# Exchange Rate Dynamics in the Chinese Foreign Exchange Market: An Order Flow Analysis

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## Abstract

This research applies the order flow analysis of exchange rate dynamics to the Chinese foreign exchange market in a vector autoregressive-modeling framework. An index order flow was constructed in the Chinese context to reflect excess demand pressure in the Chinese foreign exchange. Then a VAR model was estimated to investigate to what extent order flow may explain short-term fluctuations and long term determinations of the Chinese exchange rate.

This paper focuses on the cointegrating relation between cumulative order flow and the exchange rate of Chinese currency against the dollar. We find that in the new Chinese exchange rate policy regime, order flow as a measure of 'signed' trading volume is able to explain a significant part – one half to two-thirds – of fluctuations in the RMB-dollar exchange rate. The research uncovers the long-term cointegrating relation among the variables under examination, including order flow, macro influences and the exchange rate. The short-run dynamics show that the new Chinese policy regime is subject to significant government intervention.

**Key words**: Order Flow, Foreign Exchange Market, Exchange Rate Dynamics, and VAR Modeling

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# I. Introduction

Since the early 1980s, empirical research has cast serious doubt on the validity of macroeconomic models of exchange rates in explaining the behavior of exchange rates, especially its short-run dynamics. Meese and Rogoff (1983) demonstrated that macroeconomic models have poor explanatory performance in capturing foreign exchange rate movements. These models claim that the equilibrium exchange rate is exclusively determined by macro fundamentals and will change immediately on the impact of changes in fundamentals. Key assumptions of these models include homogeneity of investors, perfect information, no-cost of transaction and irrelevance of the transaction process to exchange rate determination. They typically deploy low frequency data (e.g. quarterly or yearly) for variables of macroeconomic fundamentals to estimate determinant of exchange rate movements. However, almost invariantly these models meet little success in capturing short-run dynamics and long run trend. Frankel and Rose (1994) show that traditional methods would get wrong signed coefficients or values not significantly different from zero. To modify the traditional models, efforts such as Mark (1995) and Taylor and McDonald (1995) were carried out to apply the cointegration technique to their analysis. But again, the performance has been poor.

In response, there has emerged a new approach to the exchange rate that features its focus on the microstructure of the foreign exchange market. It relaxes major assumptions of conventional models by assuming that (1) information structure on the foreign exchange market is not perfect and asymmetrical so existence of private information is possible; (2) market participants are heterogeneous; (3) different trading mechanisms are allowed (Lyons, 2001, p. 8). This approach proves to be capable explain a significant portion of exchange rate changes and so has been widely adopted for analyzing foreign exchange rate determination in the recent years.

In the microstructure approach to the exchange rate, order flow plays a pivotal role. Testing for its capability of transmitting information on price formation, recent empirical work has confirmed the explanatory power of order flow. Evans and Lyons (2002a) illustrate that order flow can explain about 60% and 40% of exchange rate changes in the exchange rates of DEM/USD and JPY/USD, respectively. However, prior studies are, mainly concerned with key international currency pairs. As China is the top reserve holder in the world, researchers have started to pay particular attention to the Chinese foreign exchange market. How to explain the trend of changes in the Chinese foreign exchange rate becomes a critical question.

The goal of this paper is to apply the VAR model to the China exchange rate by estimating the relation between order flow and the exchange rate in the short term and long term. In a VAR modelling framework, we try to answer the following questions:

1) Does order flow have explanatory power in the Chinese foreign exchange market?

2) To what extent does order flow capture the behaviour of the RMB exchange

rate against international currencies, particularly the US dollar?

3) To what extent can order flow analysis explain the price formation process in the Chinese foreign exchange market?

In order to explore these issues, we first construct a measure of order flow based on high frequency transaction data from the Chinese market, and compute the daily order flow. Second, we consider the trading system of the Chinese foreign exchange market. Before July 21 2005, the Chinese currency was under a fixed exchange rate regime. Since then, China has operated a managed floating exchange rate regime. Only authorized agents carry out foreign exchange transactions. Our sample covers July 1 2005 to June 30 2009, with a total of 1046 trading days.

Then, we add an additional variable, the country risk premium, which is shown to have explanatory power in prior studies. This variable is proxied by EMBI Global, which is supplied by J.P. Morgan and includes 27 countries to serve as a benchmark of investor demand for emerging markets debt.

Next, using the VAR modeling framework, we investigate into whether the cumulative order flow is cointegrated with exchange rates in the Chinese FX market.

Based on the optimal lag length of 15 using the smallest AIC, we estimate the unrestricted VAR. The results indicate that there exists unidirectional causality from order flow to exchange rate movements. The Johansen test indicates that there is one cointegrating relation in the system. Following this test, we set cointegration restriction on the system and we determine the unique long-term cointegration coefficient and the short-term factor of loading for the dynamics. This finding enables us to construct an error correction model in the multivariate setting (Vector error correction model, VECM). The results show that order flow not only Granger-causes RMB exchange rate movements, but also is significant determinant of the RMB exchange rate in the long run. In our sample, order flow explains approximately 27% of exchange rate movement for every $0.1m CNY/USD purchase.

This research therefore show that in the Chinese setting, order flow as a 'signed' measure of trading volume is able to explain a significant part – one half to two-thirds – of fluctuations in the RMB exchange rate against the dollar. This research uncovers the long-term cointegrating relation among the variables under examination, including order flow, the proxy for macro influences and the RMB/dollar exchange rate. The short-run dynamics show that the new Chinese policy regime is subject to significant government intervention.

The reminder of this paper is organized as follows. Section II briefly reviews previous studies on exchange rate dynamics in the microstructure approach. The review is grouped in two parts: one focused on theoretical underpinning of the approach and the other surveying the empirical research that applies the cointegration technique. In Section III, we introduce China’s exchange rate policy and discuss the development of China’s foreign exchange market from 1978 to 2009. Then, we examine the current Chinese foreign exchange trading system (CFETS) that is essential for the understanding of China's exchange rate policy from the microstructural perspective. Section 4 focuses on the order flow of China's foreign exchange market and discusses the construction of the index of order flow in the context of China's new exchange rate policy regime. This core variable then is deployed to develop a VAR model. Estimation of the model and interpretation of the results are all included in this section. We also discuss on the data collection, variable transformation, and modeling strategies. Section 5 offers conclusion of the research and identifies challenges for further research.

# II. Review of the Literature

In response to the poor explanatory performance in explaining foreign exchange rate movements by conventional macro models, the market microstructure approach, developed in research in the equity markets, has been widely used in analysis of exchange rate determination. O'Hara (1995, p.1) defines market microstructure as "the process and outcomes of exchanging assets under explicit trading rules". In security markets, trading has been considered a very important signal in the process of price formation. O'Hara (1995) and Madhavan (2000) identify three agents for this process: brokers, dealers and customers and the microstructure theory mainly examine dealers' behaviour. Two main strands of theories have emerged in this field, i.e. the inventory based models and the information based models.

