Essays in Microstructure Analysis in the Foreign Exchange Market

Teng Miao

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Declaration

I declare that any material contained in this thesis is my own work except where otherwise specified. I further declare that one paper titled: “Informational Links between FX and Stock Markets: Impacts of FX Order Flows on Stock Markets”, drawn from Chapter 2 of this thesis appears as working paper presented in the 5th Microstructure Conference in Financial Markets, Swiss National Bank, Zurich, Switzerland.

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Abstract

The aim of this thesis is to investigate the effects of foreign exchange order flows on exchange rate and stock market changes, in particular to examine the forecasting power of order flows and better understand the nature of the private information conveyed in order flows in the foreign exchange market.

Chapter 1 investigates the performance of foreign exchange customer order flows (six major exchange rates over 3.5 years) as an additional explanatory variable to technical analysis to forecast exchange rate changes by applying genetic algorithm non-linear methodology. Using the interval permutations technique, we suggest that the improvement of order flows to the performance of technical analysis is not consistently present.

Chapter 2 examines the role daily customer GBPUSD order flows play in explaining concurrent and future stock market changes in both UK and US, and discusses the heterogeneous effects from different groups of customers. The basic hypothesis tested is that if foreign exchange order flows have days-ahead effects on future stock market changes, it suggests that at least a part of the information carried by foreign exchange order flows is relevant for stock markets. Using daily GBPUSD order flows over 3.5 years from 2002 to 2006 provided by RBS, we find that: 1) impacts of order flows from corporate customers on stock markets are positive, while impacts of order flows from unleveraged financial institutions are negative; 2) impacts of corporate order flows are longer than those of financial order flows, especially for the US stock market, suggesting that the two groups of customers may hold different types of private price-relative information. We hypothesize that corporate customers of the bank are mainly based in the UK. When the world economy is doing well, multi-national companies are selling more goods in the US and repatriate more foreign currencies back to UK, during which more GBP or EUR are converted from US Dollars. More sales of US Dollars then reflect the good future prospects of the world economy and stocks listed in both US and UK will rise in value. For unleveraged financial institutions, when the world economy is going bad, clients of those mutual funds which are based in the UK will ask for redemptions of their funds. Assuming the bank services a client base that is UK oriented, this leads to the repatriation of money from abroad back to UK. The buying of GBP or EUR in exchange for US Dollars then takes place alongside sales of US and UK stocks. Foreign exchange flows into GBP or EUR from unleveraged funds forecast poor future stock market returns globally.

Chapter 3 empirically tests the effects of EURUSD order flows from different groups of counterparties on the US stock market changes at high frequencies ranging from 1-minute to 30-minute, using a unique set of tick-by-tick order flows data obtained from a leading European commercial bank. We find that: 1) Order flows from "corporates" are positively related to exchange rate changes, while order flows from "financials" are negatively signed, which contradict many well-documented papers such as Evans and Lyons (2002a) (this high frequency forecasting power partly explain the failure of the trading strategy based on our daily order flows data in chapter); 2) The effects of order flows from "financials" are negative on stock market changes, while the effects of orders from "corporates" are positive on stock market changes, which further confirms our findings in chapter 2. Similar to chapter 2, the cross market effects documented in chapter 3 also suggest that there is information content in foreign exchange order flows and that it is likely to be macroeconomic in nature, relevant for stock markets.

Chapter 4 concludes and suggests some directions of refinements and further research.

Introduction

The predominant macroeconomic variables based models in the foreign exchange market have been exploited for decades, with three main underlying assumptions: all information is publicly available, all market participants are homogeneous, and the market structure is irrelevant. However, many studies conclude that the macroeconomic fundamentals do not explain or forecast movements of exchange rates as predicted (see Meese and Rogoff (1983), Frankel and Rose (1995), Cheung, Chinn and Pascual (2005), Sarno and Valente (2009), among others). There is little robust evidence against the "price determination puzzle" in the foreign exchange market, until the new microstructure approach to exchange rates is introduced. According to Lyons (2001), the microstructure approach relaxes the three most uncomfortable assumptions in traditional macroeconomic fundamentals based models. In these new models, information is not necessarily publicly available, heterogeneous investors do not react to the same information in the same way, the structure of the foreign exchange market has effects on price discovery process. Two hallmarks of the new microstructure approach are order flow and bid-ask spread, with studies concentrating on the former, which is defined as net value of buyer-initiated transactions and seller-initiated transactions. Many positive conclusions in favor of the ability of order flows to explain or forecast exchange rate changes have been reached in the past decade, for example, Evans and Lyons (2002a, 2002b, 2005a, 2006), Rime (2000), Payne (2003), Marsh and O'Rourke (2005), Froot and Ramadorai (2005), Osler and Vandrovych (2009), among many others.

Evans and Lyons (2002a) find substantial explanatory power from inter-dealer order flows for the concurrent changes of exchange rates DEM/USD and USD/JPY at a daily frequency and suggest that the power is due to the private information conveyed in order flows in the foreign exchange market. Berger et al. (2008) use a set of inter-dealer order flows data, which is much longer than previous studies, to further confirm the presence of a substantial contemporaneous relationship between euro-dollar and dollar-yen inter-dealer order flows and the corresponding exchange rate changes at frequencies from one minute up to two weeks (also see Rime (2000), Evans (2002), Hau, Killeen and Moore (2002), Payne (2003), Killeen, Lyons and Moore (2005), Covrig and Melvin (2005), among many others, using inter-dealer foreign exchange order flows).

With more availability of foreign exchange customer order flows data sets, empirical research on the customer-dealer market emerges too. Evans and Lyons (2006) test links between end-user customer order flows and exchange rates changes by using data from Citibank over six and a half years, and find the impacts from various groups of clients are quite different. They suggest strong impacts of customer order flows on concurrent and future exchange rates changes, even from those groups which are thought to be mainly liquidity motivated. Fan and Lyons (2003) also find customer order flows from Citibank contribute significantly to the movements of exchange rates even at monthly frequency, and they also mention different impacts from different groups of customers on exchange rate changes. Similar results are found by Froot and Ramadorai (2005) using data from State Street, although they suggest the contemporaneous relationship between customer order flows and exchange rates is temporary, and over longer horizons macroeconomic factors have more power to explain exchange rate changes (also see Mark (1995)). Marsh and O'Rourke (2005) use a set of customer order flow data from Royal Bank of Scotland (RBS), and find strong relations between order flows and movements in the exchange rate market at both daily and weekly frequencies. Marsh and Kyriacou (2007) uses the same data set over a longer period to investigate the forecasting power of order flows using linear-methodologies, but finds nothing positive.

In chapter 1 of the thesis, we apply one of many non-linear methodologies, genetic algorithms, to order flow and technical analysis indicators to solve optimization problem to identify optimal trading strategies for six major exchange rates (EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY and GBPJPY), in which three elements are involved: foreign exchange order flows, technical analysis, and genetic algorithms. There are some papers performing analysis with two of these three elements. Neely, Weller and Dittmar (1997) apply genetic programming techniques to the foreign exchange market to search all the possible combinations of trading rules on a daily basis to find the optimal technical rules and provide strong evidence of economically and statistically significant out of sample excess returns for six major exchange rates. Gradojevic and Yang (2006) use order flows in both inter-dealer and customer currency markets to investigate the effects of order flows on exchange rate changes and conclude that the non-linear approach, specifically neural networks in their paper, is superior to traditional linear models of exchange rates. Osler (2003) uses a complete set of stop-loss and take-profit orders over a period of nine months, and provides supporting evidence to explain the phenomena that trends in the foreign exchange market tend to reverse or accelerate at key technical levels, when the price contingent orders are triggered.

To the best of our knowledge, few studies investigate both order flows technical analysis indicators by using evolutionary algorithms (i.e. combining the three elements). Bates, Dampster and Romahi (2003) use dataset of order flows from HSBC over a relatively short period of 123 observations in 2002, and find that trading based on order flows is superior to technical trading strategies. The findings also provide evidence that order flows in the foreign exchange market can improve the performance of technical trading indicators. In chapter 1, the order flows data from RBS contains 6 major exchange rates, broader than Bates et al. (2003), and covers a period of more than 3.5 years from August of 2002 to March of 2006, much longer than Bates et al. (2003).

Using the same set of data provided by RBS, Marsh and O'Rourke (2005) suggest strong contemporaneous relationship between customer foreign exchange order flows. However, Marsh and Kyriacou (2007) find no forecasting power of this set of order flows data by using linear regression models. In chapter 1, using a non-linear methodology, genetic algorithm, we too fail to find any consistent forecasting power of order flows. By using interval permutations technique, the inconsistency across different trading strategies for the six exchange rates might suggest possible structural breaks within the period of our data. We also conclude that the improvement of order flows over the performance of technical analysis is not consistently present, and even when it exists, it is relatively limited and not very encouraging. This finding is unfortunately consistent with Cheung, Chinn and Pascual (2005), who suggest the profitable rules for one currency pair may not be applicable to other exchange rates.

In foreign exchange microstructure research, a strong relation between foreign exchange order flows and changes of exchange rates has been theoretically and empirically demonstrated in many studies. Although we do not find consistent forecasting power of our order flows for exchange rate changes, we do see strong effects of customers order flows on concurrent exchange rate changes, see Marsh and O'Rourke (2005), chapter 2 of the thesis. Many of the papers in the microstructure field suggest order flows as the transmission vehicle of private information which drive exchange rates movements, the ultimate forces behind order flows and the nature of the information they contain are still not fully understood. Some argue the information may come from macroeconomic fundamentals or news announcements (e.g. Evans and Lyons (2005b, 2007)), while some others believe it may come from technical trading strategies (e.g. Osler (2003), Schulmeister (2006)). In the second chapter, we suggest some information conveyed in foreign exchange order flows is relevant for stock markets, suggesting at least some macroeconomic information content.

With rapid growth of global financial integration and capital internationalization, cross market effects are believed to exist and interactions between foreign exchange and stock markets have attracted much attention. Return and volatility spillovers across different financial markets have been demonstrated by many studies (Ajayi and Mougoue (1996), He and Ng (1998), Fleming, Kirby and Ostdiek (1998)), some of them suggesting that the cross market effects are due to information spillovers. For example, Fleming et al. (1998) investigate volatility linkages between stock, bond and money markets, and they suggest strong interactions across the different financial markets which are linked through common knowledge such as macroeconomic news and cross market hedging activities.

Although there is a substantial literature on correlations between foreign exchange order flows and exchange rate returns, research about the impact of order flows on other market returns such as stock market is still rare. Francis, Hasan and Hunter (2006) consider the role of currency order flows when dealing with relations between stock and foreign exchange markets. They investigate the dynamic relationships between various equity markets and corresponding foreign exchange markets at weekly frequency, suggesting that the return and volatility spillovers between stock and currency markets are very high. Furthermore, they also find that foreign exchange order flows play an important role in explaining equity returns and conclude that spillovers between foreign exchange and stock markets are due to information conveyed in foreign exchange order flows. One of the drawbacks in the paper is that they use the foreign currency position of the major foreign exchange market participants as a proxy to foreign exchange order flows. Conversely, our data used in chapter 2 are truly order flows, which cover a span of 3.5 years, at a daily frequency.

Another important related paper is Dunne, Hau and Moore (2006). This study finds brokered inter-dealer foreign exchange order flows contribute to the deviation between US and French equity returns, defined as "US equity return – French equity return – EURUSD return". Order flows data in Dunne et al. (2006) is from inter-dealer market covers a year in 1999, while our data used in this chapter is over 3.5 years from 2002 to 2006. More importantly, our customer foreign exchange order flows are broken into categories of different counterparties, including corporate customers, unleveraged financial institutions, and leveraged financial institutions. According to the structure of our data, we can test the heterogeneity in foreign exchange order flows.

In chapter 2 of the thesis, we provide empirical evidence that foreign exchange order flows (GBPUSD) have material contemporaneous impacts on exchange rates, and that order flows in the foreign exchange market have substantial forecasting power for stock market returns, at market, sector and individual company levels, in both UK and US. Our results indicate that impacts of order flows from corporate customers on stock markets are positive, while impacts of order flows from unleveraged financial institutions are negative, suggesting that they may hold different types of private price-relative information. For example, since (i) it is unlikely that corporations are moving capital in order to invest in the stock market and (ii) coefficients for the UK market and the US market are both positive, the relationship between foreign exchange order flows from corporate customers at day t and stock market returns at day t+1 is not caused by foreign currency buying pressure at day t. Instead, we argue that the forecasting power of corporate foreign exchange order flows must be because of some information content. We also find that effects from foreign exchange order flows can last for several days in stock markets (the delayed effects are consistent with Evans and Lyons (2005b), suggesting the information conveyed in order flows is aggregated for a while), and order flows from corporate customers have longer impacts on future stock market changes than those from financial customers, especially for the US stock market. In addition to statistical significance of our findings, we also check the predictability of foreign exchange order flows in trading strategy testing and find that for US stocks, the total return and Sharpe ratio based on foreign exchange order flow trading rules outperforms the “buy & hold” benchmark. We suggest that at least a part of the private information conveyed in foreign exchange order flows, which was previously thought to be related to macroeconomic fundamentals or technical trading signals, is also of value to stock markets.

We see clear patterns in our results in chapter 2 using daily order flows in the foreign exchange market. However, the empirical findings of daily or weekly data do not always hold in intra-day analysis. To further confirm our findings in chapter 2, in chapter 3 of the thesis we use a unique set of ultra high frequency tick-by-tick order flows data to investigate whether the intra-day cross market relationships still hold. More specifically, besides first we still check the explanatory and forecasting power of order flows on the exchange rate itself, and second we examine the effects of customer order flows in the foreign exchange market on stock market changes at high frequencies ranging from 1-minute to 30-minute.

Most of the papers in foreign exchange microstructure use low frequency data (most often daily or weekly data). Recent studies with high frequency tick-by-tick data often focus on order flow as a vehicle for macroeconomic news, and investigate the effects of news on the patterns after releases of the public information, in terms of exchange rates as well as foreign exchange order flows. For example, Almeida, Goodhart and Payne (1998) examine the changes of DEM/USD exchange rate after releases of macroeconomic news in Germany and US, and they find the impact is significant up to tens of minutes. Evans and Lyons (2008) use 4 months of tick-by-tick DEM/USD order flows data, and using five-minute frequency analysis they suggest that when news arrives, the following order flow is more important in exchange rate determination and the exchange rate can be forecasted by inter-dealer order flow in the foreign exchange market. Love and Payne (2008) analyze the number of trades as “proxy” of order flows over a period of 10 months and also suggest that the news is transmitted into prices via order flows but will be impounded into the market price faster than those suggested by Evans and Lyons (2008). Another important related paper is Osler and Vandrovych (2009). This study examines all the executed price-contingent orders (stop-loss and take-profit orders) placed at the Royal Bank of Scotland from 10 different categories of counterparties (6 from customers, 4 from inter-dealers) over 16 months in 2001 and 2002. The authors document that there are connections between foreign exchange order flows and exchange rate changes at high frequencies.

As discussed before, effects of foreign exchange order flows on stock market changes have been demonstrated by Dunne et al. (2006) and Francis et al. (2006) using low frequency order flows data. To the best of our knowledge, no one has examined this at ultra high frequencies before. The tick-by-tick foreign exchange (EURUSD) order flows data are provided by a major European commercial bank that wishes to remain anonymous. The order flows data records every trade initiated by the bank's counterparties over 25 trading days from 10/OCT/2005 to 11/NOV/2005 and includes both customer orders (corporates, financials, internal) and inter-dealer orders (interbank). The high frequency equity data are collected from TAQ (Trades and Quotes) database in WRDS (Wharton Research Data Services), including 11 market and sector level ETFs and 30 individual stocks listed in Dow Jones Industrial Average (DOW 30).

In "pure foreign exchange environment" (i.e. only considering foreign exchange order flows and exchange rates), we find impacts of foreign exchange order flows on contemporaneous and future exchange rate changes at high frequencies. Order flows from "corporates" are positively related to exchange rate changes, while order flows from "financials" are negatively "signed" (contradicts with published studies, e.g. Evans and Lyons (2006)), but will go positive when close to 30-minute frequency (then in line with daily relations between the two suggested by many other papers, such as Evans and Lyons (2006), Reitz et al. (2007)). The high frequency findings are consistent with Osler and Vandrovych (2009), which also suggest mixed signs for their 10 groups of counterparties at frequencies less than 30-minute (e.g. positive for large corporations; negative for institutional investors, broker-dealers and middle-cap corporations). The clear existence of forecasting power from order flows on exchange rate changes at high frequencies partly explain why we do not find any forecasting power in the foreign exchange market by using daily frequency data in chapter 1: the information buried in order flows can only last for minutes and will dissipate by the end of each trading day.

In “cross market environment”, we do not see clear contemporaneous relationship between foreign exchange order flows and stock market changes at high frequencies (consistent with daily results at market level in chapter 2), but we see the important role currency order flows are playing in forecasting the stock market returns over 1-minute to 30-minute horizons, after controlling for lagged exchange rate and stock market returns. The effects of order flows from “financials” are negative on stock market changes, while the effects of orders from “corporates” are positive on stock market changes, which further confirms our findings in chapter 2. In “pure foreign exchange environment”, we notice that “corporate” order flows have longer effects on exchange rate than “financial” order flows, at high frequencies. While in “cross market environment”, there is no difference in effects between the two categories of currency order flows, at high frequencies. Together with the longer effects of daily (chapter 2) foreign exchange order flows from corporations on the US stock market (than financial institutions), we suggest that information relevant for stock markets in foreign exchange order flows from both “corporate” and “financial” customers are continuously reflected into the market intraday, however, the effects of commercial order flows are fully priced into the market several days longer than those of financial order flows.

In chapter 4 of the thesis, we hypothesise some explanations on our “cross market” findings in chapter 2 and 3 (we do not use a theoretical model to empirically test our interpretations). Our main findings are that selling of US Dollars (buying of GBP and EUR) in the foreign exchange market by corporate customers has positive effects on future stock market changes, and selling of US Dollars (buying of GBP and EUR) by financial institutions has negative effects on future stock market changes. We hypothesize that corporate customers of the banks are mainly based in the UK. When the world economy is doing well, multi-national companies are selling more goods in the US and repatriate more foreign currencies back to UK, during which more British

Pounds are converted from US Dollars. More sales of US Dollars then reflect the good future prospects of the world economy and stocks listed in the US and UK will rise in value. For financial institutions, when the world economy is going bad, clients of those mutual funds which are based in London will ask for redemptions of their funds. Assuming the bank services a client base that is UK oriented, this leads to the repatriation of money from abroad back to UK. The buying of GBP (or EUR) in exchange for US Dollars then takes place alongside sales of US and UK stocks. Foreign exchange flows into Pound sterling (or Euro) from unleveraged funds forecast poor future stock market returns globally. We conclude that the private information which drives exchange rates also appears to be valuable for pricing equity markets.

The remainder of the thesis is organised as follows: Chapter 1 investigates performance of foreign exchange customer order flows as an additional explanatory variable to technical analysis to forecast exchange rate changes by applying non-linear methodology, genetic algorithms. Chapter 2 examines the role daily customer GBPUSD order flows play in explaining concurrent and future stock market changes in both UK and US, and discusses the heterogeneous effects from different groups of customers. Possible interpretations on our findings are also suggested in this chapter. Chapter 3 also empirically test effects of foreign exchange order flows from different groups of counterparties on the US stock market changes at high frequencies ranging from 1-minute to 30-minute, using a unique set of tick-by-tick order flows data. Finally, chapter 5 concludes and suggests some directions of refinements and further research.

1 Non-linear Foreign Exchange Order Flow Analysis

1.1 Introduction

Over the past decades, macroeconomic fundamentals based models of the foreign exchange market have demonstrated poor explanatory and forecasting power, especially over short and medium periods, and many studies conclude that the predominant macroeconomic variables based models do not explain movements of exchange rates as expected (see Meese and Rogoff (1983), Frankel and Rose (1995), Cheung, Chinn and Pascual (2005), Sarno and Valente (2009), among others). Interest in searching for reasonable models in the foreign exchange market has moved to microstructure approaches. Two hallmarks of the new microstructure approach are order flow and bid-ask spread, with studies concentrating on the former. Order flow as an explanatory variable has been researched in equity markets for a long time, but in the more disaggregated foreign exchange markets with no centralized trading bourses, research has started more than 10 years later than that in stock markets, due to the lack of access to appropriate data sets.

The structure of the foreign exchange market has changed considerably in the 1990s, and electronic trading is gradually dominating, which yields access to data previously not available, such as order flows. Since this change order flow data has received more and more attention in the foreign exchange market. According to Lyons (2001), the order flows based microstructure approach relaxes three of the most uncomfortable assumptions in traditional macroeconomic fundamentals based models, as follows, 1) some market participants do hold private information which can not be accessed by others; 2) heterogeneous investors do not react to the same information in the same way; 3) information flows do not affect the price immediately and they will be fully reflected into the market in a gradual manner. Many positive conclusions in favor of order flows are made in the past decade, and it appears that the macroeconomic exchange rate models miss some key features, which do matter in determining exchange rates (e.g. Evans and Lyons (2002a, 2002b, 2005a, 2006), Rime (2000), Payne (2003), Marsh and O'Rourke (2005), Froot and Ramadorai (2005), Osler and Vandrovych (2009), among many others).

In this chapter, we will also focus on the impact of order flow data on fluctuations of exchange rates, which is the prime factor of three elements (order flows, genetic algorithm, technical analysis) we consider. As noted earlier, tremendous studies in years do not solve the long-standing price determination puzzle in macroeconomic models of exchange rate, until the new microstructure approach to exchange rates is introduced. We use this unique set of customer foreign exchange order flows data to re-confirm the findings of contemporaneous relationships between order flows and exchange rates by many others, and more importantly to test the forecasting power of this data for future changes in exchange rates. Marsh and Kyriacou (2007) apply standard linear econometric models to search for the forecasting power of currency order flows in explaining future exchange rate returns, using same set of customer foreign exchange order flows data, however no positive results are found. In order to dig deeper into the data, in this chapter we apply genetic algorithms to investigate the potential non-linear relations between order flows and exchange rate changes for six major exchange rates (EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY and GBPJPY).

In addition to order flows, genetic algorithms are another element covered in this chapter. The reason why we choose genetic algorithms as the methodology to search for the potential non-linear relationships between currency order flows and exchange rate movements is as follows: 1) not only we test the predictability of order flows for exchange rate movements, we also check the outperformance of the order flows data over technical analysis indicators, and genetic algorithms are a perfect and easy means to combine both sets of indicators (order flows and technical analysis) to identify the optimal trading strategies; 2) signals for order flows and technical analysis are quite long and the magnitudes of possible combinations (candidate strategies) are quite large, so the searching process will be faster for genetic algorithms than the traditional methodologies. Although it raises a question mark of possible data snooping with use of this kind of global searching technique, we use other ways to mitigate risks of data snooping to supplement our research (e.g. interval permutations, which will be detailed in later sections).

Applications of genetic algorithm techniques to finance, especially in technical analysis trading, have experienced significant growth in recent years as well (e.g. Neely et al. (1997), among many others). As just mentioned, the last but not least part covered in this chapter is technical analysis, which continues to be investigated in theoretical and practical areas. Technical analysis indicators are widely used by market participants in the foreign exchange market to predict future price levels and enhance trading profitability. More than 90 percent of surveyed dealers in the foreign exchange market in London admit the use of technical analysis when reaching trading decisions, see Taylor and Allen (1992).

The willingness to find the potential non-linear relations in our set of currency order flows data (as mentioned before, Marsh and Kyriacou (2007) use same dataset but find no linear forecasting relationships) encourage us to combine the three elements: order flow, technical analysis and genetic algorithms. Although many studies have been done with each factor separately or at most with two factors together, little work which focused on the combination of the three has been finished (the only example we have found is Bates, Dampster and Romahi (2003)). Bates, Dampster and Romahi (2003) use dataset of order flows from HSBC over a relatively short period of 123 observations in 2002, and find that trading based on order flows is superior to technical trading strategies. The findings also provide evidence that order flows in the foreign exchange market can improve the performance of technical trading indicators. We will also investigate whether the technical analysis and order flow strategies are profitable, and more importantly whether the performance can be boosted by using order flows as additional variables, for six major exchange rates, over a period of three and a half years from August/2002 to March/2006. Compared to Bates, Dampster and Romahi (2003), our data set is much longer (three and half years vs. five months) and wider (six major exchange rates vs. three major exchange rates), and our conclusions should be more representative.

The remainder of this chapter is structured as follows. We will introduce the backgrounds of foreign exchange order flows, technical analysis and genetic algorithms in the following subsections. In section 1.2, we will go through related literature in these three areas. Data descriptions with summary statistics and preliminary linear regression analysis are detailed in section 1.3, and methodology is provided in section 1.4. Discussions of our empirical findings are presented in section 1.5. Section 1.6 concludes.

1.1.1 Order Flow in the Foreign Exchange Market

Because it impacts so many market participants and is relevant for so many various decisions, it is no exaggeration to say that exchange rate is the single most important price in an open economy. The foreign exchange market is the largest financial market in the world and it is a true 24-hour market trading approximately from 22:00 GMT on Sunday when Australian market opens to 22:00 GMT on Friday when New York market closes. Without a "centralized" trading floor, through electronic trading platforms dealers in different geographical locations with different time zones generate hundreds of thousands of orders every single minute in every trading day. According to BIS (Bank for International Settlements) report 2007 (known as Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2007), the average daily turnover in the foreign exchange market has grown to $3.2 trillion, in which spot transactions contribute around $1.0 trillion. Trading volume in the foreign exchange market and liquidity for major currencies pairs is higher than any other financial markets. With a daily trading volume that is more than 50 times larger than the New York Stock Exchange, there are always market participants willing to buy or sell currencies in the foreign exchange market. The liquidity of the foreign exchange market, especially that of the major currency pairs, helps ensure tight quotes spread and reliable market stability.

In the foreign exchange market the macroeconomic factors based models dominated research at the beginning, but they have demonstrated a lack of explanatory and forecasting power especially over short and medium horizons (see Meese and Rogoff (1983), Frankel and Rose (1995), Cheung, Chinn and Pascual (2005), Sarno and Valente (2009), among others). Interest is gradually moving to the microstructure approach, in which some previously missed important variables in traditional models are introduced. We mentioned before in this newly-built approach to exchange rates there are two main elements, order flow and bid-ask spread. Here we focus on order flow like other major paper in this field. Academics have done lots of research on this area and one of the textbooks among these popular studies is Lyons (2001), which has suggested that inter-dealer order flow can explain more than half of the volatility and movements in the foreign exchange market.

Understanding order flow is essential for appreciating how the microstructure approach to exchange rates departs from earlier approaches. Order flow is defined as net value of buyer-initiated transactions and seller-initiated transactions. It is important to recognize that transaction volume and order flow are different. Order flow is “signed” transacted volume. Transactions are signed positively or negatively depending on whether the initiator of the transaction is a buyer or a seller, respectively. For example, in the GBPUSD exchange rate (US dollars per unit of British Pounds), one participant buying ten British pounds with US dollars at GBPUSD market exchange rate means a +10 order flow denominated in British Pounds. Afterwards a sale of ten British Pounds (-10), the net order flow will be 0 ((+10) + (-10)), while the transaction volume will be 20 (10 + 10). Over periods of time, order flow can then be measured as the sum of the signed buyer-initiated and seller-initiated orders (absolute buying flows minus absolute selling flows). A positive (negative) sum means net buying (selling) pressure over the period. Thus, despite the immutable fact that all trades involve a buyer and a seller, microstructure theory provides a rigorous way of attaching a sign to individual transactions when measuring order flow.

The foreign exchange market is a two-tiered market: inter-dealer market and customer-dealer market. Individual investors, financial institutions, commercial corporations, and other market participants trade with their own foreign exchange dealers in the customer-dealer market, and dealers will trade off the unbalanced orders with the others in the inter-dealer market. Although the foreign exchange trading volume is enormous, more than half of transactions are inter-dealer orders due to inventory control and risk management by investors in the market. This is often called “hot potato trading” (see Lyons (2001)). So we usually consider the customer orders are the truly demand or supply in the foreign exchange market, while the inter-dealer market is only a place for aggregating the dispersed information. According to BIS report 2007, the share of customer-dealer orders in the foreign exchange market increased substantially from

2004 to 2007. Transactions between financial institutions and dealers as well as between commercial corporations and dealers at least doubled during this period. This phenomenon might support that customer order flows weigh more on the movement of exchange rates, and the private information conveyed in customers order flows might be more useful to explain exchange rate changes. In this chapter, we use customer foreign exchange order flows.

As noted before, there are many types of market participants in the foreign exchange market and they have different trading objectives and constraints. The heterogeneous players in the market view the macroeconomic announcements and other information like important market-moving news in different ways, so the information conveyed in order flows will be widely segmented. Even one's interpretation of the fundamental forces driving exchange rates is correct, forecasts may still go astray if short-run speculative forces carry exchange rates far away from their fundamental equilibrium path. These all determine the dispersed information carried by order flows can only be learned in a gradual manner by market participants before it is fully reflected into prices.

The key assumption underlying the role of order flow is that some information relevant to exchange rates is not publicly available. If information about fundamentals and the mapping of this information to prices are not fully public, then market participants with access to order flows learn something from the flows and the impact of news will be reflected into prices in a gradual manner. Heterogeneity across different types of customers with various trading expectations contributes to the gradual aggregation of dispersed information to form a fair market price as well. Many studies have been done to prove that order flows do convey private information to explain or forecast exchange rates (e.g. Evans and Lyons (2002a, 2005), BJønnes and Rime (2005), Berger et al (2008)), and different groups of customers have distinguish impact on movements of exchange rates (e.g. Evans and Lyons (2006), Marsh and O'Rourke (2005), Reitz, Schmidt and Taylor (2007), Osler and Vandrovych (2009)), although some find no evidence of better explanatory and forecasting ability in order flow, or the positive findings are not commercially and practically viable (e.g. Sager and Taylor (2008)).

1.1.2 Technical Analysis

Order flows in the foreign exchange market are the most important key element in this chapter, and its introductory background and the successful track record of its usefulness are discussed in the previous subsection. We will now turn to another element, technical analysis. The logic behind this prevailing tool in theoretical and practical fields will be introduced, through straightforward calculations of several simple but widely used technical indicators, and applications of signals generated by them.

Technical analysis is the examination of past price movements to forecast future price movements and it studies market psychology, price patterns and volume levels. It is perhaps the most widely used tool to interpret and predict market behavior, and is complementary to fundamental analysis. By measuring the dynamics of price movement, it is claimed that technical analysis provides insights into the bullish and bearish forces that drive markets. Those who believe technical analysis believe that everything in a market is included in the price line, which is the first principle for technical analysis (see Neely (1997), among others). The second principle is that asset prices move in trends and the third is that history repeats itself. The three are the ground for the logic and success of technical analysis.

Technical analysis has a century-long history amongst investment professionals. However, academics, especially macroeconomists, have tended to regard it with a high degree of skepticism over the past few decades largely due to their belief in the efficient markets or random walk hypothesis. The efficient markets hypothesis states that in highly competitive and developed markets it is impossible to derive a trading strategy that can generate persistent excess profits after corrections for risks and transaction costs. In the meanwhile, due to accumulating evidence that markets are less efficient than was originally believed, there has been a recent resurgence of academic interest in the claims of technical analysis.

A large number of books and academic studies provide all of the useful information about technical analysis. They provide in-depth coverage of various technical indicators and how they are computed and why they work. See Kaufman (1987), Jobman (1995), Neely (1997). Here we introduce some simple but popular technical analysis indicators and oscillators, which are partly used in our work. They are simple or exponential moving averages (SMA and EMA), Bollinger Bands and Bollinger Band Width, Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI) and Stochastic, Forecast Oscillators, Support and Resistance.

1) Moving Averages (MA)

Moving averages are one of the most popular and easy to use technical indicators and they are always a good starting point to construct trading systems. They smooth a data series and make it easier to spot trends, which form the building blocks for many other technical indicators. However, moving average crossovers (short-term moving averages and long-term moving averages penetrate each other), which are the most common trading rules, produce clearly defined buy and sell signals, and as such are the least reliable. If not used in conjunction with other technical analysis tools, these crossovers can lead to "whipsaws" (oscillations around a stable level) and many false signals. Moving average crossovers are sometimes used to confirm trading rules based on other indicators.

Simple moving averages (SMA) are constructed by the addition of the closing price of the N last periods divided by the number of periods considered, however they have many drawbacks such as lag effects. In order to reduce the lag in SMA, technicians often use exponential moving averages (EMA). EMA can reduce the lag effect by applying more weight to recent prices relative to older prices. As such, it will react quicker to recent price changes than SMA. The weighting applied to the most recent price depends on the specified period of the moving average. The shorter the EMA's period, the more weight that will be applied to the most recent price, that is, EMA puts more weight on recent prices. For example, a 10-period EMA weighs the most recent price 18.18% while a 20-period EMA weighs the most recent price 9.52%.

Here is the calculation formula of EMA,

$$\text{Current EMA} = (\text{Current Price} - \text{Previous EMA}) \times \left(\frac{2}{1+N}\right) + \text{Previous EMA}$$

For the first period's EMA, SMA is used as the previous period's EMA.

N = Number of periods

The basic trading rules from moving averages are as follows: when the short-term (faster) EMA cross the long-term (slower) EMA from below, it is a buy signal; when the short-term EMA penetrates the long-term EMA from above, it is a sell signal. Moving averages can also constitute supports or resistances by themselves for spot prices and we will talk about this later.

2) Bollinger Bands & Bollinger Band Width

Developed by John Bollinger, Bollinger Bands are an indicator that allows users to compare volatility and relative price levels over a period of time. They are trading bands plotted at 2 standard deviation levels above and below a moving average. Then we have three lines for a set of Bollinger bands,

- A simple moving average (SMA) in the middle
- An upper band (SMA plus 2 standard deviations)
- A lower band (SMA minus 2 standard deviations)

Standard deviation is a statistical term that provides a good indication of volatility. Using the standard deviation ensures that the bands will react quickly to price movements and reflect periods of high and low volatility. Sharp price increases (or decreases), and hence volatility, will lead to a widening of the bands. The length of the moving average and number of deviations can be adjusted to better suit individual preferences and specific characteristics of a security. Trial and error is one method to determine an appropriate moving average length. A simple visual assessment can be used to determine the appropriate number of periods. The bands widen during volatile markets and narrow when volatility decreases. After sharp moves, penetration of the bands is normal. If prices appear to penetrate the outer bands too often, then a longer moving average may be required. If prices rarely touch the outer bands, then a shorter moving average may be required. Besides, the number of standard deviation for Bollinger Bands can also be set by individuals when needed.

Here we normally use 20-day SMA for the center band and 2 standard deviations for the outer bands. A buy signal is given when closing price penetrates the lower band from below and a sell signal is given when closing price cross the upper band from above. Then can also provide strong thresholds: resistance for the upper band and support for the lower band.

The other derivative indicator from Bollinger Bands is called Bollinger Bands Width. Bollinger Bands measure volatility by placing trading bands around a moving average, these bands are charted two standard deviations away from the average. So as the average changes, the value of two standard deviations also changes. This value comprises the Bollinger Band Width, representing the expanding and contracting of the bands based on recent volatility. During a period of rising price volatility, the distance between the two bands will widen (Bollinger Band Width will increase). Conversely, during a period of low market volatility, the distance between the two bands will contract (Bollinger Band Width will decrease).

There is a tendency for bands to alternate between expansion and contraction. When the bands are unusually far apart, that is often a sign that the current trend may be ending. When the distance between the two bands has narrowed too far, that is often a sign that a market may be about to initiate a new trend. So when the Bollinger Band Width is larger than the previous day and closing price penetrates the lower band from below, it is a buy signal. When the Bollinger Band Width is smaller than the previous day and closing price penetrates the upper band from above, it is a sell signal.

3) MACD

Moving Average Convergence / Divergence (MACD) is one of the simplest but most reliable indicators in technical analysis. MACD reflects a difference between moving averages, which are lagging indicators as we mentioned before. These lagging indicators are turned into a momentum oscillator by subtracting the longer moving average from the shorter moving average. The resulting plot forms a line that oscillates above and below zero, without any upper or lower limits, so it is not particularly good for identifying overbought and oversold levels. We will talk about overbought and oversold in the following technical indicators, RSI and Stochastic.

The most popular formula for the "standard" MACD is the difference between an asset's 12-day and 26-day EMA (called 12/26 MACD). However, any combination of moving averages can be used. The set of moving averages used in MACD can be tailored for each individual asset. For example, in weekly charts, a faster set of moving averages may be appropriate. While for volatile stocks, slower moving averages may be needed to help smooth the data. No matter what the characteristics of the underlying asset, each individual can set MACD to suit his or her own trading style, objectives and risk tolerance. Using shorter moving averages will produce a quicker, more responsive indicator, while using longer moving averages will produce a slower indicator, less prone to whipsaws. For our purposes in this project, the traditional 12/26 MACD will be used for explanations.

A positive MACD indicates that the 12-day EMA is trading above the 26-day EMA. A negative MACD indicates that the 12-day EMA is trading below the 26-day EMA. If MACD is positive and rising, then the gap between the 12-day EMA and the 26-day EMA is widening. This indicates that the rate-of-change of the faster moving average (short-term) is higher than the rate-of-change for the slower moving average (long-term). Positive momentum is increasing and this would be considered bullish. If MACD is negative and declining further, then the negative gap between the faster moving average and the slower moving average is expanding. Downward momentum is accelerating and this would be considered bearish. MACD centerline crossovers (cross zeros) occur when the faster moving average crosses the slower moving average.

Moreover, so as to estimate the variations of the trends, a 9-day EMA of MACD is plotted along side to act as a trigger line or a signal line. A bullish crossover occurs when MACD moves above its 9-day EMA and a bearish crossover occurs when MACD moves below its 9-day EMA. A histogram (called DIF) can be used to represent the difference between MACD and its 9-day EMA. The histogram is positive when MACD is above its 9-day EMA and negative when MACD is below its 9-day EMA, which stand for bullish and bearish markets respectively.

Now we have three advantages of this indicator, MACD,

- Absolute position of the MACD
- Relative position to its trigger line
- Existence of divergences

Over time hundreds of innovative indicators were introduced in technical analysis. While many indicators have come and gone, MACD is an oscillator that has stood the test of time. The concept behind its use is straightforward and its construction is simple, so it remains one of the most widely accepted indicators. The effectiveness of MACD will vary for different assets and markets. The lengths of the moving averages can be adapted for a better fit to a particular asset or market. As with all indicators, MACD is not infallible and should be used in conjunction with other technical analysis tools.

4) RSI and Stochastic

Relative Strength Index (RSI) calculates the relationship between the average of ups and downs for the days of the period under consideration. Is the momentum increasing in the “up” or “down” direction? RSI is one of the most popular momentum oscillator measuring the velocity of price movements. The calculation of RSI is as follows,

$$RSI = 100 \times \left(\frac{EMA(n) \text{ of } U}{EMA(n) \text{ of } U + EMA(n) \text{ of } D}\right)$$

$$U = \text{today's close price - yesterday's close price}, D = 0, \text{ when it's a "up" day}$$

$$U = 0, D = \text{yesterday's close price - today's close price when it's a "down" day}$$

$$(n) = \text{Number of periods used in calculation}$$

RSI is the most popular speed indicator because it can be set up depending on user's preference over investment horizon. High frequency traders use a 5-minute RSI, monthly market investors use a 5-day RSI, portfolio managers use 14-day RSI and some mutual funds even use 34-day RSI. See weekly technical analysis reports from Societe Generale.

Another indicator with similar design with that of the RSI, is stochastic. Stochastic Oscillator is a momentum indicator that shows the location of the current close relative to the high/low range over a given number of periods. Closing levels that are consistently near the top of the range indicate buying pressure, i.e. overbought, and those near the bottom of the range indicate selling pressure, i.e. oversold. Calculation of stochastic is as follows,

$$\%K = 100 \times \left(\frac{\text{Recent Close - Lowest Low (n)}}{\text{Highest High (n) - Lowest Low (n)}}\right)$$
$$\%D = 3\text{ - period moving average of } \%K$$
$$(n) = \text{Number of periods used in calculation}$$

Stochastic Oscillator made up of %K and %D can be easily calculated as above. The driving force behind both Stochastic Oscillators is %K, which is found using the formula provided above. %D is a smoothed version of %K. One method of smoothing data is to apply a moving average, here %D is a 3-period simple moving average (SMA) of %K.

The interpretations of the two momentum oscillators are similar. Readings below 20 are considered oversold and readings above 80 are considered overbought. However, a reading above 80 was not necessarily bearish or a reading below 20 bullish. A stock can continue to rise after the indicator has reached 80 and continue to fall it has reached 20. More importantly, the horizontal lines 20 and 80 can be adjusted in various assets. The longer of the given period in the indicators, the less the overbought and oversold thresholds are distanced. For example, 20/80 for RSI 9, and 30/70 for RSI 14.

In both indicators, crossing the lower band from below suggests a buy signal, because the buying momentum starts to pick up, while crossing the upper band from above suggests a sell signal, due to the accumulating of selling pressure. In stochastic, because %D is a simple average of %K, which are long term indicator and short term indicator respectively, buy and sell signals can also be given when %K crosses above and below %D. However, crossover signals are quite frequent and can result in a lot of whipsaws, which could cause a loss and even worse if there are high transaction costs. Again, when dealing with prices by monitoring overbuying or overselling pressures, the two indicators will be considered together.

5) Forecast Oscillator

The Forecast Oscillator plots the percentage difference between the forecast price (generated by an n-period linear regression line) and the actual price. The oscillator is above zero when the forecast price is greater than the actual price. Conversely, it is less than zero if the forecast price is below the actual price. In the rare case when the forecast price and the actual price are the same, the oscillator would plot zero.

Although the indicator is not widely used by technicians, to some level it is more effective because of the rare use. Besides, people do not use it as a main indicator, while they use this indicator to grasp some rare opportunity when the difference between expected price and actual price is relatively large to improve the performance of other indicators.

6) Support and Resistance

Support and resistance lines are some levels in the technical charts where the trend of the asset will tend to stop and reverse. The mentioned moving averages and outer bands in Bollinger bands are some of examples of these levels. Some round numbers such as 1.5000 in EURUSD in recent days would also be considered as support and resistance lines. The more often the levels are tested (touched and bounced off by price), the more significance is given to that specific levels. If the price breaks past a support line, that support line often becomes a new resistance line, and vice versa. The levels are very discretionary to some extent, because in some cases they are determined just by psychological elements or its easiness to shout out during process of trading. See Olser (2003).

1.1.3 Genetic Algorithm

Of the three important factors focused in this chapter, we have discussed the basic background of order flows in the foreign exchange market and the introductory descriptions of technical analysis indicators. The final element is the genetic algorithm. We apply an advanced methodology genetic algorithm which is not often used in finance, to look for potential non-linear relations between order flows and returns in the foreign exchange market. We will go through the theory of this algorithm and the components of it using simplified examples.

The genetic algorithm as initially defined by Holland (1975), is a stochastic global search and optimization methodology that mimics the metaphor of natural biological evolution introduced by Darwin, such as inheritance, mutation, selection, and crossover. The genetic algorithm is implemented in a computer simulation in which a population of abstract representations of candidate solutions (called chromosome or individual) to an optimization problem evolves toward better solutions. The genetic algorithm is a particular class of evolutionary algorithms, which is different from conventional optimization methods and search procedures in four ways:

- Genetic algorithms traditionally work with a coding of the parameters, not the normal parameters themselves. The code is constructed by binary strings of 0s and 1s, and a row of strings form a chromosome. Genetic algorithms can only identify this type of data.
- Genetic algorithms search from a population of starting points, not a single point and work with a high level of global sampling of the search space with all possibilities of randomness.

- Genetic algorithms use payoff (objective function) information, not derivatives or other auxiliary knowledge.
- Genetic algorithms use probabilistic transition rules, not deterministic rules. Almost everything is random in genetic algorithms.

The mechanics of a standard genetic algorithm are surprisingly simple, involving nothing more complex than copying binary strings and swapping partial strings, generation by generation. We introduce a simple evolutionary process in genetic algorithms before going into details for every part.

I. Choose the initial populations of candidate solutions to the problem
II. Evaluate the fitness of each candidate individual in the population through customized problem-dependent fitness function
III. Select optimal individuals through genetic operators such as crossover and mutation as “parent” individuals
IV. Repeat evaluation and evolving process (step II and step III) on the new population of individuals until termination criteria is reached

From the typical genetic evolutionary process, we notice that there are six fundamental issues in genetic algorithms:

- chromosome representation
- initiation (creation of the initial population)
- fitness/objective/evaluation function
- selection function
- reproduction (genetic operators such as crossover, and mutation)
- termination criteria

Chromosome Representation

A genetic representation of the candidate solution is the first step in genetic algorithm, which is typically formed as an array of bits of 0s and 1s. A row of the binary string is called chromosome or individual candidate, which can be directly dealt with by genetic algorithms. Details of how to get chromosome representation in our work will be given in “Methodology” section.

Initial Population

Then a population of the individual candidates will be created, as the initiate group of candidate solutions to the target problem. The population size depends on the nature of the problem. Because the population is generated randomly, it will cover the entire range of possible solutions.

Fitness Function

Before turning to how to apply genetic algorithms and how all the controlling operators work, fitness function needs to be defined. The fitness function is defined over the genetic representation (chromosome) in a population of candidate individuals, and measures the quantity and quality of the represented solution. Then each particular chromosome can be ranked against all of the other individuals through pre-determined ranking methodology. According to the fitness, the optimal or at least individuals which are more optimal, are allowed to breed or allocated more proportion to be selected in the next generation, which will be discussed in the following “Selection Operator” part.

Selection Operator

During each successive generation, new individual solutions are selected through a fitness based process, where the fitness is computed as the designed fitness functions. Preference will be given to fitter individuals, which are typically more likely to be selected to pass on their good genes to the next generation. The selection function can be customized by users, for example, certain selection methods preferentially select the best solutions and the best three will be definitely spotted; while other more prevailing methods use stochastic process and a small proportion of less fit solutions are also likely to be selected, which helps keep the diversity of the population and avoid the premature convergence on poor solutions.

The next step is to generate the new population of candidate solutions from those selected “parent” solutions, through the reproduction parameters such as crossover operator and mutation operator. We will introduce some simplified but representative procedures during reproduction in genetic algorithms.

Crossover Operator

In genetic algorithms, crossover is a prime factor used to control the evolutions of chromosomes from one generation to the next, upon which genetic algorithm are based. Crossover makes the algorithm distinguished from other traditional optimization techniques. Many crossover methods are established, of which one-point crossover and two-point crossover simply dominate in the area.

In one-point crossover, for example, two individuals are selected from the “parent” population through the selection functions. A single crossover point along the two individuals composed of binary strings is randomly selected. All bits (points) beyond that point in each “parent” individual will be swapped between the two selected candidate solutions. By recombining portions of fitter individuals, this process is likely to create even better individuals. The resulting chromosomes are two of the “children” individuals, and will be the new candidates in the next generation.

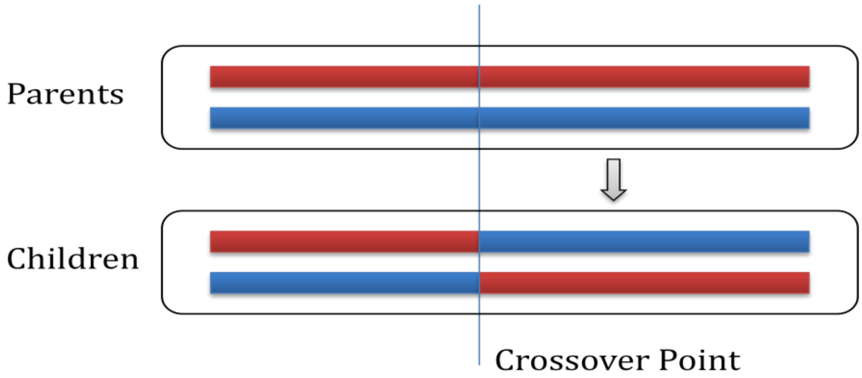


Figure 1-1: Example of One-point Crossover in Genetic Algorithms

In two-point crossover, the only difference is by selecting two crossover points rather than one in the two "parent" candidates and swapping everything between the two points between them to get the "children" candidate solutions.

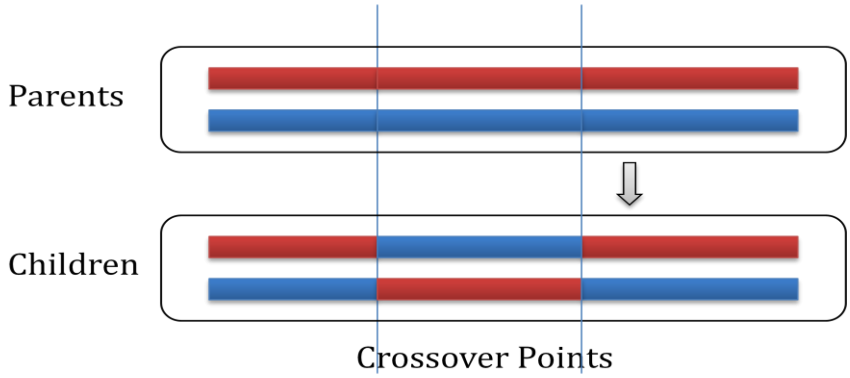


Figure 1-2: Example of Two-point Crossover in Genetic Algorithms

Mutation Operator

In genetic algorithms, mutation operator is used to maintain the genetic diversity and inhibit premature convergence on poor or local-optimal candidate individuals from one generation of a population of chromosomes to the next. This reasoning also explains the fact that most genetic algorithms avoid only taking the optimal candidate in each generation but rather a random selection with a predetermined weighting toward those that are fitter. With some low probability, a portion of the new "children" individuals generated through selection and crossover operators will have some of their bits (points or genes) flipped over, i.e. 1 is changed to 0 or 0 is changed to 1. Mutation alone induces a random walk through the search space, and the random variable will tell whether or not a particular point will be modified, i.e. mutated.

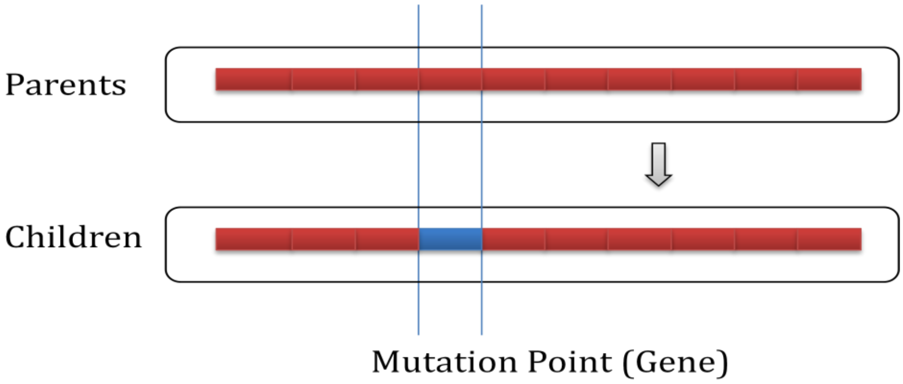


Figure 1-3: Example of Mutation in Genetic Algorithms

Termination Criteria

There is only one part in genetic algorithms we have not mentioned, the termination criteria. Generally the evolutionary process is running until a pre-determined termination condition is reached. There are several ways to determine when it stops evolving.

- a solution is found that satisfies the pre-set criteria
- fitness of optimal individual candidate has reached a plateau such that successive iterations no longer generate better solutions for a while
- the number of max generation fixed at the beginning is reached
- the computation time is reached
- manual inspection
- combination of the above

Genetic algorithms are quite efficient and robust in producing near-optimal solutions to a wide range of problems including those with high levels of uncertainty, which are not easily reduced to a precise mathematical formulation or can not be successfully solved through conventional methodologies. Genetic algorithms are also highly efficient in searching large spaces for near-optimal solutions to complex problems and so would seem well suited to trading rules selections by testing a large number of rules over a considerable number of time series data. But we still need to point out some drawbacks in genetic algorithms like any other techniques.

- Searching solutions in genetic algorithms is like climbing the several hills to the peaks simultaneously, but still one can overlook the highest mountain before climbing, which is actually the ideal solution to the problem, resulting in convergence towards local optima rather than global optimum of the problem.
- The “better” and “fitter” in fitness functions is only in comparison to other solutions, as a result, the termination criteria might be not enough to allow one to the top of the hill.
- Evaluations of fitness functions need to be performed on each individual in a population generation by generation until the stop criteria is reached, which means the time needed to reach the top of hill can be long. One needs to compromise between the quality of the best solution and the time taken in the evolutionary process of genetic algorithms.
- As with all current machine learning problems, it is worth tuning the size of initial population and genetic parameters (i.e. the crossover and mutation operators). For example, a mutation rate that is too high may lead to loss of good candidate individuals unless there exists a pre-determined best selection function to avoid the fittest candidate; while a mutation rate that is too low may lead to premature convergence on local optima. One needs to balance every parameter to stabilize the process of searching global optimum, although the randomness is the nature of genetic algorithms.

