.0488	0.0846	0.0352	0.0436	0.0349	0.0546	0.0379	0.0222
Reward/Risk Ratio	0.0442	0.0508	0.0003	0.2053	0.0441	0.1445	0.0331	0.1800	0.0069
Sortino ratio	0.0519	0.0754	0.0003	0.3276	0.0685	0.2571	0.0450	0.3576	0.0140
Skewness	-0.9972	-0.2776	-2.2849	-0.4045	-0.1166	0.0105	-0.4740	-0.0575	0.5019
Kurtosis	5.9449	3.3634	11.6806	2.5783	3.8405	2.8203	3.1240	2.5156	3.2153
95% VaR	-0.0177	-0.0179	-0.0185	-0.0183	-0.0180	-0.0187	-0.0174	-0.0177	-0.0102
99% VaR(Cornish-Fisher)	-0.0308	-0.0295	-0.0320	-0.0305	-0.0303	-0.0320	-0.0293	-0.0309	-0.0151
% of positive days	0.4962	0.5028	0.5019	0.5208	0.5047	0.5077	0.5068	0.5126	0.4961
Maximum Drawdown	0.2871	0.1938	0.4327	0.1283	0.2664	0.1742	0.2306	0.1782	0.0938
Max month rolling return	0.2000	0.2404	0.2113	0.1706	0.1711	0.1761	0.1695	0.1797	0.1547
Min month rolling return	-0.3043	-0.2576	-0.4321	-0.1555	-0.3114	-0.1742	-0.5275	-0.1937	-0.1064
Panel C: total portfolio									
Monthly Return	0.0056	0.0024	0.0024	0.0070	0.0084	0.0041	0.0035	0.0089	0.0003
t-Statistics	1.1911	0.4767	0.4577	2.0049	1.6628	1.0013	0.8274	1.8192	0.0476
Monthly Volatility	0.0328	0.0344	0.0364	0.0242	0.0351	0.0281	0.0293	0.0334	0.0448
Monthly Downside Volatility	0.0235	0.0290	0.0432	0.0147	0.0229	0.0175	0.0224	0.0182	0.0222
Reward/Risk Ratio	0.1719	0.0688	0.0661	0.2894	0.2400	0.1461	0.1207	0.2654	0.0069
Sortino ratio	0.2401	0.0818	0.0556	0.4760	0.3681	0.2342	0.1583	0.4881	0.0140
Skewness	-0.5613	-1.1360	-3.0062	-0.1214	0.4996	-0.2232	-0.6938	0.1066	0.5019
Kurtosis	4.5384	6.5003	16.4368	3.0004	6.6801	3.2889	4.1165	2.6571	3.2153
95% VaR	-0.0086	-0.0086	-0.0087	-0.0088	-0.0087	-0.0090	-0.0092	-0.0088	-0.0102
99% VaR(Cornish-Fisher)	-0.0145	-0.0145	-0.0151	-0.0144	-0.0143	-0.0143	-0.0140	-0.0143	-0.0151
% of positive days	0.5284	0.4991	0.5009	0.5133	0.5284	0.5087	0.5087	0.5145	0.4961
Maximum Drawdown	0.1100	0.1304	0.2037	0.0828	0.1032	0.0790	0.0944	0.0723	0.0938
Max month rolling return	0.0980	0.0922	0.0917	0.0863	0.1468	0.0776	0.1702	0.0958	0.1547
Min month rolling return	-0.1167	-0.1554	-0.1916	-0.0597	-0.1178	-0.0766	-0.1138	-0.0651	-0.1064

Notes: This table illustrates the performance of eight double-sort momentum strategies with trading volume as the second signal. Panel A reports a long (winners with low volume) portfolio, Panel B shows the short (losers with high volume) portfolio and Panel C summarizes the long-short portfolio. J and K denote formation and holding periods. J and K denote the formation and holding periods, respectively. The Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

Table 4.5: Performance of inter-day trading for double-sort momentum and reversal strategies.

	$J = 5d$		$J = 10d$		$J = 15d$		$J = 20d$		Benchmark
	I=30d								
	$K = 1d$	$K = 5d$	$K = 1d$	$K = 10d$	$K = 1d$	$K = 15d$	$K = 1d$	$K = 20d$	
Panel A: long portfolio									
Monthly Return	-0.0020	0.0003	0.0008	0.0026	0.0071	0.0081	0.0065	-0.0064	0.0003
t-Statistics	-0.2504	0.0348	0.1081	0.4000	0.8635	1.1617	0.6765	-0.9074	0.0476
Monthly Volatility	0.0538	0.0507	0.0526	0.0446	0.0563	0.0480	0.0660	0.0485	0.0448
Monthly Downside Volatility	0.0250	0.0311	0.0284	0.0276	0.0299	0.0263	0.0217	0.0289	0.0222
Reward/Risk Ratio	-0.0365	0.0051	0.0158	0.0584	0.1260	0.1695	0.0987	-0.1324	0.0069
Sortino ratio	-0.0786	0.0083	0.0292	0.0943	0.2369	0.3098	0.2997	-0.2216	0.0140
Skewness	1.2363	0.2549	0.3055	-0.2631	1.4715	0.0302	3.5214	0.1603	0.5019
Kurtosis	5.4860	4.1442	2.9311	2.6006	9.9353	2.7764	20.6507	3.1636	3.2153
95% VaR	-0.0151	-0.0141	-0.0150	-0.0156	-0.0150	-0.0143	-0.0147	-0.0153	-0.0102
99% VaR(Cornish-Fisher)	-0.0233	-0.0222	-0.0217	-0.0250	-0.0234	-0.0235	-0.0214	-0.0223	-0.0151
% of positive days	0.4903	0.5097	0.5068	0.5010	0.5135	0.5184	0.5116	0.4671	0.4961
Maximum Drawdown	0.1215	0.1375	0.1214	0.1033	0.1304	0.1199	0.1129	0.1267	0.0938
Max month rolling return	0.2905	0.1813	0.1869	0.1392	0.3519	0.1671	0.4924	0.1628	0.1547
Min month rolling return	-0.1567	-0.1403	-0.1440	-0.1358	-0.1325	-0.1392	-0.1396	-0.1685	-0.1064
Panel B: short portfolio									
Monthly Return	-0.0146	-0.0027	-0.0167	0.0020	-0.0094	0.0050	-0.0042	0.0004	0.0003
t-Statistics	-1.0299	-0.3669	-1.2003	0.3198	-0.8674	0.6495	-0.4259	0.0528	0.0476
Monthly Volatility	0.0970	0.0509	0.0952	0.0439	0.0746	0.0530	0.0671	0.0497	0.0448
Monthly Downside Volatility	0.1228	0.0422	0.1088	0.0313	0.0818	0.0360	0.0669	0.0343	0.0222
Reward/Risk Ratio	-0.1502	-0.0535	-0.1751	0.0467	-0.1265	0.0947	-0.0621	0.0077	0.0069
Sortino ratio	-0.1186	-0.0645	-0.1533	0.0654	-0.1154	0.1393	-0.0623	0.0111	0.0140
Skewness	-4.4401	-0.9092	-4.7717	-0.3048	-3.4009	0.0036	-2.2854	0.4444	0.5019
Kurtosis	27.1615	4.2234	30.1006	3.0437	19.4989	3.6157	11.9759	5.2027	3.2153
95% VaR	-0.0162	-0.0176	-0.0166	-0.0146	-0.0146	-0.0136	-0.0136	-0.0132	-0.0102
99% VaR(Cornish-Fisher)	-0.0248	-0.0274	-0.0244	-0.0252	-0.0233	-0.0236	-0.0231	-0.0212	-0.0151
% of positive days	0.5097	0.4913	0.4836	0.4952	0.4932	0.5010	0.4816	0.5048	0.4961
Maximum Drawdown	0.6446	0.1413	0.6257	0.1281	0.4408	0.1465	0.3548	0.1316	0.0938
Max month rolling return	0.1144	0.1976	0.1409	0.1287	0.1619	0.1795	0.1406	0.1823	0.1547
Min month rolling return	-0.8342	-0.2235	-0.8023	-0.1656	-0.5680	-0.1454	-0.4567	-0.1580	-0.1064
Panel C: total portfolio									
Monthly Return	-0.0083	-0.0012	-0.0079	0.0023	-0.0012	0.0066	0.0012	-0.0030	0.0003
t-Statistics	-1.4275	-0.2851	-1.3336	0.7558	-0.2800	1.4994	0.3452	-0.7359	0.0476
Monthly Volatility	0.0397	0.0297	0.0407	0.0211	0.0287	0.0301	0.0233	0.0281	0.0448
Monthly Downside Volatility	0.0377	0.0210	0.0453	0.0113	0.0207	0.0185	0.0161	0.0173	0.0222
Reward/Risk Ratio	-0.2082	-0.0416	-0.1945	0.1102	-0.0408	0.2187	0.0504	-0.1073	0.0069
Sortino ratio	-0.2193	-0.0586	-0.1750	0.2051	-0.0568	0.3550	0.0731	-0.1744	0.0140
Skewness	-2.2834	-0.4346	-3.7113	-0.0209	-0.2998	-0.2839	-0.4290	0.2450	0.5019
Kurtosis	12.9290	3.1153	20.7631	3.0608	3.5024	2.4521	2.9191	3.2138	3.2153
95% VaR	-0.0090	-0.0089	-0.0086	-0.0079	-0.0080	-0.0075	-0.0075	-0.0076	-0.0102
99% VaR(Cornish-Fisher)	-0.0126	-0.0136	-0.0124	-0.0121	-0.0125	-0.0126	-0.0127	-0.0114	-0.0151
% of positive days	0.4826	0.4990	0.4797	0.5290	0.5087	0.5271	0.5019	0.4826	0.4961
Maximum Drawdown	0.2101	0.0697	0.2399	0.0473	0.0835	0.0709	0.0517	0.0828	0.0938
Max month rolling return	0.0768	0.0911	0.0600	0.0592	0.0746	0.0878	0.0594	0.0688	0.1547
Min month rolling return	-0.2719	-0.0839	-0.3077	-0.0599	-0.1081	-0.0708	-0.0708	-0.0784	-0.1064

Notes: This table illustrates the performance of eight double-sort momentum strategies with reversal signals. Panel A and B show the long and short portfolios, respectively, while Panel C summarizes the long-short portfolio. J and I denote the formation period of the first signal (momentum) and the second signal (reversal), respectively. The Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

Table 4.6: Performance of inter-day trading for double-sort momentum and idiosyncratic volatility strategies.

	$J = 5d$		$J = 10d$		$J = 15d$		$J = 20d$		Benchmark
	$K = 1d$	$K = 5d$	$K = 1d$	$K = 10d$	$K = 1d$	$K = 15d$	$K = 1d$	$K = 20d$	
Panel A: long portfolio									
Monthly Return	0.0022	0.0038	0.0050	0.0051	0.0108	0.0063	0.0022	0.0079	0.0003
t-Statistics	0.3267	0.5754	0.7480	0.7402	1.3812	0.9083	0.2854	1.3372	0.0476
Monthly Volatility	0.0461	0.0460	0.0464	0.0474	0.0543	0.0476	0.0539	0.0407	0.0448
Monthly Downside Volatility	0.0252	0.0279	0.0195	0.0160	0.0219	0.0245	0.0298	0.0194	0.0222
Reward/Risk Ratio	0.0471	0.0831	0.1080	0.1068	0.1994	0.1325	0.0416	0.1950	0.0069
Sortino ratio	0.0862	0.1372	0.2568	0.3167	0.4936	0.2576	0.0752	0.4083	0.0140
Skewness	0.2019	0.1783	1.4498	3.6570	1.2795	0.6562	0.7670	0.3995	0.5019
Kurtosis	2.4824	4.0045	5.5115	20.7074	4.7413	3.5944	5.0512	2.9766	3.2153
95% VaR	-0.0132	-0.0137	-0.0115	-0.0110	-0.0112	-0.0121	-0.0119	-0.0116	-0.0102
99% VaR(Cornish-Fisher)	-0.0207	-0.0206	-0.0196	-0.0177	-0.0186	-0.0200	-0.0181	-0.0180	-0.0151
% of positive days	0.4915	0.4858	0.4991	0.4839	0.5038	0.4894	0.5039	0.5019	0.4961
Maximum Drawdown	0.0948	0.1052	0.0792	0.0801	0.0983	0.1154	0.0991	0.0833	0.0938
Max month rolling return	0.2097	0.1760	0.2667	0.3043	0.2698	0.2292	0.3533	0.1695	0.1547
Min month rolling return	-0.1545	-0.1764	-0.1019	-0.1037	-0.1216	-0.1280	-0.1278	-0.0832	-0.1064
Panel B: short portfolio									
Monthly Return	0.0029	0.0008	-0.0078	0.0079	0.0003	0.0053	-0.0003	0.0070	0.0003
t-Statistics	0.3286	0.0880	-0.6709	1.1030	0.0378	0.5802	-0.0288	0.6620	0.0476
Monthly Volatility	0.0605	0.0654	0.0801	0.0499	0.0628	0.0630	0.0741	0.0720	0.0448
Monthly Downside Volatility	0.0485	0.0441	0.0855	0.0317	0.0473	0.0391	0.0457	0.0536	0.0222
Reward/Risk Ratio	0.0474	0.0127	-0.0968	0.1592	0.0055	0.0846	-0.0042	0.0966	0.0069
Sortino ratio	0.0592	0.0188	-0.0907	0.2503	0.0073	0.1364	-0.0068	0.1297	0.0140
Skewness	-0.6965	-0.1538	-2.7636	-0.1495	-0.4062	-0.1082	-0.2437	-0.5078	0.5019
Kurtosis	3.7953	3.3821	15.2417	3.1573	4.5598	3.3728	3.3103	3.0765	3.2153
95% VaR	-0.0174	-0.0174	-0.0183	-0.0186	-0.0188	-0.0185	-0.0189	-0.0192	-0.0102
99% VaR(Cornish-Fisher)	-0.0305	-0.0280	-0.0307	-0.0296	-0.0291	-0.0307	-0.0301	-0.0331	-0.0151
% of positive days	0.4962	0.4953	0.4848	0.5038	0.5028	0.5126	0.4816	0.4942	0.4961
Maximum Drawdown	0.1885	0.1980	0.4656	0.1307	0.2906	0.1660	0.1807	0.1863	0.0938
Max month rolling return	0.1729	0.2335	0.1847	0.1526	0.2154	0.2276	0.2021	0.2005	0.1547
Min month rolling return	-0.2370	-0.2453	-0.4571	-0.1394	-0.3393	-0.1929	-0.4567	-0.2071	-0.1064
Panel C: total portfolio									
Monthly Return	0.0025	0.0023	-0.0014	0.0065	0.0056	0.0058	0.0010	0.0074	0.0003
t-Statistics	0.6404	0.5504	-0.2439	1.9306	1.2694	1.3772	0.2474	1.4918	0.0476
Monthly Volatility	0.0273	0.0293	0.0390	0.0233	0.0305	0.0290	0.0267	0.0342	0.0448
Monthly Downside Volatility	0.0161	0.0212	0.0438	0.0133	0.0198	0.0132	0.0186	0.0226	0.0222
Reward/Risk Ratio	0.0924	0.0794	-0.0352	0.2787	0.1832	0.2009	0.0361	0.2176	0.0069
Sortino ratio	0.1566	0.1096	-0.0313	0.4879	0.2814	0.4401	0.0520	0.3293	0.0140
Skewness	-0.4534	-0.4799	-3.1832	0.2886	-0.1704	0.4136	-0.1871	-0.3370	0.5019
Kurtosis	3.0464	3.5145	17.9091	4.0531	3.7256	3.0158	3.9713	3.1933	3.2153
95% VaR	-0.0087	-0.0086	-0.0088	-0.0084	-0.0083	-0.0088	-0.0094	-0.0091	-0.0102
99% VaR(Cornish-Fisher)	-0.0151	-0.0135	-0.0144	-0.0138	-0.0138	-0.0151	-0.0143	-0.0155	-0.0151
% of positive days	0.4981	0.5114	0.4811	0.5028	0.5227	0.5164	0.4971	0.5203	0.4961
Maximum Drawdown	0.0943	0.0967	0.2256	0.0561	0.0987	0.0815	0.0614	0.0938	0.0938
Max month rolling return	0.0803	0.0654	0.0749	0.0948	0.1156	0.0923	0.0859	0.0918	0.1547
Min month rolling return	-0.1302	-0.1093	-0.2131	-0.0591	-0.1186	-0.0960	-0.1015	-0.0951	-0.1064

Notes: This table illustrates the performance of eight double-sort momentum strategies with idiosyncratic volatility as the second signal. Panel A reports a long (winners with low volatility) portfolio, Panel B shows the short (losers with high volatility) portfolio and Panel C summarizes the long-short portfolio. J and K denote the formation and holding periods. The Sortino ratio is benchmarked at 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

0.68% p.mo. (i.e., 8.16% p.a.), while with the double-sort strategy of momentum and reversal signals has -0.14% as the average return p.mo.. Similarly, for the long-only (or short-only) double-sort with reversal signal, it does not improve the excess returns from the single-sort strategy. Additionally, if the double-sort strategy is practised with the idiosyncratic volatility signal, the average monthly return is 0.37% p.mo. (i.e., 4.44% p.a.), whereas the long-only strategy yields 0.54% p.mo. (i.e., 6.48% p.a.) on average.