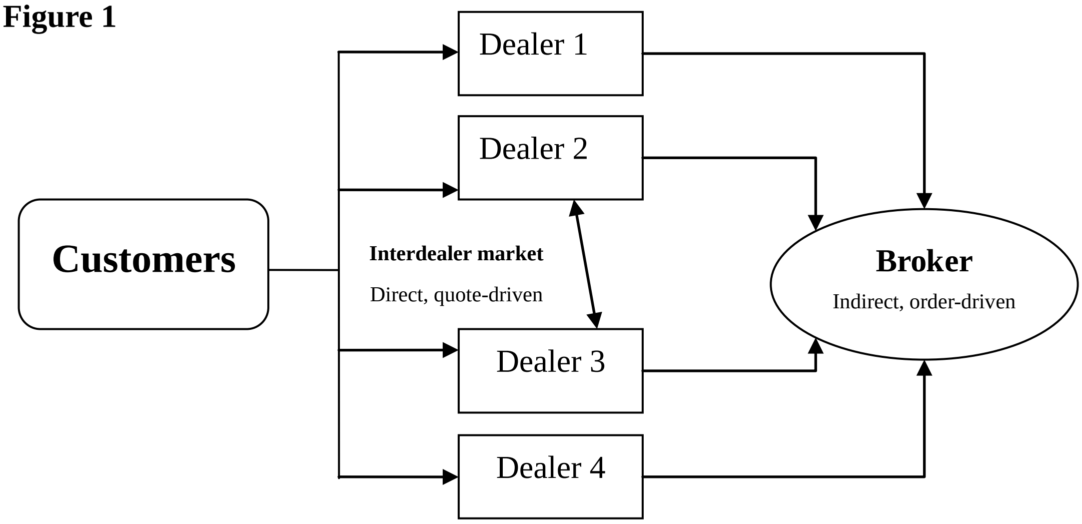
This section reviews the microstructure literature on exchange rates along the line of these two strands. In what follows, we first examine theoretical underpinning of the microstructure model and then review the empirical research which uses cointegration analysis. Gaps in the literature will finally be discussed to guide our own research.

## 2.1 Theoretical Underpinning

One critical element of the microstructure literature is its foundation on observations of key agents' behavior (Copeland, 2008). Demsetz (1968) develops a model for the security market bid-ask spread, measured as the difference between ask and bid prices. The study was among the first to highlight the importance of dealers' behavior while introducing transaction cost and regulation into securities' price formation. This emphasis on dealers' behavior has been followed by subsequent microstructure research including that in foreign exchange market.

In the currency market agents can be divided into three classes: brokers, customers and dealers. Copeland (2008) provides a graphic presentation of the general structure of currency markets:

**Figure 1**




(Source: *Foreign Exchange and International Finance*, Copeland 2008).

The figure 1 show the foreign exchange market is two-tier market, a market between customers and dealers and a market between dealers (through brokers). Dealers are the major players in this structure. Transactions in the currency market start with customers contacting the dealers to gain the buy or sell information, followed by dealers organizing different customers' price information to quote the price at which they are willing to buy or sell. Quoting of a competitive price is based on the notion that higher prices can attract market agents to sell the currency while a lower price can induce agents to buy, and dealers get their profit from the gap between the two, i.e. the bid-ask spread. On the basis of these quotes, customers then place their buy or sell orders with the dealers who in turn trade with other dealers through brokers. The market is therefore quote-driven and orders from the customers and between dealers play a pivotal role in the whole process.

Order flow is the critical variable missed out by macro models of exchange rates. Evans and Lyons (1999, 2002a, 2002b) show that order has significant and strong explanatory power for capturing exchange rate changes. It is order flow that makes distinguishes the microstructure models from macro ones.

However, the explanatory power of the order flow models however largely depends on the factors that drive the orders. In this regard, there are many empirical researches in the literature focus on order flow aggregates information and hence acts as medium linking fundamentals and exchange rate dynamics.

## 2.2 Empirical Research

In empirical specification, order flow is a major variable linking price changes and dispersed information.  Seminal research by Evans and Lyons (1999, 2002a) makes a radical departure from the conventional macro models. In what follows, we first examine the empirical research on explanatory power of order flow and then review the empirical research which uses cointegration analysis. Gaps in the literature will finally be discussed to guide our own research.

### 2.2.1 The Explanatory Power of Order Flow

In empirical specification, order flow is a major variable linking price changes and dispersed information. It is different from transaction volume in that it is signed (Lyons, 2001). Where the initiator of the transaction is on the sell side, the order flow takes a negative sign and the order flow takes on a positive sign while the initiator is on the buyer side. Order flow can be measured as the sum of the signed seller-initiated and buyer-initiated orders. A negative sum indicates net selling pressure over the period. Evans and Lyons (2002a, 2002b) regard order flow as the net balance of buyer-initiated and seller-initiated foreign exchange market transactions. Given this nature, order flow can be considered as an indicator of buying and selling pressure on a given currency that will affect its spot exchange rate.

Seminal research by Evans and Lyons (1999, 2002a) makes a radical departure from the conventional macro models. They develop a hybrid model that contains both a macro variable (interest differential) and a microstructure variable (order flow). Thus,

$$\Delta p_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \eta_t$$

Where $\Delta p_t$ is the change in the log spot rate from the end of day t-1 to the end of day t, $\Delta(i_t - i_t^*)$ is the change on the interest differential, and the $\Delta x_t$ is the order flow.

The datasets constructed are based on the four-month data of the Dutch mark and Japanese yen against the US dollar from Reuters D2000-1, respectively. They find that over 60% of USD/DEM daily changes, and 40% of USD/JPY daily changes can be explained by order flow. Evans and Lyons (2002b) extend their data set to seven currency pairs: the US dollar against the pound sterling, Belgian, French and Swiss francs, Swedish Krona, Italian lira and Dutch guilder. They find that order flow may generate $R^2$ up to 78% on daily rates.

The explanatory role of order flow in exchange rate models has been the focal point of empirical studies in the market microstructure approach. In this regard, empirical research may be grouped in terms of those using data of customer order flow and those using interdealer order flow.

For the research into the effect of customer order flow, Mende and Menkhoff (2003) use tick data from a German bank that involve the exchange rate of the euro against US dollar from July to November 2001. The data set covers customer order flow data for 87 trading days and they find a Granger-causal relationship between customer order flow and exchange rate returns.

Employing the Citibank customer order flow data (reflecting about 10% of daily customer order flow), Fan and Lyons (2003) find that real money flows can predict exchange rate trends. Evans and Lyons (2005) also use the customer order flow data of Citibank, and obtain similar results to those of Fan and Lyons (2003). Their paper additionally examines the order flow forecasting power in the exchange rate. Later, Evans and Lyons (2007) separate the Citibank customer order flow data into two frequencies, daily and weekly, and used cointegration analysis to find the relationship between the cumulative customer order flow and exchange rate movements. Marsh and O'Rourke (2005) use customer data from the Royal Bank of Scotland (one of the largest dealing banks) to analyze the relationship between daily customer order flow and exchange rate returns. Bjonnes et al. (2005) deploy further in their research, while Osler et al. (2007) analyze a single dealer reaction.

In their study of whether private information presents in the Tokyo foreign exchange market, Ito et al. (1998) find that private information is a plausible source of the changing pattern of return volatility. They also conclude that the informed order flow can predict the exchange rate of JPY/USD over short time period. Later, Danielsson and Payne (2002) examined a different data set, but obtain similar results. Bjonnes et al. (2005) utilize Norges Bank and Sveriges Riksbank trading volume data, and find that the instigating institution has the dominant role in the relationship between exchange rate and order flow.  They conclude that more than 33% of volatility can be explained by the informed order flow, while the uninformed order flow can explain 20% of volatility. Osler (2002, 2003) also argues that the exchange rate can be impacted by uninformed order flow. Bates et al. (2003), in their study of HSBC data, reach a similar conclusion.

