Empirical Analysis of Technical Trading Behaviour, Margin Trading, and Market Reaction to News in Futures Market

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by

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To my wife Chen Chen, for her persistent reliance and encouragement:

"Sometimes it's the very people who no one imagines anything of who do the things that no one can imagine."

—The Imitation Game (Alan Turing)

Abstract

This thesis comprises three chapters. It focuses on a unique dataset of the full transaction records of traders in the Chinese futures market. Empirical techniques are used to analyse technical trading behaviour, margin trading, and market reactions to news in this market. Chapter 1, "Technical Trading Behaviour: Evidence from Chinese Futures Market", creates a new computational method to capture technical trading behaviour and finds technical trader's strategies can be classified in to 11 groups in Chinese rebar futures market. We use a simple model with macroeconomic news to filter pure technical traders from the unique data. Based on the estimation of 81000 technical trading rules, we find the potential technical strategies of each trader and we use K-means clustering algorithm to classify them. The coordinates of each cluster summarize the technical trading characteristics of members in each group. High percentage of traders in each group would apply the similar and corresponding strategies; Chapter 2, "Margin Trading: Hedonic Returns and Real Losses", focus on margin trading in the Chinese rebar futures market. We find market participants have a positive chance of a large gain and a large chance of a small limited loss under the mechanism. This kind of hedonic returns looks like that of people who play in a casino or buy lottery tickets. According to the unique dataset, we show that both expected and observed losses are substantial and that the optimal portfolio never contains rebar futures. Based on the analysis of traders' behaviour, we indicate that it is hard to rationalise their trading without a hedonic motive. Their trading behaviour can be easily understood as form of entertainment, such as gambling; Chapter 3, "The Influence of Scheduled Macroeconomic Announcements on the Futures Market: Evidence from Commodity Futures in China", is a comprehensive empirical analysis of the overall Chinese futures market, which covers 23 commodities futures to observe the relationship between futures and scheduled macroeconomic news. We find the scheduled news affect commodity futures around 20 days before the announcements date and the following adjustment needs several days around the announcement date to be absorbed. Different kinds of commodities futures have different sensitivity levels to the scheduled news and this sensitivity does not depend on the trading activity. We also indicate the influence of scheduled news can happen in any stages of a business cycle. We finally use 36070 traders in the unique data to prove that market participants cannot make excess returns by following macroeconomics news in Chinese futures market.

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Declaration

I declare that chapter 1: "Technical Trading Behaviour: Evidence from Chinese Futures Market" and chapter 3: "The Influence of Scheduled Macroeconomic Announcements on the Futures Market: Evidence from Commodity Futures in China" are entirely my own, and chapter 2: "Margin Trading: Hedonic Returns and Real Losses" is my joint paper with Doctor Dan Ladley and Doctor James Rockey. Chapter 1 has been presented at the CEF conference 2015 (Taipei) and the 16th EBES conference (Istanbul). Chapter 2 will be presented at the RES conference 2016 (Sussex).

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Chapter 1

Technical Trading Behaviour: Evidence from Chinese Futures Market

Abstract

Technical traders adopt mathematical methods to formulate various technical trading rules on their trading strategies. This paper utilises two unique datasets - individual and market tick-by-tick data - to disclose the categories and characteristics of technical traders' strategies in Chinese rebar futures market. Firstly, we use a simple multiple regression model to filter technical traders in individual dataset. Then, dummy signals according to six popular kinds of technical rules are generated as benchmark by market dataset for real trading actions. According to the similarity between dummy signals with different technical rules and traders' real actions, we employ K-means algorithm to classify technical traders. Through these empirical works, technical traders in my dataset are classified into 11 groups. Finally, on the basis of 11 clusters' coordinates, the features of technical strategies in each group are summarised. We find that the most active and pure technical traders follow similar known technical trading rules and their strategies are able to capture by the provided method.

1.1 Introduction and Literature Review

Generally, trader's types have many kinds of identification, and these diversities could reflect on the trading behaviour. Current theoretical researches on market microstructures usually divide traders into informed and uninformed traders (Bagehot & Treynor, 1971) [4]. With development of the theory of financial market microstructure, traders also are classified as patient and impatient, based on the traders' risk preference and strategies (Foucault, Kadan, and Kandel, 2005) [45]. An alternate perspective to the traders' types - one that is more relevant to the price of underlying assets - classifies traders into fundamental and technical traders. According to the efficient market hypothesis, the current price of one underlying asset reflects all information of past prices, at least (Fama, 1970) [40]. Fundamentalists tend to consider all information of their investment to decide their trading strategies. Since good or bad news randomly happens and causes fluctuations in the price, fundamentalists generally trust that the abnormal price trend will go back to normal, and so take a long-term position in their trading. Technical traders, however, are obsessed with past price chart. They believe market price trends can be repeated and followed so that they use a series of trading rules based on past prices to make their trading decisions. In other words, the motivation of past price trends indicates the possible change of current prices and thus technical traders trust that they are able to recognise the change earlier with different rules in order to make a profitable strategy (Gencay, 1999) [50] [51]. With development of programming trading, more and more technical traders mix several technical trading rules in their strategies with the aid of computational power. The original day-to-day trading strategies have evolved from minute-to-minute and even second-to-second. Hence, technical traders usually take short-term positions and sometimes provide huge liquidity as noise traders in financial market (Tian, Wan, and Guo, 2002) [99]. Technical analysis in that noise trader is quite simple. They can be recognised as price trend followers as well, which means that they buy when the price goes up and sell when the price goes down (or contrary to trend). This performance would bring higher profit than fundamentalists in the short-term, and also can be existing in long-term (De Long, Shleifer, Summers, and Waldmann, 1990 & 1991; Slezak, 2003) [29] [30] [96]. So, could we know that what are technical traders' strategies in financial market and how to capture them? The aim of this paper is to investigate these questions and try to disclose the traders' strategies and behaviours from the empirical points of view. Eventually, the work employs a set of applied economic and mathematical methods to investigate and explain technical traders and their strategies.

This research concentrates mainly on the commodity futures, using rebar futures contract in Chinese futures market as the underlying asset to investigate technical trading strategies. Commodity futures market has many merits to discuss market participants' behaviours. It is well known that the main function of futures is to hedge investor's portfolio in order to guard against unexpected inflation or deflation in the future (Bodie, 1980 & 1983) [14] [13]. In addition, one contract is similar as one share in stock market, which also has higher liquidity and lower cost to trade (Wang and Yu, 2004) [101]. Compared with stock and other conventional financial market, commodity futures supply diversification and benefits for investment portfolios (Vrugt et al., 2004) [100]. Gorton and Rouwenhorst (2006) [53] claim that commodity futures can afford the weak performance of stocks, due to unexpected inflation in a period. Erb and Harvey (2006) [36] also support this point and suggest that active management of commodity futures can bring outstanding performance to investors' portfolios. Thus, various advantages of commodity futures have been discussed.

However, most of them pay attention to analysing applicability according to the profitability of different strategies. Vrugt et al. (2004) [100], for example, proves that monetary policy and other related factors can construct profitable strategies in different commodity futures. It explains that fundamentalists would find it profitable based on external information of the underlying assets in a long-term investment, but this is not a standard method to evaluate the information effect on different portfolios. Regarding technical trading strategies, many empirical works have also indicated technical trading strategies can be profitable, and several of them believe that positive profits can be generated through different technical trading rules (Park and Irwin, 2007) [88]. Donchian (1960) [31] firstly states the channel trading rules in copper futures contract, and the following developed research on his work finds that the profitability of channel rules can exceed estimated transaction costs. For instances, 5.1% to 26.6% profit rate was generated by channel trading rules system in soybean, soybean meal, and soybean oil between 1984 and 1988 (Irwin et al., 1997) [60]. 3.8% to 5.6% mean returns are achieved by moving average and trade range break out systems in 12 futures contract, which include agricultural and metal commodity futures between 1978 and 1984 (Lukac et al., 1988) [76]. Lo et al. (2000) [73], Neely (2002) [82], and Faber (2007) [38] find same evidence as Lukac's work in various financial markets. Jegadeesh and Titman (1993) [63] raised momentum strategies, and Miffre and Rallis (2007) [81] applied it to commodity futures, which brought the annual profit rate over 9%. Conversely, contrarian strategies generate abnormal returns in short-term investment of commodity futures (Lo and MacKinlay, 1990) [72]. Cornell and Dietrich (1987) [28] also document profitability of moving average and filter rules system with using Bretton Wood data. Brock et al. (1992)[19] combines momentum-based moving average and trading range break out rules to investigate the performance of technical trading strategies. Certainly, the investigation of technical trading rules has many valuable examples in foreign exchange market. Sweeney (1986)[98] indicates that filter rules, which apply in ten kinds of currencies, can bring about 80% profits in the trading. Levich and Thomas (1993)[71] find the application of filter and moving average rules is significant to trading profit of five currency futures. Longer moving average strategies can generate persisting profitability in emerging markets, which is founded by Fifield et al. (2008)[42]. Some related studies are Qi and Wu (2006)[91], Sullivan et al. (1999)[97], Neely et al. (2003 & 2009)[83] [84], Lucke (2003)[74] and Marshall et al. (2008)[79].

The above literatures discussed and investigated the profitability and capacity of technical trading strategies in different financial markets. However, this paper tries to disclose the technical trading rules that market participants employ in their trading decisions and how similar between traders' real actions and dummy actions according to different rules. Also, some previous surveys articles show the effect of technical trading strategies on individual trading behaviours, such as Lui and Mole (1998)[75] and Oberlechner (2001)[86]. They find that market participants would adopt technical trading strategies in a lot for shorter forecasting intervals. According to Gehrig and Menkhoff (2006)[49], the realisations of dummy buy or sell signals of different technical trading rules are generated by past price records. Then, traders could use these series of dummy signals of different technical trading rules to make their trading decisions.

In this paper, we collect two unique datasets to make this relevant empirical work. The first key dataset is individual tick-by-tick data. The outstanding point of this data includes traders' identification and records all of their transaction details. Based on this element, we disclose technical traders' different strategies by real market participants. More details of this dataset descriptions are in section 2. Another dataset is market price tick-by-tick data. It is used to generate dummy signals. It includes all price record also as tick-by-tick, high frequency, and per second data - which covers all selected underlying futures contracts in the individual transaction dataset. After smoothing this dataset, the dummy trading signals of selected technical trading rules are generated by the smoothing per second price data.

In this paper, we select three popular kinds of technical trading rules - Momentum, Moving Average, and Trading Range Break-out. According to intraday trading time in Chinese futures market, each kind of rules has different parameter settings and generates a technical strategies universe with 13,500 different rules. And, we introduce the contrarian rules of the above three rules. Hence, the amount selected rules in this research are $\mathbf{13500 * (3+3) = 81000}$. Then, we combine the dummy signals and traders' real action together to calculate the similarity between them. Based on the similarities between each trader's real actions and each rules' dummy signals, we employ K-means clustering algorithm to classify technical traders. Referring to the clustering results, technical traders' strategies can be divided into 11 groups in my dataset. At the end, on the basis of coordinates of 11 clusters, the characteristics of technical strategies in each group are disclosed.

The structure of this paper is as below: section 2 describes the details of datasets in this empirical work; section 3 details the process of filtering technical traders, and the generation and matching of dummy trading signals; section 4 shows the working of K-means cluster algorithm and its results; section 5 introduces a simple regression model to disclose the features of strategies in each group; and section 6 displays the conclusion of this paper.

1.2 Data Description

In the financial market, futures market is regarded as being a high-liquidity market similar to stock and foreign currency. Normally, most products on futures market are commodities, such as corn and copper, although previous research in this area mostly analysed stock index futures. However, commodity futures could be more influenced by macroeconomic effects and the risk level is higher than the other financial market due to its attribute of hedging and higher leverage rate (Fabozzi, Fuss, & Kaiser, 2008)[39]. Investors should be more careful about their investment than stock market due to the trading assets, which may reflect on the benefit of their business. Thus, if the fundamental traders occupied a lot of part of participants, it brings an advantage to this research that the pure technical traders could be captured by some special methods. If most main macroeconomic and other external elements are not able to influence traders' behaviour, the traders would be recognised as pure technical traders. Thus, this paper utilises the comprehensive tick-by-tick transaction data which can fully reflect market participants' trading behaviour, even better than stock and currency market to disclose technical traders. The trading behaviour can be more efficient and significant to capture, investigate, and identify.

The data collection in this paper is from one of most influential futures brokerage (company) and one famous data statistics company in China. In the Chinese financial market, the role of market maker does not exist during research period. Thus, the further complex consideration of market maker should be avoided. All market participants are under a fair market mechanism. The function of futures brokers is just to transfer the participants' order to the main exchange: Shanghai Futures Exchange, Zhengzhou Commodity Exchange, and Dalian Commodity Exchange. The data only covers one main commodity - Rebar (RB), which is used to trade at the Shanghai Futures Exchange.

Even the Chinese futures market is unique to other main futures market, such as LME and CBO. This market also is one of the most active markets in the world. Nevertheless, Chinese financial derivative has even just started developing in the past 20 years, and financial derivatives had a speedy promotion until now. Futures is a relative measure product in Chinese financial derivative market and it plays an important role in the global futures market: e.g., Shanghai Futures Exchange is the second biggest exchange for copper trading in the world. Specially, Chinese rebar futures is the most traded metal futures, which has the highest volatility, turnover, and open interest in the whole world during the research period. Thus, we choose rebar contract by some following reasons. The rebar contract was launched on 27th March, 2009. As we know, the main function of rebar is for building and infrastructure construction. For China - the biggest developing country, real estate, industry, public equipment, and many other social constructions cannot be promoted without rebar. Also, the Chinese mainland has a great inventory of iron ore, which is the raw material of rebar. Thus, the demand and supply volume of rebar is absolutely enough to support a high liquidity trading market. To reduce the risk, steel industries and steel trading business, which need or produce rebar, do not only consider the spot market but also invest in the futures market for hedging or arbitrage. This is also an interesting and special futures market in that it looks like a pure speculative financial market. Shanghai Futures Exchange does not encourage retail traders to delivery real commodities after execution day, which means that nearly all of market participants, except institutional traders, must close out all of their positions before the end of each contract.

The utilised data in this paper includes two main datasets and one created timing announcement data series. The first data base (data1) is the tick-by-tick high frequency-data of rebar contracts transaction (transaction order book, individual data) from the above mentioned futures company. The research period is from the starting date of rebar contract (27/03/2009) to the end of October in 2012 (31/10/2012). There are 19,933 traders, which include 19,760 individual and 173 institutional traders, taking part in rebar futures contract in this period. The data records cover each investor's transaction details, which includes contract code (identify different contracts), trader code (identify different traders which is the most outstanding point in this data), transaction time (accurate to seconds), transaction price, individual trading volume, individual position (net and real)[1], trading indication (open or offset and long or short)[2], and type-sign of investors (individual or institution). The total records of this database are 4,427,131. Different commodity futures contract may have different number of contracts in one year. For rebar contract, there are 12 contracts in one year. Each contract starts trading at the beginning of each month and delivery or execute at the same time (15th in each month) in next year. For example, rb201006 started trading on June 16th 2009 and delivered on June 15th 2010. Because rebar contract launched at March, 2009, the first contract is named rb200909. Thus, the investigated data covers and indicates rebar futures contracts from rb200909 to rb201310 with contract code and the data has complete records of rb200909 to rb201210 and incomplete records of rb201211 to rb201310. These total 50 contracts establish a different cross-section to different traders. Trader code marks different 19,933 investors. This paper only discusses investors' transaction part. So, the records only contain investors' transaction orders and do not cover the investors' other bid and ask orders.

The second dataset is the tick-by-tick high frequency data (data2) of the whole market price records. We collect the data from the mentioned data statistic company[3]. This dataset is different from data1. It just displays the whole market dynamics of transaction but not include any individual transaction details. The data records all transactions of each trading day during the research period and also includes transaction price, trading volume, and other information which can be matched with the first part of data. However, this paper proposes to investigate individual trading behaviour. This data does not attempt the identification of different investors. Thus, it is auxiliary data for the data1. The important role of the data2 is to provide total market position and generate dummy trading signals based on different technical trading rule in the following, which cannot be realised by data1.

Meanwhile, this paper also utilises some main macroeconomics index announcement to identify fundamental and technical traders which the method refers to Jiang, Lo, and Valente (2013)[64]. The rebar market is quite sensitive by government macroeconomic policy because of its main functions, as described above. Therefore, the

[1]Net position means investor will sell or buy how many contracts of commodity on delivery day after one transaction.

[2]In the futures market, long means investors expect to buy futures contracts, and short means investors expect to sell futures contracts. Open and offset (close) indicate the investors' real position. Investors can either take long or short position for their open position. Offset position is the opposite act to open position (Hull, 2012)[58].

[3]http://www.gtafe.com

third part of data is about the announcement time of the macroeconomic index. An examination of whether this public information can affect investors' preference and act could reveal potentially useful results.

We choose five key macroeconomic indexes which are quite related and influential to rebar market: Producer Price Index (PPI), Purchase Management Index (PMI), Real Estate Climate Index (REI), Entrepreneur Climate Index (EI), and Gross Domestic Product (GDP). The announcement time of PPI, PMI, and REI is announced monthly, and for EI and GDP is announced quarterly by the Chinese government. If the traders' trading volume is related to some indexes, it means that these traders are not purely technical investors. If trader's volumes do not have any relationships to these macroeconomic indices, these groups of traders would be recognised as pure technical traders.

1.3 Empirical Analysis

In the first step, we use a simple multiple regression model to filter pure technical traders in the data1. Before this work, there are two important problems requiring handling at first. One is endogenous of transaction price due to the data1 is just a part of the whole market and the other one is about removing irrational trading behaviour at the end of trading time of a single contract.

1.3.1 Handling Endogenous Variables and Irrational Transaction

The endogenous variable is the transaction price, which is unavoidable. In the regression model, we use the trading volume for each transaction to be the instrument of trader's dynamics and behaviour and other elements to be the explanatory variable for their behaviour, such as transaction price. It directly adopts transaction price rather than returns or profitability as an explanatory variable in the model. However, as discussed before, the owned transaction price data should be recognised as an endogenous variable since the data1 is just a part of the whole market. For instance, the data is just a part of the total market records. Other investors' behaviour (in the error term, cannot be observed) can not only influence market price change, but also impact the traders' trading volume in the researcher's owned data. On the one hand, outside of this owned data, investors affect market price changes - which also mean these acts impact inside sample investors' transaction prices. On the other hand, outside sample investors' trading volume can significantly affect inside sample traders' trading volume due to herding (Nofsinger & Sias, 1999)[85]. This paper refers to the theorem of Instrumental Variable Estimation (IV) to deal with this problem. Based on Wooldridge (2011)[103], the instrumental variables should be absolutely exogenous to the regression model and should have high correlation to independent variable with no sensible relations to dependent variable, and then the two-stage least square (2sls) can be dividedly achieved. Thus, we made four kinds of average price rely on the data1 and data2 as the instrumental variables to transaction price in this research sample: ap1 - previously average 1 hour total records' price of broker sample; ap2 - previously average 500 records' price of broker sample; ap3 - previously average 1 hour total records' price of market sample; ap4 - previously average 500 records' price of market sample. The ap1 and ap2 depend on the research sample, and ap3 and ap4 depend on the second part of total market data. These four IVs are the average price of the historical tick records. Thus, they are absolutely exogenous to the transaction price and trading volume. Also, all IVs have more than a 97% correlation with the transaction price in my original sample. Then, we adopt OLS to get the predict value of transaction price with the four IVs: ap1 to ap4 and the exogenous factors, individual position, and other factors. The price-hat (predict value of price) takes the place of original price in the regression model. Generally speaking, this method divides 2sls into two steps. It causes different stand errors for the final results. However, the significance will not have any changes. This paper only pays attention on the significance of all the explanatory variables, which means it does not consider the coefficient. Thus, the dividing method is reasonable for utilization. Meanwhile, in the regression of this paper, the explained variable is trading volume of each transaction record. In order to reduce the simultaneity bias, we process the initial data. The initial data of trading volume is nominal - which contains the number of units of contract trade. Regarding the rebar futures contract, one trading unit of contract actually is equal to 10 tons of rebar. Thus, we adopt using nominal trading volume to multiply 10 to achieve real trading volume in order to deflate the price effect.

The second problem is called "irrational trading behaviour" which, firstly, occurs at the end of the trading time of a single futures contract. This behaviour means that investors' trading behaviour is uncorrelated with market price, holding position, and any other factors. Previous research on trading behaviour in futures market, generally speaking, missed this question. For one futures contract, it has its active period and also has its inactive period. For the instance of rebar futures, one contract change from active to inactive before three months to the execution date generally in China. But for the stock market, the trading time is continuous even if the listed company is delisted. The question, then, is if an irrational trader still holds some contracts just before delivery day, he will drop his position even the market price is too unexpected for his portfolio. The reason is that such investors do not have real commodities for delivery, and also do not have utilization of commodities. The mechanism corresponds with the regulation of Shanghai Futures Exchange. Such market participants only have one aim is to speculate in this market. They just propose to speculate and not hedging or arbitrage. And, speculators occupy a huge part of futures markets so that most of them tend to clear out their position before execution date. Currently, there is no good method dealing with this problem. Thus, we require making a strong assumption in this paper that: The unreasonable trading behaviour only occurs in the last two trading month for each futures contract. This setting is based on the trend variation of total 50 contracts' market position and trading activity of the data1 and data2. We checked all 50 rebar contracts' market position and trading activity trend. It is clear that all of contract's total market position and total trading volume has a significant decreasing trend in the last two months. In other words, it means the contract becomes inactive generally two months before the delivery day. Therefore, we move out all the transaction records from data during last two months of each rebar contracts because the trading during last two months of each futures contracts may contain irrational trading behaviours. We also examine and use this new data and original data to do the same test. The results show that they are quite different that has many significance changes. Thus, we utilise this new data to continue the empirical research. The total records do not decline too much and just change to 4,427,131.

1.3.2 Multiple Regression Model for Filtering Pure Technical Traders

In this section, we design a reasonable multiple regression model to filter pure technical traders for Chinese rebar futures. The regression model is divided into two parts: the first part identify the fundamental relations between individual trading volume and market price (transaction price) and individual net position. The second part of data can indicate each investor's different trading behaviour, and show the difference of the above relations between each other and fundamental effects. The regression model is as below:

$$\begin{aligned}
\boldsymbol{ln(v)} &= \boldsymbol{C + \alpha ln(price) + \beta ln(position)} \\
&\quad \boldsymbol{+ \sum_{i=0}^{n} d_i[\alpha_i ln(price) + \beta_i ln(position)} \\
&\quad \boldsymbol{+ \gamma_i \triangle T_{PPI} + \delta_i \triangle T_{PMI} + \varphi_i \triangle T_{REI} + \theta_i \triangle T_{EI} + \rho_i \triangle T_{GDP}] + \varepsilon}
\end{aligned}$$

Where,

$$\begin{aligned}
\boldsymbol{position_t} &= \boldsymbol{market\ position_t - individual\ net\ position_t} \\
\boldsymbol{\triangle T_{macro-index}} &= \boldsymbol{min(\triangle t, \triangle t + 1)} \\
\boldsymbol{\triangle t + 1} &= \boldsymbol{D_{A+1} - D_o} \\
\boldsymbol{\triangle t} &= \boldsymbol{D_o - D_A}
\end{aligned}$$

And, $\boldsymbol{D_{A+1}}$ is the next announcement date of each macroeconomic index, $\boldsymbol{D_A}$ is the last monthly announcement date, and $\boldsymbol{D_o}$ is the transaction of each record occurred date.

In the regression model, $\boldsymbol{C}$ is constant item, $\boldsymbol{\varepsilon}$ is error term to show the difference between fundamental effects and individual effects for each trader, $\boldsymbol{v}$ is individual trading volume in each transaction, $\boldsymbol{price}$ is the described price-hat instead of transaction price (market price) for each record, $\boldsymbol{position}$ is individual net position - which refers to the number of units of corresponding contracts each participant holds, implying the difference between opened and closed positions. In addition, we suppose to see the fluctuation of individuals' net position so that the $\boldsymbol{position}$ actually equal currently total $\boldsymbol{market\ position}$ minus current $\boldsymbol{individual\ net\ position}$. The total market position is invoked by market data and based on same time points in both transaction and market data. Then, the variable of position is the individual net position variation tendency. We take the logarithm for these three variables in order to reduce the number size and decline the effect of heteroscedasticity. These first two items on the right hand can show the fundamental relationship between individual trading volume and two controlled factors (price and position).

For the following items, $\boldsymbol{d}$ is the dummy setting for different traders which depend on the size of research sample (can be set from 1 to 19,933 to identify different traders). In the bracket, the first two items indicate the difference of significance between the whole situation and each trader's situation, in other words, they implies trading responses of different investors. The next group of variables describe announcement time of the above five macroeconomic variables. The setting of $\boldsymbol{T}$ is the time changing trend between monthly (or quarterly) announcement and next announcement time of each macroeconomic index. We choose the maximum value between $\triangle \boldsymbol{t} + \mathbf{1}$ and $\triangle \boldsymbol{t}$ (the definition as above) in order to observe the influencing timing trend of each index. This performance is used to identify and disclose whether the trader may consider the macroeconomic information of these five indexes with the public time of indexes pass by. The data is cross-section data so that we just adopt simple OLS method to estimate (ignore normal time series issue, such as stationary) the relations and the $\boldsymbol{T}$ is used to observe the trading activity of each trader for each observation. Pure technical traders ignore other news so that the five relevant indices cannot influence decided trading volume of pure technical traders. The reason for only selecting pure technical traders is that their strategies should not contain any external elements and only depend on the calculation of previous price. In other words, their strategies should be captured by computational and methodical method. That would be the initial step to disclose traders' behaviours and will be extend to fundamental and mixed type of traders in the future works. In attention, the main function of this regression is based on the regression results of this five macroeconomic timing variables, which can indicate who are pure technical traders. Also, in order to identify whether investors tend to buy or sell, we split the data into long and short two groups.

The working sample is huge, so that the investigation is divided into two parts. The first part is working on total sample through all records. This initial research only chooses 100 investors (dummy setting: n = 100) to analyses the individual trading behaviour in the bracket of the regression model. These 100 investors are the most active traders (If one given trader exist two or more contracts, we only identify the most trading contract as his instrument.), who have the most transaction records, in my sample. No. 100 trader still has 3,726 records during the research period. And, the total records of top 100 traders are 863,953, which is about 22% of the total records. They seem to be using algorithm to execute their technical strategies at a high frequency level. Because they are the most active traders, they should have significance to investigate and summarise the total sample of technical traders. In addition, these top 100 traders are organised according by the amount of their records. And, NO.4, 8, 15, 70, 71, 77, 79 traders are institutional investors and others are individual investors. This status is also consistent with real situation that individual investors hold most amounts of market participants. Even there are 173 institutional traders in all sample, which is slightly grater than the selecting results, we still believe the occupation of institutional traders in 100 most trading traders is reasonable. Institutional traders should have more abilities and should be more possible to use algorithm strategies to make high frequency trading so that the occupation of institutional traders in top most trading traders should be grater than the whole sample. Thus, this paper should not exist selectivity or survivorship bias. More details for traders that whatever telephone, manual, or other entry, the final submission is executed by the terminal of brokerage. Therefore, if the trader has a lot of transactions, he must operate trading by himself, in the office or at home. That is directly passed to the brokerage and immediately executed in the terminal.

According to the second part, it is the research on single active futures contract. Since, rebar futures contract started on March 27th 2009 in Chinese futures market, there are only September, October, November, and December contracts that existed in 2009. The trading volume and market position situation of each included contracts. From 2010 to 2012 (also content contracts in 2013), January, May, and October contracts are relatively active contracts. This is caused by the seasonal economic cycle reason in China. Therefore, based on the variation trends of trading volume, market position, and amount of trading record, this part chooses the contracts with boldface letter as the investigated single contract in the **Table 1.1**.

Thus, these 15 individual contracts, listed in bold in the **Table 1.1**, are surveyed in the second part of each single futures contract. The method is same as the first part. But, the investigated traders increased from 100 to 200 because the decline of sample size. These 200 investors are the top most trading people for each single rebar futures contract individually. Therefore, the total research samples are 16 (15 active contracts + 1 whole contract). Meanwhile, we have also made a secondary task. Based on individual position, immediate transaction price, and their product (real transaction value), we assumed investors' wealth is the maximum product and sort the rank of them in each individual contract. That might help to identify how trader's endowments affect their trading behaviour.

Table 1.1: **Maximum Market Positions and Number of Trading Records of Each Rebar Futures Contract**

Contract Code	Maximum Market Position	Total Trading Records	Contract Code	Maximum Market Position	Total Trading Records
rb0909	**423,426**	**79,028**	**rb1110**	**888,390**	**363,451**
rb0910	397,842	30,407	rb1111	1,534	119
rb0911	**895,870**	**142,224**	rb1112	584	2
rb0912	**1,008,870**	**190,001**	**rb1201**	**772,958**	**142,304**
rb1001	**1,140,896**	**243,295**	rb1202	2,292	2
rb1002	**1,011,436**	**123,746**	rb1203	308	9
rb1003	195,814	19,258	rb1204	556	8
rb1004	53,498	1,745	**rb1205**	**865,430**	**211,069**
rb1005	**1,074,692**	**374,967**	rb1206	1,906	22
rb1006	53,270	1,789	rb1207	0	0
rb1007	9,626	335	rb1208	0	0
rb1008	17,078	1,333	rb1209	2,038	77
rb1009	26,948	1,442	**rb1210**	**959,664**	**161,609**
rb1010	**1,497,516**	**619,286**	rb1211	1,310	13
rb1011	26,292	1,782	rb1212	1,264	54
rb1012	36,544	1,567	**rb1301**	**1,891,202**	**340,220**
rb1101	**1,426,002**	**417,135**	rb1302	3,404	27
rb1102	21,718	427	rb1303	244	14
rb1103	13,024	658	rb1304	0	0
rb1104	13,044	358	**rb1305**	**1,114,852**	**95,830**
rb1105	**1,328,002**	**326,670**	rb1306	0	0
rb1106	1,556	138	rb1307	0	0
rb1107	7,690	114	rb1308	0	0
rb1108	506	4	rb1309	788	14
rb1109	2,746	1,289	rb1310	1,790	38
				total	3,893,880

According to the regression results, if all of the five macroeconomic timing variables are not significant to the traders' trading volume, which means the macro or external factors are not able to affect the trading behaviour, this group of traders should be recognised as pure technical traders. The initial results show how many technical traders of top 200 active traders existing in these 15 samples as the following **Table 1.2**:

Table 1.2: **Number of Pure Technical Traders in Long and Short Groups of Top 200 Most Trading Traders**

	Long	Short		Long	Short
rb0909	61	59	rb1105	69	65
rb0911	81	74	rb1110	77	69
rb0912	67	74	rb1201	70	61
rb1001	52	64	rb1205	59	68
rb1002	79	74	rb1210	55	78
rb1005	54	55	rb1301	65	62
rb1010	54	73	rb1305	79	105
rb1101	64	79			

After statistics, there are about 50 traders are recognised as pure technical traders in each contract, who both long and short do not have significance between macroeconomic indexes and their trading volume. Thus, we can say that the pure technical traders generally occupy about 25% of the top 200 most active traders.

1.3.3 Investigated Sample and Technical Trading Rules Selection

The pure technical traders are selected by the filter model. However, some of them own fewer records in the sample of data1 (less observations). Thus, we select the research sample of traders who satisfy two conditions: 1, the traders must be pure technical traders who have been filtered. 2, the transaction records in their single trading contract must be more than 1500 records in one contract. Therefore, we select traders from top 200 most active traders in each main futures contract. Some of them appear and can be selected in different contract, but we only choose one to symbolise this special traders. For instance, if trader 666 is identified as technical trader in two contracts, we only choose one contract as his research sample. After statistics, we choose 81 traders from each of 15 main contracts into the research sample. They are pure technical traders and have transaction records between 1500 and 12000. These 81 traders' behaviour can be representative to all of technical traders. All the following research is based on these 81 traders. Certainly, Technical Traders only focus on the historical price chart. They use the historical data to design a lot of different technical trading rules in order to execute their trading strategies. We select three kinds of popular technical trading rules as the bench mark of pure technical traders to investigate their behaviours.

Regard technical trading strategies, this research only selects three popular classes of technical trading rules (Momentum, Moving Average, and Trading Range Breakout). The signals of different rules are generated by the time division data. Based on the price trend and different regulations, the rules show the dummy trading signals at each time and the dummy signal may same as traders' real trading action if the traders follow the rule. This research also covers the contrarian rules of the three selected rules. The principles are same but the generated signals are opposite to the momentum. Thus, six kinds of rules are covered actually. The following descriptions include all details of each rule:

$\boldsymbol{P_t}$: market price of a future contract
$\boldsymbol{I_t}$: +1: long; -1: short; 0: keep neutral
$\boldsymbol{t \in \{1, 2, ..., 13500\}}$: 1 trading day = 3.75 hour = 225 minutes = 13500 seconds

Trading time from SHANGHAI Futures Exchange in one day:
10:15-10:30: Short Break
10:30-11:30: Trading (1 hour)
11:30-13:30: Noon Break
13:30-15:00: Trading (1 and half an hour)
Total: 3.75 hours

1. Momentum Rule (MO) refers to Conrad & Kaul (1998)[27] and Chan et al. (2000)[24]. It is the basic rule of technical traders. The indicator shows whether market price change of a contract is positive or negative over a time period. If the current price is higher (or lower or equal) than the price at a defined time point, the rule would show the buy (or sell or keep nature) signals. The principle is that technical traders trust the price movements will bring the same price movements as before. It depends on the difference between current and previous price.

$$\boldsymbol{I_t(n) = \begin{cases} +1 & if\ P_t > P_{t-n} \\ 0 & if\ P_t = P_{t-n} \\ -1 & if\ P_t < P_{t-n} \end{cases}}$$

Also, based on the momentum rule, we introduce Contrarian Rule (IMO) which is the opposite rule to momentum. They have same principle but inverse execution: when the price change is positive (or negative), the traders will sell (or buy).

$$\boldsymbol{I_t(n) = \begin{cases} +1 & if\ P_t < P_{t-n} \\ 0 & if\ P_t = P_{t-n} \\ -1 & if\ P_t > P_{t-n} \end{cases}}$$

2. Moving Average Rule (MA) considers the weighting of all prices during a previously defined trading period. Most previous research covers this rule, such as Boswijk, Griffioen, and Hommes (2000)[15]. Through calculating average price over a specific period, trader can identify whether traders act transaction. If the current price is higher (or lower or equal) than the average price during the previous trading period, the rule indicate the buy (or sell or keep nature) signals. We also introduce Contrarian Moving Average Rule (IMA), which have the inverse signals to MA.

$$\boldsymbol{MA:\ I_t(n) = \begin{cases} +1 & if\ P_t > MA_t \\ 0 & if\ P_t = MA_t \\ -1 & if\ P_t < MA_t \end{cases}}$$

$$\boldsymbol{IMA:\ I_t(n) = \begin{cases} +1 & if\ P_t < MA_t \\ 0 & if\ P_t = MA_t \\ -1 & if\ P_t > MA_t \end{cases}}$$

$$\boldsymbol{Here,\ MA_t = \frac{\sum_{i=t-n+1}^{t} P_t}{n}}$$

3. Trading Range Breakout Rule (BO) is generally known as price channel systems. We refer to the literature from Park and Irwin (2005)[88]. When we define a specific trading period, BO shows a buy signal if the last (current) price is the highest price and generates a sell signal if the last (current) price is the lowest price during the period. As the mention from Jackson and Ladley (2013)[61], the principle of BO is to utilise the local maximum and minimum price as the motivation of technical traders in order to implement their strategies. Based on different periods, the trader seeks the extreme price as their "support", and they trust that the price trend will follow this "support". We still introduce the Contrarian Trading Range Breakout

Rule (IBO) as the same principle of IMO and IMA.

$$\boldsymbol{BO:\ I_t(n) = \begin{cases} +1 & if\ P_t > max(P_{t-1}, P_{t-2}, ..., P_{t-n}) \\ -1 & if\ P_t < min(P_{t-1}, P_{t-2}, ..., P_{t-n}) \\ & I_{t-1} \end{cases}}$$

$$\boldsymbol{IBO:\ I_t(n) = \begin{cases} +1 & if\ P_t < max(P_{t-1}, P_{t-2}, ..., P_{t-n}) \\ -1 & if\ P_t > min(P_{t-1}, P_{t-2}, ..., P_{t-n}) \\ & I_{t-1} \end{cases}}$$

Before the first breakout, the indicator always stays equal to 0. After the first breakout, if the price does not satisfy the condition of changing indicator, the indicator follows the last (previous) indicator.

To summarize, above are the six popular kinds of technical rules, which are selected in this paper. According to them, technical traders may become "winner" to achieve profits by these fixed strategies (also, may become "loser"). The algorithms are able to help technical traders buy and sell on correct time by the various setting of observing periods, even helping trader to adjust the combination of rules and change the timing setting in order to optimize strategies. Although there are a lot of other types of rules, such as filter and channel range, these six rules are representative and and widely applied in technical trading.

1.3.4 Smoothing Data and Generation of Dummy Signals

All the mentioned technical trading rules need to be calculated and generated by time division data. Most previous research used the data with same time interval, such as daily data. In other words, the data does not need to be modified (smoothing) because the same time interval is a kind of time series data and also it is the main feature of time division data. However, this paper utilises tick-by-tick data (both data1 and data2), which has the different time intervals for each record. Tick-by-tick data is the records of all transactions in the market. When one transaction happens, the data will add one record. Therefore, tick-by-tick data cannot be directly adopted to generate dummy signals of technical rules.

Even so, we use smoothing technique to transfer the tick-by-tick data to the time-series data in order to guarantee that there is only one price at each trading second. The aim is to use all the total market information to identify different trading rules. Thus, we utilise data2, which includes all ticks for all contracts, to smooth in order to generate dummy trading signals under different technical rules. We refer the generally smoothing method from Simonoff (1998)[95], which is "following smoothing method". This algorithm is described as below: we assume one of the occurred time point of record is "M" and the next time point with price change is "N" (M and N are seconds). The prices of these two time points are $\boldsymbol{P_M}$ and $\boldsymbol{P_N}$. $\boldsymbol{N - M = T}$ is the time difference. We consider that there is no price change between "M" and "N". Thus, the price movement per unite time between time "M" and "N" is constant and equal to $\boldsymbol{P_M}$. Through continually duration, all time points will have a same record, and it follows the following smoothing principle:

$$\begin{aligned} \boldsymbol{P_M} &= \boldsymbol{P_M} \\ \boldsymbol{P_{M+1}} &= \boldsymbol{P_M} \\ &\vdots \\ \boldsymbol{P_{N-1}} &= \boldsymbol{P_M} \\ \boldsymbol{P_N} &= \boldsymbol{P_N} \end{aligned}$$

For instance of real process, the following **Table 1.3** is the effective picture of data2 before and after smoothing process:

Table 1.3: **Market Tick-by-Tick Data Before and After Smoothing**

Time	Price
2009/12/15 09:32:15	3770
2009/12/15 09:32:22	3769
2009/12/15 09:32:29	3771
2009/12/15 09:32:32	3769
2009/12/15 09:32:33	3769
2009/12/15 09:32:34	3768
2009/12/15 09:32:44	3769
2009/12/15 09:32:59	3770
2009/12/15 09:33:00	3769
2009/12/15 09:33:13	3767
2009/12/15 09:33:14	3769
2009/12/15 09:33:15	3768
2009/12/15 09:33:16	3769
2009/12/15 09:33:22	3770
⋮	⋮

Time	Price
2009/12/15 09:32:15	3770
2009/12/15 09:32:16	3770
2009/12/15 09:32:17	3770
2009/12/15 09:32:18	3770
2009/12/15 09:32:19	3770
2009/12/15 09:32:20	3770
2009/12/15 09:32:21	3770
2009/12/15 09:32:22	3769
2009/12/15 09:32:23	3769
2009/12/15 09:32:24	3769
2009/12/15 09:32:25	3769
2009/12/15 09:32:26	3769
2009/12/15 09:32:27	3769
2009/12/15 09:32:28	3769
2009/12/15 09:32:29	3771
2009/12/15 09:32:30	3771
2009/12/15 09:32:31	3771
2009/12/15 09:32:32	3769
2009/12/15 09:32:33	3769
2009/12/15 09:32:34	3768
2009/12/15 09:32:35	3768
⋮	⋮

The time series (time division) data has been created in the last step so that we start completing the generation of dummy trading signals with different rules. Due to the huge data size, we utilise C++ to create all dummy signals. All algorithms and computational programs are realised by Microsoft Visual C++6.0 and QT 5.1.1. For the rules, we select 6 classes of rules, and each class of rules includes 13,500 types by different parameters. So, the amount of rules is $\mathbf{6 * 13500 = 81000}$ in the universe. Also, the main research contracts are 15 mentioned active contracts previously, thus we split 15 contracts as individual contracts to generate signals with 81,000 rules. Then, we make a huge technical data base (data3, it actually is "upgrade and smoothing data of data2), which includes 15 files to indicate 15 contracts. In each file, it contains a matrix, where the column indicates 81,000 rules and the row indicates the price movement of the contract after smoothing data. Because the amount of observations of 15 contracts is not same, the size of matrix is not same. Thus, the columns (rules) are fixed as 81,000, and the rows are between 1,539,342 and 3,308,235.

Then, we have produced and introduced data3, which is very important to explain the effect of all selected technical rules. The next step is finding a way to link data3 to data1 in order to investigate pure technical traders' strategies. It is difficult to investigate every trader's specific behaviour, and so we tend to classify different types of technical traders. In each type, members should have generally similar strategies. In next section, we describe our method to link data1 and data3 and also show adopted classification method, which is K-means clustering algorithm.

1.4 Trader Classification

1.4.1 Data Reconstitution

There is a connection between data1 and data3. We adopt a simple and sensible method, which is to calculate the similarity (%, as percentage) between 81 traders' real actions and dummy signals of each rule. In data3, as we introduced, it is time series data which means there is only one record (dummy signal) of one rule for all possible trading time. In data1, all traders' real actions are included as -1 and 1 which indicate sell and buy with accurate time points. As above, the selected research sample covers 81 pure technical traders, and they have different amounts of transactions (observations or actions).We firstly filter 81 traders' data from data1 to create 81 individual datasets. Next, we insert dummy signals of all rules from data3 into each individual dataset with considering same time points. Due to the range of time points of data3 contains all time points of data1, each trader's real action must have their correspondently dummy signals with different rules with matching same time points. In other words, the originally individual dataset only include two columns - occurred time points and real actions, and now, 81,000 columns are added in the reconstituted dataset. Each column indicates the dummy trading signals of one specific technical rule. Then, we get 81 matrices for 81 traders, and the size of each matrix is: observations (row: each trader's amount of records) multiply 81,002 (columns: 2 original columns include time point and real action, and 81,000 columns of dummy signals).

For each individual dataset, we can utilise basic computer techniques to calculate the similarity between traders' real actions and dummy signals. This similarity implies how well the percentage of real actions of each trader are same as each rule's dummy signals. Thus, each of 81 matrices just provides one notice - the similarity. After statistic and combine all information from 81 matrices in one sheet, we achieve a significant matrix, and the size is 81000*81 (include title row and first column, in fact, it is 81001*82), which covers 81 traders' similarity to all 81,000 rules. We put a short sample as below:

Table 1.4: **Similarity Matrix between 81 Traders and 81000 Technical Trading Rules**

rule	p01	p02	p03	p04	p05	p06	.
.	.	.	.	.	.	.	.
MO_13493	49.69%	46.58%	50.00%	44.00%	52.80%	46.98%	.
MO_13494	49.69%	46.58%	50.77%	44.00%	52.80%	46.61%	.
MO_13495	49.91%	46.58%	50.77%	44.00%	52.80%	47.51%	.
MO_13496	49.82%	46.58%	50.35%	44.00%	52.80%	47.46%	.
MO_13497	50.00%	46.58%	50.63%	44.00%	51.80%	47.57%	.
MO_13498	50.13%	46.58%	50.21%	44.00%	52.80%	47.57%	.
MO_13499	50.22%	46.58%	50.21%	44.00%	51.80%	47.51%	.
MO_13500	50.40%	46.58%	50.14%	44.00%	51.80%	47.57%	.
MA_1	19.66%	23.29%	35.44%	31.20%	36.10%	25.92%	.
MA_2	29.60%	28.37%	51.62%	47.42%	44.80%	46.55%	.
MA_3	36.50%	34.01%	58.65%	54.07%	50.70%	55.85%	.
MA_4	42.13%	37.71%	63.85%	58.92%	60.50%	61.04%	.
MA_5	46.00%	41.68%	67.23%	58.48%	62.80%	61.46%	.
MA_6	48.99%	43.62%	69.69%	59.11%	69.50%	62.32%	.
MA_7	51.50%	45.10%	68.00%	60.78%	69.40%	63.76%	.
MA_8	52.42%	46.86%	69.06%	63.27%	71.30%	65.85%	.
MA_9	53.39%	47.50%	71.80%	63.46%	71.50%	67.45%	.
.	.	.	.	.	.	.	.

In the **Table 1.4**, the first row indicates 81 traders from p01 to p81, and the first column indicates all 81,000 rules (MO_1 to 13,500, MA_1 to 13,500, BO_1 to 13,500, IMO_1 to 13,500, IMA_1 to 13,500, IBO_1 to 13,500). For example, the first cell under p01 "49.69%" menas all transactions action of trader 1 have 49.69% same trading actions to the dummy signals by according to the rule of MO_13493. This constructed matrix is the parent sample of traders' classification, because the similarities traders' different preference of each selected technical rules. Thus, we classify 81 traders in different groups based on the above mentioned similarity.

1.4.2 K-Means Clustering Algorithm

Cluster analysis[4] is used to classify many objects in different groups (clusters) with same features. In each group, there is a centroid, and all members have similar characteristics or coordinates to the centroid. Thus, we tend to adopt this method to group technical traders. There are various clustering algorithm. In statistical analysis, clustering analysis generally put all observations in a multi-dimensional space, and each observation becomes a point with n-dimensional attributes in the space (if the space has n dimensions). Based on the distance between each point and centroid, the algorithm select nearby points to each centroid as a group, which is centroid-based clustering. In my research, the similarities of each trader to each rule are seen as attributes in the clustering space, so that clustering algorithm is easy and sensible to realise classification of technical traders. The logistic design is to put all 81 traders in the space: in other words, 81 points would be grouped. For every point, there are 81,000 attributes marking point's features, which imply the traders' different preferences for technical rules. Therefore, the above mentioned space is an 81,000-dimensional space for clustering. Centroid-based clustering generally has two popular ways. The first way is hierarchical clustering, and its principle is "from bottom to top". Each point is one centroid at the beginning of clustering process. Then, the algorithm continuously merges close centroids to create a new centroid before finding the optimal number of centroid. After that, the process classifies all points in the space with optimal centroids. The other popular way of centroid-based clustering is K-means clustering, which we adopt in this work.

The main principle of K-means clustering is to partition all observations in the space into k groups. The clustering results also depend on the optimal distance, which is the least mean of all distance between member points and their individual centroids. The variety of distance can be appointed, such as city block and hamming

[4]For the Information and knowledge of clustering analysis, we refer to "Maimon, O. Z., & Rokach, L. (2010)[77], Data Mining and Knowledge Discovery Handbook. New York, Springer".

distance. In this research, we utilise Matlab R2012b to realise K-means clustering because Matlab has standard procedure package of K-means. Also, we adopt the default distance - squared Euclidean distance (SED) of this automatic procedure. More details about the principle of SED are in **Appendix A.3**. The difference between K-means and hierarchical clustering is that we must appoint the number of k before analysis, for example, if k = 3, all points in the space will be divided into three groups. After identifying k, the algorithm starts stochastically set k centroids in the space. In the assignment step, K-means repeatedly moves the centroids until finding the optimal distance as above description. Then, the clustering is finished and we can get a sensible classification of traders.

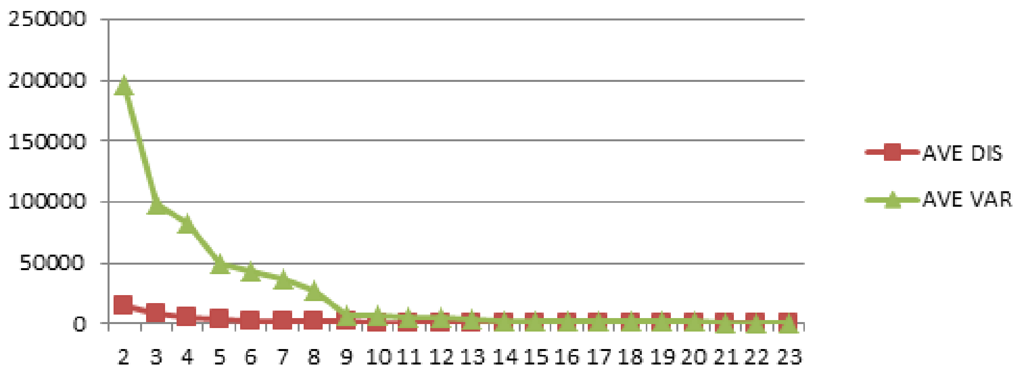
There is one significant problem is that how to decide the number of k. We cannot randomly set a number of k with our "intuition". There are many methods discussing in clustering area. In this paper, we refer to the method of "low average sum of variance and distance" (Maimon & Rokach, 2010)[77]. The principle of this method is that, with increasing number of k setting, in each cluster, the average sum of distance between each point and their centroids and average sum of variance of distance in each group will be decreasing. When these two sums are close to 0 or at a lowest level in the dimension, they will not have a big change. Then, the corresponding number of k should be the decided and optimal k in the algorithm. Although, this is a roughly estimated method for k clusters, we designed three projects (three samples) to prove the correct number of k.

1.4.3 Clustering Results

In project one, we put the 81000*81 matrix in the K-means algorithm and get the following statistic results, **Figure 1.1**. Where, the x-axis is the number of k. We make 23 times of clustering with setting k equal 2 to 23. The y-axis is the value of average sum of distance and variance[5]. According to the graph, there is a huge decrease of ASD and ASV with increasing number of cluster (k). After k = 11, the ASD and ASV become stable. Thus in project one, all 81 traders should be divided into 11 groups with 81,000 attributes (rules).

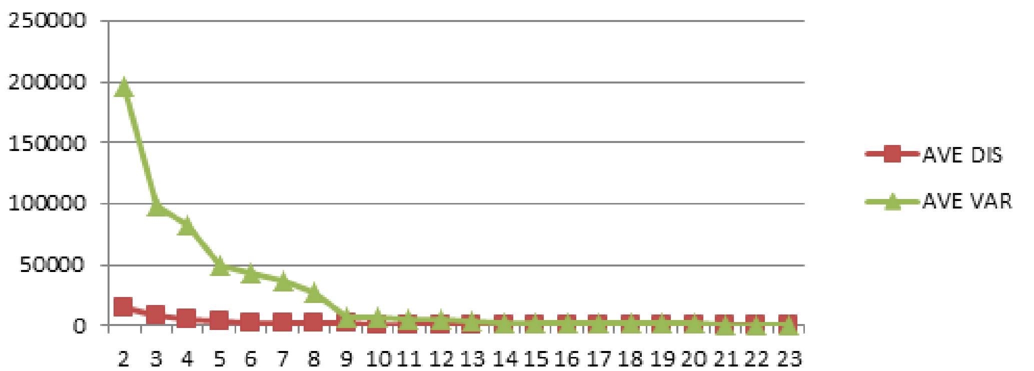
[5]Average sum of distance (ASD): After clustering, algorithm captures the sum of distance between every point and their attributive cluster (Person to Centroid distance) in k groups, and then gets average of k sums. Average sum of variance (ASV): Also, we write a procedure to calculate variance of P to C distance in every group. Less variance implies more stable and optimal members in each group.