Comparing Tables 4.5 and 4.6, it is observed that the double-sort strategy with volatility signal improves the performance of the double-sort strategy with the reversal signal. In the case of the double-sort with the idiosyncratic volatility, the average returns, the standard deviation of the trading returns and the risk/reward ratios are often lower relative to the single-sort strategies. Momentum and reversal strategies are usually investigated with daily or monthly data in the existing literature. It supports that the overreaction/underreaction of new information is general in the financial markets at different timescales. For instance, De Bondt and Thaler (1985) and Jegadeesh and Titman (1993) display that momentum/reversal strategies generate excess returns consistently in the US stock market with various time horizons for the formation and holding periods, while Bianchi, Drew, and Fan (2015) characterize different holding and formation periods with the same type of strategies for the international commodity futures markets. To sum up, the attitude in digesting the new information is not uniform for different markets or asset classes. This study makes a contribution to current literature by applying the intra-day date for exploring the momentum/reversal trading strategies.

4.4.1 Intra-day trading with overnight information

In the intra-day momentum/reversal trading strategies part, two types of backtesting frameworks are implemented with and without overnight information. In the first framework, all the products are ranked by their performance in the first J minutes of the trading session at 9:00 am, while the formation period includes the overnight information (previous trading day's data) in the second framework. Specifically, if the product returns are calculated from last J intervals data (i.e., in the common timeline) until the market open of the following trading day as the starting point of the out-of-sample backtesting, and repeat the ranking until the termination of the current trading day. Under this circumstance, the inclusion of the overnight information is implemented for determining whether any significant difference in the backtesting of the momentum/reversal strategies is created.

In Tables 4.7, 4.8, 4.9 and 4.10, the results with and without the overnight information are documented one next to each other. In Table 4.7, the inclusion of the overnight information improves the profitability in 11 out of 12 cases of the strategies considered with the only exception at the 60-minute formation period for the long-only portfolio. Additionally, in Table 4.8, the double-sort strategy with the overnight information included yields better results in all the 12 different trading strategies considered. In Table 4.9, the same observation is valid with one exception of the 60-minute formation period in the long-only strategy. Finally, in Table 4.10, the only exceptions are in the 30- and 60-minute formation periods in the long-only strategy. The exception occurs in the 60-minute formation period, which shows that as the morning sessions' formation periods get longer, the importance of the yesterday's overnight information decreases. This is intuitively clear since most financial news in China is announced at either 9:30 a.m., 9:45 a.m. or 10:00 a.m. including the official news on foreign trades, inflation, and PMI. Thus, it is quite natural to observe that the inclusion of overnight information improves the profitability of the formation periods up to 9:30 a.m. or 9:45 a.m. at most. Overall, our results verify the intuitive fact that the inclusion of the overnight trading hours in the ranking of the futures contracts' returns improves the profitability of all types of strategies considered. High profitability of the trading strategy with overnight information possibly be explained by that the financial information arrival from the overseas market affect the commodity futures prices when the domestic news is absent.

4.4.2 Performance of the single- and double-sort strategies

Across the universe of active strategies based on single- and double-sort momentum/reversal signals discussed both with the inter-day and intra-day trading, the active investment portfolio outperforms the passive benchmark in almost all of the cases from the view of risk-adjusted returns. The average reward/risk ratio of active strategies is 0.78 p.mo., while that of the benchmark is only -0.25. Even if the investor can forecast the market direction successfully in this sample period, the benchmark earns a Sharpe ratio of 0.25 for the short-only position.

The performance of intra-day trading with respect to different strategies is reported in Tables 4.7, 4.8, 4.9 and 4.10, respectively. Several points are worth highlighting when comparing the results of inter-day strategies. Within the class of active single- and double-sort momentum/reversal strategies, the best performance is obtained at the intra-day trading ($J = 10m$, $K = 10m$ case) with the single-sort reversal signal, where the monthly average profit is 3.78% as reported in Table 4.7. In the comparison of Tables 4.3 and 4.7, the improvement in the intra-day trading case is observed clearly. Interestingly, the single-sort momentum strategy in the intra-day trading is positive, whereas the reversal single-sort strategy provides excess returns consistently in the case of intra-day trading. In other words, for the inter-day horizon past winners (losers) continue to perform well (badly) in the holding period; however, for the intra-day horizon the winners (losers) of the last 10 minutes perform worse (better) in the next 10 minutes of the holding period. Therefore, the opposite trading strategy based on the contrarian position is implemented.

According to Table 4.7, all active strategies based on the reversal signal generate much higher returns compared to the passive benchmark while the active strategies only bear the limited additional risk for the excess returns. On average, the monthly standard deviation of the double-sort strategies with volume is 2.79% compared to the 2.40% of the passive benchmark. Furthermore, the 95% VaR (normality assumption) and the 99% VaR (Cornish-Fisher) of active strategies are lower than the passive benchmark. This demonstrates that an investor may capture excess profits from strategies based on reversal signals with bearing a limited higher level of risk.

For both the single- and double-sort strategies, it is important to mention that intra-day trading performs better than the inter-day trading from the view of returns. Tables 4.8 and 4.10 illustrate that trading volume and idiosyncratic volatility as the second-ranking signal improve the performance of the reversal strategies in a few cases with long formation periods. Table 4.9 demonstrates that the momentum as the second sort signal does not improve the reversal returns, which might be intuitive since the combing momentum and reversal trading strategies are only valid in specific data frequencies.[25] This observation is consistent with the inter-day trading, which concludes that combing momentum and reversal strategy does not work in this case.

It is obvious that the single-sort with reversal strategy provides higher profit than the double-sort strategy in the comparison of Tables 4.7, 4.8 and 4.10. Overall, the average monthly returns of single-sort reversal strategies are 1.36% (16.32% p.a.) compared to the 1.09% (13.08% p.a.) and 1.16% (13.92% p.a.) for the double-sort strategies with volume and volatility, respectively. Apparently, the single-sort strategies bear higher risks compared to the double-sort strategies. For instance, the monthly standard deviation of the single-sort strategies increases substantially to 2.91% (10.08% p.a.), which is higher than double-sort strategies with volume and volatility at 2.79% (9.66% p.a.) and 2.47% (8.56% p.a.), respectively. Similarly, the 95% VaR (normality assumption) and the 99% (Cornish-Fisher) provide the consistent observation, which demonstrates that the single-sort reversal strategies do bear additional risks. However, the additional risks involved in the single-sort strategies are not fully rewarded by the market. This is implied with respect to the Sortino ratios. The annual Sortino ratios for the double-sort strategies are superior to single-sort strategies (1.26, on average, for double-sort with volume, 3.30 for double-sort with volatility and 1.34 for single-sort reversal.) From a risk-adjusted view with downside volatility, double-sort strategies with volatility are the most successful investment strategies, which generate the highest monthly return of 2.58% (30.96% p.a.), the average monthly return of 1.16% (13.92% p.a.), the highest monthly Sortino ratio of 3.35 (11.60 p.a.) and the average monthly Sortino ratio of 0.95 (3.30 p.a.), within the universe of active investment strategies considered.

[25] See Bianchi, Drew, and Fan (2015) for details.

From the comparison of inter-day and intra-day trading, the following findings can be summarized. At first, the momentum signal provides excess returns in the inter-day trading and the reversal effect wins extra profits in the intra-day case. This result indicates that the momentum and reversal effect earns excess returns in different investment horizons (Conrad and Kaul, 1998; Bianchi, Drew, and Fan, 2015). Meanwhile, the result fills the gap between stock markets and futures markets with respect to intra-day momentum and reversal. Opposite to Gao, Han, Li, and Zhou (2017) and Komarov (2017), the trading strategy based on reversal signals provides excess returns significantly and consistently in the intra-day specifications. Secondly, the single-sort strategies are improved uniformly in the inter-day trading by considering the trading volume as the second signal. Additionally, the single-sort strategies are improved occasionally in the intra-day case by implementing the trading volume and idiosyncratic volatility as the second sort signal. This situation affirms the conclusion of Lee and Swaminathan (2000) and Fuertes, Miffre, and Perez (2015) that past returns, trading volume and idiosyncratic volatility have significant predictive power for returns. Furthermore, the excess returns from some trading strategies in this study are dominated by short positions, and this is inconsistent with past studies based on other samples (Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Bianchi, Drew, and Fan, 2015). The intuitive explanation for this difference is the downward trend of the commodity futures prices in the slowing Chinese economy, where investors use the commodity futures to bet on the continuation of the slowdown in the Chinese economy. Finally, intra-day trading earns higher returns compared to the inter-day due to high-frequency investments. Nevertheless, higher rebalancing frequency of the portfolio causes higher transaction costs in intra-day trading.

In the existing literature, the extensive post-holding analysis of momentum/reversal strategies is normally performed in order to explore the market correction for information underreaction/overreaction. Bianchi, Drew, and Fan (2015) show that the financial market correction for overreaction (i.e., reversal) provides excess returns over long terms compared to the market correction for underreaction (i.e., momentum) which captures profits over medium periods. This argument is supported by other studies (Conrad and Kaul, 1998; Asness et al., 2013; Moskowitz, Ooi, and Pedersen, 2012). However, the past post-holding analysis only considers the inter-day trading and focuses on weekly or monthly level data. This study utilizes the intra-day trading and high-frequency data to address the gap in the existing literature. The reversal strategy is shown to be profitable over short periods (i.e., intra-day level). This finding supports that the momentum life cycle (MLC) hypothesis of Bernstein (1987) and Lee and Swaminathan (2000), which reflects the interaction between price momentum and reversals. MLC claims that the market correction performs circularly, from overreaction (i.e., reversal) to underreaction (i.e., momentum), and finally overreaction (i.e., reversal).[26]

For a robustness check, Figure 4.1 displays the performance of the inter-day trading strategies in four sub-samples, Figure 4.2 shows the performance of the intra-day cases in the same sub-samples. According to Figure 4.1, it is demonstrated that the double-sort strategy with trading volume performs the best across all the inter-day strategies considered. From Figure 4.2, although the single-sort reversal strategy provides the highest return, the improvements of double-sort strategies with trading volume and volatility are indicated with respect to consistency in sub-periods. Our findings verify the conclusion of Lee and Swaminathan (2000) and Fuertes, Miffre, and Perez (2015) that the predictive factors of futures returns can be explored by past returns, trading volume and idiosyncratic volatility.

[26]This phenomenon also supports the mean-reverting theory in Fama and French (1988).

Table 4.7: Performance of intra-day trading for single-sort reversal strategies.

	Without previous day's information				With previous day's information				Benchmark
	$J = 10m$	$J = 20m$	$J = 30m$	$J = 60m$	$J = 10m$	$J = 20m$	$J = 30m$	$J = 60m$	
	$K = 10m$				$K = 10m$				
Panel A: long portfolio									
Monthly Return	0.0275	0.0085	-0.0027	0.0017	0.0309	0.0137	-0.0009	-0.0025	-0.0084
t-Statistics	4.4031	1.3884	-0.5354	0.2925	4.6712	1.9740	-0.1380	-0.3045	-2.4348
Monthly Volatility	0.0432	0.0427	0.0349	0.0415	0.0459	0.0481	0.0445	0.0571	0.0240
Monthly Downside Volatility	0.0263	0.0256	0.0230	0.0231	0.0191	0.0318	0.0246	0.0362	0.0125
Reward/Risk Ratio	0.6355	0.2004	-0.0773	0.0422	0.6742	0.2849	-0.0199	-0.0440	-0.3514
Sortino ratio	1.0430	0.3338	-0.1174	0.0757	1.6159	0.4317	-0.0360	-0.0694	-0.6783
Skewness	0.2695	-0.3248	-0.3703	1.2287	0.3320	-0.3616	0.5091	0.9314	1.2143
Kurtosis	3.2603	2.6917	3.0920	7.9096	2.5535	3.7374	4.1424	8.5003	5.4950
95% VaR	-0.0113	-0.0112	-0.0125	-0.0107	-0.0113	-0.0117	-0.0136	-0.0138	-0.0083
99% VaR(Cornish-Fisher)	-0.0179	-0.0165	-0.0152	-0.0140	-0.0189	-0.0195	-0.0187	-0.0196	-0.0110
% of positive days	0.5900	0.5464	0.5189	0.5360	0.5890	0.5350	0.5123	0.5161	0.4688
Maximum Drawdown	0.1018	0.1001	0.0767	0.1013	0.0968	0.1380	0.1202	0.1692	0.0731
Max month rolling return	0.1645	0.1274	0.1035	0.1855	0.1776	0.1484	0.1540	0.2426	0.0864
Min month rolling return	-0.1095	-0.1203	-0.1004	-0.1157	-0.1122	-0.1658	-0.1480	-0.2068	-0.0882
Panel B: short portfolio									
Monthly Return	0.0393	0.0131	0.0036	0.0026	0.0447	0.0202	0.0093	0.0081	-0.0084
t-Statistics	4.7462	1.5120	0.4264	0.4579	5.4260	2.2678	0.9990	1.1909	-2.4348
Monthly Volatility	0.0574	0.0599	0.0577	0.0386	0.0571	0.0619	0.0644	0.0470	0.0240
Monthly Downside Volatility	0.0708	0.0649	0.0555	0.0353	0.0700	0.0731	0.0635	0.0374	0.0125
Reward/Risk Ratio	0.6851	0.2182	0.0615	0.0661	0.7832	0.3273	0.1442	0.1719	-0.3514
Sortino ratio	0.5552	0.2014	0.0640	0.0722	0.6395	0.2769	0.1462	0.2164	-0.6783
Skewness	-1.7817	-1.7314	-1.3395	-1.2725	-1.5410	-1.8316	-1.4707	-0.6598	1.2143
Kurtosis	9.2720	7.8189	7.5429	5.8878	8.4192	8.5943	7.4026	4.0328	5.4950
95% VaR	-0.0099	-0.0102	-0.0108	-0.0102	-0.0106	-0.0115	-0.0124	-0.0125	-0.0083
99% VaR(Cornish-Fisher)	-0.0162	-0.0142	-0.0118	-0.0128	-0.0174	-0.0170	-0.0150	-0.0167	-0.0110
% of positive days	0.6345	0.5824	0.5455	0.5360	0.6269	0.5814	0.5634	0.5521	0.4688
Maximum Drawdown	0.2239	0.2363	0.2284	0.1196	0.2189	0.2580	0.2701	0.1340	0.0731
Max month rolling return	0.1641	0.1160	0.1338	0.0891	0.1729	0.1296	0.1402	0.1316	0.0864
Min month rolling return	-0.2124	-0.2355	-0.2312	-0.1474	-0.2268	-0.2625	-0.2855	-0.1668	-0.0882
Panel C: total portfolio									
Monthly Return	0.0334	0.0108	0.0004	0.0022	0.0378	0.0170	0.0042	0.0028	-0.0084
t-Statistics	8.3162	2.6490	0.1022	0.6341	9.4703	3.8141	0.8890	0.5829	-2.4348
Monthly Volatility	0.0278	0.0283	0.0291	0.0235	0.0277	0.0308	0.0327	0.0331	0.0240
Monthly Downside Volatility	0.0363	0.0201	0.0210	0.0151	0.0000	0.0232	0.0211	0.0171	0.0125
Reward/Risk Ratio	1.2003	0.3823	0.0148	0.0915	1.3669	0.5505	0.1283	0.0841	-0.3514
Sortino ratio	0.9211	0.5384	0.0204	0.1429	Inf	0.7307	0.1992	0.1631	-0.6783
Skewness	-1.1959	-0.5600	-0.5121	0.2210	-1.0946	-0.5121	-0.3182	0.3439	1.2143
Kurtosis	6.9114	3.6759	3.8094	3.9375	6.8977	4.1886	4.0672	3.1983	5.4950
95% VaR	-0.0051	-0.0060	-0.0062	-0.0056	-0.0053	-0.0064	-0.0073	-0.0070	-0.0083
99% VaR(Cornish-Fisher)	-0.0116	-0.0101	-0.0091	-0.0088	-0.0119	-0.0117	-0.0115	-0.0121	-0.0110
% of positive days	0.6458	0.5739	0.5199	0.5284	0.6572	0.5862	0.5426	0.5199	0.4688
Maximum Drawdown	0.0897	0.0880	0.1000	0.0647	0.0915	0.0910	0.1205	0.0710	0.0731
Max month rolling return	0.1006	0.0764	0.0783	0.0910	0.1292	0.0864	0.0949	0.1023	0.0864
Min month rolling return	-0.0789	-0.0892	-0.0918	-0.0945	-0.0885	-0.0927	-0.1237	-0.1061	-0.0882

Notes: This table illustrates the performance of eight single-sort reversal strategies. Panel A reports the long (losers) portfolio, Panel B shows the short (winners) portfolio and Panel C summarizes the long-short (losers-winners) portfolio. J and K denote the formation and holding periods. The Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

Table 4.8: Performance of intra-day trading for double-sort reversal and volume strategies.