Market conditions are another factor to be considered. Lyons (1996) and Payne (2000) have touched upon this area in their previous studies. Danielsson, Payne and Luo (2002) demonstrate a non-linear relationship between order flow and exchange rate movements. Using a sample of data from Reuters D2000-2 and the time period from September 1999 to July 2000, Danielsson, Payne and Luo (2002) finds that the sensitivity of the result depends on the different measures of market conditions. Osler (2002) presents significant evidence that under different hypotheses the limit order has different impacts on the New York morning trading and London afternoon trading sessions.

Studies of interdealer order flow and exchange rate movements can be found in for example Danielsson et al. (2002). They investigate into ten-month order flow data from the Reuters D2000-2 data platform, and find that order flow Granger-cause exchange rate returns. Fisher and Hillman (2003) follow Evans and Lyons (2002a, 2002b), but get lower $R^2$ statistics results. Actually, the feedback effects make the OLS estimate of the coefficient $\beta$ biased. Therefore, the feedback trading effect of the exchange rate on order flow which displayed by Evans and Lyons will misleading and spurious.

Microstructure models have been estimated by a variety of methods, including those of OLS, GMM, GARCH and VAR. To take feedback effect of exchange rate on order flow in consideration, the VAR modelling seems to be a preferred strategy in the literature.

### 2.2.2 Cointegration between Order Flow and Exchange Rate

In an early study of the NYSE, Hasbrouck (1991) develops a simple linear VAR model for the microstructure study. Payne (2003) borrowed this modelling strategy to analyzing the foreign exchange market. He draws on the one week exchange rate of USD/DEM from Reuters D2000-2, and the time period 6 October to 10 October 1997. Results show that 60% of variation can be explained by the private information. Payne concludes that an informed order flow has explanatory power for exchange rate returns.

Froot and Ramadorai (2005) set up a VAR model to analyse order flow as a major medium of that affect exchange rate movements along with fundamentals. Froot and Ramadorai (2005) divide the exchange rate returns into permanent and transitory shocks, and study the interactions between them. They illustrated that order flow is related to short-term currency returns while fundamentals better explain long-term returns. This highlights the importance of research into the role of order flow in short-term dynamics and long-term determination of the exchange rate.

For cointegration analysis, while Rime (2001) deploys single equation residual-based tests for cointegration, Bjonnes and Rime’s (2005) cointegration analysis applies the Johansen technique that is system based. Killen et. al (2006) make use of both the single equation and system method.

Rime et al. (2010) argue that order flow of other currencies should be included in the model specification as they can greatly increase the explanatory power of interdealer order flow. In an earlier study, Rime (2001) use five major currency pairs: DEM/USD, GBP/USD, CHF/USD CAD/USD and JPY/USD from July 1995 to September 1999. The result of cointegration tests show that the exchange rates for DEM/USD, GBP/USD and CHF/USD have a cointegrating relationship with order flow, but the exchange rates for CAD/USD and JPY/USD do not. Rime (2001) concludes that the lagged order flow has explanatory power in exchange rate movements.

The information based models implies that order flow should permanently affect market prices hence exchange rates should be cointegrated with cumulative order flow. Recent research has uncovered evidence for such a stable long-term relationship for several currency pairs (Rime, 2001, Bjonnes and Rime, 2005, and Killen et al. 2006). Bjonnes and Rime (2005) use two methods in their paper. They use a major Scandinavian bank’s tick by tick data with four dealers and covering March 2-6, 1998. Applied the Johansen approach, they find there is no evidence of inventory control via dealer’s price but private information is confirmed. They show that the order flow and exchange rate price are cointegrated. That means the order flow and exchange rate price have long-time relationship.

Recently, Killeen et al. (2006) deploy the Electronic Broking System (EBS) daily data, and find similar results from the cointegrating vector tests. They use the FRF/DEM data covering four month data in the interdealer market from EBS. They find the significant evidence of cointegration that order flow have permanent effect on exchange rate price.

Boyer and van Norden (2006) however call for caution believing that their results are selective, sometime statistically weak and suffer from small sample bias. They perform cointegration tests on a dataset of Evans and Lyons (2002a, 2002b), which is commonly used in other research. They claimed that some researchers use the selective evidence to presents their cointegration result and some are also weak. And other researchers are using small samples to presents cointegration. These small samples will increase the number of variables and the number of lags as well. This will affect the covariance matrix of the residuals. However, under the no cointegration null hypothesis, it can be use the bootstrap or other methods to find the proper distribution. Strikingly, they do not find evidence of cointegration between order flow and exchange rates.

Of these, in this paper using the VAR modelling framework, we investigate into whether the cumulative order flow is cointegrated with exchange rates in the Chinese FX market.

# III. Order Flow Analysis of Exchange Rate Dynamics in China

To better our understanding of the Chinese exchange rate policy, we follow the microstructure approach to analyzing exchange rate dynamics in the Chinese foreign exchange market, as opposed to traditional macro models. At the core of this approach is the variable of order flow, which we will first construct a new index as its proxy reflecting excess demand pressure in the Chinese foreign exchange. In a VAR modeling framework, we try to answer the following questions:

1) Does order flow have explanatory power in the Chinese foreign exchange market?

2) To what extent does order flow capture the behavior of the RMB exchange rate against international currencies, particularly the US dollar?

3) To what extent can order flow analysis explain the price formation process in the Chinese foreign exchange market?

## 3.1 Order Flow and its Measure

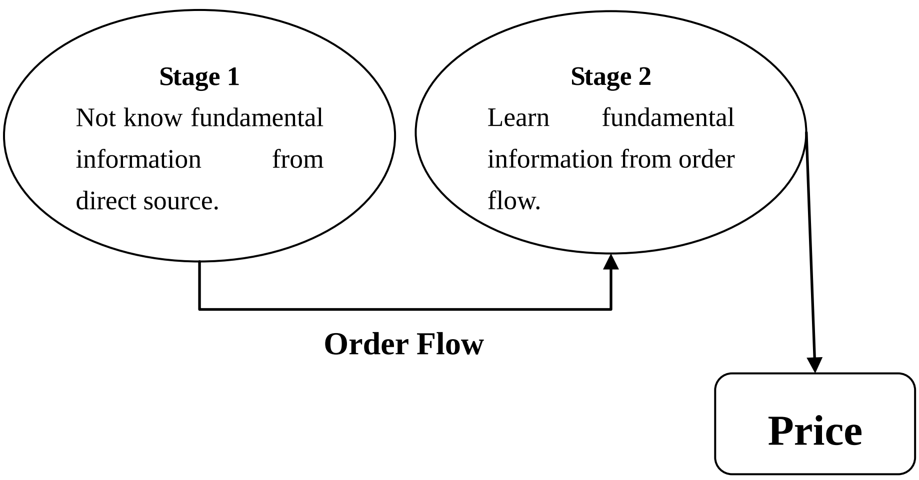
Lyons (2001) points out that order flow and bid-ask spread is the core microstructure variables to transmit and reflect private information. These microstructure attributes define, respectively, the volume and price of foreign exchange transactions. In particular, order flow, as the aggregator of dispersed information regarding macro fundamentals, is the medium between macroeconomic fundamentals and exchange rates hence is the critical driving force behind exchange rate dynamics. However, this variable is not directly observable, so we need to construct a measure of order flow as our first step in the order flow analysis of the Chinese foreign exchange market.