Genetic algorithms only consider solutions with the same, fixed length of binary strings which suits our problem, because we select certain number of trading rules in our research. An extension by Koza (1992), called genetic programming, allows the length of candidate individuals to vary within the solution space. The reason that the length can be changing is that, in genetic programming, the chromosomes are actual computer programs rather than data structures. This methodology is much closer to something that actually changes the behavior of a computer rather than simply a data structure inside the computer. It is actually a specialization of genetic algorithms where each individual is a computer program. In genetic algorithms, the variety of chromosomes is finite because their size is fixed and the interpretation of these chromosomes is based on their fitness functions, which limits the evolutionary phenomenon of creativity. However, in genetic programming, the possibility for the variety of chromosomes is infinite because the size of candidate individuals is of variable length and is executable code in itself. For us, genetic algorithms are well suited to accomplish our work.

1.2 Literature Review

Chronologically speaking, before the 1970s the dominant approach of exchange rates modeling was the goods market approach, in which the movements of foreign currencies mainly came from purchases and sales of goods, such as import and export of iron ores and cars. An increase in exporting items leads to “surplus” for the country, and the underlying currency will appreciate due to demand created by the “surplus”. In the 1970s, the asset market approach emerged. In addition to the trade of goods, demand of currency also comes from purchases and sales of assets, such as bonds and equities. The predominant macroeconomic variables based models in the foreign exchange market have been exploited since then, with three main underlying assumptions: all information is public, agents are homogeneous, and market structure is irrelevant. However, many studies conclude that the macroeconomic variables, such as interest rates, GDP and PPP (Purchasing Power Parity), which underlie the asset approach do not explain movements of exchange rates as predicted. See Meese and Rogoff (1983), Frankel and Rose (1995), Cheung, Chinn and Pascual (2005), Sarno and Valente (2009), among others.

Although macroeconomic fundamentals in traditional monetary models appear to be important determinants of exchange rates movements over relatively long horizons or during extreme situations such as hyperinflation, there seems that persistently large portions of fluctuations in the foreign exchange market can not be explained by macroeconomic variables. In their seminal work Meese and Rogoff (1983) come to the conclusion that at horizons of up to one year, traditional macroeconomic exchange rate models are able to explain a small fraction of exchange rate changes and none of them can outperform the simple random walk. They tested three currency pairs against US dollars and find that random walk model is better for all the three pairs at the 6 and 12 months horizons and for two out of three pairs at the 1 month horizon. Afterwards, a large number of studies have subsequently claimed to find success of different fundamental based exchange rates models over various time periods, but the success of the models has not proven to be robust. Frankel and Rose (1995) conclude that “the Meese and Rogoff analysis at short horizons has never been convincingly overturned or explained”. Cheung, Chinn and Pascual (2005) reassess the forecasting ability of a set of macroeconomic fundamentals based models developed in the 1990s, and they find no consistent performance for any single model. They find some models may outperform at certain horizons for some currency pairs, but models which are a good fit for one exchange rate may lose their forecasting capability for another. Even if positive results from one model are found, the consistency of the models is always an issue and the success of the models may be currency or time period specific. Cheung et al. (2005) concludes that “no model consistently outperforms a random walk”.

With longer data sets and more complicated econometrics methods, it is true that over horizons of more than one year, the performance of macroeconomic variables based exchange rate models appear to improve. But still, the relationship between the fundamentals and exchange rate changes can only be detected empirically over a rather long time horizon. Mark (1995) presents evidence that long term movements in the foreign exchange market are predictable and the results are statistically significant. Mark (1995) points out that the bias adjusted slope coefficient and R^2 increase with the forecast horizon and the out of sample predictions generally outperform the random walk at the longer horizons. However, even the fitness of models over periods more than one year, is challenged by many. For example, Kilian (1999) applies bootstrapping methodology on data set in Mark (1995) and finds no statistically significant predictability of the model.

Tremendous studies in years do not find much robust evidence against the “price determination puzzle” in the foreign exchange market, until the new microstructure approach to exchange rates is introduced. Intuitively as noted before, it seems that in theory there must be some link between economic fundamentals and exchange rates, at least in the long run. But why do such traditional macroeconomic variables based models of exchange rates perform so poorly? Rogoff (1999) give us the following reasons,

- There might be other factors moving exchange rates that macroeconomic fundamentals based models do not capture
- Money demand is not stable over the past years

- Assumptions and principles such as PPP used in the models may not hold

The three explanations contribute to at least a part of failure in the macroeconomic variables based models. Like others we focus on the missing factors such as order flow which is believed to be the crucial one of the possible missing variables. Order flow is used in the process of trading yet the mechanism of transactions within structures of the market is never a consideration in traditional exchange rates models. The lack of appropriate variables in macroeconomic fundamentals based models brings the foreign exchange rate research into a brand new area, microstructure approach. Many positive conclusions in favor of order flows are made in the past decade, and it appears that the macroeconomic exchange rate models miss some key features, which do matter in determining exchange rates (e.g. Evans and Lyons (2002a, 2002b, 2005a, 2006), Rime (2000), Payne (2003), Marsh and O'Rourke (2005), Froot and Ramadorai (2005), Osler and Vandrovych (2009), among many others).

Market microstructure theory is defined as "the process and outcomes of exchanging assets under explicit trading rules" in O'Hara (1995). Many factors in the market can influence prices, like rules of trading, different market participants, and structure of markets. All of them play key roles, both in theoretical models and in empirical applications. The theoretical foundations to microstructure analysis have been elaborated by Kyle (1985) as well as Glosten and Milgrom (1985). Market microstructure has been analyzed in equity markets and bond markets for a while (e.g. Glosten and Harris (1988)), and since the mid 1990s market microstructure has been gradually introduced in the foreign exchange market, partly due to increasing access to order flows data with introduction of electronic trading in the market. Among many related studies, Evans and Lyons (2002a) find that order flow can explain more than 60% changes of exchange rates. Gehrig and Menkhoff (2004) conclude that order flow is almost as important as fundamental analysis and technical analysis. The order flow contains non-public information and up to two thirds of public information is transferred through order flow.

Based on market microstructure theory, microstructure approaches to exchange rates also resolve another problem in traditional macroeconomic variables based models stated by Rogoff (1999), some assumptions may not hold over time. Lyons notes that traders in the foreign exchange market make their decisions based on a totally different set of information from those assumed in macroeconomics based models of exchange rates. According to Lyons (2001), the microstructure approach relaxes three of the most uncomfortable assumptions in traditional macroeconomic fundamentals based models:

1) all foreign exchange relevant information is publicly available
2) all market participants are rationally homogenous
3) trading mechanisms affect the prices the same way

The relaxations of these three assumptions are the distinctions of microstructure approaches to exchange rates from the traditional macro-based models. After abandoning the assumptions, they are as follows,

1) some market participants do hold private information which can not be accessed by others
2) heterogeneous investors do not react to the same information in the same way
3) information flows do not affect the price immediately and they will be fully reflected into the market in a gradual manner

To emphasize the fitness of the ideal theory in microstructure approach to exchange rates, it is worthy of mentioning briefly the key properties of the foreign exchange market determined by its unique market structures. The foreign exchange market is a two-tier market which is composed of inter-dealer market and dealer-customer market. According to their objectives, customers initiate order flows and fulfill their demand by liquidity from dealer in customer-dealer market. Dealers will trade away any unexpected positions with each other in inter-dealer market. Because there is no physical trading floor in the foreign exchange market, the transactions are done through electronic trading platforms between customers and dealers around the globe. So we know that exist naturally the low degree of transparency, heterogeneous investors, gradual trading process in the foreign exchange market. All of the characteristics in trading exchange rates, however, make order flows the unique candidate to explain the market.

We will discuss the microstructure approach to exchange rates together with its relaxations of assumptions in traditional models and the structure properties of the foreign exchange market.

Private Information in the FX Market

Dispersed information hidden behind the transactions of various types of customers across different locations determines the naturally existence of private information in the foreign exchange market. Most of the papers in the field of microstructure approach to exchange rates view order flows as proxies of private information, because information relevant to exchange rates are not always observable to all market participants. The process of gradual aggregation of information conveyed in order flows by trading in the foreign exchange market where information is of the disperse type is the foundation of the microstructure theory.

At the beginning, some papers focus on currency futures market due to lack of availability of appropriate data set of order flows in the spot foreign exchange market, but obviously futures market is too small compared to the whole foreign exchange market and consequently the results are arguably not representative especially in nowadays. Rosenberg and Traub (2006) suggest that information relevant to exchange rates in futures market in 1996 is much greater than that in 2006, perhaps because the increase of transparency in the spot foreign exchange market. But they find that order flow in currency futures market predicts short-term spot exchange rate changes, and suggest the possible existence of informed investors in the currency futures market. With the increase of availability of data in the foreign exchange market, spot exchange rates and order flow data attract more attention. Many studies prove that order flows (inter-dealer order flows and customer-dealer order flows) do convey private information which is not available to others in the markets and order flow is the driver of prices in the foreign exchange market.

Evans and Lyons (2002a) use inter-dealer order flow data set containing both Deutsch Mark and Japanese Yen against US Dollars and find substantial explanatory power from order flows for the concurrent changes of both exchange rates at a daily frequency (R^2 is 0.64 for DEM/USD, while 0.45 for USD/JPY). They also conclude that the power is due to the private information conveyed in order flows in the inter-dealer foreign exchange market. Many studies follow their way to confirm the strong relations between inter-dealer order flows and exchange rate returns. Danielsson, Payne and Luo (2002) also test the impact of inter-dealer order flows on exchange rate changes, and they use the transaction level data to find strong contemporaneous relationship at frequencies from five minutes up to one week. For some currency pairs, the explanatory power of inter-dealer order flows increase with decline of frequency, i.e. the highest R^2 is found at one day and one week horizons. A very long span of inter-dealer order flows data from EBS is used in Berger et al. (2008) and their results also support the previous conclusions. The dataset they use covers six years from 1999 to 2004, which is much longer than previous studies about inter-dealer order flows, and also EBS dominates euro-dollar and dollar-yen inter-dealer electronic trading, which makes their conclusions more representative. They confirm the presence of a substantial contemporaneous relationship between euro-dollar and dollar-yen inter-dealer order flows and the corresponding exchange rate changes at frequencies from one minute up to two weeks, although at longer horizons than two weeks, the association is weaker. Many other similar papers, by using different sets of data in the inter-dealer foreign exchange market, support the same positive conclusions, see Rime (2000), Evans (2002), Hau, Killeen and Moore (2002), Payne (2003), Killeen, Lyons and Moore (2005), Covrig and Melvin (2005), among others.

Explanatory power of order flows can be improved by including order flows of other exchange rates. Evans and Lyons (2002b) use daily foreign exchange inter-dealer order flows of nine currencies all against US dollars, and they find that the jointly explanatory power of all nine exchange rates on each single currency pair is substantial, ranging from 45% to 78%. Lyons and Moore (2008) also suggest that transactions in the foreign exchange market should affect prices across currencies by considering integration of triangular trading among US Dollars, Euro and Japanese Yen. Also see Rime, Sarno and Sojli (2010), among others. This findings support the existence of international financial integration and the interactions between different markets across different countries will be larger and stronger with globalization and internationalization.

With more availability of foreign exchange customer order flows data sets, empirical research on the customer-dealer market emerges too. We can get a rough idea from “hot potato trading”, if inter-dealer order flow is the driver of the exchange rates, customer-dealer order flow is the ultimate catalyst of the inter-dealer order flow, at least in terms of private information. Evans and Lyons (2006) test links between end-user customer order flows and exchange rates changes by using data from Citibank over six and a half years, and find the impacts from various groups of clients are quite different. They also provides evidence that not only the contemporaneous relationships between order flows and exchange rates still exist in the customer-dealer market, but also the forecasting ability of order flows is strong, even from those groups which are thought to be mainly liquidity motivated. Evans and Lyons (2005a) also use the same set of customer order flow data to forecast exchange rate changes by testing over the true out-of-sample period of three years, and suggest that the micro-based models perform better than a random walk over horizons ranging from one day to one month. Fan and Lyons (2003) as well state that they find customer order flows from Citibank contribute significantly to the movements of exchange rates even at monthly frequency, and they also mention massively different impacts from different groups of customers on the exchange rate. Similar results are also found by Froot and Ramadorai (2005) by using data from State Street, although they suggest the contemporaneous relationship between customer order flows and exchange rates are temporary, and over longer horizons more than one year macroeconomic factors have more power to explain exchange rate changes. Marsh and O’Rourke (2005) use another set of customer order flow data from Royal Bank of Scotland, and support the positive relations between order flows and movements in exchange rate market at both daily and weekly frequencies. Marsh and Kyriacou (2007) uses similar dataset to investigate the forecasting power of order flows by using linear-methodologies, but finds nothing positive. In this chapter, using the same set of data (same as Marsh and Kyriacou (2007)) we will test the potential forecasting capability in customer order flows by using non-linear methodology. Osler and Vandrovych (2009) use another set of customer price-contingent order flows data (by using executed stop loss and profit taking orders) from RBS and further confirm the presence of contemporaneous relationships especially between orders from hedge funds and exchange rate changes. Many other related studies have been done, see Lyons (2001), Rime (2000), Bjønnes, Rime and Solheim (2005), Bjønnes and Rime (2005), Reitz et al. (2007), among others. Because customer order flow data is bank specific, even that the results are mixed can be accepted, but to our best knowledge, most of papers about relationship between customer order flows and exchange rate changes report good findings to some extent.

Heterogeneity in the FX Market

Dispersed information not only comes from trading activities of various non-financial corporations and financial institutions. Scheduled macroeconomic announcements such as GDP and CPI reports are also a source. If the Rational Expectation Hypothesis holds, market participants in the foreign exchange market should treat same news in same way and a “no trade” equilibrium would be reached if everyone is rational. This is not consistent with the reality of the foreign exchange market, where order flows are often large upon the arrival of news and signify the presence of heterogeneity in the market.

Rational Expectation Hypothesis is an underlying assumption in the traditional models of exchange rates, substantial studies show the inadequacy of the theory to explain exchange rate changes. See Frankel and Froot (1987). Intuitively on the structure of the foreign exchange market and even psychological factors in all agents in the market, different views based on heterogeneity of the foreign exchange market is a normal scenario. Dornbusch (1989) states that “there is now overwhelming evidence that the hypothesis of informed, rational speculation must be rejected, the rejection is not enough because there is no alternative paradigm”. But now we have order flows in the foreign exchange market, and microstructure approach to exchange rates.

To generate trading volume in the foreign exchange market, it is important to have heterogeneous investors in the market. MacDonald and Marsh (1996) show that there is heterogeneity in market participants’ expectations, which is mainly coming from “the idiosyncratic interpretation of widely available information”. Among others who suggest the importance of heterogeneity in the foreign exchange market, Bacchetta and Wincoop (2006) consider the combination of macroeconomic fundamentals based models and micro-based exchange rates models and conclude that investor heterogeneity is key to understanding exchange rate dynamic, especially at short horizons.

Like we mentioned in customer order flows in the foreign exchange market, groups of investors with different objectives and constraints will react differently to the same information even observed simultaneously. Evans and Lyons (2006) find that for different customers such as corporations and financial institutions, the degree of effect from them on prices are very different, supporting the presence of heterogeneity in the market. Evans and Lyons (2007) conclude that customers which typically demand liquidities such as financial institutions are positively correlated with exchange rates, while commercial corporations are usually negatively correlated with exchange rates. Marsh and O'Rourke (2005) also test the relations and suggest the same results by using a different set of customer order flows data. Also see Osler and Vandrovych (2009), among many others. Heterogeneity in non-major currency markets is confirmed by Bjønnes and Rime (2005) as well. Payne (2003) employs the VAR framework to test whether there are private information effects on exchange rates due to asymmetric information in the inter-dealer foreign exchange market and reports supportive evidence. Another proof of heterogeneity in the foreign exchange market is from Bhattacharya and Weller (1997) and Vitale (1999), who suggest that the market reaction to a central bank intervention depends on the degree of heterogeneity across trader beliefs about fundamentals as well as intervention signals.

Gradual Learning Process in the FX Market

Heterogeneous shifts in money demands or risk preferences or the other objectives produce currency transactions, which in turn inform the market about those shifts through order flows during process of trading in a gradual manner. If the relations between order flows and exchange rate returns are due to private information and heterogeneity in the foreign exchange market, what is the nature of the information, where is it coming from, and how is it transmitted into exchange rate?

Evidence that order flows more closely to macroeconomic fundamentals is found by Evans and Lyons (2007) by combining macro (news, fundamentals) and micro (order flows) elements in their approach. They indicate that customer order flows from Citibank have substantial forecasting power on macroeconomic announcements such as GDP and inflation at horizons from one to six months. Many other studies also suggest the close relationship between exchange rates and macroeconomic news, for example, Engel and West (2005), Andersen et al. (2003a) among others. To test the impact from news on exchange rates, many find the two "news to prices" channels co-exist in the foreign exchange market, which are direct channel in which common knowledge is absorbed directly by investor, and indirect channel in which order flows are involved during trading process. Love and Payne (2008) analyze 10 months of high frequency order flows data of three currency pairs and also conclude that more than a half of effects from news on exchange rates are through order flows, although they mention the changes in exchange rates will be fully reflected within 2 minutes of release of macroeconomic news. Evans and Lyons (2008) analyze Deutsch Mark / US Dollar inter-dealer order flows and the corresponding exchange rate, and conclude that two thirds of the impact from news announcements on exchange rate changes is transmitted through order flow. If order flows can help to forecast macro-variables, it means at least a part of explanatory and forecasting power in order flows is still from macroeconomic fundamentals, and this is called the indirect effect of news. The learning process in the trading of exchange rates is also borne out by the predictability of order flows, through which the dispersed information across agents in the market around the globe is aggregated and impounded into prices gradually. More studies which conclude findings of forecasting power of foreign exchange order flows for exchange rate changes have been done, for example, Rime, Sarno and Sojli (2010), among others.

Evans and Lyons (2005b) examine the effects of news on transactions in different groups of customers in the foreign exchange market, and they find arrival of news generate subsequent changes in their trading behaviors which will last for days. They provide strong evidence that investors in the foreign exchange market are not responding to news instantaneously, and there is a clear existence of gradual learning process in the market. The other work from Evans and Lyons (2008) concludes the same results by using inter-dealer order flows in the foreign exchange market. Cai, Howorka and Wongswan (2008) use a relatively long span of dataset of USDJPY and EURUSD from EBS and show significant evidence for informational linkages between different financial centers. Information carried by order flows initiated in one region will lead to changes in the other regions through gradual trading process, among global dealers in the foreign exchange market. Among many other studies, Carlson and Lo (2006) test the transmission of a single event, interest rate decisions, into exchange rates, and shows the necessity of trading process in the foreign exchange market to aggregate views through order flows.

Chances of learning new information from customer and other dealers' order flows, together with private information, heterogeneous views from different agents in the two-tiered foreign exchange market, make the foundation of microstructure approach to exchange rates. A substantial number of papers emphasize the importance of order flows in the foreign exchange market, although some still argue the impact of order flows in terms of the private information, permanent effect and its practical value. Breedon and Vitale (2004) argue that "the strong contemporaneous correlation between order flow and exchange rates is mostly due to liquidity effects", which means the contemporaneous relationship between order flows and exchange rates is not due to unknown crucial information conveyed in order flows. Froot and Ramadorai (2005) although suggest the substantial effects from order flows on exchange rate changes, the impact is only transitory which do not convey information about macroeconomic fundamentals. Their argument is also supported by Berger et al. (2008). Another finding contrary to order flows theory is that feedback trading, implying that the causality in the relationship between order flows and exchange rate is running exchange rate to order flows. Many studies emphasize this, see Payne and Vitale (2003), Sager and Taylor (2008) among others. Sager and Taylor (2008) also cast doubt on the profitability and predictability of exchange rate models based on commercially available order flows with publication delays by challenging their practical values. However, no one is fully in contradiction with the microstructure theory in which order flows play a critical role during trading process to aggregate dispersed information.

Next we will briefly go through some key literature on technical analysis and genetic algorithms, especially those analyzed together with order flows. Neely et al. (1997) summarize several popular technical trading rules and patterns. Economists are traditionally skeptical of the value of technical analysis and think no one can beat the market without taking extra risks, but why does technical analysis still prevail in the market? Some explanations are the frictions of the foreign exchange market, information asymmetry, cost of private information, psychology of investors, or the slow transmission of information through order flow during trading process due to its low transparency.

A large number of studies on technical analysis have been done since 1980s, and many of them investigate simple trading rules such as simple moving averages and filtering rules. See Dooly and Shafer (1983) in the foreign exchange market, Brock et al. (1992) in stock market, among others. Osler and Chang (1995) is one of the early papers which apply much more complicated technical trading rules to identify price patterns, such as head and shoulders. Like many others, these studies find the profitability of technical trading and report the significance of their results. To further confirm the success of technical analysis trading by dealing with increasingly enormous sets of technical indicators, more complex algorithms and methodologies in technical analysis are introduced, for example, genetic algorithms and neural networks.

Obviously genetic algorithms are not designed particularly for the foreign exchange market, or even finance. After genetic algorithms are initially introduced by Holland (1975), they have been shown to be an effective strategy in the off-line design of control systems by a number of practitioners. Krishnakumar and Goldberg (1992) as well as Bramlette and Cusin (1989) have demonstrated how genetic optimization methodologies can be applied to derive superior controller structures in aerospace applications in less time in terms of function evaluations than traditional methodologies. Porter and Mohamed (1993) presente schemes for the genetic design of multivariable flight control systems using eigenstructure assignment, while Varsek et al. (1993) demonstrate how genetic algorithms can be used in the selection of controller structures. Besides the broad use of genetic algorithms in engineering, the applications of this artificial intelligence technique to finance have experienced significant growth in past decades. For example, Chidambaran and Trigueros (1998) suggest financial applications in option pricing for equity derivatives market.

More relevantly, an increasing amount of attention has been paid on these genetic approaches in technical analysis trading. Allen and Karjalainen (1999) use genetic programming to identify profitable technical trading rules in the stock market. They find that there is significant excess return over "buy and hold" benchmark after taking account of transaction cost. Dunis and Zhou (1998) develop a foreign exchange trading system that uses genetic algorithms to optimize the parameters of only one technical analysis indicator – RSI (Relative Strength Index). Dempster and Jones (2001) also focus on genetic programming to get the best parameters of different technical rules, but they find a number of popular technical indicators based trading rules to be loss-making when applied individually in a systematic manner. However, both academics and practitioners usually use combinations of a broad range of technical analysis indicators rather than individual indicators.

In this chapter, we also consider several popular and widely used simple technical analysis indicators, and we choose appropriate combinations of them when searching for the profitable trading rules for every exchange rate. The simplicity of technical trading indicators will not affect the quality of the conclusions. Brock, Lakonishok, and LeBaron (1992) suggest that the indicators are chosen ex post and the unavoidable dangers of biasing results can be minimized by selecting the simple class of rules that are widely used for a long period of time. Neely, Weller and Dittmar (1997) suggest that the searching procedure of genetic programming limits the bias even more. Neely et al. (1997) apply genetic programming techniques to the foreign exchange market to search all the possible combinations of trading rules on a daily basis to find the optimal technical rules, which generate maximum positive returns. They provide strong evidence of economically and statistically significant out of sample excess returns for six major exchange rates, and they find the existence of consistency of technical trading rules across different currencies, i.e. the trading rules which are good in one currency pair are also good for another exchange rate in most cases. However, in the contrast to the success of the low frequency daily technical analysis indicators, Neely and Weller (2001) find no evidence of significant out of sample excess returns for intraday high frequency trading in the foreign exchange market, by applying either genetic programming technique or an optimized linear forecasting model. Many other related studies focus on the identification of profitable technical trading strategies by making a complex trading platform in the foreign exchange market, see Dempster and Jones (2001), Dempster and Leemans (2004), among others. Gradojevic and Yang (2006) use order flows in both inter-dealer and customer currency markets to investigate the effects of order flows on exchange rate changes and they conclude that the non-linear approach, specifically neural networks in their paper, is superior to traditional linear models of exchange rates.

Among papers which focus on combinations of order flows, technical analysis and genetic algorithms, there are also some studies investigating the properties of order flows by checking them with technical analysis indicators, such as supports and resistance levels as well as moving averages. Osler (2003) uses a complete set of stop-loss and take-profit orders over a period of nine months, and suggest that stop-loss orders cluster just several basis points above (below) key supports and resistance levels such as round numbers for stop-loss buying (selling) orders, while take-profit orders cluster at those round number levels. The findings provide supporting evidence to explain the phenomena that trends in the foreign exchange market tend to reverse at key technical levels and that trends tend to accelerate after crossing some supports or resistance levels too, when the price contingent orders are triggered. Also see Osler (2005). More evidence is shown by Schulmeister (2006), which examines the performance of 1024 technical trading models based on moving averages and momentum indicators, and find not only profitability of technical trading over out-of-sample period, but also strong mutually reinforcing interactions between order flows and technical trading signals in the foreign exchange market. Similarly, it has been found that trend is often strengthened when some key levels are broken and it is concluded that order flows are not only driven by announcements of macroeconomic news, but also by technical analysis indicators of exchange rates.

To our best knowledge, few studies investigate both order flows technical analysis indicators by using evolutionary algorithms. Bates, Dampster and Romahi (2003) use dataset of order flows from HSBC over a relatively short period of 123 observations in 2002, and find that trading based on order flows is superior to technical trading strategies. The findings also provide evidence that order flows in the foreign exchange market can improve the performance of technical trading indicators. Of three currency pairs (EURUSD, GBPUSD, USDJPY) they examine, some strategies in USDJPY can not be identified by its evolutionary system, due to a low signal to noise ratio caused by similarities across order flows and technical indicators.

Our work also combines order flow analysis, technical analysis and genetic algorithms and applies genetic algorithms to order flows and technical analysis indicators for major exchange rates over periods of three and a half years. Compared to Bates, Dampster and Romahi (2003), our data set is much longer (three and half years vs. five months) and wider (six major exchange rates vs. three major exchange rates), and our conclusions should be more representative.

1.3 Data

1.3.1 Data Descriptions

The customer order flows dataset used in this chapter is provided by Royal Bank of Scotland. According to several Euromoney (2003 to 2008) surveys, RBS remains world top 10 in 2003, and gradually grows and stays in top 5 in the league table of overall market share in the foreign exchange market in 2008. This data set contains daily measures of actual transactions with prices for most of the major exchange rates, and we focus on US Dollars, Euro, British Pound Sterling, and Japanese Yen, which are the most traded currencies in the markets. Based on ISO international standard to define the names of currencies by applying three-letter currency codes, the currencies can be simplified to record as USD, EUR, GBP and JPY, respectively. Then we get the exchange rates from the four representative currencies, and they are EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY and GBPJPY. Every currency pair indicates the foreign currency's (first three-letter currency code) value of a unit of the home currency (second three-letter currency code). For example, EURUSD stands for the value of US dollars of one unit of Euro.

The data for all the exchange rates are at a daily frequency over a period of more than three and a half years, from August of 2002 to March of 2006. Due to lack of recording of transactions on thin or closing trading days for RBS such as some public holidays including New Year, Good Friday, Easter Monday, and Christmas for different countries over time, the number of the total trading days for every exchange rate is slightly different, but normally it is between 880 and 890 active trading days for all six currency pairs as follows: EURUSD 887 days, EURGBP 885 days, USDJPY 890 days, GBPUSD 887 days, EURJPY 884 days, and GBPJPY 886 days.

The foreign exchange market is an 24 hour-trading market except on weekends, where it is open to trade approximately from GMT 22:00 on Sunday when Australia market starts to GMT 22:00 on Friday when New York market finishes. The customer order flows data from RBS is aggregated over 24 hours from midnight London to midnight London of the following day.

As noted in the introduction, aggregation of dispersed information across the market especially in the “decentralized” foreign exchange market is the foundation of the well-found explanatory and forecasting power of order flows. In addition to the dispersed nature of the foreign exchange market, the various trading objective from different types of clients contributes more to the heterogeneity. Our order flows data from customers are grouped according to the types of customers with different trading objectives, into four categories. They are non-financial corporations (Corp), unleveraged financial institutions (Unlev) such as mutual funds and pension funds, leveraged financial institutions (Lev) including hedge funds, and others (Others) whose order flows do not fit into one of the previous three groups, such as central banks. Addition of order flows from all the four categories is denoted as “total” flows (Total).

The corresponding exchange rate GBPUSD is the price at 4pm New York time (9pm London time), and then the daily exchange rate return is calculated by log of the prices, which is expressed as the value of US Dollars of one unit of British Pound. Trading activities in the foreign exchange market decrease after 9pm London time because major economic news which can move the markets has already been released in Europe and US. The 3-hour (from 9pm and 12pm London time) mismatch between daily order flows data and the corresponding close price does not affect our research too much. More importantly, when considering the forecasting power from order flows for exchange rates in the following day, the mismatch effect is weaker. We conclude that 9pm London time exchange rates data are reasonable for our research.

We will report summary statistics and preliminary linear regression analysis on order flows for six major exchange rates in the following.

1.3.2 Data Statistics

For confidentiality reason we can not disclose the magnitudes of our order flows data, and the following table lists the simplified market share of the six major currency pairs, based on their absolute value of daily net order flows.

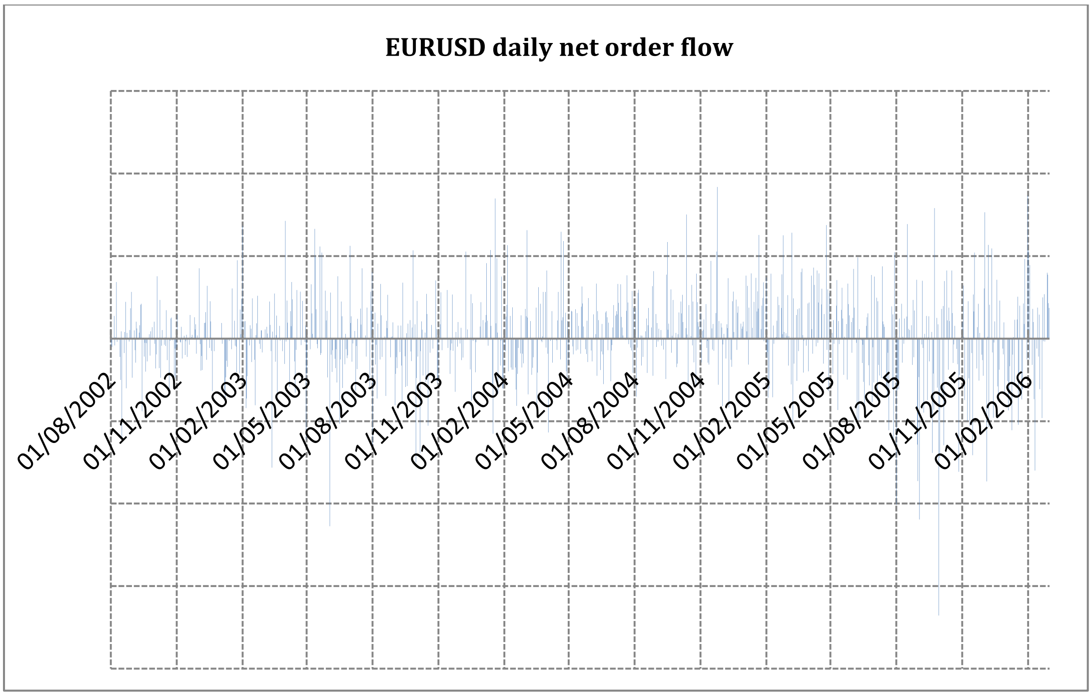
	EURUSD	EURGBP	USDJPY	GBPUSD	EURJPY	GBPJPY	Total
Corp	37.27%	18.09%	17.67%	17.96%	6.80%	2.22%	100%
Unlev	33.18%	12.77%	25.74%	17.13%	8.09%	3.10%	100%
Lev	38.49%	12.42%	23.55%	16.87%	7.50%	1.16%	100%
Others	31.80%	14.12%	25.27%	13.53%	12.64%	2.64%	100%
Total	31.42%	15.89%	23.98%	14.87%	11.16%	2.68%	100%

Notes: The table reports share of the six foreign exchange order flows for different groups of customers, over a period from 2/Aug/2002 to 2/Mar/2006.

Table 1-1: Share of Exchange Rates for Different Groups

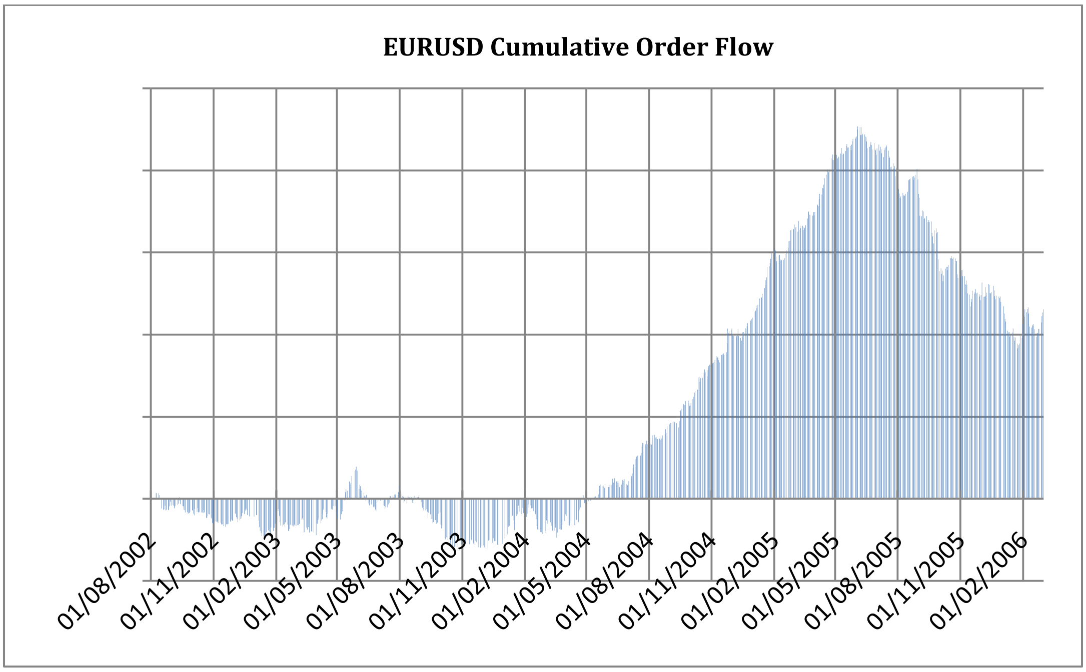
We see that EURUSD is more than 30% for all the six currency pairs in all categories and this is in line with the reality of the broad foreign exchange market, market share of EURUSD trading is the biggest in the global currency market. USDJPY is more than 20% in all but one categories (non-financial corporation is 17.67%), while both EURGBP and GBPUSD are in range between 10% and 20%. EURJPY and GBPJPY are known as cross currencies which are the least active in the six currency pairs, especially for GBPJPY, shares in almost all of the categories are less than 3%. From the market share analysis, our research will concentrate on EURUSD, USDJPY and GBPUSD due to their comparatively higher market share, as well as EURGBP due to the order flow data provided by RBS which relatively dominates the EURGBP trading in the foreign exchange market.

Because EURUSD market is our main focus, in the following we plot the net and cumulative order flows over time by using EURUSD as an example.



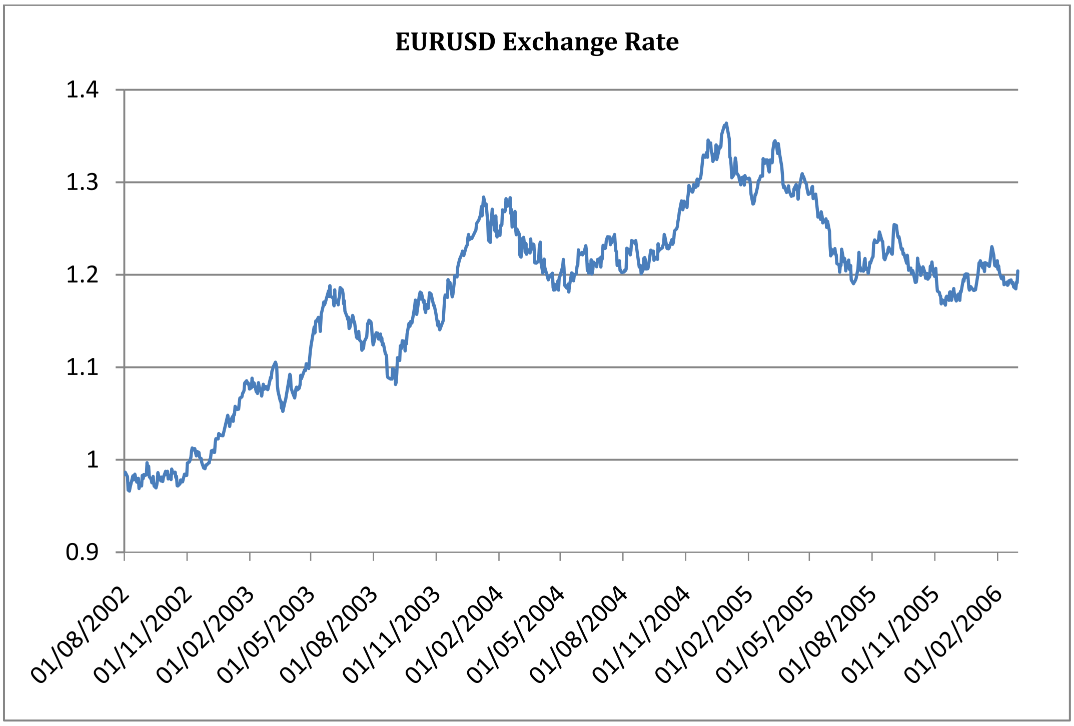
Notes: The figure shows EURUSD daily net order flows over a period from 2/Aug/2002 to 2/Mar/2006. Magnitudes of the data are not provided due to confidentiality.

Figure 1-4: EURUSD Daily Net Order FLow



Notes: The figure shows EURUSD daily cumulative order flows over a period from 2/Aug/2002 to 2/Mar/2006. Magnitudes of the data are not provided due to confidentiality.

Figure 1-5: EURUSD Cumulative Order Flow



Notes: The figure shows movement of EURUSD currency pair over a period from 2/Aug/2002 to 2/Mar/2006.

Figure 1-6: EURUSD Exchange Rate

In figure 1-4 of net order flows, the positive value means buying pressure from customers, otherwise seller-initiated orders dominate. In figure 1-5 of cumulative order flows and figure 1-6 of the EURUSD exchange rate, we see similar movements between order flows and the exchange rates.

The following tables provide the descriptive statistics for absolute net order flows of all categories for all the six currency pairs, and we can compare their trading ranges and volatilities. To make comparisons easy, absolute value of total net order flows for each pair is scaled to have a mean of unity (i.e. each number is standardized by dividing the value of mean of total order flows).

EURUSD	Corp	Unlev	Lev	Others	Total
Mean	0.50	0.22	0.34	0.78	1.00
Median	0.38	0.12	0.23	0.57	0.75
Min	0.00	0.00	0.00	0.00	0.00
Max	3.20	4.13	2.38	8.20	8.56
Std. Dev.	0.46	0.34	0.35	0.78	0.93

GBPUSD	Corp	Unlev	Lev	Others	Total
Mean	0.51	0.24	0.31	0.71	1.00
Median	0.34	0.14	0.18	0.48	0.69
Min	0.00	0.00	0.00	0.00	0.00
Max	5.77	3.81	4.39	13.21	11.97
Std. Dev.	0.56	0.34	0.41	0.82	1.03

EURGBP	Corp	Unlev	Lev	Others	Total
Mean	0.48	0.17	0.22	0.69	1.00
Median	0.34	0.07	0.09	0.42	0.66
Min	0.00	0.00	0.00	0.00	0.00
Max	6.65	4.78	7.07	6.94	7.23
Std. Dev.	0.57	0.34	0.45	0.93	1.07

EURJPY	Corp	Unlev	Lev	Others	Total
Mean	0.26	0.15	0.19	0.88	1.00
Median	0.12	0.07	0.09	0.51	0.63
Min	0.00	0.00	0.00	0.00	0.00
Max	6.94	3.68	2.18	11.96	11.77
Std. Dev.	0.52	0.25	0.28	1.12	1.19

USDJPY	Corp	Unlev	Lev	Others	Total
Mean	0.31	0.22	0.27	0.82	1.00
Median	0.20	0.13	0.17	0.55	0.73
Min	0.00	0.00	0.00	0.00	0.00
Max	4.63	2.48	1.91	6.09	6.24
Std. Dev.	0.36	0.28	0.30	0.88	0.97

GBPJPY	Corp	Unlev	Lev	Others	Total
Mean	0.35	0.24	0.12	0.77	1.00
Median	0.17	0.06	0.00	0.38	0.56
Min	0.00	0.00	0.00	0.00	0.00
Max	18.35	30.26	11.96	30.93	31.19
Std. Dev.	0.86	1.14	0.52	1.77	1.73

Notes: The table reports summary statistics for daily order flows of different groups ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions, "Others" for other customers) for six exchange rates. All numbers are standardized by dividing the mean value of total order flows for each currency pair. The sample period is 2/Aug/2002-2/Mar/2006.

Table 1-2: Summary Statistics for All Groups for Six Exchange Rates

We notice that the currency market volatility is very high from the standard deviations and maximum value in all six exchange rates. For example in GBPJPY, most of the standard deviations are more than its mean value and the maximum value are much higher compared to the other currency pairs. The main reason is that the market share of GBPJPY is relatively low, even not too heavy trading may lead to a massive impact on the price.

For all six currency pairs, volatility in group "Others" compared to that in groups "Corp", "Unlev" and "Lev" is higher. The reason behind this might be the different trading purposes of different parties in "Others", in which order flows from all the leftover miscellaneous clients including central banks are counted. Most of the activities by central banks are passive, and the uncertainty of low probability events as well as psychological factors from other participants force central banks to take actions to intervene the markets. It is not a surprise that the central banks will be volatile in trading.

Correlations analysis between different categories for each of the six currency pair is reported as follows, and from this analysis we can get the rough idea of how differently the categories of market participants react over the same period of time.

EURUSD	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0.034	1			
Lev	0.018	0.053	1		
Others	-0.08	-0.011	-0.08	1	
Total	0.426	0.319	0.316	0.735	1

GBPUSD	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0.039	1			
Lev	0.07	0.112	1		
Others	-0.118	-0.017	-0.043	1	
Total	0.475	0.336	0.394	0.675	1

EURGBP	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0.098	1			
Lev	-0.029	0.008	1		
Others	-0.059	-0.009	-0.091	1	
Total	0.47	0.308	0.262	0.739	1

EURJPY	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0.014	1			
Lev	-0.006	0.033	1		
Others	-0.076	0.024	-0.038	1	
Total	0.302	0.221	0.183	0.883	1

USDJPY	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0.021	1			
Lev	0.034	0.067	1		
Others	-0.076	0.021	0.021	1	
Total	0.292	0.299	0.336	0.845	1

GBPJPY	Corp	Unlev	Lev	Others	Total
Corp	1				
Unlev	0	1			
Lev	0.034	0.017	1		
Others	-0.012	-0.427	-0.153	1	
Total	0.461	0.174	0.147	0.67	1

Notes: The table reports correlations of daily order flows between different groups ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions, "Others" for other customers) for six exchange rates. The sample period is 2/Aug/2002-2/Mar/2006.

Table 1-3: Correlations between All Groups for Six Exchange Rates

The correlation results show that there are no obvious correlations between various groups of clients in all six exchange rates. It shows negative correlation between the group "Others" and other participants (Corp, Unlev and Lev) but it is very close to 0, we can not conclude that customers in group "Others" are mostly placing orders in the opposite directions. Only for EURJPY, unleveraged financial institutions are positively correlated with group "Others", but due to the small market share for this pair, it does not mean too much.

To sum up from correlation analysis, we do not see clear existence of interactions between trading actions from different groups, which indicates the high quality of grouping heterogeneity in our customer order flows data.

1.3.3 Standard Linear Regression Analysis

To compare results between linear models and non-linear methodologies, firstly we report summary of the standard linear regression analysis to get the big picture of contemporaneous relations between daily net order flows and daily exchange rate returns. The regression model is as follows,

$$R_t^{FX} = C + \beta \mathrm{totalOF}_t^{FX} + \varepsilon$$

In the standard regression equation, R stands for the daily exchange rate return in log exchange rates, C is the constant, OF represents total order flows for each currency pair, ε is the error term, and β is the coefficient estimates. The following table 1-4 reports the regression results, upon which we can make some preliminary judgment on linear relationships between the total currency order flows and exchange rate changes for every currency pair.

	Coefficient	Std. Error	t-stats	p-value
EURUSD	0.108	0.079	1.364	0.173
EURGBP	0.229	0.101	2.278*	**0.023**
USDJPY	0.501	0.091	5.487*	**0.000**
GBPUSD	0.421	0.137	3.062*	**0.002**
EURJPY	1.419	0.175	8.127*	**0.000**
GBPJPY	1.599	0.568	2.816*	**0.005**

Notes: The table reports OLS estimates for the regression: $R_t^{FX} = C + \beta \mathrm{totalOF}_t^{FX} + \varepsilon$ **for six exchange rates. An asterisk (*) indicates significance at 10% or better. In all equations which have statistically significant relationships,** R^2 **is around 4% and up to 5%.**

Table 1-4: Effects of Order Flow on Contemporaneous Exchange Rate

Based on p-value, coefficient estimates of order flows for USDJPY, GBPUSD, EURJPY and GBPJPY are statistically significant at the 1% significance level, while it is significant for EURGBP as well at the 5% significance level. The statistical significance of the coefficient disappears only for EURUSD possibly because order flows from only RBS are not representative enough to move the EURUSD exchange rate. It is a very comfortable conclusion that customer order flows in the foreign exchange market can explain fluctuations of exchange rates.

We perform another regression analysis with the dependent variable exchange rate return one day ahead to see if there is any forecasting power from order flows on exchange rate movements by using linear methodology. The regression model is,

$$R_{t+1}^{FX} = C + \beta \mathrm{totalOF}_t^{FX} + \varepsilon$$

The results are listed in the following table 1-5.

	Coefficient	Std. Error	t-stats	p-value
EURUSD	0.001	0.079	0.008	0.994
EURGBP	0.032	0.102	0.319	0.75
USDJPY	0.032	0.093	0.343	0.732
GBPUSD	0.104	0.138	0.749	0.454
EURJPY	0.258	0.181	1.424	0.155
GBPJPY	-0.746	0.57	-1.307	0.191

Notes: The table reports OLS estimates for the regression: $R_{t+1}^{FX} = C + \beta \mathrm{totalOF}_t^{FX} + \varepsilon$ **for six exchange rates. An asterisk (*) indicates significance at 10% or better. R^2 is up to negligible.**

Table 1-5: Effects of Order Flow on Future Exchange Rate

Compared to the contemporaneous regression, the results here are very negative. Based on p-value of coefficients, we do not see any forecasting power in the total currency order flows for any exchange rate by using standard linear forecasting regressions. Because the regression models assume that the relations between order flows and exchange rates are linear, is there any predictability in order flows data by using non-linear methodologies? We will use genetic algorithms to investigate potential non-linear relations, while the negative results from linear regressions do not bother us too much.

1.4 Methodology

In the following we will discuss five components of methodology,

1. Data transformation: how to transform order flow and technical indicators data into binary codes (1s and 0s) which genetic algorithms can indentify. Examples are used to state the process of conversion and the meaning of the codes.
2. Fitness function: how to derive the formula to calculate the return of the tested trading strategy.
3. Evolution procedures: step by step introduction of genetic algorithms for the specific process of our work.
4. Parameter choices: which input parameters need to be selected and what are the different effects on the results of various parameter selections.
5. Interval permutations: how to shuffle the orders of the three periods to six different groups of training interval, selection interval and prediction interval, and the reasons for the interval permutations.

1.4.1 Data Transformation

There are several fundamental components in genetic algorithms: chromosome representation (i.e. problems coding), creation of the initial population, selection, crossover and mutation operators, termination criteria and the fitness/objective function. The starting point of using genetic algorithms to search optimal solutions to problems is to convert the problems to formats that genetic algorithms can identify to work with, so the first of all is data transformation. This often amounts to representing the solution space as a finite number of rows of strings with binary bits (1s and 0s). In our research, both the net order flows and technical analysis indicators can be easily presented in this form. We will use examples in the following to suggest the process of data transformation.

Our customer order flows are categorized into four groups according to types of the bank's clients. They are non-financial corporations (Corp), unleveraged financial institutions (Unlev), leveraged financial institutions (Lev) and other financial institutions (Others). Total flows are simply the sum of order flows of all the four groups, denoted as Total. For each of the six major exchange rates (EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY, and GBPJPY), derived from the difference between daily customers buying and selling orders of the base currency, we get the daily net order flows (i.e. buyer-initiated orders minus seller-initiated orders) for every category of clients for each currency pair. Then we generate a set of time series of binary indicators for all the categories based on whether the number of net order flows is positive or negative. If the net order flow of exchange rate is positive, the binary code is 1, otherwise the binary code is 0. Then we get a five-digit binary string at every time point for order flow data.

Corp	Unlev	Lev	Others	Total
0	1	1	0	1

Table 1-6: Example of Order Flow Binary Indicators

The 1 under Lev (Unlev) means the net order flow of leveraged financial institutions (unleveraged financial institutions) are the net buyer of the base currency at the point of time, indicating a buying pressure to the base currency. As such, the 0 under Corp (Others) means the net order flow of non-financial corporations (other institutions) for the base currency is not positive at the moment, showing a selling pressure to the base currency.

The conversion of technical analysis indicators to binary strings is similar. We select several simple but representative technical analysis indicators, and they are EMA (Exponential Moving Averages), Bollinger Bands, MACD (Moving Averages Convergence / Divergence), and Stochastic Oscillators. We can easily get many reasonable buy and sell signals from these indicators, and if it is a buy signal, 1 is recorded like in the conversion of order flows indicators, otherwise 0 is written down.

We describe some buy and sell signals in the following,

- We firstly use the EMA as an example. If 5-day EMA crosses 10-day EMA from below, it indicates buying pressure is accumulating, we record this as 1 in the binary strings. While if 5-day EMA penetrates 10-day EMA from above, it suggests a selling pressure and the binary code is 0. Or if 5-day EMA consolidates above 10-day EMA, indicating strong tendency to be upward trend, we get a 1, otherwise 0.
- For MACD, a bullish moving average crossover occurs when MACD moves its 9-day EMA from below (denoted as 1), while a bearish signal occurs when MACD crosses its 9-day EMA from above (denoted as 0). And also, either MACD>0 or DIF>0 means a bullish market (recorded as 1), otherwise a bearish market (recorded as 0).
- For Stochastic, when the line is consolidating below horizontal line 20 where it indicates oversold, it is a buy signal, denoted as 1. When the line is above horizontal line 80, where it means overbought, it is a sell signal, denoted as 0.

So like the conversion of net order flows, we can also get a row of binary string for technical analysis indicators at every point of time,

1	0	0	0	1	1	0	1

Table 1-7: Example of Technical Analysis Binary Indicators

Final step in the conversion procedure is the combination of the two strategies (order flows and technical analysis), in which the format and meaning of the binary string is the same as previous two strategies, as follows,

0	1	0	0	0	1	0	1	1	1	0	0	0

Table 1-8: Example of Combination Binary Indicators

Then we get three sets of binary strings which are order flows (OF), technical analysis (TA) and combination of the two (COM) for each currency pair over the whole period of time, and an example (OF data) is given in the following.

Corp	Unlev	Lev	Others	Total
0	1	1	0	1
0	1	0	0	1
1	0	1	1	0
1	0	0	0	1
0	1	0	1	0

1	1	0	0	1
0	1	1	1	1
1	0	0	0	0

Figure 1-7: "State Matrix" for OF data (order flows data)

Here we use OF set as an example, for each day there is a binary string to represent the state of that day, over time we have a matrix of binary strings (called as "state matrix") which show the state for every day. The methodologies to get the "state matrix" for TA and COM are same.

