Durham E-Theses

Microstructure Analysis of Price Discovery, Information-based Trading and Intervention in Foreign Exchange Markets

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Microstructure Analysis of Price Discovery, Information-based Trading and Intervention in Foreign Exchange Markets

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A thesis submitted in partial fulfilment of the requirements for the

degree of Doctor of Philosophy in Accounting and Finance

School of Economics, Finance and Business

University of Durham

May 2015

To My Parents, Wife and Son

Abstract

Motivated by the disconnection between dealer-level (DL) and market-level (ML) models, and the inadequacy of theoretical macro models in explaining the behaviour of the exchange rate, this thesis first studies the microstructure of the foreign exchange market and links the behaviour of dealers to exchange rate determination. We develop a model incorporating both information effect and inventory effect in an environment that is closer to reality.

Secondly, the order flow model explains around 13% of exchange rate movement per transaction for CNY/USD. In addition, we adopt the probability of information-based trading (PIN) model and the autoregressive conditional duration (ACD) model to directly study the information content of trading duration in the Chinese foreign exchange market. The estimated results provide some evidence that both the expected component and the unexpected component of trading duration are relevant to the arrival rate of informed traders. Signed expected and unexpected trading durations of order flow are proven to contain information in addition to order flow. The final effect of trading duration is a composite result between uninformed and informed traders. Therefore, the impact of trading duration differs according to different market situations.

Thirdly, using the Logit model and Ordered Logit model in the estimation, we find that the Chinese government prefers a gradual achievement of its target exchange rate, and 'leans-against-the-wind' with a 150-day moving average and target appreciation rate. The driving force of intervention is asymmetric and dynamic. In addition, the

Chinese government is found to show more tolerance toward USD appreciation (CNY depreciation) than to USD depreciation (CNY appreciation), except during periods when it actively accelerates the appreciation of CNY to counter a high rate of inflation. Our model is proved to perform better than OLS estimation and to improve prediction ability.

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Declaration

The content of this doctoral dissertation is based on research work carried out at Durham University Business School, UK. No content of this thesis has previously been submitted for any other degree or qualification in this or any other institution.

ACKNOWLEDGEMENTS

First of all, I would like to express my great gratitude to my supervisor, Dr Zhichao Zhang. His wisdom and knowledge have introduced me to this amazing research area, and helped me overcome one problem after another. His constructive advice has continuously broadened my horizon and guided my research to the present achievement. I also owe sincere thanks to my current co-supervisor Dr Danny Chow, and ex-co-supervisor Dr Wenxuan Hou, for their helpful suggestions on the writing and structure of my research.

I am especially indebted to one of the most important people in my life, my wife Dr Wenting Zhang, who is my soul mate now and for the rest of my life. Without her encouragement, I would not have made the decision to pursue study for a PhD degree. Thank you for your support at every step along my journey to the doctoral destination. I cherish every moment with you in our academic discussions and in our family life. Together, we are the world. Thank you also for bringing such a lovely boy into our family. Both of you have made our world so happy, spiritually rich and colourful.

I would like to express my appreciation to Durham city and Durham University. In this place, I met my soul mate and got to know so many friends. I am grateful for all the support I have received from Durham University staff, especially in the Doctoral Office of the Business School, the International Office and the Finance Office. I especially enjoyed the time when I worked at the International Office. Durham, you are such a beautiful and peaceful place that I will never stop missing you. You have given me so many unforgettable memories.

I would not have become the person I am without the precepts and examples from my parents. I still remember how concerned you were when I was playing games before the college entrance examination. You did not blame me, but allowed me freedom to learn how to do the right things at the right time. I remember how proud you were when I was admitted to Peking University and then Durham University. I remember your tears at my wedding even though you turned away to hide them. To both of you, and to my brother, thank you for your unconditional love for me all my life. Thank you for your unfading support, no matter where I have wanted to go or what I have wanted to do.

My son, you are the best gift God has given me and my family. When I first saw you, you were so tiny and fragile that I did not dare even to touch you. Seeing you growing up day by day, I am getting to know the weight of responsibility of being a father. Thank you for letting me know the sacrifice my parents have made in raising me. Thank you also for bringing our family so much happiness. You are so lovely that I cannot stop loving you. May you be always healthy and happy.

Chapter 1

Introduction

With rapid economic growth and increasing economic might, the Chinese foreign exchange market has experienced steady development. According to data from Wind Info, in 2012 the annual trading volume of the spot business was 2484 billion US dollars and the number of transaction deals was 242 thousand. By 2014, these figures had increased by 32.69% and 41.69% per year, respectively, with trading volume reaching 4108 billion US dollars, and the number of transactions increasing to 444 thousand. In 2014, the trading volume of China's foreign exchange market was more than 6 times that of the stock market.[1] Given the growing size and importance of the Chinese foreign exchange market, it is important to pursue a better understanding of this market, including price discovery, trading patterns and the role of government.

1.1 Motivations and Contributions of the Thesis

Differing from the stock market, the foreign exchange market is a global market, and measured in terms of relative values of different currencies. In this market, national economic conditions, rather than performance of individual companies, are generally perceived to be the driving force behind movements of the exchange rate. Reflecting this, early studies of the exchange rate are dominated by macroeconomic models.

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[1] The data is collected from Wind Info and both numbers are in the same currency, i.e. the Chinese renminbi.

Many macro models, such as the theory of Purchasing Power Parity (PPP), have become classical themes of economics textbooks.

However, macroeconomic models fail to capture exchange rate dynamics, and are not necessarily better than a simple random walk model in explaining and forecasting exchange rate movements (Meese and Rogoff 1983, Cheung, Chinn, and Pascual 2005). Motivated by the inadequacy of macroeconomic models, researchers have sought alternative methods for studying exchange rate dynamics. One prominent line of enquiry is the microstructure study of the foreign exchange market. The key concept of microstructure research is order flow.[2]

Under different assumptions of market structure, the microstructure approach to foreign exchange markets can be divided into dealer-level (DL) and market-level (ML) models. The DL model focuses on the price formation of individual market participants. The problems associated with this model lie in its assumptions of a simple market structure and of incoming transactions as the unique source of order flow. These assumptions are not consistent with the fact that the foreign exchange market is in reality both a quote-driven and an order-driven market, with multi-dealers. This shortcoming is alleviated in the multi-structure framework of the ML model, which focuses on the market-wide price formation. However, the ML model over-simplifies the individual price formation process and ignores the rich content of individual dealers who might enter into the market-wide exchange rate formation.

Motivation 1: Given that there exists a gap between the DL model and ML model in terms of assumptions and model derivation, the first motivation of this thesis is to

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[2] Order flow is usually defined as the imbalance of buyer-initiated transactions and seller-initiated transactions.

develop a market-wide order flow model for the exchange rate with rich content of market participants under a microstructure framework, filling the gap between the DL model and ML model.

Calculation of order flow requires high frequency transaction data on trading directions. As such, in academic research, the microstructure framework was first applied to equity markets, where trading data were effectively centralized owing to the fast development of electronic trading systems. Unlike the stock market, the foreign exchange market is decentralized, less transparent and involves multi-dealers. In adapting the microstructure model to the foreign exchange market, a main difficulty has been the availability of high frequency transaction data. However, thanks to the dramatic development of electronic and internet technology in recent years, data availability has become less of an issue. Moreover, a series research pioneered by Evans and Lyons (2002) has further advanced the microstructure study of exchange rates. Consequently, the application of a microstructure framework to the study of the foreign exchange market has become a promising area for research. Its success is, however, limited by its strong requirements for high frequency transaction data, especially in the emerging markets.

In contrast to the extensive discussion on main trading currency pairs in the developed markets, research on emerging foreign exchange markets has been scant. While in the limited literature available order flow is found to play an important role in explaining exchange rate dynamics, the order flow model of emerging markets captures a relatively smaller part of exchange rate movement than in developed markets. Investigations are required to find other forces in addition to order flow in the case of emerging foreign exchange markets.

Motivation 2: The second motivation of the thesis is to examine the relationship between order flow and exchange rate in one of the most important emerging markets, the Chinese foreign exchange market. The research also tries to discover some variables in addition to order flow that may contribute to explaining exchange rate dynamics in China.

Another research area within a microstructure framework is the investigation of official intervention in the foreign exchange market. Not surprisingly, there is an extensive body of literature focusing on foreign exchange intervention in the developed markets. Many of those studies are focused on the effectiveness of intervention. As argued by Menkhoff (2012), over the last decade the major central banks in the developed markets have almost ceased engaging in foreign exchange intervention. In contrast, in the emerging markets foreign exchange intervention is widely used as an important tool for managing the exchange rate. Consequently, the emerging markets have attracted more research interest.

Research into China's intervention proves to be a challenge. Because the country does not disclose any information on official intervention in the foreign exchange market, researchers often use changes in China's foreign exchange reserve as an indicator for official intervention operations. This is because the Chinese yuan is undervalued, and the Chinese government tends to keep the exchange rate stable and stop appreciation of the currency. Therefore, the Chinese government has to buy US dollars, which is associated with the increase in the country's foreign exchange reserves. According to the data from Wind Info shown in Figure 1.1, China's foreign exchange reserve increased rapidly during the last decade, from 624 billion US dollars in January 2005 to a peak level of 3993 billion US dollars in June 2014. The sustained increase in the

country's foreign exchange reserve has been considered as evidence of continuous intervention in the Chinese foreign exchange market.
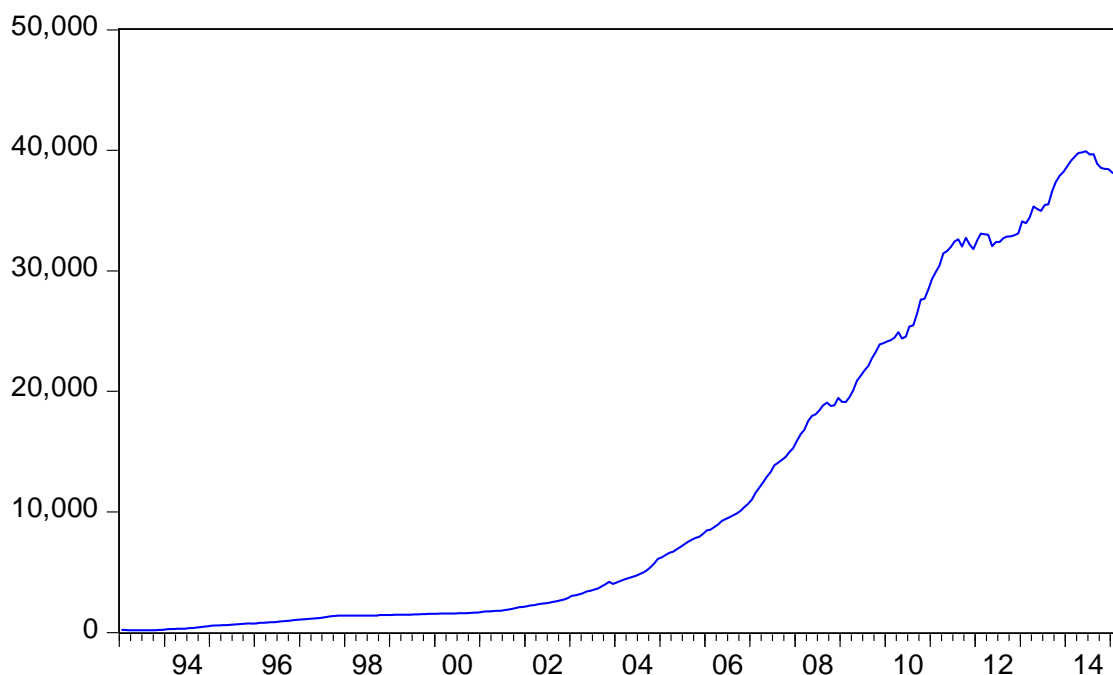
Figure 1.1 China's foreign exchange reserve (01/1993-03/2015)

Motivation 3: Given the importance of foreign exchange intervention in emerging markets, and the limited research on the reaction function of the central bank, the final motivation of this thesis is to discover the driving forces behind foreign exchange intervention in China.

This thesis intends to contribute to the literature in the following aspects:

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- *Microstructure analysis:* This thesis applies microstructure analysis, a framework that has emerged from recent foreign exchange market research, to study one of the most important emerging foreign exchange markets, that of China. The research adopts both theoretical and empirical perspectives. This could help improve our understanding of the Chinese foreign exchange market in terms of price discovery, thus enriching the microstructure research in the Chinese foreign exchange market.

- *A newly developed model:* In this thesis, I develop a new exchange rate pricing model under the microstructure framework. By studying the price setting behaviours of individual dealers in a multi-structure market, the model shows how diversified individual quoted prices become the market-wide exchange rate. Compared to existing models, this model is more realistic and provides richer content on the pricing impact of order flow, filling the gap between the DL model and the ML model.

- *High frequency data:* We collect tick data for CNY/USD transactions. The highest frequency used in this thesis for estimation is tick-by-tick, and the lowest frequency is daily.

- *Information content of trading duration:* The current literature explains the information content of trading duration by analysing the impact of trading duration on exchange rate movement and volatility. This thesis adopts the probability of information-based trading (PIN) model and the autoregressive conditional duration (ACD) model to directly examine the relationship between

both components of trading duration and the two components of information-based trading.

- *Markov regime switching:* The information content of trading duration varies across trading hours, assets and markets. Therefore, this thesis introduces a nonlinear model, the Markov regime-switching model, to study the time-varying relationship between exchange rate movement and both components of trading duration in different trading regimes.

- *Identification of intervention:* Since the intervention data is not readily available from official sources, it is difficult to conduct data-driven microstructure research into the foreign exchange intervention in China. This thesis develops indicators of intervention from news reports and the setting of central parity rate (CPR) far away from the market closed price with daily data for around two years. Based on the features of the foreign exchange market management system, we define another kind of intervention, CPR intervention, in addition to the traditional central bank trading (CBT) intervention.

- *New driving force:* This thesis takes into consideration many possible driving forces discussed in the literature: for example, deviation from the target exchange rate, excess volatility, interest rate differential, national economy and intervention persistence. In addition, we introduce two new determinants of intervention, i.e. deviation from the target appreciation rate and a measure of market liquidity. This is in accordance with the characteristics of foreign exchange intervention in China.

● *Dynamics of intervention strategy:* Our intervention data cover an eventful period, characterized by the high inflation rate, pressure of renminbi (CNY) appreciation, announcement of equilibrium of CNY/USD, enlargement of market elasticity, reform of intervention strategy, and the implementation of Quantitative Easing Ⅲ (QEⅢ), among others. Through estimation of the Ordered Logit model and examination of its forecasting ability, we study the Chinese government's attitude towards exchange rate movement and, more importantly, seek to discover any change in its intervention strategy.

1.2 Research Questions and Main Findings of the Study

In view of the growing importance of China's economy and the acceleration of RMB internationalization, this thesis attempts to provide a deeper understanding of the Chinese foreign exchange market. For this purpose, we adopt the microstructure methodology that has dominated recent research of the foreign exchange market to develop an exchange rate pricing model, to study exchange rate determinants empirically, and to discover the driving force of foreign exchange market intervention in China. More specifically, this thesis aims to answer the following questions:

Question 1: How is the price of foreign exchange discovered in the alternative model within a microstructure framework?

Starting from the price discovery of individual dealers with a set of past information, we define the quoting strategies in a multi-structure market. Our model allows heterogeneous price setting, and diversified tools and motivations to make a deal. Market-wide exchange rate is determined by market equilibrium in the interdealer

market. The features of the model tell us that competition is an important factor in determining the quotes of exchange rate. More specifically, when the number of dealers increases, the market is more competitive, and the quotes of exchange rate are closer to dealers' expected value.

Question 2: In the process of price discovery, in what ways or through what channels does order flow influence the exchange rate?

Our model shows that order flow impacts on the exchange rate via the information channel and the inventory channel. The information channel is realized through the trading of customers with private information and the optimal quoting strategy of dealers reacting to incoming information. The inventory channel is valid when dealers wish to share overnight risk with the public and stay with no net position at the end of the trading day. Therefore, the coefficient on order flow in the exchange rate discovery process reflects both information effect and inventory effect. Specifically, the impact of order flow on the exchange rate is related to macro variables, overnight market risk, the number of dealers, parameters of utility function and risk-bearing capacity.

Question 3: Does order flow have significant impact on the exchange rate, and to what extent does order flow explain exchange rate movement?

Because of the difficulty in collecting tick-by-tick transaction data in the Chinese foreign exchange market, there is little evidence to show the price impact of order flow on exchange rate. To the best of my knowledge, there is still a gap in the empirical research of order flow model on CNY/USD in ultra-high frequency. This thesis examines the relationship between order flow and exchange rate movement

with high frequency data from the Chinese foreign exchange market. Our results confirm the importance of order flow in capturing exchange rate dynamics. Consistent with the literature, order flow explains around 12% of exchange rate changes per transaction, which is relatively low compared with the developed market. In addition, the price impact of order flow is larger when the market is volatile and illiquid than when the market is placid and liquid. Our findings help to understand the intraday exchange rate dynamics and are meaningful to market participants, especially to those interested in ultra-high frequency transaction.

Question 4: Assuming that trading duration probably contains information in addition to order flow, what is the information content of trading duration in the Chinese foreign exchange market?

Because the microstructure approach to foreign exchange markets usually adopts an order flow model with fixed time intervals, such as weekly or daily, irregular time intervals between two consecutive transactions are ignored, which may lead to the loss of information on the behaviours of market participants. By adopting the PIN model and ACD model, this thesis examines the relationship between two components of trading duration and two components of information-based trading. Our results provide evidence that on average both components of trading duration are related to the arrival rate of informed traders, but not to the probability of information occurring.

Question 5: Given that the information content of trading duration has been confirmed in literature on equity and derivatives markets, it is logical to infer that

trading duration may have a significant impact on exchange rate changes and volatility. If so, in what ways?

Not surprisingly, information content of trading duration is not conclusive in the literature. One theory advocates that long trading duration implies low trading intensity of informed traders, leading to small exchange rate movement and low volatility. However, another theory argues that discretionary uninformed traders will choose the time to trade in order to minimize adverse selection costs; therefore, long trading duration mirrors the low trading intensity of discretionary uninformed traders and high proportion of informed traders, and short trading duration is associated with large exchange rate movement and high volatility. According to the literature, the sign of price impact of trading duration varies with trading hours, different assets, and different markets. This thesis adopts a nonlinear methodology, i.e. the Markov regime-switching model, to study information content of both components of trading duration on the Chinese foreign exchange market. The model is able to capture different relationships between trading duration and exchange rate movement in different regimes. It is supposed to provide more information which may be lost in the linear model. Our results support both theses, but ultimately the outcome of trading duration is a composite result due to both informed and uninformed traders. The sign of trading duration depends on the market structure and situation. We also examine the relationship between conditional volatility and both components of trading duration in the framework of an ACD-GARCH model. Conditional volatility is found to be mainly determined by signed expected trading duration.

Question 6: What are the driving forces behind central bank intervention in the Chinese foreign exchange market? If there are different types of intervention, is there any difference in the policy reaction function?

Based on the features of the Chinese foreign exchange market management system, this thesis defines two types of foreign exchange intervention in the country, namely CBT intervention and CPR intervention. Since the Chinese government does not disclose intervention records, we compose indicators of intervention based on media reports and from the information of the CPR as against the market closing price. Through estimating both the Logit model and the Ordered Logit model, we find that the driving forces behind foreign exchange intervention in China are asymmetric and dynamic. In general, the Chinese government follows a 'lean-against-the-wind' policy when intervening in the market, and prefers a gradual approach in moving towards its target appreciation rate. However, following the government announcement that the CNY/USD exchange rate has reached equilibrium, the target appreciation rate ceases to be a driving force for intervention. CBT intervention is concerned with interest rate differential and is launched mainly to protect the Chinese foreign exchange market from attacks by international hot money. In contrast, CPR intervention is more concerned with the domestic economy. Appreciation-targeted CBT intervention is conducted to remove excess volatility and to provide market liquidity when necessary.

Question 7: Given the general opinion that the Chinese government frequently intervenes in the foreign exchange market, what is the attitude of the Chinese government toward the direction of exchange rate movement?

Our results from estimating the neutral band of non-intervention for both types of foreign exchange intervention show that the government's attitude toward exchange rate movement depends on its policy target. In general, the Chinese government is more tolerant of USD appreciation (CNY depreciation) than USD depreciation (CNY appreciation). When China is facing a high inflation rate, the Chinese government actively speeds up the appreciation of CNY in order to offset import inflation. In this case, the government would show more tolerance of USD depreciation (CNY appreciation) than USD appreciation (CNY depreciation).

Question 8: With the discovery of the driving forces of intervention in the Chinese foreign exchange market, how well will our model perform in predicting China's official foreign exchange intervention?

In terms of the maximum predicted probability, our model of the intervention indicators can correctly predict above 70% of both types of intervention. It proves to perform better than a constant probability model. The forecasting ability may change depending on the government's intervention strategy. After the central bank announcement of its intention to reduce the intervention frequency, and to improve intervention techniques, CBT intervention becomes harder to predict. Instead, CPR intervention becomes a more important intervention tool than CBT intervention, and the forecasting ability of our model on CPR intervention is improved.

1.3 Organization of the Thesis

The rest of this thesis is structured as follows:

- Chapter 2 reviews in depth the related literature of key DL and ML models. It also provides a review of the microstructure literature on the foreign exchange market, the information content of trading duration, and the research on driving forces of foreign exchange intervention.

- Chapter 3 describes the structure of the foreign exchange market. In accordance with this structure, we develop an alternative order flow model, in steps, to capture exchange rate dynamics. Our model is set in a more realistic environment and provides richer content than the models in the previous literature.

- Chapter 4 examines the empirical relation between order flow and the exchange rate using high frequency data. Inspired by the success of trading duration in the equity market and derivative market, we introduce trading duration in addition to order flow to capture exchange rate movement. This chapter investigates the information content of trading duration directly, and the impact of both components of trading duration on exchange rate movement and volatility in different market situations.

- Chapter 5 defines two types of intervention and potential driving forces behind intervention in the Chinese foreign exchange market. We study the intervention asymmetry and dynamics of the driving forces for intervention. The forecasting ability of the model is also examined in light of various criteria.

- Chapter 6 concludes the thesis. It summarizes the main findings, discusses the research implications and offers suggestions for future research.

Chapter 2

Literature Review

Before embarking upon our empirical work, this chapter provides an in-depth review of the theoretical framework of different types of order flow model. It also seeks to give a picture of the empirical work on exchange rate dynamics in the microstructure framework, the information content of trading duration, and intervention reaction function in different countries. In other words, this chapter is intended to provide a useful background on the research topic, and a thorough overview of the relevant microstructure literature.

2.1 Literature on DL and ML Models

This section aims to give a general survey of DL and ML models. The DL models focus on the factors that influence the behaviour of individual market participants in price setting, and thus connect micro variables such as order flow and inventory with exchange market quotes. In contrast, the ML model studies market-wide exchange rate formation.

2.1.1 Dealer-level models

From among the many optimizing models of the foreign exchange market, the following section will introduce the DL models of Lyons (1995), Huang and Stoll (1997) and Ding (2006) in chronological order.

2.1.1.1 Lyons' model

Lyons' structural model is extended from that of Madhavan and Smidt (1991). It is an optimizing model with information set, agents and expectations built on the Bayesian rule. There are three signals in the informational setting: public signal S_t, private signal C_{jt} and additional public signal G_t. All the signals are assumed to reflect the value of the exchange rate. Two equations are important in the model. First:

$$Q_{jt} = \theta(\mu_{jt} - P_{it}) + X_{jt} \qquad (2.1)$$

where Q_{jt} is possible trading volume from dealer j consistent with the regret-free property[3] at time t. μ_{jt} denotes dealer j's expectation of the currency value conditional on available information at time t. It is a function of S_t and G_t. P_{it} is transaction price of dealer i and X_{jt} means liquidity demand of dealer j at time t. In fact, the realized trading volume will reflect private information C_{jt}. With the Bayesian rule, market makers are able to extract private information from dealer j's trades. The other important equation is an optimal strategy in many inventory models:

$$P_{it} = \mu_{it} - \alpha(I_{it} - I_i^*) + \gamma D_t \qquad (2.2)$$

where I_{it} is dealer i's current inventory level at time t. I_i^* denotes the desired inventory position of dealer i. D_t is direction indicator at time t, set at 1 in an ask

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[3] 'Regret-free' here means that the dealer will set the price to incorporate all the potential trading volume so that he will not regret making the quote.

trade and -1 in a bid trade. It can be seen that the dealer will reduce his quotes when the current inventory is higher than the desired position, and vice versa. While the μ_{it} is defined as a function of any Q_{jt}, the information effect will enter into the model through conditional expectation and co-exists with the inventory effect:

$$P_{it} = (1 - \rho)G_t + \rho S_t + \frac{1 - \phi}{\phi\theta}Q_{jt} - \frac{\alpha}{\phi}(I_{it} - I_i^*) + \frac{\gamma}{\phi}D_t \tag{2.3}$$

Using available data to proxy for G_t and considering S_t as $\mu_{it} + \varepsilon_{i,t}$, the empirical model to be tested is as follows:

$$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \beta_6 B_t + \varepsilon_{it} \tag{2.4}$$

where B_t is brokered order flow at time t, which proxies for G_t. β_1 measures the information effect and β_3 measures the inventory effect.

2.1.1.2 Huang and Stoll's model

Huang and Stoll (1997) develop an indicator model, in which direction of transaction but not trading volume is important. It provides a flexible model to examine a number of variations on microstructure issues. There are two basic equations in the model. The first is the relationship between fundamentals and private information:

$$V_t = V_{t-1} + \alpha \frac{S}{2} Q_{t-1} + \varepsilon_t \tag{2.5}$$

where V_t signifies unobservable fundamentals at time t, which is similar to conditional expectation μ_{it} in Lyons' model. S denotes constant spread and Q_{t-1} is the buyer-seller indicator at time $t-1$, namely incoming order flow. As can be seen from the equation, the unobservable fundamentals element is adjusted by private information revealed in the incoming order flow of last trade. Hence, information effect enters into the model. The other basic equation is based upon the characteristics of inventory theory. That is, the dealer will set the midpoint quote as fundamentals with an adjustment of accumulative inventory in order to control inventory position within the desired level:

$$M_t = V_t + \beta \frac{S}{2} \sum_{i=1}^{t-1} Q_i \tag{2.6}$$

where M_t is midpoint quote and $\sum_{i=1}^{t-1} Q_i$ denotes the accumulative inventory level at time t. Note the assumption that incoming order request is the only resource to control inventory position. In that case, current inventory level would equal the quantity of cumulative incoming order flow. With the common factor V_t the general price equation is:

$$P_t = M_t + \frac{S}{2} Q_t + \eta_t \tag{2.7}$$

where P_t is dealer's price at time t. Both the information effect and inventory effect enter into the Huang and Stoll model. The final empirical formulation is as follows:

$$\Delta P_t = \frac{S}{2}(Q_t - Q_{t-1}) + (\alpha + \beta)\frac{S}{2}Q_{t-1} + e_t \tag{2.8}$$

While α and β measure the information effect and inventory effect respectively, they cannot be separately estimated. In order to overcome this drawback, Huang and Stoll suggest two methods to separate the information effect and inventory effect:

- Inventory effect indicates that order flow exhibits negative serial correlation. So they assume:

$$\mathrm{E}(Q_{t-1}|Q_{t-2}) = (1 - 2\pi)Q_{t-2} \tag{2.9}$$

where π is the probability that the sign of order flow at time t is opposite to that of order flow at time $t-1$. Combining the equations (2.5) and (2.6), the final empirical formulation would become:

$$\Delta M_t = (\alpha + \beta)\frac{S_{t-1}}{2}Q_{t-1} - \alpha(1 - 2\pi)\frac{S_{t-2}}{2}Q_{t-2} + e_t \tag{2.10}$$

The GMM procedure is able to estimate α and β so as to separate the information effect and inventory effect.

- Inventory effect on quote changes arises from inventory changes in both the stock under test and other stocks:

$$M_t^k = V_t^k + \beta^k \frac{S^k}{2} \sum_{i=1}^{t-1} Q_i^* \tag{2.11}$$

Q_i^* is aggregate order flow of market portfolio at time i. Considering the equation (2.7), the model then becomes:

$$\Delta P_t^k = \frac{S^k}{2} \Delta Q_t^k + \alpha^k \frac{S^k}{2} Q_{t-1}^k + \beta^k \frac{S^k}{2} Q_{t-1}^* + e^k \tag{2.12}$$

in which the information effect and inventory effect can be separately estimated.

2.1.1.3 Ding's model

Ding's (2006) model is one of the few optimizing models of the foreign exchange market. It describes the price setting behaviour of a typical dealer with incoming order request as the unique resource to make a deal. Ding's paper contains a number of assumptions:

- Dealers (totalling M in number) have identical constant absolute risk-averse utility function $U(x) = -e^{-Ax}$.

- T numbers of orders are divided into T sub-periods.

- Dealer i begins with cash C_i and enters the market with a fixed cost $\bar{F}_i$.

- Public information is released at the beginning of the period and dealers revise their quotes immediately, which means $p_{0,i}^{post} = p_{0,i}^{ante} + r$. Here the superscript post means ex post and ante denotes ex ante.

- Dealers' inventory levels are uniformly distributed within [-R, R] and the starting level for dealer i is $\varepsilon_{0,i}$.

- When a request arrives, the probabilities of buying and selling behaviour are equal.

- Expected quote movement $E(z_t | S_{t,i})$ in sub-period t is proportional to order size $Q_{t,i}$ in the corresponding sub-period. Here $S_{t,i}$ is the information set for dealer i in sub-period t.

The market structure in Ding's model is quite simple. As shown in Figure 2.1 below, after the customer sends a transaction request, the dealer will consider his current inventory position and decide on the regret-free bid and ask quotes in order to respond to the requests. Quote shading requires the dealer to lower his prices when the inventory level is higher and raise his prices when the inventory level is lower. The dealer's utility maximization problem is essentially an optimal strategy problem in the auction market. The optimal price setting of the dealer is the Nash equilibrium incorporating the inventory effect. When the customer receives quotes, he will make a decision to buy, to sell or not to trade. Under the assumption mentioned above, private information is released by incoming order flow and enters into the price setting via the

utility function in the dealer's expected wealth. Then the period ends and the next

trading period begins with the same procedure.
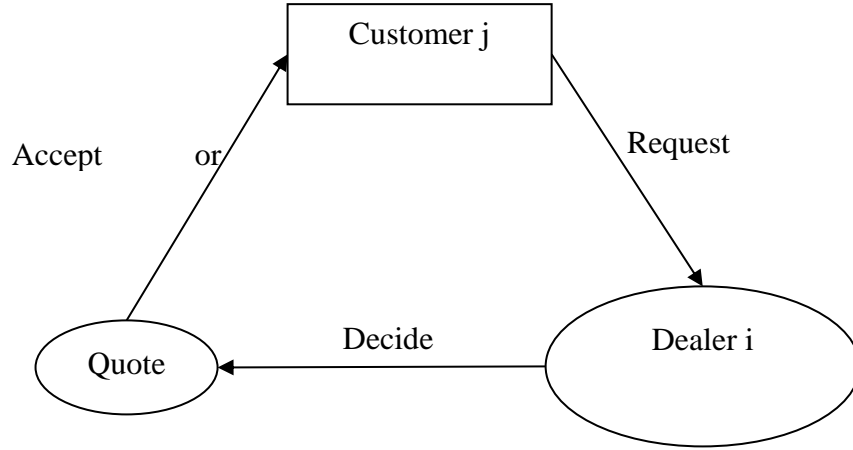
Figure 2.1 Process of exchange rate determination in Ding's model

While Ding's model defines the exchange rate as the middle point of bid-ask quotes,

both the information effect and inventory effect enter into the exchange rate

determination. The final equation in a sub-period is as follows:

$$P_{t,i}^{post} = P_{t-1,i}^{post} - A\sigma^2 \left(1 - \frac{1}{M}\right) I_{t,i}^{ante} + \beta_i Q_{t,i}$$

(2.13)

$$I_{t+1,i}^{ante} = I_{t,i}^{post} = I_{t,i}^{ante} - Q_{t,i}$$

Here σ^2 is conditional volatility of the exchange rate. Exchange rate movement in the whole period is the integration of all the sub-periods.

$$P_{T,i}^{post} = P_{0,i}^{post} + r + \left[A\sigma^2\left(1 - \frac{1}{M} + \beta_i\right)\right]Q_{0-T,i}$$

(2.14)

$$+ \left[A\sigma^2\left(1 - \frac{1}{M}\right)\right]\left(\sum_{t=1}^{T-1} Q_{0-t,i} - T\varepsilon_{0,i}\right)$$

where r is the exchange rate increment after public information is released. $Q_{0-t,i}$ denotes accumulated order flow within period $[0-t]$.

2.1.2   Market-level models

The ML models develop price formation in a multi-structure framework of foreign exchange market. This allows diversified ways to make a deal, in contrast to the unique source of incoming order in the DL model, and empirical research has shown the ML models to be more successful. The following section will introduce the ML models of Evans and Lyons (2002) and Cao, Evans, and Lyons (2006), in chronological order.

2.1.2.1 Evans and Lyons' model

Evans and Lyons (2002) assume a three-round trading model to describe the microstructure of the foreign exchange market (Figure 2.2 below). This is a revision of the simultaneous-trade model derived by Lyons (1997).
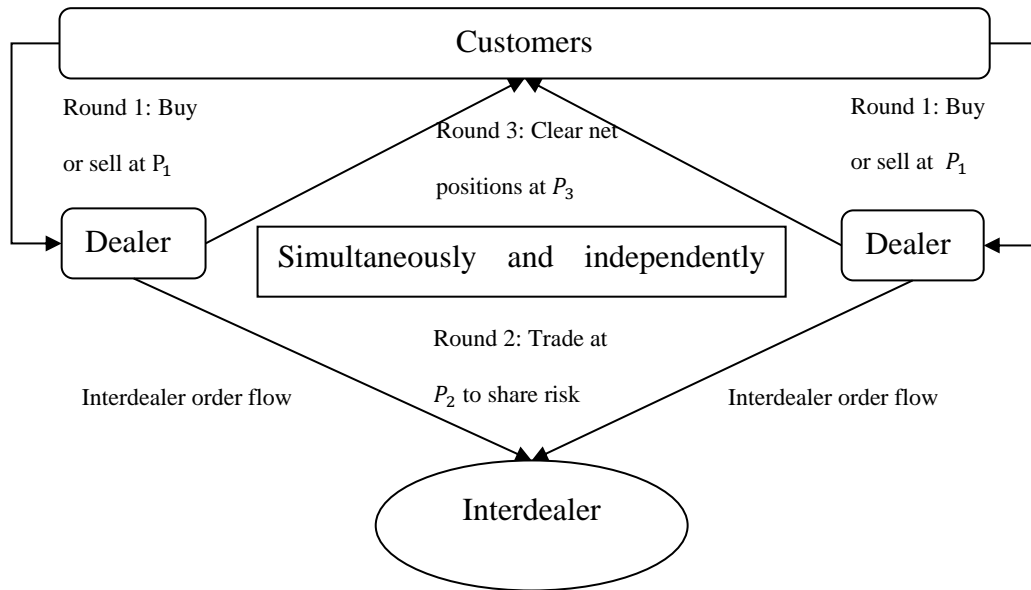
Figure 2.2 Microstructure of the portfolio shift model

In round 1, dealers simultaneously and independently quote scalar prices $P_{i,1}$, at which they promise to accept any size of order. Then every dealer observes customer order flow $C_{i,1}$. In round 2, dealers again simultaneously and independently quote scalar prices $P_{i,2}$ in the interdealer market. In this round, dealers expect customer order flow to be a noise around the value of the exchange rate and thus $P_{i,2}$ is the same as $P_{i,1}$. However, when dealers trade in the interdealer market they recognize customer order flow as portfolio shift and adjust their expectations on the exchange rate correspondingly. They have accurate foresight on the price in round 3 and conduct speculative orders. In round 3, dealers simultaneously and independently

quote scalar prices $P_{i,2}$ in order to share overnight risk with the public. Hence, we have:

$$\sum_i C_{i,1} + \sum_i C_{i,3} = 0 \qquad (2.15)$$

With the assumption of no infinitely elastic relationship between demand and returns, it can be seen that:

$$\sum_i C_{i,3} = \gamma\left(E[P_{3,t+1}|\Omega_3] - P_{3,t}\right) \qquad (2.16)$$

According to Lyons (1996), dealers' interdealer order flows will be proportional to their own customer order flows in equilibrium. Therefore:

$$\alpha^{-1}\Delta x_t + \gamma E[P_{3,t+1}|\Omega_3] - \gamma P_{3,t} = 0 \qquad (2.17)$$

Solve this equation as:

$$P_{3,t} = E[P_{3,t+1}|\Omega_3 + \alpha\gamma^{-1}\Delta x_t] \qquad (2.18)$$

Assuming the risky asset (the exchange rate) has payoff Δr per period while risk-free returns are one, while the public holds no private information:

$$E[P_{3,t+1}|\Omega_3] = P_{i,1} = P_{i,2} = P_{3,t-1} + \Delta r \qquad (2.19)$$

Equation (2.18) becomes:

$$P_{3,t} = \sum_{i=1}^{t} \Delta r_i + \alpha\gamma^{-1}\sum_{i=1}^{t-1} \Delta x_i \qquad (2.20)$$

and then:

$$\Delta P_{3,t} = \Delta r_t + \alpha\gamma^{-1}\Delta x_t \qquad (2.21)$$

The final equation has been frequently tested and has received much supportive evidence. However, while order flow here indicates the compensation of the dealer for holding foreign currency, it does not distinguish the information effect from the inventory effect.

2.1.2.2 Cao, Evans and Lyons' model

The model proposed by Cao, Evans, and Lyons (2006) adopts a new concept, inventory information. According to the authors, the bond and FX markets have no private information about nominal cash flow. Therefore, there is no superior information about fundamentals. When participants have been convinced that superior information exists, they advocate inventory information, which is a kind of private information unrelated to fundamentals. It appears in the transactions and is observed

only by trading parties, mainly market makers. With regard to pricing ability, inventory information could predict future price by forecasting future discount factors.