### 3.1.1 Definition of Order Flow

O’Hara (1995, p.1) defines market microstructure as “the process and outcomes of exchanging assets under explicit trading rules”. This definition broadly explains the microstructure approach that looks at participants in the market and their constraints in the trading process. The application of this approach to foreign exchange market has produced some promising results in explaining exchange rate changes. Central to this progress is the application of the order flow analysis.

Order flows are a variable that may reveal the 'motive' of the participant initiating the transaction in foreign exchange. Evans and Lyons (2002) show that order flows provide information about the necessary risk premiums required to clear the market. They can also reflect return-relevant information that is dispersed among market participants (Evans and Lyons, 2003). Given that macro statistics are an aggregate of an array of micro information and are usually announced with a lag, it is also possible such micro information may be released to the market through customer order flows. Consequently, order flows may reflect dispersed micro elements of information that will be aggregated and published as macro fundamentals. By observing order flows, market-makers who determine the exchange rate can collect such information from traders, and therefore can aggregate information, which they previously did not have, into the exchange rate (Rime, 2006). Empirical analysis shows that order flows are able to explain a significant part – one half to two-thirds – of the exchange rate fluctuations (Evans, 2002). The following figure shows the information processing stages.

**Figure 1**




(Source: Lyons 2001, *The Microstructure Approach to Exchange Rates*).

Order flow is different from transaction volume in that it is signed (Lyons, 2001). Where the initiator of the transaction is on the sell side, the order flow takes a negative sign and the order flow takes on a positive sign while the initiator is on the buyer side.  Then order flow can be measured as the sum of the signed seller-initiated and buyer-initiated orders. A negative sum indicates net selling pressure over the period. Evans and Lyons (2002a, 2002b) therefore regard order flow as the net balance of buyer-initiated and seller-initiated foreign exchange market transactions. Given its nature, order flow can be considered as an indicator of buying and selling pressure on a given currency that will affect its spot exchange rate.

### 3.1.2 Construction of the Measure of Order Flow

Order flows are not directly observable. One way to capture the order flow is from the transaction records (Lyons, 2001). However, in the real world, confidentiality means that complete transaction records are not available to researchers. In this situation, there are two proposed methods for computing order flow. One is to estimate one period and the next period end-user currency holdings from portfolio holdings. The other is to compare two sequential time periods, quoting price from transaction price (Evans, 2010). In this section we follow the latter method to construct measures of order flow without details of every transaction.

Order flow is transaction volume that is signed. So in order to obtain the order flow, it is necessary to get the transaction volume. In the foreign exchange market, there are two major electronic trading platforms: Thomson Reuters and the Electronic Brokerage System (EBS). Reuters generally provides data only on the number, not the volume, of trades. However, since, as shown in Bjonnes and Rime (2005) and Killen et al. (2006), analyses based on trade size and number of trades are not qualitatively different, our not having the trade volume should not influence the empirical analysis and results.

On the other hand, in order to figure out the order flow we need to identify whether the trade is buyer or seller initiated, and most data do not supply the trade direction. We now first tackle this problem by finding different methods to infer trade direction from adjacent prices and quotes.

To understand how these algorithms work, Let $S^B_t$ and $S^A_t$ denote the most recent bid and ask quotes for FX before a trade takes place at time t with a transaction price of $S_t$. There are two major methods of inferring trade direction, as follows:

(1) Tick test, which use changes in trade prices to infer direction. For this test we compare the previous trade price and current trade price. If the trade occurs at a higher price than the previous trade (an uptick), it is classified as a buy. If the trade occurs at a lower price than the previous trade (a downtick) it is classified as a sell. When the price change between trades is zero (a zero tick), the trade is classified using the last price that differs from the current price. Lyons (1995) and Sias and Starks (1997) have used the tick test. The rules used to identify whether the trade is initiated by the buyer or seller of FX are laid out in the following table.

**Table 1**

| Algorithm | Condition | Inference for trade at *t* |
|---|---|---|
| Tick Test | $S_t > S_{t-1}$ | Buyer-Initiated |
| | $S_t < S_{t-1}$ | Seller-Initiated |

The reverse tick test is similar, but uses the next trade price to classify the current trade. If the next trade occurs on an uptick or zero uptick, the current trade is classified as a sell. If the next trade occurs on a downtick or zero downtick, the current trade is classified as a buy.

(2) The Lee and Ready Method. Lee and Ready (1991) extend the tick test to infer

trade direction by comparing trade prices to quotes. For this test we need the bid-ask price and account the midpoint price data. Trades above or below the midpoint are classified as buys or sells. Here the current transaction price, $S_t$, is first compared against the midpoint of the prevailing quotes, $1/2(S^A{}_t + S^B{}_t)$. If this comparison fails to identify the initiator because $S_t = 1/2(S^A{}_t + S^B{}_t)$, the trade is then classified using the tick test. The rules used to identify whether the trade is initiated by the buyer or seller of FX are displayed in the following table.

**Table 2**

| Algorithm | Condition | Inference for trade at *t* |
|---|---|---|
| | $S_t > 1/2(S^A{}_t + S^B{}_t)$ | Buyer-Initiated |
| | $S_t < 1/2(S^A{}_t + S^B{}_t)$ | Seller-Initiated |
| | | Lee and Ready (1991) |
| | $S_t = 1/2(S^A{}_t + S^B{}_t)$ and $S_t > S_{t-1}$ | Buyer-Initiated |
| | $S_t = 1/2(S^A{}_t + S^B{}_t)$ and $S_t< S_{t-1}$ | Buyer-Initiated |

For our research, the original foreign exchange quote data are from Olsen Data. However, they only supply the bid, ask and mid quote data for every tick. We contribute to the literature by identifying how to use the bid and ask quote in construct the index of order flow in this setting. In this paper, we use the quote test which is a combination of the tick test and the midquote test. For example, if the current trade price is closer to the last ask quote that it can be classified as buyer initiated and signed +1. If the current trade price is closer to the last bid quote that it can be classified as seller initiated and signed -1. We use the direction of the last price change to determine when the current price is equal to the midquote.

## 3.2 Source of Data

Of the two major electronic trading platforms in the foreign exchange market, Reuters generally provides data only on the number, not the volume, of trades. For confidentiality reasons, the complete transaction records are not available to researchers. The original foreign exchange rate transaction data for this paper come from Olsen Data. Olsen Financial Technologies is one of the world's largest database providers. They supply tick-by-tick prices for researchers and financial institutions, including the high-frequency data for foreign exchange, futures, interest rates and other markets.

The dataset of this research comprises foreign exchange transactions data of Chinese renminbi (RMB) against the US dollar between July 1st 2005 and June 30th 2009, covering 1046 trading days. Trades are recorded 24 hours a day, in Beijing Time (GMT+8). To construct a spot order flow, a value of +1 is assigned to each buy trade and -1 to each sell trade. One-day spot order flow is then equal to the sum of the trade signs over a 24-hour period. The daily order flow is the difference between the buyer-initiated and seller-initiated of the whole day.

Measurements of three further variables, the spot rate, interest rate differentials and country risk premiums, are as follow. The spot rate change (RMB/USD) is the first difference of log exchange rate transaction price. This data set excludes Chinese holidays. If day t is Monday then day t-1 should be the Friday of the previous week. The interest rate differential is the daily overnight interest rate of RMB (Shibor) minus the daily overnight interest rate of the dollar (Federal Reserve); the source is DataStream. These interest rate data are on an annual basis and for the time period 0 to 24 pm. Finally, we introduce an additional variable, the country risk premium. The daily country risk premium data cover a 24 hour period; they are equal to the Emerging Market Bond Index Global (EMBI Global) calculated by JP Morgan; the source is DataStream. Further data details will be given in the section on VAR specifications.

