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PRICE DISCOVERY IN THE FOREIGN EXCHANGE MARKET

A THESIS SUBMITTED TO THE CASS BUSINESS SCHOOL,
CITY UNIVERSITY OF LONDON, FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY IN THE FACULTY OF FINANCE

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Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institution of learning.

Abstract

This thesis investigates the price discovery in the foreign exchange market using high frequency data. Traditional exchange rate models assume market homogeneity and the sole existence of public information. However, recent studies suggest such assumptions are not well founded and have generated the ‘disconnection’ puzzle of exchange rates deviating from their fundamentals in the short and medium term. Using EFX tick-by-tick data, we find that information is not always available to all and the actual price discovery process is dynamic and asymmetric. It suggests that some market participants, trading systems or even exchange rates may possess private information, which helps them to lead others in finding the equilibrium prices. It further reveals the importance of studying the microstructure of the foreign exchange market, which may in the future solve the ‘disconnection’ puzzle that has baffled the exchange rate theory for the past decades.

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Chapter 1

Introduction

Traditional models of exchange rate determination concentrate on relatively long-run aspects by using low frequency data. Two important assumptions of these models are that the market participants are homogeneous and only public information is available to all. By assuming homogeneous expectations and the non-existence of private information, the exchange rate could be discovered by objective analysis of the participants. Such a price is hence considered intrinsic value. However, Isard (1995) suggests that ‘... it is hardly conceivable that rational market participants with complete information about macroeconomic fundamentals could use that information to form precise expectations about the future market-clearing levels of exchange rates.’

Indeed, traditional macro models based on such assumptions are not well founded and lack empirical support. For instance, Meese and Rogoff (1983) test the forecasting performance of monetary and portfolio balance models of the 1970s and find the forecasting power of regressions based on fundamentals to be less good than that of the simple random walk. Furthermore, their results reveal

that the explanatory power of macroeconomic data for exchange rates is poor¹.

The ‘disconnection’ puzzle, at least in the short and medium term, is subsequently pointed out by Frankel and Rose (1995): ‘To repeat a central fact of life, there is remarkable little evidence that macroeconomic variables have consistent strong effects on floating exchange rates, except during extraordinary circumstances such as hyperinflations.’

On the assumption of market homogeneity, Flood (1991) argues that, ‘at the level of detail involved in microstructural studies, the homogeneity assumption is not an excusable flaw; in a homogeneous market why – let alone how – would anyone trade?’ In real world, investors differ in key determinants of economic behaviours: information, beliefs, preferences and wealth. Transaction costs also influence their demand for and supply of assets². Surveys conducted in the foreign exchange market suggest that traders’ expectations are strongly heterogeneous and the distribution of expectations becomes wider at longer forecast horizons³.

The assumption of only public information being available in the market is also questionable. Numerous works suggest that information is not necessarily available to all in the foreign exchange market. There are many factors that may contribute to the existence of private information in the foreign exchange market.

These factors include private information on central bank interventions,

¹ Frankel and Rose (1995) and Cheung et al. (2005) also provide comprehensive study on this issue and reach the same conclusion.

² See Easley and O’Hara (2003).

³ See e.g. Allen and Taylor (1990), Taylor and Allen (1992), Cheung and Wong (1999), Marsh, Cheung and Chinn (2004).

information embedded in order flow, and better interpretation of public information⁴. As Frankel and Rose (1995) suggest, understanding the sources of private information and how it is transmitted among dealers may help explain some of the apparent anomalies in the foreign exchange market.

Newly found market heterogeneity and private information in the research of the foreign exchange market generate increasing interest in the study of exchange rate price discovery. Price discovery is first defined as the process by which markets find equilibrium prices (Schreiber and Schwartz (1985)). In economic terms, in a market where the demand curve is sloping, due to the heterogeneous propensities of the traders to buy or sell securities, it needs to find the clearing price that balances the aggregate demand and supply. This function is key to the efficient operation of the markets, in terms of time and the cost of the transactions. With the rapid development of microstructure theory during the 1990s, the investigation of price discovery has evolved away from such stochastic nature of supply and demand to information aggregation properties of prices⁵. The definition of price discovery has been changed to the dynamic process of incorporating information into the market prices in an efficient and timely fashion⁶. For instance, if an asset is traded in parallel trading venues, it is of interest to investigate which market is the first to incorporate newly emerged information. Other issues include how trading motivations, trading mechanisms,

⁴ See e.g. Ito, Lyons, and Melvin (1998), Melvin and Yin (2000), Sapp (2002), and Covrig and Melvin (2002).

⁵ See O'Hara (1995).

⁶ See e.g. Lehmann (2002), and Yan and Zivot (2007).

market liquidity and asymmetric information affect the efficacy of the price discovery process. Particularly, the existence of private information stirs great interest, as the microstructure models suggest that market dynamics will be affected by the presence or absence of informed traders.

Since the last two decades, several intertwined factors have contributed to the rapid development of price discovery study in the foreign exchange market. One is the introduction of microstructure framework into the study of the foreign exchange market⁷, which is partly due to the disappointing performance of the traditional exchange rate theories. Another important factor is the gradually increased availability of high frequency exchange rate data, especially those of order flow⁸. Other factors include the development of more advanced econometrics models and diversified research approaches such as survey studies on market participants.

This thesis studies the price discovery in the foreign exchange market by using high frequency exchange rate data. It consists of three interrelated papers that examine the dynamic price discovery process in different exchange rate systems or markets at high frequency by applying various research approaches. All empirical results suggest that at high frequency, the process of price discovery in the foreign exchange market is dynamic and asymmetric, i.e. some systems, market participants or markets possess more information, or acquire the

⁷ A first comprehensive introduction of microstructure theory into the foreign exchange market is provided in Flood (1991).

⁸ See Lyons (1995) for the seminal work of testing microstructure hypotheses in the foreign exchange market using order flow data.

information earlier than others.

The first paper, *Price discovery between indicative and transaction data*, investigates the price discovery in two sets of high frequency data, namely D2000-1 and EFX data. To study the heterogeneity in the foreign exchange market, extra information is needed to separate the data by features such as quoting banks and their geographic locations. EFX data used throughout the thesis are unique in that they provide prices with a quoting bank's identity and location. Such information is unavailable in other data sets due to mostly commercial confidentiality concerns. Although EFX data, as indicative data, are not associated with high information quality compared with transaction data and firm quotes, there is no comprehensive study that investigates such an issue. Hence, this paper serves such a purpose. Three months of DEM/USD and GBP/USD exchange rates data from EFX data and D2000-1 transaction data are studied and compared over the period. Several rigorous approaches are used to study the statistical features of and price discovery between the two data sets. Error Correction model (ECM) based information share techniques are used to quantitatively measure the contributions of each data system in terms of market information. Generalized impulse response analysis is employed to capture the dynamic interactions among the prices and order flow. The empirical results suggest that EFX data actually contain more information and lead the D2000-1 data in terms of price discovery. Compared to previous papers such as Goodhart et al. (1996) and Danielsson and Payne (2002), it uses much larger sample data

and more diversified research methods. Since currently there are no data sets containing more detailed information on exchange rate prices than the EFX data set⁹, such investigation confirms its unique value and calls for more future work to be conducted upon it.

The second paper, *Do top banks in FOREX business know more*, investigates directly how macro news is mapped into exchange rates through the dynamic information sharing process between major trading banks and the rest of the banks. Traditional asset market approach assumes exchange rates instantly incorporate all publicly available information, making public information useless for producing excess returns. However, in real world information may be distributed asymmetrically among traders and the news can be digested in prolonged time by the market. Even if all traders receive the same news in the form of public announcement, they still may interpret it differently. As a matter of fact, public announcements only rarely provide a direct statement of the value of the asset. In most cases one has to make use of other information to figure out the impact of the news on the asset value, which causes individual trader with fragmented information to have different interpretations over the same public announcement. Financial markets cannot be well understood unless the asymmetries in the information dispersion and assimilation process are studied. Employing ECM-based information share techniques invented separately by Gonzalo and Granger (1995) and Hasbrouck (1995), the paper investigates the

⁹ Lyons (2001) offers a good survey on current available high frequency data in the foreign exchange market.

information sharing process of the foreign exchange dealers around the major U.S. announcements. It is found that top trading banks take a dominant share of market information throughout our sample period. Their information share further expands during some major categories of U.S. news announcements. Previous studies of private information in the foreign exchange market involve factors such as the closer ties to the central bank of certain commercial banks (Sapp (2002)) and dealers' advantage of geographical location which helps them in obtaining private information (Covrig and Melvin (2002)). Our findings suggest that market participants, differentiated by their sizes, are heterogeneous in terms of their information collection and interpreting capability.

The third paper, *Asymmetric linkages between high-frequency exchange rates*, extends the study of price discovery into cross-currency volatility linkages. This study is motivated by the precursory findings that currency order flow contains private information. Since DEM/USD generates far larger order flow than GBP/USD in global trading, it is hypothesized that more information is contained in DEM/USD. It is also motivated by Lyons and Evans' (2000b) portfolio shifts model in which information integration is important in multi exchange rates price discovery. The pricing of exchange rates are interlinked by information embedded in each of them. If more information is incorporated in DEM/USD than in GBP/USD, the volatility transmission between them should be asymmetric, with more spillover from DEM/USD to GBP/USD than the reverse. Two multivariate GARCH models are employed to test the hypothesis

and the findings provide supportive evidence. One is the VARMA-GARCH-CCC (VGC) model, which is a combination of the VARMA-GARCH (Ling and Mcleer (2003)) and the constant conditional correlation model (Bollerslev (1990)). It is a restricted-correlation model but allows direct interpretation of the estimated parameters. However, it lacks the full interaction of the elements of covariance matrix and error terms. Therefore we add BEKK model to remedy the deficiency and use ‘news impact surface’ (Kroner and Ng (1998)) to interpret the result. Our findings suggest that information asymmetry not only exists at the micro level, such as among market participants, it also exists among exchange rates. It is the first volatility linkage study using high frequency exchange rate data, as far as we know.

Thus, the thesis is making two general contributions to the literature on microstructure of finance. It finds that the homogeneity of market agents at lower frequency, weekly or daily, disappears in high frequency foreign exchange rate data,. This uncovered heterogeneity can be explained by the different risk profiles, information sets, and institutional constraints of market players. For instance, it suggests that the different size of market players could contribute to their information advantage in both daily trading and interpretation of macro announcements. The other contribution is the finding that the information is distributed asymmetrically among markets or their participants. One piece of supporting evidence is that, although exchange rates all carry important macro information concerning the global and national economy, some exchange rates

contain more such information than others and the information could be transmitted to other exchange rates through volatility linkage. More detailed description of the contributions is however presented in each of the three papers that form the three main chapters of the thesis.

The organization of the thesis is as follows. Chapter 2 gives an overview on the features of the foreign exchange market and recent development of theories and studies in the field. Chapter 3 investigates the price discovery between two sets of data used by current studies and provides critical support for using EFX data as this thesis does. Chapter 4 studies the information sharing between big banks and the rest of the market and how it changes during twenty one categories of U.S. macro news announcements. Chapter 5 tests the asymmetric volatility linkage between two major exchange rates using multivariate GARCH models. Chapter 6 summarizes the main findings and suggests future research directions.

References

- Allen H., M. P. Taylor. 1990. Charts, noise, and fundamentals in the foreign exchange market. *Economic Journal*, 29: 49–59.
- Cheung, Y-W, Chinn, M-D, and A. G. Pascual. 2005. Empirical exchange rate models of nineties: Are any fit to survive? *Journal of International Money and Finance*, 24: 1150-1175.
- Cheung, Y-W, Chinn, M-D, and I. W. Marsh. 2004. How Do UK-Based Foreign Exchange Dealers Think Their Market Operates?. *International Journal of Finance and Economics*, v9: 289-306.
- Cheung, Y. W., and C. P. Wong. 2000. A survey of market practitioners' views on exchange rate dynamics. *Journal of International Economics*, 51: 401–419.
- Covrig, V., M. Melvin. 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen? *Journal of Empirical Finance*, 9: 271–285.
- Easley, D., and M. O'Hara. 2003. Microstructure and asset pricing. In *Handbooks of the Economics of Finance*, edited by G. M. Constantinides, M. Harris and R. Stulz. Elsevier.
- Flood, M. D. 1991. Microstructure theory and the foreign exchange market. *Federal Reserve Bank of St. Louis Review*, 73: 52-70.
- Frankel, J., and A. Rose. 1995. Empirical research on nominal exchange rates. In *Handbook of International Economics*, edited by G. Grossmand and K. Rogoff. Amsterdam: Elsevier Science.
- Gonzalo, J. and C.W.J. Granger. 1995. Estimation of common long-memory components in cointegrated systems. *Journal of Business & Economic Statistics*, 13: 27-35.
- Hasbrouck, J. 1995. One Security, Many Markets: Determining the contributions to Price Discovery. *The Journal of Finance*, 4: 1175-1199.
- Isard, P. 1995. *Exchange Rate Economics*. Cambridge: Cambridge University Press.
- Ito, T., Lyons, R. K., and M. T. Melvin. 1998. Is there private information in the FX market? The Tokyo experiment. *Journal of Finance*, 53: 1111–1130.

Lehmann, B. N. 2002. Some desiderata for the measurement of price discovery across markets. *Journal of Financial Markets*, 5: 259-276.

Lyons, R. 1995. Tests of Microstructural Hypotheses in the Foreign Exchange Market. *Journal of Financial Economics*, 39: 321-351.

Meese, R., and K. Rogoff. 1983. The out-of-sample failure of empirical exchange rate models. In *Exchange Rate and International Macroeconomics*, edited by J. Frenkel. Chicago: University of Chicago Press.

Melvin, M., and X. Yin. 2000. Public Information Arrival, Exchange Rate Volatility and Quote Frequency. *Economic Journal*, 110: 644-661.

O'Hara, M. 1995. *Market Microstructure Theory*. Cambridge, MA: Blackwell Publishers.

Sapp, S. 2002. Price Leadership in the Spot Foreign Exchange Market. *Journal of Financial and Quantitative Analysis*, 37: 425-448.

Schreiber, P. S., and R. A. Schwartz. 1986. Price discovery in securities markets, *Journal of Portfolio Management*, 12: 43-48.

Taylor M. P., and H. Allen. 1992. The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, 11: 304-314.

Yan, B-C, and E. Zivot. 2007. The dynamic of price discovery. University of Washington. Working paper.

Chapter 2

The Foreign Exchange Market and Theory Development

2.1 Introduction

The foreign exchange market possesses many unique features that differentiate itself from other financial markets such as bond and equity markets. And these exact features make the study of the foreign exchange markets intriguing, challenging and equally promising. For instance, although the foreign exchange market is the most liquid market in terms of its colossal global turnover, the significant deviations from uncovered interest rate parity make it difficult to be termed as an efficient market under the traditional efficient market framework¹⁰. Another example is that the actual transactions are executed in parallel markets, including inter-dealer and customer-dealer markets, making the foreign exchange market largely a decentralized market, which is in stark contrast to equity market where centralization takes dominant role.

Only by understanding the institutional features of the foreign exchange

¹⁰ See in Taylor (1995) and Sarno and Taylor (2002).

market, could one establish realistic assumptions and approaches to the study of this market. And this understanding of the market details is exactly the foundation of new models that bridge the macro and micro approaches and create innovative methods to tackle the ‘disconnection’ puzzle in the foreign exchange market¹¹. As Frankel et al. (1996) correctly put it: ‘it is only natural to ask whether empirical problems of the standard exchange-rate models ... might be solved if the structure of foreign exchange markets was to be specified in a more realistic fashion.’

This chapter is hence divided into two parts. The first half gives an overview of the institutional features of the foreign exchange market, while the second half focuses on the current development of exchange rate theory.

2.2 Features of the Foreign Exchange Market

In this study, foreign exchange market mainly refers to traditional foreign exchange market or spot market in particular. Although there are many important market features to be discussed, only three aspects that are closely related to the thesis are presented and analyzed, i.e., recent market activities, decentralized market structure and market heterogeneity. However, for a thorough review on the structure of the foreign exchange market, one could refer to Lyons (2001), Sarno and Taylor (2002), and Sager and Taylor (2006).

¹¹ See e.g. Evans and Lyons (2002a, b), and Bacchetta and Wincoop (2006).

2.2.1 Recent Activities of the Foreign Exchange Market

Compared to other markets, the turnover generated by the foreign exchange market is huge. In April 2004, the average daily global turnover was estimated at \$1.9 trillion (Table 2.1). Of this total turnover, spot transactions, outright forwards, and foreign exchange swaps take \$621 billion, \$208 billion and \$944 billion respectively. As foreign exchange swaps do not generate order flow, hence impose no significant effect on exchange rates¹², spot transactions are quite important judged by its share in the remaining turnover.

The April 2004's global trading volume is a 57% increase over April 2001's figure of \$1.2 trillion. BIS (2005) considers the strong surge is supported by several factors. One is that between 2001 and 2004, the trendy exchange rates and relatively high volatility cause the momentum strategy, i.e. buying currencies that appreciate persistently, to be quite successful. Another strategy called 'carry trade' is also widely taken by currency traders. It takes advantage of the interest differentials between two currencies by borrowing low interest rate currency to build position in high interest rate currency, hoping that the latter does not depreciate significantly. As a matter of fact, such a strategy, if applied by considerable portion of the dealers in the markets, can actually depress the funding currency and push up the target currency, which make the

¹² FX swap involves transactions with equal sized but opposite-direction transactions. See Lyons (2001).

strategy even more profitable. With more asset managers and hedge funds treating currency as an asset class, the search for yield also contributes to the increase of trading activities in the foreign exchange market¹³.

The decomposition of turnover by types of counterparties has changed considerably (Table 2.2). The share of trading between reporting dealers continue to fall from 59% in 2001 to 53% in 2004. The share decrease is first caused by the ongoing consolidation in the banking industry. During 10 years of the 1990s, the combined market share of the top ten dealers has risen from around 40 percent to around 50 percent¹⁴. The number of banks accounting for 75 percent of global turnover has also declined significantly for the past 10 years since 1995¹⁵. Trading between banks and financial customers rose strongly from 28% to 33%, which could be mainly explained by the increased activity of hedge funds and commodity trading advisers (CTA) and continuing growth of trading by asset managers. The share of trading between banks and non-financial customers also increased slightly to 14%. It reflects the fact that, with global increasing profitability of firms, corporate treasurers follow the investment strategies used by financial investors in their search of excess returns.

As the international money, the dollar is still the most traded currency, taking one side of 89% of all transactions. Euro and yen are next two most traded, with their shares of total turnover being 37% and 20% respectively. The

¹³ Galati and Melvin (2004).

¹⁴ BIS (1999a).

¹⁵ BIS (2005).

share of pound sterling increased from 13% to 17%, mainly due to its investment vehicle and valuation effects.

Similar to the decomposition by types of currencies, the geographical distribution of the turnover did not change substantially. UK still attracted the largest share of global trading, accounting for 31% of total turnover. US increased its share from 17% to 19%. The remaining most active trading centres are Japan (8%), Singapore (5%), Germany (5%), Hong Kong SAR (4%), Australia (3%) and Switzerland (3%).

2.2.2 Decentralized Foreign Exchange Market

Decentralized market is defined as where 'prices are quoted and transactions are concluded in private meetings among agents.'¹⁶ In foreign exchange markets, market-makers, brokers and customers are separated physically from each other, and transactions are conducted through telephone, telex and computer network. The actual transactions take place in a two-tier market where customers trade with dealers in the first tier and then dealers trade with each other in the second tier of interdealer market.

Nowadays, increasing portion of deals also goes through brokered markets, which may be classified as quasi-centralized. Such a market system is different from centralized market like most equity markets. Centralized market is believed

¹⁶ See Wollinsky (1990).

to be more efficient by providing transparency and eliminating arbitrage opportunities¹⁷. However, decentralized market is more stable and less likely to crash, as Perraudin and Vitale (1996) suggest.

One direct effect of decentralized market is that the prices are fragmented, i.e. transactions could occur simultaneously with different prices in different trading venues, though the deviations should not be sufficiently large. Another implicit effect is that the market lacks transparency. In the foreign exchange market, there is no disclosure requirement on the transactions. Hence trade or order flow is not fully observable to traders. As a consequence, order flow contains less information than it would do in centralized market, and the speed of information transmission can also be more slow.

Electronic brokers, such as Reuters Dealing 2000-2 system¹⁸ and Electronic Broking System (EBS) Spot Dealing system, are rapidly gaining market share from traditional indirect interdealer market. Reuters Dealing 2000-2 service is an anonymous electronic matching application for the foreign exchange spot market. More than 1,100 banks subscribe to the service and they are distributed over 40 countries. EBS spot is an order-driven screen based electronic FX trading system. In its April 2004 survey, Bank of England reports that 66 percent of the inter-dealer spot business in the UK is executed through EBS system. Regarding the trading decomposition of currency pairs, euro/USD and USD/JPY are traded primarily on EBS, while GBP/USD is traded primarily

¹⁷ See Garbade (1978), Glosten and Milgrom (1985).

¹⁸ Now it has been updated to D3000.

on Reuters Dealing 2000-2.

The changing structure of the foreign exchange market gives rise to new challenge on the study of the market. As micro foundation becomes important part of the modelling of the foreign exchange rates, it is imperative to correctly capture the evolving institutional features of the market. It also requires future studies to select data from more representative data source when electronic trading systems shift their market dominance.

2.2.3 Heterogeneous Market Participants

An important flaw of traditional macro models is negligence of micro foundation in the foreign exchange market. Newly established exchange rate models however realize such a problem and begin to bring realistic market behaviour into their innovative approaches. Therefore to understand the market participants, such as their trading motivations, is imperative in correctly modelling the price discovery process. In this section, different classifications of market participants are introduced to help us understand the ultimate driving force of exchange rates.

One simple classification of the market participants would be the dealers and customers. In the interdealer market, dealers include market makers, leverage traders, and proprietary traders. Market makers provide liquidity to customers and improve market efficiency by executing customer orders with

best available prices. Traditionally, market maker would adjust spread to protect themselves from informed customers. The enhanced market competition however forces market makers to focus on one side of the market at a time to facilitate customer trades instead of seeking profits¹⁹. Leverage traders focus on short term investment windows, such as hourly or daily, and mainly deal with large trading banks orders. Proprietary traders share the same investment horizon as leverage traders, however with more risk control concern from their senior management. In general, risk control measures have been greatly enhanced especially since the Long-Term Capital Management crisis. Risk management practices like Value at Risk (VaR) have been widely applied to limit the risk taken by dealers. Greater awareness of risk at the micro level in some way contributes to the less opportunity of extreme event in the marketplace.

Customers are in the outer layer of the two-tier foreign exchange market and they access the liquidity of the interdealer market via dealers. Customers in the foreign exchange market include corporations, hedge funds, commodity trading advisors (CTAs), central banks and individual investors. Customer trading has been the key to the answer of the disconnection puzzle embedded in the traditional macro models, as new micro models suggest. For instance, Evans and Lyons (2004) find that customer order flow at Citibank forecasts up to half of changes in the U.S. and German fundamental variables.

¹⁹ See e.g. in Danielsson and Payne (2001).

Customers can be categorized into different classes using different criteria. For instance, Sager and Taylor (2006) differentiate them in three distinctive ways. One is passive versus active customers, which mainly depends on their trading strategies. Most financial customers, i.e. hedge funds and CTAs, fall into active customer category. Active customers conduct profit seeking investment and implement active portfolio investment strategies. Passive customers could be multinationals that passively purchase or sell their currencies according to their business needs such as dealing with international merges and acquisitions, international revenue accruals and hedging demands. An alternative customer classification would be informed and uninformed investors. Customers are treated as informed if the information they possess help them better predict the future move of exchange rates. Such investors could be large banks, central banks, and possibly some hedge funds. Large banks are capable of generating large customer order flow that could contain fundamental information. Major central banks can directly influence the exchange rates by openly intervening the foreign exchange markets. Nowadays, Sovereign Wealth Funds (SWFs) that manage a nation's savings become another important source of customer order flow that is closely watched by other market participants.

2.3 Development in the Exchange Rate Theory

The exchange rate theory has entered a new stage since the criticism of

traditional macro models in the 1980s. The new micro approach that combines traditional macro theory and micro foundation is one of the major theoretical break-through that appears to be promising in solving the disconnection puzzle. Some other approaches such as chaotic models also show alternative attempts to tackle the challenge. In the first part of this section, new theories that tend to correct the traditional macro models are introduced. Due to the critical importance of the order flow in establishing hypotheses throughout the thesis, the second part stresses the theoretical implications of order flow in the price discovery process. In the last section, the literature on private information in the foreign exchange market is reviewed to reveal academic efforts to correct one of the fundamental flaws of the traditional macro models.

2.3.1 From Macro to Micro Approaches

The unsatisfactory performance of the traditional macro models prompts new studies based on more realistic observation of the day-to-day running of the foreign exchange market. Goodhart is one of the great pioneers that cast their eyes into the microstructure of the market and raise fundamental challenges on the traditional macro models. Based on his nearly two decades' experience in the Bank of England, Goodhart finds that many assumptions of the 70s and 80s macro models do not fit into the reality of the marketplace. For instance, in challenging the homogeneity assumption, Goodhart (1988) remarks, 'the basic

information that speculators use can reasonably vary. As already noted, it is perfectly rational for some to assume (the continuation of) random walks; others may use fundamental analysis and predict some reversion to a long-term equilibrium; others again may use even technical analysis (Chartism).’ Such observation is later confirmed by Allen and Taylor (1990).

Lyons (1995) is the first to formally test microstructure paradigm in the foreign exchange market. In 1996, the NBER’s publication of a collection of essays on the microstructure of the foreign exchange market becomes a milestone for the development of the new approach to the study of price discovery in the foreign exchange market. *The Microstructure Approach to Exchange Rates* (2001) is Lyons’ invaluable attempt to synthesize contemporary research to build a new hybrid model that bridge the gap between the macro and micro models to better explain and forecast the exchange rate movements.

In the new micro model of the foreign exchange market (Evans and Lyons (2005)), the key emphasis has been put on the information approach of the microstructure theory, instead of the inventory and industrial organization approaches that are also prevalent in other microstructure models. In contrast to traditional macro modelling of exchange rates, new micro model admits that the information needed to form equilibrium prices is dispersed at micro-level. Only by aggregating the heterogeneous micro-level activity can the market produce macro measures such as consumption, inflation, money demand and output. Many papers have found that order flow performs such an information

aggregating function, which would be introduced in the next section.

There are also other lines of research that aim at solving the same disconnection problem but with different approaches. The new open-economy macro approach establishes fully specified micro-foundations under a general equilibrium framework, which also allows for rigorous welfare analysis²⁰. However, it inherits many assumptions from the traditional monetary models such as continuous stock equilibrium in money markets and short-run PPP. It is also sensitive to the particular specification of the micro-foundations and thin on the information environments in which it operates.

Bacchetta and Wincoop (2003) explicitly introduce investor heterogeneity into their model to explain the disconnection puzzle. Two types of heterogeneous information are incorporated into the model. One type is the dispersed information of investors about future fundamentals. And the other type is non-fundamentals based heterogeneity that involves rational investors who trade for liquidity or hedging demand. Based on the assumption of rational expectation, their model suggests that greater dispersion of information across investors can generate greater price impact from non-fundamental trades. Although the conclusion is appealing, more work needs to improve the rational expectation assumption and details of market heterogeneity such as different types of investors. For instance, Bacchetta and Wincoop (2007) believe that random walk expectations are common when using carry trade strategies. i.e.,

²⁰ For a thorough review of the new-open macro approach, see in Obstfeld and Rogo (1996), Sarno (2000) and Lane (2001).

borrowing low interest rate currency to invest in currency with higher interest rate without considering exchange rate movement²¹. Another fact is that the order flow generated by financial institutions introduces positive exchange rate returns while order flow generated by corporate (non-financial) has opposite effect on exchange rate²².

Chaotic models of foreign exchange markets (Grauwe et al. (1993)) are based on the criticism of impractical rational expectation assumption implicit in the 'news' model (Mussa (1979)). In rational expectations literature, it is customary to neglect the explosive speculative bubble which may be an alternative answer to the disconnection puzzle. A simple market behaviour model in foreign exchange market may consist of two types of market participants, namely fundamentalists and chartists. Fundamentalists base their expectation on their structural model of the economy, while chartists extrapolate past movements of exchange rates. By ignoring the market impact of the chartists, the fundamentalists do not qualify as having rational expectation. The destabilizing influence of chartists can therefore lead to market chaos as simulations show. It hence explains why the foreign exchange market deviates from its underlying fundamentals. However, chaos models are highly sensitive to the initial conditions and values of some of the parameters. Another problem is that in order to prove the existence of chaos, a large number of observations

²¹ For more empirical evidence on carry trade, see Bazan et al. (2006), and Burnside et al. (2006).

²² See e.g., Fan and Lyons (2003).

over a long horizon are needed, which is difficult given the relatively short floating experience of major exchange rates.

2.3.2 Order Flow and Fundamentals

However, all this rapid development in the study of the foreign exchange market for the past two decades could have been unimaginable without the newly emerged high frequency data, and those with order flow information. Order flow is a measure of net buying pressure defined as the net of buyer- and seller-initiated currency transactions (Lyons (2001)).

The standard macro models are based on one important assumption that only public information matters, i.e. there is only common knowledge macroeconomic information exists in the market place. However, models based on such assumption fare poorly in forecasting short and medium term exchange rate. Since Meese and Rogoff's (1983) seminal paper of testing the performance of the traditional macro models, it has been widely accepted that the public information approach is deficient. A thorough study of the market would suggest that many variables that join the determination of the exchange rates are not known to everyone, such as investors' individual risk preferences, money demands, hedging demands and firms' productivities.

Therefore, in finding the equilibrium price, the foreign exchange market needs to aggregate the dispersed information in a timely fashion. However, the

foreign exchange market lacks transparency due to its decentralized market structure. Dealers can only garner information from their own customer order flow, while individual customer has no means to know each other's information. Such information environment makes order flow the key to the determination of exchange rates.

A series of studies by Lyons and Evans, among others, suggest that order flow could be a key channel to aggregate the dispersed private information²³. The dispersed information model²⁴ consists of a two-stage trading mechanism that first absorbs fundamental information from customer trading and then translates it into equilibrium exchange rates through interdealer trading. The role of customer order flow therefore is important as it allows dealers to aggregate macro information that dispersed among customers that create real economic activities. For instance, Payne (2003) finds that around 40% of information incorporated in the interdealer system is transmitted through order flow. Nonetheless information distilled from customer order flow largely depends on the size of transactions a dealer could generate and it contains considerable amount of noise.

2.3.3 Private Information in the Marketplace

Realizing the heterogeneity in the marketplace, one line of research starts to

²³ See e.g. Covrig and Melvin (2002), Payne (2003), Evans and Lyons (2004) and Rime, Sarno and Sojli (2007).

²⁴ See e.g. Lyons (2001), Evans and Lyons (2002a, b), and Evans and Lyons (2007).

focus on finding private information that has previously been ignored under traditional macro economics framework in foreign exchange market. There are several channels that could contribute to dealers' private information, such as dealers' nationality, close relations with central banks, and large trading capacity, especially with customers.

In the foreign exchange market, information, especially macro news, is crucial to the pricing of exchange rates. However, public news is mostly announced with fixed schedule and therefore only reflects the past state of the economy. Dealers located in a certain economic zone have advantages of more information sources for local economic activities, especially from customers. Therefore they stand a better chance to correctly forecast the performance of the economy. For instance, Covrig and Melvin (2002) investigate the USD/JPY market. They find the quotes from Japanese traders lead the rest of the market when the informed market participants are active. Price discovery test also suggest that Japanese quotes contribute more than the rest-of-the-world during such period.

Another line of studies directly investigate the central bank interventions' effect on private information. Central bank intervention is a unique feature that differentiates foreign exchange market from other financial markets. Central bank's direct involvement in the trading of targeted currency sends signal to the market and changes their expectation on the equilibrium prices. However, central bank is also a customer in the foreign exchange market. Its selection of

trading banks suggests that certain banks may have superior access to such information and cause them to lead others in price discovery. For instance, Peiers (1997) find that Deutschebank leads other banks in price quoting up to one hour prior to Bundesbank intervention. Sapp (2002) also confirms that result. Dominguez (2003) suggests that some traders know the Fed's intervention at least one hour prior to its public release.

Survey studies on the dealers of the FX markets also shed some lights on the issue²⁵. For instance, in the survey conducted by Cheung and Chinn (2001), fifty percent of the surveyed dealers believe that large players in the foreign exchange markets possess a competitive advantage. Such an advantage derives from better information and a large customer base. The latter is directly linked to customer orders that contain dispersed information on the fundamentals. As Goodhart (1988) suggests, 'A further source of informational advantage to the traders is their access to, and trained interpretation of, the information contained in the order flow.'

As the state of economies is revealed gradually and disparately to foreign exchange dealers, with little information flow among each other due to large portion of trades being carried out under the opaque decentralized interdealer system, any information garnered or deduced from all possible non-public sources could become private information. For example, large banks could deduce information on trade balance from their customers that conduct

²⁵ See, e.g., Cheung and chinn (2001), and Cheung, Chinn and Marsh (2004).

international trade long before the public announcement ²⁶.

²⁶ Lyons (1997) tested trade balance's effect on traders trading. He found that the real trade in goods and services generates FX orders that provide information to dealers about trade balances long before published statistics are available.

References

Allen H., M. P. Taylor. 1990. Charts, noise, and fundamentals in the foreign exchange market. *Economic Journal*, 29: 49–59.

Bacchetta, P., and Wincoop, E. V. 2003. Can information heterogeneity explain the exchange rate determination puzzle? Working paper.

_____. 2007. Random walk expectations and the forward discount puzzle. *American Economic Review, Papers and Proceedings*, 94: 114-118.

Bazan, C., Kuntara P., and Lee R. T.. 2006. Random walk currency futures profits revisited. Unpublished working paper.

BIS. 1999. Triennial central bank survey of foreign exchange and derivatives market activity 1998:Final Results. Bank for International Settlements.

_____. 2005. Triennial Central Bank Survey – Foreign exchange and derivatives market activity in 2004. Bank for International Settlements.

Bollerslev, T. 1990. Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *The Review of Economics and Statistics*, MIT Press, 72: 498-505.

Burnside, C., Martin E., Isaac K., and Sergio R. 2006. The returns to currency speculation. National Bureau of Economic Research. Working Paper 12489.

Covrig, V., M. Melvin. 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen? *Journal of Empirical Finance*, 9: 271–285.

Danielsson, J., Love, R. 2005. Feedback trading. Mimeo, London School of Economics.

Danielsson. J., Payne R. 2002. Real trading patterns and prices in spot foreign exchange markets. *Journal of International Money and Finance*, 21: 203-222.

Fan, M., and R. Lyons. 2002a. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy*, 110: 170-180.

_____. 2002b. Informational integration and FX trading. *Journal of International Money and Finance*, 21:807-31.

_____. 2004. Exchange-rate fundamentals and order flow. Mimeo, Georgetown University.

_____. 2005. A new micro model of exchange rate dynamics. Working paper.

Fan M, Lyons R. K. 2003. Customer trades and extreme events in foreign exchange. In *Monetary History, Exchange Rates and Financial Markets: Essays in Honour of Charles Goodhart*, Mizen P (ed.). Edward Elgar: Northampton; 160–179.

Frankel, J. A., and G. G. Giovannini. 1996. Introduction. In *The Microstructure of Foreign Exchange Markets*. Frankel J. A., G. G. Giovannini (eds). University of Chicago Press: Chicago; 1–15.

Galati, G., and M. Melvin. 2004. Why Has FX Trading Surged? Explaining the 2004 Triennial Survey. BIS Quarterly Review (December), 67–98.

Garbade, K. D. 1978. The effect of interdealer brokerage on the transactional characteristics of dealer markets. *Journal of Business*, 51: 477-98.

Glosten, L. R. and P. R. Milgrom. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14: 71-100.

Gonzalo, J., and S., Ng, 2001, A systematic framework for analyzing the dynamic effects of permanent and transitory shocks. *Journal of Economic Dynamics and Control*, 25: 1527-1546.

Goodhart, C. 1988. The foreign exchange market: a random walk with a dragging anchor. *Economica*, 55: 437–460.

Grauwe, P. D., Dewachter, H., and M. Embrechts. 1993. *Exchange Rate Theory: Chaotic Models of Foreign Exchange Markets*. Blackwell, Oxford.

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery, *Journal of Finance*, 50: 329-339.

Kroner K. F., V. K. Ng. 1998. Modelling asymmetric comovements of asset returns. *The Reviews of Financial Studies*, 11: 817-844.

Lane, P. R. 2001. The new open economy macroeconomics: a survey. *Journal of International Economics*, 54: 235–266.

Ling, S. and McAleer, M. 2003. Asymptotic theory for a new vector

ARMA-GARCH model. *Econometric Theory*, 19: 280-310.

Lyons, R. 1995. Tests of Microstructural Hypotheses in the Foreign Exchange Market. *Journal of Financial Economics*, 39: 321-351.

_____. 2001. *The Microstructure Approach to Exchange Rates*. MIT Press: Cambridge, MA.

Meese, R., and K. Rogoff. 1983. The out-of-sample failure of empirical exchange rate models. In *Exchange Rate and International Macroeconomics*, edited by J. Frenkel. Chicago: University of Chicago Press.

Mussa, M. L. 1979. Empirical regularities in the behavior of exchange rates and theories of the foreign exchange market. Vol. II Carnegie-Rochester Conference Series on Public Policy.

Obstfeld, M. and R. Kenneth. 1996. *Foundations of International Macroeconomics*. Cambridge, Massachusetts: MIT Press.

Payne R. 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61: 307–329.

Perraudin, W., and P. Vitale. 1996. Interdealer trade and information flows in a decentralised foreign exchange market. In *The Microstructure of Foreign Exchange Markets*, edited by Frankel, J. A., Galli, G., and Giovannini, A., The University of Chicago Press: 73-106.