Consistent with other literature, inventory information influences price transitorily when market makers change prices to control inventories. However, inventory information impacts on the exchange rate permanently, even after market makers share risk economy-wide, because assets are imperfectly substitutable. Most of the literature ignores this effect, as authors assume that inventory risk is diversifiable at the economy-wide level. Theoretically, the effect of inventory information on the exchange rate is based on two factors: less than perfect transparency, and risk aversion. Lower transparency implies that inventory information is not instantly observable. Risk aversion ensures that inventory information influences the exchange rate via the avoidance of inventory risk.

The model proposes the following four rounds in price discovery:

Round 1: Dealer i quotes P_{i1t}, liquidity demand customers trade with dealers, and net customer order flow x_{it} is realized as private inventory information for dealer i.

Round 2: Dealer i quotes P_{i2t} and trades with other dealers. Net interdealer order flow for the whole market Z_t is then publicly observable.

Round 3: Dealer i quotes P_{i3t}, then trades with other dealers again to offset unexpected incoming flow $T'_{i2t} - E[T'_{i2t}|\Omega_{i2t}]$ in round 2 and expected incoming flow T'_{i3t} in this round. Also, dealers trade because their speculative demands change after they observe net interdealer order flow in round 2. At the end of round 3, cash flow R_t for risky asset (the exchange rate) is realized.

Round 4: Dealer i quotes P_{i4t} and trades widely with the public to share risk. Because in this round the inventory of liquidity supply customers is not mean-revert, the exchange rate moves permanently due to the permanent inventory shift of liquidity supply customers.

The solution to this model is similar to that of Evans and Lyons (2002). However, this model adopts a period for cash flow to be realized. In detail, cash flows for both risky assets and riskless assets are realized at the end of round 3:

$$P_{1t} = P_{2t} = P_{3t} = E\left[P_{4t}\big/(1 + r) \mid \Omega_{3t} \right] + \lambda Z_t \qquad (2.22)$$

When the information of interdealer order flow is completely shared, dealers set their prices the same as in rounds 1 and 2. The influence of order flow is reflected when dealers wish to share overnight risk with the public and thus adjust their prices. In fact this is the inventory effect; more specifically, information here enters into the model via round 4.

2.2 Literature on Microstructure Studies and the Information Content of Trading Duration

In view of the fact that an extensive body of empirical work (Meese and Rogoff 1983, Cheung, Chinn, and Pascual 2005) points out the failure of macroeconomic models, especially in capturing exchange rate dynamics in a short horizon, many studies have advocated a new perspective, the microstructure model. The key concern of exchange rate microstructure research is the trading process of exchange rate, and this approach

allows extraneous information. The most important determinant of microstructure models is order flow. Since the seminal work of Evans and Lyons (2002) pointed out that order flow models explain more than 60% of DM/USD change and more than 40% of Yen/USD change with daily frequency, order flow has frequently been taken into account in microstructure research on exchange rate. For example, Berger et al. (2008) study the correlation between interdealer order flow and exchange rate with EUR/USD and USD/JPY, two of the most liquid currency pairs. Their frequency ranges from one minute to three months. They point out that the impact of order flow is significant at short horizon, but becomes weaker with the increase of horizon. The correlation becomes stronger when the market is less liquid. King, Sarno, and Sojli (2010) study the predictive ability of order flow on the CAD/USD exchange rate return. They adopt daily data covering 11 years. Order flow is found to have strong forecasting power for CAD/USD return by out-of-sample forecasting. In addition, Gradojevic (2012) provides evidence that order flow and CAD/USD movement have a causal relationship, which is influenced by customer type, regime and frequency. However, most studies focus on the main trading currencies or developed markets. Very few pay attention to the emerging markets, probably due to the unavailability of transaction data.

According to the findings of Chen, Chien, and Chang (2012), the relationship between order flow and exchange rate movement is more significant for high trading intensity currency pairs rather than low trading intensity currency pairs. The importance of order flow in explaining exchange rate dynamics needs to be tested in emerging markets. De Medeiros (2004) examines the same model used by Evans and Lyons (2002), in the Brazilian foreign exchange market. The results prove the relationship

between order flow and exchange rate, but with lower R^2. He argues that the order flow model omits some variables, among them country-risk premium. Wu (2012) adopts data containing all customer transactions and interdealer transactions in the Brazilian foreign exchange market. The results confirm the importance of order flow in capturing exchange rate dynamics. Moreover, because the Brazilian foreign exchange market is smaller and less liquid than the DM/USD market, the price impact of order flow is around five times larger than the results of Evans and Lyons (2002) for DM/USD. This is further confirmed by the results of Duffuor, Marsh, and Phylaktis (2012). They study both black and official exchange rate in the Ghanaian market at weekly frequency. The impact of order flow is larger during crisis periods with an illiquid market than in stable periods with more liquidity. The study by Zhang, Chau, and Zhang (2013) is one of very few based on the Chinese foreign exchange market in an order flow model framework. Using a vector autoregressive model, the authors confirm the long-term cointegrating relationship between order flow and exchange rate. Similar to the results for emerging markets, the R^2 is only 0.13, which is lower than the results for developed markets. Cheung and Rime (2014) argue that the impact of order flow is restricted in the mainland market, due to heavy government control and the absence of international participants. Instead, they study the offshore RMB exchange rate, named CNH, and the interaction between the offshore and onshore markets. They conclude that the offshore market is more effective than its onshore counterpart, because their model, augmented with the variables emerging market currency volatility index, interest rate differential, CNH order flow, limit order imbalance, change of CPR and deviation from CPR, captures 39 percent of daily CNH changes compared to 29 percent of daily CNY changes.

Among these variables, order flow contributes to the explanatory power by 12 to 14 percent.

Inspired by the literature, we can conclude that more variables besides order flow are necessary in the price discovery of exchange rate with low trading intensity currency or in the emerging markets. As has been pointed out by Diamond and Verrecchia (1987), Easley and O'Hara (1992), irregular time intervals between consecutive transactions contain information on the causation of different types of time interval. Therefore, the fixed time intervals frequently used in the microstructure literature might lose information on the behaviours of market participants. According to Easley and O'Hara (1992), informed traders enter the market when news arrives and liquidity traders appear at a constant arrival rate. Therefore, short trading duration implies the occurrence of news and high arrival rate of informed traders, associated with high volatility. Admati and Pfleiderer (1988) argue a completely opposite relationship between trading duration and volatility. As well as liquidity traders with constant trading intensity, there are discretionary uninformed traders who will choose the time to trade in order to minimize adverse selection cost. Therefore, long trading duration implies inactivity of discretionary uninformed traders and high proportion of informed traders, leading to high volatility.

In one of the earliest studies on price impact of trading duration, Dufour and Engle (2000b) adopt a VAR model with the 18 most traded stocks in the New York Stock Exchange (NYSE). Their findings show that short trading duration is associated with large price impact and high autocorrelation of signed transaction, which is consistent with the theory of Easley and O'Hara (1992) that short trading duration implies news arrival, which leads to an increase in the number of informed traders. Similar results

are confirmed by Spierdijk (2004), who extends Dufour and Engle (2000b) model to incorporate trade size and volatility for 5 frequently traded stocks in the NYSE. She also points out that large trade size leads to an increase in trading intensity, but large return reduces trading intensity. Manganelli (2005) argues that the conclusion of Dufour and Engle (2000b) is only valid for frequently traded stocks. She studies the relationship between expected duration, expected volume and variance of return for 10 stocks in the NYSE, divided into two groups according to trading intensity. Short expected trading duration is found to follow large price movement and high trading volume in frequently traded stocks. However, the evidence is weak for infrequently traded stocks. Holder, Qi, and Sinha (2004) adopt a similar methodology to that of Dufour and Engle (2000b) with additional variables, namely the number of active traders on the trading floor, and trading volume on ten-year Treasury Note futures contracts traded at the Chicago Board of Trade. Contrary to the findings on the equity market, trading duration and the number of active traders positively impact on futures contract return and the sign of transaction. This is consistent with the theory of Admati and Pfleiderer (1988) that long trading duration denotes a high proportion of informed traders. Trading volume, conversely, is negatively related to futures contract return.

Since the introduction of the ACD model, it has frequently been extended: see Pacurar (2008) for a comprehensive survey and Leiva et al. (2014) for a recently developed version. ACD models divide trading duration into expected component and unexpected component. Some studies adopt an ACD model to examine the information content of both components of trading duration. Engle (2000) introduces the ACD-GARCH model, which is applied to IBM stock in the NYSE. Both expected

arrival rate and unexpected trading duration are considered in the variance equation of the GARCH model. Consistent with the model of Diamond and Verrecchia (1987), long trading duration follows falling price, because of short sell restrictions in the market. In addition, consistent with Easley and O'Hara (1992), expected arrival rate is positively related to volatility, and unexpected trading duration is negatively related to volatility. Yang (2011) introduces the ACD-VECM model to examine the asymmetric price impact of transactions for seven stocks in the Australian Stock Exchange. Both components of trading duration are contained in the equation of bid price change and ask price change. Consistent with the findings of Dufour and Engle (2000b), a transaction shortly after another one is associated with large price impact, which implies high level of information-based trading. In addition, the source of price impact is attributed to the unexpected component of trading duration rather than the expected trading duration. Inspired by Dufour and Engle (2000b), Sita (2010) extends the model of Madhavan, Richardson, and Roomans (1997) to incorporate two components of trading duration, namely expected trading duration and first-order covariance of standardized trading duration. The former represents market liquidity while the latter mirrors trading behaviours of informed traders. With the GMM estimation results of thirty stocks in the Helsinki Stock Exchange (HEX), he argues that trading duration is an important element of trading cost. However, the signs of expected trading duration and innovation of trading duration are either positive or negative depending upon the stock. Sita and Westerholm (2011) adopt a similar GMM methodology and consider trading duration or volume separately as trading intensity. Their data contain only one of the most active stocks in HEX, and intraday estimated results are shown every two hours. Both components of trading duration enhance the price impact of a transaction. However, the impacts can be either positive

or negative in different trading hours. Bowe, Hyde, and McFarlane (2013) extend Sita and Westerholm (2011) model to incorporate signed trading volume together with expected trading duration and covariance of standardized trading duration. They adopt tick-by-tick data of 28-day equilibrium interbank interest rate futures contracts in the Mexican Derivatives Exchange. Signed trading duration innovation negatively impacts on return, but the evidence is weak. The price change is mainly attributed to expected trading duration and the correlation is positive. Contrary to the results of Dufour and Engle (2000b), this is consistent with Admati and Pfleiderer (1988), who find that long trading duration implies high proportion of informed traders.

To conclude, the fact that order flow explains a relatively smaller part of exchange rate in emerging markets than it does in developed markets has motivated many studies to find other price-relevant variables. Since the information hidden behind trading duration has been frequently confirmed by research in the equity and derivatives markets, it could have been expected to apply to the foreign exchange market as well. However, the information content of trading duration is not conclusive. It can be completely different for different trading hours, different assets or different markets. This thesis is motivated by the unsolved question in the microstructure research of price discovery. It attempts to fill the gap in the literature with regard to the information content of trading duration in emerging foreign exchange markets.

2.3 Literature on Intervention Reaction Function

There is a wide literature on the effectiveness of foreign exchange intervention (e.g., Fatum, Pedersen, and Sørensen (2013), Vitale (2011), Disyatat and Galati (2007); and see Menkhoff (2012) for a comprehensive survey of emerging markets). By contrast, the driving force behind the intervention has received much less attention. Because foreign exchange intervention is not frequently or regularly implemented, for a given period of days the majority of intervention observations are zero. OLS estimation thus is no longer consistent, because intervention is nonlinear. One solution is to introduce a binary choice model, which could describe the influence of the driving forces on the probability of intervention. Different types of model, namely the Probit, Logit and Log-log models, may be applied for different distributions. One feature of binary choice models is that the value assigned to the dependent variable is either 0 or 1. If the intervention amount is available, a censored model, namely the Tobit model, may be adopted to incorporate the non-linearity of intervention data. Herrera and Özbay (2005) point out that the intervention reaction function is heteroskedastic and non-normal. They introduce Powell's censored least absolute deviations estimator to deal with these problems. Another method, as advocated by Chen, Chang, and Yu (2012), is the incorporation of the Tobit model with a GARCH method. This allows the residual of the Tobit model to be estimated by an ARMA process and deals with the problem of heteroskedasticity.

Although the binary choice model and the Tobit model perform well in capturing purchase intervention and sale intervention separately, they cannot incorporate both types of intervention in a single equation. A popular solution in the literature is the friction model, which assumes that intervention is only carried out if the determinant

factor is larger than a threshold value. This model is considered to better describe the features of intervention data. However, Jun (2008) argues that the friction model is not necessarily better than a simple linear model in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). If we are concerned only with the intervention probability, or if the intervention indicator is available, the most suitable model will be an ordered dependent variable model. This could be the Ordered Probit model, Ordered Logit model or Ordered Log-log model, depending upon the distribution. Another model that can incorporate both purchase intervention and sale intervention is the regime-switching model. This allows intervention reaction function changes according to market conditions, such as deviation from the target exchange rate or excess volatility.

This section will review the literature on the intervention reaction function, classified by the estimation techniques adopted.

2.3.1   Binary choice approach

OLS estimation is an elementary econometric method, widely used in the literature. However, few studies implement OLS estimation to research central bank intervention reaction function (Ito 2002). One of the most important features of intervention data is that the majority of daily observations are non-intervention. In other words, the relationship between intervention and determinants is nonlinear. Therefore, OLS estimation of intervention reaction function is inconsistent. One solution is to use a binary choice model in the estimation:

$$y_t^* = \beta_0 + \beta x_t + \varepsilon_t$$

<div align="right">(2.23)</div>

$$y_t = \begin{cases} 1 & if & y_t^* > 0 \\ 0 & if & y_t^* \leq 0 \end{cases}$$

where y_t is a dummy variable which describes the state of intervention (valued as 1) or non-intervention (valued as 0), y_t^* measures the determinant factor of central bank intervention and is unknown to the public, x_t represents explanatory variables in the reaction function. If ε_t follows a normal distribution/logistic distribution/extreme value distribution, equation (2.23) is named the Probit/Logit/Log-log model.

Baillie and Osterberg (1997b) consider the net amount of combined intervention of USD/DM by both the Federal Reserve and the Bundesbank, and the combined intervention of USD/Yen by both the Federal Reserve and the Japanese central bank from August 6th 1985 to March 1st 1990. The Probit model is applied to estimate the asymmetric reaction of purchase intervention and sale intervention. Deviation from the target exchange rate, as documented by Funabashi (1989), is a determinant factor in the majority of estimated reaction function. Excess volatility, however, is less conclusive. Greater excess volatility increases the probability only of purchase intervention of USD/Yen. Baillie and Osterberg (1997a) also point out that volatility of exchange rate, but not volatility of forward premium, influences the behaviour of central bank intervention.

Similarly, Dominguez (1998) studies the US, German and Japanese intervention for the USD/DM and USD/Yen exchange markets, with an extended dataset from January

1977 to December 1994. The variables considered in the reaction function are deviation from 10-day moving average of exchange rate and deviation from 10-day moving average of volatility. No evidence is found to demonstrate the influence of deviation from either target exchange rate or volatility.

Humpage (1999) estimates a Probit model as a proxy for Federal Reserve intervention in the DM/USD and Yen/USD markets from February 1987 to February 1990. Contrary to the finding of Dominguez (1998), deviation from 10-day moving average and 10-day rolling standard deviation are both significant in the estimation results.

McKenzie (2004) conducts a Probit analysis on the relationship between the Reserve Bank of Australia intervention and conditional volatility of USD/AUD exchange rate return. The data covers 14 years from 12th December 1983 to 31st December 1997. Conditional volatility is proved to be an important driving force behind central bank intervention. However, the prediction ability varies depending upon the features of intervention policy. Therefore, sub-period analysis is important in the research of intervention reaction function.

Akinci et al. (2005) estimate the intervention reaction function of the Turkish central bank with data spanning the period May 16th 2001 to December 31st 2003. In the Probit estimation results, the percentage deviations from long-run trend (90-day moving average), and exchange rate volatility, are found to be significant in the reaction function of both purchase intervention and sale intervention.

Frenkel, Pierdzioch, and Stadtmann (2002) adopt the Logit model in their research. The data set covers the period 1991 to 2001. The factors in the intervention reaction function include deviation from short-term exchange rate (25-day moving average),

deviation from long-term exchange rate (purchasing power parity exchange rate level, PPP), exchange rate volatility (absolute exchange rate return, lagged day and previous five days), and intervention persistence (lagged intervention). The results indicate that deviation from exchange rate plays an important role in the reaction function of the Bank of Japan, and that there is persistence of intervention.

Jackman (2012) argues that the Log-log model is better suited to estimation where intervention data is asymmetric and heavily skewed. The distribution is said to follow an extreme value distribution. She studies a pegged economy in Barbados where the central bank cannot determine the amount and time of intervention, but intervenes only to clear the market. Therefore, in investigating the intervention reaction function from January 2003 to December 2011, the research considers interest rate differential, real estate capital flow, tourism variable (proxy for current account transaction flow), conditional volatility of oil price (proxy for current account transaction flow) and the lag of intervention. The persistence of intervention and influence of oil price are proved in both purchase intervention and sale intervention. In addition, there is evidence of asymmetry of purchase intervention and sale intervention. The tourism variable and interest rate differential are significant in sale intervention but not in purchase intervention. Real estate capital flow influences purchase intervention but not sale intervention.

2.3.2   Tobit approach

If our concern is with the quantity of intervention rather than the probability, the Tobit model will be a better solution to the problem of OLS estimation.

$$y_t^* = \beta_0 + \beta x_t + \varepsilon_t, \qquad \varepsilon_t | x_t \sim N(0, \sigma^2)$$

(2.24)

$$y_t = \begin{cases} y_t^* & if \quad y_t^* > 0 \\ 0 & if \quad y_t^* \leq 0 \end{cases}$$

where y_t denotes intervention amount, and residual follows normal distribution.

Almekinders and Eijffinger (1994) point out that OLS estimation is inappropriate when large proportions of intervention data are zero. They adopt the Tobit model to estimate the reaction function of DM/USD intervention conducted by both the Deutsche Bundesbank and the Federal Reserve. For the four sample periods of data, ranging from September 1987 to October 1989, negative deviation from desired exchange rate (7-day moving average) and rise of conditional volatility will increase the volume of intervention.

Rogers and Siklos (2003) focus their research on two small open economies that implement an inflation-target regime: Australia and Canada. Since the intervention data are not disclosed, the authors take the closing balance of the Canada Exchange Fund Account and the account for Australia foreign exchange operation as proxies, with data covering the period from January 2nd 1989 to September 2nd 1998. Due to the proxy formation of intervention data, the majority of data for Canada are non-zero, but in the case of Australia 1554 days have no activity. Therefore, OLS estimation is executed for the Bank of Canada intervention, while for the intervention of the Reserve Bank of Australia a Tobit model with Heckman's two-stage procedure is estimated. The results confirm the lean-against-the-wind policy for both countries, but

the role of implied volatility and uncertainty (kurtosis of the implied risk-neutral probability density functions) varies depending on the choice of sample period.

Herrera and Özbay (2005) implement a Tobit model in their research of the intervention reaction function of the Central Bank of the Republic of Turkey. The data set is for the period from November 1st 1993 to December 31st 2003, which contains two different exchange rate regimes – a managed float regime and a free float. The authors test the persistence of intervention (the lag of dependent variable), deviation from the short-term exchange rate (the previous day exchange rate), deviation from the past level of exchange rate (20-day moving average), conditional volatility, and interest rate differentials. When the purchase and sale intervention are estimated separately, the difference in the estimation results suggests that the intervention reaction functions of purchase and sale are asymmetric. The findings confirm the existence of intervention persistence and support the determination of conditional volatility and interest rate differentials in the intervention reaction function. However, deviation from the target exchange rate is quite sensitive to exchange rate regime and estimation method. Herrera and Özbay (2005) also point out that the Turkey Central Bank intervention reaction function is heteroskedastic and non-normal, which will lead to inconsistency in the Tobit estimation. Therefore, they introduce Powell's censored least absolute deviations estimator into the Tobit model. The results show that the problems of heteroskedasticity and non-normality will lead to overestimation or underestimation of the influence of excess exchange rate volatility in the intervention reaction function.

Another method to deal with heteroskedasticity is to introduce the GARCH process into the residual of the Tobit model. Having confirmed the conditional

heteroskedasticity through an ARCH test, Chen, Chang, and Yu (2012) adopt a Tobit-GARCH model to capture both the majority of zero values of dependent variable and conditional heteroskedasticity. The dataset contains timestamp and volume of Bank of Japan intervention from April 1st 1991 to July 2nd 2004. The reaction function contains a number of variables, including deviation from short-term target exchange rate (exchange rate one day before), deviation from medium-term target exchange rate (21-day moving average), deviation from long-term target exchange rate (150-day moving average), the Federal Reserve intervention on JPY/USD, interest rate differential, the first-day business effect, stock market index and the lagged intervention. While the Tobit-GARCH model captures conditional heteroskedasticity of intervention, it also outperforms the Tobit model, OLS, Probit model and GARCH model in terms of the Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). The Tobit and Probit models incorrectly assume homoskedasticity in the estimation, while the GARCH model tends to underestimate the volatility and ignores the majority of zero observations, and OLS ignores both of these. The results also show that the Bank of Japan follows a policy of leaning-against-the-wind. Deviation from long-term target exchange rate, and Federal Reserve intervention, are important in the Bank of Japan intervention behaviour. In contrast, persistence of intervention is found only in certain periods covered by their data.

2.3.3 Friction/Threshold approach

As has been discussed frequently in the literature, the Probability model and Tobit model are advocated as superior to OLS estimation. However, both models are only able to capture either purchase intervention or sale intervention. Therefore, a friction approach is introduced to contain both purchase intervention and sale intervention

simultaneously in the same model. The friction approach is in fact a threshold model. As the majority of intervention data are zero but the explanatory factors in the reaction function are non-zero, it is reasonable to assume that the central bank only intervenes if the determinant factor has a value larger than a certain threshold. Therefore, a friction model is described as below:

$$y_t^* = \beta_0 + \beta x_t + \varepsilon_t, \quad \varepsilon_t | x_t \sim N(0, \sigma^2)$$

(2.25)

$$y_t = \begin{cases} y_t^* - u_1 & if \quad y_t^* > u_1 > 0 \\ 0 & if \quad u_2 \leq y_t^* \leq u_1 \\ y_t^* - u_2 & if \quad y_t^* < u_2 < 0 \end{cases}$$

where y_t indicates observed quantity of intervention, u_1 and u_2 denote superior threshold and inferior threshold respectively. As can be seen from the model, the central bank intervenes only if y_t^* is outside the threshold interval $[u_2, u_1]$.

Almekinders and Eijffinger (1996) implement a friction model in their research of DM/USD intervention by the Deutsche Bundesbank, and DM/USD, Yen/USD intervention by the Federal Reserve over the period from February 23rd 1987 to October 31st 1989. Consistent with the results of Almekinders and Eijffinger (1994), both Deutsche Bundesbank and the Federal Reserve are found to conduct a lean-against-the-wind policy and to react to the deviation of conditional volatility from the Louvre level. In addition, the Federal Reserve prefers depreciation of the USD rather than appreciation, according to the estimated value of intervention thresholds.

Kim and Sheen (2002) employ a friction model to test the intervention reaction function of the Reserve Bank of Australia. Their data covers 14 years, from December 13th 1983 to December 31st 1997. They introduce trend deviation (150-day moving average of USD/AUD), conditional volatility, interest rate differential, profitability of intervention, inventory and lag of intervention into the reaction function. With the exception of inventory motivation, where results are mixed due to measurement errors to proxy the variable, all other factors are found to influence the exchange rate intervention. In addition, consistent with the statement of intervention target, the Reserve Bank of Australia is found to intervene only when the volatility is low and the trend is clear. Jun (2008) studies the daily intervention of DM/USD by the Federal Reserve and German Bundesbank separately from January 5th 1987 to January 22nd 1993. Percentage deviation from 7-day moving average and volatility are considered in the reaction function. The author introduces Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as measurements of model performance. Comparing the friction approach with a simple linear model, in general RMSE of the friction model is found to be larger, but MAE is smaller in both in-sample fitting and out-of-sample forecasting performance. Given that the result could depend on the explanatory variables included and the measurement of forecasting performance, the friction model is not necessarily better than a simple linear model.

If we are interested only in the probability rather than the quantity of intervention, or if for some reason we can collect only the intervention indicator (1, 0, -1), another type of friction model, the Ordered Probit model, would be preferred. The Ordered Probit model specification is quite similar to equation (2.25), with the only difference being that y_t is an intervention dummy with the value of (1, 0, -1):

$$y_t^* = \beta_0 + \beta x_t + \varepsilon_t, \quad \varepsilon_t | x_t \sim N(0, \sigma^2)$$

(2.26)

$$y_t = \begin{cases} 1 & if \quad y_t^* > u_1 \\ 0 & if \quad u_2 \le y_t^* \le u_1 \\ -1 & if \quad y_t^* < u_2 \end{cases}$$

1 indicates domestic currency appreciation intervention, 0 indicates no intervention and -1 indicates domestic currency depreciation intervention. Because intervention amount is highly relevant to the success of intervention to move exchange rate, intraday information is important to estimate the reaction and thus daily intervention amount.

In order to avoid endogeneity problems, Ito and Yabu (2007) propose an intervention indicator in place of intervention amount. They believe the scarcity of intervention days is due to the political cost, which could make it difficult to get a permit for intervention. Therefore, once a permit is approved, intervention probably takes place over the next several days. In addition, Ito and Yabu (2007) adopt heteroskedasticity-and-autocorrelation-consistent (HAC) standard errors in the Ordered Probit model to deal with the problem of heteroskedasticity. The Bank of Japan is found to conduct lean-against-the-wind intervention in response to deviation from short-term target exchange rate (exchange rate one day before), deviation from medium-term target exchange rate (21-day moving average), and deviation from long-term target exchange rate (5-year moving average) in the period from April 1st 1991 to December 31st 2002. In addition, the persistence of intervention is proved and the political costs of yen appreciation and yen depreciation are asymmetric.

Another type of threshold model applied in the literature is the regime-switching model. While the objective of the central bank might change over time, the regime-switching model allows us to capture the different intervention behaviour of the central bank based on different market conditions. ÖzIü and Prokhorov (2008) introduce a regime-switching model as below:

$$
y_t^* = \begin{cases} \beta_0^1 + \beta^1 x_t + \varepsilon_t^1 & if \ \ u_1^1 \le \eta_t \le u_2^1 \\ \qquad \qquad \qquad . \\ \qquad \qquad \qquad . & , \ \ \varepsilon_t^{i=1,\dots,m}|x_t \sim N(0,\sigma^2) \quad (2.27) \\ \qquad \qquad \qquad . \\ \beta_0^m + \beta^m x_t + \varepsilon_t^m & if \ \ u_1^m \le \eta_t \le u_2^m \end{cases}
$$

where y_t^* denotes intervention amount, x_t indicates determinant market conditions of intervention, and η_t is the threshold variable, which could be one of the determinant market conditions. As can be seen in equation (2.27), intervention reaction function is allowed to change according to the value of the threshold variable.

ÖzIü and Prokhorov (2008) adopt a two-regime-shift model separately for managed float exchange rate regime and free float exchange rate regime in Turkey. The sample period is from November 1st 1993 to May 15th 2006. During the period of managed float regime, the central bank is considered to follow a policy of maintaining the currency peg. However, this assumption is contrary to the central bank announcement that it intervenes only in order to remove excess volatility. The result is consistent with the exchange rate policy target announced by the central bank, while the threshold variable in the managed float regime is deviation from 22-day moving average, and that in the free float regime is excess volatility.

Chapter 3

Order Flow and Price Discovery in the Foreign Exchange Market: Theoretical Perspective

3.1 Introduction

Many models have been developed to capture the behaviour of the exchange rate, based on different perceptions and approaches. Traditionally, the macroeconomic models have been dominant in the research of foreign exchange markets. These have included, for example, the early model of PPP (Cassel 1918) and the subsequent models, such as the balance of payment flow approach (Kouri 1976), flexible-price monetary model (Bilson 1978, Frenkel 1976), sticky-price monetary model (Dornbusch 1976, Frankel 1979, 1981) and productivity-based model (Owen 2001).

However, macroeconomic models have met serious challenges from empirical research. Little supportive evidence has been found for them, and more often the evidence suggests that macro models are not better than a simple random walk model in explaining and forecasting exchange rate variation. Meese and Rogoff (1983) compare the flexible-price monetary model, sticky-price monetary model and the sticky-price model that incorporates the current account to a random walk model, with a view to testing the out-of-sample predictive accuracy for dollar/pound, dollar/mark,

dollar/yen and a weighted dollar-based exchange rate. They conclude that the forecasting ability of the three models under test cannot outperform that of the random walk model. Using a variety of criteria such as mean squared error (MSE), direction of change, and consistency, Cheung, Chinn, and Pascual (2005) conduct a similar test based on three models – interest rate parity, productivity-based model and a composite specification – in addition to PPP and the sticky-price monetary model. All the tested models are found to be not necessarily more successful than the random walk model, as they might perform well in a currency pair with one criterion but poorly in another currency pair with another criterion.

The failure of the macroeconomic model in explaining the movement of the exchange rate, especially the short-run dynamic, has led economists to seek alternative ways to consider the behaviour of the exchange rate. A prominent attempt is one that turns its attention to the microstructure of the foreign exchange market. Originally developed for analysing the equity market, the key concept in the micro perspective is order flow. For example, the influential research by Evans and Lyons (2002) proved that the micro variable order flow can influence the exchange rate movement. They built a hybrid model which includes both macro variable and micro variable – more specifically, interest rate differential and order flow -and found that order flow can explain more than 60% of USD/DEM and 40% of USD/JPY daily movements. Subsequently, many researchers have focused on microstructure analysis, especially on the order flow. By considering the effect of market transaction process on exchange rate determination, which is lacking in the macro models, this approach has achieved promising results in recent years. Its success is, however, limited by its strong requirements for high frequency transaction data, especially in the emerging

markets. Indeed, so far it has suffered from a number of drawbacks in this regard, such as the lack of detailed data on dealers' transactions. This has been improved recently, since the advent of availability of tick-by-tick data thanks to the rapid development of internet and related technology. As a result, there has been a great deal of progress in the research of the microstructure of foreign exchange markets.

According to the composition of order flow, the microstructure approach to exchange rates can be classified into DL and ML models. DL models focus on the factors that influence the behaviour of individual market participants, dealers for example, in price setting, and thus connect micro variables such as order flow and inventory with exchange market quotes. For the most part, DL models are borrowed from the relatively better developed research of equity markets. Madhavan and Smidt (1991) model incorporates both asymmetric information (information effect) and inventory control (inventory effect). The information effect is reflected by informed dealers' demand, and thus relates to trading volume. Lyons (1995) extends the Madhavan and Smidt model by introducing market-wide order flow, and allows dealers to control inventory via outgoing and brokered trade. He examines the mark/dollar market and tests the null hypothesis while allowing different inventory control methods. Both information effect and inventory effect are significant in the data, and the null hypothesis cannot be rejected. Therefore, he concludes that in the tested model, incoming order flow indicates market-wide order flow.

Another microstructure model is Huang and Stoll's (1997) indicator model, so-called because the direction of trade but not trading volume influences information cost. Ding (2006) develops a microstructure model for the foreign exchange market from a different angel. The model relaxes the assumption of identical price, which is derived

from the principle of no arbitrage, and combines customer trade and interbank trade as the same incoming trading process.

However, using the incoming transaction request as the unique source of order flow has been reported as problematic. Romeu (2005) re-examines Lyons' (1995) result with the same dataset. The test highlights the instability of the DL model and detects two structural breaks in the estimate of Lyons' data. Hence the data are split into three sub-samples based on the two breaks and the DL model is found to be misspecified. Meanwhile, the inventory effect and information effect are not simultaneously supported in the sub-samples. Bjǿnnes and Rime (2005) collect a new detailed transaction dataset for four interbank dealers. The data reflect different trading styles by different interbank dealers. The Madhavan and Smidt model and the Huang and Stoll model are adopted to examine the relationship between dealer behaviour and exchange rate setting. With the Madhavan and Smidt model, there is no evidence to support the inventory effect and information effect predicted by Lyons (1995). However, the test result of the Huang and Stoll model indicates that incoming order flow contains a strong information effect.

Under the assumption that the dealer only receives incoming orders, the only means to control inventory is quote shading. In order to attract more buyer- (seller-) initiated orders and reduce (increase) inventory level, the dealer has to make the price more attractive and decrease (increase) his market quotes. However, in the multi-structure of the foreign exchange market, dealer behaviour is much more diversified and there is a wide choice of inventory control tools. Hence, the basic assumptions of simple market structure and limited methods to control inventory represent problems of the DL model.

In contrast, the ML model, which studies market-wide exchange rate formation, has been proved empirically to be more successful. A frequently discussed model derived by Evans and Lyons (2002) fills the gap between macrostructure and microstructure models, augmenting traditional macro variables with order flow. It develops a multi-structure of the foreign exchange market, comprising the customer market and the interbank market. Dealers are allowed diversified styles in their trading behaviour, which includes incoming orders, outgoing orders, customer orders, limit orders and market orders. The model is quite successful in capturing the daily movement of mark/dollar (over 60%) and yen/dollar (over 40%) exchange rates. Its stability has been proved by the robust testing of different currencies and frequencies (see for example Payne (2003), Froot and Ramadorai (2005), Berger et al. (2008), Smyth (2009), and Breedon and Vitale (2010).

This study attempts to bridge the disconnection between DL and ML models. In doing so it develops a model with richer contents than those of Evans (2002) or Ding (2006). In order to avoid the drawbacks of the DL model and allow diversified dealer behaviour, this chapter adopts a multi-structure of the foreign exchange market similar to that proposed by Evans and Lyons (2002). Our model starts with the study of dealer behaviour, in other words, his price setting strategy according to the available information set. It allows heterogeneous market participants to hold different private information, which leads to different expectations on the exchange rate. While the Bayesian-Nash equilibrium in Evans and Lyons' model is somewhat forward looking, our model abandons this kind of perspective and instead defines the information set at every step. Then dealer behaviour is consistent with the Nash equilibrium, and his price setting is optimal with the available information.

The remaining sections of this chapter are organized as follows: Section 2 describes the general structure of the foreign exchange market. Section 3 explains our assumptions and provides an overview of the process of model derivation. Section 4 concludes the chapter, and summarizes the contribution of our model.

3.2 Structure of the Foreign Exchange Market

The foreign exchange market comprises the interdealer market and the customer market. The interdealer market has direct trades and broker trades, while the customer only trades with dealers and has no access to the interdealer market. The customer could be a central bank, importer, exporter or financial institution.

Features of the foreign exchange market are as follows (Rime 2003):

- Trading is decentralized rather than centralized as for equity markets.

- Trading is continuous as opposed to a call market.

- It is a multi-dealer market as opposed to a single-dealer market.

- Liquidity is both quote-driven (quotes given on request) and order-driven (limit orders, auction market).

- It has lower transparency compared to the stock market.

In the customer market, the only trading option is direct incoming order request. It is a quote-driven market in which dealers give quotes on request and customers trade on the quotes. In contrast, the interdealer market is more diversified and transparent.

Dealers have the option to conduct direct or indirect trade. The direct option involves a similar market making to that in the customer market and the submission of order requests to other market makers. With the indirect option, dealers are able to submit limit orders to decide the price, volume and direction to trade, or can conduct a market order to trade at the best available price immediately in the market. The importance of the indirect channel is increasing, especially after the introduction of electronic brokers, which makes it more convenient for dealers to share risk and aggregate information.

According to Rime (2003) and Bjønnes, Rime, and Solheim (2005), the behaviour of a typical dealer shows the following characteristics:

- Adverse selection protection: spread will be wider when trading size increases because this can prevent huge losses in trades with asymmetric information.

- Risk management: spread should contain compensation for providing liquidity and the risk thereof.

- Order processing costs and rents: spread should cover the cost to process the order, property rent and other necessary costs.

- A typical dealer replies to the request and will increase the spread with trading size to protect himself against informed traders. After observing the direction of trades, he will revise the midpoint. For inventory controls, he will reduce both his bid and ask quotes when the inventory is higher.

- Dealers are liquidity providers intraday, while non-financial customers provide

overnight liquidity. Therefore, dealers will not stay with the overnight imbalance position and will close their net position with non-financial customers.

3.3 Theoretical Framework of the Model

Inspired by Evans and Lyons (2002) and taking into consideration the structure of the foreign exchange market, this chapter takes three steps to model the process of exchange rate movements.

Step 1: This first step describes the behaviour of customers and dealers in the customer market, which is crucially important for exchange rate movement in the short run. As shown above, customers initiate the trade and send order requests to dealers. Dealers set prices based on available information and respond to the requests. Customers receive dealers' prices and decide whether, and at what volume, to trade.

Step 2: This step characterizes the behaviour of dealers in the interbank market. It plays a key role in the connection between DL and ML models, representing one of the main contributions of this chapter. In this step dealers observe their own customer order flow and generate different expectations on the value of the exchange rate. Price setting is based on expectation; thus, our model allows the existence of heterogeneous price and market depth. After risk and information are completely shared through interbank transactions, the market is in equilibrium and the behaviour of dealers represents the behaviour of the market.

Step 3: This step illustrates the behaviour of dealers when offsetting the imbalance of inventory position. Dealers trade with customers (probably non-financial institutions) again in order to share the overnight risk with the public or to meet government

regulations.[4] Payoffs for holding foreign currency (asset) and domestic currency (asset) are realized at the very beginning of the next period.