## 3.3 Methodology

The empirical methodology of microstructure theory has two major parts: a statistical model and a structural model (Lyons, 2001). Both types of model are suitable for market maker markets, especially the foreign exchange market. There are two typical statistical models: Vector Autoregression (VAR) and Trade-Indicator. The main structural model is the Dealer-Problem approach. This paper tests the empirical implications of the Portfolio Shift model (Evans and Lyons, 2002a) and uses the VAR framework to estimate the explanatory power of order flow for exchange rate movement in China's foreign exchange market.

The VAR model was introduced by Sims (1980), and was applied by Hasbrouck (1991) for microstructure theory in the securities market. In recent literature, this tool has been commonly used for currencies (see such as Evans, 2002; Payne, 2003; Froot and Ramadorai, 2005; Danielsson and Love, 2006).

### 3.3.1 The VAR Model

Before estimating the VAR approach, we consider the assumptions of the model. The VAR model in this empirical work is based on the following behavioural assumptions:

1. The public information immediately reflects the quotes, and
2. The informed traders exploit their profit through using their market orders.

Let $Y_t$ represent a vector of transaction characteristics and $Z_t$ be the lag of each transaction characteristic, where $t$ is an event-time observation counter. The VAR model used in this empirical work is as follows:

$$Y_t = BZ_t + E_t \qquad (1)$$

And,

$$Y_t = \begin{pmatrix} P_t \\ X_t \\ (i-i^*)_t \\ R_t \end{pmatrix}_{4\times 1} \; ; \; B = \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,4r} \\ \vdots & \ddots & \vdots \\ \beta_{4,1} & \cdots & \beta_{4,4r} \end{bmatrix}_{4\times 4r} \; ;$$

$$Z_t = \begin{pmatrix} P_{t-1} \\ \vdots \\ R_{t-r} \end{pmatrix}_{4r\times 1} \; ; \; E_t = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{pmatrix}_{4\times 1} \; .$$

Where,

$P_t$ is the change of exchange rate;

$X_t$ is the accumulated order flow;

$(i-i*)_t$ is the interest rate differential;

$R_t$ is the country risk premium.

The VAR equations are estimated by OLS and are reported with heteroskedasticity robust standard errors.

## 3.3.2 Variable Space in the VAR Specification

The specifications of the VAR model built to test for exchange rate changes are demonstrated in the following equation:

$$Y_t = \Gamma Y_{t-1} + \varepsilon_t \qquad (2)$$

Where,

$$Y_t^{'} = [P_t X_t (i-i*)_t R_t]$$

$P_t$ stands for the change of exchange rate; $X_t$ stands for the accumulated order flow; $(i-i*)_t$ stands for the interest rate differential; $R_t$ stands for the country risk premium.

We include another variable in the variable space when investigating the explanatory power of order flow for the RMB/USD exchange rate. This additional variable represents the country risk premium. The variable $P_t$ and the companion matrix $\Gamma$ are allowed for a general number of lags and are constant across currencies. $\mathrm{E}[\varepsilon_t \varepsilon_t^{'}] = \Sigma$ is the covariance matrix; it allows residuals across currencies for contemporaneous correlation.

Theoretically, the cost of credit represents a marginal loan for country *i* during the year *t*. However, in practice, the cost of credit is difficult to measure. Berganza et al. (2004) claim that the best available proxy to measure country risk premium, and the most widely used in the literature, is the Emerging Markets Bonds Indices (EMBI). The EMBI Global includes 27 countries, and serves as a benchmark of investor demand for emerging markets debt. According to J.P. Morgan (1999): "The country risk premium equals returns for US dollar-denominated Brady bonds, loans, Eurobonds, and US dollar-denominated local markets instruments for emerging markets minus total returns for US Treasury bonds with similar maturity (the stripped yields of the EMBI for each country)." In this paper we download the EMBI daily data of China from DataStream. The descriptive statistics for the variables are recorded in Table 3.

**Table 3**

**Descriptive Statistic Summary of Estimation Variables**

| Daily Frequency | Exchange Rate | Order Flow | Interest Rate | Country Risk Premium |
|---|---|---|---|---|
| Obs. | 1043 | 1043 | 1043 | 1043 |
| Mean | 2.012771 | -101.8523 | 0.016226 | 5.636288 |
| Median | 2.029923 | -16 | 0.024 | 5.62293 |
| Maximum | 2.11342 | 2927 | 0.0393 | 5.789648 |

| | | | | |
|---|---|---|---|---|
| Minimum | 1.917055 | -5313 | -0.0372 | 5.535699 |
| Skewness | -0.264437 | -0.676844 | -0.56015 | 0.400754 |
| Kurtosis | 1.44834 | 14.10706 | 1.757416 | 2.014375 |
| Std. Dev. | 0.067095 | 549.2065 | 0.01781 | 0.073659 |
| Jarque-Bera | 116.7881 | 5440.947 | 121.6437 | 70.13613 |
| Probability | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Source: *Olsen Data and DataStream.*

### 3.3.3 Lag length

While the VAR as a modeling framework has its unique advantages. one of the major difficulties in deploying this framework involves how to determine the appropriate lag length for the variables in the system. Two methods for choosing the optimal VAR lag length have been suggested in the literature, the methods based on information criteria and on cross-equation restrictions. Cross-equation restriction method requires the Block F-test, which would make it intractable in the VAR setting (Brooks, 2009). We therefore use the Akaike Information Criteria method. The Information Criteria method is required where the number of independent variables is higher; it provides a balance between increase of penalty term and reduction of RSS. The multivariate information criteria can be defined by the following equation:

$$AIC = \log\left|\hat{\Sigma}\right| + \frac{2k^{'}}{T}\log(\log(T)) \qquad (3)$$

Where, $T$ is the total number of observations; $k^{'}$ is the number of repressors; $\hat{\Sigma}$ is the residuals variance-covariance.

$$T = p^2 k + p \qquad (4)$$

This means the *k* lags of the *p* variables in the *p* equations in the VAR.

We perform the ADF test and find the smallest AIC for the optimal lag length. The results are shown in Table 4.

**Table 4**

**Optimal Lag Length from AIC**

| Lag | AIC | SC | Lag | AIC | SC |
|---|---|---|---|---|---|
| 1 | -12.3003 | -12.2053 | 16 | -12.7072 | -11.458 |
| 2 | -12.2908 | -12.1197 | 17 | -12.6893 | -11.3621 |
| 3 | -12.2953 | -12.048 | 18 | -12.6818 | -11.2767 |
| 4 | -12.2915 | -11.9678 | 19 | -12.6603 | -11.177 |
| 5 | -12.2918 | -11.8916 | 20 | -12.6497 | -11.0881 |
| 6 | -12.2858 | -11.809 | 21 | -12.6366 | -10.9966 |
| 7 | -12.2657 | -11.7122 | 22 | -12.6365 | -10.918 |
| 8 | -12.2606 | -11.6303 | 23 | -12.6405 | -10.8434 |
| 9 | -12.2917 | -11.5845 | 24 | -12.6246 | -10.7487 |
| 10 | -12.2714 | -11.4871 | 25 | -12.6251 | -10.6704 |
| 11 | -12.2504 | -11.3889 | 26 | -12.6139 | -10.5802 |
| 12 | -12.238 | -11.2992 | 27 | -12.6003 | -10.4874 |
| 13 | -12.2337 | -11.2175 | 28 | -12.5944 | -10.4022 |
| 14 | -12.2366 | -11.1428 | 29 | -12.606 | -10.3345 |
| **15** | **-12.7277** | **-11.5562** | 30 | -12.5909 | -10.2399 |

**Note:** The table shows the VAR lag order selection criteria. Optimal lag length is chosen using the Akaike information criterion, which is reported under the column head of AIC

From the table we find the smallest AIC from the lag length 15. In estimating the VAR system, we then decide a lag length of 15 for each variable in the system.