Figure 1.1: **Average Sum of Distance (ASD) and Variance (ASV) in Project 1**



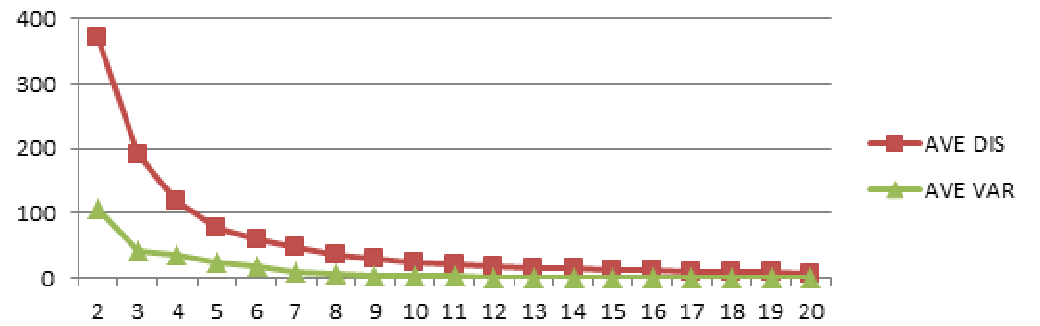
Project 1: It initially proves the number of classifications in the research, and it covers all investigated rules. However, this is a biased estimation, and the dimensional-space is very complex. Thus, we designed other two projects to support the clustering results. The principle is that we reduce the dimension of attributes in the space - We remove a lot of rules from the original 81,000 rules with two different criterions.

Figure 1.2: **Average Sum of Distance (ASD) and Variance (ASV) in Project 2**



Project 2: Setting intervals of the rules and choosing the rules to cluster, and the interval setting rule is in **Appendix A.1** (286*6 = 1716 rules). The feature here lies in choosing a rule every 5, 10, 15, 30 seconds before the five minutes ends, and then choosing a rule every 50 seconds until one day ends (13,500 seconds). We can see the variation in **Figure 1.2**

Figure 1.3: **Average Sum of Distance (ASD) and Variance (ASV) in Project 3**



Project 3: Similar to P2, but it refers to the previous research. It has fewer rules to cluster, and the interval setting rule is in **Appendix A.2** (90*6 = 540 rules). The feature is that choosing a rule every 5, 10, 15, 30, 60 (1 min.), 600 (10 min.), 1200 (20 min.) seconds with increasing time. The **Figure 1.3** display the variation of ASD and ASV in project 3.

Then, the space becomes smaller (1716 and 540 dimensional-space) but the common features have not been changed because the selected rules are constructed by a standard and regular interval. It looks like the general sampling estimation. If the clustering results of this two small spaces are same as the original one, 11 should be recognised as the correct number of k. The above two graphs show the clustering results of project two and three. X-axis and y-axis have the same explanations of P1.

We make 20 operations of P2 for the number of k equals 2 to 20 and 15 operations of P3 for the number of clusters equals 2 to 15. Also, due to the K-means algorithm randomly set the centroids, we run the program ten times for each project in order to get the relatively optimal clusters and keep a low level of variance. In the graph, it is very clearly that after grouping 81 traders into 11 groups, the ASD and ASV become stationary, which is the best evidence to support the clustering results of project one. The specific clustering results of P1, P2, and P3 are in the following **Table 1.5, 1.6, and 1.7** individually, we use 1 to 81 to label 81 traders in this three tables.

Fortunately, no matter which project, some members are always in one group, in other words, the clustering of project one is successful. Therefore, all selected 81 pure technical traders can be classified in 11 groups with 81,000 attributes (technical trading rules).

Table 1.5: **Clustering Results of Project 1**

Group	Members in P1:
1	1, 8, 9, 16, 20, 22, 24, 33, 34, 37, 38, 44, 46, 48, 50, 53, 62, 63, 74
2	15, 26, 57, 68, 71, 73
3	11, 21, 40, 41, 58, 75, 77, 79
4	3, 4, 12, 23, 27, 28, 36, 43, 51, 67, 69, 80
5	25, 39, 54, 66, 72
6	18
7	10, 59, 61
8	42, 47, 78
9	13, 14, 17, 19, 29, 30, 32, 52, 64, 81
10	2, 5, 6, 31, 55, 60, 65, 70, 76
11	7, 35, 45, 49, 56

Table 1.6: **Clustering Results of Project 2**

Group	Members in P2:
1	1, 8, 16, 20, 22, 24, 31, 33, 34, 37, 38, 44, 46, 48, 50, 53, 60, 62, 63, 76
2	15, 26, 57, 68, 71, 73
3	54, 66, 67, 69, 72
4	10, 21, 40, 58, 75, 77, 79
5	4, 11, 12, 23, 25, 27, 36, 39, 41, 43, 51, 80
6	18
7	59, 61, 74
8	42, 47, 78
9	3, 6, 9, 13, 14, 17, 19, 28, 29, 30, 32, 52, 64, 81
10	2, 5, 55, 65, 70
11	7, 35, 45, 49, 56

Table 1.7: **Clustering Results of Project 3**

Group	Members in P3:
1	54, 66, 72
2	39, 41, 42, 51, 77
3	2, 5, 15, 26, 55, 57, 65, 70, 71, 73
4	18
5	4, 11, 75, 79
6	33, 47, 58, 62, 80
7	1, 3, 8, 20, 24, 27, 28, 34, 38, 50, 53, 61, 63, 67, 69
8	6, 9, 13, 14, 16, 17, 19, 29, 30, 32, 52, 64, 68, 74, 81
9	22, 31, 37, 44, 48, 59, 60, 76
10	10, 12, 21, 23, 36, 40, 43, 46, 78
11	7, 25, 35, 45, 49, 56

1.5 Empirical Results–Trader's Characteristics

The key point of clustering is to use the centred coordinates to describe the members' attribute in each group. After clustering process of project one, 81 pure technical traders are divided into 11 groups. Thus, the 11 centroids summarise characteristics of members in their individual set. We operate the algorithm with setting k = 11 about 50 times to achieve relatively lest ASD and ASV. The results of coordinates construct an 11*81,000 matrix, where 11 rows imply 11 centroids and 81,000 columns imply similarity degree with 81,000 technical rules. Using this matrix, we start further exploring trading strategies for each group. Based on the coordinates of centroid, which rule is much related to traders' real actions are very clear. If the similarity of the rule is higher, the rule is much more related to real actions. Then, the set of rules with higher similarity construct traders' strategies for each different group because the higher similarity implies the trader trend to adopt the rule. In the following steps, we select higher similarity rules and return to the dataset of dummy signals to draw out dummy signals according to the specific rules for every trader. Then, we make a simple regression between each trader's real action and dummy signals with rules of higher similarity, so that it supports the relationship between specific rules and traders' strategies. The selected technical rules cover six kinds of rules as mentioned before. Also, we extend the time length to 13,500 seconds, which is trading time in one day, for each variety. Thus, the amount rules are 13,500*6 = 81,000 as discussed above. We adopt a simple regression model to investigate the effect of rules to traders' real actions as following:

$$\boldsymbol{S_j = C + \sum\nolimits_{i=1}^{13500} MA_i + \sum\nolimits_{i=1}^{13500} MO_i + \sum\nolimits_{i=1}^{13500} BO_i}$$

$$\boldsymbol{+ \sum\nolimits_{i=1}^{13500} IMA_i + \sum\nolimits_{i=1}^{13500} IMO_i + \sum\nolimits_{i=1}^{13500} IBO_i + \varepsilon}$$

Where, $\boldsymbol{S}$ is traders' real action as the dependent variable. The corner mark $\boldsymbol{j}$ of $\boldsymbol{S}$ is label of different traders from 1 to 81. $\boldsymbol{MA}$, $\boldsymbol{MO}$, $\boldsymbol{BO}$, $\boldsymbol{IMA}$, $\boldsymbol{IMO}$, $\boldsymbol{IBO}$ are corresponding signals with different rules to individual trader. In each kind of rule, it includes 13500 rules. The constant term here is $\boldsymbol{C}$ and the error term is $\boldsymbol{\varepsilon}$. The independent variables are all dummy signals with all 81000 rules. Thus, we make 81 regressions with this model, and in each model, the total observations are equal to the total transaction records for each individual trader. However, this is the original investigated model. It cannot be realised due to the huge similar signals with different rules. In other words, the problem of collinearity happens. Each signals' variable only include 1, 0, and -1. The same or correlated variables possibly exist in total 81000 rules (after experiment, same rules exist). The general methods of this question are to remove the same or correlated variables in the model. However, this is not advisable in this research. For example, if the vector of BO22 is equal to MA16 for trader 1, we do not know which rule we need to remove. If we remove both two rules, it influences the regression results because MA16 (or BO22) may be very significant to trader 1's real trading. So, we stop investigating all 81000 rules and contact clustering results to seek some main significant rules with Top Six Project.

Top Six Project (T6) only selects the rules with highest similarity from MA, MO, BO, IMA, IMO, and IBO. After clustering, T6 chooses the most similarity rules from total six kinds of rules based on the centroid's coordinate in each group. Thus, 11 groups with top six highest rules are filtered. In each group, the six rules construct the key strategies of members. It is sensible to imply member's main strategies because the 11 centroid's coordinates indicate trading characteristics of all members in each group and also the top six rules' selection avoids "conflicts" between the same and correlated rules. Therefore, the original multiple-regression model can be transformed and simplified as:

$$\boldsymbol{S_{jg} = C + MA_{rg} + MO_{rg} + BO_{rg} + IMA_{rg} + IMO_{rg} + IBO_{rg} + \varepsilon}$$

Where, $\boldsymbol{S}$ still is traders' real action and the amount of observations is the total trader's individual transaction records($\pm$). The following independent variables only content six specific rules based on the results of clustering. The corner mark $\boldsymbol{g}$ is from 1 to 11 which label the different group, $\boldsymbol{j}$ is from 1 to 81 which label the different traders, and $\boldsymbol{r}$ is the mark of rules which is selected from 1 to 13500. As described before, based on the 11 clusters' coordinates, six rules of $\boldsymbol{MA}$, $\boldsymbol{MO}$, $\boldsymbol{BO}$, $\boldsymbol{IMA}$, $\boldsymbol{IMO}$, and $\boldsymbol{IBO}$ with the greatest similarity can be selected in each group. They are components of T6's multiple regression. We return to the step of generating dummy trading signals of the six selected rules for each trader, and combine the six vectors and individual trader's real action in a new matrix. Then, we operate a T6's multiple regressions for each of 81 traders. The amounts of regressions are 81 and they actually divided into 11 groups as clustering. The regression results disclose the significance of selected rules to traders' real actions. The following **Tables 1.8** summarise the final results.

Table explanation: The first row indicates the means of each column. The first

Table 1.8: **Significance Percentage of Top Six Technical Trading Rules in 11 Clustering Groups**

Group	Amount of Traders	Highest Six Rules	Significant Traders	Significant Probability
1	19	bo13	17	89.47%
		ma312	13	68.42%
		mo251	12	63.16%
		ibo990	10	52.63%
		ima6355	9	47.37%
		imo13406	8	42.11%
2	6	bo351	5	83.33%
		ma539	6	100.00%
		mo387	6	100.00%
		ibo3573	6	100.00%
		ima9094	4	66.67%
		imo6375	4	66.67%
3	8	bo7320	3	37.50%
		ma11723	4	50.00%
		mo11973	5	62.50%
		ibo122	7	87.50%
		ima296	4	50.00%
		imo235	6	75.00%
4	12	bo1	10	83.33%
		ma18	10	83.33%
		mo13136	9	75.00%
		ibo113	9	75.00%
		ima11694	7	58.33%
		imo7583	9	75.00%
5	5	bo8	5	100.00%
		ma41	5	100.00%
		mo13114	5	100.00%
		ibo453	5	100.00%
		ima1136	3	60.00%
		imo556	4	80.00%
6	1	bo506	1	100.00%
		ma3503	1	100.00%
		mo1297	1	100.00%
		ibo13476	0	0.00%
		ima10	1	100.00%
		imo9780	0	0.00%
7	3	bo13500	1	33.33%
		ma13383	1	33.33%
		mo12971	2	66.67%
		ibo369	2	66.67%
		ima1011	3	100.00%
		imo887	2	66.67%
8	3	bo2484	1	33.33%
		ma5232	2	66.67%
		mo3071	2	66.67%
		ibo94	3	100.00%
		ima212	2	66.67%
		imo275	2	66.67%
9	10	bo32	6	60.00%
		ma65	10	100.00%
		mo92	8	80.00%
		ibo5425	9	90.00%
		ima13393	7	70.00%
		imo11704	6	60.00%
10	9	bo40	8	88.89%
		ma215	8	88.89%
		mo193	8	88.89%
		ibo11156	6	66.67%
		ima12324	4	44.44%
		imo13146	7	77.78%
11	5	bo13227	5	100.00%
		ma20	4	80.00%
		mo13414	2	40.00%
		ibo68113	4	80.00%
		ima2170	5	100.00%
		imo536	5	100.00%

and second columns show the code of group and amount of members in the group. The third column shows the six specific rules with highest similarity in each group. Then, the following 4 columns show how many traders are affected by the six rules and how many are not, and the probability of total traders. For instance, the second big row actually includes 19 regressions for 19 traders in group 1. The rule of BO13 has effect to 17 traders in this group, and the occupation is 89.47%.

If we set 60% as standard, this group of traders tends to use bo13, ma312, and mo251 in their strategy. Traders in group 2 utilise ma539, mo387, and ibo3575 in their strategy absolutely. Still considering 60%, traders tend to put mo11973, imo235, and ibo122 in their strategy in group 3. In group 4, most traders adopt bo1 and ma18 rules. All traders utilise bo8, ma41, and mo13114 in their strategy. There is only one trader in this group. But, he is very interesting because he also is single trader in one group of project 2 and 3. The size of trader is small in this group so that the adopted rules are not clear. The rule of ibl94 is adopted for this group of traders. This also is a small group so that the indication is not very clear. These 10 traders utilise ma65 and tend to adopt ibo5425 and mo92 in their strategy. Most traders in this group adopt bo40, ma215, and mo193 in their strategy. The five traders in the last group use the ima2170, imo536, and bo13227 in their strategy. Obviously, traders would utilize multiple rules and switch to create multiple strategies due to achieve more profit or get optimal strategies. Thus, they may use genetic algorithm to evolute and optimise strategies in every trading days. However, the main combination of them should be disclosed by this method. The results are according to the coordinates of clusters in each group. Hence, the strategies set can prefer the features of technical traders. Market participants can follow or “snipe” technical trading in the financial market based on the strategies in each group, especially, when they have enough information.

1.6 Conclusion

This is an empirical research on technical trading strategies. The contribution of this research was to indicate technical trading behaviour for real traders in Chinese futures market and create a new method to capture technical trading strategies. We think that is more accurate than directly make an interview to traders we do not think they would like to tell the truth of this sensitive topic. However, this method would be very useful to supervision department of exchange to monitor abnormal (see high frequency traders) participants in the market. We selected rebar futures contracts, which is one of main commodity futures in Chinese futures market, as the underlying asset to investigate. According to the unique feature of the dataset, traders have their own identification. The top 200 most active traders were the main research object since they were more likely to be the technical traders and employ program trading. We chose five related macroeconomic indexes to rebar market as the filter factor by using a simple multiple-regression model to filter technical traders. The results showed that in each contract, technical traders occupied about 30% from the top 200 most active traders. Since it is high frequency per second data, we used similar tick-by-tick data which recorded the complete market price trend of each contract without traders' identification, to generate dummy signals with a series of technical trading rules. Then, the dummy signals of each selected technical rules and each trader's real action were combined and matched according to same transaction time. We calculated the similarity between them which indicated each trade's motivation to employ each rule. We selected only 81 technical traders from 15 most active contracts in my dataset for investigation. Based on the similarity matrix, we adopted K-means clustering algorithm to classify these 81 traders. The clustering results showed that they could be divided into 11 groups with different technical strategies. In order to avoid same or correlated dummy signals with different rules, we chose the top six highest rules based on the coordinates of 11 clusters to state whether these six rules were significant to trader's real actions. The results indicated that most members, in the different groups, had to have one or more significant technical rules to their real action. More details are displayed in section 5. In addition, this research has its limitation. It is hard to forecast the traders' actions out of sample. It is better to utilized for brokerage or exchange, who have satisfied information and details to observe a lot of traders, that would be more efficient. Meanwhile, for the future works, we will link the classified rules in the market data to test whether the selected rules are profitable and we also would check profitability of the selected pure technical traders to observe do they win or loss in the market.

Chapter 2

Margin Trading: Hedonic Returns and Real Losses

Abstract

Margin trading is popular with retail investors around the world. This is a puzzle since, as we show, margin trading has a negative expected return. Our explanation is that whilst lowering mean returns the collateral requirement imposed by margin calls also induces positive skew in the distribution of returns. As a result investments in assets with otherwise symetric returns instead offer limited losses and a small but positive chance of a large gain. Thus, margin trading offers the same hedonic returns associated with lottery tickets, lottery-type stocks, and gambling. We test this hypothesis using a unique dataset of the trading histories of futures traders on the Shanghai Futures Exchange. We show that both expected and observed losses are substantial and that the optimal portfolio never contains Rebar futures. Analysing traders' behaviour we show that whilst hard to rationalise without a hedonic motive, that trading behaviour can be easily understood as a form of entertainment.

2.1 Introduction

The Little Crash in '62 as described in the classic account of Brooks (2014) [20] was the result of limited liquidity and panic. In particular it was the result of the limited liquidity and panic of retail investors trading on the margin. Kindleberger (2000) [68] identifies a similar role for margin traders and their brokers in the 1929 Crash[6]. While Brunnermeier and Pedersen (2009) [21] discusses their role in many more recent crises. Margin trading, however, remains a common but relatively understudied feature of financial markets. This is perhaps surprising because, as this paper shows, margin trading, by retail investors, leads to a significantly lower but skewed returns.

Regardless of whether a crash is transitory like in '62, or not as in '29, the type of liquidity spiral described anecdotally by Brooks (2014) [20] and formally by Brunnermeier and Pedersen (2009) [21] led to the ruin of many margin investors. Of course, in such large crises many investors suffer (and many profit) but as we will study formally, margin traders risk the loss of their entire investment in even quite prosaic markets. Given then the obvious hazards of trading on the margin, the natural question is why is margin trading ubiquitous? Our explanation is that the collateral requirement imposed by margin calls induces positive skewness in the distribution of these returns, making such investments more similar to a lottery. Investments in otherwise pedestrian assets will now offer lower average returns but with limited losses and a small but positive chance of a large gain. Thus, the continuing appeal of margin trading is that the lowered financial returns are compensated by the hedonic returns accruing from the positive skew in the distribution of returns that margin trading induces. We test this hypothesis using a unique dataset on the full trading histories of traders on the Shanghai Futures Exchange (SHFE). We show that traders incur large losses, average returns are **−27%**, are not operating

[6]Brooks (2014) [20] describes how the Dow Jones incurred its second largest ever loss on the Monday and fell further on Tuesday morning. Yet it was as brief as it was deep. That afternoon the market started to recover, and its losses had been eliminated completely one trading day later by the end of Thursday. Brooks, citing the NYSE official reports, emphasises the role of private individuals' behaviour in precipitating the crash. The majority of private investors traded on the Margin, that is they traded mostly with borrowed money secured with a small amount of collateral. As the market fell reducing the value of their portfolios and thus eliminating their collateral these investors – presumably unable or unwilling to provide additional collateral – were forced by their brokers to liquidate their positions to eliminate their debts. That is they were subject to margin calls. Indeed many had already faced such calls over the prior weekend providing the initial downwards acceleration. The large volume of selling induced by this led to further price falls, further margin calls, and a vicious downwards spiral. In Brooks's account, the precipitous fall in the market – so rapid the Dow Jones ticker tape was unable to keep up – is arrested only by the entry of institutional investors who begin perceive value in the market, and who crucially, had ample liquidity.

an optimal portfolio, and their behaviour would be extremely hard to rationalise without a hedonic motive.

This explanation builds on the findings of a prominent recent literature which studies the motivations and behaviour of retail traders. That is non-professional investors of relatively small amounts who trade routinely. Since such routine trading is known to be 'Hazardous to Your Wealth' (see the seminal papers of Barber and Odean (2000)[7], and Barber et al. (2009)[6]) the available explanations are that these investors are either deluded – say because they weight probabilities inaccurately (see, Barberis, 2012[8]) –, or are deriving some other, non-pecuniary, benefit from their trading. What one might call fun (see, Barberis and Xiong, 2012[10]; Ingersoll and Jin, 2012[59]; Dorn and Sengmueller, 2009[33]; and Dorn et al., 2012[32])[7]. That is, by altering the distribution of returns, trading on the margin makes investment more entertaining.

This is a consistent with a small but prominent literature has emerged which studies *trading as gambling.* A key early contribution was that of Golec and Tamarkin (1998)[52] who showed that investors prefer so called lottery stocks (again, those with high skewness in the returns) subsequent work has shown that lottery-ticket purchasers tend to buy lottery-type stocks (see, Kumar, 2009[69]), investors in regions with a greater proportion of Catholics compared to Protestants and thus fewer religious presumptions against gambling trade more lottery type stocks, (see, Kumar et al., 2011[70]), investors who say they enjoy investing are found to trade more (Dorn and Sengmueller, 2009[33]), option prices reflect retail investors compensating intermediaries for additional risk for lottery type payoffs (Boyer and Vorkink, 2014[17]), and investors trade less, especially in lottery stocks when lottery wins are large (see, Gao and Lin, 2015[48] and Dorn et al., 2012[32])[8].

Read together, this literature constitutes an emerging body of evidence that an important motivation for individual traders is that it provides similar types of entertainment as lottery tickets, or other gambles. This evidence is, whilst convincing, in an important sense indirect. That is, the nature of the activity is inferred from its correlates. Thus, we infer that trading is often a substitute for gambling since when lotteries are more available or of larger value we observe less trading. Moreover, in

[7]Investors' utility functions were originally analysed in the classic papers of Friedman and Savage (1948)[47] and Markowitz (1952)[78], since the seminal work of Shiller and others (see, Shiller (2000)[94] for a survey), these have been generalised to incorporate insights from Behavioural Economics and elsewhere – such as prospect theory, see Barberis and Huang (2008)[9] for an excellent example. Other forms of motivation, such as the competitiveness preferences proposed by Parco et al. (2005)[87] and Sheremeta (2010)[93] may also play a role but there is no evidence for such behaviour in a large and anonymous context such as we study.

[8]Bhattacharya and Garrett (2008)[12] provide evidence that lotteries that offer more skewness offer lower returns, suggesting a similar trade-off.

places where we expect less gamblers we observe fewer gambling traders, and indeed traders who say they enjoy gambling/trading are seen to do it more.

This paper provides the first direct evidence of participation in financial markets as a source of entertainment. In particular we will focus on the trading of *Rebar* futures on the Shanghai Futures Exchange (SHFE). Rebar are reinforcing steel bars, widely used with concrete in the construction of buildings. We use a unique database of the full portfolio histories of individual clients of a leading Chinese retail brokerage. We will show that the returns obtained from margin trading of Rebar futures made are consistent only with a substantial hedonic motive and are not rationalisable as an investment. We will see that margin-trading means that the returns to any underlying asset are transformed to have lottery-type returns. This is because, the rules of the SHFE and other exchanges, operate a system of margin-calls through by which the maximum debt of the trader is limited. If a trader fails to produce additional capital given a fall in the value of their portfolio then this portfolio is closed. This means that distribution of returns is truncated on the lefthand-side leading to skewed lottery type returns. One implication of this is that different margin requirements alter the lottery-ness of the activity. We will show that the expected return of a investing on the margin is negative, and that there exists no optimal portfolio of which margin traded Rebar futures are a part ruling out more sophisticated portfolio diversification strategies. Having shown that the properties of the asset are similar to gambling – a highly skewed distribution of returns with a negative expectation, and like lottery tickets not useful for any other purpose. We will then show that the nature of the trading behaviour is consistent with entertainment but not investment – trades tend to be limited to a small period each day – with the average position held for under one day. Further traders seem to gamble a fixed-pot, after which they leave the market for some time.

The literature on margin trading is relatively limited. Notably, Brunnermeier and Pedersen (2009)[21] use a formal model to understand the effects of margin trading on markets. In their model market liquidity interacts with the ability of investors to borrow to trade, and they show how this interaction can destabilise markets, increase volatility and induce 'liquidity spirals' like those in '29, '62, as well as those from the early 1980's onwards that they describe in their study. Their paper thus provides an important contribution to understanding the aggregate effects of margin trading, and our paper seeks to complement it by understanding the micro-foundations of the decision to trade on the margin. Recent empirical work has sought to shed further light on the relationship between margin trading and liquidity. Kahraman and Tookes (2013)[65] uses the staged introduction of margin trading for different assets in India to provide evidence that margin trading leads to a substantial reduction in the spread. On the other hand, Wang (2014)[102] using data for Chinese ETFs shows that allowing margin trading and short-selling can reduce liquidity by discouraging trading by uninformed investors. Heimer (2015)[56] studies the impact of leverage constraints by comparing leverage-limited US traders with their unconstrained EU counterparts. By studying contemporaneously traded FX markets he shows that leverage constraints limit losses. In his view, leverage constraints serve to limit poor-decisions by over-confident traders. Our, not-contradictory, explanation is that lower leverage constraints will mean expected returns are higher due to fewer margin calls. He worries about over confidence, we are more sanguine and argue that the losses traders incur in the context we study may be understood as simply the price of the hedonic returns they enjoy. To support this view, we show that although traders' financial losses are substantial, that their behaviour is consistent with deriving considerable hedonic returns.

This paper is organised as follows, the next section briefly introduces some of the institutional details of the SHFE and our data. Section 3 demonstrates why margin trading should be associated with lower returns and more skewness. Section 4 shows that Rebar traded on the margin are never in an optimal portfolio. Section 5 discusses key features of traders' behaviour to further advance the argument that they are largely motivated by hedonic returns. Section 6 closes the paper.

2.2 Context and Data

The Shanghai Futures Exchange (SHFE) has become the largest metals futures market in the world. Rebar futures were introduced on 27/03/2009 as a method for construction companies to manage their exposure to price changes. Contracts are first traded a year in advance of the delivery date, and there are thus twelve contracts being traded at any given time. Trading is undertaken with an account at one of 198 brokerage firms[9]. These brokerages typically offer margin accounts and individuals submit orders via terminal or telephone which are then immediately relayed to the market. A crucial feature of this market is that only registered institutional traders with a warehouse may take receipt of the Rebar itself and all other traders' positions are liquidated one month before delivery is due.

As it is less often studied than other longer-established financial markets we provide additional details of the market's institutional characteristics in **Appendix B.3**.

Our data are provided by one of the 198 brokerage firms. They cover the period

[9]These are called *Registered Chinese Futures Companies.*

27th March 2009 to 30th of September 2013. During this period we observe the exact trading history for all of 22411 clients of this brokerage firm. That is, for a given client, we observe each order submitted (for Rebar), its form (limit or market), size, price, and the precise time it was submitted. We also observe the precise details of how, when and if the order was fulfilled. If a client also trades other futures we also observe the aggregate daily change in the value of these assets. We match these data to tick-by-tick data for each Rebar futures contract obtained from Guotaian and Weisheng.

Whilst we cannot be sure, there is every reason to believe that the individuals who use the brokerage we study are representative of the market as a whole and thus we are comfortable making inferences about the broader population of retail SHFE traders. Equally, comparison with the fee structure and margin requirements of competing firms suggests that there is little un-ordinary about the firm we study other than it is amongst the largest of such firms. Finally, it is worth noting that our data start on the same day as Rebar are first traded on the SHFE thus ensuring that we can be confident that none of our results are unique to some sub-period of Rebar trading history.

2.3 Margin Trading and Lotteries

2.3.1 Explain and Define Margin Trading

Traders, whether private individuals or institutions, can often use the assets they trade as collateral to finance buying more. Given that such assets fluctuate in value, they are unable to borrow against the full purchase-price of these assets and must instead also provide some additional collateral. For individual investors, this process often takes the form of a margin account in which investors are able to purchase assets up to the value of some multiple of the collateral they have provided. Thus, if an individual posts collateral of $\$1,000$ and there is a margin requirement of 10% they may purchase assets up to the value $\$10,000$. This leverage will increase the variance of the returns, a 10% appreciation in the value of the assets now doubles the investor's initial collateral whilst a depreciation reduces it to 0. This second possibility is a key feature of margin trading – brokers and often exchanges typically require that an investor has positive collateral. If it is reduced to 0 then they are required to provide additional funds or their positions are closed to prevent further losses. This, requirement for additional funds is known as a *Margin Call*. These margin calls induce asymmetry in the returns distribution there is now no chance of an investor losing more than their original stake without further investment.

They also change the time-series properties of an investment as an asset that may previously have been well-described by a Brownian motion, and thus memoryless, now becomes a first-hitting process in which once a boundary value has been crossed (the margin call requirement) the asset takes value of $\mathbf{0}$ thereafter. This has the important implication that, given sufficient volatility, the investor can no-longer expect to obtain an average return simply by buying the asset and holding it. Thus, whilst margin trading limits large losses it also reduces the average return as now there is an increased probability that the return is zero. The remainder of this section formalises our intuition about the mean and the skewness of the returns distribution before taking it to our data on Rebar futures.

2.3.2 Margin Trading has a negative expected return (at any horizon)

The expected return $\boldsymbol{E[r^x_{ct}]}$ of an asset $\boldsymbol{x}$ with weakly positive returns over a period $\boldsymbol{t}$ where $\boldsymbol{c}$ is the price of $\boldsymbol{x}$ that triggers a margin call is given by:

$$\boldsymbol{E[r^x_{ct}] = E[r^x_t|x > c] \cdot P(x > c) + E[r^x_t|x \leq c] \cdot (1 - P(x > c))} \tag{2.1}$$

We assume that the mean return on the asset, given a movement which takes it below the margin threshold is negative. A margin call always involves some loss, the exact amount will depend on the degree of leverage and the size of the price movement. Here it suffices to denote the return given a margin call as $\boldsymbol{\gamma}$. That is, $\boldsymbol{E[r^x_t|x \leq c] > 0 > E[r^x_{ct}|x \leq c] = \gamma}$. Thus, (2.1) simplifies to:

$$\boldsymbol{E[r^x_{ct}] = E[r^x_t|x > c] \cdot P(x > c) + \gamma} \tag{2.2}$$

It follows that since the return given a margin requirement is lower when it binds than for the same realisation of $\boldsymbol{x}$ without such a requirement and the return is the same when it does not bind that returns are lower in the presence of margin calls. That is given $\boldsymbol{\gamma < E[r^x_t|x \leq c]}$ and $\boldsymbol{E[r^x_t|x > c] = E[r^x_{ct}|x > c]}$, which follows $\boldsymbol{E[r^x_{ct}] < E[r^x_t]}$. Writing $\boldsymbol{P(x > c)}$ as a first-hitting process with boundary $\boldsymbol{x_c}$ gives:

$$\boldsymbol{P(x > c) = 1 - \frac{1}{\sqrt{2\pi\sigma^2 t}}\{\exp(-\frac{(x - x_0)^2}{2\sigma^2 t}) - \exp(-\frac{(x - (x_0 - 2x_c))^2}{2\sigma^2 t})\}} \tag{2.3}$$

The return is then given by:

$$\boldsymbol{E[r^x_{ct}] = E[x_t | x_t > x_c] \cdot P(x > c) + \gamma \cdot [1 - P(x > c)]} \tag{2.4}$$

Note, that we can think about the absence of a margin requirement as either having no impact on the return in which case: $\boldsymbol{E[r_t] = E[x|x > x_c] + E[x|x \leq x_c]}$ or equivalently that the margin requirement never binds, i.e.: $\boldsymbol{x_c = -\infty}$, which implies that $\boldsymbol{E[r_t] = E[x|x > c] = E[x]}$. Inspection of 2.3 shows the probability of margin requirement being violated is increasing in the volatility $\boldsymbol{\sigma^2}$ and the holding period $\boldsymbol{t}$. This is natural as an asset with no volatility would never trigger a margin call, but also highlights that if margin requirements are well matched to assets' properties then more volatile assets would be associated with higher margin requirements. Of course, this would reduce the skewness of the returns distribution, and hence the hedonic returns. We shall see in Section 5 that whilst we would expect margin investors to be disproportionately sensitive to volatility we in fact observe the opposite. We summarise this argument with the following proposition:

Proposition 1. *The expected return $\boldsymbol{E[r^x_{ct}]}$ of an asset $\boldsymbol{x}$ over a period $\boldsymbol{t}$ with margin requirement $\boldsymbol{c}$ is decreasing in $\boldsymbol{c}$ and always lower than the return in the absence of a margin requirement.*

2.3.3 Margin Trading makes returns skewed

The previous section showed the effect of a margin requirement on mean returns. This section will examine the impact on skewness. Barberis (2012)[10] studies how the use of a stopping rule, such as an individual who has lost their gambling money leaving the casino, leads to a skewed-distribution of returns even given binomial gambles. Normally, in a financial market there is no such stopping rule and an investor may hold a position and thus wait, potentially indefinitely, to obtain the average return. Even if a position is closed it is unlikely to lead to the loss of all of ones funds. Margin trading changes this, the combination of greater leverage and limited liquidity means that the probability at any given horizon of losing the entire initial investment in a portfolio is substantial.

We now show that the possibility of margin calls leads to a right-skewed, 'lottery', returns. To do so we study the properties of a truncated normal distribution.The focus on the normal distribution is important as truncation does not lead to skewness for all distributions. But, there are good theoretical and empirical reasons for believing that returns in our case our approximately normally distributed. In particular, a standard assumption of Brownian motion implies that returns should be normally distributed, whilst **Figures 2.1** and **Figure 2.4** allows us to verify that this is the case in practice. The moments of truncated distributions are comparatively understudied and we extend a recent paper of Pender (2015)[90] who uses Hermitian polynomials to characterise the moments of a truncated normal distribution. We can thus make the following claim:

Proposition 2. *The derivative of the skewness with respect to the lower truncation point* $\boldsymbol{A}$ *is positive, thus a larger margin requirement increases the skewness of the returns of a given asset* $\boldsymbol{X}$

$$\frac{\partial Skew_{\boldsymbol{X}}}{\partial \boldsymbol{A}} = \frac{\partial \boldsymbol{E}[(\boldsymbol{x} - \boldsymbol{\mu_x})^3]}{\partial \boldsymbol{A}} > \boldsymbol{0} \tag{2.5}$$

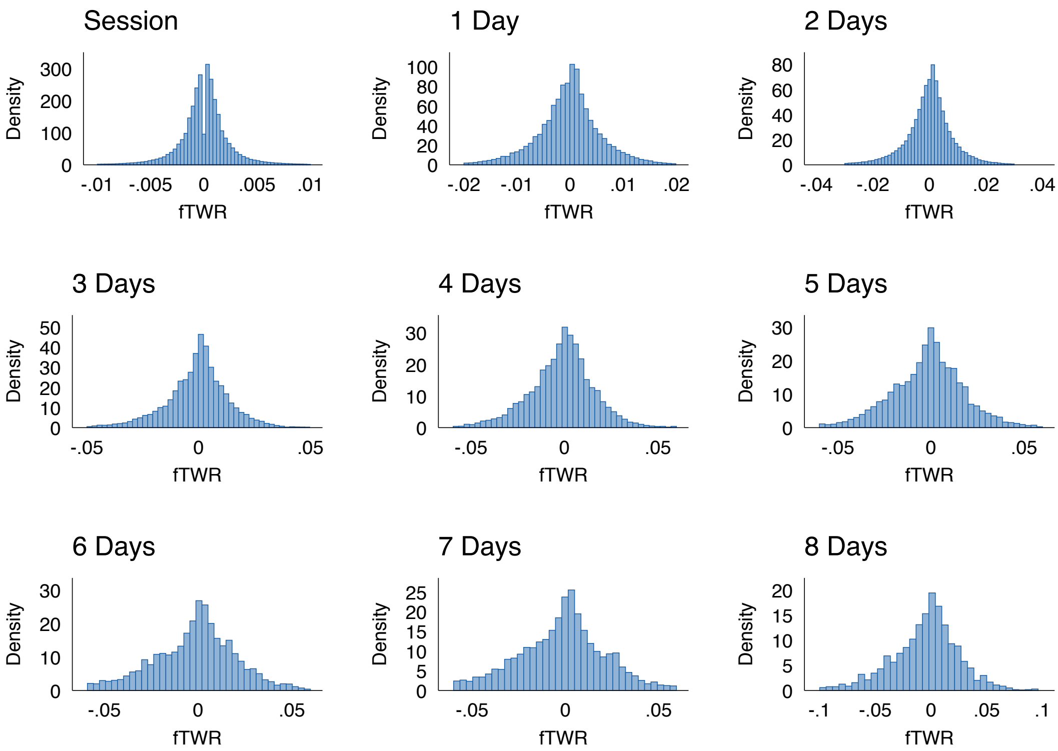
Proof. The proof is in **Appendix B.4**. □

It is important to note that the above result is dependent on the underlying distribution. For example truncation does not necessarily result in skewness in a pareto distribution. However, as we show raw returns for the market we consider follow a normal distribution.

Figure 2.1 plots the distribution of returns over holding periods observed in the real data (from the price of continuous contract). Inspection of **Figure 2.1** shows that the distribution of returns for Rebar are approximately normal, perhaps even negatively skewed. Barberis (2012)[8] studies how the use of a stopping rule, such as an individual who has lost their gambling money leaving the casino, leads to a skewed-distribution of returns even given binomial gambles. Normally, in a financial market there is normally no such stopping rule and an investor may hold a position and thus wait, potentially indefinitely, to obtain the average return. Even if a position is closed it is unlikely to lead to the loss of all of ones funds. Margin trading changes this, the combination of greater leverage and limited liquidity means that the probability at any given horizon of losing the entire initial investment in a portfolio is substantial.

A key feature of the SHFE is that market movements are limited to $\pm$ **7%** a day. If the movement is larger than that then trading is suspended. The margin requirement is SHFE is **7%** and the Broker's margin requirement is **11%** thus an investor will never make a loss and should always retain some funds. Crucially, it prevents the investor from ever going into debt. It means that whilst the magnitude of the upside return is limited on any given day by reinvesting the original gains plus minus any losses on subsequent days we will observe the familiar lottery-type

Figure 2.1: **Final Total Weighted Return by Position Duration**

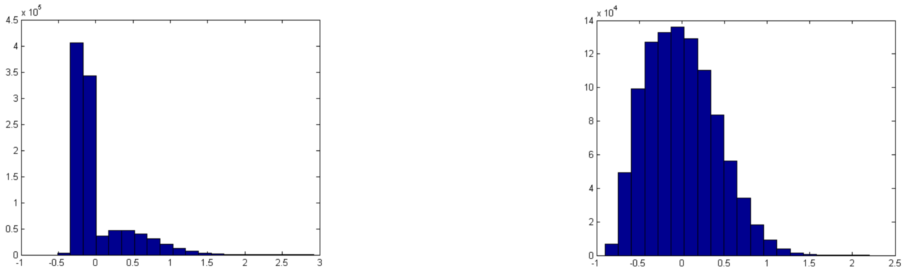


Each graph shows the distribution of returns for positions held for a specified length.$fTWR$ is the absolute return of each position for a given maximum length, weighted by its size. The top left histogram shows the size-weighted distribution of returns for positions held for one trading session or less. The eight remaining plots are analogous for longer holding periods. The distribution is truncated for clarity, at $\pm\mathbf{0.01}$ for sessional returns, and $\pm\mathbf{\{0.02, 0.03, 0.05, 0.06, 0.06, 0.06, 0.06, 0.1\}}$ for the 1-Day, 2-Day returns, etc.

returns pattern. Losses are always truncated at the level of the original stake, whilst gains are unbounded. This complicates an analytical extension of Barberis (2012) [8] and we now use simulation to study quantitatively how the existence of a margin call skews individual returns given the empirical asset returns distribution. The results suggest that although these distributions of single-period asset returns are approximately normal, that distribution of individual returns taking into account the margin requirement is highly skewed.

A numerical simulation is used to illustrate the effect of margin trading on the distribution of individual returns. We estimate a GARCH(1,1) ARIMA(1,1,0) model based on changes in the Rebar future price for the entire period covered by our data March 2009 to September 2013. In order to treat long and short positions equally we set the drift term equal to zero. Using this model we simulate 5 million independent twenty-one days price paths. For each path we calculate the returns of traders with long and short positions in the futures contract. Margin accounts for each trader are endowed with initial wealth and updated as prices change. If traders lose money such that they violate their margin requirement they reduce their positions by the minimum amount such that this is no longer the case. We contrast the returns of margin traders with those of a trader holding the asset without leverage. For margin traders we calculated results for long and short positions and for different numbers of initial contracts. In line with market rules, the margin requirement is set to **7%** and the maximum price change on any day is **7%**[10]. Each contract is for 10 hands of Rebar and the initial price for each hand is RMB 3000. Traders start the simulation with initial wealth equal to **15%** of the contract value.

Figure 2.2: **Simulated Returns to Margin Trading**



(a) **Initial Position of 1 Contract** (b) **Initial Position of 5 Contracts**

Results are the simulated absolute returns of traders with an initial position of 1 contract and 5 contracts respectively, and wealth of **15%** of the value of these positions over 21 trading days. This is equivalent to RMB 4,500 and 22,500 respectively. Traders are assumed to partially close positions in response to margin calls and to use any profits to open additional positions. The simulated distribution of prices is estimated using a GARCH(1,1) ARIMA(1,1,0) model for the Rebar future price for the entire period covered by our data March 2009 to September 2013. In order to treat long and short positions equally the drift term is set equal to zero.

Panels 2.2b and **2.2a** of **Figure 2.2** show the simulated returns distribution of traders. The left hand figure illustrates the case of traders with a single long futures contract, whilst the right hand figures shows the distribution for a trader who initially holds 10 contracts. We first consider the case with traders with a single long or single short contract. The average return for an un-leveraged trader over the period is 0 whilst the leveraged long and short traders returns are approximately **-1%**. Importantly, regardless of whether a trader takes a long or short position the margin account results in negative returns, and in both cases by the end of the simulation approximately **88%** of traders have incurred sufficient losses that they can no longer meet their margin requirements and so have no futures contracts. We see

[10]Whilst the brokers' requirement is **12%** this is understood to be negotiable, thus assuming only the SHFE represents the minimum chance of Margin Calls, and thus the least skewed distribution.

that both distributions have a negative mean and are heavily skewed, as predicted by Propositions 1 and 2 respectively. The lower skewness for the larger initial position reflects that individuals faced with a margin call may close one or more open positions and continue to hold the remainder of their portfolio. Interestingly, as we will see below, most of the investors we study open one position at a time.

2.3.4 Most traders lose money at at least this rate

We now use individual account histories to show that most traders lose money at at least this rate. Note, however, that if an individual is willing to provide additional capital when faced with a margin call then we will not observe either the reduced returns or the additional skew. This is because, in effect, the individual is not leveraged. In reality few individuals will be willing to fully underwrite their trading, and so we should expect a different returns distribution before and after they have committed all of the funds they are willing or able to commit. It is further likely that the total funds individuals are willing to commit to trading will vary over time. Of course, how much additional money an individual is willing to commit is unobservable as is its change.

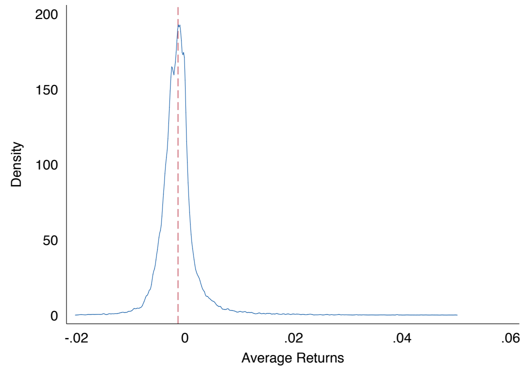
To proceed we first consider the overall distribution of average-daily returns, and then provide evidence for the margin-call as the source of lower returns and excess positive-skew by analysing the distribution of returns, per position.

The traders in our data do not trade every day and often go months without trading or having open positions. It is appropriate therefore, and will be useful when we consider the position returns, to treat these episodes as separate. We split their trading history into a set of mutually exclusive sub-periods using a k-means based algorithm described in **Appendix B.6**.

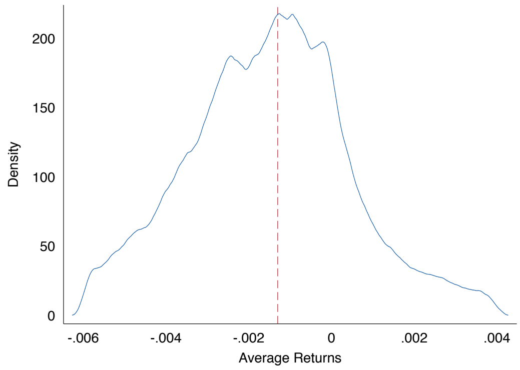
We calculate traders' average daily returns in each of these sub-periods and these are reported in **Figure 2.3**. Both panels present kernel density plots, truncated for clarity. **Panel 2.3a** limits the returns to between $\mathbf{-2\%}$ and $\mathbf{5\%}$ and **Panel 2.3b** to between $\mathbf{0.2\%}$ and $\mathbf{0.5\%}$. In both cases the dashed vertical line describes the mean daily return of $\mathbf{-0.123\%}$ equivalent to an annualised return of $\mathbf{-27\%}$[11]. Put differently, this distribution implies that $\mathbf{88\%}$ of traders will lose money on an average day and conditional on loosing their average return will be $\mathbf{-0.274\%}$. The large difference in the conditional and unconditional return is suggestive of the positive skew in the data. This skewness can be seen in both **Panel 2.3a** and more easily

[11] This figure is based on a trading year of 250 days.

Figure 2.3: **Average Daily Returns Including Transaction Costs**



(a) **The distribution is truncated for clarity, at −0.02 and 0.05**



(b) **The distribution is truncated for clarity, at −0.006 and 0.004**

Average returns are calculated based on the absolute return over the duration of the positions held that day. Returns include the observed trading costs which vary between 0.0068% and 0.03% . As described in Section 2.5.3: a small fraction of traders achieve large returns but the reported distributions are truncated for clarity at -0.02 and 0.05 and -0.006 and 0.004 for the left and right panels respectively. The red dashed vertical line is the mean daily return.

in the truncated distribution in **Panel 2.3b**[12]. Inspection of **Panel 2.3b** makes plain the positive skew in the distribution of returns. Comparing the distribution either side of the mean line shows that whilst losses are clustered near the mean, the positive returns are much more dispersed.

Measured numerically, the skewness is **5.69**, this is more than in the simulations where it is **1.4**. Whilst, the calibration is deliberately simple and we have not attempted to calibrate it to the empirical data this discrepancy likely reflects additional, non-modelled, sources of variation in the empirical data such as trading frequency, and willingness to re-invest.

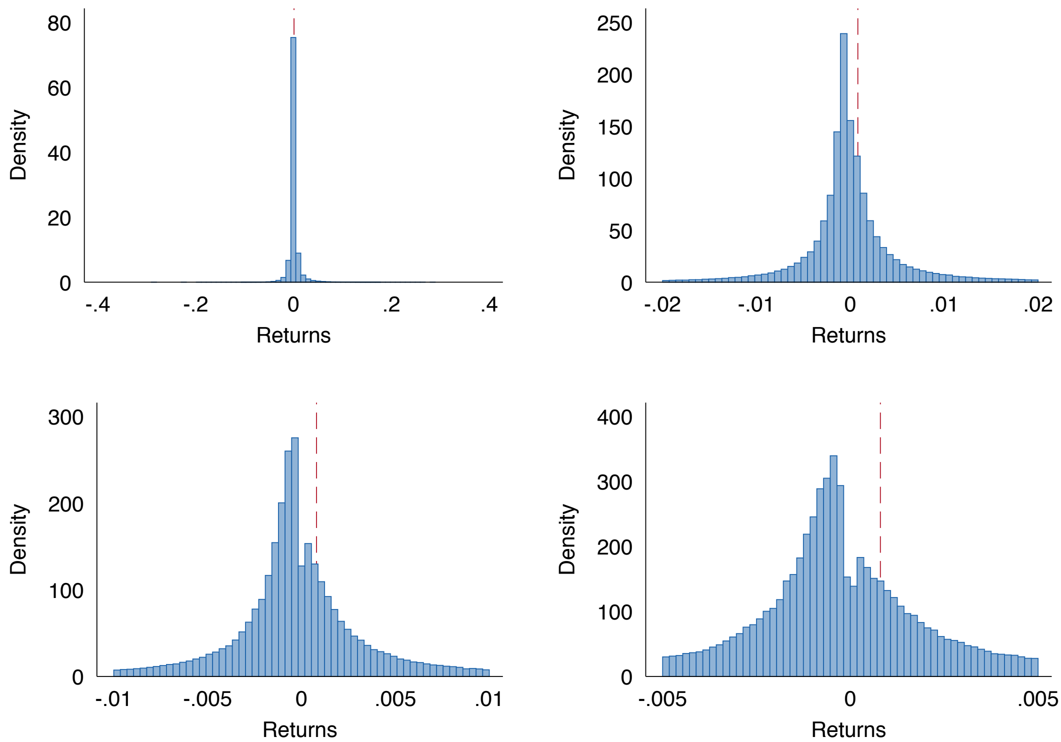
The implication of **Figure 2.3** is clear: the margin traders we study almost all obtain returns substantially worse than **0**. We now wish to understand why this is. Given that traders may take a long or a short position, the negative price trend over the period we study cannot be the cause. **Figure 2.4** plots the returns for all positions taken in our data. The data are clearly approximately-normally distributed and the mean is in fact positive although this is due to a small number of extremely profitable positions taken. There is some evidence of skewness, which is unsurprising given that many of the positions taken will be incompletely underwritten.

To demonstrate that it is the return distribution of leveraged traders that induces the skewness we we now seek to identify those most likely to be not in a position

[12]Our preferred measure excludes sub-periods for which there is less than 10 days trading activity. All our results are robust to this choice and a comparison is reported in **Figure B.1** in **Appendix B.2**

to underwrite their trades. To do so we treat the amount an individual is willing to commit to trading as being fixed in each of these sub-periods. We then treat the amount an individual is willing to invest in a given sub-period as a strictly increasing function of the amount invested and any profits, in that sub-period, to date. That is, even if they withdraw money from their trading account we assume that they will be willing to re-deposit those funds in the current sub-period. The length-distribution of these sub-periods is described in **Figure B.2** in **Appendix B.2**. Thus, constrained traders are those for whom the maximum committed funds has already been reached, and whom have insufficient funds in their brokerage account to open additional positions. As discussed in detail below the average position is relatively small and held for under a day. Such relatively frequent, high-cost trading has been previously been documented as a key reason why retail investors often fare badly (see Barber and Odean, 2000[7] and Barber et al., 2009[6]). **Figure 2.5** thus compare the returns for constrained and non-constrained investors after trading costs.