Rime, D., Sarno L., and Sojli, E. 2007. Exchange rate forecasting, order flow and macroeconomic information. Working Paper, Norges Bank.

Sager, M., and Taylor, M. 2006. Under the microscope: the structure of the foreign exchange market. *International Journal of Finance and Economics*, 11: 81-95.

Sapp, S. 2002. Price leadership in the spot foreign exchange market. *Journal of Financial and Quantitative Analysis*, 37: 425-448.

Sarno, L. 2000. Towards a new paradigm in open economy modelling: where do we stand? Working paper.

Sarno, L., and M. P. Taylor. 2002. *The Economics of Exchange Rates*. Cambridge University Press: Cambridge.

Taylor M. P. 1995. The economics of exchange rates. *Journal of Economic*

Literature, 33: 13–47.

Wolinsky, A. 1990. Information revelation in a market with pairwise meetings. *Econometrica*, 58: 1-23.

Table 2.1
Global foreign exchange market turnover

Daily average in April, in billions of US dollars						
	1989	1992	1995	1998	2001	2004
Spot transactions	317	394	494	568	387	621
Outright forwards	27	58	97	128	131	208
Foreign exchange swaps	190	324	546	734	656	944
Estimated gaps in reporting	56	44	53	60	26	107
Total turnover	590	820	1,190	1,490	1,200	1,880

Notes: The figures have been adjusted for local and cross-border double-counting. Non-US dollar legs of foreign currency transaction were converted from current US dollar amounts into original currency amounts at average exchange rates for April of each survey year and then reconverted into US dollar amounts at average April 2004 exchange rates.

Table 2.2
Reported foreign exchange market turnover by counterparty

As a percentage of global turnover				
	1995	1998	2001	2004
With reporting dealers	64	64	59	53
With other financial institutions	20	20	28	33
With non-financial customers	16	17	13	14
Local	46	46	43	38
Cross-border	54	54	57	62

Notes: The figures have been adjusted for local and cross-border double-counting. The report excludes estimated gaps.

Chapter 3

Price Discovery between Indicative and Transaction Data

3.1 Introduction

With more quotes and transaction data being available the value of the indicative data has gradually been downgraded. The excessive and sometimes irrelevant quotes from aggressive banks that need to build up a market presence, and the occasional quoting strategy of copying quotes from fellow banks has resulted in indicative data being treated with caution when extracting information from them.

However, formal and conclusive research on the issue has yet to be provided. The few earlier papers are based on a very short sample period of either one day, or one week. For example, Goodhart et al. (1996) compare one day of DEM/USD EFX data with those from D2000-2, but with no time stamp on the data. The two data sets are matched by maximising the correlation between the transaction and indicative data. They find that at 10 minute frequency the statistical discrepancy between the two data sets is largely

insignificant.

Danielsson and Payne (2002) extend the time window to five days (6th to the 10th of October, 1997), which is still too short for any meaningful conclusion. They process the data at 20 seconds frequency as a compromise between the different frequencies of the two series. Basic statistics, such as quote frequency, spread and return moments are investigated and compared for the two data sets. Using Hasbrouck's ECM based information share, they find that D2000-2 has a dominant role in pricing the information except during midnight hours. However, all these differences disappear when they aggregate the data into 5 and 10 minute frequency.

In our paper, we use indicative data from Reuters high-frequency EFX quotes on the DEM/USD and GBP/USD. The corresponding transaction data are D2000-1 inter-dealer transaction data on the same currency pairs.²⁷ Our sample data span 82 trading days, increasing substantially the time window compared to previous work, and making our empirical tests more reliable. Furthermore, instead of only focusing on DEM/USD, we also introduce GBP/USD to make the comparison of the two data sets more conclusive.

We employ various methods to compare the indicative data and their corresponding transaction data. We conduct first cross correlation tests to investigate the lead and lag relation between the indicative and transaction return series. We find that both indicative currency pair data sets lead transaction data

²⁷ The EFX and Reuters D2000-1 data sets are provided by Olsen & Associate and Martin Evans respectively.

by around 5 to 10 minutes. We then use Hasbrouck's (1995) information share technique to recover the information content of the two data sets, which further suggests that indicative data have the dominant role in mapping the fundamental information into the prices. We vary the data frequency of the data by using real transaction time, 5 and 10-minute calendar time frequency to test the robustness of our results. Furthermore, we perform our tests for different trading sessions according to the opening and closing times of major foreign exchange markets in order to eliminate the trading zone effect on the 24-hour global foreign exchange trading.

Finally, due to the growing importance of order flow in exchange rate theory, we investigate whether our indicative data are relevant to the relationship between the order flow from the D2000-1 data and transaction prices. Order flow is the difference between the volume of dollar buyers initiated trades and that of the seller initiated trades. Micro-based foreign exchange models treat order flow as an important channel to map the widely dispersed fundamental information on to exchange rates. In Lyons and Evans' various models (see e.g. Lyons 2001), the causality runs strictly from order flow to exchange rates. By applying generalized impulse response method to both price series and order flow, we first find that the D2000-1 prices take longer (up to 5 to 10 minutes) to absorb one standard error of shock from the EFX price, compared to the time that EFX price takes to absorb one standard error of shock from the D2000-1 price. This confirms the results of the cross-correlation test. Adding to these

findings is that the shock from EFX data imposes similar impact on order flow as the shock from D2000-1. However, we find that there is no significant impact from the shock of order flow to prices at both 5 and 10 minutes frequency. Though the prices and order flows display obvious co-movements during our sample period, it seems that order flow has more of a latent response to changes in prices, which is in contrast to Lyons' (2001) claim that order flow explains exchange rates at lower frequencies (1 hour or daily frequency). Granger causality tests confirm this result and cast doubt on the importance of order flow as an important determinant of exchange rates at high frequency.

The paper is structured as follows. In section 3.2, we give a description of our data sets and how we process them before we conduct our empirical tests. In section 3.3, we carry out a simple lead-lag return analysis and then the routine unit root and cointegration tests. In section 3.4, we estimate the Hasbrouck information share for both prices. In section 3.5, we introduce the order flow to the price data and perform generalized impulse response analysis and Granger causality tests. In the final section, we briefly summarize the results and the significance of our findings.

3.2 Data and Sample Details

3.2.1 Data

EFX indicative high-frequency data are collected from Reuters EFX page. These

tick-by-tick data are provided by different participating banks with each bid and ask pair stamped with time down to the second and other information, such as dealer's bank code and location. Indicative quotes are free from transaction obligations and are considered more as an advertising method to maintain the banks' market presence. However, one should also note that due to reputation concern, the quote would not deviate too much from the market price. Another important feature is that indicative data are not subjected to the consent from any other party like transaction data and hence, are capable of instant update when news hit the market.

Reuters D2000-1 data are inter-bank transaction data. An electronic record is produced because quotes and trades are executed electronically. Each deal is time stamped to seconds with transaction size and transaction signs²⁸. Unlike EFX data, transaction data do not usually include detailed information on the involved counterparties; therefore not allowing any investigation on the existence of heterogeneous information.

3.2.2 Sample Details

Eight fields are included in EFX data: date, time, bid, ask, nation, city, bank and filter. Reuters D2000-1 contains nine fields: month, day, hour, minute, seconds, time index, transaction sign, price, and volume (see Table 3.1). At first glance,

²⁸ If it is dollar buyer initiated trade, 1 is recorded. Otherwise 0 is filled in.

EFX data provide more information on the quoting bank's identity, while D2000-1 offers unique record of the transaction signs and trading volume, although the later figures lack accuracy²⁹.

The sample data span from 1st of May to 30th of August 1996, with a total of 121 calendar days, including weekends and holidays. There are 313,845 and 612,260 quotes in GBP/USD and DEM/USD respectively in the EFX data set, which are much larger than those of D2000-1, with corresponding 52,318 and 257,398 ticks of data. This difference is more obvious in GBP/USD, with the size of EFX data being nearly six times that of the D2000-1.

To check the basic statistical characteristics of both data sets, we first plot the average intraday quote frequency of the data sets in both currency pairs in Figures 3.1 and 3.2. Each half-hour session's total quotes (trades) are divided by the daily total quotes (trades). The peaks and lows of the two data sets generally coincide with each other throughout the day. However, the transaction data reveal more concentrated trading activity during London and New York trading hours. Indicative data instead display less dramatic rise and fall of quoting activity during these sessions.

Another method to study the intensity of the quoting or transaction activities is duration, which stands for the elapsed time (in seconds) in between two neighbouring quotes or transactions. Following Engel and Russell (1997),

²⁹ See Evans (2002). Due to lack of information on the exact size of each trade, he aggregates the transaction signs of the trades, which took place during each time interval as a proxy for the volume figure.

we eliminate the impact of automatic quoting by excluding those quotes with price changes of less than 5 basis points in the indicative data. Both the EFX and D2000-1 data sets share the same highest clustering of duration under 10 seconds, nearly 17% of all quotes (see Figures 3.3 and 3.4). From 40 seconds on, the duration patterns deviate from each other, with EFX experiencing a much more gradual decline in density while D2000-1 swinging around EFX. One significant feature of D2000-1 is its relative lack of transaction duration of near 50-60 seconds. There is no explanation for this distinct feature as far as we know. However, transaction frequency clusters again between 60 and 120 seconds, counting for over 30% of total transactions.

Such differences indicate an issue of unsynchronized data when comparing these two data sets. Indicative data can be updated without any transaction taking place, while transaction data are the result of a mutual agreement of a pair of trading banks, and as a result take place at a lower frequency. Since it is deemed that transaction data bear more information and take place at lower frequency compared with their indicative counterpart, we use transaction data as the benchmark to process our indicative data.

First, we filter indicative data using transaction data time stamp. For each transaction price, we locate its nearest indicative data in terms of time and form a matching transaction and indicative data pair. This procedure returns us with highly simultaneous price series in both currency pairs. The two data sets in GBP/USD have a time discrepancy of average 0.04 seconds and a standard

deviation of 22 seconds, and the pairs in DEM/USD differ with an average of 0.1 seconds and a standard deviation of 11 seconds. The differences between the processed time stamps of the pairs of indicative and transaction data sets in both exchange rates are insignificant.

Second, to reflect the bid and ask shift of the transaction data, we choose the corresponding bid and ask price of the indicative data. This process is based on the transaction sign of each trade. For instance, for a dollar buyer initiated trade in D2000-1, the closest EFX bid is selected as the matching price.

After the above mentioned process, and excluding weekends and holidays, we have 82 trading days, 51,741 pairs of GBP/USD prices and 255,481 pairs of DEM/USD prices left. The 5 and 10-minute frequency data are obtained by choosing the last pair of prices in each time slot. Such a method sacrifices more available updated quotes in indicative data, but avoids comparing stale transaction data with indicative data. Therefore, any subsequent empirical comparison of these two data sets may underestimate the information content of the indicative data.

The descriptive statistics of both data sets are displayed in Table 3.2. The statistics on the first moments of the prices indicate that indicative data are generally a couple of basis points lower than transaction data. There is no documented explanation for such findings.

3.3 Preliminary Data Analysis

In this section, we first provide tests on the cross correlations of the return series using different data frequency and exploring the lead and lag pattern of the two data sets. Lead and lag analysis gives us a preliminary picture of the relationship between the returns of the prices by comparing the data at different leads and lags. Any significant lead or lag pattern may suggest that one price leads the other in mapping information on to its returns.

We then perform unit root tests for each price to investigate whether the price series are nonstationary and integrated of order one, i.e., a $I(1)$ process. Subsequently, we conduct the Johansen (1988) test to investigate whether the two sets of prices for each currency pair are cointegrated. By establishing the unit root and cointegration relation in the prices, we can investigate the information share between them, using a technique based on the Error Correction Model.

3.3.1 Cross-correlations of Return Series

If two prices are based on the same fundamental asset, their return series should be correlated due to the shared determinants. In frictionless and complete markets, there should be complete simultaneity between the price movements. However, at higher frequency, if one market processes new information faster than the other market, it is possible for it to consistently lead the other market.

Even though previous papers (see e.g. Danielsson and Payne, 1997) associate indicative data with stale or lagged quotes compared to transaction data, we hold the opposite view. One reason is that indicative quotes are in essence advertising signals to potential customers, and hence should contain fresh information to inform the market. Furthermore, theoretically indicative data could be updated in the absence of a transaction and therefore, should be more efficient in delivering information. Cross-correlation tests of the return series offers a means to prove our hypothesis.

In Figures 3.5 and 3.6, we present the cross-correlation results of the return series of both data sets for the two currency pairs at 5-minute and 10-minute frequency respectively. The 95% confidence levels are formed by calculating $\pm 2/\sqrt{T}$, with T being usable observations, which are the dotted lines in both graphs. Positive lags at the X axis indicate that EFX quotes are in the lead. At 5 minute frequency, we find that EFX leading quotes show a significant positive correlation with the lagged D2000-1 prices at lag 1 in GBP/USD and at lags 1 and 2 in DEM/USD. The 10-minute frequency results confirm that EFX quotes lead D2000-1 prices by about 10 minutes.

The lead-lag analysis demonstrates an asymmetric relation between the returns of the two data sets, with no significant correlation when D2000-1 is in the lag. Such findings are in contrast to Danielsson and Payne's (1997). Based on 20 seconds frequency, they find that D2000-2 returns lead EFX returns by 2 and 3 minutes. However, positive correlation also exists when EFX is the one in

the lag, which suggests that the cross-correlation is less asymmetric. In our case the predictive power runs only from EFX data to D2000-1, with D2000-1's return imposing no predictive power on EFX's return at all.

3.3.2 Unit Root Tests

To investigate the cointegration between the two prices, as a routine, we first test whether the time series contain unit root. Specifically, if two time series are both nonstationary at their level, but become stationary after first differencing, we denote them as $I(1)$ processes, or integrated of order one. Cointegration becomes relevant if the linear combination of both $I(1)$ series is stationary.

The augmented Dickey-Fuller (1981) test is used in our unit root tests, which extends the basic Dickey-Fuller test by including a parametric correction for higher-order correlation by assuming that the time series follows an $AR(p)$ process and adding p lagged difference terms of the dependent variable to the right-hand side of the regression. We select the lag length p by using Schwarz Information Criterion (SIC) (see Schwarz (1978)). Three types of unit root tests, including no intercept or trend, only intercept, and only trend, are conducted. We only present the result with the intercept unless otherwise results are found. Since our further empirical tests involve all three kinds of time frequency, i.e., transaction time, 5 and 10-minute frequency, unit root tests are conducted on each one of them.

In Table 3.3, we present both t -statistics and p -value of the unit root tests.

Overall, we conclude that all price series are $I(1)$ process.

3.3.3 Cointegration Tests

The object of the cointegration test is to determine whether two nonstationary series are cointegrated. As pointed out by Engle and Granger (1987), if a linear combination of two or more nonstationary series is stationary, then the series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables. The cointegration relationship forms the basis of the VEC specification.

The cointegration tests used are based on the methodology developed by Johansen (1991, 1995a). We first consider a VAR of order p :

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t \quad (1)$$

where y_t is a k -vector of non-stationary $I(1)$ variables, and ε_t is a vector of innovations. We may rewrite this VAR as,

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

where

$$\Pi = \sum_{i=1}^p A_i - I_t, \quad \Gamma_i = -\sum_{j=i+1}^p A_j.$$

Granger's representation theorem asserts that if the coefficient matrix Π

has reduced rank $r < k$, then there exist $k \times r$ matrix α and β each with rank r that $\Pi = \alpha\beta'$ and $\beta' y_t$ is $I(0)$. And subsequently r is the number of cointegrating relations and each column of β is the cointegrating vector. Johansen's method is to eliminate the Π matrix from an unrestricted VAR and to test whether the restrictions implied by the reduced rank of Π could be rejected. Cointegration tests establish the fact that there exists a long term equilibrium relation between two nonstationary series, which form the basis for the VEC (Vector Error Correction) model. In Equation (2), the elements of α are known as the adjustment parameters in the VEC model.

Though there is no possible arbitrage to keep the long run equilibrium relation between the indicative prices and transaction prices, as the former prices have no binding obligation of actual transaction, reputation and commercial concerns would drive dealers to quote on the fundamental market information. As a consequence, the indicative and transaction prices are both based on the same information related to the currency pair, and these two prices are expected to be cointegrated.

We conduct the cointegration tests by choosing the lag interval that minimizes the SIC. Based on the chosen lag length, we carry out the five standard types of cointegration tests with the option of including or excluding intercept or trend in the cointegration system. We determine the number of cointegrating vectors by comparing the maximum eigenvalues with their corresponding critical values. The (nonstandard) critical values are taken from

Osterwald-Lenum (1992). In Table 3.4, we present the cointegration results. In all of the tests, we can reject that there is no cointegrating relationship but cannot reject that there is one cointegrating vector at the 5% significance level.

In the following section, we explore the information share between the prices from the two data sets using the cointegration results.

3.4 Information Share

3.4.1 Error Correction Model and Fundamental Value

In economics, fundamental value is essentially an abstract concept that cannot be observed directly. However, we can always assume that, in the long run, the fundamental value would manifest itself and transient information would disappear. In this specification, fundamental value could be identified as the permanent component of a price series. Price discovery therefore describes how one price series incorporates the permanent component into the price system, either in a static or dynamic sense. We follow Lehmann (2002) to explain the information share technique suggested by Hasbrouck (1995).

We start with one pair of cointegrated price series. For most microstructure models, we assume that the efficient price follows a random walk, as stated in a structural model:

$$p_t = lm_t + s_t, \quad p_t = \begin{pmatrix} p_{1t} \\ p_{2t} \end{pmatrix}, \quad s_t = \begin{pmatrix} s_{1t} \\ s_{2t} \end{pmatrix} = Y(L)v_t, \quad l = \begin{pmatrix} 1 \\ 1 \end{pmatrix}. \quad (3)$$

where m_t is the underlying efficient price and s_t is the transient microstructure noise.

From (3) above, the first difference of p_t has the moving average representation

$$\Delta p_t = \Psi(L)\varepsilon_t = lu_t + \Delta s_t = lu_t + (1-L)Y(L)v_t, \quad \Psi(L) = \sum_{j=0}^{\infty} \Psi_j L^j \quad (5)$$

so that Δs_t is a covariance stationary but noninvertible moving average. Since

$$\Psi(L) \equiv \Psi(1) + (1-L)\Psi^*(L), \quad \Psi_i^* = -\sum_{j=i+1}^{\infty} \Psi_j, \quad (6)$$

p_t and Δp_t can be rewritten as

$$p_t = \Psi(1) \sum_{s=0}^t \varepsilon_s + \Psi^*(L)\varepsilon_t, \quad \Delta p_t = \Psi(1)\varepsilon_t + \Psi^*(L)\Delta\varepsilon_t = \Psi(1)\varepsilon_t + (1-L)\Psi^*(L)\varepsilon_t, \quad (7)$$

where $\Psi^*(L)\varepsilon_t$ is covariance stationary and its first difference $(1-L)\Psi^*(L)\varepsilon_t$ is a stationary, noninvertible moving average. Since

$z_t = (1-L)p_t$ is stationary, it must omit the stochastic trend $\Psi(1) \sum_{s=0}^t \varepsilon_s$,

implying that $(1-L)\Psi(1) = 0$ and thus $\Psi(1) = l(\psi_1\psi_2)$ which is intuitively obvious since the two prices share the same implicit efficient price.

This representation underlies the Hasbrouck (1995) information shares approach. The long run impact of ε_t , u_t , and v_t on Δp_t may be found by evaluating both $\Psi(L)$ and $(1-L)Y(L)$ in (5) at $L=1$, yielding

$$\Psi(1)\varepsilon_t = lu_t \quad (8)$$

and the resulting perfect correlation arising from the relation $\psi'\varepsilon_t = u_t$ implies

$$E[l'l'u_t^2] = E[\Psi(1)\varepsilon_t\varepsilon_t'\Psi(1)'] = E[l\Psi'\varepsilon_t\varepsilon_t'\Psi l'] \Rightarrow \sigma_u^2 = \Psi'\Sigma_\varepsilon\Psi \quad (9)$$

Hasbrouck's information shares involve decomposing $\Psi'\Sigma_\varepsilon\Psi$ into components attributed to price innovations in the two markets, where in our case they are the two prices from the two data sets. This attribution is unique when said price innovations are uncorrelated, in which case the decomposition is given by:

$$1 = \frac{\Psi_1^2}{\Psi'\Sigma_\varepsilon\Psi} \sigma_{\varepsilon_1}^2 + \frac{\Psi_2^2}{\Psi'\Sigma_\varepsilon\Psi} \sigma_{\varepsilon_2}^2 \quad (10)$$

However, when the reduced form residuals are correlated, the decomposition is

$$1 = \frac{\Psi_1^2}{\Psi'\Sigma_\varepsilon\Psi} \sigma_{\varepsilon_1}^2 + \frac{\Psi_2^2}{\Psi'\Sigma_\varepsilon\Psi} \sigma_{\varepsilon_2}^2 + 2 \frac{\Psi_1\Psi_2}{\Psi'\Sigma_\varepsilon\Psi} \sigma_{\varepsilon_1}^2 \sigma_{\varepsilon_2}^2 \quad (11)$$

and there is a range of possible attributions corresponding to different allocation of the covariance form to each market. Hasbrouck suggests change the order of the prices, hence the object of the Cholesky decomposition, till all possible orderings are realized, and then calculate the average result. In our case, there are only two price series and hence only two possible rotations of the orders.

3.4.2 Information Share Results

In order to circumvent the contemporaneous residual correlation problem and the ambiguity produced by the reordering procedure, Hasbrouck used ultimate high frequency price series, to reduce this side effect on the information share formula. In our paper, the correlation issue is less serious due to the highly

simultaneous data we process. Our analysis produces results with much tighter bands than most previous studies, which use the information share technique. In both currency pairs, we test the information share of the two data sets at the transaction frequency. We test the robustness of our results using 5 and 10-minute frequency.

We first test for the information share in both currency pairs. We also present the contemporaneous residual correlation in the VEC model. In GBP/USD the indicative and transaction data have a low residual correlation of 16.6% (see the last column of the third row in Table 3.5). The information share attributed to the indicative data EFX is as high as 83%, with relatively tight lower and upper bands of 77% and 89%, respectively. In DEM/USD, with the residual correlation as low as 4.2%, the information share attributes 85% of the total information to the EFX data. The lower and upper bands, as predicted, are only 1.5% away from the average result, indicating a much reliable decomposition. These figures suggest that EFX data take a dominant role in the price discovery process. Using 5 and 10-minute frequency, although the information shares are reduced for EFX data, the conclusion is not fundamentally changed.

We check whether the information share changes during the 24-hour trading days, by separating the trading hours into 7 sessions, which correspond to the opening and closing times of the major foreign exchange markets. The 7 sessions are: 1) 21:00 to 8:00, the period between New York and Tokyo closing

times, representing the Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, the period until the opening of New York; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours until New York closes.

The results are displayed in the middle columns of Table 3.5.³⁰ We also plot them in Figures 3.7 and 3.8. The information share of EFX data peak during London trading (session 3) and overlapping hours (session 5), with GBP/USD having a higher peak in London trading hours, and DEM/USD have a higher peak in overlapping hours. During closing and opening hours, EFX price experiences a drop in information share. These patterns suggest that during two of the peak trading hours, EFX data actually possess higher information content even though there is a substantial increase in the transaction frequency of D2000-1 data.

3.5 Generalized Impulse Response Analysis

In this section, we focus on the dynamic interaction between indicative and transaction prices using impulse response analysis. Due to the importance of the order flow in recent developments in exchange rate theory, we also include in our analysis the order flow from the D2000-1 data set.

³⁰ To calculate the information share of the each session, we use SUR (seemingly unrelated regression) and delete any lagged returns that belong to last day in each equation.

3.5.1 Order flow Analysis

Order flow is a measurement of the difference between buyer initiated trades and seller initiated trades. It is a well investigated factor in microstructure research in equity markets due to the much earlier availability of the data. However, in foreign exchange markets it was introduced by Goodhart and Flood in the late 80s and early 90s. With the seminal paper by Lyons (1995) and the gradual release of data from major trading banks and systems, order flow has become the utmost key word in exchange rate theory.

In foreign exchange microstructure theory, order flow is an important channel for heterogeneously dispersed liquidity information and asymmetric private information on exchange rates (see e.g. Lyons, 1995, Evans, 2002, and Breedon and Vitale, 2005). In traditional canonical models (see e.g. Glosten and Milgrom, 1985) there is two-way causality between price and order flow. In Evans and Lyons (2002) model, the causality runs strictly from order flow to price. A close investigation however reveals that they use hourly frequency and prices are taken as the last price while order flow is the interim aggregate. Therefore, if the actual causality happens at higher frequency, say at 5 to 10 minute frequency as in our case, the information contained in the order flow can well lead the latent price at the end of an hour, even though the true lead and lag pattern is the other way around, i.e., from price to order flow. This mistake could

be further amplified by using daily closing prices to compare intraday day accumulated order flow, as in Killeen et al. (2006) where they find the same conclusion of one way Granger causality from order flow to exchange rates. Our impulse response tests indicate that it might not be the case when using higher frequency data. Causality tests further confirm our findings.

3.5.2 Generalized Impulse Response Analysis

The order flow data in D2000-1 is the transaction sign counts of the inter-bank deal, which does not reveal the exact size of the deal involved. Though the sign of each trade itself could be random, the accumulated order flow could be non-stationary for a given time window. ADF tests indicate that order flow data in both exchange rates are $I(1)$ processes at both 5 and 10 minute frequency (see Table 3.6).

We first look at the movements of the three series, i.e. EFX, D2000-1 and order flow, during our sample period (see Figures 3.9 and 3.10). In order to demonstrate the positive correlation between order flow and the price levels graphically, order flows of both currency pairs are defined as net dollar seller initiated trades. Such a modification is applied in the following empirical tests. The general co-movement between the order flow and prices is apparent, especially in DEM/USD. This suggests that prices and order flow form a system and share the same fundamentals. We are more interested, however, in the

dynamic interaction among the three variables.

We introduce Hasbrouck's (1991) vector autoregression (VAR) model to investigate this issue,

$$\Delta p_{DL,t} = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{1,t} \quad (12)$$

$$\Delta p_{EF,t} = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{2,t} \quad (13)$$

$$\Delta x_t = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{3,t} \quad (14)$$

where $\Delta p_{DL,t}$, $\Delta p_{EF,t}$ and Δx_t stand for D2000-1, EFX price change and order flow change respectively.³¹

As both prices p_t and the order flow x_t are $I(1)$ process, the differenced variables at the left hand sides are stationary. The changes of the order flow are divided by 1,000 to make them comparable to those of prices changes. The estimations are corrected by White's heteroskedasticity consistent standard errors. The optimum lag length is chosen by SIC.

Dynamic analysis of VAR models is routinely carried out using the 'orthogonalized' impulse responses. However, the involved Cholesky decomposition is not invariant to the ordering of the variables in the VAR. Therefore we use Pesaran and Shin's (1998) generalized impulse response approach to analyze the interactions. The generalized impulse responses from an innovation to the j -th variable are derived by applying a variable specific

³¹ It should be noted that we have not included an error correction term as the three series have not been found to be cointegrated.

Cholesky factor computed with the j -th variable at the top of the Cholesky ordering. It only coincides with orthogonalized approach when the investigated variable is put at the top of the ordering.

Figure 3.11 to 3.16 display the impulse response of both prices and order flow in the two currency pairs. Due to space concern, we only present the results at the 5-minute frequency. There is no qualitative difference in the results at the 10 minute frequency.

In GBP/USD currency pair, we find that the response of EFX price to one standard error of D2000-1 price impulse becomes insignificant around lag 2 or 10 minutes (Figure 3.11). However, the effect of one standard error of EFX impulse in D2000-1 disappear after around lag 6 or 30 minutes (Figure 3.12). In both Figures 3.11 and 3.12, the responses of order flow to the shocks from the two prices build up from lag 1 until lag 3, and then slide to insignificance at lag 4 or 20 minutes. In stark contrast, we could not find any significant response from the two prices to the order flow shock (Figure 3.13).

In DEM/USD currency pair the impulse response profiles are slightly different. Again, the response of EFX price to the D2000-1 impulse dies out at lag 2 to 3 (Figure 3.14). However, the response of D2000-1 to the impulse of EFX takes 15 minutes (at lag 3) to reach insignificance. In both Figures 3.14 and 3.15, the responses of order flow to the price shocks quickly slide to near zero around 10 minutes, and then reach their peaks after another 5 minutes. The impacts of the prices' shocks on the order flow continue to exist even over 30

minutes, which is different from those profiles in GBP/USD currency pair.

Finally, there is no significant response of prices to the order flow shock.

To summarize, the impulse response analysis in both currency pairs indicates that the shocks from EFX have much longer impact on D2000-1 data than vice versa. EFX data' impulses also have similar significant impact like those of D2000-1 on order flow. And order flow imposes no impact on prices, in contrast to the claims that order flow contains private information that is not revealed in prices.

In Tables 3.7 and 3.8, we present the Granger causality tests on order flow with indicative and transaction data at both frequencies³². The causality is unambiguously one direction from prices to order flow, with literally no causality from order flow to prices. The results are more obvious at 10 minute frequency than 5 minute frequency. Combined with the impulse response analysis, order flow is a latent and passive response to prices at high frequency. Even if order flow does carry dispersed information among dealers, it can not happen at such high frequency, as opaque de-centralized market institution stops individuals from quickly aggregating information from disintegrated order flows.

³² Since there is no cointegration between prices and order flow as we have tested, the Granger causality test is not affected by the complicated issues caused by ECM (see Toda and Phillips, 1993).

3.6 Conclusion

By comparing various statistical features of the EFX and D2000-1 data sets, we find that, contrary to previous studies, the indicative data are not inferior in terms of quality of information. More precisely, both lead-lag and impulse response analyses conclude that the indicative data lead the transaction data by 5 to 10 minutes. Furthermore, information share technique indicates a dominant role for the indicative data in mapping information. By adding order flow in the trivariate generalized impulse response analysis, we find that EFX price has a similar impact on order flow as D2000-1 price. The finding that order flow has no significant impact on prices may be due to that, at high frequency, the information embedded in the order flow is difficult to be aggregated by traders.

These findings are supportive of studies using indicative data, since the quality of their data has never been formally tested. The different merits of indicative and transaction data in reflecting market information suggest that we should combine both types of data to reveal the hidden picture of the heterogeneously distributed information in foreign exchange markets.

References

Breedon, F., and P. Vitale. 2005. An empirical study of liquidity and information effects of order flow on exchange rates. Working paper.

Danielsson, J., R. Payne. 2002. Real trading patterns and prices in spot foreign exchange markets. *Journal of International Money and Finance*, 21: 203-222.

de Jong, F., R. Mahieu, and P. Schotman. 2001. Price discovery on foreign exchange markets with differentially informed traders. Working paper.

Dickey, D. A., and W. A. Fuller. 1981. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49: 1057-1072.

Dufour, A., R. F. Engle. 2000. Time and the price impact of a trade. *Journal of Finance*, 55: 2467-2498.

Engle, R.F., C. J. W. Granger. 1987. Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55: 251-276.

Engle, R. F. and A. J. Patton. 2004. Impacts of trades in an error-correction model of quote prices. *Journal of Financial Markets*, 7: 1-25.

Engle R. F. and J. R. Russell. 1997. Forecasting the frequency of changes in quoted foreign exchange prices with the autoregressive conditional duration model. *Journal of Empirical Finance*, 4: 187-212.

Evans, M., D., 2002, FX trading and exchange rate dynamics, *The Journal of Finance*, 6: 2405-2447.

Evans, M., D., and R. K. Lyons. 2002. Time-varying liquidity in foreign exchange, *Journal of Monetary Economics*, 49: 1025-1051

Gonzalo, J., and S. Ng. 2001. A systematic framework for analyzing the dynamic effects of permanent and transitory shocks, *Journal of Economic Dynamics and Control*, 25: 1527-1546.

Goodhart, C., T. Ito, R. Payne. 1996. One day in June, 1993: a study of the workings of Reuters D2000-2 electronic foreign exchange trading system. In: *The Microstructure of Foreign Exchange Markets*. University of Chicago Press, Chicago, 107-179.

Hasbrouck, J. 1991. Measuring the information content of stock trades. *Journal*

of Finance, 46: 179-207.

_____. 1995. One security, many markets: Determining the contributions to price discovery. *Journal of Finance*, 50: 329-339.

Johanson, S. 1988. Statistical Analysis of Co-integrating Vectors. *Journal of Economic Dynamic and Control*, 12: 231-254.

Killeen., W., P., Lyons., R., K., and Moore., M., J. 2006. Fixed versus flexible: lesson from EMS order flow. *Journal of international Money and Finance*, 25: 551-579

Lehmann, B., N. 2002. Some desiderata for the measurement of price discovery across markets. *Journal of Financial Markets*, 5: 259-276.

Lyons, R. 1995. Tests of Microstructural Hypotheses in the Foreign Exchange Market. *Journal of Financial Economics*, 39: 321-351.

_____. 2001. *The Microstructure Approach to Exchange Rates*. Cambridge, MA: MIT press.

Osterwald-Lenum, M. 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank tests statistics. *Oxford Bulletin of Economics and Statistics*, 54: 461-472.

Pesaran M.H., and R.P. Smith. 1995. Estimation of long-run Relationships from Dynamic Heterogeneous Panels. *Journal of Econometrics*, 68: 79-113.

Toda, H. Y. and P. C. B. Phillips. 1993. Vector autoregressions and causality. *Econometirca*, 61:1367-1393.

Table 3.1

Two ticks of sample data

EFX	Date	Time	Bid	Ask	Nation	City	Bank	Filter	
	1996-5-1	0:00:12	1.5	1.506	392	1	532	1	
D2000-1	Month	Day	Hour	Minute	Sec	T_ind.	B/S	Price	Vol
	5	1	1	15	35	501.05	0	1.5047	0

Note: These two ticks of data relate to GBP/USD. In the rows of EFX data, the codes for the nation, city and bank are assigned by the Reuters system. Filter column checks whether the price is an outlier, with number 1 indicating a good data and 0 otherwise. In the rows of D2000-1 data, T_index is converted time index of the transaction time. B/S stands buyer or seller initiated trade. Vol is the volume. The corresponding DEM/USD data have the same format.

Table 3.2
Properties of processed data sets with transaction time

GBP/USD	Mean	Median	Max	Min	Std. D.	Skew	Kurtosis
D2000-1	1.5397	1.5450	1.5650	1.4895	0.0167	-1.0137	2.9501
EFX	1.5393	1.5445	1.5682	1.4895	0.0167	-1.0136	2.9512
DEM/USD	Mean	Median	Max	Min	Std. D.	Skew	Kurtosis
D2000-1	1.5090	1.5182	1.5510	1.4638	0.0237	-0.1285	1.4205
EFX	1.5087	1.5180	1.5488	1.4635	0.0237	-0.1282	1.4198

Notes: The statistical results include all sample data of 82 trading days. There are in total of 51,741 pairs of GBP/USD prices and 255,481 pairs of DEM/USD prices. We use D2000-1's time stamp as the benchmark time to locate the nearest EFX data. The bid-ask selection for EFX data is also based on the D2000-1 order flow sign.

Table 3.3
Results of unit-root tests

	Transaction Time		5-Minute		10-Minute	
	EFX	D2000-1	EFX	D2000-1	EFX	D2000-1
GBP/USD						
<i>t-Sta.</i>	-2.01	-1.97	-2.39	-2.37	-1.94	-1.95
<i>Prob.</i>	0.28	0.30	0.14	0.15	0.31	0.31
DEM/USD						
<i>t-Sta.</i>	-1.13	-1.05	-1.08	-1.09	-1.09	-1.08
<i>Prob.</i>	0.71	0.74	0.73	0.72	0.72	0.73

Note: The two currency pairs from the two data sets are converted into the three frequencies before testing for unit-root. Both t-statistics and p-values are presented.

Table 3.4
Results of cointegration tests

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Sta.	5% Critical Value	1% Critical Value
GBP/USD - Transaction Frequency				
None *	0.07	3931.83	11.22	0.00
At most 1	0.00	1.18	4.13	0.32
GBP/USD - 5-minute Frequency				
None *	0.24	2264.14	15.89	1.00
At most 1	0.00	6.90	9.16	0.13
GBP/USD - 10-minute Frequency				
None *	0.24	1930.19	15.89	1.00
At most 1	0.00	4.89	9.16	0.30
DEM/USD - Transaction Frequency				
None *	0.03	6907.16	15.89	1.00
At most 1	0.00	2.09	9.16	0.76
DEM/USD - 5-minute Frequency				
None *	0.24	4877.84	15.89	1.00
At most 1	0.00	2.01	9.16	0.78
DEM/USD - 10-minute Frequency				
None *	0.24	2831.07	11.22	0.00
At most 1	0.00	0.82	4.13	0.42

Notes: The methodology is based on Johansen (1991 and 1995a). The optimum lag is chosen by Schwarz Information Criterion. The critical values are taken from Osterwald-Lenum (1992).

Table 3.5
Information share results of EFX data

GBP/USD EFX Information Share									
	1	2	3	4	5	6	7	ALL	Resid Corr
Trans.	61%	78%	90%	78%	93%	89%	74%	83%	17%
5-Min	49%	62%	83%	70%	81%	78%	65%	73%	50%
10-Min	42%	54%	74%	64%	67%	62%	60%	67%	60%

DEM/USD EFX Information Share									
	1	2	3	4	5	6	7	ALL	Resid Corr
Trans.	71%	79%	90%	82%	87%	82%	80%	85%	42%
5-Min	67%	76%	84%	69%	81%	77%	75%	81%	34%
10-Min	53%	71%	78%	61%	70%	66%	64%	76%	54%

Notes: The information share of the EFX data is calculated using ECM based Hasbrouck's (1995) technique. The columns numbered from 1 to 7 stand for the different trading zones of a complete trading day. The last two columns are the information share of the EFX data of the whole sample period and the residual correlation of the ECM, respectively.