## 3.4 Modelling Process and Estimation Results

Before formally investigating the VAR model, we check the stationary of the variables in the system. We find that all the variables except order flow have a unit root. Table 5 shows the results of Augmented Dickey-Fuller test.

**Table 5**

**Summary of Unit Root Results for Level Data**

| ADF Test | **Exchange Rate** | **Order Flow** | **Interest Rate** | **Country Risk Premium** |
|---|---|---|---|---|
| t-statistic | -0.655845 | -28.99653 | -1.470185 | -0.29206 |
| Prob. | 0.8553 | 0.0000 | 0.5486 | 0.9235 |
| Test Result | Unit Root | No Unit Root | Unit Root | Unit Root |
| | 1% level | | -3.436407 | |
| Critical Value | 5% level | t-statistic | -2.864103 | |
| | 10% level | | -2.568186 | |

**Note:** The table summarizes unit root results from level data. This test uses Augmented Dickey-Fuller Test equation is automatically based on SIC, maximum lag being 21.

We then move to estimate a unrestricted VAR with 15 lags to investigating into the long-run relation between the variables of interest. Following the modeling strategy of general to specific, we will form a vector error correction model (VECM) using the detected long-run, cointegrating relation. The VECM will then be used to estimate a structural system in the setting of a parsimonious VAR. On route, we also test for the Granger Causality in the system.

## 3.4.1 Unrestricted VAR

Our first results concern the unrestricted VAR, given by equation (1) with 15 lags. Estimation results are collected in Table 6. $\sum_i \beta_i$ is the sum of the asymmetric information coefficients from the VAR. Indicatively, the coefficient on the variable of order flow is significant and positive. The Granger Causality regression shows that order flow Granger causes exchange rate movements and that lags of order flow are significant in the equation for exchange rate movement. In other words, order flow Granger-causes exchange rate movement. Overall, this test result shows for the first time that there exists unidirectional causality from order flow to exchange rate movement.

**Table 6**

**Summary of Unrestricted VAR Results**

| | $P_t$ | $X_t$ | $(i-i^*)_t$ | $R_t$ |
|---|---|---|---|---|
| Lag | 15 | 15 | 15 | 15 |
| AIC | -11.34269 | 15.46647 | -8.865285 | -7.953966 |
| $\Sigma_i \beta_i$ | 1.001218 | 2.7134E-07 | -0.0089243 | -0.0006845 |
| $x^2(\beta_i)$ | Dependent Variable | 31.9852 | 21.7862 | 20.0074 |
| Prob. | | (0.0065) | (0.1135) | (0.1717) |
| $x^2(\beta_i)$ | 16.25055 | Dependent Variable | 39.81971 | 10.62851 |
| Prob. | (0.3656) | | (0.0005) | (0.7785) |

**Notes:** The table summarizes the unrestricted VAR results for the level data. The row headed 'Lag' reports the number of lags in the VAR, chosen using the AIC which is reported in the second row. The third row is the sum of the asymmetric information coefficients from the VAR. The forth row gives a Wald test statistic for the null hypothesis that all variables are zero.

## 3.4.2 The Long-Run Equilibrium

We next test for cointegration ranks in the system using the Johansen systemic approach. Results are reported in Table 7. One significant cointegration rank likely exists in our model, which prompts us to set the cointegration rank =1 to restrict the system. The long-run cointegration coefficients are given by β, while the α coefficients give the short-term adjustment speed to the deviations from the long run equilibrium. .

**Table 7**

**Summary of Johansen Cointegration Test**

| Number of CE | Eigen value | Trace Statistics | 0.05 CV | Prob. |
|---|---|---|---|---|
| None * | 0.04304 | 73.47696 | 47.85613 | 0.0000 |
| At most 1 | 0.021165 | 28.2512 | 29.79707 | 0.0746 |
| At most 2 | 0.00595 | 6.25958 | 15.49471 | 0.6648 |
| At most 3 | 1.21E-04 | 0.124603 | 3.841466 | 0.7241 |

Tests of cointegration restrictions

| B(1,1)=1 | $P_t$ | $X_t$ | $(i-i^*)_t$ | $R_t$ |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| β | 1.0000 | -0.000228 | -0.251809 | 0.74035 |
| | (0.0000) | (3.30E-5) | (0.61181) | (0.14675) |
| α | -0.00155 | 2189.118 | -0.003109 | -0.004908 |
| | (0.00062) | (410.744) | (0.00215) | (0.00337) |

**Note:** From the table, the trace test statistic indicates 1 cointegrating relation at the 0.05 level. The system then is restricted by cointegration rank one. The cointegration coefficients and adjustment coefficients with their standard error are all shown in the table. Lags interval (in first differences) being 1 to 14.

Table 7 shows that the cointegration coefficients on order flow and the risk premium are significant at the 5% level. The long-run relationship is shown in the following equation:

$$P_t = 0.000228*X_t + 0.251809*(i-i^*)_t - 0.74035*R_t. \qquad (5)$$

From equation (5), we find that the cointegration coefficient β on the order flow variable $X_t$ is correctly signed and significant. The interest differential is also correctly signed but insignificant. That the β coefficient on order flow variable $X_t$ is positive implies a higher CNY price of dollars when the net buying imbalance is higher. Given a coefficient of 0.0000228 in the RMB exchange rate equation, every 10% increase in order flow will increase the RMB price of the dollar by 0.228 % within the day. The variable that captures the macro fundamental influence – the interest differential - is signed positive. This may reflect the fact that the interest differential can be considered as risk-free return of currency investment, if the interest rate of the dollar $i_t$ is not changed while the interest rate of the RMB $i_t^*$ increased. It is also plausible that, under uncovered interest parity, CNY/USD will increase to make room for dollar depreciation. All these mean that the long-run cointegration coefficient β on the interest differential is signed correctly. The long-run cointegration coefficient β on the country risk premium is also significant. We also present a graph which shows responses of the shocks of these variables to exchange rate movements.

Using the cointegration coefficients from Table 10, we construct the error correction term as follows:

$$1 = P_t + (-0.000228)*X_t + (-0.251809)*(i-i^*)_t + 0.74035*R_t.$$

This error correction presentation then is used to construct the VECM model, with all the original variables differenced by one period to make I (0), i.e. stationary. Regression results from estimating this system, the sum of the asymmetric information coefficients and Granger Causality test are listed in Table 8. From the Table, one can find not only the long-run relation of between exchange rate changes and its determinants, but also the short-run dynamics of the system adjusting to the long-run equilibrium.