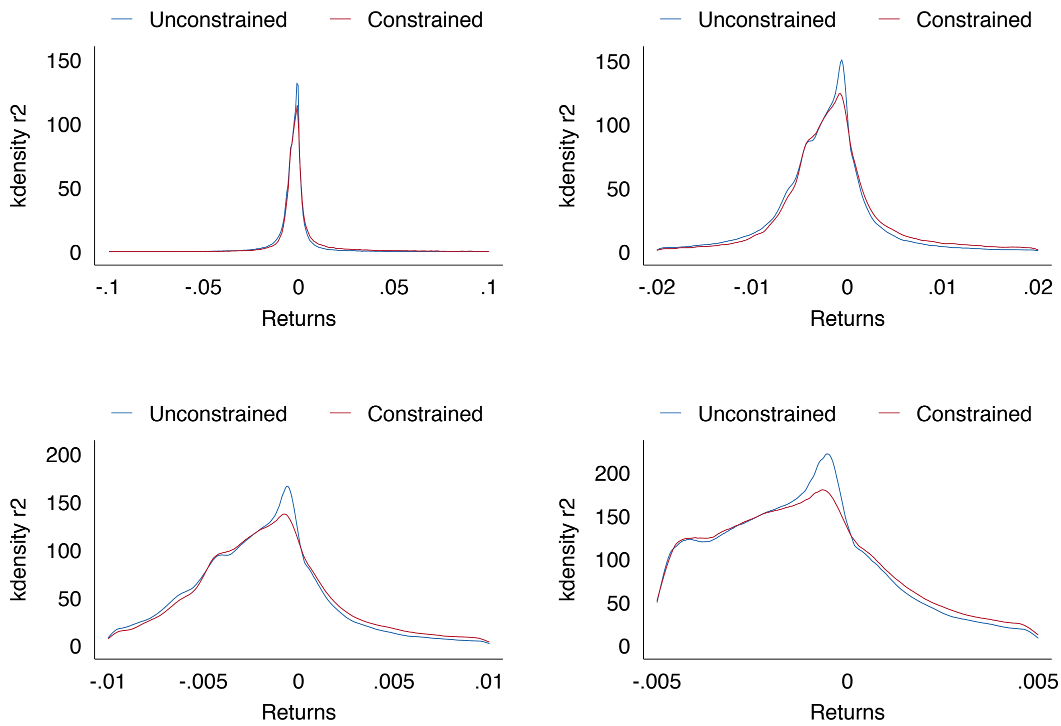
Figure 2.4: **Returns, per position, Excluding Transaction Costs**



The top-left distribution is truncated for clarity, at $\pm\mathbf{0.1}$, the top right distribution at $\pm\mathbf{0.02}$ the bottom left distribution at $\pm\mathbf{0.01}$, and the bottom right distribution at $\pm\mathbf{0.005}$.

Comparison of the red line, describing the traders more likely to be constrained,

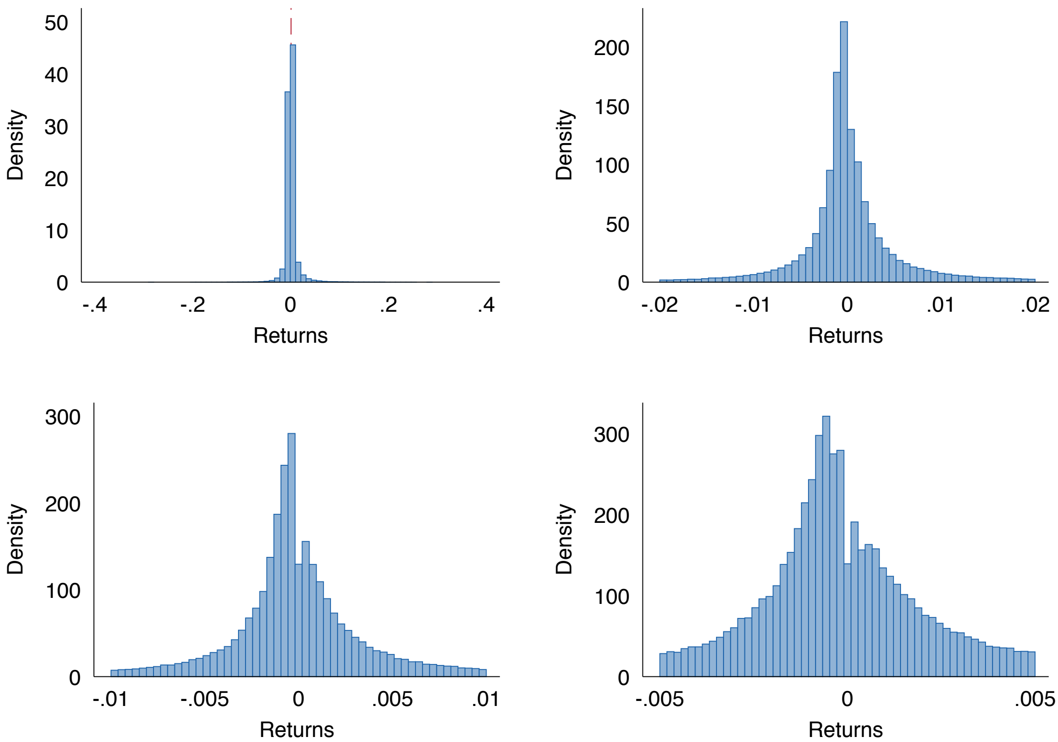
Figure 2.5: **Comparison of Returns Distributions of Constrained and Unconstrained Traders**



The top-left distribution is truncated for clarity, at $\pm\mathbf{0.1}$, the top right distribution at $\pm\mathbf{0.02}$ the bottom left distribution at $\pm\mathbf{0.01}$, and the bottom right distribution at $\pm\mathbf{0.005}$.

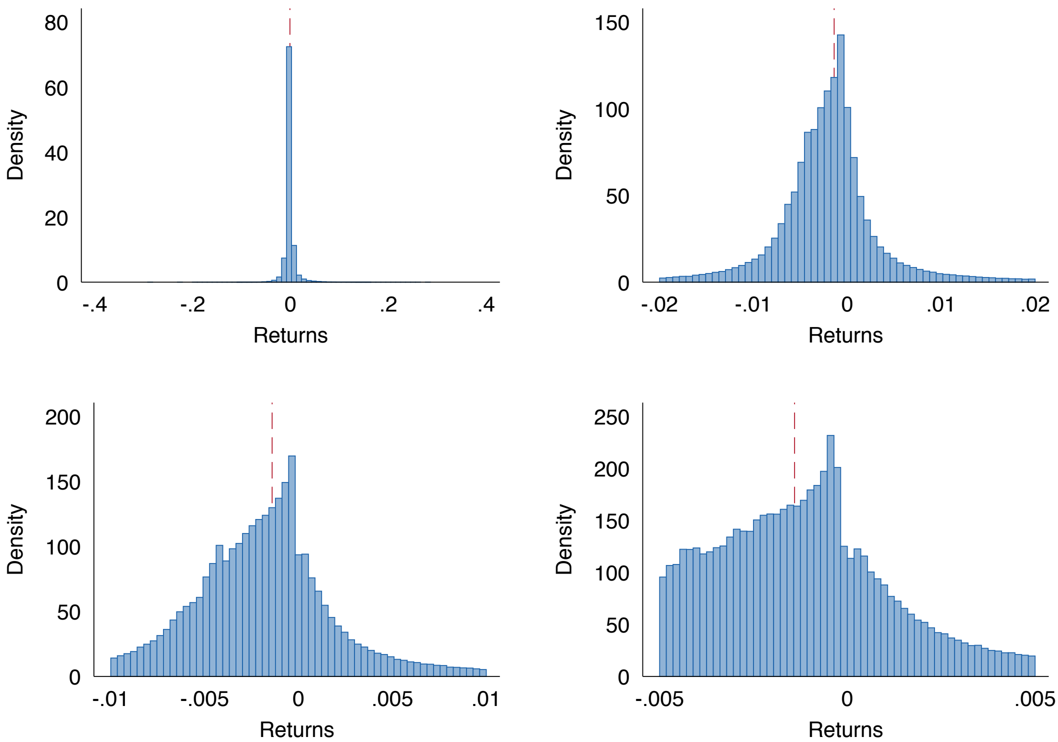
and the blue line those more likely to be unconstrained makes clear the effect of margin trading. The constrained traders earn lower returns but have more skewness in their returns. That the distribution for the unconstrained investors is not more different likely reflects noise, and our imperfect proxy for who is constrained is immediate compared to the overall distribution of returns in **Figure 2.6**. Comparison of the returns with and without trading costs in **Figures 2.6** and **2.7** also suggest that the regular trading also seems to induce substantial changes in the distribution of returns, making identifying the differences yet more difficult. Furthermore, the distribution is considerably more noisy than results of the simulation reported in **Figure 2.2** as many we identify as constrained will in fact not be. But, it is nonetheless clear that that being more likely to be leveraged is associated with a substantial increase in skewness, and a reduction in the average return.

Figure 2.6: **Returns, per position, Excluding Transaction Costs, Non-Constrained Traders**



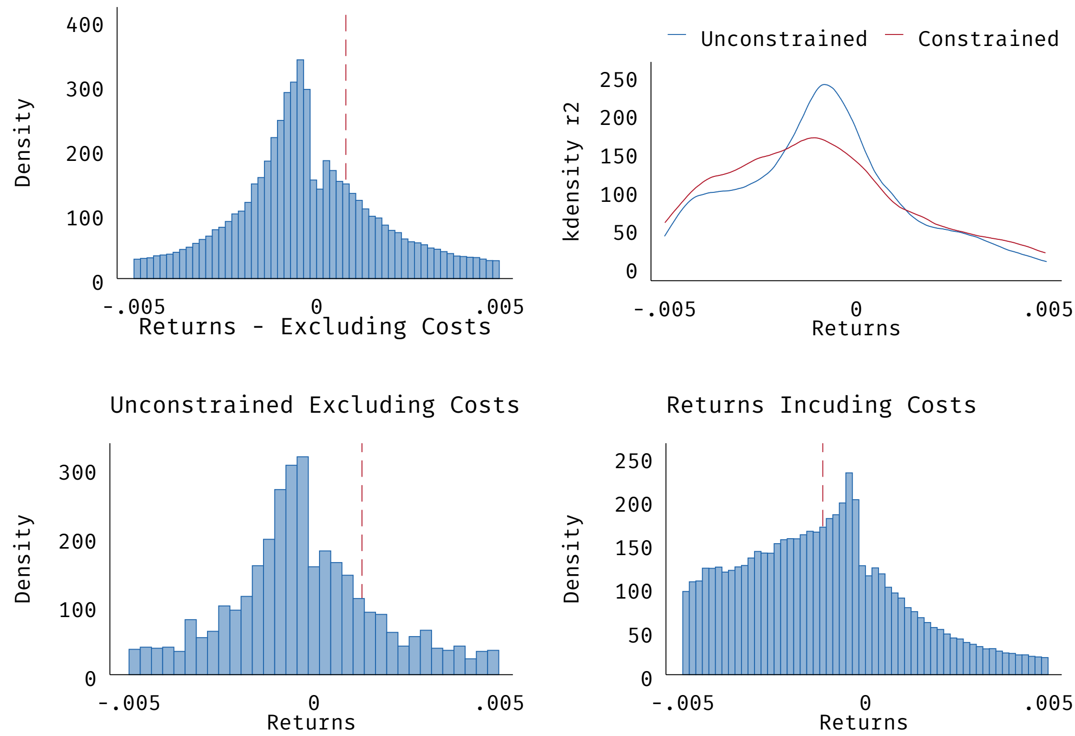
The top-right distribution is truncated for clarity, at $\pm\mathbf{0.02}$, the bottom left distribution at $\pm\mathbf{0.01}$, and the bottom right distribution at $\pm\mathbf{0.005}$.

Figure 2.7: **Returns Including Transaction Costs**



The top-right distribution is truncated for clarity, at $\pm\mathbf{0.02}$, the bottom left distribution at $\pm\mathbf{0.01}$, and the bottom right distribution at $\pm\mathbf{0.005}$.

Figure 2.8: **Average Daily Returns for Constrained and Unconstrained Traders**



The figures describe the difference in the absolute returns obtained by *constrained* – those traders identified as having no additional investable funds – and *unconstrained* traders – those able to meet a margin call with additional funds, before and after trading costs are taken into account. The top left histogram plots the distribution in absolute average daily returns excluding transaction costs for all traders. The red dashed vertical line is the mean daily return, as it is below. The top right figure plots two kernel density plots showing the difference in the distribution of returns obtained by constrained and unconstrained traders. The lower left figure plots the distribution of returns obtained by unconstrained traders before trading costs. The bottom right histogram describes the distribution of average daily returns after costs for all traders. All distributions are truncated at $\mathbf{-0.005}$ and $\mathbf{0.005}$ for clarity.

2.4 Margin Trading and the Optimal Portfolio

The previous section showed that traders were making negative returns from their Rebar investments. One explanation for this is that they are using Rebar futures to hedge other risks. This section considers, and dismisses, the possibility that traders could be investing in Rebar at a loss as part of managing a long-term portfolio. In its simplest form such an argument is a claim that whilst investing in Rebar on the margin may have a negative return that it would allow investors to achieve a sufficient reduction in the variance of their portfolio returns to be worthwhile. We take this claim seriously and outline how it may be possible in theory but impossible in practice.

We first show that it is essentially impossible for Rebar to be used to hedge risk efficiently. For any feasible asset, it is shown that the investor would be better taking a combination of the asset and cash paying a return of zero than a portfolio including Rebar.

We consider two assets, $\boldsymbol{a}$ and $\boldsymbol{b}$, with returns $\boldsymbol{r_a}$ and $\boldsymbol{r_b}$ that are normally distributed with standard deviations $\boldsymbol{\sigma_a}$ and $\boldsymbol{\sigma_b}$ respectively. The portfolio comprising these two assets with weight $\boldsymbol{w}$ of asset $\boldsymbol{a}$ has resturn $\boldsymbol{r}$:

$$\boldsymbol{r = wr_a + (1 - w)r_b} \tag{2.6}$$

And variance:

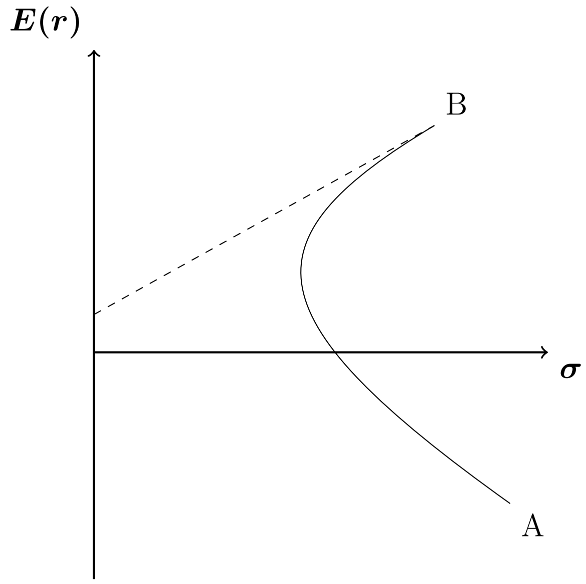
$$\boldsymbol{\sigma^2 = w^2\sigma_a^2 + (1 - w)^2\sigma_b^2 + 2\rho w(1 - w)\sigma_a\sigma_b} \tag{2.7}$$

Where $\boldsymbol{\rho}$ is the covariance of assets $\boldsymbol{a}$ and $\boldsymbol{b}$. The range of possible portfolio returns and standard deviations is shown in Figure 2.9. Rearranging and solving for $\boldsymbol{r}$ gives:

$$r = \frac{r_b\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)} - r_a\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)} + \sigma_a^2 r_b - \sigma_a\sigma_b\rho(r_a+r_b) + r_a\sigma_b^2}{\sigma_a^2 - 2\sigma_a\sigma_b\rho + \sigma_b^2} \tag{2.8}$$

Equation 2.8 describes the typical risk return trade-off for a portfolio. We refer to the asset with lower return, corresponding to Rebar, as asset A and the asset with higher return corresponding to another asset, or portfolio of assets, as B. To demonstrate that Rebar never appears in an optimal portfolio we show that for all portfolio's a higher expected return, for a given level of variance, may be obtained by taking a combination of asset B and the risk-less asset than by including Rebar.

Figure 2.9: **Optimal Portfolio Frontier**



We note that unlike standard portfolio theory taking a short position in Rebar does not extend the efficient frontier beyond asset B. The negative return of Rebar comes from margin trading and not from the asset itself - therefore taking a short position in Rebar does not result in a positive return. Whilst Rebar may provide diversification benefits it has such a high negative return that it never increases expected returns. The highest expected return is, therefore, found in the portfolio solely consisting of B.

In order to demonstrate that the diversification benefit of Rebar is outweighed by its negative expected return it is shown that the efficient frontier is always dominated by the return that may be obtained from taking an appropriate portfolio of asset B and the risk-less asset. In other words the efficient frontier always lies below the straight line connecting the risk-free rate and asset B. To do this it is sufficient to prove that the derivative of the efficient frontier at Asset B is less than that of the straight-line representing portfolios composed of a mixture of asset B and a risk-less asset. This is because the second derivative of the risk-return curve is negative in the upper portion, therefore if the condition is met the efficient frontier will always be below the straight line.

The return at point B is dependent on the identify and characteristics of asset B. For assets with higher returns the straight line becomes progressively steeper, individuals will rationally be willing to sacrifice ever more return for a given reduction in variance. Thus, at some point given $-1 < \rho < 1$ the optimal portfolio will include some Rebar. However, we show that this will only be the case, given annualised returns of Rebar of -0.27, standard deviation of 0.13 and a correlation of $\boldsymbol{-0.15}$[13], for assets with returns far in excess of those realistically observable. In particular, it is not true if assets have returns less than **1000%**. In particular, setting:

$$\frac{\partial r}{\partial \sigma} = \frac{s(r_b - r_a)}{\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)}} \tag{2.9}$$

Then it may be verified that if $\boldsymbol{r_a = -0.27}$, $\boldsymbol{\sigma_a = 0.13}$, $\boldsymbol{0 \leq w \leq 1}$, $\boldsymbol{\sigma_b > 0}$, $\boldsymbol{-1 < \rho < 1}$, and $\boldsymbol{r_b > 0}$ then no point exists such that:

$$\frac{s(r_b - r_a)}{\sqrt{\sigma_a^2\sigma_b^2\left(\rho^2-1\right)+\sigma^2\left(\sigma_a^2-2\sigma_a\sigma_b\rho+\sigma_b^2\right)}} - \frac{r_b}{\sigma_b} < 0 \tag{2.10}$$

If $\boldsymbol{0 < r_b \leq 1000}$ and $\boldsymbol{\sigma_b = 0.13}$ (equal to that of Rebar). Note that this range may be much larger but given no asset normally exists with a Sharpe ratio near to $\frac{r_b}{\sigma_b} = \frac{1000}{0.13}$ there is no need to look further.

In support of this argument in **Appendix B.5** we demonstrate that Rebar does not ever appear in the optimal portfolio given the assets available to Chinese investors during the period. We find no evidence that an optimal portfolio, of any size, would contain leveraged Rebar investments.

In the next section we also show that the modal position is opened for less than a day, such frequent trading is incompatible with an explanation of portfolio optimisation given that traders face substantial trading costs. Thus, we have seen that a portfolio explanation is not only unlikely in theory, it is rejected by the data.

2.5 Behaviour

We have now ruled out classical-investment motivations for margin trading. Margin Trading reduces expected returns and is associated with a high chance of a complete loss of the initial investment. Neither are such investments ever part of an optimal portfolio. This section now provides evidence that observed behaviour is consistent with hedonic or gambling-type motivations. We show that traders open their positions only briefly, but too often, and that they do not exploit arbitrage opportunities. Moreover, we will show that the average trader is heavily liquidity constrained and that almost all trade is focused on three out of twelve contracts. We begin by analysing the properties of Rebar Futures and then the behaviour of individual investors.

[13]This correlation is the largest negative correlation between Rebar and any of 9000 other Chinese assets.

2.5.1 Aggregate Behaviour

Figure 2.10 describes the market properties of Rebar. We focus on 2012 for clarity, but the conclusions are the same for other years in our sample and **Figures B.9 – B.12** in **Appendix B.2** reproduce **Figure 2.10** for the other years in our sample. **Panel 2.10a** describes the prices of the 12 contracts traded during 2012. The thick blue line is the average of the Tianjin and Shanghai spot prices[14]. We can see that whilst the individual future prices tend to be relatively similar, albeit with important exceptions, they are often quite different from the spot price.

Panel 2.10b describes a very important feature of the market – almost all of the trading volume is concentrated on three contracts: January, March, and October. Moreover, one contract is traded almost exclusively at any one time. Looking at **Figure 2.11** which is a stacked bar chart showing the composition of total trading volumes over time it is clear that almost all of the volume is accounted for by one of these three contracts at any point throughout the whole period. **Panel 2.10c** shows the total market position by contract which makes clear that not only are only three contracts being traded but positions are only being opened in these three contracts[15]. Why trading is concentrated on these three contracts in particular is unclear but does not seem to have any substantive economic basis. **Figure B.14** in **Appendix B.2** reports net Chinese imports of Steel, and Rebar specifically, by month. It also reports the sales of one of the largest domestic Steel manufacturers[16]. It is clear that whilst there is some seasonal fluctuation – imports are lower in the first few months, perhaps due to Chinese New Year and cold winter weather prohibiting building – that there is no reason in the sales data for traders' exclusive focus on January, March, and October. Notably, there is almost no activity in the other contracts. This is evidence that these traders are not opening positions to hedge their exposure to Steel price changes. Given that there is no plausible use of steel that only takes place in three months a year, and it is costly and bulky to store then any hedging strategy should involve all twelve contracts in at least some proportion. On the other hand if trading is seen as gambling then the focus on one of three contracts at any given time is easily rationalisable, and informally can be seen to reflect a co-ordination equilibrium. Every additional trader on a given contract increases market liquidity and activity, and incorporates a wider range of beliefs about the future. This means prices change more rapidly and the spread

[14] Unsurprisingly,given the distance involved the two are related but not identical, as can be seen in **Figure B.15** in **Appendix B.2**.

[15] All twelve contracts are graphed but the other nine are indistinguishable from the x-axis.

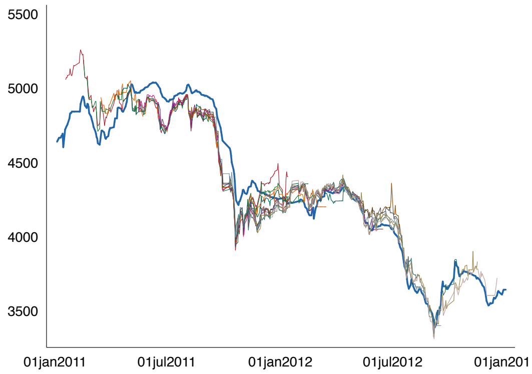
[16] We are unable to name this firm for confidentiality reasons.

is narrower. This allows for there to be sufficient price variation even if traders open positions for relatively short periods of time that doing some constitutes an enjoyable gamble. The benefits conferred by each additional trader are enjoyed by all other traders, and these economies of scale lead to a single contract being traded at a time, even if the choice of which is largely arbitrary.

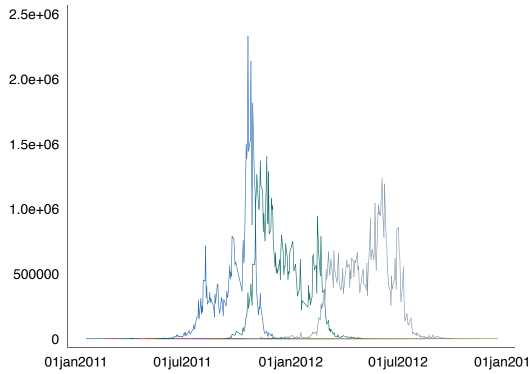
Considering **Panel 2.10d** shows that there is considerable variation in volatility over time. Comparison with **Panel 2.10b** suggests that this is related to the volume of trading, again consistent with the 'trading as gambling' hypothesis. Note, however, that whilst there is also volatility in the Rebar spot-price, that this is doesn't predict all of the volatility observed in the Futures prices. If we consider the full sample of volatility reported in **Figure B.16** in **Appendix B.2**, then the lack of any obvious pattern becomes clearer still. It is difficult to make arguments about causality, but it is certainly plausible that it runs from both volume to volatility and vice-versa with additional volatility attracting more traders and more traders potentially increasing volatility.

One interesting consequence of the focus of trading activity on these three contracts is it seems to have had no impact on the efficiency of the market. If markets were efficient then both the correlation between the change in the (log of) the spot price $\boldsymbol{\Delta log(s_t)}$ and the change in the (log of) the future price, $\boldsymbol{\Delta log(f_t)}$ should be close to unity. In fact, as reported by **Table B.1** they are always substantially lower. Cointegration-based tests of market-efficiency, allowing for non-risk neutrality (see Chowdhury (1991)[25]), tell the same story and are reported in **Table B.2**. We do the test based on the daily settlement price of each Rebar futures contract. This may reflect the practical difficulties involved in Rebar arbitrage, the Rebar are bulky and there are restrictions on whom may take delivery. But, Rebar are not perishable and easily saleable and so it is also perhaps surprising that no arbitrageur has emerged as these difficulties should be far from insurmountable. Of course, if as conjectured the Futures Market is largely comprised of speculators then there is less reason to believe that there should be an equilibrium and returns to arbitrage may be lower.

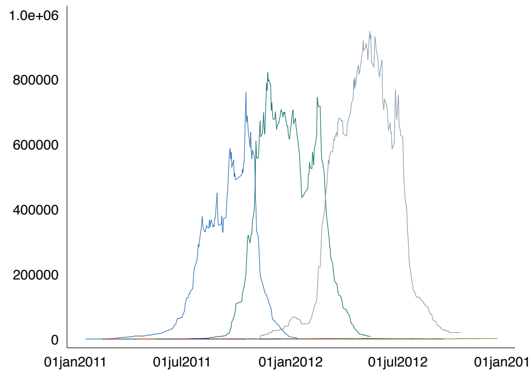
Figure 2.10: **2012 Rebar Contracts**



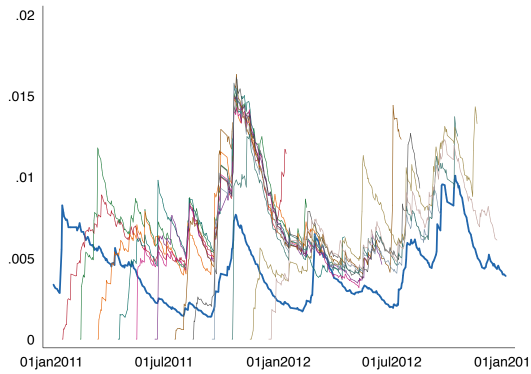
(a) **Price**



(b) **Volume**



(c) **Market Position**

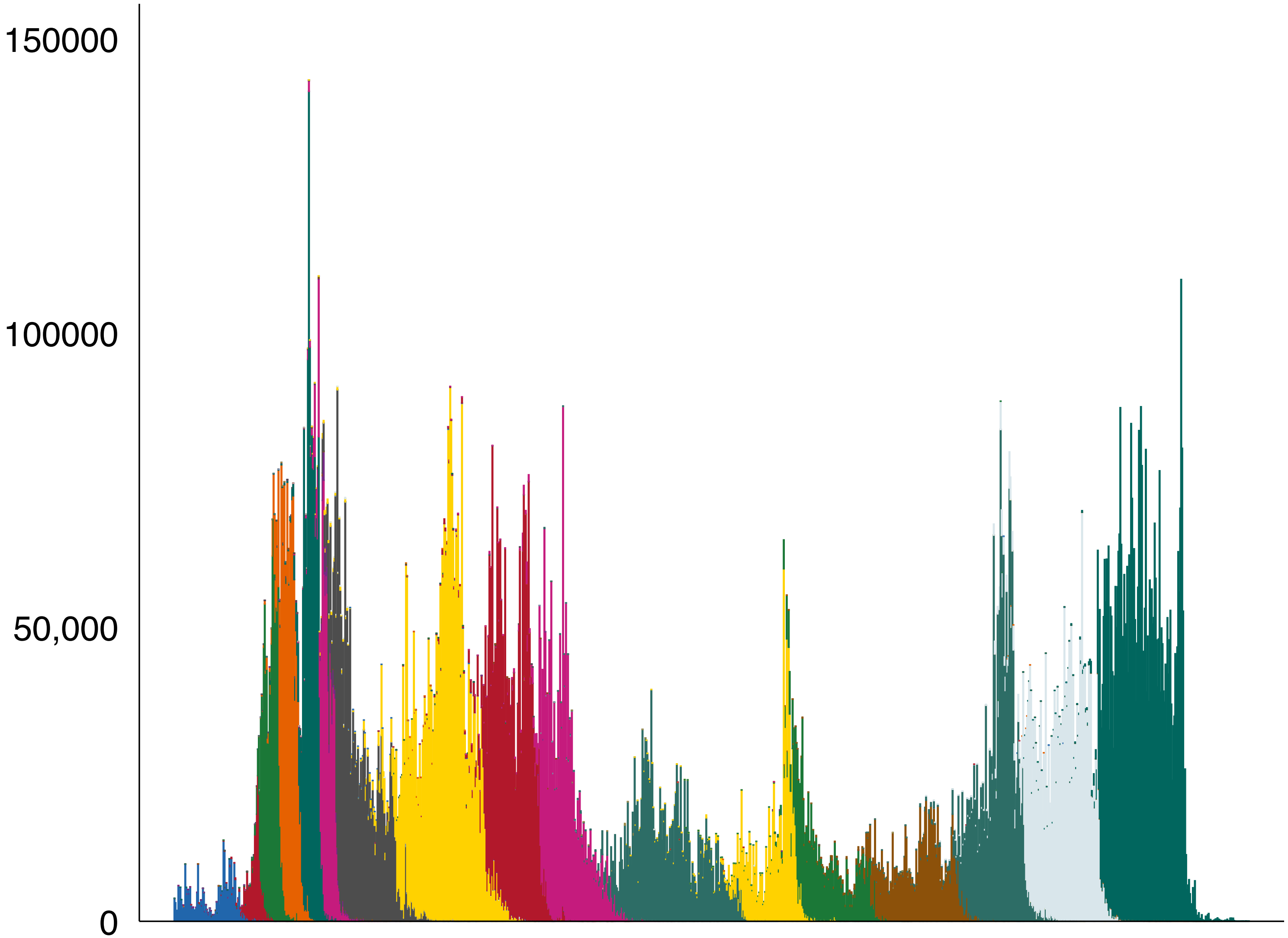


(d) **Volatility**

[a]

[a]Figures describe Price (in RMB), Volume (Contracts), Net Market Position (Open Interest), Volatility (Exponential Moving Average of the Variance of the Log Return lambda = 0.94) of contracts RB1201-RB1212 that is contracts for delivery in 2012. In Figure 2.10(a) the thick blue line is the volume weighted average of the price of all 12 contracts. Figure 2.10(b) reflects that only three contracts have any substantial volume of trades as does 2.10(c). The thick blue line in panel 2.10(d) shows the average price volatility of all contracts.

Figure 2.11: **One Rebar Contract Accounts For Almost All Trading Volume at Any Given Time**



2.5.2 Traders Trade open positions briefly too often

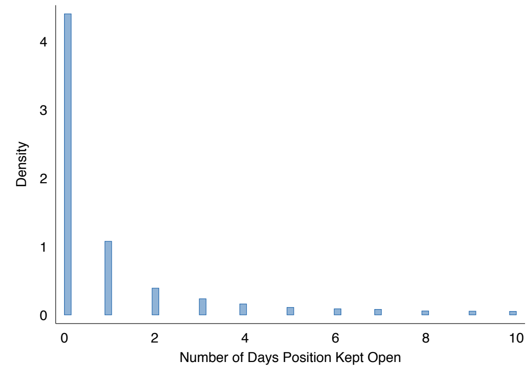
If the traders we study are trading as as a form of recreation then we should expect to observe behaviour consistent with this. In particular, assuming that our Traders are not all night-workers then we should expect them to have limited time in the day if it is only recreation. Whereas, if it were their principle occupation then they should have more time available for it. **Figure 2.12** provides evidence that this is the case. In **Panel 2.12a** we can see that almost all positions are held for less than a day. This is consistent with a trader only being able to manage their position in a short period during the day, on say their lunch break, and thus being concerned about large moves in the price when they are away. It is also consistent with a trader not-deriving (as much) gambling type utility from changes in the price that they do not monitor.

Panel 2.12b describes the distribution of how long traders spend in the market. That is the length of time between their first and their last trader of the day. Of course, we can not rule out that they are closely monitoring the market for the remainder of the time but this does not seem consistent with the other evidence. We see that the average trader is in the market for around one and a half hours a day, moreover we see that very few traders trade for more than two hours.

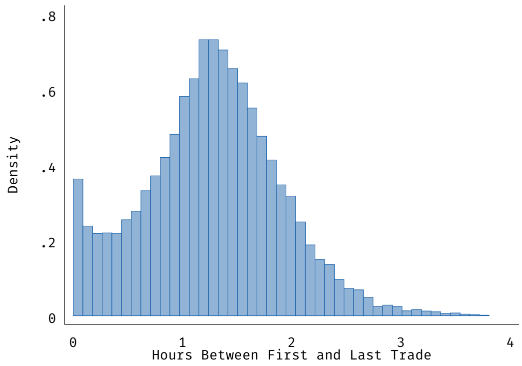
Opening positions for only a couple of hours is an example of behaviour that is not consistent with trading for profit (Barber and Odean, 2000 [7]), but is consistent with hedonic motivations (Dorn and Sengmueller, 2009 [33]). Traders will incur fees that are large in comparison with the standard-deviation of prices over the position duration, thus damaging further – as seen above – the poor returns offered by margin trading. This is exacerbated as discussed below, by the small size of the average position opened. Most often, just one contract. As shown in **Figure B.17** in **Appendix B.2** these contracts are also almost exclusively limit orders. Of these a good number are marketable limit orders. If the market was used for investment purposes then this additional liquidity would earn these traders a return, but as it is not, as revealed by the moribund nature of the nine non-traded contracts each year then this liquidity has little value. Thus, the positive effects of margin traders proposed by Brunnermeier and Pedersen (2009) [21] and for which Kahraman and Tookes (2013) [65] find compelling evidence for Indian financial markets, where the introduction of margin trading in a market leads to significant increases in market liquidity, are not found in the SHFE context.

Figure 2.12: **Trading Behaviour is Consistent with Recreation**

(a) **Most Positions Are Closed Within a Day**



(b) **Average Traders Spend Around 1.5 Hours Trading A Day**



[a]

[a]Figure 2.12(a): A position is closed within the day if the trader both begins and ends the day with no open positions. A position being open for two days implies that there are two days (in which the market is open) between the trader opening their position and closing it. Figure 2.12(b): The dependent variable is the number of hours (or fraction thereof) between a trader's first submitted order and their last submitted order. The relatively few traders who submit only one order on a day are treated as being in the market until the end of the session.

2.5.3 Small Fraction of Traders Make Huge Profits

By no means do all traders lose money. In particular there is a small number of traders who enjoy very substantial profits. Whilst, this is likely to partly reflect good luck it may also reflect differences in strategies. **Figure 2.13** shows that one key way in which they differ is that the most successful traders maintain their positions for much longer. For the most successful **0.01%** the average is now a week compared to less than a day for the modal trader. Considering instead the top **1%** they still maintain their positions for substantially longer than their less successful peers. These longer holding periods may be a consequence of success as well much as a cause, given the scale of these traders profits they are presumably in a position to fully underwrite their positions allowing them to enjoy a higher average return than their leveraged peers.

The second key difference is described in **Figure 2.14**. The most successful traders trade very frequently, with 400 trades a day not being uncommon. This again may reflect affluence, perhaps itself caused by their success, but it might also suggest a form of algorithmic trading. The heaviest traders execute over 3000 trades a day or one every 5 seconds. Alternatively, it might be one account being operated by a number of individuals concurrently. One thing that is clear is that these traders are not operating as market-makers, like all of the traders in our data, they almost exclusively use marketable limit orders, and the fees they pay mean that

Figure 2.13: **Top Traders Hold Their Positions Longer**

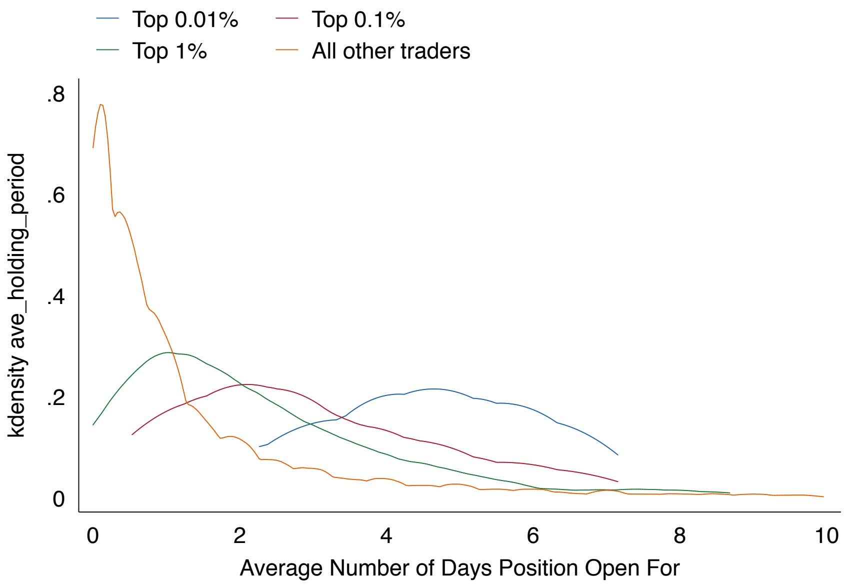
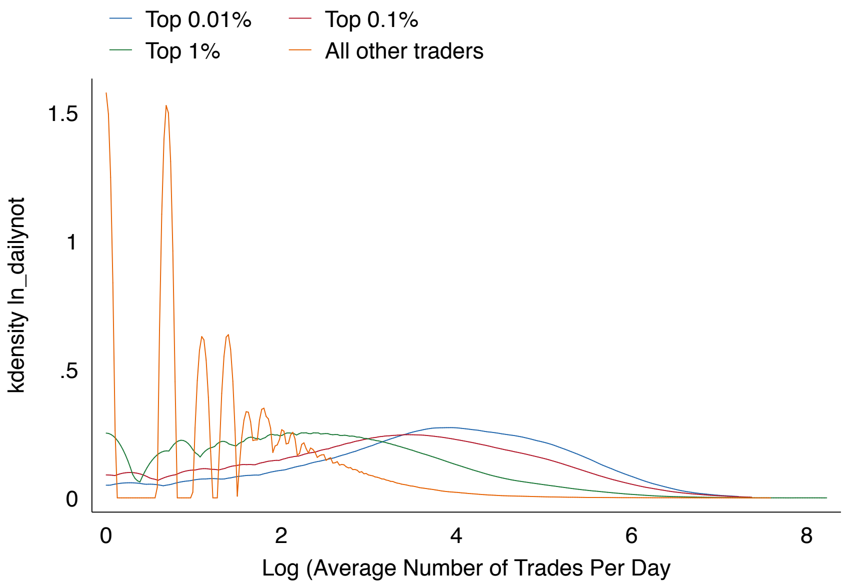


Figure 2.14: **Number of Trades Per Day – Top Traders (log)**



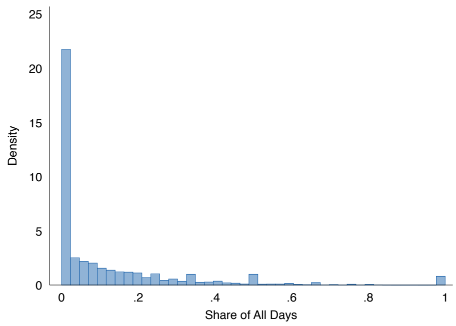
such market making would not be profitable. An alternative interpretation of this combination of high trade volumes and long-held position is that the most successful traders are those who place large bets on the trend rather than the high-frequency fluctuations.These traders are would thus be making many trades increase the size of their position and then holding in the hope of a price change. Of course this is a strategy that is more feasible for very liquid traders and thus not an option for most market participants.

2.5.4 Traders are Often Financially Constrained

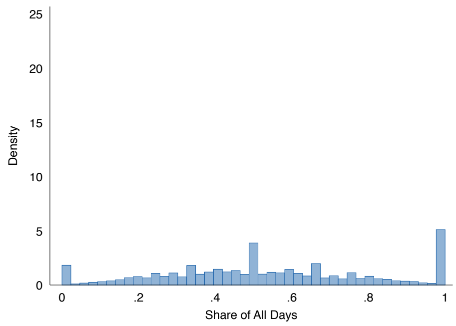
Another characteristic of trading as gambling is that it may be done with a very limited and fixed budget. **Figure 2.15** describes how often traders are liquidity constrained. Specifically, it describes the proportion of all days in which their accounts are active that they fall into one of four categories. **Panel 2.15a** describes how often individuals are unable to trade at all – that is, they have no open positions and insufficient available funds to open one. We can see that this is only rarely the case – perhaps because traders in this situation cease using their account. **Panel 2.15b** shows that similarly very few traders ever have sufficient funds in their account to open a position and do not do so that day. **Panels 2.15c** and **2.15d** do the same for traders who already have one position open. What we can see is that ignoring the large numbers of traders who are never constrained in **Panels 2.15a** and **2.15c** that distributions are otherwise approximately uniform suggesting that those traders who are ever constrained are constrained on average around half of the time. One reason for this is that traders may not keep unnecessary funds in their account – moving money only when necessary for a trade. But, this is interesting in and of itself as this explanation implies that these traders either do not anticipate trading again or do not anticipate needing to transfer more funds for their future trades (because the initial ones were profitable). The other, non-contradictory explanation is that traders, like visitors to casinos, have a fixed budget and 'play' with this. Note, that this explains the **12%** of individuals reported by the left-hand spike in **Panel 2.15d** who given they have an open position are never able to open another. That is, they only ever trade one contract. The spike in **Panel 2.15c** suggests that there are similarly around a quarter of traders who are never constrained given that they have an open position. This might comprise individuals who choose not to use their full margin (see **Figure 2.16**), or richer individuals who tend to trade many contracts, or simply those who know they will trade more in the future and leave funds in their account for this purpose. Taken together, we argue that the substantial proportion of traders who are constrained much of the time, and those who only ever open the smallest possible position is consistent with gambling type behaviour.

Figure 2.15: **A Lack of Liquidity often Prevents Traders Increasing their Position**

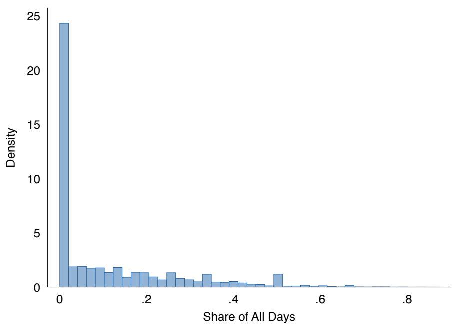
(a) **No Position, Can Not Open One**



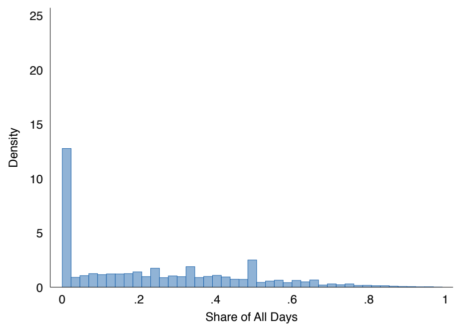
(b) **No Position, Could Open One**



(c) **Open Position, Can Not Open More**



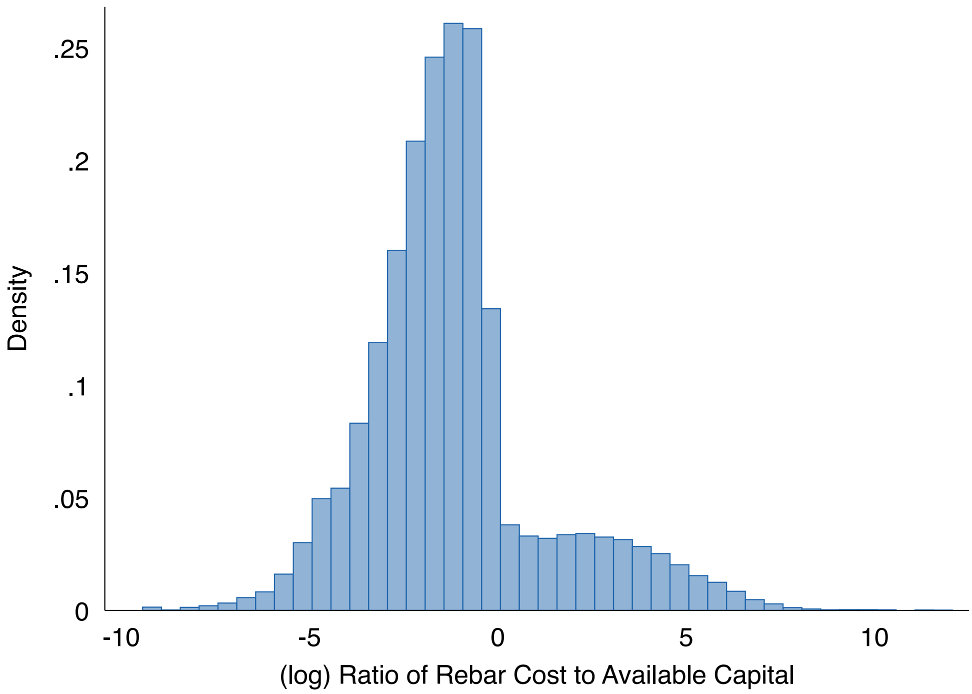
(d) **Open Position, Could Open More**



[a]

[a]Figure describes the percentage of traders who lack liquidity. Figure 2.15(a) plots the proportion of all trader-days in which a trader has insufficient funds in their account to open a position and where they do not already have an open position. Figure 2.15(b) similarly describes the proportion of trader-days in which a trader has no open position but could afford to open one if they preferred. Figure 2.15(c) describes the share of trader-days in which an individual with at least one open position can not afford to open another. Finally, Figure 2.15(d) describes the fraction of trader-days with open positions and sufficient liquidity to open further positions.

Figure 2.16: **Traders often only have sufficient liquidity to buy one hand of Rebar**



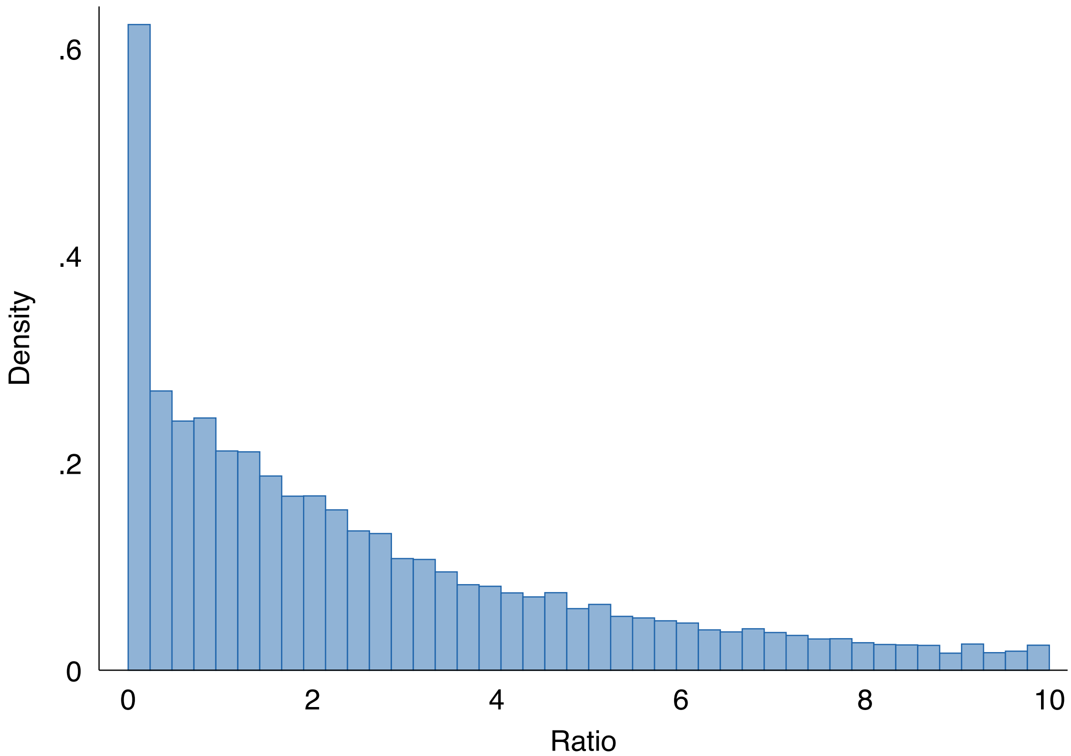
2.5.5 They tend to only trade one asset

A key difference between the implications of traders seeking investment returns and those motivated, in part, by hedonic returns The final aspect of traders' behaviour that we consider is the fraction of their trading activity accounted for by Rebar futures. Traders have access to **40** different assets, and if they were simply trying to maximize their risk adjusted returns then we should expect them to trade a number of these given the covariance structure. That is, even if Rebar are never in an optimal portfolio, conditional on trading Rebar we should expect traders to also trade other assets. However, **Figure 2.17** shows that **60%** of traders trade exclusively Rebar. Moreover, nearly all individuals have a ratio of non-Rebar trade volumes to Rebar volumes of **1** or less suggesting that they trade as much Rebar as anything else.[17] That there is a long-tail of individuals trading significantly more of other assets than Rebar might suggest that there is a fraction of relatively sophisticated investors. In fact, inspection of **Figure 2.18** suggests that almost all traders trade on a given day Rebar *or* another asset. Thus, whilst some traders' preferred asset may vary over the period very few frequently trade more than one on any one

[17]We do not observe the full trading history for other assets, but we do observe changes in individuals' margin accounts due to this trading. We are thus able to reconstruct the aggregate extent and outcomes of their trades in all other assets.

day. This is perhaps unsurprising given the lack of liquidity that characterises most traders seen in **Figure 2.15**.

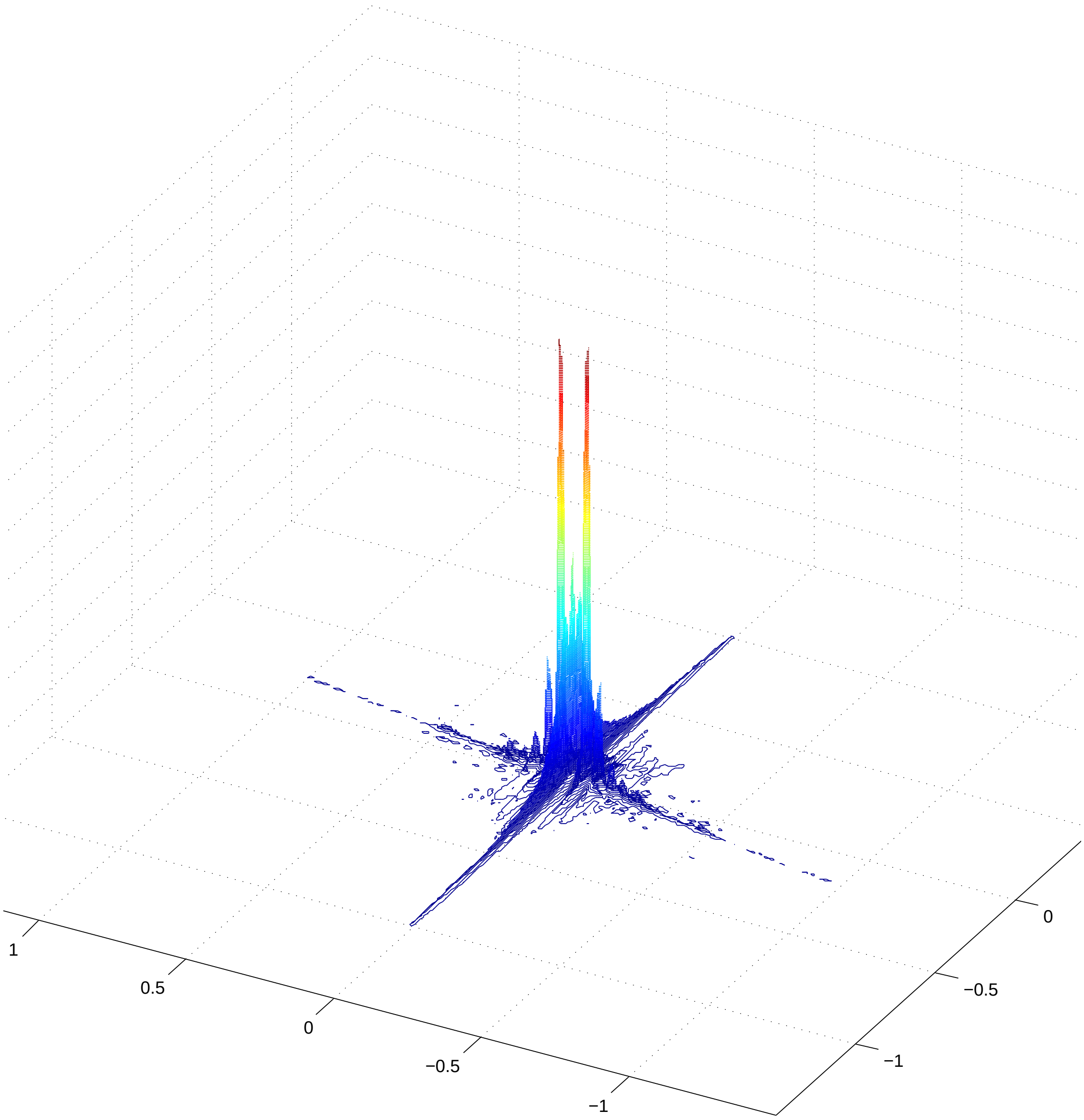
Figure 2.17: **Ratio of Trade Values in Non-Rebar Assets to Rebar Futures**



a

[a]The variable Ratio describes the ratio of the total value of trades in non-rebar assets to the total value of rebar trades for each trader-day pair. The total for the non-rebar trades is the sum of all non-rebar assets available to clients of the brokerage.