Step 1

Our model starts with the behaviour of trade initiators, namely customers, in the foreign exchange market. Customers are distributed widely in the economic system. They could be, for example, exporters, importers, corporations, financial institutions or central banks. Different customers may hold different information about the state of the economy. For example, exporters and importers naturally have better information on their own business. They are able to get (albeit partial) first-hand information on aspects of the macro-economy such as conditions of demand, supply and prices (inflation) from their own business perspective. Financial institutions are usually better equipped to analyse and predict financial parameters, including possible movements of exchange rates or the returns of international portfolio investment, which have a bearing on purchase or sale of foreign currencies. The central bank embodies the policy intention of the government and thus its interventions in the foreign exchange market often reflect the expectation or goal of the government. Here, our model assumes that customers hold different private information $f_{pi,t}$ and that demand is a linear function of expected returns.

The story begins, therefore, when customers send their order requests to dealers. Dealers have the responsibility to quote on the requests. The key role of price setting is to indicate the expected value of the exchange rate, which is closely related to available information on fundamentals. Without unexpected shocks, it is reasonable to

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[4] In some countries, such as China, government regulations restrict the size of overnight inventory position of market makers.

say that fundamentals are stationary in dealers' minds. Thus, fundamentals are assumed to follow:

$$f_t = f_{t-1} + u_t \tag{3.1}$$

where u_t follows $N(0, \sigma_u^2)$.

According to the theory of Present Value, the exchange rate is determined by discounted future values. Following the formation of Evans and Lyons (2006) we have:

$$V_{1,t} = (1 - \gamma)E_t^D \sum_{i=0}^{\infty} \gamma^i f_{t+i} \tag{3.2}$$

where γ is the discount factor. Assuming stationarity of fundamentals, equation (3.2) becomes:

$$V_{1,t} = (1 - \gamma)\sum_{i=0}^{\infty} \gamma^i E_t^D(f_{t+i}) = (1 - \gamma)\sum_{i=0}^{\infty} \gamma^i f_t = (1 - \gamma)f_t \frac{1 - \gamma^{\infty}}{1 - \gamma} \tag{3.3}$$

while $0 < \gamma < 1$, equation (3.3) becomes:

$$V_{1,t} = f_t \tag{3.4}$$

In order to make an optimal decision on the price setting, obtaining information on expected value of the exchange rate is not sufficient. It is critical to know in what particular way the dealer will react to the expected value. Therefore, utility function of dealers is required. Motivated by Evans and Lyons (2002) and Ding (2006), our model assumes an identical utility function for all dealers:

$$U(W) = -e^{-AW} \tag{3.5}$$

Equation (3.5) is a constant absolute risk aversion function with a constant parameter A. The price setting problem in this step then becomes a utility maximization problem. The information available to dealers is common public information on fundamentals f_t and their own inventory level $I_{1i,t}$.

Proposition 1: *In a competitive market with available information set* $\Omega_{1i,t} = \{f_t, I_{1i,t}\}$, *the optimal pricing strategy of dealer* i *is:*

$$P_{1i,t} = P_{1i,t}^O = f_t \tag{3.6}$$

where $P_{1i,t}$ is price setting of dealer i in step 1 at time t and O denotes other dealers. After customers receive quotes from dealers, they decide whether to trade, the volume to trade and the direction to trade.

Proof:

After customers send purchase order requests, there are three possible outcomes. If dealer i quotes a lower price than others, customers will take all the desired volume on his price. If dealer i sets the same price as others, customers will have no preference as to with whom to trade. Thus, our model assumes customers will trade with corresponding dealers who have received the requests. Dealer i gets a random share of trading volume. Third, if dealer i's price is higher than others, no transaction will be conducted with his higher quote. Then the utility of dealer i for unit of desired volume with different price levels is shown to be:

$$
U = \begin{cases}
-e^{-A[P_{1i,t}+(I_{1i,t}-1)V_{1i,t}]} & , if\ P_{1i,t} < P^O_{1i,t} \\
-e^{-A[\phi P_{1i,t}+(I_{1i,t}-\phi)V_{1i,t}]} & , if\ P_{1i,t} = P^O_{1i,t} \\
-e^{-AI_{1i,t}V_{1i,t}} & , if\ P_{1i,t} > P^O_{1i,t}
\end{cases}
\tag{3.7}
$$

where ϕ is the possibility of customers sending their order requests to dealer i. It can be seen that the Nash-equilibrium is $P_{1i,t} = P^O_{1i,t} = V_{1,t} = f_t$ as for any $\delta > 0$, $P_{1i,t} = V_{1i,t} + \delta > V_{1i,t}$, $P_{1i,t} + (I_{1i,t} - 1)V_{1i,t} = (I_{1i,t} + \delta)V_{1i,t} > I_{1i,t}V_{1i,t}$, while $U'(x) > 0$, dealer i has motivation to reduce his price until $P_{1i,t} = V_{1i,t}$. The optimal prices for dealers equal their own expected value of the exchange rate. While all dealers observe the same fundamentals information, dealers share a common expected value and thus $P_{1i,t} = P^O_{1i,t} = V_{1,t} = f_t$.

In the case where customers send sell order requests, the utility will be:

$$U = \begin{cases} -e^{-A[(I_{1i,t}+1)V_{1i,t}-P_{1i,t}]} & ,if\ P_{1i,t} > P^O_{1i,t} \\ -e^{-A[(I_{1i,t}+\phi)V_{1i,t}-\phi P_{1i,t}]} & ,if\ P_{1i,t} = P^O_{1i,t} \\ -e^{-AI_{1i,t}V_{1i,t}} & ,if\ P_{1i,t} < P^O_{1i,t} \end{cases} \qquad (3.8)$$

Similarly, the Nash-equilibrium is $P_{1i,t} = P^O_{1i,t} = V_{1,t} = f_t$.

Proposition 2: *Customers will trade on the basis of their own private information, and the quantity is:*

$$C_{i,t} = \lambda f_{pi,t} \qquad (3.9)$$

where $C_{i,t}$ is customer order flow and λ is risk-bearing capacity of customers.

Proof:

Customers hold private information $f_{pi,t}$ but are unable to get accurate information on the whole economy. Therefore, $f_{pi,t}$ follows unknown distribution $D(f_{p,t}, \sigma^2_{f,t})$ with unknown $f_{p,t}$. While customers can observe only their own private information, it is reasonable that customers believe their information is a reflection of the future exchange rate. The expectation becomes:

$$E^i_t(f_{pi,t}|\Omega^C_{1i,t}) = f_{pi,t} \qquad (3.10)$$

where $\Omega_{1i,t}^C = \{f_t, f_{pi,t}, P_{1i,t}\}$ is the information set faced by customers. From equation (3.4), it is straightforward that $V_{i,t+1}^C = f_{t+1}^C$. Considering the linear relationship between demand and expected returns, one can get:

$$C_{i,t} = \lambda\left[E_t^i\left(V_{i,t+1}^C|\Omega_{1i,t}^C\right) - P_{1i,t}\right] = \lambda\left[E_t^i\left(f_t + f_{pi,t}|\Omega_{1i,t}^C\right) - f_t\right] = \lambda f_{pi,t} \qquad (3.11)$$

Step 2

This step studies the behaviour of dealers in the interbank market. Transactions in the customer market have been conducted and dealer i observes his own net customer order flow $C_{i,t}$, current inventory position $I_{2i,t}$, his price in step 1 $P_{1i,t}$ and all the other relevant information in step 1 $\Omega_{1i,t}$. As mentioned above, customer order flow contains private information from the customer. Dealer i will extract information from customer order flow and adjust his expected value of the exchange rate:

$$V_{2i,t} = V_{1i,t} + \frac{1}{\lambda}C_{i,t} \qquad (3.12)$$

where $V_{2i,t}$ is the expected currency value of dealer i after he receives customer order flow in the customer market. With heterogeneous information and expectations, dealers set prices to trade in the interbank market. This is in fact an auction market with independent private value.

Proposition 3: *With information set* $\Omega_{2i,t} = \{f_t, I_{1i,t}, I_{2i,t}, C_{i,t}, P_{1i,t}\}$, *the optimal quoting strategy of dealer* i *is :*

$$P_{2i,t} = f_t + \frac{1}{\lambda} C_{i,t} + S\theta$$

$$S = \begin{cases} -1 & , if\ C_{i,t} > 0 \\ 0 & , if\ C_{i,t} = 0 \\ 1 & , if\ C_{i,t} < 0 \end{cases} \qquad\qquad (3.13)$$

$$\theta = \frac{1}{A} \ln \left(\frac{M - 1 + Ab}{M - 1} \right)$$

Here $P_{2i,t}$ is price setting after the transactions in the customer market. M indicates the number of dealers and b is the scale parameter of distribution of expected value. θ is a function of the quantity of dealers.

Proof:

The sign of $C_{i,t}$ influences the derivation of dealer's utility and thus causes the dealer to make different decisions over price setting. It is desirable to consider the model in different cases of $C_{i,t}$. The simplest case is when $C_{i,t} = 0$. The dealer gets no new information and thus quotes the same price as that in step 1, which is $P_{2i,t} = f_t$. If $C_{i,t} > 0$, it means that dealer i receives net purchase transaction in the customer market and holds a negative inventory position. In this case, the gain from every unit

of inventory is $P_{1i,t} = f_t$. The cost will be $P_{2i,t}$ (if a deal is made) or $V_{2i,t}$ (if no deal).

The equation below shows the utility under different deal conditions:

$$U = \begin{cases} W = -e^{-A(f_t - P_{2i,t})} & , if\ deal\ is\ made \\ W = -e^{-A(f_t - V_{2i,t})} & , if\ no\ deal\ is\ made \end{cases} \qquad (3.14)$$

The probability of a deal is the probability of price being higher than others. The expected utility is then:

$$E(U) = -e^{-A(f_t - P_{2i,t})} Pr\{P_{2i,t} > P_{2i,t}^O\}$$

$$+\left(-e^{-A(f_t - V_{2i,t})}\right)\left(1 - Pr\{P_{2i,t} > P_{2i,t}^O\}\right) \qquad (3.15)$$

Rearranging equation (3.15), it becomes:

$$E(U) = e^{-Af_t}(e^{AV_{2i,t}} - e^{AP_{2i,t}})Pr\{P_{2i,t} > P_{2i,t}^O\} - e^{-A(f_t - V_{2i,t})} \qquad (3.16)$$

Intuitively, the higher the probability of dealer i's expected value being greater than that of the others, the higher the probability of dealer i's price setting being better. Our model assumes that dealers share a common Laplace Distribution on expected value:

$$Pr\{P_{2i,t} > P_{2i,t}^O\} = Pr\{V_{2i,t} > V_{2i,t}^O\} = \left[F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-1} \qquad (3.17)$$

where $P_{2i,t}^{-1}(\ )$ is an inverse function of $P_{2i,t}$ and $V_{2i,t} = P_{2i,t}^{-1}(P_{2i,t})$. $F(\ )$ indicates the cumulative distribution function. Laplace Distribution is a continuous probability distribution that contains two exponential distributions. The formation of probability density function is shown below:

$$f(x) = \frac{1}{2b}\begin{cases} e^{-\frac{\mu-x}{b}} &, if\ x < \mu \\ e^{-\frac{x-\mu}{b}} &, if\ x \geq \mu \end{cases} \qquad (3.18)$$

where μ is the mean of the distribution and b is a scale parameter. The corresponding cumulative distribution function is:

$$F(x) = \begin{cases} \dfrac{1}{2}e^{\frac{x-\mu}{b}} &, if\ x < \mu \\ 1 - \dfrac{1}{2}e^{-\frac{x-\mu}{b}} &, if\ x \geq \mu \end{cases} \qquad (3.19)$$

Substituting equation (3.17) into (3.16), the expected utility becomes:

$$E(U) = e^{-Af_t}(e^{AV_{2i,t}} - e^{AP_{2i,t}})\left[F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-1} - e^{-A(f_t - V_{2i,t})} \qquad (3.20)$$

In order to solve the utility maximization problem, we take the first-order differential by $P_{2i,t}$.

$$\frac{(M-1)\left[F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-2}F'\left(P_{2i,t}^{-1}(P_{2i,t})\right)\left(e^{AV_{2i,t}}-e^{AP_{2i,t}}\right)}{P'_{2i,t}\left(P_{2i,t}^{-1}(P_{2i,t})\right)}$$

$$-Ae^{AP_{2i,t}}\left[F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-1}=0$$

(3.21)

Rearranging equation (3.21), and recall that $V_{2i,t}=P_{2i,t}^{-1}(P_{2i,t})$, we have:

$$(M-1)\left[F\left(V_{2i,t}\right)\right]^{M-2}F'\left(V_{2i,t}\right)e^{AP_{2i,t}}+Ae^{AP_{2i,t}}\left[F\left(V_{2i,t}\right)\right]^{M-1}P'_{2i,t}\left(V_{2i,t}\right)$$

(3.22)

$$=(M-1)\left[F\left(V_{2i,t}\right)\right]^{M-2}F'\left(V_{2i,t}\right)e^{AV_{2i,t}}$$

Taking integration on both sides:

$$\left[F\left(V_{2i,t}\right)\right]^{M-1}e^{AP_{2i,t}}=\int_{-\infty}^{V_{2i,t}}(M-1)[F(x)]^{M-2}F'(x)e^{Ax}dx \qquad (3.23)$$

The only information available to dealer i is the formation of Laplace Distribution and his own expected value of the exchange rate. Therefore, it is reasonable that dealer i takes his expected value of the exchange rate $V_{2i,t}$ as the mean μ of distribution when he makes a decision on the price setting. Substitute equation (3.19) into (3.23):

$$\left[\frac{1}{2}e^{-\frac{V_{2i,t}-V_{2i,t}}{b}}\right]^{M-1}e^{AP_{2i,t}}$$

$$(3.24)$$

$$= \int_{-\infty}^{V_{2i,t}}(M-1)\left[\frac{1}{2}e^{\frac{x-V_{2i,t}}{b}}\right]^{M-2}\frac{1}{2b}e^{\frac{x-V_{2i,t}}{b}}e^{Ax}dx$$

Rearranging equation (3.24):

$$\left(\frac{1}{2}\right)^{M-1}e^{AP_{2i,t}} = \left(\frac{1}{2}\right)^{M-1}\int_{-\infty}^{V_{2i,t}}\frac{(M-1)}{b}\left[e^{\frac{x-V_{2i,t}}{b}}\right]^{M-1}e^{Ax}dx \qquad (3.25)$$

$$e^{AP_{2i,t}} = \int_{-\infty}^{V_{2i,t}}\frac{(M-1)}{b}e^{\frac{(M-1+Ab)x-(M-1)V_{2i,t}}{b}}dx \qquad (3.26)$$

$$e^{AP_{2i,t}} = \frac{M-1}{M-1+Ab}e^{AV_{2i,t}} \qquad (3.27)$$

Taking logarithm of both sides, the optimal quoting strategy of dealer i is solved:

$$P_{2i,t} = V_{2i,t} - \theta = f_t + \frac{1}{\lambda}C_{i,t} - \theta$$

$$(3.28)$$

$$\theta = \frac{1}{A}\ln\left(\frac{M-1+Ab}{M-1}\right)$$

Similarly, if $C_{i,t} < 0$, the utility of a unit of volume would be:

$$U = \begin{cases} W = -e^{-A(P_{2i,t}-f_t)} & \text{, if deal is made} \\ W = -e^{-A(V_{2i,t}-f_t)} & \text{, if no deal is made} \end{cases} \quad (3.29)$$

and thus expected utility becomes:

$$E(U) = -e^{-A(P_{2i,t}-f_t)} Pr\{P_{2i,t} < P_{2i,t}^O\}$$

$$(3.30)$$

$$+\left(-e^{-A(V_{2i,t}-f_t)}\right)\left(1 - Pr\{P_{2i,t} < P_{2i,t}^O\}\right)$$

Clearly,

$$Pr\{P_{2i,t} < P_{2i,t}^O\} = Pr\{V_{2i,t} < V_{2i,t}^O\} = \left[1 - F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-1} \quad (3.31)$$

By solving the utility maximization problem, we obtain:

$$\frac{-(M-1)\left[1 - F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-2} F'\left(P_{2i,t}^{-1}(P_{2i,t})\right)\left(e^{-AV_{2i,t}} - e^{-AP_{2i,t}}\right)}{P_{2i,t}'\left(P_{2i,t}^{-1}(P_{2i,t})\right)}$$

$$(3.32)$$

$$+Ae^{-AP_{2i,t}}\left[1 - F\left(P_{2i,t}^{-1}(P_{2i,t})\right)\right]^{M-1} = 0$$

Rearranging equation (3.32) to:

$$(M-1)\left[1-F\left(V_{2i,t}\right)\right]^{M-2}F'\left(V_{2i,t}\right)e^{-AP_{2i,t}}$$

$$+Ae^{-AP_{2i,t}}\left[1-F\left(V_{2i,t}\right)\right]^{M-1}P'_{2i,t}\left(V_{2i,t}\right) \tag{3.33}$$

$$=(M-1)\left[1-F\left(V_{2i,t}\right)\right]^{M-2}F'\left(V_{2i,t}\right)e^{-AV_{2i,t}}$$

Taking integration of both sides:

$$\left[1-F\left(V_{2i,t}\right)\right]^{M-1}e^{-AP_{2i,t}} = \int_{V_{2i,t}}^{+\infty}(M-1)[1-F(x)]^{M-2}F'(x)e^{-Ax}dx \tag{3.34}$$

While $x \geq V_{2i,t}$, cumulative distribution function in equation (3.19) should be expressed as the case when $x \geq \mu$:

$$\left[\frac{1}{2}e^{-\frac{V_{2i,t}-V_{2i,t}}{b}}\right]^{M-1}e^{-AP_{2i,t}}$$

$$\tag{3.35}$$

$$=\int_{V_{2i,t}}^{+\infty}(M-1)\left[\frac{1}{2}e^{-\frac{x-V_{2i,t}}{b}}\right]^{M-2}\frac{1}{2b}e^{-\frac{x-V_{2i,t}}{b}}e^{-Ax}dx$$

The solution is:

$$e^{-AP_{2i,t}} = \frac{M-1}{M-1+Ab}e^{-AV_{2i,t}} \tag{3.36}$$

and the optimal quoting strategy becomes:

$$P_{2i,t} = V_{2i,t} + \theta = f_t + \frac{1}{\lambda}C_{i,t} + \theta$$

$$\tag{3.37}$$

$$\theta = \frac{1}{A}\ln\left(\frac{M-1+Ab}{M-1}\right)$$

When M is approaching infinity, θ is approaching zero:

$$\lim_{M\to\infty}\theta = \lim_{M\to\infty}\frac{1}{A}\ln\left(1+\frac{Ab}{M-1}\right) = \frac{1}{A}\ln 1 = 0 \tag{3.38}$$

Therefore, the quoting strategy captures the features of the competition. When the competition of a market rises, the number of dealers M increases, making their quotes closer to their expected values of the exchange rate.

As can be seen, the quoting strategy of dealers captures the real-time states of the interbank market. Given trading volume Q, the market depth in the quoting strategy mentioned above can be calculated as:

$$\frac{2}{\lambda}Q + 2\theta \qquad\qquad (3.39)$$

In a competitive market, market depth is nearly proportional to twice trading volume.
This is consistent with the finding of Rime (2003), which is shown in Figure 3.1.
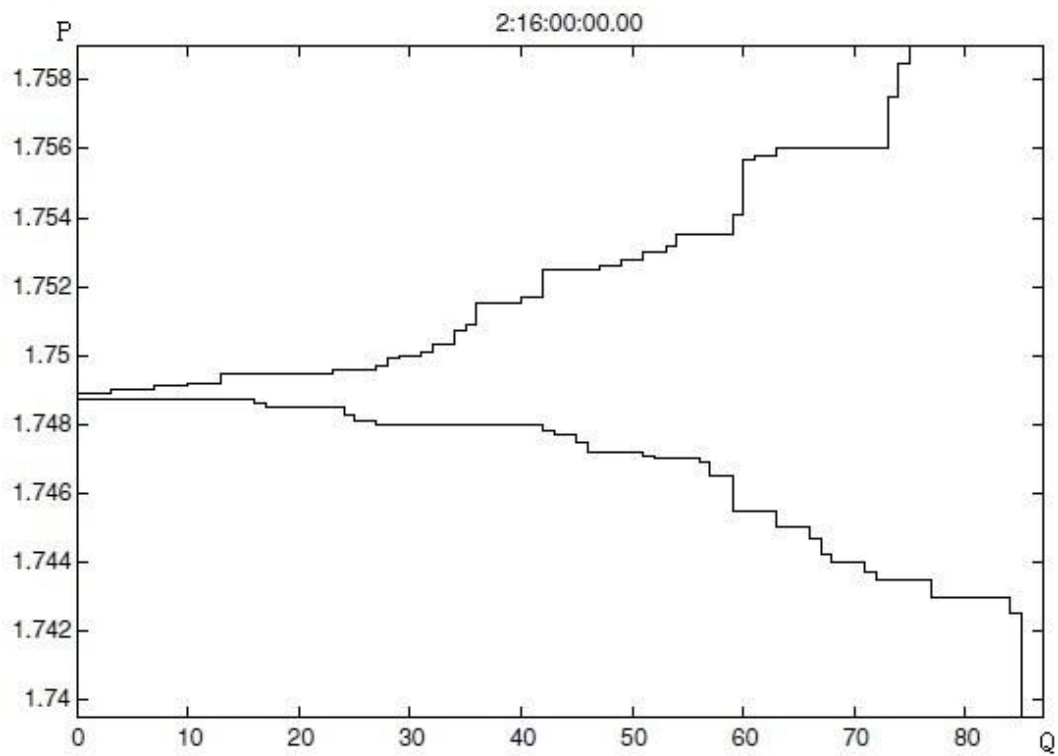
Figure 3.1 Depth of bid and ask quotes at a time point in Reuters D2000-2 (Rime 2003)

Figure 3.1 shows the depth of bid and ask quotes at 16:00 in Reuters D2000-2 when both the European market and the American market are active. The X-axis is accumulative order flow and the Y-axis is exchange rate. The depth of bid and ask are similar and spread between bid (lower) curve and ask (upper) curve increases when trading size becomes larger.

After dealer i observes others' quotes, he may conduct speculative transactions to make profits. However, this may be regarded as the initial trial and error in the process of exchange rate determination and this chapter elects to concentrate on studying speculative demand and price setting in equilibrium.

Proposition 4: *In a competitive market that is assumed to have no arbitrage, the optimal quoting strategy in the interbank market ensures market equilibrium as:*

$$P_{2,t} = f_t + \frac{1}{M\lambda} \sum_i^M C_{i,t} \tag{3.40}$$

where $P_{2,t}$ denotes the price in equilibrium.

Proof:

Remember that dealer i will end with a negative inventory position in the customer market if $C_{i,t} > 0$. In order to share risk, he would like to buy foreign currency at $P_{2i,t} = f_t + \frac{1}{\lambda} C_{i,t} - \theta$. Similarly, dealer j would like to sell at $P_{2i,t} = f_t + \frac{1}{\lambda} C_{i,t} + \theta$ when $C_{i,t} < 0$. While $P_{2i,t} > P_{2j,t}$, the deal will be matched. $P_{2i,t}$ decreases and $P_{2j,t}$

increases. The assumption of no arbitrage requires $P_{2i,t} = P^O_{2i,t}$, and competition

makes $\theta = 0$. The pricing problem is then solved:

$$P_{2i,t} = f_t + \frac{1}{\lambda}C_{i,t} = f_t + \frac{1}{\lambda}C^O_{i,t} = P^O_{2i,t} \tag{3.41}$$

Rearranging equation (3.41) to:

$$C_{i,t} = C^O_{i,t} = \frac{1}{M}\sum_i^M C_{i,t} \tag{3.42}$$

The optimal pricing strategy in equilibrium becomes:

$$P_{2,t} = f_t + \frac{1}{M\lambda}\sum_i^M C_{i,t} \tag{3.43}$$

It should be noted that our model does not make any assumption or impose any

limitation on the process from heterogeneous information to market equilibrium with

information completely shared. It could be that other dealers send order requests and

trade directly. Alternatively it might be that dealer i's limit order is matched to the

limit orders of other dealers by a broker or electronic trading system and he trades

indirectly. This captures different types of trading tools in the interbank market.

Proposition 5: *In equilibrium, speculative demand is eliminated and imbalance of customer order flow equals imbalance of interbank order flow.*

$$\sum_{i}^{M} T_{i,t} = \sum_{i}^{M} C_{i,t} \tag{3.44}$$

Proof:

Following Evans and Lyons (2002), the wealth of dealer i after he conducts speculative demand is:

$$W = C_{i,t}(f_t - P_{2i,t}) + [D_{i,t} + E(T_{i,t}^O | \Omega_{2i,t}^e)](P_{2,t} - P_{2i,t}^O)$$

$$\tag{3.45}$$

$$-T_{i,t}^O(P_{2,t} - P_{2i,t})$$

where $T_{i,t}^O$ is the hedge demand against incoming order flow and the information set $\Omega_{2i,t}^e = \{f_t, I_{1i,t}, I_{2i,t}, C_{i,t}, P_{1i,t}, P_{2i,t}, P_{2i,t}^O, P_{2,t}\}$. In equilibrium, $T_{i,t}^O = 0$ and $P_{2i,t} = P_{2i,t}^O = P_{2,t}$. There would be no additional benefit to gain from holding any speculative demand. The assumption of no arbitrage eliminates speculative demand and thus:

$$D_{i,t} = 0 \tag{3.46}$$

Consider the relationship between customer order flow and interbank order flow:

$$\sum_{i}^{M} T_{i,t} = \sum_{i}^{M} C_{i,t} + \sum_{i}^{M} D_{i,t} \qquad (3.47)$$

Therefore, net customer order flow is the same as net interbank order flow:

$$\sum_{i}^{M} T_{i,t} = \sum_{i}^{M} C_{i,t} \qquad (3.48)$$

Proposition 5 does not imply that dealers are purely liquidity providers. In the real-time exchange market, dealers could have speculative demand based on their private information. However, dealers will take the opposite position on speculative demand at a profitable price until market equilibrium is achieved. Therefore, our model allows the existence of diversified trading styles as seen among the dealers studied by Bjønnes and Rime (2005). Equation (3.48) describes the relationship between imbalance of customer order flow and imbalance of interbank order flow, but not the relationship between trading volumes in the customer market and that in the interbank market. In addition to the possible speculative demand, the frequency of transactions in the interbank market is higher than in the customer market, in order to share risk and information. Therefore, our model also allows larger trading volume in the interbank market than in the customer market.

In the model of Evans and Lyons (2002), the speculative demand of dealer i is $D_{i,t} = \alpha C_{i,t}$, with $\alpha > 0$. The relationship between customer order flow and interbank order flow would be $T_{i,t} = (\alpha + 1)C_{i,t}$. However, in the third trading round to share overnight risk with the public, the quantity to trade is $\sum_i^M C_{i,t}$. This indicates that dealers will hold $\alpha \sum_i^M C_{i,t}$ of inventory position overnight. This is contrary to the finding of Bjønnes, Rime, and Solheim (2005) that dealers will not stay with any overnight imbalance position. For this aspect, our model obeys the evidence found in the literature.

<u>Step 3</u>

Inspired by Cao, Evans, and Lyons (2006), this study describes the inventory effect in the process of sharing overnight risk with the public. In order to avoid overnight risk, the quantity to trade with the public is inventory position $I_{3i,t}$. Dealer i quotes lower price $P_{3i,t}$ to ensure sufficient expected returns for the public to absorb imbalance of inventory position.

$$I_{3i,t} = \lambda\big[E_P\big(P_{i,t+1}|\Omega_P\big) - P_{3i,t}\big] \tag{3.49}$$

where $E_P\big(P_{i,t+1}\big)$ is expected value of the exchange rate for the public in the next period. $\Omega_P = \{f_t, P_{2,t}, P_{3i,t}, R\}$ is the information set. R indicates increment of the exchange rate in the public's expectation.

When dealers share information completely in the interbank market, the private part of information on the exchange rate is discovered. The public would recognize the

value of the exchange rate in market equilibrium. Moreover, there are many more liquidity providers among the public than there are dealers. Their risk-bearing capacity is large enough to take overnight risk. The expected value of the exchange rate in the next period for the public is the sum of equilibrium price and expected increment of the exchange rate:

$$E_P\big(P_{i,t+1}|\Omega_P\big) = P_{2,t} + R \tag{3.50}$$

Combining equations (3.49) and (3.50), the demand of the public becomes:

$$I_{3i,t} = \lambda\big[P_{2,t} - P_{3i,t} + R\big] \tag{3.51}$$

Now, all the information available to dealer i is information set $\Omega_{2i,t}$, price equilibrium in the interbank market $P_{2,t}$, information of public demand function $P_{3i,t}$, $I_{3i,t}$, R and risk-free payoff for holding domestic currency r_d.

Proposition 6: *With information set $\Omega_{3i,t} = \{\Omega_{2i,t}, P_{2,t}, I_{3i,t}, P_{3i,t}, R, r_d\}$, the expected value of the exchange rate for dealer* i *in the next period is:*

$$E\left(P_{1i,t+1}|\Omega_{3i,t}\right) = P_{1,t} + \left(\frac{A}{2}\sigma_P^2 - \frac{1+r_d}{\lambda}\right)I_{3i,t}$$

$$(3.52)$$

$$+R(1+r_d) + \frac{1}{M\lambda}\sum_i^M T_{i,t}$$

Here $E\left(P_{1i,t+1}|\Omega_{3i,t}\right)$ is the expected value of the exchange rate for dealer i in the next period. σ_P^2 is volatility of $E\left(P_{1i,t+1}|\Omega_{3i,t}\right) - P_{2,t}$.

Proof:

In order to solve the expected value of the exchange rate in the next period, one needs to calculate the benefit from controlling inventory and the compensation for holding risky assets overnight. The expected utility in these two cases is:

$$E(U) = \begin{cases} -e^{-AI_{3i,t}(P_{3i,t}-P_{2,t})(1+r_d)} & , if\ deal\ is\ made \\ E\left(-e^{-AI_{3i,t}(P_{1i,t+1}-P_{2,t})}|\Omega_{3i,t}\right) & , if\ no\ deal\ is\ made \end{cases}$$

$$(3.53)$$

For the utility function $U = -e^{-Ax}$, it is known that if x is normally distributed with $N(\mu, \sigma^2)$, $E(U) = -e^{-A(\mu-\frac{1}{2}A\sigma^2)}$. Therefore, expected utility of dealer i is:

$$E(U) = \begin{cases} -e^{-AI_{3i,t}(P_{3i,t}-P_{2,t})(1+r_d)} & , if\ deal\ is\ made \\ -e^{-A\left[I_{3i,t}(E(P_{1i,t+1}|\Omega_{3i,t})-P_{2,t})-\frac{A}{2}I_{3i,t}^2\sigma_P^2\right]} & , if\ no\ deal\ is\ made \end{cases}$$

$$(3.54)$$

To make the expected utilities indifferent to dealer i, we need:

$$-AI_{3i,t}(P_{3i,t} - P_{2,t})(1 + r_d)$$

$$= -A\left[I_{3i,t}(E(P_{1i,t+1}|\Omega_{3i,t}) - P_{2,t}) - \frac{A}{2}I_{3i,t}^2\sigma_P^2\right]$$

(3.55)

Rearranging equation (3.55) we have:

$$E(P_{1i,t+1}|\Omega_{3i,t}) - P_{2,t} = (P_{3i,t} - P_{2,t})(1 + r_d) + \frac{A}{2}I_{3i,t}\sigma_P^2 \qquad (3.56)$$

Combined with the demand function of the public in equation (3.51), the expected value of the exchange rate in the next period becomes:

$$E(P_{1i,t+1}|\Omega_{3i,t}) - \left(f_t + \frac{1}{M\lambda}\sum_i^M C_{i,t}\right)$$

(3.57)

$$= -\left(\frac{1}{\lambda}I_{3i,t} - R\right)(1 + r_d) + \frac{A}{2}I_{3i,t}\sigma_P^2$$

Rearranging equation (3.57) to:

$$E\left(P_{1i,t+1}|\Omega_{3i,t}\right) = f_t + \left(\frac{A}{2}\sigma_P^2 - \frac{1+r_d}{\lambda}\right)I_{3i,t} + R(1+r_d) + \frac{1}{M\lambda}\sum_i^M C_{i,t} \quad (3.58)$$

Recall that $P_{1,t} = f_t$ and $\sum_i^M C_{i,t} = \sum_i^M T_{i,t}$, then:

$$E\left(P_{1i,t+1}|\Omega_{3i,t}\right) = P_{1,t} + \left(\frac{A}{2}\sigma_P^2 - \frac{1+r_d}{\lambda}\right)I_{3i,t}$$

$$(3.59)$$

$$+R(1+r_d) + \frac{1}{M\lambda}\sum_i^M T_{i,t}$$

In this step, dealers hold the same level of inventory position $I_{3i,t}$ after market equilibrium in the interbank market. The common public demand function ensures that they will quote the same price to close inventory position. Therefore, all the dealers have the same information in the same public environment and thus show the same behaviour. Price setting of dealer i is sufficient to represent the market-level movement of the exchange rate. Rearranging equation (3.52), one obtains the equation for the motion of the exchange rate:

$$\Delta P_{1,t} = \left(\frac{A}{2}\sigma_P^2 - \frac{1+r_d}{\lambda}\right)I_{3i,t} + R(1+r_d) + \frac{1}{M\lambda}\sum_i^M T_{i,t} \quad (3.60)$$

$\Delta P_{1,t}$ is the exchange rate movements between the beginning of time t and t + 1. As can be seen from equation (3.60), our model is composed of three parts. The first part

incorporates the inventory effect. If $\frac{A}{2}\sigma_P^2 < \frac{1+r_d}{\lambda}$, the exchange rate is negatively associated with the inventory position. The second part, $R(1 + r_d)$, captures the influence of macro variables. The third item, $\frac{1}{M\lambda}\sum_i^M T_{i,t}$, represents the information effect. The coefficient on the informative part is positive. This is consistent with the findings in the literature that the information effect should be positively correlated with exchange rate movements.

Consider the relationship between the inventory position in step 1, $I_{1i,t}$, and in step 3, $I_{3i,t}$. According to Proposition 4, equilibrium in the interbank market requires dealers to quote the same price, and optimal quoting strategy in market equilibrium states that dealers share the imbalance of customer order flow jointly and equally. Therefore, the change of inventory position from the beginning of step 1 to the end of step 2 is the average of net customer order flow.

$$I_{3i,t} = I_{1i,t} - \frac{1}{M}\sum_i^M C_{i,t} \tag{3.61}$$

Substituting equation (3.61) into (3.60), we obtain:

$$\Delta P_{1,t} = \left(\frac{A}{2}\sigma_P^2 - \frac{1+r_d}{\lambda}\right)I_{1i,t} + R(1+r_d) + \left(\frac{2+r_d}{\lambda} - \frac{A}{2}\sigma_P^2\right)\frac{1}{M}\sum_i^M T_{i,t} \tag{3.62}$$

Note that if dealers end without any inventory positions in a trading period, they must start with zero inventory position in the next trading period. The inventory position in step 1 should be zero:

$$I_{1i,t} = 0 \tag{3.63}$$

Movements of the exchange rate then become:

$$\Delta P_{1,t} = R(1 + r_d) + \left(\frac{2 + r_d}{\lambda} - \frac{A}{2}\sigma_P^2\right)\frac{1}{M}\sum_i^M T_{i,t} \tag{3.64}$$

The parameter on order flow in equation (3.64) incorporates both inventory and information effects, while $\frac{A}{2}\sigma_P^2 < \frac{1+r_d}{\lambda}$, $\frac{A}{2}\sigma_P^2 < \frac{2+r_d}{\lambda}$. The correlation between exchange rate movements and order flow is positive. While the debate on reasons for the empirical success of order flow is still unresolved, our model says that order flow effect is a composite result of both inventory and information effects.

3.4 Conclusion

The microstructure approach to the exchange rate has emerged as a promising alternative to macro models. However, there is still a scarcity of literature providing a theoretical framework that treats the exchange rate determination as a process driven by the interaction between the interbank and customer markets. To fill this critical void, this chapter develops a theoretical model to bridge DL and ML models. Based

on the study of optimal reaction of dealers to incoming information, associated with the condition of market equilibrium, our model builds the connection between dealers' behaviour and the market's behaviour, changing price setting at the dealer level to exchange rate determination at the market level.

This chapter sheds new light on the process of exchange rate determination under the influence of inventory and information effects. Compared to the existing literature, the model offers the following advantages:

- Compared to Lyons' model, Huang and Stoll's model and Ding's model, our model is developed in a more realistic environment with multi-structure framework of the foreign exchange market. It has no restrictive assumptions or limitations with regard to dealers' trading styles. It allows diversified tools and motivations to make a deal, beyond the controlling of inventory by incoming order requests.

- Compared to Evans and Lyons' model and Cao, Evans and Lyons' model, our model allows heterogeneous expectations of the exchange rate and thus heterogeneous price setting in the interbank market. It captures the features of the real-time exchange market and market depth. It also shows that the extent to which dealers' quotes reflect the expected value of the exchange rate depends on the extent of competition in the interbank market. Therefore, the parameters of individual dealers enter into the order flow model and it is said to influence the impact of order flow on exchange rate.

- Proposition 6 is the original contribution of this chapter. Compared to Evans and Lyons' model and Cao, Evans and Lyons' model, our model incorporates both the information effect and inventory effect. Information effect enters into the

model by way of the behaviour of customers with private information and the reaction of dealers' optimal quoting strategy to incoming information. Realized order flows in the customer market and the interbank market are carriers of information. Inventory effect enters into our model by quote shading when dealers try to share risk with the public and stay with no overnight imbalance of inventory position. In addition, the model in Proposition 6 gives a deeper picture of the composition of order flow impact on exchange rate and provides a theoretical tool to analyse the relationship between market parameters and the impact of order flow.