**Table 8**

**Summary of Vector Error Correction Model Estimation Results**

Error Correction Term

$CointEq1 = P_t + (-0.000228)*X_t + (-0.251809)*(i-i^*)_t + 0.74035*R_t$

Regression Result

| | | $\Delta P_t$ | $\Delta X_t$ | $\Delta(i-i^*)_t$ | $\Delta R_t$ |
|---|---|---|---|---|---|
| | $\alpha$ | -0.00155 | 2189.118 | -0.003109 | -0.004908 |
| | $\Sigma_i\delta_i$ | 0.0798 | 78834.63886 | -0.0326 | -0.151035 |
| $\Delta P_{t-i}$ | $x^2(\beta_i)$ | | 9.668356 | 8.709574 | 13.91423 |
| | Prob. | | 0.786 | 0.8492 | 0.4561 |
| | $\Sigma_i\delta_i$ | -2.7156E-06 | -3.519516 | 3.2904E-06 | -1.0952E-05 |
| $\Delta X_{t-i}$ | $x^2(\beta_i)$ | 34.04531 | | 96.70529 | 8.117178 |
| | Prob. | 0.002 | | 0.0000 | 0.8831 |
| | $\Sigma_i\delta_i$ | 0.0769145 | -28720.7597 | -1.163084 | -0.085596 |
| $\Delta(i-i^*)_{t-i}$ | $x^2(\beta_i)$ | 16.17512 | 35.27562 | | 9.027061 |
| | Prob. | 0.3028 | 0.0013 | | 0.8293 |
| | $\Sigma_i\delta_i$ | 0.007406 | -30862.1678 | 0.126582 | -0.013763 |
| $\Delta R_t$ | $x^2(\beta_i)$ | 19.62508 | 9.451003 | 26.81571 | |
| | Prob. | 0.1424 | 0.8011 | 0.0203 | |
| R-squared | | 0.087805 | 0.502041 | 0.187332 | 0.074105 |
| Adj. R-squared | | 0.034201 | 0.47278 | 0.139577 | 0.019697 |

**Note:** The table shows the results of estimating the VECM. CointEq1 is the errer correction to the cointegration equation. $\alpha$ is the adjustment coefficient while. $\Sigma_i\delta_i$ is the sum of the asymmetric information coefficients from the VECM. The following line gives a Wald test statistic for the null hypothesis that all are zero. Lags interval (in first differences): 1 to 14.

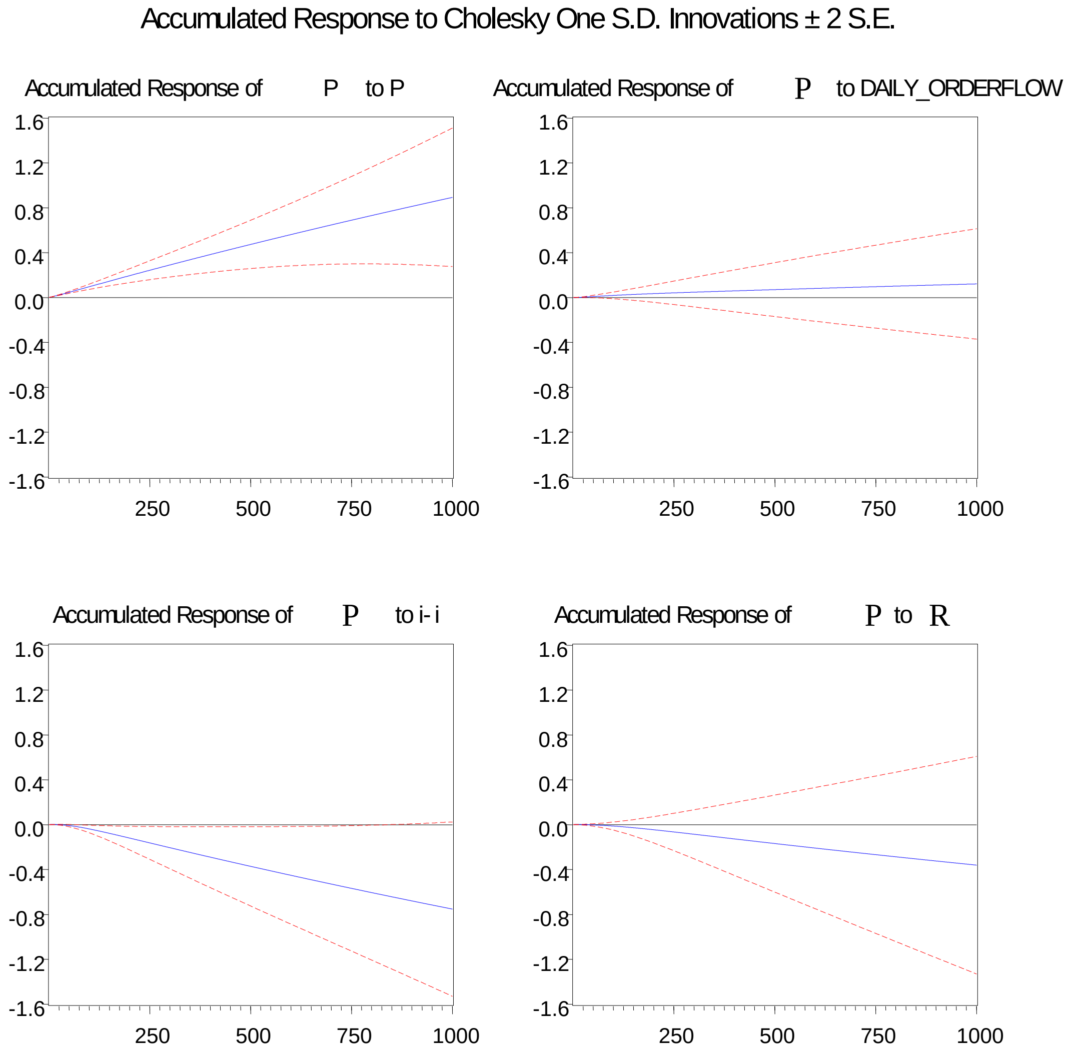
In the equation for exchange rate movements $\Delta P_t$, we find lags of order flow $\Delta X_{t-i}$ are significant. The result from vector error correction model estimates is similar to that of unrestricted VAR. This means that order flow not only Granger-causes exchange rate movements but also has explanatory power in capturing changes in the Chinese exchange rate in the long run. For example, order flow explains approximately 0.0027% of exchange rate movements for every 10% changes in the order flow of CNY/USD.

Comparing our specification with that of Evans and Lyons (2002a), although the coefficients are both significant, the $R^2$ of our model is lower. Evans and Lyons (2002a) get 0.64 and 0.46, but our $R^2$ is only 0.0878. Two possible reasons may explain the differences. First, as mentioned preciously, in developing countries there tends to be more government intervention in the foreign exchange; for example, in their analysis of order flow in Brazil, the De Medeiros (2005) obtained 0.06 $R^2$ in the R$/US$. Second, for the long term, not only is order flow correctly signed and significant; we also include the correctly signed interest rate differential and significant country risk premium.

Next, we explore the responses of the system to the shocks. The impulse responses and variance decomposition results are shown in the following figures.