Figure 2.18: **Joint Density Distribution of Trading Amount in Non-Rebar Assets to Rebar Futures**



Units are in 10,000 RMB

2.6 Conclusion

Margin trading is popular with retail investors around the world. This is puzzling since, as we have shown, margin trading has a negative expected return. Our explanation is that whilst lowering mean returns that the collateral requirement imposed by margin calls also induces positive skew. Investments in otherwise pedestrian assets will now offer limited losses and a small but positive chance of a large gain. Thus, margin trading offers the same hedonic returns associated with lottery tickets, lottery-type stocks, and gambling. We test this hypothesis using a unique dataset on the full trading histories of Rebar futures traders on the Shanghai Futures Exchange (SHFE). We show that both expected and observed losses are substantial and that the optimal portfolio never contains Rebar futures. Analysing traders' behaviour we show that whilst hard to rationalise without a hedonic motive, that trading behaviour can be easily understood as form of entertainment.

There are implications of trading as entertainment, and of margin trading as entertainment in particular, for policy. In particular, a system in which those trading for hedonic reasons are more separate from those trading for investment may have much to recommend it. In particular, it may limit the amplifying properties of margin trading for the systemic consequences of large price shocks. In one sense the Rebar market we study is an example of this – its pricing is unrelated of that to the underlying asset and almost all trading is accounted for by traders whose behaviour can be best explained by hedonic or entertainment motivations. A large sell-off in this market would be less likely to engender the negative-spiral Brooks described happening in '62.

Chapter 3

The Influence of Scheduled Macroeconomic Announcements on the Futures Market: Evidence from Commodity Futures in China

Abstract

The nature of an underlying asset's response to scheduled macroeconomic announcements and the level to which it reflects its fundamental value in financial market needs more recognition. Can we observe any advanced or hysteretic effects of scheduled news on any underlying assets based on daily information? If it is, can market participants make excess returns by adopting and following the relevant information? This empirical work discusses these issues and provides evidence through analysis on the existing 23 kinds of futures in the Chinese futures market, during 2009 to 2013. The following conclusions have been made: 1) the scheduled macroeconomic news start affecting the futures market around 20 trading days before the announcement date; 2) the news has an effect on futures price, and futures prices respond to corresponding adjustments around the announcement date rather than on the date; 3) the sensitivity level of most metals, raw materials and the industrial product futures is higher than most agricultural futures in China; 4) the influenced level of each futures contract does not depend on the trading activity; 5) the opposite view to previous research is that no evidence indicates that the influences of scheduled news take place in different stages of a business cycle rather than only in expansion or contraction; 6) based on real 36070 traders, we find that losing traders are more sensitive and affected by macroeconomic news than traders who make profits.

3.1 Introduction and Relevant Literature Reviews

Based on reviewing the efficient-market hypothesis (Fama, 1998)[41], the prices of underlying assets should reflect all information in an efficient financial market. For the commodity futures market, the information should cover official macroeconomic announcements, such as GDP and CPI, by governmentally official statistics. The reason is that commodities are physical assets and controlled by the demand and supply of a country and the governmental announcement indirectly interprets the ability of demand and supply of the commodity. Generally speaking, most governmental announcements are scheduled rather than the stochastic event in the market as the description in EMH. This way, the financial market's response to scheduled news becomes a popular issue for investigation. According to the type of efficiency, the market should correspondingly respond to the news very quickly in order to reflect the real fundamental value of the underlying assets. During the last 20 years, many relevant researches have proved that the reaction speed can be accurate to intraday market price, even accurate to tick-by-tick market price fluctuation. However, can underlying assets actually absorb information from public scheduled announcement very quickly and even immediate to happen in all area of financial market? Even if it is truth, could this also happen in an inefficient market, such as the described Chinese futures market? Our paper doubts these questions and returns to daily frequency data for analysis, and finds that that the influences of governmentally scheduled announcements need a long time to reflect rather than close to immediately respond through the market.

Meanwhile, many previous researches indicate that market participants who own information advantages can make excess profits than other people in financial market. Scheduled macroeconomic news interprets the fundamental information to any kinds of underlying assets. People who utilise fundamental information to trade are recognised as rational traders and they try to avoid the price bias of noise trading by making corresponding adjustments according to scheduled news announcements. Therefore, this paper sets and investigates another hypothesis to link the previous research that whether fundamental trading makes excess returns in Chinese futures market. We will see whether trader make profit or loss under the reaction on scheduled news. To conclude, we find that losing traders are more sensitive and affected by macroeconomic news that profitable traders; in other words, the scheduled macroeconomic events cannot bring excess benefits in Chinese futures market.

We firstly review the relevant literatures to summarise the previous research findings. In the 1980s, many economists provide a similar but weak empirical evidence for the effects on varies of underlying assets, see Schwert (1981)[92], Pearce and Roley (1985)[89], and Hardouvelis (1987)[55]. The paper of Barnhart (1989)[11] was the first comprehensive research on the effects of macroeconomic news on the prices of underlying assets. He stated why official announcements could influence commodity price, especially monetary news, and provided evidence that some commodities' prices are affected by a few types of announcements - especially money supply. He also declared the process by which macroeconomic news changed the price of commodities - which was supported by Gorton & Rouwenhorst (2006)[53] and Kat & Oomen (2007)[66].

According to their claim, the news announcements can bring two variations in any underlying asset markets: the change of inflation or currency policy can bring the variation of market participants' investment portfolio and also change the supply and demand of commodities. These two variations disclose opposite effects of macroeconomic announcements on commodity markets. Regarding the first variation, announcements can bring negative effects to the commodity markets. If the real announcements of the news about interest rate are higher than expectations, it implies an overheating economic situation in the country. It would increase the storage fees of physical commodities, and meanwhile, bonds or other currency financial markets can bring more benefits than before and become increasingly attractive to investors. Thus, the prices of commodities could decrease due to the exit of many investors from the commodity market, turning to bond markets with higher interest rate. More evidences are from Chambers (1985)[23] and Frankel (2006)[46].

Regarding the second variation, Brevik and Kind (2004)[18] provides evidence to show that a real announcement value that was higher than the expectation of the economic situations would increase the demand of physical commodities - which could bring an increasing price in short term as a positive effect to the market. Overall, different types of macroeconomic news are able to cause both positive and negative effects on varies underlying assets. Christie-David, Chaudhry, and Koch (2000)[26] and Cai, Cheung, and Wong (2001)[22] adopt daily market data of gold and silver to find similar results as Barnhart. However, the problem is that they cannot find many significant types of effective economics news on varieties of underlying assets based on daily frequency data of both individual underlying assets and comprehensive indices[18].

After that, economists started suspecting that the insignificant types of news were caused by the statement of the above two opposite arguments. They trust that dif-

[18]Individual underlying asset means such as individual share or individual futures. Comprehensive index means such as NASDAQ composite index or Standard & Poor 500, which reflects the overall situation of the market

ferent status of economic situation can separate and break the dependence of the two arguments. Therefore, based on some official or authoritative definition of business cycle of a country, economists were trying to prove that macroeconomic news could have impact on the price of underlying asset, especially for some national bond, comprehensive indices or funds, such as T-bond, in different states of a business cycle. It is still based on the daily frequency data. However, the findings are still weak even they are too much better than not separating business cycle in different status. The key previous relevant literature is from Body, Hu, and Jagannathan (2005) [16]. Their papers systematically analysed the effects of unemployment news on stock prices. They described that the unemployment could be recognised as significantly effective news on stock market if the business cycle is separated into expansion and contraction to investigate the initial issue. Their work reaches a consensus with different kinds of news with some previous relevant researches, here refers to McQueen and Roley (1993) [80] and Andersen, Bollerslev, Diebold, and Vega (2007) [2].

Because there are still no existing clear results to significantly describe the relationship between macroeconomics announcements and financial market, economist started querying whether daily or other low frequency data of any varieties of underlying assets were not able to reflect the influences of scheduled macroeconomic announcements on the price in the market. Meanwhile, they started making the hypothesis that the price of underlying assets could be absorbing the effects of news very quickly, rather than a long time to respond, so that the data frequency of research increases and grows in accuracy, in order to investigate whether the price of underlying assets could respond to the effects of news in a very short term. "In one minute" is the answer of how long market price completes adjustments after announcement time (Ederington and Lee (1993, 1995)) [34] [35].

Fleming and Remolona (1997, 1999) [43] [44] and Andersen, Bollerslev, Diebold, and Vega (2003) [1] provide similar results based on intraday data. They found many types of news have significant effects on the price, volatility, and trading volume of some corresponding underlying assets. The variation of affected variables have a clearly sudden change after announcement time and then the variation becomes stable very quickly in the following several minutes or hours after announcement time. To sum up, the key references are from Balduzzi, Elton, and Green (2001) [5], which provides initial research method for our paper, even though it utilised intraday data. They found that at least one of 17 public announcements must have a significant effect on U.S. 30-year bond, 10-year note, two-year note, and three-month bill. In addition, the affected period is just in 15 minutes. 15 minutes after announcement time, the sudden variation of volatility, trading volume, and bid-ask spread would tend to become stable and return to normal level. We refer their method in our paper but conclude different results based on daily basis.

In conclusion, current research on this area has been accurate to a very short term by intraday high-frequency data. However, our paper asks the question: is there any advanced or hysteretic influence of scheduled news on any individual underlying assets? Can news be absorbed very quickly in the market? Previous research shows that there are not many significant types of news influencing quickly based on only observing daily data. However, almost all of the previous researches use only the data from USA and adopt the comprehensive index alone to describe an overall situation of the whole market. That is not enough to be convincing. This paper adopts 23 different commodities and index futures in Chinese futures market to provide evidence for the existence of the advanced and hysteretic impacts of scheduled macroeconomic announcement on each commodity. The aim of this paper is not to accurately define the sign and size of effects, or to reject the results of previous researches that news can be responded very quickly. Instead, this paper attempts to bring new evidence from other markets and alternative underlying assets to indicate that existing varies types of news can significantly impact on the price of underlying assets based on daily frequency data.

We firstly utilise a classical method from Keown and Pinkerton (1981) [67] to investigate when the scheduled announcements start impact on Chinese futures market. We find that the scheduled macroeconomic news start affecting the futures market before around 20 trading days to announcement date, and also, it indicates that the news has effects on futures price, and futures prices respond through a corresponding adjustment around the announcement date, rather than the date of announcement itself. Then, we adopt the traditional OLS method to estimate the effects of selected 15 kinds of macroeconomic news on each of 23 kinds of futures. We find most of 23 commodities futures are affected by at least three kinds of macroeconomic news. Meanwhile, the affected level of most metals, raw material, and the industrial product futures is quite higher than most agricultural futures in China. Based on the classification of active and inactive contracts, we find that the influenced level of each futures contract does not depend on the trading activity. We utilise price trends to define the situation of business cycle of each futures, and then this paper state the argument to previous research that no evidence indicates that the influences of scheduled news absolutely happens in different statuses of a business cycle. We also refer the transformation of regression method of Balduzzi, Elton, and Green (2001) [5] to view the advanced and hysteretic effects of news on each selected futures. The results of most futures correspond to the initial results in this paper.

Therefore, we provide more detail to illustrate the reaction of futures market with scheduled macroeconomic news through this paper. Last but not at least, we utilise the empirical data to observe whether traders achieve excess profits by following macroeconomic news. The results imply that losing traders are more sensitive and affected by macroeconomic news than profitable traders.

This paper is constructed in the following sections: section 1 includes introduction and previous relevant literature reviews of this research; section 2 introduces a part of datasets and adopts the above mentioned classic method to investigate the effective period of scheduled macroeconomic news on 23 suitably selected commodities futures; In section 3, we utilise the traditional regression model to investigate any effects of public news that can influence the commodities in Chinese futures market. The investigation concentrate on both continuous and individual contracts of all selected 23 contracts; section 4 is an extension of section 2, where we utilise the transformed OLS model to support the initial results in section 2; In section 5, we use real traders to recognise whether their returns are affected by scheduled macroeconomic news; section 6 brings this paper to a conclusion.

3.2 When does Scheduled Announcement Start Influencing the Market?

If the scheduled macroeconomic news has effects on the underlying assets, the abnormal returns of the assets must have a special variation during an unknown period. How long for this period and is this period before, cross, or after announcement time? By investigating and recognising this period, we can find when the news starts impacting the market. In this section, we refer the classic method of Keown and Pinkerton (1981)[67] to observe whether the scheduled announcement of macroeconomics news brings abnormal returns, and when it starts - if the special change of abnormal returns was generated.

The original function of this method is used to disclose insider's trading behaviour and information leakage in the period of the first public announcement of a proposed merger of a listed company. If the merger information leaks, the share price of related list company would increase before the real announcement time. More relevant references are followed by Jain and Sunderman (2014)[62] and Aspris, Foley, Frino, and Faff (2014)[3]. We refer this method and paraphrase it in a scheduled news announcement. The effect of public announcements of macroeconomics is also sensitive to any prices of financial market. Especially in commodity market, the news would impact the price by influencing the demand and supply of a physical asset. Thus, the advanced expectation of scheduled news can be recognised as an information leakage according to this method, which would bring subtle changes to the market before announcement time. The special change would be the beginning of reaction in the market, and then we can find the wanted period via observing the variation of abnormal returns.

3.2.1 Data Description

The significant difference between stock and futures is that the "life" of most individual futures contracts is only one year. In order to manage risk, China Securities Regulatory Commission requires all retail traders to clear out all of their holding positions before the delivery day, to prevent credit risk where they are unable to execute delivery. Thus, market participants are not able to hold any kinds of futures contracts (positions) more than its trading period. However, one kind of futures can have many different deliveries setting in one year based on different months to generate various monthly contracts: rebar has 12 monthly contracts in one year and they are delivered around 15th in each month. During the research period (2009.01.01 to 2013.12.31) of the Chinese futures market, there were 40 kinds of commodity futures and 1 index futures existing in the four main futures exchanges: Shanghai Futures Exchange (SHFE) mainly operates industrial materials and precious metals futures, Zhengzhou Commodity Exchange (CZCE) operates agricultural futures, Dalian Commodity Exchange (DCE) operates futures of agricultural products in north China and some main industrial raw materials futures, and China Financial Futures Exchange (CFFEX) mainly operate index futures in financial market. We obtained the daily data of all commodities futures from GUOTAIAN[19] and WEISHENG[20] statistic companies. These 41 futures are described in **Table C.1**. They have been transformed to 39 futures due to some historical merges and changes; for more details, refer to **Table C.1** in **Appendix C.1**.

We firstly introduce the daily data, which covers all contracts in **Table C.1** and includes the records of date, daily settlement price, trading volume, open interest, and turnover. We also got the details of continuous contracts of all listed commodities futures. Most previous research used continuous contract to avoid the problem of low trading time of only one contract. However, this paper believes that concentrating on individual contracts is better than continuous contracts to observe the absorption of news in futures market. But, continuous contract is a good benchmark to view the status of the whole period and compare individual contract. Thus, we

[19] http://www.gtafe.com
[20] http://www.wstock.net

also include them in the research. In Chinese Futures market, continuous contract is constructed by the most active contract, and the most active contract is decided by the amount of open interest. Since the research period is decided by the rebar individual transaction data, which is between 01/01/2009 and 31/10/2013, this paper only selects 23 suitable commodities during that period in this research. Among of them, 8 commodities are from DCE: LLDPE, soybean meal, soybean oil, soybean 2, coking coal, PVC, corn, palm oil; 8 commodities are from SHFE: silver, aluminium, rebar, PB, rubber, copper, wire rod, zinc; and 7 commodities are from CZCE: PTA, sugar, rapeseed meal, rap oil, methanol, cotton, common wheat. Other commodity futures cannot be satisfied for this research with some problems, such as the time to market being lower than one year, and spot price being hard to achieve. We also introduce the spot price of these 23 commodities to calculate abnormal returns, and the information about spot prices corresponding to the selected futures is obtained from Bloomberg. Bloomberg recorded historical spot price of these 23 commodities of some main and typical spot markets of each commodity in China. The declaration of each spot market is described in **Table C.2** in **Appendix C.1**.

The data of scheduled announcement of macroeconomic is collected from NBSC and Bloomberg. The Chinese government has one official department to announce national statistics data, which is the National Bureau of Statistics of China (NBSC). We downloaded and arranged all announcements with announcement time points from the official website of NBSC[21]. By using Bloomberg terminal, we selected 15 suitable types of macroeconomic news and collect the real announced values and median forecast values for the investigation of next section. In addition that, there is no fixed announcement time of each type of news, such as CPI may announce at one of 9:30, 9:40, 10:00, or 13:30. **Table C.3** in **Appendix C.1** covers details of these 15 types of announcement.

3.2.2 Methodology to Investigate the Length of Affected Period

The method of Keown and Pinkerton (1981)[67] originally used the daily price of listed company and S&P 500 index to calculate abnormal returns. In this paper, we use futures price and spot price to replace them. That is sensible because the spot price of a commodity can be recognised as a fundamental value of the futures price and the futures price is the expectation of spot price in the future. Based on daily base, any difference between the return of spot and futures market is the

[21] http://www.stats.gov.cn

abnormal returns of that commodity. So that, the daily returns of spot and futures are calculated as:

$$\boldsymbol{R_{f,c,t} = ln(P_{f,c,t+1}) - ln(P_{f,c,t})}$$

$$\boldsymbol{R_{s,c,t} = ln(P_{s,c,t+1}) - ln(P_{s,c,t})}$$

Where, $\boldsymbol{p_{f,c,t}}$ is the settlement price of futures contract $\boldsymbol{f}$ (generally, the length or life of one futures contract is one year (about 250 trading days) in China) of commodity $\boldsymbol{c}$ on day $\boldsymbol{t}$ and $\boldsymbol{p_{s,c,t}}$ is the spot price of commodity $\boldsymbol{c}$ on day $\boldsymbol{t}$. Returns are generated by the price of each individual contract data, continuous contract data, and spot market data. According to the same trading date and announcement date, we combine them together with announcement time points (mark) to each contract in order to generate homogeneous time series. The daily abnormal returns are estimated by the following regression model:

$$\boldsymbol{R_{f,c,t} = \alpha_{f,c} + \beta_{f,c} R_{s,c,t} + \tilde{\varepsilon}_{f,c,t}}$$

Where, $\boldsymbol{\alpha_{f,c}}$ and $\boldsymbol{\beta_{f,c}}$ provide intercept and slope and indicate the linear relationship between the return of futures contract $\boldsymbol{f}$ of commodity $\boldsymbol{c}$ and the return of spot market of commodity $\boldsymbol{c}$; $\boldsymbol{R_{s,c,t}}$ is the return of spot market of commodity $\boldsymbol{c}$ on day $\boldsymbol{t}$ and $\boldsymbol{R_{f,c,t}}$ is the return of futures market of contract $\boldsymbol{f}$ of commodity $\boldsymbol{c}$ on day $\boldsymbol{t}$; $\boldsymbol{\tilde{\varepsilon}_{f,c,t}}$ is the unsystematic component of the return of contract $\boldsymbol{f}$. Then, we use the following equation to calculate the abnormal return:

$$\boldsymbol{\widehat{\varepsilon}_{f,c,t} = R_{f,c,t} - (\widehat{\alpha}_{f,c} + \widehat{\beta}_{f,c} R_{s,c,t})}$$

Where, $\boldsymbol{\widehat{\alpha}_{f,c}}$ and $\boldsymbol{\widehat{\beta}_{f,c}}$ are the estimates of intercept and slope in the estimating regression model.

We exclude contracts with fewer than 160 trading days, and separate suitable contracts (remain 783 individual contracts and 23 continuous contracts of 23 commodities) into different samples to execute the above process. For example, if one contract includes $\boldsymbol{n}$ time points of announcement, we capture the data from 125 days before time point $\boldsymbol{n}$ to 30 days after time point $\boldsymbol{n}$ as sample $\boldsymbol{n}$. The number of total samples is 5938. From the 125 days before announcement date, we only use the data of first 100 trading days to execute estimating regression model to predict $\boldsymbol{\alpha}$ & $\boldsymbol{\beta}$. This setting refers to the key reference again and Halpern (1976)[54] in order to reduce the bias in the estimation of the intercept and slope between spot and futures returns. Our research has a try on futures contract and tests whether it is also useful to have multiple samples of one underlying asset, with the samples having overlap sections. The daily average of abnormal returns is defined as:

$$\boldsymbol{\bar{\varepsilon}_t = \frac{1}{n}\sum\nolimits_{sample=x}^{n}\sum\nolimits_{f=1}^{Noc}\sum\nolimits_{c=1}^{23}\widehat{\varepsilon}_{f,c,t}}$$

And, the cumulative average abnormal return is defined as:

$$\boldsymbol{\overline{CAR}_t = \bar{\varepsilon}_t + \overline{CAR}_{t-1}}$$

We can flexibly capture different commodities with $\boldsymbol{n}$ samples in order to calculate average abnormal returns to view their own variation. Also, the maximum setting of $\boldsymbol{n}$ is 5938, which can bring the whole average of all samples. We also can set $\boldsymbol{c}$ and $\boldsymbol{NoC}$ in order to collect different commodities ($\boldsymbol{c}$) with different number of contracts ($\boldsymbol{NoC}$). The $\boldsymbol{t}$ is defined from -125 (the day before 125 days to announcement day) to +30 (the day after 30 days to announcement day).The theory is that if the macroeconomic news has no effects on the futures market, the estimated average residuals (AR) and cumulative average residuals (CAR) should fluctuate across zero randomly. If the expectation of scheduled announcement has effects on the futures market, the average and cumulative average returns should have a clear direction between before and after several days to the announcement date.

3.2.3 Empirical Results of Influencing Time

Figures C.1 to C.5 in **Appendix C.2** show the scatter graphs of AR and CAR in three different sample sizes. **Figure C.1** includes scatter and line graphs of AR and CAR of the whole 5938 samples. **Figure C.2 and C.3** show the AR and CAR of 23 commodities futures, which are only averaged by all individual contracts of each commodity. **Figure C.4 and C.5** display the pattern of AR and CAR of 23 commodities futures, which are only averaged by continuous contracts. All figures indicate some clear patterns. For AR, it is stable and across zero randomly. There is no clear direction, sudden rising or declining, around announcement date. However, it is very surprising that most graphs of CAR show a clear direction. The CAR was fluctuating without any huge changing across 0 at the beginning, but it appears a more and more clear direction with approaching announcement date. The initially change sudden happens around 10 to 20 days of most commodities before announcement date. In addition, the graph is similar in both figures of individual and continuous contracts. Even the results of AR is not same as past relevant research with same method, the results of CAR is quite similar and corresponding with the results of same method before. **Table C.4** in **Appendix C.1** includes statistics and records of AR of total averaged sample (covers all individual contracts and continuous contracts), t-statistics value, CAR, and percentage of samples with positive abnormal returns between 26 days before and 16 days after announcement date. T statistics value should be significant around announcement date as previous research. Contrarily, our results show that there is no significant proof to show that the average abnormal returns would leave the mean of the whole sample so that AR is continuously stable and randomly crossing zero. However, the date before 14 days to announcement is a turning point. After this day, the CAR keeps negative and never back to positive, and become lower and lower. Meanwhile, the percentage of positive samples changes from all more than 50% to lower than 50% on some days. Based on the whole sample, it means the expectation of the market starts changing around announcement date, and the expectation is bad to lead to generate greater negative abnormal returns (absolute value) than positive one so that the CAR become lower and lower. The CAR is relevantly stable at the end of the period, which is the similar description for each commodity individually. We also separately test and observe each individual commodity, and almost all 23 commodities have that turning point and the turning point is around 10 to 20 trading days before announcement date.

Therefore, the initial founding of this paper is that scheduled announcements of macroeconomics news start affecting the Chinese futures market 2 to 4 trading weeks before the announcement date. It can be caused by two reasons: firstly, most financial institution's forecasts of macroeconomics publish around two trading weeks before the official scheduled announcements. That may cause changing expectation of all market participants. Secondly, eventually our created samples are overlapped samples due to the news announced frequently and some news announced on the same day. It causes that there are many different points to the past relevant research. Previous researches for this method only focus on merge announcement, which is absolute good news to a listed company and must bring the market price of the share to increase. Thus, the directions of AR and CAR are clearly increasing and suddenly going up around announcement time. However, for futures market and macroeconomic news, it covers all changes with both good and bad news. The direction can be upward and downward due to the attitude of news to different commodities. Also, the announcement of mergers is secret and not easy to know before the first public announcement. Macroeconomic news is scheduled and able to be expected by the market and all participants. All selected scheduled announcements are published monthly so that the scheduled news may continuously affect the market and also influence the expectation of next announcement. The period is four trading weeks, which is maximally advanced, affecting length of our results and also is approximate one month trading time.

Therefore, we conclude that the scheduled announcements act on these selected commodity futures during about the whole month. Based on above initial results, we use alternative traditional methods to investigate and support it in next following sections.

3.3 Do Scheduled News Announcements Influence Chinese Futures Market based on the Observance of Daily Data?

In this section, we use daily data of all selected 32 kinds of futures (after data cleaning) to investigate scheduled announcements of Chinese macroeconomic news influence futures market based on daily frequency data. If it is working, the paper would show the influencing size and sign of effects between news and price of each commodity. Based on the news data from Bloomberg, we calculate news surprise to reflect the impact of macroeconomics news to futures market. It is hard to see or find out the significant effects from scheduled news on any financial market in daily frequency data, except splitting data periods into expansion and recession with business cycle (Hess, Huang, and Niessen, 2008)[57]. This is because previous research has found out the value of news would be absorbed in one hour after announcements (Balduzzl, Elton, and Green, 2001)[5]. However, as we mentioned above, the data is from China and it describes individual underlying assets rather than comprehensive indices. Through adopting a simply traditional regression model between daily changes in price, volume, open interest and news surprise (indicate the news variation), in this section, we find out opposite results that selected 15 macroeconomic announcements significantly influence these 32 kinds of futures in different degrees of significance rather than none. Meanwhile, we use price trend of individual contracts to define a business cycle of a variety of futures in order to prove that the effects of scheduled news do not happen only in any fixed status of a business cycle.

3.3.1 Data Cleaning Process

We adopt the most popular method to calculate news surprise, instead of the real value of announcement, in order to investigate the effects of these several news on each selected futures contracts. The trading time of one contract is almost one year, which corresponds to around 250 trading days (only soybean and index futures are two special varieties). Due to some of our collected commodity futures launched in the second half year of 2013 (see **Table C.1**), we firstly clean the data to keep the suitable futures contracts, which have at least 125 trading days, amount of half trading days of one standard year. After this cleaning process, we still reserve total 1241 contracts with 32 different kinds of futures constructing the initial dataset of this section (original number is 1557 contracts with 38 commodities and one index futures). The retained kinds of futures and the surplus number of contracts are recorded in **Table C.5** in **Appendix C.1**. We have checked that the continuous contracts of all of these 32 kinds of futures satisfy the condition of at least 125 trading days so that the investigating total number of contracts is 1241 individual contracts plus 32 continuous contracts. In addition, the trading time and cycle of HuShen300 index futures is quite different from other commodity futures. The define of cycle starts with two continuous two-month contracts, and then one nine-month contract, and next two continuous two-month contracts, and then one nine-month contract by parity of reasoning. Therefore, there is no fixed delivery month with a fixed number of contracts, and the amount of trading days of one third of contracts is around 160 trading days (nine months) and others with about 40 trading days (two months). Thus, the cleaning process is not able to process the HuShen300 index futures, especially for the two-month contract, so that we reserve all contracts of the only index futures in the following research. Meanwhile, we use announcement surprises to define the change of macroeconomics news. Bloomberg provides an estimation of the median forecast and real values which are published by Bloomberg and NBSC. The standard deviations and number of observations of each announcement are recorded in **Table C.3** as previous descriptions.

3.3.2 Methodology to Measure Effects of News on Chinese Futures Market

We use the traditional calculation method to compute the size of the announcements surprises, here refers to Balduzzi, Elton, and Green (2001) [5], Boyed, Hu, and Jagannathan (2005) [16], and Erenburg, Kurov, and Lasser (2005) [37]. The news surprises are computed by:

$$\boldsymbol{SS_n = \frac{A_n - F_n}{STD(A_n - F_n)}}$$

Where, $\boldsymbol{n}$ is the identify code of different news, which is from 1 to 15 in this paper. $\boldsymbol{A}$ is the real value of each announcement. $\boldsymbol{F}$ is the median of forecast value from Bloomberg. The difference between real value and forecast value is the surprises.

We use the surprises to divide the standard deviation of all observations of surprises to generate standardised surprise, in order to conveniently explain the definition and unify measurement. When we regress the daily returns, daily change of trading volume, and daily change of market position (open interest) of each contract on surprises, the coefficients in the regression interpret the change of one of above three variables for a unit change of standard deviation in the announcement surprise. Based on previous research, our research does not only regress returns on the surprise, but also introduce the daily change in trading volume and market position as the other two dependent variables in other two regressions. We adopt the simple regression models:

$$\boldsymbol{ln(\frac{P_t}{P_{t-1}}) * 100 = \beta_{0,t} + \sum\nolimits_{n=1}^{15} \beta_{n,t} SS_{n,t} + \varepsilon_t}$$

$$\boldsymbol{\frac{TV_t - TV_{t-1}}{TV_{t-1}} = \beta_{0,t} + \sum\nolimits_{n-1}^{15} \beta_{n,t} SS_{n,t} + \varepsilon_t}$$

$$\boldsymbol{\frac{MP_t - MP_{t-1}}{MP_{t-1}} = \beta_{0,t} + \sum\nolimits_{n=1}^{15} \beta_{n,t} SS_{n,t} + \varepsilon_t}$$

Where, we use nature logarithm return to represent the change of price: $\boldsymbol{P_t}$ is the price of one contract on day t and $\boldsymbol{P_{t-1}}$ is the price on day $\boldsymbol{t-1}$. We multiple 100 on the logarithm return due to the origin value is quite small so that the explanation is change to change in percentage. $\boldsymbol{\beta_{0,t}}$ and $\boldsymbol{\varepsilon_t}$ are the constant and error term in each regression. Coefficient $\boldsymbol{\beta_{n,t}}$ interprets the relationship between three dependent variables and announcement $\boldsymbol{n}$ on day $\boldsymbol{t}$. Because we utilise 15 types of news, $\boldsymbol{n}$ is equal 1 to 15. Standardised news surprise is $\boldsymbol{SS_{n,t}}$ and it denotes the surprise of announcement $\boldsymbol{n}$ on day $\boldsymbol{t}$. If there is no announcement of news $\boldsymbol{n}$ on day $\boldsymbol{x}$, the standardised surprise is zero on day $\boldsymbol{x}$. In the second and third type of regressions, we change the dependent variable to the percent change in trading volume and market position. It is also sensitive to observe the market. If scheduled news have effects on the market, the daily total trading volume and daily open interest should have simultaneous variation to reflect the influences of the announcements. We adopt these three regression models on all 1241 individual contracts and 32 continuous contracts respectively.

In addition, the regressions model about the effect of news surprise on the change in daily trading volumes and market positions is not suitable to all continuous contracts of each commodity. As mentioned previously, a continuous contract is constructed by the most active contract of each commodity (index) futures one by one. Thus, when the most active contract replace, there is a huge jump suddenly happening in the recode of both trading volume and open interest because there are two different contracts before and after the jump. These jumps significantly influence the calculation of percent changing in trading volume and market position so that we do not use it for the continuous contracts. However, it is still suitable to each individual contract and investigation on price of continuous contract. The prices of different contracts absolutely are not equal most times, but they have a high correlation and low difference between each other when they have an overlapping trading period. For instance, rebar futures have 12 contracts in one year. Each contract starts trading at mid-month and delivering at same mid-month in next year. Generally speaking, the active contracts of rebar are the January, May, and October contracts so that, for May and October contracts, the overlapping trading periods is between October (current year) to May (next year). The October contract commonly would replace and take the position of the most active contract from May (last year) contract around March, when the open interest of May (last year) contract becomes lower than October contract. The real replacing day is decided by all four main exchanges, with consideration for the above situation. There would be a big gap of trading volume and open interest between two contracts, but the price difference is small so that the price in continuous contract could be used in the research. Thus, the similar huge jumps in trading volume and open interest between replacing the most active contracts cannot happen in price.

The above description also is an argument and query to previous research which adopt continuous futures contracts to discuss the effects of scheduled announcements on trading volume. If the compilation mechanism of continuous contract in Chinese futures market is same as their adopted financial makers, this problem should be considered and described clearly at the beginning. Meanwhile, we use all daily data to make the regression, which includes all announcement and none-announcement days, rather than only covering announcement days. It would cause the R-square in each regression become relevant low. However, it is better to observe the price, trading volume, open interest variation of each commodity against news announcement if the news surprises have the same variation as dependent variables.

3.3.3 Empirical Results Based on Daily Data

3.3.3.1 Results from Daily Continuous Contracts

We firstly explain the results of 32 continuous contracts because they interpret the overall situation of each commodity futures. All results are in **Table C.6** in **Appendix C.1**, which is separated into two tables. The first column in each table includes the name of 15 types of news. The first row in each table identifies all commodities and index. For the main contents, it includes estimated coefficients of all regressions and we use colour to sign the significance level which is better to overview the situation of effects than the common starts. Deep green is 1% significant level, light green is 5% significant level, yellow is 10% significant level, and no colour means insignificant. The results show quite different number of significant news to previous research. Based on daily frequency, it is hard to find out which news is able to influence futures market previously. However, it is clear that many kinds of futures are affected by more than three macroeconomic announcements. Specially, the futures of metal, raw material, and industrial product are affected by different news in different degrees. Scheduled news relatively has no significance on most agricultures futures relatively, such as cotton and soybean oil.

The response coefficients of 15 macroeconomic announcements to each kind of futures are reasonable and sensible. For example about industrial production futures, rebar is influenced by CPI, M2, and FCR. One unit positive surprise of one standard deviation in broad money (M2) and foreign exchange reserve of China (FCR) can provide 0.27% and 0.19% price increase in the futures of rebar. One unit negative surprise of one standard deviation in the percentage change in consumer price index promote 0.27% price of rebar futures. Regarding raw material futures, for instance again, GDP, FA, M2 and FCR, can make a significant impact on the futures price of fuel oil in China. One unit's increase in news surprise with one standard deviation of GDP, FA (fixed assets investment), and FCR leads to 0.35%, 0.30%, and 0.48% price increase in the futures price of fuel oil. M2 takes an opposite function that one unit decrease in its surprise with one standard deviation promote the fuel oil futures price increase 0.55%. Reviewing agricultural futures, few of them are affected by scheduled announcements, especially for rapeseed and rapeseed meal. That should be caused by the great production of rapeseed in the southern of China so that the futures about rapeseed are influenced by macroeconomics and different to other agricultural futures. This is because it corresponds with China's economics national condition. Even China is agricultural country, China still needs a lot of import from outside. For instance, the national production of soybean is not enough to support the production of soybean oil, and so a lot of soybean is imported from America. Thus, a big part of the magnitude of effects on the futures and spot price is occupied by the price of origin. The outside influence should be equal or more significant to the agricultural commodities' price than China's scheduled macroeconomics news at daily frequency instrument so that we cannot find some effective announcements to agricultural futures. However, China is more dependent on heavy industry and energy utilisation to support its economy. That is also the reason that the categories of raw material and industrial product futures are influenced greater and more sensitive than agricultural futures. In addition, energy mineral resource is different to crops. The influence of nature factors on resource or production is quite small. Therefore, most industrial futures are influenced by Chinese scheduled macroeconomic announcements, which take the main magnitude in the effects.

3.3.3.2 Results from Daily Individual Contracts

We use the same regression methods on daily individual contracts to view the stability of the effects of scheduled announcements on the price of each commodity and index futures. According to the previous description, we adopt percent change in trading volume and market position instead of logarithm returns to create the other two types of regressions. The key aim of this step for regressing all individual contracts separately is to observe how many contracts or the percentage of contracts that can be influenced by macroeconomic news, rather than viewing estimated coefficients to judge the sign and size of the effects. We describe the results of three kinds of regressions in **Table C.7**: ***lrsp*** for logarithm returns of daily settlement price, **Table C.8**: ***ctv*** for percentage change in daily trading volume, and **Table C.9**: ***cmp*** for percentage change in daily market position. These three tables have same pattern. The first row indicates all repressors, which are all 15 macroeconomic announcements and constants item. The content includes the percentage number of affected contracts. For example in **Table C.7**, "nid" is the name id of each commodity, and the first commodity futures is LLDPE (linear low density polyethylene) as recorded before. The total number of contracts of LLDPE with at least 125 trading days is 60. In the 60 individual regressions with dependent variable as "lrsp", 17 regressions show the results that CPI has significant relationship to logarithm returns, which means 17 contracts are influenced by CPI. Therefore, we calculate the percentage is (17/60) * 100% = 28%, which is showing in the first cell under "CPI". In addition, due to we tend to save the step, we fill the table directly using the calculated percentage rather than the number of affected contracts. We use this way to calculate this percentage for each type of news against each commodity. In all three tables, we use bold type to mark key results. “NoC1” is a column to record the number of contracts of each kind of futures. “NoC2” (at the bottom of each table) is a row to record the total number of affected contracts of all futures by one macroeconomic announcement. We use “P1” to record the percentage between “NoC2” against the whole number of contracts (1241). For instance in **Table C.7** as well, the number of affected contracts of all 39 types of futures by CPI is 359 so that “P1” record percentage is equal to (359/1241) * 100% = 29%. For the last two columns at the right of the tables contain information of “NoC3” and “P2”. “NoC3” is the average number of influenced contracts for each commodity. Still for instance of LLPDE in 60 regressions, 17, 26, 11, 16, 9, 20, 21, 19, 14, 11, 21, 11, 16, 15, and 15 contracts are correspondingly affected by CPI, GDP, NYL, PPI, EXP, VIO, IP, FA, M2, IMP, RS, BOT, RSCG, FCR, and PMI. Thus, the average number of affected contracts of LLDPE is equal $\mathbf{\frac{17+26+11+16+9+20+21+19+14+11+21+11+16+15+15}{15} = 16}$. Since we selected 15 types of macroeconomic news, we make the sum of affected contracts divide 15 to define the average number of affected contracts. Then, “P2” is the percentage between “NoC3” and “NoC1”. 16/60 * 100% = 26% is the percentage of average number of affected contracts of LLDPE. We use the same explanations in **Table C.7, C.8, and C.9**. But, the interpretation is between scheduled macroeconomics announcements against logarithm returns, change in trading volume, and change in open interest individually in different tables.

Most of “P1” in **Table C.7, C.8, and C.9** are around 20% to 40%, which give us enough confidence and evidence to support the macroeconomic news influence individual contracts and these results can be found in daily data. In addition, through the results of individual contracts, we find it is not completely corresponding to previous research. We claim two arguments here. The first argument is about active contracts that there is no evidence indicating scheduled announcement can only affects active contracts. As mentioned before, there are generally 12 contracts of each type of futures in one trading year. But, we cannot define all contracts to be active contracts. In fact, only three to five contracts can be recognised as active contracts of each commodity, since their trading volumes and open interest is much higher than other monthly contracts. Contracts such as rebar, January, May, and October contracts are active contracts and their daily open interest could be 1000 times of other monthly contracts. Thus, 20% to 40% is a reasonable number and similarly equal to the occupation of active contracts (3/12 * 100% = 25%). But after statistics, these affected 20% to 40% contracts are not exactly active contracts.

We still adopt the results of individual rebar futures to explain. **Table C.10** in **Appendix C.1** includes the results of all 57 (satisfied condition: at least 125 trading days) rebar individual contracts in three type of regressions (dependent variables as lrsp, ctv, and cmp). The cells with deep green colour indicate the corresponding type of announcement in the first row has effect on the corresponding contract in the first column at 5% significant level. It is clear to observe that some contracts are affected by many type of news, but some other contracts cannot be influenced by any of selected 15 announcements. In addition, not all of the active contacts are affected by many type of news, such as RB1205 contract was only influenced by NYL (new Yuan (RMB) loans). Therefore, it discloses the macroeconomics news absolutely has significant effects on each commodity futures, but it is not related to the high trading activity of underlying assets. We describe that the news influence the market in two stages. Firstly, the news influence the spot price of each commodity or index (for index, the effects should be on the stock price of the weighted stock in HuShen300 index). Then, spot price has price pointing function on futures price, but all contracts would response the news rather than only active contracts so that the regression results of 20% to 40% of contracts are affected depends on the news effects (good or bad) on the price of underlying assets. The second point view is from market participants. As we mentioned in section 2, market participants would have a reasonable expectation on the scheduled announcements. Once the real value of announcements is published, most of them tend to adjust their trading strategies with unscrambling different news. If many traders have action based on macroeconomics news, the daily trading volume, open interest, and price must have a significant variation on announcement date. Thus, we also find some significant relationships between news and change in trading volume and open interest in **Table C.10** (middle and right parts). Therefore, the response of each individual contract does not depend on the activity of contracts, and it is actually depending on the news absorbing of price.

The second argument of these results is discussion to previous research. Past researches adopted several comprehensive indices, such as S&P 500 index, or national bond to conclude that scheduled announcements have significant on these overall underlying assets in different periods of economic cycle (expansion or recession). We also find no evidence to support that macroeconomics news can absolutely and fixedly affect the price of commodity futures in China during both expansion and recession periods. We also find there are no absolute effects of news on futures price during an alternative period - stable period in the business cycle of an underlying asset. Previous researches used official publications to define expansion and recession of a national business cycle, such as CFNAI (Chicago Fed National Activity Index) and NBER (The National Bureau of Economic Research), and then, they investigate the overall underlying assets to analyse the aim research question. Because our research concentrates on specific one commodity, there is no an official or generalised definition to recognise which period belongs to expansion or recession of one futures and also we cannot have an overall definition of business cycle of all commodities due to the business cycle between each kind of futures are quite different, such as rebar and zinc. Thus, we alternatively use the price line graphs of each individual contract to roughly define the business cycle of each commodity. We still utilise the results in **Table C.10** and other figures with rebar futures as the key example to explain.

Figure C.6 in **Appendix C.2** is the k lines and trading volumes line charts of rebar continuous contract. Because rebar started trading in the March of 2009, the data before the publication time is not achieved. But based on the spot price record from Bloomberg, we find it is an expansion period from 2009 to 2011 due to the spot price of rebar was increasing from 3300 to 5000. Thus, due to the high correlation between spot and futures price, we see the peak price 5110 in **Figure C.6**. After a stable period, the rebar enter a recession until now also referring to **Figure C.6**. How about the individual contracts? We plot the price trend of all regressed rebar contracts separately in **Figure C.7** from **Appendix C.2**, which could be recognised as continuous segmentation of **Figure C.6**. We add fit line in each line graph of **Figure C.7** to view the price trend of each contract, in other words, upward, horizontal line, and downward fit lines separately indicate definition of expansion, stable, and recession of each contract. Combining these line graphs and the results in **Table C.10**, there is no evidence to support the news can absolutely influence futures price only during one kind of status of underlying assets' business cycle. The effects can happen in all expansion, stable, and recession period. For example, RB0910 to RB1006 contracts should be recognised as trading in stable period, however, RB0910 to RB1002 contracts were affected by more than five types of announcements but RB1003 to RB1005 were only influenced by two. RB1104 to RB1207 contracts include both expansion and recession periods, but some contracts were affected by more than five types of news and some others were able to be influenced by lower than one type of news. So, we provide the evidence to argue previous research that the effects of scheduled news on the price cannot depend on the business cycle of underlying assets, and that evidence might be only suitable to the investigation on comprehensive underlying assets.

3.4 Do Scheduled Announcements Influence the Chinese Futures Market during a Long Period?

In this section, we try to make a combination of the results between section 2 and 3 to observe do scheduled announcements can really affect the Chinese futures market starting before around 20 trading days to announcement date. In the section 3, we adopt daily logarithm returns to identify the price variation day by day. However, according to the results in section 2, the scheduled announcement would influence the futures market during the whole month. In order to be better to observe and prove the effects, we change the construction of returns in different periods to investigate.

3.4.1 Regression Model Transformation

The idea still refers to Balduzzi, Elton, and Green (2001)[5]. We change the calculation format of logarithm returns to identify the variation of price in different period as the following regression model:

$$\boldsymbol{ln(\frac{P_{t+15}}{P_{t-x}}) * 100 = \beta_{0,t} + \sum_{n=1}^{15} \beta_{n,t} SS_{n,t} + \varepsilon_t}$$

Where, $\boldsymbol{\beta_{0,t}}$ & $\boldsymbol{\varepsilon_t}$ are still the constant and error term in all regressions. Standardised news surprise is $\boldsymbol{SS_{n,t}}$ as well. For the dependent variable, we use the nature logarithm returns between the price after 15 days to the announcement date and the price before $\boldsymbol{x}$ days to the announcement date to display the different variations. Given six values of $\boldsymbol{x}$, We initially set $\boldsymbol{x}$ is equal to 20, which show the price change between before 20 days and after 15 days to announcement date and the coefficients in the corresponding regressions means the effects of different types of news on the price variation. In addition, the initialisation corresponds to the results in the section 2 where around 20 trading days before the announcement date, the macroeconomic news start affecting the futures market and continuous to around 15 trading days after announcement date. If it is correct, we would see the largest number of affected contracts in the regressions under this setting. Then, we change the setting of $\boldsymbol{x}$ to 10, 5, and 0 to reduce the variation period step by step. The expectation of the results would be seeing reduction of the number of influenced contracts. When, we set $\boldsymbol{x}$ is equal to 0, the regression results starting reflecting the effects of price after announcements. We also set the other two values of $\boldsymbol{x}$, -5 and -10, to observe any reactions of announcement at time t on the price between time t+5 or t+10 to time t+15. Also for the expectation, none or few contracts would be affected by scheduled news if it is related to the results in section 2.

3.4.2 Empirical Results in Six Settings of Returns

We firstly introduce the results of continuous contracts as before and use the similar statistic method as section 3 to record the regression results in **Table C.11 to C.16** in **Appendix C.1**. Because there are 23 suitable kinds of futures contracts and each variety has six types of logarithm returns setting which correspond to the commodities selection in section 2, we separate them into these six tables and each table contains four kinds of futures. For instance in **Table C.11**, the first column records contain in each row. Under the name of futures, we separate six regressions as "a15b20", which means before 20 days to after 15 days, to "a15a10", which means after 10 days to after 15 days. The key contains in the tables cover all coefficients, number of observations, and some other statistics values of each regression. We also use deep green, light green, yellow, and white to indicate the significant level at 1%, 5%, 10%, and insignificant.

We combine **Table C.6, Figure C.3, and Table C.11 to C.16** to jointly expound the results. In the section one, we only adopt 23 commodities futures to investigate due to the unachievable spot price and other related limitations. Therefore, we use the CAR line graphs in **Figure C.3** from section 2 as reference substance to discuss and summarise. These 23 commodities futures are LLDPE, PTA, sugar, sliver, rapeseed meal, rap oil, soybean oil, soybean 2[22], methanol, cooking coal, PVC, aluminium, rebar, cotton, common wheat, PB, rubber, copper, wire rod, zinc, corn, and palm oil, which are covered by 32 commodities futures in section 2 to 4 and enough to be on behalf of all. We refer to the results in **Table C.6** that most of selected 23 commodities futures are affected by scheduled announcements without some of agriculture futures cannot be influenced at daily frequency (in short term) as we discussed before. The line graphs of corresponding futures in **Figure C.3** indicate that futures price would make a relatively reaction with starting before around 20 trading days to announcement date, such as LLDPE, rubber, and rebar. According to the results in **Table C.11 to C.16**, most of the above described 23 commodities futures have the similar reaction as results in **Table C.6 and Figure C.3**.

In detailed, we roughly separate 23 commodities into two categories according to the results in **Table C.6, Figure C.3, and Table C.11 to C.16** to define their different reactions to scheduled news. The first group includes most commodities, which are LLDPE, PTA, sugar, silver, rapeseed meal, rap oil, methanol, coking coal, PVC, aluminium, rebar, common wheat, PB, rubber, copper, zinc, wire rod, and

[22]Soybean 1 is Non-GMO soybean and Soybean 2 is GMO soybean which most are from global market. GMO: genetically modified organisms.

palm oil. All of them have similar CAR trends in **Figure C.3** (define upward and downward as same trend[23]) and significantly affected by at least one macroeconomic news according to **Table C.6**. For these commodities futures, it is clear that the number of reacted types of news is mostly greater than 5 before announcement date; however, this number generally reduce to lower than three after announcement date for the members of group 1. Moreover, the coefficients, which interpret the reaction level, become lower and lower after announcement date. For example, M2 (broad money) influence LLDPE continuous to setting logarithm returns between the price after 5 days and the price after 15 days to announcement date. From "a15b20" to "a15ab0", the coefficients are higher than 2%, which indicate that a unite stander deviation of a positive surprise of broad money would bring at least 2% price increase of LLDPE futures in different periods. However, when the setting of period changes to "a15a5", the coefficient decreases to 1.5% and only remains at 1% significant level. Also, when the setting progress to "a15a10", the coefficient becomes quite small (about 0.2%) and there is no significance. This description is suitable for most investigated futures in this group that the coefficient must have a clear decline after announcement date. Meanwhile, in the long term investigation, the effective types of news are changed referring the difference between results in **Table C.11 to C.16 and Table C.6**. For instance, the price of rebar futures is affected by CPI, M2, and FCR, according to results in **Table C.6**, based on the regression on daily logarithm returns (short term). But in the long term regarding the results in **Table C.15**, the effective types of news mainly include and change to EXP, IMP, FCR, and BOT. This phenomenon is common to other commodities in group 1, and it is because the related commodity futures need long time to response on the price from some news effects in long term. Also, other news may impact related commodity futures in the short term immediately, rather than absorbing news with a long time.