1.4.2 Fitness Function

We now turn to the fitness/objective function, which is used to evaluate the performance of every trading strategy discussed above. We consider investors that trade fixed sized amounts in every exchange rate. When entering the market, they borrow the home currency or the foreign currency, and the money will be converted to another currency with the current exchange rate. At this time, they hold one currency cash and another currency debt. When they want to close the position, they convert the money back to the original currency with the new exchange rate and pay back the loan. We get the fitness functions for long positions and short positions of home (base) currency, respectively, as follows,

$$\text{Long position: } C[\frac{F_t}{F_{t'}}(1-c)^2-1] \qquad \text{Short position: } C[(1-c)^2-\frac{F_t}{F_{t'}}]$$

F_t is exchange rate at trade exit and $F_{t'}$ is exchange rate at trade entry. C stands for size of trading (when only considering the percentage of return, C equals to 1) and c is transaction cost such as trading slippage and bid/ask spread when placing orders. The method to calculate the return is similar to the work by Dempster et al. (2003). For simplification, one can use log return of exchange rates as an alternate evaluation function, which is more popular in academia as well as in real world and easier to calculate to be a perfect approximation.

1.4.3 Evolution Procedure

We introduced background of all components of genetic algorithms in previous sections, and now we turn to the details of the evolutionary process used in our work in the following,

I. Randomly generate certain size of initial population of candidate solutions (chromosomes composed of binary strings). We choose 20 individuals in each population.

II. Evaluate the performance of each candidate individual over the training period. The return is calculated according to the fitness function. Get all the values of individuals in the initial population and rank them from highest down to lowest according to fitness.

III. Select the best individual based on the fitness value, and substitute the worst three individuals by this best one. Then randomly select the temporary "parent" population according to weighting of each individual based on its fitness value. Crossover individuals pair by pair and mutate individuals one by one, based on pre-determined probabilities. A new "children" population of individuals, which size is the same as the previous "parent" population, is created, i.e. the next generation.

IV. Repeat the step II and step III until the termination criterion is reached. Here we use, "when the number of generation reaches 50, the iteration will stop".

V. Choose the best three rules to test over the selection period and select the best (called in-sample return) as the optimal rule. Test the real forecasting power of the best rule in the prediction interval, as the out-of-sample return.

We will use several graphs in the following to demonstrate the evolutionary process in genetic algorithms for our problem, and we still stick to OF data as an example. According to the five steps mentioned above, we firstly randomly generate an initial population of 20 candidate solutions (denoted as "strategy matrix"), which are composed of binary strings of 0s and 1s. To match with the "state matrix", the length of the candidate solution depends on the type of dealt data, and here we choose 5 bits as the buy signal (first half) and the other 5 bits as the sell signal (second half), for OF set (similarly, for TA set, 8 bits for buy signal and sell signal; for COM set, 13 bits for buy signal and sell signal).

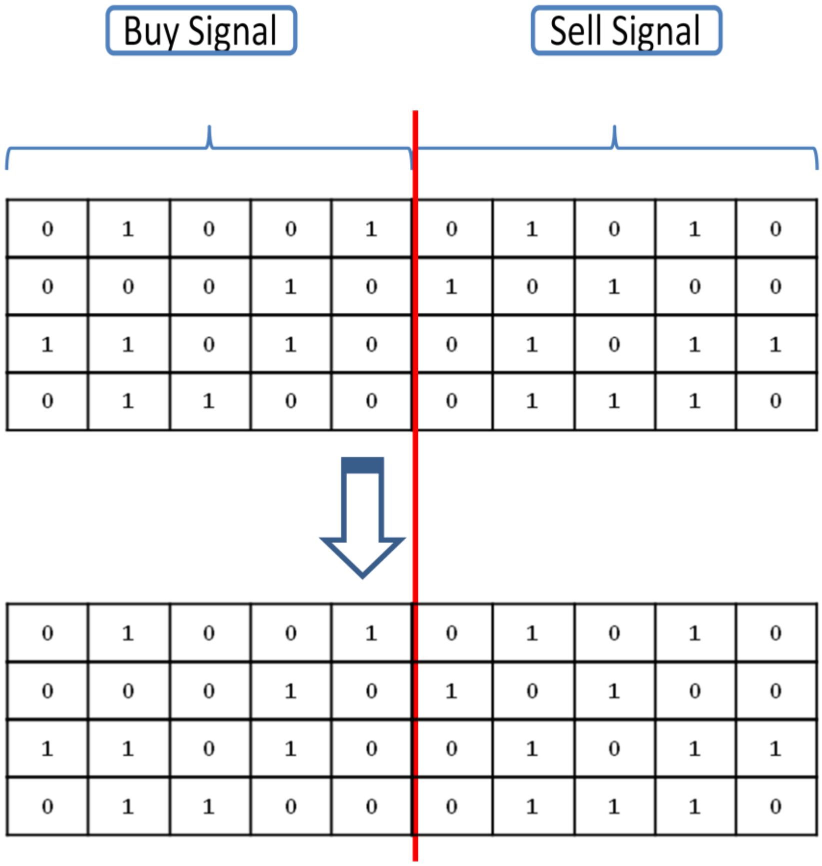


Figure 1-8: "Strategy Matrix" for OF data (order flows data)

Now we have 20 candidate solutions in the first generation of population, and we call it “strategy matrix”. Based on each buy signal and sell signal, computer will search for same patterns in the “state matrix”, and with corresponding daily price we can evaluate each strategy pair (i.e. buy and sell signals) over a certain period of time. Then we get 20 fitness values for a generation of candidate solutions.

Based on their fitness values, as mentioned before, we can do some evolutionary moves such as crossovers and mutations among the 20 candidate solutions. We use the following graphs to illustrate the typical genetic algorithm process, which is introduced in details in previous sections.

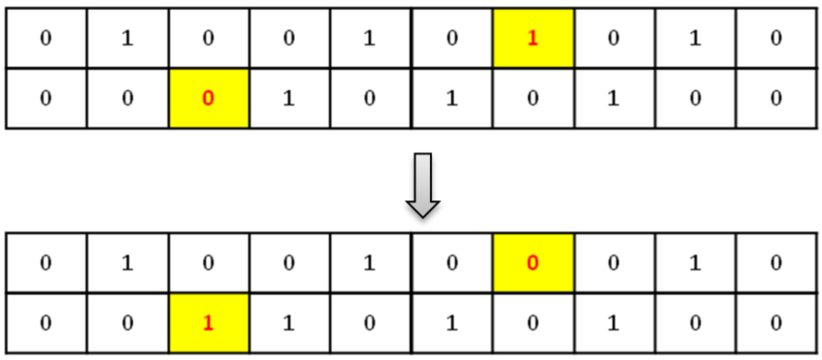


Figure 1-9: Mutation

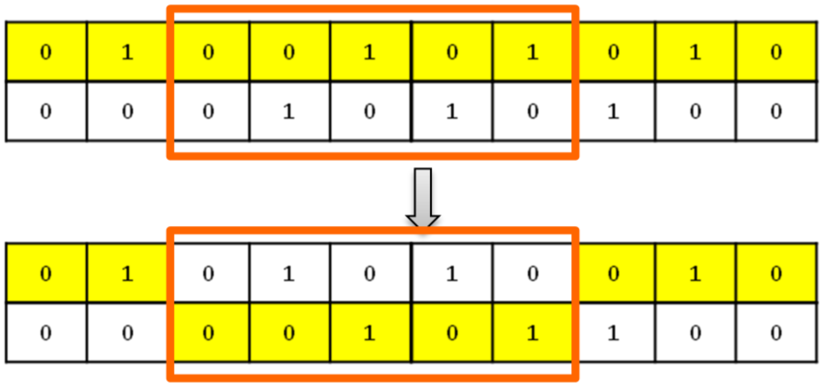


Figure 1-10: Crossover

Such process will repeat for all the candidate solutions in one generation, and it will happen to pre-determined number of generations or until some pre-determined criteria is met. In this chapter for our problem, we choose 50 as our maximum generation.

Up to now, two input parameters (size of initial population which is 20 and maximum generation to terminate which is 50) have been determined in the evolution procedures. Other parameters and the selection of parameters such as crossover rate and mutation rate will be detailed in the following.

1.4.4 Parameter Choice

Five input parameters need to be decided for the genetic algorithms in our work and they are,

- size of the initial population
- maximum generation of the evolution process
- crossover rate
- mutation rate
- transaction cost including trading slippage and bid/ask spread

We already set the first two input parameters in the previous part of this section and they are 20 for the size of initial population and 50 for the maximum generation during evolutionary process. As already discussed, there are no certain rules to determine the parameters. The stochastic nature of genetic algorithms determines the randomness and instability during evolution. The next two inputs, crossover rate and mutation rate, need to be adjusted according to calculation time, evolution efficiency and quality of the optimal strategy. For example, if the crossover rate and mutation rate are too high, the result will be full of jumps and not stable when evolution ends. If crossover rate and mutation rate are too low, evolution will not converge to the global optimum over short period of time and when touching 50 generations, the result will be premature. The final input, transaction cost, is determined by real trading experience, 0.03%. No work mentions exactly how to choose the trading cost parameter and we just average the maximum and minimum bid-ask spreads for the six major currency pairs to get the around number, around 0.03%.

Although we discuss the choice of input parameters, in theory the selections of the first four parameters should not affect the final results as long as the algorithm is running long enough and is well designed. However due to the random nature of the genetic process from the beginning to the end, stochastic evolutionary paths and unstable results are normal to see, in theoretical work as well as practical area. We need to balance the quality of the optimal strategy and the evolution process. We will perform some parameter sensitivity analysis to check our genetic algorithm and set our own input parameters. We use technical analysis indicators (TA) in EURUSD 1-2-3 (refer to the following part “Interval Permutations”) as examples to shows our findings, in which return is the out-of-sample return.

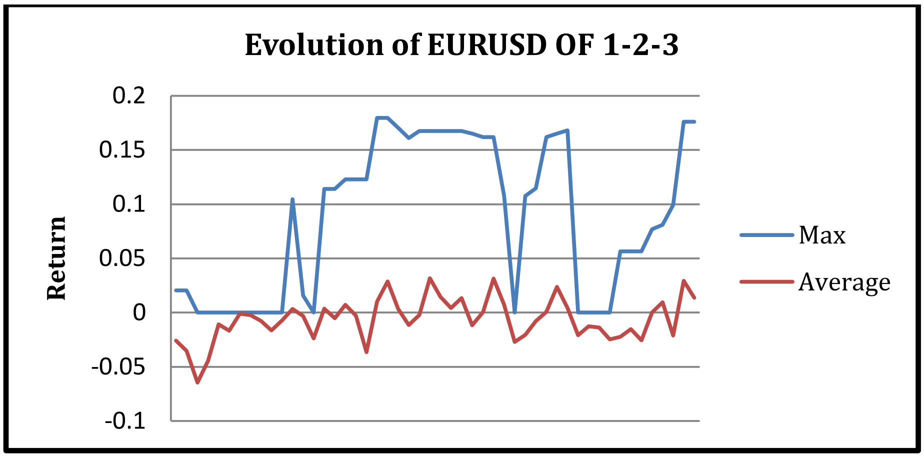
EURUSD 1-2-3 TA set					
Nind	**Maxgen**	**Pc**	**Pm**	**Trans. Cost**	**Return**
20	50	0.2	0.01	0.0003	-0.0977
50	50	0.2	0.01	0.0003	0.002
20	100	0.2	0.02	0.0003	-0.0977
20	50	0.5	0.02	0.0003	0.0416
20	50	0.2	0.1	0.0003	0.0416

Notes: The table reports results of input parameter sensitivity analysis. Nind is the size of the initial population, Maxgen stands for the number of maximum generations, Pc and Pm are crossover rate and mutation rate, respectively, Trans. Cost means transaction cost. The data used in this evolutionary process is period 1 (training interval), i.e., from August/2002 to October/2003.

Table 1-9: Input Parameters Sensitivity Analysis

We choose several combinations of parameters to get a big picture of the impact from changing inputs. In theory, if the genetic algorithms work perfectly well, the returns in last column should be equal for all of the combinations of initial input parameters. Although we have some equal numbers and the evolution does exist, we can not be totally satisfied with the results. The unstable returns might affect the quality of our conclusions to some extent. However, we should point out that, if we re-run the evolutionary process two or three more times with same inputs, the algorithms can almost always spot the near-optimal same return, in this case, 0.0416. This further confirms our assumption that randomness dominates the evolutionary process, because sometimes the algorithms do not mutate enough to avoid premature convergence on poor solutions. So as to balance the time of evolutionary process and quality of final results, we think our conclusions will not be affected too much because the evolution does exist in our genetic algorithms, and the robustness problem can be improved if we do more times of genetic evolutions.

The following figure shows the process of evolution when mutation rate is 10% and we can see the volatility of the process is high compared to when mutation rate is 1% (see the “Empirical Results” section). The result is in line with the impact of changing mutation rate in this section, small change of mutation rate leads to massive drift in the evolution process and then the final results.



Notes: The graph shows the process of evolution over 50 generations. The data used in this process is period 1 (training interval), i.e., from August/2002 to October/2003. The red lines are average fitness of all the individuals in each generation and the blue lines are the maximum fitness in each generation.

Figure 1-11: Evolutionary Process With 10% Mutation Rate

Considering the explanations of the parameters sensitivity analysis as well as the performance of genetic algorithms, as long as it does not make massive impact on the purpose of our work, it is tolerable. Then we choose the following parameters as our final inputs.

- Nind = 20
- Maxgen = 50
- Pc = 0.2
- Pm = 0.01
- Transaction Cost = 0.03%

Nind is size of the initial population, Maxgen stands for the number of maximum generations, Pc and Pm are crossover rate and mutation rate respectively.

1.4.5 Interval Permutations

In order to find the optimal results and test the consistency of our findings, we will divide the time series data into three intervals. The three and a half years (around 890 days) for every currency pair are divided into three roughly equal periods (around 297 for each), which are the training interval, selection interval, and prediction interval, respectively. The first two periods are in-sample regions and the last prediction period is the out-of-sample interval used as the real forecasting period. The training period is used to search trading strategies, over which we identify several optimal rules based on fitness functions. We select the fittest strategy over the selection interval out of the top ones from the training period, and finally test the best one in the prediction interval, the out-of-sample region, to see the real forecasting performance of the optimal rule.

To make the conclusions more convincing, we will test the consistency of the results by comparing findings through interval permutations. For example, originally we use periods 1, 2, 3 (denoted as 1-2-3) as the training interval, selection interval, and prediction interval, respectively. By changing the order of the three periods, we will also use the periods 2, 3, 1 (denoted as 2-3-1) as the training interval, selection interval, and prediction interval, respectively, to test the forecasting power of order flow data and if the order flow can be used to improve the performance of technical analysis indicators. From mathematical perspective, there are six different combinations of the three intervals and they are 1-2-3, 2-3-1, 3-1-2, 2-1-3, 3-2-1, and 1-3-2, as denotations of training-selection-prediction. We think this way of testing can give us more evidence and confidence on the results and raise the credibility of the conclusions.

1.5 Empirical Results

In this section, we will discuss our findings of each currency pair in the order of EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY and GBPJPY. As discussed before, we focus on the first four exchange rates. EURUSD, USDJPY and GBPUSD are due to their relatively high market share, while EURGBP is included because of the degree of dominance by our order flow data supplier, Royal Bank of Scotland (RBS), in this market. The final two currency pairs, EURJPY and GBPJPY are widely quoted Japanese Yen-crossed exchange rates, but their market share are very low, so we will pay less attention to them.

We will firstly concentrate the most on EURUSD market due to its around 30% of share in the foreign exchange market to show the procedures of what we are doing and the results of all interval permutations when testing the consistency of the strategies. The work is done for all three sets of indicators, order flow (OF), technical analysis (TA), and combination of the two (COM).

1.5.1 EURUSD

The euro-dollar market is, by any measure, the biggest financial market in the world, accounting for almost 30% of all activities in the foreign exchange market with EURUSD daily trading volume averaging more than five times the daily volume of all of the world's equity markets combined. We can also spot its highest market share from the analysis of our order flows data in the previous “Data Statistics” section, which is 31.42% in our simplified six exchange rates trading environment based on absolute net order flows.

Time series data are divided into three intervals. The first, second and last periods are called training period, selection period and prediction period, respectively. We denote this as 1-2-3. Trading period is also our evolution period, over which the evolutionary process is performed by genetic algorithms. Selection period is used as a “cushion” for double confirmation of our findings through evolution in training period, and selection period is denoted as the "real" in-sample term. Prediction period is the out-of-sample used as the "real" forecasting term. We also test the performance of the strategy by doing interval permutations to test the consistency of the results. For example, after we change the order of the original three periods (1-2-3), we get that the third, first and second are training set, selection set and prediction set, respectively. In this case, we denote it as 3-1-2. The following figure will show the procedure and consequence of the permutation.

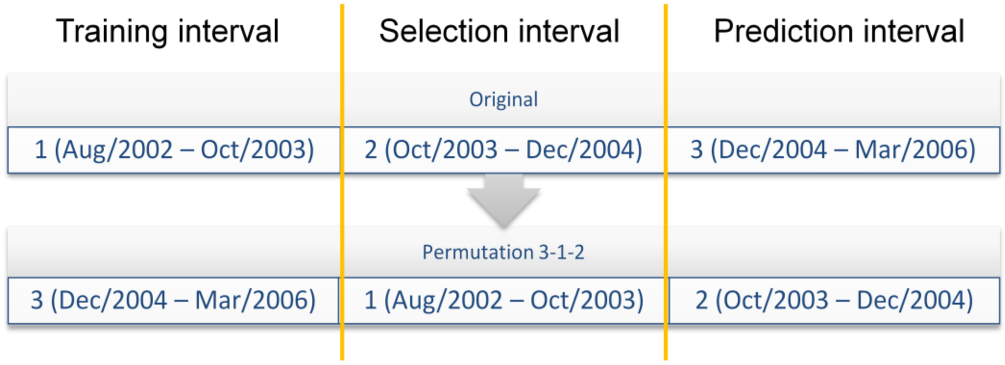
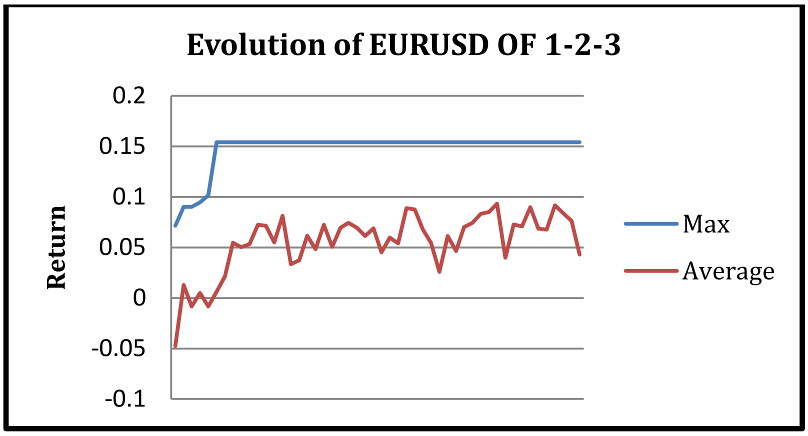


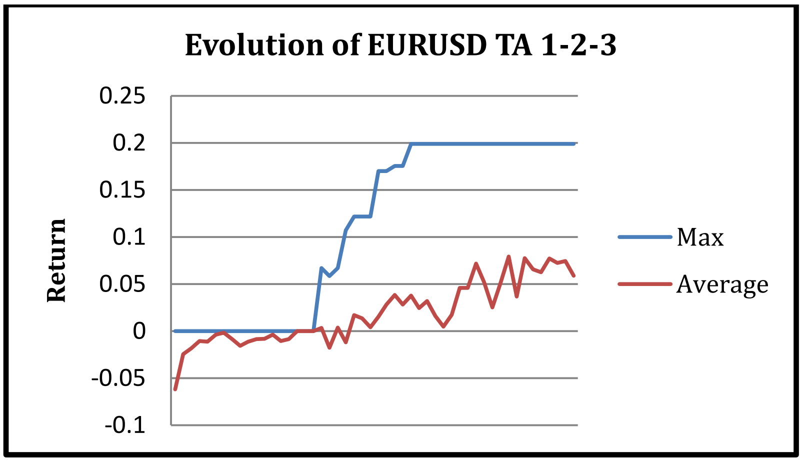
Figure 1-12: Example of Interval Permutations

For any permutations, the three intervals, training period, selection period and prediction period, are always in the same order, from left to right.

In theory, we can see that there are six different combinations of the three intervals and they are 1-2-3, 2-3-1, 3-1-2, 2-1-3, 3-2-1, and 1-3-2, as denotations of training-selection-prediction. For EURUSD, we will talk about the results of all of the six combinations in the following.

Evolution process happens in the training interval. Because we have six combinations of the three intervals for EURUSD, and three groups of indicators, technical analysis (TA), order flows (OF), combination of the two (COM), we will have 18 genetic evolution figures for EURUSD only. Here we take two as examples (TA 1-2-3 and OF 1-2-3) to describe the genetic algorithm.



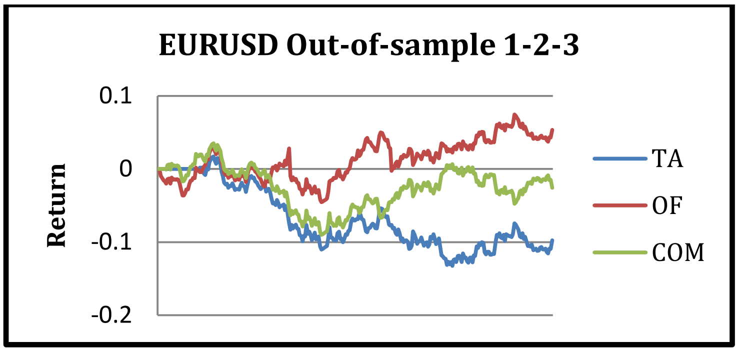


Notes: The evolutionary process is running over training period for EURUSD 1-2-3, i.e., over period 1: from August/2002 to October/2003. The two graphs show the process of genetic algorithms over 50 generations. The red lines are average fitness of all the individuals in each generation and the blue lines are the maximum fitness in each generation.

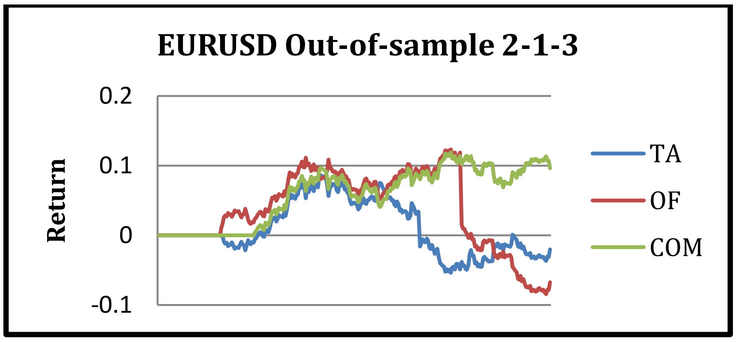
Figure 1-13: Examples of Genetic Evolutions

From figure 1-8, we can see the existence of evolution in both of the graphs, and the first one converges to the best later than the second. The difference of time to converge and the volatility of the red lines indicate the randomness of genetic algorithms.

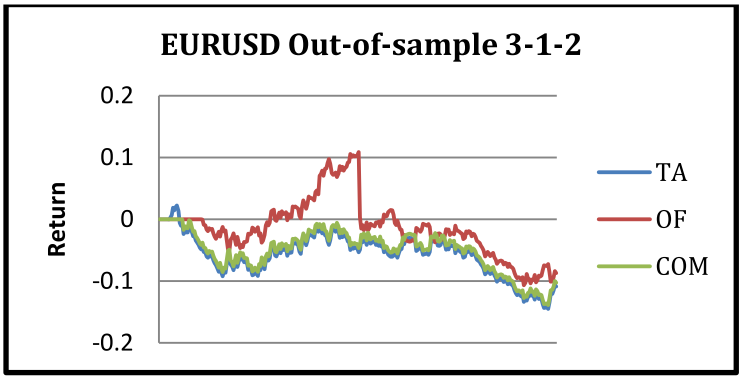
Now we turn to the out-of-sample (prediction period) returns for all three groups (TA, OF and COM), through which we can judge the real predictability and profitability of the optimal strategy. There are six out-of-sample graphs in total for all of the six permutations (1-2-3, 3-1-2, 2-1-3, 2-3-1, 3-2-1, and 1-3-2) and in each of them the three groups of various indicators are represented by three different colored lines (here we allocate red, blue and green lines to OF, TA and COM, respectively). Below each graph, the three rows of binary strings (1s and 0s) are the optimal signals for the three groups (OF (5+5), TA (8+8) and COM (13+13)).



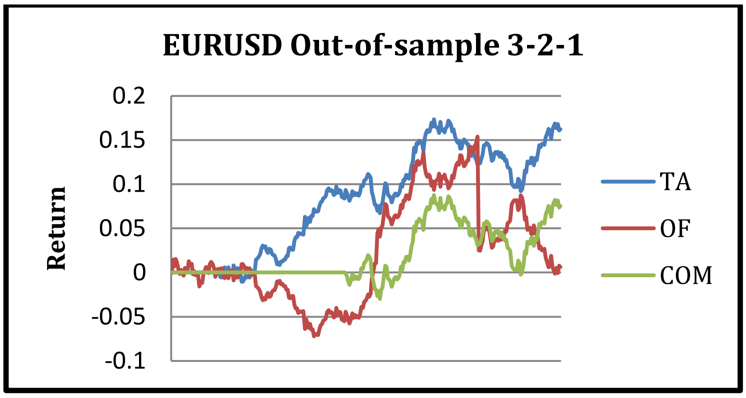
1	0	1	0	1	0	1	0	0	1																
0	0	0	0	1	1	0	0	0	0	0	1	1	1	1	0										
1	0	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1	1	0	0	0	1	0	1	0	0



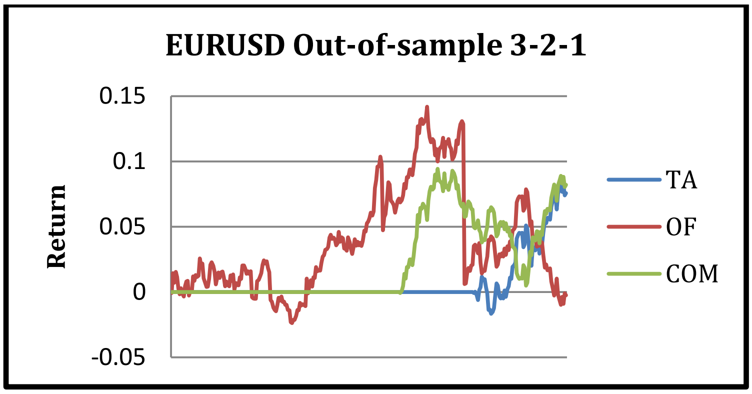
0	1	1	1	1	0	1	0	1	0																
0	0	1	0	1	0	1	0	0	0	0	0	0	1	0	1										
0	0	0	1	1	1	1	0	1	0	0	1	1	0	1	1	1	0	0	0	1	0	0	1	1	1



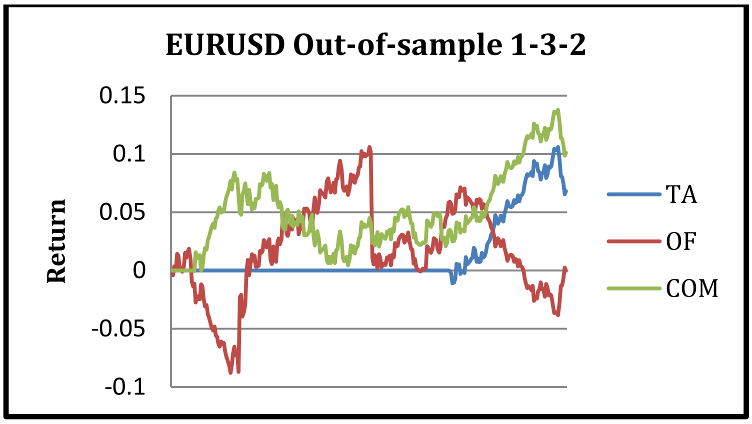
0	1	1	0	1	1	1	0	1	1																
1	1	0	0	1	0	0	1	1	1	0	0	1	0	0	0										
0	1	0	0	1	1	1	0	0	0	1	1	0	0	1	0	1	1	0	1	1	1	1	1	0	0



1	0	1	1	0	1	0	1	1	0																
1	1	1	0	1	1	0	1	0	1	0	0	1	0	1	1										
1	1	0	0	0	0	1	1	1	1	1	1	0	0	1	1	0	1	0	1	0	0	0	0	1	1



1	0	0	0	1	1	0	1	1	0																
0	1	0	0	1	0	0	0	0	0	0	1	0	1	1	0										
0	1	1	1	0	0	0	0	1	1	0	0	1	0	1	1	0	1	1	0	1	0	0	1	0	1



1	0	0	0	1	0	1	0	0	1																
1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	1										
0	1	0	0	1	1	1	1	0	0	0	0	0	1	1	0	1	1	0	0	0	1	1	1	0	1

Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3 and 2-1-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2 and 1-3-2, the out-of-sample period is period 2 (from October/2003 to December/2004); for 3-2-1 and 2-3-1, the out-of-sample period is period 1 (from August/2002 to October/2003). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-14: EURUSD Out-of-sample Results

We will compare the out-of-sample return in the figures together with the following table 1-10, which reports in-sample and out-of-sample returns with turnover (number of trades, i.e. number of switches between long and short).

EURUSD Interval Permutations

EURUSD 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	5	12.95%	1	-9.77%
order flow	14	-5.60%	13	5.35%
combination	2	1.83%	2	-2.58%

EURUSD 2-1-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	9.21%	7	-2.04%
order flow	9	-4.71%	6	-6.75%
combination	3	12.53%	3	9.64%

EURUSD 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	-16.34%	1	-10.87%
order flow	9	12.21%	11	-8.68%
combination	1	-16.18%	1	-10.22%

EURUSD 2-3-1	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	3	5.37%	1	16.23%
order flow	2	8.84%	7	0.61%
combination	5	-3.54%	1	7.53%

EURUSD 3-2-1	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	4	11.29%	4	7.56%
order flow	9	4.53%	15	-0.25%
combination	3	-2.86%	1	8.20%

EURUSD 1-3-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	-9.85%	1	6.80%
order flow	10	-3.61%	14	-0.02%
combination	1	-11.60%	1	10.11%

Notes: The table reports in-sample and out-of-sample returns and trading turnover for all six interval permutations for EURUSD. The in-sample and out-of-sample periods are selection and prediction intervals for every permutation, i.e., for 1-2-3, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 2-1-3, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the in-sample period is period 3 (from December/2004 to March/2006) and the out-of-sample period is period 1 (from August/2002 to October/2003); for 3-2-1, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 1 (from August/2002 to October/2003); for 1-3-2, the in-sample period is period 3 (from December/2004 to March/2006) and the out-of-sample period is period 2 (from October/2003 to December/2004).

Table 1-10: EURUSD Results

We describe the findings one by one for each interval permutations.

In EURUSD 1-2-3, the in-sample returns for TA and COM are positive but the out-of-sample returns are negative for both of the two strategies (-9.77% and -2.58%). Although the out-of-sample return in COM does suffer less loss, partly due to the positive out-of-sample return in OF, we do not see improvement from OF in terms of in-sample returns (12.95% and 1.83%). The out-of-sample returns in TA and COM are both less than their corresponding in-sample returns and even negative, which means the lack of real forecasting power. We can not comfortably conclude that the additional order flow improve the performance of technical analysis.

In EURUSD 2-1-3, the out-of-sample return in COM is much higher than out-of-sample return in TA and it is positive (9.64% and -2.04%), which shows some improvement by choosing order flow as additional variables when modeling. But still for out-of-sample return in TA, it becomes worse when compared to its in-sample return (-2.04% and 9.21%). Further we do not see predictability from the negative out-of-sample return in OF (-6.75%).

In EURUSD 3-1-2, out-of-sample returns in TA and COM are virtually equal and they are very negative (-10.87% and -10.22%). In the EURUSD 3-1-2 figure, we can also see the returns for these two over the period are almost the same, mainly resulting from the low number of trades and that transaction dates are very close. The longer binary strings for COM and TA than OF contribute partly to the low trading frequency for the two groups of strategies. For example, for TA set, 8 bits for buy signal and the other 8 bits for sell signal. There are 512 combinations for each theoretically, and we only have around 900 trading days (for the forecasting period, it's only around 300). On average the turnover for each buy and sell signal is less than 2 times. For COM set, the combinations are even larger, and then the trading frequency is even lower. Lack of active trading signals probably makes the strategy, as well as our results, less concrete to some extent. And again like in EURUSD 2-1-3, the out-of-sample return in OF is turning to negative, which shows the inconsistency of predictability of order flows in the foreign exchange market.

In the next three interval permutations, the results are mixed too. The opposite results give us doubt on the persistence of improvement power of order flows.

In EURUSD 2-3-1, the COM strategy reduces the profitability of the TA indicators in in-sample and out-of-sample, and the returns in OF do not show the persistence of a good strategy as well (0.61% and 8.84%). While in EURUSD 3-2-1 and EURUSD 1-3-2, OF strategy enhances the performance of TA set in out-of-sample. However, the opposite findings in in-sample shows the improvement is not stable. And also the only one time of trading for out-of-sample region raises the problem of randomness and casts doubt on the comparisons of the results across the different permutated groups.

After considering the performances of strategies for OF, TA and COM for all six interval permutations, we also evaluate the signals themselves. Here we use OF as an example, as follows.

1	0	1	0	1	0	1	0	0	1
0	1	1	1	1	0	1	0	1	0
0	1	1	0	1	1	1	0	1	1
1	0	1	1	0	1	0	1	1	0
1	0	0	0	1	1	0	1	1	0
1	0	0	0	1	0	1	0	0	1

Table 1-11: OF signals for all six interval permutations

Table 1-11 summarizes the six optimal signals for OF set for the six interval permutations for EURUSD. For example, the first signal means when “corporate” buys, “unleveraged financial” sells, “leveraged financial” buys, “other” sells, and “total” buys, the strategy buys; while when “corporate” sells, “unleveraged financial” buys, “leveraged financial” sells, “other” sells, and “total” buys, the strategy sells. However, we do not see a clear economic logic behind such a signal, which suggests possible data mining bias (we will talk about this issue later in this section). And also when we consider all the six permutations, we don't see clear patterns (i.e. similar buy and sell signals) and consistent positive economic meanings for our trading signals. It is the same case for the strategies of TA and COM sets. This finding is unfortunately consistent with Cheung, Chinn and Pascual (2005), who suggest the profitable rules for one currency pair may not be applicable to other exchange rates.

Another point we notice in the graphs of out-of-sample returns for all the six permutations is there are some steep drops over relatively short period of time, especially for the OF signals. We suggest two reasons: 1) the strategy's extreme performance is mainly due to the sudden change in the foreign exchange market within several days; 2) the drops are due to the relatively short length of signals for OF data set: because only five digits long bit string for a buy signal or sell signal, if the two signals are adjacent or very close to each other (i.e. buy & sell within very few days), the sudden change of the strategy's position and the sudden turnaround of direction in the market will push the already bad situation to an even worse one.

Considering all of the six tables and figures, we suggest that technical analysis does not perform very well and order flow alone does not always generate positive returns, at least for our data set. Order flows improve the technical analysis slightly but not consistently.

Before we turn to results of other currency pairs, we will discuss the possibility of data snooping in our research. Using global search method such as genetic algorithms, there inevitably might be risks of data snooping. Based on our findings of EURUSD, we do not see consistent performance of our strategies and the signals do not have recognizable patterns as well as obvious economic meanings. This lack of economic value casts more doubts about data snooping. However, interval permutations technique is used to mitigate the risk of data snooping, and we believe this methodology can help demonstrate more complete and concrete conclusions. The use of interval permutation also contributes to the inconsistency of our results while easing away the possibility of data snooping, and to some extent the inconsistency means there is no data snooping in our research. Another annoying fact is that, given our bad results in this chapter, we don't have to worry too much about data snooping.

1.5.2 EURGBP, USDJPY & GBPUSD

Now we turn to the next three exchange rates, EURGBP, USDJPY and GBPUSD. The reason that we choose the three as the second block is mentioned in the previous sections (EURGBP due to this pair’s dominant role by the Royal Bank of Scotland in the foreign exchange market, USDJPY and GBPUSD due to their comparatively higher market shares). For the three currency pairs, all of the evolutions and returns figures can be found in the appendix, we list the tables with summary of returns for the three groups of indicators (TA, OF, and COM) and only consider three combinations of the three intervals, 1-2-3, 3-1-2, and 2-3-1. We notice that the three permutations cover all occupying possibilities of every interval, i.e. any one period covers any of the three intervals (training, selection and prediction intervals). We think the results should be representative enough for the three currency pairs.

EURGBP Interval Permutations

EURGBP 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	3	4.26%	5	-0.57%
order flow	8	6.80%	8	-2.19%
combination	5	3.73%	3	1.91%

EURGBP 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	2	-9.74%	3	2.21%
order flow	11	1.98%	3	1.70%
combination	1	9.11%	2	-3.53%

EURGBP 2-3-1	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	4	0.63%	2	-9.34%
order flow	12	0.07%	6	-4.16%
combination	2	-5.43%	1	9.82%

Notes: The table reports in-sample and out-of-sample returns and trading turnover for three representative interval permutations for EURGBP. The in-sample and out-of-sample periods are selection and prediction intervals for every permutation, i.e., for 1-2-3, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the in-sample period is period 3 (from December/2004 to March/2006) and the out-of-sample period is period 1 (from August/2002 to October/2003).

Table 1-12: EURGBP Results

For EURGBP, most of the out-of-sample returns are also lower than the in-sample returns in TA, OF, and COM across all three permutations, with one exception of COM strategy in EURGBP 2-3-1, in which the out-of-sample return is better than the in-sample return (9.82% and -5.43%). But that result is compromised somewhat by the low trading turnover. And as in EURUSD, we find mixed results here, too. The improvement of order flow to TA indicators in EURGBP 1-2-3 and EURUSD 2-3-1 is positive, but the result in EURGBP 3-1-2 is opposite. The number of trades is still very small for COM set, especially for EURGBP 3-1-2 and 2-3-1, partly due to the longer binary strings.

USDJPY Interval Permutations

USDJPY 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	2	8.18%	1	-8.84%
order flow	15	1.87%	11	-5.54%
combination	3	5.74%	6	-0.91%

USDJPY 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	5	-0.20%	7	2.60%
order flow	10	1.05%	7	4.14%
combination	4	-1.43%	3	3.39%

USDJPY 2-3-1	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	3	-5.32%	7	7.63%
order flow	12	-2.62%	14	4.44%
combination	1	-11.35%	3	6.22%

Notes: The table reports in-sample and out-of-sample returns and trading turnover for three representative interval permutations for USDJPY. The in-sample and out-of-sample periods are selection and prediction intervals for every permutation, i.e., for 1-2-3, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the in-sample period is period 3 (from December/2004 to March/2006) and the out-of-sample period is period 1 (from August/2002 to October/2003).

Table 1-13: USDJPY Results

For USDJPY, the strategies in TA, OF and COM still can not show consistent profitability from in-sample to out-of-sample. The trading frequency in OF is higher than that in TA and COM as other currency pairs. The improvement of order flow to TA indicators is also not consistently significant for different interval permutations. The mixed results cast more doubt on the persistence of improvement power of order flows.

GBPUSD Interval Permutations

GBPUSD 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	2	3.77%	1	-0.93%
order flow	12	8.99%	5	8.03%
combination	3	14.29%	1	-6.45%

GBPUSD 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	-6.62%	3	-9.47%
order flow	14	4.16%	8	-0.87%
combination	3	-8.31%	5	-6.91%

GBPUSD 2-3-1	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	9	-0.44%	6	-2.36%
order flow	14	-2.68%	15	-3.08%
combination	2	8.47%	3	5.90%

Notes: The table reports in-sample and out-of-sample returns and trading turnover for three representative interval permutations for GBPUSD. The in-sample and out-of-sample periods are selection and prediction intervals for every permutation, i.e., for 1-2-3, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the in-sample period is period 3 (from December/2004 to March/2006) and the out-of-sample period is period 1 (from August/2002 to October/2003).

Table 1-14: GBPUSD Results

Most of the out-of-sample returns in GBPUSD are negative with two exceptions out of nine (8.03% in OF in GBPUSD 1-2-3, and 5.90% in COM in GBPUSD 2-3-1). And also we do not see big improvement of COM strategy by adding order flows compared to the pure TA strategy. The in-sample profitability still can not stretch into out-of-sample consistently. For example, in GBPUSD 1-2-3, the in-sample return is nearly 15% but the out-of-sample return is worse than -6%. Again, for GBPUSD, the mixed results do not give us any solid conclusions.

1.5.3 EURJPY & GBPJPY

We will discuss the low market share Japanese Yen-crossed exchange rates together to complete our findings. Due to their low market share, we only consider two combinations of the three intervals.

EURJPY Interval Permutations

EURJPY 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	5	-3.29%	3	-3.40%
order flow	16	-5.60%	24	4.13%
Combination	4	11.89%	5	-0.25%

EURJPY 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	8.64%	3	4.89%
order flow	12	7.19%	13	-1.12%
combination	2	-18.01%	4	7.48%

GBPJPY Interval Permutations

GBPJPY 1-2-3	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	1	3.63%	1	-0.24%
order flow	4	14.15%	7	-2.18%
Combination	1	4.46%	4	-12.12%

GBPJPY 3-1-2	in-sample		out-of-sample	
	no. of trades	return	no. of trades	return
technical analysis	2	3.52%	3	-5.34%
order flow	8	-2.91%	6	5.89%
combination	2	14.46%	1	0.52%

Notes: The table reports in-sample and out-of-sample returns and trading turnover for two selected interval permutations for EURJPY and GBPJPY. The in-sample and out-of-sample periods are selection and prediction intervals for every permutation, i.e., for 1-2-3, the in-sample period is period 2 (from October/2003 to December/2004) and the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the in-sample period is period 1 (from August/2002 to October/2003) and the out-of-sample period is period 2 (from October/2003 to December/2004).

Table 1-15: EURJPY and GBPJPY Results

For EURJPY, we do not see consistent improvement of order flow to TA strategy from in-sample to out-of-sample as well as across different interval permutations, even there is, the out-of-sample return is negative (-0.25% in COM in EURJPY 1-2-3), or the improving out-of-sample return in COM is shadowed by the disappearance of that power in in-sample (TA and COM in EURJPY 3-1-2). Both of them indicate inconsistency of the strategy. While for GBPJPY, same mixed results have been found. For example, even though the out-of-sample return in COM in GBPJPY 3-1-2 is better than that in TA, compared to the in-sample 14.46%, 0.52% of the out-of-sample return is not an encouragement. It is a bitter consistence to always get mixed findings.

1.6 Conclusions

Over the past years, the widely proved misfit in traditional macroeconomic fundamentals based models of the foreign exchange market have failed to explain and forecast changes of exchange rates. After failure to improve the macro-based models by inducing complex methodologies, more and more efforts are paid into searching for a new kind of models distinctive from the traditional models. So interest in the foreign exchange market has begun to move to microstructure approaches, in which order flow analysis dominates. Proponents of the order flow approach argue that order flows have proved to contain private information and the dispersed information across agents located in different financial centers is gradually aggregating and fully impounded into prices in the foreign exchange market.

In this chapter, we apply one of many non-linear methodologies, genetic algorithms, to order flow and technical analysis indicators to solve optimization problem to identify optimal trading strategies for six major exchange rates (EURUSD, EURGBP, USDJPY, GBPUSD, EURJPY and GBPJPY). The dataset from Royal Bank of Scotland covers a period of more than three and a half years from August of 2002 to March of 2006. By using genetic algorithms, we investigate whether technical analysis as well as order flows in the foreign exchange market is profitable and whether the performance of technical trading can be improved when importing order flows as additional variables. We get the following findings,

1. For all six major exchange rates, most of the out-of-sample technical analysis returns are negative, while some of the out-of-sample returns of order flow based rules are better (partly in line with previous studies, like Evans and Lyons (2002a), among others). But the mixed results from six different exchange rates show inconsistency in our findings.
2. The improvement of order flows to technical analysis is not consistent either, and even when it exists, the enhancement is relatively limited. This contradicts the findings of Bates, Dampster and Romahi (2003), who use a relatively short period of data. The interval permutations methodology we use to test the

consistency of our conclusions makes it difficult to find solid results unless the relationship between order flows and exchange rate changes are persistently stable over any period of time. This might be due to structural breaks within the period of our data.

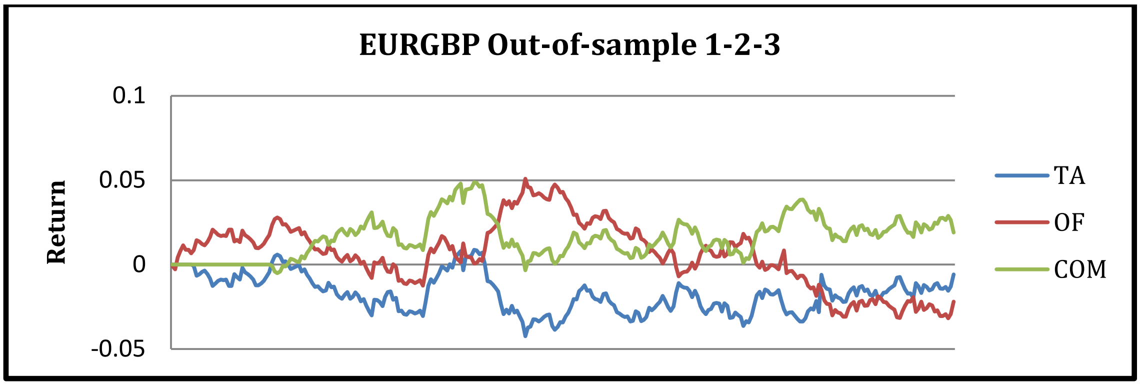
3. The trading frequency based on order flow indicators is higher than technical analysis and the combination of the two, partly due to the shorter binary strings when the signals are dealt in genetic algorithms. Bates, Dampster and Romahi (2003) also find some strategies in USDJPY which can not be identified by its evolutionary system, due to a low signal to noise ratio caused by similarities across order flows and technical indicators.

Our results show some power of private information carried in order flows and this is very much in line with previous work in foreign exchange microstructure field. See Evans and Lyons (2002a, 2002b, 2005, 2006), Rime (2000), Payne (2003), Marsh and O'Rourke (2005), Osler and Vandrovych (2009), etc, among many others. But for the improvement to the performance of technical analysis, the result is not consistently positive. We conclude that the improvement is not consistently present, and even when it exists, it is relatively limited and not very encouraging. The application of all possible interval permutations might partly attribute to the negative findings, which is similarly in line with those in Cheung, Chinn and Pascual (2005), the profitable rules for one currency pair may not be applicable to the other exchange rates.

Appendices

1. Besides EURUSD out-of-sample returns reported in section 1.5, figures of out-of-sample returns for 5 other currency pairs of interval permutations. The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The number of figures for each exchange rate is as follows, 3 EURGBP, 3 USDJPY, 3 GBPUSD, 2 EURJPY, and 2 GBPJPY.