Table 3.6
Unit-root test on order flow

Null Hypothesis: Order flow has a unit root				
Exogenous: Constant and trend				
Lag Length: Automatic based on SIC				
	GBP/USD		DEM/USD	
	5-Minute	10-Minute	5-Minute	10-Minute
<i>t-Stat.</i>	-1.49709	0.461431	-1.66038	-1.58001
<i>Prob.</i>	0.8309	0.9854	0.7687	0.8011

Notes: The order flow data are the accumulated transaction signs of each 5 or 10 minutes, depending on the converted frequency. The test includes a constant and a trend. Both t-statistics and p-value are displayed.

Table 3.7
Granger causality test of order flow and prices at 5-m frequency

5-Minute	Null Hypothesis:	F-Sta.	Prob.
GBP/USD Obs: 8034	Order flow does not Granger Cause EFX	1.18	0.10
	EFX does not Granger Cause Order Flow	4.63	2.40E-46
	Order flow does not Granger Cause D2000-1	1.16	0.13
	D2000-1 does not Granger Cause Order Flow	4.21	1.50E-39
DEM/USD Obs:17178	Order Flow does not Granger Cause EFX	1.08	0.22
	EFX does not Granger Cause Order Flow	10.71	2.00E-299
	Order flow does not Granger Cause D2000-1	1.12	0.13
	D2000-1 does not Granger Cause Order Flow	8.73	5.00E-230

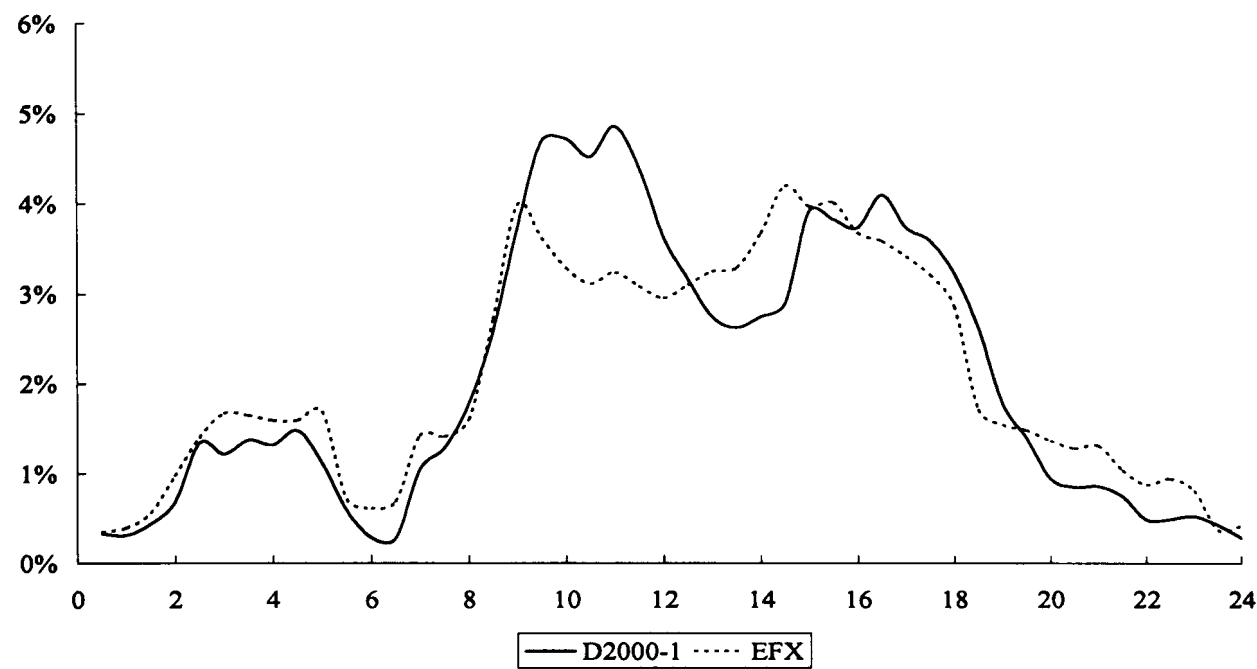
Notes: The two-way causality tests are conducted on the order flow and the two currency pairs from the two 5-minute data sets. Both F-statistics and p-value are displayed in the last two columns.

Table 3.8
Granger causality test of order flow and prices at 10-m frequency

10-Minute	Null Hypothesis:	F-Sta.	Prob.
GBP/USD Obs: 7206	Order flow does not Granger Cause EFX	0.94	0.66
	EFX does not Granger Cause Order Flow	5.90	5.20E-67
	Order flow does not Granger Cause D2000-1	1.03	0.39
	D2000-1 does not Granger Cause Order Flow	4.41	1.60E-42
DEM/USD Obs: 10132	Order Flow does not Granger Cause EFX	0.93	0.69
	EFX does not Granger Cause Order Flow	17.00	1.00E-263
	Order flow does not Granger Cause D2000-1	1.16	0.13
	D2000-1 does not Granger Cause Order Flow	12.99	3.00E-193

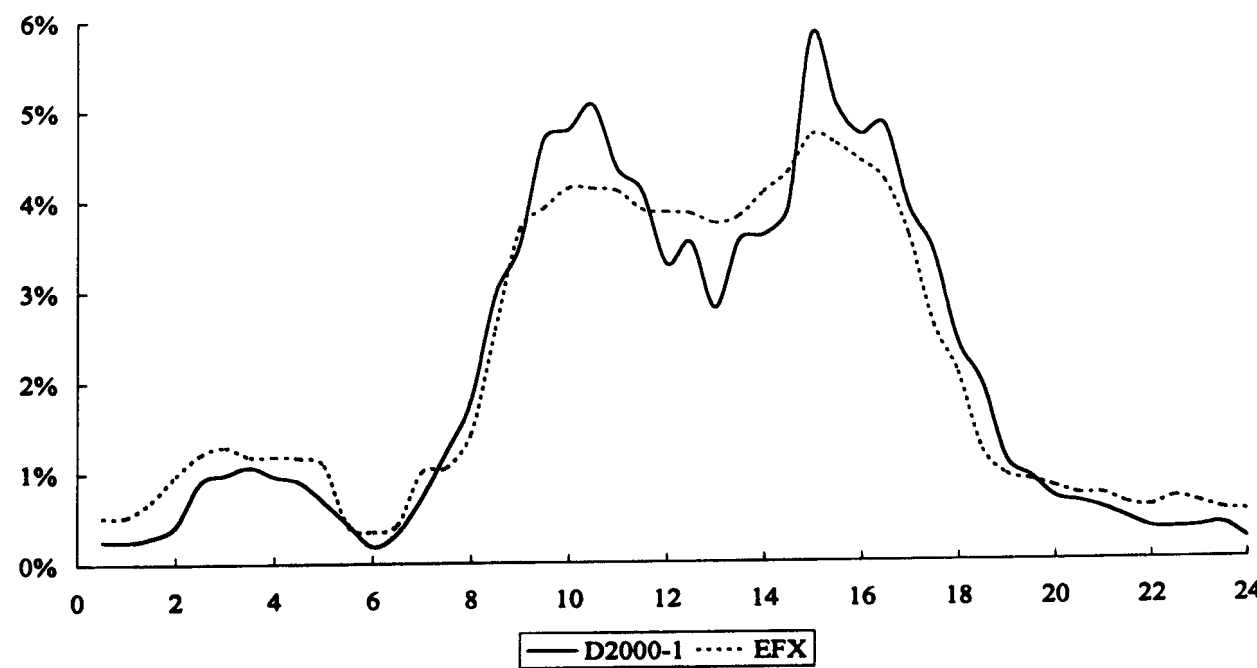
Notes: The two-way causality tests are conducted on the order flow and the two currency pairs from the two 10-minute data sets. Both F-statistics and p-value are displayed in the last two columns.

Figure 3.1
GBP/USD intraday quote (trade) frequency



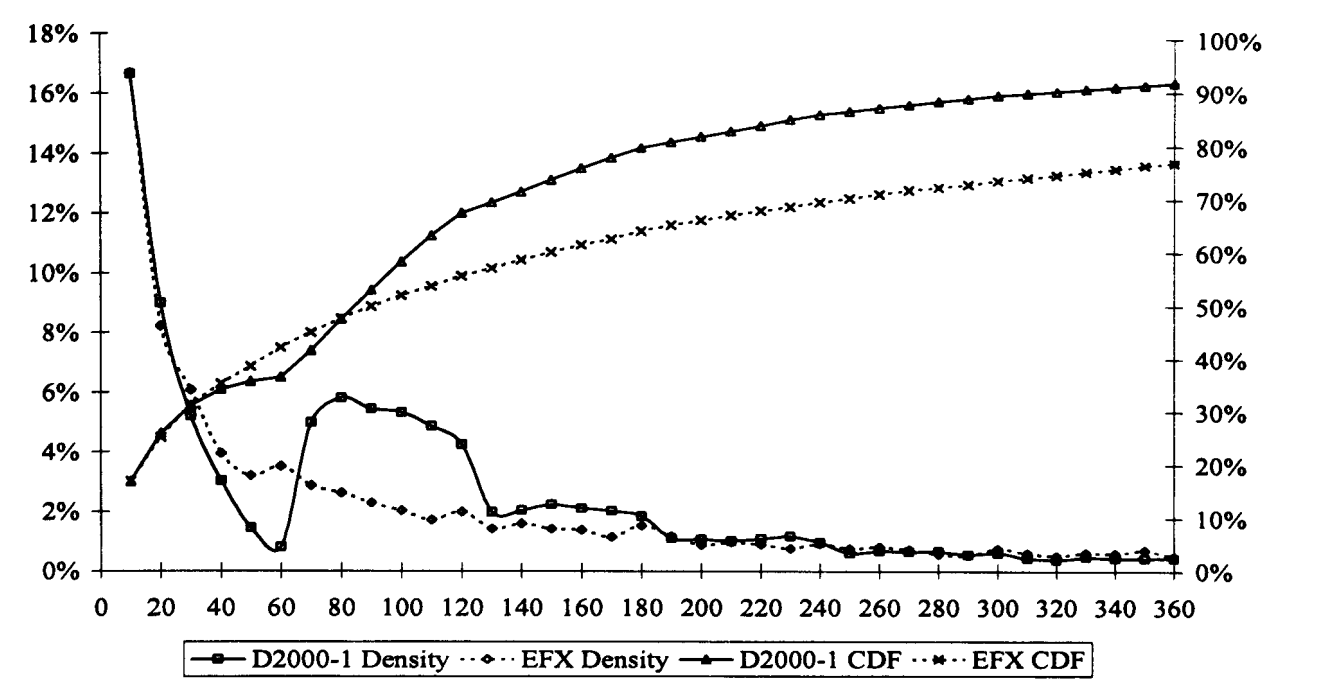
Notes: The intraday GBP/USD quote (trade) frequency is calculated by counting each half hour's prices and then dividing it by the total number of the sample average daily counts. Along the x-axis is the time index of each half hour starting from GMT 00:00.

Figure 3.2
DEM/USD intraday quote (trade) frequency



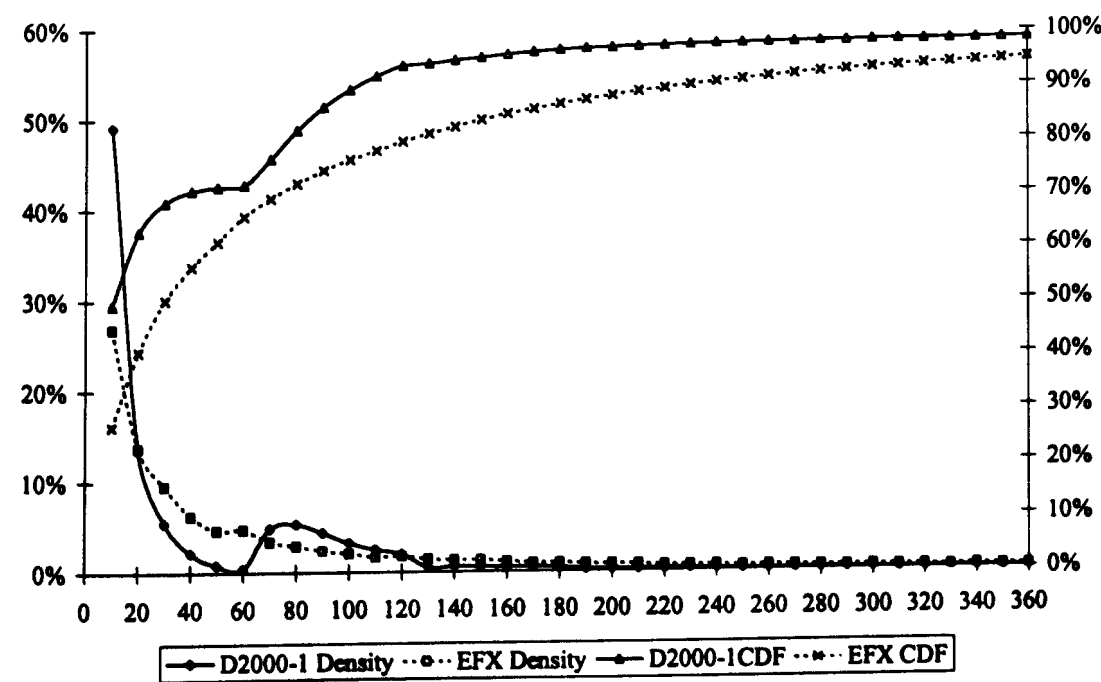
Notes: The intraday DEM/USD quote (trade) frequency is calculated by counting each half hour's prices and then dividing it by the total number of the sample average daily counts. Along the x-axis is the time index of each half hour starting from GMT 00:00.

Figure 3.3
Duration distribution of GBP/USD



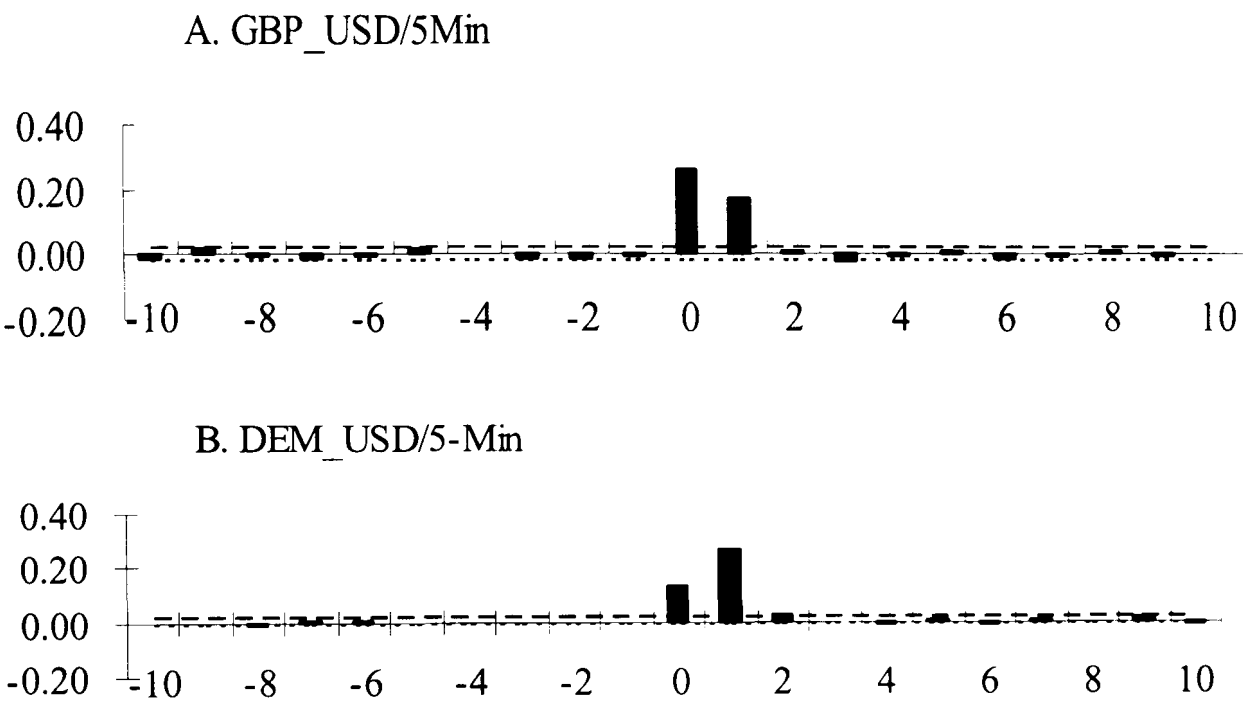
Notes: The D2000-1 density is based on the duration distribution of all prices. Cumulative distribution function (CDF) is the accumulated density for all duration. The duration density for EFX data is processed on quotes with changes larger than 5 basis points. The primary Y-axis corresponds to the density of the durations and the secondary Y-axis is the corresponding cumulative frequency. The X-axis indicates seconds.

Figure 3.4
Duration distribution of DEM/USD



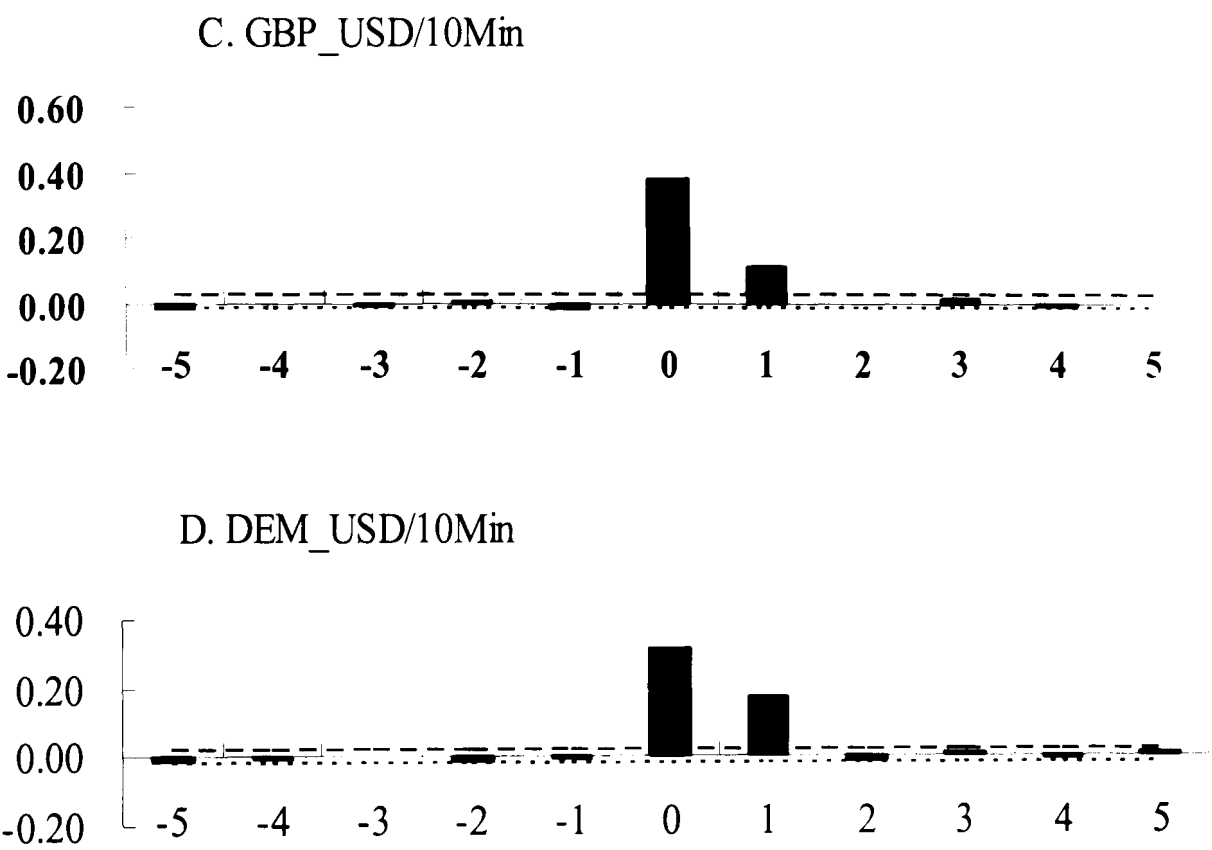
Notes: See notes to Figure 3-3.

Figure 3.5
Cross-correlation of EFX and D2000-1 data at 5-m frequency



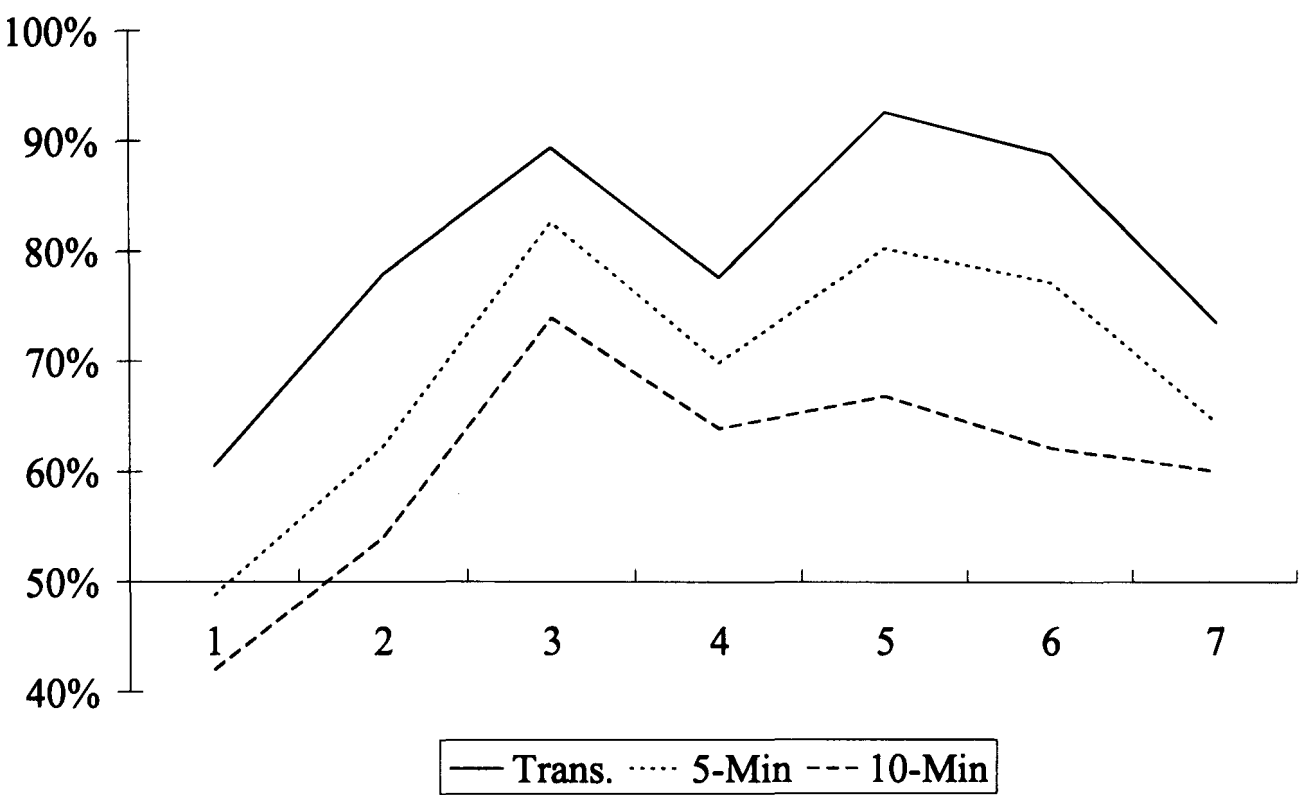
Notes: The 95% confidence levels are formed by calculating $\pm 2/\sqrt{T}$, with T being usable observations, which are the dotted lines in both graphs. Positive lag at the X axis indicate that EFX quotes are at the lead and vice versa.

Figure 3.6
Cross-correlation of EFX and D2000-1 data at 10-m frequency



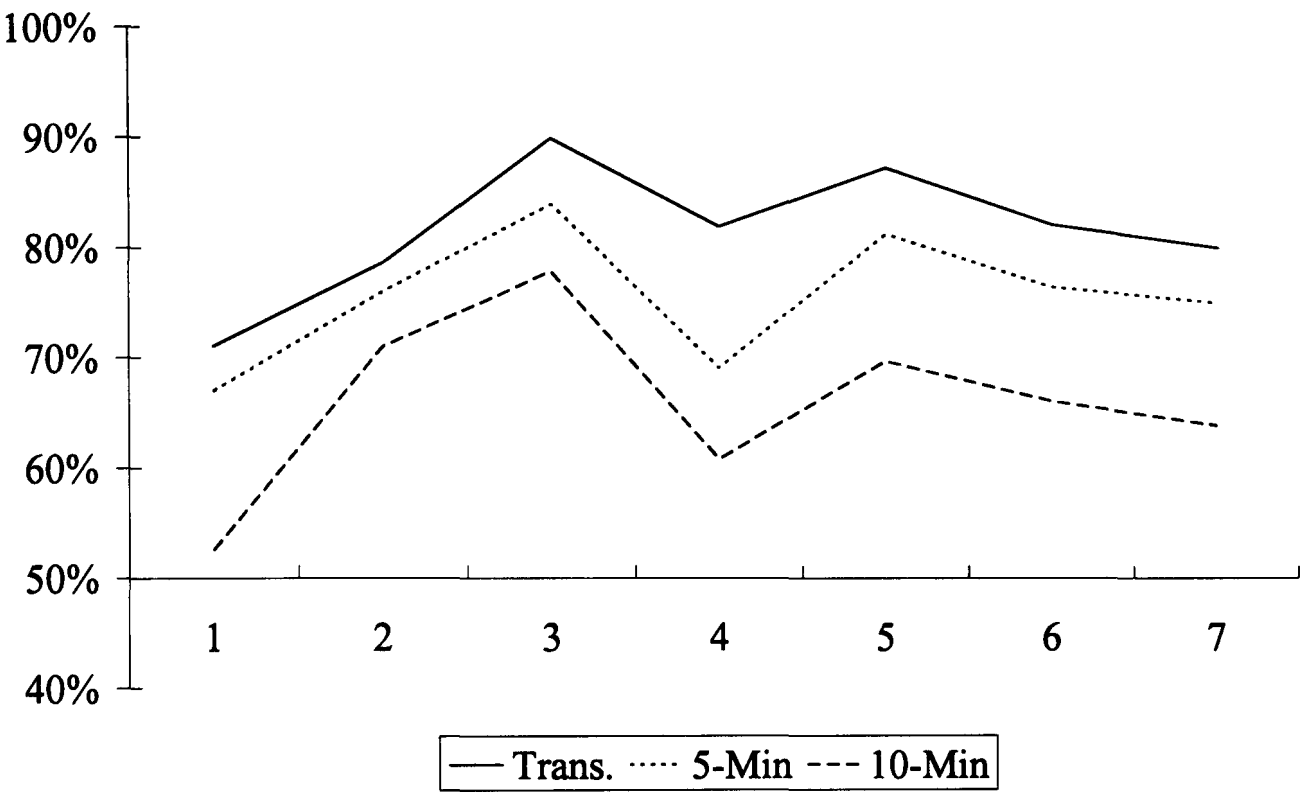
Notes: The 95% confidence levels are formed by calculating $\pm 2/\sqrt{T}$, with T being usable observations, which are the dotted lines in both graphs. Positive lag at the X axis indicate that EFX quotes are at the lead and vice versa.

Figure 3.7
GBP/USD - information share of EFX during trading sessions



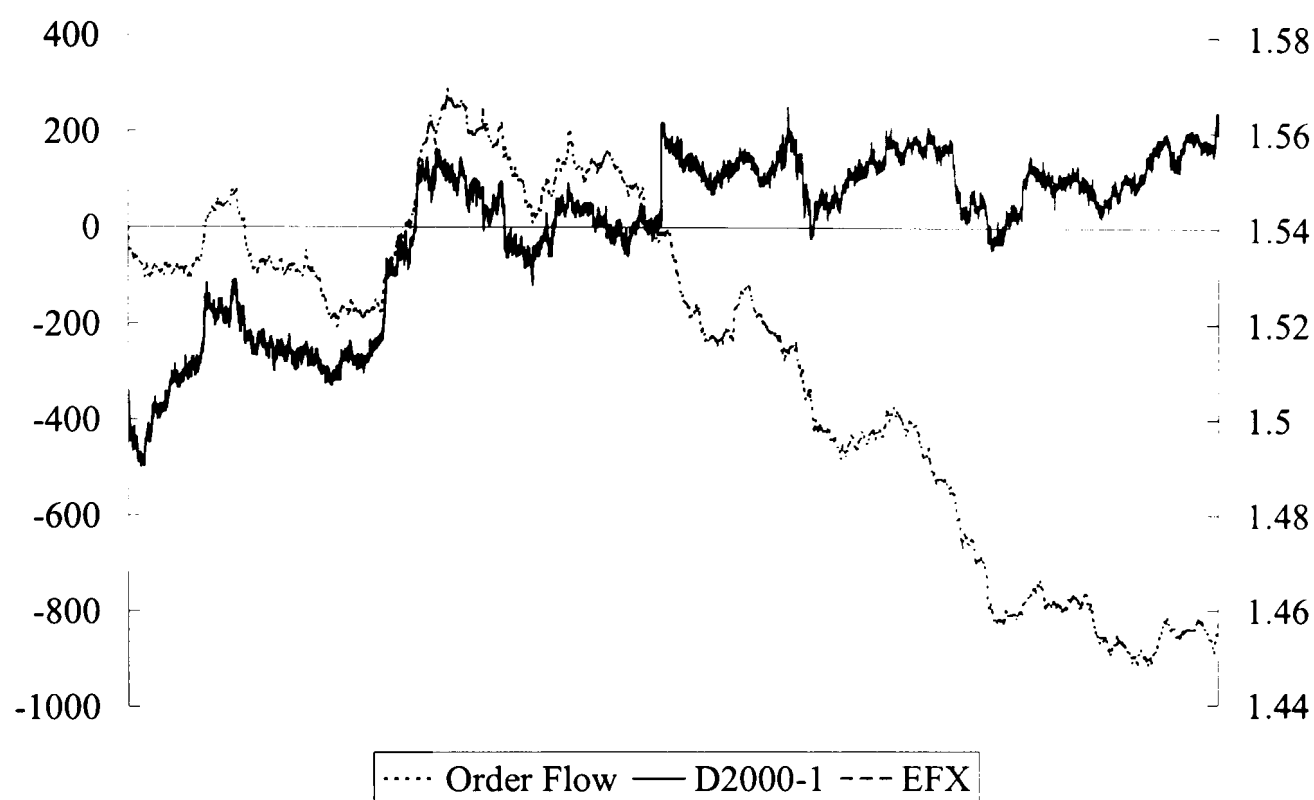
Notes: We separate the trading hours into 7 sessions that corresponds to major FX markets' openings and closings. The 7 sessions are 1) 21:00 to 8:00, New York closes till Tokyo closes, representing Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, hours till New York opens; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours till New York closes.

Figure 3.8
DEM/USD - information share of EFX during trading sessions



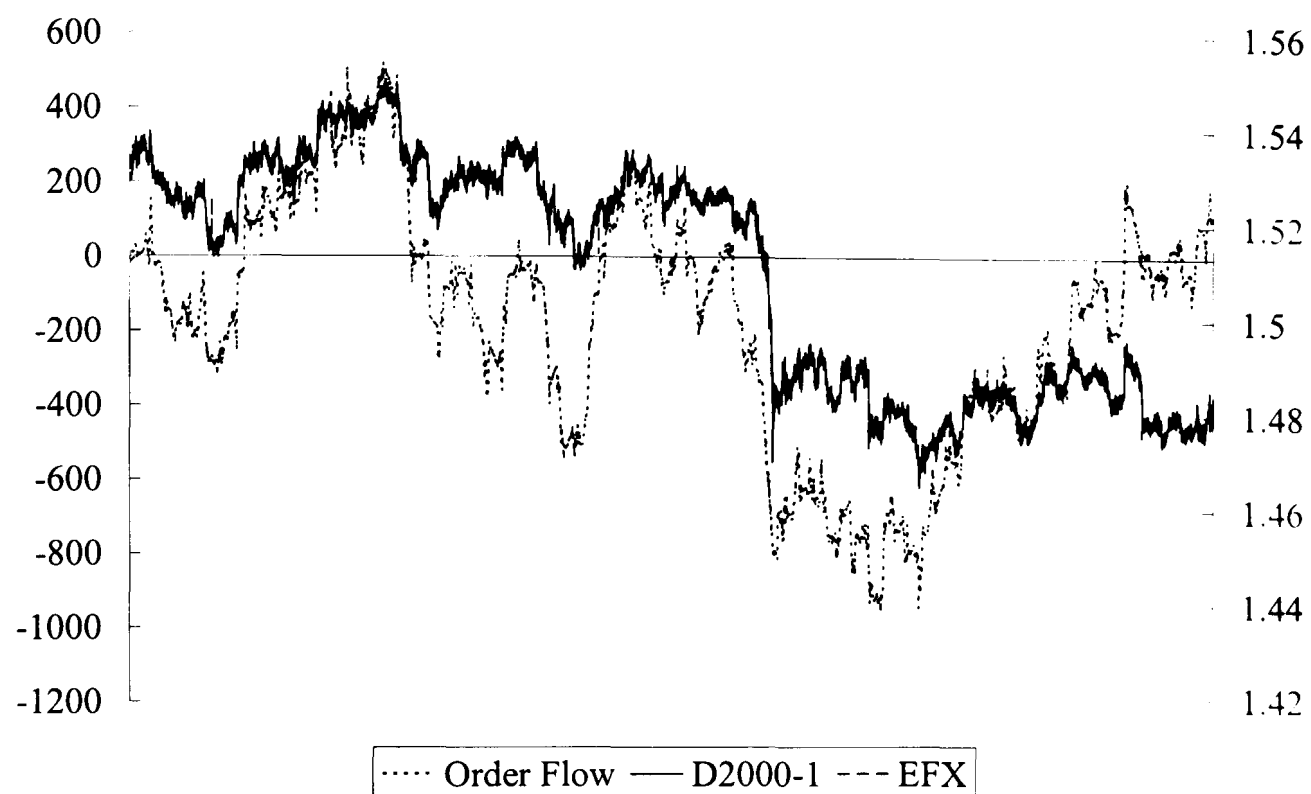
Notes: We separate the trading hours into 7 sessions that corresponds to major FX markets' openings and closings. The 7 sessions are 1) 21:00 to 8:00, New York closes till Tokyo closes, representing Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, hours till New York opens; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours till New York closes.

Figure 3.9
Order flow and prices in GBP/USD (10-M)



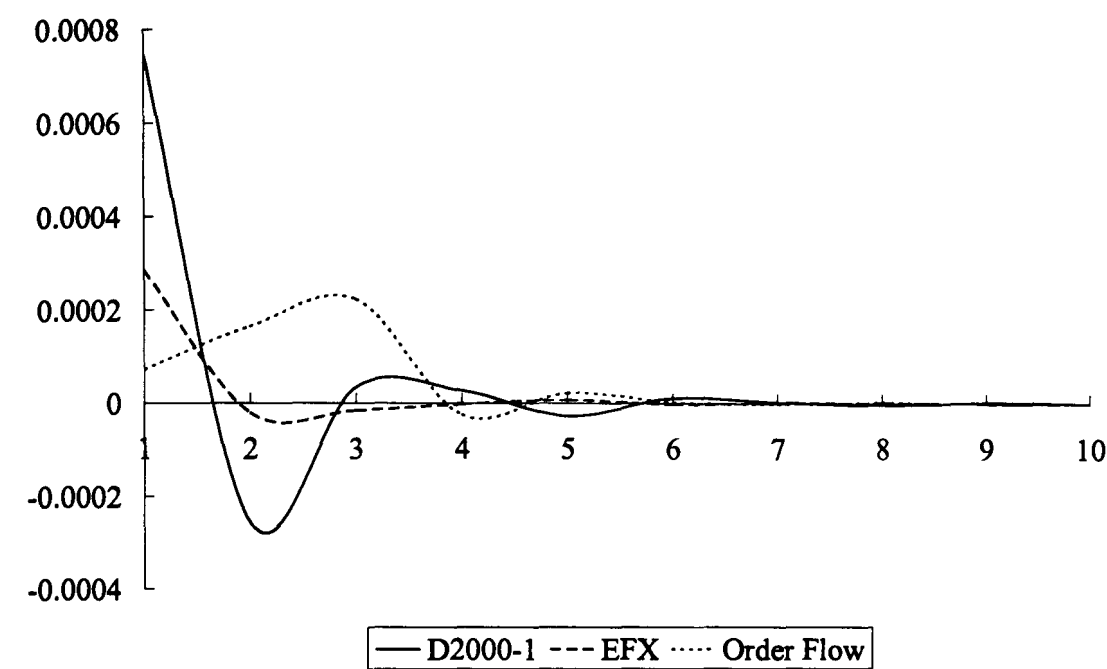
Notes: Order flow is the cumulative transaction signs for each 10 minute session during our sample period. The 10-minute frequency prices of the two data sets literally overlap each other due to long time window. The primary Y-axis measures the order flow while the secondary Y-axis is for the price level.