Other surplus commodities, all of them are agriculture commodity futures, which include soybean meal, soybean oil, soybean 2, cotton, and corn. These commodities are classified in group 2. Regarding the line graphs in **Figure C.3**, the CAR of soybean meal, soybean oil, and cotton display a similar trend as the member of group 1, and the CAR of soybean 2 and corn do not have a clear trend or we can see a relevant stable and fluctuated trend crossing zero. We firstly concentrate on the three normal members of group 2. The related results in **Table C.6** show that there are also no intraday effects of scheduled announcements on these three commodities futures. In other words, it indicates that these three commodities futures cannot

[23] Here, we defined the trend in the section 2 that the CAR would cross zero and never go back to positive (or negative).

be controlled by news in short term. Meanwhile, the CAR graphs of them show that they might be affected by announcements in long term. It is also confirmed by the results in **Table C.11 to C.16**, but it is quite different to the results of the members in group 1. When we increase length of price variation to observe the effects in long term, the reactions on the price of these three commodities futures are changed. The results of price variation periods before announcement date show that the number of effectively different announcements is lower than the number after announcement date, which is an opposite results to group 1. It means that the effects of scheduled news actually start impacting these three futures around announcement date rather than before about 20 trading days. Thus, the previous discussion of soybean futures should be updated to show that similar commodity futures would be influenced by announcements in long term and we cannot view any absorbing process in short term. Regarding the opposite results to the member of group 1, it is also happening to soybean 2 and corn. Although their CAR line graphs in **Figure C.3** are relatively stable, which disclose that there might be no long term effects from news against these two commodities, the change of number of effective news is also existing and confirmed in **Table C.11 to C.16**. There is little news and they do not continuously and significantly influence these two commodities in different returns variation periods. It indicates these two commodities futures are also affected by scheduled announcements during a long period. In the short term according to Table 6, soybean 2 and corn cannot have significant effects from macroeconomic news.

Meanwhile, we provide the results of transformed regressions on individual contracts to support above founding in section 2. In **Table C.17** in **Appendix C.1**, we only introduce 23 selected commodities futures to represent all to explain as same as section 2. In the first column, we use "a15b20" to "a15a10" to sign the different period of returns variation settings. We still use the same definition of "P2", which is the percentage of average number of affected contracts, to describe the responding situation of each commodity. We use red colour to mark commodities in group 1 and black colour to mark members in group 2. It is very clear that the "P2" is in a decreasing trend of most members of group 1. For most of them, the biggest percentage of average number of affected contracts exists at "a15b20" or "a15b10", which is corresponding to all results from section 2 to 4 that the scheduled macroeconomics news would start influencing the futures market before around 20 trading days to announcement date. Also, we cannot define the case is absolute to happen for all futures due to different underlying assets must has different reflection in the market. The members of group 2 show the other situation that the highest

"P2" exist at "a15b0" or after it. It means that the effects of news on these four commodities futures delay (soybean2 is exception). Generally, the effects would be present after the announcement date, for the reason discussed before. However, we still have enough confidence to claim that scheduled macroeconomic announcements have effects on Chinese futures market and the influencing periods is longer than intraday absorbing. Different commodities need a long time to response news.

3.5 Do Market Participants Make Excess Returns by Following Scheduled Macroeconomic News?

In this section, we use a simple method to briefly investigate whether trading according to scheduled macroeconomic news are able to bring excess returns to market participants. According to our previous research, we have the data which records traders' all daily information of rebar futures contract, including such as daily profit or loss and trading volumes, from one big futures brokerage in China. We have continually been updating our data and currently extending to 31/10/2013 with 50 contracts. The daily information covers details of 36,070 traders. After statistics, 8991 traders are profitable, 26998 traders are losing, and 81 traders are keeping nature. Are their trading actions affected by macroeconomic news? We use a similar regression method as before to express this question. The idea is still referring to Balduzzi, Elton, and Green (2001) [5]. We now use individual daily trading volumes and variation of daily trading volumes of each selected trader to symbolise traders' daily trading activity. We want to see whether the selected 15 macroeconomic news have effects on their trading activity so that we use the regression model as:

$$\boldsymbol{TV_t = \beta_{0,t} + \sum\nolimits_{n=1}^{15} \beta_{n,t} * SS_{n,t} + \varepsilon_t}$$

$$\boldsymbol{TV_t - TV_{t-1} = \beta_{0,t} + \sum\nolimits_{n=1}^{15} \beta_{n,t} * SS_{n,t} + \varepsilon_t}$$

Where, the first regression uses daily trading volumes and the second regression uses the variation of daily trading volumes as the dependent variable to indicate the trading activity of each trader. For the right hand, they are similar as before, just includes the calculated news surprise of the selected 15 macroeconomic news. We make regressions on these two models for 36,070 traders one by one in order to see is there any significant relationship between traders' trading activity and announcement of macroeconomic news, and then we get the results in **Table C.18** in **Appendix C.1** after statistics.

Table C.18 includes two types of statistics tables. The first part of table shows that each kind of news can influence (has significance) how many traders. For example, 1534 (5.68%) traders' trading activities are affected by CPI from 26998 losing traders, which mean the news surprise of CPI is significant to trading volume in these 1534 regressions. We can see the corresponding results of other type of macroeconomic news - both in trading volume and variation of volumes - which show that the affected number of losing traders is higher than the number in profitable traders. This implies that if trader follows scheduled macroeconomic news would have more likely to lose money rather than make excess returns. It is also corresponding to the second part of **Table C.18**.

The second part of the table records the number of traders who are affected by the various amount types of news. For example, according to trading volumes as the dependent variable, we can see three columns under "losing traders". They mean 0 type of macroeconomic news can influence 9161 traders and this number of traders occupies 33.93% in all losing traders, and same explanation is suited for following number of 2 to 15 types of news. We can see that the number of affected (significant) traders is greater than the number of profitable traders in different level of number of news so that it is corresponding to the previous results.

Overall, we provide this evidence to indicate that traders, who are following scheduled macroeconomics news as the key fundamental information to make trading decisions, cannot make excess return in Chinese futures market. Indeed, the scheduled news may lead market participants to loss their money. This futures market is inefficient and cannot invest only with fundamental information. It is also relevant to the results in previous section that the news reaction would be very late to happen in the market rather than in the short term. Thus, traders make trading decision with news announcement is not successful in the market.

3.6 Conclusion

This paper is the first to research the effects of scheduled macroeconomic announcements on individual futures through the comprehensive analysis for Chinese futures market. We firstly adopt 23 kinds of suitable commodity futures to investigate when scheduled macroeconomic announcements start influencing the market. The results show that around 20 trading days before announcement time, the news effects start acting on the whole market. We select 32 categories of futures in Chinese futures market during 01/01/2009 to 31/12/2013. Based on daily data of these futures contract, we provide new evidence from individual futures contract that the scheduled news have effect on futures price, and futures prices response corresponding adjustment on announcement date. Meanwhile, the affected level of most metal, raw material, and the industrial product futures is quite higher than most agricultural futures due to China' fundamental realities. We also find the affected level of each futures contract does not depend on the trading activity. The price of not only active futures contracts but also inactive futures contracts were affected by different types of news and adjusted on announcement date. We also find the effects can happen in any status of a commodity's business cycle. No evidence indicates that the influences of scheduled news absolutely happen in expansion, or stable, or recession periods in a business cycle. Furthermore, we changed the dependent variable of regressions to observe the effects in long term in order to support the results in section 2. We find most commodities futures are affected by scheduled macroeconomic news starting before around 20 trading days to announcement date as our expectation in section 1. We cannot absolutely claim that it is must happen for other underlying assets, but it is a comprehensive analysis on Chinese futures market due to we have selected almost products in this market. It is a break to the previous research in this area that we use the recent year data to provide the evidence that the price of an underlying assets would responds the scheduled announcements in several days before and after announcement date rather than absorbing news in the announcement day. We cannot say no reasonable to previous intraday research in this area and our intraday analysis would be investigated in the future. But at least, we use the similarly simple econometric method to get the significant results based on daily frequency data rather than the intraday or high frequency data. At the end, we utilise individual capital information to observe whether scheduled macroeconomic news can help market participants to make excess profits. The results claim that news cannot bring more profits in the inefficient market. Market participants would be more likely to lose money with fundamental news in the market.

Appendix A

to Chapter 1

A.1 Interval Setting of K-Means Project 2: Table A.1

	sec.	min.	hour.	day (3.75h per day)
start 5 sec. interval	1	0.017	0.000	0.000
	5	0.083	0.001	0.000
	10	0.167	0.003	0.001
	15	0.250	0.004	0.001
	20	0.333	0.006	0.001
	25	0.417	0.007	0.002
start 10 sec. interval	30	0.500	0.008	0.002
	40	0.667	0.011	0.003
	50	0.833	0.014	0.004
start 15 sec. interval	60	1.000	0.017	0.004
	75	1.250	0.021	0.006
	90	1.500	0.025	0.007
	105	1.750	0.029	0.008
start 30 sec. interval	120	2.000	0.033	0.009
	150	2.500	0.042	0.011
	180	3.000	0.050	0.013
	200	3.333	0.056	0.015
	210	3.500	0.058	0.016
	240	4.000	0.067	0.018
	250	4.167	0.069	0.019
	270	4.500	0.075	0.020
start 50 sec. interval	300	5.000	0.083	0.022
	350	5.833	0.097	0.026
	400	6.667	0.111	0.030
	450	7.500	0.125	0.033
	500	8.333	0.139	0.037
	550	9.167	0.153	0.041
	600	10.000	0.167	0.044
	650	10.833	0.181	0.048
	700	11.667	0.194	0.052

Table A.1: **Interval Setting of K-Means Project 2**

A.2 Interval Setting of K-Means Project 3: Table A.2

	sec.	min.	hour.	day (3.75h per day)
start 5 sec. interval	5	0.083	0.001	0.000
	10	0.167	0.003	0.001
	15	0.250	0.004	0.001
	20	0.333	0.006	0.001
	25	0.417	0.007	0.002
	30	0.500	0.008	0.002
	35	0.583	0.010	0.003
	40	0.667	0.011	0.003
	45	0.750	0.013	0.003
	50	0.833	0.014	0.004
	55	0.917	0.015	0.004
start 10 sec. interval	60	1.000	0.017	0.004
	70	1.167	0.019	0.005
	80	1.333	0.022	0.006
	90	1.500	0.025	0.007
	100	1.667	0.028	0.007
	110	1.833	0.031	0.008
	120	2.000	0.033	0.009
	130	2.167	0.036	0.010
	140	2.333	0.039	0.010
	150	2.500	0.042	0.011
	160	2.667	0.044	0.012
	170	2.833	0.047	0.013
	180	3.000	0.050	0.013
	190	3.167	0.053	0.014
	200	3.333	0.056	0.015
	210	3.500	0.058	0.016
	220	3.667	0.061	0.016
	230	3.833	0.064	0.017
	240	4.000	0.067	0.018
	250	4.167	0.069	0.019
	260	4.333	0.072	0.019
	270	4.500	0.075	0.020

	280	4.667	0.078	0.021
	290	4.833	0.081	0.021
start 15 sec. interval	300	5.000	0.083	0.022
	315	5.250	0.088	0.023
	330	5.500	0.092	0.024
	345	5.750	0.096	0.026
	360	6.000	0.100	0.027
	375	6.250	0.104	0.028
	390	6.500	0.108	0.029
	405	6.750	0.113	0.030
	420	7.000	0.117	0.031
	435	7.250	0.121	0.032
	450	7.500	0.125	0.033
	465	7.750	0.129	0.034
	480	8.000	0.133	0.036
	495	8.250	0.138	0.037
	510	8.500	0.142	0.038
	525	8.750	0.146	0.039
	540	9.000	0.150	0.040
	555	9.250	0.154	0.041
	570	9.500	0.158	0.042
	585	9.750	0.163	0.043
start 30 sec. interval	600	10.000	0.167	0.044
	630	10.500	0.175	0.047
	660	11.000	0.183	0.049
	690	11.500	0.192	0.051
	720	12.000	0.200	0.053
	750	12.500	0.208	0.056
	780	13.000	0.217	0.058
	810	13.500	0.225	0.060
	840	14.000	0.233	0.062
	870	14.500	0.242	0.064
start 1 min. interval	900	15.000	0.250	0.067
	960	16.000	0.267	0.071
	1020	17.000	0.283	0.076
	1080	18.000	0.300	0.080
	1140	19.000	0.317	0.084

	1200	20.000	0.333	0.089
	1260	21.000	0.350	0.093
	1320	22.000	0.367	0.098
	1380	23.000	0.383	0.102
	1440	24.000	0.400	0.107
	1500	25.000	0.417	0.111
	1560	26.000	0.433	0.116
	1620	27.000	0.450	0.120
	1680	28.000	0.467	0.124
	1740	29.000	0.483	0.129
start 10 min. interval	1800	30.000	0.500	0.133
	2400	40.000	0.667	0.178
	3000	50.000	0.833	0.222
	3600	60.000	1.000	0.267
start 30 min. interval	4500	75.000	1.250	0.333
	6300	105.000	1.750	0.467
	8100	135.000	2.250	0.600
	9900	165.000	2.750	0.733
	11700	195.000	3.250	0.867
one day	13500	225.000	3.750	1.000

Table A.2: **Interval Setting of K-Means Project 3**

A.3 Principle of K-Means Clustering with Squared Euclidean Distance

We use $\boldsymbol{p_{c,n,d}}$ to indicate the coordinates of all points in the space and $\boldsymbol{ce_{c,n,d}}$ to indicate the centroids' coordinates. Where in the lower right corner, $\boldsymbol{c}$ is the mark of cluster (group), $\boldsymbol{n}$ is the number of points, and $\boldsymbol{d}$ is the dimension of the space. For instance, 4 traders are labelled as 1, 2, 3, 4 in an x dimensional-space, and their coordinates are "$\boldsymbol{p_{c,1,x}}$, $\boldsymbol{p_{c,2,x}}$, $\boldsymbol{p_{c,3,x}}$, $\boldsymbol{p_{c,4,x}}$". If setting $\boldsymbol{k = 2}$ in the algorithm, the procedure estimates two original centroids in the space, and their coordinates are "$\boldsymbol{ce_{2,n,x}}$, $\boldsymbol{ce_{2,n,x}}$". Also, the algorithm randomly estimates point 1 and 2 attribute to cluster 1 and point 3 and 4 attribute to cluster 2. Then, the algorithm starts doing the first calculation of SED between points and centroids.
Squared Euclidean Distance (SED):

$$\boldsymbol{d(P,Q) = (p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2 = \sum\nolimits_{i=1}^{n} (p_i - q_i)^2}$$

For centroid one to point 1 and 2:

$$\boldsymbol{d(ce_{1,n,x}\ ,\ p_{c,1,x}) = \sum\nolimits_{i=1}^{x} (ce_{1,n,i} - p_{c,1,i})^2}$$

$$\boldsymbol{d(ce_{1,n,x}\ ,\ p_{c,2,x}) = \sum\nolimits_{i=1}^{x} (ce_{1,n,i} - p_{c,2,i})^2}$$

For centroid two to point 3 and 4:

$$\boldsymbol{d(ce_{2,n,x}\ ,\ p_{c,3,x}) = \sum\nolimits_{i=1}^{x} (ce_{2,n,i} - p_{c,3,i})^2}$$

$$\boldsymbol{d(ce_{2,n,x}\ ,\ p_{c,4,x}) = \sum\nolimits_{i=1}^{x} (ce_{2,n,i} - p_{c,4,i})^2}$$

Then, the procedure calculates the average distance in each group:

$$\boldsymbol{Average\ Distance\ of\ Group\ 1\ (avdg1) = \frac{d(ce_{1,n,x}\ ,\ p_{c,1,x}) + d(ce_{1,n,x}\ ,\ p_{c,2,x})}{2}}$$

$$\boldsymbol{Average\ Distance\ of\ Group\ 2\ (avdg2) = \frac{d(ce_{2,n,x}\ ,\ p_{c,3,x}) + d(ce_{2,n,x}\ ,\ p_{c,4,x})}{2}}$$

Based on $\boldsymbol{avdg1}$ and $\boldsymbol{avdg2}$, two centroids start moving to a new position in order to get the optimal distance in each group. The centroids' movement will change the members in each group and calculate new $\boldsymbol{avdg1}$ and $\boldsymbol{avdg2}$. After a lot of time, a set of $\boldsymbol{avdg1}$ and a set of $\boldsymbol{avdg2}$ are created, and also the optimal clusters are achieved based on optimal average distance:

$$\boldsymbol{Optimal\ Average\ Distance\ of\ Group1 = min.(avdg1)}$$

$$\boldsymbol{Optimal\ Average\ Distance\ of\ Group2 = min.(avdg2)}$$

The finally optimal centroids are captured, and their coordinates is identified with x dimensions. These coordinates is very significant because it is recognised as implying the attributes of all members in each group. In this paper, 81 traders are divided into 11 groups with an 81,000 dimensional space. The coordinates are the similarity between traders' real actions and dummy actions with different technical trading rules. Thus, the clusters' coordinates indicate and imply the trading strategies of members in each group.

Appendix B

to Chapter 2

B.1 Additional Tables

Table B.1: **Correlations Between the Price of Rebar Futures and the Spot Price by Contract**

ccode	contract_code	spot_op	spot_cp	spot_sp	dspot_dop	dspot_dcp	dspot_dsp
1	**rb0909**	0.9265	0.939	0.9338	0.5378	0.3908	0.4763
2	rb0910	0.9305	0.9402	0.9369	0.5667	0.4149	0.5309
3	**rb0911**	0.9166	0.925	0.9243	0.4916	0.3532	0.4842
4	**rb0912**	0.9007	0.9025	0.9023	0.4841	0.311	0.4332
5	**rb1001**	0.8877	0.8961	0.8948	0.407	0.2781	0.4177
6	**rb1002**	0.8535	0.8553	0.8549	0.4342	0.2326	0.3682
7	rb1003	0.8174	0.818	0.8166	0.4187	0.2665	0.3938
8	rb1004	0.722	0.7395	0.7359	0.3819	0.254	0.37
9	**rb1005**	0.5565	0.5485	0.5514	0.3978	0.2385	0.3885
10	rb1006	0.3603	0.3375	0.3442	0.4223	0.2395	0.3781
11	rb1007	0.2907	0.2716	0.2765	0.3654	0.2206	0.3593
12	rb1008	0.1374	0.1268	0.1304	0.1885	0.1339	0.2174
13	rb1009	0.1704	0.1417	0.1486	0.4139	0.2469	0.3813
14	**rb1010**	0.0938	0.0715	0.0769	0.4021	0.2516	0.3769
15	rb1011	-0.0035	-0.0212	-0.0164	0.3158	0.2746	0.3731
16	rb1012	0.2229	0.2179	0.2182	0.3809	0.3041	0.4459
17	**rb1101**	0.4894	0.4879	0.4901	0.4351	0.2278	0.3923
18	rb1102	0.6955	0.693	0.6945	0.409	0.2768	0.4104
19	rb1103	0.8601	0.8568	0.8547	0.4111	0.2797	0.3885
20	rb1104	0.9421	0.9406	0.941	0.4242	0.2702	0.3726
21	**rb1105**	0.9586	0.9545	0.9582	0.3775	0.2197	0.3307
22	rb1106	0.9598	0.9596	0.9626	0.2304	0.2213	0.3198
23	rb1107	0.8956	0.8922	0.8994	0.3026	0.1498	0.2943
24	rb1108	0.8905	0.8919	0.8951	0.3126	0.2564	0.3342
25	rb1109	0.7871	0.7876	0.7742	0.3108	0.1566	0.2302
26	**rb1110**	0.4994	0.4811	0.488	0.2963	0.0975	0.258
27	rb1111	0.7002	0.7008	0.67	0.1862	0.294	0.3371
28	rb1112	0.7979	0.7975	0.798	0.1444	0.2159	0.2219
29	**rb1201**	0.8501	0.8423	0.846	0.3312	0.234	0.301
30	rb1202	0.9114	0.9056	0.9082	0.19	0.2497	0.2571
31	rb1203	0.931	0.9262	0.9291	0.2394	0.1269	0.2192
32	rb1204	0.9502	0.9507	0.951	0.235	0.1805	0.242
33	**rb1205**	0.9523	0.9509	0.9521	0.2122	0.2282	0.2884
34	rb1206	0.9548	0.9523	0.9543	0.2551	0.2467	0.2844
35	rb1207	0.9313	0.9248	0.9273	0.2468	0.2634	0.2627
36	rb1208	0.9327	0.9324	0.9344	0.2602	0.1787	0.2361
37	rb1209	0.9355	0.9366	0.9384	0.2743	0.1552	0.2832
38	**rb1210**	0.9356	0.9343	0.9345	0.2696	0.2202	0.303
39	rb1211	0.9442	0.9487	0.9477	0.2303	0.2619	0.2997
40	rb1212	0.9737	0.9741	0.975	0.3401	0.2282	0.2988
41	**rb1301**	0.9672	0.9638	0.966	0.356	0.1323	0.3085
42	rb1302	0.956	0.9549	0.9562	0.2743	0.1489	0.2847
43	rb1303	0.9406	0.9394	0.9426	0.2379	0.1311	0.2566
44	rb1304	0.8977	0.8925	0.8932	0.3196	0.2101	0.2584
45	**rb1305**	0.8175	0.8061	0.8135	0.3328	0.1013	0.2611
46	rb1306	0.8088	0.8013	0.8076	0.2734	0.145	0.2746
47	rb1307	0.8516	0.846	0.8481	0.2888	0.1631	0.2387
48	rb1308	0.8348	0.8264	0.8352	0.2377	0.0823	0.1995
49	rb1309	0.7768	0.761	0.768	0.2343	0.1053	0.2386
50	**rb1310**	0.8015	0.7867	0.7933	0.2621	0.0668	0.2051

[a]

[a]The column Spot Opening is the correlations between the Spot price of Rebar and the Opening price of Rebar Futures. Spot Closing is the correlation between the Spot price of Rebar and the Closing Price of Rebar Futures, and Settlement similarly the correlation with the reported settlement price. The columns Spot Opening, Spot Closing, and Settlement report the correlations between the first differences of the prices. Bold-font contract-code denotes that a contract was one that was heavily traded as discussed in Section 2.3.

Table B.2: **Statistic Values of Cointegration Coefficients Between Rebar Future and Spot Prices**

contract_code	zt_sp	zt_closep	zt_openp	cv1	cv5	cv10
rb0909	-2.061824	-2.310218	-2.016986	-3.99087	-3.388401	-3.080588
rb0910	-2.136368	-2.460739	-2.211394	-3.979425	-3.382108	-3.076252
rb0911	-2.055226	-2.431218	-2.408609	-3.968035	-3.375834	-3.071926
rb0912	-2.367171	-2.664835	-2.763126	-3.960499	-3.371676	-3.069057
rb1001	-2.553358	-2.987737	-3.15173	-3.952904	-3.367481	-3.066159
rb1002	-2.214163	-2.561056	-2.841519	-3.950667	-3.366246	-3.065305
rb1003	-1.663231	-2.081258	-2.047714	-3.943452	-3.362254	-3.062547
rb1004	-0.8537756	-1.195176	-1.693503	-3.944695	-3.362942	-3.063022
rb1005	-0.0288209	-0.401354	-0.6619505	-3.941891	-3.36139	-3.061949
rb1006	-0.7650189	-0.8802948	-0.8542097	-3.942271	-3.361601	-3.062095
rb1007	-0.8133765	-0.8778396	-0.8654661	-3.94208	-3.361495	-3.062022
rb1008	-0.5969464	-0.6085895	-0.6088969	-3.942271	-3.361601	-3.062095
rb1009	-0.5704673	-0.6208844	-0.5346499	-3.942658	-3.361815	-3.062243
rb1010	-1.594402	-1.603626	-1.571321	-3.942271	-3.361601	-3.062095
rb1011	-0.7719072	-0.7649922	-0.7812673	-3.942854	-3.361923	-3.062318
rb1012	-1.227393	-1.227124	-1.231443	-3.942854	-3.361923	-3.062318
rb1101	-1.664842	-1.712773	-1.571604	-3.942271	-3.361601	-3.062095
rb1102	-2.509947	-2.484268	-2.503999	-3.943052	-3.362032	-3.062394
rb1103	-3.182515	*-3.433907*	-2.95594	-3.942271	-3.361601	-3.062095
rb1104	-3.153931	*-3.637122*	*-3.601951*	-3.942464	-3.361707	-3.062169
rb1105	***-4.698465***	***-5.779963***	***-5.168481***	-3.942658	-3.361815	-3.062243
rb1106	***-4.290554***	***-4.859574***	***-7.019799***	-3.942464	-3.361707	-3.062169
rb1107	-1.545668	-2.773187	-2.674246	-3.94208	-3.361495	-3.062022
rb1108	-3.195582	*-3.660013*	*-3.940197*	-3.943452	-3.362254	-3.062547
rb1109	-2.11182	-2.37104	-2.909051	-3.942271	-3.361601	-3.062095
rb1110	-2.181396	-2.283105	-2.176383	-3.941703	-3.361286	-3.061878
rb1111	-1.772157	-1.954097	-2.749549	-3.943654	-3.362366	-3.062624
rb1112	-1.271592	-1.227701	-2.125191	-3.943859	-3.362479	-3.062703
rb1201	-1.524608	-1.730227	-1.704761	-3.942271	-3.361601	-3.062095
rb1202	-2.066962	-2.081814	-2.868077	-3.941891	-3.36139	-3.061949
rb1203	-2.851469	-2.970309	-3.168954	-3.941703	-3.361286	-3.061878
rb1204	-2.98824	-3.108104	*-3.460228*	-3.94208	-3.361495	-3.062022
rb1205	-2.455209	-2.884923	*-3.425945*	-3.942271	-3.361601	-3.062095
rb1206	-2.746734	-2.870959	*-3.402933*	-3.941891	-3.36139	-3.061949
rb1207	-2.660377	-2.58595	-2.693344	-3.942271	-3.361601	-3.062095
rb1208	-2.69733	-2.736931	-2.921962	-3.94208	-3.361495	-3.062022
rb1209	-2.315394	-2.722481	-2.92434	-3.941891	-3.36139	-3.061949
rb1210	-2.939048	-3.343492	-3.315974	-3.942271	-3.361601	-3.062095
rb1211	*-3.36699*	*-3.45513*	*-3.869884*	-3.941891	-3.36139	-3.061949
rb1212	*-3.657959*	***-4.010996***	*-3.939469*	-3.941891	-3.36139	-3.061949
rb1301	-2.7531	-3.351752	-3.062837	-3.94208	-3.361495	-3.062022
rb1302	-2.691849	-3.151795	-3.284088	-3.941891	-3.36139	-3.061949
rb1303	-2.755022	-2.981925	*-3.443694*	-3.942271	-3.361601	-3.062095
rb1304	-2.574518	-2.763306	-2.984844	-3.942271	-3.361601	-3.062095
rb1305	-2.310214	-2.613629	-2.494753	-3.942271	-3.361601	-3.062095
rb1306	-2.605087	-2.769753	-2.925976	-3.942854	-3.361923	-3.062318
rb1307	-2.868155	-3.006962	-2.935654	-3.942854	-3.361923	-3.062318
rb1308	-2.27039	-2.503049	-2.626662	-3.942658	-3.361815	-3.062243
rb1309	-1.676116	-1.952291	-2.120736	-3.942854	-3.361923	-3.062318
rb1310	-2.419628	-2.604103	-2.589369	-3.943052	-3.362032	-3.062394

B.2 Additional Figures

Figure B.1: **Average Returns Measure**

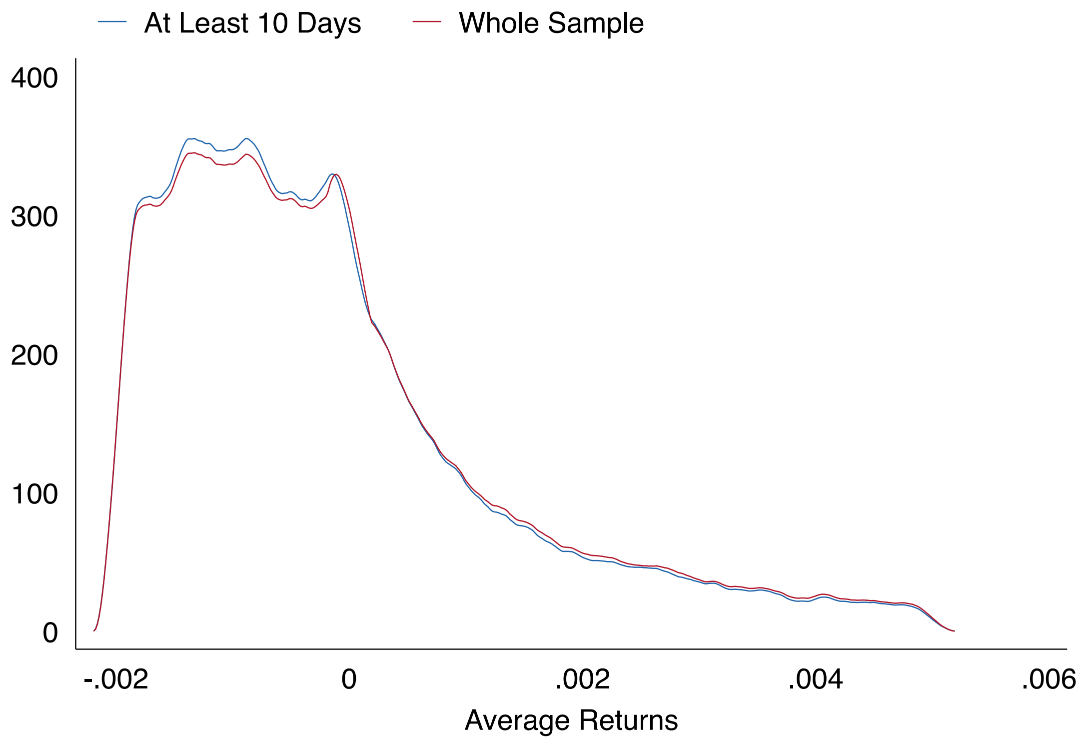
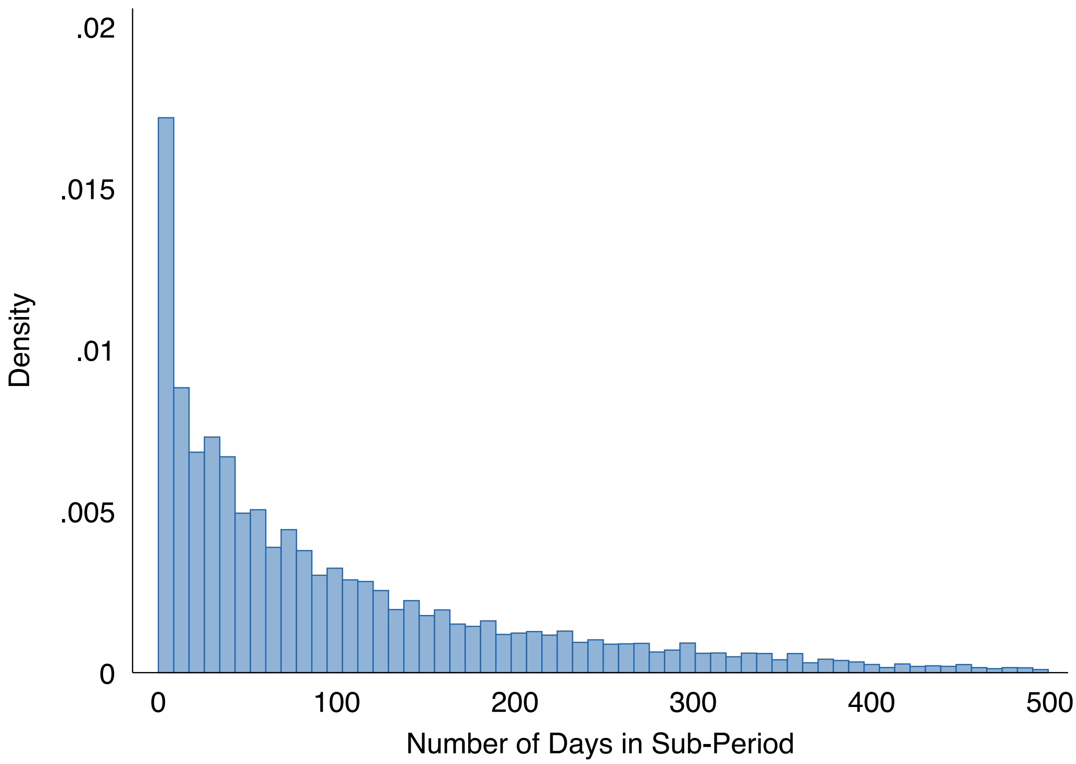
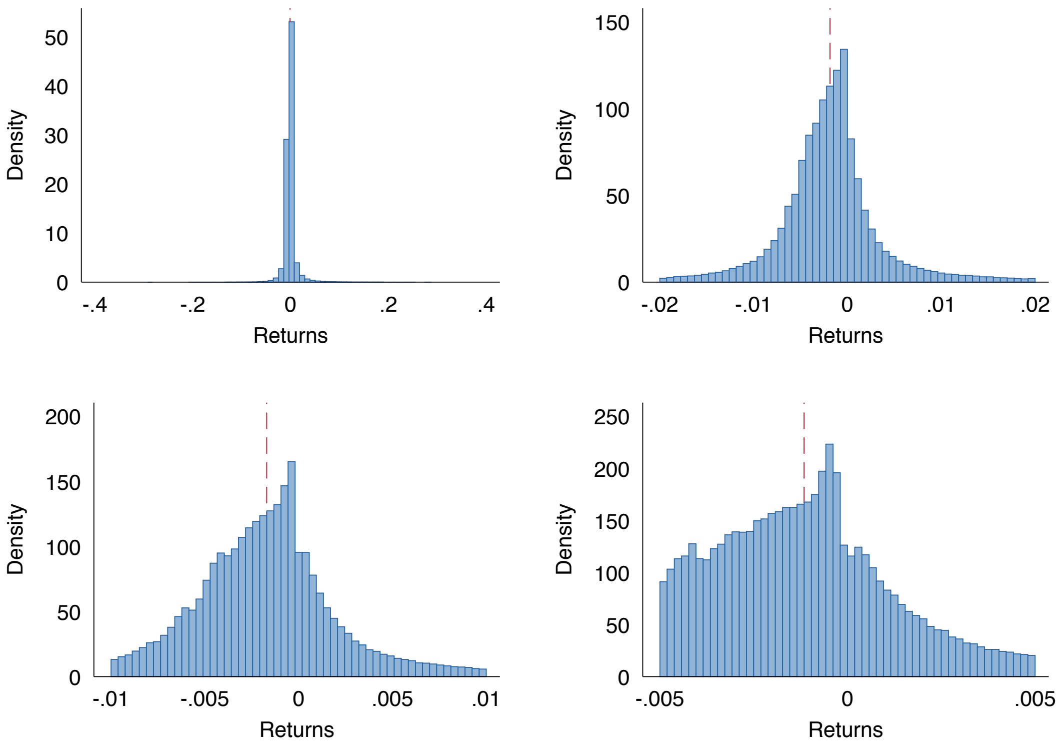


Figure B.2: **Number of Days in Trading Sub-Periods**



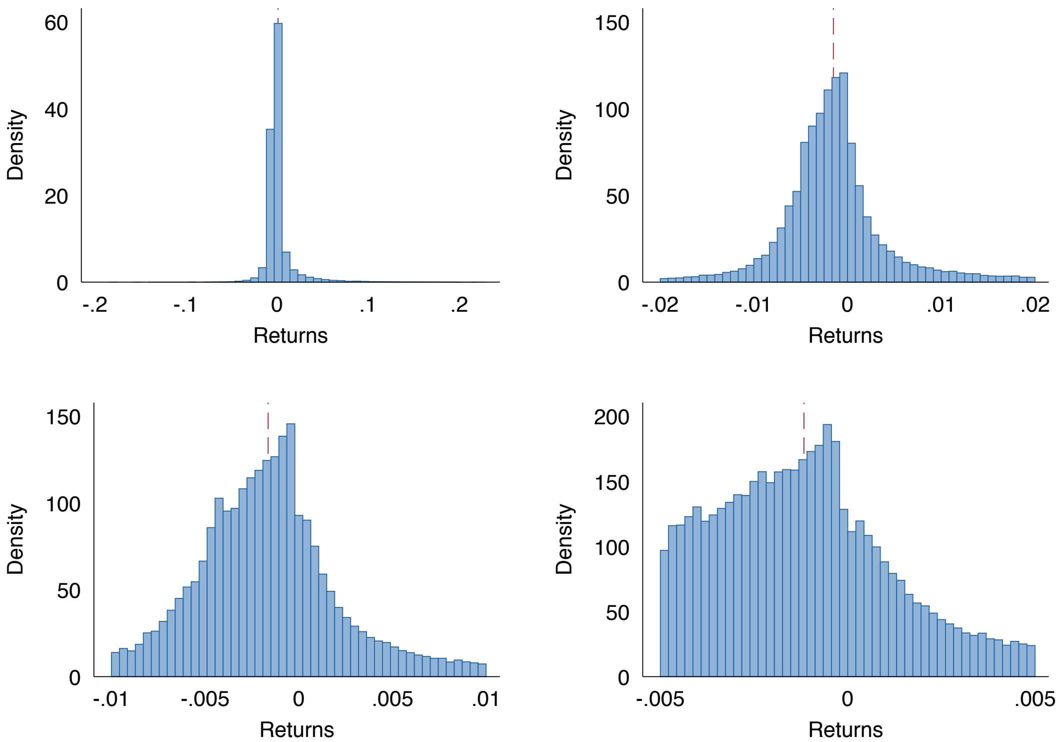
Distribution is Trucated at 500 days for clarity.

Figure B.3: **Returns, per position, Including Transaction Costs – Unconstrained Traders**



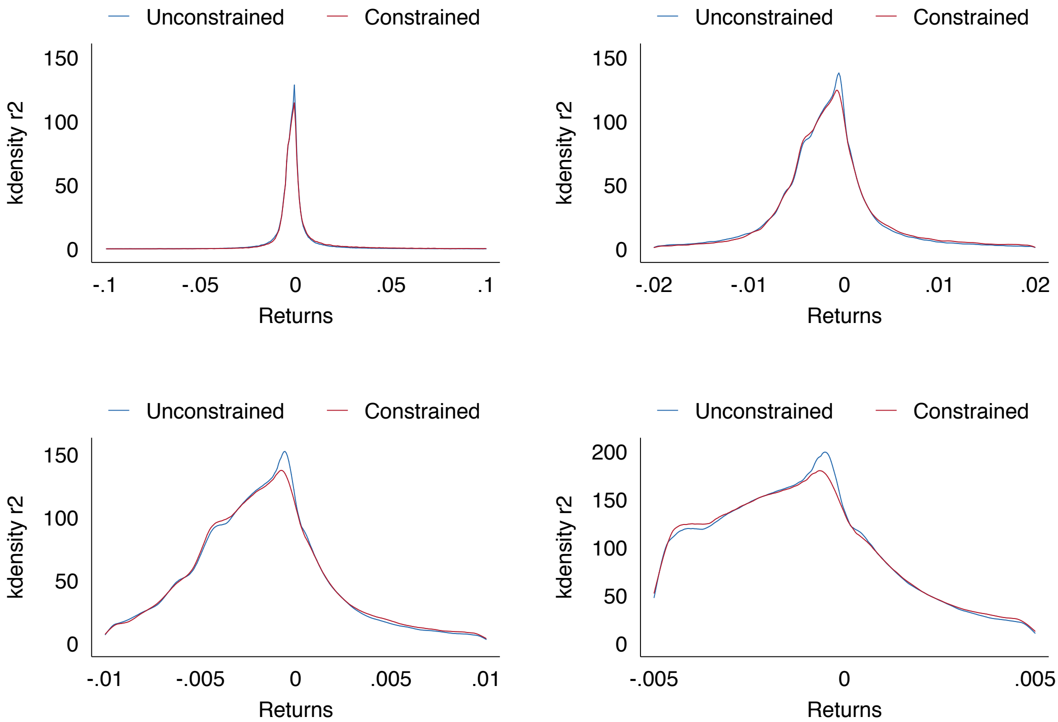
The top-right distribution is truncated for clarity, at **±0.02**, the bottom left distribution at **±0.01**, and the bottom right distribution at **±0.005**.

Figure B.4: **Returns, per position, Including Transaction Costs – Constrained Traders**



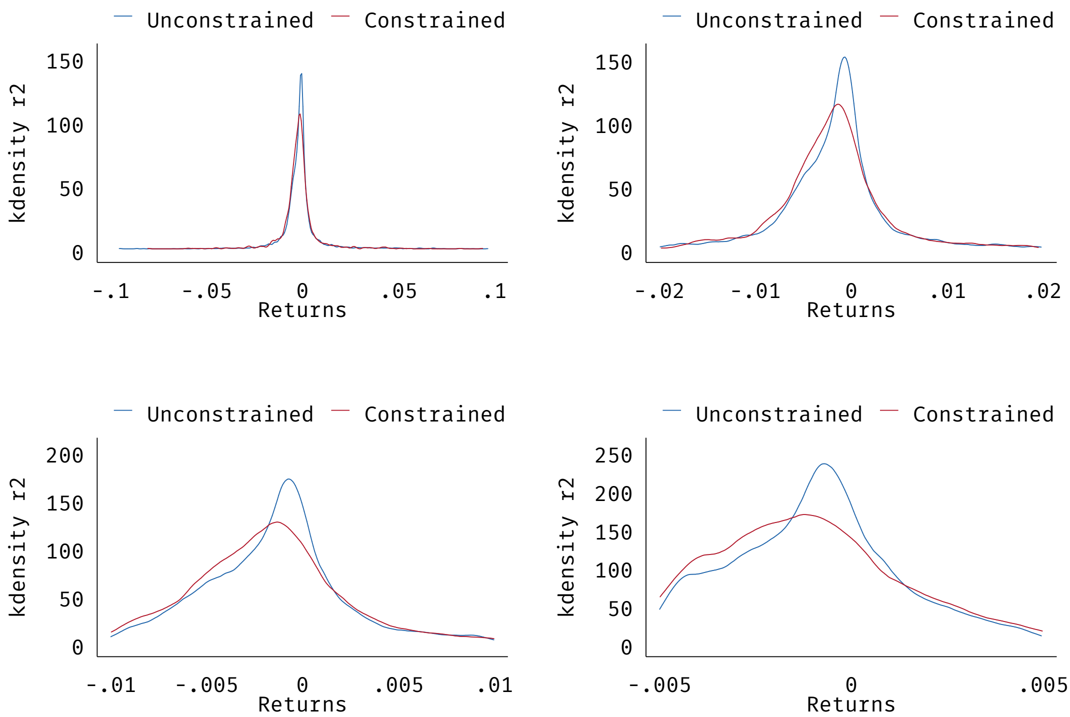
The top-right distribution is truncated for clarity, at **±0.02**, the bottom left distribution at **±0.01**, and the bottom right distribution at **±0.005**.

Figure B.5: **Comparison of Returns Distribution Constrained and Unconstrained Traders**



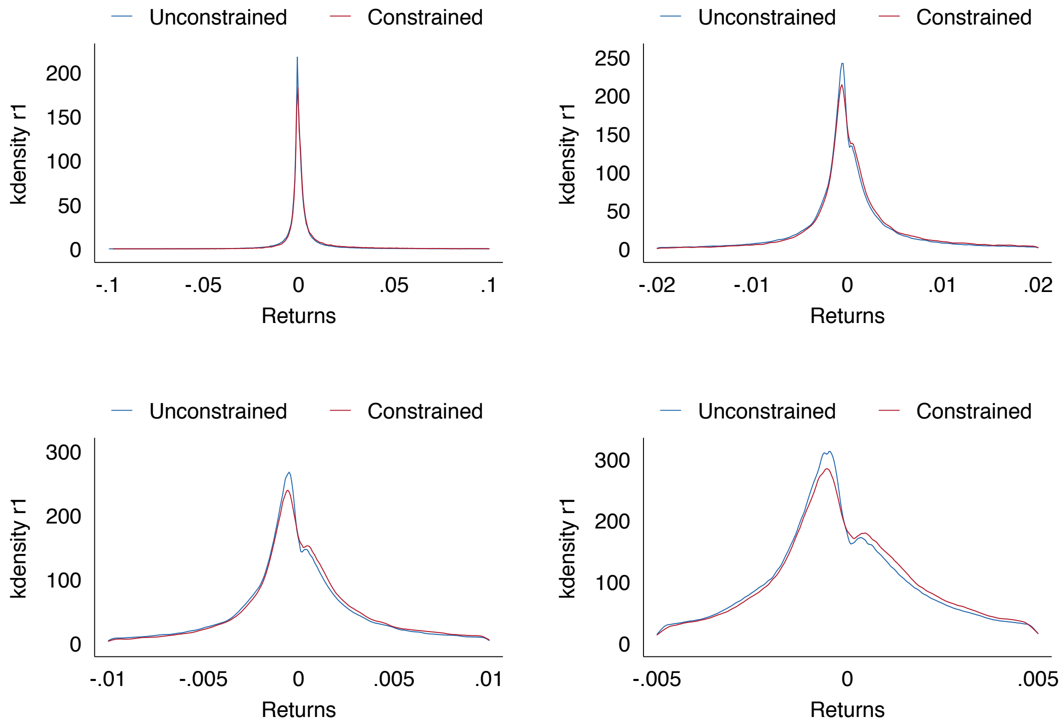
The top-right distribution is truncated for clarity, at $\pm$**0.02**, the bottom left distribution at $\pm$**0.01**, and the bottom right distribution at $\pm$**0.005**.

Figure B.6: **Comparison of Returns, After Trading Costs, Distribution Constrained and Unconstrained Traders**



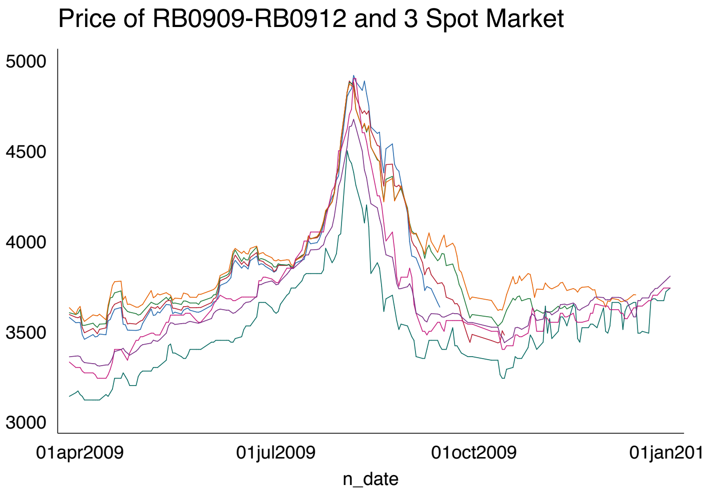
The top-right distribution is truncated for clarity, at **±0.02**, the bottom left distribution at **±0.01**, and the bottom right distribution at **±0.005**.

Figure B.7: **Comparison of Returns Distribution Constrained and Unconstrained Traders**

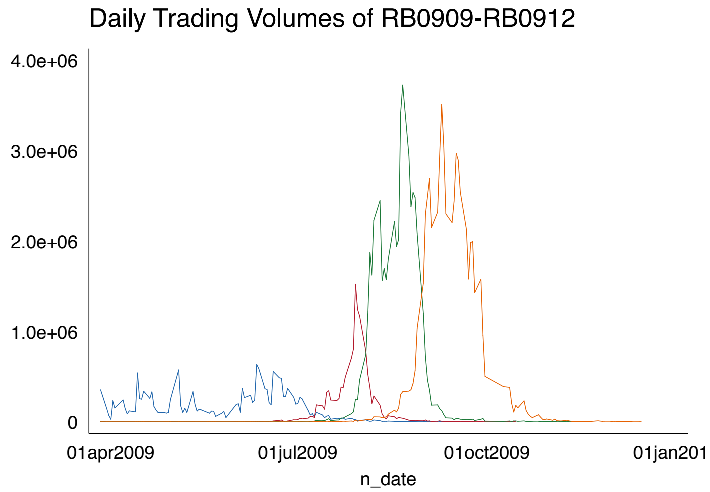


The top-right distribution is truncated for clarity, at $\pm\mathbf{0.02}$, the bottom left distribution at $\pm\mathbf{0.01}$, and the bottom right distribution at $\pm\mathbf{0.005}$.