	Without previous day's information				With previous day's information				Benchmark
	$J = 10m$	$J = 20m$	$J = 30m$	$J = 60m$	$J = 10m$	$J = 20m$	$J = 30m$	$J = 60m$	
	$K = 10m$				$K = 10m$				
Panel A: long portfolio									
Monthly Return	0.0196	0.0092	0.0066	0.0024	0.0213	0.0126	0.0065	0.0034	-0.0084
t-Statistics	5.2459	2.6066	2.0510	0.7516	4.9721	2.8582	1.5264	0.7055	-2.4348
Monthly Volatility	0.0259	0.0245	0.0223	0.0217	0.0297	0.0307	0.0296	0.0335	0.0240
Monthly Downside Volatility	0.0131	0.0190	0.0138	0.0166	0.0194	0.0223	0.0249	0.0246	0.0125
Reward/Risk Ratio	0.7572	0.3762	0.2960	0.1085	0.7177	0.4125	0.2203	0.1018	-0.3514
Sortino ratio	1.5031	0.4860	0.4782	0.1416	1.1009	0.5671	0.2617	0.1387	-0.6783
Skewness	1.2647	-0.7876	-0.4766	-0.0471	0.3733	-0.3122	-0.7340	-0.3805	1.2143
Kurtosis	7.7989	4.4050	2.6047	8.7725	4.7119	4.8995	6.1455	6.5053	5.4950
95% VaR	-0.0067	-0.0070	-0.0069	-0.0064	-0.0071	-0.0075	-0.0077	-0.0085	-0.0083
99% VaR(Cornish-Fisher)	-0.0128	-0.0108	-0.0100	-0.0087	-0.0137	-0.0126	-0.0117	-0.0128	-0.0110
% of positive days	0.5824	0.5455	0.5625	0.5559	0.5691	0.5682	0.5616	0.5331	0.4688
Maximum Drawdown	0.0621	0.0682	0.0813	0.0781	0.0815	0.0964	0.1069	0.1228	0.0731
Max month rolling return	0.1358	0.0845	0.0762	0.1118	0.1397	0.1045	0.1070	0.1139	0.0864
Min month rolling return	-0.0844	-0.0753	-0.0757	-0.1061	-0.1066	-0.1023	-0.1109	-0.1264	-0.0882
Panel B: short portfolio									
Monthly Return	0.0261	0.0040	0.0012	0.0024	0.0311	0.0121	0.0065	0.0095	-0.0084
t-Statistics	2.8504	0.4435	0.1484	0.5123	3.4672	1.2215	0.6477	1.3032	-2.4348
Monthly Volatility	0.0634	0.0623	0.0575	0.0321	0.0622	0.0688	0.0696	0.0503	0.0240
Monthly Downside Volatility	0.0673	0.0720	0.0566	0.0233	0.0674	0.0865	0.0715	0.0385	0.0125
Reward/Risk Ratio	0.4114	0.0640	0.0214	0.0739	0.5004	0.1763	0.0935	0.1881	-0.3514
Sortino ratio	0.3880	0.0554	0.0218	0.1019	0.4623	0.1402	0.0910	0.2458	-0.6783
Skewness	-1.5715	-3.0909	-2.2848	-0.5610	-1.4118	-2.7463	-1.9885	-0.7034	1.2143
Kurtosis	8.9024	17.5660	12.7278	4.5624	8.2678	15.3450	9.9907	3.6701	5.4950
95% VaR	-0.0109	-0.0114	-0.0114	-0.0103	-0.0117	-0.0125	-0.0126	-0.0122	-0.0083
99% VaR(Cornish-Fisher)	-0.0164	-0.0132	-0.0124	-0.0139	-0.0176	-0.0157	-0.0156	-0.0194	-0.0110
% of positive days	0.5985	0.5492	0.5379	0.5275	0.6165	0.5767	0.5492	0.5445	0.4688
Maximum Drawdown	0.2490	0.3217	0.2764	0.1123	0.2449	0.3508	0.3213	0.1320	0.0731
Max month rolling return	0.1510	0.1015	0.1181	0.0844	0.1723	0.1348	0.1531	0.1370	0.0864
Min month rolling return	-0.2504	-0.3258	-0.2780	-0.1362	-0.2540	-0.3542	-0.3298	-0.1694	-0.0882
Panel C: total portfolio									
Monthly Return	0.0229	0.0066	0.0039	0.0024	0.0262	0.0124	0.0065	0.0064	-0.0084
t-Statistics	5.5688	1.5486	0.9882	1.0387	6.2358	2.6425	1.2943	1.7332	-2.4348
Monthly Volatility	0.0285	0.0295	0.0275	0.0158	0.0291	0.0325	0.0349	0.0257	0.0240
Monthly Downside Volatility	0.0319	0.0365	0.0309	0.0124	0.0297	0.0417	0.0366	0.0191	0.0125
Reward/Risk Ratio	0.8038	0.2235	0.1426	0.1499	0.9001	0.3814	0.1868	0.2502	-0.3514
Sortino ratio	0.7181	0.1806	0.1268	0.1900	0.8845	0.2972	0.1781	0.3377	-0.6783
Skewness	-1.2931	-3.1433	-2.2627	-0.8838	-0.3565	-2.6934	-2.0748	-0.5298	1.2143
Kurtosis	7.8434	18.2872	11.6338	6.4832	6.0264	15.6312	10.4497	4.8197	5.4950
95% VaR	-0.0049	-0.0052	-0.0054	-0.0048	-0.0051	-0.0057	-0.0061	-0.0066	-0.0083
99% VaR(Cornish-Fisher)	-0.0102	-0.0070	-0.0067	-0.0073	-0.0107	-0.0087	-0.0085	-0.0111	-0.0110
% of positive days	0.6231	0.5492	0.5511	0.5379	0.6203	0.5729	0.5606	0.5388	0.4688
Maximum Drawdown	0.0928	0.1509	0.1276	0.0651	0.0832	0.1607	0.1583	0.0832	0.0731
Max month rolling return	0.0973	0.0610	0.0717	0.0622	0.1221	0.0954	0.0831	0.1081	0.0864
Min month rolling return	-0.0967	-0.1516	-0.1301	-0.0781	-0.0911	-0.1639	-0.1633	-0.1008	-0.0882

Notes: This table illustrates the performance of eight double-sort reversal strategies with trading volume as the second signal. Panel A reports the long (losers with low volume) portfolio, Panel B shows the short (winners with high volume) portfolio and Panel C summarizes the long-short portfolio. J and K denote the formation and holding periods. Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

Table 4.9: Performance of intra-day trading for double-sort reversal and momentum strategies.

	Without previous day's information				With previous day's information				Benchmark
	$J=10m$	$J=20m$	$J=30m$	$J=60m$	$J=10m$	$J=20m$	$J=30m$	$J=60m$	
	$I=60m$				$I=60m$				
	$K=10m$				$K=10m$				
Panel A: long portfolio									
Monthly Return	0.0108	0.0022	-0.0006	0.0008	0.0143	0.0013	0.0013	-0.0032	-0.0084
t-Statistics	3.1542	0.5808	-0.1628	0.2349	2.8529	0.2824	0.2278	-0.7462	-2.4348
Monthly Volatility	0.0238	0.0258	0.0264	0.0228	0.0346	0.0327	0.0409	0.0293	0.0240
Monthly Downside Volatility	0.0133	0.0154	0.0169	0.0183	0.0183	0.0155	0.0222	0.0173	0.0125
Reward/Risk Ratio	0.4553	0.0838	-0.0235	0.0339	0.4118	0.0408	0.0329	-0.1077	-0.3514
Sortino ratio	0.8141	0.1403	-0.0367	0.0423	0.7786	0.0861	0.0605	-0.1825	-0.6783
Skewness	-0.0476	0.2049	0.1413	-0.6912	1.1020	0.7806	0.8997	0.1017	1.2143
Kurtosis	2.6095	3.1583	3.9180	3.5747	5.6416	3.6613	4.8291	3.0930	5.4950
95% VaR	-0.0070	-0.0076	-0.0078	-0.0068	-0.0088	-0.0096	-0.0096	-0.0092	-0.0083
99% VaR(Cornish-Fisher)	-0.0136	-0.0117	-0.0115	-0.0100	-0.0172	-0.0151	-0.0155	-0.0142	-0.0110
% of positive days	0.5123	0.5085	0.5057	0.5369	0.5265	0.5038	0.5009	0.5028	0.4688
Maximum Drawdown	0.0422	0.0635	0.0708	0.0620	0.0925	0.0708	0.0897	0.0816	0.0731
Max month rolling return	0.0919	0.0856	0.0887	0.0545	0.1404	0.0978	0.1451	0.0919	0.0864
Min month rolling return	-0.0611	-0.0714	-0.0676	-0.0832	-0.0830	-0.0829	-0.0973	-0.0918	-0.0882
Panel B: short portfolio									
Monthly Return	0.0214	0.0084	0.0070	0.0009	0.0325	0.0165	0.0122	0.0085	-0.0084
t-Statistics	3.9132	1.3209	1.4039	0.2179	4.0562	1.7583	1.8027	1.6371	-2.4348
Monthly Volatility	0.0379	0.0440	0.0347	0.0282	0.0556	0.0651	0.0470	0.0361	0.0240
Monthly Downside Volatility	0.0516	0.0593	0.0332	0.0223	0.0756	0.1012	0.0527	0.0346	0.0125
Reward/Risk Ratio	0.5648	0.1907	0.2026	0.0315	0.5855	0.2538	0.2602	0.2363	-0.3514
Sortino ratio	0.4149	0.1414	0.2119	0.0398	0.4303	0.1634	0.2321	0.2460	-0.6783
Skewness	-1.3397	-3.5486	-1.4406	-0.7614	-0.9675	-3.9985	-2.0145	-1.4113	1.2143
Kurtosis	9.6085	21.4860	7.7267	5.5097	9.3301	24.8378	10.4985	6.3360	5.4950
95% VaR	-0.0067	-0.0066	-0.0067	-0.0065	-0.0083	-0.0092	-0.0093	-0.0079	-0.0083
99% VaR(Cornish-Fisher)	-0.0112	-0.0091	-0.0096	-0.0085	-0.0143	-0.0121	-0.0127	-0.0114	-0.0110
% of positive days	0.5578	0.5369	0.5360	0.5123	0.5824	0.5616	0.5625	0.5417	0.4688
Maximum Drawdown	0.1505	0.2403	0.1404	0.0980	0.2078	0.3618	0.2168	0.1494	0.0731
Max month rolling return	0.1369	0.1038	0.1020	0.0832	0.2144	0.1672	0.1325	0.0885	0.0864
Min month rolling return	-0.1468	-0.2519	-0.1453	-0.1015	-0.2083	-0.3695	-0.2241	-0.1524	-0.0882
Panel C: total portfolio									
Monthly Return	0.0161	0.0053	0.0032	0.0008	0.0234	0.0089	0.0068	0.0027	-0.0084
t-Statistics	6.0069	1.7960	1.3753	0.4247	6.9562	2.3109	2.3954	0.9912	-2.4348
Monthly Volatility	0.0186	0.0204	0.0161	0.0135	0.0233	0.0268	0.0196	0.0187	0.0240
Monthly Downside Volatility	0.0201	0.0210	0.0090	0.0090	0.0196	0.0460	0.0114	0.0143	0.0125
Reward/Risk Ratio	0.8670	0.2592	0.1985	0.0613	1.0040	0.3335	0.3457	0.1431	-0.3514
Sortino ratio	0.8018	0.2509	0.3546	0.0923	1.1940	0.1942	0.5940	0.1870	-0.6783
Skewness	-0.5266	-1.7009	-0.0693	-0.1674	-0.0129	-3.2799	0.2973	-0.7638	1.2143
Kurtosis	6.0794	10.9750	2.9584	2.8779	4.3394	19.5479	4.2335	3.8098	5.4950
95% VaR	-0.0035	-0.0039	-0.0039	-0.0036	-0.0047	-0.0051	-0.0056	-0.0051	-0.0083
99% VaR(Cornish-Fisher)	-0.0073	-0.0057	-0.0060	-0.0056	-0.0093	-0.0077	-0.0081	-0.0072	-0.0110
% of positive days	0.5947	0.5398	0.5218	0.4896	0.6098	0.5473	0.5445	0.5199	0.4688
Maximum Drawdown	0.0646	0.0927	0.0445	0.0292	0.0693	0.1394	0.0561	0.0582	0.0731
Max month rolling return	0.0729	0.0636	0.0446	0.0396	0.0893	0.0768	0.0848	0.0426	0.0864
Min month rolling return	-0.0655	-0.0996	-0.0507	-0.0478	-0.0719	-0.1405	-0.0697	-0.0669	-0.0882

Notes: This table illustrates the performance of eight double-sort reversal strategies with momentum signals. Panels A and B shows the long and short portfolios, respectively, while Panel C summarizes the long-short portfolio. J and I denote the formation period of the first signal (reversal) and the second signal (momentum) respectively. Sortino ratio is benchmarked at 0%. Reward/risk is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

Table 4.10: Performance of intra-day trading for double-sort reversal and idiosyncratic volatility strategies.