EURGBP



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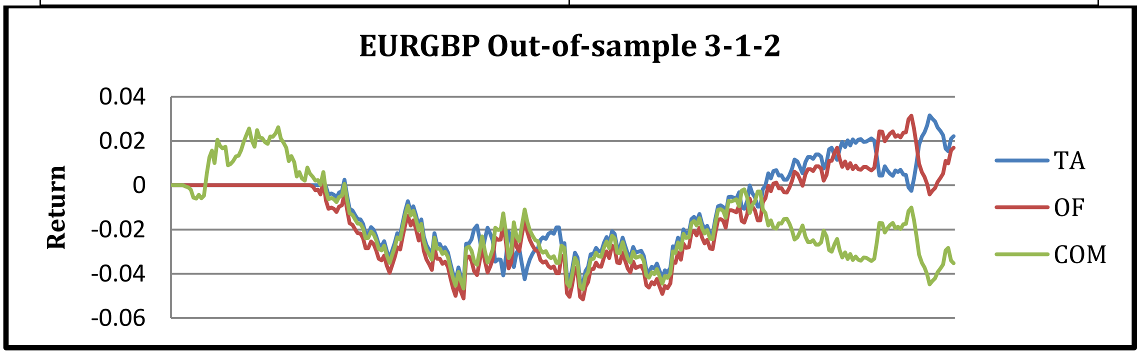

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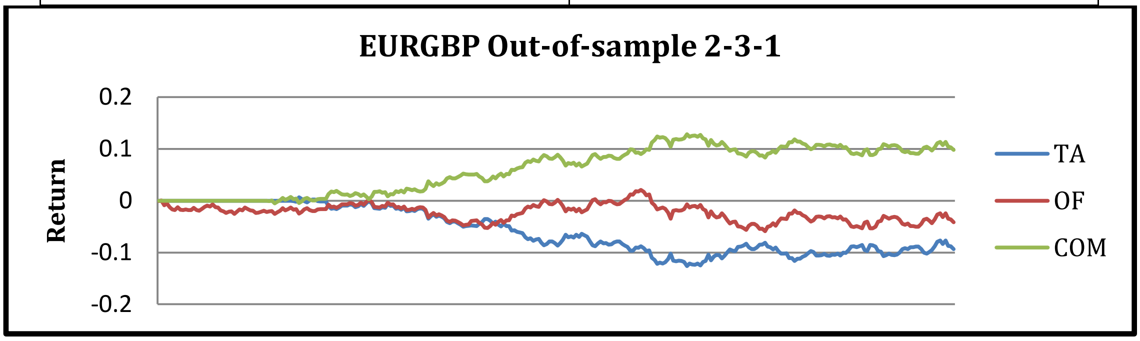

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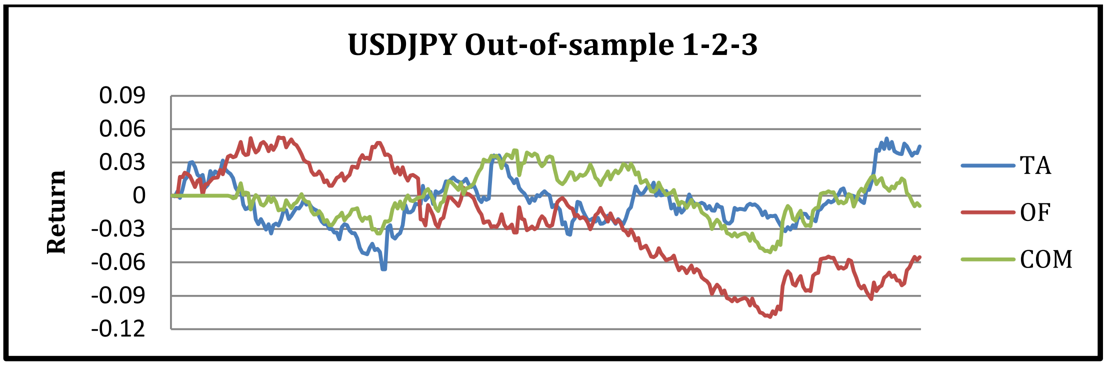
Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the out-of-sample period is period 1 (from August/2002 to October/2003). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-15: EURGBP Out-of-sample Returns

USDJPY



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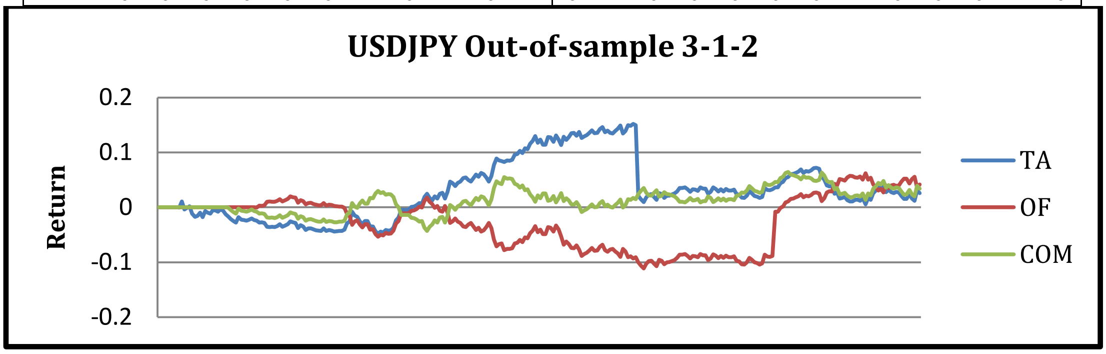

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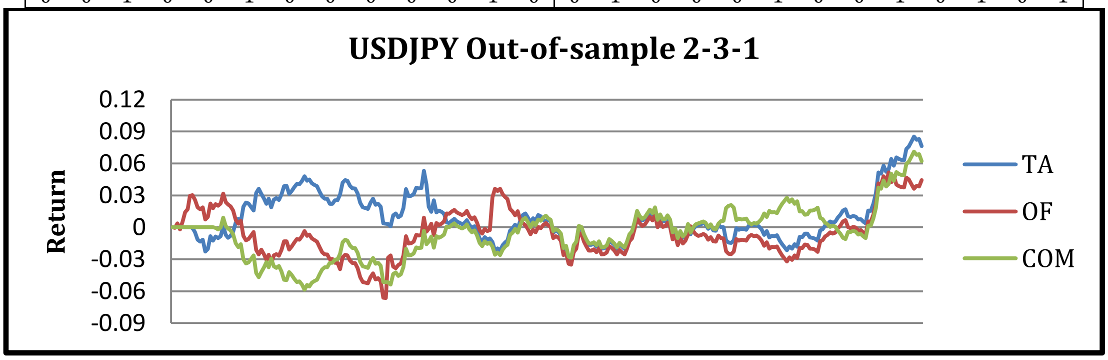

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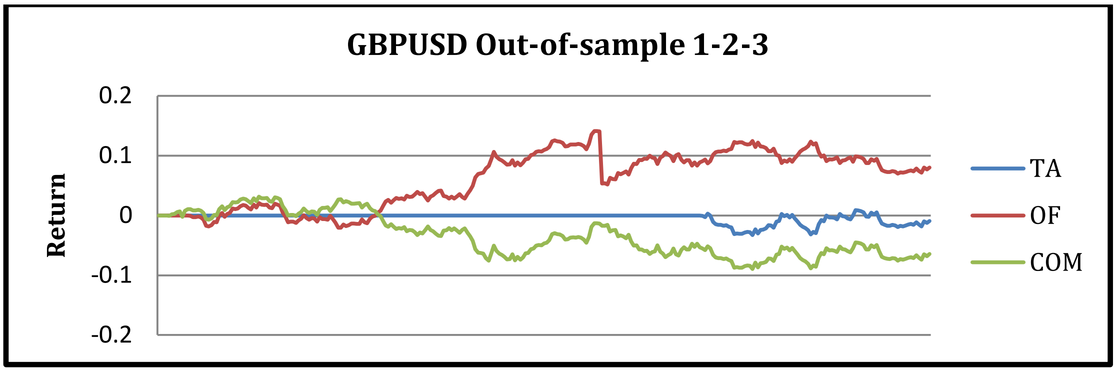
Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the out-of-sample period is period 1 (from August/2002 to October/2003). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-16: USDJPY Out-of-sample Returns

GBPUSD



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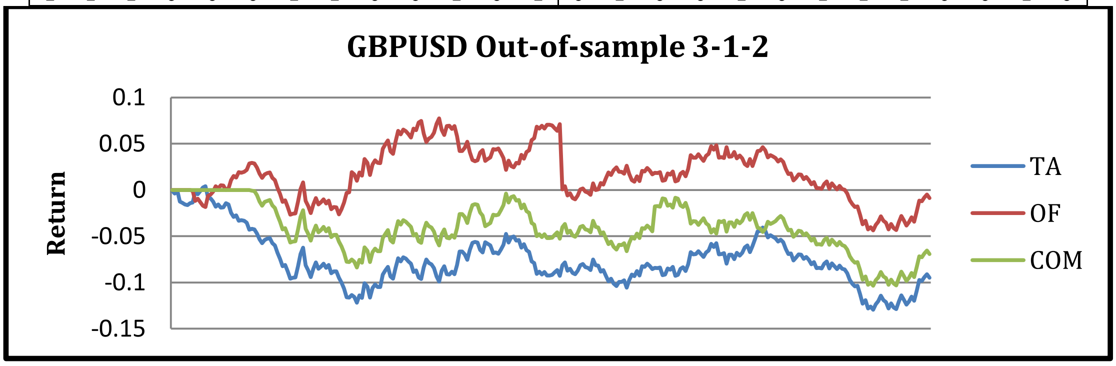

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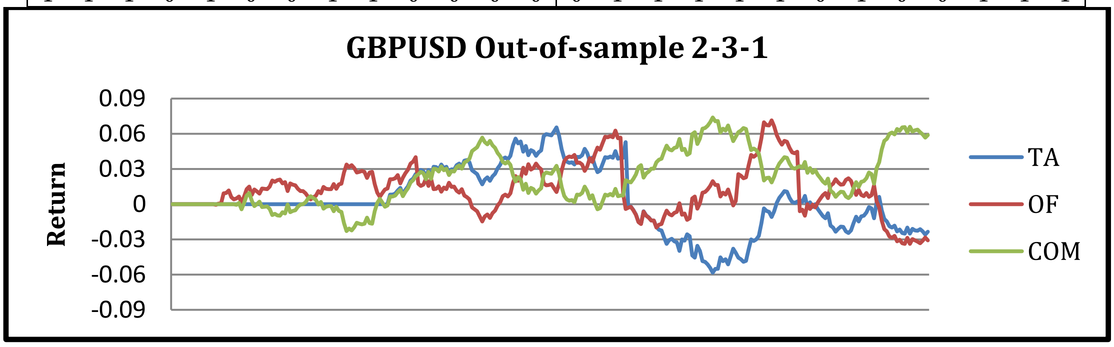

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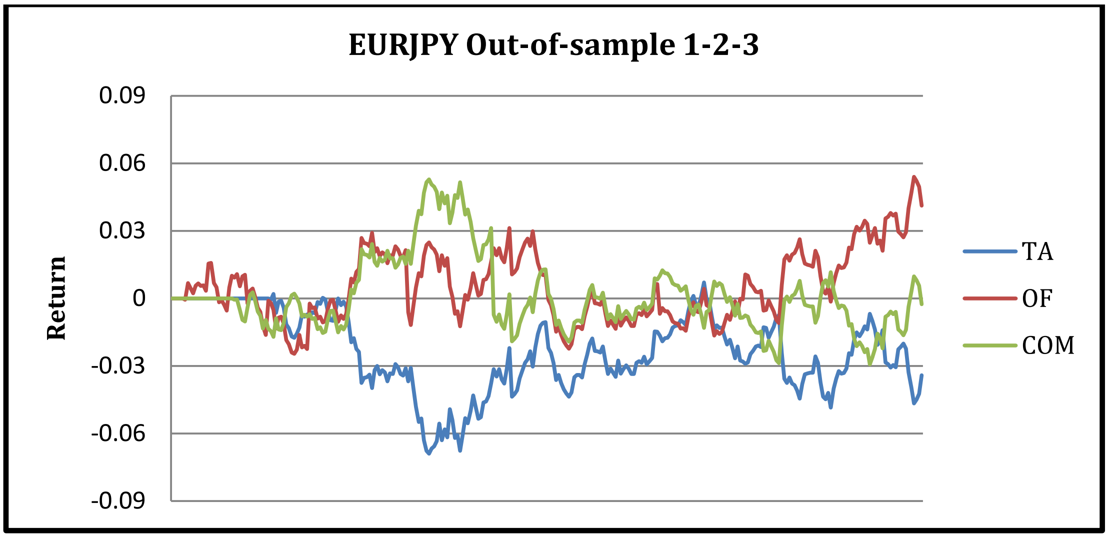
Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the out-of-sample period is period 2 (from October/2003 to December/2004); for 2-3-1, the out-of-sample period is period 1 (from August/2002 to October/2003). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-17: GBPUSD Out-of-sample Returns

EURJPY



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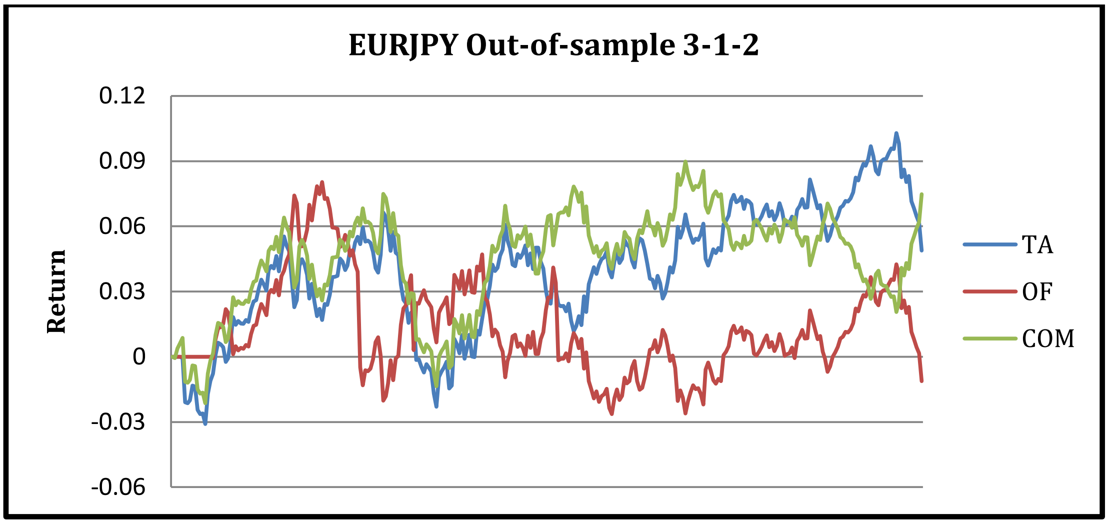

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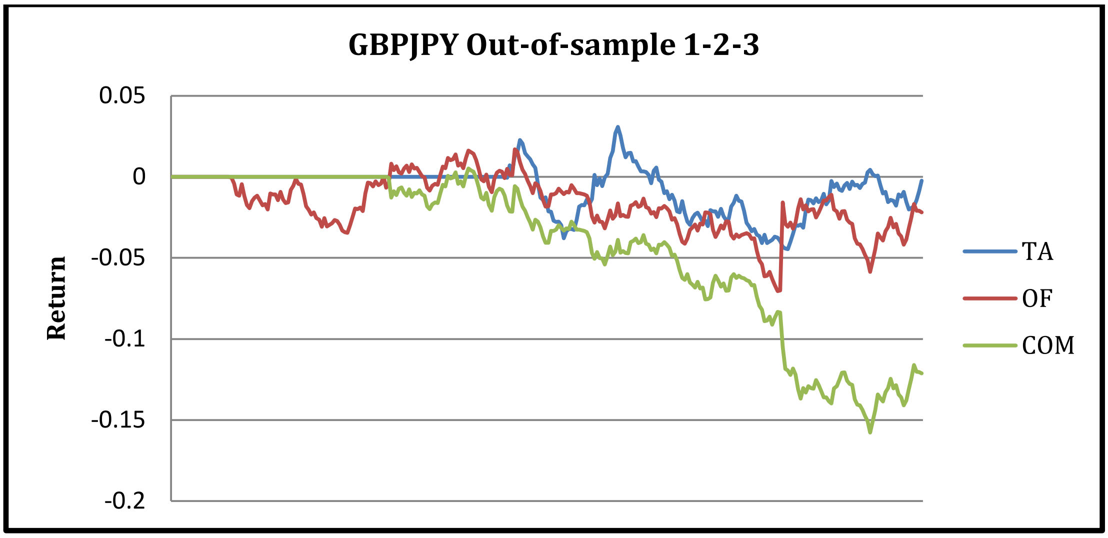
Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the out-of-sample period is period 2 (from October/2003 to December/2004). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-18: EURJPY Out-of-sample Returns

GBPJPY



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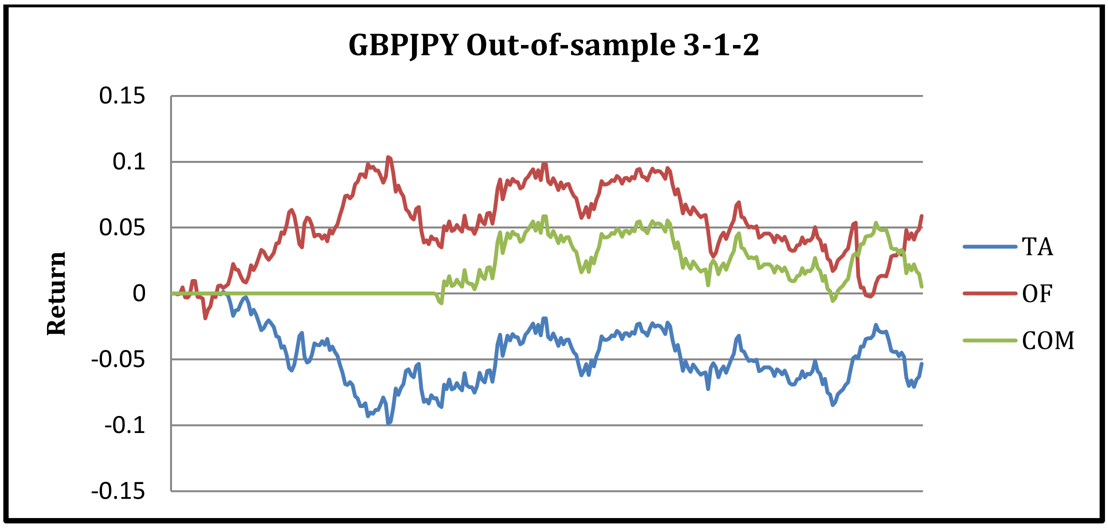

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Notes: The figures report out-of-sample returns for six different interval permutations for EURUSD. The out-of-sample periods are the prediction intervals for every permutation, i.e., for 1-2-3, the out-of-sample period is period 3 (from December/2004 to March/2006); for 3-1-2, the out-of-sample period is period 2 (from October/2003 to December/2004). The blue lines are TA returns, the red lines stand for OF returns, and the green lines represent COM returns. The three rows of 1s and 0s are corresponding buying (first half) and selling (second half) signals for OF, TA, and COM, respectively.

Figure 1-19: GBPJPY Out-of-sample Returns

2 Linear Pure-FX and Cross-Market Daily Order Flow Analysis

2.1 Introduction

In foreign exchange microstructure research, a strong relation between foreign exchange order flows and changes of exchange rates has been theoretically and empirically demonstrated in many studies. Although most of the papers in the microstructure field consider order flows as the transmission vehicle of private information which drive movements of exchange rates, the ultimate forces behind order flows and the nature of the information they contain are still not fully understood. Some argue the information may come from macroeconomic fundamentals or news announcements by investigating critical economic calendars (e.g. Evans and Lyons (2005b, 2007)), while some others believe it may come from technical trading strategies by investigating key price levels in technical analysis (e.g. Osler (2003), Schulmeister (2006)).

With rapid growth of global financial integration and capital internationalization, cross market effects are believed to exist and interactions between foreign exchange and stock markets have attracted attention. Many papers suggest potential links between foreign exchange market and stock markets, such as return spillovers and volatility spillovers (see Ajayi and Mougoue (1996), He and Ng (1998), Fleming, Kirby and Ostdiek (1998)), and some of them even conclude that the cross market effects are due to information spillovers. For example, Fleming et al. (1998) investigate volatility linkages between stock, bond and money markets, and they suggest strong interactions across the different financial markets which are linked through common knowledge such as macroeconomic news and cross market hedging activities.

Although there is a substantial literature on correlations between foreign exchange order flows and exchange rate returns, research about the impact of order flows on other market returns is still rare. Albuquerque, Francisco and Marques (2008) test the roles US stock order flows play in explaining and forecasting exchange rate movements and conclude that market wide private information conveyed in order flows of US stock markets, especially those companies with high export exposures, drives changes of exchange rate to some extent. On the other side, Dunne, Hau and Moore (2006), and Francis, Hasan and Hunter (2006) both investigate effects of currency order flows on stock market movements, and the suggestions that the cross-market informational links might exist re-confirm the possibility of information content carried by order flows across different markets. All the findings suggest the existence of informational links between the two different financial markets, using order flows data in foreign exchange and stock markets.

Inspired by all the cross market literature, in this chapter we investigate the relationship between foreign exchange order flows and fluctuations of stock markets to see if there is interdependence between the two different markets and if any information conveyed in foreign exchange order flows is also relevant to the stock market. With such a unique set of proprietary customer currency order flows data, based on the hypothesis of potential links between the foreign exchange market and stock markets through informational channel, we can investigate impacts of our set of foreign exchange order flows on stock market changes. There might be some other variables or factors which will have impacts on stock markets, however we only look at the information available from perspective of dealers in the foreign exchange market, so we only consider currency order flows and exchange rate changes when we test the relationship between foreign exchange and stock markets. The reasons why we focus on GBPUSD currency pair are as follows: 1) RBS (our order flows data provider) trades through Reuters foreign exchange trading platform which dominates Sterling trading in the currency market; 2) UK and US have two of the most important and most traded stock market exchanges and indices: FTSE 100 and Dow Jones Industrials 30. And also as discussed in chapter 1, in our disaggregated customer order flows data which are categorized into different groups of customers (corporate, unleveraged financial, leveraged financial, and other undefined), the foreign exchange order flows from different types of customers are not obviously correlated and even marginally negatively correlated. The negligible correlations within groups of our data determine the heterogeneity in currency order flows, and together with the advantages of our Sterling currency pairs mentioned above, we consider our GBPUSD customer order flows data representative with a high quality to do research.

Compared to similar work which has been done, our research contributes to the foreign exchange and stock market microstructure literature, especially in the cross market microstructure areas, in several ways:

1) In addition to the well established relations between foreign exchange order flows and exchange rate changes (to re-confirm Evans and Lyons (2002a), among many others), we also investigate whether exist impacts of our set of foreign exchange order flows on stock market returns. To the best of our knowledge, few studies address the relationship between foreign exchange order flows and stock market movements, and Dunne, Hau and Moore (2006) and Francis, Hasan and Hunter (2006) are the only ones related.
2) Compared to the closest two papers, our data has higher qualities in several ways. Francis et. al. (2006) use the foreign currency position of the major foreign exchange market participants as a proxy to foreign exchange order flows (i.e. not truly transacted order flows) on a weekly basis. The reporting lags and the validity of the proxy to order flows cast doubt on their conclusions. While our data used in this chapter are truly order flows, at a daily frequency. Order flows data in Dunne et al. (2006) is from the inter-dealer market and covers a year in 1999, while our data used in this chapter is over 3.5 years from 2002 to 2006. As noted in chapter 1, we believe our data is more representative and good enough to come to concrete conclusions.
3) More importantly, our customer foreign exchange order flows are broken into categories of different counterparties, including corporate customers, unleveraged financial institutions, and leveraged financial institutions. Due to the nature of our disaggregated foreign exchange customer order flow data, we can test the heterogeneity across market participants (in comparison to Dunne et al. (2006) and Francis et al. (2006), none of which can address the effects from different types of customers due to the data they use).
4) We not only investigate statistical relationship between currency order flows and stock market changes, we also check the economic significance of impacts of foreign exchange order flows on stock market returns by testing simple order flows-based trading strategies. To complete our findings, we also evaluate the forecasting power of currency order flows for changes in stock markets over

longer horizons up to 10 days. Based on our hypothesis, if we find positive results, i.e. there exist significant relationships between currency orders and stock market returns, we suggest it could be information content. We try our best to give more interpretations on our findings in later sections and we suggest the links can not be easily explained by other reasons, such as price pressure, or risk premium, etc. We try to conclude that at least a part of private information conveyed in foreign exchange order flows, which was previously thought to be related to macroeconomic fundamentals or technical analysis strategies, is relevant for the stock market.

The remainder of this chapter is structured as follows. The next section 2.2 provides a brief review of the relevant literature about interactions between foreign exchange and stock markets with use of microstructure approaches. Section 2.3 states the descriptions and statistics about our data set and section 2.4 presents methodologies we use and hypotheses we test. In section 2.5 we present the results and suggest some interpretations on our findings. Section 2.6 concludes.

2.2 Literature Review

In this chapter, our main purpose is to test the correlations across different financial markets, i.e. between foreign exchange and stock markets. In this section, we present some key literature related to the cross market effects.

Failures of traditional macro-based exchange rate models (see Meese and Rogoff (1983), Frankel and Rose (1995), among others) inspire the alternative ways to solve the "price determination puzzle" in the foreign exchange market. Evans and Lyons (2002a) include order flow as a variable to explain contemporaneous daily foreign exchange returns and find substantial increase of explanatory power compared to the traditional exchange rate models. The success of microstructure approach to exchange rates confirms the importance of order flows in the foreign exchange market (see survey by Osler (2008)). Osler (2008) surveys the recent empirical literature on foreign exchange microstructure areas and addresses three main explanations that the order flow can help to drive the exchange rate: 1) inventory effect, 2) liquidity effect, 3) private information. Both inventory effect and liquidity effect are normally taking place passively. Like findings by many others (Evans and Lyons (2002a, 2006), Marsh and O'Rourke (2005), Reitz et al. (2007), Osler and Vandrovych (2009), among others), we suggest the customer initiated order flows are due to private information more often than the other two reasons.

As discussed in chapter 1, many suggest that private information conveyed in foreign exchange order flows is related to macroeconomic fundamentals. See Evans and Lyons (2005b, 2007), Rime, Sarno and Sojli (2010) among many others (details of these papers are presented in chapter 1). Moreover, order flows in the foreign exchange market are also related to technical trading strategies. Using a complete set of price contingent orders over a period of nine months, Osler (2003) suggests that executed stop-loss and take-profit orders cluster around some key technical price levels, which partly contribute to the acceleration or reversal of trends in the foreign exchange market when the orders are triggered. Also see Osler (2005). More evidence is provided by Schulmeister (2006), which finds strong mutually reinforcing interactions between order flows and technical trading signals in the foreign exchange market and concludes that foreign exchange order flows are not only driven by announcements of macroeconomic news, but also by technical analysis signals, by investigating 1024 technical trading models based on standard moving average and momentum indicators.

Is there any other source of the information in foreign exchange order flows? We suggest a hypothesis that the private information conveyed in foreign exchange order flows is relevant for stock markets. With increase of international capital flows across countries and easier access to global stock markets, the growing fraction of equity flows in international capital flows underlines the potential relationship between foreign exchange and stock markets. For example, the US gross cross border transactions including equity and bond were equivalent to 4% of GDP in 1975, the figure increased to 100% in 1990, and 245% in 2000, and much of the increase in capital flows is due to trade in equity and debt markets (see Hau and Rey (2006)).

Foreign Exchange and Stock Markets Interactions

Many studies of the relationship between foreign exchange and stock markets have been performed but results are very mixed. Jorion (1990) examines the foreign exposure of US multinational companies and fails to find significant relations between foreign exchange and stock returns, and the value of the dollar differs across the industries of the US stock market. Also see Jorion (1991). Consistent with this earlier research, Bartov and Bodnar (1994) also fail to find a significant correlation between abnormal returns of firms and dollar exchange rate changes, but they do find that lagged changes of dollars can explain the current abnormal returns of stocks. They describe the reasons why the exchange rate movements should affect the stock prices, especially those companies with international activities; and they suggest the mispricing in stock markets contributes to the failure to find contemporaneous relationship between the two different financial markets (i.e. the shocks in exchange rates affect stock markets with delay, as opposed to “instantaneously”). Ajayi and Mougoue (1996) also suggest there are strong relations between the two markets. They show that increases in stock prices have a negative short-run (due to inflation expectations) effect on the local currency and long-run positive effect (due to willingness to hold the local currency denominated assets), while the appreciation of the local currency have positive short-run and long-run effects on the stock prices (they suggest currency depreciation have bad effects on imports and may lead to a bearish stock market). Abdalla and Murinde (1997) investigate the interactions between exchange rates and stock prices in four Asian countries. By applying cointegration approach to a bivariate vector autoregressive model, they find positive results in two of the four countries and unidirectional causality from exchange rates to stock prices in three of the four countries. He and Ng (1998) also confirm the relationship between foreign exchange and stock markets, and conclude that 25 percent of 171 Japanese stocks have economically significant positive exposure effects on stock returns. In addition to the previous studies which focus on return spillovers between different markets, Fleming, Kirby and Ostdiek (1998) investigate volatility linkages between stock, bond and money markets, and they suggest strong interactions across the different financial markets which are linked through common knowledge such as macroeconomic news and cross market hedging activities. The suggested information spillovers suggest one more way to explain the cross market effects.

The previous papers mentioned focus on return or volatility spillovers across different markets (i.e. pure return or volatility relations between foreign exchange and stock markets), in which there is no involvement of information content in order flows. In this chapter we will use foreign exchange order flow as the most important independent variable, so the literature covering international capital flows and foreign exchange order flows are more relevant to us.

Hau and Rey (2004) use portfolio rebalancing theory to test whether international equity flows drive exchange rates and stock prices, and find the relations hold well. Internationally diversified investors hold assets across countries within which the expected returns and risks are balanced. In response to stock and foreign exchange markets shocks, the prices of assets as well as exchange rates will fluctuate, and the new equilibrium require sales of assets in some countries and purchases of assets in others. This generates international capital flows and foreign exchange transactions, when international investors transfer capital from one country to another. Hau and Rey (2006) also find net international equity flows into foreign markets are positively correlated with the appreciation of exchange rates. More importantly, they conclude that with higher ratio of stock market capitalization to GDP, this relation is stronger, which suggests that the interactions between foreign exchange and stock markets exist. Froot, O'Connell and Seasholes (2001) only focus on the impact of international flows on local stock markets without considering the foreign exchange market, although the results are also positive. We conclude from these studies that the capital flows around the globe induced by stock markets have been increasing in recent years, and there might be a potential link between cross border portfolio flows, foreign exchange order flows, stock market flows and the corresponding exchange rates and equity returns.

Some of the literature suggests a positive relation between foreign exchange and stock markets in developed countries, Gyntelberg, Loretan, Subhanij and Chan (2008) consider market microstructure issues of international capital flows in Thailand. This is the first paper in this area which focuses on a developing country. They find positive evidence that the non-resident capital flows into Thailand significantly explain the local returns in Thailand's stock and foreign exchange markets. They conclude that the onshore aggregated foreign exchange customer order flows which are induced by stock market transactions have larger impact on exchange rate, than those flows induced by bond trading. Foreign investors acquire the Thai Baht needed to buy shares in the local stock market by selling US Dollars in the foreign exchange market. They suggest that the private information conveyed in foreign exchange order flows which drive exchange rate might come from stock market. Although this result in only based on a small developing economy which has strict foreign currency control policy, this is still encouraging in explaining the nature of the information carried by order flows.

Cross Market Interactions with Currency and Equity Order Flows

Other than the research on correlations between international capital flows' movements and different financial markets across different financial centers, there are some other studies which use both non-resident and domestic resident flows to analyze market microstructure issues across two or more markets (i.e. they do not differentiate foreign investor initiated flows from domestic resident initiated flows).

Evans and Lyons (2002b) use daily inter-dealer foreign exchange order flows of nine currencies all against US Dollars and find that the combined explanatory power of all nine exchange rates on each single currency pair is substantial, from 45% to 78%. Danielsson, Payne and Luo (2002) use the number of trades as a proxy to foreign exchange order flow, and suggest that GBP exchange rates are dominated by trading flows in EURUSD. Lyons and Moore (2008) also suggest that transactions in the foreign exchange market have effects across currencies by testing the integration of triangular trading of EURUSD, USDJPY, and EURJPY. They indicate that the explanatory power of order flows can be improved by including order flows of other currency pairs. Cai, Howorka and Wongswan (2008) use USDJPY and EURUSD order flows from EBS and suggest informational linkages across different financial centers, based on spillovers in returns, volatilities and order flows across different regions. They find that the information originating from Europe-America overlap trading region is the most important source of spillovers to other regions, and suggest the importance of London as a financial center and the importance of US economic data releases. In this chapter, we use GBPUSD order flows data which are mainly traded during the Europe-America overlapping time.

Although there is a substantial literature on correlations between foreign exchange order flows and exchange rate returns, research about the impact of order flows on other market returns such as stock market is still rare. Francis, Hasan and Hunter (2006) consider the role of currency order flows when dealing with relations between stock and foreign exchange markets. By using the Multivariate-GARCH model, they examine the dynamic relationships between various equity markets and corresponding foreign exchange markets at weekly frequency, suggesting that the return and volatility spillovers between stock and currency markets are very high. Furthermore, they also find that foreign exchange order flows play an important role when explaining stock returns. When controlling for foreign exchange order flows in the return and volatility spillovers model, there is a dramatic reduction in the coefficients of first and second moments of relations between the two different financial markets. They conclude that spillovers between foreign exchange and stock markets are due to information conveyed in foreign exchange order flows. One of the drawbacks in the paper is that they use the foreign currency position of the major foreign exchange market participants as a proxy to foreign exchange order flows (i.e. not truly transacted order flows). The reporting lags and the validity of the proxy to order flows cast doubt on their conclusions. Conversely, our data used in this chapter are truly order flows, which cover a span of three and a half years, at a daily frequency.

Dunne, Hau and Moore (2006) obtain a structural relationship between exchange rates, stock prices and the corresponding equity and foreign exchange order flows, between US and France. They find that the US and French stock market order flows, together with corresponding Euro-Dollar exchange rate returns, jointly explain almost 60% of daily changes in S&P 100 and 40% in CAC 40 indices. They also find brokered inter-dealer foreign exchange order flows contribute to the deviation between US and French equity returns, defined as "US equity return – French equity return – EURUSD return". Order flows data in Dunne et al. (2006) is from inter-dealer market covers a year in 1999, while our data used in this chapter is over 3.5 years from 2002 to 2006. More importantly, our customer foreign exchange order flows are broken into categories of different counterparties, including corporate customers, unleveraged financial institutions, and leveraged financial institutions. According to the structure of our data, we can test the heterogeneity in foreign exchange order flows.

Both Dunne, Hau and Moore (2006) and Francis, Hasan and Hunter (2006) check the impacts of foreign exchange order flows on exchange rate changes. Albuquerque, Francisco and Marques (2008) test relations between the two markets in the opposite direction: order flows in the stock market on exchange rate determination. Stocks in the same industries will be driven by common information and order flows in one industry in the stock market may hold marketwide private information. Especially if the industry has large currency exposure, intuitively the exchange rate returns can be driven by this information (this further expands the well-believed return spillover across different markets, as discussed before in this section). They separate firm-specific and marketwide private information in order flows in the US stock market, and suggest that the marketwide private information derived from order flows in the stock market forecast equity and foreign exchange returns. Chai-Anant and Ho (2008) turn to developing Asian countries and further confirm that the equity order flows have explanatory power for movements of exchange rates.

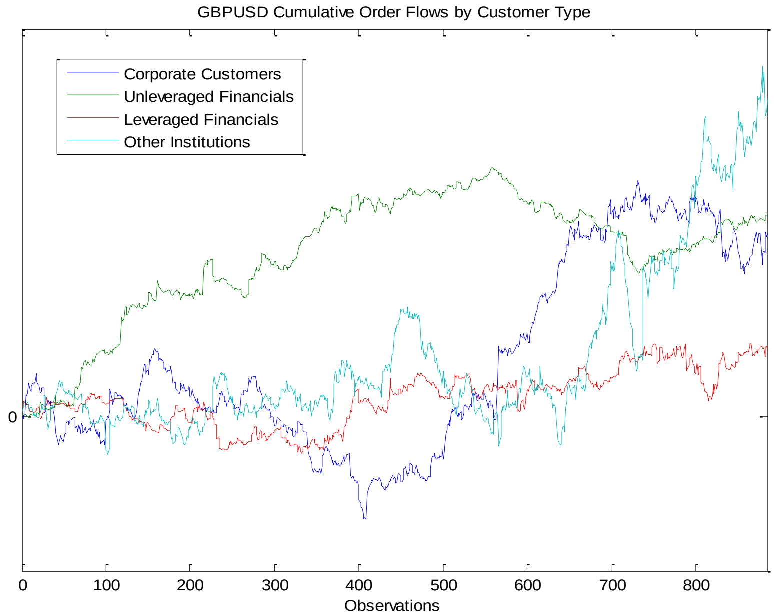
Up to now, we see clear evidence that interactions between different markets (functionally and geographically) around the world exist, and that the foreign exchange and equity order flows might be vehicles of transmissions of private and public information.

2.3 Data

2.3.1 Data Descriptions

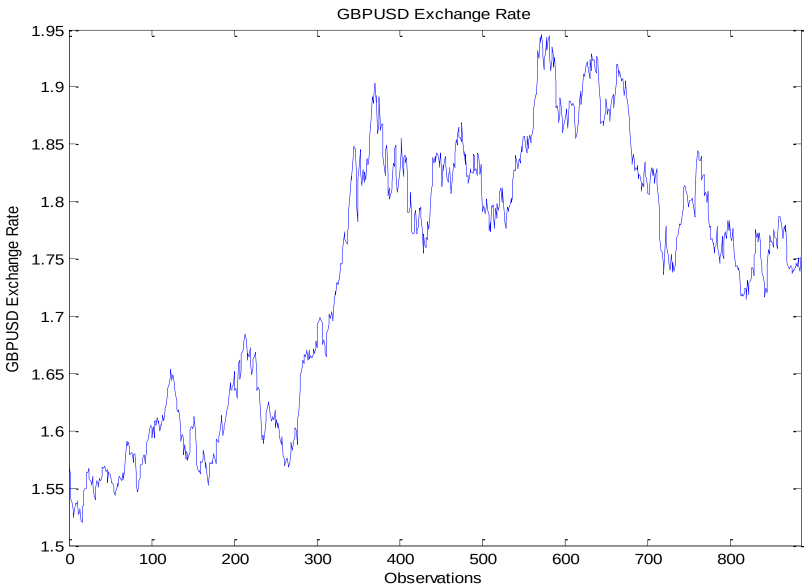
There are three main components of our data we use in this chapter. The first is daily customer foreign exchange order flows, defined as the difference between the value of buyer-initiated transactions and seller-initiated transactions for the base currency. We focus on the flow data of British Pound - US Dollar pair, which is denoted as GBPUSD in the following, and for GBPUSD, the base currency is British pound. The second component of our dataset is the daily price of GBPUSD exchange rate. Both of the first two parts come from Royal Bank of Scotland (RBS) as discussed in chapter 1. The last component of our data is stock market prices, including the daily prices of listed companies in FTSE 100 and DOW JONES INDUSTRIALS (DOW 30 thereafter) as well as the two market indices, and major sector indices of FTSE 350 in the UK and S&P 500 in the US. The stocks data are collected from Datastream.

Same as chapter 1, the GBPUSD order flows data are from RBS, trading through Reuters, which dominates Pound sterling trading in the foreign exchange market. The customer GBPUSD order flow data covers 884 trading days from August of 2002 to March of 2006. The customer order flow in one day is aggregated over 24 hours from midnight London to midnight London the next day. The corresponding exchange rate GBPUSD is the price at 4pm New York time (9pm London time), and then the daily exchange rate return is calculated by log of the prices, which is expressed as the value of US Dollars of one unit of British Pound. Order flows are broken into four groups of customers. Commercial corporations denoted as Corp, include international companies and other non-financial corporations. Financial corporations consist of leveraged financial institutions such as hedge funds (denoted as Lev), and unleveraged real money institutions such as mutual funds and pension funds (denoted as Unlev). Other institutions, denoted as Others, those not covered by the three categories fall into this group. Because of the unknown diversified features of this group, we do not focus on them in this chapter, but we still include this category in our regression models.



Notes: The figure shows the accumulation of GBPUSD order flows from different customers: corporate customers, unleveraged financial customers, leveraged financial customers, and other institutions. The sample period is from 1/Aug/2002 to 2/Mar/2006 (884 trading days).

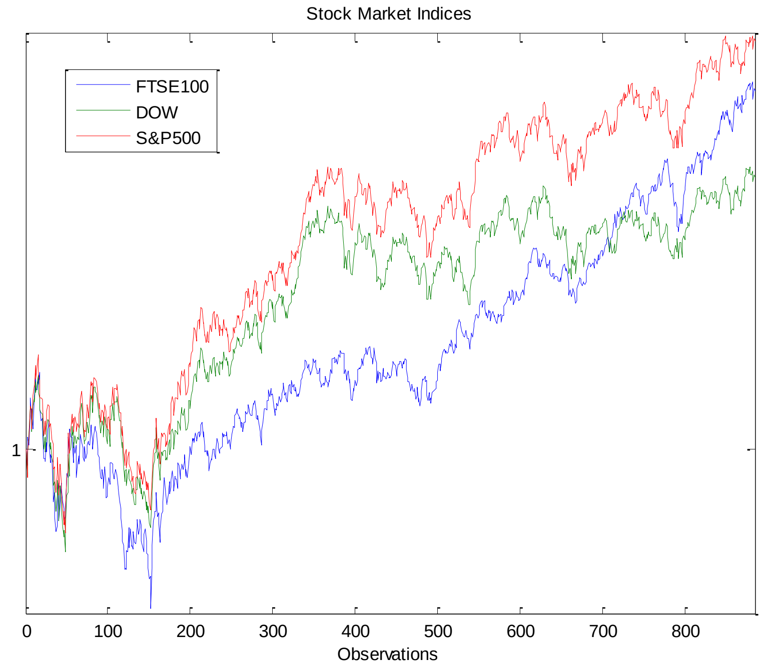
Figure 2-1: GBPUSD Cumulative Order Flows by Customer Type



Notes: The figure shows the price of the GBPUSD exchange rate. The sample period is from 1/Aug/2002 to 2/Mar/2006 (884 trading days).

Figure 2-2: GBPUSD Exchange Rate

In this chapter we focus on two of the most important stock exchanges in the world, London Stock Exchange (LSE) and New York Stock Exchange (NYSE). In terms of trading volume, LSE is the biggest in Europe and so is NYSE in America. We collect closing prices of companies listed in FTSE 100 and DOW 30 and the closing market indices, as well as the closing sector indices from FTSE 350 and S&P 500. The closing time for LSE is 4:30pm GMT (London time), while for NYSE it is 4pm New York time, which is 9pm GMT (London time). FTSE 100 is a capitalization-weighted index and represents the 100 largest UK-domiciled blue chip companies, which counts more than 80% of the capitalization in LSE. DOW 30 is a price-weighted index which consists of 30 blue chip and normally leading companies in their own sectors. Because the constituents in indices are changing all the time, we use the list of companies in December of 2008 for both FTSE 100 and DOW 30. After we date back to cover our sample period (from Aug/2002 to March/2006) and filter out the non-traded companies, we get 84 companies for FTSE and 30 for DOW 30. In addition to individual companies, we also collect closing price data of 32 sectors in FTSE 350 for UK and 14 major sectors in S&P 500 for US.



Notes: The figure reports changes in different stock markets. For simple comparison, the subsequent prices are all divided by the first day price of the corresponding series. The sample period is from 1/Aug/2002 to 2/Mar/2006.

Figure 2-3: Comparative Stock Market Indices

2.3.2 Data Statistics

Because of the high confidentiality of proprietary order flows data, we do not disclose the magnitude of our data. The following two tables provide summary statistics for real and absolute values of order flows of all customer types (table 2-1 and table 2-2).

GBPUSD	Corp	Unlev	Lev	Others	Total
Mean	0.243	0.260	0.085	0.412	1.000
Median	-0.029	0.017	0.003	0.029	0.524
Min	-29.971	-19.861	-36.321	-46.211	-59.341
Max	47.770	31.577	24.455	109.413	99.123
Std. Dev.	6.247	3.415	4.249	8.972	11.853

Notes: The table reports summary statistics for real value of GBPUSD order flows from all groups of customers ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions, "Others" for other customers). All numbers are standardized by dividing the mean value of total order flows. The sample period is 2/Aug/2002-2/Mar/2006.

Table 2-1: Summary Statistics for Real Value of GBPUSD Order Flows

In table 2-1, we find that median number across all categories is around zero, which indicates that the buying and selling orders are nearly balanced over time. From minimum, maximum numbers as well as standard deviations, we conclude that order flows fluctuate substantially over time within each group. And also across all categories, the "others" is the extremely volatile which shows the mixed and unstable feature of this category, and that's one of the reasons we do not focus on this group in our study (we do not find positive evidence even if we want because of this mixed nature, but we still include the category for completeness).

GBPUSD	Corp	Unlev	Lev	Others	Total
Mean	0.505	0.238	0.312	0.705	1.000
Median	0.342	0.139	0.176	0.477	0.689
Min	0.001	0.000	0.000	0.001	0.000
Max	5.767	3.812	4.385	13.209	11.967
Std. Dev.	0.561	0.338	0.407	0.823	1.030

Notes: The table reports summary statistics for absolute value of GBPUSD order flows from all groups of customers ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions, "Others" for other customers). All numbers are standardized by dividing the mean value of total order flows. The sample period is 2/Aug/2002-2/Mar/2006.

Table 2-2: Summary Statistics for Absolute Value of GBPUSD Order Flows

In table 2-2, from the mean number, we observe the average trading size in each group. Together with the mean number in “real number” table, we can get the share of different types of customers through RBS based on two standards. The following table shows the percentage of real and absolute value of average order flows from different customer groups for GBPUSD.

Customer Type	Corp	Unlev	Lev	Others
GBPUSD Share	24.30%	26.00%	8.50%	41.20%

Table 2-3: Share of Different Groups based on Real Order Flows

Customer Type	Corp	Unlev	Lev	Others
GBPUSD Share	28.70%	12.80%	16.80%	37.90%

Table 2-4: Share of Different Groups based on Absolute Order Flows

Table 2-3 and table 2-4 present the share of GBPUSD orders from different customers. In both of the tables, we see share of other customers is highest (41.2% and 37.9%) which imply the diversified nature in that category. When doing regressions, we include all the four groups of customers to reflect the completeness of our findings, even though some group weight is higher. This will make our comparisons across the groups more representative, at least not disguised.

	Corp	Unlev	Lev	Others	FTSE100	DOW	SP500
Corp	1.000						
Unlev	0.039	1.000					
Lev	0.070	0.113	1.000				
Others	-0.118	-0.016	-0.041	1.000			
FTSE100	0.007	-0.006	-0.018	-0.018	1.000		
DOW	0.017	0.004	0.016	-0.017	0.302	1.000	
SP500	0.038	-0.054	0.004	-0.019	0.444	0.578	1.000

Notes: The table reports correlations of 1) GBPUSD order flows between different groups (“Corp” for commercial corporations, “Unlev” for unleveraged financial institutions, “Lev” for leveraged financial institutions, “Others” for other customers) and 2) GBPUSD order flows and changes in market level equity prices. The sample period is 2/Aug/2002-2/Mar/2006.

Table 2-5: Correlations between Order Flows and Stock Market Changes

We see that there are low correlations between commercial corporations, unleveraged and leveraged financial institutions. The contemporaneous correlations between foreign exchange order flows and stock market indices are low as well. Moreover, the correlations between three major equity market indices are relatively high (more than 0.3).

2.4 Methodology & Hypotheses

We will empirically test the following nine hypotheses to explore the relations between foreign exchange customer order flows and stock market returns. All regression equations are estimated by Ordinary Least Square and they are calculated by using robust standard errors to avoid potential heteroskedasticity. In the forecasting regressions, we also include the lagged dependent variables and lagged exchange returns to mitigate potential misspecifications in the models.

Our customer order flows data is GBPUSD, which links the UK and the US. We test the following hypotheses in the UK stock market (FTSE 100 companies, FTSE 100 and FTSE 350 indices, and the major sector indices in FTSE 350), and in the US stock market (the listed companies in DOW 30, the DOW 30 and S&P 500 market indices, and the S&P 500 major sector indices).

In previous sections, we mentioned that most of the empirical studies about foreign exchange order flows in exchange rate microstructure areas suggest significant impact of order flows on contemporaneous exchange rate changes, especially at short to medium-term horizons. Because of the heterogeneity within and across different groups of agents, the dispersed private information carried by order flow is aggregated slowly before being fully priced into exchange rates, which leads to the potential forecasting power of order flows for exchange rate changes. So firstly we briefly test the following relations.

Hypothesis 1: foreign exchange customer order flows are contemporaneously correlated to changes of corresponding exchange rates.

$$R_t^{FX} = C + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$$

H_0: $\beta_i = 0$ for any i;

H_1: $\beta_i \neq 0$ for at least one i.

Hypothesis 2: foreign exchange customer order flows have forecasting power for changes of corresponding exchange rates.

Hypothesis 3: correlations between foreign exchange customer order flows from different groups of customers and fluctuations of corresponding exchange rates are systematically different in size and/or sign.

$$R_{t}^{FX} = C + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta_i OF_{t-1,i}^{FX} + \varepsilon$$

H_0: $\beta_i = 0$ for any i;

H_1: $\beta_i \neq 0$ for at least one i.

Based on the literature surveyed earlier, and of key relevance to this chapter, we also test hypotheses regarding relations between foreign exchange order flows and stock market returns.

We now turn our attention to the cross market effects, i.e. the impacts of foreign exchange order flows on stock market changes. After we check the influence of foreign exchange order flows on stock markets at market and sector levels, we turn into their impacts on individual stocks. We will also check if there are common characteristics among those companies which are affected in the same way. We test the following hypotheses.

Hypothesis 4 & 7: foreign exchange customer order flows have contemporaneous effects on movements of stock market prices, at levels of both indices (**Hypothesis 4**) and individual companies (**Hypothesis 7**).

$$R_t^S = C + \lambda R_t^{FX} + \sum_{i=1}^{4} \beta_i OF_{t,i}^{FX} + \varepsilon$$

H_0: $\beta_i = 0$ for any i;

H_1: $\beta_i \neq 0$ for at least one i.

Hypothesis 5 & 8: foreign exchange customer order flows have forecasting power for movements of stock market prices, at levels of both indices (**Hypothesis 5**) and individual companies (**Hypothesis 8**).

The heterogeneity of different customers in the foreign exchange market has been supported by many studies. Private information conveyed in foreign exchange order flows can drive exchange rates due to heterogeneous investors with different views and expectations. Different customers with their own trading objectives and constraints determine exchange rates in different ways. If foreign exchange order flows do have effects on stock market changes, the heterogeneity should still hold as the following hypothesis.

Hypothesis 6 & 9: foreign exchange customer order flows from different groups with distinct properties and different objectives of trading activities, have different impacts on stock market indices (**Hypothesis 6**) and individual stocks (**Hypothesis 9**).

$$R_t^S = C + \gamma R_{t-1}^S + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta_i OF_{t-1,i}^{FX} + \varepsilon$$

H_0: $\beta_i = 0$ for any i;

H_1: $\beta_i \neq 0$ for at least one i.

For all the regression equations, R^S stands for daily stock market return and R^{FX} stands for exchange rate changes. Foreign exchange order flows are denoted as OF_i^{FX} (i = 1 for non-financial corporations, 2 for unleveraged financial institutions, 3 for leveraged financial institutions, and 4 for other institutions), and C is the constant.

2.5 Empirical Findings

In this section, we empirically test the hypotheses listed in the previous section, about the relations between foreign exchange order flows, exchange rates returns and stock market returns at market, sector and individual company levels.

2.5.1 Hypotheses 1-3 Testing for UK

Hypotheses 1, 2 and 3 state the basic relations between order flows and exchange rate changes in the foreign exchange market. Many papers, including Evans and Lyons (2002a, 2006), Berger et al. (2008), have documented the effect of foreign exchange order flows on exchange rate movements. We find that order flow imbalances between buyer-initiated and seller-initiated transactions have strong contemporaneous influence on changes of corresponding exchange rates (**Hypothesis 1**), but very little predictive power from order flows in this relationship (**Hypothesis 2**). Because of heterogeneity of market participants, e.g. different interpretations of the same information, different expected underlying values of assets and economies, as well as the different trading motives across groups of customers, the flows from various types of market players in the foreign exchange market have different impacts on fluctuations of exchange rates (**Hypothesis 3**). See Evans and Lyons (2006), Marsh and O'Rourke (2005), Osler and Vandrovych (2009), among others. We use the following tables 2-6 and 2-7 to summarize the relationships.

	Coefficient	Std. Error	t-Statistic	Prob.
CORP	-0.0261	0.0274	-0.9507	0.3420
UNLEV	0.1512*	0.0492	3.0747	**0.0022**
LEV	0.2307*	0.0439	5.2555	**0.0000**
OTHERS	0.0028	0.0180	0.1569	0.8754

Notes: The table reports OLS estimates for the regression: $R_t^{FX} = C + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$ for GBPUSD. An asterisk (*) indicates significance at 10% or better. R^2 is 5.7% in the regression. Coefficient stands for the percentage of change in exchange rate for 100 million GBP into the market.

Table 2-6: Effects of GBPUSD Order Flows on Contemporaneous GBPUSD Returns

	Coefficient	Std. Error	t-Statistic	Prob.
CORP	0.0025	0.0254	0.0981	0.9219
UNLEV	0.0382	0.0469	0.8149	0.4154
LEV	-0.0299	0.0365	-0.8208	0.4120
OTHERS	0.0166	0.0174	0.9572	0.3387

Notes: The table reports OLS estimates for the regression: $R_t^{FX} = C + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta i OF_{t-1,i}^{FX} + \varepsilon$ for GBPUSD. R^2 is negligible. Coefficient stands for the percentage of change in exchange rate for 100 million GBP into the market.

Table 2-7: Effects of GBPUSD Order Flows on Future GBPUSD Returns

Our results show that foreign exchange customer order flows from both unleveraged and leveraged financial institutions have significant and positive contemporaneous impact on foreign exchange returns, while the commercial companies-initiated order flows have negative but insignificant correlations with foreign exchange returns. Our findings that the contemporaneous relations between order flows and exchange rates exist with heterogeneous impacts from different types of customers, are consistent with most of the published papers. See Evans and Lyons (2006), Reitz et al. (2007), among others. Although we mentioned before that due to low transparency of the foreign exchange market and gradual learning process of private information conveyed in order flows, foreign exchange order flows could have forecasting power too. However we do not find any in our data set (consistent with the analysis of Marsh and Kyriacou (2007)).

2.5.2 Hypotheses 4-6 Testing for UK

Some studies conclude that the private information carried by order flows in the foreign exchange market, which drive exchange rates, is from the different knowledge of current and expectations of macroeconomic fundamentals, see Evans and Lyons (2007), among others. While some others (see Osler (2003, 2005), Schulmeister (2006)) suggest that the technical trading signals are another force behind order flows which drive movements of exchange rates. The changes in one market might be due to information also relevant to other markets. See Evans and Lyons (2002b), Francis, Hasan and Hunter (2006), Dunne, Hau and Moore (2006), Albuquerque, Francisco and Marques (2008). We empirically test the cross market interactions, i.e. **Hypotheses 4 and 5**: foreign exchange customer order flows have impacts on contemporaneous and future changes in stock markets. We regress the changes of UK stock market and sector indices on different groups of customer order flows in the foreign exchange market, and we find that the contemporaneous correlations are not as significant as that between order flows and foreign exchange returns.

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
FTSE 100	0.0096	0.1727	-0.0106	-0.0940	-0.0420	-0.6067
FTSE 350	0.0076	0.1476	-0.0200	-0.1906	-0.0349	-0.5345
FTSE 100 GROWTH	0.0193	0.3395	0.0081	0.0759	-0.0410	-0.6142
FTSE 100 VALUE	0.0009	0.0160	-0.0275	-0.2283	-0.0425	-0.5785
FTSE 350 GROWTH	0.0182	0.3355	0.0019	0.0182	-0.0361	-0.5593
FTSE 350 VALUE	-0.0010	-0.0208	-0.0381	-0.3531	-0.0338	-0.5023
FTSE 350 AERO/DEFENCE	-0.0167	-0.2142	-0.1143	-1.0510	0.0370	0.4590
FTSE 350 AUTO & PARTS	0.0138	0.1598	-0.0877	-0.5556	0.1207	1.0805
FTSE 350 BANKS	0.0198	0.3126	-0.0577	-0.4540	-0.0670	-0.8393
FTSE 350 BEVERAGES	-0.0506	-1.0353	0.2118	1.7755	0.0533	0.7511
FTSE 350 CHEMICALS	-0.0255	-0.4286	-0.3663	-2.1209	0.0803	0.8370
FTSE 350 CON & MAT	-0.0082	-0.1791	-0.0580	-0.6622	-0.0318	-0.4531
FTSE 350 ELECTRICITY	0.0045	0.0891	-0.0452	-0.4585	0.0464	0.6870
FTSE 350 ELTRO/ELEC EQ	0.1798	1.6051	-0.2643	-0.9342	-0.0056	-0.0401
FTSE 350 EQT IVST INS	-0.0250	-0.6130	-0.0891	-0.8883	0.0018	0.0289
FTSE 350 EX.INV.TRUSTS	0.0082	0.1589	-0.0188	-0.1785	-0.0355	-0.5424
FTSE 350 FD & DRUG RTL	0.0232	0.4204	-0.0470	-0.4120	0.0582	0.7496
FTSE 350 FD PRODUCERS	0.0732	1.4265	0.0674	0.4783	-0.0249	-0.3438
FTSE 350 FXD LINE T/CM	-0.0333	-0.4092	-0.1114	-0.6142	-0.0894	-0.7576
FTSE 350 GEN RETAILERS	-0.0086	-0.1548	-0.1199	-1.2875	0.0122	0.1502
FTSE 350 GENERAL FIN	-0.0197	-0.3856	-0.1604	-1.4244	-0.0366	-0.4825
FTSE 350 H/C EQ & SVS	-0.1070	-1.6665	-0.0955	-0.8033	0.0089	0.0937
FTSE 350 INDS ENG	-0.0331	-0.8248	-0.0999	-1.0889	0.0738	1.1908
FTSE 350 INDS TRANSPT	0.0263	0.5814	0.0424	0.5309	0.0014	0.0258
FTSE 350 INDUSTRIAL MET	0.5455	2.1898	-1.1539	-1.0870	-0.3797	-1.4993
FTSE 350 LIFE INSURANCE	-0.0258	-0.2889	-0.1283	-0.7056	-0.1119	-1.0300
FTSE 350 MEDIA	-0.0181	-0.2772	0.0540	0.3961	-0.0146	-0.1805
FTSE 350 MINING	0.0162	0.1844	-0.0977	-0.6342	-0.0499	-0.4454
FTSE 350 NONLIFE INSUR	-0.0756	-0.6630	-0.1492	-1.2759	-0.0746	-0.8042
FTSE 350 OIL & GAS PROD	0.0299	0.4174	0.1399	0.8983	-0.0595	-0.5419
FTSE 350 PERSONAL GOODS	0.0478	0.7822	0.1318	0.9328	0.0242	0.2628
FTSE 350 PHARM & BIO	0.0402	0.4949	-0.0356	-0.3186	-0.0331	-0.4033
FTSE 350 REAL ESTATE	-0.0903	-1.8771	-0.1012	-1.3627	0.0350	0.5454
FTSE 350 S/W & COMP SVS	0.0023	0.0326	-0.1499	-0.6801	0.0125	0.0886
FTSE 350 SUPPORT SVS	0.0344	0.7087	0.0214	0.1868	0.0130	0.1907
FTSE 350 TCH H/W & EQ	0.2095	1.2148	0.0699	0.2020	-0.1637	-0.9605
FTSE 350 TOBACCO	0.0512	0.9472	0.0870	0.7416	-0.0278	-0.4081
FTSE 350 TRAVEL & LEIS	0.0007	0.0161	-0.0538	-0.5983	0.0375	0.5324

Notes: In the regression $R_t^S = C + \lambda R_t^{FX} + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on concurrent stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is negligible.