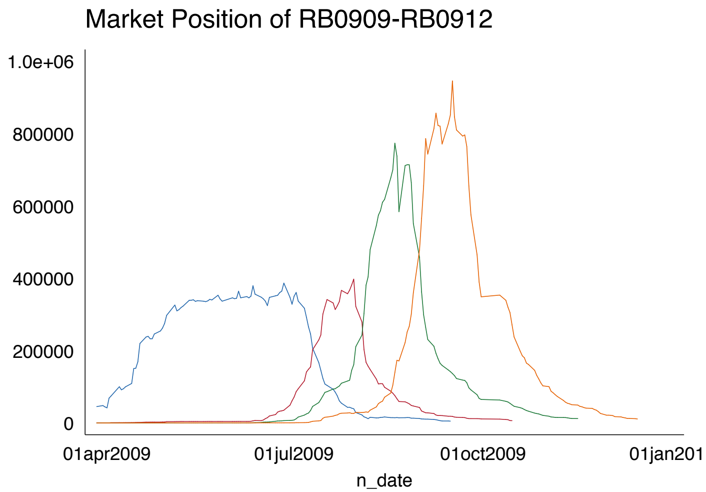
Figure B.8: **2009 Rebar Contracts**



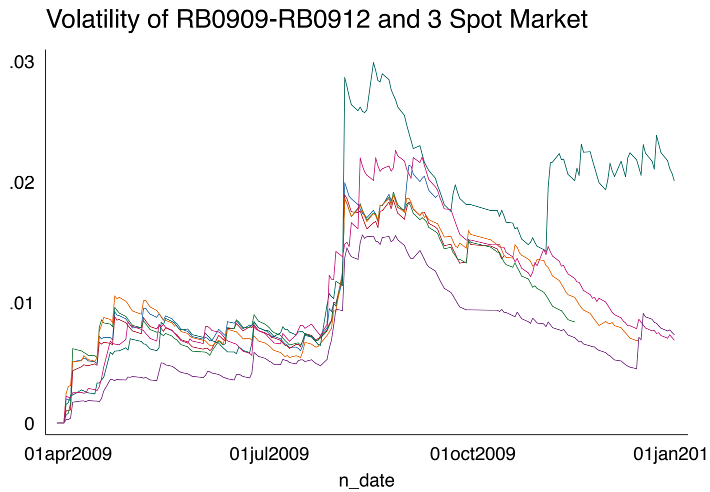
(a) **Price**



(b) **Volume**

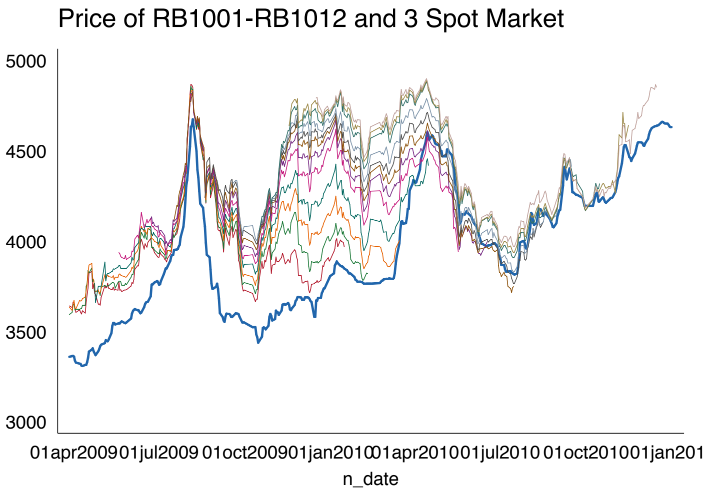


(c) **Market Position**

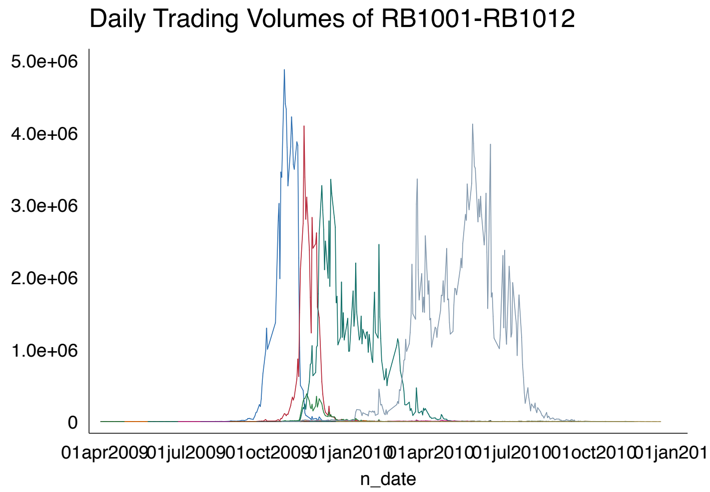


(d) **Volatility**

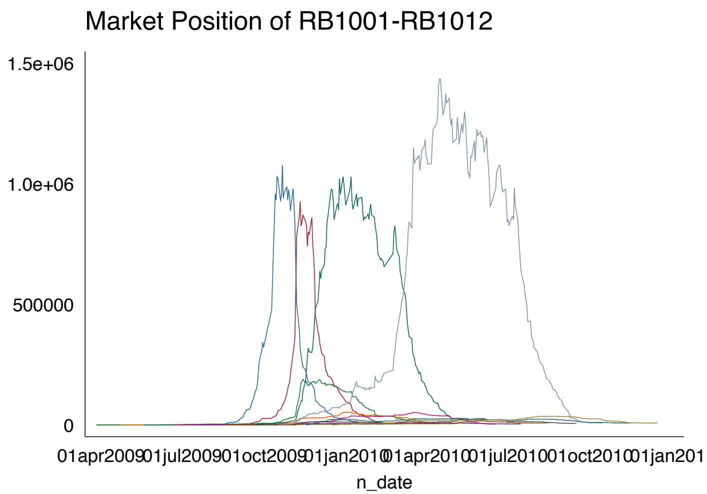
Figure B.9: **2010 Rebar Contracts**



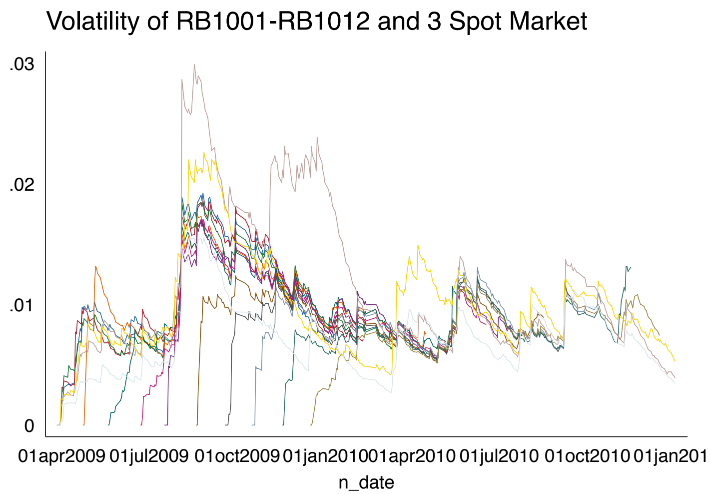
(a) **Price**



(b) **Volume**

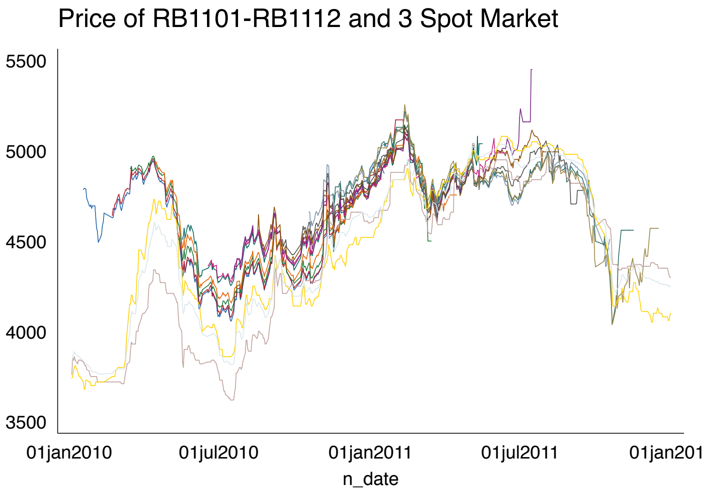


(c) **Market Position**

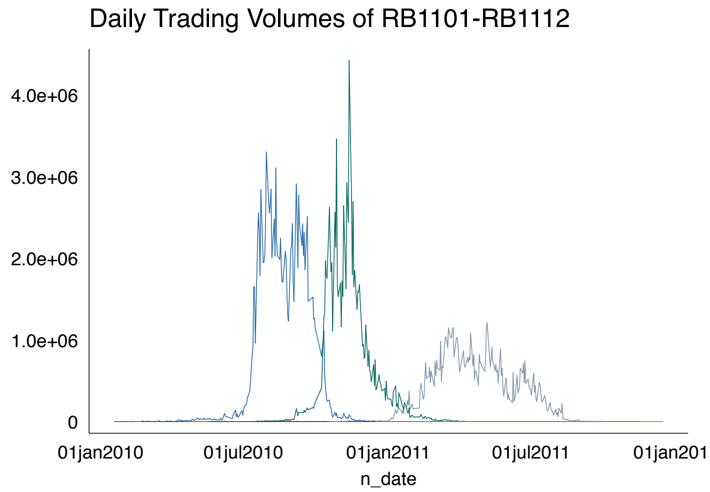


(d) **Volatility**

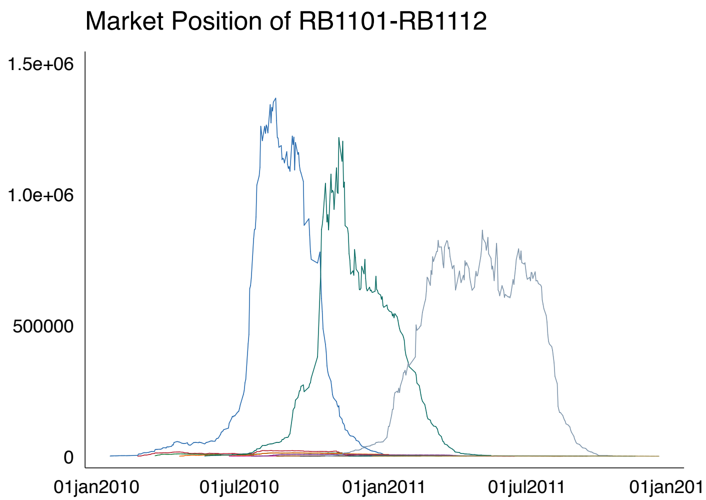
Figure B.10: **2011 Rebar Contracts**



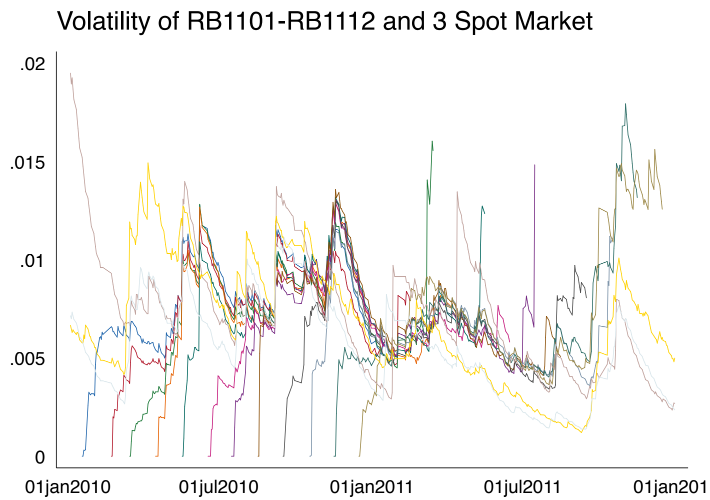
(a) **Price**



(b) **Volume**

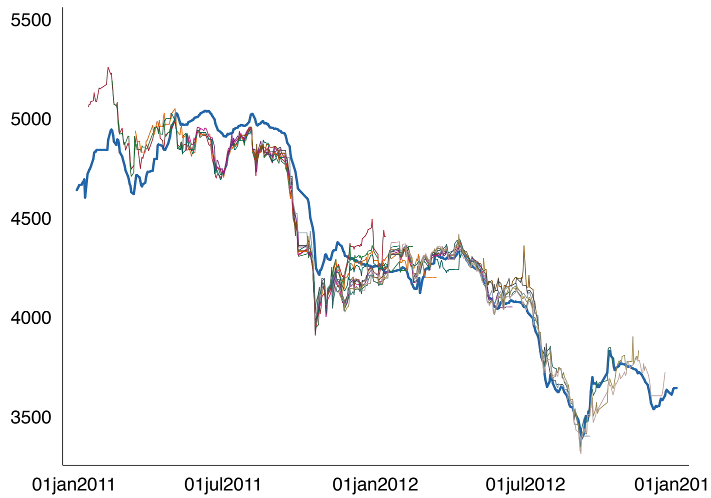


(c) **Market Position**

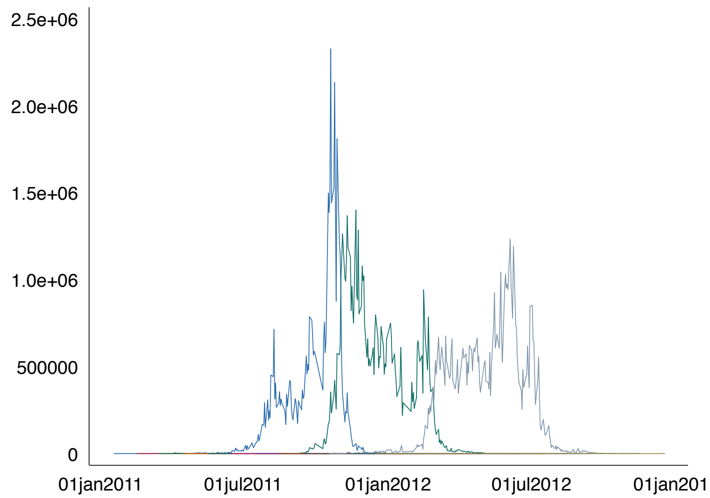


(d) **Volatility**

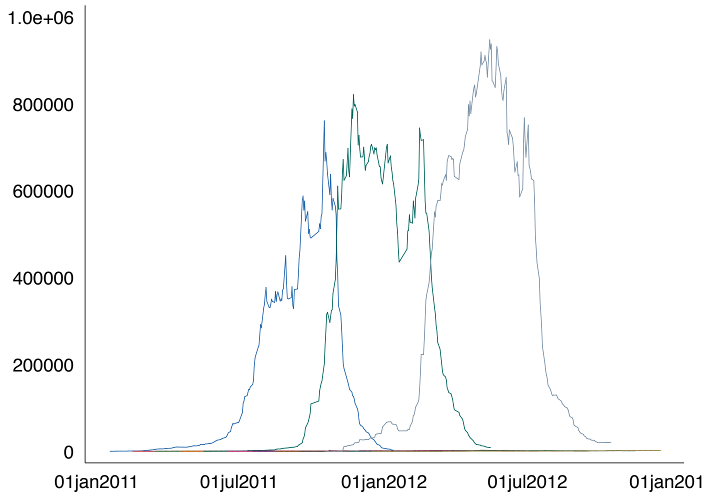
Figure B.11: **2012 Rebar Contracts**



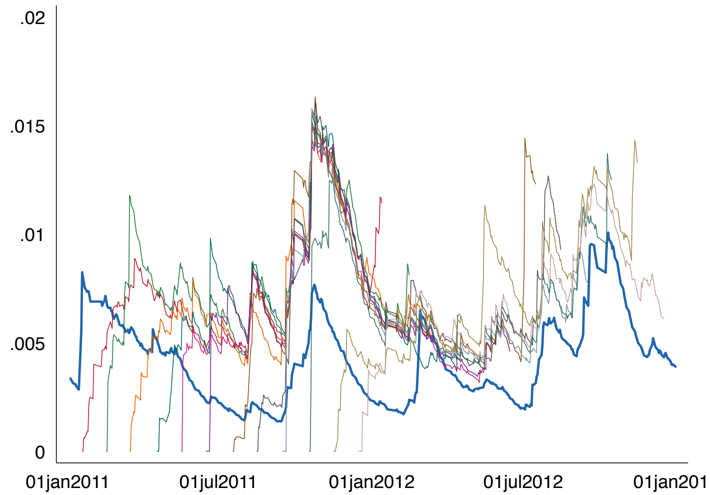
(a) **Price**



(b) **Volume**

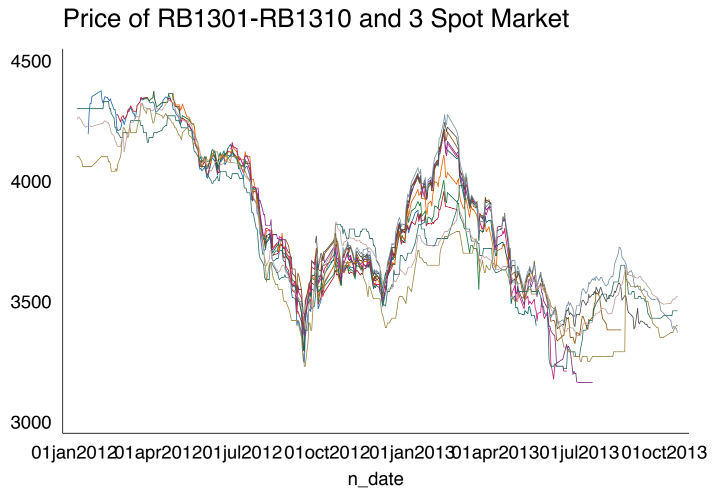


(c) **Market Position**

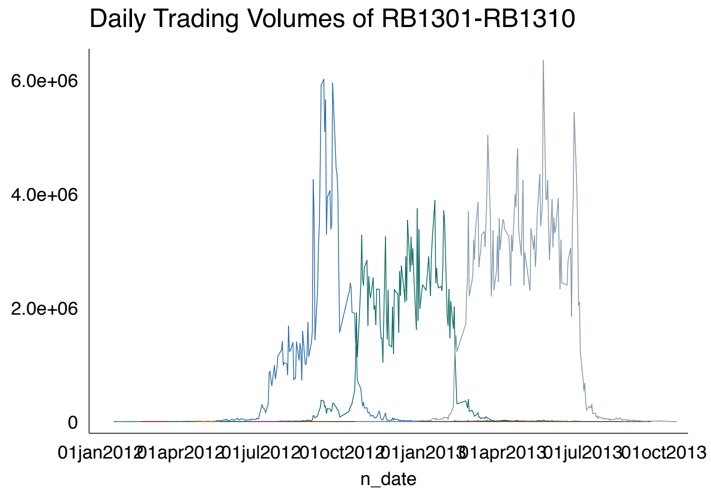


(d) **Volatility**

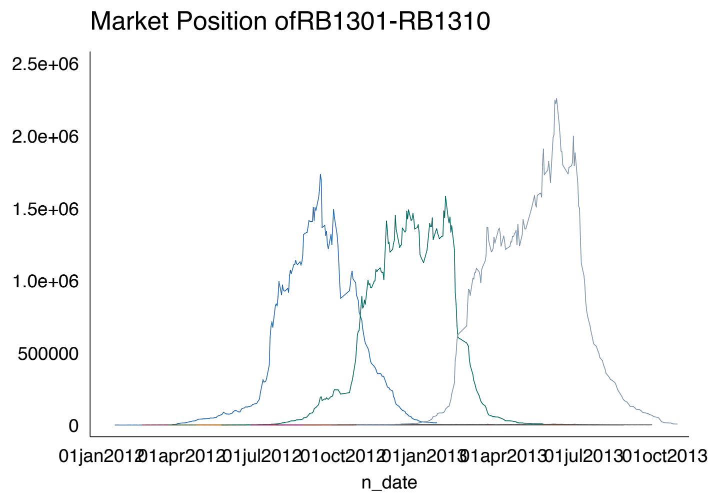
Figure B.12: **2013 Rebar Contracts**



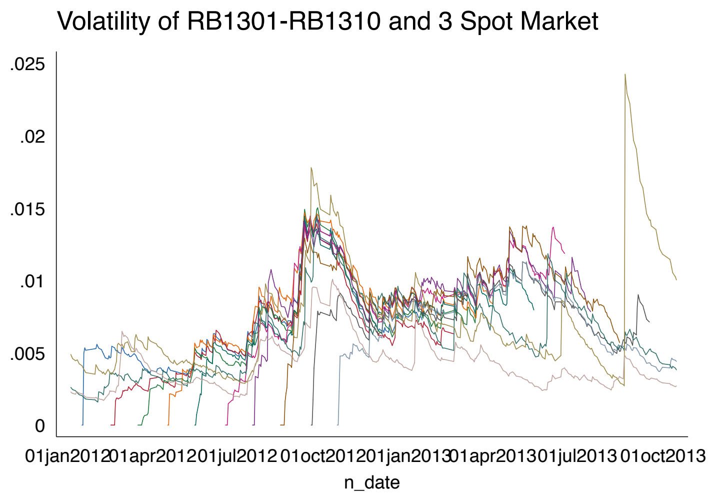
(a) **Price**



(b) **Volume**



(c) **Market Position**



(d) **Volatility**

Figure B.13: **Ratio of Trade Values in Non-Rebar Assets to Rebar Futures**

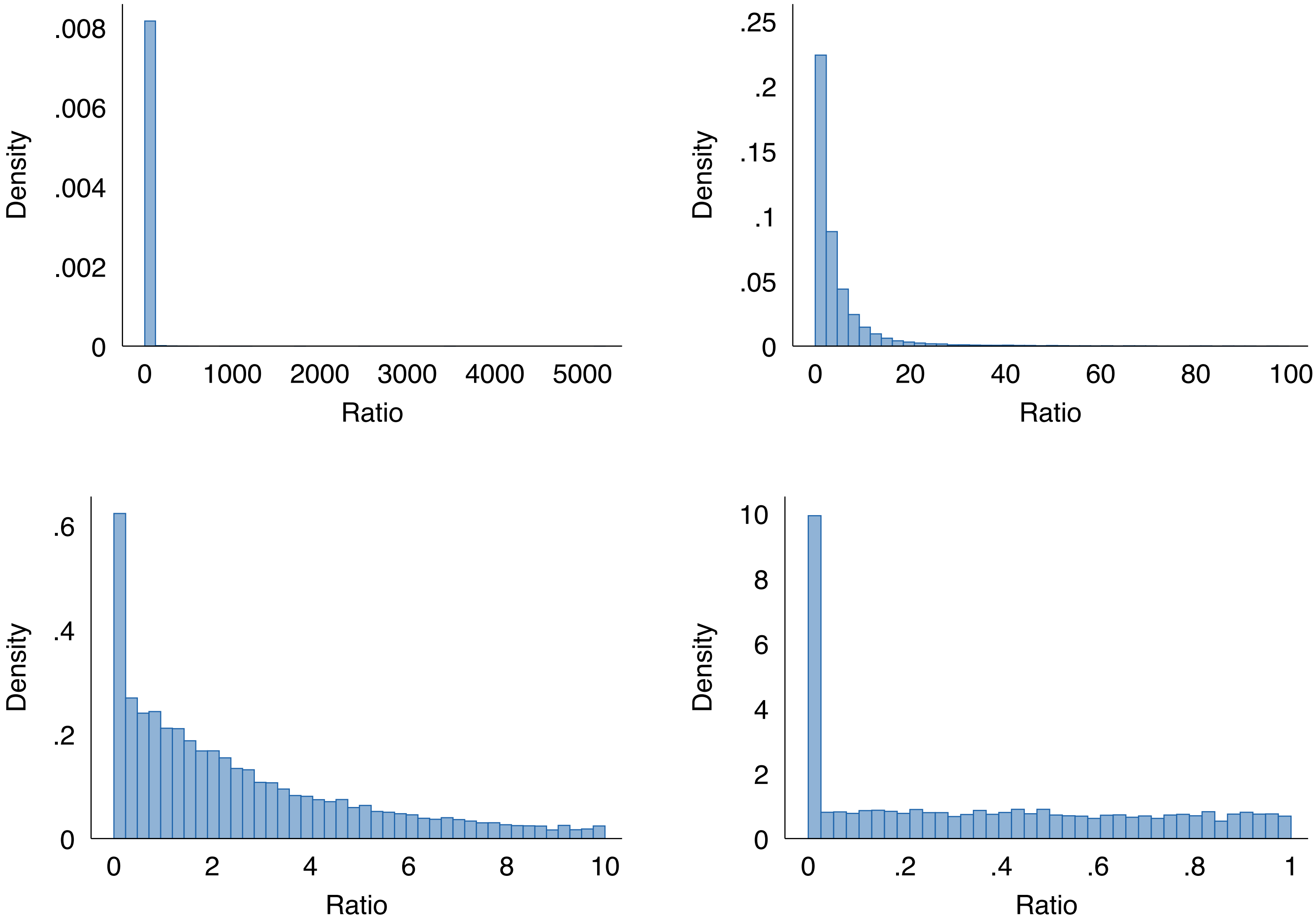


Figure B.14: **Monthly Net Steel Imports**

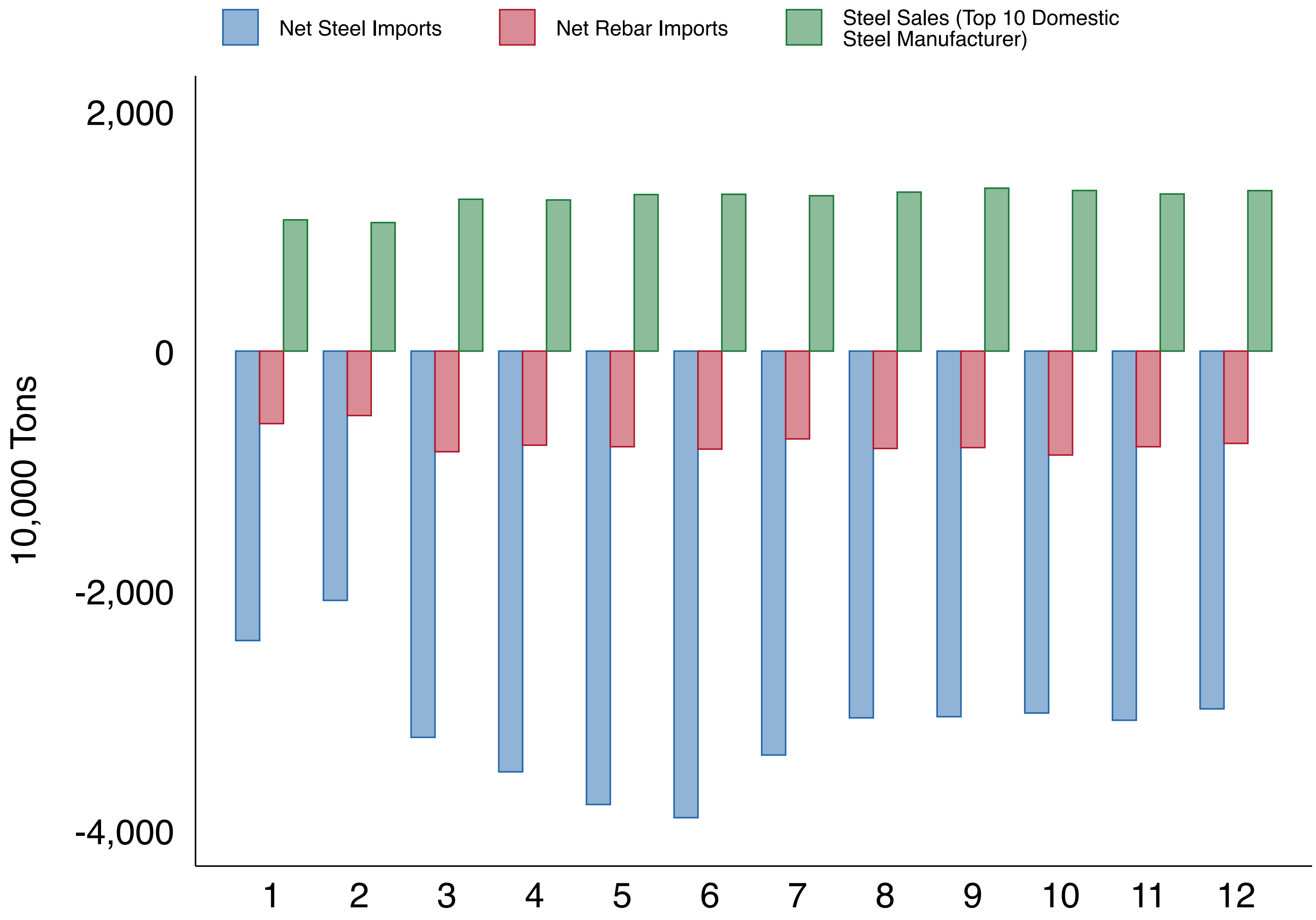


Figure B.15: **Rebar Spot Prices**

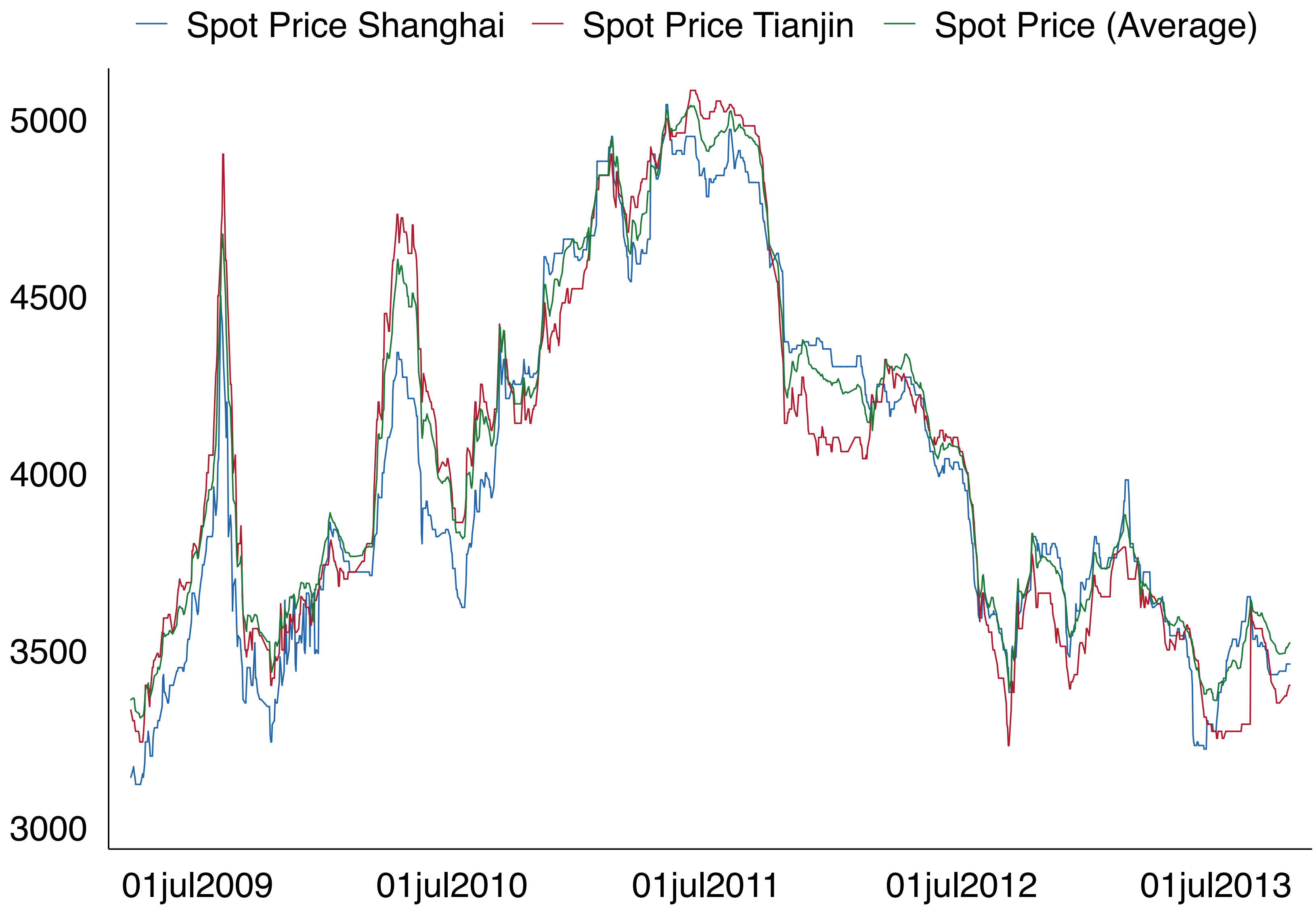


Figure B.16: **Price Volatility – Whole Sample**

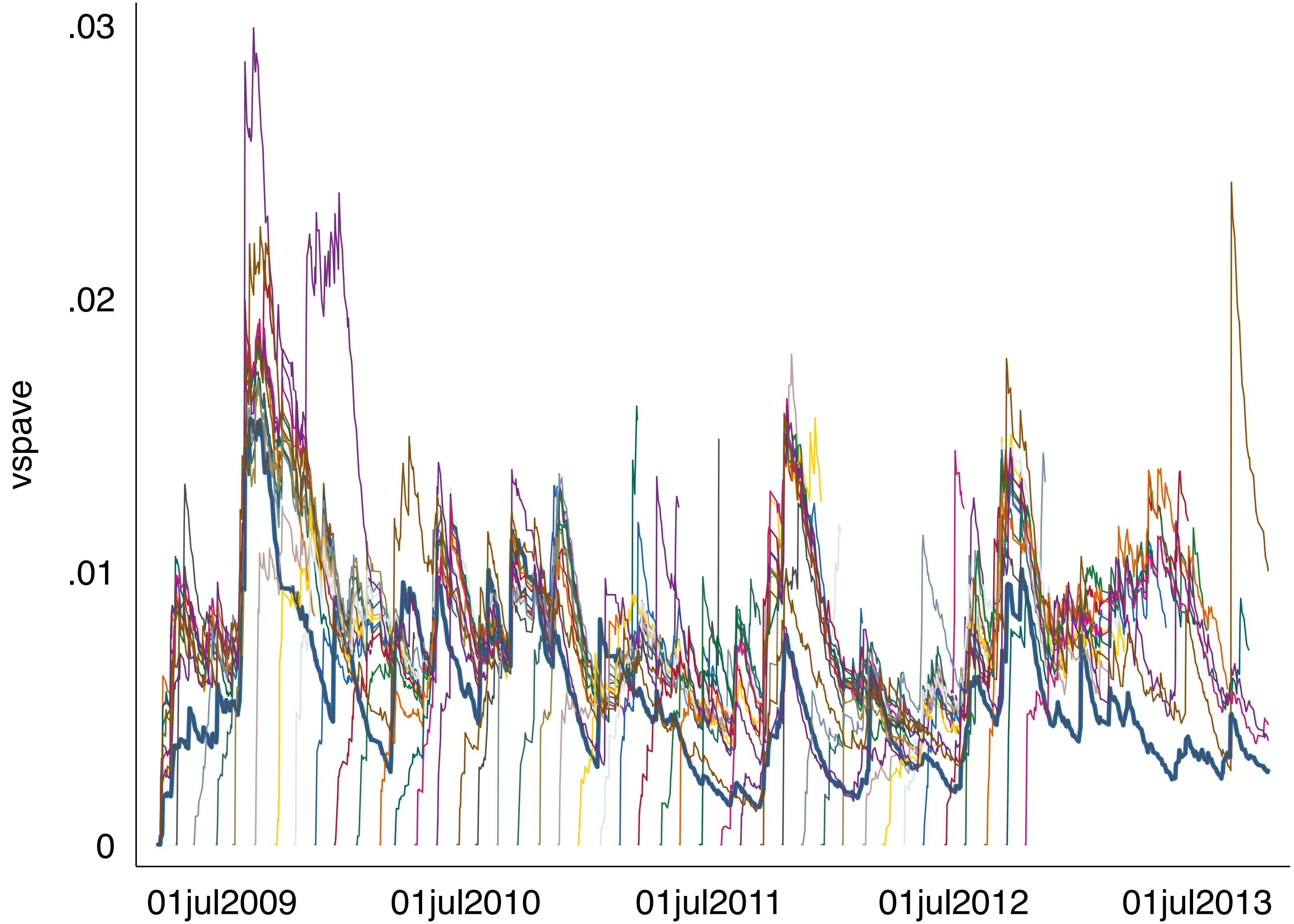
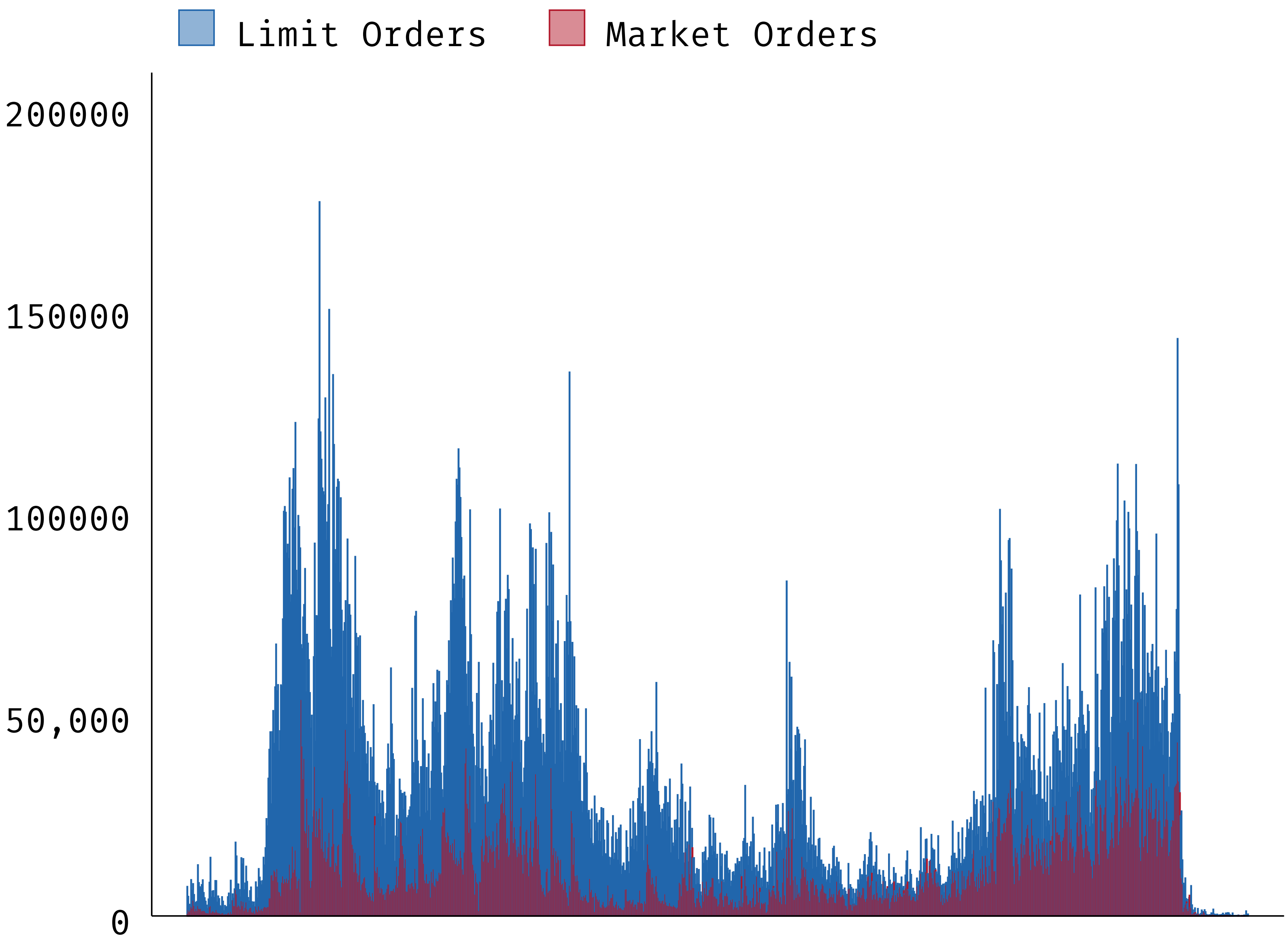


Figure B.17: **Market and Limit Orders**



B.3 Further Dataset Description

This paper focuses on Rebar futures contracts. Rebar are mainly used in construction, and thus given the rate of development in China it has been the country with the largest market for Rebar, by volume, for the past 20 years. In order to manage risk and hedging in Rebar market, Rebar futures contract were introduced on 27/03/2009 in SHANGHAI Futures Exchange (SHFE). Since then, Rebar futures contracts have become one of the most actively traded commodity futures in Chinese financial markets, and also the Rebar futures market has become the biggest metallic futures market in the world based on trading volumes and turnover.

The mechanism of Rebar futures is similar to other commodity futures. There are 12 Rebar futures contracts each starting trading in the middle of a given month. The trading time of each contract is one year. For instance, RB1210 (RB is the initial commodity code of Rebar futures) implies one Rebar futures contract which started trading in the middle of October in 2011 and delivered in the middle of October in 2012. Without holidays and weekends, the amount of trading days of each contract is around 230 days. Daily trading time, as set by SHFE is 3.75 hours per day (3.58 hours before 27/06/2010).

Trading Chinese futures, is open to anyone willing to open an account with a registered Chinese futures company (henceforth, brokerage). Currently, the total number of brokerages is 198. During the period covered by our data, the brokerage did not function as a market maker. Rather, they only executed their clients' orders on the relevant Chinese futures exchanges. After opening an account, traders may put money in their margin account and start trading all futures traded in China. By whichever means orders are received, telephone or computer, the brokerage submits orders to exchanges by computer only, and thus we record precise timings about when orders are submitted and fulfilled.

The SHFE has strict rules that only registered institutional traders can delivery of real commodities. Individual traders, who still hold any positions one month before delivery is due will have their positions liquidated. Registered institutional traders must own production capacity or a storage warehouse to be eligible to take delivery, and the Chinese Securities Regulatory Commission (CSRC) randomly or systematically checks these requirements are met in order to protect both trading parties.

Rebar futures are traded such that, the trading unit 'one hand' is equal to 10 tons of Rebar. SHFE set margin ratio based on different market situations. During the period studied, the transaction fee of Rebar futures is between **0.007%** and

0.03%. The margin ratio of Rebar futures is between **5%** and **12%**, although **7%** for almost the whole period we study. The brokerage also sets a new margin ratio, which is generally **4%** higher than the margin ratio of the SHFE. This is designed to protect traders from mandatory liquidation. Based on this two margin ratios from SHFE and brokerage, traders have two margin requirements "deadlines". Assuming a trader has open positions, they must ensure sufficient funds are in their margin account, as given by the Brokerage's margin ratio. When the money in a trader's account is lower than the margin requirement of the brokerage, the brokerage would give this trader a margin call in order to provide them the opportunity to provide additional funds as collateral. If the trader does not add funds to their margin account and the further losses are incurred such that the lower margin requirement of SHFE is violated then the SHFE will mandatorily liquidate all positions of this trader.

Our empirical work utilizes various data sets of Rebar futures. More specifically, these data sets are divided into two groups: market information and individual information. Market information is easily obtained. Some daily public data is downloaded from the official website of SHFE, such as daily price and volumes data of Rebar futures contracts. Some high frequency data is bought from GUOTAIAN and WEISHENG Statistics Companies, such as tick-by-tick data of each Rebar futures contract.

Regarding individual information, we collected full order book (transaction and entrust) of Rebar futures trading of 22,087 traders from one of the biggest Chinese futures companies (brokerages). All relevant data were obtained and are held legally by Guanqing Liu for the purpose of academic research.The data covers Rebar futures contracts from RB0909 to RB1310 (total 50 contracts). Entrust data has 4,837,819 observations and covers 22,441 traders. Transaction data has 5,652,091 observations and covers 22,087 traders.

B.4 Proof of Proposition 2

Pender (2015)[90] shows that $\boldsymbol{X \sim N(q, v)}$ with upper and lower truncation points $\boldsymbol{A}$ and $\boldsymbol{B}$ has Skewness:

$$\text{Skew}(\boldsymbol{A, B, q, v}) = \frac{\left(\frac{h_2(\chi)\psi(\chi)-h_2(\phi)\psi(\phi)}{\theta(\phi)-\theta(\chi)} - \frac{3(((\chi\psi(\chi)-\phi\psi(\phi))(\psi(\chi)-\psi(\phi)))(\theta(\phi)-\theta(\chi)))}{\theta(\phi)-\theta(\chi)} + \frac{2(\psi(\chi)-\psi(\phi))^3}{(\theta(\phi)-\theta(\chi))^3}\right)}{\left(1 - \frac{(\psi(\chi)-\psi(\phi))^2}{(\theta(\phi)-\theta(\chi))^2} + \frac{\chi\psi(\chi)-\phi\psi(\phi)}{\theta(\phi)-\theta(\chi)}\right)^{3/2}} \tag{B.1}$$

Differentiating (B.1), and setting both the mean, $\boldsymbol{m = 1}$, and the variance, $\boldsymbol{q = 1}$ with respect to $\boldsymbol{A}$ gives:

$$\frac{\partial \text{Skew}(\boldsymbol{X})}{\partial \boldsymbol{A}} = \frac{\boldsymbol{N}}{\boldsymbol{D}} = \frac{\boldsymbol{N_1 + N_2 + N_3 + N_4 + N_5 + N_6}}{(\boldsymbol{D_1 + D_2})^{3/2}} \tag{B.2}$$

Where:

$$N_1 = \frac{24e^{-2(A-1)^2-\frac{3}{2}(B-1)^2}(-e^{\frac{1}{2}(A-1)^2} + e^{\frac{1}{2}(B-1)^2})^3}{\pi^2(erf(\frac{A-1}{\sqrt{2}}) - erf(\frac{B-1}{\sqrt{2}}))^4} \qquad N_2 = \frac{2(A-2)Ae^{-(A-1)^2-\frac{1}{2}(B-1)^2}(-e^{\frac{1}{2}(A-1)^2} + e^{\frac{1}{2}(B-1)^2})}{\pi(erf(\frac{A-1}{\sqrt{2}}) - erf(\frac{B-1}{\sqrt{2}}))^2}$$

$$N_3 = \frac{3(A-2)Ae^{-A^2+A-\frac{B^2}{2}-1}(-e^{\frac{A^2}{2}+B} + e^{\frac{B^2}{2}+A})}{2\pi} \qquad N_4 = \frac{3(A-1)e^{-(A-1)^2}(A-(B-1)e^{\frac{1}{2}(A-B)(A+B-2)} - 1)}{2\pi}$$

$$N_5 = \frac{(A-1)e^{-\frac{A^2}{2}+A+B-\frac{B^2}{2}-1}(e^{\frac{1}{2}(B-1)^2}((A-2)A-2) + 2e^{\frac{1}{2}(A-1)^2})\sqrt{\frac{2}{\pi}}}{erf(\frac{A-1}{\sqrt{2}}) - erf(\frac{B-1}{\sqrt{2}})} \qquad N_6 = \frac{12\sqrt{2}(A-1)e^{\frac{1}{2}(-3)(A-1)^2-(B-1)^2}(e^{\frac{1}{2}(A-1)^2} - e^{\frac{1}{2}(B-1)^2})^2}{\pi^{3/2}(erf(\frac{A-1}{\sqrt{2}}) - erf(\frac{B-1}{\sqrt{2}}))^3} \tag{B.3}$$

$$D_1 = -\frac{2e^{-(A-1)^2-(B-1)^2}(e^{\frac{1}{2}(A-1)^2} - e^{\frac{1}{2}(B-1)^2})^2}{\pi(erf(\frac{A-1}{\sqrt{2}}) - erf(\frac{B-1}{\sqrt{2}}))^2} \qquad D_2 = \frac{((A-1)e^{-\frac{1}{2}(A-1)^2} - (B-1)e^{-\frac{1}{2}(B-1)^2})\sqrt{\frac{2}{\pi}}}{erf(\frac{B-1}{\sqrt{2}}) - erf(\frac{A-1}{\sqrt{2}})} + 1$$

We consider the relevant case where there is only lower truncation, that is $\boldsymbol{B} = \infty$, some tedious algebra gives:

$$\frac{\partial \text{Skew}}{\partial \boldsymbol{A}}\bigg|_{B=\infty} = \frac{\boldsymbol{3(A-1)^2 e^{-(A-1)^2}}}{\boldsymbol{2\pi\left(1-\frac{\sqrt{\frac{2}{\pi}}(A-1)e^{-\frac{1}{2}(A-1)^2}}{erf(\frac{A-1}{\sqrt{2}})}\right)^{3/2}}} > \boldsymbol{0} \tag{B.4}$$

Given that $\boldsymbol{A} \neq \boldsymbol{1}$, this is always positive confirming that the Skewness is almost everywhere increasing in the truncation point. $\square$

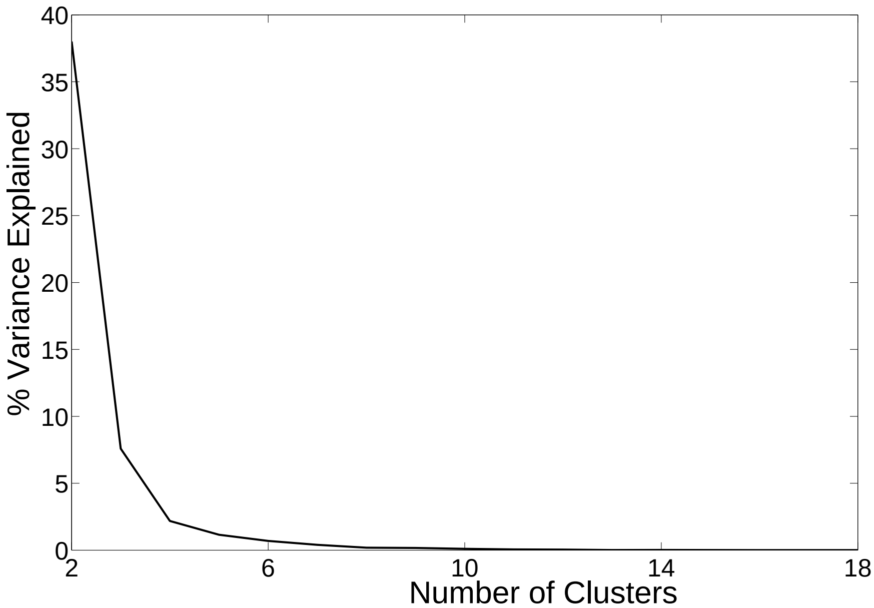
B.5 Optimal Portfolio

We initially consider empirically the composition of the Optimal Portfolio. This composition depends on the set of assets available. We obtained daily price-data for around 8,500 other financial assets and commodities available to Chinese investors. Note, that limitations on foreign investment mean that we can be confident this represents, broadly speaking, the universe of available financial investments.21 We exclude real estate assets as the implied investment size and time horizon for such investments is very different to that observed for Rebar and thus it is implausible that Rebar could be part of hedging strategy for such assets. Solving for the optimal portfolio for a broad range of time periods and time horizons we never find that margin-traded Rebar are included. This is surprising as normally one would expect, if there were no constraints on the number of assets in the portfolio, for all assets to have a positive weight. One might attribute this result to the consistent negative trend across the period but given that traders could open short or long positions this argument carries little weight.

B.6 Trading Periods Algorithm

A given sub-period may be regarded as a group of trades which are close together in time and separated from other groups of trades by a period of no trades. We identify these periods separately for each individual automatically using the k-means algorithm. This looks at the history of an individual's trading volumes (or total position size). The optimal number of clusters for each trader is determined by applying an automated version of the 'elbow' heuristic. This approach identifies the number of clusters such that adding additional clusters only has a small effect on explaining further variance. The optimal number of clusters is then the point in variance explained/clusters space which is furthest form the 45 degree line – the elbow or corner in the graph of variance explained against clusters. For example, in the case presented in **Figure B.18** this suggests that **4** is the optimal number of clusters.

Figure B.18: **Identifying the Number of Separate Trading Episodes**



[a]

[a]The vertical axis reports the proportion of variance explained by the last cluster while the horizontal axis reports the total number of clusters. Thus, in the example the second cluster explains around 40% of the variance, the third around 7% the fourth around 3%, and the 18th approximately 0% of the variance.