The model in this chapter raises several issues which deserve further research. First, order flow is calculated according to a method developed in the equity market. While this method has been used for more than a decade, and performs reasonably well, it is desirable to develop a method to construct the order flow index that takes specific consideration of characteristics of the foreign exchange market. Second, a natural extension of the study would be to test the model empirically. Specification of the empirical model and the appropriate method to adopt are unknown at this stage, especially for an environment where very high frequency data will be deployed. Future research should strive to use some real data to test the model. However, currently, most data are private. A market dealer/trading platform cannot disclose their individual customer information for confidentiality reasons. If, in the future, I am able to obtain relevant data, I will include it in my future research. The results obtained from using the derived model can be compared with the standard model, so that the differences in the results can be used to justify the derived theoretical model. Third, it is worth finding a way to measure influences of the inventory effect and

information effect on exchange rate movements separately, because our model incorporates both these effects. Finally, it would be interesting to apply the model to the mature and emerging markets respectively and study the potential differences.

Chapter 4

Trading Intensity, Information-based Trading and Price Impact in the Chinese Foreign Exchange Market

4.1 Introduction

In light of the fact that macro exchange rate models have received little support in empirical research, the microstructure of the foreign exchange market has attracted growing attention. In their seminal work, Evans and Lyons (2002) conclude that the order flow model captures above 60% of daily change for DM/USD, and more than 40% of daily change for Yen/USD. Subsequent research has shown order flow to be an important indicator to capture the dynamics of exchange rates for various currency pairs (Duffuor, Marsh, and Phylaktis 2012, Evans and Lyons 2005, Berger et al. 2008, Zhang, Chau, and Zhang 2013, Cheung and Rime 2014). The majority of empirical studies on order flow models adopt fixed time intervals such as weekly, daily, or 5-minute intervals. However, as has been pointed out by Diamond and Verrecchia (1987), Easley and O'Hara (1992), the time between two consecutive transactions contains information on the reasons for different types of time interval. Ignoring irregular time intervals in ultra-high frequency data might lead to losing information on the behaviours of market participants behind transactions. Prior studies (Dufour and Engle 2000b, Manganelli 2005, Holder, Qi, and Sinha 2004) on the information

content of trading duration have been mainly concerned with the stock market, option market and futures market. Little attention has been paid to foreign exchange markets, especially those in the emerging market economies. As the importance of China for the international economy is growing, attempts to provide a fuller picture on the Chinese foreign exchange market are necessary and desirable for market participants and regulators.

Given the availability of ultra-high frequency data on exchange rate transactions, this chapter aims to answer the following questions:

(1) Does order flow have significant impacts on the exchange rate in ultra-high frequency transaction? Although order flow has been proved to play an important role in capturing daily exchange rate changes in China, the ultra-high frequency relation between order flow and exchange rate movement needs to be explored.

(2) What exactly is the information content of trading duration? In the research to date, the information content of trading duration has normally been detected by the significant relation between trading duration and price changes, and is usually explained theoretically. However, exactly what information is contained in trading duration, and the validity of that information, still require further research.

(3) How does trading duration impact on exchange rate changes and volatility? Evidence on impact of trading duration on exchange rate return and volatility has not been conclusive. One theory (Easley and O'Hara 1992) advocates that long trading duration mirrors no news and low activity of informed traders, leading to small exchange rate changes and low volatility. However, according to another theory (Admati and Pfleiderer 1988), there are discretionary uninformed traders who are able

to choose the time to trade in order to minimize adverse selection cost. They will postpone their trading if there is a high arrival rate of informed traders. Therefore, long trading duration implies the absence of discretionary uninformed traders and a high proportion of informed traders, a situation associated with large exchange rate changes and high volatility. Both theories sound convincing and both are supported by empirical research. The present study aims to discover the reason behind these completely opposite results, and whether trading duration has an impact on exchange rate returns and volatility in the Chinese foreign exchange market.

This chapter contributes to the literature of microstructure studies on exchange rates in several ways. First, this research is one of the very few to study the microstructure of the Chinese foreign exchange market. Given that China is one of the biggest economies in the world, it is surprising that the literature on the dynamics of the Chinese foreign exchange market is quite limited. One possible reason is the lack of high frequency data. Our study enriches the line of microstructure study by providing analysis with ultra-high frequency data. This could help improve the understanding of foreign exchange markets in the emerging world. Second, by adopting the probability of information-based trading (PIN) model and the autoregressive conditional duration (ACD) model, this chapter presents a picture on the intraday pattern of informed traders, the probability of information occurring and trading duration. Given that the literature relates trading duration to arrival of informed traders theoretically, one of our contributions is to study directly the relationship between the content of information-based trading and both components of trading duration. Third, we try to uncover the trading behaviours of market participants hidden behind high frequency data. Guided by both the theoretical underpinning in Chapter 3 on the role of order

flow in price discovery and further discussions in this chapter on the PIN model, we test the price impacts of both variables as they are closely related. While it is well established in the literature the empirical significance of order flow, special emphasis is applied to the PIN variable in terms of its effects on prices through signed expected trading duration and signed unexpected trading duration in the Chinese foreign exchange market. It is natural to expect that exchange rate dynamics would change in different market situations. Distinct from many previous studies on trading duration, this study adopts a nonlinear model, the Markov regime-switching model, to investigate the relation between exchange rate returns and both signed components of trading duration in different market regimes. We also study impacts of the arrival rate (reciprocal of trading duration) on conditional volatility. For the first time in the literature, we develop a micro structure framework that captures comprehensively the critical role of order flow in exchange rate dynamics as well as the price impacts across difference market regimes. In addition, our model finds that the intraday pattern of informed trading in the Chinese foreign exchange market shows a time-of-the-day effect. This sheds critical lights on the possible strategy of secret official intervention, which would affect for market liquidity situations depending when the intervention is being conducted.

The main findings of this chapter can be summarized as follows. First, the probability of information-based trading is highest around the beginning and end periods of trading hours, and lowest during lunch time. This gives a U-shaped intraday pattern. In contrast, trading duration shows a distinctive inverted U-shaped intraday pattern. Some evidence is found that on average both expected and unexpected trading durations are relevant to the arrival rate of informed traders, but not to the probability

of information occurring. Second, trading duration in the Chinese foreign exchange market exhibits high persistence. A long trading duration is normally followed by another long trading duration. Third, order flow is proved to be an important determinant in ultra-high frequency exchange rate returns. Price impact of order flow is larger when the market is illiquid. Furthermore, both signed expected trading duration and signed unexpected trading duration contain information in addition to order flow. Our model captures around 13 per cent of exchange rate changes per transaction with linear estimation. This is consistent with the results of Zhang, Chau, and Zhang (2013), who adopt daily order flow in the Chinese foreign exchange market. Fourth, consistent with the theory of Engle and Russell (1998), expected arrival rate plays a more important role in capturing conditional volatility than does the unexpected arrival rate. Fifth, our estimation results support both theories on the trading behaviours of informed traders and discretionary uninformed traders. However, we argue that the final effect of trading duration on exchange rate is a composite result due to activities of uninformed and informed traders. It is also influenced by market structure and situation. In a placid market, short expected trading duration implies high trading intensity of existing informed traders, leading to large exchange rate changes and increased volatility. When the market is volatile, liquidity traders are expelled from the market. Long expected trading duration means a high proportion of informed traders, which is associated with large exchange rate changes and increased volatility. Because the number of market participants is limited in the interdealer market, the number of informed traders is limited and discretionary uninformed traders dominate the signed unexpected trading duration of order flow. This is found to have a positive impact on the exchange rate in different market regimes.

The rest of this chapter is organized as follows: Section 2 summarizes the descriptive statistics of the data. Section 3 introduces the PIN model and illustrates the intraday pattern of PIN. Section 4 introduces the ACD model and provides a picture on the intraday pattern of trading duration; this captures time clustering and divides trading duration into expected component and unexpected component. Section 5 examines the relation between different information components of PIN and different components of trading duration. Section 6 explores the price impact of signed expected trading duration and signed unexpected trading duration in both the linear model and nonlinear model. Section 7 presents the estimation results of the ACD-GARCH model. Section 8 summarizes the main findings and implications of the research.

4.2 Introduction to the Chinese foreign exchange market

From 1949 to 1978 trading in foreign exchange was prohibited in China. Only the central bank could trade with western countries, while individuals could apply for a very limited amount of US dollars for business use. From 1978, Deng Xiaoping established the open-door policy in China. The Chinese foreign exchange rate was set to follow the fixed USD exchange rate regime. In April 1994 the interbank foreign exchange trading system was established in Shanghai, under which the People's Bank of China (Central Bank) and the State Administration of Foreign exchange (SAFE) set up the China Foreign Exchange Trading System (CFETS), and the RMB was first traded in the interbank market.

4.2.1 Trading System

Since 1994, the electronic RMB trading platform, the CFETS, has played an important role in foreign exchange market operations. April 2007 saw the establishment of a new generation trading system and in 2009 the CFETS upgraded the RMB electronic trading system, which now supports the CFETS Straight Through Process (CSTP). CSTP can support a range of products in the foreign exchange trading system, including foreign exchange Spot, Forward, NDF, Swap, Cross Currency Swap, and Option. The CFETS is based on members' cooperatives, and all financial institutions that satisfy the requirements set by the regulators can apply for membership. The trading system serves the needs of various trading modes, such as anonymous trading and bilateral trading. It also includes One Click, Limit Order, Anonymous Inquiry Trading and Bilateral Inquiry Trading modes. The system offers the USD, EUR, JPY, HKD, GBP, AUD, NZD, SGD, CHF, and CAD against CNY for major trading currency pairs.[5] For regional trading, the system offers trading in CNY against the MYR, RUB, THB and KZT. The trading hours for most products are from 9:30 to 23:30[6] (Chinese Holidays excluded). The CFETS provides a centralized clearing service for anonymous trading, and for bilateral trading clear and settle are based on agreement with each trading party.

4.2.2 Trading Mechanism

In 2005, the Chinese monetary authority established the managed floating exchange rate regime based on market supply and demand with reference to a basket of currencies. The People's Bank of China (PBC) announces the Central Parity Rate

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[5] Here we mainly introduce the RMB/FX Spot market.
[6] The trading hours is extended to 9:30 - 23:30 after 4th January 2016.

(CPR) every business day with crawling bands. In 2005, the RMB/USD exchange rate floating band could not move above or below 0.3%. In 2007 the floating band was expanded to 0.5%, and in 2012 it became 1%. It was extended again in 2014 to 2%. On August 11, 2016 the PBC announced an improvement to CPR quotation whereby the market maker supplied quotation[7] should reference the previous day's interbank market closing rate, and take into account the changes of the previous day's international major currency exchange rates and foreign exchange market supply and demand, for fine tuning.

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[7] The major market maker should supply their quotation to the CFETS before the interbank market opening time for the intraday CPR calculation.

Table 4.1 The calculation method of the Central Parity Rate

The Central Parity Rate	Calculation Method
The CPR of USD/CNY	The CPR of USD/CNY is calculated in the following way: On each business day the market makers should give the CFETS their quote prices before the market opening time. The CFETS excludes the highest price and the lowest price, then calculates the weight average of the remaining prices as the intraday CPR. The market makers' trading volumes and their market-making performance are used as indicators to determine the weights.
The CPR of HKD/CNY and CAD/CNY	The CPR of HKD/CNY and CAD/CNY are transformed from the central parity of USD/CNY cross rate with reference to the price of HKD/USD and CAD/USD at 9am in the international FX market, respectively.
The CPR of EUR/CNY, JPY/CNY, GBP/CNY, AUD/CNY, NZD/CNY, SGD/CNY, CHF/CNY, MYR/CNY and RUB/CNY	On each business day the market makers give their quote price to the CFETS before market opening time. Then the CFETS calculates the average price as the CPR of RMB against EUR, JPY, GBP, AUD, NZD, SGD, CHF, MYR and RUB for the intraday.

Notes: All the calculation methods are based on the People's Bank of China authorized official website, China Money.

http://www.chinamoney.com.cn/fe/Channel/2781516, last accessed on 18 March 2016.

4.3 Data Description

Due to data availability, the raw data in this chapter is tick transaction data of CNY/USD in the Chinese foreign exchange market between 9th December 2009 and 13th December 2012. It is collected from Reuter Xtra 3000 and covers around three

years, with 733 trading days. The available variables are timestamp, transaction price, bid quote and ask quote. For the convenience of analysis, this chapter prepares the raw data in the following ways. First, the Lee and Ready (1991) algorithm is applied to determine the direction of every transaction. Specifically, every time-stamped transaction is defined as buyer-initiated transaction (valued as 1) or seller-initiated transaction (valued as -1). Second, the duration between two transactions is calculated from the timestamp. Third, if transactions are dealt at the same time, they are considered as one observation; transaction directions are summed up, and this is the order flow. Fourth, in order to eliminate the effect of overnight information, the first observation of every trading day is excluded. We also delete some transaction data without bid and ask price around the early trading. Fifth, observations whose transaction direction cannot be determined are excluded from our dataset. Sixth, this chapter deletes all the transactions outside the opening hours. As a result, finally, the data reduces from 158646 observations to 155721 observations.

Table 4.2 Descriptive statistics (09/12/2009–13/12/2012)

	ΔP_i	OF_i	x_i
Observations	155721	155721	155721
Mean	$9.09 \times e^{-7}$	-0.0928	123.4021
Median	0	-1	46
Minimum	-0.5363	-2	1
Maximum	0.5424	9	15120
Std. Dev.	0.0127	1.01	301.0962
Skewness	0.1477	0.1869	13.2272
Kurtosis	183.8759	1.1418	265.6339
Jarque-Bera	$2.12 \times e^{8}$***	23309.83***	$4.52 \times e^{8}$***

Notes: ΔP_i is the log difference of the exchange rate times 100. OF_i means the difference between buyer-initiated transaction and seller-initiated transaction at one time, named order flow. x_i is calculated as $t_i - t_{i-1}$, which denotes actual duration between transactions. Jarque-Bera is the statistics of normality test. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Table 4.2 presents the descriptive statistics of exchange rate returns, order flow and trading duration. Exchange rate returns are calculated from the log difference of two consecutive exchange rates times 100. It is interesting that CNY/USD depreciated from 6.8276 on 9th December 2009 to 6.232 on 13th December 2012, a decrease of around 8.72%. However, intraday exchange rate changes in our data are not as obvious, since the mean of ΔP_t is nearly zero and the median is exactly zero. The maximum exchange rate change is almost the same as the minimum exchange rate change. From the raw data, it can be found that the majority of CNY/USD

depreciation happens around the beginning of trading hours and after the market has closed. The accumulated depreciation rate around opening time reaches as high as 7.73%, and that after the market has closed is around 0.87%. These trades are deleted during the preparation of the data. As can be seen in the second column of Table 4.2, seller-initiated transactions dominate in the Chinese foreign exchange market: mean and median of order flow are -0.0928 and -1, respectively. x_i denotes transaction duration; the calculation formula is $x_i = t_i - t_{i-1}$, where t_i denotes the arrival time of point process i. The average of trading duration is 123.4 seconds. Trading intensity in our data sample differs widely. The shortest trading duration is only 1 second, while in an inactive market it can reach as long as 15120 seconds.

4.4 Intraday Pattern of Informed Trading

Given a sample of transaction data, how to discover the information content of transactions is a problem. Easley et al. (1996) develop a structural sequential trading model based on Kyle (1985), Easley and O'Hara (1987) to calculate the probability of information-based trading. In this section, we adopt the PIN model to analyse the information pattern within one day.

4.4.1 The PIN model

The sequential trade model introduced by Easley et al. (1996) describes the behaviours of market making in a mixed setting of discrete-and-continuous time.

```
                                                              Buy Arrival Rate
                                                                     ε
                                   Bad News
                                                              Sell Arrival Rate
                                      δ
                                                                   ε + μ
             Information
                                                              Buy Arrival Rate
                α
                                   Good News                       ε + μ
                                     1− δ
                                                              Sell Arrival Rate
                                                                     ε
               No
            Information                                       Buy Arrival Rate
              1− α                                                  ε

                                                             Sell Arrival Rate
                                                                     ε
```
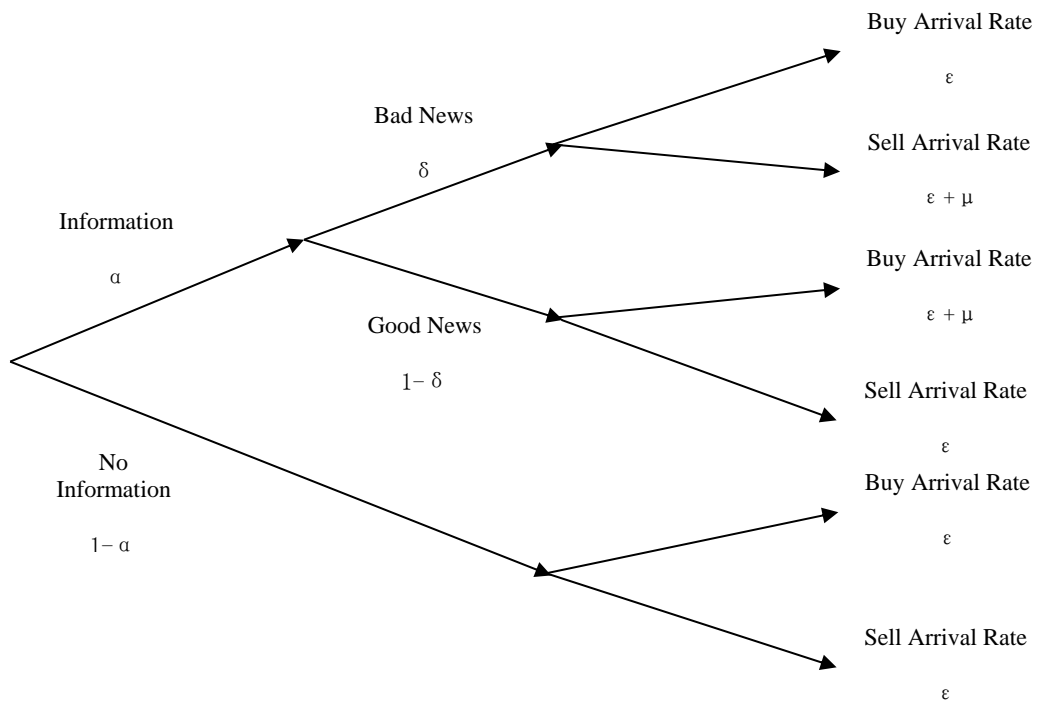
Figure 4.1 Trading process of the PIN model

As can be seen in Figure 4.1, nature determines whether an information event happens before trading hours, and the probability is α. Once information appears, the probability of it being good news is $1 - \delta$ and the probability of it being bad news is δ. There are three types of market participants: the market maker, informed trader and uninformed trader. They are all assumed to be risk neutral and competitive. Informed

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traders are able to observe the type of information. Under the assumption of risk neutral and competitive, his optimal reaction is to buy the asset at good news and sell at bad news. The arrival rate of informed traders is ε and follows a Poisson process. Uninformed traders also follow an independent Poisson process, and arrive at the rate of μ. Uninformed traders cannot observe the information events, and buy or sell the asset regardless of whether an information event occurs. Therefore, both the buy arrival rate at good news and the sell arrival rate at bad news are $\varepsilon + \mu$. In the remaining cases, the buy arrival rate or the sell arrival rate is ε. The market maker knows the probability of an information event occurring, the probability of different types of information and the arrival rate of orders. However, he does not know which path has been determined by nature: good news, bad news or no information. Because the market maker is risk neutral and competitive, the posted bid and ask prices are the expected values of the asset conditional on available information. He adopts the Bayes rule to update the belief on information events. The likelihood of observing any sequence of buyer-initiated transactions and seller-initiated transactions on a good-news day of total time T is:

$$e^{-(\epsilon+\mu)T} \frac{[(\varepsilon + \mu)T]^B}{B!} e^{-\varepsilon T} \frac{(\varepsilon T)^S}{S!} \tag{4.1}$$

Similarly, the likelihood of observing orders on a bad-news day is given by:

$$e^{-\varepsilon T} \frac{(\varepsilon T)^B}{B!} e^{-(\varepsilon+\mu)T} \frac{[(\varepsilon + \mu)T]^S}{S!} \tag{4.2}$$

On a day with no information, the likelihood becomes:

$$e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \qquad (4.3)$$

ε is the arrival rate of uninformed traders to buy and sell assets, μ represents the arrival rate of informed traders, T denotes the total time of trading period, B is the number of buyer-initiated trades and S means the number of seller-initiated trades.

Therefore, the likelihood of observing trading activity with unknown type is equal to the weighted average of three types of information:

$$L\big((B,S)|\theta\big) = \alpha(1-\delta)e^{-(\varepsilon+\mu)T}\frac{[(\varepsilon+\mu)T]^B}{B!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}$$

$$\times\ e^{-(\varepsilon+\mu)T}\frac{[(\varepsilon+\mu)T]^S}{S!} + (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}$$

$$(4.4)$$

where α is the probability of an information event happening, and δ is the probability of information being good news. Across I independent trading days, the likelihood becomes:

$$L(M|\theta) = \prod_{i=1}^{I} L\big(\theta|(B_i, S_i)\big) \qquad (4.5)$$

In order to deal with the convergence problem in numerical maximization when the numbers of buyer-initiated transactions and seller-initiated transactions are large, we follow Aktas et al. (2007) to adopt a common term from the probability of three branches, and the likelihood function is rewritten as:

$$L(M|\theta) = \sum_{t=1}^{T} [-2\varepsilon + M_t \ln(z) + (B_t + S_t)\ln(\varepsilon + \mu)]$$

(4.6)

$$+ \sum_{t=1}^{T} \ln[\alpha(1-\alpha)e^{-\mu}z^{S_t-M_t} + \alpha\delta e^{-\mu}z^{B_t-M_t} + (1-\alpha)z^{B_t+S_t-M_t}]$$

where $M_t = min(B_t, S_t) + \frac{max(B_t, S_t)}{2}$ and $z = \frac{\varepsilon}{(\varepsilon+\mu)}$.

According to Easley, Hvidkjaer, and O'Hara (2002), Easley et al. (2008), Easley et al. (1996), PIN is calculated as the unconditional probability of informed trading:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

(4.7)

4.4.2   Estimation results

Our data spans the period from 9th December 2009 to 13th December 2012. On 9th December 2010, the China Foreign Exchange Trade System (CFETS) announced that it would shorten the trading day by one hour, so that trading hours changed from 9:30-17:30 to 9:30-16:30. In order to unify the trading hours of the data for analysis, we

divide our data into two sub-samples. The first sub-sample ranges from 9th December 2009 to 10th December 2010, with trading hours between 9:30 and 17:30; the second ranges from 13th December 2010 to 13th December 2012, with trading hours between 9:30 and 16:30.

First, the Lee and Ready (1991) algorithm is applied to determine the trade direction. Specifically, if transaction price is larger than middle price, it is defined as buyer-initiated transaction (valued as 1). If transaction price is smaller than middle price, it is defined as seller-initiated transaction (valued as -1). In the case that transaction price equals middle price, it is defined as buyer-initiated transaction if transaction price is larger than the previous one, and as seller-initiated transaction if transaction price is smaller than the previous one. Second, in order to contain sufficient data to calculate PIN parameters and the value of PIN, we calculate the number of buyer-initiated transactions and seller-initiated transactions within a trading period lasting 30 minutes, and all the trading days within the same trading period are adopted to determine PIN parameters, excluding the trading days with no transactions. Third, PIN package in R lab is introduced to compute the PIN parameters, which minimizes the log-likelihood function (4.6). Finally, PIN is calculated from equation (4.7).

Table 4.3 Intraday pattern of parameters and PIN (09/12/2009–10/12/2010)

Timestamp	ε	μ	α	δ	PIN
09:30 – 10:00	1	1	0.1298	0.4029	0.061
10:00 – 10:30	0.9152	1	0.7201	0.9979	0.2823
10:30 – 11:00	1	1	0.1872	0.154	0.0856
11:00 – 11:30	1	1	0.1857	0.1561	0.085
11:30 – 12:00	1	1	0.1876	0.1375	0.0858
12:00 – 12:30	1	0.0243	0.4795	1	0.0058
12:30 – 13:00	0.9226	0.0057	0.5956	0.9733	0.0018
13:00 – 13:30	0.9999	0.9995	0.2097	0.3514	0.0949
13:30 – 14:00	1	1	0.2082	0.109	0.0943
14:00 – 14:30	1	1	0.2001	0.137	0.0909
14:30 – 15:00	1	1	0.1884	0.1524	0.0861
15:00 -15:30	1	1	0.1865	0.1551	0.0853
15:30 – 16:00	1	1	0.184	0.1586	0.0842
16:00 – 16:30	0.9997	0.9113	0.1178	0.9929	0.051
16:30 – 17:00	0.9209	0.9838	0.4911	0.9093	0.2078
17:00 – 17:30	0.9999	1	0.1707	0.1771	0.0786

Notes: This table shows the intraday pattern of PIN parameters and the PIN value every 30 minutes. ε is the arrival rate of uninformed traders, μ is the arrival rate of informed traders, α is the probability of information event relevant to asset value, δ denotes the probability of an information event being bad news, PIN is the measurement of asymmetric information.
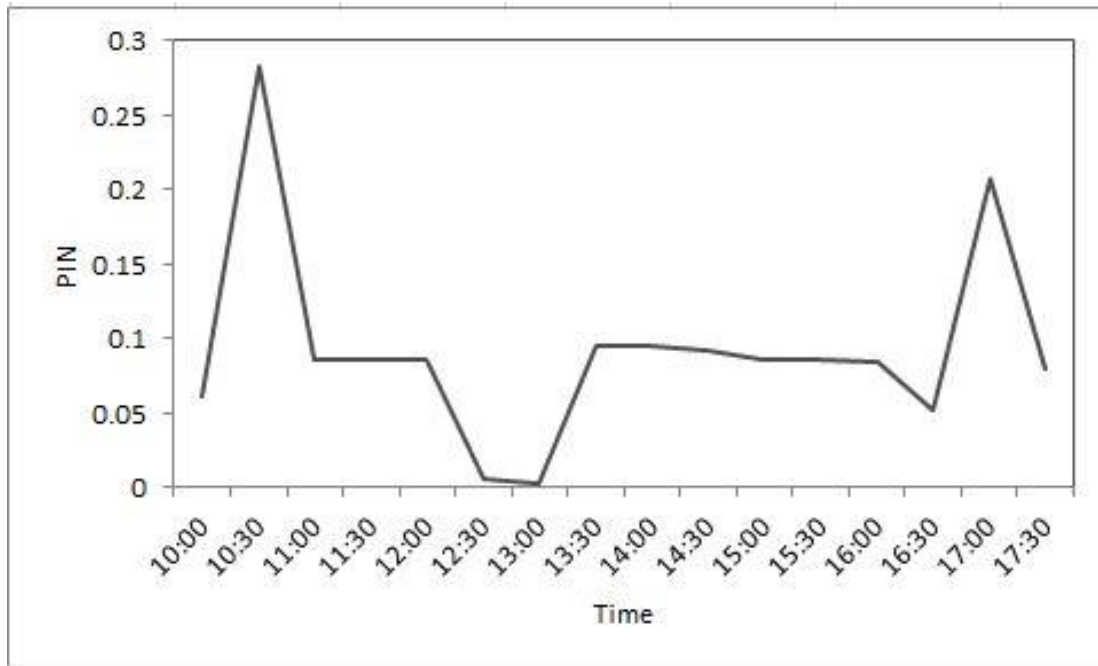
Figure 4.2 Intraday pattern of PIN (09/12/2009-10/12/2010)

Table 4.3 shows the estimated parameters and PIN for each trading period from 9th December 2009 to 10th December 2010. As can be seen from the second column, the arrival rate of uninformed traders remains high all day, as shown by the fact that the majority of ε equal 1, and all are above 0.9. Informed traders normally arrive at a high rate, but this drops dramatically around lunch time, which is from 12:00 to 13:00. During trading hours, information is most likely to arrive thirty minutes after the market opens (10:00-10:30), at lunch time (12:00-13:00) and in the half hour before the end of trading hours (16:30-17:00). Figure 4.2 shows the intraday pattern of PIN between 9th December 2009 and 10th December 2010. There are two trading periods with higher PIN, which are around half an hour after the market opens (10:00-10:30) and half an hour before the market closes (16:30-17:00). During lunch time (12:00-13:00), although the probability of information event is large, the arrival rate of

informed traders is quite low. Therefore, PIN reaches its minimum value of the day around lunch time.

Table 4.4 Intraday pattern of parameters and PIN (13/12/2010–13/12/2012)

Timestamp	ε	μ	α	δ	PIN
09:30 – 10:00	1	1	0.1975	0.3378	0.0899
10:00 – 10:30	1	1	0.4117	0.7815	0.1707
10:30 – 11:00	1	1	0.196	0.0893	0.0893
11:00 – 11:30	1	1	0.1934	0.093	0.0882
11:30 – 12:00	1	1	0.2087	0.1268	0.0945
12:00 – 12:30	1	$1.0012 \times e^{-6}$	0.2685	0.6276	$1.3441 \times e^{-7}$
12:30 – 13:00	0.9388	0.0028	0.5025	1	0.0007
13:00 – 13:30	0.9998	0.997	0.2192	0.3515	0.0985
13:30 – 14:00	1	1	0.2297	0.0942	0.103
14:00 – 14:30	1	1	0.1928	0.0939	0.0879
14:30 – 15:00	1	1	0.1886	0.0987	0.0862
15:00 -15:30	1	1	0.4761	0.3395	0.1923
15:30 – 16:00	1	1	0.1481	0.2884	0.0689
16:00 – 16:30	1	1	0.13	0.4266	0.061

Notes: This table shows the intraday pattern of PIN parameters and the PIN value every 30 minutes. ε is the arrival rate of uninformed traders, μ is the arrival rate of informed traders, α is the probability of information event relevant to asset value, δ denotes the probability of information event being bad news, PIN is the measurement of asymmetric information.
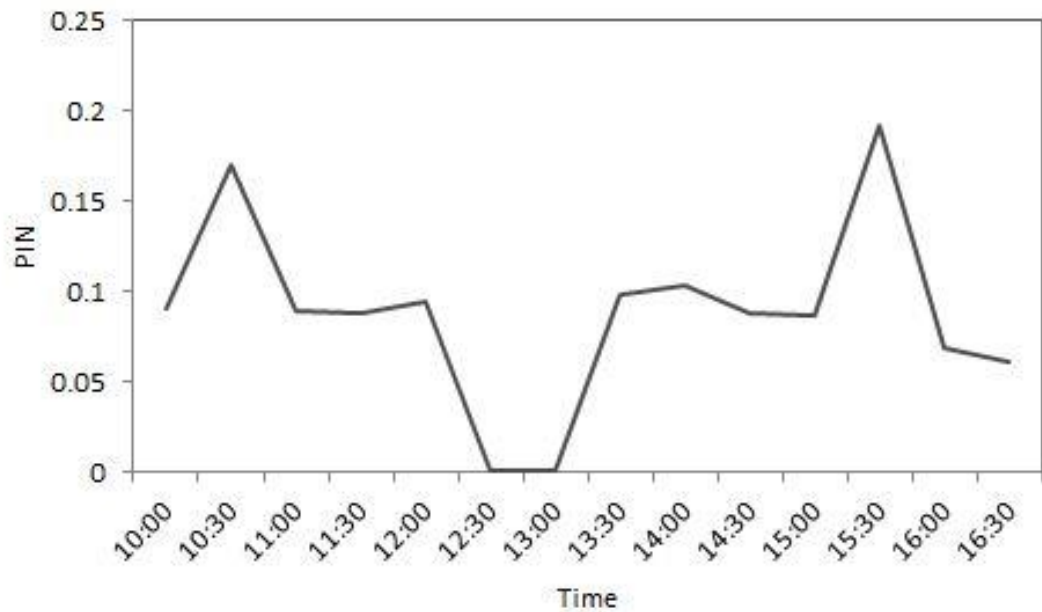
Figure 4.3 Intraday pattern of PIN (13/12/2010-13/12/2012)

Table 4.4 presents the estimated parameters and PIN for each trading period from 13th December 2010 to 12th December 2012. Similar to the first sub-period, the arrival rate of uninformed traders remains high all day. Informed traders arrive at a high rate during regular trading hours but are almost absent during lunch time (12:00-13:00). There is a higher probability of information event happening during the second half hour of trading (10:00-10:30), the second half hour of lunch time (12:30-13:00) and one hour before the market closes (15:00-15:30). A similar intraday pattern of PIN is illustrated in Figure 4.3. PIN reaches one of its peak values from 10:00 to 10:30 and drops to its valley bottom around lunch time (12:00-13:00). The second peak is between 15:00 and 15:30, one hour before the end of trading hours.

As can be seen above, although trading hours differ between the two sub-samples, asymmetric information exhibits similar intraday patterns. There is a high probability of information being revealed half an hour after the market opens and thus we see a higher PIN. During lunch time, informed traders are probably absent from the market and PIN reaches its minimum value. In line with the fact that the trading day in this sub-period has been cut short by one hour, the higher probability of information arrival and higher PIN move one and a half hours ahead of the time in the previous sub-period, from 16:30-17:00 to 15:00-15:30.

Our result is consistent with the finding of Chung, Li, and McInish (2005) that the arrival rate of uninformed traders ε stays at a high level, which is around 1 in our data and 0.8822 on average in their sample of 538 NYSE stocks with 30-minute interval. Compared to the stock market, the participation of uninformed traders in the foreign exchange market is enhanced, because liquidity is both quote-driven and order-driven. According to Easley, Kiefer, and O'Hara (1997), the estimated parameters of PIN vary largely depending on different stocks. Similarly, it is possible to find the estimated parameters varying across different markets. On average, the probability of information event happening α is 0.2668, in contrast to 0.4712 as found by Chung, Li, and McInish (2005). Besides economic condition and fundamental value, the stock market could be impacted by individual events such as merger and acquisition, growth of revenue, and change of company strategy. The frequency of information event is normally higher in the stock market than in the foreign exchange market. Compared with the average μ in the stock market, which is 0.2984 in the results of Chung, Li, and McInish (2005), informed traders arrive at a high level in the Chinese foreign exchange market, except at lunch time.

Attention should be paid to two features of the Chinese foreign exchange market. One is the possibility of central bank intervention. As a market participant, the central bank represents the political targets of the government. Therefore, it is a kind of informed trader, with policy information. A high arrival rate of central bank activity indicates frequent foreign exchange intervention. The other feature is the market structure of the Chinese foreign exchange market. Customers, such as import and export enterprises, represent an important information resource. They cannot make a deal in the interdealer market and must therefore trade with dealers. The customer information gradually arrives in the interdealer market when dealers, especially the big state-owned banks, trade for customers. Both the central bank and state-owned banks will break during lunch time, and at that time the arrival rate of informed traders is lowest.

4.5 Intraday Pattern of Trading Intensity

One feature of our high frequency data is irregular time-spacing. As has been pointed out by Diamond and Verrecchia (1987), Easley and O'Hara (1992), the time between two consecutive transactions contains information on the reasons for different types of time interval. A seminal model to capture trading duration is the ACD model introduced by Engle and Russell (1997, 1998). However, the estimation should be performed with certain necessary constraints, in order to keep all the possible conditional durations positive. More importantly, the standard ACD model overreacts to extreme (very short or very long) trading duration, which suggests that a nonlinear formation of ACD model will be more appropriate. Therefore, this section adopts one extension of the ACD model, namely the Box-Cox ACD model, to study two

components of trading duration: the expected component and the unexpected component.

4.5.1 The Box-Cox ACD model

The Box-Cox ACD model is one of the extensions of the ACD model introduced by Dufour and Engle (2000a). The main assumption of the Box-Cox ACD model is that trading duration is determined by the expected and standardized durations:

$$x_i = \psi_i e_i \tag{4.8}$$

where subscript i is a sequence of variable. The standardized duration e_i follows an independent and identical distribution, with $E(e_i) = 1$. Furthermore, expected duration is conditional on past standardized duration and expected duration. The conditional mean function in the Box-Cox model is the nonlinear formation:

$$ln\,\psi_i = \omega + \sum_{j=1}^{p} \theta_j \varepsilon_{i-j}^{\beta} + \sum_{j=1}^{q} \varphi_j \,ln\,\psi_{i-j} \tag{4.9}$$

The conditional mean function in equation (4.9) shows a formation similar to that of the class of GARCH models. So the econometrical model is specified accordingly. But while GARCH models usually describe volatility clustering, the Box-Cox model will capture clusters of trading duration.