Figure 3.10
Order flow and prices in DEM/USD (10-M)



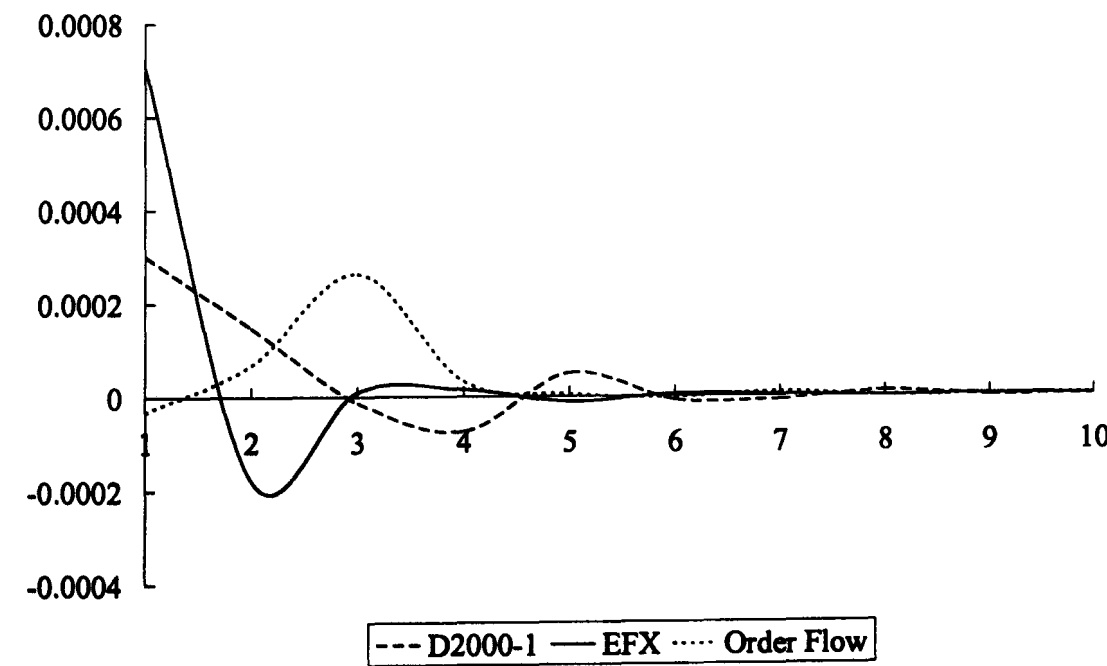
Notes: Order flow is the cumulative transaction signs for each 10 minute session during our sample period. The 10-minute frequency prices of the two data sets literally overlap each other due to long time window. The primary Y-axis measures the order flow while the secondary Y-axis is for the price level.

Figure 3.11
Generalized impulse response to D2000-1 shock (GBP/USD)



Notes: These are the generalized impulse responses to one S.E. of D2000-1 shock in GBP/USD currency pair. Each lag stands for 5 minute.

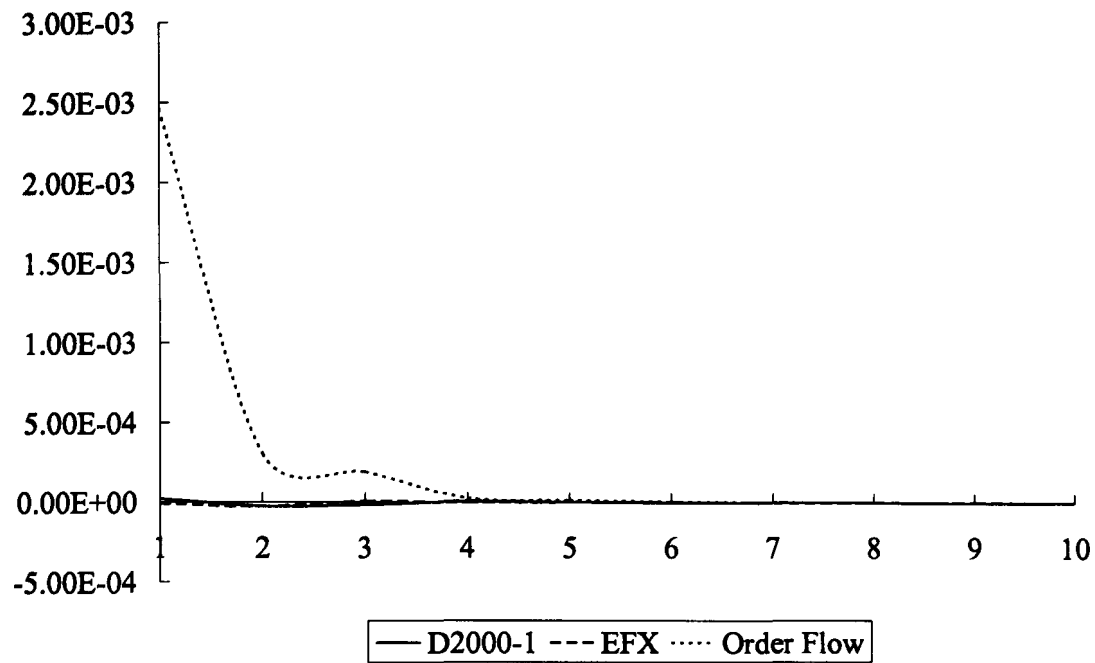
Figure 3.12
Generalized impulse response to EFX shock (GBP/USD)



Notes: These are the generalized impulse responses to one S.E. of EFX shock in GBP/USD currency pair. Each lag stands for 5 minute.

Figure 3.13

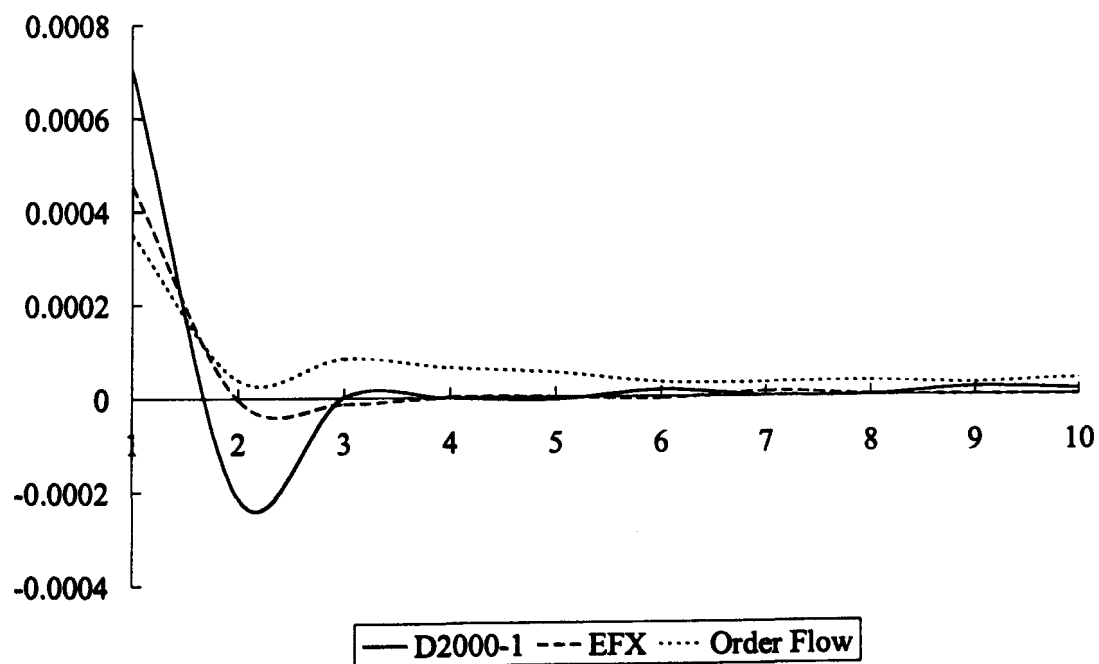
Generalized impulse response to order flow shock (GBP/USD)



Notes: These are the generalized impulse responses to one S.E. of order flow shock in GBP/USD currency pair. Each lag stands for 5 minute.

Figure 3.14

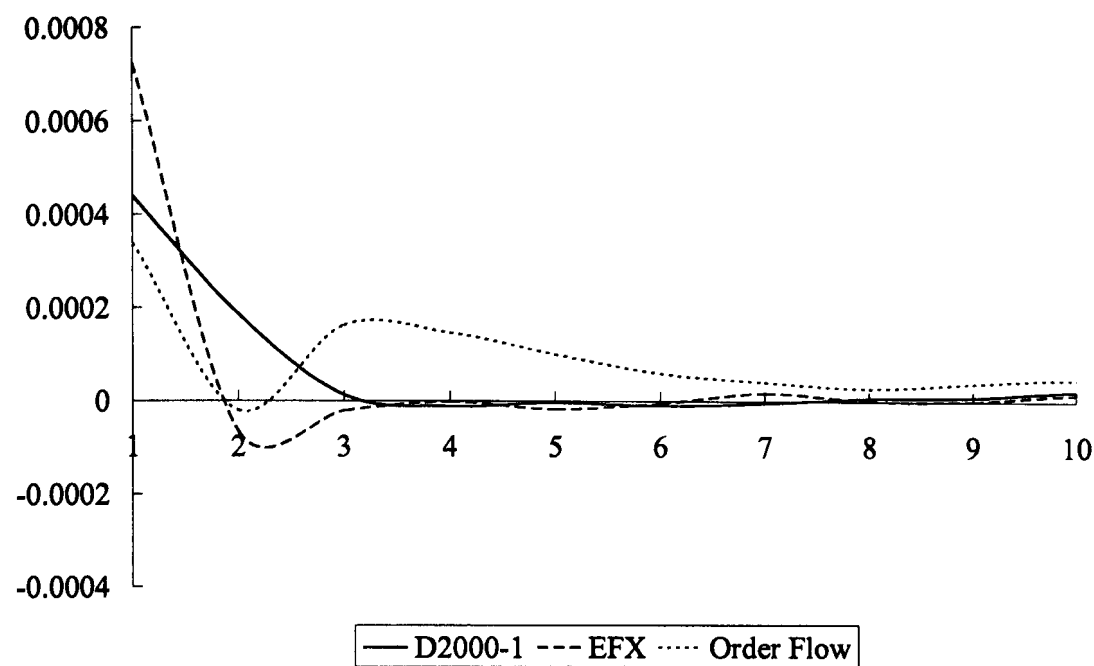
Generalized impulse response to D2000-1 shock (DEM/USD)



Notes: These are the generalized impulse responses to one S.E. of D2000-1 shock in DEM/USD currency pair. Each lag stands for 5 minute.

Figure 3.15

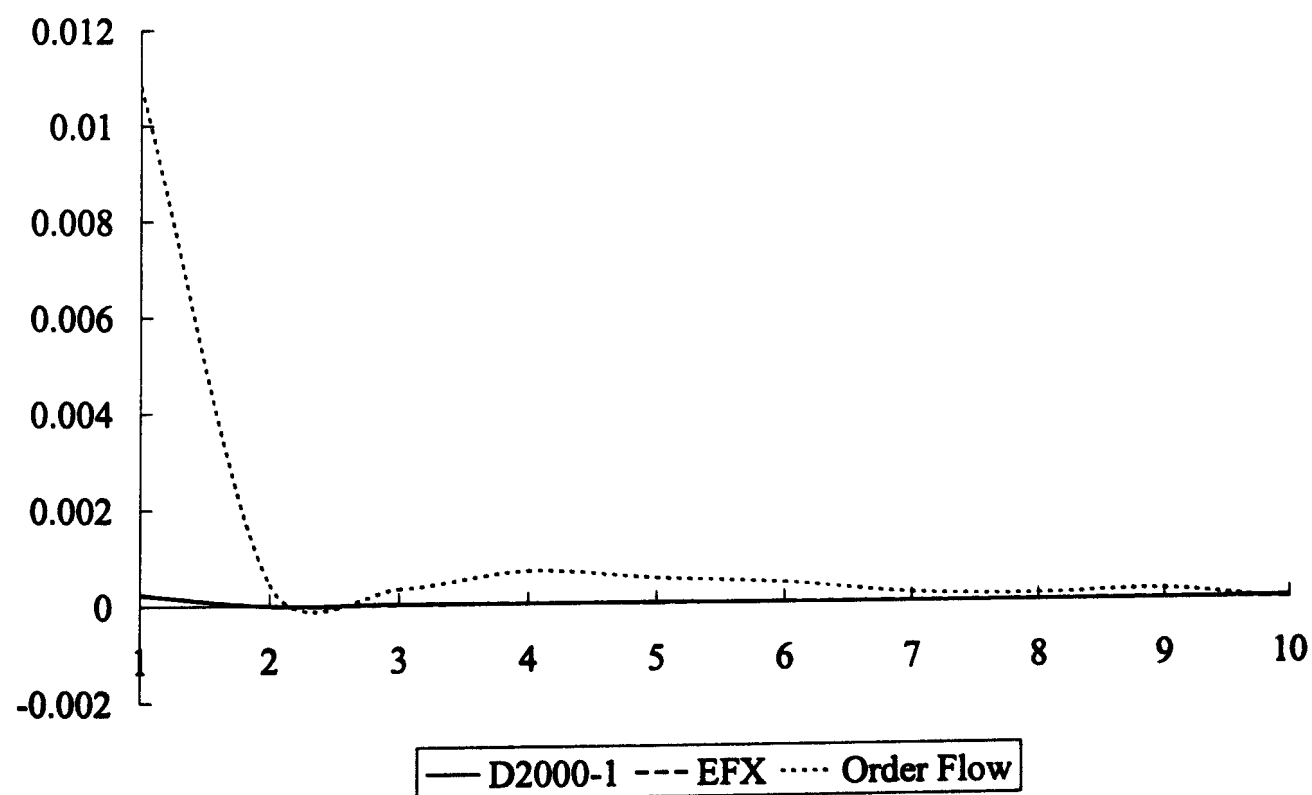
Generalized impulse response to EFX shock (DEM/USD)



Notes: These are the generalized impulse responses to one S.E. of EFX shock in DEM/USD currency pair. Each lag stands for 5 minute.

Figure 3.16

Generalized impulse response to order flow shock (DEM/USD)



Notes: These are the generalized impulse responses to one S.E. of order flow shock in DEM/USD currency pair. Each lag stands for 5 minute.

Chapter 4

Do Top Banks in FOREX Business Know More?

4.1 Introduction

Though the foreign exchange market is the largest financial market with a daily turnover of \$US 1.9 trillion³³, it is not necessarily a market of perfect competition. According to Euromoney (May, 1995), the largest 10 foreign exchange banks accounted for 45% of global foreign exchange business in 1994. Consolidation in the banking sector since then brought further concentration in the foreign exchange market. The BIS triennial survey (2005) reports a substantial decline since 1995 in the number of banks accounting for 75% of local turnover. In the U.S., there were only 11 banks conducting 75% of foreign exchange market transactions in 2004, compared to 13 banks in 2001, and to 20 banks in both 1998 and 1995. The same trend is found in the UK foreign exchange market. Such concentration suggests that top banks in foreign exchange business may exert greater impact on the price formation process than

³³ BIS triennial survey 2005.

the relatively smaller banks. Supportive evidence for that is found in Cheung and Chinn's (2001) survey of the US market where 50% of currency traders agreed that there are dominant players in the GBP/USD market.

Such findings motivate our investigation on the information asymmetry in the spot foreign exchange market and its implications for the existence of private information. We test the hypothesis that top trading banks in the foreign exchange business have more information on the macro economy. The dominant banks' information advantage over their rivalries can be interpreted under a microstructure framework, where transactions play a central, causal role in price determination.³⁴ In the foreign exchange market prices are determined collectively by macro economic factors, such as economic growth, consumption, unemployment and interest rates. Information about them is not directly observable on a real-time base, but dispersed widely among heterogeneous market players prior to public announcements. Even after the actual announcements, their interpretation is subject to the individual market participant's judgment. One needs to jigsaw together the dispersed partial information in order to form a complete picture of the macro economy. In foreign exchange markets customer order flow is one of the potential sources, which helps trading banks to aggregate this dispersed information and 'feel' the general movements of the economy.³⁵ For example, Lyons (1997) finds that

³⁴ See, e.g., Glosten and Milgrom (1985) and Kyle (1985).

³⁵ See, e.g., Lyons (1995), Bjonnes and Rime (2005), Rime (2001), Payne (2003) and Evans and Lyons (2005a).

foreign exchange order flows generated by international trades and services help dealers to 'know' the trade balance figures long before the statistics are published. One hence may expect that the more order flow a trader processes, the more information she could garner from it. Therefore, the dominant role of major banks in the global foreign exchange transactions may cause them in turn to have a dominant share of market information.

We test this hypothesis by examining the information share of the top trading banks relative to that of the rest of the banks in the GBP/USD market.³⁶ We also test whether this information advantage is prevalent during general scheduled macro news.

Our paper relates to previous work, which has studied the existence of private information and the effects of news in the foreign exchange market. A number of studies have examined the possible existence of private information by looking at the price leadership amongst trading banks around central bank interventions. For example, Piers (1997) examines the quoting behaviour of dealers in the DEM/USD market around Bundesbank interventions from October 1992 to September 1993 and finds evidence of price leadership by Deutsche Bank before the announcement of interventions. However, when de Jong, Mahieu, Schotman, and van Leeuwen (1999) repeated the analysis and Dominguez and Panthaki (2003) expanded it to include Federal Reserve intervention activities no specific bank was found to act as price leader. In

³⁶ The top 10 banks are selected by Euromoney's biennial survey.

contrast, Sapp (2002) using a bigger sample of DEM/USD quotes from the Reuters' FAFX system from January 1991 to September 1993, finds that Chemical Bank's quotes are the first to contain new information. However, in the periods of uncertainty around central bank intervention, evidence suggests Deutsche Bank is the price leader. Thus, the results found in the above studies regarding price leadership amongst banks around central bank interventions as a public news item are mixed.

Another group of studies has investigated the impact of macroeconomic news on exchange rates in isolation from quantities. For example, Almeida et al. (1998) study the different reactions of DEM/USD to German and U.S. macro announcements. Andersen and Bollerslev (1998) examine the impact of macroeconomic announcements on the volatility of DEM/USD, while Andersen, Bollerslev, Diebold and Vega (2003) expand the number of exchange rates to five and find significant and asymmetric response to good and bad U.S. scheduled news. Bauwens et al. (2005) investigate both scheduled and unscheduled news announcements on the EUR/USD volatility and find the volatility increases before the announcements. Finally, Dominguez and Panthaki (2006) further expand the news selections into those related to fundamental, technical analysis and order flow, and their effects on the EUR/USD and GBP/USD exchange rates. Their results suggest other non-scheduled news also matters in foreign exchange markets.

Finally, another group of studies has investigated the impact of

macroeconomic news as a joint quantity and price response. They examined whether macro announcement surprises have a systematic and significant effect on both order flows and prices. For example, Carlson and Lo (2006) apply a case-study approach and analyse the impact of a single macro announcement. They find that market characteristics were affected for hours following the announcement. Evans and Lyons (2003), Love and Payne (2007), Rime, Sarno and Sojli (2007) examine several news arrivals but over a few months and find that macroeconomic information releases have systematic effects on order flow and as established in earlier studies on exchange rate transaction prices. However, their results show that a substantial amount of the transmission of macroeconomic news to prices is incorporated via the trading process, i.e. order flow significantly increases the explanatory power of exchange rate fluctuations as compared to news alone.³⁷

Our work has a number of novel features compared to previous research in this area. First, our study is one of the first to test general macro news effects under the heterogeneity market assumption, in contrast to previous work, which either implies the market homogeneity assumption, or only tests for the central bank intervention as public news under the heterogeneity assumption. Due to commercial confidentiality reasons, the data on prices and order flows are aggregated at certain lower frequency with no information on the identity of the

³⁷ Evans and Lyons (2003) use DEM/USD over 4 months, from 1st of May to the 31st August 1999; Love and Payne (2007) use transaction data on EUR/USD, GBP/EUR and GBP/USD over 10 months, from the 1st December to the 24th of July 2000; and Rime, Sarno and Sojli (2007) examine EUR/USD, GBP/USD and USD/JPY from the 13th Feb 2004 – 14th Feb 2005.

trading banks. Some studies, however, do find that at least different types of dealers exert a different impact on prices because of their different trading motivations (see e.g. Fan and Lyons, 2003, and Evans and Lyons, 2005b).³⁸

Second, our focus is on the top trading banks in the GBP/USD market as a group versus the rest of the market players, as opposed to the behaviour of individual dealer's quotes in earlier studies. We call the latter tests 'individual tests' compared to our approach, which we refer to as 'group tests'. Our grouping method, i.e. top trading banks compared to the rest of the market players grouped as another entity called non-top group, catches the major factors that contribute to market heterogeneity. We use a unique GBP/USD database, which identifies the quoting banks and enables us to group the top banks according to the Euromoney survey. Our group approach is more appropriate for studying the impact of general macro announcements on the price discovery. The individual tests relate mainly to German central bank intervention as in Peiers (1997) and Sapp (2002). For German central bank interventions, certain banks have an advantage compared to other banks in detecting and interpreting the interventions. For example, Deutschebank traded a significant portion of the intervention related market order of the Bundesbank, the German central bank. As a result, it could garner private information on the future movements of the exchange rate from these orders (see Covrig and Melvin (2002)). This, however,

³⁸ Both studies use customer trade data, which span over 6 years, on a daily frequency and relate to Citibank, whose market share in major customer business is about 10-15 percent. However, the data are split into three customer-type categories, hedge funds, mutual funds and non-financial corporations, which allow the authors to examine the differential impact of news.

might not necessarily be the case with forecasting and interpreting general macro announcements. The information on these announcements is widely dispersed amongst traders and customers, hence no order flows containing information on any category of macro news are directed to, or monopolized by a specific bank. However, if order flow does contain information, the aggregation of large banks could be expected to collectively process much more order flow than any individual bank. Therefore, private information should be detected by the group method as we have defined it above. This allows us to test whether size is an important factor which contributes to the information advantage of the trading banks during normal times, and in particular during times of public news.

Furthermore, our approach is more appropriate for our sample of 5 years, which is used to derive robust results, as opposed to the short horizons of earlier studies. Due to the natural market evolution, some banks may not possess informational advantage after a year or two, and in some cases even discontinue their market presence. In addition, the competition among electronic trading systems also changes the availability of some banks' quotes. These factors impose a challenge to long horizon tests of 5 to 10 years. In contrast, a group is a portfolio and hence is subject to continuous update of its components limiting the negative impact of the above mentioned factors.

Another feature of our work is the focus on GBP/USD. Most of the earlier work has been on DEM/USD, for short periods when using high frequency data

and covering a few dealers. We use indicative GBP/USD data, which include all market players, over the period of January 1994 to December 1998, and calculate the information shares using both the Hasbrouck (1995) information share (IS) technique, and the Gonzalo and Granger (1995) common component (PT) method. Previous related work has relied on one of these methods.

Our results show that the top 10 banks, out of one hundred quoting banks, have a dominant share (monthly average of over 70%) of the price information in the Reuters EFX system. Furthermore, when testing 21 categories and 1035 items of U.S. announcements, we find that during some categories of news announcements, the top 10 banks' information share is further expanded to around 80%. The results indicate that size is an important factor, which contributes to the information advantage of trading banks. They also indicate that top trading banks might have either more private information over public news, or might be better at interpreting macro news. We further explore this view by examining the relationship between the top trading group's information share and the volatility of GBP/USD. We find a positive association, which according to Admati and Pfleiderer (1988) is an indication of informed trading as informed traders are prone to transact during periods of high volatility.

The structure of the remainder of the paper is as follows. Section 4.2, looks at the selection of the top trading banks, exchange rate data and macro announcements used in our tests. Section 4.3, describes our methodology. Section 4.4, reports the empirical results and discusses the implications. Section

4.5, concludes the paper.

4.2 Data

4.2.1 Selection of the Top Trading Banks

We use Euromoney's biennial foreign exchange market polls as a guide for our selection of top banks. We include the voted top 10 banks in GBP/USD market into the top group, and leave the rest of the banks in what we call the non-top group. All the quotes from the top group will be treated as being from one entity, and the same applies to the non-top group. Using such a method, we investigate whether the top group takes up more information share during normal intraday trading time and whether scheduled macro news impact on their information share.

The first 5 criteria used by Euromoney to rank the banks are reported in Table 4.1.³⁹ Those are price and quote speed, which are directly related to information (see Melvin and Yin (2000)); customer relationship, i.e. better relationship suggests more efficient information flow between banks and their customer; and higher credit rating and liquidity, which also suggest greater market trading capability, which enables banks to infer more private information from customer order flow. The top ten banks in GBP/USD market from 1994 to 1998 voted in the survey are displayed in Table 4.2.

³⁹ See Euromoney, May 1995.

4.2.2 Exchange Rate Data

Our data are EFX tick-by-tick GBP/USD spot quotes, as posted on the Reuters 'FXFX' screen, which have subsequently been collected and filtered by the Olsen and Associates (O&A) over the period January of 1994 to December of 1998. It should be noted that our paper is the first one to use GBP/USD data, which identify the banks that made the quotes.

The EFX data are indicative quotes, which means that even though the dealers may intend to trade at their quoted prices they have no commitment to do so. Goodhart, Ito and Payne (1996) and Danielsson and Payne (2002) find that the basic characteristics of 5-minute foreign exchange returns constructed from quotes closely match those calculated from transactions prices. Phylaktis and Chen (2006) compare four months (inside this paper's time window) of EFX data to D2000-1 transaction data, and find that EFX data are in fact superior to the latter data set by measuring the embedded information. Since around this sample period Reuters' trading system takes more than 90% of the world's direct inter-dealer transactions⁴⁰, this finding is supportive of the quality of the data used in this study.

There are also other reasons why indicative data are more suitable than transaction data in conducting our empirical tests. For example, Goodhart and

⁴⁰ See in Evans (2002).

O'Hara (1997) suggest that indicative quotes are better than transaction prices in demonstrating traders' heterogeneous price interpretation, as transaction price needs agreement between two parties, while the indicative quotes are not so restrictive. Hasbrouck (1995) indicates that an analysis of a stock, if based on last sale prices, would have problems of autocorrelation induced by infrequent trading. Though this issue is less severe in foreign exchange markets, the last sale prices would be less informative. Indicative quotes, on the other hand, could be updated in the absence of trades. Finally, an empirical investigation using transaction data may turn out to be biased because it ignores the informational content of non-trading intervals. This sampling bias is reduced when using bid-ask quote series, which are continuously updated by the market makers.

In Table 4.2, we can find that the voted top 10 banks in GBP/USD are roughly the same during the years 1994-95, 1996-97, and 1998. Thus, we form three different top groups for those three time periods. The rest of the banks in each period are allocated to the non-top group.

After setting up the two groups, we count the quotes for each group during our sample period. Figure 4.1 shows that from October 1995 onwards, the total quotes appearing on the FFX have more than doubled. The Olsen & Associates, which provide our data, explain that this is due to the different data delivery method of Reuters before and after October 1995. The data fed into the system since then have been significantly increased. However, the quotes from the top group are relatively stable at 25% of total quotes. As we show later, the

information shares of both groups experience no fundamental change following the quote frequency jump.⁴¹

Figure 4.2 presents the intraday quotes distribution of both groups. As the top group is composed of only European and U.S. banks, its quoting activity is heavily concentrated during London and New York trading hours. Non-top group's quoting distribution reflects Asian trading banks' presence during Tokyo trading hours.⁴²

We investigate only trading hours between 8:00 to 16:00 GMT, when London and New York markets are active to avoid sparse trading. We exclude weekends and holidays for the same reason. There are in total 1,214 valid trading days during our sample period. Following general practice, we convert our data into 5-minute frequency.

4.2.3 Macro Announcement Data

In our analysis, we test the effects of 21 categories of US government macro

⁴¹ The increased data fed into the Reuters system decrease the average quote duration from around 6 seconds to 3 seconds, which have no big impact on the data we selected at a 5 minute frequency.

⁴² The 24-hour trading day is usually separated into 7 sessions that correspond to the opening and closing times of major foreign exchange markets. The 7 sessions are: 1) 21:00 to 8:00, the period between the closing time of New York and the closing time of Tokyo, which represents the Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, the hours until New York opens; 4) 12:00-13:00, the first hours of New York opening; 5) 13:00-15:00, the overlapping trading hours of the two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, the hours till New York closes.

announcements, as listed in Table 4.3.⁴³ We exclude 8 categories of announcements from the 29 categories of major US macro announcements, because of either the high frequency of announcements (e.g. initial claim is announced weekly), or because they overlap with other announcements, e.g. civilian unemployment rate is announced at the same time as the non-farm payroll. Except for GDP related announcements, which are quarterly, and Fed funds rate announcements, which are on a six-week base, all remaining items of news are announced monthly.

The news effect is investigated during a 4-hour time window, 2 hours before and 2 hours after a specific announcement. The concern is that the information over the public news could be revealed after as well as before the announcement, if there is asymmetric information. Private information should cause the price to adjust itself before the announcements, and then to continue to affect the news interpretation.

Though some announcements, e.g. the target federal funds rate announcements from FOMC, are announced outside our daily GMT window, we still include them due to their importance.⁴⁴ In our sample period, we have a total of 1035 items of valid announcements.

⁴³ The scheduled announcement time data are provided by Francis X. Diebold.

⁴⁴ We assume that the announcement takes place at 14.00 GMT. The information share over this news category is therefore mainly a measurement of the top group's capability of forecasting the actual result, and not of their news interpreting power after the announcement.

4.3 Methodology

4.3.1 Measures of Information Share

IS and PT models are the two most prevalent common factor models. They are directly related and the results of both models are primarily derived from the vector error correction model (VECM). They provide similar results if the VECM residuals are uncorrelated. However, if substantial contemporaneous correlations exist the two models usually provide different results. Hasbrouck (1995) handles this correlation by using Cholesky factorization. Therefore, the IS results are variable order dependent. Hasbrouck (1995) suggests that different orders may be used and upper and lower information share bounds be averaged to arrive at a final information share result. However, the bounds are often very much apart since high frequency exchange rate data have a high residual correlation. Therefore in our paper, we use both IS and PT models as complementary methods. The following estimation approaches for both models are mainly adapted from Baillie et al. (2002).

We consider the two price quotes from the two groups of banks to be $I(1)$ processes, $P_t = (p_{1t}, p_{2t})'$ with the differential being the error correction term $d_t = \beta' P_t = p_{1t} - p_{2t}$, where β is the cointegration vector. Both models start from the estimation of the following VECM:

$$\Delta P_t = \alpha \beta' P_{t-1} + \sum_{j=1}^k A_j \Delta P_{t-j} + e_t, \quad (1)$$

where α is the error correction vector and e_t is a zero-mean vector of serially

uncorrelated innovations with covariance matrix Ω

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}. \quad (2)$$

The VECM has two parts: the first part, $\alpha\beta' P_{t-1}$, represents the long-run or equilibrium dynamics between the price series, and the second part, $\sum_{j=1}^k A_j \Delta P_{t-j}$, shows the short-term deviation induced by market imperfections.

Hasbrouck (1995) transforms Eq. (1) into a vector moving average (VMA) in an integrated form

$$P_t = \psi(1) \sum_{s=1}^t e_s + \psi^*(L) e_t, \quad (3)$$

where $\psi(L)$ and $\psi^*(L)$ are matrix polynomials in the lag operator, L . If we denote $\psi = (\psi_1, \psi_2)$ as the common row vector in $\psi(1)$, Eq. (3) becomes

$$P_t = \iota \psi \left(\sum_{s=1}^t e_s \right) + \psi^*(L) e_t, \quad (4)$$

where $\iota = (1, 1)'$ is a column vector of ones.

Hasbrouck (1995) states that the increment ψe_t in Eq. (4) is the component of the price change that is permanently impounded into the price and is presumably due to new information. If price innovations are significantly correlated across prices, Hasbrouck (1995) uses Cholesky factorization $\Omega = MM'$ to eliminate the contemporaneous correlation, where:

$$M = \begin{bmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{bmatrix}. \quad (5)$$

If we further denote $\alpha \perp = (\gamma_1, \gamma_2)'$, which is also the Γ in Gonzalo and Granger (1995)'s PT model, then the information shares of the two prices are:

$$S_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \text{ and} \quad (6)$$

$$S_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}. \quad (7)$$

In order to get the information share of each group, the order of them is changed and the calculation process is repeated. The average of the two results is suggested by Hasbrouck to be the information share.

Gonzalo and Granger (1995) define the common factor to be a combination of the variables P_t , such that $h_t = \Gamma P_t$, where Γ is the common factor coefficient vector. The information shares of the two prices according to the PT model are as follows:

$$S_1 = \frac{\gamma_1}{\gamma_1 + \gamma_2}, \text{ and} \quad (8)$$

$$S_2 = \frac{\gamma_2}{\gamma_1 + \gamma_2}. \quad (9)$$

Thus, the Granger and Gonzalo's (1995) approach is concerned with only the error correction process, which involves only permanent as opposed to transitory shocks that result in a disequilibrium. It ignores the correlation among the two prices and measures each price's contribution to the common factor on the basis of its error term. The price, which adjusts the least to the other price movements has the leading role in the price discovery process. In contrast, Hasbrouck (1995) defines price discovery in terms of the variance of the innovations to the common factor assuming that price volatility reflects the flow of information. Information share in this model is each price's relative

contribution to the variance.⁴⁵

We conduct the usual procedures of unit root and cointegration tests before the information shares of each group are estimated. Unless otherwise stated, the price series in our empirical tests satisfy both conditions.

4.3.2 Estimation Process and Confidence Bands

We measure information shares of prices quoted between 8:00 to 16:00 GMT, when London and New York markets are active. As a result, a directly estimated ECM would cause lagged returns to contain the overnight price jump and the previous trading day's price changes. We thus use return series that exclude overnight and previous trading day's returns and apply Seemingly Unrelated Regression (SUR) method.

SUR, also known as the Zellner's method, estimates the parameters of the system while taking heteroskedasticity and contemporaneous correlation in the errors across equations into consideration. The ECM is expressed in the SUR form with the cointegration vector restricted to be $(1 \ -1)$. The optimum lag order is specified by minimizing Schwarz-Bayesian criterion (BIC). Lagged

⁴⁵ According to Baillie et al. (2002) the two models complement each other and provide different views of the price discovery process between markets. On the other hand, de Jong (2002) concludes that Hasbrouck's measure is a more proper measure of the amount of information generated by each market. Harris et al. (2002) have different view and employ Granger and Gonzalo (1995) to estimate and test common factor components attributable to each market. The market with the highest normalised factor weight has the biggest contribution to revelation of the innovations underlying the common stochastic trend in that stocks.

overnight and previous trading day's returns and price levels are accordingly purged when the regressions are estimated.

We employ the bootstrapping method to find the confidence bands of the information share. Following Li and Maddala's (1997) suggestion, we use the stationary bootstrap method to resample the residuals, i.e. the bootstrapped residual block length follows a geometric distribution. Specifically, let ε_1^* be the first randomly resampled observation from estimated $\{\hat{\varepsilon}_t\}(t=1,\dots,n)$ so that $\{\varepsilon_1^* = \hat{\varepsilon}_j\}$ for $1 \leq j \leq n$. Then the adjacent $\{\varepsilon_2^*\}$ has the following distribution

$$\Pr(\{\varepsilon_2^* = \hat{\varepsilon}_{j+1}\}) = 1 - p \quad \text{and} \quad \Pr(\{\varepsilon_2^* = \hat{\varepsilon}_i\}) = p, \quad (10)$$

where p ($0 \leq p \leq 1$) is the probability of the geometric distribution of the random block length, and $1 \leq i \leq n$.

The stationary bootstrap method keeps the stationary nature of the resampled residuals compared to the moving block method. It is also less sensitive to the selection of the probability p .

We first estimate the ECM with optimum lag with the purged return series. The estimated parameters and residuals are stored. The resampled residuals are then inserted back into the estimated ECM. With the new Δp_t constructed from the resampled residuals, the ECM is estimated again and the information shares recalculated. All of the ECM estimation is corrected for heteroskedasticity. We repeat the process by 200 times and the 95% and 5% confidence bands of the information shares are hence obtained.

4.4 Empirical Results

4.4.1 Preliminary Analysis

Before estimating the information shares of our two groups of trading banks, we examine the lead-lag relationships between them. This is a preliminary analysis, which tests the speed of the information embedded in the return of the two prices.⁴⁶ If the top group's quotes are faster in incorporating trading information into the price, its return should lead the non-top group's return, i.e. the top group's return could predict the non-top group's return.

We estimate the cross correlations between two series p and q as follows

$$r_{p,q}(l) = \frac{c_{pq}(l)}{\sqrt{c_{pp}(0)} \cdot \sqrt{c_{qq}(0)}}, \quad (11)$$

where $l = 0, \pm 1, \pm 2, \dots$ and

$$c_{pq}(l) = \begin{cases} \sum_{t=1}^{T-l} ((p_t - \bar{p})(q_{t+l} - \bar{q}))/T & l = 0, 1, 2, \dots \\ \sum_{t=1}^{T+l} ((q_t - \bar{q})(p_{t-l} - \bar{p}))/T & l = 0, 1, 2, \dots \end{cases} \quad (10)$$

Figure 4.3 shows the lead lag relationship between the returns of the two groups. The contemporaneous correlation between the two return series is understandably high at 0.27. When the top group's return is in the lag, the correlation is around 0.1 and statistically significant. However, when the non-top group's return is in the lag, there is no significant correlation, which suggests that the predictability runs only in one direction, from the top group to the rest of

⁴⁶ Many studies have investigated the lead and lag relationships between cash and futures markets, see e.g. Chan (1992); de Jong and Nigman (1997).

the trading banks.

4.4.2 Information Shares

We subsequently estimate the top group's monthly information share during the 60 months of our sample period. Since we only consider the London and New York trading hours, we eliminate overnight lag returns to avoid overnight price jumps generating excessive noise and use seemingly unrelated regression (SUR) to estimate our models. Throughout this paper, we only present the top group's result, since the top and non-top groups' information shares add up to 100%. Thus, the non-top group's information share is 100% minus the top group's information share.

In Figures 4.4 and 4.5, we present the information share of the top group using the PT and IS methods respectively. As it can be seen the top group's information share fluctuates around 70% in most of the months. The only months that deviate from the average are at the beginning and end of our period. During the five years, the top group's informational share as a percent of total market information is 73% by PT model (71% by IS model) (see Table 4.4). Over the 60 months, only once the top group's information share drops below 50% according to both models. In Table 4.5 we present the yearly results in order to see the trend more clearly. The top group starts with a relatively small share in 1994, then experiences a rise in 1995 and once again a fall in 1996. For

the next two years its share jumps significantly and reaches around 80% in 1998.

The general upward trend of the top group's information share is in line with the increased market concentration in the global foreign exchange business.