Table 2-8: Effects of GBPUSD Order Flows on Contemporaneous UK Stock Market Returns

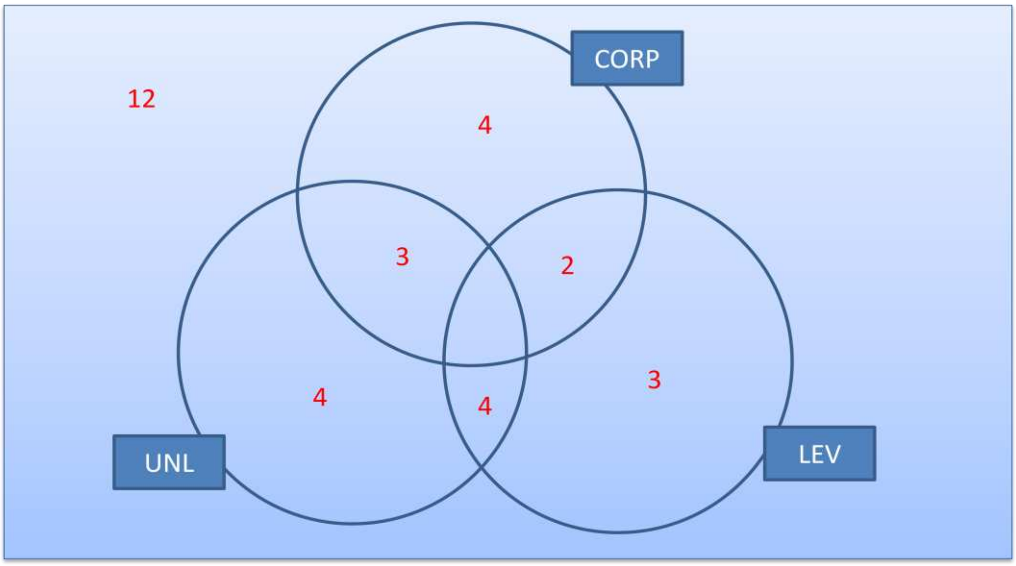
Although we do not observe clear contemporaneous relationship between foreign exchange order flows and the UK stock market, foreign exchange order flows have effects on future changes in the UK stock market.

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
FTSE 100	0.1034	1.9460	-0.1298	-1.3146	0.0598	1.1721
FTSE 350	0.0986	1.9932	-0.1328	-1.4330	0.0648	1.3239
FTSE 100 GROWTH	0.0999	1.8877	-0.1437	-1.4521	0.0810	1.5605
FTSE 100 VALUE	0.1074	1.9641	-0.1165	-1.1346	0.0391	0.7196
FTSE 350 GROWTH	0.0976	1.9131	-0.1462	-1.5317	0.0846	1.6658
FTSE 350 VALUE	0.1001	2.0325	-0.1209	-1.2936	0.0474	0.9350
FTSE 350 AERO/DEFENCE	0.1021	1.4772	-0.1373	-1.0045	0.0700	0.7077
FTSE 350 AUTO & PARTS	0.1612	2.5025	-0.2162	-1.6237	0.1642	1.7453
FTSE 350 BANKS	0.0867	1.4131	-0.2229	-1.9896	0.0603	1.0316
FTSE 350 BEVERAGES	0.0773	1.2758	-0.1181	-0.7450	0.0918	1.4212
FTSE 350 CHEMICALS	0.0457	0.7485	-0.0661	-0.4233	0.0507	0.6103
FTSE 350 CON & MAT	0.0741	1.4675	-0.1626	-2.0106	0.1593	2.4976
FTSE 350 ELECTRICITY	0.0674	1.4151	-0.0444	-0.4945	0.0680	1.0202
FTSE 350 ELTRO/ELEC EQ	0.1663	1.3868	-0.4187	-2.0814	0.0563	0.3469
FTSE 350 EQT IVST INS	0.0906	2.1414	-0.1710	-2.0321	0.0236	0.4477
FTSE 350 EX.INV.TRUSTS	0.0988	1.9875	-0.1320	-1.4195	0.0654	1.3348
FTSE 350 FD & DRUG RTL	0.0813	1.4664	0.0403	0.4397	0.0320	0.4154
FTSE 350 FD PRODUCERS	0.0484	0.9707	-0.1559	-0.7528	0.0019	0.0278
FTSE 350 FXD LINE T/CM	0.1328	1.5116	-0.0575	-0.2865	-0.0506	-0.5123
FTSE 350 GEN RETAILERS	0.0865	1.7131	-0.0397	-0.3523	0.0943	1.2755
FTSE 350 GENERAL FIN	0.0668	1.2352	-0.1618	-1.5362	0.1694	2.4563
FTSE 350 H/C EQ & SVS	0.0641	1.1033	-0.1851	-1.4399	0.1534	1.7397
FTSE 350 INDS ENG	0.0773	1.5548	-0.2116	-2.2493	0.1190	1.7258
FTSE 350 INDS TRANSPT	0.1211	2.7267	-0.1049	-1.2645	0.0651	1.0663
FTSE 350 INDUSTRIAL MET	0.1023	0.3881	-1.0766	-1.4947	0.1921	0.6740
FTSE 350 LIFE INSURANCE	0.1724	1.8337	-0.2923	-1.6805	0.0182	0.1765
FTSE 350 MEDIA	0.0578	0.8504	-0.1349	-1.1621	0.1974	2.4612
FTSE 350 MINING	0.1175	1.5024	-0.2713	-2.0125	0.0938	0.8253
FTSE 350 NONLIFE INSUR	0.0992	1.5015	-0.1960	-1.5193	0.0212	0.2713
FTSE 350 OIL & GAS PROD	0.1156	1.4907	-0.0649	-0.4796	0.0726	0.8199
FTSE 350 PERSONAL GOODS	-0.0263	-0.3980	0.0268	0.1863	0.0601	0.6984
FTSE 350 PHARM & BIO	0.1365	2.0303	-0.1994	-1.5097	0.0585	0.6646
FTSE 350 REAL ESTATE	0.0460	1.0079	-0.0825	-0.9702	-0.0096	-0.1734
FTSE 350 S/W & COMP SVS	-0.0170	-0.2036	-0.2578	-1.6581	0.1023	0.9534
FTSE 350 SUPPORT SVS	0.0741	1.5676	-0.2802	-2.8733	0.1141	1.9161
FTSE 350 TCH H/W & EQ	0.3066	1.8913	-0.3951	-1.1993	0.2785	1.7378
FTSE 350 TOBACCO	0.0750	1.4164	0.1781	1.8667	-0.1373	-2.0197
FTSE 350 TRAVEL & LEIS	0.0742	1.6621	-0.0478	-0.5041	0.1062	1.6752

Notes: In the regression $R_t^S = C + \gamma R_{t-1}^S + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta i OF_{t-1,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-9: Effects of GBPUSD Order Flows on Future UK Stock Market Returns

We test FTSE 100 and FTSE 350 indices, the corresponding growth and value indices, and FTSE 350 sector indices including main 32 sectors in the UK, making 38 indices in total. We do not find strong contemporaneous relations between foreign exchange order flows and stock market returns, but we find statistically significant one day ahead forecasting power of order flows for the UK stock market changes, in some of the sectors and market indices. We use the figure 2-4 to present our findings on FTSE 350 sector indices,



Notes: The figure shows the number of FTSE 350 sector indices which are significantly affected by GBPUSD order flows from different groups of customers. The number outside circles means the number of sectors which are not affected by any group of customers ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions).

Figure 2-4: UK Stock Market Results for Sectors

For market level indices (FTSE100, FTSE350 and corresponding growth and value indices), all 6 indices for commercial corporations are statistically significant but only one in total for the two types of financial institutions (1 out of 12) are significant, at the 90 percent confidence level. Quantitatively for sector level indices, 9 out of 32 sector indices for commercial corporations, 10 out of 32 for unleveraged financial institutions and 10 out of 32 for leveraged financial institutions are statistically significant. 9 sector indices are significantly affected by two different categories of order flows, while only 12 sector indices are not affected at all by foreign exchange order flows. The findings suggest that,

1) The information conveyed in foreign exchange order flows may be at least partly relevant for stock markets.
2) Order flows in the foreign exchange market at day t are not fully priced by the stock market at the same day, and the effects show up in the following day, t+1. The lagged effect from order flows on stock market may be as a result of the gradual learning process across markets.
3) Commercial corporations have some forecasting power for the stock market, which act totally differently from they do in the foreign exchange market, where they have neither contemporaneous impact nor forecasting power for exchange rate changes. Foreign exchange order flows from both unleveraged and leveraged financial institutions also have predictive power for stock market returns, together with the contemporaneous association between their foreign exchange order flows and exchange rates.

Perhaps the key finding in this chapter is that foreign exchange order flows from different groups of customers have different impact on stock market returns. That's our **Hypothesis 6**. We illustrate the difference with red and blue colors in the results table. We briefly list the relations in the follow summary table 2-10.

FX Order Flows	UK Stock Returns
CORP	+
UNLEV	-
LEV	+

Notes: The table reports dominant signs of effects of order flows from different customers ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions) on future UK stock market changes.

Table 2-10: Signs of Effects of FX order flows on the UK stock market

We find that foreign exchange order flows from commercial corporations have a positive impact on the next day stock market returns, order flows from unleveraged and leveraged financial institutions have negative impacts on stock market returns at day t+1, and flows from leveraged financial institutions have positive impacts on stock market returns (order flows from other institutions are very mixed, so we exclude this category). In addition to the statistical significance in the regressions models, we present more about signs of coefficients for all indices from the three different groups to underline the dominance and uniformity in every category. For commercial companies, the coefficients of all but 2 out of 38 market and sector indices returns are positive. For unleveraged and leveraged financial institutions, the coefficients of all but 3 out of 38 are negative and positive, respectively. The result indicates the consistency of our findings across the UK stock market.

The existing correlations between foreign exchange order flows, exchange rate returns and stock market returns imply that at least a part of private information conveyed in foreign exchange order flows is relevant for the stock market. Due to different objectives of trading activities and heterogeneous views on economies or values of financial assets, the impacts of foreign exchange order flows from various types of customers on stock market are totally different. The following table shows the impacts of foreign exchange order flows on same day changes of exchange rates and next day stock market returns.

FX Order Flows	FX Returns	UK Stock Returns
CORP	-	+
UNLEV	+*	-
LEV	+*	+

Notes: The table reports signs of effects of order flows from different customers ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions) on contemporaneous exchange rate and future UK stock market changes. An asterisk (*) indicates significance at 10% or better, in "FX Returns" column. The signs in "UK Stock Returns" indicate the significantly dominant ones in that category of customers.

Table 2-11: Signs of Effects of FX order flows on FX and UK stock markets

For non-financial corporations, the non-informative group of order flows we previously thought uninformative in the foreign exchange market seems to have some information about stock market values. When the commercial companies buy British Pounds in the foreign exchange market at day t, UK stock market will go up at day t+1, although the exchange rate GBPUSD will not be affected significantly, either on day t or day t+1.

We do not see common links among the sectors of which the relations between foreign exchange order flows and stock market prices are significant. For example, they are not all capital intensive sectors nor are they all export-oriented sectors. Albuquerque et al. (2008) suggest the companies which have currency exposures will have impact on exchange rates, but here we do not observe noticeable currency exposures in the related stock sectors. We can see more about this in the following individual stocks results.

For unleveraged financial institutions, we know from previous results that foreign exchange order flows in this group have a significant positive impact on exchange rate changes. But we find that in the UK stock market, the foreign exchange order flows from unleveraged financial institutions have negative impact on next day stock market returns. When unleveraged institutions buy British Pounds in the foreign exchange market at day t, the UK stock market will decrease at day t+1.

For leveraged financial institutions, we find that foreign exchange order flows in this group have a positive impact on contemporaneous exchange rate returns as well as next day stock market returns. When leveraged financial institutions buy British Pounds in the foreign exchange market at day t, the UK stock market will increase at day t+1.

2.5.3 Hypotheses 7-9 Testing for UK

After considering the impact of foreign exchange order flows on stock markets at market and sector levels, according to **Hypotheses 7, 8 and 9**, we will check the relations between foreign exchange order flows from the three different categories and individual companies in the UK stock market. We can further confirm the relations between the two different financial markets and see if there are any common features within companies which report significant coefficients. Magnitudes of coefficient estimates mean the change in stock market prices with 100 million British Pounds into the market. The details are shown in the following tables 2-12 and 2-13.

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
Alliance Trust PLC	-0.0327	-0.8699	-0.0780	-0.8937	-0.0030	-0.0500
Amec PLC	0.0760	0.8498	-0.0215	-0.1108	0.0451	0.3794
Anglo American PLC	0.0133	0.1349	-0.1218	-0.6774	-0.0872	-0.6833
Antofagasta PLC	0.0294	0.3981	0.1014	0.7035	-0.1770	-1.4756
Associated British Foods PLC	-0.0181	-0.3051	0.0393	0.3456	-0.0301	-0.4094
Astrazeneca PLC	-0.0453	-0.4738	-0.0332	-0.1893	0.0242	0.2505
Autonomy Corp. PLC	-0.1803	-1.1798	-0.3771	-1.1628	0.0738	0.2619
Aviva PLC	0.0160	0.1596	-0.0785	-0.3726	-0.1741	-1.2815
BAE Systems PLC	0.1072	0.8497	-0.1332	-0.7179	0.0597	0.4471
Barclays PLC	-0.0004	-0.0051	-0.0344	-0.1994	-0.0956	-0.8555
BG Group PLC	0.0237	0.3015	0.1212	0.7271	0.1477	1.2070
BHP Billiton PLC	-0.0257	-0.2800	-0.1104	-0.6810	0.0204	0.1660
BP PLC	0.0265	0.3519	0.1193	0.7408	-0.0788	-0.6574
British Airways PLC	-0.0386	-0.3648	-0.1428	-0.5281	-0.0140	-0.0867
British American Tobacco PLC	0.0373	0.5743	0.1153	1.0319	-0.0334	-0.4096
British Land Company PLC	-0.1387	-2.1609	-0.1627	-1.5447	0.0190	0.2060
British Sky Broadcasting PLC	-0.0379	-0.3548	0.0551	0.3039	0.0541	0.5027
BT Group PLC	-0.0649	-0.7083	-0.0688	-0.3270	0.0314	0.2572
Bunzl PLC	-0.0041	-0.0540	0.1211	0.8141	-0.0201	-0.1861
Cable & Wireless PLC	0.2539	1.3085	0.3434	0.8364	-0.0791	-0.3952
Cadbury PLC	0.0964	1.4470	0.0489	0.3492	0.0420	0.5067
Cairn Energy PLC	-0.0068	-0.0744	0.5290	2.4974	-0.1056	-0.6264
The Capita Group PLC	0.0474	0.4946	0.0810	0.3636	-0.0527	-0.3726
Carnival PLC	0.0469	0.5306	-0.0328	-0.2236	-0.0248	-0.2269
Centrica PLC	0.0047	0.0664	0.0867	0.6173	0.0483	0.4774
Cobham PLC	-0.0323	-0.5242	-0.1401	-1.3505	0.0386	0.4164
Compass Group PLC	-0.1502	-0.9778	0.2483	1.1227	-0.1525	-1.0290
Diageo PLC	-0.0820	-1.4771	0.2119	1.4620	0.0410	0.5766
First Group PLC	0.0265	0.3640	0.3122	1.9376	-0.0821	-0.7716
Friends Provident PLC	0.0041	0.0404	-0.3537	-1.6046	-0.1082	-0.7612
G4S PLC	0.0378	0.3504	-0.1378	-0.6566	-0.0097	-0.0682
Glaxosmithkline PLC	0.0899	1.0261	-0.0603	-0.5117	-0.0725	-0.7749
Hbos PLC	-0.0038	-0.0380	0.0097	0.0533	0.0189	0.1682
HSBC Holdings PLC	0.0361	0.6398	-0.1226	-1.0263	-0.0668	-0.8800
Icap PLC	-0.0222	-0.3266	-0.0798	-0.5233	-0.0972	-1.0068
Imperial Tobacco Group PLC	0.0296	0.4796	0.0638	0.4090	-0.0497	-0.6058
International Power PLC	-0.0610	-0.6102	-0.1236	-0.6601	-0.2104	-1.3997
Invensys PLC	0.2361	1.0869	-0.2080	-0.4394	-0.0905	-0.3081
Johnson Matthey PLC	-0.0467	-0.6798	-0.0989	-0.6335	0.0547	0.5624
Kingfisher PLC	-0.0831	-0.9311	-0.2584	-1.5235	0.1338	1.1115
Land Securities Group PLC	-0.0960	-1.3959	-0.0690	-0.7005	0.0173	0.1868
Legal & General Group PLC	-0.0152	-0.1496	-0.1227	-0.6641	-0.1140	-0.9177
Liberty International PLC	-0.0160	-0.3292	-0.0951	-0.9319	0.0251	0.3510
Lloyds TSB Group PLC	-0.0646	-0.7278	-0.0730	-0.4143	-0.0942	-0.8967
London Stock Exchange Group PLC	-0.0707	-0.9084	-0.1639	-1.1954	0.0071	0.0766
Lonmin PLC	0.1451	1.4399	-0.0298	-0.1835	-0.0269	-0.2391
Man Group PLC	0.0112	0.1441	-0.1191	-0.7858	-0.0929	-0.8536
Marks & Spencer Group PLC	0.0078	0.0960	0.1244	0.7758	0.0484	0.4237
National Grid PLC	-0.0214	-0.3516	0.0415	0.3441	-0.0584	-0.7208
Next PLC	-0.1306	-1.6672	-0.2571	-1.4032	-0.0144	-0.1209
Old Mutual PLC	-0.0173	-0.1744	-0.0461	-0.2512	-0.1529	-1.0700
Pearson PLC	-0.0306	-0.3697	0.1802	1.0249	-0.1098	-1.0110
Prudential PLC	-0.0603	-0.5364	-0.0901	-0.3726	-0.1237	-0.9113
Reckitt Benckiser PLC	0.0587	0.9096	0.1638	1.1258	0.0109	0.1101

Reed Elsevier PLC	0.0728	0.8908	0.0044	0.0277	-0.0269	-0.3190
Rexam PLC	-0.0304	-0.4905	0.2425	1.4017	-0.0393	-0.4046
Rio Tinto PLC	0.0546	0.5664	-0.0013	-0.0078	-0.0657	-0.5369
Rolls-Royce Group PLC	-0.0872	-0.8663	-0.0076	-0.0328	0.0597	0.4980
Royal Bank Of Scotland Group PLC	0.0392	0.4184	0.0459	0.3085	-0.1389	-1.3690
Royal Dutch Shell PLC	0.0228	0.2892	0.2460	1.4084	-0.1039	-0.9117
RSA Insurance Group PLC	-0.1724	-0.8706	-0.2363	-0.9424	-0.1525	-0.8484
Sabmiller PLC	0.0263	0.3869	0.1702	1.4084	0.0320	0.2810
The Sage Group PLC	-0.0029	-0.0270	-0.2312	-0.8074	0.0149	0.0861
Sainsbury (J) PLC	0.0026	0.0336	-0.0498	-0.2973	0.0085	0.0782
Schroders PLC	-0.0130	-0.1240	-0.1086	-0.4160	-0.0698	-0.4680
Scottish & Southern Energy PLC	0.0223	0.3951	-0.0895	-0.6939	0.0595	0.8319
Severn Trent PLC	0.0026	0.0390	-0.1163	-0.9886	-0.0686	-0.8811
Shire PLC	0.1603	1.4517	-0.0163	-0.0853	-0.0427	-0.3692
Smith & Nephew PLC	-0.1095	-1.3654	-0.2255	-1.4904	-0.0590	-0.4999
Smiths Group PLC	-0.0971	-1.0851	-0.1131	-0.9266	-0.0187	-0.2264
Stagecoach Group PLC	-0.1063	-0.7747	0.5009	1.8047	-0.1647	-0.8728
Standard Chartered PLC	0.0792	0.9967	-0.0562	-0.3861	-0.1534	-1.3144
Tesco PLC	0.0527	0.7914	-0.0805	-0.5636	0.0726	0.7636
Thomson Reuters PLC	-0.1766	-1.1816	0.2721	1.1198	-0.0678	-0.3955
TUI Travel PLC	0.0597	0.7526	0.2217	1.3615	0.1100	1.0043
Unilever PLC	0.0890	1.4015	0.1152	0.6166	-0.0578	-0.5934
United Utilities Group PLC	-0.0474	-0.7258	-0.1325	-1.3202	0.1046	1.2558
Vodafone Group PLC	-0.0173	-0.1851	-0.1244	-0.6218	-0.1160	-0.8776
Whitbread PLC	-0.0389	-0.6798	-0.0266	-0.1827	-0.0086	-0.1070
Wolseley PLC	-0.0878	-1.2018	0.1489	1.1052	-0.0452	-0.4140
Wood Group (John) PLC	0.0659	0.5800	-0.2553	-1.2589	0.1174	0.8151
WPP Group PLC	0.0251	0.2800	0.1333	0.7234	-0.0030	-0.0256
Xstrata PLC	0.0030	0.0323	-0.4498	-2.1745	-0.0927	-0.6170
3I Group PLC	-0.0372	-0.4387	-0.0299	-0.1313	-0.0042	-0.0334

Notes: In the regression $R_t^S = C + \lambda R_t^{FX} + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on concurrent stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is negligible.

Table 2-12: Effects of GBPUSD Order Flows on Contemporaneous UK Stock Market Returns

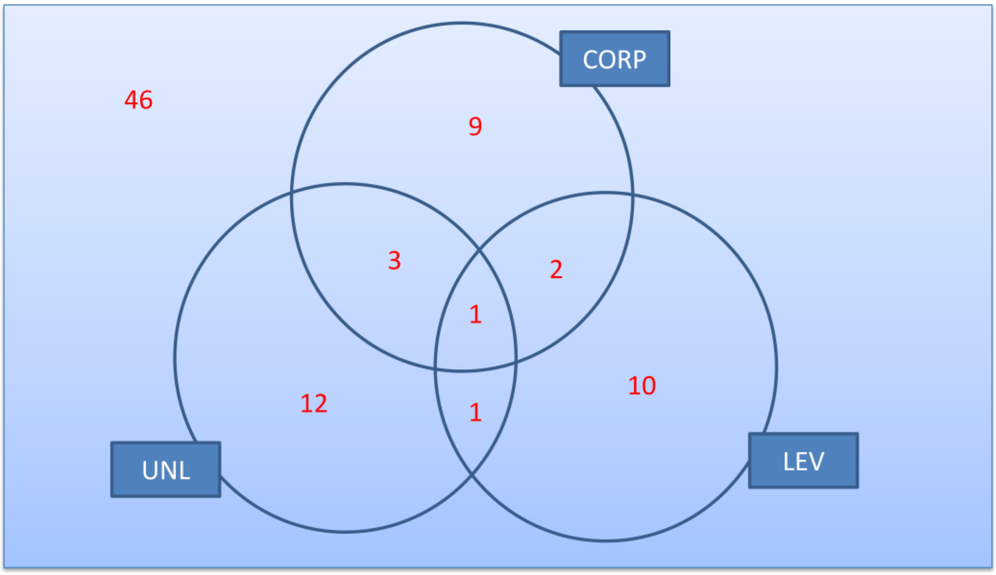
Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
Alliance Trust PLC	0.0833	1.9901	-0.1862	-2.1472	0.0229	0.4288
Amec PLC	0.1567	1.3744	-0.2486	-1.2007	-0.0196	-0.1316
Anglo American PLC	0.1498	1.6504	-0.4725	-2.9959	0.1189	0.9151
Antofagasta PLC	0.0354	0.4715	0.0409	0.2938	-0.0690	-0.5468
Associated British Foods PLC	0.0414	0.7176	-0.0523	-0.4147	0.1062	1.4622
Astrazeneca PLC	0.1970	2.4482	-0.2064	-1.2348	0.0147	0.1309
Autonomy Corp. PLC	0.3253	1.9998	-0.1020	-0.4154	-0.0909	-0.2195
Aviva PLC	0.1180	1.1030	-0.3951	-1.6810	-0.1841	-1.4182
BAE Systems PLC	0.0899	0.7540	-0.4198	-1.8534	0.1386	0.8337
Barclays PLC	0.0975	1.0994	-0.2228	-1.5407	0.2084	2.1381
BG Group PLC	0.0300	0.3440	-0.0864	-0.6106	0.1082	1.1279
BHP Billiton PLC	0.1298	1.4232	-0.1089	-0.7047	0.0506	0.3908
BP PLC	0.0986	1.1782	-0.1053	-0.7172	0.0601	0.5825
British Airways PLC	-0.0296	-0.2104	-0.3976	-1.3147	0.0768	0.4001
British American Tobacco PLC	0.0609	1.0287	0.1461	1.2148	-0.1903	-2.4984
British Land Company PLC	0.0208	0.3015	0.0678	0.5389	-0.0124	-0.1290
British Sky Broadcasting PLC	0.0691	0.7979	-0.1157	-0.8212	0.2557	1.8718
BT Group PLC	0.1386	1.5397	0.0511	0.3071	0.0298	0.2830
Bunzl PLC	0.0640	0.9598	-0.2807	-1.9127	0.1720	1.7528
Cable & Wireless PLC	-0.1009	-0.7486	0.2243	0.9221	-0.0309	-0.1945
Cadbury PLC	0.0435	0.6410	-0.0531	-0.3638	-0.0633	-0.7123
Cairn Energy PLC	0.1014	0.9625	0.1024	0.5503	0.0989	0.6218
The Capita Group PLC	0.1685	1.5998	-0.2059	-1.0135	0.1914	1.4440
Carnival PLC	0.0589	0.7211	-0.0494	-0.3647	0.1288	1.1589
Centrica PLC	0.0915	1.0029	0.1921	1.0497	0.0433	0.4297
Cobham PLC	0.0514	0.8629	-0.0220	-0.1790	0.0289	0.3277
Compass Group PLC	0.1341	1.1615	-0.5223	-2.6000	0.0007	0.0043
Diageo PLC	0.0736	1.0704	-0.0994	-0.6047	0.0995	1.3693
First Group PLC	-0.0088	-0.1195	-0.1807	-1.1803	0.1681	1.4102
Friends Provident PLC	0.1457	1.2960	-0.5686	-2.8200	0.1741	1.2722
G4S PLC	0.2310	2.3659	0.1397	0.6606	0.0561	0.4295
Glaxosmithkline PLC	0.1089	1.4862	-0.2307	-1.5468	0.0946	0.9626
Hbos PLC	0.0183	0.1981	-0.3198	-1.6404	0.0326	0.3661
HSBC Holdings PLC	0.0999	2.1011	-0.1704	-1.5862	0.0183	0.3347
Icap PLC	0.0761	1.0411	-0.0688	-0.5287	0.1648	1.4046
Imperial Tobacco Group PLC	0.0477	0.7612	0.1635	1.5415	-0.0959	-1.1445
International Power PLC	0.1885	1.6945	-0.3063	-1.0893	0.4764	2.5230
Invensys PLC	0.1569	0.7681	-0.9202	-2.4358	0.1455	0.4648
Johnson Matthey PLC	0.1497	2.1682	-0.0196	-0.1309	0.1642	1.6526
Kingfisher PLC	0.1177	1.3768	0.0800	0.4966	0.0036	0.0328
Land Securities Group PLC	0.0752	1.1994	-0.0993	-0.9145	-0.0503	-0.6273
Legal & General Group PLC	0.1272	1.1802	-0.2569	-1.2173	0.1183	0.8934
Liberty International PLC	-0.0048	-0.0865	-0.0626	-0.6335	-0.0001	-0.0022
Lloyds TSB Group PLC	0.0647	0.6940	-0.3199	-1.8339	0.1637	1.6334
London Stock Exchange Group PLC	0.1289	1.7723	-0.2656	-1.9078	0.2620	2.4955
Lonmin PLC	0.2362	1.9142	-0.3633	-1.7150	-0.0558	-0.3634
Man Group PLC	-0.0656	-0.9007	0.1217	0.6130	0.0815	0.7281
Marks & Spencer Group PLC	0.1461	1.9787	-0.0505	-0.2800	0.0187	0.1161
National Grid PLC	0.0303	0.5215	-0.2418	-1.9514	0.1234	1.5994
Next PLC	0.1137	1.6089	-0.0606	-0.3113	0.2079	2.1573
Old Mutual PLC	0.1364	1.4853	-0.0448	-0.2632	0.0896	0.7347
Pearson PLC	0.0528	0.6289	-0.3313	-1.7792	0.1018	1.0134
Prudential PLC	0.2407	2.1542	-0.3082	-1.3671	0.2184	1.5086
Reckitt Benckiser PLC	-0.0248	-0.3594	0.0410	0.2652	0.0733	0.8062

Reed Elsevier PLC	0.1218	1.2544	-0.0651	-0.5339	0.1655	1.5889
Rexam PLC	0.0680	1.0225	-0.2395	-1.6251	0.2266	2.5865
Rio Tinto PLC	0.0886	1.0937	-0.2829	-1.7426	0.1005	0.8152
Rolls-Royce Group PLC	0.0136	0.1442	-0.5557	-2.2763	0.0450	0.3147
Royal Bank Of Scotland Group PLC	0.0678	0.8089	-0.1770	-1.1460	0.0306	0.3502
Royal Dutch Shell PLC	0.1780	2.3672	-0.0624	-0.4058	0.0904	1.0340
RSA Insurance Group PLC	0.1294	0.9079	-0.2453	-0.8426	0.0439	0.2566
Sabmiller PLC	0.0871	1.2645	-0.0582	-0.3063	0.0298	0.3297
The Sage Group PLC	-0.0745	-0.5772	-0.2425	-1.2053	0.0480	0.3154
Sainsbury (J) PLC	0.0411	0.5746	0.1074	0.6777	0.0296	0.2835
Schroders PLC	0.0961	0.9586	-0.3629	-1.8453	0.1518	1.1801
Scottish & Southern Energy PLC	0.0570	1.2015	0.1356	1.2700	0.0087	0.1188
Severn Trent PLC	0.1170	1.6705	-0.0518	-0.4700	0.0177	0.2068
Shire PLC	0.0704	0.7174	-0.2575	-1.4722	-0.0443	-0.3327
Smith & Nephew PLC	0.0368	0.5203	-0.0126	-0.0564	0.1553	1.2935
Smiths Group PLC	0.1340	1.9404	-0.0639	-0.3979	0.0778	0.8656
Stagecoach Group PLC	0.1148	0.7841	-0.1325	-0.3827	-0.0058	-0.0222
Standard Chartered PLC	0.0967	1.3671	-0.1552	-1.1246	0.1895	1.8788
Tesco PLC	0.1078	1.6401	0.0040	0.0380	0.0599	0.6499
Thomson Reuters PLC	-0.0203	-0.1570	-0.0558	-0.2080	0.3181	1.7705
TUI Travel PLC	0.0929	1.0091	-0.1697	-0.9038	0.0426	0.3299
Unilever PLC	0.0606	0.9910	-0.2625	-0.8412	0.0220	0.2453
United Utilities Group PLC	0.1083	1.3276	0.1481	1.6095	-0.0207	-0.2983
Vodafone Group PLC	0.1414	1.4377	-0.1086	-0.4570	-0.0011	-0.0099
Whitbread PLC	0.0743	1.0153	-0.1512	-1.1329	0.1261	1.3887
Wolseley PLC	0.0574	0.7987	0.0035	0.0266	0.1629	1.6664
Wood Group (John) PLC	0.1796	1.3255	-0.0934	-0.4944	0.1028	0.6819
WPP Group PLC	0.0843	0.8861	-0.1059	-0.5338	0.2906	2.4687
Xstrata PLC	-0.0589	-0.5618	0.1239	0.6560	0.3587	2.4161
3I Group PLC	0.1199	1.3576	-0.5242	-1.8934	0.0920	0.7993

Notes: In the regression $R_t^S = C + \gamma R_{t-1}^S + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta i OF_{t-1,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-13: Effects of GBPUSD Order Flows on Future UK Stock Market Returns

Similar to our previous findings, we find that for individual stocks in the UK market, the relations between foreign exchange order flows and stock market returns hold, i.e. there are no contemporaneous relationship between foreign exchange order flows and stock market returns, but order flows in the foreign exchange market have forecasting power for some of listed companies in the stock UK market and the impacts from different groups of customers are significantly different. Positive foreign exchange order flows from commercial companies and leveraged financial institutions at day t forecast positive stock returns at day t+1, while unleveraged financial institutions forecast negative stock returns. More specifically, we use the following figure 2-5 to show our findings,



Notes: The figure shows the number of FTSE 100 individual stocks which are significantly affected by GBPUSD order flows from different groups of customers. The number outside circles means the number of companies which are not affected by any group of customers.

Figure 2-5: UK Stock Market Results for Individual Stocks

For non-financial corporations, stock returns of 75 out of 84 companies listed in FTSE 100 are positively affected by foreign exchange order flows from this group, 15 of which are statistically significant at the 10% significance level. Similar figures are, 66 out of 84 of which 17 are significant for unleveraged financial institutions, and 68 out of 84 of which 14 are significant for leveraged financial institutions. 6 stocks are affected significantly by more than one category of order flows, and 1 stock is associated by all three groups of customer order flows, which is London Stock Exchange Group PLC. Again we note that corporate and leveraged order flows into British Pounds today are associated with stock price rises tomorrow, while the relationship is negative for unleveraged foreign exchange order flows.

As discussed in hypothesis 4, 5 and 6, we see similar results at individual stock level, unfortunately we still do not find links between the companies which are significantly affected by foreign exchange order flows. The listed stocks in which we find nothing common may be just selected by clients according to their own strategies. Maybe we can see some common nature across the companies in our non-financial corporations group which buy and sell the listed stocks in FTSE, but unfortunately we do not have details of the clients in foreign exchange order flows. However, by any means, we can not deny the existence of interactions between the foreign exchange and stock markets.

2.5.4 Hypotheses 4-9 Testing for US

We find clear forecasting power of foreign exchange order flows for UK stock market returns, and the impacts from different groups of customers are completely different. Based on bilateral directions of GBPUSD, we also need to check the relations between foreign exchange order flows and the US stock market and report the results at market, sector and individual stock levels in the following tables. The order flow we use here is the same as we do for the UK market, GBPUSD, meaning buying Pound sterling in exchange for US Dollars. Magnitudes of coefficient estimates mean the change in stock market prices with 100 million British Pounds into the market.

<u>Contemporaneous</u>

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
DOW	0.0569	1.1990	-0.1572	-1.8107	0.0108	-0.1523
S&P500	0.0589	1.2274	-0.1580	-1.7987	0.0369	0.5129
S&P500 ENERGY	0.0264	0.3682	0.0051	0.0374	0.0389	0.3844
S&P500 MATERIALS	0.0672	1.1988	-0.1871	-1.5057	0.0195	0.2397
S&P500 INDUSTRIAL CONGLOMERATE	0.0595	0.9345	-0.2881	-1.8610	0.0362	0.4057
S&P500 CONSUMER SERVICES	-0.0216	-0.4383	-0.1919	-1.7067	0.0567	0.7396
S&P500 CONSUMER DURABLES & APP	-0.0102	-0.1782	-0.2736	-2.3231	0.0389	0.4917
S&P500 HEALTH CARE EQUIP	0.0386	0.7454	-0.0483	-0.5174	0.0184	0.2902
S&P500 HEALTH CARE FACILITIES	0.0122	0.1404	-0.1442	-0.9063	0.0660	0.6489
S&P500 HEALTH CARE PROV & SERV	0.0086	0.1298	-0.0218	-0.1857	-0.0250	-0.2935
S&P500 BANKS	0.0936	1.6688	-0.1523	-1.4283	0.0400	0.5620
S&P500 INSURANCE	0.0739	1.1244	-0.2439	-1.9188	0.0708	0.8734
S&P500 IT SERVICES	0.1114	1.1985	-0.2249	-1.6328	0.0128	0.1132
S&P500 IT CONS & O/SVS	-0.0816	-0.6854	-0.2207	-1.0764	-0.0965	-0.6853
S&P500 TELECOM SERV	0.1581	1.9069	-0.2628	-1.3067	0.1489	1.6404
S&P500 UTILITIES	0.0041	0.0675	-0.0606	-0.5586	0.1153	1.5215

Notes: In the regression $R_t^S = C + \lambda R_t^{FX} + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on concurrent stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 in most regressions is negligible.

Table 2-14: Effects of GBPUSD Order Flows on Contemporaneous US Stock Market Returns

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
3M Company	0.0179	0.2742	-0.1193	-1.0029	0.0882	0.9196
AT & T Inc	0.1912	1.9706	-0.3517	-1.5832	0.1633	1.4769
Alcoa Incorporated	0.0702	0.8038	-0.1563	-0.7455	0.0359	0.2728
American Express Company	0.1747	2.2743	-0.3237	-1.7739	0.0614	0.5378
Bank Of America Corp.	0.0995	1.7401	-0.1638	-1.4010	0.0593	0.7736
The Boeing Company	-0.0075	-0.0889	-0.2617	-1.5197	0.1013	0.8527
Caterpillar Inc	0.0293	0.3007	-0.0932	-0.5416	-0.0700	-0.5300
Chevron Corp.	0.0137	0.1891	-0.1188	-0.8720	0.0231	0.2428
Citigroup Inc	0.1353	1.5912	-0.2881	-1.3278	0.0334	0.2597
The Coca Cola Company	-0.0580	-0.9693	0.0208	0.1885	-0.0577	-0.7786
EI Du Pont De Nemours	0.1064	1.5245	-0.1406	-1.0188	-0.0192	-0.2069
Exxon Mobil Corp.	0.0465	0.6381	-0.0222	-0.1594	0.0811	0.8431
General Electric Company	0.0840	1.1723	-0.3403	-1.9483	0.0678	0.6740
General Motors Corp.	-0.0487	-0.4054	-0.3200	-1.5303	-0.0606	-0.3038
Hewlett-Packard Company	0.1157	0.9818	-0.3925	-1.3947	0.1623	1.1343
Home Depot Inc	-0.0032	-0.0376	-0.2874	-1.5620	0.0385	0.3857
Intel Corp.	0.1150	0.9515	-0.1065	-0.4526	0.1086	0.8067
International Business Machines Corp.	0.0982	1.5196	-0.0560	-0.3831	-0.0276	-0.3052
JP Morgan Chase & Company	0.2502	2.2457	-0.1342	-0.7172	0.0762	0.6454
Johnson & Johnson	0.0884	1.5009	-0.0556	-0.5594	0.0161	0.2082
Kraft Foods Inc	0.0187	0.3188	-0.1708	-1.3586	0.0790	0.9200
McDonalds Corp.	-0.0859	-1.1880	-0.1681	-1.1263	0.0664	0.6049
Merck & Company Inc	0.1294	1.0726	-0.0135	-0.0744	0.0153	0.1298
Microsoft Corp.	0.0429	0.6127	-0.1770	-1.0317	0.0407	0.4664
Pfizer Inc	0.1087	1.2649	-0.0204	-0.1126	-0.0726	-0.6525
The Procter & Gamble Company	0.0371	0.6682	-0.0551	-0.5564	0.0359	0.5339
United Technologies Corp.	-0.0184	-0.2267	-0.0858	-0.5269	0.1577	1.6151
Verizon Communications	0.1350	1.4717	-0.1342	-0.7182	0.1429	1.4189
Wal Mart Stores Inc	0.0225	0.3615	-0.3793	-2.3934	0.0039	0.0489
The Walt Disney Company	0.0144	0.1528	-0.1999	-1.0617	-0.0130	-0.1011

Notes: In the regression $R_t^S = C + \lambda R_t^{FX} + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on concurrent stock market changes at individual stock levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is negligible.

Table 2-15: Effects of GBPUSD Order Flows on Future US Stock Market Returns

Forecasting

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
DOW	0.1110	2.5274	-0.2298	-2.6631	-0.0075	-0.1251
S&P500	0.1152	2.4360	-0.2356	-2.7209	-0.0095	-0.1337
S&P500 ENERGY	0.1072	1.3183	-0.1467	-1.2886	-0.0482	-0.3939
S&P500 MATERIALS	0.1044	1.7133	-0.2145	-1.9348	0.0057	0.0718
S&P500 INDUSTRIAL CONGLOMERATE	0.1137	1.9795	-0.2328	-2.0264	0.0517	0.6639
S&P500 CONSUMER SERVICES	0.1074	1.9149	-0.1385	-1.5966	0.0757	0.9448
S&P500 CONSUMER DURABLES & APP	0.0810	1.5169	-0.1855	-2.0022	-0.0209	-0.2734
S&P500 HEALTH CARE EQUIP	0.0991	2.2763	-0.1572	-1.8888	0.0527	0.7102
S&P500 HEALTH CARE FACILITIES	0.1198	1.4391	-0.5037	-1.3386	-0.1202	-1.2112
S&P500 HEALTH CARE PROV & SERV	0.1169	2.1533	-0.2695	-1.6268	-0.0215	-0.2466
S&P500 BANKS	0.0692	1.4079	-0.2271	-2.5245	0.0017	0.0258
S&P500 INSURANCE	0.1308	2.2223	-0.2890	-2.1041	-0.0106	-0.1304
S&P500 IT SERVICES	0.1490	2.0157	-0.0146	-0.0976	-0.3063	-1.4588
S&P500 IT CONS & O/SVS	-0.0024	-0.0143	0.1995	0.8041	0.1528	0.8358
S&P500 TELECOM SERV	0.1119	1.6049	-0.3005	-2.2485	-0.0099	-0.0917
S&P500 UTILITIES	0.0042	0.0832	-0.1547	-1.5805	0.0335	0.4568

Notes: In the regression $R_t^S = C + \gamma R_{t-1}^S + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta_i OF_{t-1,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-16: Effects of GBPUSD Order Flows on Contemporaneous US Stock Market Returns

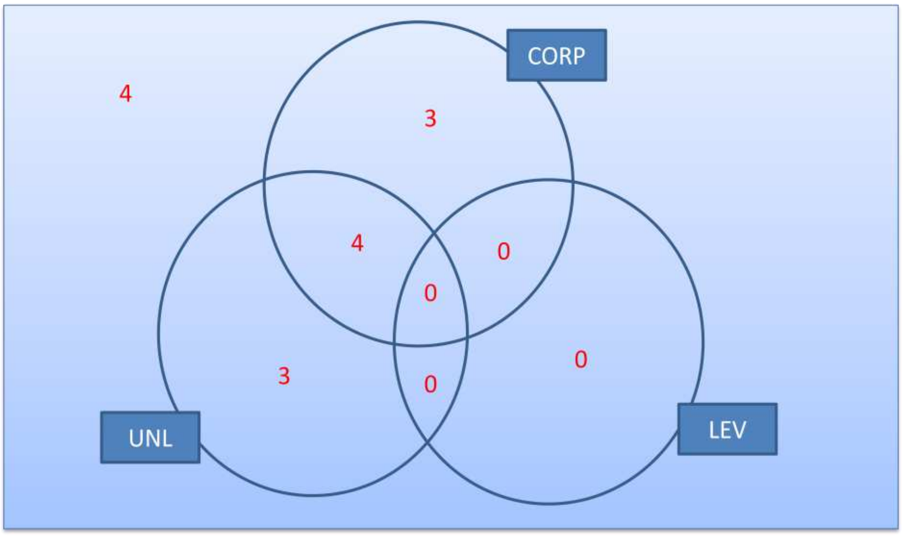
Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
3M Company	0.0855	1.5786	-0.1376	-1.4096	-0.0958	-1.0381
AT & T Inc	0.0397	0.4482	-0.3695	-2.2016	0.0222	0.1711
Alcoa Incorporated	0.1151	1.1648	-0.3252	-1.6269	-0.0099	-0.0798
American Express Company	0.1114	1.5299	-0.1757	-1.1919	-0.0493	-0.4590
Bank Of America Corp.	0.0447	0.8743	-0.2305	-2.4374	-0.0281	-0.4065
The Boeing Company	0.0679	0.9572	-0.2149	-1.3682	0.1206	1.1294
Caterpillar Inc	0.1304	1.5081	-0.2902	-2.1600	0.0549	0.4978
Chevron Corp.	0.1048	1.4469	-0.2399	-1.7985	-0.1601	-1.3132
Citigroup Inc	0.0815	1.0761	-0.2055	-1.5248	-0.1035	-1.0274
The Coca Cola Company	0.0312	0.5709	-0.0671	-0.6065	0.0192	0.2599
EI Du Pont De Nemours	0.1580	2.4625	-0.2747	-2.1235	0.0516	0.6706
Exxon Mobil Corp.	0.1242	1.6339	-0.1380	-1.1293	0.0213	0.1851
General Electric Company	0.1160	1.7468	-0.2095	-1.5306	0.0848	0.9818
General Motors Corp.	0.0802	0.8136	-0.5528	-3.3370	0.0593	0.3582
Hewlett-Packard Company	0.0910	0.8641	-0.0885	-0.4014	0.1137	0.8540
Home Depot Inc	0.1836	2.2845	-0.4120	-2.7609	0.0010	0.0082
Intel Corp.	0.2051	1.8760	-0.4624	-2.4925	-0.0439	-0.3419
International Business Machines Corp.	0.0998	1.2798	-0.2280	-1.8738	-0.1662	-2.0111
JP Morgan Chase & Company	0.1251	1.5967	-0.3441	-2.0281	-0.0320	-0.3222
Johnson & Johnson	0.0704	1.3659	-0.0446	-0.3456	-0.1067	-1.2848
Kraft Foods Inc	0.0295	0.4960	-0.1824	-1.2444	0.1509	1.4200
McDonalds Corp.	0.0628	0.8097	-0.2752	-1.7461	0.2232	1.5424
Merck & Company Inc	0.1235	1.4082	0.0513	0.2872	-0.1218	-1.2358
Microsoft Corp.	0.1819	2.5901	-0.2218	-1.4811	0.0445	0.5118
Pfizer Inc	0.1757	2.6551	-0.0539	-0.4084	-0.2243	-2.2880
The Procter & Gamble Company	0.0868	1.6946	-0.0659	-0.7541	-0.0012	-0.0186
United Technologies Corp.	0.0733	1.0101	-0.3231	-2.6517	0.0000	0.0000
Verizon Communications	0.0514	0.7013	-0.2119	-1.4984	-0.0048	-0.0410
Wal Mart Stores Inc	0.1224	1.9504	-0.3271	-2.6377	-0.0099	-0.1325
The Walt Disney Company	0.1178	1.5113	-0.0735	-0.4342	-0.1390	-1.0968

Notes: In the regression $R_t^S = C + \gamma R_{t-1}^S + \lambda R_{t-1}^{FX} + \sum_{i=1}^{4} \beta_i OF_{t-1,i}^{FX} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future stock market changes at individual stock levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-17: Effects of GBPUSD Order Flows on Future US Stock Market Returns

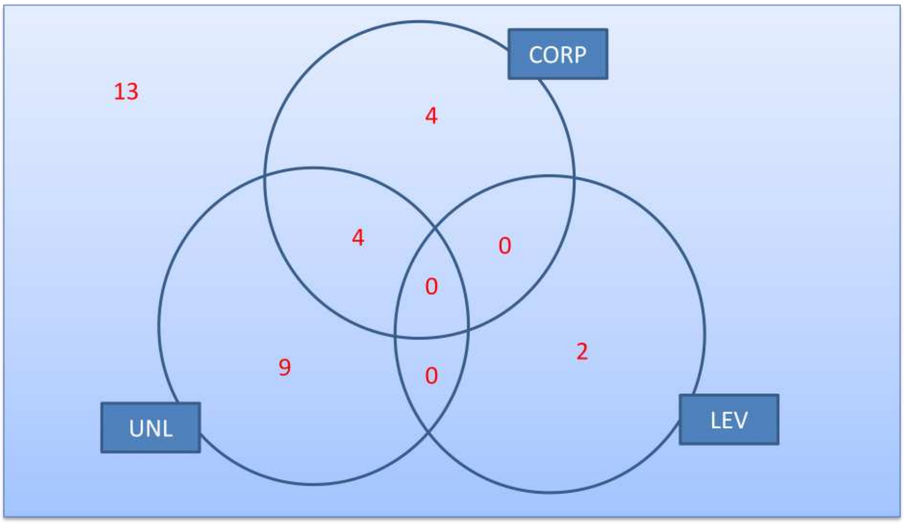
Because of the similar results between UK and US stock markets, we only briefly report the results about relations between foreign exchange order flows and US stock market returns. Similar to findings in the UK stock market, the contemporaneous relationship between foreign exchange order flows and US stock market changes is negligible, at market, sector and individual stock levels. While the forecasting power of order flows for the US stock market is even stronger than that for the UK stock market.

Same as discussions for the UK stock market, the following two figures present the number of sectors or companies listed in the US which are significantly affected by different types of customers in the foreign exchange market.



Notes: The figure shows the number of S&P 500 sector indices which are significantly affected by GBPUSD order flows from different groups of customers. The number outside circles means the number of sectors which are not affected by any group of customers.

Figure 2-6: US Stock Market Results for Sectors



Notes: The figure shows the number of DOW 30 individual stocks which are significantly affected by GBPUSD order flows from different groups of customers. The number outside circles means the number of companies which are not affected by any group of customers.

Figure 2-7: US Stock Market Results for Individual Stocks

In the results of US stock market and S&P 500 sector indices, for commercial companies, the coefficients of all but 1 out of 16 indices are positive, 8 of which are statistically significant at the 10% significance level. For unleveraged financial institutions, the coefficients of all but 1 out of 16 are negative, 7 of which are statistically significant. However, for leveraged financial institutions, the impacts of foreign exchange order flows on US stock market are mixed and less significant. While in the results of the 30 individual stocks listed in DOW JONES, for commercial corporations, returns of all of the 30 stocks are positively affected by foreign exchange order flows, of which 8 are significant at the 10% significance level. For unleveraged financial institutions, all of companies are negatively driven by foreign exchange order flows, of which 13 are significant. For leveraged financial institutions, 14 out of 30 are positively affected and 16 are negatively affected by foreign exchange order flows, of which only 2 companies are significant. The findings for US stock market further confirm the forecasting power of foreign exchange order flows for the stock market, with more consistency and uniformity for the US stock market compared to the UK stock market.

The summary table is as follows,

FX Order Flows	FX Returns	US Stock Returns
CORP	-	+
UNLEV	+*	-
LEV	+*	N/A

Notes: The table reports signs of effects of order flows from different customers (“Corp” for commercial corporations, “Unlev” for unleveraged financial institutions, “Lev” for leveraged financial institutions) on contemporaneous exchange rate and future US stock market changes. An asterisk (*) indicates significance at 10% or better, in “FX Returns” column. The signs in “US Stock Returns” indicate the significantly dominant ones in that category of customers.