	Without previous day's information				With previous day's information				Benchmark
	$J=10m$	$J=20m$	$J=30m$	$J=60m$	$J=10m$	$J=20m$	$J=30m$	$J=60m$	
	$K=10m$				$K=10m$				
Panel A: long portfolio									
Monthly Return	0.0099	0.0042	-0.0011	-0.0031	0.0079	0.0012	-0.0053	-0.0111	-0.0084
t-Statistics	3.6141	1.3318	-0.3960	-1.2875	1.9292	0.3363	-1.5729	-2.6875	-2.4348
Monthly Volatility	0.0175	0.0203	0.0172	0.0154	0.0285	0.0240	0.0231	0.0286	0.0240
Monthly Downside Volatility	0.0105	0.0141	0.0142	0.0123	0.0162	0.0171	0.0195	0.0219	0.0125
Reward/Risk Ratio	0.5644	0.2080	-0.0619	-0.2011	0.2785	0.0485	-0.2270	-0.3879	-0.3514
Sortino ratio	0.9429	0.2996	-0.0751	-0.2510	0.4905	0.0681	-0.2694	-0.5059	-0.6783
Skewness	-0.3773	-0.4817	-0.7443	-0.6319	1.1916	-0.6143	-0.7671	-0.2512	1.2143
Kurtosis	3.0926	2.8372	3.1461	3.2910	8.2379	4.3870	3.6219	4.2845	5.4950
95% VaR	-0.0063	-0.0065	-0.0063	-0.0061	-0.0077	-0.0078	-0.0080	-0.0087	-0.0083
99% VaR(Cornish-Fisher)	-0.0100	-0.0094	-0.0074	-0.0063	-0.0127	-0.0111	-0.0100	-0.0111	-0.0110
% of positive days	0.5610	0.5355	0.5244	0.5355	0.5407	0.5170	0.5076	0.4896	0.4688
Maximum Drawdown	0.0545	0.0532	0.0568	0.0436	0.0590	0.0805	0.0675	0.0968	0.0731
Max month rolling return	0.0613	0.0578	0.0461	0.0310	0.1344	0.0640	0.0595	0.0750	0.0864
Min month rolling return	-0.0593	-0.0713	-0.0665	-0.0637	-0.0729	-0.0864	-0.0937	-0.1070	-0.0882
Panel B: short portfolio									
Monthly Return	0.0416	0.0210	0.0151	0.0060	0.0407	0.0253	0.0172	0.0167	-0.0084
t-Statistics	5.5634	3.1698	2.1728	0.9728	4.4593	2.7843	1.7070	2.0820	-2.4348
Monthly Volatility	0.0479	0.0424	0.0444	0.0395	0.0632	0.0630	0.0699	0.0554	0.0240
Monthly Downside Volatility	0.0291	0.0267	0.0278	0.0353	0.0722	0.0663	0.0698	0.0393	0.0125
Reward/Risk Ratio	0.8689	0.4950	0.3393	0.1519	0.6436	0.4019	0.2464	0.3005	-0.3514
Sortino ratio	1.4321	0.7849	0.5427	0.1698	0.5630	0.3818	0.2466	0.4238	-0.6783
Skewness	-0.4333	0.0005	-0.1283	-1.1393	-1.3206	-1.4259	-1.6972	-0.2904	1.2143
Kurtosis	3.5253	4.6548	3.2466	5.8860	7.7811	8.9106	8.2835	3.2796	5.4950
95% VaR	-0.0103	-0.0108	-0.0104	-0.0107	-0.0114	-0.0124	-0.0125	-0.0130	-0.0083
99% VaR(Cornish-Fisher)	-0.0181	-0.0173	-0.0160	-0.0139	-0.0185	-0.0174	-0.0166	-0.0180	-0.0110
% of positive days	0.6308	0.5820	0.5831	0.5565	0.6335	0.5833	0.5805	0.5748	0.4688
Maximum Drawdown	0.0876	0.1060	0.0951	0.1247	0.2332	0.2545	0.2845	0.1295	0.0731
Max month rolling return	0.1805	0.1532	0.1132	0.1030	0.1956	0.1862	0.1418	0.1514	0.0864
Min month rolling return	-0.0968	-0.1111	-0.1170	-0.1392	-0.2501	-0.2591	-0.2997	-0.1409	-0.0882
Panel C: total portfolio									
Monthly Return	0.0258	0.0126	0.0070	0.0015	0.0243	0.0132	0.0060	0.0028	-0.0084
t-Statistics	6.9956	4.0774	2.1860	0.4784	6.4912	3.1361	1.2569	0.7270	-2.4348
Monthly Volatility	0.0236	0.0198	0.0205	0.0194	0.0259	0.0292	0.0330	0.0265	0.0240
Monthly Downside Volatility	0.0077	0.0110	0.0146	0.0172	0.0142	0.0288	0.0290	0.0151	0.0125
Reward/Risk Ratio	1.0925	0.6368	0.3414	0.0747	0.9369	0.4527	0.1814	0.1049	-0.3514
Sortino ratio	3.3473	1.1487	0.4792	0.0843	1.7146	0.4602	0.2063	0.1837	-0.6783
Skewness	-0.6288	-0.2050	-0.5168	-1.2848	-0.3198	-1.2423	-1.4940	0.0514	1.2143
Kurtosis	3.0136	2.8276	3.2569	6.0418	2.8154	7.3023	7.7882	2.7161	5.4950
95% VaR	-0.0044	-0.0049	-0.0051	-0.0053	-0.0053	-0.0055	-0.0060	-0.0061	-0.0083
99% VaR(Cornish-Fisher)	-0.0097	-0.0086	-0.0079	-0.0068	-0.0104	-0.0090	-0.0085	-0.0093	-0.0110
% of positive days	0.6330	0.5721	0.5654	0.5388	0.6278	0.5729	0.5455	0.5284	0.4688
Maximum Drawdown	0.0332	0.0407	0.0424	0.0687	0.0523	0.1111	0.1347	0.0540	0.0731
Max month rolling return	0.1037	0.0638	0.0549	0.0499	0.1127	0.0925	0.0768	0.0675	0.0864
Min month rolling return	-0.0317	-0.0559	-0.0576	-0.0708	-0.0579	-0.1248	-0.1420	-0.0922	-0.0882

Notes: This table illustrates the performance of eight double-sort reversal strategies with idiosyncratic volatility as the second signal. Panel A reports the long (losers with low volatility) portfolio, Panel B shows the short (winners with high volatility) portfolio and Panel C summarizes the long-short portfolio. J and K denote the formation and holding periods. Sortino ratio is benchmarked at 0%. Reward/risk ratio is equivalent to the Sharpe ratio as the risk-free rate is equal to 0%. Benchmark is the equal-weighted average return for all commodities on the contract with the highest liquidity. The number of commodities on each side is one decile of the number of available commodities. Rounding errors may exist due to limited space.

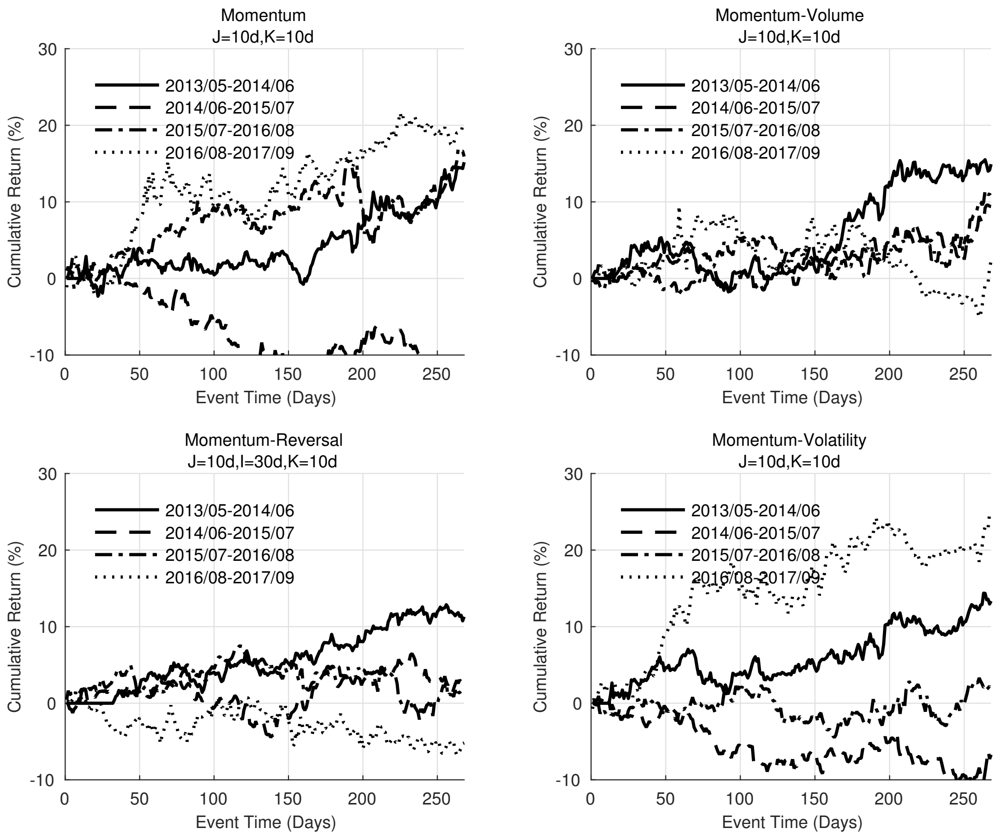

Figure 4.1: Cumulative returns for inter-day trading

Notes: This figure illustrates the cumulative momentum portfolio returns with the selected performance of single-sort and double-sort strategies. J and K represent the formation and holding period respectively, and I denotes the reversal ranking period in the momentum-reversal strategy. The x-axis shows the post-formation event days. The y-axis indicates the cumulative portfolio return. Four sub-periods are equally presented in the 2013-2017 period.

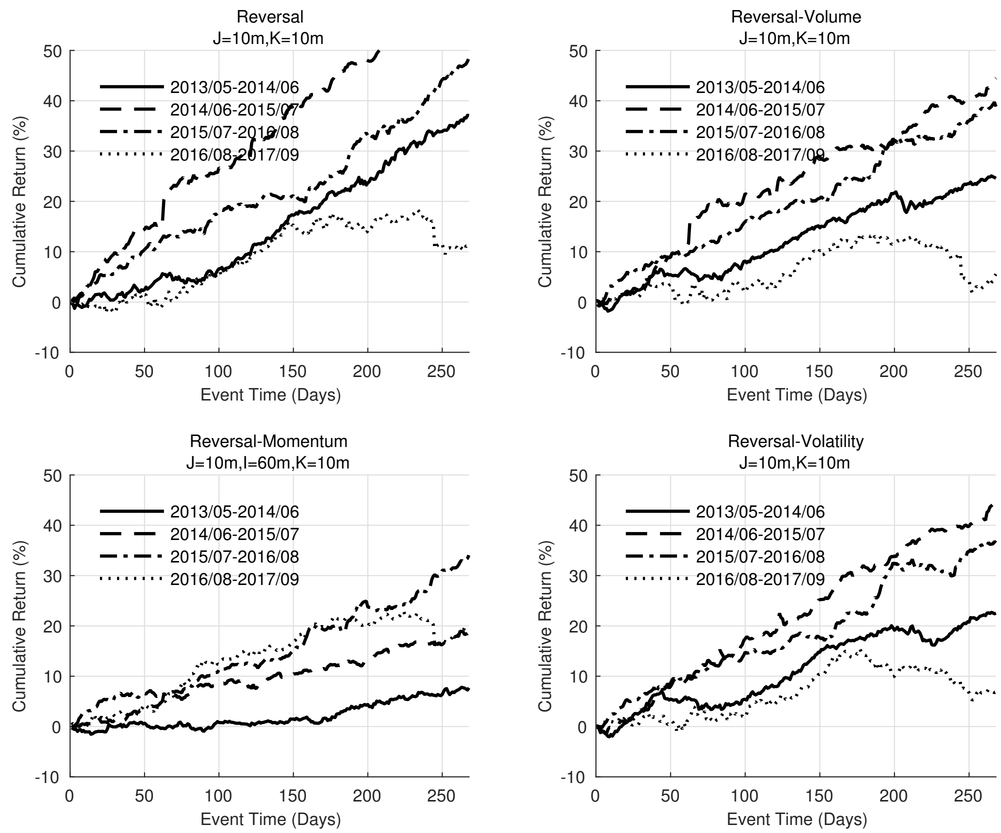

Figure 4.2: Cumulative returns for intra-day trading with overnight information
Notes: This figure illustrates the cumulative momentum portfolio returns with the selected performance of single-sort and double-sort strategies. J and K represent the formation and holding period respectively, and I denotes the momentum ranking period for the reversal-momentum strategy. The x-axis shows the post-formation event days. The y-axis indicates the cumulative portfolio return. Four sub-periods are equally presented in the 2013-2017 period.

4.5 Factor Analysis

For determining the explanatory power of potential risk factors of the investment profits based on momentum/reversal strategies, the commodity market index, bond futures and equity index futures are utilized in the regression framework, which is given by

$$r_t = \alpha_i + \beta_i F_{i,t} + \epsilon_{i,t}, \tag{4.2}$$

where r_t is the long-short portfolio return and $F_{i,t}$ is the underlying index return such as stock index futures and bond futures returns.

In Table 4.11, it is presented that the single-factor regression results of the single-sort momentum and double-sort trading volume strategies with the Chinese index futures returns. The R-square values around 50% for long/short positions separately with the passive benchmark indicate the consistency with Bakshi et al. (Forthcoming 2017), which proposes that the market average factor has significant explanatory power to the return dynamics in the considered portfolios of commodity futures. However, the low R-square values and insignificant statistics support the findings of the recent studies implying that the profits of long-short active investment strategies in commodity futures cannot be explained by traditional risk factors due to the passive long-only property of these indexes (Erb and Harvey, 2006; Basu and Miffre, 2013; Bianchi, Drew, and Fan, 2015). The low correlation between the futures investment portfolio return and the traditional market index return confirms that the futures trading provides diversify benefits for financial market investors. It should be added that the correlation between the index and the commodity futures is often insignificant in the higher frequency of returns, however, for the lower frequencies, such as for weekly and monthly returns, the correlation between the financial and commodity futures might be more pronounced.

Table 4.11: Factor regression of single- and double-sort strategies.

	Momentum			Momentum-Volume		
	Long	Short	Long-Short	Long	Short	Long-Short
Panel A: China 500 Index Futures						
Intercept	0.0002	-0.0005	-0.0001	0.0009	-0.0005	0.0002
t-Value	0.3368	-0.7610	-0.4263	1.5170	-0.7080	0.5811
IC	0.0428	-0.0853	-0.0212	0.0365	-0.0994	-0.0315
t-Value	2.3799	-3.4443	-2.0325	2.5418	-4.7124	-3.6155
R-sq	0.0064	0.0302	0.0056	0.0099	0.0509	0.0203
Panel B: Shanghai & Shenzhen 300 Index Futures						
Intercept	-0.0001	0.0000	0.0000	0.0003	0.0004	0.0004
t-Value	-0.1475	-0.0492	-0.1750	0.9498	1.0693	1.8147
IF	0.0717	-0.1226	-0.0254	0.0554	-0.1446	-0.0446
t-Value	3.8247	-4.7926	-2.3097	3.5470	-5.2821	-4.2893
R-sq	0.0114	0.0355	0.0044	0.0152	0.0532	0.0209
Panel C: Shanghai 50 Index Futures						
Intercept	0.0003	-0.0005	-0.0001	0.0009	-0.0006	0.0002
t-Value	0.4071	-0.8402	-0.4410	1.6474	-0.8588	0.5465
IH	0.0957	-0.1216	-0.0130	0.0637	-0.1312	-0.0338
t-Value	3.4138	-3.3164	-0.7700	2.5441	-3.5388	-2.4259
R-sq	0.0160	0.0309	0.0010	0.0153	0.0447	0.0118
Panel D: 5-year Treasury Futures						
Intercept	0.0003	-0.0003	0.0000	0.0008	-0.0003	0.0003
t-Value	0.5305	-0.4366	0.0891	1.3818	-0.4062	0.7900
T	-0.1790	0.2408	0.0309	-0.1447	0.3121	0.0837
t-Value	-0.8917	1.4702	0.2971	-1.0401	1.5426	0.7870
R-sq	0.0013	0.0029	0.0001	0.0016	0.0049	0.0014
Panel E: 10-year Treasury Futures						
Intercept	0.0000	0.0000	0.0000	0.0003	0.0005	0.0004
t-Value	0.0800	-0.0094	0.0661	0.8780	1.1314	1.8841
TF	-0.1540	0.2855	0.0658	-0.1908	0.3798	0.0945
t-Value	-0.7776	1.7306	0.6912	-1.6491	1.9523	1.1275
R-sq	0.0007	0.0026	0.0004	0.0021	0.0045	0.0012
Panel F: Passive Benchmark						
Intercept	0.0001	0.0000	0.0001	0.0003	0.0005	0.0004
t-Value	0.3172	0.0291	0.2379	1.2918	1.8210	1.9559
Benchmark	1.1872	-1.1380	0.0246	0.8286	-1.3475	-0.2595
t-Value	20.7413	-22.0690	0.5149	13.4151	-27.5069	-5.7898
R-sq	0.4846	0.4795	0.0007	0.4471	0.6053	0.0942

Notes: This table illustrates the factor regression of single- and double-sort strategies in index futures of China. The formation period is 5 trading days and the holding period is 1 trading day. The dependent variables are the strategy returns and the independent variables are the index futures returns. Panels A-E report the 5 index futures traded on China Financial Futures Exchange (CFFE) respectively, and Panel F reports the equal-weighted benchmark portfolio. Sample period is from 2013-2017. Newey and West (1987) standard errors are employed. The coefficient estimation and R-square are reported, the statistical significance is documented in terms of t-Value.