We test the robustness of the grouping method and estimate the information share of the top 5 banks instead of the top 10. The top 5 banks in the Euromoney survey are unchanged during our five year sample period, though a few of them went through merger and acquisition. In Figure 4.6, we find that the information share of the top 5 banks is less stable than that of the top 10 banks. The average monthly information share drops to 62% (PT) and to 60% (IS) of the total market information. The number of months during which the top 5 banks information drops below 50% has increased to 8 months (PT) and 10 months (IS). Although the top 5 banks still take the dominant share of the market information, this advantage is not as strong as before. This could be due to the strengthening of the rivalry group.

4.4.3 Market Volatility and Information Share

In this section, we explore whether the fluctuations of the top group's information share could be linked to market volatility. Admati and Pfleiderer (1988) suggest that volatility is associated with private information. To maximize their potential profit from their private information, informed traders are prone to transact during periods of high trading activity. Thus, the informed

transactions are linked with increased volatility. In the context of our paper, the above implies that we should expect the information share of the top group to be positively correlated with the market volatility.

Figure 4.7 shows the scatter plot of the monthly GBP/USD volatility, as proxied by the standard deviation, against the information share of the top group (PT). The positive correlation between the market volatility and information share is indicated by the fitted regression line. More specifically, the regression suggests that a 10% increase in the top group's information share corresponds to 0.2% rise of market volatility (see Table 4.6). Given that the average monthly market volatility is 3%, this positive link is relatively strong. This provides supporting evidence on the private information content of the top group's information share.

4.4.4 Information Share during Macro Announcements

To test whether macro announcements have any impact on the information share of the top banks, we import 21 U.S. news announcements and estimate the information share of the top banks during these announcement days for each type of news separately. More specifically, the prices quoted in between the four hours around the announcement, 2 hours before and 2 hours after, are collected first. Then all the prices from the two groups are compiled into two time series and the SUR method is applied. Though UK macro announcements may have an

impact on the information share of the banks, we assume that these effects are insignificant.⁴⁷

The results are reported in Tables 4.7 and 4.8 and displayed in Figure 4.8. Among the 21 announcements, the two GDP announcements and the Fed funds rate produce the largest information shares (over 80% according to the PT model) for the top 10 banks. This is an interesting finding compared to Evans and Lyons (2005b) result. In their paper, GDP preliminary and Fed funds rate announcements are the only two announcements that have a significant impact on order flow for just one day, while their other 16 announcements have relatively longer effects. It may suggest that these two announcements cause more concentrated and intensive reaction from market players, which forces the top banks to release their information advantage in only a few hours, instead of spreading the advantage over several days like in the case of other announcements. Another interesting finding is that the trade balance, which is an important determinant in traditional exchange rate theory, contributes very little to the information advantage of the top banks. This may be explained by the relatively easy predictability of the trade balance figure by the market players. Therefore, top banks are less likely to know more than their rivalries.

We are also interested in the news effect by allocating macro announcements into different categories. Following Andersen et al (2003), we allocate news into 8 different groups, such as real activity, forward looking and

⁴⁷ As reported in Andersen et al. (2003), the impact of most non-US announcements is insignificant on the level of major exchange rates.

net export etc. Table 4.9 reports the result. As we can see, FOMC, i.e. Fed funds rate, is related with the highest information share from the top banks. Given the importance of the interest rates in the foreign exchange market, this is a reasonable result. GDP announcements are the category of news that are linked to the next highest information share. As an indicator of economic growth, GDP has long been one of the important determinants of exchange rates. Treasury budget, as the only category in the Government purchase category, has the next highest information share together with prices. It may have an impact on exchange rates through its effect on interest rates. An expanded treasury budget deficit would indicate an increase in interest rates, increased capital flows and an effect on the exchange rate.

4.5 Conclusion

This study is one of the first papers to tackle directly the information asymmetry issue in the foreign exchange market. Traditional exchange rate theory assumes that the agents in a given market are homogeneous and therefore, the price formation process is only determined by public information. However, when we cast our eyes in the foreign exchange market, the assumption of market players' homogeneity is unsound and misleading. Correctly assessing and depicting the picture of market participants' heterogeneity in an information sense may help us solve and explain the exchange rate determination puzzle.

We investigate this information asymmetry by testing the hypothesis that major trading banks in the foreign exchange market have more information on the macro economy garnered from the larger order flow they process. According to Evans (2002) trading banks collect information from the customer trading, inter-dealer trading, and from after-announcement news interpretation, or non-common-knowledge. Using indicative GBP/USD data over the period of January 1994 to December 1998, we indeed find that the top 10 trading banks,⁴⁸ out of one hundred quoting banks, have a dominant share (monthly average of over 70%) of the price information in the Reuters EFX system. We also test whether this information advantage is prevalent during general scheduled macro news. After testing 21 categories and 1035 items of U.S. announcements, we find that during some categories of news announcements, the top 10 banks' information share is further expanded to around 80%. This suggests that top trading banks might have either more private information over public news, or might be better at interpreting macro news. This view is also supported by the positive association between the information share of the top trading group and the volatility of GBP/USD for according to Admanti and Pfleiderer (1998) informed traders are prone to transact during periods of high trading activity. It should be noted that this is the first study to test general scheduled macro news effects under the heterogeneity market assumption, in contrast to previous work, which either implies the assumption of market

⁴⁸ The top 10 banks are selected by Euromoney's biennial survey.

homogeneity, or only tests the impact of central bank intervention as public news under the heterogeneity market assumption.

Further research could focus on examining other contributing factors to the information asymmetry in the foreign exchange market apart from the size of the order flow. For example, does geographic location contribute to traders' private information?

References

- Admati, A., P. Pfleiderer. 1988. A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, 1: 3-40.
- Almeida, A., C. Goodhart, and R. Payne. 1998. The effects of macroeconomic news on high frequency exchange rate behaviour. *Journal of Financial and Quantitative Analysis*, 33:383-408.
- Andersen, T.G., and T. Bollerslev. 1998. Deutsche mark-dollar volatility: intraday activity patterns, macroeconomic announcements, and longer-run dependencies. *Journal of Finance*, 53: 219-265.
- Andersen, T. G., T. Bollerslev, and F. Diebold, and C. Vega. 2003, Micro effects of macro announcements: real-time price discovery in foreign exchange. *American Economic Review*, 93: 38-62.
- Baillie, R T., G. G. Booth, Y. Tse, and T. Zabotina. 2002. Price Discovery and Common Factor Models, *Journal of Financial Markets*, 5: 309-321.
- BIS, 2005. Triennial Central Bank Survey – Foreign exchange and derivatives market activity in 2004.
- Bauwens, L., W.B. Omrane, and P. Giot. 2005. News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance*, 24:1108-1125.
- Bjønnes, G.H. and D. Rime. 2001. Customer Trading and Information in Foreign Exchange Markets. Working paper # 4. Stockholm Institute for Financial Research.
- Carlson, J., and M. Lo. 2006. One minute in the life of the DM/\$: Public news in an electronic market, *Journal of International Money and Finance*, 25: 1090-1102.
- Chan, K.. 1992. A further analysis of the lead-lag relationship between the cash market and stock index futures market. *Review of Financial Studies*, 5: 123-152.
- Cheung, Y. –W.. and M. D. Chinn. 2001. Currency traders and exchange rate dynamics: A survey of the US Market. *Journal of International Money and Finance*, 20: 439-471.

Covrig, V., and M. Melvin. 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen? *Journal of Empirical Finance*, 9: 271-285.

Danielsson, J., and R. Payne. 2002. Real trading patterns and prices in the spot foreign exchange markets. *Journal of International Money and Finance*, 21: 203-222.

de Jong, F. and T. Nijman. 1997. High frequency analysis of lead-lag relationships between financial markets. *Journal of Empirical Finance*, 4: 259-277.

Dominguez, K., and F. Panthaki. 2003. The market microstructure of central bank intervention. *Journal of International Economics*, 59: 25-45.

Euromoney, May 1995, Treasurers put their views on banks. 65-76.

_____, May 1997, Taken aback by a leap forward, 61-76.

_____, May 1995, Life after execution, 89-104.

Evans, M., D. 2002. FX trading and exchange rate dynamics, *The Journal of Finance*, 6: 2405-2447.

Evans, M., and R. Lyons. 2003. How is Macro News Transmitted to Exchange Rates? NBER Working Paper 9433.

_____, 2005, Exchange rate fundamentals and order flow, typescript, U.C. Berkeley.

_____, 2005, Do currency markets absorb news quickly? *Journal of International Money and Finance*, 24: 197-217.

Fan, M., and R. Lyons. 2001. Customer-dealer trading in the foreign exchange market, typescript, UC Berkeley.

Glosten, L., and P. Milgrom. 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 13: 71-100.

Gonzalo, J. and C.W.J. Granger. 1995. Estimation of common long-memory components in cointegrated systems. *Journal of Business & Economic Statistics*, 13: 27-35.

Goodhart, C., T. Ito, and R. Payne. 1996. One day in June 1993: A Study of the Working of Reuters 2000-2. In *The Microstructure of Foreign Exchange markets*, J. Frankel, G. Galli, and A. Giovanni, eds. Chicago, IL: Univ. of Chicago Press.

Goodhart, C., and M. O'Hara. 1997. High Frequency Data in Financial Markets: Issues and Applications. *Journal of Empirical Finance*, 4: 73-114.

Hasbrouck, J. 1995. One Security, Many Markets: Determining the contributions to Price Discovery. *The Journal of Finance*, 4: 1175-1199.

Kyle, A.. 1985. Continuous auction and insider trading. *Econometrica*, 53: 13-32.

Li, H., and G. S. Mandala. 1997. Bootstrapping cointegrating regressions. *Journal of Econometrics*, 80: 297-318.

Love, R., and R. Payne. 2004. Macroeconomic news, order flows, and exchange rates, typescript, London School of Economics.

Lyons, R.. 1995. Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39: 321-351.

Lyons, R. 1997. A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, 42:275-298.

Melvin, M., and X. Yin. 2000. Public information arrival, exchange rate volatility and quote frequency. *Economic Journal*, 110: 644-661.

Payne, R. 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61: 307-329.

Peiers, B. 1997. Informed traders, intervention and price leadership: A deeper view of the microstructure of the foreign exchange market. *Journal of Finance*, 52: 1589-1614.

Phylaktis, K. and L., Chen. 2006. Price discovery in indicative and transaction FX prices system -- A comparison of D2000-1 and EFX data, working paper, Cass Business School.

Rime, D. 2000. U.S. Exchange Rates and Currency Flows, unpublished working paper.

Sapp, S. 2002. Price leadership in the spot foreign exchange market. *Journal of Financial and Quantitative Analysis*, 37: 425-448 .

Yao, J.. 1998. Market making in the interbank foreign exchange market. Salomon Center for the Study of Financial Institutions. Working Paper s-98-3, New York, NY.

Table 4.1

Euromoney survey's criteria of top banks

	Corporations	Institutions	Banks	Others	Total
1. Relationship	100	10	48	7	165
2. Price alone	91	14	49	10	164
3. Quote speed	74	12	50	9	145
4. Credit rating	66	10	27	7	110
5. Liquidity	41	11	38	7	97

Source: Euromoney research, Euromoney May 1995. There were in total 16 criteria listed in the original table. The first column displays the most important 5 criteria judged by the total votes (given in the last column) from the customers of currency trading banks. The votes from each business type of customers are listed separately in the columns in the middle.

Table 4.2

Top ten banks in GBP/USD

99	98		97	96		95	94	
1	1	HSBC	1	4	HSBC Midland	1	1=	NatWest Markets
2	2	Citibank	2	1	Chase	2	4	HSBC Mkts/Midland
3	3	Chase Mahattan	3	3	BZW	3	3	Barclays
4	4	NatWest Global	4	2	NatWest	4	1=	Citibank
5	5	Barclays Capital	5	5	Citibank	5	5	Chase Mahattan
6	6	Deutsche Bank	6	-	Royal Bank of Canada	6	9	Chemical
7	7	Royal Bank of Canada	7	6	Standard Chartered	7	10	Bank of America
8	-	Warburg Dillon Read	8	7	Bank of America	8	-	Lloyds
9	9	Bank of America	9	-	SBC Warburg	9	-	Standard Chartered
10	12	ABN Amro	10	9	Deutsche Morgan Grenfell	10	6	Indosuez

Source: Euromoney, May of 1995, 1997, and 1999.

Table 4.3
U.S. announcements

	Item	Frequency	EST	#N
1	GDP Advanced	QTR	8:30	13
2	GDP Preliminary	QTR	8:30	16
3	GDP Final	QTR	8:30	13
4	Fed Funds Rate	6WK	14:20	38
5	Personal Income	MTH	8:30	45
6	Factory Orders	MTH	10:00	51
7	Consumer Confidence	MTH	10:00	53
8	Index of Leading Indicators	MTH	8:30	55
9	Housing Starts	MTH	8:30	57
10	Durable Goods Orders	MTH	*8:30	57
11	Construction Spending	MTH	10:00	57
12	Retail Sales	MTH	8:30	58
13	Treasury Budget	MTH	14:00	58
14	Consumer Price Index	MTH	8:30	58
15	Business Inventories	MTH	*10:00	58
16	Nonfarm Payrolls	MTH	8:30	58
17	Consumer Credit	MTH	15:30	58
18	Industrial Production	MTH	9:15	58
19	NAPM	MTH	10:00	58
20	Capacity Utilization	MTH	9:15	58
21	Merchandise Trade Balance	MTH	8:30	58
				Total #N
				1035

Notes: * The announcement time were irregular or changed during our sample period.
The third column reports the scheduled announcements frequency, where QTR, MTH and 6WK stand for quarterly, monthly and 6 weeks respectively. EST is the U.S. Eastern Standard Time. Last column reports the total number of the corresponding announcements during our sample period

Table 4.4
Statistics of top group’s monthly information share

	Mean	Std. D.	Kurtosis	Skewness	Min	Max	Count
PT	73.1%	10.5%	0.29	0.09	45.7%	98.2%	60
IS	71.2%	8.4%	1.01	0.41	49.1%	94.6%	60

Table 4.5
Yearly information share of top group

	1994	1995	1996	1997	1998
PT	67.5%	72.1%	68.4%	76.3%	81.0%
IS	68.2%	69.8%	68.6%	72.3%	77.2%

Table 4.6
Market volatility and information share

$$v_t = c + \beta PT_t + \varepsilon_t$$

Coefficient	Estimate	Std. Error	t-Statistic	Prob.
c	0.01	0.01	1.55	0.13
β	0.02	0.01	2.28	0.03
Obs. 60	R-squared		0.08	

Notes: v_t is the monthly GBP-\$US volatility, and PT_t is the monthly top group’s information share. Estimation is done by the ordinary least square.

Table 4.7

Macro news and top-group's information share – PT approach

News	PT	Bootstrap 95%	Bootstrap 5%
GDP Preliminary	87.8%	95.9%	71.0%
GDP Final	83.4%	89.9%	76.1%
Fed Funds	82.5%	88.9%	77.0%
Retail Sales	81.0%	88.4%	75.1%
Consumer Confidence	79.8%	86.3%	74.3%
Government Budget Deficit	78.2%	82.3%	73.1%
CPI	78.2%	83.1%	73.9%
Business Inventories	76.1%	81.0%	70.5%
Housing Start	75.7%	79.1%	71.4%
NAPM	75.0%	82.8%	59.8%
Durables	74.8%	80.5%	69.3%
Non-farm Employment	74.5%	79.8%	69.6%
Unemployment	74.5%	79.2%	69.0%
Capacity Utility	74.2%	79.7%	70.7%
Industrial Production	74.2%	80.1%	69.8%
Factory Orders	74.1%	78.0%	70.1%
Personal Income	73.5%	82.1%	66.4%
Consumer Credit	72.1%	77.8%	66.7%
Trade Balance	71.3%	75.9%	67.8%
Leading	71.0%	77.7%	64.3%
GDP Advanced	67.8%	86.4%	58.3%
Construction Spending	59.3%	75.6%	46.1%

Notes: The information share of the top group is estimated by creating time series of prices quoted in between the 4 hours around the announcement, with 2 hours before and 2 hours after the news. Then all the prices from the two groups are compiled into two time series and the aforementioned SUR method is applied. The results only shows PT approach, and those from IS are qualitatively no different.

Table 4.8

Macro news and top-group's information share – IS approach

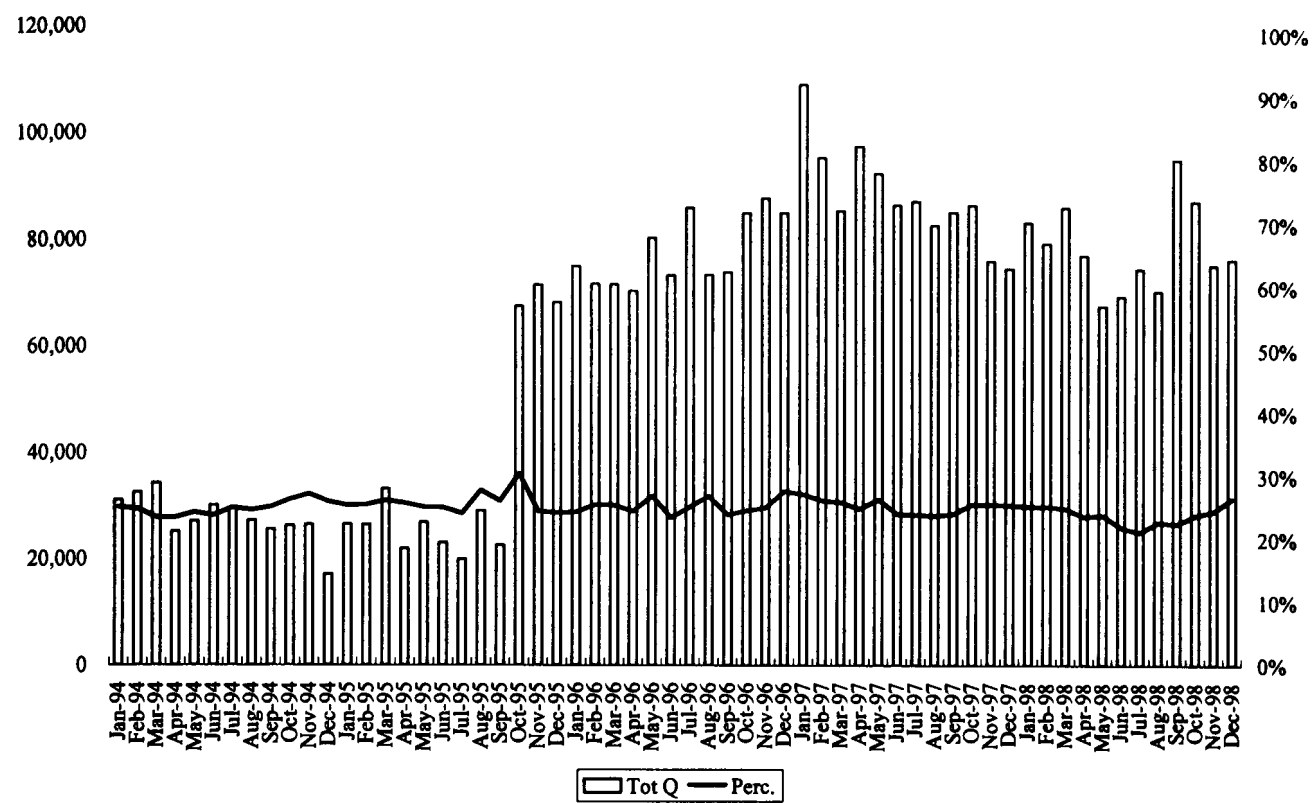
News	IS	Bootstrap 95%	Bootstrap 5%
GDP Preliminary	85.8%	91.9%	71.7%
Fed Funds	80.3%	83.3%	75.6%
GDP Final	79.7%	85.4%	72.9%
Retail Sales	77.4%	82.6%	73.2%
Consumer Confidence	76.4%	81.5%	72.0%
CPI	76.2%	80.4%	72.8%
Government Budget Deficit	76.2%	79.5%	71.9%
Factory Orders	73.3%	76.7%	69.5%
Business Inventory	73.1%	77.3%	68.3%
Capacity Utility	72.3%	77.7%	69.0%
Industrial Production	72.3%	77.9%	68.3%
Non-farm Employment	72.3%	75.7%	69.2%
Unemployment	72.3%	75.6%	68.5%
Housing Start	72.1%	75.7%	68.2%
Durables	71.9%	76.0%	67.6%
Personal Income	71.5%	78.1%	65.5%
Trade Balance	70.1%	74.7%	66.5%
Consumer Credit	69.6%	73.1%	65.5%
NAPM	69.1%	77.0%	59.8%
Leading	68.4%	73.6%	62.8%
GDP Advanced	67.2%	79.1%	58.2%
Construction Spending	61.6%	74.8%	49.4%

Table 4.9

News effect by category

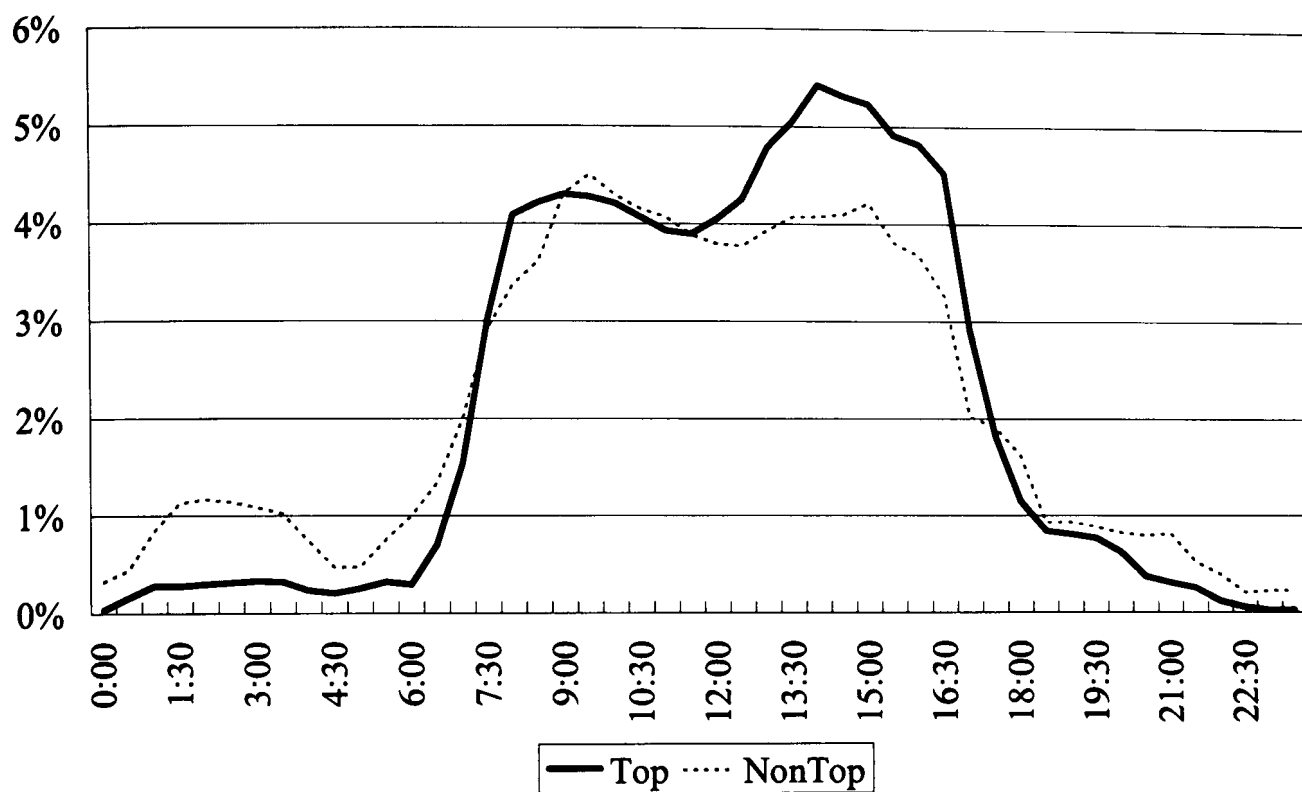
	Category	#N	PT	IS
1	FOMC	38	82.5%	80.3%
2	GDP	42	79.6%	77.6%
3	Government Purchase	58	78.2%	76.2%
4	Prices	58	78.2%	76.2%
5	Forward Looking	223	75.4%	71.5%
6	Real Activity	277	74.9%	72.6%
7	Net export	58	71.3%	70.1%
8	Investment	223	71.1%	70.0%

Figure 4.1
Monthly quotes from top group



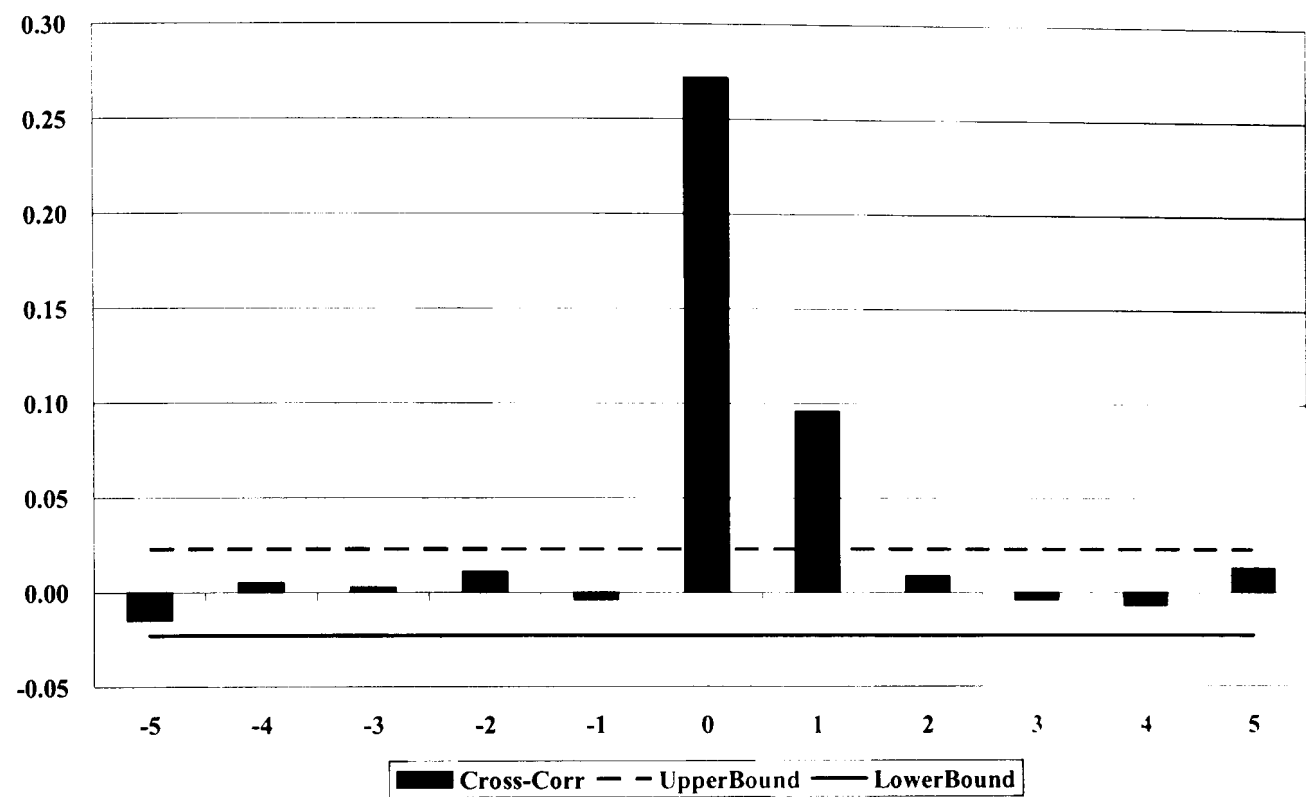
Notes: The column stands for the number of quotes from the top ten banks, as the top group, in each month. The line stands for the percent of the top group's quotes compared to that of total quotes from all the banks in the same month.

Figure 4.2
Daily quotes distribution of both groups



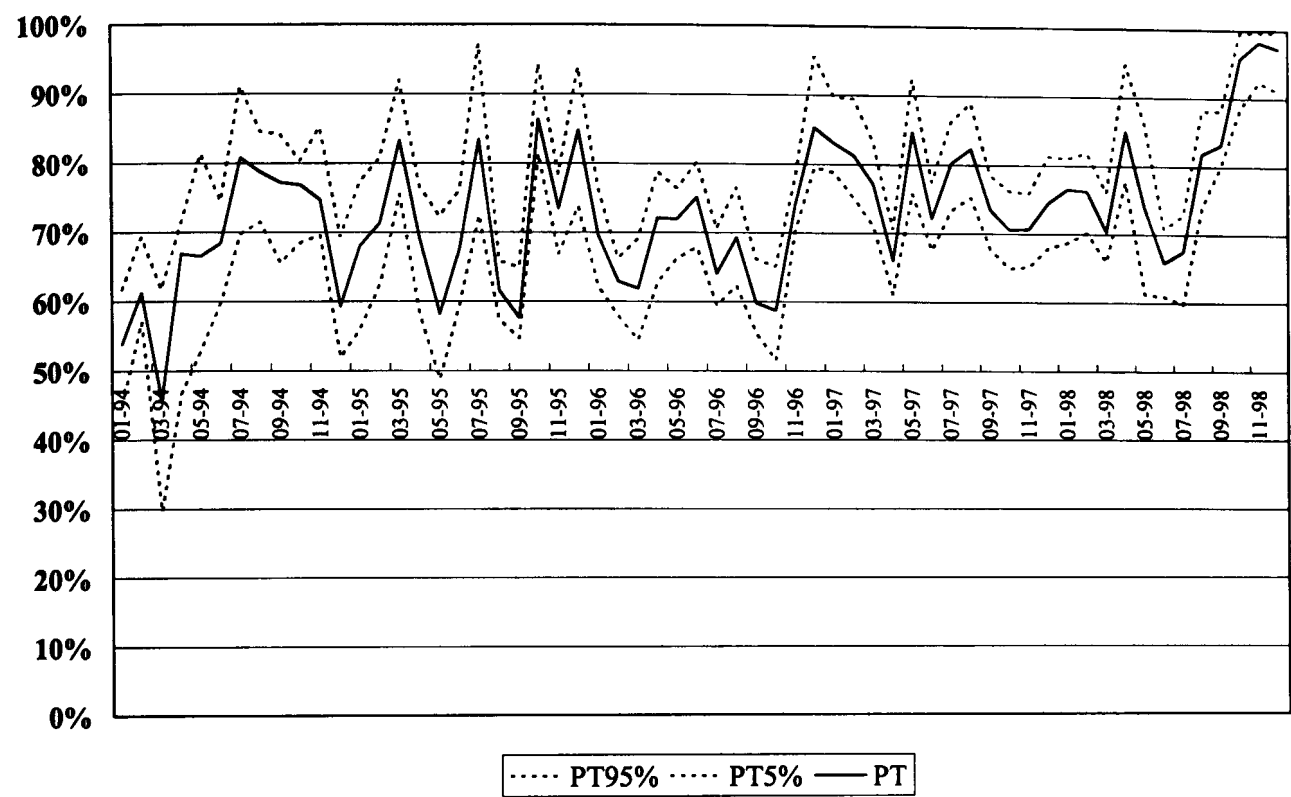
Notes: Each half hour's quotes are aggregated and presented as the percentage of total quotes of individual group. The intraday result is the average of the sample period. The 24-hour trading day can usually be separated into 7 sessions that corresponds to major FX markets' openings and closings. The 7 sessions are 1) 21:00 to 8:00, New York closes till Tokyo closes, representing Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, hours till New York opens; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours till New York closes.

Figure 4.3
Cross correlations of the top and non-top group's return



Notes: The positive figure on the x-axis means that top group's return is in the lag. Each lag stands for 5 minute. The upper and lower bounds of the cross correlogram are the approximate two standard error bounds computed as $\pm 2/\sqrt{T}$, where T is the available number of observations.

Figure 4.4
Top group’s monthly information share – PT method



Notes: The 95% and 5% confidence bands are calculated by stationary bootstrapping the ECM by 200 times and then the 10th and 190th largest re-estimated information share values are chosen.

Figure 4.5
Top group’s monthly information share – IS method

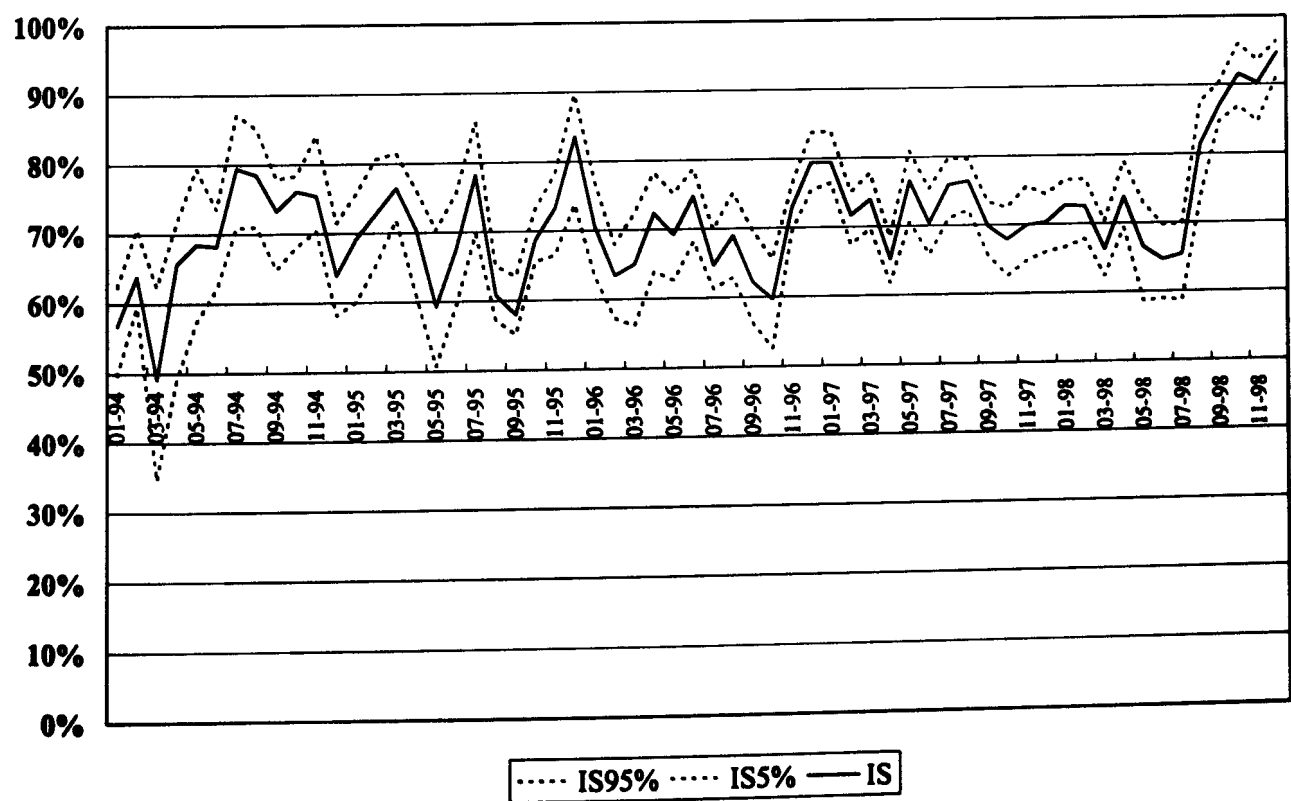


Figure 4.6
Top 5 banks' monthly information share

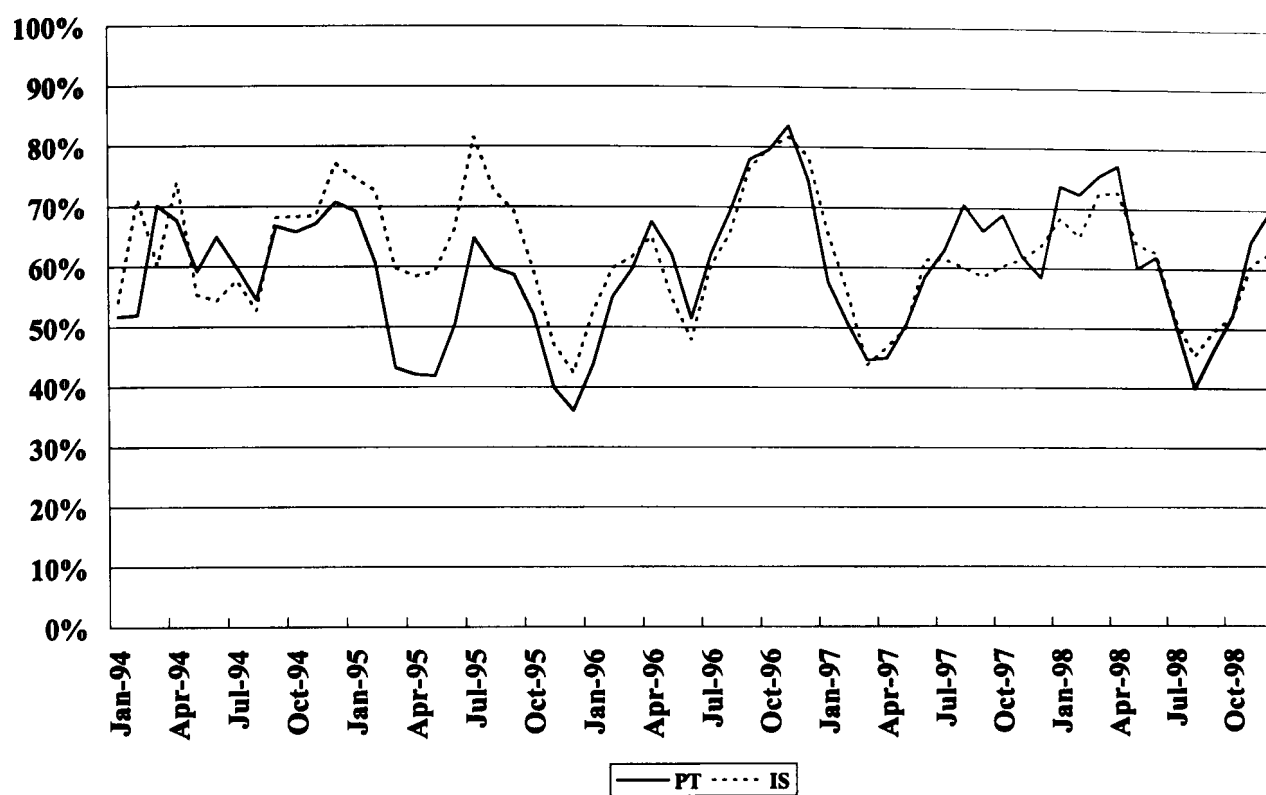
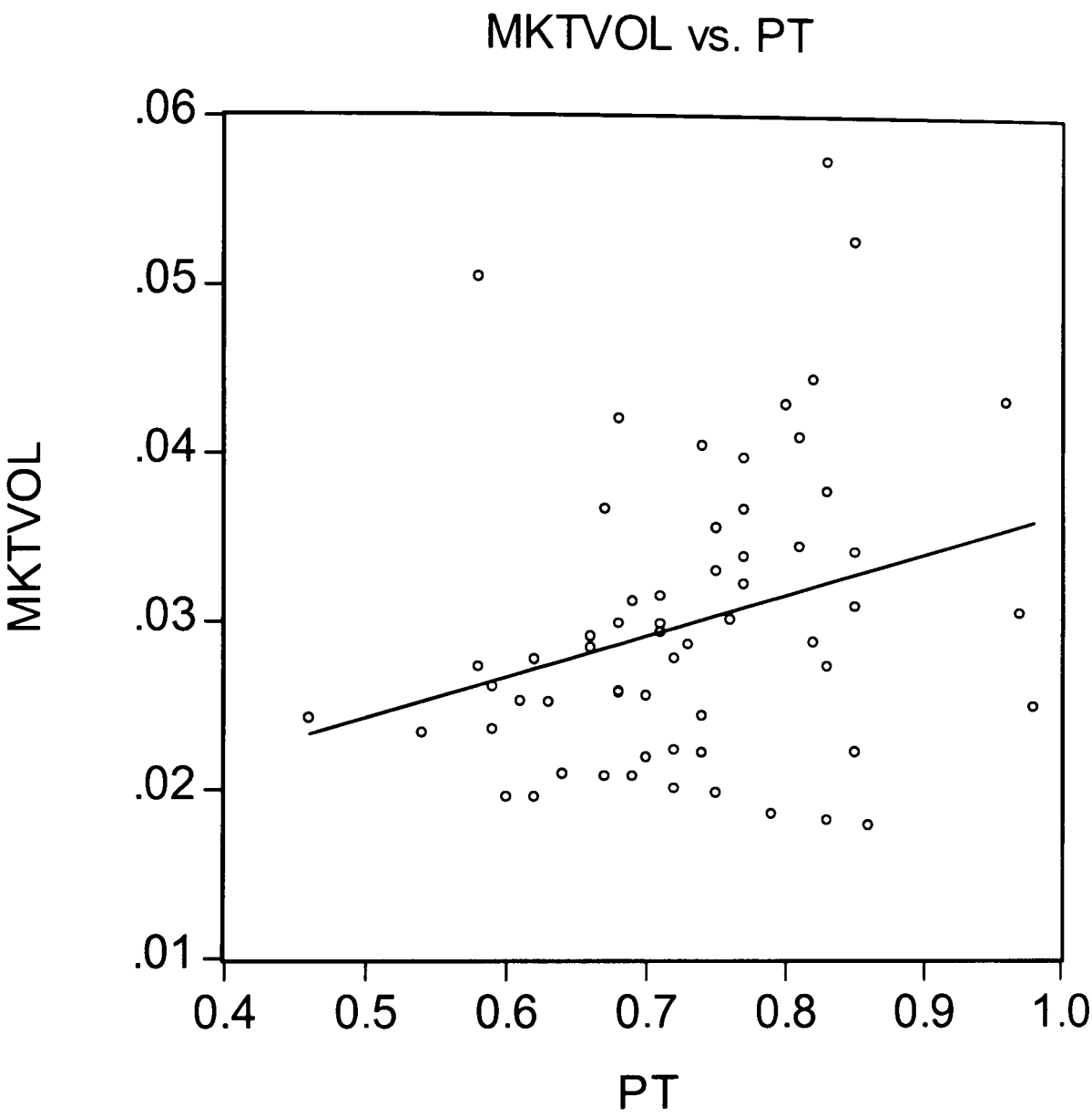