Appendix C

to Chapter 3

C.1 Tables

Table C.1: **Futures in Research Period:** Mung bean has delisted on 2010.03.23 and the name of strong wheat 2 changed to common wheat on 2012.11.22, thus we exclude mung bean and combine strong wheat 2 and common wheat as common wheat in the list. "–" in start date means that commodity went public before 2009.01.01 and "–" in end date means that commodity was still in the market at least on 2013.12.31. So after processing, there are 39 kinds of futures in the list with different number of contracts (NoC column).

id	**ex**	**name**	**start date**	**end date**	**NoC**
1	DCE	LLDPE	–	–	72
2	CZCE	PTA	–	–	72
3	CZCE	sugar	–	–	39
4	SHFE	silver	20120510	–	28
5	CZCE	glass	20121203	–	22
6	CZCE	rapeseed_meal	20121228	–	12
7	CZCE	rap_oil	–	–	36
8	CZCE	thermal_coal	20130926	–	13
9	DCE	soybean_meal	–	–	48
10	DCE	soybean_oil	–	–	48
11	DCE	soybean1	–	–	39
12	DCE	soybean2	–	–	36
13	SHFE	gold	–	–	70
14	CZCE	methanol	20111028	–	34
15	DCE	coking_coal	20130322	–	18
16	DCE	coke	20110415	–	40
17	CZCE	japonica_rice	20131118	–	5
18	DCE	PVC	20090525	–	64
19	SHFE	aluminum	–	–	72
20	SHFE	rebar	20090327	–	64
21	CZCE	cotton	–	–	36
22	CZCE	common_wheat	20120117	–	36
23	SHFE	pb	20110324	–	40
24	CZCE	strong_wheat1	–	–	36
25	SHFE	fuel_oil	–	–	66
26	SHFE	asphalt	20131009	–	11
27	SHFE	rubber	–	–	60
28	DCE	iron_ore	20131018	–	10
29	SHFE	copper	–	–	72
30	DCE	blockboard	20131206	–	9
31	DCE	egg	20131108	–	8
32	SHFE	wire_rod	20090327	–	64
33	SHFE	zinc	–	–	72
34	CZCE	rapeseed	20121228	–	8
35	DCE	corn	–	–	36
36	CZCE	early_indica_rice	20090420	–	32
37	DCE	m.d.fiberboard	20131206	–	9
38	DCE	palm_oil	–	–	72
39	CFFEX	HuShen300	20100416	–	48

Table C.2: **23 Selected Commodities Futures:** 8 from DCE, 8 from SHFE, and 7 from CZCE. Spot price of each commodity is sorted and collected from Bloomberg.

ex	name	NoC	Spot Price Declaration
DCE	LLDPE	72	Average of Xiamen & Lanzhou
CZCE	PTA	72	Average of North China
CZCE	sugar	39	Average of Liuzhou & Yingkou
SHFE	silver	28	Shanghai Changjiang Statistic
CZCE	rapeseed_meal	12	Port of Huangpu
CZCE	rap_oil	36	Jiangsu Province
DCE	soybean_meal	48	Average of Shandong & Liaoning Provinces
DCE	soybean_oil	48	Shandong Province
DCE	soybean2	36	Dalian
CZCE	methanol	34	Average of North China
DCE	coking_coal	18	Taiyuan
DCE	PVC	64	Shandong Province
SHFE	aluminum	72	Shanghai Changjiang Statistic
SHFE	rebar	64	National Average
CZCE	cotton	36	Beijing
CZCE	common_wheat	36	Shandong Province
SHFE	pb	40	Shanghai Changjiang Statistic
SHFE	rubber	60	Hainan Province
SHFE	copper	72	Shanghai Changjiang Statistic
SHFE	wire_rod	64	National Average
SHFE	zinc	72	Shanghai Changjiang Statistic
DCE	corn	36	Dalian
DCE	palm_oil	72	Average of South China

Table C.3: **15 Types of Macroeconomic News:** Total observations are 784 between 2009.01.01 and 2013.12.31. 1 type of index, 3 types of money, and others types are increasing percentage.

name	**detail**	**type**	**Std. of Surprise**	**Obs.**
CPI	comsumer price index	on year-on-year basis	0.0024344	60
GDP	gross domestic product	on year-on-year basis	0.0019222	60
NYL	new RMB (Yuan) Loans CNY	money	101.6033	60
PPI	producer price of industrial products	on year-on-year basis	0.0040425	55
EXP	export	on year-on-year basis	0.0762061	20
VIO	value of industrial output	on year-on-year basis	0.0123516	20
IP	industrial production	on year-on-year basis	0.0050437	60
FA	fixed assets	on year-on-year basis	0.0091471	55
M2	broad money	on year-on-year basis	0.0097988	60
IMP	import	on year-on-year basis	0.0774077	54
RS	retail sales	on year-on-year basis	0.0126228	60
BOT	balance of trade	money	8.940237	60
RSCG	retail sales of consumer goods	on year-on-year basis	0.0071302	52
FCR	foreign exchange reserve	money	77.17278	55
PMI	purchase management index	index	0.7871208	53
				784

Table C.4: **Statistics Over 26 days before and 16 days after announcement date**

x	AR	T	CAR	p
-26	0.0003	-0.25	0.0000	52%
-25	0.0000	-0.24	0.0000	52%
-24	-0.0006	-0.23	-0.0006	50%
-23	0.0000	-0.22	-0.0005	53%
-22	0.0008	-0.20	0.0003	55%
-21	-0.0001	-0.23	0.0002	51%
-20	0.0004	-0.20	0.0006	53%
-19	0.0004	-0.22	0.0010	54%
-18	-0.0003	-0.23	0.0007	51%
-17	-0.0005	-0.22	0.0002	51%
-16	0.0001	-0.22	0.0003	52%
-15	0.0000	-0.20	0.0003	50%
-14	-0.0011	-0.22	-0.0008	46%
-13	0.0001	-0.20	-0.0007	53%
-12	0.0005	-0.21	-0.0001	54%
-11	-0.0002	-0.23	-0.0003	49%
-10	-0.0010	-0.22	-0.0014	49%
-9	-0.0004	-0.22	-0.0018	52%
-8	-0.0003	-0.21	-0.0021	50%
-7	0.0000	-0.24	-0.0021	51%
-6	0.0005	-0.22	-0.0015	54%
-5	0.0007	-0.23	-0.0008	52%
-4	-0.0004	-0.23	-0.0012	49%
-3	0.0003	-0.22	-0.0009	53%
-2	0.0002	-0.22	-0.0006	54%
-1	-0.0009	-0.24	-0.0016	46%
0	0.0012	-0.24	-0.0004	58%
1	-0.0007	-0.21	-0.0011	47%
2	0.0007	-0.23	-0.0005	54%
3	0.0002	-0.22	-0.0002	51%
4	-0.0011	-0.22	-0.0013	48%
5	-0.0012	-0.20	-0.0024	49%
6	0.0000	-0.24	-0.0024	52%
7	-0.0002	-0.22	-0.0026	49%
8	0.0006	-0.22	-0.0020	53%
9	-0.0008	-0.21	-0.0028	50%
10	-0.0001	-0.23	-0.0030	50%
11	-0.0007	-0.22	-0.0036	49%
12	0.0002	-0.22	-0.0035	54%
13	0.0010	-0.24	-0.0024	56%
14	0.0001	-0.24	-0.0023	52%
15	0.0003	-0.24	-0.0020	53%
16	-0.0002	-0.22	-0.0023	52%

Table C.5: **Suitable Investigated Kinds of Futures, and the Number of Contracts in Each Futures**

ex	**name**	**NoC**
DCE	LLDPE	**60**
CZCE	PTA	**60**
CZCE	sugar	**33**
SHFE	silver	**20**
CZCE	glass	**13**
CZCE	rapeseed_meal	**7**
CZCE	rap_oil	**30**
DCE	soybean_meal	**40**
DCE	soybean_oil	**40**
DCE	soybean1	**33**
DCE	soybean2	**30**
SHFE	gold	**60**
CZCE	methanol	**26**
DCE	coking_coal	**9**
DCE	coke	**33**
DCE	PVC	**55**
SHFE	aluminum	**60**
SHFE	rebar	**57**
CZCE	cotton	**30**
CZCE	common_wheat	**30**
SHFE	pb	**33**
CZCE	strong_wheat1	**30**
SHFE	fuel_oil	**55**
SHFE	rubber	**50**
SHFE	copper	**60**
SHFE	wire_rod	**57**
SHFE	zinc	**60**
CZCE	rapeseed	**4**
DCE	corn	**30**
CZCE	early_indica_rice	**28**
DCE	palm_oil	**60**
CFFEX	HuShen300	**48**

Table C.6: **Effect of News Surprises on Daily Logarithm Returns of 23 Different Futures**

news	LLDPE	PTA	sugar	silver	rapeseed_meal	rap_oil	soybean_meal	soybean_oil	soybean2	methanol	coking_coal	PVC
CPI	-0.15	-0.06	-0.22	-0.17	0.13	0.04	-0.17	-0.14	-0.07	-0.48	-0.58	-0.29
GDP	0.42	0.45	0.22	1.53	0.40	0.07	-0.11	0.20	0.02	0.65	-0.12	0.20
NYL	0.30	0.30	0.07	0.31	0.55	0.19	0.06	0.18	0.00	0.16	-0.87	0.17
PPI	0.39	0.15	-0.23	-0.94	-0.76	-0.18	0.01	-0.04	-0.05	1.29	-0.45	0.04
EXP	-0.07	0.48	-1.18	1.38	1.15	0.19	0.72	0.20	0.40	-0.79	-9.17	0.65
VIO	0.42	0.57	0.31	-3.11	-2.37	0.00	0.14	0.13	0.06	-2.06	5.83	0.15
IP	-0.35	-0.15	-0.27	6.53	0.70	-0.12	-0.08	-0.06	-0.01	2.90	0.00	-0.06
FA	-0.04	0.29	-0.12	0.12	0.49	0.19	0.17	0.13	-0.07	-0.71	-7.10	-0.34
M2	-0.35	-0.54	-0.01	-0.62	0.03	-0.44	-0.26	-0.36	-0.37	0.34	0.20	-0.03
IMP	0.26	-0.35	0.89	-1.41	-1.35	-0.06	-0.48	0.00	-0.32	0.24	9.49	-0.56
RS	0.19	0.34	0.13	-0.05	-3.17	0.03	0.17	0.12	0.29	1.02	6.34	0.07
BOT	0.30	-0.19	1.00	-1.38	-1.21	0.13	-0.60	-0.01	-0.37	0.53	6.65	-0.37
RSCG	0.06	0.04	0.25	0.55	-0.23	-0.02	-0.03	-0.03	-0.31	-1.74	0.00	-0.16
FCR	0.10	-0.07	-0.22	-0.63	-0.50	0.15	0.20	0.26	0.47	-0.09	1.33	-0.01
PMI	0.07	0.47	0.57	0.46	1.59	-0.03	-0.03	0.03	0.03	0.04	5.95	0.06
_cons	0.03	0.03	0.05	-0.09	0.05	0.00	0.02	0.01	0.01	0.00	-0.21	0.00
N	1210	1189	1211	393	239	1211	1211	1211	1068	502	165	1102
R-sq	0.02	0.02	0.03	0.05	0.02	0.01	0.00	0.01	0.01	0.03	0.14	0.01
adR	0.00	0.01	0.01	0.01	-0.04	0.00	-0.01	-0.01	-0.01	0.00	0.06	-0.01
AIC	4156.06	3966.03	3663.66	1517.93	875.49	3489.17	4005.28	3639.16	3144.14	1531.56	563.99	3169.11
BIC	4237.64	4047.32	3745.25	1581.51	931.11	3570.75	4086.86	3720.75	3223.71	1599.06	595.05	3249.19

news	aluminum	rebar	cotton	common_wheat	pb	rubber	copper	wire_rod	zinc	corn	palm_oil	
CPI	-0.08	-0.27	-0.16	0.01	-0.14	-0.40	-0.06	-0.69	-0.12	0.18	-0.22	
GDP	0.17	0.33	0.09	0.26	0.77	1.07	0.33	0.99	0.25	0.00	0.19	
NYL	0.08	-0.14	0.02	0.21	0.39	0.15	0.07	0.01	-0.05	0.14	0.21	
PPI	0.17	-0.03	-0.10	-0.01	-0.29	0.34	0.31	0.06	0.41	0.06	-0.05	
EXP	-0.45	0.16	0.16	0.07	-0.44	0.45	0.15	-0.30	0.07	0.39	0.20	
VIO	0.17	0.11	0.28	0.01	0.86	0.24	0.40	0.57	0.41	0.06	0.21	
IP	-0.02	0.01	0.02	-0.01	-0.58	-0.20	-0.13	0.16	-0.25	0.03	-0.02	
FA	-0.01	0.19	0.05	-0.03	0.25	0.41	0.35	0.23	0.54	-0.01	0.05	
M2	-0.23	0.27	-0.20	-0.20	-0.29	0.01	-0.43	0.71	-0.40	-0.14	-0.38	
IMP	0.65	-0.05	-0.09	0.00	0.40	-0.19	0.43	0.34	0.54	-0.27	0.04	
RS	0.04	0.12	0.25	0.04	-0.74	0.03	0.09	0.57	0.10	0.13	0.12	
BOT	0.62	-0.08	-0.19	-0.09	0.87	-0.04	0.45	0.39	0.58	-0.35	-0.02	
RSCG	-0.11	0.00	0.03	-0.06	0.14	0.47	0.16	-0.37	0.03	-0.08	-0.02	
FCR	0.16	0.19	0.19	-0.16	0.02	0.51	0.33	-1.63	0.46	-0.01	0.38	
PMI	-0.19	0.10	0.11	0.11	-0.24	0.31	-0.38	0.04	-0.36	0.08	0.06	
_cons	0.01	0.00	0.04	0.04	-0.05	0.04	0.06	0.02	0.02	0.04	0.01	
N	1211	1134	1211	884	595	1210	1210	639	1210	1211	1210	
R-sq	0.01	0.01	0.01	0.00	0.03	0.02	0.02	0.03	0.02	0.01	0.01	
adR	0.00	-0.01	-0.01	-0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	
AIC	2976.52	3298.48	3625.18	2569.02	1725.53	4710.93	4339.79	2449.16	4197.61	2224.26	3984.67	
BIC	3058.11	3379.01	3706.77	2645.57	1795.74	4792.50	4421.37	2520.52	4279.19	2305.85	4066.25	

Table C.7: **Percentage of number of Affected Contracts for Logarithm Returns of Daily Settlement Price Regressions**

lrsp																			
nid	**NoC1**	**CPI**	**GDP**	**NYL**	**PPI**	**EXP**	**VIO**	**IP**	**FA**	**M2**	**IMP**	**RS**	**BOT**	**RSCG**	**FCR**	**PMI**	**_cons**	**NoC3**	**P2**
LLDPE	60	28%	43%	18%	27%	15%	33%	35%	32%	23%	18%	35%	18%	27%	22%	22%	0%	**16**	**26%**
PTA	60	32%	57%	48%	28%	33%	62%	63%	50%	40%	35%	53%	30%	43%	32%	33%	0%	**26**	**43%**
sugar	33	18%	24%	21%	30%	36%	33%	30%	18%	12%	42%	27%	30%	45%	15%	15%	9%	**9**	**27%**
silver	20	35%	20%	15%	25%	35%	60%	85%	65%	50%	20%	60%	35%	40%	50%	25%	0%	**8**	**41%**
glass	13	85%	77%	23%	23%	69%	69%	85%	62%	23%	85%	62%	54%	46%	31%	69%	0%	**7**	**57%**
rapeseed_meal	7	0%	14%	29%	0%	29%	29%	57%	29%	14%	29%	14%	29%	43%	29%	57%	0%	**2**	**27%**
rap_oil	30	30%	57%	20%	23%	27%	50%	57%	40%	30%	20%	40%	17%	47%	20%	10%	13%	**10**	**32%**
soybean_meal	40	18%	33%	8%	20%	33%	53%	48%	28%	33%	35%	40%	28%	33%	23%	18%	3%	**12**	**30%**
soybean_oil	40	33%	55%	15%	25%	33%	58%	53%	30%	25%	28%	40%	28%	48%	25%	13%	8%	**13**	**34%**
soybean1	33	12%	15%	24%	15%	27%	36%	30%	12%	33%	24%	24%	24%	21%	18%	9%	0%	**7**	**22%**
soybean2	30	20%	47%	23%	30%	17%	50%	43%	37%	27%	23%	40%	17%	50%	27%	7%	0%	**9**	**30%**
gold	60	23%	42%	38%	40%	23%	40%	57%	25%	40%	27%	30%	27%	57%	38%	33%	0%	**22**	**36%**
methanol	26	15%	38%	12%	23%	15%	38%	42%	23%	12%	15%	31%	15%	27%	8%	15%	0%	**6**	**22%**
coking_coal	9	44%	56%	0%	33%	33%	33%	33%	67%	44%	44%	44%	33%	22%	11%	44%	56%	**3**	**36%**
coke	33	27%	45%	21%	15%	30%	45%	39%	36%	30%	30%	33%	27%	27%	30%	6%	21%	**10**	**30%**
PVC	55	36%	51%	24%	31%	20%	36%	42%	42%	25%	16%	40%	15%	40%	25%	16%	0%	**17**	**31%**
aluminum	60	17%	35%	30%	13%	38%	33%	35%	30%	28%	47%	35%	38%	38%	25%	35%	12%	**19**	**32%**
rebar	57	47%	53%	44%	35%	35%	53%	44%	54%	25%	39%	67%	37%	61%	30%	16%	7%	**24**	**43%**
cotton	30	33%	27%	23%	37%	23%	40%	50%	30%	27%	23%	43%	20%	43%	20%	20%	20%	**9**	**31%**
common_wheat	30	23%	30%	13%	27%	23%	43%	37%	33%	20%	23%	30%	20%	30%	27%	20%	7%	**8**	**27%**
pb	33	24%	58%	27%	18%	33%	42%	45%	36%	30%	30%	42%	36%	42%	9%	27%	0%	**11**	**34%**
strong_wheat1	30	13%	23%	33%	30%	40%	33%	33%	10%	30%	43%	37%	40%	33%	30%	7%	13%	**9**	**29%**
fuel_oil	55	24%	36%	22%	18%	29%	33%	47%	33%	18%	25%	22%	27%	38%	27%	7%	0%	**15**	**27%**
rubber	50	44%	56%	26%	30%	26%	52%	52%	28%	26%	28%	42%	24%	48%	26%	24%	0%	**18**	**35%**
copper	60	40%	47%	20%	30%	38%	42%	40%	42%	20%	30%	33%	27%	35%	25%	23%	8%	**20**	**33%**
wire_rod	57	28%	19%	23%	32%	21%	39%	28%	28%	25%	21%	32%	21%	35%	19%	18%	2%	**15**	**26%**
zinc	60	35%	38%	27%	38%	33%	57%	50%	50%	27%	33%	45%	35%	32%	40%	22%	3%	**22**	**37%**
rapeseed	4	0%	50%	25%	0%	75%	75%	100%	50%	0%	75%	50%	75%	25%	0%	0%	0%	**2**	**40%**
corn	30	23%	43%	20%	30%	53%	43%	37%	40%	30%	47%	40%	53%	50%	27%	13%	0%	**11**	**37%**
early_indica_rice	28	14%	25%	36%	32%	36%	46%	39%	36%	25%	36%	36%	32%	25%	36%	32%	7%	**9**	**32%**
palm_oil	60	27%	33%	25%	23%	30%	37%	42%	35%	37%	28%	28%	30%	28%	23%	7%	7%	**17**	**29%**
HuShen300	48	42%	44%	33%	27%	19%	25%	15%	17%	27%	29%	31%	44%	13%	23%	35%	4%	**14**	**28%**
NoC2	**1241**	**359**	**504**	**318**	**336**	**369**	**536**	**542**	**429**	**342**	**375**	**470**	**358**	**471**	**321**	**255**	**62**		
P1	N/A	**29%**	**41%**	**26%**	**27%**	**30%**	**43%**	**44%**	**35%**	**28%**	**30%**	**38%**	**29%**	**38%**	**26%**	**21%**	**5%**		

Table C.8: **Percentage of number of Affected Contracts for Percentage Change in Daily Total Trading Volumes Regressions**

ctv																			
nid	**NoC1**	**CPI**	**GDP**	**NYL**	**PPI**	**EXP**	**VIO**	**IP**	**FA**	**M2**	**IMP**	**RS**	**BOT**	**RSCG**	**FCR**	**PMI**	**_cons**	**NoC3**	**P2**
LLDPE	60	15%	33%	12%	23%	12%	40%	38%	33%	13%	10%	35%	10%	43%	18%	17%	57%	**14**	**24%**
PTA	60	23%	32%	13%	23%	18%	35%	42%	42%	27%	20%	33%	20%	43%	25%	17%	73%	**17**	**28%**
sugar	33	30%	15%	24%	18%	33%	30%	33%	24%	24%	33%	12%	30%	30%	12%	24%	82%	**8**	**25%**
silver	20	35%	60%	10%	15%	20%	60%	60%	50%	10%	20%	50%	20%	60%	35%	20%	85%	**7**	**35%**
glass	13	23%	31%	23%	46%	38%	31%	46%	38%	23%	38%	38%	46%	31%	23%	23%	77%	**4**	**33%**
rapeseed_meal	7	57%	43%	29%	57%	29%	43%	43%	57%	43%	43%	43%	14%	43%	71%	29%	57%	**3**	**43%**
rap_oil	30	37%	27%	13%	33%	37%	37%	47%	23%	13%	33%	40%	33%	30%	17%	17%	67%	**9**	**29%**
soybean_meal	40	30%	25%	18%	38%	18%	33%	35%	38%	28%	15%	25%	18%	35%	30%	15%	73%	**11**	**27%**
soybean_oil	40	28%	28%	20%	28%	13%	30%	28%	28%	23%	13%	38%	13%	33%	13%	15%	68%	**9**	**23%**
soybean1	33	6%	27%	18%	15%	15%	21%	24%	24%	15%	12%	18%	12%	27%	21%	21%	85%	**6**	**19%**
soybean2	30	27%	43%	13%	30%	13%	43%	43%	30%	10%	23%	33%	20%	33%	30%	23%	50%	**8**	**28%**
gold	60	32%	38%	23%	32%	20%	37%	35%	33%	25%	17%	38%	18%	40%	28%	25%	67%	**18**	**29%**
methanol	26	23%	35%	12%	42%	19%	38%	38%	35%	8%	19%	35%	19%	46%	15%	12%	50%	**7**	**26%**
coking_coal	9	11%	33%	22%	0%	33%	67%	44%	56%	44%	44%	56%	33%	56%	33%	11%	44%	**3**	**36%**
coke	33	3%	33%	15%	15%	21%	27%	33%	30%	24%	15%	33%	15%	45%	27%	24%	45%	**8**	**24%**
PVC	55	18%	25%	18%	33%	24%	27%	36%	29%	13%	24%	33%	20%	35%	15%	20%	55%	**14**	**25%**
aluminum	60	22%	37%	13%	25%	17%	27%	30%	28%	20%	17%	40%	15%	23%	20%	25%	83%	**14**	**24%**
rebar	57	32%	32%	19%	30%	23%	37%	39%	26%	16%	23%	39%	21%	33%	26%	28%	81%	**16**	**28%**
cotton	30	30%	23%	17%	37%	33%	33%	27%	47%	17%	33%	40%	37%	37%	33%	27%	93%	**9**	**31%**
common_wheat	30	17%	30%	20%	23%	23%	17%	23%	27%	17%	30%	30%	20%	33%	23%	33%	60%	**7**	**24%**
pb	33	9%	36%	18%	18%	27%	39%	36%	36%	12%	24%	30%	21%	24%	30%	15%	21%	**8**	**25%**
strong_wheat1	30	20%	27%	10%	20%	10%	20%	17%	13%	10%	10%	23%	7%	20%	10%	10%	93%	**5**	**15%**
fuel_oil	55	22%	38%	20%	18%	13%	40%	42%	38%	20%	9%	40%	9%	35%	25%	16%	69%	**14**	**26%**
rubber	50	20%	38%	16%	22%	12%	40%	42%	28%	22%	10%	26%	12%	30%	32%	18%	82%	**12**	**25%**
copper	60	25%	38%	32%	25%	17%	37%	27%	28%	23%	20%	38%	15%	28%	30%	22%	88%	**16**	**27%**
wire_rod	57	25%	39%	18%	32%	23%	26%	37%	32%	19%	23%	39%	19%	26%	25%	21%	51%	**15**	**27%**
zinc	60	30%	20%	8%	23%	30%	25%	22%	23%	13%	28%	37%	28%	13%	13%	23%	88%	**14**	**23%**
rapeseed	4	0%	75%	25%	0%	25%	50%	50%	75%	25%	50%	25%	50%	25%	25%	25%	50%	**1**	**35%**
corn	30	33%	37%	20%	30%	37%	30%	27%	43%	17%	33%	37%	40%	33%	27%	0%	83%	**9**	**30%**
early_indica_rice	28	21%	36%	18%	25%	32%	29%	43%	46%	18%	29%	46%	29%	43%	32%	11%	75%	**9**	**30%**
palm_oil	60	18%	22%	10%	25%	20%	32%	33%	27%	15%	25%	42%	20%	32%	22%	17%	48%	**14**	**24%**
HuShen300	48	38%	40%	46%	33%	23%	27%	8%	17%	33%	27%	25%	38%	13%	33%	27%	38%	**14**	**28%**
NoC2	**1241**	**296**	**403**	**225**	**327**	**262**	**408**	**418**	**389**	**237**	**263**	**430**	**253**	**401**	**298**	**247**	**843**		
P1	N/A	**24%**	**32%**	**18%**	**26%**	**21%**	**33%**	**34%**	**31%**	**19%**	**21%**	**35%**	**20%**	**32%**	**24%**	**20%**	**68%**		

Table C.9: **Percentage of nubmber of Affected Contracts for Percentage Change in Daily Market Position Regressions**

cmp																			
nid	**NoC1**	**CPI**	**GDP**	**NYL**	**PPI**	**EXP**	**VIO**	**IP**	**FA**	**M2**	**IMP**	**RS**	**BOT**	**RSCG**	**FCR**	**PMI**	**_cons**	**NoC3**	**P2**
LLDPE	60	8%	18%	17%	12%	5%	17%	12%	18%	10%	8%	23%	10%	22%	18%	12%	20%	**8**	**14%**
PTA	60	17%	28%	20%	20%	20%	28%	25%	30%	17%	18%	42%	20%	37%	15%	15%	30%	**14**	**23%**
sugar	33	18%	21%	6%	15%	21%	18%	21%	27%	12%	15%	15%	15%	27%	12%	21%	24%	**6**	**18%**
silver	20	30%	65%	30%	25%	45%	60%	60%	65%	35%	40%	60%	40%	45%	45%	45%	75%	**9**	**46%**
glass	13	15%	31%	8%	15%	46%	54%	62%	62%	15%	38%	46%	38%	46%	8%	23%	15%	**4**	**34%**
rapeseed_meal	7	14%	71%	43%	29%	43%	57%	71%	57%	57%	57%	57%	57%	29%	43%	0%	29%	**3**	**46%**
rap_oil	30	13%	20%	7%	23%	27%	13%	23%	17%	13%	30%	27%	30%	33%	13%	17%	23%	**6**	**20%**
soybean_meal	40	23%	18%	13%	13%	25%	23%	28%	20%	20%	23%	20%	25%	25%	25%	20%	10%	**8**	**21%**
soybean_oil	40	15%	23%	8%	20%	20%	30%	30%	28%	10%	20%	35%	20%	38%	10%	13%	8%	**8**	**21%**
soybean1	33	9%	27%	3%	6%	9%	18%	18%	15%	15%	9%	12%	9%	12%	12%	15%	15%	**4**	**13%**
soybean2	30	20%	33%	13%	37%	3%	37%	40%	37%	20%	7%	30%	0%	53%	20%	10%	0%	**7**	**24%**
gold	60	17%	30%	18%	30%	25%	28%	32%	28%	25%	27%	38%	23%	32%	18%	10%	22%	**15**	**25%**
methanol	26	19%	19%	12%	12%	8%	23%	31%	15%	0%	8%	23%	12%	23%	8%	8%	23%	**4**	**15%**
coking_coal	9	44%	33%	11%	44%	44%	11%	0%	33%	22%	44%	0%	44%	11%	44%	11%	11%	**2**	**27%**
coke	33	18%	30%	15%	18%	21%	33%	36%	27%	12%	21%	33%	18%	30%	30%	6%	18%	**8**	**23%**
PVC	55	16%	29%	15%	22%	16%	29%	33%	22%	20%	15%	16%	15%	31%	15%	9%	16%	**11**	**20%**
aluminum	60	30%	32%	15%	22%	18%	30%	33%	28%	27%	20%	38%	18%	30%	27%	30%	80%	**16**	**27%**
rebar	57	16%	26%	19%	26%	14%	37%	39%	32%	28%	14%	28%	14%	37%	16%	23%	46%	**14**	**25%**
cotton	30	20%	40%	10%	40%	10%	37%	40%	33%	27%	13%	30%	10%	43%	17%	30%	20%	**8**	**27%**
common_wheat	30	17%	17%	10%	23%	13%	17%	13%	10%	13%	17%	23%	13%	20%	20%	3%	3%	**5**	**15%**
pb	33	27%	33%	15%	27%	33%	27%	24%	39%	12%	24%	30%	30%	30%	18%	15%	64%	**9**	**26%**
strong_wheat1	30	7%	30%	7%	7%	17%	13%	27%	13%	10%	17%	30%	17%	33%	10%	13%	53%	**5**	**17%**
fuel_oil	55	13%	27%	11%	13%	7%	11%	15%	18%	9%	7%	24%	9%	22%	16%	15%	42%	**8**	**14%**
rubber	50	22%	34%	16%	24%	24%	38%	40%	40%	16%	24%	28%	24%	40%	30%	20%	66%	**14**	**28%**
copper	60	23%	40%	25%	27%	30%	38%	33%	35%	22%	35%	37%	30%	33%	20%	27%	62%	**18**	**30%**
wire_rod	57	14%	16%	9%	14%	5%	21%	23%	23%	9%	11%	21%	9%	25%	12%	11%	9%	**8**	**15%**
zinc	60	25%	33%	17%	17%	33%	27%	33%	32%	23%	32%	30%	32%	30%	22%	13%	78%	**16**	**27%**
rapeseed	4	0%	25%	25%	0%	75%	25%	25%	50%	0%	75%	25%	50%	0%	75%	25%	25%	**1**	**32%**
corn	30	17%	33%	13%	33%	23%	30%	37%	37%	13%	23%	37%	23%	43%	7%	23%	13%	**8**	**26%**
early_indica_rice	28	32%	36%	18%	32%	32%	32%	29%	36%	36%	36%	25%	29%	29%	36%	11%	21%	**8**	**30%**
palm_oil	60	22%	22%	7%	20%	20%	32%	38%	25%	5%	18%	23%	18%	33%	15%	10%	10%	**12**	**21%**
HuShen300	48	44%	44%	38%	25%	15%	21%	8%	19%	27%	21%	29%	23%	8%	27%	15%	25%	**12**	**24%**
NoC2	**1241**	**244**	**361**	**186**	**263**	**244**	**341**	**361**	**343**	**218**	**251**	**358**	**244**	**376**	**238**	**199**	**403**		
P1	N/A	**20%**	**29%**	**15%**	**21%**	**20%**	**27%**	**29%**	**28%**	**18%**	**20%**	**29%**	**20%**	**30%**	**19%**	**16%**	**32%**		

Table C.10: **Results of Affected Rebar Futures Contracts in Three Types of Regressions**

lrsp																	ctv																cmp															
ccode	CPI	GDP	NYL	PPI	EXP	VIO	IP	FA	M2	IMP	RS	BOT	RSCG	FCR	PMI	cons	CPI	GDP	NYL	PPI	EXP	VIO	IP	FA	M2	IMP	RS	BOT	RSCG	FCR	PMI	cons	CPI	GDP	NYL	PPI	EXP	VIO	IP	FA	M2	IMP	RS	BOT	RSCG	FCR	PMI	cons
RB0910	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0
RB0911	1	0	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	1
RB0912	1	0	0	0	0	0	0	1	0	0	1	0	1	1	1	0	1	0	1	0	1	0	0	1	1	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
RB1001	1	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	1	0	1	0	1	1	0	0	0	0	0	1	0	1	1
RB1002	1	1	1	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1
RB1003	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1
RB1004	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
RB1005	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	1
RB1006	0	0	0	1	1	0	0	0	0	1	0	1	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	1	1	0	1	0	1	1	0	0	0	1	1	0	1
RB1007	1	1	1	1	1	0	0	0	0	1	0	1	1	0	0	0	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
RB1008	1	0	1	1	1	0	1	0	1	1	1	1	0	0	0	0	1	1	0	1	0	1	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
RB1009	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1010	1	0	1	1	1	1	1	0	0	1	1	1	0	1	0	0	0	1	0	1	0	1	0	0	0	0	1	0	1	1	1	1	0	1	0	0	0	1	1	1	1	0	1	0	1	0	1	0
RB1011	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	0	1	1	0	0	0	1	0	1	0	0	1	0	1	0	1	1	1	0	1	1	0	0	0	1	1	0	0	0	0	1	0	0
RB1012	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
RB1101	0	0	1	1	0	0	1	0	1	0	1	0	0	1	0	0	1	1	0	0	0	1	1	1	0	0	1	0	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	0	1	0
RB1102	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1103	0	1	1	0	0	1	1	1	1	0	1	0	1	1	0	0	0	1	0	0	1	1	0	0	0	1	0	1	0	0	0	1	1	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0
RB1104	1	1	0	1	0	1	1	1	1	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
RB1105	0	1	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0	1	0	1	0	0	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1106	1	0	0	1	1	1	1	1	0	1	1	0	1	0	0	0	1	0	0	1	0	0	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1107	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	1	1	0	1	0	1	1	0	1
RB1108	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1109	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
RB1110	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	0	1	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0	0	1	0	1	0	1	0
RB1111	0	1	0	0	1	1	0	0	0	1	1	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1112	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	1	1	0	0	0	0	0	1	0	0	0
RB1201	1	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0	0	1	0	0	0	1	0	1	1	1	1	0	1	1	0	0	1	1	1	0	0	0	0	1	0	1	0
RB1202	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
RB1203	0	1	0	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	1	0	0	0	1	0	0	0	1	0	1	1	1	0	0	0	0	1	0	0	0
RB1204	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1205	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1	1	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
RB1206	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
RB1207	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0
RB1208	1	1	1	0	0	1	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1209	1	1	1	0	0	1	1	1	0	1	0	1	1	0	0	1	1	1	1	1	0	1	1	0	0	0	0	0	1	1	0	1	0	1	0	1	0	1	1	0	0	0	1	0	1	0	1	1
RB1210	1	1	1	0	1	1	0	0	0	1	1	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1211	0	0	0	0	1	0	0	1	0	1	1	1	0	0	0	0	0	1	0	1	1	1	1	1	0	1	1	1	1	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0
RB1212	0	1	0	0	1	1	1	0	0	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	1	1	0	0	0	1	0	1	0	0	1
RB1301	0	1	0	0	0	1	1	1	0	0	1	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
RB1302	0	1	0	0	1	1	1	1	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	1	0	0	1
RB1303	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1304	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	1	1	1	0	1	0	0	0	1	0	0	0	0	1	1	0	1
RB1305	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1
RB1306	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	0	0	1	0	1	1
RB1307	1	1	0	0	0	0	1	1	0	0	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	0	0	0	0
RB1308	1	1	0	0	0	1	1	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RB1309	1	1	0	0	0	1	0	1	1	0	1	0	1	1	0	0	0	1	0	0	1	1	0	1	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
RB1310	1	1	0	0	0	1	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1
RB1311	1	1	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	1	0	0	0	1	1	1	0	1	1	0	1	0	0	1	0	0	0	1	0	1	1	0	0	0	1	0	0	0	0	0
RB1312	0	1	0	0	1	1	1	1	0	1	1	1	1	0	0	0	0	1	0	1	0	1	1	1	0	0	1	0	1	0	0	1	0	0	1	0	1	0	0	0	1	1	0	1	0	0	0	0
RB1401	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	1	0	1	0	1	1	0	1	0	1	0	1	1	1	1	0	1	0	1	0	0	1
RB1402	0	1	0	1	0	1	1	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1
RB1403	0	1	1	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	1	0	0	0	1
RB1404	1	0	1	1	0	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	1	0	0	0	0	1	0	1	0	1	1	0	1	0	0	0	1
RB1405	1	0	0	1	1	1	1	1	0	1	1	1	1	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
RB1406	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	0	0	1	0	1	1	1	1	0	0	0	0	1	0	0	0	0	1	0	1	1	1	1	0	1	1	1	1	0	0	1

Table C.11: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part I**

Futures	LLDPE						PTA					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0052	-0.0103	-0.0107	-0.0115	-0.0032	-0.0001	-0.0111	-0.0171	-0.0177	-0.0211	-0.0096	-0.0038
GDP	0.0188	0.0083	0.0062	-0.0009	0.0047	-0.0013	0.0440	0.0164	0.0191	0.0159	0.0103	-0.0002
NYL	-0.0277	-0.0209	-0.0227	-0.0197	-0.0113	-0.0058	-0.0284	-0.0106	-0.0072	-0.0061	-0.0023	0.0031
PPI	-0.0120	-0.0066	0.0030	0.0035	0.0092	0.0058	0.0039	0.0006	0.0026	0.0023	0.0054	0.0062
EXP	-0.0498	-0.0779	-0.0774	-0.0667	-0.0191	-0.0085	-0.0591	-0.0568	-0.0482	-0.0703	-0.0370	-0.0234
VIO	0.0201	0.0266	0.0157	0.0076	-0.0043	-0.0015	-0.0024	0.0124	0.0076	0.0013	-0.0032	-0.0034
IP	-0.0115	-0.0048	-0.0156	-0.0116	-0.0117	-0.0134	-0.0132	-0.0049	-0.0048	-0.0040	-0.0089	-0.0038
FA	0.0014	0.0044	0.0109	0.0091	0.0066	0.0080	0.0001	0.0004	0.0065	0.0054	0.0042	0.0012
M2	0.0229	0.0229	0.0358	0.0270	0.0150	0.0023	0.0166	0.0169	0.0327	0.0268	0.0189	0.0087
IMP	0.0479	0.0769	0.0820	0.0693	0.0195	0.0153	0.0674	0.0587	0.0527	0.0703	0.0360	0.0267
RS	0.0209	0.0174	0.0131	0.0077	0.0005	0.0011	0.0031	0.0047	0.0048	-0.0018	-0.0001	0.0013
BOT	0.0403	0.0588	0.0571	0.0533	0.0082	0.0049	0.0478	0.0440	0.0325	0.0574	0.0245	0.0201
RSCG	0.0006	-0.0052	0.0034	-0.0001	0.0044	0.0052	0.0133	-0.0003	0.0072	0.0047	0.0055	0.0025
FCR	0.0290	0.0167	0.0120	0.0024	0.0040	0.0059	0.0392	0.0215	0.0151	0.0078	0.0096	0.0037
PMI	0.0291	0.0070	0.0098	0.0056	0.0006	-0.0067	0.0337	0.0179	0.0257	0.0162	0.0070	-0.0003
_cons	0.0082	0.0055	0.0046	0.0037	0.0022	0.0010	0.0075	0.0052	0.0045	0.0036	0.0022	0.0010
N	1210	1210	1210	1210	1210	1210	1189	1189	1189	1189	1189	1189
R-sq	0.019	0.022	0.032	0.023	0.012	0.016	0.016	0.012	0.023	0.022	0.017	0.012
arsq	0.007	0.009	0.020	0.011	0.000	0.004	0.004	-0.001	0.010	0.009	0.004	-0.001
AIC	-2700.78	-3013.82	-3216.80	-3496.15	-3949.70	-4820.09	-2248.84	-2674.93	-2968.88	-3330.07	-3892.79	-4762.56
BIC	-2619.21	-2932.25	-3135.23	-3414.58	-3868.13	-4738.51	-2167.55	-2593.63	-2887.58	-3248.77	-3811.50	-4681.27
Futures	sugar						silver					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0084	0.0021	0.0066	0.0031	0.0099	0.0019	0.0485	0.0644	0.0484	0.0483	-0.0074	-0.0122
GDP	0.0121	0.0026	0.0047	0.0029	-0.0028	-0.0046	0.0107	-0.0033	-0.0390	-0.0517	-0.0314	-0.0265
NYL	-0.0230	-0.0179	-0.0162	-0.0105	-0.0057	-0.0040	-0.0172	0.0010	-0.0170	-0.0184	-0.0023	0.0085
PPI	0.0021	-0.0134	-0.0089	-0.0087	-0.0039	-0.0032	0.0320	-0.0618	-0.0815	-0.0567	-0.0545	-0.0118
EXP	0.0054	0.0165	0.0291	0.0278	0.0151	0.0090	-0.1152	-0.0540	-0.0401	-0.0611	0.0325	0.0145
VIO	0.0219	0.0285	0.0172	0.0124	0.0110	-0.0003	0.0215	-0.1694	-0.1710	-0.0589	-0.0010	0.0065
IP	-0.0128	-0.0048	-0.0067	-0.0017	-0.0037	-0.0019	0.0921	0.3878	0.4031	0.2268	0.0421	0.0060
FA	0.0026	-0.0044	0.0049	0.0046	0.0010	-0.0030	0.4085	-0.0495	-0.0656	0.0025	-0.0194	0.0201
M2	0.0117	0.0070	0.0177	0.0157	0.0108	0.0058	-0.0263	-0.0477	-0.0301	-0.0256	0.0114	0.0120
IMP	-0.0055	-0.0176	-0.0253	-0.0225	-0.0094	-0.0071	0.0957	0.0482	0.0376	0.0701	-0.0221	0.0000
RS	0.0065	0.0031	0.0047	0.0008	0.0003	-0.0015	-0.2068	-0.0764	-0.0641	-0.0879	-0.0042	-0.0158
BOT	-0.0139	-0.0223	-0.0279	-0.0270	-0.0124	-0.0129	0.0840	0.0504	0.0324	0.0487	-0.0415	-0.0189
RSCG	0.0118	0.0070	0.0085	0.0042	0.0042	0.0022	-0.5910	-0.0192	0.0013	0.0083	-0.1090	-0.0854
FCR	0.0402	0.0283	0.0288	0.0226	0.0112	0.0116	-0.0544	-0.0426	-0.0213	-0.0250	0.0069	-0.0069
PMI	0.0313	0.0206	0.0196	0.0112	0.0075	-0.0011	0.0261	0.0348	0.0284	0.0335	0.0448	0.0202
_cons	0.0123	0.0095	0.0078	0.0060	0.0040	0.0019	-0.0297	-0.0218	-0.0174	-0.0124	-0.0091	-0.0045
N	1211	1211	1211	1211	1211	1211	393	393	393	393	393	393
R-sq	0.016	0.019	0.017	0.013	0.012	0.007	0.033	0.035	0.032	0.034	0.024	0.022
arsq	0.004	0.006	0.005	0.001	-0.001	-0.005	-0.005	-0.004	-0.006	-0.005	-0.015	-0.017
AIC	-2717.24	-3124.49	-3403.61	-3790.32	-4365.91	-5253.97	-571.97	-702.32	-786.66	-908.69	-1097.64	-1413.82
BIC	-2635.65	-3042.90	-3322.02	-3708.73	-4284.33	-5172.38	-508.39	-638.74	-723.08	-845.11	-1034.06	-1350.24

Table C.12: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part II**

Futures	rapeseed_meal						rap_oil					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0143	0.0160	0.0058	-0.0011	0.0096	0.0000	0.0052	0.0007	-0.0012	-0.0048	-0.0031	0.0022
GDP	0.0575	-0.0751	-0.0774	-0.0631	-0.0024	-0.0113	0.0062	-0.0064	-0.0001	-0.0035	0.0011	-0.0010
NYL	-0.0199	-0.0032	-0.0049	-0.0144	-0.0169	-0.0039	-0.0167	-0.0106	-0.0132	-0.0096	-0.0069	-0.0040
PPI	0.0828	0.0369	-0.0163	0.0073	0.0479	0.0378	-0.0003	-0.0038	-0.0007	0.0033	0.0070	0.0060
EXP	-0.0444	-0.1154	-0.0764	-0.0498	-0.0290	-0.0263	0.0002	-0.0191	-0.0108	-0.0320	-0.0235	-0.0139
VIO	0.1054	0.7087	0.4606	0.2540	0.2553	0.2260	-0.0045	0.0003	-0.0009	0.0005	-0.0055	-0.0023
IP	-0.1267	-0.5513	-0.3122	-0.0784	-0.2124	-0.1888	-0.0116	-0.0097	-0.0118	-0.0052	-0.0060	-0.0067
FA	0.1472	-0.3590	-0.2466	-0.1552	-0.0449	-0.1123	0.0058	0.0115	0.0085	0.0034	0.0043	0.0039
M2	0.0251	-0.0047	-0.0060	-0.0047	-0.0004	-0.0010	0.0126	0.0074	0.0171	0.0149	0.0154	0.0096
IMP	0.0886	0.1290	0.1274	0.0826	0.0353	0.0481	0.0180	0.0260	0.0228	0.0396	0.0253	0.0173
RS	-0.2558	0.3851	0.2378	0.0736	0.0654	0.1027	0.0016	-0.0032	-0.0021	-0.0033	-0.0074	-0.0061
BOT	0.0418	0.0881	0.0755	0.0393	0.0186	0.0245	0.0143	0.0272	0.0179	0.0309	0.0216	0.0151
RSCG	-0.7395	1.0886	0.5829	0.1319	0.0348	0.1692	0.0064	0.0019	0.0032	-0.0010	0.0028	0.0039
FCR	-0.0203	-0.0094	-0.0055	-0.0018	-0.0015	0.0097	0.0301	0.0207	0.0204	0.0138	0.0049	0.0005
PMI	0.0257	0.0711	0.0569	0.0474	0.0673	0.0414	0.0075	0.0003	-0.0002	-0.0002	0.0007	-0.0028
_cons	-0.0033	-0.0007	-0.0006	0.0006	0.0003	-0.0006	0.0025	0.0015	0.0013	0.0010	0.0006	0.0003
N	239	239	239	239	239	239	1211	1211	1211	1211	1211	1211
R-sq	0.075	0.064	0.056	0.047	0.040	0.046	0.011	0.009	0.014	0.015	0.015	0.016
arsq	0.012	0.001	-0.008	-0.017	-0.025	-0.018	-0.001	-0.003	0.002	0.002	0.003	0.003
AIC	-665.43	-717.32	-727.25	-740.76	-793.77	-949.29	-3410.15	-3770.06	-4019.50	-4406.92	-4865.01	-5622.28
BIC	-609.80	-661.70	-671.63	-685.14	-738.14	-893.67	-3328.56	-3688.48	-3937.92	-4325.33	-4783.42	-5540.69
Futures	soybean_meal						soybean_oil					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0011	-0.0026	-0.0080	-0.0092	-0.0028	0.0015	0.0092	0.0021	-0.0006	-0.0002	-0.0006	0.0028
GDP	0.0056	-0.0029	-0.0021	0.0022	0.0044	-0.0026	0.0219	0.0077	0.0094	0.0092	0.0092	0.0007
NYL	-0.0119	-0.0110	-0.0146	-0.0168	-0.0158	-0.0075	-0.0171	-0.0173	-0.0164	-0.0152	-0.0102	-0.0058
PPI	-0.0072	-0.0069	-0.0017	-0.0012	0.0017	0.0034	0.0015	-0.0007	-0.0016	0.0024	0.0068	0.0045
EXP	-0.0193	-0.0335	-0.0485	-0.0458	-0.0210	-0.0122	-0.0503	-0.0519	-0.0316	-0.0507	-0.0403	-0.0195
VIO	0.0006	0.0014	-0.0016	-0.0046	-0.0070	-0.0047	-0.0005	0.0028	0.0035	0.0013	-0.0052	-0.0040
IP	-0.0016	-0.0068	-0.0056	-0.0038	-0.0029	-0.0056	-0.0170	-0.0131	-0.0130	-0.0083	-0.0110	-0.0098
FA	0.0066	0.0070	0.0040	0.0062	0.0049	0.0042	0.0103	0.0144	0.0129	0.0036	0.0067	0.0052
M2	0.0219	0.0211	0.0301	0.0254	0.0207	0.0126	0.0089	0.0100	0.0138	0.0096	0.0102	0.0096
IMP	0.0307	0.0320	0.0517	0.0497	0.0219	0.0168	0.0594	0.0542	0.0395	0.0553	0.0401	0.0232
RS	0.0061	-0.0005	0.0012	-0.0030	-0.0088	-0.0069	0.0048	0.0004	0.0043	-0.0005	-0.0073	-0.0061
BOT	0.0259	0.0226	0.0406	0.0316	0.0134	0.0140	0.0561	0.0483	0.0304	0.0451	0.0341	0.0201
RSCG	-0.0021	-0.0034	-0.0022	-0.0026	0.0017	0.0049	0.0076	0.0030	0.0032	-0.0015	0.0053	0.0057
FCR	-0.0034	-0.0101	-0.0136	-0.0108	-0.0071	-0.0088	0.0298	0.0239	0.0227	0.0154	0.0108	0.0029
PMI	0.0076	-0.0051	-0.0032	-0.0017	-0.0038	-0.0080	0.0156	0.0033	0.0038	0.0002	0.0000	-0.0028
_cons	0.0064	0.0043	0.0037	0.0028	0.0018	0.0009	0.0037	0.0021	0.0016	0.0011	0.0007	0.0003
N	1211	1211	1211	1211	1211	1211	1211	1211	1211	1211	1211	1211
R-sq	0.005	0.009	0.014	0.020	0.014	0.015	0.014	0.013	0.016	0.014	0.018	0.018
arsq	-0.007	-0.004	0.002	0.007	0.002	0.003	0.002	0.001	0.003	0.002	0.005	0.006
AIC	-2811.47	-3152.68	-3380.03	-3724.41	-4229.03	-5109.97	-3088.61	-3452.34	-3734.90	-4126.48	-4619.79	-5453.78
BIC	-2729.88	-3071.09	-3298.44	-3642.82	-4147.44	-5028.38	-3007.02	-3370.75	-3653.31	-4044.89	-4538.21	-5372.19

Table C.13: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part III**

Futures	soybean2						methanol					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0046	0.0012	-0.0032	-0.0014	0.0028	0.0073	0.0311	0.0169	0.0142	0.0130	0.0079	0.0022
GDP	0.0147	0.0057	0.0052	0.0065	0.0087	0.0043	0.0029	-0.0082	-0.0053	-0.0095	-0.0100	-0.0081
NYL	-0.0156	-0.0131	-0.0085	-0.0115	-0.0105	-0.0046	-0.0135	-0.0020	0.0028	0.0087	0.0007	0.0044
PPI	-0.0032	-0.0038	-0.0003	-0.0006	0.0039	0.0039	0.0152	0.0012	0.0403	0.0388	0.0188	0.0054
EXP	-0.0455	-0.0534	-0.0445	-0.0370	-0.0201	-0.0177	-0.1480	-0.1253	-0.1130	-0.0807	-0.0402	0.0073
VIO	0.0046	0.0040	0.0066	0.0071	0.0006	-0.0015	0.0105	0.0282	0.0082	-0.0060	-0.0333	-0.0017
IP	0.0068	0.0016	0.0012	0.0029	-0.0007	-0.0031	0.0016	0.0049	0.0509	0.0551	0.0435	0.0016
FA	0.0008	0.0030	0.0054	0.0040	0.0037	0.0027	0.0527	0.0093	-0.0243	-0.0075	0.0078	0.0131
M2	0.0016	0.0014	0.0087	0.0094	0.0046	0.0062	-0.0057	-0.0145	-0.0236	-0.0279	-0.0122	-0.0084
IMP	0.0361	0.0410	0.0397	0.0327	0.0167	0.0176	0.1484	0.1236	0.1145	0.0855	0.0343	-0.0142
RS	0.0030	0.0015	0.0045	0.0057	-0.0002	-0.0039	0.0261	0.0405	0.0249	0.0222	0.0188	0.0004
BOT	0.0411	0.0467	0.0403	0.0301	0.0175	0.0203	0.1365	0.1193	0.1159	0.0880	0.0459	-0.0015
RSCG	-0.0088	-0.0093	-0.0083	-0.0137	-0.0039	0.0048	0.0076	-0.0037	-0.0288	-0.0287	-0.0187	0.0010
FCR	0.0159	0.0003	-0.0051	-0.0006	-0.0031	-0.0016	-0.0022	-0.0046	-0.0050	-0.0033	0.0089	-0.0030
PMI	0.0168	0.0049	0.0057	0.0070	0.0017	-0.0024	0.0588	0.0281	0.0249	0.0343	0.0286	0.0105
_cons	0.0047	0.0029	0.0023	0.0017	0.0010	0.0005	0.0060	0.0045	0.0040	0.0030	0.0018	0.0004
N	1068	1068	1068	1068	1068	1068	502	502	502	502	502	502
R-sq	0.013	0.011	0.011	0.016	0.010	0.013	0.044	0.026	0.042	0.049	0.031	0.011
arsq	-0.001	-0.003	-0.003	0.002	-0.004	-0.001	0.015	-0.004	0.012	0.020	0.001	-0.020
AIC	-3396.43	-3641.53	-3788.36	-4054.19	-4410.90	-5030.92	-1362.96	-1437.08	-1508.95	-1639.15	-1828.86	-2078.64
BIC	-3316.85	-3561.95	-3708.78	-3974.61	-4331.33	-4951.34	-1295.46	-1369.58	-1441.45	-1571.65	-1761.36	-2011.15
Futures	coking_coal						PVC					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	-0.0143	0.0701	0.0621	0.0473	0.0230	0.0008	-0.0103	-0.0107	-0.0073	-0.0065	0.0006	0.0010
GDP	-0.2264	-0.1319	-0.0827	-0.0702	0.0458	-0.0207	0.0284	0.0117	0.0067	0.0075	0.0052	0.0007
NYL	0.0025	-0.0295	0.0188	-0.0014	-0.0022	-0.0014	-0.0205	-0.0119	-0.0077	-0.0043	-0.0013	-0.0001
PPI	0.0761	0.0364	0.0101	0.0263	0.0217	0.0405	-0.0020	-0.0063	-0.0036	-0.0038	-0.0008	-0.0001
EXP	-0.8049	-0.6531	-0.6243	-0.3734	-0.0585	0.0399	-0.0381	-0.0436	-0.0308	-0.0274	-0.0064	0.0013
VIO	0.2763	0.2961	0.1635	0.0824	-0.1440	-0.0288	-0.0106	0.0089	0.0074	0.0023	-0.0009	-0.0022
IP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0157	0.0063	0.0151	0.0134	0.0027	-0.0071
FA	0.1555	0.0113	0.0327	0.1149	0.1536	0.0776	-0.0077	0.0033	0.0016	-0.0009	-0.0047	0.0060
M2	-0.0267	-0.0110	-0.0209	-0.0226	-0.0020	-0.0306	0.0185	0.0198	0.0170	0.0074	0.0040	0.0035
IMP	0.7880	0.6022	0.5923	0.3353	0.0057	-0.0686	0.0441	0.0466	0.0383	0.0305	0.0041	-0.0024
RS	-0.0042	0.1522	-0.0582	-0.1042	-0.4047	-0.0472	-0.0008	0.0073	0.0022	-0.0001	-0.0014	-0.0017
BOT	0.5495	0.4717	0.4504	0.2648	0.0208	-0.0410	0.0331	0.0396	0.0264	0.0244	0.0041	0.0002
RSCG	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0110	0.0118	0.0128	0.0095	0.0049	0.0092
FCR	0.0058	-0.0314	-0.0544	-0.0305	-0.0100	0.0261	0.0281	0.0133	0.0125	0.0097	0.0095	0.0040
PMI	0.2040	0.1805	0.2050	0.1639	0.1232	0.0516	0.0031	-0.0071	-0.0013	-0.0041	-0.0064	-0.0021
_cons	-0.0170	-0.0131	-0.0136	-0.0119	-0.0082	-0.0043	-0.0017	-0.0011	-0.0008	-0.0006	-0.0006	-0.0003
N	165	165	165	165	165	165	1102	1102	1102	1102	1102	1102
R-sq	0.077	0.082	0.086	0.069	0.071	0.080	0.020	0.018	0.016	0.010	0.005	0.006
arsq	-0.003	0.003	0.007	-0.011	-0.009	0.001	0.006	0.004	0.003	-0.004	-0.008	-0.008
AIC	-352.84	-389.50	-425.21	-468.24	-560.09	-687.71	-3286.33	-3548.88	-3735.81	-3980.89	-4403.97	-5068.13
BIC	-321.78	-358.44	-394.15	-437.18	-529.03	-656.65	-3206.25	-3468.80	-3655.73	-3900.81	-4323.90	-4988.05