4.6 Data Snooping

In the financial market, the study on investment strategies is always challenged by the data snooping issue. The issue is that a trading rule is judged as profitable by luck or noise in the data, particularly in the case that investigates a large number of trading strategies (Sullivan et al., 1999; Bajgrowicz and Scaillet, 2012). This study evaluates the profitability of various single- and double-sort trading rules based on momentum/reversal and other price-volume signals. Data mining checks are practiced applying the White (2000) Reality Check (RC) and Hansen (2005) Superior Predictive Ability (SPA) tests in order to discuss whether the excess returns of investment strategies are just due to chance.[27] The null hypothesis is that the maximum average return of the active investment strategies being tested is the same as the average return of the passive benchmark. The alternative is that the maximum average return of the investment strategies is greater than the average return of the passive benchmark. Although there are two levels of trading frequency (inter-day and intra-day) in this study, the data snooping check is employed on the daily return series, and three different bootstrap block sample sizes are implemented, namely 5, 10 and 20 days. For each sample size in the robustness test, both stationary and block bootstraps are implemented on 1,000 replications.[28] Comparisons of various active investment strategies and the passive benchmark are employed to indicate the data mining effect.

Table 4.12 shows the RC and SPA results with respect to different investment rules implemented in the low- and high-frequency dataset. Overall, the *p*-values consistently reflect the rejection of the data snooping hypothesis in the high-frequency case (intra-day trading with or without the overnight information), hence ensuring that the profitability of trading rules is not only because of data mining. However, the inter-day trading strategies suffer some data-mining effects in this sample period,

[27]We gratefully follow Bianchi, Drew, and Fan (2015) to determine data-mining effects by these two approaches.

[28]We also gratefully acknowledge Kevin Sheppard's BSDS Matlab function on the robustness check. The two approaches of bootstrap are based on Politis and Romano (1992) and Politis and Romano (1994), respectively.

particularly in the case of double-sort strategy with momentum and reversal.

Table 4.12: Data-snooping test for strategy superiority.

Trading strategy	Bootstrap dependence	Bootstrap method	Inter-day trading		Intra-day trading #1		Intra-day trading #2	
			RC p-values	SPA p-values	RC p-values	SPA p-values	RC p-values	SPA p-values
Single-sort	$q = 0.2$	Stationary	0.1210	0.1010	**	**	**	**
		Block	0.1180	0.1220	**	**	**	**
	$q = 0.1$	Stationary	0.1300	0.1280	**	**	**	**
		Block	0.1090	0.1260	**	**	**	**
Momentum/Reversal	$q = 0.05$	Stationary	0.1210	0.1180	**	**	**	**
		Block	0.1140	0.1210	**	**	**	**
Double-Sort	$q = 0.2$	Stationary	0.1560	0.1520	**	**	**	**
		Block	0.1640	0.1470	**	**	**	**
	$q = 0.1$	Stationary	0.1670	0.1720	**	**	**	**
		Block	0.1500	0.1480	**	**	**	**
Volume	$q = 0.05$	Stationary	0.1670	0.1600	**	**	**	**
		Block	0.1910	0.1510	**	**	**	**
Double-Sort	$q = 0.2$	Stationary	0.3480	0.3250	**	**	**	**
		Block	0.3320	0.3600	**	**	**	**
	$q = 0.1$	Stationary	0.3820	0.3400	**	**	**	**
		Block	0.3300	0.3720	**	**	**	**
Momentum&Reversal	$q = 0.05$	Stationary	0.3540	0.3290	**	**	**	**
		Block	0.3220	0.3700	**	**	**	**
Double-Sort	$q = 0.2$	Stationary	0.3270	0.3190	**	**	**	**
		Block	0.2980	0.3130	**	**	**	**
	$q = 0.1$	Stationary	0.3360	0.3660	**	**	**	**
		Block	0.3240	0.2940	**	**	**	**
Volatility	$q = 0.05$	Stationary	0.3110	0.3010	**	**	**	**
		Block	0.3120	0.3220	**	**	**	**

Notes: This table demonstrates the Reality Check (RC) (White, 2000) and Superior Predictive Ability (SPA) (Hansen, 2005) test results in terms of p-values. The tests are implemented for strategy excess profits against the equal-weighted benchmark. The parameter q is the geometric distribution that denotes the block-size in the bootstrap samples, where the expected block size is represented by $1/q$. For each test, the bootstrap is replicated 1,000 times. The techniques of stationary and block bootstraps are based on Politis and Romano (1992) and Politis and Romano (1994). The fundamental signal is momentum in the inter-day trading and reversal in the intra-day trading. There are eight inter-day trading rules within each strategy. Four trading rules are included in each of the two separate intra-day trading strategies; #1 represents the intra-day trading with the previous day's information and #2 represents the intra-day trading without the previous day's information. Significant p-values display that the strategies outperform the benchmark.

* indicates significance at the 5% level.

** indicates significance at the 1% level.

4.7 Transaction Costs

Existing literature estimates the transaction costs as the fixed commission fees plus the bid-ask spread at multiple tick sizes (Shen et al., 2007; Szakmary et al., 2010; Dewally, Ederington, and Fernando, 2013; Clare et al., 2014). Complementarily, several studies following Locke and Venkatesh (1997) claim that the futures market's transaction costs (range from 0.04%% to 3.3%%) appear low relative to the tick size (Miffre and Rallis, 2007; Bianchi, Drew, and Fan, 2015; Fuertes, Miffre, and Perez, 2015). Alternatively, Marshall, Nguyen, and Bisaltanachoti (2011) determine the transaction costs using various aspects, such as spread, depth, immediacy and resiliency. It is widely recognized that transaction costs in futures markets are much less than the equity markets (Jegadeesh and Titman, 1993; Locke and Venkatesh, 1997; Lesmond, Schill, and Zhou, 2004). Moreover, in many stock markets, including the Chinese stock market, investors are not allowed to do intra-day trading.[29]

This study utilizes the most actively traded contracts for avoiding the liquidity issues prominently and calculates the precise transaction cost estimation for performing the most realistic analysis, and the calculation details for the transaction costs are summarized as follows. The average price of products considered in the sample is divided by the minimum price tick and the commission fees, respectively. Table 4.2 presents the estimated values of transaction costs for each futures product traded in the market in terms of basis points per trade. The table displays the transaction cost estimation in this study, the estimated commission is from 0.3%% to 1.7%% with a mean of 0.7%%,[30] and estimated minimum price tick is from 1%% to 9%% with an average of 4%%.[31] In some specific periods, the exchange provides discounts for commission fees[32], with the objective to inflate the trade and raise the liquidity of

[29] In the Chinese mainland stock markets the T+1 rule is applied. For instance, the investor cannot sell the stock on the same day when the stock is bought, so the investor has to wait for the next trading day to sell the stock.

[30] The commission is estimated by fees ÷ average price ÷ contract units since it is charged by contract.

[31] Minimum price tick is for commodity units, so it is equal to minimum price tick ÷ average price.

[32] From 1 April, 2014, there are nine commodity futures in the Chinese market that charge no fees for closing the position within the same day when the position is opened.

some contracts.

The net returns are calculated by subtracting the transaction costs[33] whenever a trade is executed. Complementarily, a round-way transaction cost is subtracted when a roll-over happens during the holding periods. This study forms the long-short portfolios with different holding periods and from a set of commodities that are highly liquid. Hence, it is unlikely that the transaction costs exceed the levels estimated in this study except for the case of submitting very large order sizes without order splitting techniques. For instance, when an order is submitted with a very large order size relative to the usual trading volume of a particular contract, the market impact will lead the real costs to exceed the estimations documented in Table 4.2. Additionally, due to the high rebalancing times in the high-frequency trading, it is likely that the excess returns are wiped out by the transaction costs.

Due to the limited space, the representative strategies are plotted, including the transaction cost analysis in Figure 4.3, where other results are similar and available upon request. The outcomes with transaction costs considered show that the single- and double-sort strategies based on the momentum signal with long holding periods can generate excess returns consistently. Meanwhile, Figure 4.3 highlights that the double-sort strategy with trading volume apparently does not have the momentum crash effect, and the abnormal returns are significantly positive in both bull and bear markets in China.[34] However, the cumulative returns from intra-day trading with transaction cost considered reflects a straight downward line, which indicates that the return from high-frequency trading based on reversal signals fails to exceed the transaction costs embedded.

To provide a robustness check, this study performs the break-even transaction cost analysis following Fuertes, Miffre, and Perez (2015), which calculates the required level of cost per futures trade execution that provides the average returns of the strategy equal to zero for each investment rule. In the sample included in this study, the break-even costs are increasing with the holding period of the investment. The

[33]In this study, the one-way transaction cost included is equal to the commission fees plus one half minimum tick size, which is in agreement with industry practices in the Chinese futures market.

[34]See Daniel and Moskowitz (2016) for details. This phenomenon illustrates the particular natures of the Chinese commodity futures market.

outcomes are presented in Table 4.13, which are consistent with Fuertes, Miffre, and Perez (2015). Across the universe of strategies included, the break-even cost level is equal to 14%% with the 10-day formation and holding period, which exceeds the average of commission fee plus half of the tick size (around 2.7%%). Therefore, excess returns remain robust after including transaction costs for the low intensive momentum/reversal trading strategies (Fuertes, Miffre, and Rallis, 2010; Fuertes, Miffre, and Perez, 2015; Bianchi, Drew, and Fan, 2015).

Table 4.13: Performance of single- and double-sort strategies with transaction costs.

	J=5d		J=10d		J=15d		J=20d	
	K=1d	K=5d	K=1d	K=10d	K=1d	K=15d	K=1d	K=20d
Momentum	-0.0052	-0.0039	0.0024	0.0071	0.0113	0.0033	0.0118	0.0028
Break-even cost	0.0000	-0.0002	0.0001	0.0018	0.0003	0.0013	0.0003	0.0015
Momentum-Volume	0.0006	0.0005	-0.0013	0.0060	0.0052	0.0034	0.0007	0.0084
Break-even cost	0.0001	0.0003	0.0001	0.0016	0.0002	0.0014	0.0001	0.0040
Momentum-Reversal	-0.0143	-0.0033	-0.0131	0.0012	-0.0062	0.0058	-0.0041	-0.0036
Break-even cost	-0.0002	-0.0001	-0.0002	0.0005	0.0000	0.0022	0.0000	-0.0014
Momentum-Volatility	-0.0039	0.0002	-0.0059	0.0055	0.0019	0.0051	-0.0024	0.0069
Break-even cost	0.0001	0.0003	0.0000	0.0015	0.0001	0.0020	0.0000	0.0034
Average return	-0.0057	-0.0016	-0.0045	0.0049	0.0031	0.0044	0.0015	0.0036
Average break-even cost	0.0000	0.0000	0.0000	0.0014	0.0002	0.0017	0.0001	0.0019

Notes: This table illustrates the monthly net mean returns of the single-sort and double-sort strategies, where the net performance is calculated relative to the summation of commission fee plus one half price minimum tick per trade. The column below the return reports the break-even cost of the long-short portfolios defined as the transaction cost per trip that would earn zero net returns. The number of commodities on each side is one decile of the number of available commodities. J denotes the formation period and J represents the holding period, and the ranking period of reversal signal is 30 days.

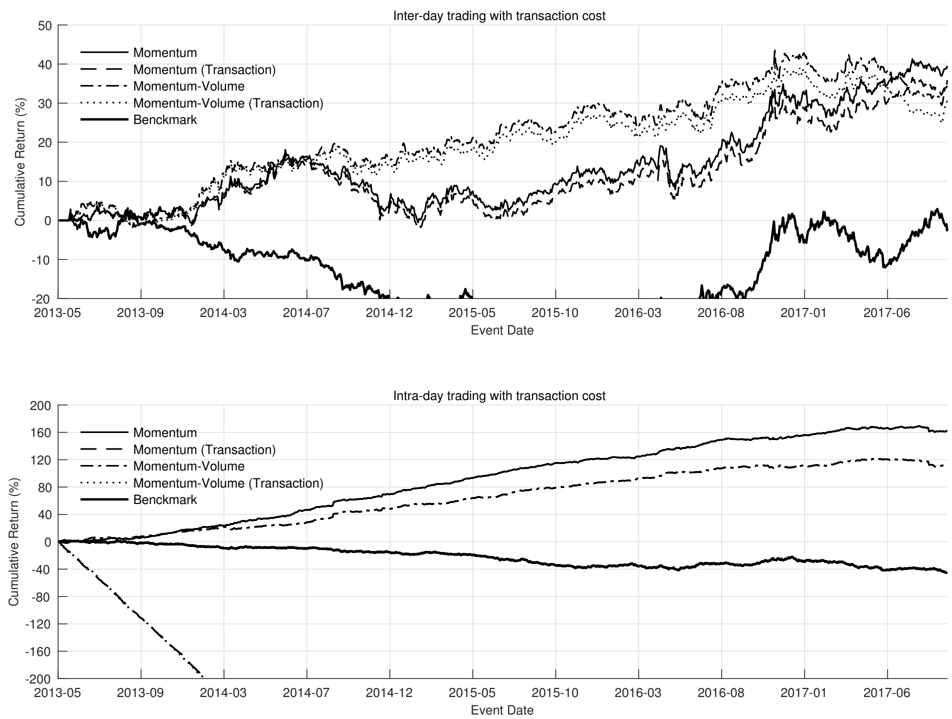

Figure 4.3: Cumulative returns with transaction cost.

Notes: This figure illustrates the cumulative long-short portfolio returns with the transaction cost, which is the summation of commission fee and a half price tick size per trade. The upper panel displays the return of two selected inter-day trading strategies with the formation and holding period both being 10 days. The lower panel shows the intra-day trading returns. We report the single-sort and trading volume double-sort strategy with 10-minute formation period and 10-minute holding period with the previous day's information, which is the trading strategy with the highest profit. The x-axis shows the post-formation event days. The y-axis indicates the cumulative portfolio return. Sample returns are presented in the 2013-2017 period.

4.8 Summary

This chapter comprehensively analyses the profitability of the single- and double-sort momentum/reversal trading strategies at the inter- and intra- day trading frequencies in the Chinese commodity futures market. Unlike the existing literature, the dataset is constructed from the highest liquid contract of the day for each product and transaction costs are estimated precisely by the commission fees and minimum price tick sizes of each product futures contract. Hence, the approach employed in this chapter is reliable and in agreement with the practice of backtesting in the financial industry. Although the global influence of the Chinese commodity futures markets is existing and growing, academic literature focuses on the commodity futures traded in a few developed economies. The Chinese commodity futures market, which currently is the global leader with respect to the trading volume of many products, is worthy to receive increasing interest in academic research. To our best knowledge, this study is the first comprehensive study on the complete commodity futures markets of China employing both low- and high-frequency data.