Figure 2 shows the VAR impulse response of exchange rate movements to the shocks of all the other variables. The first graph shows that the exchange rate has a positive and stable shock to the next term exchange rate. The other three graphs show that the exchange rate movement happens immediately and stably in response to various shocks. Figure 3 demonstrates the components of the variance of exchange rate movements. The graph shows that the size of the permanent exchange rate shock is reduced while timing increases, but other variables increase over time. Table 12 shows the proportion of the permanent variance over different time periods. The results show that the proportion of the interest differential increases with time. In the long horizon, the interest differential has a strong influence on exchange rate movements. Country risk premium shows a similar tendency but to a much lesser extent. In the short horizon, order flow responds immediately to exchange rate movements and more strongly than other variables, excluding the RMB exchange rate itself.

**Figure 2**




**Note:** This figure shows the response of exchange rate movements to each variable shock. The blue line is the response of exchange rate movements, while the dashed red lines display 2 standard error bounds.

**Figure 3**

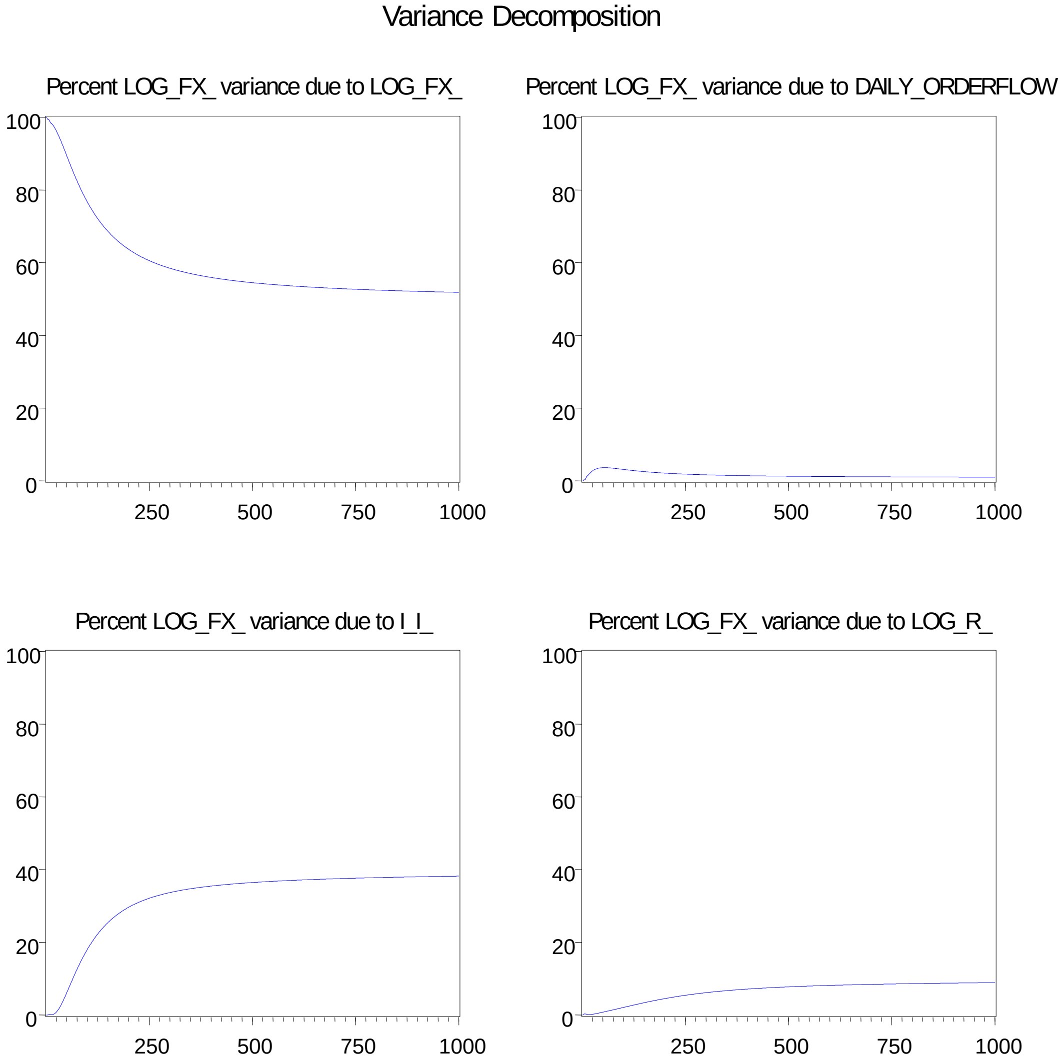



**Table 12**

| Period | S.E. | | | | |
|---|---|---|---|---|---|
| 1 | 0.00081 | 100 | 0 | 0 | 0 |
| 10 | 0.002512 | 98.69765 | 0.945329 | 0.109403 | 0.247615 |
| 100 | 0.01091 | 76.71567 | 3.157416 | 18.02018 | 2.106737 |
| 500 | 0.028665 | 54.49854 | 1.281163 | 36.4454 | 7.7749 |
| 1000 | 0.039286 | 51.8381 | 1.018449 | 38.20696 | 8.936493 |

**Note:** This table shows the components of the variance of exchange rate movements. Time period is from 1 to 1000. The residual-based bootstrap of the model uses 1000 bootstrap replications.

# V. Conclusion

This research concerns the long term determinants and short term dynamics of the Chinese exchange rate, with a particular emphasis on the role of cumulative order flow in the process. Using an innovative method without every transaction record details, we construct a measure of daily order flow in the Chinese setting to reflect excess demand pressure in the Chinese foreign exchange market. A new variable, i.e. the country risk premium, is included in the variable space, along with the exchange rate, order flow and interest rate differential. To investigate the behaviour of the Chinese exchange rate in terms of its short-run dynamics and long-run equilibrium, we develop a VAR framework for the estimation. We find that cumulative order flow is cointegrated with exchange rates in China's foreign exchange market. We find that in the new Chinese exchange rate policy regime, order flow as a 'signed' measure of trading volume is able to explain a significant part – one half to two-thirds – of fluctuations in the RMB exchange rate against the dollar.

Evidence shows that order flow has a strong and positive explanatory power in the Chinese foreign exchange market. We find that the coefficient β on our order flow variable $X_t$ is positive, suggesting its positive association with the CNY price of the dollar. The coefficient is 0.0000228 in the RMB equation, which implies that on a day with a 10% increase in net purchase of dollars, the RMB price of the dollar would increase by 0. 228 %. The outcome of impulse responses indicates that order flow responds immediately and more strongly than other variables (excluding exchange rates themselves) to the exchange rate movement over the short horizon. In the long horizon, the interest rate differential has a strong influence on exchange rate movement. Country risk premium shows a similar tendency but to a lesser extent.

Comparing our specification with that of Evans and Lyons (2002), we find an interesting detail. The coefficients in our research and theirs are both significant, but our $R^2$ is quite low, only 0.0878, while Evans and Lyons (2002) get 0.64 and 0.46. But this is consistent with finding of similar research into Brazil, also a major emerging economy.  It seems that that government intervention in the emerging foreign exchange market may be the cause for this difference.

In summary, this research uncovers the long term cointegrating relationship among the variables under examination, including order flow, the proxy for macro influences and the exchange rates. The short run dynamics show that the new Chinese policy regime is subject to significant government intervention.

Several interesting areas have emerged for further research. First, one may improve the VAR structure to include more variables of influence. Data availability permitting, increasing the number of currency pairs seems to be promising to test for the explanatory power of order flow in cross section. Furthermore, one may divide the sample into several sub-periods based on the regime shift in the Chinese exchange rate policy, to investigate the time-varying effects of order flow on the formation of exchange rates in the Chinese foreign exchange market.

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