4.5.2 Estimation results

As pointed out above, trading hours in the Chinese market changed on 13th December 2010, which falls within our data sample period. In order to discover the intraday pattern of trading intensity accurately, this section similarly divides the data into two sub-periods.
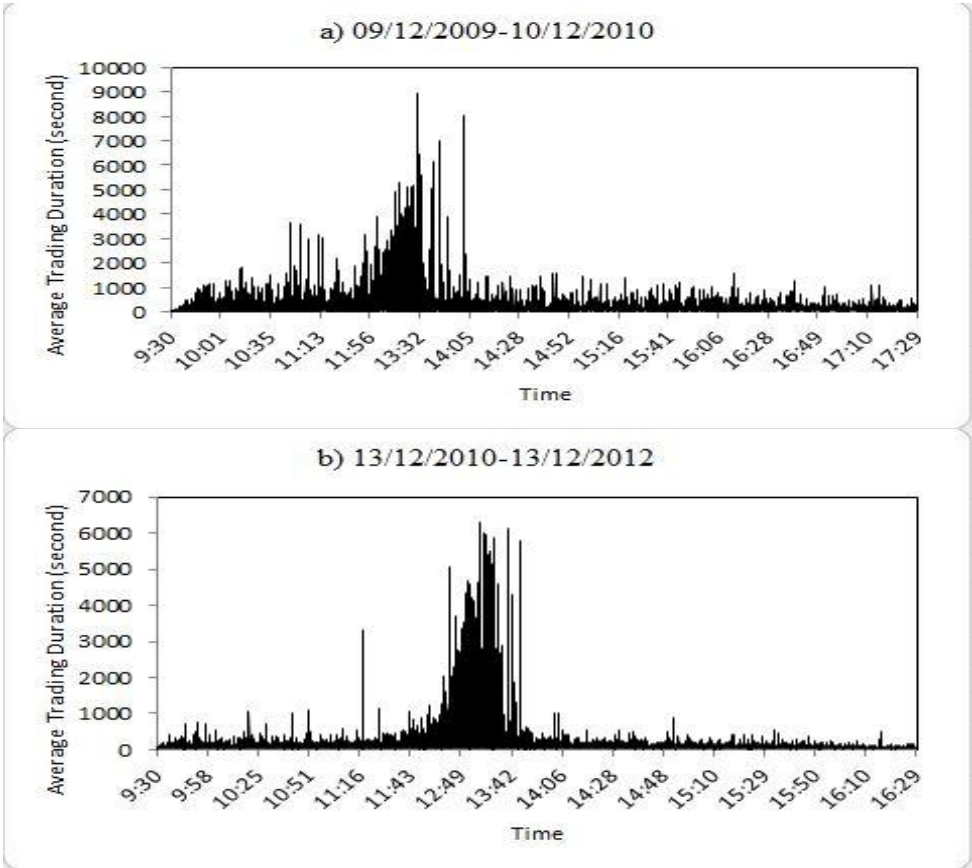
Figure 4.4 Average trading durations in a day for two sub-periods

Figure 4.4 depicts the intraday average trading durations in the two sub-periods. Consistent with the literature (Taylor 2004, Yang 2011), trading intensity in both sub-periods shows a distinctive inverted U-shaped intraday pattern. Trading duration is short at the beginning and end periods of trading hours, and much longer around lunch time. In order to eliminate the time-of-day effect (Dufour and Engle 2000b, Sita and Westerholm 2011), we use a cubic smoothing spline model to simulate the intraday periodic component. One hundred spline nodes are chosen to improve the fitting accuracy, and only unique nodes are adopted, for reasons of stability. The polynomial spline is estimated with penalized least-square and fitted to a rounding solution with unique nodes determined by the efficient algorithm introduced by Helwig (2013). After dividing original trading duration by the periodic component, we obtain diurnally adjusted trading duration $\tilde{x}_t$, with its mean equalling one.
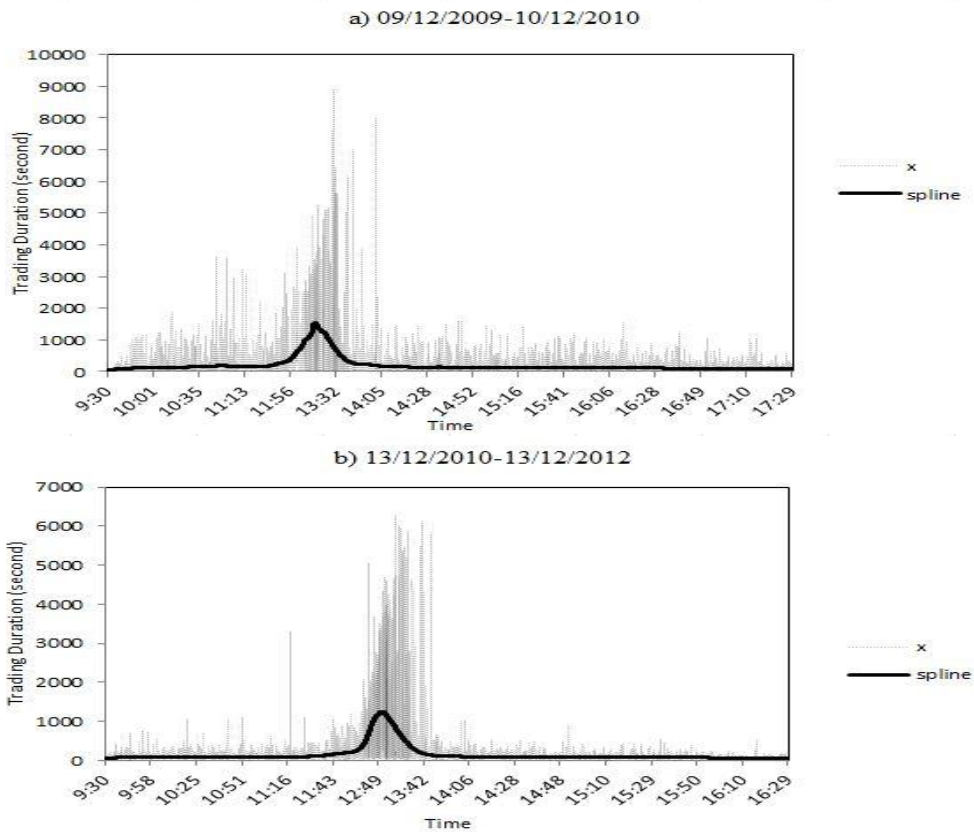
Figure 4.5 Periodic component of trading durations in a day for two sub-periods

The estimated results of the cubic smoothing spline model are presented in Figure 4.5. The dotted line shows the average trading duration, while the solid line denotes the estimated periodic component of trading duration. In both sub-periods, polynomial spline captures the feature that trading is more frequent at the beginning of market hours and around the end of the trading day, but much more infrequent around lunch time.

Table 4.5 Descriptive statistics of trading duration

	09/12/2009-10/12/2010		13/12/2010-13/12/2012	
	x_i	$\widetilde{x}_\iota$	x_i	$\widetilde{x}_\iota$
Observations	43825	43825	111896	111896
Mean	159.4292	0.9999	109.2918	0.9999
Median	87	0.5414	45	0.702
Minimum	1	0.0006	1	0.0015
Maximum	8954	51.0335	15120	161.6635
Std. Dev.	380.1122	1.422	262.433	1.1408
Skewness	10.1715	7.2223	15.5181	50.7678
Kurtosis	142.2389	117.7022	391.9679	6022.548
Ljung-Box (15 lags)	7001***	13609***	11603***	4255.9***

Notes: x_i is trading duration between two transactions and calculated as $t_i - t_{i-1}$; $\widetilde{x}_\iota$ means diurnally adjusted trading duration, which is derived from x_i divided by intraday periodic component. Ljung-Box (15 lags) is the statistics of Ljung-Box test to detect autocorrelation up to 15 lags. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Table 4.5 lists the descriptive statistics of diurnal trading duration and diurnally adjusted trading duration respectively in the two sub-periods. After eliminating the time-of-day effect, the majority of data statistics decrease compared with those of the original data. Standard deviation of trading duration is reduced from 380.1122 to 1.422 in the first sub-period, and from 262.433 to 1.1408 in the second sub-period. The mean of diurnally adjusted trading duration is reduced from 159.4292 in the first sub-period, and 109.2918 in the second, to nearly 1. Consistent with Engle and

Russell (1997), there is clear excess dispersion for both the original data and adjusted data in both sub-periods, as shown by the fact that standard deviations are larger than the corresponding means. The last row of Table 4.5 reports the statistics of Ljung-Box test with 15 lags. All the data series in both sub-periods show significant autocorrelation, as Ljung-Box test is rejected in all cases.

Over-dispersion in our data implies that the unconditional distribution of trading duration is probably not exponential distribution, although this does not mean that conditional distribution of trading duration could not be exponential. According to Dufour and Engle (2000a), among exponential distributions, i.e. the Weibull distribution and Generalized Gamma distribution, Weibull distribution is the most appropriate for standardized duration. Furthermore, ACD(1,1) normally performs well in capturing the temporal dependence of trading duration (Pacurar 2008). Therefore, in this section we adopt the Box-Cox ACD(1,1) model with Weibull distribution (W-BC-ACD model). We adopt fACD package in R lab to estimate all the parameters in equation (4.9).

Table 4.6 Estimation results of W-BC-ACD(1,1) model

Parameters	09/12/2009–10/12/2010	13/12/2010–13/12/2012
ω	0.0034***	0.0025***
	(0.0005)	(0.0003)
θ	0.048***	0.0528***
	(0.0024)	(0.0015)
β	0.8004***	0.835***
	(0.0209)	(0.014)
φ	0.9968***	0.9822***
	(0.0006)	(0.0012)
γ	1.1089***	1.4132***
	(0.0038)	(0.0027)
L-Likelihood	-39042.6	-98458.8
Ljung-Box (1 lag)	0.2808	0.0036
Ljung-Box (15 lags)	95.422***	108.07***

Notes: ω, θ, β and φ are estimated parameters of equation (4.9). The figure shown below in parentheses is the standard error. γ is the shape parameter of Weibull distribution. Ljung-Box (1 lag) is the statistics of Ljung-Box test to detect autocorrelation of standardized duration with 1 lag. Ljung-Box (15 lags) is Ljung-Box test up to 15 lags. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

After regressing the W-BC-ACD(1,1) model on diurnally adjusted trading duration in the two sub-periods, the estimation results are shown in Table 4.6. Our model captures trading duration clustering quite well, as shown by the fact that all the coefficients are highly significant for both sub-periods. It is proved to be more appropriate in removing temporal dependence of trading duration than the standard

ACD model, as β is significant at 1% level. Both θ and φ are positively significant. Therefore, a longer (shorter) trading duration would be expected after a longer (shorter) time interval of no transaction. High persistence of trading duration is detected for both sub-periods: estimated values of φ are 0.9968 from 9th December 2009 to 10th December 2010, and 0.9822 from 13th December 2010 to 13th December 2012. Both are a whisker away from 1. Because the absolute values of φ in both sub-periods are smaller than 1, conditional mean of our estimated model is stationary. In both sub-periods, the shape parameters of Weibull distribution γ are significant and larger than 1. Hazard function for Weibull distribution is monotonically increasing, but not the flat conditional hazard function implied by exponential distribution. In other words, the probability of transaction arrival is increased after a long time interval of no trade. As can be found in Table 4.6, estimated parameters of the W-BC-ACD(1,1) model in the two sub-periods are quite similar. This provides some evidence that the feature of trading duration clustering probably does not suffer from dramatic change after the reduction of trading hours.

The last two rows present the results of the Ljung-Box test of standardized duration with 1 lag and 15 lags, respectively. Autocorrelation of standardized duration in both sub-periods disappears with only 1 lag. In addition, the statistics of Ljung-Box test up to 15 lags for diurnally adjusted trading duration are dramatically reduced, from 13609 and 4255.9 to 95.422 and 108.07. However, both are still rejected by the Ljung-Box test and autocorrelation could still exist. The standard deviation has been reduced from 1.422 to 1.0667 for the first sub-period and from 1.1408 to 0.8924 for the second sub-period. The extent of excess dispersion is reduced, and even becomes under dispersion in the second sub-period. The W-BC-ACD(1,1) model proves to be

able to significantly reduce temporal dependence of trading duration, although it does not remove it completely.

4.6 Information Content of Trading Duration

The information content of trading duration has attracted extensive attention in the literature. Its relation with information-based trading is commonly confirmed by the evidence that higher price change is found to be associated with short trading duration (Dufour and Engle 2000b, Yang 2011). Other studies divide the trading duration into temporal component and innovation component, arguing that the temporal component of trading duration captures the liquidity effect, whereas the innovation component represents the dynamic behaviour of informed traders (Sita 2010, Sita and Westerholm 2011, Bowe, Hyde, and McFarlane 2013). This section aims to study empirically the relation between information-based trading and trading duration.

If the PIN model is a good measure of information asymmetry and if trading duration does contain information, there should be a relation that can be detected in our data. As discussed above with regard to the trading process of the PIN model, information-based trading is relevant to two components: the probability of information arriving α, and arrival rate of informed traders μ. Intuitively, the next questions will be which of these is relevant to trading duration, and to which part of trading duration: the expected component or the unexpected component? In order to answer our questions, this section will regress different models among PIN, the probability of information occurring, the arrival rate of informed traders, expected trading duration, standardized trading duration and exchange rate returns. We average all the ultra-high frequency

variables on every transaction within every 30 minutes to match the frequency of the

PIN model.

Table 4.7 Information content of trading duration (09/12/2009–10/12/2010)

Panel A	PIN		μ		α		$\overline{\Delta P_i}(10^4)$	
	OLS	Ridge	OLS	Ridge	OLS	Ridge	OLS	Ridge
Constant	1.2407* (0.6783)	0.8085	8.7816* (4.3366)	7.3178	-1.2439 (2.0682)	-0.0861	-0.518 (0.401)	-0.5922
$\overline{\psi_i}$	-0.5255 (0.4423)	-0.3177 (0.2502)	-3.2483 (2.5955)	-2.5663* (1.3235)	0.255 (1.3158)	-0.066 (0.33)	-6.13 (5.65)	0.651** (0.2698)
$\overline{e_i}$	-0.6171** (0.2693)	-0.3947 (0.2493)	-4.6206** (1.9929)	-3.8458*** (1.3193)	1.2542 (0.8482)	0.4253 (0.3297)	7.86 (5.78)	1.029*** (0.2671)
$\overline{R^2}$	0.0693		0.3083		-0.0327		0.4732	
CVD	$5.6 \times e^{-5}$		$1.9 \times e^{-5}$		$6.6 \times e^{-5}$		0.0008	

Panel B	$\overline{\psi_i}$	$\overline{\psi_i}$		$\overline{e_i}$	$\overline{e_i}$		$\overline{\Delta P_i}(10^4)$	$\overline{\Delta P_i}(10^4)$	
	OLS	OLS	Ridge	OLS	OLS	Ridge	OLS	OLS	Ridge
Constant	1.01*** (0.017)	1.0566*** (0.0471)	-0.9986	1.0294*** (0.0255)	1.0582*** (0.0464)	1.039	-0.819 (0.775)	-0.0891 (0.357)	-0.2936
PIN	-0.1239 (0.1956)			-0.2079 (0.2042)			6.74* (3.52)		
μ		-0.0433 (0.0466)	-0.00005 (0.00009)		-0.0637 (0.049)	-0.0436* (0.0259)		-0.368 (0.937)	0.0292 (0.4867)
α		-0.0736 (0.0676)	-0.00008 (0.0002)		0.0269 (0.0375)	0.033 (0.0471)		6.87 (4.31)	5.108*** (1.5081)
$\overline{R^2}$	-0.0436	-0.0769		0.0065	0.0992		0.0202	0.4517	
CVD		0.0165			0.0075			0.0028	

Notes: $\overline{\Delta P_i}$ is the average log return of every transaction within every 30-minute period. $\overline{\psi_i}$ denotes the average expected duration of every transaction within every 30-minute period. $\overline{e_i}$ means the average standardized duration of every transaction within every 30-minute period. $\overline{R^2}$ is adjusted R square. CVD is the smallest condition number of covariance matrix from coefficient variance decomposition to detect potential collinearity. The variables in the first row of each panel are dependent variables. The variables in the first column are explanatory variables. In the equation of $\overline{\Delta P_i}$ as dependent variable, all the independent variables are times -1 if $\overline{\Delta P_i}$ is negative in order to measure quantity impact of independent variables without regarding exchange rate appreciation or depreciation. All the coefficients and standard deviations in equation $\overline{\Delta P_i}$ are times 10^4 for convenience of reading. Models are estimated by OLS with HAC robust errors and Ridge regression with normal distribution. The figures in parentheses are standard errors. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Table 4.7 shows synthetically the estimation results of our model from 9th December 2009 to 10th December 2010. The first row in panel A and panel B represents dependent variables of the estimated model, and the first column contains independent variables. All the models with two or more independent variables are estimated by two methods: OLS with heteroskedasticity-and-autocorrelation-consistent (HAC) robust errors, and Ridge regression with normal distribution and the optimal ridge parameter determined by the method of Cule and De Iorio (2012) in order to deal with the problem of collinearity. The last row of panel A and panel B lists the smallest condition number of covariance matrix from variance decomposition, which is a collinearity test based on the results of OLS with HAC robust errors. Expected trading duration $\overline{\psi_i}$ is said to be potentially collinear with standardized trading duration $\overline{\varepsilon_i}$, because the smallest condition numbers for the four models in panel A are all below 0.001.

The second and third columns in panel A of Table 4.7 report the estimated results of PIN regressing on expected trading duration and standardized trading duration. The unexpected component of trading duration is found to negatively and significantly influence the probability of information-based trading. The shorter the unexpected trading duration is, the higher the PIN is. The coefficient of standardized trading duration becomes insignificant in Ridge regression of the same model.

When we regress the arrival rate of informed traders μ on the two components of trading duration, standardized trading duration is negatively significant in both OLS and Ridge regression. In other words, if the unexpected component of trading duration

decreases, the arrival rate of informed traders increases. Informed traders prefer a liquid market and short expected trading duration is associated with the high arrival rate of informed traders. However, the evidence is weak, since expected trading duration is only weakly significant in Ridge regression. In contrast, for both components of trading duration there is no evidence that they impact on the probability of information occurring α, and coefficients are insignificant in both OLS and Ridge regression. The estimated model is inappropriate and $\overline{R^2}$ is negative. Intuitively, this is consistent with the assumption of the PIN model that the probability of information happening is determined by nature, and not influenced by trading intensity.

The last two columns of panel A present a first picture on price impacts of trading duration. The log exchange rate returns can be positive or negative. The sign only represents depreciation or appreciation of the exchange rate. We assume that informed traders will trade once price-relevant information occurs, and trading duration impacts only on the quantity of exchange rate returns, but not the sign. Therefore, all the explanatory variables are times the sign of exchange rate returns. Estimated results of OLS with HAC robust errors have obvious collinearity because all the coefficients are insignificant and $\overline{R^2}$ is large. The ridge parameter cannot be determined automatically. Therefore, we adopt one principal component to determine the ridge parameter, using the same algorithm as in the method of Cule and De Iorio (2012). On average, both longer expected trading duration and unexpected trading duration are associated with a larger exchange rate change. The results are left for comparison purposes only, and further research with ultra-high frequency data will be conducted in the next section.

Panel B of Table 4.7 lists the estimated influence of PIN, μ and α on expected trading duration, standardized trading duration and log exchange rate return. Collinearity between the arrival rate of informed traders and the probability of information occurring has not been significantly detected in the first four models. However, they perform poorly between 9th December 2009 and 10th December 2010. $\overline{R^2}$ is quite low or negative, and all the coefficients are insignificant, with the exception that the arrival rate of informed traders is negatively weak significant in explaining the unexpected component of trading duration by Ridge regression. In the last two models of panel B, all the independent variables are again times the sign of exchange rate returns. Although the smallest condition number of the last model is larger than 0.001, there is clear evidence that signed arrival rate of informed traders and signed probability of information occurring have collinearity, as both coefficients are insignificant and $\overline{R^2}$ is large. There is weak evidence that larger exchange rate changes are associated with higher PIN, which is mainly determined by the probability of information arrival.

Table 4.8 Information content of trading duration (13/12/2010–13/12/2012)

Panel A	PIN		μ		α		$\overline{\Delta P_i}(10^4)$	
	OLS	Ridge	OLS	Ridge	OLS	Ridge	OLS	Ridge
Constant	-0.9742 (1.951)	-0.0191	-2.5564 (14.0581)	0.3555	-2.053 (6.1618)	-0.2015	0.27 (0.273)	0.263
$\overline{\psi_i}$	1.1301 (0.8953)	0.503 (0.364)	8.6024 (5.6037)	6.3673 (3.8872)	-0.3092 (2.5676)	-0.5923 (0.707)	1.64 (7.84)	0.608*** (0.1257)
$\overline{e_i}$	-0.0778 (1.2709)	-0.4023 (0.47)	-5.2877 (10.6199)	-5.9488 (5.0159)	2.6326 (3.8316)	1.0586 (0.913)	-0.392 (7.88)	0.6054*** (0.1274)
$\overline{R^2}$	0.0008		0.2117		-0.0522		0.6113	
CVD	$5.1 \times e^{-6}$		$1.2 \times e^{-6}$		$2.7 \times e^{-6}$		$6 \times e^{-5}$	

Panel B	$\overline{\psi_i}$	$\overline{\psi_i}$		$\overline{e_i}$	$\overline{e_i}$		$\overline{\Delta P_i}(10^4)$	$\overline{\Delta P_i}(10^4)$	
	OLS	OLS	Ridge	OLS	OLS	Ridge	OLS	OLS	Ridge
Constant	0.9969*** (0.0097)	0.9869*** (0.0092)	0.9951	1.0024*** (0.0077)	1.0069*** (0.006)	1.0025	0.233 (0.297)	0.174 (0.302)	0.2022
PIN	0.1309* (0.0627)			-0.0846 (0.0503)			11.69*** (2.17)		
μ		0.0262*** (0.0075)	0.0187** (0.0086)		-0.0175*** (0.005)	-0.0129* (0.0068)		1.13*** (0.216)	0.9861*** (0.343)
α		-0.0039 (0.0235)	-0.0108 (0.026)		0.0121 (0.0152)	0.0139 (0.0207)		0.961 (0.848)	1.282 (1.1972)
$\overline{R^2}$	0.0839	0.1977		0.0331	0.1575		0.5572	0.6293	
CVD		0.0012			0.0035			0.033	

Notes: $\overline{\Delta P_i}$ is the average log return of every transaction within every 30-minute period. $\overline{\psi_i}$ denotes the average expected duration of every transaction within every 30-minute period. $\overline{e_i}$ means the average standardized duration of every transaction within every 30-minute period. $\overline{R^2}$ is adjusted R square. CVD is the smallest condition number of covariance matrix from coefficient variance decomposition to detect potential collinearity. The variables in the first row of each panel are dependent variables. The variables in the first column are explanatory variables. In the equation of $\overline{\Delta P_i}$ as dependent variable, all the independent variables are times -1 if $\overline{\Delta P_i}$ is negative, in order to measure quantity impact of independent variables without regarding exchange rate appreciation or depreciation. All the coefficients and standard deviations in equation $\overline{\Delta P_i}$ are times 10^4 for convenience of reading. Models are estimated by OLS with HAC robust errors and Ridge regression with normal distribution. The figures in parentheses are the standard errors. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

The same models are conducted with data from 13th December 2010 to 13th December 2012, and estimated results are shown in Table 4.8. The smallest condition numbers for the four models in panel A are all less than 0.001. Similar to the results for the first sub-period, unexpected trading duration and standardized trading duration are again detected to have potential collinearity. The ridge parameter of the four models cannot be determined automatically, and once again, we adopt one principal component to determine ridge parameter. Neither OLS with HAC robust errors nor Ridge regression to deal with collinearity is able to provide supporting evidence on the performance of our estimated models, except for the last model estimated by Ridge regression. Consistent with the results in the first sub-period, both signed expected trading duration and signed unexpected trading duration are found to positively and significantly impact on the exchange rate change.

In panel B, we first discover the impact of PIN on the two components of trading duration. PIN is found to positively influence the expected component of trading duration, but the impact is weak. Then, we study more specific information content and regress expected trading duration and standardized trading duration respectively on two elements of information content of PIN, namely the arrival rate of informed traders μ and the probability of information occurring α. Again, there is no clear evidence to prove that μ and α have collinearity. The arrival rate of informed traders but not the probability of information happening has significant impact on both expected component and unexpected component of trading duration. When there are more informed traders, expected trading duration tends to be longer. A high arrival rate of informed traders makes transactions more risky to liquidity traders, because of

asymmetric information. In this situation liquidity providers tend to be expelled from the market and market liquidity becomes inactive, leading to the decrease of expected trading intensity. Conversely, a higher arrival rate of informed traders is associated with shorter unexpected trading duration. In the last model with Ridge regression, the ridge parameter cannot be determined automatically, and again we adopt one principal component for estimation. Consistent with the results in the first sub-period, on average, with higher PIN there is larger exchange rate change. However, this is mainly determined by the arrival rate of informed traders, and not the probability of information arriving.

This section provides some empirical evidence on the information content of trading duration. Attention should be paid to the drawbacks of the PIN model. First, the calculation of PIN varies among different studies in the literature (Chung, Li, and McInish 2005), and further discussion is needed as to which measure is better. Second, the information content of trading duration is tested on the average value of every transaction within every 30-minute period in a day, including exchange rate returns, expected component and unexpected component of trading duration. This might eliminate some information contained in our high frequency data and conceal the significant relation between trading duration and information-based trading. Furthermore, the model assumes constant probability of information happening, constant probability of good news and bad news, and the constant arrival rate of informed traders and uninformed traders within the estimation period. Finally, a large data sample is required to ensure the estimated parameters are sufficiently accurate. Therefore, further research is needed to develop a new model or an improved PIN

model (Easley et al. 2008) in order to measure asymmetric information in high frequency data.

4.7 Price Impact of Trading Duration

In their seminal work on the microstructure of the foreign exchange market, aimed at discovering the connection between daily exchange rate returns and daily order flow, (Evans and Lyons 2002) find that order flow explains a large proportion of exchange rate changes. However, ignoring the timing of transactions might lead to loss of information. This section aims to discover the price impact of order flow and trading duration with ultra-high frequency data.

4.7.1 The estimated model

A basic order flow model describes only the relationship between exchange rate returns, order flow and interest rate differential. The econometrical formula is:

$$\Delta P_i = c + \rho_1 OF_i + \rho_2 IR_i + \epsilon_i \qquad (4.10)$$

where, OF_i is order flow, and IR_i is interest rate differential. Inspired by Dufour and Engle (2000b), Sita and Westerholm (2011), Bowe, Hyde, and McFarlane (2013), we introduce two explanatory variables into our estimated model: signed expected trading duration of order flow ($sign(OF_i)\psi_i$) and signed unexpected trading duration of order flow ($sign(OF_i)e_i$). The highest frequency of the interest rate is daily, which cannot satisfy the high frequency of other data. Therefore, it is removed from our model. The specification of the final model then is:

$$\Delta P_i = c + \rho_1 OF_i + \rho_2 sign(OF_i)\psi_i + \rho_3 sign(OF_i)e_i + \epsilon_i \qquad (4.11)$$

where, $sign(OF_i)$ is valued as +1 if OF_i is buyer-initiated and as -1 if OF_i is seller-initiated. It will become 0 if OF_i is 0. We adopt signed trading duration of order flow because it reflects both direction and duration of transactions. Our model is slightly different from the models adopted by Bowe, Hyde, and McFarlane (2013), Sita and Westerholm (2011), which try to capture bid-ask spread or price impact on the components of trading cost such as order handling cost and adverse selection cost. In contrast, our model focuses on the transaction price determinants extended from the order flow model. Furthermore, in the discussion above there is some evidence that unexpected component of trading duration but not innovation of trading intensity is relevant to the arrival rate of informed traders. Signed trading duration reflects the timing of transaction and probably contains information on foreign exchange transactions. Therefore, this section examines signed unexpected trading duration of order flow, but not signed innovation of trading intensity.

4.7.2 A simple OLS estimation

For a first picture of the price impact of trading duration, we estimate a simple linear model by OLS with HAC robust errors. Models (1) and (3) are benchmark models containing order flow as the only independent variable. The model specification for the respective periods is:

$$\Delta P_i = c + \rho_1 OF_i + \epsilon_i \qquad (4.12)$$

where c is constant and OF_i is order flow. Models (2) and (4) are extended models and their specification across the sub-sample periods is equation (4.11). The estimation results are shown in Table 4.9.

Table 4.9 OLS estimation results of price impact

Parameters	09/12/2009–10/12/2010		13/12/2010–13/12/2012	
	(1)	(2)	(3)	4)
$c(10^4)$	5.19***	5.72***	3.58***	3.59***
	(0.306)	(0.316)	(0.232)	(0.234)
$OF_i(10^4)$	37.16***	52.91***	48.29***	43.99***
	(0.795)	(1.64)	(0.63)	(6.16)
$sign(OF_i)\psi_i(10^4)$		-19.13***		3.26
		(1.1)		(6.24)
$sign(OF_i)e_i(10^4)$		2.98***		1.03***
		(0.452)		(0.38)
$\overline{R^2}$	0.1229	0.1321	0.132	0.1321

Notes: Figures in parentheses are the standard errors. $\overline{R^2}$ is adjusted R square. All the coefficients and standard deviations are times 10^4 for convenience of reading. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Order flow is positively significant at 1% level in both sub-periods. One unit of buyer-initiated transaction will increase exchange rate returns by 0.0053% from 9th December 2009 to 10th December 2010, and by 0.0044% from 13th December 2010 to 13th December 2012. The coefficient on signed expected trading duration is

negatively significant from 9th December 2009 to 10th December 2010 and insignificant from 13th December 2010 to 13th December 2012. In other words, exchange rate changes are smaller when expected trading duration is longer. There are two plausible explanations for this result. First, recalling the finding in the above section, informed traders prefer a liquid market, where it is easier for them to make profits based on private information. An inactive market with fewer informed traders thus leads to smaller exchange rate changes. Second, as has been argued by Madhavan, Richardson, and Roomans (1997), Sita and Westerholm (2011), Yang (2011), informed traders will split large trades into small orders for easier execution. Because ψ_i captures the expected component of duration clustering, it is related to both the persistence of liquidity traders and continuous trading of existing informed traders. Therefore, shorter expected trading duration probably implies higher activity of existing informed traders, thus leading to larger exchange rate changes.

The signed unexpected trading duration of order flow is positively significant at 1% level in both sub-periods. This is the same as the result in the above section, that longer unexpected trading duration is associated with larger exchange rate changes. This seems to conflict with the finding that longer unexpected trading duration is associated with a lower arrival rate of informed traders and thus leads to a smaller exchange rate change. Attention should be paid to the structure of the Chinese foreign exchange market. The interdealer foreign exchange market in China adopts a membership system, so that unlike the stock market, only a limited number of members are able to participate. Therefore, the number of informed traders in the foreign exchange market is much smaller than in the stock market, leading to a weak rate of increase of informed traders. According to Admati and Pfleiderer (1988), in

addition to informed traders, discretionary uninformed traders will choose the time to trade in order to minimize adverse selection cost. The unexpected component of trading duration should capture the rate of growth in the number of both uninformed traders and informed traders. When there are more informed traders arriving, unexpected trading duration should be shorter. However, the higher arrival rate of informed traders will reduce trading activities of discretionary uninformed traders. Unexpected trading duration will thus increase. Both the higher arrival rate of informed traders and inactive trading of discretionary uninformed traders increase the proportion of informed traders in the market. Our results show that absence of discretionary uninformed traders dominates the unexpected component of trading duration in both sub-periods. A longer signed unexpected trading duration of order flow is associated with a greater proportion of informed traders, leading to larger exchange rate changes. The estimated results in both sub-periods are quite similar, and our model explains 13.21% of exchange rate returns in ultra-high frequency data. Consideration of trading duration improves the explanatory power of the model by 0.92% in the first sub-period and 0.01% in the second sub-period. The small improvement in the second sub-period is probably due to the insignificance of signed expected trading duration, which might be because information is lost due to the linear framework of OLS estimation.

4.7.3 A Markov regime-switching estimation

The simple OLS estimation results have provided a general picture on the price impact of order flow and signed trading duration. However, it is possible that the information content of trading duration varies with market conditions. This section adopts a well-known nonlinear model, the Markov regime-switching model, to

investigate the relationship between exchange rate returns, order flow and signed trading duration of order flow in different regimes.

We adopt a two regimes Markov switching model for estimation of equation (4.11). Both expected component and unexpected component of trading duration are introduced into the determinant of time-varying regime transition probability. Figure 4.6 illustrates exchange rate returns from 9th December 2009 to 10th December 2010, with regime 1 highlighted by grey bars.
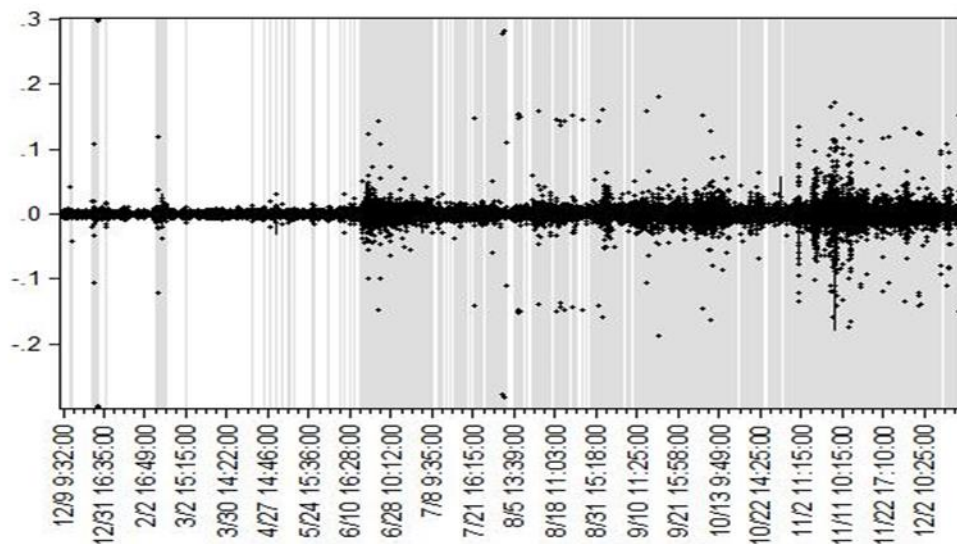
Figure 4.6 Exchange rate returns in regime 1 (09/12/2009-10/12/2010)

From the figure, it is clear that regime 1 is detected as having larger exchange rate change. Exchange rate return in regime 1 reaches an average of 0.00057%, which is 4.07 times that in regime 2. In regime 1, exchange rate return ranges from -0.2962% to 0.3006%. In contrast, in regime 2 the range is only -0.0118% to 0.0106%. Figure

4.7 illustrates exchange rate returns from 13th December 2010 to 13th December 2012, with regime 2 highlighted by grey bars.
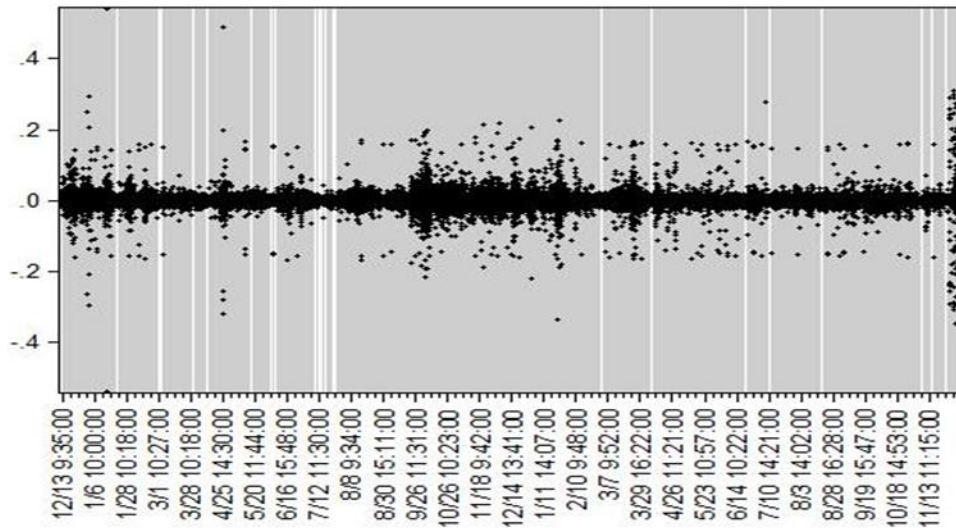
Figure 4.7 Exchange rate returns in regime 2 (13/12/2010-13/12/2012)

The average of exchange rate returns in regime 2 is 0.00031%, which is 11.07 times that in regime 1. In regime 2, exchange rate returns range from -0.5363% to 0.5424%. In contrast, the range in regime 1 is only -0.0167% to 0.0169%. Figure 4.7 seems to have a very high level of regime persistence because it needs to present much more data than Figure 4.6 within the same size of picture. In fact, 6989 out of 43825 observations in the first period are LH regime, which is 15.95%. In the second period, 13287 out of 111896 observations are LH regime, and the proportion is 11.87%. The second period has a lower proportion of LH regime. However, the difference is not large.

Estimation results of the two regimes Markov switching model are shown in Table 4.10. From 9th December 2009 to 10th December 2010, regime 1 is more volatile than regime 2, as shown by the fact that standard deviation of regime 1 is larger than that of regime 2. Conversely, from 13th December 2010 to 13th December 2012, regime 2 has higher volatility than regime 1. Therefore, the Markov regime-switching model detects two kinds of regime in our data: large exchange rate changes with high volatility (LH regime) and small exchange rate changes with low volatility (SL regime).

Estimated coefficients of equation (4.11) in both sub-periods exhibit similar results. All the coefficients are significant at 1% level, except for the signed unexpected trading duration of order flow in the LH regime from 13th December 2010 to 13th December 2012.

In the first sub-period, order flow is found to be positively related to exchange rate returns in both regimes. Consistent with findings by Wu (2012), Duffuor, Marsh, and Phylaktis (2012), order flow is much more informative in the LH regime, which is associated with lower market liquidity, and one unit of buyer-initiated transaction will increase exchange rate returns by 0.0046%. This is 0.0021% greater than for the SL regime. In the SL regime, the foreign exchange market is placid, and there is little evidence to suggest that informed traders are active there. If price-relevant information occurs, informed traders prefer getting into the market when it is full of liquidity. In addition, shorter expected trading duration may be associated with higher activity of existing informed traders, and thus greater exchange rate changes. This is consistent with the findings from OLS estimation.

In the LH regime, the price impact of signed expected trading duration is opposite to that in the SL regime. Both large exchange changes and high volatility show that informed traders are active in the market. Recall the findings above that the high arrival rate of informed traders makes transactions riskier to liquidity traders, because they suffer asymmetric information. This will expel the existing liquidity traders and make them inactive. Longer signed expected trading duration of order flow is associated with a higher proportion of informed traders, leading to greater exchange rate changes.

Consistent with the findings from OLS estimation, changes of discretionary uninformed traders' trading intensity dominates the unexpected component of trading duration in both regimes. A new finding is that reduction of discretionary uninformed traders' trading intensity is larger in the LH regime, as shown by the fact that coefficient on signed unexpected trading duration is greater than that in the SL regime.

P_{11} means the probability of staying in Regime 1 if the previous one is also Regime 1. As can be seen from the estimation results of time-varying regime transition probability between 9th December 2009 and 10th December 2010, both the expected and the unexpected components of trading duration positively influence the probability of the market remaining in Regime 1; in other words, the LH regime. According to the theory of Admati and Pfleiderer (1988), uninformed traders will choose the time to trade in order to minimize adverse selection cost. When the foreign exchange market is already in the LH regime, long expected trading duration and unexpected trading duration imply inactivity of existing liquidity traders and discretionary uninformed traders and therefore high proportion of informed traders.