Table 2-18: Signs of Effects of FX order flows on FX and US stock markets

As shown before, in the foreign exchange market, order flows (net buying of GBP) initiated by financial institutions have significant and positive contemporaneous correlations with exchange rate returns (GBPUSD), while corporations are negatively but insignificantly associated with exchange rate returns (GBPUSD). As for the interactions between foreign exchange order flows and the US stock market, at market, sector and individual stock levels, positive foreign exchange order flows (net buying of GBP) at day t from corporations forecast positive stock market returns at day t+1, while order flows from unleveraged financial institutions forecast negative stock market returns at t+1. For leveraged financial institutions, there is no clear relationship between foreign exchange order flows and stock market changes.

Now we have the cross market results (i.e. effects of currency order flows on changes in stock markets) for both UK and US markets, and we will suggest some interpretations on our cross market findings, in the following section.

2.5.5 Results Interpretations

In this section, we explain our findings customer by customer. We check the cross market links between foreign exchange order flows and stock market returns at a daily frequency, but find no significant contemporaneous relationship. However we find very strong forecasting power of our currency order flows for stock market changes. According to the positive results, here we focus on interpretations on cross market forecasting power. To simplify the task and to clarify the discussion, we use results of FTSE sectors and S&P 500 sectors as examples.

The following two tables (table 2-19 and 2-20) show the number of stock market sectors (both UK and US) which are significantly affected by our set of currency order flows from different type of customers. Red shaded cells mean the impacts are significantly positive, and blue shaded cells mean the impacts are significantly negative. The UK stock market has 32 sectors and the US stock market has 14 sectors.

FX Customer OF	+Relationship	-Relationship
CORP	9	0
UNLEV	1	9
LEV	10	1

Table 2-19: Impacts of currency orders on UK stock sectors

FX Customer OF	+Relationship	-Relationship
CORP	7	0
UNLEV	0	7
LEV	0	0

Table 2-20: Impacts of currency orders on US stock sectors

For each category of clients, we first summarize the results, and then suggest possible interpretations on the results.

Commercial Corporations

We can observe from the above two tables (table 2-19 and 2-20) that order flows which entail buying of British Pounds and selling of US Dollars from commercial customers have positive effects on both future UK and US stock market prices. Based solely on the results, since (i) it is unlikely that corporations are moving capital in order to invest in the stock market at most times (other than Mergers & Acquisitions oriented activities) and (ii) coefficients for the UK market and the US market are both positive (green circled number), the relationship between foreign exchange order flows from corporate customers at day t and stock market returns at day t+1 is not caused by foreign currency buying pressure at day t. Instead, we argue that the forecasting power of corporate foreign exchange order flows must be because of some information content, which are related to macroeconomic fundamentals in global stock markets.

Regarding the nature of the information, we give several possible interpretations.

When good performance in the global economy is on the horizon, sales of goods overseas by multi-national companies will accelerate. Some mega international corporations have very high portion of sales of their products in foreign countries, so they can observe the trend of sales and then sense the current and future state of global economy based on the business activities. The sales of items in foreign countries will bring back foreign currencies across board home. And the orders should contain some information about this kind of global macro related information. We hypothesize that corporate customers of RBS are mainly based in the UK, and that more sales of their products in the US will lead to the repatriation of more foreign currency (US Dollars) back to UK. Consequently the net buying of British Pounds and net selling US Dollars will be a signal of a good world economy, and then the stocks in both UK and US will increase in value. So the information conveyed in foreign exchange order flows from non-financial corporations, which are mainly based in the UK, maybe relevant for stock markets, which are connected with global economic health.

And also we know some big corporations have their own finance department and they will use the large amount of outstanding cash in hand to do investment to preserve the value of their assets and even enhance their asset value to cover costs in other areas such as their under-funded pension schemes. In addition to this, the other reason for the finance departments to be involved in buying and selling of currencies and stocks are due to active mergers and acquisitions especially over blossom business cycles. For example, it is said that the finance unit of Porsche is actually the largest “hedge fund” in the world, and the director of the department is the fund manager who has the most asset under management. In 2008, Volkswagen stock price quadrupled over two days and then down 40 percent in the third day. The crazy incident happened totally due to the private information about the mergers and acquisitions rumors about Porsche and Volkswagen, which will be more active with a boom global economy. In the meantime, all the other financial institutions which have large short exposures to Volkswagen do not know this kind of information and get hit hard. Even for those unleveraged long only financial institutions, they sweat a bit with such a rollercoaster ride. We suggest if investors can observe this kind of inflows and outflows of currencies especially when the deal involves international mergers and acquisitions, they can to some extent foresee the trend of some listed companies in stock markets.

Let's go back to the above two tables. The positive signs of coefficients for both UK and US stock markets can not be explained by any other driving factors such as price pressure, risk premium, but information content, because 1) this is a cross market relationship, and 2) the force which drives stock markets has impacts on both countries, which simultaneously affect outlook and expectations of the two different markets. To explain such a cross market link, we suggest that there exist an informational link between our currency order flows from corporate customers and changes in stock markets, to some extent.

Unleveraged Financial Institutions

For the two tables (table 2-19 and 2-20), we notice that net buying of British Pounds and selling of US Dollars from unleveraged financial institutions have negative effects on future UK and US stock market prices. We know that financial institutions often trade in stock markets, and then currency orders initiated by financial customers sometimes will be used to buy and sell stocks in equity markets. For results about the US stock market, i.e. relationship between net selling of US Dollars and downward prices in US stocks (red circled cell in US table), can partly explained by price pressure, if the cross border capital movements between two different financial markets go smoothly. However, For results about the UK stock market, the net buying of British pounds by unleveraged financial institutions is not related to the depreciation of UK stocks due to pure price pressure. And also because this is a cross market relationship, there is no way the driving force could be something like risk premiums, from currency dealer's perspective. So we also suggest the information content conveyed in this currency order flows from unleveraged financial institutions explains parts of this cross market relationships.

Similar to corporate customers, about the nature of the possible information content carried by currency order flows, we also give several possible interpretations.

For unleveraged financial institutions, when the world economy is going bad, clients of those mutual funds which are based in London will ask for redemptions of their funds. Assuming RBS services a client base that is UK oriented, this leads to the repatriation of money from abroad back to the UK as overseas holdings are liquidated (alongside UK investments) in order to pay redemptions. The buying of British Pounds in exchange for US Dollars then takes place alongside sales of US and UK stocks. So foreign exchange flows into Pound sterling from unleveraged funds forecast poor future stock market returns globally, then there should be some information hidden in order flows in the foreign exchange market, which is relevant for stock markets and expectations on future global economic health.

Another possible explanation is called “risk on, risk off theme”. We hypothesize that the bank's clients are based in London and use Pound sterling as their base currency. In recent years a risk driven theme emerges: when market is volatile and full of turbulences, i.e. risk off theme, the investors will sell the risky and even high yield assets and bring the overseas foreign currency denominated assets back to the UK. Before doing that the foreign currency will be converted to British pounds. This will contribute some to the negative relationships between buying of sterling and downward trends of global financial markets, especially when the market is experiencing financial crisis. And also this differentiates mutual funds from hedge funds, because mutual funds normally are not allowed to take short positions. When the bad scenario is on, they will get hit even harder due to their long only positions. Conversely, when the global economy is good and every investor can afford to take more risks, the low risk gear is on (risk on theme). UK unleveraged financial institutions will go overseas to search for new opportunities. By doing this, they will sell British pounds, and the behavior of buying global stocks will coincide with the uptrend of US and UK stock markets.

Last but not least explanation is about portfolio balancing requirements. According to Hau and Rey (2006), many real money portfolio managers who hold internationally diversified stocks will rebalance the holdings, when foreign stock markets are volatile or when exchange rates are away from their expected values. For example, when the stock prices in the UK go up or the British pounds appreciate a bit, the share denominated in British Pounds in one's portfolio is relatively heavy based on the balance of expected returns and risks in the portfolio manager's objective. Some of the stocks will be sold and then the British Pounds from the revenue will be converted to other currencies. Even intuitively the causality would be from stock market shocks to net buying or selling of foreign exchange order flows, the slow learning process between the two different financial markets can contribute to a part of negative impacts of currency order flows on stock market changes.

Same as corporate clients, we think information content is the best way to explain such a cross market relationship, and we suggest that there exist an informational link between our currency order flows from unleveraged financial customers and changes in stock markets, to some extent.

Leveraged Financial Institutions

From the above two tables (table 2-19 and 2-20), we also see that daily foreign exchange order flows from leveraged financial customers (typically hedge funds) have positive effects on future UK stock market changes, while there is no such effects for changes in the US stock market. Due to its cross market relationship and the trading objective and characteristics of hedge funds, we still suggest to some extent the existence of information content, as follows:

1) It is believed that hedge funds have their own private information and proprietary analysis on future fundamentals of economies or assets in financial markets. Based on speculative properties of hedge funds, we suggest that some of foreign exchange order flows which are perusing currency speculations hidden in stock markets. One of the reasons is that such investors try to earn

excessive returns from both foreign exchange and stock markets. The other reason is that they anticipate appreciation of one currency by buying companies denominated in that currency. All of these contribute to the positive impact from foreign exchange order flows on the UK stock market.

2) Compared to mutual funds, hedge funds can employ more financial instruments such as taking short positions to mitigate the side effects of unexpected volatilities in the financial markets. Many market neutral or even some marginal long biased long short equity funds can generate absolute returns which are irrespective of conditions of the markets. This determines that they are different from mutual funds (as mentioned above), which mainly passively rebalance their portfolios, and hedge funds are actively seeking profits based on their own set of information.
3) Last but not least, some hedge funds are even market brokers themselves, and they know much information about trading activities in the market (more importantly, they know how to and they are allowed to take advantage of others with this information, compared to those big investment banks), and they will hedge themselves against the uncomfortable exposures during market volatilities. However, based on our dataset we do not know the components of the client base. If we can get details about the customers, we can get more concrete conclusions.

Finally we talk about the difference between UK and US stock markets. Because customers of RBS are hypothesized to be mainly located in London and they trade mainly in the UK. The opinion from leveraged financial customers will be more diversified on prospects of the US stock market, and more idiosyncratic risk will be considered in the US. We suggest that this category of clients have information advantages on the UK stock market rather than the US market thanks to their familiarity with the companies listed in the London stock exchange relative to those listed in the New York stock exchange, and this possibly explains why we only find the effects from leveraged customers for UK only.

As noticed in the table 2-19, the positive impact of currency order flows from leveraged financial institutions on UK stock market changes can be seen as price pressure (red circled in table 2-19). However, as noted before, leveraged financial institutions have access to private information and have their own proprietary models to value the market. That's why we suggest that relationships between order flows from hedge funds and UK stock market movements are not due to pure price pressure. Consequently we stick to our information theory, which can explain all impacts of foreign exchange order flows we found for all three different types of clients.

We emphasize that these explanations are mere conjectures. It has not been possible to gather concrete information from the data suppliers about the nature of their client bases. From the above results and suggested interpretations, we find consistent existence of relationship between foreign exchange order flows and stock market changes. Our interpretations are based on their different trading objectives and investment constraints of different customers such as corporations, mutual funds, and hedge funds. The private information which drives exchange rates appears to be valuable for pricing equity markets. In the following sectors we apply several methodologies to explore the robustness of our results.

2.5.6 Overlapping Effects Check

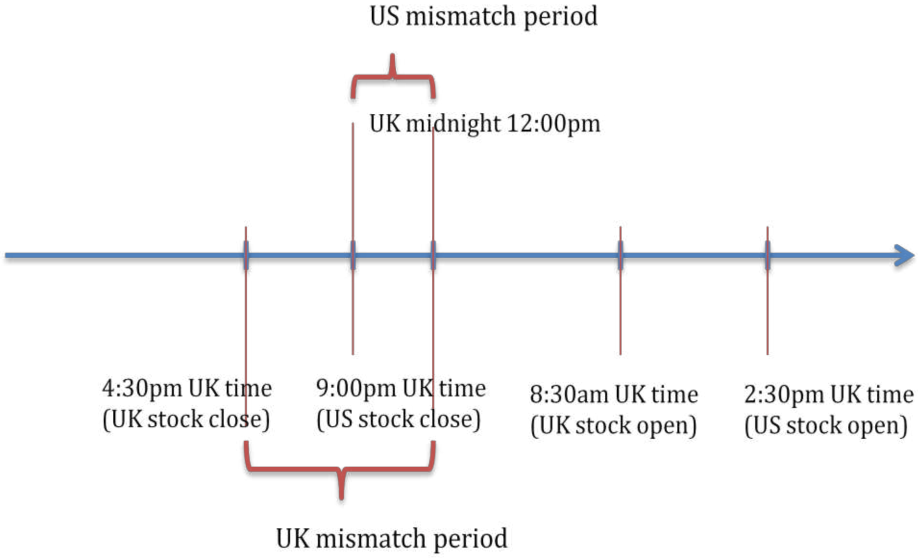


Figure 2-8: Overlapping Effects

As discussed before, we notice there are mismatch periods between daily foreign exchange order flows and closing prices in the UK as US stock market. The UK stock market closes at 4:30pm London time, so the foreign exchange order flows between 4:30pm and midnight will be included in day t order flows and used to explain the next day (t+1) stock market returns. This seven and a half hours mismatch may affect our conclusions due to the high level of trading in the foreign exchange market in this period. In the US stock market, which closes at 9pm London time (4pm New York time), there is only three hour mismatch period when foreign exchange trading is very thin. However, we still need to check the overlapping effect in the US stock market to confirm our conclusions. To do this, we will check the impacts of foreign exchange order flows on stock market returns based on open to close prices (to disregard the overlapping period) as well as close to open prices (to check more about the nature of foreign exchange order flows during the overlapping period). Regressions are as follows,

$$R^{S}_{o-c,t} = C + \gamma R^{S}_{o-c,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta i OF^{FX}_{t-1,i} + \varepsilon$$

$$R^{S}_{c-o,t} = C + \gamma R^{S}_{c-o,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta i OF^{FX}_{t-1,i} + \varepsilon$$

In the first regression, we regress next day open to close return on today's open to close return, exchange rate return and daily customer foreign exchange order flows from four different groups. By this means, we totally ignore the possible problem of biased results by only using historical (though private) information to forecast future price. In the second, we regress next day close to open return on today's close to open return, exchange rate return and daily customer foreign exchange order flows from four different groups. We can check to what extent the significant results in our original close to close return regressions can be explained overnight as well as the next day.

The next tables 2-19 and 2-20 show the results based on open-close return and close-open return of individual stocks in the UK stock market,

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
Alliance Trust PLC	0.0919	2.2599	-0.1617	-1.9081	0.0132	0.2600
Amec PLC	0.0827	0.7559	-0.2476	-1.3108	-0.0958	-0.6997
Anglo American PLC	0.1794	2.2026	-0.3756	-2.7683	0.0561	0.4399
Antofagasta PLC	0.0614	0.7496	-0.0213	-0.1399	-0.0443	-0.3856
Associated British Foods PLC	0.0468	0.8436	0.0676	0.4405	0.0378	0.5051
Astrazeneca PLC	0.1902	2.7620	-0.1815	-1.2836	-0.0412	-0.4228
Autonomy Corp. PLC	0.5036	3.5388	-0.1446	-0.6265	-0.3057	-0.9609
Aviva PLC	0.0965	1.0097	-0.2032	-1.0741	-0.2497	-1.9934
BAE Systems PLC	0.0874	0.7723	-0.1163	-0.6314	0.0593	0.3922
Barclays PLC	0.0803	1.0257	-0.1253	-0.9340	0.0770	0.7977
BG Group PLC	0.0184	0.2346	-0.0126	-0.0913	0.1220	1.2773
BHP Billiton PLC	0.1120	1.3913	-0.0774	-0.5571	0.0603	0.5622
BP PLC	0.1168	1.7649	-0.0948	-0.7488	0.0304	0.3172
British Airways PLC	-0.0115	-0.0911	-0.1104	-0.4504	-0.0290	-0.1527
British American Tobacco PLC	0.0571	0.9256	0.3201	2.6816	-0.1610	-2.2904
British Land Company PLC	0.0238	0.3419	-0.0506	-0.3223	0.0305	0.3029
British Sky Broadcasting PLC	0.0655	0.8243	-0.2097	-1.6727	0.2391	1.9541
BT Group PLC	0.0885	1.0646	0.1257	0.8135	-0.0712	-0.6564
Bunzl PLC	0.1463	2.0066	-0.1589	-0.9867	0.1446	1.2833
Cable & Wireless PLC	-0.0129	-0.1261	0.0842	0.3902	-0.1388	-0.9790
Cadbury PLC	-0.0414	-0.5514	-0.0661	-0.4357	0.0093	0.0956
Cairn Energy PLC	0.0591	0.5576	0.0969	0.6489	0.0827	0.6347
The Capita Group PLC	0.1145	1.0719	-0.1041	-0.5010	0.1304	1.0364
Carnival PLC	0.0988	1.1130	0.0117	0.0834	0.0404	0.4001
Centrica PLC	0.0237	0.2665	0.1353	0.8684	0.0833	0.7275
Cobham PLC	0.0772	1.3522	-0.0658	-0.5879	0.0603	0.7195
Compass Group PLC	0.0691	0.7109	-0.3602	-1.7943	0.0813	0.7060
Diageo PLC	0.0798	1.2148	-0.0775	-0.4824	0.0822	1.1480
First Group PLC	-0.0354	-0.4843	-0.0566	-0.3243	0.1761	1.3773
Friends Provident PLC	0.1567	1.4324	-0.4508	-2.1506	0.1835	1.3226
G4S PLC	0.2136	2.3836	-0.0051	-0.0269	0.0014	0.0112
Glaxosmithkline PLC	0.1280	1.9649	-0.1173	-0.7409	0.0462	0.5060
Hbos PLC	0.0504	0.6734	-0.1581	-0.9948	-0.0512	-0.6581
HSBC Holdings PLC	0.0786	2.2450	-0.0828	-0.9742	-0.0025	-0.0506
Icap PLC	0.0131	0.1852	-0.0381	-0.3004	0.1306	1.2073
Imperial Tobacco Group PLC	0.0556	0.8845	0.1401	1.3308	-0.1115	-1.0998
International Power PLC	0.0742	0.7038	-0.1923	-0.8796	0.4468	2.8756
Invensys PLC	0.0574	0.3078	-0.2103	-0.4101	0.2361	0.8126
Johnson Matthey PLC	0.1367	1.9686	0.0994	0.6229	0.1920	1.8655
Kingfisher PLC	0.0795	0.9735	0.0433	0.2682	0.0330	0.3019
Land Securities Group PLC	0.0205	0.3352	-0.1898	-1.6850	-0.0429	-0.5153
Legal & General Group PLC	0.0797	0.8303	-0.2285	-1.2261	0.1210	0.9510
Liberty International PLC	0.0101	0.1676	-0.0259	-0.2712	-0.0175	-0.2665
Lloyds TSB Group PLC	0.0167	0.2279	-0.2727	-2.1431	0.0867	0.9132
London Stock Exchange Group PLC	0.0521	0.6708	-0.0416	-0.2583	0.1568	1.4491
Lonmin PLC	0.2609	2.2811	-0.4260	-2.1903	-0.0703	-0.4669
Man Group PLC	-0.0054	-0.0643	-0.0814	-0.6540	0.1199	1.0257
Marks & Spencer Group PLC	0.1244	1.7340	-0.0107	-0.0657	-0.0192	-0.1183

National Grid PLC	0.0891	1.3703	-0.1422	-1.1885	0.1311	1.5386
Next PLC	0.0772	1.2073	-0.1335	-1.0024	0.2001	2.2051
Old Mutual PLC	0.0557	0.7263	0.0502	0.3061	0.0638	0.5373
Pearson PLC	0.0145	0.1908	-0.2316	-1.4099	0.0615	0.6679
Prudential PLC	0.1462	1.4884	-0.3296	-1.7307	0.0812	0.7104
Reckitt Benckiser PLC	-0.0492	-0.7416	0.0733	0.3970	0.0937	0.9692
Reed Elsevier PLC	0.1327	1.4473	-0.1005	-0.8702	0.1285	1.3629
Rexam PLC	0.1371	2.0211	-0.3322	-2.5935	0.1850	2.1812
Rio Tinto PLC	0.0562	0.7911	-0.1672	-1.2344	0.0481	0.4659
Rolls-Royce Group PLC	0.0474	0.5450	-0.3474	-1.5459	0.0095	0.0711
Royal Bank Of Scotland Group PLC	0.0654	0.9111	-0.1082	-0.8315	0.0038	0.0442
Royal Dutch Shell PLC	0.1813	2.7310	-0.0584	-0.4137	0.0475	0.5579
RSA Insurance Group PLC	0.0735	0.6005	-0.0088	-0.0300	-0.0348	-0.2183
Sabmiller PLC	0.0669	1.0305	-0.0537	-0.2684	-0.0104	-0.1135
The Sage Group PLC	-0.1144	-0.9567	-0.0961	-0.4650	-0.0405	-0.2817
Sainsbury (J) PLC	0.0138	0.1984	0.1713	1.1306	0.1119	1.1039
Schroders PLC	0.0990	1.0682	-0.3507	-2.1288	0.2018	1.6955
Scottish & Southern Energy PLC	0.0358	0.6830	0.2096	1.6921	-0.0104	-0.1304
Severn Trent PLC	0.0590	0.8860	-0.0193	-0.1586	-0.0181	-0.1903
Shire PLC	-0.0172	-0.2022	-0.2657	-1.5759	-0.0409	-0.3362
Smith & Nephew PLC	0.0354	0.4761	-0.2172	-1.1619	0.2427	1.8966
Smiths Group PLC	0.0826	1.2400	0.0010	0.0063	0.0450	0.5310
Stagecoach Group PLC	0.0535	0.3848	-0.1732	-0.5252	-0.0772	-0.3411
Standard Chartered PLC	0.1119	1.4506	-0.0292	-0.1866	0.0760	0.8628
Tesco PLC	0.1233	1.8934	0.0396	0.3100	-0.0122	-0.1270
Thomson Reuters PLC	-0.0484	-0.4286	-0.0599	-0.2299	0.2517	1.5265
TUI Travel PLC	0.1149	1.0611	-0.1008	-0.5083	0.0252	0.2067
Unilever PLC	0.0648	1.1766	-0.2915	-0.9552	-0.0370	-0.4505
United Utilities Group PLC	0.1307	1.8836	0.1892	1.8356	-0.0506	-0.6776
Vodafone Group PLC	0.1108	1.4478	-0.1769	-1.1835	-0.0169	-0.1653
Whitbread PLC	0.0752	0.9630	0.0263	0.1939	0.0523	0.5418
Wolseley PLC	0.0669	0.9552	0.0765	0.5833	0.1398	1.4955
Wood Group (John) PLC	0.1198	1.0197	0.0955	0.5823	0.1639	1.1615
WPP Group PLC	0.0923	1.1223	-0.0481	-0.2932	0.2592	2.2099
Xstrata PLC	-0.0395	-0.3612	0.1368	0.8326	0.3027	2.1282
3I Group PLC	0.0598	0.7024	-0.1323	-0.7987	0.0576	0.5210

Notes: In the regression $R^{S}_{o-c,t} = C + \gamma R^{S}_{o-c,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t-1,i} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future UK stock market changes ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. For regressions with significant coefficients, R^2 is up to 5%.

Table 2-21: Effects of GBPUSD Order Flows on Future UK Stock Market Returns (Open-Close)

In the UK stock market, based on open-close returns, the impacts from foreign exchange order flows on stock market returns do not change a lot compared to those calculated by close-close returns. The uniformity of signs in each category still holds well. For non-financial corporations, stock returns of 74 out of 84 companies listed in FTSE 100 are positively affected by foreign exchange order flows from this group, and the relations of 16 out of 84 stocks are statistically significant at the 10% significance level. Similar figures are, 63 out of 84, of which 14 are significant for unleveraged financial institutions, and 57 out of 84, of which 11 are significant for leveraged financial institutions.

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
Alliance Trust PLC	-0.0074	-0.3393	-0.0248	-0.6695	0.0083	0.2540
Amec PLC	0.0709	1.0615	-0.0186	-0.1286	0.0695	0.6942
Anglo American PLC	-0.0287	-0.7712	-0.0932	-1.2572	0.0633	1.1630
Antofagasta PLC	-0.0294	-0.6241	0.0543	0.6408	-0.0307	-0.4817
Associated British Foods PLC	-0.0029	-0.0927	-0.1289	-1.0193	0.0709	1.5612
Astrazeneca PLC	0.0043	0.1044	-0.0247	-0.3061	0.0589	0.9389
Autonomy Corp. PLC	-0.1851	-1.6893	0.0496	0.2827	0.2084	1.1507
Aviva PLC	0.0176	0.3749	-0.1867	-1.5901	0.0716	0.9989
BAE Systems PLC	0.0081	0.1548	-0.3085	-2.2190	0.0897	1.4520
Barclays PLC	0.0190	0.4504	-0.0981	-1.1293	0.1282	2.2840
BG Group PLC	0.0099	0.2570	-0.0821	-1.3026	-0.0120	-0.2557
BHP Billiton PLC	0.0181	0.3941	-0.0278	-0.3077	-0.0115	-0.1625
BP PLC	-0.0206	-0.5870	-0.0133	-0.1964	0.0266	0.5345
British Airways PLC	-0.0147	-0.2609	-0.2835	-1.5955	0.0987	1.2020
British American Tobacco PLC	-0.0040	-0.1075	-0.1893	-2.5300	-0.0298	-0.7252
British Land Company PLC	0.0032	0.0891	0.1246	1.3217	-0.0451	-0.8767
British Sky Broadcasting PLC	0.0063	0.1644	0.0882	1.0401	0.0090	0.1490
BT Group PLC	0.0516	1.2976	-0.0665	-0.7874	0.0971	1.8012
Bunzl PLC	-0.0822	-1.7867	-0.1341	-1.5349	0.0319	0.4142
Cable & Wireless PLC	-0.0896	-1.2278	0.1432	1.0893	0.1081	1.3198
Cadbury PLC	0.0767	1.8716	0.0050	0.0620	-0.0769	-1.2752
Cairn Energy PLC	0.0418	1.0167	0.0268	0.3203	0.0119	0.1535
The Capita Group PLC	0.0509	1.1241	-0.1072	-1.1803	0.0603	0.9153
Carnival PLC	-0.0382	-0.7992	-0.0359	-0.3786	0.0858	1.1427
Centrica PLC	0.0673	1.9055	0.0466	0.6123	-0.0451	-0.7358
Cobham PLC	-0.0252	-1.1206	0.0469	0.8672	-0.0316	-0.9557
Compass Group PLC	0.0769	1.0539	-0.1900	-2.1110	-0.0714	-0.5696
Diageo PLC	-0.0006	-0.0220	-0.0374	-0.5206	0.0118	0.3315
First Group PLC	0.0221	0.3566	-0.1744	-1.5200	0.0055	0.0652
Friends Provident PLC	-0.0098	-0.1874	-0.0775	-0.7805	-0.0007	-0.0120
G4S PLC	0.0149	0.2529	0.1615	1.4352	0.0627	0.6855
Glaxosmithkline PLC	-0.0183	-0.5320	-0.1118	-1.4483	0.0449	1.0658
Hbos PLC	-0.0310	-0.6967	-0.1644	-1.9149	0.0809	1.4829
HSBC Holdings PLC	0.0205	0.7804	-0.0831	-1.4724	0.0211	0.5980
Icap PLC	0.0640	1.8237	-0.0299	-0.6218	0.0350	0.6684
Imperial Tobacco Group PLC	-0.0113	-0.3412	0.0198	0.3128	0.0173	0.3054
International Power PLC	0.1178	1.8532	-0.1020	-0.6164	0.0428	0.4870
Invensys PLC	0.0858	1.0171	-0.6910	-1.2808	-0.0873	-0.6092
Johnson Matthey PLC	0.0194	0.4966	-0.1115	-1.2403	-0.0403	-0.6431
Kingfisher PLC	0.0328	0.7246	0.0426	0.5225	-0.0281	-0.4748
Land Securities Group PLC	0.0567	1.8146	0.0920	1.1457	-0.0077	-0.1727
Legal & General Group PLC	0.0488	1.0712	-0.0186	-0.2175	-0.0017	-0.0278
Liberty International PLC	-0.0119	-0.3579	-0.0235	-0.4477	0.0109	0.2610
Lloyds TSB Group PLC	0.0482	1.0404	-0.0500	-0.5198	0.0767	1.4917

London Stock Exchange Group PLC	0.0773	1.6610	-0.2219	-1.2403	0.1069	1.6998
Lonmin PLC	-0.0302	-0.8395	0.0571	0.5156	0.0157	0.2529
Man Group PLC	-0.0591	-1.1337	0.2112	1.3535	-0.0365	-0.5816
Marks & Spencer Group PLC	0.0222	0.5599	-0.0437	-0.6119	0.0354	0.5779
National Grid PLC	-0.0512	-1.2976	-0.1052	-1.3279	-0.0046	-0.0831
Next PLC	0.0430	1.2006	0.0891	0.7169	0.0188	0.3625
Old Mutual PLC	0.0864	1.8780	-0.0913	-1.1944	0.0527	0.9614
Pearson PLC	0.0368	0.9321	-0.0970	-0.9746	0.0420	0.6973
Prudential PLC	0.0957	1.8226	0.0218	0.1802	0.1377	1.5727
Reckitt Benckiser PLC	0.0228	0.5641	-0.0544	-0.6253	-0.0267	-0.6490
Reed Elsevier PLC	-0.0154	-0.4541	0.0318	0.4802	0.0342	0.7203
Rexam PLC	-0.0660	-1.8026	0.0632	0.6994	0.0413	0.7482
Rio Tinto PLC	0.0285	0.6420	-0.1157	-1.3250	0.0557	0.7751
Rolls-Royce Group PLC	-0.0291	-0.6064	-0.1935	-1.6511	0.0277	0.5524
Royal Bank Of Scotland Group PLC	0.0023	0.0696	-0.0716	-1.0136	0.0303	0.6202
Royal Dutch Shell PLC	-0.0075	-0.2422	0.0018	0.0299	0.0422	0.8381
RSA Insurance Group PLC	0.0557	0.8100	-0.2449	-1.6743	0.0776	1.0348
Sabmiller PLC	0.0153	0.4230	-0.0244	-0.3575	0.0310	0.6536
The Sage Group PLC	0.0371	0.7288	-0.1495	-1.2877	0.0950	1.2487
Sainsbury (J) PLC	0.0253	0.6232	-0.0620	-0.6582	-0.0895	-1.4104
Schroders PLC	0.0009	0.0184	-0.0008	-0.0061	-0.0549	-0.7446
Scottish & Southern Energy PLC	0.0187	0.5692	-0.0651	-0.6812	0.0132	0.2558
Severn Trent PLC	0.0603	1.5162	-0.0240	-0.2772	0.0376	0.7401
Shire PLC	0.0805	1.4522	-0.0014	-0.0172	0.0005	0.0070
Smith & Nephew PLC	0.0050	0.1353	0.2113	2.0266	-0.0869	-1.3645
Smiths Group PLC	0.0622	1.5945	-0.0850	-0.7526	0.0306	0.5265
Stagecoach Group PLC	0.0715	0.9167	0.0198	0.1059	0.0604	0.6031
Standard Chartered PLC	-0.0226	-0.4845	-0.1264	-1.3427	0.1207	1.8286
Tesco PLC	-0.0189	-0.4830	-0.0354	-0.4207	0.0702	1.6922
Thomson Reuters PLC	0.0376	0.5957	-0.0265	-0.1772	0.0655	0.7609
TUI Travel PLC	-0.0249	-0.4850	-0.0822	-0.8846	0.0145	0.2525
Unilever PLC	-0.0075	-0.3024	0.0186	0.2967	0.0607	1.1697
United Utilities Group PLC	-0.0103	-0.2823	-0.0231	-0.3457	0.0084	0.1799
Vodafone Group PLC	0.0308	0.6403	0.0646	0.4839	0.0160	0.3170
Whitbread PLC	0.0017	0.0477	-0.1811	-2.1856	0.0700	1.3729
Wolseley PLC	-0.0122	-0.3092	-0.0820	-0.8037	0.0242	0.3709
Wood Group (John) PLC	0.0495	0.6239	-0.1493	-1.2911	-0.0832	-0.8876
WPP Group PLC	-0.0084	-0.1841	-0.0600	-0.5254	0.0297	0.5106
Xstrata PLC	-0.0211	-0.3871	0.0468	0.4635	0.0584	0.8058
3I Group PLC	0.0608	1.4197	-0.3893	-1.5471	0.0308	0.5445

Notes: In the regression $R^{S}_{c-o,t} = C + \gamma R^{S}_{c-o,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta i OF^{FX}_{t-1,i} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on UK future stock market changes ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. For regressions with significant coefficients, R^2 is up to 5%.

Table 2-22: Effects of GBPUSD Order Flows on Future UK Stock Market Returns (Close-Open)

In the UK stock market, based on close-open returns, the impacts from foreign exchange order flows on stock market returns are relatively smaller than those calculated by close-close returns, and the uniformity of signs in each category is also weaker. For non-financial corporations, stock returns of 51 out of 84 companies listed in FTSE 100 are positively affected by foreign exchange order flows from this group, and the relations of 11 out of 84 stocks are statistically significant at the 10% significance level. Similar figures are, 59 out of 84, of which 8 are significant for unleveraged financial institutions, and 62 out of 84, of which 5 are significant for leveraged financial institutions. This suggests that the strong correlations based on close-close stock market returns are not driven by the overlapping data period.

We use the following table 2-21 to show the different effects based on three different sets of stock market returns,

	No. of significant companies		
	close-close	**open-close**	**close-open**
COPR	15 (75)	16 (74)	11 (51)
UNLEV	17 (66)	14 (63)	8 (59)
LEV	14 (68)	11 (57)	5 (62)

Notes: The table reports the difference of results based on three different sets of returns for the UK stock market (close-close, open-close, close-open). It reports the number of companies which are significantly affected by foreign exchange order flows from different customers, and the number in parentheses means total companies which have same signs corresponding to significant relations. Total companies are 84 in the UK stock market.

Table 2-23: Overlapping Effects for the UK Stock Market

We notice that the results based on open-close returns are similar to those based on original close-close returns, although there is several hours overlapping period between order flows and close-close stock market returns. The overnight close-open returns are less correlated with foreign exchange order flows. Our conclusions based on close-close returns should be good enough to be representative. Even stronger evidence can be found in the US market, where the overlapping period is shorter and when the foreign exchange market trading is very thin.

The next tables 2-22 and 2-23 show the results based on open-close return and close-open return of individual stocks in the US stock market,

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
3M Company	0.0719	1.4961	-0.1176	-1.3285	-0.0918	-1.2324
AT & T Inc	0.0140	0.1960	-0.3198	-2.1666	-0.0579	-0.5205
Alcoa Incorporated	0.0251	0.3133	-0.2914	-1.6877	-0.0174	-0.1567
American Express Company	0.0653	1.0025	-0.1460	-1.0104	-0.1091	-1.0656
Bank Of America Corp.	0.0476	1.0573	-0.2468	-2.6083	-0.0564	-0.8052
The Boeing Company	0.0193	0.3090	-0.2084	-1.6850	0.0331	0.3716
Caterpillar Inc	0.0343	0.4853	-0.2340	-1.8537	0.0426	0.4378
Chevron Corp.	0.0609	0.9498	-0.1926	-1.5673	-0.1707	-1.6879
Citigroup Inc	0.0336	0.4717	-0.1915	-1.3830	-0.1433	-1.6327
The Coca Cola Company	0.0331	0.7123	-0.0729	-0.6690	0.0059	0.0860
EI Du Pont De Nemours	0.1470	2.7175	-0.2765	-2.3144	-0.0301	-0.4247
Exxon Mobil Corp.	0.1026	1.5399	-0.1174	-1.0208	-0.0085	-0.0833
General Electric Company	0.1008	1.7726	-0.1754	-1.3612	0.0563	0.7488
General Motors Corp.	0.0352	0.4047	-0.4359	-2.8077	-0.0330	-0.2549
Hewlett-Packard Company	0.0755	0.8835	-0.3171	-1.7792	0.1039	0.8414
Home Depot Inc	0.1296	1.8701	-0.3865	-3.1547	0.0165	0.1612
Intel Corp.	0.1325	1.5493	-0.3917	-2.5687	-0.0858	-0.7052
International Business Machines Corp.	0.0946	1.6473	-0.2004	-1.9452	-0.1009	-1.3553
JP Morgan Chase & Company	0.0966	1.3088	-0.2403	-1.5325	-0.0639	-0.7681
Johnson & Johnson	0.0721	1.4577	-0.0578	-0.4929	-0.1161	-1.4783
Kraft Foods Inc	0.0539	0.9850	-0.2025	-1.4675	0.0895	1.3424
McDonalds Corp.	0.0647	0.9149	-0.2034	-1.4138	0.2369	1.8133
Merck & Company Inc	0.1259	1.6498	-0.0153	-0.1239	-0.1101	-1.1939
Microsoft Corp.	0.1239	2.0035	-0.2296	-1.8169	0.0353	0.4823
Pfizer Inc	0.1328	2.1722	0.0406	0.3467	-0.1660	-1.8840
The Procter & Gamble Company	0.0819	1.5930	-0.1130	-1.3850	-0.0387	-0.6806
United Technologies Corp.	0.0854	1.5759	-0.2734	-2.5554	-0.0470	-0.5324
Verizon Communications	-0.0130	-0.2213	-0.1979	-1.4621	-0.0623	-0.6336
Wal Mart Stores Inc	0.0997	1.7290	-0.3628	-3.1474	-0.0076	-0.1093
The Walt Disney Company	0.1091	1.5722	-0.0844	-0.6424	-0.1318	-1.3707

Notes: In the regression $R^{S}_{o-c,t} = C + \gamma R^{S}_{o-c,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t-1,i} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on US future stock market changes ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. For regressions with significant coefficients, R^2 is up to 5%.

Table 2-24: Effects of GBPUSD Order Flows on Future US Stock Market Returns (Open-Close)

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
3M Company	0.0132	0.4680	-0.0139	-0.3256	-0.0086	-0.2132
AT & T Inc	0.0081	0.1703	-0.0191	-0.1968	0.0659	1.1570
Alcoa Incorporated	0.0873	1.6663	-0.0261	-0.3274	0.0067	0.0991
American Express Company	0.0366	0.8280	-0.0104	-0.1898	0.0551	1.0983
Bank Of America Corp.	-0.0030	-0.0942	0.0163	0.4111	0.0285	0.7682
The Boeing Company	0.0477	1.3197	0.0009	0.0119	0.0786	1.4786
Caterpillar Inc	0.0955	2.3229	-0.0534	-0.9147	0.0125	0.2677
Chevron Corp.	0.0425	1.2945	-0.0428	-0.6645	0.0111	0.2682
Citigroup Inc	0.0505	1.0214	-0.0195	-0.2929	0.0394	0.6733
The Coca Cola Company	0.0002	0.0068	0.0033	0.0565	0.0135	0.3629
EI Du Pont De Nemours	0.0031	0.0915	0.0144	0.2287	0.0814	1.7971
Exxon Mobil Corp.	0.0189	0.5126	-0.0230	-0.4086	0.0258	0.5669

General Electric Company	0.0082	0.2118	-0.0236	-0.3632	0.0323	0.6679
General Motors Corp.	0.0423	0.9239	-0.0830	-1.1656	0.0819	0.9981
Hewlett-Packard Company	0.0144	0.2255	0.2382	1.6995	0.0080	0.1022
Home Depot Inc	0.0533	1.1743	-0.0125	-0.1663	-0.0152	-0.2084
Intel Corp.	0.0700	1.0766	-0.0492	-0.4314	0.0440	0.6167
International Business Machines Corp.	0.0024	0.0455	-0.0195	-0.3472	-0.0583	-1.0682
JP Morgan Chase & Company	0.0257	0.4423	-0.1010	-1.7292	0.0325	0.5184
Johnson & Johnson	-0.0074	-0.2725	0.0149	0.2257	0.0088	0.1915
Kraft Foods Inc	-0.0248	-0.4457	0.0223	0.2915	0.0586	0.6683
McDonalds Corp.	0.0000	-0.0009	-0.0660	-0.6049	-0.0155	-0.2306
Merck & Company Inc	-0.0056	-0.1218	0.0770	0.6000	-0.0120	-0.2073
Microsoft Corp.	0.0602	1.6885	0.0200	0.3076	0.0103	0.2225
Pfizer Inc	0.0395	0.8644	-0.0932	-1.2340	-0.0574	-1.0159
The Procter & Gamble Company	-0.0016	-0.0585	0.0537	1.3476	0.0421	1.2794
United Technologies Corp.	-0.0121	-0.2913	-0.0483	-0.8224	0.0409	1.0817
Verizon Communications	0.0542	1.2827	-0.0036	-0.0462	0.0498	0.8885
Wal Mart Stores Inc	0.0255	0.7770	0.0646	1.0892	-0.0071	-0.1461
The Walt Disney Company	0.0086	0.1978	0.0183	0.2036	-0.0065	-0.0801

Notes: In the regression $R^{S}_{c-o,t} = C + \gamma R^{S}_{c-o,t-1} + \lambda R^{FX}_{t-1} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t-1,i} + \varepsilon$, the table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on US future stock market changes ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. For regressions with significant coefficients, R^2 is up to 5%.

Table 2-25: Effects of GBPUSD Order Flows on Future US Stock Market Returns (Close-Open)

From the results in the US stock market, we can also get the following table 2-24 to show the different effects of foreign exchange order flows on stock market returns based on the three different sets of returns (close-close, open-close, close-open),

	No. of significant companies		
	close-close	**open-close**	**close-open**
COPR	8 (30)	6 (29)	3 (23)
UNLEV	13 (29)	14 (29)	2 (18)
LEV	N/A	N/A	N/A

Notes: The table reports the difference of results based on three different sets of returns for the US stock market (close-close, open-close, close-open). It reports the number of companies which are significantly affected by foreign exchange order flows from different customers, and the number in parentheses means total companies which have same signs corresponding to significant relations. Total companies are 30 in the US stock market.

Table 2-26: Overlapping Effects for the US Stock Market

Similarly to results in the UK stock market, effects of foreign exchange order flows on US stock open-close returns do not change much compared to those calculated by close-close returns. From the weak results based on overnight close-open returns, the three hours overlapping period between foreign exchange order flows and close-close returns in the US stock market can even be ignored.

2.5.7 Longer Horizons Forecasting

So far in this chapter all forecasting has been just one day ahead. We now also also test the predicting power of order flow for stock market returns over longer horizons, from 2 days up to 10 days. We use the following regression model to check the development of impact of order flows from different groups of customers on UK and US stock markets,

$$R_{t,t+m}^{S} = C + \gamma R_{t}^{S} + \lambda R_{t}^{FX} + \sum_{i=1}^{4} \beta i OF_{t,i}^{FX} + \varepsilon$$

$R_{t,t+m}{}^{S}$ is stock market return at longer horizons, in which m stands for the number of days. R^{FX} is the difference in the log of the daily exchange rate, i.e. daily exchange rate return, while OF^{FX} stands for daily foreign exchange order flows from four different groups of customers.

In the following six tables (three categories of order flows with two stock markets at sector and market levels, in both UK and US), we separately report their development along with time for each group of customers. As noted before, significantly positive coefficients of order flows in the regression are highlighted in red, while blue color means significantly negative coefficients of order flows. Then we can observe the impact evolution of foreign exchange order flows on changes of stock markets. For consistency and comparison reasons, we report results by both using net buying of Pound sterling, base currency in the exchange rate GBPUSD, as the net foreign exchange order flows, i.e. British Pounds are base currency for both UK and US.

Index	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats	Corp	t-Stats
FTSE 100	0.103	1.946	0.050	0.731	0.064	0.707	0.121	1.215	0.085	0.783	0.064	0.524	0.128	0.937	0.097	0.751	0.049	0.327	-0.014	-0.087
FTSE 350	0.099	1.993	0.051	0.809	0.064	0.750	0.122	1.290	0.086	0.836	0.067	0.573	0.125	0.950	0.102	0.816	0.058	0.396	-0.004	-0.026
FTSE 100 GROWTH	0.100	1.888	0.046	0.682	0.050	0.550	0.102	1.025	0.052	0.484	0.031	0.258	0.107	0.802	0.074	0.579	0.029	0.194	-0.033	-0.205
FTSE 100 VALUE	0.107	1.964	0.054	0.768	0.077	0.829	0.141	1.373	0.118	1.049	0.099	0.764	0.152	1.056	0.124	0.910	0.073	0.463	0.008	0.046
FTSE 350 GROWTH	0.098	1.913	0.048	0.732	0.050	0.572	0.103	1.054	0.053	0.501	0.032	0.274	0.103	0.783	0.075	0.592	0.031	0.213	-0.030	-0.189
FTSE 350 VALUE	0.100	2.032	0.055	0.871	0.075	0.886	0.140	1.483	0.117	1.123	0.100	0.829	0.147	1.092	0.129	1.007	0.084	0.563	0.021	0.133
FTSE 350 AERO/DEFENCE	0.102	1.477	0.046	0.357	0.041	0.256	0.068	0.379	-0.017	-0.079	0.063	0.250	0.149	0.502	0.117	0.403	0.126	0.415	0.158	0.487
FTSE 350 AUTO & PARTS	0.161	2.503	0.154	1.765	0.157	1.298	0.320	2.334	0.269	1.683	0.254	1.437	0.288	1.525	0.419	2.133	0.466	2.145	0.492	2.233
FTSE 350 BANKS	0.087	1.413	0.025	0.321	0.035	0.326	0.102	0.850	0.053	0.421	0.063	0.440	0.108	0.677	0.075	0.476	0.060	0.322	0.011	0.054
FTSE 350 BEVERAGES	0.077	1.276	0.019	0.246	0.086	0.837	0.184	1.795	0.134	1.169	0.075	0.625	0.096	0.727	0.010	0.071	-0.059	-0.416	-0.071	-0.508
FTSE 350 CHEMICALS	0.046	0.748	0.062	0.758	-0.022	-0.207	0.035	0.283	-0.032	-0.242	-0.061	-0.386	-0.066	-0.401	-0.135	-0.827	-0.221	-1.281	-0.202	-1.075
FTSE 350 CON & MAT	0.074	1.467	0.053	0.783	0.079	0.842	0.166	1.648	0.159	1.312	0.155	1.057	0.176	1.080	0.239	1.404	0.266	1.421	0.268	1.290
FTSE 350 ELECTRICITY	0.067	1.415	0.047	0.686	0.077	0.934	0.043	0.483	0.035	0.378	0.067	0.631	0.090	0.806	0.060	0.531	0.059	0.456	0.048	0.351
FTSE 350 ELTRO/ELEC EQ	0.166	1.387	0.238	1.392	0.178	0.834	0.390	1.570	0.354	1.234	0.288	0.901	0.358	0.993	0.511	1.334	0.515	1.221	0.484	1.087
FTSE 350 EQT IVST INS	0.091	2.141	0.078	1.435	0.062	0.825	0.144	1.606	0.122	1.254	0.121	1.044	0.164	1.264	0.153	1.165	0.100	0.666	0.062	0.366
FTSE 350 EX.INV.TRUSTS	0.099	1.988	0.051	0.800	0.064	0.749	0.122	1.284	0.086	0.829	0.067	0.565	0.124	0.946	0.102	0.810	0.057	0.392	-0.005	-0.031
FTSE 350 FD & DRUG RTL	0.081	1.466	0.066	0.885	0.014	0.157	0.099	0.964	0.075	0.618	0.117	0.914	0.202	1.450	0.156	1.186	0.183	1.338	0.174	1.223
FTSE 350 FD PRODUCERS	0.048	0.971	0.036	0.590	0.063	0.782	0.142	1.576	0.107	1.050	0.095	0.839	0.155	1.238	0.139	1.129	0.091	0.667	0.055	0.383
FTSE 350 FXD LINE T/CM	0.133	1.512	0.053	0.481	0.122	0.899	0.225	1.450	0.210	1.237	0.252	1.313	0.324	1.482	0.314	1.473	0.176	0.744	0.063	0.246
FTSE 350 GEN RETAILERS	0.086	1.713	0.069	0.859	0.113	1.173	0.243	2.231	0.216	1.770	0.193	1.391	0.117	0.746	0.117	0.760	0.140	0.863	0.082	0.467
FTSE 350 GENERAL FIN	0.067	1.235	0.074	0.981	0.055	0.559	0.129	1.090	0.113	0.837	0.087	0.582	0.151	0.896	0.194	1.101	0.171	0.866	0.093	0.463
FTSE 350 H/C EQ & SVS	0.064	1.103	-0.016	-0.200	-0.087	-0.828	0.044	0.381	0.000	0.003	-0.085	-0.622	-0.164	-1.063	-0.182	-1.079	-0.209	-1.141	-0.341	-1.809
FTSE 350 INDS ENG	0.077	1.555	0.119	1.767	0.090	1.021	0.161	1.523	0.159	1.259	0.169	1.184	0.180	1.132	0.202	1.251	0.127	0.716	0.045	0.236
FTSE 350 INDS TRANSPT	0.121	2.727	0.106	1.641	0.085	1.049	0.191	1.965	0.189	1.810	0.181	1.553	0.154	1.190	0.164	1.265	0.141	0.976	0.112	0.713
FTSE 350 INDUSTRIAL MET	0.102	0.388	0.076	0.274	0.352	0.782	0.379	0.751	0.493	0.749	0.443	0.704	-0.100	-0.135	0.126	0.185	-0.120	-0.167	-0.334	-0.410
FTSE 350 LIFE INSURANCE	0.172	1.834	0.064	0.461	0.027	0.136	0.096	0.462	0.078	0.346	0.019	0.071	0.054	0.191	-0.006	-0.020	0.020	0.062	-0.084	-0.244
FTSE 350 MEDIA	0.058	0.850	-0.001	-0.012	-0.049	-0.426	0.035	0.254	-0.031	-0.213	-0.048	-0.301	0.035	0.191	0.046	0.257	0.020	0.099	-0.065	-0.308
FTSE 350 MINING	0.117	1.502	-0.051	-0.496	-0.084	-0.627	-0.069	-0.436	-0.118	-0.671	-0.168	-0.850	-0.116	-0.554	-0.080	-0.379	-0.137	-0.598	-0.254	-1.063
FTSE 350 NONLIFE INSUR	0.099	1.501	0.063	0.665	0.018	0.137	0.029	0.193	0.073	0.452	0.063	0.344	-0.017	-0.087	-0.007	-0.033	0.036	0.157	0.015	0.059
FTSE 350 OIL & GAS PROD	0.116	1.491	0.107	1.103	0.170	1.416	0.159	1.232	0.170	1.108	0.079	0.472	0.211	1.158	0.157	0.876	0.068	0.345	-0.045	-0.212
FTSE 350 PERSONAL GDS	-0.026	-0.398	-0.021	-0.259	-0.033	-0.331	0.051	0.454	0.002	0.013	0.041	0.295	0.046	0.314	-0.088	-0.590	-0.145	-0.902	-0.132	-0.755
FTSE 350 PHARM & BIO	0.136	2.030	0.057	0.611	0.012	0.109	0.060	0.454	-0.038	-0.250	-0.067	-0.423	0.027	0.157	0.025	0.139	-0.045	-0.225	-0.113	-0.561
FTSE 350 REAL ESTATE	0.046	1.008	0.016	0.262	0.021	0.299	0.124	1.553	0.112	1.237	0.038	0.329	0.069	0.553	0.071	0.559	0.067	0.456	-0.007	-0.043
FTSE 350 S/W & COMP SVS	-0.017	-0.204	-0.022	-0.188	-0.060	-0.370	-0.069	-0.362	-0.005	-0.023	0.018	0.077	0.118	0.456	0.141	0.525	0.005	0.016	-0.028	-0.091
FTSE 350 SUPPORT SVS	0.074	1.568	0.056	0.841	0.052	0.587	0.123	1.163	0.076	0.654	0.059	0.439	0.120	0.773	0.162	1.033	0.155	0.833	0.146	0.719
FTSE 350 TCH H/W & EQ	0.307	1.891	0.185	0.845	0.474	1.073	0.758	1.435	0.981	1.754	1.164	1.968	1.195	1.964	1.371	1.898	1.329	1.662	1.367	1.750
FTSE 350 TOBACCO	0.075	1.416	0.047	0.657	0.101	1.158	0.180	2.001	0.109	1.112	0.066	0.631	0.169	1.394	0.089	0.657	0.042	0.280	-0.021	-0.126
FTSE 350 TRAVEL & LEIS	0.074	1.662	0.059	0.876	0.041	0.476	0.130	1.273	0.099	0.843	0.112	0.843	0.174	1.158	0.149	0.978	0.175	1.102	0.116	0.715

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from “Corp” customers on future UK stock market changes at market and sector levels (“Corp” for commercial corporations) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-27: Longer Horizon Effects of “Corp” Order Flows on the UK Stock Market