Below is a summary of the empirical findings.

- Comparing the inter- and intra-day trading rules reflects that the latter case performs better for all the single- or double-sort strategies discussed when the transaction costs are not included. Monthly returns as high as 3.78% can be obtained with the intra-day trading strategies, but these profit opportunities vanish after transaction costs are taken into account while the inter-day trading strategies generate abnormal returns even after the transaction costs are included.

- The single-sort reversal strategies produce excess returns in the intra-day trading while the single-sort momentum strategies provide abnormal returns in the inter-day trading, namely, a reversal pattern appears for the previous winners at the minute level data, while in the inter-day level data previous winners reflect the continuative trend.

- The comparison between the single- and double-sort strategies indicates that employing the second sort with the volume signal performs more efficiently than the reversal and idiosyncratic volatility indicators applied to the second sort. Similarly, the same conclusion is produced by the ranking of the double-sort strategies for intra-day trading.

- The inclusion of the overnight price information improves the performance of all the strategies for the short holding periods up to 30-45 minutes in the case of intra-day trading. The possible rationale is that the overnight price information involves the news from the overseas markets that might direct the Chinese commodity futures prices at the beginning of the morning session, while the major financial news in the domestic market arrives after the first 45 minutes of the morning trading hours.

- The factor analysis demonstrates that traditional risk factors such as equity or bond indices do not have the interpretative power for the abnormal returns of momentum/reversal trading strategies. However, the market average factor (i.e., passive benchmark) is able to explain the return dynamics in the test portfolios of commodity futures.

- The robustness of the empirical results is verified by using sub-periods analysis and the data snooping test (i.e., reality check and superior predictive ability tests). Complementarily, the transaction costs section affirms the profitability of the trading strategies based on momentum/reversal signals. As a general remark, the liquidity issues in the commodity futures must be addressed carefully, and this study suggests that the dataset of futures prices should be constructed from the most actively traded (i.e., high trading volume and open interests) contracts for each trading day since each product has its own characteristics in the timing of roll-over between different maturity contracts. This study provides significant insight regarding the profitability of a wide range of momentum and reversal trading strategies in the commodity futures markets.

- Last but not least, this chapter confirms the practical significance of the market analysis performed in Chapter 2. Associated with the previous chapters, it is verified that the Chinese commodity futures market produces abnormal returns via quantitative investment strategies (i.e., pairs trading or momentum/reversal trading). Therefore, the main objective of this thesis, to provide empirical suggestions for investors by using econometric tools in the market, is satisfied.

Additionally, this study makes the contribution to the academic with respect to theoretical aspects. Past studies on momentum/reversal trading focus on low-frequency data, and claim that financial markets exhibit short-term return continuation and long-term return reversal (Conrad and Kaul, 1998; Miffre and Rallis, 2007; Shen et al., 2007). To the best of our knowledge, this is the first study employs comprehensive high-frequency data and realistic framework to examine the momentum/reversal trading strategies in the Chinese futures market. The analysis based on high-frequency indicates that the futures data exhibits a short-term reversal in high-frequency level. This finding is a compensation for past studies and an evidence for the Momentum Life Cycle (MLC) in Lee and Swaminathan (2000). The momentum profits do not only reverse if the positions are maintained long enough (i.e., several months), but also reverse if the positions are maintained really short (i.e., several minutes). Specifically, the profitability of trading signals moves from momentum to reversal in the low-frequency data while it moves from reversal to momentum in the high-frequency data, so the evidence of cyclicity is provided.

Theoretically speaking, financial assets experience periods of investor favouritism and neglect. Assets that experience overreaction have a decreasing price, but the price would be undervalued eventually and the price starts to increase, then another overvalued happens and the price starts to decrease again. In the long term, this kind of movements from overreaction to underreaction and to another overreaction are exhibited in the financial market circularly. Therefore, the profitability of trading signals moves between momentum and reversal circularly. Given this framework, this study confirms that trading volume may provide ancillary information in realizing the momentum and reversal profit, which is also consistent with the Momentum Life Cycle Hypothesis.

Moreover, our findings affirm that the long-short portfolio returns by momentum/reversal trading cannot be explained by traditional market factors (i.e., market indexes). This finding is consistent with existing literature on the commodity futures (Shen et al., 2007; Miffre and Rallis, 2007; Fuertes, Miffre, and Perez, 2015), suggesting that the reason is the passive and long-only feature of these market risk factors. The low explanatory power of traditional risk factors for momentum/reversal returns makes the commodity-based momentum/reversal portfolio excellent candidates for inclusion in well-diversified portfolios. Given the popularity of momentum/reversal strategies, the evidence of MLC provides the possibility that the momentum/reversal portfolio can be regarded as a common factor for investors. Future studies may employ the portfolio returns based on the momentum/reversal strategy as a risk factor.

From the view of practitioners, the market overreaction/underreaction in the Chinese futures may come from the heavy concentration of trend-following strategies rather than arbitrage/market making types employed by CTAs. As an increase of implementing the arbitrage and market making strategies by CTAs in the market, the profit comes from overreaction/underreaction is reduced, which is confirmed by the sub-period analysis in this study.

Chapter 5

Conclusion

This thesis provides a comprehensive investigation of the Chinese futures market with respect to the statistical characteristics and the empirical analysis of investment strategies. The performances of two representative strategies, namely pairs trading and momentum trading, separately implemented by the market-neutral and trend-following investors, are analysed via the backtesting. Due to the limitation imposed on the index futures after 2015, the financial futures is not a potential candidate to justify the performance of trading strategies. Meanwhile, the different underlying assets between financial and commodity futures lead to the differences on statistical characteristics documented in Chapter 2. Therefore, this thesis considers only the commodity futures data in the backtesting section. Additionally, both the low- and high-frequency data are utilized in this study in order to illustrate the entire futures market in China.

Complementary to the existing literature, this thesis employs some practical techniques for performing the most realistic backtesting results. Firstly, the implementation of the most actively traded contract makes a contribution to avoid the liquidity issue. Furthermore, precise estimates of transaction costs for the commodity futures market are utilized to produce accurate returns. Moreover, the inclusion of out-of-sample backtesting without future information is helpful to demonstrate the practicality of the results. Thus, the main conclusion of this thesis can be presented as follows.

The difference in the investor behavior and investment horizon between the stock and futures markets in China leads to the realization that the stylized facts in stock markets cannot be simply generalized to the case of futures markets. Chinese stock markets are participated by a large amount of individual investors, whereas the futures markets are dominated by institutional investors (i.e. hedge funds or futures companies.). Normally, the hedge funds/CTAs trade the futures contracts in short investment horizons since the invested futures contracts lack cash-flow generation. Therefore, short-term investment strategies are widely implemented in the Chinese futures markets. Hence, this thesis suggests considering the certain similarities between the stock and futures markets and also the differences with respect to some properties stylized facts when investing in futures contracts.

The market analysis shows that there are many pairs of futures products that are co-integrated in the Chinese futures markets. Therefore, statistical arbitrage trading strategies, such as pairs trading, can be justified within this framework. The profitability of pairs trading with Chinese commodity futures confirms this observation. Meanwhile, the empirical results demonstrate that the maximum holding periods obviously impact the profitability of pairs trading in the Chinese commodity futures market. This thesis finds that the pairs trading profits are a compensation for the spread divergence risk during the potentially longer holding periods; therefore, the abnormal returns do not necessarily imply market inefficiency when the higher maximum drawdown associated with the holding period of the spread position is taken into account. Thus, not only the traditional risk-adjusted returns measures such as the Sharpe ratio but also the maximum drawdown are crucial to justify the performance of investment strategies.

On the other hand, the anatomy of Chinese futures markets demonstrates that the serial correlation in most of the futures returns is weak for the daily returns, whereas it is considerable for all the products for the high-frequency data. The different results of serial correlation analysis lead to explore the profitability of trading strategies based on serial correlation, such as momentum and reversal trading. The comparison of backtesting with inter- and intra-day data displays that the intra-day momentum and reversal strategies cannot produce sufficiently high excess profits to cover the excessive costs due to the higher frequency of rebalancing. Meanwhile, the profitability of momentum and reversal strategies with lower trading frequencies shows that the maximum drawdown risk and the portfolio rebalancing frequencies need to be considered simultaneously. Additionally, the profitability of momentum/reversal strategy over inter-/intra-day separately supports the momentum life cycle (MLC) hypothesis, which implies the interaction between price momentum and reversals.

5.1 Discussion

Our findings have practical contributions to the studies on futures. The integrated analysis is provided for one important emerging market, i.e., the Chinese futures market. The anatomy chapter implies the statistical property of Chinese futures data both on low-frequency and high-frequency level. The empirical result confirms the possibility of developing profitable investment strategies. It is consistent with past studies that quantitative finance offers useful suggestions for both academia and investors.

On the other side, this study makes some theoretical contributions to the academic community. For example, a common risk factor linking to the profitability of pairs trading is found in the Chinese commodity futures market. The risk-adjusted return relationship indicates that the abnormal returns of pairs trading do not imply market inefficiency. Furthermore, the implementation of momentum/reversal strategies in the high-frequency data supports the Momentum Life Cycle (MLC) hypothesis, which demonstrates the profitability moves between momentum (underreaction) and reversal (overreaction) with respect to time horizon circularly.

Our results also raise at least three interesting question for future research. First, the principle component analysis (PCA) provides us an idea to create a market index for Chinese futures. It is valuable to propose an index which can represent the market trend. Second, the mechanism of the momentum life cycle (MLC) remains a puzzle. We show that past winners perform better in the inter-day horizon while past losers perform better in the intra-day horizon. Meanwhile, past studies show that reversals generate excess returns in long-term horizon consistently. However, we do not know the accurate time horizon that the profitability moves from momentum to reversal factors and vice versa.

Finally, we find that indicators such as past returns and trading volume have strong predictive power for future returns. The magnitude of these returns is significant to cover transaction costs under practical implementation. Therefore, given the popularity of pairs trading and momentum reversals trading, the strategy on overreaction/underreaction and overvalued/undervalued appears economically significant. However, the economic rationale behind the profitability of these investment strategies is another puzzle we leave for future research., i.e., why this information is not fully reflected in current prices.

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Appendix A

Futures Contract Maturity and Trading Liquidity

Several studies on the international futures market claim that the most liquid futures contracts are the nearest or second-nearest to maturity (Miffre and Rallis, 2007; Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Fuertes, Miffre, and Perez, 2015). However, this case is not common in the Chinese futures market, the nearest or second-nearest to maturity contract is always low-liquidity, i.e., the trading volume is nearly zero. The transaction costs to open long/short positions on the illiquid contracts are significantly high, and even the orders cannot be executed in some cases.

Table A.1 displays the market activity for selected futures products with respect to trading days. Due to the limit of space, the trading information for futures products and trading days is partially documented and the market activity is consistent. Specifically, for the trading of Coke (J) on the day of January 18, 2016, the nearest contract is J1602, since the exchange does not allow the traders to hold the position in maturity month. Panel A of Table A.1 demonstrates that the trading liquidity is really low for the nearest contract (J1602) or the second-nearest contract (J1603), while more distance contracts (i.e., J1605 or J1609) are actively traded with respect to trading volume and open interest. Similarly, for the trading of Gold (AU) on the day of January 16, 2017, Panel B of Table A.1 demonstrates that the contracts of AU1706 and AU1712 are actively traded contracts. Moreover, for the trading of Steam Coal (ZC) on the day of May 16, 2017, Panel C of Table A.1 illustrates that the contracts of ZC709 and ZC801 are actively traded. Above all, it is demonstrated that the switching dates for the highest liquidity contracts (roll-over dates) are not uniform for the Chinese futures, and the liquidity of one contract generally decreases before the expiry date approaches.

Table A.2 reports the daily trading volume of Chinese futures with respect to the actively traded contracts, closest to maturity contracts and second-closest to maturity contracts. The trading volume is documented in terms of minimum, maximum, mean and low liquidity in percentage. The low liquidity is identified by the daily trading volume less than 100. The comparison shows that there are always some low liquidity cases for the nearest or second-nearest to maturity contract in the Chinese futures market. The average daily trading volume of the actively traded contract is apparently higher than that of the nearest or second-nearest to maturity contract. Furthermore, the consistent result is demonstrated in the comparison of minimum and maximum daily volumes. Therefore, it is reasonable to employ the actively traded contracts in this study, which is also suggested by the industry practitioners actively trading on the Chinese futures.

Since the objective of this study is providing practical suggestions both for the academia and practitioners, the most realistic framework is employed. According to the low-liquidity of the nearest or second-nearest contracts proposed by past studies (Miffre and Rallis, 2007; Shen et al., 2007; Fuertes, Miffre, and Rallis, 2010; Fuertes, Miffre, and Perez, 2015), this study applies the self-complied dataset[1] following the industry tradition, which is expected to provide the realistic and practical results.

For the consideration of roll-over returns, the daily log-returns are calculated from the close to pre-close prices when there is no roll-over between contracts, whereas if there is a roll-over happening, the return is obtained from the close to open price.

[1]The most actively traded contract is identified by the trading volume and open interest after the market closed every day, if the contract with the maximum trading volume is same as the one with the maximum open interest, the underlying contract will be the main contract for the next trading day, otherwise, the contract with the further maturity month will be the main contract.

The intuition behind this technique is that the holding positions would switch to the new active contract at the market open time. Additionally, the movement between the old and new active contracts occur regularly because most traders and CTAs appreciate short investment horizons (i.e. daily or few days) in the futures markets. This confirms that the financial industry does not pay much attention to the fixed roll-over rules, which is generally applied in the academic papers.

Table A.1: Market activity for selected futures products

Contract	Pre. Settlement	Open	High	Low	Close	Settlement	Volume	Open Interest
Panel A: Coke (J) on January 18, 2016								
J1602	0.00	0.00	0.00	658.00	658.00	658.00	0	90
J1603	0.00	0.00	0.00	656.00	656.00	656.00	0	20
J1604	0.00	0.00	0.00	760.50	760.50	760.50	0	82
<u>J1605</u>	625.00	640.50	622.50	639.00	627.50	634.00	227946	131530
J1606	622.00	640.00	622.00	640.00	632.00	629.50	8	4
J1607	0.00	0.00	0.00	606.00	608.00	606.00	0	8
J1608	0.00	0.00	0.00	624.50	626.50	624.50	0	2
J1609	608.00	624.50	606.00	624.00	613.00	617.50	23930	25512
J1610	0.00	0.00	0.00	627.50	623.00	627.50	0	4
J1611	615.50	615.50	607.00	608.00	603.50	611.00	10	26
J1612	620.00	620.00	619.50	619.50	619.50	619.50	4	6
J1701	598.50	618.00	558.00	618.00	603.50	610.50	500	214
Total	0.00	0.00	0.00	0.00	0.00	0.00	252398	157498
Panel B: Gold (AU) on January 16, 2017								
AU1701	269.00	0.00	0.00	0.00	269.00	269.00	0	372
AU1702	267.95	269.00	270.35	268.95	270.25	269.55	28	160
AU1703	268.50	269.35	270.50	267.95	269.25	269.30	18	16
AU1704	268.60	269.35	270.85	269.20	270.85	269.70	18	306
<u>AU1706</u>	271.35	271.60	273.45	270.45	272.95	271.70	215196	382384
AU1708	271.55	272.50	274.30	272.50	274.05	272.65	74	176
AU1710	274.20	273.65	275.10	273.65	275.10	274.15	10	136
AU1712	273.90	274.40	276.60	273.40	276.00	275.00	3142	9334
Total							218486	392884
Panel C: Steam Coal (ZC) on May 16, 2017								
ZC706	563.60	555.00	574.40	554.40	574.40	564.60	8	26
ZC707	541.60	0.00	0.00	0.00	0.00	541.60	0	0
ZC708	521.20	0.00	0.00	0.00	0.00	522.80	0	2
<u>ZC709</u>	510.80	510.80	522.00	508.00	521.60	514.40	187226	413674
ZC710	510.40	515.00	515.00	515.00	515.00	515.00	2	4
ZC711	517.00	0.00	0.00	0.00	0.00	522.40	0	2
ZC712	518.40	505.40	515.60	489.80	513.60	505.40	120	4
ZC801	516.60	517.80	526.80	514.20	526.60	519.60	7304	30772
ZC802	502.80	0.00	0.00	0.00	0.00	505.80	0	2
ZC803	529.80	0.00	0.00	0.00	0.00	529.80	0	0
ZC804	473.40	0.00	0.00	0.00	0.00	476.20	0	2
ZC805	493.60	491.60	497.00	491.20	497.00	493.20	98	236
Total							194758	444724

Notes: This table displays three examples (i.e., Coke, Gold and Steam Coal) in terms of market activity with respect to trading date in the Chinese market. The contract is represented by products ID plus maturity month, for example, J1602 denotes that the Coke futures (J) with maturity in February of 2016. The trading information including the volume and open interest are documented. Prices with values of 0.00 mean that there is no trade for that contract. The nearest, second-nearest to maturity contracts and most actively traded contracts are highlighted in boldface and underline. The market data is downloaded from the exchange website, http://www.dce.com.cn/dalianshangpin/xqsj/tjsj26/rtj/rxq/index.html (Coke-DCE), http://www.shfe.com.cn/statements/dataview.html?paramid=kx (Gold-SHFE), http://www.czce.com.cn/portal/DFSStaticFiles/Future/2017/20170516/FutureDataDaily.htm (Steam Coal-CZCE), respectively.