This increases the probability of the foreign exchange market remaining in the LH regime.

When the foreign exchange market is in the SL regime, if expected trading duration is long and market liquidity is inactive, the market will be less favoured by informed traders. Furthermore, long expected trading duration implies a low probability of continuous trading by existing informed traders. Therefore, the probability of transition from SL regime to LH regime decreases.

On average, both regimes are highly persistent. There is high probability of the market trading remaining in the original regime: 0.8048 for LH and 0.9493 for SL. Non-discretionary liquidity traders and discretionary uninformed traders have stronger power to dominate the market, and transition probability from LH regime to SL regime is 0.1952, which is 3.85 times the probability of transiting from SL regime to LH regime. The average of time-varying expected durations for different regimes is extremely large, because very few expected durations implied by the transition matrix are unrealistically extremely large. If we define expected durations longer than 10000 as extreme values, the percentages of observations for LH regime and SL regime are 0.09% and 0.79% respectively. After removing extreme values, the expected durations on average for LH regime and SL regime are 16.7672 and 233.7768, respectively. The duration of market remaining in the SL regime is much longer than that in the LH regime.

For the period from 13th December 2010 to 13th December 2012, regime 1 is detected as a SL regime and regime 2 is a LH regime. Estimation results are quite similar to those in the first sub-period. Order flow has greater price impact, and one unit of

buyer-initiated transaction leads to 0.0043% of exchange rate changes in the SL regime, and 0.0134% in the LH regime. The coefficients on signed trading duration of order flow have the same sign as in the first sub-period. For the transition probability, when the market is already in a SL regime, long expected trading duration implies inactive market liquidity and existing informed traders. It is less attractive to informed traders, and the probability of the market remaining in the SL regime increases. Conversely, long unexpected trading duration denotes a large proportion of informed traders, which thus decreases the probability of the market staying in the SL regime. When the market is in a LH regime, inactivity of either existing liquidity traders or discretionary uninformed traders will make it harder for the market to become placid and the probability of transition from LH regime to SL regime decreases.

Both regimes are highly state dependent and the probability of the market staying in the original regime is high. It is not easy for informed traders to agitate the foreign exchange market, since the probability of transition from SL regime to LH regime is only 0.0312. In addition, the expected duration of SL regime is longer than that of LH regime. All the evidence indicates that the dynamic structure of the market and the behaviours of market participants do not exhibit a dramatic change between the two sub-periods.

Table 4.10 Estimation results of Markov regime-switching model

Parameters	09/12/2009–10/12/2010		13/12/2010–13/12/2012	
	Regime 1	Regime 2	Regime 1	Regime 2
$c(10^4)$	18.2***	2.12***	2.05***	12.82***
	(2.69)	(0.136)	(0.122)	(2.61)
$OF_i(10^4)$	45.87***	24.99***	42.97***	134.16***
	(10.14)	(0.29)	(0.512)	(4.31)
$sign(OF_i)\psi_i(10^4)$	84.63***	-4.95***	-11.26***	22.3***
	(11.33)	(0.324)	(0.497)	(2.58)
$sign(OF_i)e_i(10^4)$	10.45***	1.56***	0.807***	0.631
	(3.05)	(0.112)	(0.146)	(2.71)
$\log(\sigma)$	-3.8092***	-6.0301***	-5.6044***	-3.4677***
	(0.0018)	(0.0035)	(0.0022)	(0.0015)
$P_{11} - c$	0.0492		1.3632***	
	(0.1484)		(0.1335)	
$P_{11} - \psi_i$	0.7408***		2.2286***	
	(0.1812)		(0.1373)	
$P_{11} - e_i$	0.8106***		-0.1132***	
	(0.0756)		(0.0145)	
$P_{21} - c$	-0.2916**		-0.871***	
	(0.1361)		(0.1101)	
$P_{21} - \psi_i$	-3.295***		-0.3484***	
	(0.1703)		(0.1033)	
$P_{21} - e_i$	0.000013		-0.1192***	
	(0.0383)		(0.0409)	
Expected durations	3343323	801.6473	1.9e+10	9.365

	(6.5e+08)	(26545.15)	(4.8e+12)	(1384.753)
Expected durations	16.7672	233.7768	40.7792	5.0028
(remove extreme values)	(164.2147)	(825.9191)	(110.79)	(20.0796)
Regime 1	0.8048	0.1952	0.9688	0.0312
	(0.0871)	(0.0871)	(0.0115)	(0.0115)
Regime 2	0.0507	0.9493	0.2078	0.7922
	(0.0405)	(0.0405)	(0.0175)	(0.0175)

Notes: Figures in parentheses are the standard errors. All the coefficients and standard deviations of explanatory variables are times 10^4 for convenience of reading. σ is standard deviation in different regimes. $P_{11} - c$, $P_{11} - \psi_i$, $P_{11} - e_i$, $P_{21} - c$, $P_{21} - \psi_i$ and $P_{21} - e_i$ are logistic coefficients on regime transition probability of constant, expected trading duration and unexpected trading duration. Expected duration shows mean and standard deviation of regime duration. Expected durations (excluding extreme values) are calculated after we remove the time-varying expected durations of regimes longer than 10000. The last two rows present mean and standard deviation of time-varying regime transition probability. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

4.8 Relations between Trading Duration and Volatility

According to Engle and Russell (1998), conditional instantaneous volatility is related to conditional hazard function of trading duration. Recalling that our estimated shape parameters of Weibull distribution γ are positive, conditional instantaneous volatility should positively link to expected arrival rate $\frac{1}{\psi_i}$. As has been discussed above, trading duration significantly influences the probability of transition between the LH regime and the SL regime. It is probable that it has a significant impact on volatility, as well as exchange rate returns. This section will study directly the relationship between trading duration and volatility.

4.8.1 BC-ACD-EGARCH model

Following the ACD-GARCH model introduced by Engle (2000), the conditional volatility for a transaction is formulated as:

$$V_{i-1}(\Delta P_i | x_i) = h_i \tag{4.13}$$

Given that volatility is normally measured at a constant time interval, the conditional volatility of one unit of time can be defined as:

$$V_{i-1}\left(\frac{\Delta P_i}{\sqrt{x_i}} | x_i\right) = \sigma_i^2 \tag{4.14}$$

In order to capture asymmetric impact of trading duration on conditional volatility, we adopt the EGARCH model in this section. The final model to measure conditional volatility per unit of time is shown as:

$$\frac{\Delta P_i}{\sqrt{x_i}} = c + \rho_1 OF_i + \rho_2 sign(OF_i)\psi_i + \rho_3 sign(OF_i)e_i + \epsilon_i$$

$$\tag{4.15}$$

$$log(\sigma_i^2) = \omega + \sum_{j=1}^{p} \theta_j \left|\frac{\epsilon_{i-j}}{\sigma_{i-j}}\right| + \sum_{j=1}^{k} \delta_j \frac{\epsilon_{i-j}}{\sigma_{i-j}} + \sum_{j=1}^{q} \varphi_j \ln(\sigma_{i-j}^2) + \rho_4 \frac{1}{\psi_i} + \rho_5 \frac{1}{\varepsilon_i}$$

Conditional volatility per transaction is defined as:

$$\Delta P_i = c + \rho_1 OF_i + \rho_2 sign(OF_i)\psi_i + \rho_3 sign(OF_i)e_i + \epsilon_i$$

(4.16)

$$log(h_i) = \omega + \sum_{j=1}^{p} \theta_j \left|\frac{\epsilon_{i-j}}{\sigma_{i-j}}\right| + \sum_{j=1}^{k} \delta_j \frac{\epsilon_{i-j}}{\sigma_{i-j}} + \sum_{j=1}^{q} \varphi_j \ln(h_{i-j}) + \rho_4 \frac{1}{\psi_i} + \rho_5 \frac{1}{\varepsilon_i}$$

For comparison, we estimate a benchmark model similar to equations (4.15) and (4.16), but the mean equation contains only a constant term, without any other explanatory variables.

4.8.2   Estimation results

Following Engle (2000), the absolute value of $\frac{\Delta P_i}{\sqrt{x_i}}$ is adjusted by the same simulation method of the spline model as used in trading duration, in order to remove time-of-day effect. In this section, EGARCH(1,1) with one lag of asymmetric impact on conditional volatility is estimated.

Table 4.11 Estimation results of BC-ACD-EGARCH(1,1) model

Parameters	09/12/2009–10/12/2010				13/12/2010–13/12/2012			
	$\widetilde{\Delta P_t}$	$\Delta P_i(10^4)$	$\widetilde{\Delta P_t}$	$\Delta P_i(10^4)$	$\widetilde{\Delta P_t}$	$\Delta P_i(10^4)$	$\widetilde{\Delta P_t}$	$\Delta P_i(10^4)$
c	0.0121***	-0.0904	0.0157***	0.875***	0.0215***	1.07***	-0.0008	-0.291**
	(0.0014)	(0.0572)	(0.0011)	(0.06)	(0.0016)	(0.0996)	(0.002)	(0.121)
ρ_1	0.5658***	16.97***			0.9567***	42.05***		
	(0.0043)	(0.138)			(0.0087)	(0.405)		
ρ_2	-0.1266***	-1.07***			-0.3707***	-13.94***		
	(0.0024)	(0.0623)			(0.0078)	(0.351)		
ρ_3	-0.0704***	-0.0025			-0.1116***	0.0663		
	(0.0012)	(0.0473)			(0.002)	(0.11)		
ω	-0.0633***	-1.1689***	-0.4249***	-1.6303***	-0.2462***	-1.1465***	-0.2366***	-1.0039***
	(0.0118)	(0.0894)	(0.0088)	(0.0289)	(0.0067)	(0.0143)	(0.0037)	(0.0095)
θ_j	4.332***	2.5234	0.3828***	0.3881***	0.4588***	0.4204***	0.2882***	0.3183***
	(1.0048)	(1.5369)	(0.006)	(0.0051)	(0.0122)	(0.0062)	(0.0027)	(0.0026)
δ_j	1.6093***	0.7008	0.0813***	0.0888***	-0.0029	-0.0085***	-0.0372***	-0.0442***
	(0.3749)	(0.4274)	(0.0041)	(0.0036)	(0.0036)	(0.003)	(0.0025)	(0.0023)
φ_j	0.9755***	0.9272***	0.9103***	0.8906***	0.9267***	0.9204***	0.9406***	0.9308***
	(0.0008)	(0.001)	(0.0021)	(0.0021)	(0.0008)	(0.001)	(0.0007)	(0.0007)
ρ_4	0.0693***	0.2884***	0.1703***	0.1701***	0.0711***	0.1113***	0.0504***	0.0888***
	(0.0027)	(0.0046)	(0.0059)	(0.0059)	(0.006)	(0.0071)	(0.0038)	(0.0044)

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ρ_5	0.00003	-0.0001	-0.0056***	-0.006***	0.0044***	-0.0007	0.001**	-0.0052***
	(0.00009)	(0.0002)	(0.0001)	(0.0001)	(0.0006)	(0.0008)	(0.0005)	(0.0004)
Df	2.0009***	2.0105***	3.4325***	4.2922***	2.3237***	2.609***	3.5769***	4.0423***
	(0.0004)	(0.0129)	(0.0502)	(0.0584)	(0.0209)	(0.0233)	(0.0326)	(0.0351)
Ljung-Box (5 lags)	0.0806	0.0284	0.7897	0.02	0.0063	0.1381	0.0017	0.0139
Ljung-Box (15 lags)	0.1553	0.1003	0.9768	0.043	0.0176	0.3698	0.0053	0.0418

Notes: c, ρ_1, ρ_2, ρ_3, ω, θ_j, δ_j, φ_j, ρ_4 and ρ_5 are the estimated parameters of equations (4.15) and (4.16). df is the student distribution statistics. The figures in parentheses are the standard errors. The last two rows present the Q-statistics of Ljung-Box test on the squared standardized residuals for 5 lags and 15 lags. $\widetilde{\Delta P_t}$ is diurnally adjusted exchange rate return per unit of time. All the coefficients and standard deviations of explanatory variables in the mean equation of (4.16) are times 10^4 for convenience of reading. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Estimation results of equations (4.15) and (4.16) and of the benchmark models are presented in Table 4.11. Our model performs well in capturing volatility clustering in exchange rate returns per unit of time, and exchange rate returns per transaction. The Ljung-Box tests on the squared standardized residuals for both 5 lags and 15 lags are insignificant in all estimated models. Student t distribution proves to be a better fit than normal distribution and the student distribution statistics are significant at 1% level in all estimated models.

Consistent with our findings above, order flow impacts positively on both exchange rate returns per unit of time and exchange rate returns per transaction in both sub-periods. In addition, longer signed expected trading duration of order flow is

associated with smaller exchange rate changes per unit of time and per transaction in both sub-periods.

Conditional volatility exhibits high persistence, as shown in the evidence that φ_j in the majority of models is greater than 0.9. News impact is found to be asymmetric and the asymmetric terms δ_j are significant at 1% level in the majority of our estimated models. Between 9th December 2009 and 10th December 2010, the Chinese foreign exchange market seems to react much more violently to news on Chinese RMB depreciation than to news on appreciation. Conversely, from 13th December 2010 to 13th December 2012, conditional volatility is much larger with Chinese RMB appreciation than with depreciation.

Consistent with the theory of Engle and Russell (1998), conditional volatility is mainly determined by the expected arrival rate, but not the unexpected arrival rate. In all the estimated results of variance equations, the expected arrival rate is significant at 1% level and positively related to conditional volatility.

Furthermore, the coefficient on the expected arrival rate is much larger than that on the unexpected arrival rate. In addition to more active trading of existing informed traders, a higher expected arrival rate implies higher market liquidity, which is more attractive to informed traders, and thus conditional volatility will increase. The probability of the market remaining in the SL regime decreases and the probability of transition from SL regime to LH regime increases.

An interesting result is that signed unexpected trading duration of order flow is negatively related to exchange rate returns per unit of time in both sub-periods. Also,

the unexpected arrival rate is found to positively impact on conditional volatility per unit of time. This seems to conflict with our findings above. However, note that exchange rate return per unit of time is calculated as the exchange rate return divided by trading duration. It thus naturally has negative correlation with unexpected trading duration, and conditional volatility tends to be positively correlated with unexpected arrival rate.

The results of exchange rate returns per transaction are composite effects of trading duration and exchange rate returns per unit of time. This is proved by the fact that signed unexpected trading duration of order flow and unexpected arrival rate in equation (4.16) are no longer significant. Further, between 9th December 2009 and 10th December 2010, the unexpected arrival rate negatively impacts on conditional volatility in the benchmark model. As for the estimation results of the benchmark model in the second sub-period, the unexpected arrival rate changes its sign from positive for conditional volatility per unit of time to negative for conditional volatility per transaction. In other words, a higher unexpected arrival rate implies more participation by discretionary uninformed traders and lower proportion of informed traders, leading to a decrease of conditional volatility. Both the probability of the market remaining in the SL regime and the probability of it transiting from LH regime to SL regime increase.

4.9 Conclusions

In this chapter, we adopt a PIN model to examine the intraday pattern of informed trading in the Chinese foreign exchange market. Information generally arrives half an hour after the market opening, during lunch time and half an hour before the end of

trading hours. However, informed traders are inactive during lunch time. The probability of information-based trading is thus highest around the beginning and closing of the business of the day, and lowest during lunch time. This is consistent with the time-of-day effect.

Following Dufour and Engle (2000a), we adopt the W-BC-ACD model to capture the clustering of trading duration. This allows us to discover the information content of both expected trading duration and unexpected trading duration. Expected trading duration shows the persistence of liquidity traders and existing informed traders. Unexpected trading duration represents the change of trading activity of discretionary uninformed traders and new informed traders. Our estimation outcome provides some evidence that both components of trading duration matter to the arrival rate of informed traders, but not to the probability of information occurring.

In addition, we uncover evidence that supports the theory of Engle and Russell (1998). Specifically, conditional volatility is positively related to expected arrival rate. Furthermore, conditional volatility in the Chinese foreign exchange market is mainly determined by the expected arrival rate, but not the unexpected arrival rate. However, this research shows that the negative impact of trading duration on exchange rate returns per unit of time, and conditional volatility per unit of time, should be carefully explained in the ACD-GARCH model introduced by Engle (2000). When the dependent variable is the exchange rate returns divided by trading duration, it will naturally be negatively related to trading duration.

Finally, order flow plays an important role in capturing exchange rate dynamics, and the price impacts are greater in a LH regime when the market is illiquid than in a SL

regime. We find that, in addition to order flow, both expected component and unexpected component of trading duration contain information for the process of price discovery, and thus, by including these in the estimation, the explanatory power of our model is improved. The two components reflect the trading behaviours behind the transactions of uninformed traders and informed traders. The effect of trading duration on exchange rate returns is a composite result from the complicate behaviours of both uninformed traders and informed traders, and not due simply to active informed traders or the absence of uninformed traders.

In the Chinese foreign exchange market, when the market is placid there is no clue to prove the active trading of informed traders. Short expected trading duration implies high trading intensity of existing informed traders and plentiful market liquidity, which is preferred by informed traders, followed by large exchange rate changes and high volatility. Correspondingly, the participation by informed traders is noticeable when exchange rate changes are large and volatility is high. Liquidity traders will postpone their trading and the expected trading duration will be long. Absence of liquidity traders will increase the probability of the market remaining in the LH regime. With regard to the unexpected component of trading duration, discretionary uninformed traders prefer to leave the market when there are informed traders, and long unexpected trading duration implies a high proportion of new informed traders; thus exchange rate changes are large and volatility will be high.

Given that trading duration is related to both exchange rate returns and volatility, taking into consideration the effects of trading duration will be helpful for understanding the process of price discovery and asset pricing. Furthermore, our findings provide advice with regard to the trading strategy of market participants and

central bank intervention. Uninformed traders are advised to trade carefully if expected trading duration is short and unexpected trading duration is long in a placid market. This further implies high trading intensity of existing informed traders and a large proportion of new informed traders.

Our findings also suggest that secret central bank intervention in the foreign exchange market is better conducted when the market is liquid, since during these periods it is more difficult for the market to discover the intervention, and on average this would lead to a larger impact of intervention on the exchange rate and its changes. Given that the press usually suspects that the central bank conducts intervention around the beginning and end of business hours, it seems that our suggested intervention strategy coincides with the practice. When the market expected value of the exchange rate is outside the fluctuation band around the CPR, the exchange rate exhibits large changes and stays around the edges of the fluctuation band. Before the exchange rate reaches its market expected value, liquidity traders reduce their trading activity, which renders the market illiquid, with only informed traders left. Unless the central bank intervenes to provide liquidity or market expectation changes, the liquidity situation will worsen.

Chapter 5

Driving Forces behind Official Intervention in the Foreign Exchange Market

5.1 Introduction

In the foreign exchange intervention research, many studies attempt to discover what drives the official intervention. Historically, intervention in foreign exchange markets has usually been kept secret, and in the absence of public announcements the early researches sought out the data from news reports (Galati and Melick 1999, Dominguez 1998, Bonser-Neal and Tanner 1996). Even today, only very few countries would disclose official intervention information. Therefore, the literature on the intervention reaction function is limited to certain developed markets, such as the USA (Baillie and Osterberg 1997b, Humpage 1999), Germany (Dominguez 1998, Jun 2008), Japan (Frenkel, Pierdzioch, and Stadtmann 2002, Chen, Chang, and Yu 2012, Ito and Yabu 2007) and Australia (McKenzie 2004, Rogers and Siklos 2003, Kim and Sheen 2002). Among the emerging markets, Turkey is the focus of most researches, for example Akinci et al. (2005), Herrera and Özbay (2005), ÖzIü and Prokhorov (2008).

This chapter attempts to discover the driving forces of foreign exchange intervention in the second biggest economy of the world, China. As one of the most important

emerging markets, China is attracting increasing research attention with regard to its economic and financial regime. This study will enrich the line of research on foreign exchange intervention in emerging markets. According to the features of China's foreign exchange regime, we define another type of intervention in addition to the traditional intervention via transaction (central bank transaction intervention, or CBT), namely the central parity rate (CPR) intervention. Seven factors are considered: deviation from the target exchange rate, excess volatility, interest rate differential, national economy, intervention persistence, deviation from target appreciation rate and market liquidity. We introduce 1-day moving average, 21-day moving average, and 150-day moving average as the target exchange rate, and price impact, return reversal and effective cost as the measurements of market liquidity. We ignore return reversal because it is collinear with price impact. Finally, our reaction function comprises ten factors.

Since intervention data is not disclosed by the Chinese government, we collect the indicators of intervention from news reports from 4th January 2011 to 13th December 2012. Because of this, we can only decide the sign of intervention. The dependent variables are assigned the value of -1, 0 or 1. Therefore, this chapter adopts a Logit model to capture the asymmetric reaction function of appreciation-target intervention and depreciation-target intervention. In addition, we use the Ordered Logit model to examine both types of intervention in the same equation and estimate the neutral band of non-intervention.

First, consistent with the literature, the Chinese government is proved to 'lean-against-the-wind', and intervention persistence is significant in the majority of our estimations. In addition, the Chinese government is concerned with a gradual

achievement of the appreciation target, especially before 12th June 2012 in our sample. The results for excess volatility are less conclusive, showing that only appreciation-target CBT intervention is carried out to remove excess volatility.

Intervention is asymmetric and dynamic. After 12th June 2012, the target appreciation rate ceases to be a driving force of intervention. Besides the common significance of interest rate differential, appreciation-target CBT intervention aims to provide liquidity when the foreign exchange market is illiquid. By contrast, CPR intervention is more concerned with the national economy. We also compare the Logit model with the OLS model in terms of in-sample fitting performance and out-of-sample forecasting performance. We find that the Logit model is a better choice in terms of both RMSE and MAE.

Second, with the potential driving forces considered in our model, the Chinese government is generally more tolerant of appreciation of the USD (CNY depreciation) than of USD depreciation (CNY appreciation). The exception to this is during the period before 12th June 2012, when the central bank actively accelerated the appreciation of CNY to counter the high rate of inflation, thus showing more tolerance of USD depreciation (CNY appreciation) than USD appreciation (CNY depreciation).

Third, when we compare the predictive ability of our model with a constant probability, our model is shown to improve the accuracy of prediction of intervention. We also introduce noise-to-signal ratio to minimize the problems of surprise and false alarm. After 12th June 2012, following a central bank announcement that it would reduce the frequency of intervention and improve the method of intervention, CBT

intervention becomes irregular and harder to predict. The neutral band of non-intervention is not significant and intervention is no longer persistent. In contrast, CPR intervention becomes a more frequently used tool. It is easier to predict than before 12th June 2012.

The rest of this chapter is organized as follows: Section 2 discusses main aspects of the driving force considered in our investigation. Section 3 defines two methods of intervention in China and describes the data sources. Section 4 presents the estimation results, including the final estimated equation decided upon, the breakpoint detected and the results of the Logit model and Ordered Logit model. Section 5 presents conclusions, based on the main findings.

5.2 Driving Forces of Intervention: Theoretical Underpinning

In order to study the driving forces of central bank intervention, most studies assume an intervention reaction function. Some derive the reaction function from a monetary authority loss function (Almekinders and Eijffinger 1996, Ito and Yabu 2007, Chen, Chang, and Yu 2012, Frenkel, Pierdzioch, and Stadtmann 2002). The simplest case, which is also the most frequently used in the literature, presents a cost function of intervention with the target exchange rate:

$$E_{t-1}(Loss_t) = E_{t-1}(P_t - P_t^T)^2 \tag{5.1}$$

where $E_{t-1}()$ denotes expectation at time t-1, P_t is the actual exchange rate at time t, and P_t^T represents the target exchange rate. The actual exchange rate is assumed to

follow a random walk and when there is intervention, the exchange rate process becomes:

$$P_t = P_{t-1} + \rho INT_t + u_t \qquad (5.2)$$

where INT_t indicates intervention at time t and u_t is a white noise. Substituting equation (5.2) into equation (5.1) and minimizing the loss function with respect to INT_t, the intervention reaction function is:

$$INT_t^* = -\frac{1}{\rho}(P_{t-1} - P_t^T) \qquad (5.3)$$

where INT_t^* is the optimal intervention. However, it is inadequate to consider only the target exchange rate in the loss function of the Chinese monetary authority. Da Silva and Nunes (2007) introduce a central bank loss function with richer contents:

$$Loss_t^{CB} = \sum_{i=t}^{\infty} \rho^{i-t} \left[\frac{(\alpha INT_i)^2}{2} + \frac{\beta(INT_i - INT_i^e)^2}{2} + \frac{\gamma(P_i - P_i^T)^2}{2} \right] - U_t \qquad (5.4)$$

where ρ is a discount factor, INT_i denotes the degree of intervention, INT_i^e means intervention expected by the speculator, α measures the intervention costs via the portfolio balance channel, and β captures the intervention costs through the expectation channel. γ represents the costs of deviation from the target exchange rate.

U_t represents the utility function of domestic residences. Correspondingly, the loss function of a representative speculator is shown as:

$$Loss_t^S = \sum_{i=t}^{\infty} \rho^{i-t} \left[\frac{(INT_i^e - INT_i)^2}{2} \right] - U_t \qquad (5.5)$$

After minimizing both equations (5.4) and (5.5) by INT_i, we can get the Nash equilibrium as:

$$INT_t^* = \frac{1}{\alpha^2} \left[\frac{\partial U_t}{\partial INT_t} - \gamma (P_t - P_t^T) \frac{\partial P_t}{\partial INT_t} \right] \qquad (5.6)$$

As can be seen from equation (5.6), if intervention cost in terms of the portfolio balance effect is large, the degree of intervention will become smaller. Foreign exchange intervention is concerned not only with the target exchange rate, but also with the wellbeing of domestic residences. The governor of the People's Bank of China (PBOC) has made clear that monetary policy in China should not simply target a single 'low inflation' objective, but must also consider economic growth, employment and balance of payments (Ni 2011). Given that the objective of intervention is complex and does not simply target a single objective, the driving forces of intervention in equation (5.6) will be discussed further below.

5.2.1 Deviation from target exchange rate

As can be seen in equations (5.3) and (5.6), the target exchange rate is important in the study of intervention reaction function. However, the target exchange rate is an elusive concept. Some studies, such as Frenkel, Pierdzioch, and Stadtmann (2002), advocate the PPP as the proxy for long horizon target exchange rate. Another frequently adopted measure is the moving average of the exchange rate. The order of moving average varies among studies. Geršl and Holub (2006) consider the exchange rate on previous day as the target exchange rate; Almekinders and Eijffinger (1996) and Jun (2008) adopt a 7-day moving average; ÖzIü and Prokhorov (2008) advocate a 22-day moving average; Akinci et al. (2005) use the 90-day moving average, while Neely (1998), LeBaron (1999) and Kim and Sheen (2002) suggest that 150 days is a common horizon among market traders. Alternatively, Ito and Yabu (2007) model the long-term target exchange rate as a combination of 1-year moving average, 3-year moving average and 5-year moving average. However, Herrera and Özbay (2005) argue that the central bank will not target the exchange rate at the long horizon due to the lack of independence in a managed floating rate regime. Following Chen, Chang, and Yu (2012), we consider three types of moving average of the exchange rate in this chapter:

$$SDER_t = P_{t-1} - P_{t-2} \tag{5.7}$$

$$MDER_t = P_{t-1} - \frac{1}{21}\sum_{i=1}^{21} P_{t-1-i} \tag{5.8}$$

$$LDER_t = P_{t-1} - \frac{1}{150} \sum_{i=1}^{150} P_{t-1-i} \qquad \text{(5.9)}$$

where $SDER_t$ is deviation from the short-term target exchange rate, $MDER_t$ is deviation from the medium-term target exchange rate, $LDER_t$ is deviation from the long-term target exchange rate, and P_{t-1} is the actual exchange rate.

5.2.2 Excess volatility

Volatility is a measure of market disorder. It is another driving force frequently discussed in the literature. High volatility in the foreign exchange market will increase trading cost of market traders and affect the confidence of importers and exporters. If the central bank prefers a stable market, then when the volatility of the foreign exchange market is higher, it may intervene to reduce the volatility and smooth the exchange rate. Technically, volatility is well described by the conditional variance estimated in the series of GARCH models. Kim and Sheen (2002) and Herrera and Özbay (2005) incorporate conditional variance into the intervention reaction function. Jun (2008) compares conditional variance with the equilibrium level (1.8255) of the Louvre Accord.[8] ÖzIü and Prokhorov (2008) consider the difference between conditional variance and unconditional variance, referred to as excess exchange rate volatility. In this chapter, we adopt excess volatility, and the conditional variance is estimated by a GARCH (1,1) model as below:

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[8] The Louvre Accord was established on February 22nd 1987 in order to counter the influence of excess depreciation of USD on the world economy. It marked a new phase of exchange rate policy, and JPY/USD suffered a large depreciation temporarily.

$$\Delta P_t = \beta_0 + \beta_1 INT_t + \beta_2(i_t - i_t^*) + u_t \tag{5.10}$$

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} + \gamma I(INT_t) \tag{5.11}$$

where ΔP_t is 100 times the difference of the log exchange rate, INT_t is intervention, i_t is the overnight interest rate of Shibor (Shanghai Inter-bank Offer Rate), i_t^* is the overnight interest rate of Libor (London Inter-bank Offer Rate), h_t is conditional variance, and $I(INT_t)$ is the dummy indicator of intervention, which takes the value 1 when there is intervention and 0 otherwise. The unconditional variance of the exchange rate is calculated as:

$$\sigma^2 = \frac{\omega}{1 - \alpha - \beta} \tag{5.12}$$

where σ^2 denotes unconditional variance, and ω, α and β are the coefficients estimated in equation (5.11). Then the proxy for the excess exchange rate volatility is the difference between conditional variance and unconditional variance:

$$EV_t = h_t - \sigma^2 \tag{5.13}$$

where EV_t indicates excess exchange rate volatility.

5.2.3 Interest rate differential

Interest rates represent the return on investment in a currency. If the difference between the interest rate of CNY and that of USD increases, the return on investment in the Chinese yuan increases. An increase in the value of the Chinese RMB means appreciation of the Chinese currency. Interest rate differential may be considered as a proxy of potential excessive exchange rate overshooting by the central bank. If the central bank wishes to smooth the deviation from the target exchange rate, it will intervene in the foreign exchange market (Kim and Sheen 2002, Herrera and Özbay 2005). In this chapter, interest rate differential is defined as the overnight Shibor for China minus overnight Libor:

$$IR_t = i_t - i_t^*$$
(5.14)

where IR_t is interest rate differential, i_t is overnight Shibor, and i_t^* is overnight Libor.

5.2.4 National economy

China is one of the biggest exporters in the world. In 2013, the value of the country's exports reached 2.21 trillion USD. Exchange rate is an important factor affecting the amount of export. If the Chinese yuan appreciates, the price of China commodities rises in foreign currency, and China's export will decrease. In order to maintain the national export competitiveness and economic growth, the central bank may intervene to combat the appreciation. Following Chen, Chang, and Yu (2012), we take the Shanghai Stock Exchange Composite Index as a proxy for the national economy. The factor in the intervention reaction function is defined as:

$$NE_t = 100 \times \Delta ln(SI_t) \qquad\qquad (5.15)$$

where NE_t is national economy, and SI_t represents the Shanghai Stock Exchange Composite Index.

5.2.5 Intervention persistence

Persistence of intervention refers to the fact that once intervention occurs, it will probably last for several days. Consideration of this factor has been introduced as the lag of intervention into the central bank reaction function (Frenkel, Pierdzioch, and Stadtmann 2002, ÖzIü and Prokhorov 2008, Jackman 2012). Ito and Yabu (2007) assert that persistence of intervention is due to political cost. Political cost is usually a consideration in the process to design the optimal intervention strategy. Before the execution of intervention, the central bank should engage in discussion with the Minister of Finance and other ministers. It should also negotiate with other major countries with relevant intervention currencies. Therefore, once intervention is approved, the political cost of a second intervention will be smaller than that of the first, and intervention will probably continue for several days. Another explanation of intervention persistence is the will to maintain policy credibility. If the exchange rate is considered as a policy instrument, intervention reflects a policy signal. The central bank will not favour invalid intervention or missing the intervention target. Therefore, intervention probably continues to ensure the credibility of the announced policy. In this chapter, we introduce the lag of intervention in the central bank reaction function.

5.2.6 Deviation from the target appreciation rate

At the beginning of 2011, many institutions predicted that CNY/USD would appreciate by around 5% during that year. Interestingly, the central bank was frequently observed in the market, especially during December 2011. It was noted that the central bank tolerated appreciation of the Chinese yuan in order to meet the target appreciation rate decided at the beginning of 2011. Finally, the market closing price of CNY/USD on December 30th 2011 (6.294) showed an appreciation of 4.5% compared with the market close price on December 31st 2010 (6.5897). The Chinese government is dovish, and it is reasonable to assume that the central bank prefers a gradual appreciation of the Chinese yuan, especially to counter the high rate of inflation in 2011. In this chapter, we introduce Deviation from the Target Appreciation Rate (DTAR) as one of the driving forces behind central bank intervention:

$$DTAR_t = 100 \times \frac{P_{t-1} - P_t^T}{T_t} \qquad (5.16)$$

where P_{t-1} is the actual exchange rate of CNY/USD at the close of business at time t-1, P_t^T represents the target exchange rate, T_t indicates the working days left at time t until the end of year. The appreciation rate of the year 2011 was around 5%; therefore P_t^T is set as 95% of the actual exchange rate on December 31st 2010. In contrast, in 2012 there is no evidence that the central bank intervened in the foreign exchange market in order to achieve the target appreciation rate. At the beginning of the year 2012, many institutions predicted that the Chinese yuan would appreciate by 3% to

4%. However, the Chinese government frequently stated that the exchange rate of CNY/USD had reached the equilibrium level. At the end of 2012, the actual exchange rate of CNY/USD had appreciated by only 1%. Therefore, we assume that P_t^T equals the actual exchange rate on December 30th 2011. As can be seen from equation (5.16), the further the deviation of the exchange rate from P_t^T, the larger the $DTAR_t$ is, and the higher the probability of central bank intervention. If the date is approaching the end of the year, $DTAR_t$ will become large and the central bank will probably intervene.

5.2.7 Market liquidity

Liquidity is a critical attribute of financial markets. A liquid market means it is easier to make transactions between market participants; when there is less liquidity, the reverse is true. In China, the exchange rate regime does not allow the Chinese yuan to fluctuate freely, but only within a designated fluctuation band. When the market expected value of the Chinese yuan is outside the fluctuation band, the market price will deviate from the market expectation and no transactions will be dealt, leading to a lack of market liquidity. In order to make the foreign exchange market stable and healthy, it is likely that the central bank will intervene to provide liquidity, to adjust the market expectation and finally to recover the liquidity of the market. Hence, market liquidity is a special driving force in the regime of the Chinese foreign exchange market. Following Mancini, Ranaldo, and Wrampelmeyer (2013), two categories[9] of liquidity are considered in this chapter.

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[9] This chapter takes excess volatility as one of the driving forces of intervention; therefore, the third category of liquidity proposed by Mancini, Ranaldo and Wrampelmeyer (2013) – price dispersion (volatility) - is not considered here.

5.2.7.1 Price impact and return reversal

Price impact reflects the movement of exchange rate reacting to order flow. When there is more market liquidity, the price change in response to a transaction is smaller (Kyle 1985, Rosu 2009). Evans and Lyons (2002) derive a price impact model which describes the relationship between the exchange rate and order flow. When the return reversal is introduced, the price impact model becomes:

$$\Delta P_t = \propto + L_t^{(pi)} x_t + \sum_{k=1}^{K} L_{t,k}^{(rr)} OF_{t-k} + u_t \tag{5.17}$$

where ΔP_t is the log exchange rate return, $\propto$ is constant, $L_t^{(pi)}$ denotes price impact measure of liquidity, OF_t means order flow, $L_t^{(rr)} = \sum_{k=1}^{K} L_{t,k}^{(rr)}$ indicates liquidity dimension of return reversal, and u_t is residual. If a market lacks liquidity, market price will overreact to order flow. Although part of the price change is temporary and caused by risk-averse liquidity traders, reversal to fundamental value will be slow, due to illiquidity (Banti, Phylaktis, and Sarno 2011, Campbell, Grossman, and Wang 1993, Foucault, Kadan, and Kandel 2005). Following Mancini, Ranaldo, and Wrampelmeyer (2013), this chapter calculates 100 times log exchange rate returns from the one minute closing exchange rate and regresses equation (5.17) with one minute frequency of each day. Order flow is calculated as the net of buyer-initiated trades and seller-initiated trades. Three lags of order flow are considered in the regression. Finally, we get the daily observations of $L_t^{(pi)}$ and $L_t^{(rr)}$.

5.2.7.2 Trading cost

Trading cost is an important aspect of liquidity. Logically, lower trading cost makes transaction easier, and consequently there is more liquidity. A widely used measure of liquidity in this regard is bid-ask spread. However, bid-ask spread is limited as a liquidity measure in that it is precise only if the transaction is executed at the posted quotes. In the first leg of transaction with new traders, when the volume of order is quite large and where it is dealt as a limit order, bid-ask spread is no longer a precise measure of trading cost (Grossman and Miller 1988). If we can get the transaction price, effective costs can be calculated as:

$$L^{(ec)} = \begin{cases} 100 \times \dfrac{(P - P^M)}{P^M}, & \text{for buyer-initiated trades} \\ 100 \times \dfrac{(P^M - P)}{P^M}, & \text{for seller-initiated trades} \end{cases} \tag{5.18}$$

$$P^M = \frac{P^A + P^B}{2} \tag{5.19}$$

where $L^{(ec)}$ indicates the liquidity dimension of effective cost, P is transaction price, P^M is mid quote, P^A means ask quote, and P^B means bid quote. Daily observation of $L^{(ec)}$ is calculated as the average of effective costs of all the transactions each day.