Table C.14: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part IV**

Futures	aluminum						rebar					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	-0.0030	-0.0146	-0.0121	-0.0121	-0.0055	0.0006	-0.0087	-0.0142	-0.0139	-0.0131	-0.0072	-0.0007
GDP	0.0123	0.0017	0.0018	0.0006	0.0050	0.0013	0.0233	0.0195	0.0138	0.0084	0.0034	-0.0009
NYL	-0.0188	-0.0079	-0.0080	-0.0074	-0.0033	0.0003	-0.0310	-0.0185	-0.0072	-0.0058	-0.0066	-0.0041
PPI	0.0010	-0.0012	-0.0003	-0.0020	0.0010	-0.0011	-0.0068	-0.0065	-0.0025	0.0034	0.0057	0.0027
EXP	-0.0625	-0.0459	-0.0394	-0.0378	-0.0351	-0.0162	-0.1116	-0.0973	-0.0698	-0.0713	-0.0575	-0.0439
VIO	0.0057	0.0070	0.0064	0.0050	0.0005	-0.0019	-0.0014	-0.0004	0.0074	-0.0003	0.0023	-0.0016
IP	-0.0033	-0.0004	0.0005	-0.0013	-0.0014	-0.0001	0.0204	0.0173	0.0104	0.0076	0.0009	-0.0035
FA	-0.0025	0.0034	0.0023	0.0030	0.0000	-0.0010	0.0096	0.0168	0.0152	0.0096	0.0087	0.0015
M2	0.0112	0.0148	0.0131	0.0142	0.0088	0.0056	0.0205	0.0202	0.0169	0.0108	0.0058	0.0000
IMP	0.0606	0.0431	0.0388	0.0356	0.0313	0.0152	0.1142	0.0952	0.0676	0.0635	0.0512	0.0384
RS	0.0037	0.0031	0.0027	0.0005	-0.0025	-0.0011	0.0173	0.0106	0.0035	-0.0044	-0.0013	-0.0046
BOT	0.0490	0.0340	0.0270	0.0265	0.0248	0.0136	0.1039	0.0832	0.0525	0.0592	0.0502	0.0344
RSCG	-0.0005	0.0011	0.0009	0.0001	0.0017	0.0029	-0.0025	-0.0019	0.0043	0.0036	0.0052	0.0024
FCR	0.0331	0.0191	0.0210	0.0162	0.0134	0.0048	0.0549	0.0460	0.0385	0.0311	0.0217	0.0168
PMI	0.0153	0.0019	0.0059	0.0035	0.0029	0.0012	0.0030	-0.0145	-0.0129	-0.0156	-0.0051	-0.0043
_cons	0.0050	0.0033	0.0027	0.0019	0.0013	0.0008	0.0004	0.0003	0.0003	0.0003	0.0003	0.0000
N	1211	1211	1211	1211	1211	1211	1134	1134	1134	1134	1134	1134
R-sq	0.024	0.025	0.027	0.032	0.022	0.009	0.021	0.023	0.021	0.020	0.013	0.015
arsq	0.012	0.013	0.015	0.020	0.009	-0.003	0.008	0.010	0.008	0.006	0.000	0.002
AIC	-4061.32	-4486.09	-4737.91	-5073.93	-5519.50	-6327.09	-2627.13	-2979.37	-3256.00	-3633.36	-4147.58	-5018.86
BIC	-3979.73	-4404.50	-4656.33	-4992.34	-5437.92	-6245.50	-2546.60	-2898.84	-3175.46	-3552.83	-4067.04	-4938.32
Futures	cotton						common_wheat					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	-0.0081	-0.0112	-0.0073	-0.0083	-0.0029	0.0016	-0.0012	-0.0019	-0.0055	-0.0045	0.0021	0.0005
GDP	0.0218	0.0167	0.0131	0.0152	0.0033	-0.0046	-0.0053	0.0009	0.0086	0.0068	0.0116	-0.0040
NYL	-0.0085	-0.0020	-0.0027	-0.0035	-0.0030	0.0007	0.0076	0.0061	0.0029	0.0014	-0.0053	-0.0007
PPI	0.0108	0.0034	-0.0026	-0.0003	0.0043	0.0031	-0.0038	-0.0015	-0.0030	-0.0023	0.0006	-0.0011
EXP	-0.0170	-0.0351	-0.0168	-0.0365	-0.0332	-0.0165	0.0496	0.0432	0.0444	0.0439	0.0241	0.0146
VIO	0.0014	0.0044	0.0021	-0.0037	-0.0041	-0.0023	-0.0032	0.0035	0.0011	0.0011	0.0017	-0.0005
IP	-0.0079	-0.0024	-0.0059	-0.0061	-0.0085	-0.0069	-0.0013	-0.0002	-0.0014	-0.0021	-0.0022	-0.0039
FA	-0.0005	0.0021	0.0014	-0.0009	-0.0040	0.0019	0.0033	0.0005	0.0002	-0.0013	-0.0010	-0.0011
M2	0.0023	0.0033	0.0054	0.0021	0.0013	0.0023	-0.0016	0.0071	0.0077	0.0088	0.0063	-0.0015
IMP	0.0452	0.0500	0.0330	0.0444	0.0333	0.0229	-0.0391	-0.0396	-0.0386	-0.0429	-0.0242	-0.0132
RS	0.0195	0.0112	0.0143	0.0053	0.0002	0.0015	0.0059	0.0088	0.0077	0.0061	0.0076	0.0029
BOT	0.0192	0.0346	0.0189	0.0353	0.0278	0.0192	-0.0426	-0.0414	-0.0493	-0.0527	-0.0242	-0.0145
RSCG	0.0149	0.0059	0.0121	0.0097	0.0072	0.0078	0.0029	-0.0038	-0.0027	-0.0059	-0.0070	-0.0042
FCR	0.0599	0.0455	0.0348	0.0232	0.0206	0.0084	0.0023	-0.0036	0.0002	0.0029	0.0073	0.0068
PMI	0.0046	-0.0045	0.0016	-0.0035	-0.0058	-0.0038	-0.0062	-0.0115	-0.0097	-0.0104	-0.0072	-0.0044
_cons	0.0132	0.0093	0.0076	0.0057	0.0039	0.0020	0.0095	0.0077	0.0067	0.0057	0.0038	0.0019
N	1211	1211	1211	1211	1211	1211	884	884	884	884	884	884
R-sq	0.014	0.011	0.012	0.009	0.009	0.012	0.009	0.010	0.012	0.014	0.016	0.008
arsq	0.002	-0.001	0.000	-0.003	-0.003	0.000	-0.008	-0.007	-0.005	-0.003	-0.001	-0.009
AIC	-2215.37	-2744.00	-3076.46	-3487.09	-4132.00	-5150.97	-3018.77	-3148.91	-3263.66	-3423.52	-3765.42	-4301.76
BIC	-2133.79	-2662.42	-2994.87	-3405.50	-4050.41	-5069.38	-2942.22	-3072.35	-3187.11	-3346.97	-3688.87	-4225.21

Table C.15: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part V**

Futures	pb						rubber					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0125	0.0104	0.0075	0.0100	0.0049	−0.0006	0.0133	−0.0082	−0.0028	−0.0098	−0.0012	0.0022
GDP	0.0158	−0.0260	−0.0266	−0.0251	−0.0191	−0.0129	0.0418	0.0225	0.0076	−0.0041	−0.0035	−0.0054
NYL	−0.0178	0.0062	0.0083	0.0078	−0.0012	0.0024	−0.0374	−0.0126	−0.0054	−0.0018	−0.0009	0.0039
PPI	−0.0123	−0.0305	−0.0225	−0.0071	−0.0170	0.0030	−0.0087	−0.0132	−0.0112	−0.0037	−0.0018	−0.0003
EXP	−0.0922	−0.0088	0.0031	0.0185	−0.0014	−0.0120	−0.0601	−0.0761	−0.0362	−0.0806	−0.0237	0.0065
VIO	0.0166	0.0689	0.0858	0.0372	0.0276	−0.0005	0.0156	0.0186	0.0122	0.0051	−0.0091	−0.0051
IP	0.0202	−0.0688	−0.0750	−0.0186	−0.0310	0.0013	−0.0107	−0.0043	−0.0012	−0.0046	−0.0161	−0.0083
FA	−0.0155	0.0136	−0.0041	−0.0027	0.0113	−0.0035	0.0019	0.0043	−0.0006	−0.0029	0.0061	0.0036
M2	0.0118	−0.0118	−0.0320	−0.0263	−0.0184	−0.0093	0.0128	0.0136	0.0244	0.0135	0.0103	0.0069
IMP	0.0913	0.0107	−0.0006	−0.0097	−0.0046	0.0089	0.0748	0.0797	0.0411	0.0678	0.0144	−0.0051
RS	−0.0188	0.0002	−0.0352	−0.0322	−0.0162	−0.0049	0.0288	0.0143	0.0095	0.0018	−0.0064	−0.0047
BOT	0.0708	0.0009	−0.0102	−0.0155	−0.0024	0.0090	0.0689	0.0712	0.0335	0.0623	0.0106	−0.0087
RSCG	−0.0107	0.0356	0.0357	0.0057	0.0123	−0.0048	0.0127	0.0127	0.0094	−0.0012	0.0084	0.0086
FCR	0.0033	−0.0187	−0.0110	−0.0134	−0.0099	−0.0081	0.0576	0.0335	0.0240	0.0167	0.0065	0.0136
PMI	0.0031	0.0004	0.0062	0.0076	0.0131	0.0054	0.0502	0.0196	0.0259	0.0225	0.0119	−0.0010
_cons	−0.0140	−0.0112	−0.0092	−0.0071	−0.0047	−0.0023	0.0116	0.0082	0.0069	0.0053	0.0031	0.0014
N	595	595	595	595	595	595	1210	1210	1210	1210	1210	1210
R-sq	0.019	0.024	0.031	0.023	0.034	0.015	0.018	0.011	0.010	0.010	0.008	0.007
arsq	−0.006	−0.002	0.006	−0.003	0.009	−0.010	0.006	−0.002	−0.003	−0.003	−0.004	−0.005
AIC	−1914.14	−1996.59	−2050.90	−2174.27	−2420.78	−2786.14	−1713.34	−2151.99	−2393.53	−2776.26	−3282.39	−4077.85
BIC	−1843.92	−1926.37	−1980.68	−2104.05	−2350.57	−2715.92	−1631.77	−2070.42	−2311.96	−2694.68	−3200.81	−3996.27
Futures	copper						wire_rod					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	−0.0020	−0.0197	−0.0172	−0.0155	−0.0034	0.0029	−0.0007	−0.0082	−0.0061	−0.0023	−0.0087	−0.0059
GDP	0.0259	0.0024	−0.0017	−0.0084	−0.0100	−0.0049	−0.0021	−0.0030	0.0144	−0.0103	0.0170	0.0271
NYL	−0.0343	−0.0172	−0.0145	−0.0088	−0.0051	−0.0034	−0.0369	−0.0413	−0.0288	−0.0167	−0.0129	−0.0163
PPI	−0.0095	−0.0087	−0.0033	0.0016	−0.0018	−0.0021	−0.0236	−0.0158	−0.0087	−0.0105	−0.0031	−0.0008
EXP	−0.0476	−0.0598	−0.0362	−0.0630	−0.0216	0.0033	−0.1293	−0.1194	−0.1357	−0.1142	−0.0841	−0.0702
VIO	0.0044	0.0074	0.0044	−0.0033	−0.0068	−0.0085	−0.0205	−0.0144	−0.0033	−0.0089	0.0075	−0.0041
IP	−0.0107	−0.0089	−0.0027	−0.0009	−0.0090	−0.0068	0.0014	0.0068	0.0091	0.0047	0.0053	0.0032
FA	0.0160	0.0211	0.0121	−0.0003	0.0066	0.0068	0.0076	0.0242	0.0285	0.0151	0.0145	0.0107
M2	0.0279	0.0252	0.0354	0.0212	0.0152	0.0174	0.0366	0.0284	0.0320	0.0188	0.0240	0.0234
IMP	0.0550	0.0626	0.0379	0.0539	0.0152	−0.0006	0.1552	0.1425	0.1643	0.1370	0.1032	0.0854
RS	0.0199	0.0145	0.0076	−0.0008	−0.0014	−0.0005	−0.0074	−0.0093	0.0007	−0.0027	0.0102	−0.0097
BOT	0.0432	0.0483	0.0277	0.0432	0.0110	−0.0023	0.1286	0.1271	0.1531	0.1185	0.0877	0.0689
RSCG	0.0014	−0.0001	0.0082	−0.0054	0.0049	0.0063	−0.0012	0.0118	0.0041	−0.0014	−0.0063	0.0111
FCR	0.0361	0.0160	0.0079	0.0083	0.0031	0.0073	0.0309	0.0474	0.0463	0.0426	0.0121	0.0064
PMI	0.0216	−0.0045	0.0075	0.0080	0.0049	0.0000	0.0078	−0.0001	0.0005	−0.0013	−0.0078	−0.0040
_cons	0.0179	0.0125	0.0105	0.0081	0.0053	0.0027	0.0029	0.0020	0.0014	0.0013	0.0009	0.0006
N	1210	1210	1210	1210	1210	1210	639	639	639	639	639	639
R-sq	0.016	0.019	0.016	0.015	0.010	0.014	0.021	0.026	0.030	0.028	0.024	0.034
arsq	0.004	0.007	0.004	0.002	−0.003	0.002	−0.003	0.003	0.006	0.005	0.001	0.011
AIC	−2434.30	−2841.82	−3074.91	−3460.66	−3871.85	−4628.46	−1255.45	−1462.04	−1618.98	−1823.81	−2053.79	−2462.07
BIC	−2352.72	−2760.24	−2993.34	−3379.09	−3790.28	−4546.88	−1184.09	−1390.68	−1547.62	−1752.45	−1982.44	−2390.71

Table C.16: **Regression Results of 23 Continuous Contracts with Dependent Variables as Logarithm Returns in Six Different Periods Part VI**

Futures	zinc						corn					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	-0.0008	-0.0191	-0.0138	-0.0163	-0.0004	0.0028	0.0016	-0.0031	-0.0036	-0.0056	-0.0025	-0.0004
GDP	0.0023	-0.0171	-0.0168	-0.0155	-0.0040	-0.0031	0.0170	0.0109	0.0098	0.0073	0.0065	0.0028
NYL	-0.0313	-0.0176	-0.0115	-0.0061	-0.0016	0.0039	-0.0101	-0.0078	-0.0069	-0.0053	-0.0052	-0.0025
PPI	-0.0159	-0.0124	-0.0035	-0.0034	-0.0011	-0.0018	0.0013	-0.0060	-0.0054	-0.0082	-0.0014	-0.0029
EXP	-0.0805	-0.0659	-0.0499	-0.0691	-0.0386	-0.0207	-0.0190	-0.0158	-0.0085	0.0005	-0.0109	-0.0086
VIO	0.0083	0.0084	0.0071	0.0001	-0.0029	-0.0077	-0.0102	-0.0043	-0.0035	-0.0040	-0.0037	-0.0026
IP	-0.0081	-0.0055	-0.0024	0.0009	-0.0083	-0.0061	-0.0015	0.0048	0.0042	0.0038	0.0034	0.0018
FA	0.0078	0.0157	0.0104	-0.0017	0.0028	0.0039	-0.0035	-0.0055	-0.0036	-0.0031	-0.0043	-0.0030
M2	0.0217	0.0208	0.0129	0.0141	0.0070	0.0077	0.0007	0.0032	0.0051	0.0077	0.0041	0.0014
IMP	0.0824	0.0745	0.0589	0.0631	0.0304	0.0195	0.0156	0.0146	0.0108	-0.0020	0.0111	0.0095
RS	0.0146	0.0119	0.0103	-0.0048	-0.0037	-0.0024	0.0002	0.0008	0.0023	0.0009	-0.0016	-0.0023
BOT	0.0690	0.0581	0.0423	0.0542	0.0274	0.0223	0.0189	0.0172	0.0114	0.0003	0.0120	0.0080
RSCG	0.0040	0.0045	0.0045	-0.0013	0.0034	0.0047	-0.0013	-0.0024	-0.0005	0.0001	0.0040	0.0022
FCR	0.0391	0.0234	0.0229	0.0136	0.0070	-0.0013	0.0164	0.0107	0.0113	0.0008	0.0025	0.0025
PMI	0.0255	-0.0079	0.0028	-0.0003	0.0002	-0.0011	0.0098	0.0025	0.0005	-0.0010	-0.0024	-0.0021
_cons	0.0100	0.0066	0.0056	0.0041	0.0027	0.0014	0.0111	0.0083	0.0066	0.0050	0.0034	0.0017
N	1210	1210	1210	1210	1210	1210	1211	1211	1211	1211	1211	1211
R-sq	0.016	0.019	0.013	0.013	0.006	0.008	0.014	0.011	0.012	0.016	0.014	0.011
arsq	0.004	0.007	0.000	0.001	-0.006	-0.004	0.001	-0.002	-0.001	0.003	0.002	-0.001
AIC	-2503.50	-2865.63	-3082.93	-3430.18	-3935.95	-4738.81	-4587.25	-4986.90	-5255.42	-5635.27	-6149.50	-7017.15
BIC	-2421.93	-2784.06	-3001.36	-3348.61	-3854.38	-4657.24	-4505.67	-4905.31	-5173.84	-5553.68	-6067.92	-6935.56
Futures	palm_oil						HuShen300					
Period	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10	a15b20	a15b10	a15b5	a15ab0	a15a5	a15a10
CPI	0.0123	0.0068	0.0011	0.0038	0.0030	0.0043	0.0228	-0.0018	0.0023	0.0008	-0.0034	-0.0008
GDP	0.0162	0.0025	0.0048	0.0073	0.0081	-0.0033	0.0102	-0.0050	-0.0176	-0.0065	-0.0036	-0.0050
NYL	-0.0222	-0.0196	-0.0190	-0.0191	-0.0110	-0.0046	-0.0322	-0.0307	-0.0160	-0.0115	-0.0048	0.0001
PPI	0.0008	-0.0022	-0.0039	-0.0002	0.0040	0.0025	0.0076	0.0060	0.0065	0.0091	0.0122	0.0031
EXP	-0.0748	-0.0567	-0.0318	-0.0446	-0.0346	-0.0334	-0.1212	-0.1262	-0.0802	-0.0731	-0.0676	-0.0431
VIO	0.0034	0.0074	0.0105	0.0084	0.0000	0.0019	0.0508	0.0244	0.0436	0.0360	-0.0042	-0.0129
IP	-0.0232	-0.0172	-0.0151	-0.0070	-0.0104	-0.0093	-0.0637	-0.0151	-0.0367	-0.0419	0.0124	0.0211
FA	0.0025	0.0063	0.0049	-0.0021	0.0030	0.0050	-0.0413	-0.0149	-0.0224	-0.0367	-0.0211	-0.0217
M2	0.0118	0.0115	0.0157	0.0086	0.0098	0.0072	0.0009	-0.0042	-0.0183	-0.0143	-0.0168	-0.0081
IMP	0.0863	0.0592	0.0379	0.0490	0.0326	0.0347	0.1196	0.1308	0.0844	0.0764	0.0653	0.0452
RS	0.0088	0.0027	0.0089	0.0042	-0.0029	-0.0013	-0.0376	-0.0183	-0.0244	-0.0326	-0.0085	0.0027
BOT	0.0763	0.0468	0.0210	0.0334	0.0257	0.0315	0.1123	0.1143	0.0665	0.0655	0.0571	0.0353
RSCG	0.0034	0.0007	-0.0013	-0.0058	0.0017	0.0012	0.0187	0.0172	0.0260	0.0242	0.0022	-0.0082
FCR	0.0405	0.0376	0.0361	0.0227	0.0158	0.0071	0.0412	0.0399	0.0330	0.0158	0.0046	0.0089
PMI	0.0178	0.0044	0.0046	0.0024	0.0007	-0.0043	0.0283	0.0025	0.0046	0.0060	0.0034	-0.0008
_cons	0.0044	0.0028	0.0021	0.0015	0.0009	0.0004	-0.0077	-0.0060	-0.0053	-0.0044	-0.0030	-0.0015
N	1210	1210	1210	1210	1210	1210	899	899	899	899	899	899
R-sq	0.014	0.012	0.015	0.012	0.011	0.015	0.019	0.019	0.016	0.014	0.014	0.012
arsq	0.002	0.000	0.003	0.000	-0.001	0.003	0.002	0.002	-0.001	-0.002	-0.002	-0.005
AIC	-2518.01	-2895.61	-3216.80	-3627.95	-4157.21	-5023.36	-2019.33	-2242.11	-2402.68	-2656.54	-3057.95	-3687.36
BIC	-2436.43	-2814.04	-3135.23	-3546.38	-4075.64	-4941.79	-1942.51	-2165.29	-2325.86	-2579.72	-2981.13	-3610.54

Table C.17: **Percentage of Average Number of Affected Contracts of 23 Commodities in Six Different Setting of Returns Periods**

Commodity	LLDPE		PTA		sugar		silver		rapeseed_meal	
period	P2	MM	P2	MM	P2	MM	P2	MM	P2	MM
a15b20	39%	max	37%	max	27%	max	50%		55%	
a15b10	36%		33%		26%		51%	max	61%	max
a15b5	36%		36%		26%		48%		50%	
a15b0	35%		36%		22%		48%		56%	
a15a5	30%	min	32%		19%	min	46%		50%	min
a15a10	32%		29%	min	23%		40%	min	58%	
Commodity	rap_oil		soybean_meal		soybean_oil		soybean2		methanol	
period	P2	MM	P2	MM	P2	MM	P2	MM	P2	MM
a15b20	36%		29%		40%		41%	max	49%	
a15b10	42%	max	26%	min	34%		40%		52%	
a15b5	30%		32%		32%	min	33%		53%	
a15b0	34%		29%		35%		35%		54%	max
a15a5	36%		34%	max	36%		34%		46%	
a15a10	27%	min	31%		41%	max	33%	min	37%	min
Commodity	coking_coal		PVC		aluminum		rebar		cotton	
period	P2	MM	P2	MM	P2	MM	P2	MM	P2	MM
a15b20	50%		42%	max	38%	max	33%	max	32%	min
a15b10	68%		37%		36%		31%		32%	
a15b5	68%		33%		34%		32%		36%	
a15b0	73%	max	32%	min	31%		25%	min	37%	max
a15a5	45%		39%		30%		31%		32%	
a15a10	39%	min	39%		26%	min	32%		33%	
Commodity	common_wheat		pb		rubber		copper		wire_rod	
period	P2	MM	P2	MM	P2	MM	P2	MM	P2	MM
a15b20	34%	max	42%	max	41%	max	38%	max	35%	
a15b10	33%		42%		33%		33%		32%	
a15b5	29%		36%		35%		34%		36%	max
a15b0	29%		39%		35%		33%		29%	min
a15a5	28%	min	34%	min	27%	min	32%		33%	
a15a10	36%		37%		31%		29%	min	36%	
Commodity	zinc		corn		palm_oil					
period	P2	MM	P2	MM	P2	MM				
a15b20	40%	max	26%	min	41%	max				
a15b10	36%		29%		37%					
a15b5	34%		28%		35%					
a15b0	33%	min	31%		36%					
a15a5	37%		32%		34%					
a15a10	26%		32%	max	34%	min				

Table C.18: **Each Kind of News Can Influence How Many Traders and How Many Traders Are Affected by How Many Kinds of News**

tv	CPI	GDP	NYL	PPI	EXP	VIO	IP	FA	M2	IMP	HS	BOT	HSCG	FCR	PMI	_cons
Losing	1534	2698	2175	3741	2586	3964	4604	3903	2068	2473	4617	2286	5366	2564	7188	25113
26998	5.68%	9.99%	8.06%	13.86%	9.58%	14.68%	17.05%	14.46%	7.66%	9.16%	17.10%	8.47%	19.88%	9.50%	26.62%	93.02%
Nature	1	1	2	3	0	1	2	2	1	1	2	0	3	2	9	18
81	1.23%	1.23%	2.47%	3.70%	0.00%	1.23%	2.47%	2.47%	1.23%	1.23%	2.47%	0.00%	3.70%	2.47%	11.11%	22.22%
Profitable	439	753	679	1178	761	1228	1483	1270	642	752	1451	690	1707	827	2653	8097
8991	4.88%	8.38%	7.55%	13.10%	8.46%	13.66%	16.49%	14.13%	7.14%	8.36%	16.14%	7.67%	18.99%	9.20%	29.51%	90.06%

change of tv	CPI	GDP	NYL	PPI	EXP	VIO	IP	FA	M2	IMP	HS	BOT	HSCG	FCR	PMI	_cons
Losing	1350	2215	1799	2221	1591	3813	4215	3258	1752	1933	3723	1744	3947	1681	1682	3
26998	5.00%	8.20%	6.66%	8.23%	5.89%	14.12%	15.61%	12.07%	6.49%	7.16%	13.79%	6.46%	14.62%	6.23%	6.23%	0.01%
Nature	2	3	0	2	0	2	2	3	0	2	1	2	4	0	0	0
81	2.47%	3.70%	0.00%	2.47%	0.00%	2.47%	2.47%	3.70%	0.00%	2.47%	1.23%	2.47%	4.94%	0.00%	0.00%	0.00%
Profitable	423	637	550	639	483	1126	1329	1081	524	592	1173	539	1179	586	534	0
8991	4.70%	7.08%	6.12%	7.11%	5.37%	12.52%	14.78%	12.02%	5.83%	6.58%	13.05%	5.99%	13.11%	6.52%	5.94%	0.00%

tv									change of tv								
losing traders			nature traders			profitable traders			losing traders			nature traders			profitable traders		
0	9161	33.93%	0	67	82.72%	0	3186	35.44%	0	14653	54.27%	0	74	91.36%	0	5124	56.99%
1	7175	26.58%	1	8	9.88%	1	2432	27.05%	1	4140	15.33%	1	2	2.47%	1	1412	15.70%
2	3289	12.18%	2	2	2.47%	2	1031	11.47%	2	2506	9.28%	2	0	0.00%	2	736	8.19%
3	2403	8.90%	3	2	2.47%	3	785	8.73%	3	1804	6.68%	3	2	2.47%	3	527	5.86%
4	1678	6.22%	4	1	1.23%	4	517	5.75%	4	1306	4.84%	4	0	0.00%	4	375	4.17%
5	968	3.59%	5	0	0.00%	5	301	3.35%	5	960	3.56%	5	3	3.70%	5	287	3.19%
6	608	2.25%	6	0	0.00%	6	177	1.97%	6	616	2.28%	6	0	0.00%	6	211	2.35%
7	397	1.47%	7	0	0.00%	7	144	1.60%	7	361	1.34%	7	0	0.00%	7	114	1.27%
8	381	1.41%	8	1	1.23%	8	123	1.37%	8	226	0.84%	8	0	0.00%	8	78	0.87%
9	325	1.20%	9	0	0.00%	9	112	1.25%	9	183	0.68%	9	0	0.00%	9	47	0.52%
10	235	0.87%	10	0	0.00%	10	78	0.87%	10	108	0.40%	10	0	0.00%	10	32	0.36%
11	148	0.55%	11	0	0.00%	11	45	0.50%	11	72	0.27%	11	0	0.00%	11	25	0.28%
12	144	0.53%	12	0	0.00%	12	35	0.39%	12	40	0.15%	12	0	0.00%	12	13	0.14%
13	59	0.22%	13	0	0.00%	13	18	0.20%	13	16	0.06%	13	0	0.00%	13	7	0.08%
14	25	0.09%	14	0	0.00%	14	5	0.06%	14	7	0.03%	14	0	0.00%	14	3	0.03%
15	2	0.01%	15	0	0.00%	15	2	0.02%	15	0	0.00%	15	0	0.00%	15	0	0.00%
	26998			81			8991			26998			81			8991	

C.2 Figures

Figure C.1: **Scatter and Line Graphs of Average Returns (AR) and Cumulative Average Returns (CAR):** Average of all 783 individual contracts and 23 continuous contracts with 5938 partly overlapped samples.

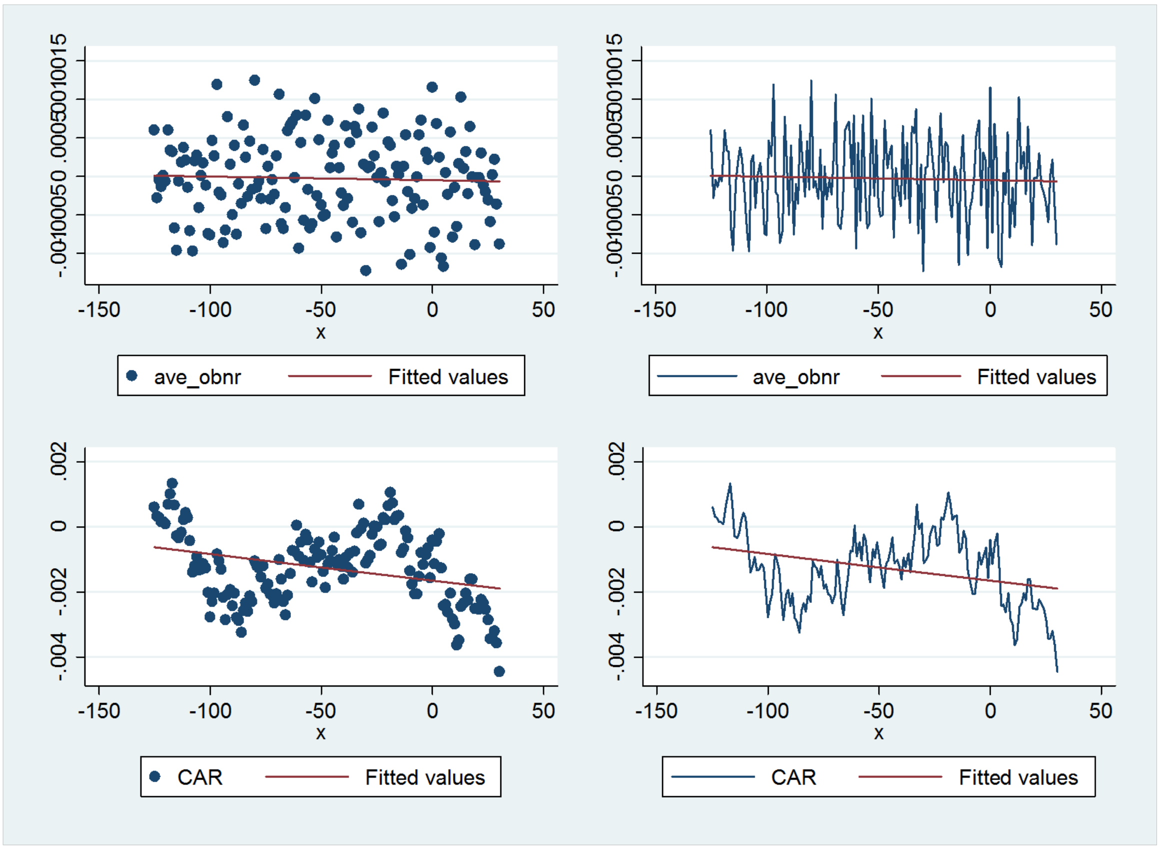


Figure C.2: **Scatter of Average Residuals of All Individual Contracts by 23 Commodities**

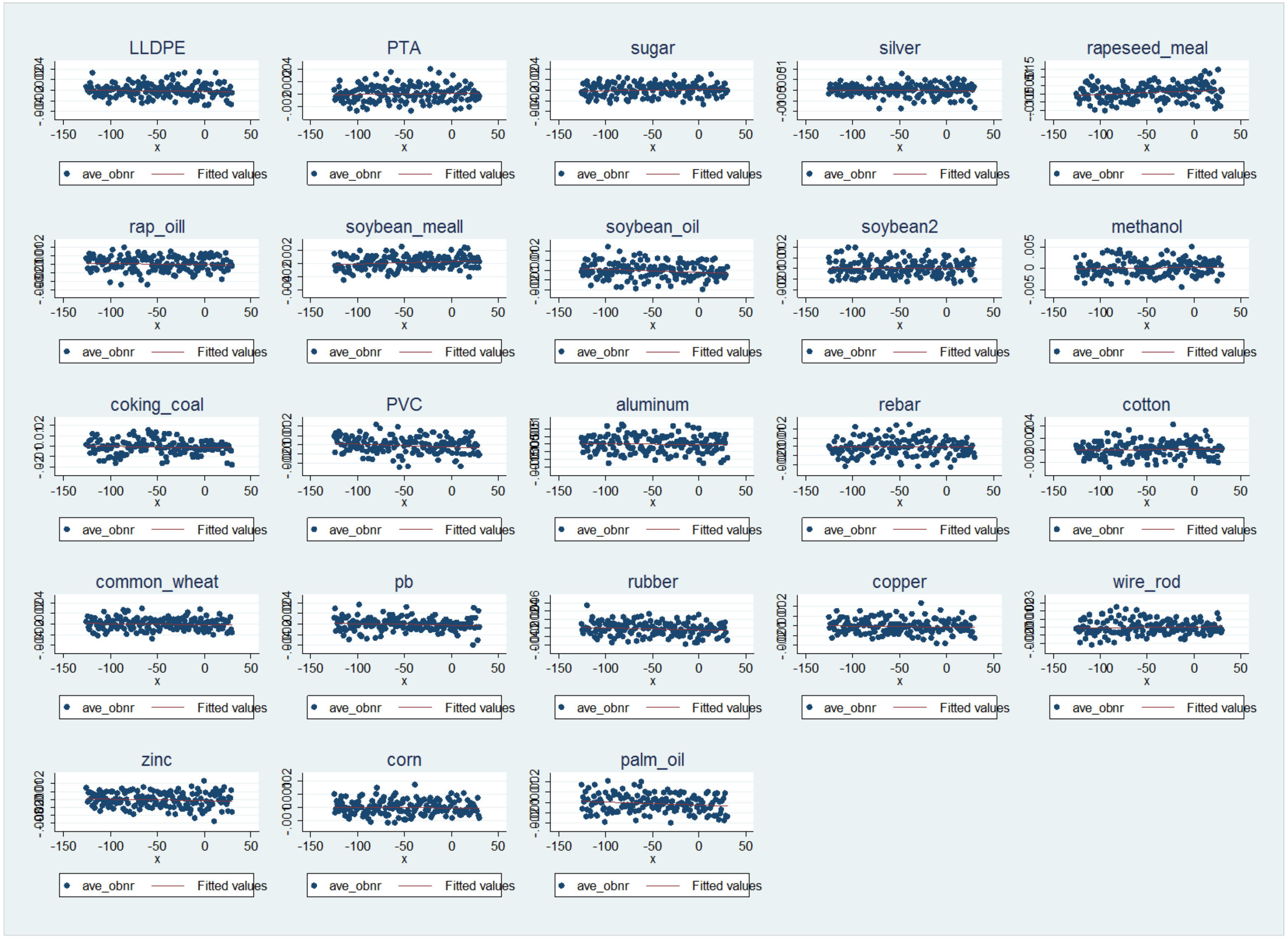


Figure C.3: **Scatter of Cumulative Average Residuals of All Individual Contracts by 23 Commodities**

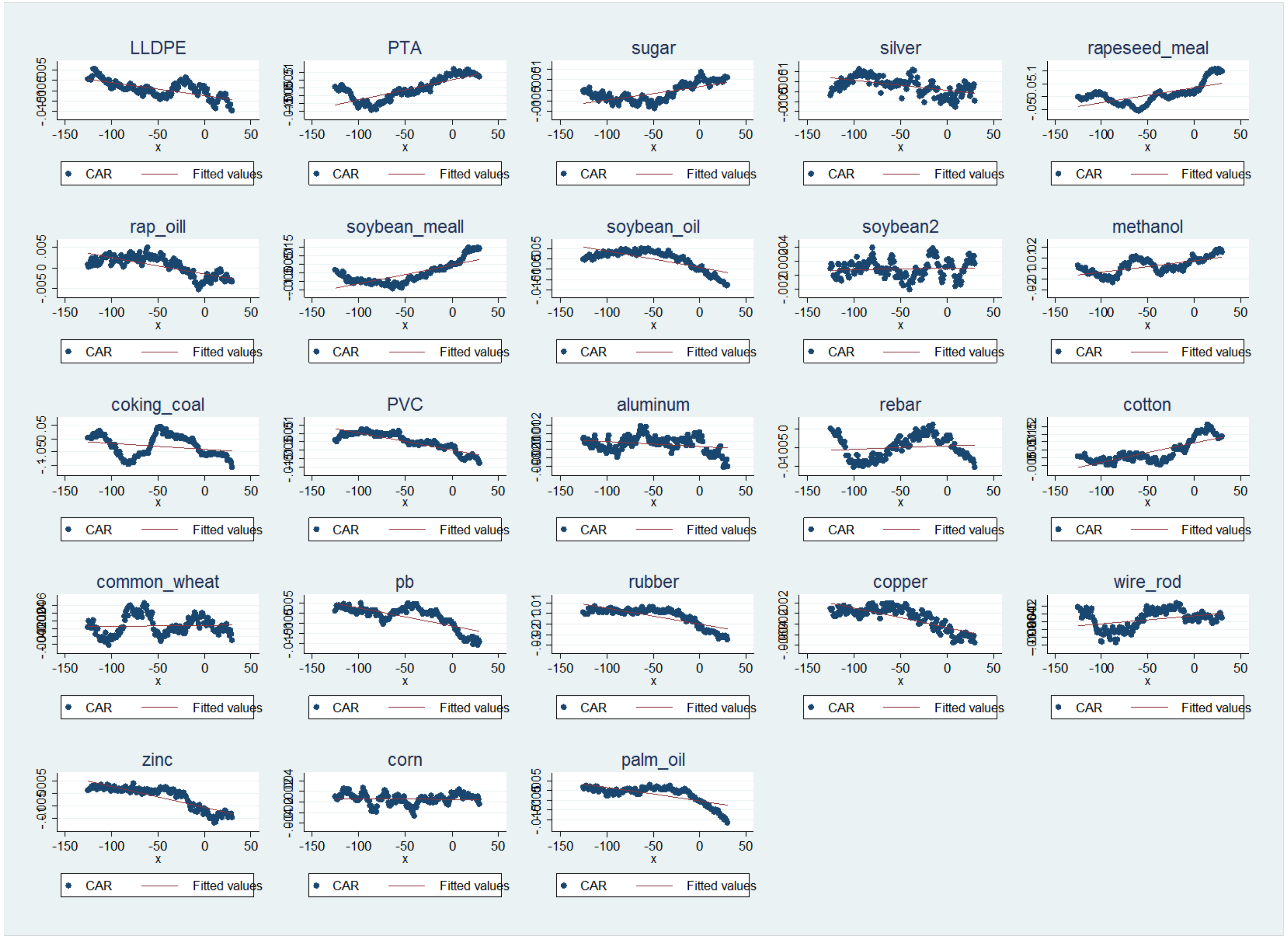


Figure C.4: **Scatter of Average Residuals of Each Continuous Contract by 23 Commodities**

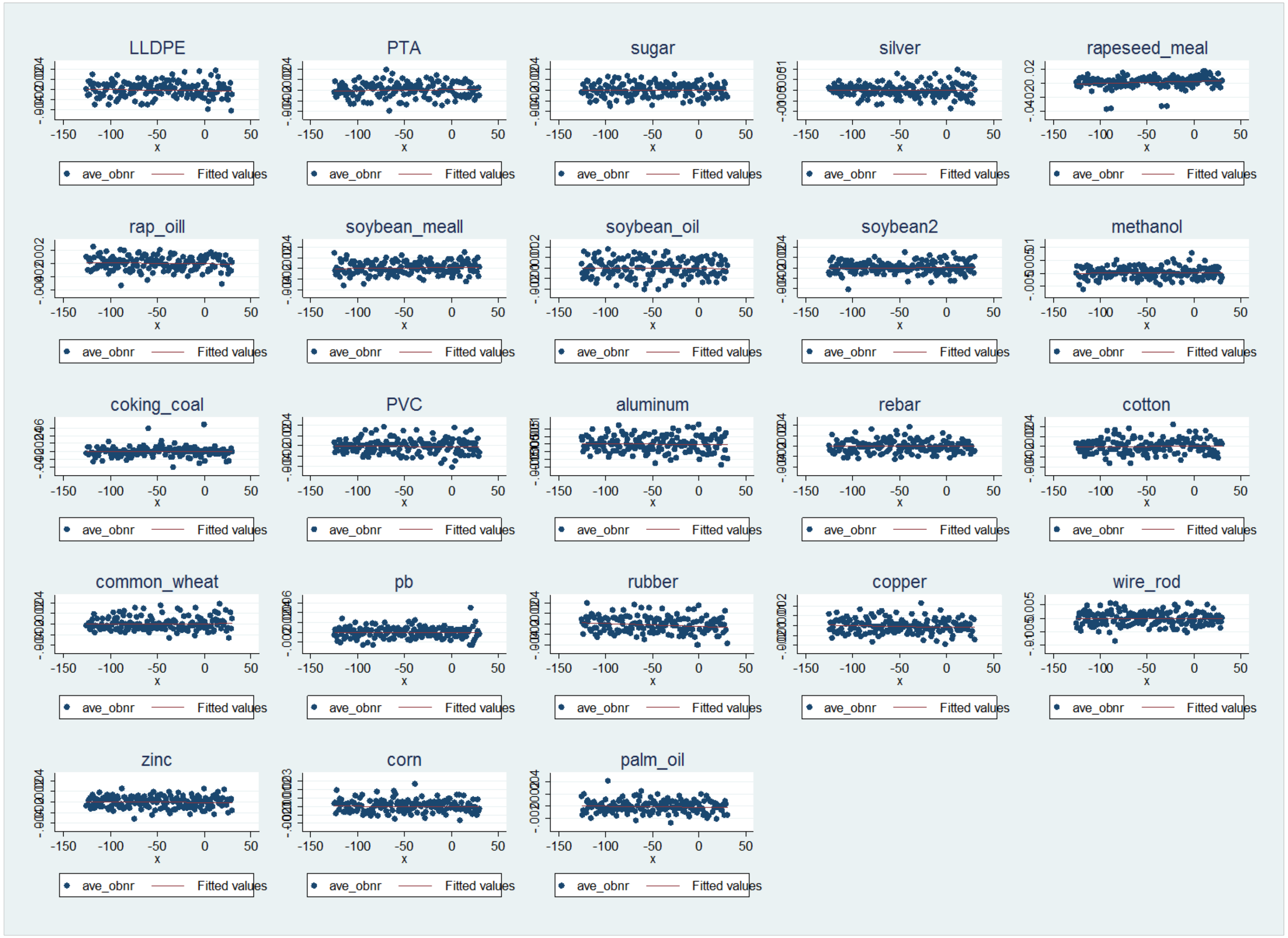


Figure C.5: **Scatter of Cumulative Average Residuals of Each Continuous Contract by 23 Commodities**

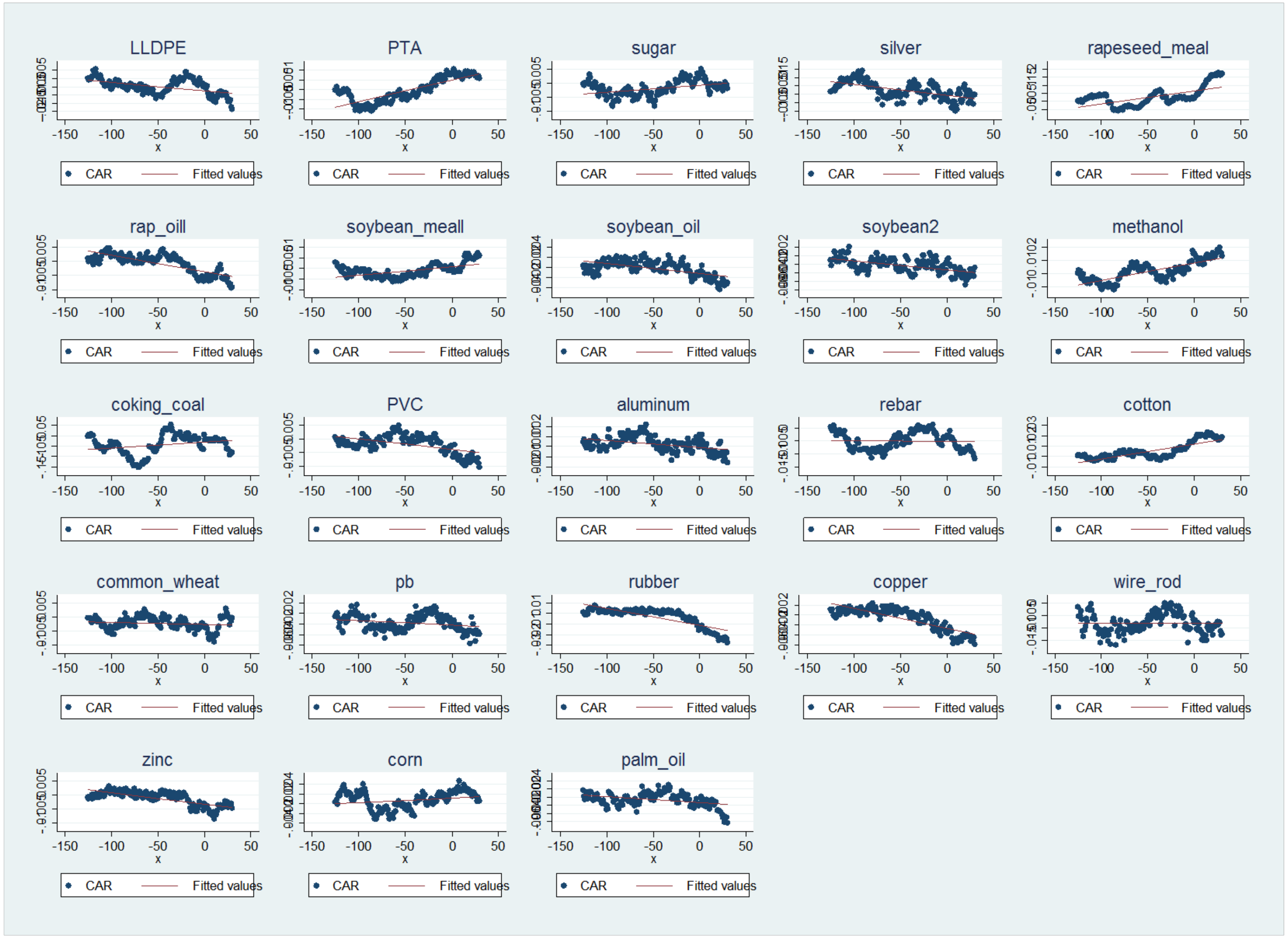
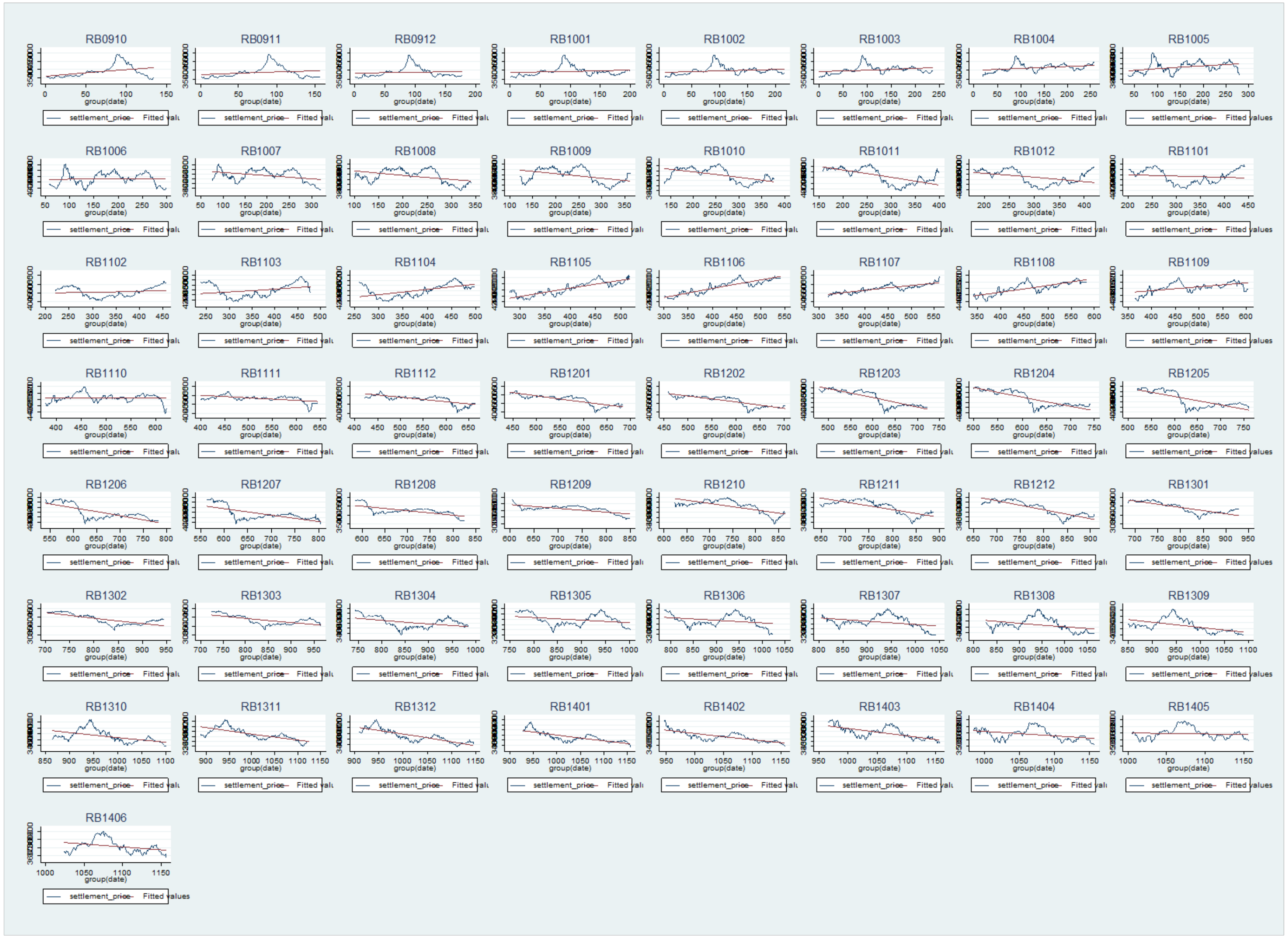


Figure C.6: **K Lines and Trading Volumes of Rebar Continuous Contract**

Figure C.7: **Daily Price Trend of All Regressed Rebar Futures Contracts from RB0910 to RB1406**



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