Table A.2: Trading volume for Chinese futures contracts

Products	Actively traded contracts				Nearest to maturity				Second-nearest to maturity			
	Minimum	Mean	Maximum	Low liquidity(%)	Minimum	Mean	Maximum	Low liquidity(%)	Minimum	Mean	Maximum	Low liquidity(%)
SHFE.CU	69828	350994	1319384	0	0	32602	119134	1	31072	238888	1162190	0
SHFE.AL	14944	192030	1115798	0	0	14714	91942	1	5362	133633	574658	0
SHFE.ZN	48202	419973	1844238	0	0	14891	186192	1	5620	302167	1844238	0
SHFE.NI	25018	628741	2027096	0	0	15880	741862	50	0	138212	1870082	39
SHFE.SN	68	16649	117778	1	0	1176	25734	73	0	4868	71278	69
SHFE.AU	30714	219938	997696	0	0	2437	75806	80	0	25030	429826	70
SHFE.AG	165778	664466	2777698	0	0	10672	441080	19	0	82078	1648032	28
SHFE.RB	998326	5500228	22361440	0	0	13190	689884	30	14	236295	4923144	7
SHFE.HC	4472	308160	1366450	0	0	1578	79242	82	0	32976	484316	71
SHFE.BU	8870	935011	5742748	0	0	15653	765152	59	0	150070	2028104	51
SHFE.RU	141414	630360	1621426	0	0	18449	640530	51	0	99645	1201474	52
DCE.C	17562	695996	3723882	0	0	56931	1040962	40	0	260095	3723882	33
DCE.CS	3930	375767	1386866	0	0	36416	611624	53	0	176413	1261036	49
DCE.A	20452	194298	1299000	0	0	19511	279206	54	0	92892	663104	46
DCE.M	390118	1952676	7651616	0	0	32604	1161044	57	0	340537	3964940	51
DCE.Y	210586	581384	1394688	0	0	10926	374026	74	0	87106	739728	67
DCE.P	121864	827984	2192238	0	0	1910	51800	82	0	59088	1696830	71
DCE.JD	48652	168588	790810	0	0	19862	423418	63	0	27752	363510	38
DCE.L	153042	662538	1945914	0	0	2260	79544	80	0	103922	1352510	72
DCE.V	1572	91559	498204	0	0	611	25498	84	0	21480	498204	72
DCE.PP	137190	722099	3628622	0	0	4378	274624	78	0	135841	2112582	71
DCE.J	17314	243581	2420704	0	0	1738	150056	80	0	32926	663158	71
DCE.JM	23972	222440	1508004	0	0	1245	100394	81	0	28781	492422	72
DCE.I	488242	2246292	7526732	0	0	12118	458882	72	0	269589	4856536	56
CZCE.CF	34264	325614	2864938	0	0	20353	508568	19	0	115618	1180982	27
CZCE.SR	148700	822613	3360972	0	0	79357	2168962	31	0	395816	3193876	45
CZCE.TA	192418	1270270	4321300	0	0	7881	211338	72	0	177029	2478650	68
CZCE.OI	19212	136881	803722	0	0	14978	319112	53	0	64611	641318	51
CZCE.MA	254140	1248577	4409694	0	0	3516	102282	78	0	189873	3226926	71
CZCE.FG	60644	401266	1918260	0	0	1641	201664	82	0	65970	764546	68
CZCE.RM	232564	1434127	6092828	0	0	65864	1771172	48	0	397072	4619488	37
CZCE.ZC	2350	227308	1700950	0	0	6567	219306	79	0	52621	838992	71
CFFEX.IF	4154	239112	2882235	0	0	226271	2882235	1	95	31318	2340449	0
CFFEX.IC	2196	37508	502523	0	0	35375	502523	1	102	5714	385745	0
CFFEX.IH	0	51185	861208	1	0	49071	861208	1	0	6699	464391	3
CFFEX.TF	1453	12195	75239	0	0	9637	75239	12	41	4321	44662	1
CFFEX.T	1235	25215	109383	0	0	17496	109383	12	28	11312	75352	2

Notes: This table displays the daily trading volumes for the Chinese futures during 2015-05-22 to 2017-08-09. The product is identified by trading exchanges plus futures ID, for example, DCE.J denotes that the Coke futures (J) traded in the Dalian Commodity Exchange (DCE). The daily trading volume is reported including the minimum, maximum, mean and low liquidity in terms of percentage. The low liquidity trading day is recorded when the daily trading volume is less than 100, which implies that the contract is really illiquid. The trading volume data is downloaded from the exchange website, http://www.dce.com.cn (DCE), http://www.shfe.com.cn (SHFE), http://www.czce.com.cn (CZCE), http://www.cffex.com.cn (CFFEX), respectively.

Appendix B

Pairs trading with the GARCH model

This appendix demonstrates that the implementation of the GARCH model in pairs trading significantly increase the duration of time spent on the modelling, but the performance of the trading strategy is not apparently improved. Table B.2 documents the profitability of pairs trading based on GARCH(1,1) model, the performance is similar to the results recorded in Table 3.8 based on the model-free standard deviation $(2-\sigma)$ approach. However, Table B.1 indicates that the time of duration spent on the GARCH model is multiple (i.e., around 500) times compared to the historical standard deviation model. The equivalent performance of model-free 2-stdev approach affirms that employing more general models does not necessarily improve the profitability of the pairs trading strategy. Therefore, this study reports the historical standard deviation model as a baseline model due to its model-free feature.

Table B.1: Duration of time spent on the backtesting of pairs trading

Model	Historical Standard Deviation $(2-\sigma)$	GARCH(1,1)
Time Duration	61 seconds	31331 seconds

Notes: This table presents the duration of time spent on the backtesting documented in Table 3.8 and Table B.2. The backtesting is conducted on a PC with 2.5 GHz Intel Core i7 CPU, 16 GB 1600 MHz DDR3 RAMs and MATLAB (2017a).

Table B.2: Profitability of pairs trading based on GARCH(1,1) model

Profitability	1 pair	2 pairs	3 pairs	4 pairs	5 pairs	6 pairs
Panel A: Termination T=22						
Average Return (%)	5.28	2.36	0.67	0.39	-2.20	-4.53
Standard Deviation (%)	17.04	17.56	15.94	16.01	13.32	10.66
Standard Error (Newey-West) (%)	8.40	8.21	7.37	7.42	6.31	5.60
Sharpe Ratio	0.13	-0.04	-0.15	-0.16	-0.39	-0.71
Return /Avg. Max.Drawdown	0.45	0.20	0.06	0.03	-0.19	-0.41
t-Statistics	0.63	0.29	0.09	0.05	-0.35	-0.81
p-Value	0.27	0.39	0.46	0.48	0.63	0.78
Median (%)	1.59	0.88	-1.40	0.08	-2.15	-5.53
Skewness	0.61	0.44	0.60	0.62	0.60	0.58
Kurtosis	2.09	2.08	2.09	2.09	2.10	2.24
Minimum (%)	-15.03	-22.25	-18.70	-18.30	-17.54	-17.91
Maximum (%)	33.54	29.95	27.43	26.37	20.69	14.75
Negative Return	44%	44%	56%	44%	67%	78%
Panel B: Termination T=44						
Average Return (%)	11.41	7.87	6.01	5.40	3.88	1.98
Standard Deviation (%)	19.08	19.43	17.01	17.45	14.53	12.13
Standard Error (Newey-West) (%)	11.25	10.06	8.61	8.64	7.21	5.87
Sharpe Ratio	0.44	0.25	0.18	0.14	0.06	-0.08
Return /Avg. Max.Drawdown	0.89	0.59	0.45	0.39	0.29	0.15
t-Statistics	1.01	0.78	0.70	0.62	0.54	0.34
p-Value	0.17	0.23	0.25	0.27	0.30	0.37
Median (%)	8.33	4.77	5.61	3.46	2.03	-0.24
Skewness	0.73	0.44	0.69	0.73	0.64	0.57
Kurtosis	2.15	1.98	2.41	2.22	2.08	2.07
Minimum (%)	-9.57	-18.18	-14.56	-14.95	-12.96	-13.15
Maximum (%)	41.85	38.64	37.80	33.83	27.61	22.28
Negative Return	33%	44%	44%	44%	44%	56%
Panel C: Termination T=66						
Average Return (%)	13.34	8.93	7.59	7.21	5.83	4.10
Standard Deviation (%)	17.82	17.16	16.37	16.65	13.67	11.75
Standard Error (Newey-West) (%)	11.47	9.55	8.83	8.87	7.37	6.10
Sharpe Ratio	0.58	0.35	0.28	0.25	0.21	0.09
Return /Avg. Max.Drawdown	1.00	0.69	0.55	0.52	0.44	0.31
t-Statistics	1.16	0.93	0.86	0.81	0.79	0.67
p-Value	0.14	0.19	0.21	0.22	0.23	0.26
Median (%)	7.65	5.92	5.18	3.93	2.12	-0.07
Skewness	0.55	0.47	0.71	0.66	0.60	0.60
Kurtosis	1.75	2.19	2.34	2.10	2.01	2.04
Minimum (%)	-7.96	-14.59	-11.40	-12.22	-9.79	-10.09
Maximum (%)	41.85	38.64	38.40	34.27	28.30	24.33
Negative Return	22%	33%	44%	44%	44%	56%
Panel D: Termination T=126						
Average Return (%)	14.47	10.92	8.58	7.99	7.30	5.63
Standard Deviation (%)	16.70	17.47	15.83	16.08	13.16	11.47
Standard Error (Newey-West) (%)	11.51	10.36	8.92	8.86	7.64	6.41
Sharpe Ratio	0.69	0.45	0.35	0.31	0.33	0.23
Return /Avg. Max.Drawdown	1.01	0.75	0.58	0.52	0.49	0.39
t-Statistics	1.26	1.05	0.96	0.90	0.96	0.88
p-Value	0.12	0.16	0.18	0.20	0.18	0.20
Median (%)	9.01	11.32	6.49	5.92	4.51	2.32
Skewness	0.57	0.30	0.63	0.63	0.54	0.55
Kurtosis	1.76	2.06	2.39	2.10	1.93	1.94
Minimum (%)	-2.26	-14.66	-11.45	-11.42	-8.07	-8.14
Maximum (%)	41.85	38.64	38.40	34.27	27.89	24.85
Negative Return	22%	44%	44%	44%	44%	44%
Panel E: Termination T=252						
Average Return (%)	14.47	10.89	8.62	8.01	7.39	5.65
Standard Deviation (%)	16.70	17.32	15.71	16.00	13.19	11.49
Standard Error (Newey-West) (%)	11.51	10.33	8.90	8.84	7.67	6.43
Sharpe Ratio	0.69	0.46	0.36	0.31	0.33	0.23
Return /Avg. Max.Drawdown	1.01	0.73	0.57	0.52	0.50	0.38
t-Statistics	1.26	1.05	0.97	0.91	0.96	0.88
p-Value	0.12	0.16	0.18	0.20	0.18	0.20
Median (%)	9.01	10.29	5.80	5.40	4.10	1.38
Skewness	0.57	0.35	0.67	0.66	0.57	0.59
Kurtosis	1.76	2.06	2.41	2.11	1.94	1.93
Minimum (%)	-2.26	-13.83	-10.90	-11.01	-7.74	-7.68
Maximum (%)	41.85	38.64	38.40	34.27	27.89	24.85
Negative Return	22%	44%	44%	44%	44%	44%

Notes: This table presents average annualized returns, standard deviations of returns and the Sharpe ratios calculated with the risk-free rate assumed as 3%. The t-statistic of the mean is computed using Newey-West standard errors with two lags. The result is calculated by repeating the out-of-sample backtesting for the 9 trading subperiods with respect to different maximum holding period. The trading threshold calculation is based on the GARCH(1,1) model, which is developed by Engle (1982).

Appendix C

First Passage Time Density

This study employs the first passage time density and the Laplace transform provided in Finch (2004) for the standardized OU process, i.e. $Z_{\bar{t}} = (X_t - \mu)/(\sigma/\sqrt{2\rho})$ and $\bar{t} = \rho t$; however, t is used instead of $\bar{t}$ with a slight abuse of notation, although it is now scaled by the speed of mean reversion parameter ρ. The standardized OU process is given as

$$dZ_t = -Z_t dt + \sqrt{2} dW_t. \tag{C.1}$$

Let the first passage time to a starting from c be denoted as

$$\tau_{a,c} = \min\{t \geq 0 : Z_t = a | Z_0 = c\}, \tag{C.2}$$

where in the standardized spread process the long-term mean becomes zero. Mean reversion of the original process in Equation 3.3 to the long-term mean level μ is equivalent to the mean reversion of the dimensionless process (in Equation C.1) to zero (i.e. $a = 0$). The probability density of the first passage time $\tau_{0,c}$ starting from the dimensionless deviation level c is given by (see Finch (2004) for details)

$$f_{0,c} = \sqrt{\frac{2}{\pi}} \frac{|c| e^{-t}}{(1 - e^{-2t})^{3/2}} \exp\left(-\frac{c^2 e^{-2t}}{2(1 - e^{-2t})} \right), \quad \text{for } t > 0. \tag{C.3}$$

Given the standardized process is at $c > 0$ (i.e. deviated away from its long-term mean), the expected value of the first hitting time to the long-term mean, i.e. $\tau_{0,c}$, is given by

$$\mathbb{E}[\tau_{0,c}] = \frac{1}{2}\sum_{k=1}^{\infty}(-1)^{k+1}\frac{(\sqrt{2}c)^k}{k!}\Gamma\left(\frac{k}{2}\right) > 0. \tag{C.4}$$

Alternatively, given that the standardized process is at the long-term mean level, i.e. $Z_0 = 0$, the first passage time to the upper threshold level $a > 0$, which is denoted as $\tau_{a,0}$, has the expected value given by

$$\mathbb{E}[\tau_{a,0}] = \frac{1}{2}\sum_{k=1}^{\infty}\frac{(\sqrt{2}a)^k}{k!}\Gamma\left(\frac{k}{2}\right) > 0, \tag{C.5}$$

where $\Gamma(.)$ is the gamma functions. Since the dimensionless system is given by ρt, expected hitting time should be divided by ρ for conversion to annualized time (see Finch (2004) for details).