5.3 Data Description

This chapter focuses on the years 2011 and 2012 for two reasons. First, the period contains a recent change in exchange rate behaviours. As shown in Figure 5.1, the

Chinese yuan (CNY) actual rate fluctuated between 6.6377 CNY/USD (January 10th 2011) and 6.2223 CNY/USD (November 27th 2012). In general, the CNY appreciated over the two years under examination in this research. An exception to this was the period from January 2012 to July 2012. The CNY/USD first fluctuated around 6.3 until mid-May 2012, and then began to depreciate. In 2012, the Chinese government frequently gave signals, both formally and informally, that the CNY/USD exchange rate had already reached the equilibrium. On April 16th 2012, the government increased the fluctuation band from 0.5 to 1 per cent of the announced central parity rate. This increased the elasticity of the Chinese foreign exchange market. Subsequently, the market exhibited a different behaviour pattern compared with the previous CNY appreciation. Therefore, the period is interesting and worthy of our attention.

Figure 5.1 CNY/USD exchange rate, January 2011 - December 2012 (Data

source: Wind Info)

The second reason lies in the change of economic environment, and thus the possibility of different intervention targets. In 2010, the Consumer Price Index (CPI) in China gradually increased from 1.5% in January to 4.6% in December. It remained at a high level throughout 2011, with the highest CPI figure, announced as 6.5%, occurring in July. The average CPI in 2011 was 5.42%, 2.09% higher than that of 2010. The Chinese government was under pressure of high inflation. It is considered that official intervention in the foreign exchange market aimed at using an appreciated CNY to combat the pressure of imported inflation. In 2012, the CPI was under control and gradually decreased to below 3% after June. CPI, reflected in active appreciation of the CNY, might no longer have been a main concern for the government. On 10th

May 2012, the central bank published the first quarter monetary policy report, announcing that it would reduce the frequency of intervention in the foreign exchange market and continue to improve the method of intervention. This implies a possible change of intervention behaviour afterwards. On 13th September 2012, the USA decided to execute Quantitative Easing Ⅲ (QEⅢ). This may have raised concerns about the condition of the Chinese economy, and in order to counter the influence of QEⅢ, the Chinese government might have tried to keep the exchange rate stable. Therefore, the eventful years of 2011 and 2012 may enable us to reach a better understanding of China's intervention behaviours.

5.3.1   The central parity rate

Currently, the Chinese government implements a managed floating exchange rate regime. The China Foreign Exchange Trade System (CFETS) is authorized by the central bank to announce the central parity rate (CPR)[10] as a benchmark before the market opens. All transactions must be dealt within the range [1-a%, 1+a%] of the CPR that day. Here a% is the fluctuation band, 1 per cent after April 16th 2012. Therefore, the central bank is able to control the highest and lowest value of the exchange rate with the announcement of CPR and the help of the fluctuation band.

5.3.2   Intervention data

In this chapter, we define two types of official intervention in the Chinese foreign exchange market. In central bank trading intervention (CBT) the central bank intervenes via buying or selling domestic currency. The biggest challenge in CBT

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[10] The formation of CPR could be found in Table 4.1.

research is that the PBOC does not disclose any intervention data. A similar problem is encountered by studies of other markets. For example, the Japanese Ministry of Finance first disclosed intervention data in July 2001. Before that, the study of intervention relied on information in news media or financial reports (Galati and Melick 1999, Dominguez 1998, Bonser-Neal and Tanner 1996). Inspired by the previous literature, we collect intervention data from Factiva based on traders' reports of possible official intervention.

The other type of intervention is through the CPR. In order to distinguish CPR intervention from routine announcements of CPR, we invent two ways to capture the intervention: (1) If the CPR announced today differs from the market behaviour yesterday (measured by the closing rate yesterday) and the difference is larger than 90% of the fluctuation band, the setting of CPR today is said to be an intervention; (2) If Factiva reports that the value of CPR differs from the market expectation, the movement of CPR explains the purpose of the central bank, or the setting of CPR is due to some event, then CPR intervention is considered to have taken place. Table 5.1 below shows examples of CBT intervention and CPR intervention.

Table 5.1 Examples of intervention

Intervention Type	Date	Description
CPR	04/01/2011	The President of China, Hu JinTao, will visit America on January 19 this year. This is one of the most important factors in the recent appreciation of the Chinese yuan.
CPR	08/04/2011	Traders point out that in order to counter imported inflation, the regulator continuously sets CPR at a high level (appreciation).
CPR	27/12/2011	The central bank continuously sets CPR at a high level (appreciation); the market suspects that this is to achieve the target appreciation rate decided at the beginning of this year.
CPR	01/06/2012	Central bank sets CPR at a high level (appreciation), against the market trend. This could be aimed at countering the expectation of depreciation.
CPR	10/10/2012	The Chinese yuan has tended to appreciate recently. However, CPR remains at the same level. It is clear that the central bank is trying to keep the exchange rate stable.
CPR	13/11/2012	The close rate of CNY/USD yesterday is 6.2291, which is 1% below the CPR on that date. However, the announcement of CPR today is 6.2891, 0.95% higher than yesterday's close rate.
CBT	26/04/2011	The central bank is suspected of selling the USD and intervening in the foreign exchange market for a second day in order to prevent the Chinese yuan from reaching the depreciation band.
CBT	09/11/2012	There is nobody to buy the USD this morning. In the afternoon, the central bank is suspected of providing liquidity and taking the Chinese yuan away from the appreciation band.

5.3.3 Statistics of dataset

The raw data in this chapter include indicators for both types of intervention, tick data of the dealt exchange rate, bid and ask prices for transactions, and daily data for the overnight rates of Shibor and Libor and the stock index. Intervention indicators are defined according to the method described above. Tick data of exchange rate transactions is collected from Reuter Xtra 3000. Overnight Shibor, overnight Libor and stock index are taken from Wind Info. Due to data availability, the tick data of exchange rate transactions ends on 13th December 2012. Therefore, the period studied in this chapter is from 4th January 2011 to 13th December 2012.

Table 5.2 Number of interventions defined (04/01/2011 –13/12/2012)

	CBT intervention	CPR intervention
Take value of 1	18	56
Take value of -1	30	119

Table 5.2 gives a general picture on defined interventions for the period from 4th January 2011 to 13th December 2012. CBT intervention is reported on a total of 48 days. Meanwhile, CPR intervention is identified on a total of 175 out of 448 working days. If the purpose of intervention is to appreciate or slow the depreciation of the USD, we label it appreciation-target intervention and assign the value 1 to the intervention indicator. For example, purchase of the USD will make its rate against the RMB appreciate, so the intervention takes the value of 1. Similarly, if intervention aims to depreciate or slow the appreciation of the USD, we name it depreciation-target intervention and the intervention indicator is valued as -1. If there is no intervention, we assign the value 0. As shown in the table, the number of observations valued at -1 is almost double that with the value 1; thus it is clear that the central bank pushes the CNY to appreciate more frequently than it promotes depreciation.

Table 5.3 Descriptions of driving force variables (04/01/2011 –13/12/2012)

	Observations	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
SDER	447	-0.0008	0.0066	-0.2641	4.8851	71.3806***
MDER	447	-0.01	0.0173	0.2068	3.5242	8.3052**
LDER	447	-0.0693	0.0526	0.9329	2.6507	67.1062***
EV	447	0.0002	0.0046	2.2414	9.7143	1213.926***
IR	448	2.8903	1.1202	1.8486	7.5682	644.7224***
NE	448	779.5967	11.9445	0.1825	1.8942	25.3104***
DTAR	447	0.1124	0.4956	2.4773	62.4855	66362.17***
$L_t^{(pi)}$	448	0.0048	0.0048	5.8527	48.9727	42009.5***
$L_t^{(rr)}$	448	-0.0025	0.0042	-6.7408	57.9429	59742.17***
$L^{(ec)}$	448	0.0054	0.0042	3.788478	25.58795	10595.68***

Notes: Jarque-Bera is the statistics of normality test. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Table 5.3 shows the statistics of independent variables in our intervention reaction function. They are derived from equations (5.7) – (5.19) mentioned above. For some variables one observation is missing, because we take the difference of the exchange rate. On average, CNY experiences an appreciation process, while the means of SDER, MDER and LDER are all negative. Conditional volatility tends to be larger than unconditional volatility, as the mean of EV is positive. The averages of $L_t^{(pi)}$ and $L_t^{(rr)}$ are positive and negative, respectively. In addition, in an exercise unreported here, test results strongly reject the null hypothesis that their means are equal to zero. This is consistent with the conclusion of Mancini, Ranaldo, and Wrampelmeyer (2013) that order flow should positively impact on the exchange rate, and price change will reverse to the fundamental after excessive appreciation (depreciation), due to illiquidity.
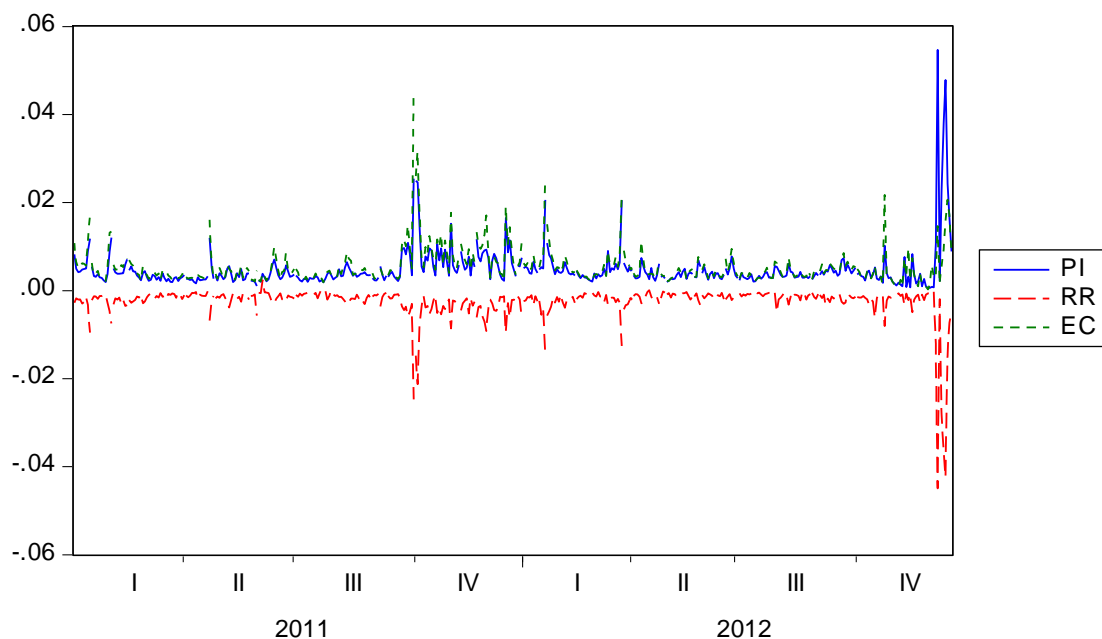
Figure 5.2 Liquidity in the Chinese foreign exchange market

Figure 5.2 provides a picture of the three measures of liquidity in our data. $L_t^{(pi)}$ and $L^{(ec)}$ follow a similar pattern across the whole period. In contrast, the trend of $L_t^{(rr)}$ is the reverse of $L_t^{(pi)}$. Around the end of September 2011, the absolute value of liquidity measures is quite large. A similar picture is detected through December 2012. On the majority of these dates, CPR is set far from the closing price on the previous day, with the probable result that the open rate hits the fluctuation band and cannot return to market expectation. Market makers have no motivation to provide liquidity because of the high risk associated with the deviation from market expected price. The foreign exchange market then becomes less liquid.

Table 5.4 Correlation of three trading cost measures

	$L_t^{(pi)}$	$L_t^{(rr)}$	$L^{(ec)}$
$L_t^{(pi)}$	1	-0.9528	0.7332
$L_t^{(rr)}$	-0.9528	1	-0.6344
$L^{(ec)}$	0.7332	-0.6344	1

As can be seen from Table 5.4, $L_t^{(rr)}$ is highly correlated with $L_t^{(pi)}$. This is consistent with the pattern shown in Figure 5.2. There is a possibility that $L_t^{(rr)}$ is collinear with $L_t^{(pi)}$. We will detect the potential collinearity and determine the final estimation model in the empirical section.

5.4 Empirical Analysis

5.4.1 Estimation model for intervention reaction function

In the sections above, we have discussed many potential driving forces of intervention. To include all the variables mentioned above into the econometric model, we have:

$$INT_t = \beta_0 + \beta_1 SDER_t + \beta_2 MDER_t + \beta_3 LDER_t + \beta_4 EV_{t-1} + \beta_5 IR_{t-1}$$

$$(5.20)$$

$$+\beta_6 NE_{t-1} + \beta_7 INT_{t-1} + \beta_8 DTAR_t + \beta_9 L_{t-1}^{(pi)} + \beta_{10} L_{t-1}^{(rr)} + \beta_{11} L_{t-1}^{(ec)} + \varepsilon_t$$

We assign one lag to variables of EV_t, IR_t, NE_t, $L_t^{(pi)}$, $L_t^{(rr)}$ and $L_t^{(ec)}$ to avoid the simultaneity problem.

In order to diagnose the potential collinearity amongst the regressors, we conduct coefficient variance decomposition based on the linear version equation (5.20). We first regress on equation (5.20) for both CBT intervention and CPR intervention using OLS with HAC, and the test results are shown in Table 5.5 and Table 5.6 below:

Table 5.5 Coefficient variance decomposition of CBT intervention

	CBT intervention					
Condition	$3.6 \times e^{-13}$	$1.44 \times e^{-11}$	$2 \times e^{-11}$	$2.45 \times e^{-11}$	$3.6 \times e^{-11}$	$1.56 \times e^{-10}$
	$3.33 \times e^{-10}$	$1.69 \times e^{-9}$	$4.37 \times e^{-8}$	$2.98 \times e^{-7}$	$2.19 \times e^{-6}$	1
	β_0	$SDER_t$	$MDER_t$	$LDER_t$	EV_{t-1}	IR_{t-1}
Associated Eigenvalue	0.0151	0.0765	0.0031	0.0001	0.0551	0.0103
	NE_{t-1}	INT_{t-1}	$DTAR_t$	$L_{t-1}^{(pi)}$	$L_{t-1}^{(rr)}$	$L_{t-1}^{(ec)}$
Associated Eigenvalue	0.011	0.0039	0.0045	0.9909	0.9898	0.1217

Notes: The condition number of each eigenvalue is shown in the first two rows. The last four rows display the decomposition proportions for each variable associated with the smallest condition number.

Table 5.6 Coefficient variance decomposition of CPR intervention

CPR intervention

Condition	$1.14 \times e^{-12}$	$9.56 \times e^{-12}$	$4.03 \times e^{-11}$	$5.38 \times e^{-11}$	$7.91 \times e^{-11}$	$1.95 \times e^{-10}$
	$3.49 \times e^{-10}$	$4.6 \times e^{-9}$	$3.18 \times e^{-7}$	$5.1 \times e^{-7}$	$2.18 \times e^{-6}$	1
	β_0	$SDER_t$	$MDER_t$	$LDER_t$	EV_{t-1}	IR_{t-1}
Associated Eigenvalue	0.0005	0.0508	0.0002	0.0035	0.126	0.004
	NE_{t-1}	INT_{t-1}	$DTAR_t$	$L_{t-1}^{(pi)}$	$L_{t-1}^{(rr)}$	$L_{t-1}^{(ec)}$
Associated Eigenvalue	0.00004	0.0924	0.0134	0.9827	0.9894	0.0363

Notes: The condition number of each eigenvalue is shown in the first two rows. The last four rows display the decomposition proportions for each variable associated with the smallest condition number.

The first two rows in Table 5.5 and Table 5.6 present the condition number of the covariance matrix. In both the CBT intervention model and the CPR intervention model, 11 out of 12 condition numbers are smaller than 0.001. The smallest values are $3.6 \times e^{-13}$ and $1.14 \times e^{-12}$, respectively. This indicates the existence of a large amount of collinearity in our estimation model. The second part of Table 5.5 and Table 5.6 shows the variance decomposition proportions associated with the smallest

condition number. In both models, only the values of $L_{t-1}^{(pi)}$ and $L_{t-1}^{(rr)}$ are larger than 0.5: for the CBT intervention model they are 0.9909 and 0.9898, respectively, and for the CPR intervention model they are 0.9927 and 0.9894. The values are all quite close to 1, which tells us that $L_{t-1}^{(pi)}$ and $L_{t-1}^{(rr)}$ have a high level of collinearity. In order to avoid the collinearity problem, we drop $L_{t-1}^{(rr)}$ from our model. The final model tested in this chapter becomes:

$$INT_t = \beta_0 + \beta_1 SDER_t + \beta_2 MDER_t + \beta_3 LDER_t + \beta_4 EV_{t-1} + \beta_5 IR_{t-1}$$

(5.21)

$$+\beta_6 NE_{t-1} + \beta_7 INT_{t-1} + \beta_8 DTAR_t + \beta_9 L_{t-1}^{(pi)} + \beta_{10} L_{t-1}^{(ec)} + \varepsilon_t$$

5.4.2 Structural break

As has been discussed above, during 2011 the CNY steadily appreciated against the USD, and the central bank is suspected to have accelerated the appreciation in order to meet a pre-determined rate. However, in 2012, the Chinese government stated that the CNY/USD exchange rate was approaching equilibrium. The exchange rate suffered a period of depreciation and then recovered gradually. A possible difference of intervention reaction function might be hidden behind different exchange rate behaviours. This section will carry out the Quandt-Andrews Breakpoint test to detect potential structural changes during the sample period. After conducting OLS regression of equation (5.21) with HAC, the Chow test is performed on every date of the middle 70% of the sample period.
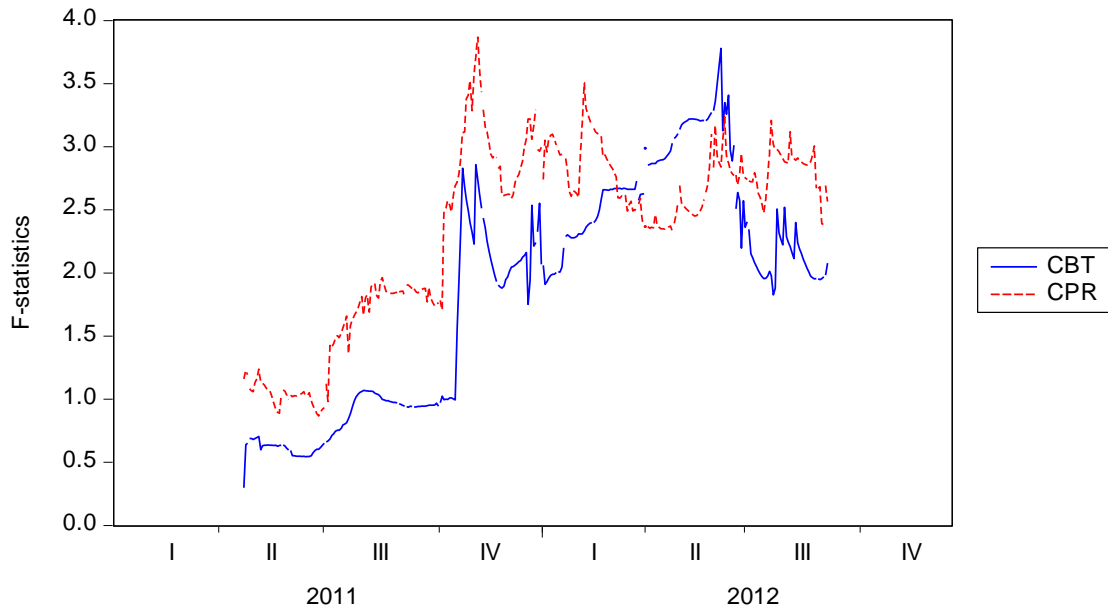
Figure 5.3 F-statistics test for breakpoints of CBT intervention and CPR

intervention

Figure 5.3 illustrates the F-statistics of the Chow test against the date. The solid line represents the test results for the CBT intervention model. There are four peaks in the middle 70% of the sample period. The largest F-statistic is 3.78, which lies at 12th June 2012. The test results for the CPR intervention model are shown by the dashed line. The largest F-statistic is 3.87, with a corresponding date of 8th November 2011. The F-statistics of the remaining peaks are all quite similar. One lies at 14th June 2012, which is quite close to the breakpoint of CBT intervention.
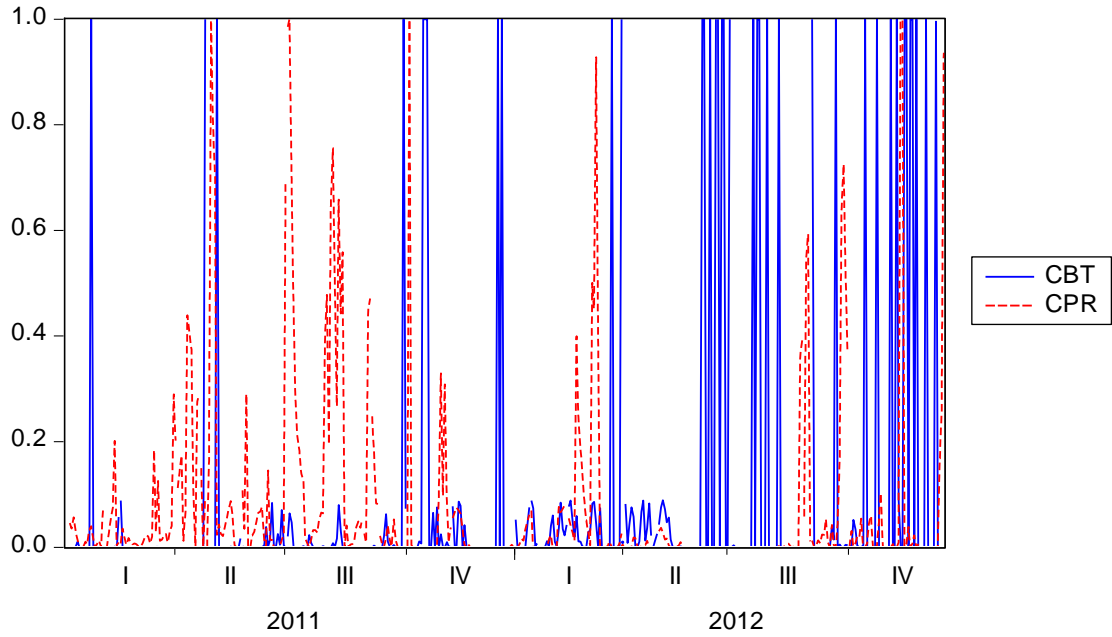
Figure 5.4 Filtered regime 2 probabilities of CBT intervention and CPR intervention

Another method introduced to detect the breakpoints is the regime-shift model. We apply the Markov switching model to regress on equation (5.21). For both CBT intervention and CPR intervention, the estimation with three regimes is not convergent. When regressing on the model with two regimes, we get the regime probability of each regime at every date. Figure 5.4 shows the probabilities of Regime 2 against the date for both CBT intervention and CPR intervention. As can be seen from the dashed line, CPR intervention is mainly in Regime 1; with regard to Regime 2, there are very few instances of probability larger than 50%. There is no obvious breakpoint in the picture. In contrast, CBT intervention is almost all in Regime 1 before 12th June 2012. After that date, Regime 2 frequently appears. Therefore, 12th

June 2012 can be defined as a breakpoint for CBT intervention. This is consistent with the results of the Quandt-Andrews Breakpoint test.

As has been discussed above, in our sample CNY started depreciating from mid-May 2012. After June 2012, the difference between the exchange rate and CPR became gradually larger. The trend reversed at the end of July and the exchange rate frequently hit the fluctuation band. The market was said to lack liquidity for a period of time. On 16th April 2012, the central bank doubled the fluctuation band. On the same date, a measure came into force allowing commercial banks to hold short positions of foreign exchange. According to the monetary policy report for the first quarter that year, published on 10th May 2012, the central bank stated that it would reduce the frequency of intervention in the foreign exchange market and continue to improve the method of intervention. The intention was to let the market forces play a more important role than before in determining the exchange rate. This could be an important reform of intervention behaviour and exchange rate determination. Based on the results of the Quandt-Andrews Breakpoint test and the Markov switching model, 12th June 2012 is detected as the date of the change of the intervention policy regime. This is around one month after the policy announcement in the first quarter monetary policy report, which can be explained by the time lag necessary for the Chinese foreign exchange administration to design and implement the operational actions. Therefore, we choose 12th June 2012 as the common breakpoint for both CBT intervention and CPR intervention.

5.4.3 Asymmetric reaction function of intervention

Intervention data differ from ordinary financial series data. During the sample period, on many days the intervention values are zero, since the central bank would not try to control the market all the time. In our data, 89.29% of the observations for CBT intervention and 60.94% of the observations for CPR intervention are zero, meaning that there is no intervention on these days. Therefore, a nonlinear model is considered a better choice for the estimation than a linear model. Also, we can collect only the indicators of intervention, but not the exact amount. In this section, we adopt a binary choice model to detect the determinants of appreciation-target intervention and depreciation-target intervention, separately.

5.4.3.1 Estimation results

Table 5.7 presents the estimation results of CBT intervention with equation (5.21). The column of appreciation-target intervention shows a dummy variable with the value of 1 if appreciation-target intervention occurs and 0 otherwise. Similarly, the column of depreciation-target intervention is a dependent variable with the value of 1 if depreciation-target intervention takes place and 0 otherwise. The whole period covers the entire sample from 04/01/2011 to 13/12/2012. Period A denotes the subsample from 04/01/2011 to 11/06/2012. Period B contains the rest of our sample, from 12/06/2012 to 13/12/2012.

As can be seen from the last row of Table 5.7, all the normality tests are rejected with 1% significance. The distribution of residual shows a fatter tail than the normal distribution. The Logit model is considered a better choice among binary choice models. Finally, we adopt the Logit model with generalized linear model standard

errors (GLM) to deal with the inconsistent problem of non-normality and the general

misspecification of the conditional distribution of intervention.

Table 5.7 Logit estimation results for CBT intervention

	Appreciation-target intervention		Depreciation-target intervention		
	Whole period	Period B	Whole period	Period A	Period B
β_0	64.6908***	-333.9747**	-0.2888**	63.3969	-181.4945
	(18.3425)	(134.6805)	(27.6908)	(49.3548)	(125.5644)
$SDER_t$	-9.9067	4.202	-73.8455	-68.5214	-106.3152
	(36.3195)	(56.6766)	(34.2342)	(51.5268)	(78.1714)
$MDER_t$	-27.1259	64.7764**	18.7945	40.5246	105.5167**
	(18.8632)	(29.5047)	(16.0641)	(34.6552)	(50.1941)
		[3.5562]			[7.2912]
$LDER_t$	-46.3051***	-93.7264***	14.4366**	-22.4878	-34.5449
	(13.248)	(28.3931)	(7.152)	(20.9438)	(44.6479)
	[-1.1159]	[-5.1456]	[0.7161]		
EV_{t-1}	-186.65**	-479.4968***	-98.6038	-81.3325	-303.2094
	(81.1529)	(174.8166)	(66.9788)	(85.87)	(194.1481)
	[-4.4983]	[-26.3244]			
IR_{t-1}	-0.5517*	-6.2584***	0.2526	-0.3351	2.5407***
	(0.3195)	(2.193)	(0.2223)	(0.5078)	(0.8894)
	[-0.0133]	[-0.3436]			[0.1756]

NE_{t-1}	-0.0923*** (0.0244) [-0.0022]	0.4438** (0.178) [0.0244]	-0.0039 (0.0358)	-0.0867 (0.0634)	0.2189 (0.1605)
INT_{t-1}	0.9831 (0.764)	1.2248 (1.0292)	2.1063*** (0.7273) [0.1045]	3.1077*** (1.1082) [0.1004]	1.0624 (1.5052)
$DTAR_t$	-2.1459*** (0.6831) [-0.0517]	0.0763 (0.6293)	1.6249*** (0.4657) [0.0806]	1.2448** (0.6333) [0.0402]	54.5033 (36.3659)
$L^{(pi)}_{t-1}$	33.1074 (36.9463)	-61.6068 (49.2862)	56.6914 (86.025)	256.1008 (445.4334)	1169.326 (794.6448)
$L^{(ec)}_{t-1}$	-9.3344 (62.4859)	396.0914*** (146.5848) [21.7454]	-44.9246 (90.4373)	-253.5029 (388.4937)	-627.6562 (618.1554)
R^2	0.4625	0.5418	0.2519	0.3096	0.4118
Jarque-Bera	144460.5***	1207.12***	22769.33***	42905.44***	9096.23***

Notes: The first row displays the estimated coefficient on CBT intervention in equation (5.21) by the Logit model. Figures in parentheses are standard errors and figures in the square brackets are the marginal effects of the exploratory variable. The whole period ranges from 04/01/2011 to 13/12/2012. Period A spans from 04/01/2011 to 11/06/2012 and Period B from 12/06/2012 to 13/12/2012. Jarque-Bera is the statistics of the normality test. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

The whole period estimation results for CBT intervention show that $LDER_t$ is negatively significant for appreciation-target intervention and positively significant for depreciation-target intervention. This indicates that the central bank is following a lean-against-the-wind policy. One hundred basis points of exchange rate deviation from the 150-day moving average will increase the probability of occurrence of appreciation-target intervention by 1.12%, and the probability of depreciation-target intervention by 0.72%. In addition, the 5% and 0% appreciation target rates for 2011 and 2012 respectively are proved, because $DTAR_t$ is negatively significant for appreciation-target intervention and positively significant for depreciation-target intervention.

The increased probabilities of intervention for 100 unit deviation are 5.17% and 8.06% respectively; this is another type of lean-against-the-wind policy, with a decided target exchange rate but no moving average. This is mainly valid during period A (from 04/01/2011 to 11/06/2012), but the driving forces of intervention seem to have changed, because $DTAR_t$ is no longer significant in period B (from 12/06/2012 to 13/12/2012).

There are differences between the reaction functions of appreciation-target intervention and depreciation-target intervention. The central bank conducts appreciation-target intervention to remove excess exchange rate volatility and to reduce the potential excessive exchange rate overshooting. More specifically, one unit of excess volatility will increase the probability of appreciation-target intervention by 449.83%, and one unit of interest rate differential tends to decrease the intervention

probability by 1.33%, because appreciation-target intervention will increase the excessive exchange rate overshooting. When the national economy is in good shape, the central bank has less motivation to intervene to depreciate the Chinese yuan to improve the competitiveness of exports. The decreased probability for 100 units of stock return is 0.22%. The depreciation-target intervention is less concerned with excess volatility and condition of the economy, as shown by the fact that EV_{t-1}, IR_{t-1} and NE_{t-1} are not significant. However, when a depreciation-target intervention has taken place on the previous day, the intervention probability today will increase by 10.45%.

There are only 3 observations of appreciation-target intervention in sub-period A, representing only 16.7% of all the appreciation-target interventions. Therefore, we ignore the estimation in sub-period A.

For period B, IR_{t-1} for depreciation-target intervention becomes significant. In 2011, CNY gradually appreciated against the USD and remained stable until the end of May 2012. Interest rate differential might not be a factor in driving the CBT intervention. However, significant changes in the foreign exchange market push the potential overshooting onto the intervention agenda, to protect the foreign exchange market from attack by international hot money. Both types of intervention are carried out to reduce the potential excessive exchange rate overshooting, and its influence increases: the probability is at least ten times that of the average of the whole period.

Attention is to be paid to the coefficients on $MDER_t$, which are both positively significant. Most of the depreciation-target intervention in period B lies between the dates 12th June 2012 and 4th September 2012. In this period, CNY is exhibiting

depreciation against the USD and deviation from the CPR becomes larger. Depreciation-target intervention changes the lean-against-the-wind policy from a 150-day moving average to a 21-day moving average.

In period B, all the appreciation-target interventions occur after 20th September 2012. The US decision to execute QEⅢ on 13th September 2012 causes a shock to China's foreign exchange market, and CNY appreciates rapidly against the USD. The exchange rate stays around the edge of the fluctuation band for a long period. $MDER_t$ is already lower than the level of the exchange rate desired by the Chinese government. Therefore, the implementation of appreciation-target intervention will increase the deviation of the exchange rate from the 21-day moving average. Even though the national economy is in good condition, appreciation-target intervention is implemented to counter the influence of QEⅢ.

Finally, attention should be paid to the behaviour of liquidity. The results show that one unit of additional effective cost increases the probability of appreciation-target intervention by 21.75%. Because the exchange rate remains around the fluctuation band for a long time, the foreign exchange market is illiquid during the second half of 2012. The lack of liquidity increases the probability of appreciation-target intervention. This is consistent with market reports that the central bank intervened to provide liquidity, especially in November and December 2012.

Table 5.8 Logit estimation results for CPR intervention

	Appreciation-target intervention		Depreciation-target intervention		
	Whole period	Period B	Whole period	Period A	Period B
β_0	94.3477***	274.9815**	-24.0711*	-6.1694	-189.9712*
	(24.6973)	(107.9742)	(14.3217)	(19.7959)	(98.7891)
$SDER_t$	-48.5732	-84.4516	-27.508	-15.3433	-107.9149*
	(37.9515)	(57.3446)	(21.1838)	(23.1097)	(65.0542)
					[-7.9965]
$MDER_t$	-2.5033	28.6601	31.0392***	23.6096	69.8991
	(17.2155)	(27.9704)	(11.2821)	(16.3654)	(43.4003)
			[4.0817]		
$LDER_t$	-17.07**	-30.6812***	1.0408	-2.1013	6.253
	(6.8192)	(9.8109)	(4.7264)	(8.9755)	(22.0365)
	[-0.9559]	[-2.884]			
EV_{t-1}	-9.3223	72.7781	-27.5795	-33.8957	-189.7923
	(54.0727)	(82.3737)	(30.9388)	(35.1498)	(119.0905)
IR_{t-1}	-0.0187	0.5764	-0.0296	-0.0822	0.1601
	(0.2451)	(0.5581)	(0.1229)	(0.1425)	(0.7564)

NE_{t-1}	-0.1257*** (0.0322) [-0.007]	-0.3626*** (0.1408) [-0.0341]	0.0283 (0.0184)	0.0054 (0.0255)	0.2453* (0.1295) [0.0182]
INT_{t-1}	1.9489*** (0.5661) [0.1091]	0.9399 (0.6486)	2.15*** (0.2715) [0.2827]	2.2292*** (0.3166) [0.3317]	0.2088 (0.7751)
$DTAR_t$	-0.6 (0.5043)	0.2788 (0.701)	1.0197*** (0.329) [0.1341]	0.8212** (0.3444) [0.1222]	0.4035 (5.5417)
$L_t^{(pi)}$	20.7083 (53.9394)	29.3841 (50.7008)	-68.5997 (127.745)	-66.5443 (197.3317)	-716.3539 (631.8521)
$L_t^{(ec)}$	-132.9584 (90.5345)	-169.2043 (114.0784)	125.3033 (106.16)	116.0207 (159.83)	507.0191 (343.2495)
R^2	0.4556	0.5349	0.2762	0.2461	0.4088
Jarque-Bera	29584.85***	542.97***	327.26***	121.43***	1186.49***

Notes: The first row displays the estimated coefficient on CPR intervention in equation (5.21) by the Logit model. Figures in parentheses are standard errors and figures in square brackets are the marginal effects of exploratory variables. The whole period ranges from 04/01/2011 to 13/12/2012. Period A spans from 04/01/2011 to 11/06/2012 and Period B from 12/06/2012 to 13/12/2012. Jarque-Bera is the statistics of the normality test. The significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

Table 5.8 illustrates the Logit estimation results for CPR intervention. There are only 10 observations of appreciation-target intervention in sub-period A, representing only 17.86% of all the appreciation-target interventions. Therefore, we ignore the estimation of appreciation-target intervention in sub-period A. A common feature of both appreciation-target intervention and depreciation-target intervention is the strong significance of intervention persistence. CPR intervention seems to have stronger continuity than CBT intervention. The persistent probabilities of CPR appreciation-target intervention and CPR depreciation-target intervention are 10.91% and 28.27% respectively, which are larger than those of CBT intervention. The driving forces for CPR intervention are simpler than those for CBT intervention, and the reaction function of CPR intervention is quite asymmetric. Appreciation-target intervention follows a lean-against-the-wind policy with a 150-day moving average, while depreciation-target intervention shows a similar policy with a 21-day moving average. However, the policy of depreciation-target intervention is not supported during either period A or period B, as $MDER_t$ is no longer significant for depreciation-target intervention. Appreciation-target intervention is also concerned with the condition of the national economy. If the economy is suffering downward pressure, the government is more likely to intervene to depreciate the RMB to maintain the competitiveness of exports. In contrast, depreciation-target intervention is conducted to meet the annual target appreciation rate. The increased probabilities for 100 unit deviation are 13.41% in the whole period and 12.22% in period A. It should be noticed that all the coefficients on liquidity are insignificant. This is because CPR is used to provide an official guide price for the exchange rate and limits its fluctuation.

Unlike CBT intervention, it involves no transaction activity and cannot provide any liquidity to the market.

5.4.3.2 In-sample fitting performance

Many studies have pointed out that OLS estimation can be inconsistent, and this is especially so given that in our sample many intervention days are assigned a value of zero. A nonlinear model such as the binary choice model is considered to perform better than an OLS model in capturing the driving forces for intervention. In order to determine which model is better, we introduce RMSE and MAE to measure the performance. Following Jun (2008), computation of the in-sample fitting RMSE and MAE is shown as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(INT_t - \widehat{INT_t}\right)^2} \qquad (5.22)$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|INT_t - \widehat{INT_t}\right| \qquad (5.23)$$

where T is the sample size, and $\widehat{INT_t}$ is the in-sample fitted value of dependant variable.