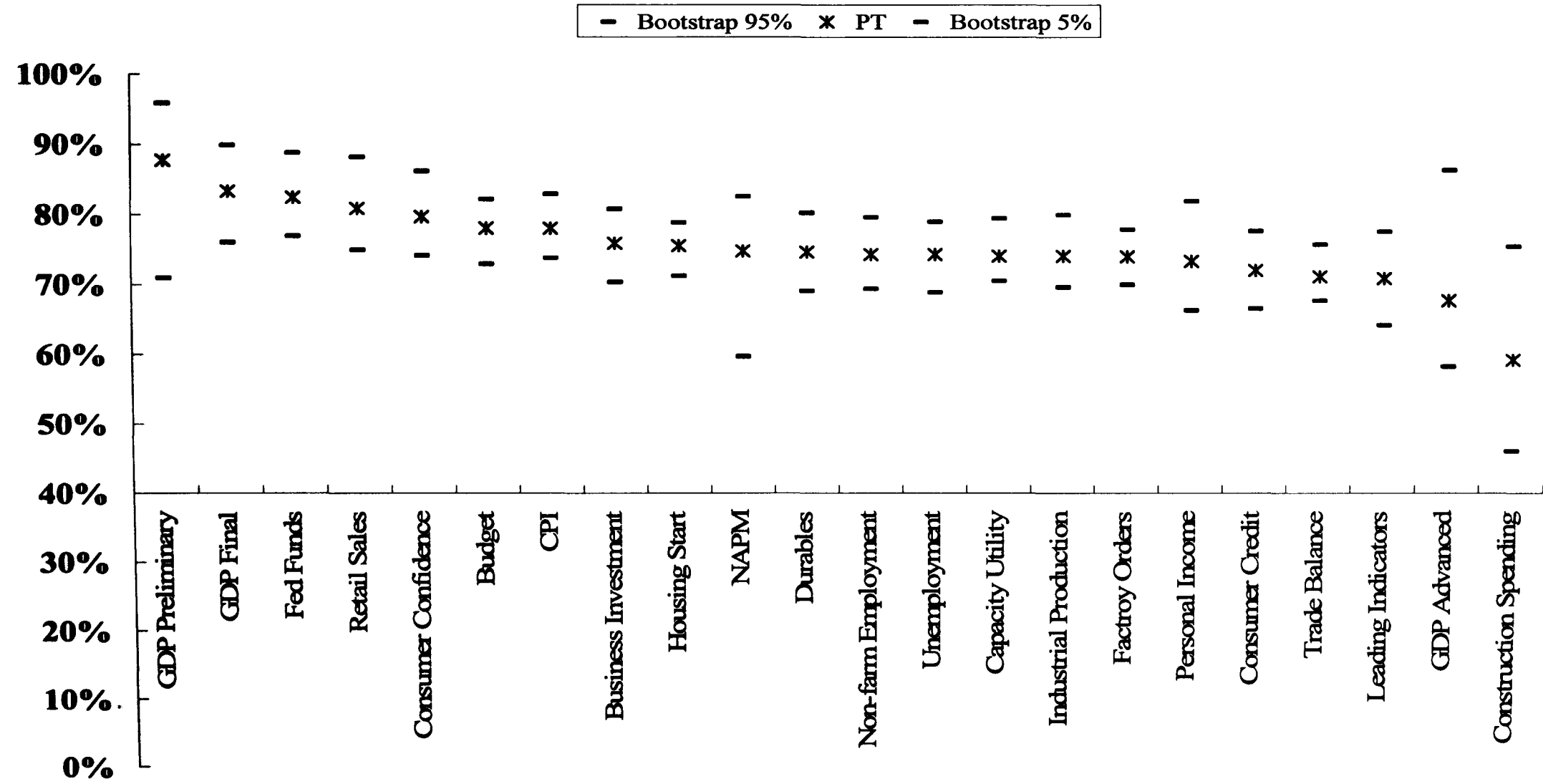
Figure 4.7
Scatter diagram of market volatility against PT with regression



Notes: The GBP/USD exchange rate monthly volatilities are plotted against the monthly PT results of the top group. The fitted line is the slope of the OLS regression of the volatilities against the PTs.

Figure 4.8

Macro announcements and top group's information share



Chapter 5

Asymmetric Linkages between High-frequency Exchange Rates

5.1 Introduction

The traditional asset market approach to the pricing of exchange rates incorporates all available public information and hence is speculative efficient. However, from the 1990s onwards, new studies suggest that not all exchange rate relevant information is publicly available. For instance, order flow could be one source for private information in the foreign exchange market⁴⁹. Such findings lead us to investigate whether global imbalance in the size of order flow among the major exchange rates introduces asymmetric linkages between them.

In our paper we test the above hypothesis for DEM/USD and GBP/USD since the difference between the sizes of the global order flow of these two exchange rates is significantly large. Although there are no formal data on the global order flow during our sample period, data from the U.S. Treasury

⁴⁹ See, e.g., Lyons (1995), Yao (1998), Bjornnes and Rime (2000), Rime (2001), Payne (2003) and Evans and Lyons (2005).

collected by Rime (2001) suggest that weekly average net purchase of mark against the U.S. dollar is roughly three times that of the pound against the U.S. dollar from July 1995 to September 1999. The ratio is in line with that of the global turnover of the two exchange rates in 1995 and 1998. BIS (2005) estimates that in 1998 DEM/USD took around 20% of global market turnover, while GBP/USD took around 8%. The figures are very similar to the 1995 results. If order flows convey private information, we hypothesize that DEM/USD incorporates more private information relevant to the equilibrium exchange rates than GBP/USD, and this asymmetric information reveals itself in the volatility transmission process, with the greater spillover effects from DEM/USD to GBP/USD.

One novel feature, which differentiates our study from previous work, is that the extant literature fails to consider the cross-currency linkages at high frequency. There are findings that indicate that the foreign exchange market may process information at a much faster speed than on a weekly or daily basis used in most studies. For example, Cheung and Chinn (2001) report that predominant surveyed foreign exchange traders from U.S. hold the view that currency adjusts to major macro news within minutes. Andersen et al. (2003) find that the currency volatility adjusts to macro news within an hour's time. Therefore, it is imperative to study the volatility linkages using high frequency data.

We estimate two complementary multivariate GARCH models. The first model is the VARMAR-GARCH-CCC (VGC) model which is a combination of

the VARMA-GARCH model (see Ling and McAleer, 2003) and the constant conditional correlation model (Bollerslev, 1990). The VGC allows direct interpretation of the parameters and Wald tests are conducted to verify the volatility transmission between the exchange rates. The second model is BEKK (see Engle and Kroner, 1995) model, which is extended to include asymmetric terms (ABEKK). Although BEKK model does not allow direct interpretation of the parameters, we use news impact surface (see Kroner and Ng, 1998) to visually depict the asymmetric volatility linkage. We use two years of 10-min frequency indicative data on DEM/USD and GBP/USD provided by Olsen & Associates. Our results suggest the linkage is significant and asymmetric, with DEM/USD imposing much larger impact on GBP/USD.

The rest of this paper is organized as follows. Section 5.2, provides a review of the literature on the volatility linkage in the foreign exchange market. Section 5.3, describes the data and seasonal adjustment procedures. Section 5.4, introduces the two multivariate GARCH models, estimation and diagnostic tests. The empirical results are presented and discussed in Section 5.5. Finally, Section 5.6 concludes the paper.

5.2 Literature Review

The issue of volatility linkages in the foreign exchange market has been studied from various perspectives. In this section, we group the previous work into three

areas, differentiated by their distinctive rationale for volatility transmission in the foreign exchange market. Those are meteor shower, economic integration and information integration theories.

Volatility linkages in the foreign exchange market start to draw attention when Engel et al. (1990) report the evidence of volatility spillover in USD/JPY across the markets of Tokyo and New York. Meteor shower is the meteorological analogy used by Engle et al. to describe the volatility transmission across the foreign exchange markets that open sequentially when the globe turns. Using a GARCH model on daily USD/JPY exchange rate, they find the news impact across terrestrial geography to be significant. Subsequent studies suggest that volatility spillover across the markets could be caused by market behaviour, stochastic policy coordination, or market inefficiency. For instance, stochastic policy coordination induced volatility spillover could be best illustrated by the events of currency intervention⁵⁰. If the Bank of Japan begins intervening in the market in support of the U.S. dollar, the uncertainty of the Fed's policy response to either approving or disapproving the appreciation of the U.S. dollar will increase the volatility across the markets. Intervention can also drive away destabilizing speculators who may reappear in other foreign exchange markets, and increase the volatility of these markets⁵¹.

Another related line of research starts to look at the volatility spillover across exchange rates instead of across geographic markets. Baillie and

⁵⁰ See e.g., Ito et al. (1992).

⁵¹ See Westerhoff and Wieland (2004).

Bollerslev (1991) investigate the Granger causality of the variance across the exchange rates using hourly observations over four major currencies against the U.S. dollar. They find strong evidence for volatility spillover from sterling to yen during the opening hours of the Asian market. Baillie et al. (1993) study the floating period of 1920s when the 'bear squeeze' episodes occurred in the foreign exchange market. Using weekly exchange rates over six currencies against the U.S. dollar, they conclude that some volatility spillover across a few of the exchange rates could be found. Speight and McMillan (2001) look at the daily currencies of the six formerly socialist countries of Eastern Europe for the period of mid 1950s to 1990. There is evidence of volatility spillover across these exchange rates. Although the above papers extend the previous studies to multivariate exchange rates, they still consider policy coordination to be the major cause of volatility spillover. This is partly due to the fact that the sample periods examined are dominated by such a factor.

Studies employing more recent data suggest economic integration as a new line of enquiry into the research of volatility spillover across the exchange rates. Economic integration increases the interactions among regional economies through the flows of international trades and capital. It also leads to financial integration that strengthens the links among the regional financial markets⁵². Exchange rates of the integrated economies would be driven by the common regional economic and financial shocks. For instance, Black and McMillan

⁵² See e.g. in Dooley and Mathieson (1994), Phylaktis (1999) and Phylaktis and Ravazzolo (2002).

(2004) use a component-GARCH model (CGARCH) to decompose conditional volatility into a long-run trend component and a short-run transitory component, where the long-run component drives the time-dependent movement. Notable volatility spillover is found among the European currencies, which indicates a strong convergence among these economies.

Evans and Lyons (2002b) suggest a third factor, namely information integration, to explain the linkages among exchange rates. Although their model is not directly linked to the study of volatility spillovers, Evans and Lyons develop a multi-currency portfolio shifts model which demonstrates that information integration⁵³ implies a link between a given exchange rate and order flows in markets for other exchange rates. In this three-round multi-currency trading model, dealers set prices for each currency in round 1 on the basis of available information and attract customer orders that represent liquidity demand shocks⁵⁴ and are not publicly observable. In round 2 of interdealer trading, dealers redistribute their inventories from trading round 1 according to their speculative demand. In round 3, dealers share overnight risk with their customers and end the day with no net position. In this last round, non-dealer public trades against the dealers with purely speculative motives and dealers need to set prices that attract the customers to absorb their inventory imbalances. In this framework, the optimum quoting strategy of the dealers

⁵³ Evans and Lyons (2002b) suggest that there are three categories of integration, i.e., speculative, geographic and information integration.

⁵⁴ They are hence independent of public-information induced return shocks.

depends on the public-information induced payoff increments and order flows, the only two channels that convey information. The customers' currency demand is influenced by their portfolio allocation decision that redistributes wealth optimally across all currencies. However, the customers' decision to rebalance and the actual quantity of the foreign currency are private information. Order flow contains private information of the stochastic portfolio rebalancing that could be motivated by time-varying risk preferences, hedging demands and changed expectations of future economic performance. Although the information is dispersed among all the private agents, it is gradually aggregated and revealed through the medium of order flow. And since other currency markets participants need to absorb the demand change due to the rebalancing, the order flow impact of one currency is persistent on the prices of the other currencies. For instance, Evans and Lyons (2000b), using daily data, find that the order flows of DEM/USD and CHF/USD enter significantly into the price determination of other six European currencies against U.S. dollar.

In this study, we follow the theory of the information integration as the rationale behind the hypothesis of asymmetric linkage between DEM/USD and GBP/USD exchange rates. Given that they are among the major exchange rates, there should exist strong portfolio balance effect that generates a dynamic volatility linkage between them. At the same time, the private information embedded in each exchange rate may be asymmetric due to the notable global imbalance of order flow generated by these two markets. It is expected that

volatility transmission would reveal such asymmetric information dispersion.

5.3 Data

5.3.1 Exchange Rate Data

The tick-by-tick indicative quotes data are provided by the Olsen and Associate. Previous studies (see Goodhart et al. (1996), Danielsson and Payne (2002) and Phylaktis and Chen (2006)) suggest that when the indicative data are aggregated to 5 and 10-min frequency, the statistical difference between these and transaction data (D2000-1 and D2000-2) is negligible. In this study, we use 10-min frequency instead of 5 to accommodate the relatively sparse quotes in early mornings and late evenings. Data employed in this study are generated by taking the average of the closest two quotes immediately before and after each 10-min spaced GMT time. As each quote contains a pair of bid and ask price, the mid price is taken and converted into log price subsequently. The mid log prices of each currency pair are the prices of mark and pound in terms of the U.S. dollar. Returns are calculated as the difference between the log-mid price at times $t-1$ to t , excluding the first return of Monday for lack of quotes during weekends. To avoid small values and enhance the estimation of volatility, all returns are multiplied by 10,000.

The sample period in this study is from January 2 of 1997 to December 30 of 1998. Several international financial events drove up the volatility of the

foreign exchange markets during this period. In 1997, large currency depreciation spread across East Asia and beyond. In 1998, another crisis hit Russia and led to the bankruptcy of LTCM. The expected launch of euro also added some uncertainty to the markets. Therefore, it would be of interests to look at cross-currency linkages when markets are rich in macro information.

The daily price movements of the two currencies during the sample period are displayed in Figure 5.1. The dollar started in 1997 on an appreciating trend against both mark and pound as a result of market expectations of monetary tightening in the U.S. and no change of monetary policy stance in Germany and the UK. From May to July the dollar moved in opposite directions against the mark and the pound. The further appreciation of dollar against the mark was due to the consensus that the euro would be introduced on schedule. The rise in the value of the pound was due to the enlarged interest rate differential between U.S. and UK. During the summer of 1997, the different price movements came to an end as the optimism in the UK economy waned. From August to November of 1997, the dollar started to depreciate, reflecting the market view that the Asian crisis would have a greater economic impact on the U.S. than on Europe. By January of 1998, market participants were coming to realize that Europe would be more exposed to the Asian crisis than previously thought. Mark was further depressed by the official declarations about interest rate convergence in Europe. From January till August of 1998, both currencies fluctuated between narrow bands against the dollar. In September of 1998, the Russian crisis started to hit

the market and pushed the dollar down until October. For the remaining two months, markets digested the shock and began to normalize.

5.3.2 Intraday Seasonal Adjustment

The foreign exchange market is traded on a global continuity, with active trading centres opening and closing at different times of the day. Such a global trading causes seasonality in the intraday return volatilities. Therefore, there is a need to adjust the returns before considering any modelling.

We adopt the seasonal adjustment procedure suggested by Bauwens et al. (2005) and divide each return by its intraday volatility index. Specifically, 10-min average volatilities for each week day are estimated and each return is divided by its corresponding weekday average volatilities⁵⁵. For example, to adjust the 10-min return at 12:00 of Monday for a specific date, we divided the return by the average 10-min volatility at 12:00 of all Mondays in the sample. This practice standardizes the return series and hence facilitates direct estimations of the empirical tests without further introducing seasonal dummies.

The weekday average 10-min volatility is presented in Figures 5.2-6. The general intraday volatility pattern is obvious throughout the weekdays. Except on Friday, volatility starts to rise from GMT 22 and 23 onwards, when Tokyo and Sydney markets open consecutively with one hour gap in between. After

⁵⁵ British summer time and U.S. daylight saving (DST) are dealt with by correcting the 1 hour gap.

Hong Kong and Singapore join the trading around midnight, volatility drops temporarily during Tokyo market lunch break around GMT 4. One hour later the volatility climbs gradually to its morning peak after London and Frankfurt markets open at GMT 8. High volatility drops again at mid day when European markets take their lunch break. From GMT 12 on, the volatility starts to rally again when New York market opens. Between GMT 14 and 16, the volatility is generally at its highest peak when both European and New York markets are active. At around GMT 17 there is a spike when European traders close their positions and leave the markets. Similarly, New York market close causes another jump of volatility at GMT 21.

Some weekday specific features also exist. The highest weekday average volatilities for the two peaks of European and New York trading hours take place on Monday morning (around GMT 8) and Friday afternoon (around GMT 16) respectively. Given that Monday morning is the time for the market to build trading positions with not much trading information to rely on, and Friday afternoon to unwind positions when all previous weekdays' unpriced information needs to be incorporated into prices, such volatility peaks are expected. The lowest volatility levels in the early morning and late night also happens on Monday morning and Friday night respectively, when trades are least likely to be executed. Such distinctive trading and information environment make the volatility patterns of Monday and Friday to be significantly different from those of the other weekdays.

In Table 5.1, the descriptive statistics of the returns of the two exchange rates both before and after seasonal adjustment are presented. As the seasonal adjustment is in effect a return standardization practice, means of both adjusted exchange rates are much closer to zero, and standard deviations of both exchange rates are reduced from around 6 to nearly 1. Skewness and kurtosis are decreased towards normal distribution of 0 and 3 respectively. The slightly higher kurtosis of standardized GBP/USD returns compared to those of DEM/USD indicates a relatively wider distribution of GBP/USD returns in our sample period. Jarque-Bera statistics indicates a significant drop of value towards normal distribution. Although the Ljung-Box Q statistics have been reduced by the standardization, there is still a strong presence of ARCH structure in the adjusted data series.

5.4 Methodology

We employ two different multivariate GARCH (MGARCH) models to study the volatility linkage between the two exchange rates. One of the MGARCH model is the VARMA-GARCH-CCC (VGC) model. VGC model is a combination of the VARMA-GARCH model (Ling and McAleer(2003)) and the constant conditional correlation model (Bollerslev (1990)). And the other is BEKK model (Engle and Kroner (1995)), which uses quadratic forms to ensure positive definiteness of the conditional variance under weak conditions. The reason for

using two models is that VGC model allows direct interpretation of the estimated parameters, which is difficult in the case of BEKK model. However, VGC is based on univariate GARCH models, and hence lacks the fully dynamic interaction of the BEKK model. Therefore, it is necessary to use both models to avoid the shortcomings caused by employing only one of them.

Specifically, VGC model allows lagged shocks from one GARCH model to affect the conditional variance of the other GARCH model. The interpretation of the estimated parameters is straightforward. However, as a restricted correlation model, VGC model is estimated as separate univariate GARCH models, i.e. the actual estimation is based on two parallel univariate GARCH models estimated at a common range and therefore lacks the full interaction of the elements of covariance matrix and error terms. In contrast, BEKK model allows for volatility transmission and dynamic conditional covariance and correlation structure and hence captures better the volatility linkage between the return series. As the parameters of the BEKK model do not allow direct interpretation due to its quadratic form, we use the ‘news impact surface’ (see Engle and Ng (1993) and Kroner and Ng (1998)) to graphically depict the volatility transmission between the exchange rates.

5.4.1 VGC Model

VGC model allows shocks of one market to affect the conditional variances of

the other markets in a multivariate system, while assuming the conditional correlations to be constant. The approach is a nonlinear combination of univariate GARCH models, which requires fewer parameters than the BEKK models. However the theoretical results on stationarity, ergodicity and moments are not as straightforward as in other multivariate GARCH models.

To incorporate the interaction of mean returns of both exchange rates into the MGARCH models, we use a VAR system as the mean equation, which also applies to the BEKK model's mean specifications. The specification of a VAR with lag length of 6 for the mean equation is chosen on the basis of the Akaike Information Criterion (AIC)⁵⁶:

$$\begin{aligned} R_{1,t} &= c_{01} + \sum_{p=1}^6 \theta_{1,1,p} R_{1,t-p} + \sum_{p=1}^6 \theta_{1,2,p} R_{2,t-p} + \mu_{1,t} \\ R_{2,t} &= c_{02} + \sum_{p=1}^6 \theta_{2,1,p} R_{1,t-p} + \sum_{p=1}^6 \theta_{2,2,p} R_{2,t-p} + \mu_{2,t} \end{aligned} \quad (1)$$

where R_1 and R_2 are deseasoned returns of DEM/USD and GBP/USD respectively, c_{01} (c_{02}) and μ_1 (μ_2) are the constant and error terms for DEM/USD (GBP/USD) respectively. $\theta_{1,1,p}$ is the coefficient of DEM/USD returns at lag p in the equation for DEM/USD returns, while the $\theta_{1,2,p}$ is the coefficient for returns of GBP/USD at lag p in the DEM/USD equation. A similar interpretation applies to the coefficients of the equation for GBP/USD.

The variance terms take the form:

⁵⁶ The Schwartz Bayesian Criterion (SBC) suggests a smaller lag length at 2, but the estimated residuals still contain serial correlation.

$$\begin{aligned}
h_{ii,t} &= c_i + \sum_{j=1}^2 a_{ij} \mu_{j,t-1}^2 + \sum_{j=1}^2 b_{ij} h_{jj,t-1} + \sum_{j=1}^2 d_{ij} \eta_{j,t-1}^2, i = 1, 2 \\
h_{ij,t} &= \rho_{ij} (\sqrt{h_{ii,t}} \sqrt{h_{jj,t}}), i \neq j
\end{aligned} \tag{2}$$

where h is the conditional covariance matrix, μ is the vector of residuals from the mean equation. η is a 2×1 vector of asymmetric GJR terms (Glosten, et al. (1993)), i.e. $\eta_t = \min[0, \mu_t]$. ρ is the constant conditional correlation. The conditional covariance of equation (2) is constrained by the product of conditional standard deviations. Although at lower frequency, i.e. daily or weekly, the correlation across currency markets is found to be time varying⁵⁷, we assume at high frequency the correlation to be constant⁵⁸. i and j refer to DEM/USD and GBP/USD respectively. Specifically, when $i = 1$, h_{11} refers to the conditional variance of DEM/USD. When $i = 1$ and $j = 2$, h_{12} refers to the conditional covariance of the two exchange rates.

To test the volatility spillover, Wald tests of the joint significance of parameters are conducted. Specifically, it tests whether the coefficients of the residual shock, asymmetric terms and conditional variance of one exchange rate are jointly statistically significant in the determination of the other exchange rate's conditional variance. If the joint tests fail to reject the null hypothesis that the three parameters are zero, then there is evidence of volatility spillover in the exchange rates. Formally, the null hypothesis for testing the spillover effect in the conditional variance of one exchange rate h_{ii} is:

⁵⁷ See Sheedy (1998), and Chang and Kim (2001).

⁵⁸ To check the possibility of dynamic conditional correlations (Engle (2002)), DCC model is tested and found to produce statistically insignificant results.

$$H_0 : a_{ij} = b_{ij} = d_{ij} = 0, \text{ where } i \neq j. \quad (3)$$

One should note that the volatility transmission could also occur indirectly through conditional covariance. However, given the assumption of constant correlation and the lack of full interaction in the conditional covariance, we only study the direct impact of conditional variance interactions.

5.4.2 BEKK Model

BEKK model is a special case of the VEC model (Bollerslev et al. (1988)). VEC model allows full interaction among the elements. In the general VEC model, the conditional variances and conditional covariances depend on the lagged values of all of the conditional variances of, and conditional covariances between, all of the returns in the series, as well as the lagged squared errors and the error cross-products. One practical shortcoming of the VEC is that the model might not yield a positive definite covariance matrix. BEKK model ensures the positivity of conditional variance by introducing a quadratic form. It can be shown that in the bivariate case the BEKK model is as general as the VEC model. Kroner and Ng (1998) extend the model to allow for asymmetry (ABEKK). Formally, BEKK model with added asymmetric terms is expressed as:

$$H_t = C'C + A'\mu_{t-1}\mu_{t-1}'A + B'H_{t-1}B + G'\eta_{t-1}\eta_{t-1}'G, \quad (4)$$

where $C'C$ is symmetric and positively definite, H is the conditional

covariance matrix and μ is the innovation vector, and η is a 2×1 asymmetric GJR terms, i.e. $\eta_t = \min[0, \mu_t]$. In our bivariate case, H is a symmetric 2×2 matrix. $H(1,1)$, $H(2,2)$ and $H(1,2)$ are the conditional variance of DEM/USD, GBP/USD and conditional covariance of the two respectively. Engle and Kroner (1995) prove that the eigenvalues of $A + B$ being less than one is the sufficient condition for volatility to decay over time. Without the asymmetric terms, BEKK model requires the estimation of $k(5k+1)/2$ parameters, where k is the number of return series. The mean equations of the BEKK model is an AR(6) process as presented in the VGC model (see equation (1)).

The parameters of A and B in Equation (4) do not have direct interpretations concerning the lagged values of volatilities or shocks. To help us explain the asymmetric effects in the conditional volatility, we employ news impact surface technique to depict the volatility transmission between the exchange rates.

The term 'news impact surface' is first coined by Kroner and Ng (1998), which is based on univariate method of 'news impact curve' by Engle and Ng (1993). Similar to the univariate application, the multivariate generalization of news impact surface plots the one series' conditional variance and covariance against the lagged shocks from the other, while holding the lagged conditional variances and covariances constant at unconditional sample mean levels.

Following Kroner and Ng (1998), we denote the lagged vector of inputs at

time $t-1$ for the determination of conditional variance or covariance h_{ij} as Φ_{t-1} , excluding lagged innovations. We further denote Φ as the unconditional mean of Φ_{t-1} . The news impact surface for h_{ij} can be therefore expressed as:

$$h_{ij,t} = h_{ij}(\mu_{i,t-1}, \mu_{j,t-1}; \Phi_{t-1} = \Phi), \quad (5)$$

where μ is the innovation.

5.4.3 Maximum Likelihood Estimation

Both MGARCH models employed in our study are estimated using quasi maximum likelihood (QML) method of Bollerslev and Wooldridge (1992). Suppose the vector stochastic process R_t with T observations is a realization of a DGP whose conditional mean and covariance matrix are approximated by a vector of parameters θ . The optimization is conducted as:

$$\max_{\theta} \log L_T(\theta) = \sum_{t=1}^T l_t(\theta), \quad (6)$$

where L is sample likelihood function. For a bivariate normally distributed variable, the conditional log-likelihood function is:

$$l_t(\theta) = -(T \log(2\pi)/2) - (1/\ln|H|) - \frac{1}{2} \log \mu' H^{-1} \mu, \quad (7)$$

where H and μ follow Equation (1), (2) and (4).

By assuming Gaussian innovations, the QML approach yields persistent estimation under the condition that the conditional mean and covariance matrix are correctly specified. Robust errors are computed that are valid under non-normality (see White, 1982). The BFGS algorithm with a convergence

criterion of 0.00001 is applied to achieve the convergence.

5.4.4 Diagnostic Tests

In this study we employ a multivariate extension of univariate ARCH detecting diagnostics of Ljung-Box portmanteau tests. The multivariate Ljung-Box Q (MLBQ) test of Hosking (1980) gives the test statistics as:

$$MLBQ = T^2 \sum_{j=1}^p (T-j)^{-1} \text{tr}\{C_{R_t}^{-1}(0)C_{R_t}(j)C_{R_t}^{-1}(0)C_{R_t}'(j)\} \quad (8)$$

where R_t is the vector of returns and $C_{R_t}(j)$ is the sample autocovariance matrix of lag order j . The null hypothesis is no ARCH effects and the statistic is distributed asymptotically as χ^2 with $2^2(p-2)$ degrees of freedom. The test is applied to both the standardized residuals and squared standardized residuals. The lag lengths are set to 6 and 12, representing serial correlation up to one and two hours respectively.

5.5 Empirical Results

5.5.1 Results for VGC Model

The estimated results of VGC (Equation (1) and (2)) are presented in Table 5.2.

Panel A of Table 5.2 displays the coefficient estimation for the mean equation of the VAR(6) system in Equation (1). C_{0i} is the constant term in the equation for the return of exchange rate i , where $i=1$ indicates DEM/USD,

and 2 indicates GBP/USD. $\theta_{i,j,p}$ is the coefficient of the lagged return of exchange rate j at lag p in equation for exchange rate i .

In the mean equation for DEM/USD, the autoregressive terms ($\theta_{1,1,p}$) are significant in 3 out of the 6 lags at 5% level. The lagged GBP/USD returns ($\theta_{1,2,p}$) fail to produce any significant impact on DEM/USD except at lag 5. In the mean equation for GBP/USD, the autoregressive terms ($\theta_{2,2,p}$) are significant at all lags, indicating a strong persistent autocorrelation. The lagged DEM/USD returns ($\theta_{2,1,p}$) enter significantly in GBP/USD equation at 1% level, with 3 out of 6 being significant and the sizes of the coefficient being relatively large. The larger impact of DEM/USD returns on GBP/USD compared to GBP/USD on DEM/USD provides evidence of asymmetric linkage at return level.

Panel B of Table 5.2 presents the empirical results of the conditional variance equation of VGC model. The 15 estimated parameters are significant at 5% with only two exceptions. The statistically significant and positive values of a_{ii} and b_{ii} with sums less than 1 suggest that there is positive persistence of the conditional variances in both exchange rates.

More important findings are the significant cross terms, namely a_{ij} , b_{ij} and d_{ij} , in each conditional variance equation. The Wald tests of volatility spillover effect presented in Panel C indicate that the volatility transmission is highly significant between the two exchange rates. The test statistics of one currency's volatility spillover into the other are all significant at 1%.

Furthermore, the volatility transmission is asymmetric between the two exchange rates. The absolute value of coefficient of lagged residual of GBP/USD in the conditional variance equation of DEM/USD (a_{12}) is much smaller than the coefficient a_{21} , suggesting that the lagged DEM/USD innovations have greater effect on the conditional variance of GBP/USD than the reverse. Similarly, the lagged conditional variance of GBP/USD (b_{12}) imposes less impact on the conditional variance of DEM/USD than the reverse (b_{21}).

The significant GJR terms of d_{ii} indicates that negative return shocks have notable impact on the exchange rates' conditional variance. The asymmetric effect in DEM/USD (d_{11}) is much smaller than that in GBP/USD (d_{22}) in terms of their absolute value. The negative return shocks tend to decrease very slightly the conditional variance in the case of DEM/USD while increase it in the case of GBP/USD. And the negative DEM/USD return shocks have significant effect (d_{21}) on the conditional variance of GBP/USD, while those of GBP/USD (d_{12}) have literally no effect on the conditional variance of DEM/USD.

The value and significance of constant correlation ρ_{12} of 0.3 indicates a low but highly statistically significant contemporaneous correlation between the two exchange rates. In Figure 5.7 we display the constant correlation against the sample correlation with an arbitrary moving window of 120 observations alongside the conditional standardized residuals for both currencies.

In Panel D the model's fitness is good in terms of the multivariate Ljung-Box Q statistics. The diagnostic tests on the standardized residuals and their squared values are all insignificant. It suggests that there is no autocorrelation in the lagged standardized residuals and ARCH effect in the squared standardized residuals.

5.5.2 Results for BEKK Model

In Table 5.3 the estimation results of BEKK model are displayed. The estimation of mean equation of BEKK is the same as estimated in the VGC model and hence is not displayed. Among the 15 estimated parameters of the conditional variance equation, 14 of them are significant at 5% level. The model diagnostics suggest relatively a good fit of the model with only the multivariate Ljung-box Q statistics for the squared standardised residuals at lag 12 not significant at 5% level. Since the parameters of the BEKK model are in the quadratic forms and difficult to interpret, we rely on the news impact surface approach to depict the volatility transmission. As the asymmetric terms of the BEKK model add complicated effect on the news impact surface, we first present the graphs without asymmetric terms in Figure 5.8. The graphs with added asymmetric terms are presented in the subsequent Figure 5.9.

The magnitudes of innovation shocks on the conditional variance and covariance are in the range of -2 to 2. Since the return series of both exchange

rates are standardized, such a shock range amounts to a range of -2 to 2 standard deviations of shocks. The labels of DEM and GBP for Y and X axis stand for the source of shocks, with DEM being DEM/USD and GBP being GBP/USD exchange rate returns respectively. In each figure, three subplots of news impact surface of corresponding conditional variances and covariance are presented.

Figure 5.8 presents the news impact surface without the asymmetric terms. In subplot (a), the surface of the conditional variance of DEM/USD is displayed. The conditional variance of DEM/USD is sensitive to the shocks from itself, displaying a 'U' shape impact curve. It suggests that the conditional variance responds more strongly to large shocks than small ones. However the impact of GBP/USD on DEM/USD is less obvious as the straight and relatively horizontal parallel lines suggest.

The news impact surface of GBP/USD's conditional variance displays a different pattern (subplot (b)). The conditional variance of GBP/USD not only responds to its own past shocks, but is also very sensitive to those from DEM/USD. The highest conditional variance of GBP/USD occurs when shocks from both currencies have opposite signs.

The subplot (c) of Figure 5.8 summarizes the impact surface of conditional covariance of the two exchange rates. The lowest covariance occurs when the shocks from both currencies take opposite signs, as expected. When both shocks are either positive or negative, the conditional variance reaches higher values. The conditional covariance is however slightly more sensitive to those shocks

from DEM/USD as the arched curve over the DEM/USD axis suggests.

In sum, Figure 5.8 indicates that there is volatility linkage between the two exchange rates, as each responds to the shocks from the other, without taking asymmetric terms into consideration. However, the volatility transmission is also asymmetric since the conditional variance of GBP/USD is much more sensitive to the shocks from DEM/USD than the reverse, which is in line with the findings from the VGC model.