Index	t+1 Unlev	t+1 t-Stats	t+2 Unlev	t+2 t-Stats	t+3 Unlev	t+3 t-Stats	t+4 Unlev	t+4 t-Stats	t+5 Unlev	t+5 t-Stats	t+6 Unlev	t+6 t-Stats	t+7 Unlev	t+7 t-Stats	t+8 Unlev	t+8 t-Stats	t+9 Unlev	t+9 t-Stats	t+10 Unlev	t+10 t-Stats
FTSE 100	-0.130	-1.315	-0.394	-3.044	-0.303	-1.933	-0.224	-1.211	-0.091	-0.517	0.015	0.073	0.030	0.122	0.035	0.149	0.013	0.054	-0.028	-0.124
FTSE 350	-0.133	-1.433	-0.399	-3.259	-0.331	-2.217	-0.260	-1.468	-0.133	-0.782	-0.039	-0.198	-0.010	-0.043	0.000	-0.002	-0.031	-0.142	-0.060	-0.279
FTSE 100 GROWTH	-0.144	-1.452	-0.404	-2.962	-0.313	-1.936	-0.216	-1.181	-0.093	-0.513	0.040	0.192	0.053	0.199	0.060	0.241	-0.004	-0.015	-0.054	-0.234
FTSE 100 VALUE	-0.117	-1.135	-0.383	-2.998	-0.292	-1.830	-0.229	-1.170	-0.086	-0.466	-0.007	-0.033	0.011	0.048	0.018	0.074	0.035	0.147	0.004	0.016
FTSE 350 GROWTH	-0.146	-1.532	-0.410	-3.136	-0.335	-2.137	-0.245	-1.376	-0.121	-0.686	0.003	0.016	0.023	0.091	0.032	0.133	-0.033	-0.141	-0.074	-0.326
FTSE 350 VALUE	-0.121	-1.294	-0.388	-3.264	-0.326	-2.200	-0.272	-1.476	-0.141	-0.804	-0.073	-0.368	-0.036	-0.164	-0.024	-0.106	-0.025	-0.114	-0.044	-0.200
FTSE 350 AERO/DEFENCE	-0.137	-1.005	-0.477	-2.734	-0.330	-1.509	-0.327	-1.355	-0.168	-0.631	-0.059	-0.183	-0.054	-0.138	-0.003	-0.008	-0.027	-0.067	-0.187	-0.409
FTSE 350 AUTO & PARTS	-0.216	-1.624	-0.704	-4.038	-0.880	-4.201	-0.944	-3.592	-0.771	-2.839	-0.811	-2.573	-0.561	-1.629	-0.668	-1.730	-0.747	-1.856	-0.813	-1.921
FTSE 350 BANKS	-0.223	-1.990	-0.477	-3.666	-0.436	-2.387	-0.269	-1.176	-0.135	-0.586	-0.003	-0.012	0.013	0.043	0.082	0.282	0.089	0.297	0.129	0.414
FTSE 350 BEVERAGES	-0.118	-0.745	-0.394	-2.134	-0.295	-1.462	-0.217	-0.885	-0.309	-1.317	-0.243	-0.890	-0.176	-0.559	-0.339	-1.076	-0.358	-1.237	-0.541	-1.772
FTSE 350 CHEMICALS	-0.066	-0.423	-0.453	-2.305	-0.464	-2.105	-0.456	-1.778	-0.353	-1.315	-0.154	-0.530	-0.190	-0.627	-0.275	-0.813	-0.314	-0.953	-0.451	-1.368
FTSE 350 CON & MAT	-0.163	-2.011	-0.482	-3.466	-0.503	-3.494	-0.463	-2.222	-0.214	-0.993	-0.199	-0.786	-0.119	-0.431	-0.099	-0.346	-0.200	-0.731	-0.140	-0.476
FTSE 350 ELECTRICITY	-0.044	-0.494	-0.190	-1.682	-0.079	-0.588	-0.136	-0.765	-0.090	-0.537	-0.098	-0.530	-0.042	-0.213	-0.210	-0.956	-0.145	-0.687	-0.263	-1.188
FTSE 350 ELTRO/ELEC EQ	-0.419	-2.081	-0.892	-3.216	-1.333	-3.337	-1.186	-2.739	-1.315	-2.333	-1.218	-1.973	-1.597	-2.221	-1.775	-2.477	-1.456	-1.643	-1.269	-1.469
FTSE 350 EQT IVST INS	-0.171	-2.032	-0.514	-4.859	-0.540	-4.094	-0.483	-2.709	-0.340	-1.849	-0.334	-1.643	-0.255	-1.061	-0.260	-1.071	-0.298	-1.203	-0.279	-1.159
FTSE 350 EX.INV.TRUSTS	-0.132	-1.419	-0.397	-3.228	-0.327	-2.182	-0.256	-1.441	-0.129	-0.758	-0.033	-0.169	-0.005	-0.023	0.005	0.020	-0.026	-0.119	-0.056	-0.259
FTSE 350 FD & DRUG RTL	0.040	0.440	-0.178	-1.053	-0.174	-0.809	-0.177	-0.696	0.073	0.289	0.238	0.804	0.109	0.403	0.118	0.389	0.028	0.098	0.036	0.134
FTSE 350 FD PRODUCERS	-0.156	-0.753	-0.315	-1.272	-0.286	-1.164	-0.322	-1.185	-0.255	-0.986	-0.149	-0.511	-0.217	-0.660	-0.244	-0.746	-0.322	-1.002	-0.386	-1.157
FTSE 350 FXD LINE T/CM	-0.058	-0.286	-0.307	-1.312	-0.046	-0.154	0.027	0.076	0.275	0.779	0.288	0.779	0.233	0.582	0.256	0.558	0.493	1.096	0.405	0.890
FTSE 350 GEN RETAILERS	-0.040	-0.352	-0.311	-2.038	-0.244	-1.257	-0.242	-1.094	0.021	0.091	0.045	0.191	0.135	0.598	0.132	0.540	0.032	0.123	0.107	0.434
FTSE 350 GENERAL FIN	-0.162	-1.536	-0.426	-3.389	-0.484	-2.907	-0.457	-2.203	-0.330	-1.372	-0.329	-1.246	-0.269	-0.913	-0.175	-0.571	-0.313	-1.012	-0.215	-0.716
FTSE 350 H/C EQ & SVS	-0.185	-1.440	-0.515	-2.524	-0.435	-1.859	-0.438	-1.674	-0.420	-1.616	-0.478	-1.641	-0.542	-1.779	-0.477	-1.461	-0.428	-1.180	-0.441	-1.112
FTSE 350 INDS ENG	-0.212	-2.249	-0.583	-4.239	-0.691	-3.477	-0.764	-3.151	-0.646	-2.468	-0.569	-1.936	-0.473	-1.506	-0.447	-1.395	-0.456	-1.422	-0.480	-1.461
FTSE 350 INDS TRANSPT	-0.105	-1.265	-0.394	-3.085	-0.416	-2.203	-0.419	-2.004	-0.313	-1.475	-0.276	-1.302	-0.252	-1.110	-0.173	-0.696	-0.180	-0.720	-0.111	-0.418
FTSE 350 INDUSTRIAL MET	-1.077	-1.495	-2.900	-3.241	-3.735	-2.820	-3.597	-2.800	-2.555	-1.947	-2.908	-2.164	-3.781	-2.560	-3.691	-2.714	-3.947	-2.716	-3.818	-2.644
FTSE 350 LIFE INSURANCE	-0.292	-1.680	-0.791	-3.296	-0.826	-2.833	-0.568	-1.628	-0.413	-1.155	-0.140	-0.355	-0.058	-0.120	0.118	0.247	-0.042	-0.082	0.026	0.049
FTSE 350 MEDIA	-0.135	-1.162	-0.481	-3.157	-0.406	-1.979	-0.387	-1.498	-0.074	-0.270	0.084	0.286	0.071	0.207	0.086	0.264	-0.078	-0.247	-0.032	-0.096
FTSE 350 MINING	-0.271	-2.013	-0.530	-2.856	-0.536	-2.747	-0.578	-2.314	-0.346	-1.222	-0.469	-1.534	-0.239	-0.755	-0.258	-0.784	-0.301	-0.922	-0.280	-0.842
FTSE 350 NONLIFE INSUR	-0.196	-1.519	-0.633	-3.227	-0.634	-2.394	-0.514	-1.861	-0.343	-1.163	-0.211	-0.634	0.011	0.031	-0.067	-0.175	-0.117	-0.283	-0.146	-0.354
FTSE 350 OIL & GAS PROD	-0.065	-0.480	-0.250	-1.356	-0.095	-0.497	-0.134	-0.625	-0.205	-0.933	-0.090	-0.364	-0.104	-0.341	-0.093	-0.305	-0.236	-0.703	-0.287	-0.942
FTSE 350 PERSONAL GOODS	0.027	0.186	-0.167	-0.811	-0.366	-1.495	-0.242	-0.824	-0.226	-0.861	-0.041	-0.150	-0.139	-0.463	-0.371	-1.092	-0.432	-1.315	-0.513	-1.464
FTSE 350 PHARM & BIO	-0.199	-1.510	-0.443	-2.012	-0.293	-1.264	-0.076	-0.312	0.111	0.446	0.249	0.842	0.333	0.931	0.315	0.908	0.229	0.691	0.113	0.339
FTSE 350 REAL ESTATE	-0.082	-0.970	-0.291	-2.321	-0.434	-2.921	-0.548	-3.159	-0.514	-2.722	-0.440	-2.048	-0.347	-1.548	-0.183	-0.763	-0.266	-1.089	-0.270	-0.972
FTSE 350 S/W & COMP SVS	-0.258	-1.658	-0.656	-3.475	-0.562	-1.768	-0.583	-1.752	-0.241	-0.631	-0.244	-0.647	-0.146	-0.368	-0.090	-0.206	-0.249	-0.539	-0.223	-0.433
FTSE 350 SUPPORT SVS	-0.280	-2.873	-0.613	-4.583	-0.650	-4.579	-0.525	-2.720	-0.380	-2.119	-0.207	-1.014	-0.172	-0.730	-0.203	-0.817	-0.169	-0.662	-0.245	-0.928
FTSE 350 TCH H/W & EQ	-0.395	-1.199	-0.372	-0.517	-0.701	-0.549	-1.047	-0.776	-0.558	-0.406	-0.955	-0.705	-0.503	-0.342	-0.873	-0.488	-1.050	-0.569	-1.087	-0.640
FTSE 350 TOBACCO	0.178	1.867	-0.003	-0.019	0.049	0.302	0.116	0.708	0.284	1.685	0.243	1.275	0.239	1.145	0.039	0.162	0.017	0.065	-0.072	-0.272
FTSE 350 TRAVEL & LEIS	-0.048	-0.504	-0.404	-2.757	-0.428	-2.517	-0.417	-2.034	-0.214	-0.988	-0.075	-0.321	0.012	0.044	0.055	0.207	-0.034	-0.134	0.011	0.046

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Unlev" customers on future UK stock market changes at market and sector levels ("Unlev" for unleveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-28: Longer Horizon Effects of "Unlev" Order Flows on the UK Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Index	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**
FTSE 100	0.060	1.172	0.096	1.142	0.054	0.497	0.091	0.725	-0.027	-0.209	-0.076	-0.493	-0.162	-1.045	-0.101	-0.632	-0.084	-0.512	-0.059	-0.334
FTSE 350	0.065	1.324	0.101	1.236	0.064	0.616	0.095	0.787	-0.017	-0.132	-0.059	-0.398	-0.146	-0.967	-0.082	-0.523	-0.067	-0.415	-0.046	-0.269
FTSE 100 GROWTH	0.081	1.560	0.125	1.487	0.101	0.902	0.135	1.051	0.018	0.135	-0.012	-0.075	-0.098	-0.636	-0.037	-0.237	-0.030	-0.183	0.000	-0.001
FTSE 100 VALUE	0.039	0.720	0.068	0.767	0.009	0.084	0.047	0.370	-0.073	-0.545	-0.136	-0.875	-0.223	-1.377	-0.163	-0.968	-0.137	-0.796	-0.114	-0.617
FTSE 350 GROWTH	0.085	1.666	0.127	1.530	0.105	0.961	0.136	1.091	0.023	0.179	-0.006	-0.041	-0.095	-0.619	-0.032	-0.206	-0.025	-0.153	0.003	0.015
FTSE 350 VALUE	0.047	0.935	0.078	0.929	0.030	0.284	0.058	0.482	-0.052	-0.416	-0.104	-0.703	-0.190	-1.232	-0.126	-0.777	-0.104	-0.626	-0.088	-0.495
FTSE 350 AERO/DEFENCE	0.070	0.708	0.173	1.020	0.149	0.663	0.139	0.517	0.064	0.228	0.137	0.429	-0.033	-0.091	0.043	0.121	0.161	0.418	0.269	0.672
FTSE 350 AUTO & PARTS	0.164	1.745	0.277	2.144	0.300	1.838	0.387	2.093	0.204	0.966	0.206	0.917	0.125	0.504	0.161	0.600	0.169	0.572	0.183	0.616
FTSE 350 BANKS	0.060	1.032	0.075	0.802	0.033	0.265	0.044	0.312	-0.016	-0.103	-0.052	-0.277	-0.164	-0.846	-0.167	-0.832	-0.136	-0.638	-0.096	-0.411
FTSE 350 BEVERAGES	0.092	1.421	0.185	2.074	0.135	1.217	0.209	1.589	0.128	0.912	0.036	0.245	-0.046	-0.322	0.079	0.538	0.035	0.220	0.031	0.180
FTSE 350 CHEMICALS	0.051	0.610	0.129	1.084	0.032	0.222	0.117	0.680	0.034	0.190	0.021	0.102	-0.011	-0.047	0.166	0.690	0.223	0.885	0.267	1.010
FTSE 350 CON & MAT	0.159	2.498	0.199	1.921	0.163	1.364	0.078	0.523	-0.014	-0.084	0.012	0.062	-0.139	-0.635	-0.073	-0.307	-0.001	-0.003	-0.073	-0.268
FTSE 350 ELECTRICITY	0.068	1.020	0.215	2.226	0.152	1.233	0.164	1.218	0.084	0.587	0.114	0.707	0.106	0.642	0.231	1.341	0.168	0.943	0.210	1.163
FTSE 350 ELTRO/ELEC EQ	0.056	0.347	0.066	0.288	0.094	0.325	0.125	0.332	0.142	0.349	0.133	0.287	0.145	0.296	0.095	0.186	0.037	0.069	0.217	0.386
FTSE 350 EQT IVST INS	0.024	0.448	0.114	1.438	0.078	0.842	0.080	0.681	0.031	0.244	0.022	0.141	-0.137	-0.824	-0.037	-0.212	-0.059	-0.318	-0.040	-0.199
FTSE 350 EX.INV.TRUSTS	0.065	1.335	0.101	1.228	0.064	0.611	0.095	0.787	-0.018	-0.139	-0.060	-0.407	-0.146	-0.968	-0.083	-0.528	-0.067	-0.417	-0.046	-0.270
FTSE 350 FD & DRUG RTL	0.032	0.415	0.099	0.920	0.062	0.509	0.017	0.126	-0.049	-0.312	-0.136	-0.715	-0.182	-0.914	0.051	0.250	0.060	0.291	0.101	0.490
FTSE 350 FD PRODUCERS	0.002	0.028	0.006	0.061	0.006	0.051	0.044	0.331	-0.054	-0.369	-0.051	-0.318	-0.106	-0.648	0.008	0.045	0.010	0.056	0.024	0.125
FTSE 350 FXD LINE T/CM	-0.051	-0.512	-0.163	-1.177	-0.213	-1.046	-0.190	-0.869	-0.274	-1.163	-0.522	-1.953	-0.487	-1.659	-0.467	-1.466	-0.392	-1.241	-0.421	-1.234
FTSE 350 GEN RETAILERS	0.094	1.276	0.189	1.576	0.098	0.711	0.141	0.906	0.001	0.006	-0.042	-0.210	-0.082	-0.369	0.088	0.379	0.091	0.374	0.017	0.068
FTSE 350 GENERAL FIN	0.169	2.456	0.232	2.151	0.218	1.637	0.198	1.222	0.143	0.816	0.085	0.435	0.022	0.107	0.091	0.417	0.139	0.580	0.070	0.285
FTSE 350 H/C EQ & SVS	0.153	1.740	0.245	2.032	0.230	1.623	0.190	1.208	0.111	0.616	0.297	1.493	0.213	0.937	0.110	0.477	0.108	0.422	0.199	0.750
FTSE 350 INDS ENG	0.119	1.726	0.167	1.707	0.143	1.174	0.150	0.977	0.009	0.054	-0.014	-0.074	-0.103	-0.520	0.063	0.298	0.147	0.627	0.155	0.642
FTSE 350 INDS TRANSPT	0.065	1.066	0.032	0.311	0.020	0.166	0.065	0.474	0.008	0.052	-0.006	-0.037	-0.080	-0.432	0.005	0.026	-0.008	-0.040	0.012	0.053
FTSE 350 INDUSTRIAL MET	0.192	0.674	-0.079	-0.121	0.147	0.212	-0.449	-0.475	-0.446	-0.515	-0.242	-0.273	-0.058	-0.067	-0.118	-0.146	0.112	0.130	-0.014	-0.016
FTSE 350 LIFE INSURANCE	0.018	0.176	0.148	1.021	0.038	0.191	0.034	0.155	-0.061	-0.252	-0.159	-0.569	-0.207	-0.695	-0.157	-0.472	-0.071	-0.202	0.090	0.237
FTSE 350 MEDIA	0.197	2.461	0.216	1.758	0.184	1.212	0.201	1.186	0.112	0.642	-0.049	-0.252	-0.180	-0.873	-0.059	-0.261	-0.067	-0.300	-0.026	-0.117
FTSE 350 MINING	0.094	0.825	0.380	2.394	0.286	1.561	0.398	1.817	0.126	0.553	0.091	0.362	-0.136	-0.509	0.060	0.215	0.010	0.036	0.010	0.034
FTSE 350 NONLIFE INSUR	0.021	0.271	-0.056	-0.439	-0.100	-0.571	-0.261	-1.256	-0.423	-1.787	-0.424	-1.619	-0.538	-1.998	-0.416	-1.442	-0.357	-1.256	-0.314	-1.033
FTSE 350 OIL & GAS PROD	0.073	0.820	0.059	0.438	0.014	0.091	0.140	0.774	-0.029	-0.150	-0.027	-0.122	-0.140	-0.656	-0.082	-0.359	-0.077	-0.340	-0.049	-0.204
FTSE 350 PERSONAL GDS	0.060	0.698	0.042	0.357	-0.053	-0.384	-0.127	-0.778	-0.264	-1.523	-0.138	-0.656	-0.168	-0.723	-0.010	-0.040	0.072	0.276	0.004	0.017
FTSE 350 PHARM & BIO	0.058	0.665	0.146	1.113	0.165	1.006	0.187	1.003	-0.004	-0.022	-0.006	-0.028	-0.042	-0.190	0.020	0.094	-0.008	-0.036	0.014	0.058
FTSE 350 REAL ESTATE	-0.010	-0.173	0.080	0.876	0.057	0.490	-0.010	-0.069	-0.075	-0.497	-0.100	-0.561	-0.143	-0.752	-0.049	-0.242	0.013	0.063	0.062	0.281
FTSE 350 S/W & COMP SVS	0.102	0.953	0.105	0.603	0.163	0.701	0.147	0.533	0.098	0.335	-0.002	-0.008	-0.282	-0.878	-0.076	-0.211	-0.037	-0.099	-0.057	-0.143
FTSE 350 SUPPORT SVS	0.114	1.916	0.155	1.598	0.158	1.333	0.186	1.282	0.083	0.536	0.061	0.333	-0.009	-0.050	0.033	0.176	0.068	0.329	0.098	0.460
FTSE 350 TCH H/W & EQ	0.278	1.738	0.290	1.101	0.380	1.260	0.307	0.920	0.099	0.259	0.022	0.054	-0.364	-0.786	-0.234	-0.457	-0.339	-0.635	-0.292	-0.531
FTSE 350 TOBACCO	-0.137	-2.020	-0.085	-0.840	-0.143	-1.243	-0.105	-0.866	-0.204	-1.506	-0.157	-1.072	-0.192	-1.244	-0.137	-0.825	-0.152	-0.860	-0.179	-0.859
FTSE 350 TRAVEL & LEIS	0.106	1.675	0.179	1.969	0.162	1.489	0.176	1.409	0.098	0.750	0.127	0.848	0.038	0.237	0.089	0.515	0.067	0.357	0.086	0.447

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$ **, the table reports effects of order flows from "Lev" customers on future UK stock market changes at market and sector levels ("Lev" for leveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better.** R^2 **is up to 5%.**

Table 2-29: Longer Horizon Effects of "Lev" Order Flows on the UK Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Index	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**
DOW	0.111	2.527	0.054	0.896	0.134	1.686	0.177	2.009	0.223	2.234	0.251	2.397	0.295	2.424	0.254	2.131	0.236	1.775	0.225	1.535
S&P500	0.115	2.436	0.065	1.071	0.140	1.809	0.185	2.132	0.219	2.209	0.274	2.619	0.327	2.704	0.282	2.363	0.249	1.877	0.237	1.653
S&P500 ENERGY	0.107	1.318	0.132	1.228	0.243	2.096	0.235	1.810	0.213	1.425	0.201	1.339	0.342	1.970	0.341	1.963	0.233	1.282	0.255	1.347
S&P500 MATERIALS	0.104	1.713	0.026	0.326	0.112	1.116	0.157	1.312	0.125	0.937	0.103	0.726	0.128	0.813	0.090	0.572	0.023	0.134	-0.001	-0.003
S&P500 INDUSTRIAL CONGLOM	0.114	1.980	0.089	1.106	0.168	1.603	0.209	1.807	0.280	2.237	0.299	2.127	0.384	2.495	0.373	2.366	0.343	1.993	0.298	1.655
S&P500 CONSUMER SERVICES	0.107	1.915	0.063	0.815	0.075	0.753	0.135	1.266	0.237	1.881	0.259	1.921	0.350	2.179	0.264	1.757	0.272	1.685	0.324	1.860
S&P500 CONSUMER DURABLES	0.081	1.517	0.067	0.935	0.210	2.177	0.236	2.247	0.298	2.494	0.408	3.230	0.479	3.336	0.449	3.120	0.394	2.448	0.374	2.195
S&P500 HEALTH CARE EQUIP	0.099	2.276	0.083	1.356	0.149	1.996	0.172	2.142	0.193	2.343	0.221	2.547	0.208	2.319	0.121	1.254	0.090	0.848	0.086	0.753
S&P500 HEALTH CARE FACIL	0.120	1.439	-0.021	-0.173	0.027	0.173	0.092	0.569	0.281	1.623	0.483	2.515	0.621	3.131	0.547	2.655	0.471	2.321	0.402	1.952
S&P500 HEALTH CARE SERV	0.117	2.153	0.009	0.116	0.099	1.003	0.174	1.547	0.252	2.214	0.380	3.116	0.521	3.875	0.392	2.740	0.341	2.265	0.267	1.626
S&P500 BANKS	0.069	1.408	0.033	0.472	0.122	1.427	0.203	1.982	0.257	2.204	0.331	2.427	0.392	2.687	0.314	2.107	0.299	2.077	0.318	2.100
S&P500 INSURANCE	0.131	2.222	0.070	0.878	0.159	1.540	0.231	2.097	0.253	2.019	0.266	1.970	0.282	1.890	0.229	1.463	0.221	1.329	0.233	1.288
S&P500 IT SERVICES	0.149	2.016	0.096	0.885	0.148	1.007	0.305	1.555	0.408	1.803	0.478	1.919	0.743	1.680	0.671	1.511	0.603	1.283	0.690	1.176
S&P500 IT CONS & O/SVS	-0.002	-0.014	-0.083	-0.546	-0.022	-0.113	-0.080	-0.361	0.041	0.135	-0.095	-0.279	0.212	0.399	-0.038	-0.070	-0.081	-0.145	0.087	0.129
S&P500 TELECOM SERV	0.112	1.605	-0.034	-0.353	0.077	0.675	0.140	1.003	0.169	1.067	0.230	1.386	0.266	1.477	0.247	1.393	0.134	0.679	0.096	0.438
S&P500 UTILITIES	0.004	0.083	0.034	0.470	0.128	1.508	0.197	2.034	0.321	2.471	0.322	2.532	0.380	2.655	0.426	2.533	0.480	2.778	0.520	2.796

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Corp" customers on future US stock market changes at market and sector levels ("Corp" for commercial corporations) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-30: Longer Horizon Effects of "Corp" Order Flows on the US Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Index	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**	**Unlev**	**t-Stats**
DOW	-0.230	-2.663	-0.373	-2.810	-0.309	-2.165	-0.143	-0.852	-0.125	-0.600	-0.087	-0.440	0.128	0.612	0.122	0.514	0.020	0.086	0.083	0.329
S&P500	-0.236	-2.721	-0.398	-3.104	-0.311	-2.180	-0.153	-0.929	-0.142	-0.700	-0.138	-0.710	0.070	0.345	0.034	0.146	-0.074	-0.328	-0.005	-0.020
S&P500 ENERGY	-0.147	-1.289	-0.234	-1.372	-0.138	-0.843	-0.092	-0.540	-0.184	-0.912	-0.128	-0.602	0.031	0.123	-0.160	-0.624	-0.346	-1.436	-0.312	-1.192
S&P500 MATERIALS	-0.214	-1.935	-0.386	-2.320	-0.215	-1.162	-0.050	-0.248	-0.008	-0.030	0.089	0.350	0.337	1.197	0.227	0.729	0.117	0.396	0.168	0.506
S&P500 INDUSTRIAL CONGLOM	-0.233	-2.026	-0.309	-1.737	-0.227	-1.131	-0.069	-0.301	0.057	0.193	0.085	0.293	0.289	0.963	0.279	0.759	0.085	0.257	0.243	0.704
S&P500 CONSUMER SERVICES	-0.139	-1.597	-0.247	-1.971	-0.344	-2.123	-0.188	-0.980	0.004	0.022	-0.015	-0.065	0.198	0.828	0.293	0.961	0.100	0.346	0.046	0.150
S&P500 CONSUMER DURABLES	-0.186	-2.002	-0.365	-2.662	-0.364	-2.365	-0.212	-1.130	-0.145	-0.663	-0.124	-0.536	0.070	0.283	0.059	0.200	0.015	0.056	0.123	0.434
S&P500 HEALTH CARE EQUIP	-0.157	-1.889	-0.321	-2.355	-0.263	-1.715	-0.078	-0.447	0.040	0.210	-0.008	-0.047	0.059	0.325	-0.050	-0.238	-0.061	-0.286	-0.147	-0.666
S&P500 HEALTH CARE FACIL	-0.504	-1.339	-0.514	-1.232	-0.593	-1.393	-0.467	-0.989	-0.477	-0.930	-0.467	-0.988	-0.923	-1.217	-1.081	-1.268	-0.913	-1.129	-0.938	-1.224
S&P500 HEALTH CARE SERV	-0.270	-1.627	-0.258	-1.420	-0.296	-1.501	-0.165	-0.703	-0.208	-0.868	-0.227	-1.002	-0.371	-1.080	-0.507	-1.364	-0.529	-1.484	-0.557	-1.557
S&P500 BANKS	-0.227	-2.524	-0.367	-2.694	-0.239	-1.508	-0.190	-0.960	-0.232	-1.017	-0.256	-1.042	0.026	0.100	0.032	0.107	-0.022	-0.083	0.102	0.388
S&P500 INSURANCE	-0.289	-2.104	-0.339	-1.880	-0.221	-1.060	0.009	0.034	-0.142	-0.478	-0.128	-0.418	0.192	0.615	0.067	0.181	0.014	0.039	0.105	0.242
S&P500 IT SERVICES	-0.015	-0.098	-0.223	-0.923	-0.246	-0.762	-0.079	-0.205	0.028	0.061	0.046	0.102	0.470	0.934	0.515	0.942	0.614	1.092	0.850	1.377
S&P500 IT CONS & O/SVS	0.200	0.804	-0.040	-0.141	-0.047	-0.132	0.107	0.242	0.205	0.411	0.515	0.983	1.238	2.190	1.159	1.804	1.303	2.013	1.481	2.139
S&P500 TELECOM SERV	-0.301	-2.248	-0.261	-1.473	-0.186	-0.741	0.058	0.208	0.055	0.182	0.148	0.481	0.387	1.249	0.371	1.093	0.251	0.708	0.293	0.776
S&P500 UTILITIES	-0.155	-1.581	-0.262	-1.604	-0.144	-0.846	-0.123	-0.657	-0.166	-0.703	-0.155	-0.626	0.012	0.035	-0.217	-0.600	-0.355	-1.012	-0.339	-0.955

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Unlev" customers on future US stock market changes at market and sector levels ("Unlev" for unleveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-31: Longer Horizon Effects of "Unlev" Order Flows on the US Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Index	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**
DOW	-0.008	-0.125	0.010	0.137	0.055	0.574	0.003	0.030	-0.058	-0.442	-0.113	-0.843	-0.158	-1.078	-0.112	-0.716	-0.133	-0.792	-0.105	-0.561
S&P500	-0.010	-0.134	-0.018	-0.235	0.055	0.559	0.002	0.020	-0.066	-0.517	-0.115	-0.870	-0.145	-1.013	-0.108	-0.703	-0.126	-0.773	-0.094	-0.521
S&P500 ENERGY	-0.048	-0.394	-0.091	-0.660	0.054	0.283	-0.034	-0.157	-0.066	-0.312	-0.077	-0.346	-0.100	-0.424	-0.045	-0.171	-0.087	-0.343	-0.054	-0.212
S&P500 MATERIALS	0.006	0.072	0.004	0.037	0.053	0.402	-0.045	-0.293	-0.139	-0.811	-0.182	-1.014	-0.276	-1.354	-0.177	-0.816	-0.206	-0.903	-0.202	-0.820
S&P500 INDUSTRIAL CONGLOM	0.052	0.664	0.069	0.633	0.159	1.216	0.051	0.335	0.024	0.135	-0.034	-0.182	-0.178	-0.916	-0.137	-0.661	-0.154	-0.690	-0.236	-0.951
S&P500 CONSUMER SERVICES	0.076	0.945	-0.064	-0.593	0.087	0.663	0.035	0.238	-0.050	-0.303	-0.168	-0.997	-0.168	-0.894	-0.128	-0.647	-0.126	-0.603	-0.065	-0.283
S&P500 CONSUMER DURABLES	-0.021	-0.273	0.006	0.063	-0.016	-0.133	-0.056	-0.417	-0.089	-0.588	-0.196	-1.203	-0.191	-1.103	-0.041	-0.211	-0.075	-0.382	-0.142	-0.690
S&P500 HEALTH CARE EQUIP	0.053	0.710	0.078	0.824	0.048	0.411	-0.001	-0.004	-0.008	-0.057	-0.016	-0.116	-0.115	-0.783	-0.084	-0.527	-0.130	-0.761	-0.141	-0.821
S&P500 HEALTH CARE FACIL	-0.120	-1.211	-0.148	-1.083	-0.108	-0.654	-0.202	-0.897	-0.297	-1.243	-0.180	-0.633	-0.206	-0.626	-0.181	-0.525	-0.223	-0.635	-0.261	-0.692
S&P500 HEALTH CARE SERV	-0.022	-0.247	-0.009	-0.074	0.031	0.224	-0.020	-0.126	-0.064	-0.368	0.011	0.059	-0.011	-0.052	-0.016	-0.078	-0.076	-0.369	-0.063	-0.305
S&P500 BANKS	0.002	0.026	-0.005	-0.060	0.081	0.714	0.052	0.391	0.016	0.108	-0.027	-0.178	-0.086	-0.518	-0.126	-0.763	-0.095	-0.508	-0.085	-0.426
S&P500 INSURANCE	-0.011	-0.130	-0.014	-0.139	0.055	0.430	-0.019	-0.133	-0.137	-0.807	-0.197	-1.170	-0.230	-1.222	-0.245	-1.220	-0.202	-0.971	-0.151	-0.658
S&P500 IT SERVICES	-0.306	-1.459	-0.213	-0.961	0.029	0.089	-0.315	-0.693	-0.453	-0.957	-0.616	-1.065	-1.007	-1.445	-1.102	-1.627	-1.213	-1.747	-1.200	-1.623
S&P500 IT CONS & O/SVS	0.153	0.836	0.235	1.171	0.414	1.180	0.181	0.360	0.492	0.725	0.081	0.127	-0.223	-0.293	-0.214	-0.269	-0.412	-0.506	-0.403	-0.475
S&P500 TELECOM SERV	-0.010	-0.092	-0.013	-0.109	0.114	0.752	-0.057	-0.327	-0.183	-0.888	-0.241	-1.028	-0.207	-0.867	-0.190	-0.809	-0.298	-1.106	-0.284	-0.964
S&P500 UTILITIES	0.033	0.457	0.000	0.002	0.145	1.170	0.030	0.221	-0.011	-0.075	-0.004	-0.021	-0.054	-0.289	0.036	0.186	-0.088	-0.446	-0.013	-0.060

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Lev" customers on future US stock market changes at market and sector levels ("Lev" for leveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is negligible.

Table 2-32: Longer Horizon Effects of "Lev" Order Flows on the US Stock Market

In the UK stock market, foreign exchange order flows (net buying of Pound sterling) from corporations at day t predict positive stock market return at day t+1. The effect will become weaker and weaker subsequently. Order flows from unleveraged financial institutions will drive the next day's stock prices down, and the effect will run through into day t+4 with even stronger magnitudes. And from day t+5, the effect starts to fade away; while order flows from unleveraged financial institutions for the UK stock market have positive effect on next day's stock market and run into day t+2, then the effect is disappearing. Results indicate that foreign exchange order flows from financial institutions will have persistent effects on UK stock market during the first several days before they start to fade away; and the effects of order flows from non-financial corporations are strongest at the following day t+1, and start to disappear.

For US stocks, the net buying of British Pounds from commercial companies at day t also positively predict the stock prices at day t+1. The effects become weaker at day t+2 before it starts to show remarkable effects from day t+4 until day t+10. Finally the effect starts to fade away in 10 days and will vanish from then. Order flows from unleveraged financial institutions will drive the next day's stock prices down until day t+2. Then the effects start to disappear from day t+3, and vanish. Like discussed before, the forecasting power over longer horizons from leveraged financial institutions for the US stock market is very weak and mixed.

We discuss the effects over longer horizons based on stock market indices. It seems that the effects of order flows from non-financial corporations on stock markets are long, especially for US. While the effects of order flows from financial institutions are relatively short. The exception is that, at sector and market levels, the effects of corporate orders on the UK stock market only last for one day. However, at individual stock level, the effects are marginally stronger (in the appendices, we report the longer horizon results based on individual stocks of both UK and US). Nonetheless, the up to 10-day ahead forecasting power shows the possibility that information content relevant for stock markets are carried by foreign exchange order flows.

2.5.8 Trading Strategy Testing

After we checked the forecasting power of foreign exchange order flows for fluctuations of stock markets by statistical criteria, we also examine the practical value by testing trading strategies based on lagged order flows as independent variables. The statistically significant relations in forecasting models do not mean that the predictability works well in trading strategy testing. On the other hand, if the relation is not significant, one can not say that the successful trading rules can not be constructed. See Gradojevic and Neely (2008).

Our data covers 884 trading days and we use 300-day rolling sample forecast to do trading strategy testing, starting from the observation 300 and using a window of 300 days to estimate coefficients and calculate future realized returns. More specifically, we perform regressions over a sampling period of the first 300 days, by using the parameters estimated, together with the value of independent variables (order flows data, exchange rate return, stock market return at day 300), we can get the position of the stock considered, based on the forecasting return, at day 301. We will repeat the strategy over time with a fixed window of 300 days, until day 883, when we forecast the last day's position for the stock in our sampling period. We use "buy and hold" return as the benchmark and the results are presented in the following tables.

UK	B&H Return	Realised Return	B&H Sharpe Ratio	Strategy Sharpe Ratio
ALL	19.16%	9.20%	0.117	0.096
SIGNIFICANT	19.03%	8.04%	0.103	0.065
CORP	22.25%	4.84%	0.122	0.036
UNLEV	18.22%	9.81%	0.087	0.063
LEV	21.49%	11.75%	0.115	0.088

US	B&H Return	Realised Return	B&H Sharpe Ratio	Strategy Sharpe Ratio
ALL	3.88%	8.76%	0.023	0.085
SIGNIFICANT	1.97%	11.46%	0.011	0.099
CORP	-2.47%	12.86%	-0.013	0.091
UNLEV	2.30%	10.96%	0.012	0.085
LEV	N/A	N/A	N/A	N/A

Notes: The table reports returns and Sharpe ratio of FX order flows based trading strategy and "buy and hold" benchmark, for UK and US stock markets. "ALL" stands for the annual return of equally weighted portfolio of all the companies (84 for UK and 30 for US). "CORP", "UNLEV" and "LEV" represent the annual return of equally weighted portfolio of companies which are significantly affected by foreign exchange order flows from non-financial corporations, unleveraged financial institutions and leveraged financial institutions, respectively. "SIGNIFICANT" is the annual return of equally weighted portfolio of companies which are significantly affected by order flows from any group of customers.

Table 2-33: FX Order Flow Trading Strategy Testing

In the two tables, for the UK stock market, the order flow trading strategy does not beat the "buy and hold" benchmark, even for the one which only uses significant companies. While for the US stock market, the return of order flow strategy more than double the "buy and hold" benchmark return (8.76% and 3.87%). If we only use significant companies, the total return of order flow strategy is improved even more (11.46% and 1.97%). It seems that the forecasting power of foreign exchange order flows for the US stock market is stronger than that in the UK market. However, from the results of Sharpe ratio (Information ratio), its absolute value is below 0.1 for all types of customer order flows (normally more than 0.5 of Sharpe ratio is a profitable trading rule), although the Sharpe ratio of the strategy for US is larger than that of the benchmark, while Sharpe ratio of the strategy for the UK stock market is even less than that of the benchmark.

2.5.9 Other Results

Bootstrapping methodology

In addition to the results from standard OLS regressions with robust standard errors, we also test the effects of foreign exchange order flows on individual stock returns in the UK and US by bootstrapping residuals of our regression models. By using the bootstrapping technique, we can get more accurate standard error bands for the coefficients. The following four tables represent the regression results by using bootstrapping, in which the results are even stronger compared to the original.

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
FTSE 100	0.1034	2.1663	-0.1298	-1.4982	0.0598	0.8225
FTSE 350	0.0986	2.1254	-0.1328	-1.6040	0.0648	0.9186
FTSE 100 GROWTH	0.0999	2.1033	-0.1437	-1.5910	0.0810	1.1008
FTSE 100 VALUE	0.1074	2.1004	-0.1165	-1.2351	0.0391	0.5039
FTSE 350 GROWTH	0.0976	2.0031	-0.1462	-1.7068	0.0846	1.2296
FTSE 350 VALUE	0.1001	2.1738	-0.1209	-1.3565	0.0474	0.6783
FTSE 350 AERO/DEFENCE	0.1021	1.4840	-0.1373	-1.0413	0.0700	0.6648
FTSE 350 AUTO & PARTS	0.1612	2.2035	-0.2162	-1.6354	0.1642	1.4823
FTSE 350 BANKS	0.0867	1.5137	-0.2229	-2.0962	0.0603	0.6843
FTSE 350 BEVERAGES	0.0773	1.4336	-0.1181	-1.1908	0.0918	1.1588
FTSE 350 CHEMICALS	0.0457	0.7056	-0.0661	-0.5395	0.0507	0.5557
FTSE 350 CON & MAT	0.0741	1.5202	-0.1626	-1.8251	0.1593	2.2076
FTSE 350 ELECTRICITY	0.0674	1.4208	-0.0444	-0.5293	0.0680	0.9938
FTSE 350 ELTRO/ELEC EQ	0.1663	1.3369	-0.4187	-1.7772	0.0563	0.2952
FTSE 350 EQT IVST INS	0.0906	1.9908	-0.1710	-2.1175	0.0236	0.3564
FTSE 350 EX.INV.TRUSTS	0.0988	2.1910	-0.1320	-1.5066	0.0654	0.9344
FTSE 350 FD & DRUG RTL	0.0813	1.4082	0.0403	0.3954	0.0320	0.3827
FTSE 350 FD PRODUCERS	0.0484	0.9416	-0.1559	-1.6991	0.0019	0.0246
FTSE 350 FXD LINE T/CM	0.1328	1.6163	-0.0575	-0.3883	-0.0506	-0.4067
FTSE 350 GEN RETAILERS	0.0865	1.6843	-0.0397	-0.3955	0.0943	1.1474
FTSE 350 GENERAL FIN	0.0668	1.1626	-0.1618	-1.5585	0.1694	2.0045
FTSE 350 H/C EQ & SVS	0.0641	0.9320	-0.1851	-1.4283	0.1534	1.5232
FTSE 350 INDS ENG	0.0773	1.5520	-0.2116	-2.2818	0.1190	1.5864
FTSE 350 INDS TRANSPT	0.1211	2.5762	-0.1049	-1.2325	0.0651	0.9644
FTSE 350 INDUSTRIAL MET	0.1023	0.3471	-1.0766	-1.8927	0.1921	0.4335
FTSE 350 LIFE INSURANCE	0.1724	1.9354	-0.2923	-1.7896	0.0182	0.1327
FTSE 350 MEDIA	0.0578	0.8584	-0.1349	-1.1253	0.1974	1.8829
FTSE 350 MINING	0.1175	1.4508	-0.2713	-1.8506	0.0938	0.7868
FTSE 350 NONLIFE INSUR	0.0992	1.3636	-0.1960	-1.5150	0.0212	0.1901
FTSE 350 OIL & GAS PROD	0.1156	1.7988	-0.0649	-0.5363	0.0726	0.7442
FTSE 350 PERSONAL GOODS	-0.0263	-0.4306	0.0268	0.2320	0.0601	0.6690
FTSE 350 PHARM & BIO	0.1365	2.0302	-0.1994	-1.6474	0.0585	0.5930
FTSE 350 REAL ESTATE	0.0460	1.0566	-0.0825	-0.9773	-0.0096	-0.1440
FTSE 350 S/W & COMP SVS	-0.0170	-0.1832	-0.2578	-1.5898	0.1023	0.7627
FTSE 350 SUPPORT SVS	0.0741	1.5231	-0.2802	-3.1717	0.1141	1.6420
FTSE 350 TCH H/W & EQ	0.3066	1.7774	-0.3951	-1.2968	0.2785	0.9995
FTSE 350 TOBACCO	0.0750	1.4892	0.1781	1.9561	-0.1373	-1.8289
FTSE 350 TRAVEL & LEIS	0.0742	1.6112	-0.0478	-0.5714	0.1062	1.5531

Notes: The table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future UK stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-34: Bootstrapping Results for the UK Stock Market

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
Alliance Trust PLC	0.0833	1.9730	-0.1862	-2.3715	0.0229	0.3710
Amec PLC	0.1567	1.4290	-0.2486	-1.2107	-0.0196	-0.1205
Anglo American PLC	0.1498	1.6840	-0.4725	-2.8550	0.1189	0.8768
Antofagasta PLC	0.0354	0.4180	0.0409	0.2549	-0.0690	-0.5238
Associated British Foods PLC	0.0414	0.7810	-0.0523	-0.5323	0.1062	1.3198
Astrazeneca PLC	0.1970	2.3033	-0.2064	-1.2875	0.0147	0.1113
Autonomy Corp. PLC	0.3253	1.9372	-0.1020	-0.3366	-0.0909	-0.3557
Aviva PLC	0.1180	1.1004	-0.3951	-2.1080	-0.1841	-1.1924
BAE Systems PLC	0.0899	0.7234	-0.4198	-1.8760	0.1386	0.7462
Barclays PLC	0.0975	1.0916	-0.2228	-1.3526	0.2084	1.5340
BG Group PLC	0.0300	0.3932	-0.0864	-0.6030	0.1082	0.9105
BHP Billiton PLC	0.1298	1.4114	-0.1089	-0.6628	0.0506	0.3595
BP PLC	0.0986	1.3673	-0.1053	-0.8115	0.0601	0.5447
British Airways PLC	-0.0296	-0.2156	-0.3976	-1.6740	0.0768	0.3805
British American Tobacco PLC	0.0609	0.9703	0.1461	1.2492	-0.1903	-1.9971
British Land Company PLC	0.0208	0.3216	0.0678	0.5643	-0.0124	-0.1309
British Sky Broadcasting Group PLC	0.0691	0.7317	-0.1157	-0.6824	0.2557	1.7891
BT Group PLC	0.1386	1.5051	0.0511	0.3127	0.0298	0.2277
Bunzl PLC	0.0640	0.9255	-0.2807	-2.1819	0.1720	1.6440
Cable & Wireless PLC	-0.1009	-0.6391	0.2243	0.6938	-0.0309	-0.1150
Cadbury PLC	0.0435	0.7028	-0.0531	-0.4408	-0.0633	-0.6258
Cairn Energy PLC	0.1014	0.8596	0.1024	0.4883	0.0989	0.5548
The Capita Group PLC	0.1685	1.5305	-0.2059	-1.0000	0.1914	1.1550
Carnival PLC	0.0589	0.7531	-0.0494	-0.3265	0.1288	1.0706
Centrica PLC	0.0915	1.0888	0.1921	1.2491	0.0433	0.3394
Cobham PLC	0.0514	0.8836	-0.0220	-0.1937	0.0289	0.3055
Compass Group PLC	0.1341	1.2276	-0.5223	-2.5729	0.0007	0.0043
Diageo PLC	0.0736	1.1640	-0.0994	-0.8854	0.0995	1.0239
First Group PLC	-0.0088	-0.1121	-0.1807	-1.2706	0.1681	1.4349
Friends Provident PLC	0.1457	1.3013	-0.5686	-2.8244	0.1741	1.0629
G4S PLC	0.2310	2.1578	0.1397	0.7216	0.0561	0.3624
Glaxosmithkline PLC	0.1089	1.4851	-0.2307	-1.6766	0.0946	0.8399
Hbos PLC	0.0183	0.2228	-0.3198	-2.0027	0.0326	0.2553
HSBC Holdings PLC	0.0999	1.9967	-0.1704	-1.7516	0.0183	0.2331
Icap PLC	0.0761	1.0581	-0.0688	-0.5002	0.1648	1.4757
Imperial Tobacco Group PLC	0.0477	0.8265	0.1635	1.5104	-0.0959	-1.0382
International Power PLC	0.1885	1.7815	-0.3063	-1.7025	0.4764	2.9687
Invensys PLC	0.1569	0.6897	-0.9202	-2.2252	0.1455	0.4236
Johnson Matthey PLC	0.1497	2.0311	-0.0196	-0.1559	0.1642	1.5563
Kingfisher PLC	0.1177	1.3359	0.0800	0.4996	0.0036	0.0285
Land Securities Group PLC	0.0752	1.2916	-0.0993	-0.9029	-0.0503	-0.5704
Legal & General Group PLC	0.1272	1.2241	-0.2569	-1.3583	0.1183	0.7641
Liberty International PLC	-0.0048	-0.0943	-0.0626	-0.6743	-0.0001	-0.0017
Lloyds TSB Group PLC	0.0647	0.7154	-0.3199	-1.9708	0.1637	1.2553
London Stock Exchange Group PLC	0.1289	1.5572	-0.2656	-1.7662	0.2620	1.9974
Lonmin PLC	0.2362	2.3109	-0.3633	-1.9318	-0.0558	-0.3738
Man Group PLC	-0.0656	-0.8046	0.1217	0.7969	0.0815	0.6508
Marks & Spencer Group PLC	0.1461	1.7552	-0.0505	-0.3409	0.0187	0.1497
National Grid PLC	0.0303	0.5210	-0.2418	-2.2503	0.1234	1.4561
Next PLC	0.1137	1.4947	-0.0606	-0.4443	0.2079	1.7957
Old Mutual PLC	0.1364	1.4763	-0.0448	-0.2581	0.0896	0.6478
Pearson PLC	0.0528	0.6203	-0.3313	-2.0987	0.1018	0.7770
Prudential PLC	0.2407	2.0983	-0.3082	-1.5087	0.2184	1.3032

Reckitt Benckiser PLC	-0.0248	-0.3820	0.0410	0.3376	0.0733	0.7428
Reed Elsevier PLC	0.1218	1.5474	-0.0651	-0.4694	0.1655	1.4269
Rexam PLC	0.0680	1.0211	-0.2395	-2.0080	0.2266	2.2048
Rio Tinto PLC	0.0886	1.0194	-0.2829	-1.8587	0.1005	0.7935
Rolls-Royce Group PLC	0.0136	0.1170	-0.5557	-2.7369	0.0450	0.2583
Royal Bank Of Scotland Group PLC	0.0678	0.8366	-0.1770	-1.2234	0.0306	0.2601
Royal Dutch Shell PLC	0.1780	2.5258	-0.0624	-0.4893	0.0904	0.8387
RSA Insurance Group PLC	0.1294	0.8813	-0.2453	-0.9062	0.0439	0.1916
Sabmiller PLC	0.0871	1.2910	-0.0582	-0.4676	0.0298	0.2889
The Sage Group PLC	-0.0745	-0.6684	-0.2425	-1.1713	0.0480	0.2747
Sainsbury (J) PLC	0.0411	0.4951	0.1074	0.7288	0.0296	0.2431
Schroders PLC	0.0961	0.9398	-0.3629	-1.9401	0.1518	0.9442
Scottish & Southern Energy PLC	0.0570	1.1229	0.1356	1.4389	0.0087	0.1182
Severn Trent PLC	0.1170	1.9319	-0.0518	-0.4729	0.0177	0.1970
Shire PLC	0.0704	0.7127	-0.2575	-1.4050	-0.0443	-0.3018
Smith & Nephew PLC	0.0368	0.4456	-0.0126	-0.0835	0.1553	1.2197
Smiths Group PLC	0.1340	1.9011	-0.0639	-0.5155	0.0778	0.7830
Stagecoach Group PLC	0.1148	0.6911	-0.1325	-0.4303	-0.0058	-0.0219
Standard Chartered PLC	0.0967	1.2861	-0.1552	-1.1339	0.1895	1.5925
Tesco PLC	0.1078	1.5426	0.0040	0.0317	0.0599	0.5764
Thomson Reuters PLC	-0.0203	-0.1468	-0.0558	-0.2213	0.3181	1.5558
TUI Travel PLC	0.0929	1.0414	-0.1697	-0.9775	0.0426	0.3105
Unilever PLC	0.0606	0.9430	-0.2625	-2.2588	0.0220	0.2146
United Utilities Group PLC	0.1083	1.9564	0.1481	1.4121	-0.0207	-0.2468
Vodafone Group PLC	0.1414	1.5845	-0.1086	-0.6542	-0.0011	-0.0078
Whitbread PLC	0.0743	1.1347	-0.1512	-1.2608	0.1261	1.2549
Wolseley PLC	0.0574	0.7543	0.0035	0.0254	0.1629	1.4098
Wood Group (John) PLC	0.1796	1.6523	-0.0934	-0.4789	0.1028	0.6091
WPP Group PLC	0.0843	0.8584	-0.1059	-0.5922	0.2906	2.0402
Xstrata PLC	-0.0589	-0.5709	0.1239	0.6638	0.3587	2.3101
3I Group PLC	0.1199	1.3059	-0.5242	-3.2282	0.0920	0.6683

Notes: The table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future UK stock market changes at individual stock levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-35: Bootstrapping Results for the UK Stock Market

Index	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
DOW	0.1072	1.6682	-0.1467	-1.2479	-0.0482	-0.4964
S&P500	0.1044	1.7095	-0.2145	-1.9248	0.0057	0.0620
S&P500 ENERGY	0.1137	1.8300	-0.2328	-1.9693	0.0517	0.5692
S&P500 MATERIALS	0.1074	1.9555	-0.1385	-1.3416	0.0757	0.9007
S&P500 INDUSTRIAL CONGLOMERATE	0.0810	1.4730	-0.1855	-1.8481	-0.0209	-0.2480
S&P500 CONSUMER SERVICES	0.0991	2.1483	-0.1572	-1.7900	0.0527	0.7703
S&P500 CONSUMER DURABLES & APP	0.1198	1.3555	-0.5037	-3.1183	-0.1202	-0.8932
S&P500 HEALTH CARE EQUIP	0.1169	1.9220	-0.2695	-2.4143	-0.0215	-0.2329
S&P500 HEALTH CARE FACILITIES	0.0692	1.3156	-0.2271	-2.3655	0.0017	0.0211
S&P500 HEALTH CARE PROV & SERV	0.1308	2.1550	-0.2890	-2.5917	-0.0106	-0.1161
S&P500 BANKS	0.1490	1.2489	-0.0146	-0.0703	-0.3063	-1.7940
S&P500 INSURANCE	-0.0024	-0.0178	0.1995	0.7985	0.1528	0.7613
S&P500 IT SERVICES	0.1119	1.6620	-0.3005	-2.3522	-0.0099	-0.0988
S&P500 IT CONS & O/SVS	0.0042	0.0747	-0.1547	-1.5064	0.0335	0.4059
S&P500 TELECOM SERV	0.0042	0.0783	-0.1547	-1.5249	0.0335	0.4109
S&P500 UTILITIES	0.2373	2.0620	-0.2476	-1.1707	-0.1915	-1.1097

Notes: The table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future US stock market changes at market and sector levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-36: Bootstrapping Results for the US Stock Market

Company	Corp	t-Stats	Unlev	t-Stats	Lev	t-Stats
3M Company	0.0855	1.4225	-0.1376	-1.2992	-0.0958	-1.0864
AT & T Inc	0.0397	0.4900	-0.3695	-2.3289	0.0222	0.1722
Alcoa Incorporated	0.1151	1.2694	-0.3252	-1.8691	-0.0099	-0.0686
American Express Company	0.1114	1.5358	-0.1757	-1.2927	-0.0493	-0.4389
Bank Of America Corp.	0.0447	0.7878	-0.2305	-2.1588	-0.0281	-0.3359
The Boeing Company	0.0679	0.8208	-0.2149	-1.5293	0.1206	0.9878
Caterpillar Inc	0.1304	1.5956	-0.2902	-1.9573	0.0549	0.4452
Chevron Corp.	0.1048	1.7001	-0.2399	-2.1634	-0.1601	-1.7646
Citigroup Inc	0.0815	1.1246	-0.2055	-1.4904	-0.1035	-0.8891
The Coca Cola Company	0.0312	0.5560	-0.0671	-0.6356	0.0192	0.2283
EI Du Pont De Nemours	0.1580	2.2681	-0.2747	-2.2264	0.0516	0.5116
Exxon Mobil Corp.	0.1242	1.8906	-0.1380	-1.1738	0.0213	0.2214
General Electric Company	0.1160	1.7170	-0.2095	-1.6638	0.0848	0.8027
General Motors Corp.	0.0802	0.7390	-0.5528	-2.7646	0.0593	0.3478
Hewlett-Packard Company	0.0910	0.7927	-0.0885	-0.4579	0.1137	0.6860
Home Depot Inc	0.1836	2.0692	-0.4120	-2.5278	0.0010	0.0075
Intel Corp.	0.2051	1.8568	-0.4624	-2.2839	-0.0439	-0.2681
International Business Machines Corp.	0.0998	1.3686	-0.2280	-1.6932	-0.1662	-1.5580
JP Morgan Chase & Company	0.1251	1.4277	-0.3441	-2.2036	-0.0320	-0.2556
Johnson & Johnson	0.0704	1.2622	-0.0446	-0.4500	-0.1067	-1.2650
Kraft Foods Inc	0.0295	0.4819	-0.1824	-1.6082	0.1509	1.6492
McDonalds Corp.	0.0628	0.7051	-0.2752	-1.7230	0.2232	1.7180
Merck & Company Inc	0.1235	1.3174	0.0513	0.3103	-0.1218	-0.8460
Microsoft Corp.	0.1819	2.4823	-0.2218	-1.6776	0.0445	0.4065
Pfizer Inc	0.1757	2.3271	-0.0539	-0.3844	-0.2243	-1.9620
The Procter & Gamble Company	0.0868	1.8119	-0.0659	-0.7856	-0.0012	-0.0178
United Technologies Corp.	0.0733	1.0398	-0.3231	-2.4112	0.0000	0.0000
Verizon Communications	0.0514	0.6771	-0.2119	-1.5164	-0.0048	-0.0434
Wal Mart Stores Inc	0.1224	1.9585	-0.3271	-2.9180	-0.0099	-0.1072
The Walt Disney Company	0.1178	1.3823	-0.0735	-0.4585	-0.1390	-1.0368

Notes: The table reports effects of order flows from "Corp", "Unlev" and "Lev" customers on future US stock market changes at individual stock levels ("Corp" for commercial corporations, "Unlev" for unleveraged financial institutions, "Lev" for leveraged financial institutions). Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-37: Bootstrapping Results for the US Stock Market

2.6 Conclusions

A substantial literature on foreign exchange microstructure studies concludes that foreign exchange order flows have significant impact on exchange rate returns, especially at short to medium-term horizons, but very few studies focus on the impact of foreign exchange order flows on fluctuations of stock markets (see Evans and Lyons (2002a), Berger et al. (2008), among many others). With increasing global financial integration and capital internationalization, we should observe more and more interactions between different markets across different regions (e.g. Francis, Hasan and Hunter (2006), Dunne, Hau and Moore (2006), among others). In this chapter, we provide empirical evidence that foreign exchange order flows have material contemporaneous impacts on exchange rates, and that order flows in the foreign exchange market have substantial forecasting power for stock market returns, at market, sector and individual company levels, in both UK and US. Our results indicate that the impacts of order flows from different groups of customers on stock markets are very different, suggesting that they may hold different types of private price-relative information. In addition to statistical significance of our findings, we also check the predictability of foreign exchange order flows in trading strategy testing and find that for US stocks, the total return based on foreign exchange order flow trading rules outperforms the "buy & hold" benchmark. However the profitability of trading strategy does not hold for UK stocks. We conclude that at least a part of the private information conveyed in foreign exchange order flows, which was previously thought to be related to macroeconomic fundamentals or technical trading signals, is also of value to stock markets.