Table 5.9 In-sample fitting performance of CBT intervention

		Appreciation-target intervention		Depreciation-target intervention		
		Whole period	Period B	Whole period	Period A	Period B
RMSE	OLS	0.1661	0.2509	0.2296	0.1842	0.2831
	Logit	**0.1642**	**0.2333**	**0.227**	**0.1762**	**0.2574**
MAE	OLS	0.0729	0.1476	0.1163	0.075	0.1898
	Logit	**0.051**	**0.1093**	**0.1011**	**0.0634**	**0.1353**

The RMSE and MAE for CBT intervention as estimated by OLS with HAC, and by Logit model with GLM, are shown in Table 5.9. The smaller values are presented in bold. In all the estimations, the Logit model outperforms OLS in terms of both RMSE and MAE. The slope of the OLS model is too steep around the non-intervention point and intervention point, and too gentle in the middle range. The Logit model limits the dependant variable within [0, 1], but OLS might fit the value out of the range. On average, the difference of errors between OLS estimation and Logit estimation is larger for intervention fit than for non-intervention fit. The Logit model is proved superior to the OLS model in terms of in-sample fitting of RMSE and MAE.

Table 5.10 In-sample fitting performance of CPR intervention

		Appreciation-target intervention		Depreciation-target intervention		
		Whole period	Period B	Whole period	Period A	Period B
RMSE	OLS	0.2466	0.313	0.3647	**0.3864**	0.2839
	Logit	**0.2327**	**0.3117**	**0.3646**	0.3866	**0.2712**
MAE	OLS	0.1438	0.2149	0.2711	0.2996	0.1878
	Logit	**0.1101**	**0.1912**	**0.2644**	**0.2982**	**0.1477**

Table 5.10 illustrates the in-sample fitting results of CPR intervention. In most cases, the Logit model captures the intervention reaction function better than the OLS model in terms of both RMSE and MAE. One exception is RMSE of depreciation-target intervention in period A. The Logit model generally produces less error with in-sample fitting in period A. However, the number of large-size errors in the Logit model is greater than that in the OLS model. RMSE of the Logit model is thus slightly larger than that of the OLS model, but the difference is only 0.0002.

5.4.3.3 Out-of-sample forecasting performance

Another method to evaluate the performance of the models is forecasting ability. In each regression, we leave k observations out of the estimation sample and forecast the dependant variable. The forecast error is derived by comparing the forecast value with the actual one. All the explanatory variables are adopted with actual value, except the lag of the dependant variable, which will be dynamically substituted by forecast value after the second step forecast. Once again, we adopt RMSE and MAE to measure the forecasting performance, and they are computed as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(INT_t - \widehat{INT_t}\right)^2} \qquad (5.24)$$

$$MAE = \frac{1}{k}\sum_{t=1}^{k}\left|INT_t - \widehat{INT_t}\right| \qquad (5.25)$$

k is the step of the forecast, and $\widehat{INT_t}$ is the out-of-sample forecasting value of the dependant variable.

Table 5.11 Out-of-sample performance of CBT intervention

Forecast Horizon	Appreciation-target intervention				Depreciation-target intervention			
	RMSE		MAE		RMSE		MAE	
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Whole period:								
1 day	0.5356	**0.0211**	0.5356	**0.0211**	0.5141	**0.00001**	0.5141	**0.00001**
1 week	**0.5442**	0.7918	**0.5229**	0.7308	0.3379	**0.006**	0.2604	**0.0044**
2 weeks	**0.6465**	0.7043	0.5813	**0.5553**	**0.2671**	0.5819	**0.2007**	0.3756
Period A:								
1 day					0.0243	**0.017**	0.0243	**0.017**
1 week					0.0577	**0.0314**	0.0549	**0.0299**
2 weeks					0.0515	**0.0316**	0.0475	**0.0298**
Period B:								
1 day	**0.309**	0.7043	**0.309**	0.7043	0.0667	**0**	0.0667	**0**
1 week	1.0131	**0.8944**	0.8753	**0.8**	0.1396	**0**	0.1331	**0**
2 weeks	0.9342	**0.7129**	0.7225	**0.5288**	0.9409	**0.6314**	0.7358	**0.3996**

In Table 5.11, the smaller value of out-of-sample forecasting RMSE and MAE for CBT intervention is presented in bold. The forecast horizons taken in this section are 1-day, 1-week and 2-weeks. In the whole period, for estimation of appreciation-target intervention, the Logit model performs better than OLS in 1-day ahead forecast, but worse in 1-week ahead forecast. Two-week ahead forecast is less conclusive. The Logit model generally produces fewer forecasting errors, but large-size errors are dominant in terms of RMSE. In period B, the Logit model is worse in 1-day ahead forecast of appreciation-target intervention but better in longer forecast horizons. For the out-of-sample forecast performance of depreciation-target intervention, the Logit model is proved to be better, with only one exception in the 2-week ahead forecast of the whole period estimation. In total, the Logit model performs better than OLS in 11 out of 15 cases in the out-of-sample forecast.

Table 5.12 Out-of-sample performance of CPR intervention

Forecast Horizon	Appreciation-target intervention				Depreciation-target intervention			
	RMSE		MAE		RMSE		MAE	
	OLS	Logit	OLS	Logit	OLS	Logit	OLS	Logit
Whole period:								
1 day	1.0273	**0.9999**	1.0273	**0.9999**	0.3363	**0.0038**	0.3363	**0.0038**
1 week	0.6515	**0.6425**	0.459	**0.4**	0.2033	**0.0113**	0.1619	**0.0093**
2 weeks	1.1485	**0.448**	0.9091	**0.2094**	0.1276	**0.025**	0.074	**0.0197**
Period A:								
1 day					0.2781	**0.2424**	0.2781	**0.2424**
1 week					0.5454	**0.5275**	0.5282	**0.4946**
2 weeks					0.4581	**0.4514**	0.439	**0.4294**
Period B:								
1 day	1.1873	**0.9989**	1.1873	**0.9989**	0.0987	**0.0003**	0.0987	**0.0003**
1 week	**0.4433**	0.6425	**0.3374**	0.4	0.1469	**0.0002**	0.1337	**0.00007**
2 weeks	2.3212	**0.4472**	1.8673	**0.2**	**0.2399**	0.4003	**0.1789**	0.2433

Table 5.12 shows the value of out-of-sample forecasting RMSE and MAE for CPR intervention, which are calculated on the basis of both Logit estimation and OLS estimation. The Logit model has better forecasting ability than the OLS model with two exceptions, namely 1-week ahead forecast of appreciation-target intervention in period B, and 2-week ahead forecast of depreciation-target intervention in period B. Overall, the Logit model is shown to be superior in terms of both RMSE and MAE in 13 out of 15 comparisons.

5.4.4 Ordered Logit model

As has been discussed frequently in the literature, the binary choice model performs well in describing models such as the reaction function of appreciation-target intervention and depreciation-target intervention separately. However, it cannot capture both types of intervention simultaneously. In this section, we introduce the Ordered Logit model to discover the driving force of both interventions in a single equation, and to find the features of political cost.

Unlike some advanced countries such as Japan, China does not implement a system of timely release of government intervention data. However, China's obvious interventions have attracted international censure, especially from the US. In this situation, the question of political cost of China's intervention, both domestic and international, is an important one for the Chinese authorities and international community alike. Economic loss, international pressure and potential influence on market activities are all critical parts of the political cost of intervention. Moreover,

failure to achieve the intended targets of intervention may compromise the authorities' credibility, representing another significant political cost.

5.4.4.1 Estimation results

Table 5.13 presents the Ordered Logit estimation results for CBT intervention in equation (5.21). In most cases, the results are consistent with those from the separate estimation of appreciation-target intervention and depreciation-target intervention. For the whole period, the Chinese central bank has carried out a lean-against-the-wind policy. However, under the Ordered Logit model the target changes to 21-day moving average in period A, and in period B 0% appreciation rate is no longer significant. For the period as a whole and for period B, CBT intervention is found to aim at reducing the exchange rate overshooting. In the whole period and in period A, it is found to maintain the competitiveness of the national economy. The coefficient on NE_{t-1} in period A is positive because the majority of CBT intervention is depreciation-target intervention, and the significance is weak. In addition, if intervention is conducted, it will continue for several days. The persistence of intervention disappears in period B.

Table 5.13 Ordered Logit estimation results for CBT intervention

	Whole period	Period A	Period B
$SDER_t$	53.2388*	51.9623	71.1814
	(30.026)	(40.9072)	(56.6334)
$MDER_t$	-11.0797	-48.5566*	-23.3361
	(13.5212)	(29.4417)	(22.9371)
$LDER_t$	-25.0886***	20.5638	-35.6061**
	(5.5492)	(16.8977)	(15.3463)
EV_{t-1}	-19.1313	23.5292	7.793
	(39.0566)	(54.8048)	(70.9178)
IR_{t-1}	-0.3376*	0.2451	-1.7437***
	(0.1916)	(0.3086)	(0.6499)
NE_{t-1}	-0.0531**	0.0997*	-0.1262
	(0.0211)	(0.0548)	(0.0862)
INT_{t-1}	0.8443*	2.4391***	-0.5301
	(0.4737)	(0.7703)	(0.5919)

$DTAR_t$	-1.8989***	-1.1517**	-0.9302
	(0.4031)	(0.5373)	(0.8339)
$L_t^{(pi)}$	32.7583	-172.9282	28.6813
	(40.8935)	(313.4125)	(51.9721)
$L_t^{(ec)}$	-52.2009	173.6194	50.1914
	(56.1411)	(250.755)	(118.5362)
u_1	-36.5504**	82.7352**	-95.2251
	(16.2843)	(42.5141)	(66.1006)
u_2	-44.4467***	73.6357*	-103.7863
	(16.1132)	(42.8733)	(66.1025)
R^2	0.2915	0.2457	0.3797

Notes: The first row displays the estimated coefficient on CBT intervention in equation (5.21) with the Ordered Logit model. Figures in parentheses are standard errors. The whole period spans from 04/01/2011 to 13/12/2012. Period A ranges from 04/01/2011 to 11/06/2012 and period B from 12/06/2012 to 13/12/2012. u_1 and u_2 denote the thresholds in equation (2.26). Significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

u_1 and u_2 in Table 5.13 denote the thresholds of the Ordered Logit model. According to Ito and Yabu (2007), the threshold is a proxy of political cost. As can be found in Table 5.13, the neutral band is asymmetric and different in each period. In general, the central bank is much more tolerant of USD appreciation (CNY depreciation) than of USD depreciation (CNY appreciation), as the neutral band of no intervention is estimated as [-44.45, -36.55]. However, the neutral band changes considerably in period A. In the year 2011, the central bank is reported to have actively accelerated CNY appreciation to counter the high rate of inflation. It shows more tolerance toward USD depreciation (CNY appreciation) than USD appreciation (CNY depreciation), and the estimation neutral band is [73.64, 82.74]. In period B, the threshold is no longer significant.

Table 5.14 Ordered Logit estimation results for CPR intervention

	Whole period	Period A	Period B
$SDER_t$	4.8354	9.0887	-39.1438
	(18.7984)	(21.0213)	(46.66)
$MDER_t$	-20.5068**	-16.2205	7.2928
	(9.203)	(14.7953)	(21.7638)
$LDER_t$	-8.09**	0.2759	-25.5373***
	(3.7504)	(8.1744)	(8.2486)
EV_{t-1}	25.5162	47.9396	91.1292
	(26.3703)	(31.6663)	(65.3699)
IR_{t-1}	-0.0557	0.0893	0.4507
	(0.1034)	(0.1251)	(0.4425)
NE_{t-1}	-0.0621***	-0.0009	-0.3024***
	(0.0151)	(0.023)	(0.0929)
INT_{t-1}	1.955***	1.9172***	0.8909**
	(0.2224)	(0.2808)	(0.4406)

$DTAR_t$	-1.0135***	-0.788**	0.144
	(0.2898)	(0.3324)	(0.6497)
$L_t^{(pi)}$	16.8847	184.3139	30.3665
	(39.5768)	(205.2556)	(48.8712)
$L_t^{(ec)}$	-136.2886***	-227.6946	-160.9922
	(49.9797)	(164.3532)	(105.0089)
u_1	-45.8405***	2.5781	-229.1922***
	(11.6681)	(17.8403)	(71.1384)
u_2	-50.4519***	-2.3837	-233.8378***
	(11.7475)	(17.8454)	(71.3299)
R^2	0.3086	0.1913	0.421

Notes: The first row displays the estimated coefficient on CPR intervention in equation (5.21) with the Ordered Logit model. Figures in parentheses are standard errors. The whole period spans from 04/01/2011 to 13/12/2012. Period A ranges from 04/01/2011 to 11/06/2012 and period B from 12/06/2012 to 13/12/2012. u_1 and u_2 denote the thresholds in equation (2.26). Significance levels are displayed as *** for 1%, ** for 5%, and * for 10%.

The Ordered Logit estimation results for CPR intervention in Table 5.14 are similar to those of the binary choice estimation discussed above. CPR intervention is found to

lean-against-the-wind with 21-day moving average, 150-day moving average and the target appreciation rate. Period A focuses on the target appreciation rate, and in period B the target becomes 150-day moving average. Persistence of intervention exists in all the periods and the central bank shows concern for the condition of the national economy both in the whole period and in period B. In the whole period estimation CPR intervention is associated with a negative cost. CPR intervention influences the exchange rate through the setting of CPR with a fluctuation band. The effect is extremely obvious if the exchange rate is around the edge of the band. This type of intervention does not involve any transactions and will not provide liquidity to the foreign exchange market. In fact, CPR intervention might even aggravate the degree of illiquidity. Therefore, caution is needed by the central bank when conducting CPR intervention to tighten the distance between the exchange rate and CPR.

Consistent with the results of CBT intervention, the neutral band of CPR tells us that the Chinese government is much more tolerant of USD appreciation (CNY depreciation) than of USD depreciation (CNY appreciation); the estimated neutral bands for the whole period and period B are [-50.45, -45.84] and [-233.84, -229.19], respectively. The threshold in period A is not significant because the exchange rate is not far away from CPR in this period.

Comparing the neutral band of CPR intervention with that of CBT intervention, it can be found that the range of neutral band $u_1 - u_2$ for CBT intervention is much larger than that for CPR intervention. In the whole period estimation, the range of neutral band for CBT intervention is 7.9, which is 71.37% larger than that for CPR intervention. CPR intervention is proved the easier and less costly of the two types of intervention operation. Intuitively, in addition to the cost of getting the permission for

intervention, CBT intervention would also incur the cost of obtaining sufficient funds to undertake the transaction intervention in the market, and the pecuniary cost of losses due to changes of the exchange rate. This is consistent with the fact that CPR intervention occurs much more frequently than CBT intervention in our sample.

In period B, the central bank is seen to gradually reduce intervention and to try to test the elasticity and self-regulation ability of the foreign exchange market. Here the central bank clearly shows more tolerance toward volatility of the exchange rate. As has been discussed above, CBT intervention appears to have acquired new driving forces, which include the intention to provide liquidity. The neutral band of CBT intervention is not significant. However, with the reduction of CBT intervention CPR intervention plays a more important role. Finally, it can be seen that the central bank still shows more tolerance of USD appreciation (CNY depreciation) than of USD depreciation (CNY appreciation), as the neutral band is [-233.84, -229.19].

5.4.4.2 Prediction performance of intervention reaction function

In order to see how helpful the intervention determinants in equation (5.21) are in predicting official intervention operation, we compare the intervention prediction ability of estimated equation (5.21) with that of a constant probability equation. A constant probability equation is the reaction function with no intervention factor in the equation. Intuitively, the classification of intervention is based on the category with maximum predicted probability.

Table 5.15 Prediction evaluation of CBT intervention

Whole period

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	30	4	13.33%	0%	13.33%	13.33%
0	398	395	99.25%	100%	-0.75%	
1	18	5	27.78%	0%	27.78%	27.78%
Total	446	404	90.58%	89.24%	1.35%	12.5%

Period A

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	15	3	20%	0%	20%	20%
0	304	304	100%	100%	0%	
1	3	0	0%	0%	0%	0%
Total	322	307	95.34%	94.41%	0.93%	16.67%

Period B

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	15	1	6.67%	0%	6.67%	6.67%
0	94	91	96.81%	100%	-3.19%	
1	15	6	40%	0%	40%	40%
Total	124	98	79.03%	75.81%	3.23%	13.33%

Notes: Correct and Correct (%) are the number and rate of correct predictions of equation (5.21) to actual intervention. Constant Correct (%) is the rate of correct predictions of intervention when the reaction function contains no factor of intervention. Gain (%) is calculated by Correct (%) minus Constant Correct (%). Percentage Gain (%) is the percentage of incorrect rate reduction for equation (5.21) compared with the constant specification.

As can be seen from Table 5.15, the constant probability equation predicts non-intervention accurately, but has no ability to capture the date of intervention. The Ordered Logit estimation of equation (5.21) is able to capture part of the intervention but slightly reduces the accuracy of non-intervention prediction. It captures CBT intervention well in the whole period estimation and period A estimation. The correct rate reaches 90.58% for the whole period, an increase of 1.35% compared to the constant specification. The percentage of incorrect rate reduction is 12.5%.

In period A, the total correct rate of equation (5.21) rises to 95.34%. The improvement of correct rate and percentage of incorrect rate reduction are 0.93% and 16.67%, respectively. CBT intervention in period B is more difficult to predict, and

the total correct rate of equation (5.21) decreases to 79.03%. However, the constant probability equation performance is much worse, and the correct rate is 3.23% lower than in equation (5.21). The incorrect rate of equation (5.21) is 13.33% lower than that of the constant specification.

It can also be found that our model has better prediction performance with regard to depreciation-target intervention in period A and appreciation-target intervention in period B. The asymmetric estimation of the reaction function sheds light on the possible reason. In period A, the exchange rate experiences active appreciation in 2011 and becomes stable afterwards. Appreciation-target intervention is rare, and $DTAR_t$ is significant. The model captures depreciation-target intervention better. In period B, in addition to the common significant driving force, appreciation-target intervention is more driven by excess volatility, national economy and foreign exchange market liquidity than is depreciation-target intervention. Our model better describes the features of appreciation-target intervention.

Table 5.16 Prediction evaluation of CPR intervention

Whole period

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	118	71	60.17%	0%	60.17%	60.17%
0	272	236	86.77%	100%	-13.23%	
1	56	34	60.71%	0%	60.71%	60.71%
Total	446	341	76.46%	60.99%	15.47%	39.66%

Period A

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	100	62	62%	0%	62%	62%
0	212	184	86.79%	100%	-13.21%	
1	10	0	0%	0%	0%	0%
Total	322	246	76.4%	65.84%	10.56%	30.91%

Period B

INT_t	Obs.	Correct	Correct (%)	Constant Correct (%)	Gain (%)	Percentage Gain (%)
-1	18	7	38.89%	0%	38.89%	38.89%
0	60	46	76.67%	100%	-23.33%	
1	46	38	82.61%	0%	82.61%	82.61%
Total	124	91	73.39%	48.39%	25%	48.44%

Notes: Correct and Correct (%) are the number and rate of correct predictions of equation (5.21) to actual intervention. Constant Correct (%) is the rate of correct predictions of intervention when the reaction function contains no factor of intervention. Gain (%) is calculated by Correct (%) minus Constant Correct (%). Percentage Gain (%) is the percentage of incorrect rate reduction for equation (5.21) compared with the constant specification.

From Table 5.16, we can see that for CPR intervention the constant probability equation again well predicts non-intervention but not intervention observations. Ordered Logit estimation captures CPR intervention better than CBT intervention and the highest correct rate is 82.61%. However, it also delivers more wrong signals for the dates without intervention. Overall, the total correct rate is smaller in the prediction of CPR intervention. On a more positive note, the improvement made by the equation (5.21) estimation of CPR intervention compared to the constant specification is much greater than the improvement for CBT intervention. The increase in the correct rate and the percentage reduction in the incorrect rate are respectively 15.47% and 39.66% for the whole period, 10.56% and 30.91% for period A, and 25% and 48.44% for period B. Similar to the results for CBT intervention, the

correct rate of depreciation-target intervention in period A is larger and the reaction function of appreciation-target intervention performs better in period B due to the asymmetric effects of the driving forces.

5.4.4.3 Minimization of surprise and false alarm

In the prediction of intervention, there could be two types of error. Type one is a surprise, when no signal of intervention is predicted but an intervention actually occurs. Type two is a false alarm, where an intervention is predicted but does not actually take place. Also, it should be noted that intervention has direction. It is possible that an actual intervention takes place as predicted, but the direction is opposite to the prediction. Ito and Yabu (2007) label this as correct signal and argue that there is no such case in their data. In our sample, a few observations have higher fitted probability of appreciation-target intervention (depreciation-target intervention) than that of depreciation-target intervention (appreciation-target intervention), when in fact it is depreciation-target intervention (appreciation-target intervention) that occurs. In order to remove these noises and discover the optimal cut-off, we classify this case as a false alarm.

Table 5.17 The framework of surprise and false alarm

	Correct intervention	No intervention or wrong intervention
Signal was issued	A	B
Signal was not issued	C	D

Notes: A is the number of the interventions as correctly predicted, including the direction. B is the number of type two errors. C is the number of type one errors. D is the number of non-interventions as predicted.

Table 5.17 summarizes the framework of predicted and actual intervention. A is the number of interventions correctly predicted, including the direction; B represents the number of false alarms; C indicates the number of surprises; D is the number of days when no signal of intervention is predicted and there is no actual intervention. Following Ito and Yabu (2007), the noise-to-signal ratio is adopted to minimize the problems of surprise and false alarm. The ratio is defined as:

$$Noise-to-signal\ ratio = \frac{B/(B+D)}{A/(A+C)} \qquad (5.26)$$

$\frac{A}{A+C}$ is the ratio of the correct signal to actual intervention. $\frac{B}{B+D}$ is the noise ratio of no intervention and intervention with wrong predicted direction. Cut-off point is chosen from [0, 1] to seek minimization of the value of the noise-to-signal ratio. If the fitted

probabilities of both appreciation-target intervention and depreciation-target intervention are greater than the cut-off value, the direction of intervention is determined by the larger fitted probability. We ignore the minimization results due to B=0.

Table 5.18 Optimal results of noise-to-signal ratio for intervention

	CBT intervention			CPR intervention		
	Whole period	Period A	Period B	Whole period	Period A	Period B
Cut-off	68%	38%-40%	63%-70%	78%	73%	82%
A	7	6	6	33	26	26
B	1	2	1	5	5	1
C	41	12	24	140	83	37
D	397	302	93	268	208	60
Signal	0.1458	0.3333	0.2	0.1908	0.2385	0.4127
Noise	0.0025	0.0066	0.0106	0.0183	0.0235	0.0164
Noise-to-signal ratio	0.0172	0.0197	0.0532	0.096	0.0984	0.0397

Table 5.18 shows the optimal results of surprise and false alarm problem for both CBT and CPR interventions. In the period A estimation of CBT intervention, the optimal cut-off points are 38%-40%. Six out of 18 interventions are correctly predicted and the signal ratio is 33.33%. Two out of 304 non-intervention observations are predicted as intervention, and the noise ratio is 0.66%. The noise-to-signal ratio is 1.97% in period A and quite predictable. In the period B estimation of CBT intervention, the optimal cut-off points range from 63% to 70%; 6 out of 30 interventions are correctly captured and the signal ratio is 20%. There is only 1 false alarm against 94 non-intervention days, and the noise ratio is 1.06%. The noise-to-signal ratio in period B reaches 5.32%, which is much larger than in period A. This is consistent with the discussion above, where it is stated that intervention is harder to predict in period B.

Columns 5-7 of Table 5.18 report the results of CPR intervention. In period A the optimal cut-off point is 73%; 26 out of 109 interventions are correctly predicted and the signal ratio is 23.85%. A signal is issued for 4 days with no intervention and 1 day with wrong intervention direction. The noise ratio is 2.35% and the noise-to-signal ratio is 9.84%. In period B, the cut-off point is 82% and the signal ratio reaches as high as 41.27%. Only 1 false alarm occurs due to the wrong prediction of intervention direction and the noise signal is 1.64%. The noise-to-signal ratio is 3.97%, which is much smaller than that in period A. CPR intervention is found to be more unpredictable in period A than in period B.

5.5 Conclusions

Although foreign exchange market intervention has attracted much research attention, most studies focus on the effects of intervention. There is very little research that attempts to discover the driving forces behind the intervention, and even less focus on the emerging markets. This chapter enriches the line of studies on intervention reaction function in emerging markets. It develops a new model to capture the driving force of intervention, providing insights into a large emergent economy that is not well researched in the English language literature. It also provides empirical insights into the attitude of government toward exchange rate movement and the behaviour of central bank intervention. The specific findings are as follow:

1) The return reversal of order flow is highly correlated with price impact of order flow. Their trends in our sample are similar, but the direction is completely opposite. The exchange rate movement due to order flow is always associated with overreaction and return reversal in the Chinese foreign exchange market.

2) With the help of the Quandt-Andrews Breakpoint test and the regime-shift model, 12th June 2012 is detected as a breakpoint of intervention reaction function in our sample

3) In this chapter, we introduce both a Logit model and an Ordered Logit model to capture the driving forces of intervention. In general, the Chinese government prefers a gradual achievement of its target exchange rate. It is found to lean-against-the-wind with both 150-day moving average and the target appreciation rate, which is 5% in 2011 and 0% in 2012. However, the reaction functions of appreciation-target intervention and depreciation-target intervention

are asymmetric and dynamic. Before 12th June 2012, both CBT intervention and CPR intervention are more concerned with the target appreciation rate, and the persistence is significant. After 12th June 2012, CBT intervention is freer, that is irregular and less predictable, and both neutral band of non-intervention and intervention persistence are not significant. In addition to the common significance of interest rate differential, appreciation-target CBT intervention is responsive to excess volatility and the national economy. The intervention also aims to provide liquidity when the foreign exchange market is illiquid. For CPR intervention, conditions of the national economy are a significant driving force.

4) In general, the Chinese government is more tolerant of USD appreciation (CNY depreciation) than USD depreciation (CNY appreciation). However, this can change according to the political target. Before 12th June 2012, the central bank actively accelerated the appreciation of CNY and was more tolerant towards USD depreciation (CNY appreciation) than USD appreciation (CNY depreciation). After 12th June 2012, despite the central bank announcement that it would allow market forces to play a more important role than before in determining the exchange rate, it continues to show more tolerance towards USD appreciation (CNY depreciation) rather than USD depreciation (CNY appreciation).

5) In the majority of cases in our estimations, the Logit model is proved to perform better than the OLS model in terms of RMSE and MAE for both in-sample fitting and out-of-sample forecasting comparisons.

6) The introduction of driving forces into the reaction function does improve the prediction performance. In the second half year of 2012, the central bank announced that it would reduce the frequency of intervention, and CBT

intervention is more difficult to predict after 12th June 2012 than before that date. Conversely, CPR intervention becomes a more frequently used tool, and it is harder to predict before 12th June 2012 than after that date.

In this chapter, deviation from desired level of the exchange rate is an important driving force of central bank intervention. In some cases, lack of liquidity in the foreign exchange market is another determinant factor. This chapter reports the degree of increased probability of intervention when the driving forces increase. However, what extent of deviation from desired level of the exchange rate and what degree of market illiquidity is necessary to trigger central bank intervention require further research. The degree of tolerable deviation, but not the formal declaration of exchange rate trading band, represents the valid fluctuation band desired by the central bank. If the central bank is willing to increase the flexibility of the Chinese foreign exchange regime, it can and should allow greater tolerance toward deviation from the desired level of the exchange rate.

Our findings do reveal that China has changed its mode of intervention since 12th June 2012. The central bank has reduced the amount of CBT intervention and has started to provide liquidity when it is needed in the market. This is an attempt in the right direction toward the reform of China's foreign exchange system. However, the central bank still relies heavily on CPR intervention to control the level and growth of the renminbi exchange rate. How to moderate or even totally abandon such CPR intervention will be a great challenge to the further reform of China's exchange rate regime.

Chapter 6

Conclusions

6.1 Main Findings

This thesis is among the few to apply a microstructure methodology to the Chinese foreign exchange market. Motivated by the scarcity of theoretical models to capture price discovery of the exchange rate in a multi-structure market and by the disconnection between the DL model and ML model, and starting from the pricing strategy of individual dealers with past information available, this thesis first develops a model to describe the transition process from individual price setting to market-wide exchange rate. Compared to the existing literature, our model provides richer content in the order flow model in a more realistic environment.

Consistent with the features of the foreign exchange market in reality, the model points out that the number of dealers, which is relevant to market competition, is an important factor to influence the market depth and pricing strategy. When the market is more competitive, the quotes of individual dealers will become closer to their expected value of the exchange rate.

In addition, our model shows that the empirical success of order flow on the exchange rate is related to both information effect and inventory effect. The information effect is incorporated into the model when customers with private information trade with dealers in the customer market, and is realized in the optimal quoting strategy of

dealers to incoming orders. Inventory effect influences the price setting of the exchange rate when dealers wish to share overnight risk with the public and stay with no imbalance of inventory position. The model provides detail on the components of price impact of order flow on exchange rates. Specifically, the impact of order flow on the exchange rate is positively related to macro variables and negatively related to overnight market risk, the number of dealers, parameters of utility function and risk-bearing capacity.

This theoretical model entails an important assumption, namely that the market dealer will not hold an overnight position. It is quite helpful for the monetary authorities of some emerging markets to restrain excessive currency speculation, especially in China. Furthermore, the Chinese foreign exchange markets study and copy the advanced markets for the purpose of renminbi internationalization. With the rapid growth of the transaction volume of the Chinese foreign exchange market, it will become more mature and closer to those of the developed countries. Hence this model provides a theoretical tool to study the Chinese foreign exchange market.

With regard to the relationship between order flow and exchange rate movement in China, as far as I can discover there remains a gap in the empirical research of order flow model on CNY/USD in ultra-high frequency. Our results confirm that order flow plays an important role in determining exchange rate dynamics in ultra-high frequency. The influence of order flow is greater when the market is volatile and lacks liquidity. According to our model, the number of dealers in the market reduces when the market is illiquid. Therefore, the impact of order flow increases.

Given that order flow captures a relatively smaller part of exchange rate movement in the emerging markets than it does in the developed market, we consider trading duration as a further potential factor to capture the process of price discovery, in addition to order flow.

Although it has been argued that the time between two consecutive transactions contains information, the information content of trading duration is usually detected by its significant relationship with asset price movement and volatility. With the help of the PIN model and the ACD model, we are able to provide a picture on intraday pattern of information-based trading and trading duration. Then, it becomes possible to study directly the information content of both expected and unexpected components of trading duration. In our sample period, the probability of information-based trading is highest around the beginning and end of trading hours, and lowest during lunch time. This is consistent with the intraday pattern of trading duration, which exhibits a distinctive inverted U-shape with relatively long trading duration during lunch time. Our empirical investigation shows that both components of trading duration are relevant to the arrival rate of informed traders, but not to the probability of information occurring.

Incorporating two components of trading duration in the order flow model, our results suggest that trading duration does contain additional information besides order flow, and enhances the explanatory power of our model. The impact of trading duration on exchange rate movement is not induced simply by active informed traders or inactive uninformed traders. Instead, it is a composite result reflecting complicate behaviours of both informed traders and uninformed traders. When the market is placid, little evidence can be found that informed traders are active. Uninformed traders will trade

as they plan to. Short expected trading duration is mainly associated with the high trading intensity of existing informed traders, leading to large exchange rate movement and increased volatility. The activity of existing informed traders will increase the probability of transition from a small exchange rate change with low volatility (SL) regime to a large exchange rate change with high volatility (LH) regime. When the market is volatile with large exchange rate movements, it is evident that informed traders are active. This expels existing liquidity providers, and long expected trading duration implies a high proportion of informed traders, thus associating with large exchange rate movement and high volatility. The probability of the market staying in a LH regime will increase. The unexpected component of trading duration indicates an increase in both informed traders and uninformed traders. Due to the membership system of the Chinese foreign exchange market, the possible growth in the number of informed traders is limited, and discretionary uninformed traders dominate the signed unexpected trading duration. The impacts of signed unexpected trading duration are positive in both market regimes.

We further examine the relation between trading duration and conditional volatility in the framework of the ACD-GARCH model. Our results confirm the positive correlation between the expected arrival rate and conditional volatility. Expected arrival rate plays a more important role than the unexpected arrival rate in capturing conditional volatility.

Finally, we extend our microstructure analysis to official foreign exchange intervention in China. In total, we examine seven factors with ten variables as potential determinants in the intervention reaction function. The Chinese government is found to follow a 'lean-against-the-wind' policy with 150-day moving average in

the foreign exchange market. It prefers to achieve the target exchange rate gradually and the target rate of appreciation is significant in two types of intervention. However, the effects of the driving forces are asymmetric. After the government announcement that the Chinese yuan has reached equilibrium, the target appreciation rate ceases to be a significant driving force for both CBT intervention and CPR intervention. Appreciation-target CBT intervention undertakes more tasks and has a more wide-ranging purpose than the depreciation-target CBT intervention. Appreciation-target CBT intervention is found to be conducted to remove excess volatility, counter the influence of QEIII and provide liquidity when necessary. In addition, the driving forces of CBT intervention and CPR intervention are different. CBT intervention is more responsive to the interest rate differential, while CPR intervention is more concerned with the condition of the national economy. CPR intervention is easier and less costly to implement than CBT intervention, since the range of neutral band for CPR intervention is narrower than that for CBT intervention; correspondingly, CPR intervention is more persistent and more frequently conducted than CBT intervention.

The Chinese government shows more tolerance of USD appreciation (CNY depreciation) than USD depreciation (CNY appreciation). One exception is when the government actively speeds up the appreciation of CNY in order to counter a high rate of inflation. In that situation the government shows more tolerance towards USD depreciation (CNY appreciation) than USD appreciation (CNY depreciation).

With the inclusion of intervention determinants specific to the Chinese market, the forecasting ability of our model improves. Our model correctly predicts above 70% of intervention indicators in total, based on the category with maximum predicted probability. Following the central bank announcement of its intention to reduce the

frequency and improve the method of intervention, China's intervention strategy does change: CBT intervention becomes more flexible, the intervention persistence disappears, and the neutral band of CBT intervention is no longer significant.

While CBT intervention is less predictable, the Chinese CPR intervention becomes a relatively more frequently used tool and more predictable. Although the central bank has stated its intention to allow market forces to play a greater role in determining the exchange rate than was previously the case, the neutral band of CPR intervention tells us that the government is still more tolerant of USD appreciation (CNY depreciation) than USD depreciation (CNY appreciation).

6.2 Implications and Future Research

This thesis provides a microstructure analysis of price discovery, trading duration and official intervention to better our understanding of the working of the foreign exchange market in emerging market economies, with specific reference to China. Important implications can be drawn for both market participants and policy makers.

First, given the fact that it is not straightforward to influence macro variables, overnight market risk, parameters of the utility function and risk-bearing capacity, a more effective way to improve market efficiency is to increase the number of dealers and market capacity. This could increase the market liquidity and decrease the trading cost of market participants, improving the process of price discovery.

Second, since trading duration is proved to be an important factor in affecting exchange rate movement, consideration of this factor will help us understand the process of price discovery and asset pricing. With a better understanding of the

trading behaviours behind trading duration, we suggest that uninformed traders should trade carefully in the market if expected trading duration is short and unexpected trading duration is long, even if the market looks calm. That situation probably implies high activity of existing informed traders and high proportion of newly arrived informed traders.

Third, we suggest that secret CBT intervention should be implemented when the market is liquid. This could make it harder for the market to discover the intervention, and on average make it easier to intervene to influence the exchange rate. According to the evidence uncovered by our empirical investigation, the Chinese government tends to engage in CBT intervention around the beginning and end of trading hours. These are the critical times for the market participants to anticipate market changes.

Fourth, our results confirm that the Chinese central bank has changed its intervention regime since June 2012. After that date, CBT intervention becomes more flexible. While this represents a positive step in the right direction, the central bank still intervenes extensively, especially through the setting of the CPR to manage the exchange rate. Problems may appear, for example, when the market anticipates that the true value of the exchange rate will move outside the fluctuation band around the CPR, leading to large exchange rate movements. Government intervention may mitigate the situation, but the exchange rate might remain for a long time around the edge of the band. In response, liquidity providers will postpone their transactions and the market will become illiquid, with only informed traders left. Unless market expectation changes, market liquidity would be in a better situation if the central bank were to cease its CPR intervention to let the market find the appropriate level of the exchange rate at which the market could become liquid by itself. Alternatively, the

central bank would have to re-engage in CBT intervention to provide liquidity, which would run contrary to reform intentions.

Despite the extensive research carried out for this thesis, there is scope for further exploration of the foreign exchange market in emerging economies like China from a microstructure perspective.

First, the calculation of order flow is borrowed from the equity market and has been used for more than a decade. Although the current formation of order flow has performed fairly well until now, it will be useful to develop a new construction of order flow based on the features of the foreign exchange market.

Second, the theoretical model developed in this thesis sheds new light on the price discovery in the order flow model. However, this raises the challenge of discovering to what extent empirical evidence can be found to support the theoretical insights. Furthermore, in order to estimate the specific parameters of such a theoretical model, it is necessary to find an appropriate methodology that is able to construct a variable that summarizes the effects of several parameters. Also, while the research reported in this thesis considers emerging foreign exchange markets, it would be interesting to see whether it could be applied to developed markets, or whether new insights can be drawn from comparing these research findings with results from studies on developed markets.

Third, due to data availability, this research adopts a static PIN model. Important information may be lost in such a static setting since the model assumes constant probability of information happening, constant probability of good news and bad news, and the constant arrival rate of informed traders and uninformed traders within

the estimation period. Once data availability is considerably improved such that a large enough data sample may be gathered, the model may perform well in a dynamic setting, which may significantly enhance our understanding of the working of the foreign exchange market in China, including the information content of trading duration in high frequency data.

Fourth, our intervention data are collected from media reports. However, it is debatable whether these media reports can accurately indicate the actual intervention operations in China. A proper measure of China's intervention operations would represent a great improvement to the calibration of the research in this area, allowing us to study more accurately the driving forces of intervention and intervention effects. A promising avenue for such improvement will be to decipher the intervention information from changes in the official holdings of foreign reserves. This will involve transformation of low frequency foreign reserves data into high frequency. The mission is challenging, but the reward could be great.

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