Appendix D

Elliot, Van Der Hoek and Malcolm's Kalman Filter Method

Elliot et al. (2005) consider that the spreading process is a noisy system with a mean-reverting state process. Therefore, the Kalman filter technique can be used to filter the noise and obtain better estimates of the true mean-reverting OU process. Elliot et al. (2005) employ two EM algorithms for implementing the Kalman filter, which are given in Shumway and Stoffer (1982) and Elliot and Krishnamurthy (1999), respectively. This study implements the Shumway and Stoffer (1982) EM algorithm in the empirical analysis. Next, the Kalman filter method proposed by Elliot et al. (2005) is briefly introduced.

Consider a state process $\{x_k | k = 0, 1, 2, ...\}$ where x_k represents the value at time $t_k = k\tau$ for $k = 0, 1, 2, ...$ It is assumed that $\{x_k\}$ is mean reverting:

$$x_{k+1} - x_k = (\tilde{a} - \tilde{b}x_k)\tau + \sigma\sqrt{\tau}\epsilon_{k+1}, \tag{D.1}$$

with $\sigma \geq 0, \tilde{b} > 0, \tilde{a} \in \mathcal{R}$ (which is non-negative without any loss of generality), and $\{\epsilon_k\}$ is i.i.d Gaussian $\mathcal{N}(0, 1)$.

Equation D.1 can be written as

$$x_{k+1} = A + Bx_k + C\epsilon_{k+1}, \tag{D.2}$$

where $A = \tilde{a}\tau \geq 0, 0 < B = 1 - \tilde{b}\tau < 1$ and $C = \sigma\sqrt{\tau}$, provided $\tau > 0$ and small so that $\left|1 - \tilde{b}\tau\right| < 1$. The state process can also be regarded as $x_k \approxeq X(k\tau)$ where $\{X(t)|t \geq 0\}$ satisfies the stochastic differential equation:

$$dX(t) = (\tilde{a} - \tilde{b}X(t))dt + \sigma dW(t), \tag{D.3}$$

with $\{W(t)|t \geq 0\}$ denoting a standard Brownian motion. The SDE can be written in the form

$$dX(t) = -\rho(X(t) - \mu)dt + \sigma dW(t), \tag{D.4}$$

with $\rho = \tilde{b}$ and $\mu = \tilde{a}/\tilde{b}$, which corresponds to our original model in Equation 3.3. Therefore, the OU process can be used as an approximation to Equation D.2 with $\tilde{a} = A/\tau$, $\tilde{b} = (1 - B)\tau$ and $\sigma = C/\sqrt{\tau}$ with the calibrated values A, B, C.

Consider an observation process $\{y_k\}$ of $\{x_k\}$ given as

$$y_k = x_k + D\omega_k, \tag{D.5}$$

with $\{\omega_k\}$ being i.i.d Gaussian $\mathcal{N}(0, 1)$ and independent of the $\{\epsilon_k\}$ in Equation D.1 and $D > 0$.

The observed values $\{y_k\}$ are the observed values of the spreading process at time t_k, which is a noisy observation of some mean-reverting state process $\{x_k\}$. The parameters of the system can be estimated by solving Equations (31)-(42) in the Shumway and Stoffer (1982) smoother approach, which is an off-line calculation and makes use of smoother estimators for the Kalman filter.

In the Shumway and Stoffer (1982) smoother approach, the smoothers (for $k \leq N$) are defined as

$$\begin{aligned} \hat{x}_{k|N} &= \mathbb{E}[x_k|\mathcal{Y}_N], && \text{(D.6)} \\ \Sigma_{k|N} &= \mathbb{E}[(x_k - \hat{x}_{k|N})^2|\mathcal{Y}_N] = \mathbb{E}[(x_k - \hat{x}_{k|N})^2], && \text{(D.7)} \\ \Sigma_{k-1,k|N} &= \mathbb{E}[(x_k - \hat{x}_{k|N})(x_{k-1} - \hat{x}_{k-1|N})]. && \text{(D.8)} \end{aligned}$$

The above smoothers can be computed by

$$\begin{aligned}
\mathcal{J}_k &= \frac{B\Sigma_{k|k}}{\Sigma_{k+1|k}}, && \text{(D.9)}\\
\hat{x}_{k|N} &= \hat{x}_{k|k} + \mathcal{J}_k[\hat{x}_{k+1|N} - (A + B\hat{x}_{k|k})], && \text{(D.10)}\\
\Sigma_{k|N} &= \Sigma_{k|k} + \mathcal{J}_k^2[\Sigma_{k+1|N} - \Sigma_{k+1|k}], && \text{(D.11)}\\
\Sigma_{k-1,k|N} &= \mathcal{J}_{k-1}\Sigma_{k|k} + \mathcal{J}_k\mathcal{J}_{k-1}[\Sigma_{k,k+1|N} - B\Sigma_{k|k}], && \text{(D.12)}\\
\Sigma_{N-1,N|N} &= B(1 - \mathcal{K}_N)\Sigma_{N-1|N-1}, && \text{(D.13)}
\end{aligned}$$

where initial values for this backward recursion $\hat{x}_{N|N}$ and $\Sigma_{N|N}$ are obtained from the Kalman filter along with other estimates recursively as follows:

$$\begin{aligned}
\hat{x}_{k+1|k} &= A + B\hat{x}_{k|k}, && \text{(D.14)}\\
\Sigma_{k+1|k} &= B^2\Sigma_{k|k} + C^2, && \text{(D.15)}\\
\mathcal{K}_{k+1} &= \Sigma_{k+1|k}/(\Sigma_{k+1|k} + D^2), && \text{(D.16)}\\
\hat{x}_{k+1|k+1} &= \hat{x}_{k+1|k} + \mathcal{K}_{k+1}[y_{k+1} - \hat{x}_{k+1|k}], && \text{(D.17)}\\
\Sigma_{k+1|k+1} &= D^2\mathcal{K}_{k+1}. && \text{(D.18)}
\end{aligned}$$

Given $v_j = (A, B, C^2, D^2)$, and initial values for the Kalman filter $\hat{x}_0 =^{j-1} \hat{x}_{0|N}$ and $\Sigma_{0|0} =^{j-1} \Sigma_{0|N}$, which are the smoothers from the previous step $(j-1)$. The updates $v_{j+1} = (\hat{A}, \hat{B}, \hat{C}^2, \hat{D}^2)$ are computed as follows:

$$\begin{aligned}
\hat{A} &= \frac{\alpha\gamma - \delta\beta}{N\alpha - \delta^2}, && \text{(D.19)}\\
\hat{B} &= \frac{N\beta - \gamma\delta}{N\alpha - \delta^2}, && \text{(D.20)}\\
\hat{C}^2 &= \frac{1}{N}\sum_{k=1}^{N}[(x_k - \hat{A} - \hat{B}x_{k-1})^2|\mathcal{Y}_N], && \text{(D.21)}\\
\hat{D}^2 &= \frac{1}{N+1}\sum_{k=0}^{N}[(y_k - x_k)^2|\mathcal{Y}_N], && \text{(D.22)}
\end{aligned}$$

where

$$\begin{aligned}
\alpha &= \sum_{k=1}^{N} \mathbb{E}[x_{k-1}^2|\mathcal{Y}_N] = \sum_{k=1}^{N}[\Sigma_{k-1|N} + \hat{x}_{k-1|N}^2], && \text{(D.23)}\\
\beta &= \sum_{k=1}^{N} \mathbb{E}[x_{k-1}x_k|\mathcal{Y}_N] = \sum_{k=1}^{N}[\Sigma_{k-1,k|N} + \hat{x}_{k-1|N}\hat{x}_{k|N}], && \text{(D.24)}\\
\gamma &= \sum_{k=1}^{N} \hat{x}_{k|N}, && \text{(D.25)}\\
\delta &= \sum_{k=1}^{N} \hat{x}_{k-2|N} = \gamma - \hat{x}_{N|N} + \hat{x}_{0|N}, && \text{(D.26)}
\end{aligned}$$

and the right-hand side of equations D.21 and D.21 can be computed as

$$\begin{aligned}
\hat{C}^2 &= \frac{1}{N}\sum_{k=1}^{N}[\Sigma_{k|N} + \hat{x}_{k|N}^2 + \hat{A}^2 + \hat{B}^2\Sigma_{k-1|N} + \hat{B}^2(\hat{x}_{k-1|N})^2 \\
&\quad -2\hat{A}\hat{x}_{k|N} + 2\hat{A}\hat{B}\hat{x}_{k-1|N} - 2\hat{B}\Sigma_{k-1,k|N} - 2\hat{B}\hat{x}_{k|N}\hat{x}_{k-1|N}], && \text{(D.27)}\\
\hat{D}^2 &= \frac{1}{N+1}\sum_{k=0}^{N}[y_k^2 - 2y_k\hat{x}_{k|N} + \Sigma_{k|N} + \hat{x}_{k|N}^2]. && \text{(D.28)}
\end{aligned}$$

In this study, a MATLAB code has been written for this estimation based on $N+1$ observations $y_0, y_1, ..., y_N$. Then the parameters are estimated following the above steps.

To check the robustness of this method, a numerical example for the simulation and estimation of the state process is included to verify the convergence of the Shumway and Stoffer (1982) algorithm for the Kalman filter. 1,000 values are simulated with parameters $A = 0.3$, $B = 0.75$, $C = 0.4$ and $D = 0.6$, where the EM algorithm is initialized with $A_0 = 0.5$, $B_0 = 0.9$, $C_0 = 0.3$, and $D_0 = 0.7$, with $\hat{x_{0|0}} = 0$ and $\Sigma_{0|0} = 0.1$. The EM algorithm was iterated 150 times. Figure D.1 shows the simulation process by generating random numbers from i.i.d Gaussian $\mathcal{N}(0,1)$ distributions. Figure D.2 illustrates convergence of the maximum likelihood estimates of all parameters.

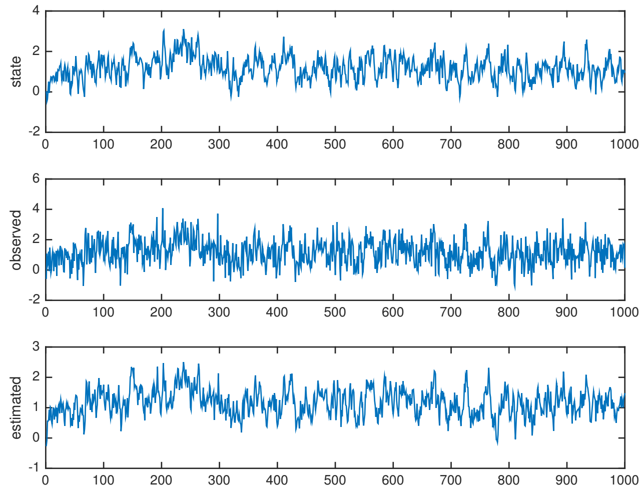

Figure D.1: Simulated and estimated data series for the Kalman filter

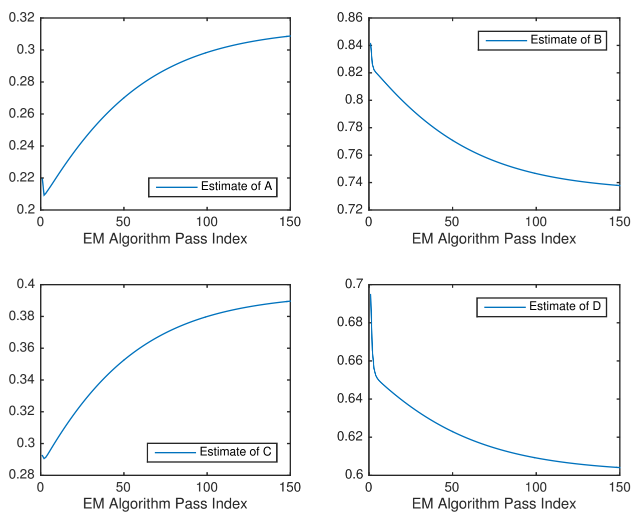

Figure D.2: Convergence of the maximum likelihood estimates for the Kalman filter

Appendix E

Zeng and Lee Method

Zeng and Lee (2014) suggest the investor chooses the best threshold level in terms of maximizing the expected profit per unit time. If the thresholds are narrow around the mean level, then the time it takes to return to the equilibrium level is short and the profit per trade is low; however, if the trading thresholds are far away from the long-term mean, the profit in each trade is high, and thus on average it takes long to realize the profit. Since the transaction cost is definitely positive in real trading, only case 2 in Zeng and Lee (2014) is considered in this study. Zeng and Lee (2014) propose the optimal trading thresholds as a function of parameters of the OU process and the transaction cost. Therefore, a polynomial expression is derived for the expectation of the first-passage time of the OU process with a two-sided boundary, and the analytic formulas for optimal trading thresholds are obtained as the solution for the following problem:

$$\begin{aligned} \max \qquad & f(a,b) = \frac{a-b-\lambda}{E[\tau_1]+E[\tau_2]} = \frac{a-b-\lambda}{\frac{1}{2}\sum_{n=0}^{\infty} \frac{(\sqrt{2}a)^{2n+1}-(\sqrt{2}b)^{2n+1}}{(2n+1)!}\Gamma\left(\frac{2n+1}{2}\right)} \\ \text{subject to} \quad & -a \leq b \leq \min\{0, a-\lambda\}, \end{aligned} \tag{E.1}$$

with the transaction cost in the dimensionless system given in Equation C.1 as $\lambda > 0$, a and b are the upper and lower thresholds, respectively. The first passage time to the long-term mean is denoted by τ_1 and the waiting duration until the next trading opportunity is denoted by τ_2. Mathematically, τ_1 and τ_2 are defined as follows:

$$\tau_1 = \min\{t \geq 0 : Z_t = b | Z_0 = a\}, \tag{E.2}$$

$$\tau_2 = \min\{t \geq 0 : Z_t = a | Z_0 = b\}, \tag{E.3}$$

where Z_t is the standardized mean-reverting process given in Equation C.1. The solution of $a = -b$ can be calculated by solving Equation E.4.

$$\frac{1}{2}\sum_{n=0}^{\infty}\frac{(\sqrt{2}a)^{2n+1}}{(2n+1)!}\Gamma\left(\frac{2n+1}{2}\right) = \left(a - \frac{\lambda}{2}\right)\frac{\sqrt{2}}{2}\sum_{n=0}^{\infty}\frac{(\sqrt{2}a)^{2n}}{(2n)!}\Gamma\left(\frac{2n+1}{2}\right), \tag{E.4}$$

where standardized $\lambda = \lambda^* \frac{\sqrt{2\theta}}{\sigma}$ with the real transaction cost denoted as λ^*. In this situation, the open/close trading thresholds are $\mu \pm a\frac{\sigma}{\sqrt{2\theta}}$, where μ, σ, and θ are estimates for the OU process. The equation is difficult to be solved symbolically; alternatively, it is solved by the bisection method in this paper.

Appendix F

Göncü and Akyıldırım Method

Göncü and Akyıldırım (2016a) derive an optimal threshold level that maximizes the probability of successful termination (mean-reversion probability) of the spread portfolio for a given investment horizon. The objective function is given as (see Göncü and Akyıldırım (2016a) for details)

$$\max_c P(\tau < T) = \max_c \int_0^T f_{0,c} dt, \tag{F.1}$$

where $T > 0$ represents the investment horizon of the investor. The solution of this problem is derived as

$$c^*(T) = \sqrt{\frac{1 - e^{-2T}}{e^{-2T}}}, T > 0, \tag{F.2}$$

which is an increasing function with respect to the investment horizon T, with $f_{0,c}$ is given in Equation C.3. In this method, the upper and lower thresholds are $\mu \pm c^* \frac{\sigma}{\sqrt{2\theta}}$, where μ, σ, and θ are estimated from the spread process.

Note that there is an important difference between the trading rules in the Zeng and Lee (2014) method versus the 2-stdev and Göncü and Akyıldırım (2016a) methods. In Zeng and Lee (2014) the trade cycles are longer since a trader that opens a spread position at the upper (lower) threshold closes it at the lower (upper) threshold instead of at the long-term mean level. In the 2-stdev and Göncü and Akyıldırım (2016a) methods, the trader closes the position whenever the long-term mean level is reached.