Figure 5.9 presents the news impact surface with asymmetric terms, i.e. negative return shocks are differentiated from positive ones. The news impact surface of conditional variance of DEM/USD with asymmetric terms is presented in subplot (a) of Figure 5.9. The response of DEM/USD is largely unchanged when the shocks from DEM/USD and GBP/USD are both positive. When both exchange rates produce negative shocks, the conditional variance of DEM/USD drops. As the VGC model (d_{11}) suggests, the asymmetric terms of DEM/USD lowers its conditional variance. When negative shocks from GBP/USD combine with positive DEM/USD shocks, the conditional variance of DEM/USD only responds to those large negative GBP/USD shocks with values less than minus 1. VGC model suggest that negative GBP/USD shocks (d_{12}) tend to raise conditional variance of DEM/USD, which is also reflected in the impact surface.

In subplot (b) of Figure 5.9, the news impact surface of GBP/USD with asymmetric terms is displayed. The conditional variance of GBP/USD is

sensitive to shocks from both exchange rates when the shocks from them are positive. As suggested by the VGC model, the effects from the negative shocks from GBP/USD (d_{22}) and DEM/USD (d_{21}) are mixed, with the former raising the conditional variance and the later lowering it. Therefore the conditional variance of GBP/USD continues the decreasing trend in the DEM/USD shock range of $[0, -1]$, and then rises swiftly in the shock range of $[-1, -2]$. Compared to the conditional variance without the asymmetric terms (subplot (b) of Figure 5.8), GBP/USD is now very sensitive to negative shocks from both exchange rates.

The news impact surface of conditional covariance (Figure 5.9, subplot (c)) is changed correspondingly. The surface is also the same when the shocks from DEM/USD are positive. However, when the shocks from DEM/USD become negative, the conditional covariance starts to rise significantly, especially when the negative DEM/USD shocks exceed minus 1. It suggests that asymmetric terms, particularly those of DEM/USD, significantly change the conditional covariance into a more dynamic pattern. The raised conditional covariance alongside the axis of GBP/USD suggests that the volatility transmission from GBP/USD is partly compensated through the channel of conditional covariance.

In sum, the Figure 5.9 indicates that the asymmetric terms enhance the dynamic volatility linkage between the two exchange rates. The conditional variance of DEM/USD becomes sensitive to large negative GBP/USD shocks. At the same time the conditional variance of GBP/USD becomes more sensitive

to negative DEM/USD shocks. Although the volatility transmission patterns become more complex and dynamic, the conclusion of asymmetric volatility transmission, i.e., that DEM/USD imposes much larger impact on the conditional volatility of GBP/USD than the reverse, is largely unchanged from the previous analysis of Figure 5.8.

5.6 Conclusion

This study investigates the dynamic linkages between the DEM/USD and GBP/USD exchange rates in terms of volatility transmission, using high frequency data. We employ two multivariate GARCH models on two years of high frequency exchange rate data to provide evidence on our hypothesis. The empirical results suggest that such linkages are significant and asymmetric, with DEM/USD imposing stronger impact on GBP/USD than the reverse.

Such findings provide further evidence on the possible existence of private information in the foreign markets. As volatilities are linked to information, the asymmetric volatility transmission of the two exchange rates suggests the information may be distributed asymmetrically between them. We hypothesize that, based on the portfolio shift theory of Evans and Lyons (2002b), the different size of global order flow generated by the two exchange rates as a source of private information, and a possible cause of such an asymmetry. Further study therefore needs to introduce the order flows into the analysis to

confirm such a hypothesis.

References

- Adler, M, and R. Qi. 2003, Mexico's Integration into the North American Capital Market, *Emerging Markets Review*, 4: 91-120.
- Almeida, A., C., Goodhart, and R., Payne. 1998. The effects of macroeconomic news on high frequency exchange rate behaviour. *Journal of Financial and Quantitative Analysis*, 33: 383-408.
- Andersen, T. and T., Bollerslev. 1998. Deutsche mark-dollar volatility: intraday activity patterns, macroeconomic announcements, and long run dependencies. *The Journal of Finance*, 1: 219-265.
- Andersen, T. G., T. Bollerslev, and F. Diebold, and C. Vega. 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign exchange. *American Economic Review*, 93: 38-62.
- Baillie, R. T., and T., Bollerslev. 1991. Intra-day and inter-market volatility in foreign exchange rates, *Review of Economic Studies*, 58: 565-85.
- Baillie, R. T., T., Bollerslev, and M., R., Redfearn. 1993. Bear squeezes, volatility spillovers and speculative attacks in the hyperinflation 1920s foreign exchange, *Journal of International Money and Finance*, 12: 511-21.
- Bauwens, L., S., Laurent, and J. V. Rombouts. 2006. Multivariate GARCH models: a survey, *Journal of Applied Econometrics*, 21: 79-109.
- Bauwens, L., W. B. Omrane, and P. Piot. 2005. News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance*, 24: 1108-1125.
- Bekaert, G. and G. Wu. 2000. Asymmetric volatility and risk in equity markets, *The Review of Financial Studies*, 13: 1-42.
- BIS, 2005, Triennial Central Bank Survey – Foreign exchange and derivatives market activity in 2004.
- Bjønnes, G.H. and D. Rime. 2001. Customer trading and information in foreign exchange markets. Working paper # 4. Stockholm Institute for Financial Research.
- Black, A. and D. McMillan. 2004. Long run trends and volatility spillovers in daily exchange rates. *Applied Financial Economics*, 14: 895-907.

Black, F., 1976. Studies in stock price volatility changes. In *American Statistical Association, Proceedings of the Business and Economic Statistics Section*, 177-181.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH Model. *The Review of Economics and Statistics*, MIT Press, 72: 498-505.

Bollerslev, T., R. Y. Chou, and K. F. Kroner. 1992. ARCH modelling in finance. *Journal of Econometrics*, 52: 5-59.

Bollerslev, T., R. Engle, and J. Wooldridge. 1988. A capital asset pricing model with time varying covariances. *Journal of Political Economy*, 96: 116-131.

Bollerslev, T., R. Engle, and J. Wooldridge. 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time varying covariances. *Econometric Reviews*, 11:143-172.

Bonfiglioli, A. and C. Favero. 2005. Explaining co-movements between stock markets: the case of US and Germany. *Journal of International Money and Finance*, 24: 1299-1316.

Chang, K. H., and M. J. Kim. 2001. Jumps and time-varying correlations in daily foreign exchange rates, *Journal of International Money and Finance*, 20: 611-637.

Cheung, Y. -W., and M. D. Chinn. 2001. Currency traders and exchange rate dynamics: A survey of the US Market. *Journal of International Money and Finance*, 20: 439-471.

Christie, A. 1982. The stochastic behavior of common stock variances- value, lever-age, and interest rate effects. *Journal of Financial Economic Theory*, 10: 407-432.

Conrad, J., M. N. Gultekin, and G. Kaul. 1991. Asymmetric predictability of conditional variances. *The Review of Financial Studies*, 4: 597-622.

Danielsson, J., and R. Payne. 2002. Real trading patterns and prices in the spot foreign exchange markets. *Journal of International Money and Finance*, 21: 203-222.

Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of*

Business & Economic Statistics. 20: 339-50.

Engle, R. F., T. Ito, and W. L. Lin. 1990. Meteor showers of heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, 58: 525-42.

Engle, R. F. and K. F. Kroner. 1995. Multivariate simultaneous Generalized ARCH. *Econometric Theory*, 11: 122-50.

Engle, R., and V. Ng. 1993. Measuring and testing the impact of news on volatility. *Journal of Finance*, 48: 1749-1778.

Evans, M., D., and R. Lyons. 2002a. Order flow and exchange rate dynamics. *Journal of Political Economy*, 110: 170-180.

_____. 2002b. Informational integration and FX trading. *Journal of International Money and Finance*, 21:807-31.

_____. 2005. Exchange rate fundamentals and order flow, typescript, U.C. Berkeley.

Francis B. B., I. Hasan, and D. M. Hunter. 2006. Dynamic relations between international equity and currency markets: the role of currency order flow. *Journal of Business*, 79: 219-258.

Frank, H. Westerhoff, Cristian Wieland. 2004. Spillover dynamics of central bank interventions. *German Economic Review*, 5: 435-450.

Friberg, R and S. Nydahl, 1999. Openness and the exchange rate exposure of national stock markets. *International Journal of Finance and Economics*, 4: 55-62.

Gifarelli, G and G. Paladino. 2005. Volatility linkages across three major equity markets: a financial arbitrage approach. *Journal of International Money and Finance*, 24: 413-439.

Glosten, L. R., R. Jagannathan and D. E. Runkle. 1993. On the relation between the expected value of the volatility and of the nominal excess return on stocks. *Journal of Finance*, 48: 1779-1801.

Goodhart, C., T. Ito, and R. Payne. 1996. One day in June 1993: A Study of the Working of Reuters 2000-2. In *The Microstructure of Foreign Exchange markets*, J. Frankel, G. Galli, and A. Giovanni, eds. Chicago, IL: Univ. of Chicago Press.

Hafner, C. M. and H. Herwartz. 2006. Volatility impulse responses for multivariate GARCH models: an exchange rate illustration. *Journal of International Money and Finance*, 25: 719-740.

Hamao, Y., R. W. Masulis, and V. Ng. 1990. Correlations in price changes and volatility across international stock markets. *The Review of Financial Studies* 1990, 3: 281-307.

Hosking, J. R. M. 1980. The Multivariate portmanteau statistic. *Journal of the American Statistical Association*, 75, 602-608.

Ito, T., R. F. Engle, and W-L Ling. 1992. Where does the meteor shower come from?: The role of stochastic policy coordination, *Journal of International Economics*, 32: 221-240.

Kroner K. F., V. K. Ng. 1998. Modelling asymmetric comovements of asset returns. *The Reviews of Financial Studies*, 11: 817-844.

Ling, S. and M. McAleer. 2003. Asymptotic theory for a new vector ARMA-GARCH model. *Econometric Theory*, 19: 280-310.

Lyons, R., 1995, Tests of microstructural hypotheses in the foreign exchange market, *Journal of Financial Economics*, 39: 321-351.

Ma, C. K., and G. W. Kao. 1990. On exchange rate changes and stock price reactions. *Journal of Business Finance and Accounting*, 17: 441-450.

Maghrebi, N., M. J. Holmes, and E. J. Pentecost. 2006. Are there asymmetries in the relationship between exchange rate fluctuations and stock market volatility in pacific basin countries? *Review of Pacific Basin Financial Markets and Policies*, 9: 229-256.

McKenzie, M. D. 2002. The economics of exchange rate volatility asymmetry. *International Journal of Finance and Economics*, 7: 247-260.

Ng, A. 2000. Volatility spillover effects from Japan and the US to the pacific-basin. *Journal of International Money and Finance*, 19: 207-233.

Payne, R., 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61: 307-329.

Phylaktis, K. and L. Chen. 2006. Price discovery in indicative and transaction FX prices system -- A comparison of D2000-1 and EFX data, working paper, Cass Business School.

Pesaran M. H. and R.P. Smith. 1995. Estimation of long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68: 79-113.

Rime, D., 2001. U.S. exchange rates and currency flows. Working paper, Norges Bank Research Department and Stockholm Institute for Financial Research.

Sheedy, E., 1998. Correlation in currency markets: A risk adjusted perspective. *Journal of International Financial Markets, Institutions and Money*, 8: 59-82.

Sims, C.A. 1980. Macroeconomics and Reality. *Econometrica*, 48: 1-48

Speight, A. and D. G. McMillan. 2001. Volatility spillovers in East European black-market exchange rates. *Journal of International Money and Finance*, 20: 367-378.

Tse, Y. K., and A. K. Tsui, 1997. Conditional volatility in foreign exchange rates: evidence from the Malaysian Ringgit and Singapore Dollar. *Pacific Basin Finance Journal*, 5: 345-356.

Westerhoff, F. H. and C. Wieland. 2004. Spillover dynamics of central bank interventions. *German Economic Review*, 5: 435-450.

White, H. 1982. Maximum likelihood estimation of misspecified models. *Econometrica*, 50: 1-25.

Yao, J., 1998. Market making in the interbank foreign exchange market. Salomon Center for the Study of Financial Institutions Working Paper s-98-3, New York, NY.

Table 5.1
Moments of the DEM/USD and GBP/USD 10-min returns

	DEM/USD		GBP/USD	
	Returns	SA returns	Returns	SA returns
Mean	-0.01113	-0.00412	-0.00410	-0.00032
Std. Dev.	5.899	1.003	6.729	0.998
Skewness	0.397	0.033	0.018	0.010
Kurtosis	31.357	5.052	49.091	5.811
Jarque-Bera	2,486,876*	12,886*	6,565,097*	24,153*
Autocorrelation of order 1	-0.138*	-0.105*	-0.225*	-0.196*
Autocorrelation of order 2	-0.003	-0.007	-0.021*	-0.014*
Autocorrelation of order 3	0.001	0.001	-0.005	-0.006
LBQsq(4)	4,728*	2,863*	3,614*	1,906*

Notes: The SA returns are the seasonally adjusted returns by dividing the returns by their intraday average volatility index. Jarque-Bera test statistics indicate the degree of normality. LBQsq(4) is the univariate Ljung-Box Q statistics for serial correlation in squared returns up to lag 4. All the returns have been pre-multiplied by 10,000. * denotes significance at 1% level.

Table 5.2
VGC model estimation

Panel A. Mean equations

Equation for DEM/USD returns				
Coefficients	Estimation	Std. error	t-stat.	Significance
C01	-0.005	0.004	-2.35	0.01
θ1,1,1	-0.067	0.005	-13.33	0.00
θ1,1,2	-0.027	0.005	-5.40	0.00
θ1,1,3	0.007	0.005	1.36	0.09
θ1,1,4	0.006	0.005	1.21	0.11
θ1,1,5	0.013	0.005	2.63	0.00
θ1,1,6	0.003	0.005	0.55	0.29
θ1,2,1	0.004	0.005	0.83	0.20
θ1,2,2	0.000	0.005	0.08	0.47
θ1,2,3	-0.001	0.005	-0.19	0.42
θ1,2,4	-0.003	0.005	-0.56	0.29
θ1,2,5	-0.011	0.005	-2.22	0.01
θ1,2,6	0.000	0.005	0.01	0.49
Equation for GBP/USD returns				
Coefficients	Estimation	Std. error	t-stat.	Significance
C02	0.013	0.005	2.43	0.01
θ2,1,1	0.067	0.005	13.30	0.00
θ2,1,2	0.016	0.005	3.09	0.00
θ2,1,3	0.022	0.005	4.35	0.00
θ2,1,4	0.000	0.005	-0.07	0.47
θ2,1,5	0.006	0.005	1.09	0.14
θ2,1,6	0.001	0.005	0.27	0.39
θ2,2,1	-0.067	0.005	-13.40	0.00
θ2,2,2	-0.036	0.005	-7.19	0.00
θ2,2,3	-0.016	0.005	-3.25	0.00
θ2,2,4	-0.015	0.005	-2.90	0.00
θ2,2,5	-0.016	0.005	-3.19	0.00
θ2,2,6	-0.014	0.005	-2.88	0.00

Panel B: Conditional variance equation

Coefficients	Estimation	Std. error	t-stat.	Significance
Panel B. Conditional variance				
C_1	-0.0063	0.0048	-1.30	0.19
C_2	0.1127	0.0222	5.08	0.00
a_{11}	0.0486	0.0058	8.42	0.00
a_{12}	-0.0086	0.0028	-3.12	0.00
a_{21}	-0.0430	0.0047	-9.14	0.00
a_{22}	0.1291	0.0105	12.34	0.00
b_{11}	0.8514	0.0314	27.07	0.00
b_{12}	0.3650	0.1003	3.64	0.00
b_{21}	1.2062	0.2687	4.49	0.00
b_{22}	0.4153	0.1054	3.94	0.00
d_{11}	-0.0056	0.0026	-2.22	0.03
d_{12}	0.0100	0.0059	1.66	0.10
d_{21}	-0.0524	0.0000	6.30	0.00
d_{22}	0.0969	0.0000	8.94	0.00
ρ_{12}	0.3083	0.0052	59.06	0.00

Panel C: Volatility spillover test

Volatility spillover from GBP/USD to DEM/USD

Wald ($H_0: a_{12} = b_{12} = d_{12} = 0$) $\chi^2 = 86.70$ (0.00)

Volatility spillover from DEM/USD to GBP/USD

Wald ($H_0: a_{21} = b_{21} = d_{21} = 0$) $\chi^2 = 19.00$ (0.00)

Panel D. Model diagnostics

$MLBG(6)$	5.04	(0.96)
$MLBG(12)$	28.11	(0.82)
$MLBG^2(6)$	13.91	(0.73)
$MLBG^2(12)$	59.98	(0.12)
LR	-124,334.53	

Notes: For the specification of the VGC model refer to equations (1) and (2). θ_{0i} stands for the constant. $\Theta_{i,j,k}$ stands for the coefficient of the return of the same currency pair at lag k when $i = j$.

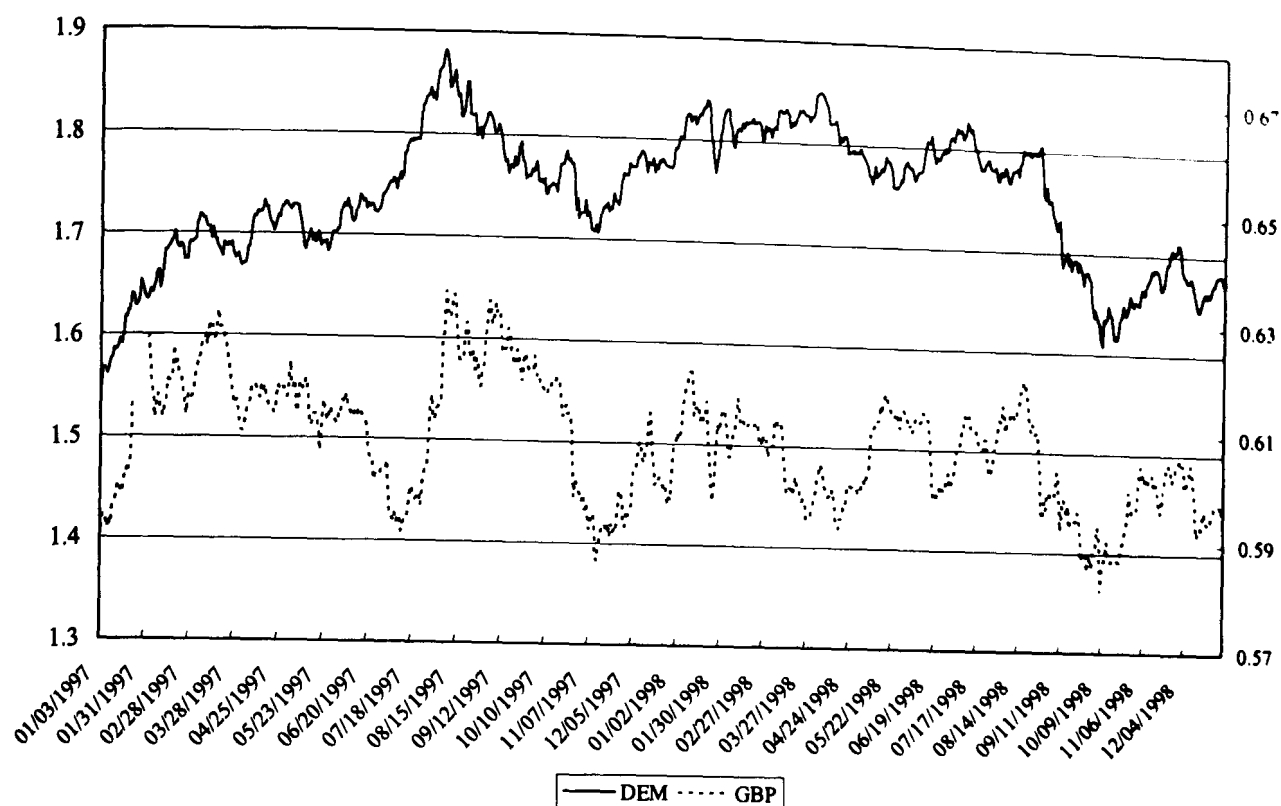
Otherwise it is the coefficient of the return from other currency pair. $MLBG(k)$ and $MLBG^2(k)$ is the multivariate Ljung-Box Q statistics of Hosking (1980) for the standardized and squared standardized residuals with lag k . p -value of each statistic is presented in the brackets. LR is the likelihood ratio. The volatility spillover test is a joint test of whether the coefficients of one currency pair's residual shock, conditional variance and asymmetric shock are significantly.

Table 5.3
BEKK estimation

Coefficients	Estimation	Std. error	t-stat.	Significance
Panel A. Conditional variance				
c_{11}	0.2802	0.0161	17.38	0.00
c_{21}	0.0304	0.0090	3.38	0.00
c_{22}	0.0080	0.0038	2.08	0.04
a_{11}	0.2681	0.0106	25.31	0.00
a_{12}	0.0073	0.0075	0.97	0.33
a_{21}	-0.1137	0.0103	-11.00	0.00
a_{22}	0.1650	0.0065	25.21	0.00
b_{11}	-0.8000	0.0083	-96.57	0.00
b_{12}	0.2623	0.0020	116.87	0.00
b_{21}	0.7736	0.0092	83.65	0.00
b_{22}	0.8682	0.0018	469.57	0.00
d_{11}	0.0426	0.0220	1.93	0.05
d_{12}	-0.1175	0.0097	-12.10	0.00
d_{21}	0.1655	0.0143	11.63	0.00
d_{22}	0.0942	0.0117	8.02	0.00
Panel B. Model diagnostics				
$MLBG(6)$	6.33	(0.90)		
$MLBG(12)$	31.35	(0.69)		
$MLBG^2(6)$	11.05	(0.44)		
$MLBG^2(12)$	52.21	(0.03)		
LR	-124,538.16			

Notes: For the specification of the BEKK model refer to equations (4). The mean equation estimation is omitted from the table as it is similar to that presented in VGC model. $MLBG(k)$ and $MLBG^2(k)$ is the multivariate Ljung-Box Q statistics of Hosking (1980) for the standardized and squared standardized residuals with lag k . p -value of each statistic is presented in the brackets. LR is the likelihood ratio.

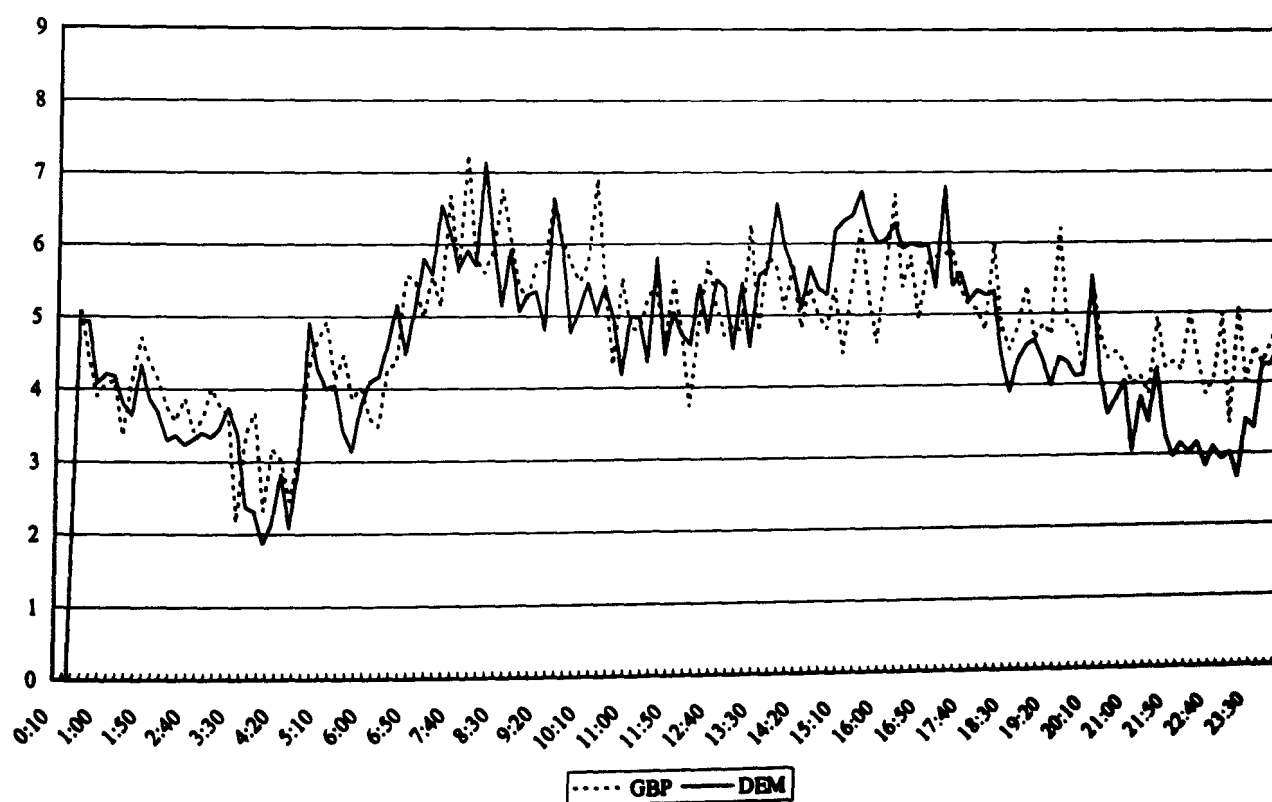
Figure 5.1
Daily price levels of two currencies (1997-98)



Source: DataStream

Notes: The DEM/USD (solid line) axis is on the left hand side and GBP/USD (dotted line) axis is on the right hand side. The daily exchange rates are priced as mark and pound per U.S. dollar.

Figure 5.2
Intraday volatility - Monday



Notes: The panel of each weekday displays the sample average 10-min volatility of that weekday.

Figure 5.3
Intraday volatility - Tuesday

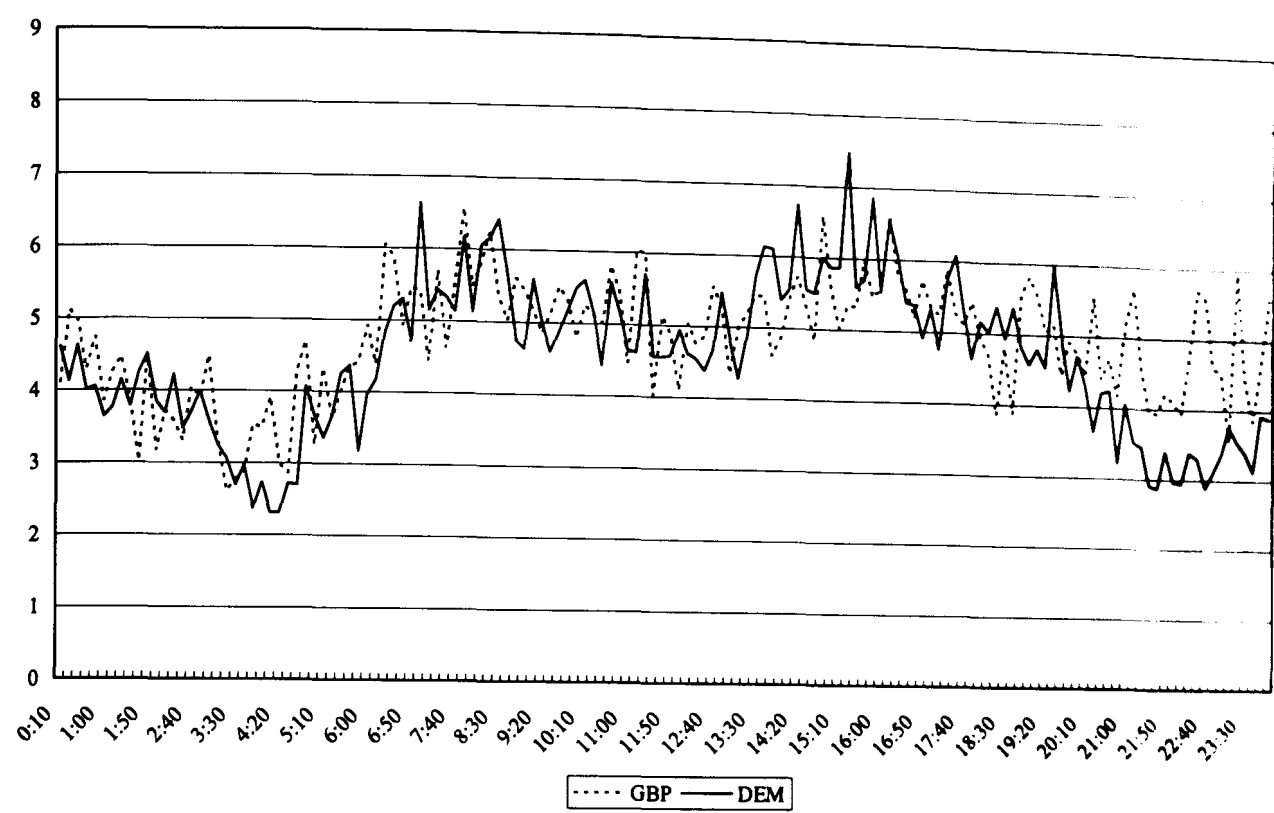


Figure 5.4
Intraday volatility - Wednesday

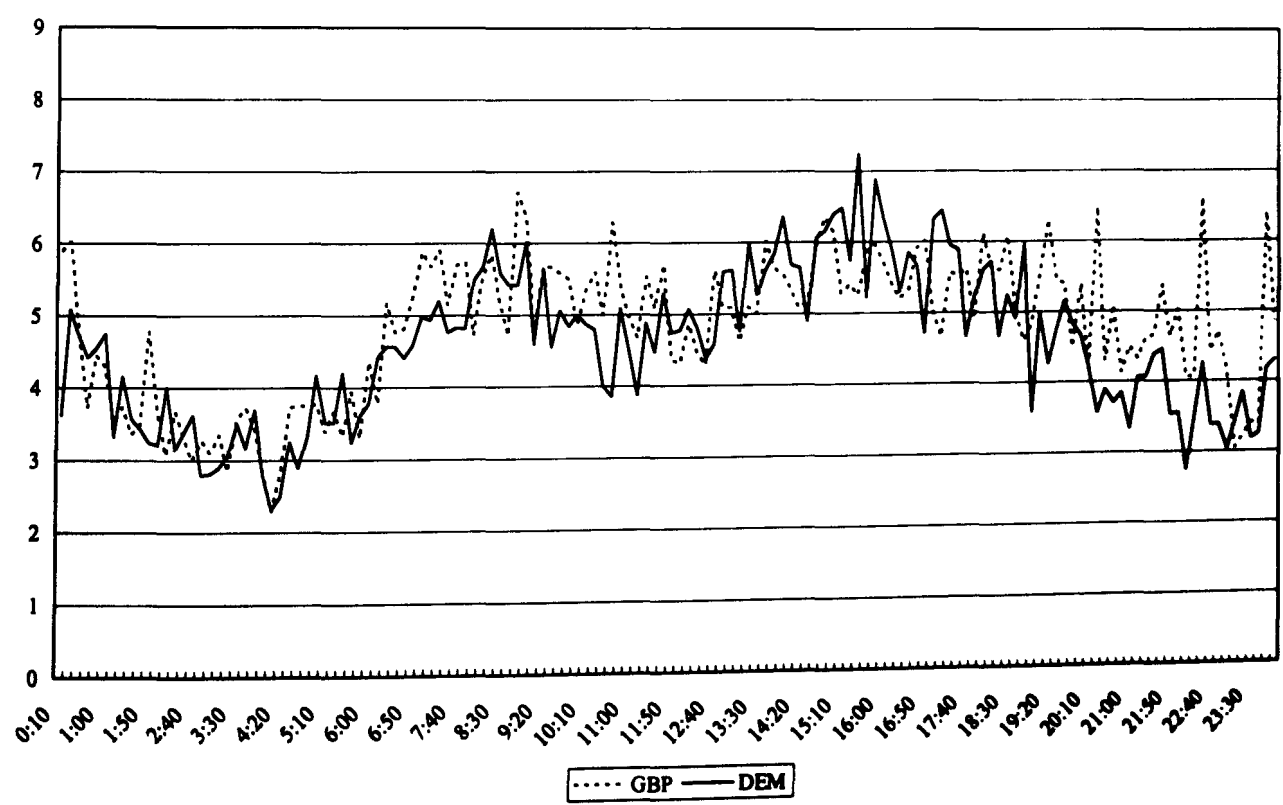


Figure 5.5
Intraday volatility - Thursday

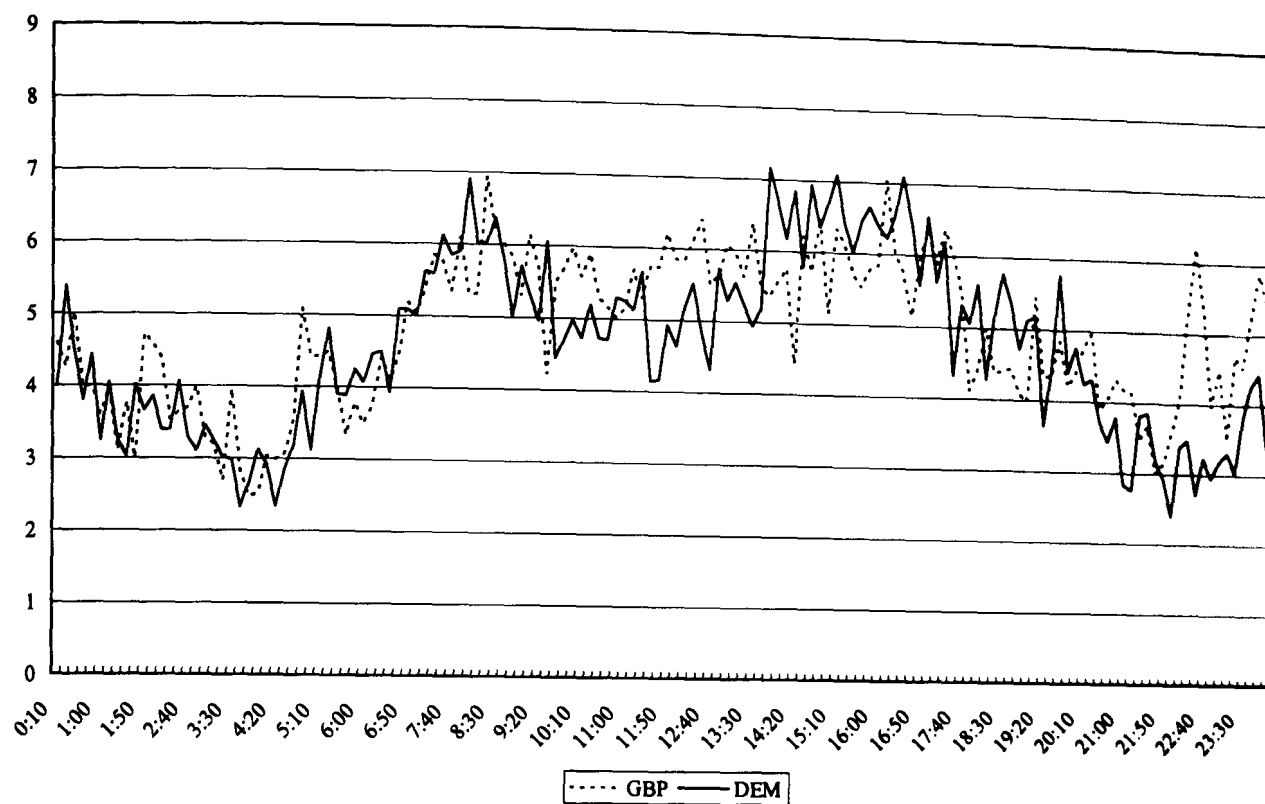


Figure 5.6
Intraday Volatility - Friday

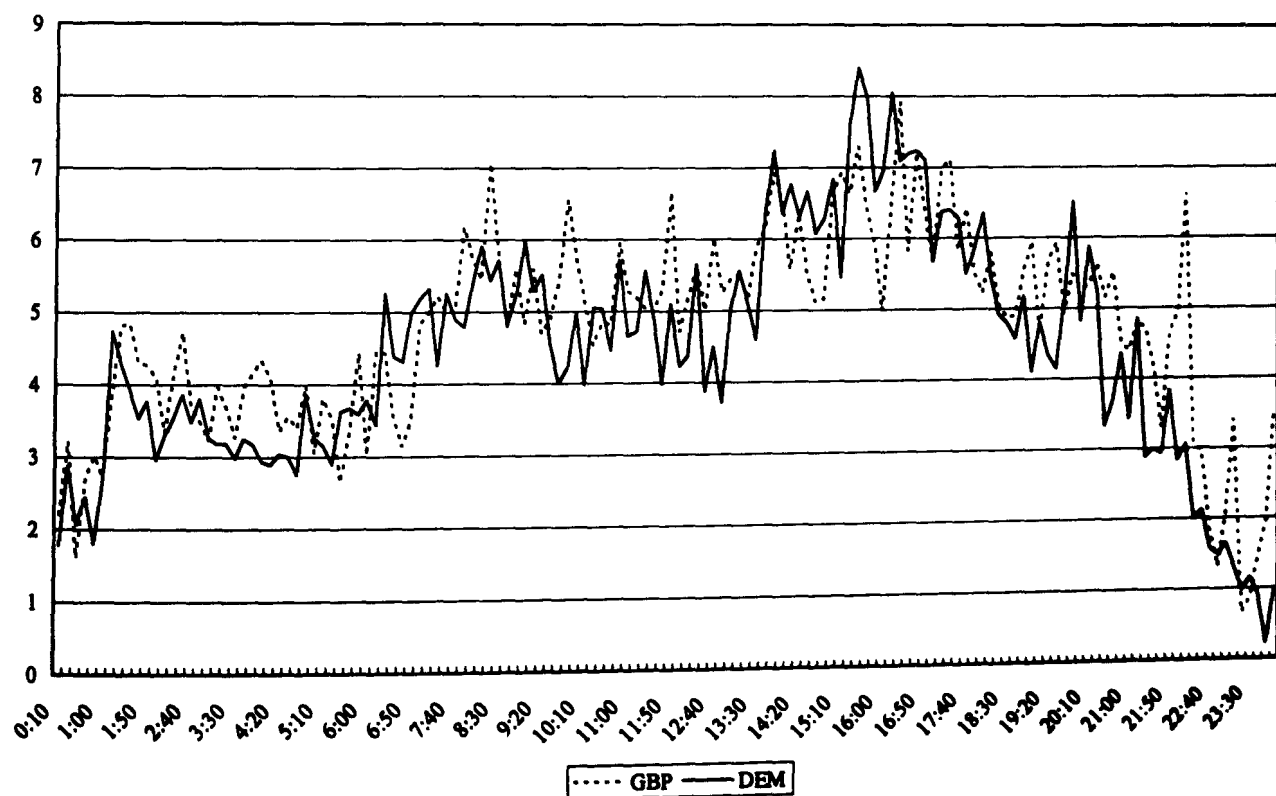
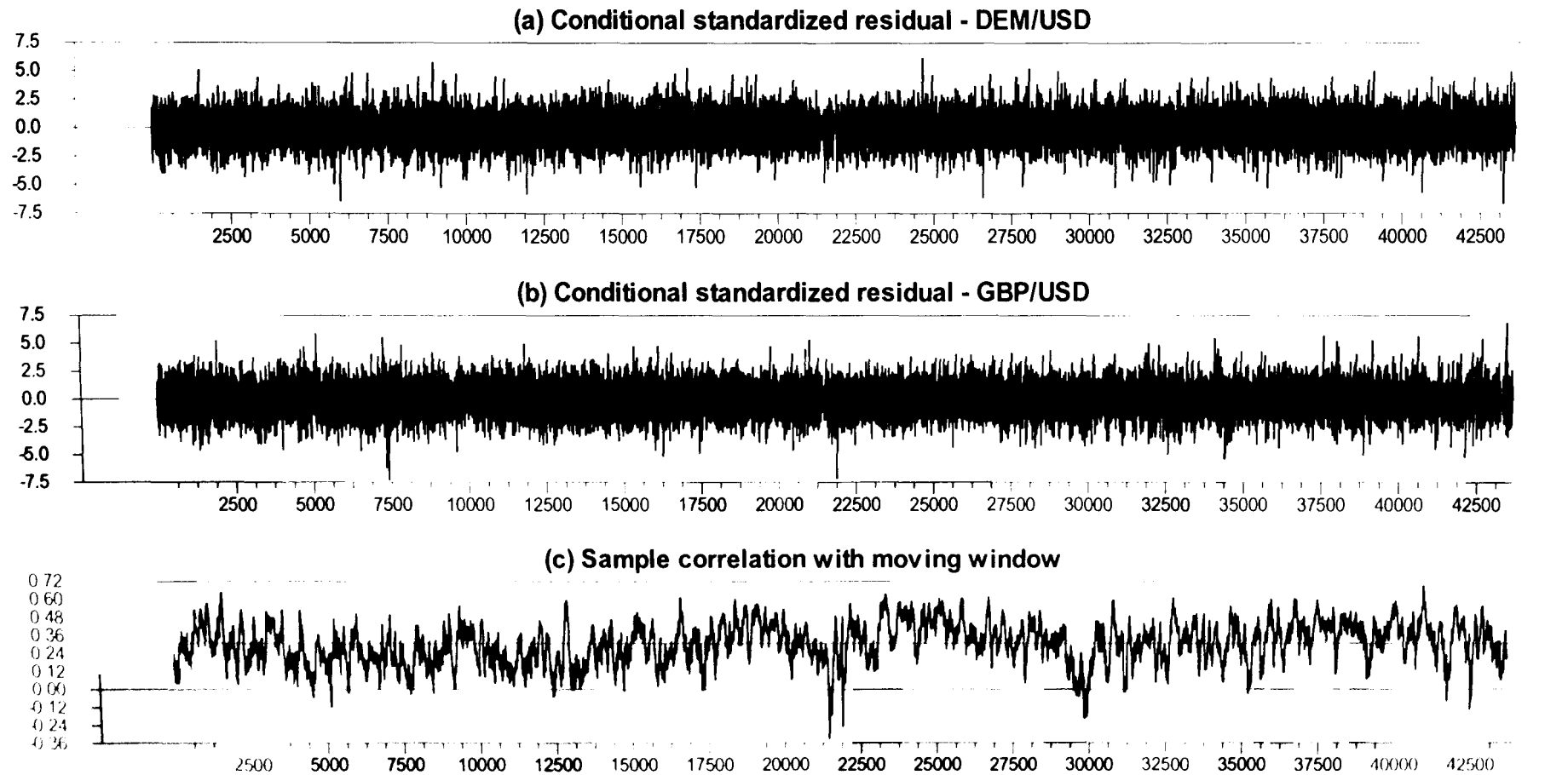
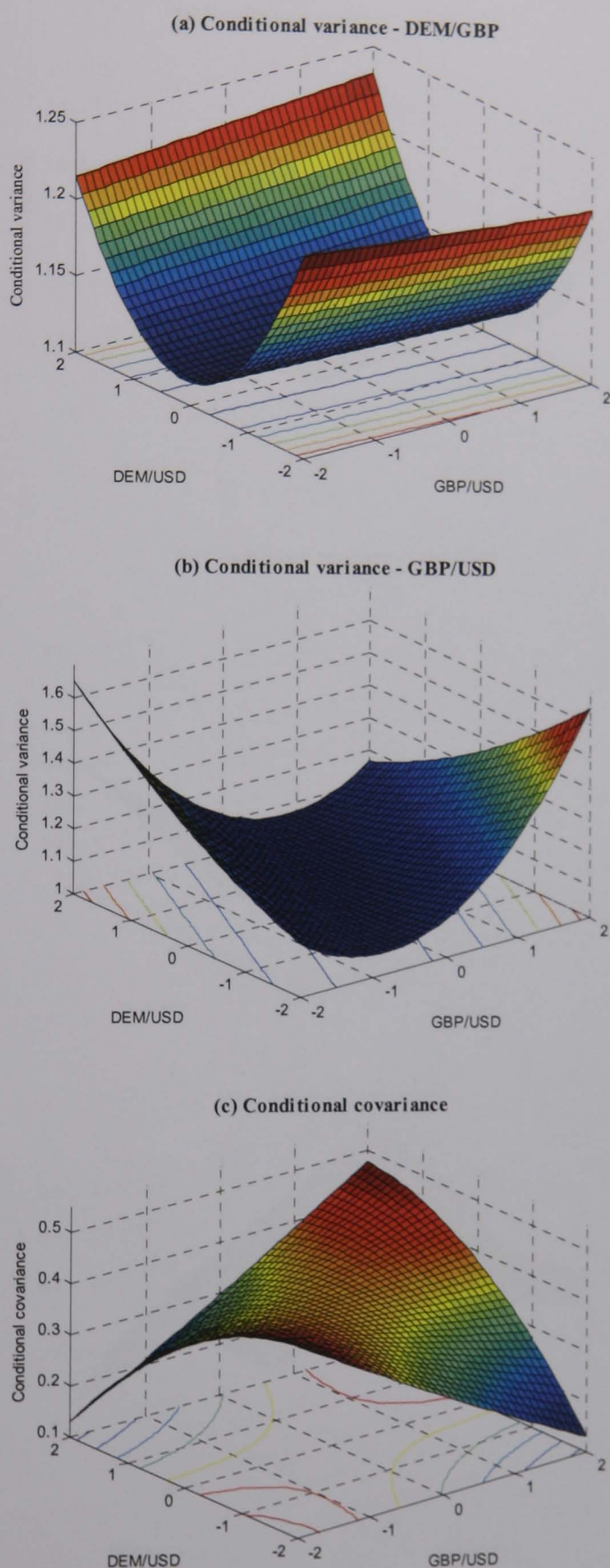


Figure 5.7
Standardized residuals and moving correlation from VGC model



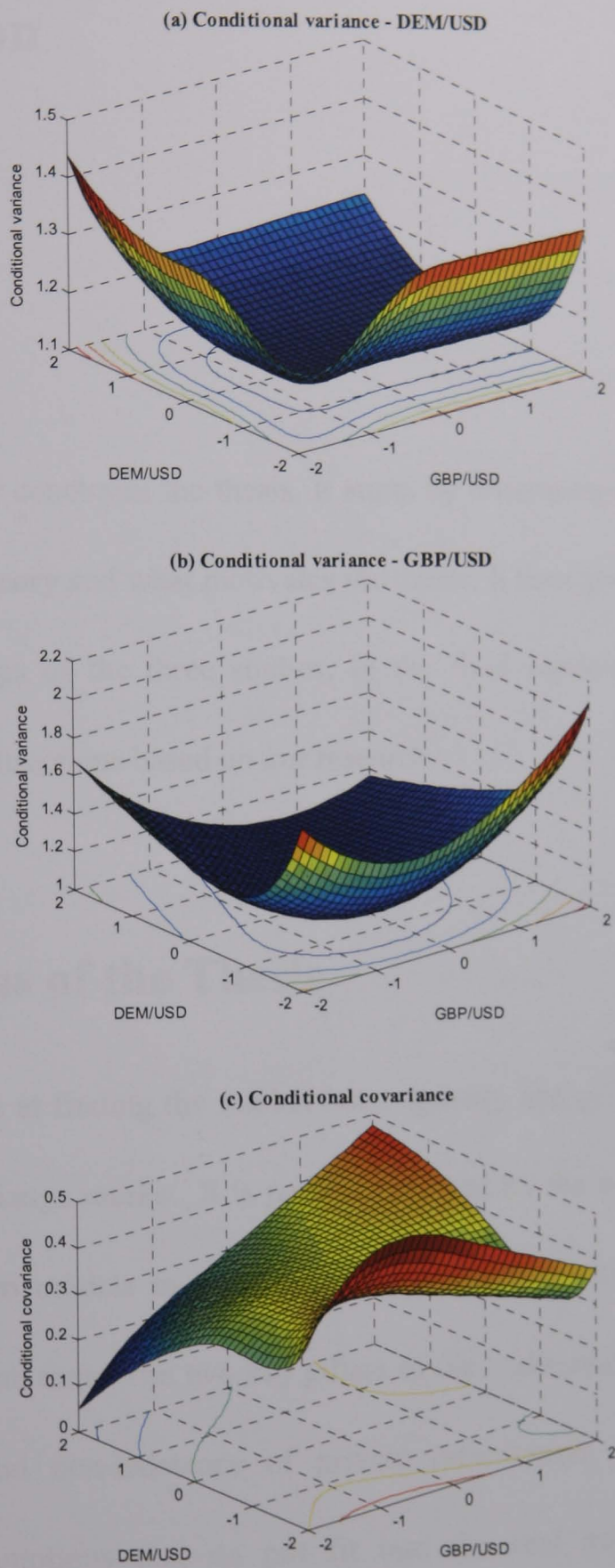
Notes: The standardized residuals are taken from the VGC model. The correlation is estimated by using an arbitrary moving time window of 120 observations. The horizontal line in graph (c) along side the moving correlation is the constant correlation of 0.308 obtained from the model.

Figure 5.8
News impact surface – without asymmetric terms



Notes: The news impact surface graphs presented are constructed by Equation (5) without taking the asymmetric terms into consideration. The X axis represents the news shock from GBP/USD and Y axis for the DEM/USD shocks. The shocks range from -2 to 2 in magnitude. The Z axis is for the conditional variance or covariance accordingly.

Figure 5.9
News impact surface – with asymmetric terms



Notes: The news impact surface graphs presented are constructed by Equation (5) with the asymmetric terms. The X axis represents the news shock from GBP/USD and Y axis for the DEM/USD shocks. The shocks range from -2 to 2 in magnitude. The Z axis is for the conditional variance or covariance accordingly.

Chapter 6

Conclusion

This last chapter concludes the thesis. It starts by reiterating the state of present exchange rate theory and what motivates the thesis. It then goes on to summarize the main findings of the three studies. In the final section we suggest some future research directions based on our research.

6.1 Origins of the Thesis

This thesis aims at finding the market heterogeneity and private information in the foreign exchange market. It is partly motivated by the poor performance of traditional macro models in explaining and forecasting exchange rates in the short and medium term. The two key pillars of the traditional models are market homogeneity and non-existence of private information. Both of them are unrealistic assumptions that do not fit into the real marketplace. Another motivation is the rapid development of the microstructure theory in the study of the foreign exchange market. It correctly acknowledges that market participants, information and trading arrangement have considerable effects on the price

discovery of exchange rates. It is important to study the micro level of the foreign exchange market which may lead to major progress in the exchange rate theory.

One important medium that connects the macro and micro studies in the foreign exchange market is order flow. Order flow is the net currency purchase and differentiates itself from traditional aggregate demand by stressing the trading initiative. In the foreign exchange market, macro information can rarely be translated directly into a specific price change and decentralized market institutions further makes the information flow opaque. In such information environment, order flow becomes the key channel for individual dealers to collect information from customers that link to the real economic activities in real time. The capability of garnering information becomes a possible criterion of judging whether private information is possessed by the dealers.

Such a chain of reasoning leads us to establish several hypotheses to be tested in the foreign exchange market. For instance, we directly hypothesize that large banks should have more information due to considerably larger customer order flow generated by their global trading than their smaller rivalry banks. Another extension of our hypothesis is to test whether there is asymmetric information linkage between major exchange rates, if a certain exchange rate is much more heavily traded than others.

6.2 Major Findings and Contributions

Employing various econometrics methods such as ECM and Multivariate GARCH models, we find positive evidence of information asymmetry in the foreign exchange market. And the degree of information asymmetry is significantly high and should not be ignored.

Firstly, we find that EFX data actually contain more information than D2000-1 data, contrary to most preconceptions held by academics. The approaches are rigorous and results are robust as we endeavour to diversify our methods and time windows. It may be due to the trading frictions and transaction record procedures that slow down the information incorporating speed of the transaction data. No matter what might be the cause, due to the fact that the availability of high frequency exchange rate data is still considerably low till this day, the EFX data can well be a reasonable resource for academics to work on in the future.

In the second paper, the hypothesis that big market players are superior in finding private information and interpreting macro news than others is tested. The big banks are selected by surveys done by Euromoney magazine on a biennial base. To test the hypothesis, we use five years of high frequency data and divide the banks into big banks group and other banks group. Employing two related information sharing techniques, we find that big banks group takes a dominant share of information during our sample period. Although the monthly information share during the five years is fluctuating, it however follows an

uptrend that reflects the increasing market concentration throughout the years. We also hypothesize that that big banks group is better at forecasting and interpreting macro news if they have better information set than other banks. We subsequently calculate the information share of the big banks group during the time of over one thousand items of U.S. macro announcements and find its information share significantly expands during announcements of some major categories of economic news. It is contrary to traditional macro models' belief that all market participants form the same rational expectation and the only information source of public news directly causes instant price adjustment. Our findings suggest that market participants actually have different information sets and interpret news with different accuracy and speed. The price discovery process in the foreign exchange market is hence dynamic and asymmetric.

In the third paper, we extend our experiment into larger context of cross-currency information linkage. This paper is also motivated by the portfolio shift model that connects the pricing of individual exchange rates into an interdependent system by order flow information. Setting the stage in global currency market, we find that DEM/USD generates far larger order flow than GBP/USD. Therefore we directly hypothesize that the former exchange rate should contain more market information than the later. And since the price discovery of one exchange rate is influenced by the other, we further hypothesize that DEM/USD imposes much larger impact on GBP/USD than the reverse in terms of volatility linkage. We introduce two complementary

multivariate GARCH models to test our hypothesis on two years of high frequency exchange rate data. The results indicate such a speculation is indeed the case. It is the first paper to test the asymmetric volatility linkage at high frequency in the foreign exchange market, as far as we know. As market participants hold the dominant view that market digests news in minutes instead of days, our findings may reflect a more realistic picture of the price discovery in the foreign exchange market than previous studies.

The robust results from the three papers indicate that market homogeneity and the only existence of public information are two unsound assumptions taken by traditional macro models. It is in support of new studies that give more attention to the microstructure of the marketplace. And many researches have already shown promising results produced by these approaches.

6.3 Future Research Directions

As market heterogeneity and private information are strongly interrelated, to extend the study of private information, future studies need to find more ways to define market heterogeneity and hence capture the private information in a specific form. For instance, dealers' geographic location could well be a source for private information due to being closer to economic activities of a certain area that may generate more exchange rate related information. Due to the rapid development of electronic trading system, future studies could also examine the

different market designs and their impact on the price discovery of exchange rates.

Bibliography

Adler, M, and R. Qi, 2003, Mexico's Integration into the North American Capital Market, *Emerging Markets Review*, 4: 91-120.

Admati, A., P. Pfleiderer. 1988. A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, 1: 3-40.

Allen H., M. P. Taylor. 1990. Charts, noise, and fundamentals in the foreign exchange market. *Economic Journal*, 29: 49-59.

Almeida, A., C. Goodhart, and R. Payne. 1998. The effects of macroeconomic news on high frequency exchange rate behaviour. *Journal of Financial and Quantitative Analysis*, 33:383-408.

Andersen, T.G., and T. Bollerslev. 1998. Deutsche mark-dollar volatility: intraday activity patterns, macroeconomic announcements, and longer-run dependencies. *Journal of Finance*, 53: 219-265.

Andersen, T. G., T. Bollerslev, and F. Diebold, and C. Vega. 2003, Micro effects of macro announcements: real-time price discovery in foreign exchange. *American Economic Review*, 93: 38-62.

Bacchetta, P., and E. V. Wincoop. 2003. Can information heterogeneity explain the exchange rate determination puzzle? Working paper.

_____. 2007. Random walk expectations and the forward discount puzzle. *American Economic Review, Papers and Proceedings*, 94: 114-118.

Baillie, R. T., and T., Bollerslev. 1991. Intra-day and inter-market volatility in foreign exchange rates, *Review of Economic Studies*, 58: 565-85.

Baillie, R. T., T., Bollerslev, and M., R., Redfearn. 1993. Bear squeezes, volatility spillovers and speculative attacks in the hyperinflation 1920s foreign exchange, *Journal of International Money and Finance*, 12: 511-21.

Baillie, R T., G. G. Booth, Y. Tse, and T. Zobotina. 2002. Price Discovery and Common Factor Models, *Journal of Financial Markets*, 5: 309-321.

Bazan, C., Kuntara P., and R. T. Lee. 2006. Random walk currency futures profits revisited. Unpublished working paper.

- Bauwens, L., S., Laurent, and J. V. Rombouts. 2006. Multivariate GARCH models: a survey, *Journal of Applied Econometrics*, 21: 79-109.
- Bauwens, L., W.B. Omrane, and P. Giot. 2005. News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance*, 24:1108-1125.
- Bekaert, G. and G. Wu. 2000. Asymmetric volatility and risk in equity markets, *The Review of Financial Studies*, 13: 1-42.
- BIS. 1999. Triennial central bank survey of foreign exchange and derivatives market activity 1998: Final Results. Bank for International Settlements.
- _____. 2005. Triennial Central Bank Survey – Foreign exchange and derivatives market activity in 2004.
- Bjønnes, G.H. and D. Rime. 2001. Customer Trading and Information in Foreign Exchange Markets. Working paper # 4. Stockholm Institute for Financial Research.
- Black, A. and D. McMillan. 2004. Long run trends and volatility spillovers in daily exchange rates. *Applied Financial Economics*, 14: 895-907.
- Black, F., 1976. Studies in stock price volatility changes. In *American Statistical Association, Proceedings of the Business and Economic Statistics Section*, 177-181.
- Bollerslev, T. 1990. Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. *The Review of Economics and Statistics*, MIT Press, 72: 498-505.
- Bollerslev, T., R. Y. Chou, and K. F. Kroner. 1992. ARCH modelling in finance. *Journal of Econometrics*, 52: 5–59.
- Bollerslev, T., R. Engle, and J. Wooldridge. 1988. A capital asset pricing model with time varying covariances. *Journal of Political Economy*, 96: 116-131.
- Bonfiglioli, A. and C. Favero. 2005. Explaining co-movements between stock markets: the case of US and Germany. *Journal of International Money and Finance*, 24: 1299-1316.
- Breedon, F., and P. Vitale. 2005. An empirical study of liquidity and information effects of order flow on exchange rates. Working paper.

- Burnside, C., Martin E., Isaac K., and Sergio R. 2006. The returns to currency speculation. National Bureau of Economic Research. Working Paper 12489.
- Carlson, J., and M. Lo. 2006. One minute in the life of the DM/\$: Public news in an electronic market, *Journal of International Money and Finance*, 25: 1090-1102.
- Chan, K.. 1992. A further analysis of the lead-lag relationship between the cash market and stock index futures market. *Review of Financial Studies*, 5: 123-152.
- Chang, K. H., and M. J. Kim. 2001. Jumps and time-varying correlations in daily foreign exchange rates, *Journal of International Money and Finance*, 20: 611-637.
- Cheung, Y. -W., and M. D. Chinn. 2001. Currency traders and exchange rate dynamics: A survey of the US Market. *Journal of International Money and Finance*, 20: 439-471.
- Cheung, Y-W, Chinn, M-D, and I. W. Marsh. 2004. How Do UK-Based Foreign Exchange Dealers Think Their Market Operates?. *International Journal of Finance and Economics*, v9: 289-306.
- Cheung, Y-W, Chinn, M-D, and A. G. Pascual. 2005. Empirical exchange rate models of nineties: Are any fit to survive? *Journal of International Money and Finance*, 24: 1150-1175.
- Cheung, Y. W., and C. P. Wong. 2000. A survey of market practitioners' views on exchange rate dynamics. *Journal of International Economics*, 51: 401-419.
- Christie, A. 1982. The stochastic behavior of common stock variances- value, lever-age, and interest rate effects. *Journal of Financial Economic Theory*, 10: 407-432.
- Conrad, J., M. N. Gultekin, and G. Kaul. 1991. Asymmetric predictability of conditional variances. *The Review of Financial Studies*, 4: 597-622.
- Covrig, V., and M. Melvin. 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen? *Journal of Empirical Finance*, 9: 271-285.
- Danielsson, J., Love, R. 2005. Feedback trading. Mimeo, London School of Economics.
- Danielsson, J., and R. Payne. 2002. Real trading patterns and prices in the spot

foreign exchange markets. *Journal of International Money and Finance*, 21: 203–222.

de Jong, F., R. Mahieu, and P. Schotman. 2001. Price discovery on foreign exchange markets with differentially informed traders. Working paper.

de Jong, F. and T. Nijman. 1997. High frequency analysis of lead-lag relationships between financial markets. *Journal of Empirical Finance*, 4: 259–277.

Dickey, D. A., and W. A. Fuller. 1981. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49: 1057–1072.

Dominguez, K., and F. Panthaki. 2003. The market microstructure of central bank intervention. *Journal of International Economics*, 59: 25–45.

Dufour, A., R. F. Engle. 2000. Time and the price impact of a trade. *Journal of Finance*, 55: 2467–2498.

Easley, D., and M. O'Hara. 2003. Microstructure and asset pricing. In *Handbooks of the Economics of Finance*, edited by G. M. Constantinides, M. Harris and R. Stulz. Elsevier.

Engle, R. F., 2002. Dynamic conditional correlation: A simple class of multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*. 20: 339–50.

Engle, R. F., C. J. W. Granger. 1987. Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55: 251–276.

Engle, R. F., T. Ito, and W. L. Lin. 1990. Meteor showers of heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, 58: 525–42.

Engle, R. F. and K. F. Kroner. 1995. Multivariate simultaneous Generalized ARCH. *Econometric Theory*, 11: 122–50.

Engle, R., and V. Ng. 1993. Measuring and testing the impact of news on volatility. *Journal of Finance*, 48: 1749–1778.

Engle, R. F. and A. J. Patton. 2004. Impacts of trades in an error-correction model of quote prices. *Journal of Financial Markets*, 7: 1–25.

Engle R. F. and J. R. Russell. 1997. Forecasting the frequency of changes in

quoted foreign exchange prices with the autoregressive conditional duration model. *Journal of Empirical Finance*, 4: 187-212.

Euromoney, May 1995, Treasurers put their views on banks, 65-76.

_____, May 1997, Taken aback by a leap forward, 61-76.

_____, May 1995, Life after execution, 89-104.

Evans, M., D., 2002, FX trading and exchange rate dynamics, *The Journal of Finance*, 6: 2405-2447.

Evans, M., D., and R. K. Lyons. 2002a. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy*, 110: 170-180.

_____. 2002b. Informational integration and FX trading. *Journal of International Money and Finance*, 21:807-31.

_____. 2002c. Time-varying liquidity in foreign exchange, *Journal of Monetary Economics*, 49: 1025-1051

_____. 2003. How is Macro News Transmitted to Exchange Rates? NBER Working Paper 9433.

_____, 2005a, Exchange rate fundamentals and order flow, typescript, U.C. Berkeley.

_____, 2005b, Do currency markets absorb news quickly? *Journal of International Money and Finance*, 24: 197-217.

Fan, M., and R. Lyons. 2001. Customer-dealer trading in the foreign exchange market, typescript, UC Berkeley.

_____. 2003. Customer trades and extreme events in foreign exchange. In *Monetary History, Exchange Rates and Financial Markets: Essays in Honour of Charles Goodhart*, Mizen P (ed.). Edward Elgar: Northampton; 160-179.

Flood, M. D. 1991. Microstructure theory and the foreign exchange market. *Federal Reserve Bank of St. Louis Review*, 73: 52-70.

Francis B. B., I. Hasan, and D. M. Hunter. 2006. Dynamic relations between international equity and currency markets: the role of currency order flow. *Journal of Business*, 79: 219-258.

- Frank, H. Westerhoff, Cristian Wieland. 2004. Spillover dynamics of central bank interventions. *German Economic Review*, 5: 435–450.
- Frankel, J., and A. Rose. 1995. Empirical research on nominal exchange rates. In *Handbook of International Economics*, edited by G. Grossman and K. Rogoff. Amsterdam: Elsevier Science.
- Frankel, J. A., and G. G. Giovannini. 1996. Introduction. In *The Microstructure of Foreign Exchange Markets*. Frankel J. A., G. G. Giovannini (eds). University of Chicago Press: Chicago; 1–15.
- Friberg, R and S. Nydahl, 1999. Openness and the exchange rate exposure of national stock markets. *International Journal of Finance and Economics*, 4: 55–62.
- Galati, G., and M. Melvin. 2004. Why Has FX Trading Surged? Explaining the 2004 Triennial Survey. *BIS Quarterly Review* (December), 67–98.
- Garbade, K. D. 1978. The effect of interdealer brokerage on the transactional characteristics of dealer markets. *Journal of Business*, 51: 477–98.
- Gifarelli, G. and G. Paladino. 2005. Volatility linkages across three major equity markets: a financial arbitrage approach. *Journal of International Money and Finance*, 24: 413–439.
- Glosten, L. R., R. Jagannathan and D. E. Runkle. 1993. On the relation between the expected value of the volatility and of the nominal excess return on stocks. *Journal of Finance*, 48: 1779–1801.
- Glosten, L., and P. Milgrom. 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 13: 71–100.
- Gonzalo, J. and C. W. J. Granger. 1995. Estimation of common long-memory components in cointegrated systems. *Journal of Business & Economic Statistics*, 13: 27–35.
- Gonzalo, J., and S., Ng, 2001, A systematic framework for analyzing the dynamic effects of permanent and transitory shocks. *Journal of Economic Dynamics and Control*, 25: 1527–1546.
- Goodhart, C. 1988. The foreign exchange market: a random walk with a dragging anchor. *Economica*, 55: 437–460.

Goodhart, C., T. Ito, and R. Payne. 1996. One day in June 1993: A Study of the Working of Reuters 2000-2. In *The Microstructure of Foreign Exchange markets*. J. Frankel, G. Galli, and A. Giovanni, eds. Chicago, IL: Univ. of Chicago Press.

Goodhart, C., and M. O'Hara. 1997. High Frequency Data in Financial Markets: Issues and Applications. *Journal of Empirical Finance*, 4: 73-114.

Goodhart, C., T. Ito, R. Payne. 1996. One day in June, 1993: a study of the workings of Reuters D2000-2 electronic foreign exchange trading system. In: *The Microstructure of Foreign Exchange Markets*. University of Chicago Press, Chicago, 107-179.

Grauwe, P. D., Dewachter, H., and M. Embrechts. 1993. *Exchange Rate Theory: Chaotic Models of Foreign Exchange Markets*. Blackwell, Oxford.

Hafner, C. M. and H. Herwartz. 2006. Volatility impulse responses for multivariate GARCH models: an exchange rate illustration. *Journal of International Money and Finance*, 25: 719-740.

Hamao, Y., R. W. Masulis, and V. Ng. 1990. Correlations in price changes and volatility across international stock markets. *The Review of Financial Studies* 1990, 3: 281-307.

Hasbrouck, J. 1991. Measuring the information content of stock trades. *Journal of Finance*, 46: 179-207.

_____. 1995. One Security, Many Markets: Determining the contributions to Price Discovery. *The Journal of Finance*, 4: 1175-1199.

Isard, P. 1995. *Exchange Rate Economics*. Cambridge: Cambridge University Press.

Ito, T., R. F. Engle, and W-L Ling. 1992. Where does the meteor shower come from?: The role of stochastic policy coordination, *Journal of International Economics*, 32: 221-240.

Ito, T., Lyons, R. K., and M. T. Melvin. 1998. Is there private information in the FX market? The Tokyo experiment. *Journal of Finance*, 53: 1111-1130.

Johanson, S. 1988. Statistical Analysis of Co-integrating Vectors. *Journal of Economic Dynamic and Control*, 12: 231-254.

Killeen., W., P., Lyons., R., K., and Moore., M., J. 2006. Fixed versus flexible: lesson from EMS order flow. *Journal of international Money and Finance*, 25:

Goodhart, C., T. Ito, and R. Payne. 1996. One day in June 1993: A Study of the Working of Reuters 2000-2. In *The Microstructure of Foreign Exchange markets*, J. Frankel, G. Galli, and A. Giovanni, eds. Chicago, IL: Univ. of Chicago Press.

Goodhart, C., and M. O'Hara. 1997. High Frequency Data in Financial Markets: Issues and Applications. *Journal of Empirical Finance*, 4: 73-114.

Goodhart, C., T. Ito, R. Payne. 1996. One day in June, 1993: a study of the workings of Reuters D2000-2 electronic foreign exchange trading system. In: *The Microstructure of Foreign Exchange Markets*. University of Chicago Press, Chicago, 107-179.

Grauwe, P. D., Dewachter, H., and M. Embrechts. 1993. *Exchange Rate Theory: Chaotic Models of Foreign Exchange Markets*. Blackwell, Oxford.

Hafner, C. M. and H. Herwartz. 2006. Volatility impulse responses for multivariate GARCH models: an exchange rate illustration. *Journal of International Money and Finance*, 25: 719-740.

Hamao, Y., R. W. Masulis, and V. Ng. 1990. Correlations in price changes and volatility across international stock markets. *The Review of Financial Studies* 1990, 3: 281-307.

Hasbrouck, J. 1991. Measuring the information content of stock trades. *Journal of Finance*, 46: 179-207.

_____. 1995. One Security, Many Markets: Determining the contributions to Price Discovery. *The Journal of Finance*, 4: 1175-1199.

Isard, P. 1995. *Exchange Rate Economics*. Cambridge: Cambridge University Press.

Ito, T., R. F. Engle, and W-L Ling. 1992. Where does the meteor shower come from?: The role of stochastic policy coordination, *Journal of International Economics*, 32: 221-240.

Ito, T., Lyons, R. K., and M. T. Melvin. 1998. Is there private information in the FX market? The Tokyo experiment. *Journal of Finance*, 53: 1111-1130.

Johanson, S. 1988. Statistical Analysis of Co-integrating Vectors. *Journal of Economic Dynamic and Control*, 12: 231-254.

Killeen., W., P., Lyons., R., K., and Moore., M., J. 2006. Fixed versus flexible: lesson from EMS order flow. *Journal of international Money and Finance*, 25:

551-579

Kyle, A.. 1985. Continuous auction and insider trading. *Econometrica*, 53: 13-32.

Kroner K. F., V. K. Ng. 1998. Modelling asymmetric comovements of asset returns. *The Reviews of Financial Studies*, 11: 817-844.

Lane, P. R. 2001. The new open economy macroeconomics: a survey. *Journal of International Economics*, 54: 235–266.

Lehmann, B. N. 2002. Some desiderata for the measurement of price discovery across markets. *Journal of Financial Markets*, 5: 259-276.

Li, H., and G. S. Mandala. 1997. Bootstrapping cointegrating regressions. *Journal of Econometrics*, 80: 297-318.

Ling, S. and McAleer, M. 2003. Asymptotic theory for a new vector ARMA-GARCH model. *Econometric Theory*, 19: 280-310.

Love, R., and R. Payne. 2004. Macroeconomic news, order flows, and exchange rates, typescript, London School of Economics.

Lyons, R.. 1995. Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39: 321-351.

_____. 1997. A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, 42:275-298.

_____. 2001. *The Microstructure Approach to Exchange Rates*. MIT Press: Cambridge, MA.

Ma, C. K., and G. W. Kao. 1990. On exchange rate changes and stock price reactions. *Journal of Business Finance and Accounting*, 17: 441–450.

Maghrebi, N., M. J. Holmes, and E. J. Pentecost. 2006. Are there asymmetries in the relationship between exchange rate fluctuations and stock market volatility in pacific basin countries? *Review of Pacific Basin Financial Markets and Policies*, 9: 229-256.

McKenzie, M. D. 2002. The economics of exchange rate volatility asymmetry. *International Journal of Finance and Economics*, 7: 247-260.

Meese, R., and K. Rogoff. 1983. The out-of-sample failure of empirical

exchange rate models. In *Exchange Rate and International Macroeconomics*, edited by J. Frenkel. Chicago: University of Chicago Press.

Melvin, M., and X. Yin. 2000. Public information arrival, exchange rate volatility and quote frequency. *Economic Journal*, 110: 644-661.

Mussa, M. L. 1979. Empirical regularities in the behavior of exchange rates and theories of the foreign exchange market. Vol. II Carnegie-Rochester Conference Series on Public Policy.

Ng, A. 2000. Volatility spillover effects from Japan and the US to the pacific-basin. *Journal of International Money and Finance*, 19: 207-233.

Obstfeld, M. and R. Kenneth. 1996. *Foundations of International Macroeconomics*. Cambridge, Massachusetts: MIT Press.

O'Hara, M. 1995. *Market Microstructure Theory*. Cambridge, MA: Blackwell Publishers.

Osterwald-Lenum, M. 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank tests statistics. *Oxford Bulletin of Economics and Statistics*, 54: 461-472.

Payne, R. 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61: 307-329.

Peiers, B. 1997. Informed traders, intervention and price leadership: A deeper view of the microstructure of the foreign exchange market. *Journal of Finance*, 52: 1589-1614.

Perraudin, W., and P. Vitale. 1996. Interdealer trade and information flows in a decentralised foreign exchange market. In *The Microstructure of Foreign Exchange Markets*, edited by Frankel, J. A., Galli, G., and Giovannini, A., The University of Chicago Press: 73-106.

Pesaran M.H., and R.P. Smith. 1995. Estimation of long-run Relationships from Dynamic Heterogeneous Panels. *Journal of Econometrics*, 68: 79-113.

Phylaktis, K. and L., Chen. 2006. Price discovery in indicative and transaction FX prices system -- A comparison of D2000-1 and EFX data, working paper, Cass Business School.

Rime, D. 2001. U.S. Exchange Rates and Currency Flows, unpublished working paper.

- Sager, M., and Taylor, M. 2006. Under the microscope: the structure of the foreign exchange market. *International Journal of Finance and Economics*, 11: 81-95.
- Sapp, S. 2002. Price leadership in the spot foreign exchange market. *Journal of Financial and Quantitative Analysis*, 37: 425-448 .
- Sarno, L. 2000. Towards a new paradigm in open economy modelling: where do we stand? Working paper.
- Sarno, L., and M. P. Taylor. 2002. *The Economics of Exchange Rates*. Cambridge University Press: Cambridge.
- Schreiber, P. S., and R. A. Schwartz. 1986. Price discovery in securities markets, *Journal of Portfolio Management*, 12: 43-48.
- Sheedy, E., 1998. Correlation in currency markets: A risk adjusted perspective. *Journal of International Financial Markets, Institutions and Money*, 8: 59-82.
- Sims, C.A. 1980. Macroeconomics and Reality. *Econometrica*, 48: 1-48
- Speight, A. and D. G. McMillan. 2001. Volatility spillovers in East European black-market exchange rates. *Journal of International Money and Finance*, 20: 367-378.
- Taylor M. P. 1995. The economics of exchange rates. *Journal of Economic Literature*, 33: 13-47.
- Taylor M. P., and H. Allen. 1992. The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, 11: 304-314.
- Toda, H. Y. and P. C. B. Phillips. 1993. Vector autoregressions and causality. *Econometrica*, 61:1367-1393.
- Tse, Y. K., and A. K. Tsui, 1997. Conditional volatility in foreign exchange rates: evidence from the Malaysian Ringgit and Singapore Dollar. *Pacific Basin Finance Journal*, 5: 345-356.
- Westerhoff, F. H. and C. Wieland. 2004. Spillover dynamics of central bank interventions. *German Economic Review*, 5: 435-450.
- White, H. 1982. Maximum likelihood estimation of misspecified models. *Econometrica*, 50: 1-25.

Wolinsky, A. 1990. Information revelation in a market with pairwise meetings. *Econometrica*, 58: 1-23.

Yan, B-C, and Zivot, E. 2007. The dynamic of price discovery. University of Washington. Working paper.

Yao, J. 1998. Market making in the interbank foreign exchange market. Salomon Center for the Study of Financial Institutions. Working Paper s-98-3. New York. NY.