We conclude the following findings:

1) Foreign exchange order flows have significant but heterogeneous contemporaneous impacts on exchange rate returns. Commercial corporations have insignificant and negative impact on exchange rate returns, while unleveraged and leveraged financial institutions have significant and positive impact on contemporaneous exchange rate changes (consistent with most of related papers, e.g. Evans and Lyons (2002a)).

2) Foreign exchange order flows have forecasting power for stock market returns and the impacts are different across different types of customers and different regions. The forecasting power is partly consistent with findings in Francis et al. (2006) and Dunne et al. (2006). However our findings about the heterogeneity of impacts are novel.

Non-financial corporations

Foreign exchange order flows (defined as net buying of British Pounds and sales of US Dollars) from commercial companies at time t have significantly positive impacts on future changes of UK and US stock markets, although they have little impact on contemporaneous or future changes of GBPUSD exchange rate. We conclude that the link between foreign exchange order flows from commercial corporations and stock market changes at least a part reflects private information conveyed in foreign exchange order flows.

Financial institutions

Foreign exchange order flows (net buying of British Pounds) from unleveraged financial institutions have significantly negative impacts on future changes of UK and US stock markets. Foreign exchange order flows from leveraged financial institutions have significantly positive impact on the UK stock market (but no robust impact on the US stock market).

The relations for financial institutions also indicate that private information carried by foreign exchange order flows, which was previously thought to be about macroeconomic fundamentals or technical analysis signals, is relevant for the stock market. However, the systematic changes in impacts across participant groups suggest considerable heterogeneity in information content.

3) The forecasting power of daily foreign exchange order flows for stock market returns at the one day horizon is strong, and the effect continues over several days. It seems that the effects of order flows from non-financial corporations on stock markets are in a gradual process since they take many days to reach peak, while the effects of order flows from financial institutions, while persistent, are maximized at the very beginning. Foreign exchange order flows seem to have a longer-term effect in the US market compared to UK, and this probably explains why our simple trading strategy is more profitable in the US stock market. The forecasting power shows the possibility that information for stock markets are carried by foreign exchange order flows. (this is in line with Evans and Lyons (2005b) that the information is aggregated for a while)

4) In addition to statistical significance of our findings, we also check the predictability of foreign exchange order flows in trading strategy testing and find that for US stocks, the total realized return based on 300-day rolling foreign exchange order flow trading rules is much better than the “buy & hold” benchmark, however the profitability of trading strategy does not hold for UK stocks.

So far we have demonstrated the nature of the statistical relationships existing between daily order flows experienced by the RBS foreign exchange desks and future stock market movements. In the following chapter 3, we will consider much higher frequency relationships using a unique trade-by-trade database of foreign exchange order flows.

Appendices

Tables of coefficients and t-statistics of order flows' effects over longer horizons for UK and US individual stocks.

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Company	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**
Alliance Trust PLC	0.083	1.990	0.063	1.209	0.016	0.243	0.100	1.351	0.084	1.043	0.056	0.601	0.096	0.959	0.079	0.724	0.026	0.211	-0.019	-0.134
Amec PLC	0.157	1.374	0.196	1.321	0.221	1.207	0.292	1.369	0.354	1.423	0.170	0.607	0.218	0.737	0.273	0.893	0.405	1.181	0.517	1.387
Anglo American PLC	0.150	1.650	-0.047	-0.419	-0.097	-0.602	-0.102	-0.563	-0.196	-1.022	-0.239	-1.096	-0.167	-0.710	-0.155	-0.675	-0.206	-0.824	-0.371	-1.468
Antofagasta PLC	0.035	0.472	0.024	0.186	-0.120	-0.750	-0.110	-0.605	-0.162	-0.786	-0.213	-0.905	-0.184	-0.770	-0.171	-0.700	-0.217	-0.852	-0.280	-0.983
Associated British Foods PLC	0.041	0.718	-0.019	-0.292	0.018	0.199	0.036	0.376	-0.013	-0.120	-0.006	-0.052	-0.022	-0.161	0.047	0.353	0.078	0.538	-0.032	-0.216
Astrazeneca PLC	0.197	2.448	0.098	0.803	-0.018	-0.118	0.020	0.114	-0.035	-0.179	-0.163	-0.762	-0.169	-0.683	-0.213	-0.782	-0.283	-1.004	-0.369	-1.235
Autonomy Corp. PLC	0.325	2.000	0.284	1.355	0.322	1.173	0.641	2.115	0.712	2.055	0.789	2.005	0.929	2.192	0.964	2.170	0.841	1.747	1.005	1.933
Aviva PLC	0.118	1.103	0.037	0.237	0.012	0.057	0.031	0.135	0.054	0.213	0.010	0.033	0.033	0.109	-0.024	-0.081	0.052	0.152	-0.072	-0.209
BAE Systems PLC	0.090	0.754	-0.003	-0.011	-0.026	-0.093	-0.095	-0.322	-0.186	-0.519	-0.004	-0.009	0.096	0.197	0.065	0.140	0.067	0.142	0.133	0.271
Barclays PLC	0.098	1.099	-0.034	-0.309	0.024	0.155	0.135	0.785	0.054	0.305	0.106	0.535	0.158	0.720	0.148	0.645	0.177	0.646	0.078	0.263
BG Group PLC	0.030	0.344	-0.046	-0.422	0.035	0.264	0.017	0.121	-0.025	-0.154	-0.122	-0.725	-0.057	-0.298	-0.097	-0.507	-0.192	-0.942	-0.311	-1.478
BHP Billiton PLC	0.130	1.423	0.013	0.111	-0.004	-0.031	-0.013	-0.076	-0.046	-0.237	-0.108	-0.499	-0.073	-0.314	-0.015	-0.066	-0.079	-0.305	-0.211	-0.784
BP PLC	0.099	1.178	0.089	0.873	0.138	1.091	0.108	0.792	0.136	0.852	0.063	0.352	0.210	1.074	0.177	0.921	0.091	0.432	-0.060	-0.268
British Airways PLC	-0.030	-0.210	-0.131	-0.682	-0.215	-0.878	-0.046	-0.158	-0.220	-0.728	-0.307	-0.878	-0.325	-0.845	-0.443	-1.145	-0.385	-0.889	-0.579	-1.224
British American Tobacco PLC	0.061	1.029	0.076	0.953	0.145	1.452	0.228	2.195	0.184	1.609	0.121	0.948	0.245	1.716	0.195	1.218	0.160	0.929	0.065	0.342
British Land Company PLC	0.021	0.301	-0.008	-0.094	0.003	0.029	0.095	0.869	0.129	0.977	0.051	0.336	0.090	0.563	0.128	0.771	0.126	0.649	-0.002	-0.010
British Sky Broadcasting Group PLC	0.069	0.798	-0.063	-0.523	-0.060	-0.405	0.071	0.431	0.116	0.681	0.169	0.878	0.330	1.460	0.411	1.822	0.340	1.365	0.172	0.648
BT Group PLC	0.139	1.540	0.087	0.716	0.300	2.122	0.405	2.444	0.356	1.858	0.345	1.657	0.359	1.611	0.340	1.496	0.239	0.992	0.120	0.448
Bunzl PLC	0.064	0.960	-0.058	-0.658	0.018	0.154	0.117	0.932	0.028	0.186	0.069	0.387	0.137	0.736	0.192	1.040	0.210	1.046	0.128	0.611
Cable & Wireless PLC	-0.101	-0.749	-0.224	-0.948	-0.207	-0.685	0.100	0.273	0.291	0.679	0.437	0.902	0.601	1.222	0.692	1.363	0.897	1.538	0.878	1.410
Cadbury PLC	0.043	0.641	0.039	0.462	0.056	0.527	0.168	1.426	0.145	1.060	0.143	0.941	0.170	0.992	0.225	1.260	0.204	1.053	0.171	0.820
Cairn Energy PLC	0.101	0.963	0.262	1.680	0.364	1.759	0.439	1.903	0.451	1.567	0.491	1.600	0.547	1.723	0.529	1.554	0.332	0.947	0.210	0.531
The Capita Group PLC	0.169	1.600	0.237	1.751	0.253	1.472	0.250	1.207	0.276	1.137	0.238	0.950	0.264	0.891	0.385	1.228	0.427	1.158	0.369	0.931
Carnival PLC	0.059	0.721	-0.067	-0.536	-0.189	-1.265	-0.095	-0.555	-0.109	-0.587	-0.109	-0.575	-0.036	-0.169	-0.095	-0.426	-0.102	-0.422	-0.170	-0.708
Centrica PLC	0.091	1.003	0.006	0.058	0.071	0.554	0.100	0.699	0.014	0.091	-0.038	-0.243	-0.088	-0.466	-0.256	-1.302	-0.211	-0.977	-0.147	-0.640
Cobham PLC	0.051	0.863	0.075	0.791	0.133	1.121	0.224	1.704	0.170	0.941	0.056	0.221	0.026	0.101	-0.033	-0.124	-0.043	-0.152	-0.080	-0.263
Compass Group PLC	0.134	1.161	-0.022	-0.157	0.007	0.043	0.159	0.768	0.087	0.402	-0.089	-0.325	0.124	0.415	-0.049	-0.152	0.029	0.078	-0.019	-0.049
Diageo PLC	0.074	1.070	0.009	0.113	0.081	0.778	0.196	1.812	0.134	1.089	0.114	0.918	0.102	0.732	0.002	0.011	-0.038	-0.247	-0.046	-0.302
First Group PLC	-0.009	-0.119	-0.015	-0.176	0.143	1.269	0.096	0.795	-0.064	-0.464	0.014	0.090	0.088	0.554	0.061	0.362	0.004	0.023	-0.036	-0.191
Friends Provident PLC	0.146	1.296	-0.016	-0.101	-0.133	-0.662	-0.052	-0.226	-0.196	-0.767	-0.321	-1.058	-0.353	-1.013	-0.321	-0.899	-0.312	-0.781	-0.377	-0.934
G4S PLC	0.231	2.366	0.191	1.639	0.211	1.443	0.284	1.760	0.346	1.886	0.113	0.545	0.130	0.579	0.150	0.626	0.158	0.587	0.168	0.558
Glaxosmithkline PLC	0.109	1.486	-0.012	-0.116	0.011	0.081	0.066	0.429	-0.086	-0.494	-0.096	-0.538	0.028	0.145	0.056	0.276	-0.010	-0.044	-0.103	-0.474
Hbos PLC	0.018	0.198	-0.025	-0.212	0.077	0.536	0.166	1.032	0.167	0.917	0.209	1.078	0.230	1.017	0.131	0.596	0.078	0.314	0.051	0.189
HSBC Holdings PLC	0.100	2.101	0.035	0.534	-0.001	-0.009	0.071	0.723	0.051	0.504	0.018	0.160	0.061	0.506	0.024	0.190	-0.024	-0.176	-0.072	-0.503
Icap PLC	0.076	1.041	0.144	1.409	0.125	0.984	0.110	0.713	0.133	0.790	0.111	0.665	0.186	1.026	0.224	1.145	0.261	1.165	0.155	0.633
Imperial Tobacco Group PLC	0.048	0.761	-0.044	-0.539	0.029	0.317	0.124	1.260	0.042	0.392	0.020	0.173	0.101	0.753	0.006	0.044	-0.046	-0.289	-0.115	-0.700
International Power PLC	0.188	1.695	0.062	0.475	0.037	0.209	-0.033	-0.181	-0.093	-0.444	-0.037	-0.155	0.002	0.009	0.003	0.011	-0.027	-0.092	-0.134	-0.412
Invensys PLC	0.157	0.768	0.171	0.584	0.098	0.268	0.458	1.076	0.327	0.664	0.176	0.336	0.118	0.203	0.256	0.415	0.286	0.440	0.040	0.059
Johnson Matthey PLC	0.150	2.168	0.073	0.773	-0.100	-0.818	-0.053	-0.418	-0.100	-0.714	-0.103	-0.635	-0.064	-0.367	-0.150	-0.849	-0.161	-0.886	-0.167	-0.890
Kingfisher PLC	0.118	1.377	-0.005	-0.036	0.056	0.373	0.173	1.067	0.125	0.662	0.218	1.013	0.038	0.170	-0.012	-0.051	0.051	0.215	0.021	0.089
Land Securities Group PLC	0.075	1.199	0.003	0.041	0.071	0.715	0.172	1.657	0.162	1.306	0.060	0.393	0.069	0.444	0.006	0.041	-0.018	-0.105	-0.043	-0.239
Legal & General Group PLC	0.127	1.180	-0.038	-0.239	0.013	0.062	0.117	0.533	0.075	0.330	-0.067	-0.252	-0.003	-0.009	-0.125	-0.431	-0.143	-0.450	-0.188	-0.565
Liberty International PLC	-0.005	-0.087	-0.051	-0.899	-0.014	-0.192	0.108	1.409	0.014	0.156	-0.071	-0.648	0.027	0.223	0.047	0.367	0.063	0.440	0.005	0.033
Lloyds TSB Group PLC	0.065	0.694	-0.039	-0.320	-0.005	-0.032	0.013	0.069	-0.094	-0.460	-0.090	-0.377	-0.076	-0.299	-0.111	-0.438	-0.087	-0.303	-0.107	-0.349
London Stock Exchange Group PLC	0.129	1.772	0.122	1.217	0.085	0.699	0.201	1.321	0.112	0.673	0.000	-0.001	0.169	0.775	0.450	1.157	0.606	1.394	0.686	1.511

Lonmin PLC	0.236	1.914	0.051	0.358	0.004	0.021	0.019	0.098	-0.091	-0.426	-0.132	-0.563	-0.214	-0.859	-0.171	-0.690	-0.235	-0.904	-0.481	-1.684
Man Group PLC	-0.066	-0.901	-0.118	-1.154	-0.170	-1.378	-0.173	-1.201	-0.113	-0.653	-0.146	-0.774	-0.139	-0.664	-0.095	-0.418	-0.247	-1.001	-0.370	-1.507
Marks & Spencer Group PLC	0.146	1.979	0.232	2.217	0.213	1.558	0.392	2.447	0.439	2.699	0.338	1.923	0.297	1.583	0.306	1.644	0.356	1.760	0.323	1.557
National Grid PLC	0.030	0.522	-0.042	-0.580	-0.052	-0.571	-0.091	-0.873	-0.144	-1.236	-0.190	-1.720	-0.161	-1.363	-0.177	-1.469	-0.216	-1.724	-0.252	-2.041
Next PLC	0.114	1.609	0.111	0.956	0.153	1.137	0.329	1.871	0.301	1.637	0.239	1.251	0.158	0.783	0.187	0.887	0.185	0.865	0.155	0.680
Old Mutual PLC	0.136	1.485	-0.044	-0.381	-0.159	-1.105	-0.145	-0.867	-0.378	-2.035	-0.485	-2.238	-0.521	-2.258	-0.570	-2.357	-0.589	-2.130	-0.683	-2.264
Pearson PLC	0.053	0.629	0.002	0.021	-0.059	-0.392	0.003	0.014	-0.033	-0.179	-0.086	-0.415	0.022	0.095	0.067	0.292	0.088	0.325	-0.030	-0.102
Prudential PLC	0.241	2.154	0.051	0.287	-0.004	-0.016	0.102	0.399	0.148	0.506	0.086	0.254	0.148	0.414	0.062	0.168	0.122	0.284	-0.104	-0.233
Reckitt Benckiser PLC	-0.025	-0.359	-0.024	-0.269	-0.044	-0.408	0.051	0.424	0.025	0.172	0.052	0.353	0.047	0.305	-0.091	-0.578	-0.144	-0.858	-0.118	-0.645
Reed Elsevier PLC	0.122	1.254	0.006	0.051	-0.020	-0.128	0.114	0.680	0.030	0.155	0.024	0.120	0.224	0.919	0.172	0.755	0.098	0.395	0.015	0.062
Rexam PLC	0.068	1.022	-0.007	-0.083	-0.002	-0.021	0.027	0.206	0.025	0.181	-0.032	-0.216	-0.036	-0.223	-0.027	-0.161	0.018	0.096	0.080	0.387
Rio Tinto PLC	0.089	1.094	-0.079	-0.704	-0.118	-0.848	-0.099	-0.573	-0.105	-0.538	-0.144	-0.655	-0.110	-0.468	-0.115	-0.482	-0.137	-0.543	-0.197	-0.738
Rolls-Royce Group PLC	0.014	0.144	-0.073	-0.522	-0.103	-0.547	-0.119	-0.505	-0.206	-0.787	-0.176	-0.581	-0.078	-0.231	-0.165	-0.509	-0.148	-0.419	-0.116	-0.323
Royal Bank Of Scotland Group PLC	0.068	0.809	-0.007	-0.067	-0.001	-0.008	0.036	0.241	-0.095	-0.565	-0.087	-0.442	0.006	0.025	-0.012	-0.050	0.011	0.039	-0.049	-0.164
Royal Dutch Shell PLC	0.178	2.367	0.153	1.629	0.274	2.240	0.297	2.183	0.296	1.792	0.211	1.174	0.339	1.760	0.257	1.310	0.186	0.851	0.124	0.526
RSA Insurance Group PLC	0.129	0.908	-0.028	-0.140	-0.115	-0.416	-0.178	-0.550	-0.097	-0.296	-0.214	-0.586	-0.329	-0.850	-0.309	-0.782	-0.252	-0.571	-0.224	-0.487
Sabmiller PLC	0.087	1.265	-0.023	-0.261	0.002	0.020	0.080	0.650	-0.001	-0.006	-0.160	-0.984	-0.103	-0.566	-0.140	-0.763	-0.221	-1.088	-0.224	-1.001
The Sage Group PLC	-0.074	-0.577	-0.064	-0.431	-0.121	-0.630	-0.125	-0.585	0.025	0.108	-0.015	-0.060	0.151	0.546	0.121	0.434	-0.028	-0.085	-0.122	-0.394
Sainsbury (J) PLC	0.041	0.575	0.063	0.607	0.035	0.235	0.105	0.610	0.051	0.250	0.109	0.474	0.100	0.390	0.163	0.623	0.201	0.759	0.037	0.140
Schroders PLC	0.096	0.959	0.110	0.751	0.104	0.537	0.264	1.193	0.242	0.976	0.229	0.882	0.334	1.150	0.321	1.118	0.399	1.233	0.294	0.912
Scottish & Southern Energy PLC	0.057	1.201	0.022	0.347	0.102	1.270	0.107	1.253	0.043	0.441	0.051	0.479	0.040	0.331	0.051	0.426	0.044	0.334	0.075	0.542
Severn Trent PLC	0.117	1.671	0.122	1.136	0.239	2.080	0.174	1.331	0.096	0.661	0.158	0.976	0.204	1.165	0.165	0.947	0.194	1.042	0.098	0.512
Shire PLC	0.070	0.717	0.059	0.485	-0.078	-0.463	-0.018	-0.096	0.053	0.251	0.026	0.118	0.174	0.702	0.332	1.278	0.249	0.856	0.397	1.235
Smith & Nephew PLC	0.037	0.520	-0.061	-0.679	-0.081	-0.668	0.076	0.569	0.030	0.209	-0.028	-0.185	-0.129	-0.781	-0.177	-0.992	-0.238	-1.287	-0.430	-2.222
Smiths Group PLC	0.134	1.940	0.005	0.062	0.124	1.090	0.235	1.790	0.141	1.006	0.185	1.188	0.222	1.313	0.220	1.223	0.246	1.312	0.187	0.897
Stagecoach Group PLC	0.115	0.784	0.152	0.732	0.338	1.492	0.424	1.811	0.178	0.488	0.213	0.535	0.016	0.035	0.031	0.067	0.024	0.051	0.082	0.167
Standard Chartered PLC	0.097	1.367	-0.008	-0.078	-0.047	-0.374	0.064	0.458	0.033	0.204	-0.034	-0.182	-0.070	-0.321	-0.062	-0.290	-0.070	-0.301	-0.123	-0.514
Tesco PLC	0.108	1.640	0.081	0.925	0.051	0.509	0.118	1.037	0.108	0.733	0.169	1.142	0.257	1.634	0.161	1.086	0.158	0.992	0.161	0.911
Thomson Reuters PLC	-0.020	-0.157	-0.102	-0.531	-0.150	-0.609	-0.146	-0.503	-0.271	-0.887	-0.218	-0.624	-0.300	-0.814	-0.452	-1.181	-0.262	-0.614	-0.293	-0.649
TUI Travel PLC	0.093	1.009	0.049	0.354	0.046	0.269	0.095	0.480	0.066	0.281	0.090	0.351	0.128	0.443	-0.004	-0.013	0.030	0.091	0.127	0.356
Unilever PLC	0.061	0.991	0.053	0.748	0.071	0.757	0.142	1.309	0.087	0.731	0.092	0.707	0.213	1.546	0.141	1.029	0.055	0.353	0.012	0.074
United Utilities Group PLC	0.108	1.328	0.111	1.151	0.163	1.448	0.161	1.351	0.136	1.045	0.136	0.992	0.128	0.785	0.098	0.605	0.081	0.441	0.141	0.715
Vodafone Group PLC	0.141	1.438	0.026	0.200	0.071	0.459	0.174	0.997	0.187	0.980	0.237	1.116	0.264	1.095	0.222	0.939	0.086	0.331	-0.044	-0.159
Whitbread PLC	0.074	1.015	0.097	1.055	0.034	0.290	0.137	1.032	0.112	0.777	0.051	0.318	0.058	0.335	0.062	0.332	0.149	0.736	0.219	1.058
Wolseley PLC	0.057	0.799	0.056	0.602	0.058	0.451	0.214	1.557	0.150	1.012	0.194	1.085	0.176	0.898	0.295	1.495	0.393	1.855	0.436	1.631
Wood Group (John) PLC	0.180	1.325	0.235	1.612	0.393	2.109	0.447	2.272	0.470	2.281	0.401	1.604	0.497	1.938	0.432	1.439	0.409	1.275	0.292	0.898
WPP Group PLC	0.084	0.886	-0.061	-0.459	-0.181	-1.099	-0.039	-0.213	-0.151	-0.785	-0.261	-1.206	-0.168	-0.663	-0.194	-0.797	-0.227	-0.901	-0.357	-1.392
Xstrata PLC	-0.059	-0.562	-0.275	-2.170	-0.248	-1.479	-0.233	-1.228	-0.246	-1.128	-0.431	-1.856	-0.373	-1.595	-0.273	-1.044	-0.461	-1.559	-0.638	-2.098
3I Group PLC	0.120	1.358	0.047	0.410	0.000	0.001	0.124	0.675	0.069	0.355	0.091	0.404	0.176	0.722	0.091	0.393	0.091	0.332	0.033	0.111

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Corp" customers on future UK stock market changes at individual stock levels ("Corp" for commercial corporations) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-38: Longer Horizon Effects of "Corp" Order Flows on the UK Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Company	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats
Alliance Trust PLC	-0.186	-2.147	-0.404	-3.324	-0.414	-3.060	-0.514	-2.777	-0.428	-2.385	-0.427	-2.210	-0.348	-1.663	-0.340	-1.603	-0.355	-1.614	-0.326	-1.414
Amec PLC	-0.249	-1.201	-0.699	-2.331	-0.966	-2.493	-0.836	-1.707	-0.738	-1.315	-0.759	-1.210	-0.385	-0.603	-0.288	-0.443	-0.273	-0.353	-0.181	-0.231
Anglo American PLC	-0.473	-2.996	-0.575	-2.726	-0.672	-3.014	-0.627	-2.381	-0.401	-1.282	-0.585	-1.706	-0.313	-0.935	-0.421	-1.210	-0.554	-1.608	-0.444	-1.237
Antofagasta PLC	0.041	0.294	-0.547	-2.500	-0.584	-2.438	-0.569	-2.020	-0.541	-1.513	-0.630	-1.634	-0.447	-1.045	-0.265	-0.586	-0.396	-0.824	-0.439	-0.928
Associated British Foods PLC	-0.052	-0.415	-0.245	-1.254	-0.201	-1.048	-0.116	-0.497	-0.077	-0.348	0.013	0.056	0.148	0.607	0.051	0.204	0.005	0.023	-0.163	-0.655
Astrazeneca PLC	-0.206	-1.235	-0.623	-2.572	-0.564	-2.119	-0.252	-0.797	-0.032	-0.088	0.026	0.067	0.092	0.199	0.127	0.290	0.144	0.332	-0.086	-0.187
Autonomy Corp. PLC	-0.102	-0.415	-0.658	-1.626	-0.722	-1.344	-1.032	-1.585	-0.583	-0.997	-0.448	-0.714	-0.136	-0.199	-0.002	-0.003	-0.361	-0.485	-0.511	-0.606
Aviva PLC	-0.395	-1.681	-0.864	-2.512	-0.894	-2.315	-0.473	-1.110	-0.399	-0.937	0.012	0.027	0.062	0.111	0.173	0.301	0.003	0.005	0.021	0.033
BAE Systems PLC	-0.420	-1.853	-0.804	-2.671	-0.394	-1.105	-0.343	-0.909	-0.279	-0.649	-0.072	-0.143	0.119	0.191	0.219	0.363	-0.061	-0.099	-0.515	-0.686
Barclays PLC	-0.223	-1.541	-0.574	-2.827	-0.489	-1.839	-0.114	-0.336	0.120	0.381	0.216	0.636	0.267	0.641	0.259	0.631	0.309	0.757	0.399	0.946
BG Group PLC	-0.086	-0.611	-0.266	-1.357	-0.067	-0.300	-0.048	-0.196	-0.022	-0.083	0.062	0.207	0.033	0.093	0.065	0.192	-0.049	-0.144	-0.140	-0.395
BHP Billiton PLC	-0.109	-0.705	-0.574	-2.731	-0.588	-2.754	-0.615	-2.079	-0.373	-1.171	-0.373	-1.079	-0.167	-0.456	-0.120	-0.317	-0.217	-0.605	-0.308	-0.836
BP PLC	-0.105	-0.717	-0.267	-1.270	-0.133	-0.662	-0.153	-0.640	-0.246	-1.020	-0.151	-0.577	-0.156	-0.482	-0.105	-0.314	-0.261	-0.718	-0.275	-0.827
British Airways PLC	-0.398	-1.315	-0.784	-1.698	-0.924	-1.488	-0.725	-1.342	-0.332	-0.593	-0.539	-0.948	-0.469	-0.791	-0.156	-0.239	-0.157	-0.224	0.269	0.370
British American Tobacco PLC	0.146	1.215	-0.130	-0.744	-0.118	-0.525	0.015	0.071	0.249	1.087	0.146	0.575	0.153	0.586	-0.084	-0.266	-0.176	-0.546	-0.331	-1.068
British Land Company PLC	0.068	0.539	-0.228	-1.514	-0.287	-1.610	-0.564	-2.738	-0.476	-1.953	-0.262	-1.008	-0.242	-0.815	-0.062	-0.192	-0.060	-0.165	-0.012	-0.031
British Sky Broadcasting Group PLC	-0.116	-0.821	-0.475	-2.370	-0.303	-1.141	-0.349	-1.059	0.030	0.096	0.128	0.376	-0.075	-0.192	-0.027	-0.068	-0.129	-0.329	0.103	0.241
BT Group PLC	0.051	0.307	-0.292	-1.233	-0.103	-0.355	-0.092	-0.288	0.180	0.532	0.464	1.143	0.456	1.092	0.422	0.987	0.347	0.825	0.168	0.408
Bunzl PLC	-0.281	-1.913	-0.505	-2.223	-0.675	-2.501	-0.677	-2.327	-0.643	-2.039	-0.654	-1.976	-0.540	-1.624	-0.396	-1.177	-0.481	-1.542	-0.534	-1.554
Cable & Wireless PLC	0.224	0.922	-0.907	-1.322	-1.419	-1.561	-1.643	-1.708	-1.277	-1.293	-1.669	-1.567	-1.762	-1.623	-2.284	-2.055	-2.260	-2.103	-2.550	-1.732
Cadbury PLC	-0.053	-0.364	-0.205	-1.081	-0.258	-1.153	-0.371	-1.569	-0.213	-0.965	-0.149	-0.576	-0.181	-0.617	-0.178	-0.539	-0.393	-1.240	-0.350	-1.063
Cairn Energy PLC	0.102	0.550	0.076	0.260	0.051	0.134	0.020	0.046	-0.052	-0.113	-0.064	-0.122	0.179	0.317	0.014	0.024	-0.184	-0.308	-0.358	-0.568
The Capita Group PLC	-0.206	-1.014	-0.856	-2.562	-0.697	-1.769	-0.345	-0.695	0.087	0.187	0.316	0.682	0.522	1.029	0.557	1.081	0.805	1.317	0.573	0.932
Carnival PLC	-0.049	-0.365	-0.409	-2.203	-0.568	-1.926	-0.510	-1.507	0.025	0.076	0.175	0.451	0.253	0.581	0.383	0.875	0.266	0.585	0.204	0.444
Centrica PLC	0.192	1.050	0.030	0.133	0.122	0.463	0.062	0.217	0.228	0.755	0.297	0.885	0.277	0.759	0.129	0.339	0.010	0.025	-0.317	-0.795
Cobham PLC	-0.022	-0.179	-0.153	-0.871	-0.353	-1.807	-0.305	-1.364	-0.115	-0.478	-0.087	-0.309	0.074	0.222	0.094	0.268	0.335	0.921	0.337	0.876
Compass Group PLC	-0.522	-2.600	-0.909	-3.266	-0.799	-2.760	-0.544	-1.438	-0.278	-0.796	-0.056	-0.138	-0.058	-0.141	-0.217	-0.489	0.055	0.116	-0.148	-0.317
Diageo PLC	-0.099	-0.605	-0.383	-1.974	-0.212	-0.992	-0.070	-0.267	-0.154	-0.580	-0.063	-0.209	0.020	0.059	-0.154	-0.464	-0.169	-0.566	-0.393	-1.236
First Group PLC	-0.181	-1.180	-0.404	-1.853	-0.597	-2.192	-0.570	-1.449	-0.299	-0.801	-0.214	-0.561	0.120	0.278	-0.024	-0.054	0.058	0.137	0.373	0.849
Friends Provident PLC	-0.569	-2.820	-1.275	-4.224	-1.148	-3.926	-1.116	-2.826	-0.895	-2.149	-0.542	-1.136	-0.251	-0.433	-0.137	-0.230	-0.148	-0.250	-0.103	-0.179
G4S PLC	0.140	0.661	-0.506	-1.852	-0.612	-1.759	-0.491	-1.297	-0.860	-2.120	-0.556	-1.367	-0.499	-0.977	-0.374	-0.756	-0.422	-0.773	-0.472	-0.755
Glaxosmithkline PLC	-0.231	-1.547	-0.405	-1.627	-0.153	-0.588	0.014	0.054	0.184	0.674	0.355	1.157	0.425	1.206	0.337	0.936	0.184	0.525	0.120	0.342
Hbos PLC	-0.320	-1.640	-0.448	-2.160	-0.316	-1.372	-0.314	-1.040	-0.216	-0.743	-0.016	-0.051	0.135	0.368	0.142	0.406	0.212	0.576	0.326	0.874
HSBC Holdings PLC	-0.170	-1.586	-0.420	-3.126	-0.506	-3.038	-0.416	-1.930	-0.309	-1.333	-0.301	-1.241	-0.312	-1.209	-0.294	-1.121	-0.382	-1.435	-0.297	-1.097
Icap PLC	-0.069	-0.529	-0.287	-1.420	-0.425	-1.637	-0.406	-1.379	-0.414	-1.274	-0.462	-1.366	-0.495	-1.467	-0.410	-1.184	-0.514	-1.335	-0.407	-0.933
Imperial Tobacco Group PLC	0.163	1.541	0.097	0.574	0.147	0.874	0.167	0.963	0.310	1.750	0.296	1.333	0.245	0.954	0.097	0.354	0.140	0.517	0.098	0.326
International Power PLC	-0.306	-1.089	-0.363	-1.195	-0.611	-1.693	-0.723	-1.853	-0.474	-1.122	-0.634	-1.413	-0.476	-0.963	-0.344	-0.627	-0.096	-0.167	-0.243	-0.397
Invensys PLC	-0.920	-2.436	-1.821	-3.606	-2.472	-3.457	-2.296	-3.248	-2.471	-2.654	-2.401	-2.389	-2.763	-2.416	-2.808	-2.449	-2.138	-1.472	-1.630	-1.174
Johnson Matthey PLC	-0.020	-0.131	-0.443	-2.486	-0.403	-2.185	-0.381	-1.919	-0.267	-1.216	-0.283	-1.154	-0.242	-0.754	-0.252	-0.755	-0.323	-0.961	-0.454	-1.440
Kingfisher PLC	0.080	0.497	-0.071	-0.321	0.074	0.291	0.043	0.134	0.558	1.695	0.455	1.416	0.570	1.812	0.525	1.590	0.405	1.216	0.654	1.897
Land Securities Group PLC	-0.099	-0.914	-0.093	-0.595	-0.258	-1.523	-0.386	-2.008	-0.244	-1.110	-0.146	-0.565	-0.130	-0.481	0.020	0.071	0.047	0.165	-0.046	-0.141
Legal & General Group PLC	-0.257	-1.217	-0.890	-3.489	-0.909	-2.871	-0.639	-1.772	-0.519	-1.402	-0.254	-0.619	-0.235	-0.472	-0.150	-0.300	-0.358	-0.708	-0.230	-0.443
Liberty International PLC	-0.063	-0.633	-0.121	-0.920	-0.099	-0.688	-0.022	-0.122	-0.087	-0.478	-0.061	-0.324	0.019	0.082	0.178	0.662	0.007	0.027	-0.027	-0.098
Lloyds TSB Group PLC	-0.320	-1.834	-0.645	-2.661	-0.515	-1.797	-0.379	-1.114	-0.165	-0.438	0.028	0.070	0.222	0.498	0.292	0.644	0.247	0.545	0.228	0.476
London Stock Exchange Group PLC	-0.266	-1.908	-0.544	-2.532	-0.773	-3.320	-0.834	-2.945	-0.868	-2.641	-0.723	-2.147	-0.603	-1.643	-0.546	-1.379	-0.804	-1.872	-0.817	-1.880

Lonmin PLC	-0.363	-1.715	-0.542	-2.175	-0.656	-2.787	-0.841	-3.131	-0.620	-2.065	-0.616	-1.784	-0.408	-1.169	-0.163	-0.424	-0.239	-0.585	-0.243	-0.572
Man Group PLC	0.122	0.613	-0.013	-0.056	-0.008	-0.032	-0.122	-0.403	-0.015	-0.043	-0.262	-0.748	-0.268	-0.651	-0.086	-0.207	-0.162	-0.384	0.073	0.172
Marks & Spencer Group PLC	-0.050	-0.280	-0.446	-1.792	-0.425	-1.320	-0.486	-1.409	-0.243	-0.666	0.056	0.158	0.289	0.824	0.248	0.636	0.086	0.208	0.127	0.312
National Grid PLC	-0.242	-1.951	-0.383	-2.280	-0.185	-1.023	-0.278	-1.227	-0.026	-0.121	0.070	0.294	0.104	0.423	0.010	0.037	-0.006	-0.025	-0.180	-0.677
Next PLC	-0.061	-0.311	-0.235	-1.005	-0.181	-0.626	-0.212	-0.557	-0.061	-0.148	0.027	0.067	0.129	0.307	0.071	0.161	0.020	0.047	0.127	0.308
Old Mutual PLC	-0.045	-0.263	-0.353	-1.715	-0.214	-0.910	-0.057	-0.153	0.166	0.488	0.262	0.630	0.522	1.145	0.703	1.521	0.551	1.057	0.415	0.833
Pearson PLC	-0.331	-1.779	-0.811	-3.434	-0.503	-2.011	-0.640	-2.403	-0.156	-0.523	-0.100	-0.307	-0.107	-0.266	-0.260	-0.680	-0.465	-1.208	-0.512	-1.239
Prudential PLC	-0.308	-1.367	-0.869	-2.907	-0.852	-2.283	-0.693	-1.694	-0.374	-0.835	-0.258	-0.544	-0.182	-0.327	0.047	0.081	-0.095	-0.150	0.122	0.183
Reckitt Benckiser PLC	0.041	0.265	-0.150	-0.718	-0.358	-1.409	-0.231	-0.748	-0.224	-0.822	-0.047	-0.164	-0.208	-0.664	-0.423	-1.193	-0.468	-1.337	-0.525	-1.414
Reed Elsevier PLC	-0.065	-0.534	-0.221	-1.022	-0.043	-0.185	0.020	0.067	0.289	0.962	0.451	1.252	0.467	1.086	0.459	1.106	0.133	0.328	-0.119	-0.284
Rexam PLC	-0.239	-1.625	-0.187	-1.294	-0.258	-1.393	-0.247	-1.025	-0.264	-1.279	-0.142	-0.638	-0.273	-1.188	0.040	0.155	-0.116	-0.422	-0.197	-0.688
Rio Tinto PLC	-0.283	-1.743	-0.581	-2.678	-0.430	-1.880	-0.572	-2.052	-0.322	-1.071	-0.465	-1.441	-0.206	-0.597	-0.228	-0.615	-0.127	-0.327	-0.131	-0.338
Rolls-Royce Group PLC	-0.556	-2.276	-1.077	-3.359	-0.982	-2.207	-0.744	-1.566	-0.220	-0.445	-0.365	-0.647	-0.347	-0.583	-0.407	-0.657	-0.379	-0.613	-0.511	-0.776
Royal Bank Of Scotland Group PLC	-0.177	-1.146	-0.494	-2.854	-0.296	-1.304	0.029	0.110	0.140	0.498	0.456	1.419	0.341	0.847	0.581	1.528	0.694	1.594	0.725	1.712
Royal Dutch Shell PLC	-0.062	-0.406	-0.335	-1.781	-0.068	-0.301	-0.153	-0.602	-0.155	-0.607	0.058	0.204	0.058	0.178	-0.059	-0.175	-0.189	-0.492	-0.324	-0.883
RSA Insurance Group PLC	-0.245	-0.843	-1.173	-3.154	-1.237	-2.532	-0.895	-1.769	-0.547	-0.950	-0.297	-0.448	0.264	0.342	0.119	0.144	0.052	0.061	-0.056	-0.065
Sabmiller PLC	-0.058	-0.306	-0.367	-1.803	-0.351	-1.623	-0.326	-1.251	-0.524	-2.077	-0.516	-1.578	-0.428	-1.168	-0.531	-1.356	-0.500	-1.315	-0.645	-1.605
The Sage Group PLC	-0.243	-1.205	-0.469	-2.039	-0.305	-0.981	-0.356	-1.048	0.173	0.415	0.092	0.195	-0.076	-0.164	0.219	0.474	-0.094	-0.193	-0.010	-0.019
Sainsbury (J) PLC	0.107	0.678	-0.228	-1.066	-0.200	-0.751	-0.056	-0.180	0.266	0.814	0.260	0.702	0.312	0.749	0.208	0.483	0.019	0.044	0.066	0.161
Schroders PLC	-0.363	-1.845	-0.784	-3.504	-0.881	-2.827	-0.679	-1.752	-0.411	-0.992	-0.367	-0.783	-0.326	-0.628	-0.303	-0.596	-0.335	-0.634	-0.198	-0.379
Scottish & Southern Energy PLC	0.136	1.270	-0.076	-0.561	0.022	0.147	-0.040	-0.223	0.063	0.328	0.109	0.512	0.075	0.315	-0.099	-0.398	-0.148	-0.535	-0.257	-0.976
Severn Trent PLC	-0.052	-0.470	0.049	0.281	0.073	0.332	0.132	0.488	0.224	0.951	0.299	1.256	0.117	0.435	0.035	0.127	0.072	0.249	0.045	0.137
Shire PLC	-0.258	-1.472	-0.620	-2.341	-0.734	-2.589	-0.835	-2.587	-0.774	-2.116	-0.594	-1.334	-0.673	-1.306	-0.910	-1.712	-1.162	-1.975	-1.152	-1.945
Smith & Nephew PLC	-0.013	-0.056	-0.453	-1.567	-0.206	-0.654	-0.127	-0.358	-0.062	-0.178	-0.100	-0.242	-0.203	-0.471	-0.072	-0.156	-0.090	-0.200	0.041	0.086
Smiths Group PLC	-0.064	-0.398	-0.371	-1.998	-0.301	-1.646	-0.441	-2.219	-0.288	-1.249	-0.103	-0.388	-0.216	-0.784	-0.220	-0.751	-0.070	-0.226	-0.094	-0.276
Stagecoach Group PLC	-0.133	-0.383	0.150	0.348	0.226	0.453	0.416	0.689	0.445	0.660	0.893	1.299	1.114	1.508	1.300	1.681	1.409	1.617	1.591	1.851
Standard Chartered PLC	-0.155	-1.125	-0.391	-2.119	-0.485	-1.853	-0.407	-1.344	-0.194	-0.653	-0.232	-0.704	-0.244	-0.738	-0.194	-0.535	-0.283	-0.755	-0.275	-0.759
Tesco PLC	0.004	0.038	-0.210	-0.924	-0.236	-0.886	-0.273	-0.884	-0.052	-0.155	0.172	0.474	-0.040	-0.126	-0.010	-0.026	-0.037	-0.108	-0.109	-0.338
Thomson Reuters PLC	-0.056	-0.208	-0.595	-1.714	-0.363	-0.867	-0.518	-1.032	-0.364	-0.607	-0.146	-0.229	-0.238	-0.341	-0.299	-0.432	-0.464	-0.636	-0.388	-0.511
TUI Travel PLC	-0.170	-0.904	-0.638	-2.828	-0.934	-3.194	-1.064	-2.943	-0.945	-2.474	-0.847	-1.930	-0.405	-0.881	-0.443	-0.840	-0.528	-1.005	-0.431	-0.807
Unilever PLC	-0.262	-0.841	-0.412	-1.093	-0.336	-0.942	-0.402	-1.012	-0.364	-0.936	-0.230	-0.525	-0.318	-0.663	-0.315	-0.695	-0.349	-0.731	-0.449	-0.926
United Utilities Group PLC	0.148	1.610	0.012	0.079	-0.162	-0.615	-0.095	-0.367	0.005	0.020	0.021	0.076	-0.016	-0.052	-0.198	-0.609	-0.228	-0.711	-0.279	-0.855
Vodafone Group PLC	-0.109	-0.457	-0.338	-1.184	-0.047	-0.133	0.043	0.108	0.272	0.676	0.306	0.732	0.239	0.526	0.234	0.446	0.650	1.252	0.615	1.150
Whitbread PLC	-0.151	-1.133	-0.455	-2.282	-0.474	-2.327	-0.373	-1.500	-0.243	-0.993	-0.268	-1.044	-0.260	-0.935	-0.356	-1.168	-0.338	-1.024	-0.387	-1.247
Wolseley PLC	0.004	0.027	-0.324	-1.703	-0.413	-2.110	-0.410	-1.716	-0.279	-1.192	-0.164	-0.613	-0.208	-0.671	-0.071	-0.196	-0.122	-0.365	-0.113	-0.316
Wood Group (John) PLC	-0.093	-0.494	-0.696	-2.658	-0.880	-2.676	-1.274	-3.193	-1.388	-3.102	-1.731	-3.647	-1.899	-3.962	-1.899	-3.899	-1.870	-4.144	-1.636	-3.252
WPP Group PLC	-0.106	-0.534	-0.564	-2.227	-0.514	-1.819	-0.481	-1.550	-0.054	-0.138	0.072	0.179	0.253	0.553	0.172	0.382	-0.006	-0.014	0.049	0.103
Xstrata PLC	0.124	0.656	-0.264	-1.038	-0.506	-1.634	-0.759	-2.094	-0.648	-1.904	-0.786	-2.145	-0.616	-1.321	-0.741	-1.299	-0.655	-1.127	-0.797	-1.350
3I Group PLC	-0.524	-1.893	-1.035	-3.247	-1.055	-3.037	-0.749	-2.074	-0.366	-0.853	-0.352	-0.829	-0.391	-0.890	-0.467	-0.995	-0.361	-0.740	-0.288	-0.620

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Unlev" customers on future UK stock market changes at individual stock levels ("Unlev" for unleveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-39: Longer Horizon Effects of "Unlev" Order Flows on the UK Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Company	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**
Alliance Trust PLC	0.023	0.429	0.047	0.609	0.066	0.779	0.086	0.779	0.051	0.417	0.073	0.506	-0.067	-0.431	0.018	0.113	-0.041	-0.237	-0.039	-0.212
Amec PLC	-0.020	-0.132	0.073	0.335	0.315	1.268	0.318	0.996	0.069	0.211	0.165	0.416	0.059	0.143	0.146	0.323	0.168	0.342	0.182	0.372
Anglo American PLC	0.119	0.915	0.434	2.450	0.320	1.511	0.375	1.528	0.081	0.326	0.044	0.163	-0.221	-0.792	-0.018	-0.061	-0.060	-0.198	-0.089	-0.279
Antofagasta PLC	-0.069	-0.547	0.015	0.086	-0.044	-0.206	0.050	0.194	-0.094	-0.345	-0.103	-0.346	-0.280	-0.828	0.012	0.033	0.041	0.107	-0.017	-0.044
Associated British Foods PLC	0.106	1.462	0.144	1.488	0.055	0.423	0.041	0.292	-0.038	-0.241	-0.043	-0.245	-0.080	-0.465	0.022	0.119	0.130	0.684	0.244	1.288
Astrazeneca PLC	0.015	0.131	0.098	0.533	0.131	0.565	0.148	0.603	-0.063	-0.254	0.059	0.215	-0.016	-0.056	0.188	0.591	0.165	0.488	0.136	0.386
Autonomy Corp. PLC	-0.091	-0.219	0.236	0.558	0.156	0.373	0.208	0.459	0.228	0.465	0.132	0.254	-0.070	-0.137	-0.115	-0.211	0.164	0.290	0.464	0.752
Aviva PLC	-0.184	-1.418	-0.067	-0.366	-0.160	-0.678	-0.177	-0.646	-0.264	-0.883	-0.346	-1.030	-0.345	-0.980	-0.244	-0.618	-0.218	-0.537	-0.001	-0.002
BAE Systems PLC	0.139	0.834	0.188	0.677	0.168	0.470	0.145	0.346	0.097	0.222	0.367	0.742	0.171	0.305	0.175	0.319	0.378	0.657	0.614	1.031
Barclays PLC	0.208	2.138	0.136	0.888	0.093	0.468	0.119	0.553	0.011	0.046	-0.078	-0.279	-0.252	-0.861	-0.290	-1.018	-0.358	-1.191	-0.317	-0.969
BG Group PLC	0.108	1.128	0.046	0.282	-0.151	-0.949	-0.022	-0.124	-0.211	-1.050	-0.097	-0.418	-0.265	-1.089	-0.019	-0.069	0.011	0.040	0.022	0.082
BHP Billiton PLC	0.051	0.391	0.275	1.512	0.206	1.003	0.359	1.420	0.038	0.143	-0.004	-0.014	-0.191	-0.577	0.042	0.121	-0.012	-0.033	0.028	0.079
BP PLC	0.060	0.583	0.045	0.308	0.018	0.105	0.150	0.763	-0.006	-0.031	-0.033	-0.139	-0.123	-0.529	-0.023	-0.091	-0.019	-0.074	0.004	0.014
British Airways PLC	0.077	0.400	0.079	0.283	0.039	0.117	-0.013	-0.034	-0.040	-0.102	-0.106	-0.242	-0.394	-0.797	-0.170	-0.325	-0.024	-0.046	0.149	0.263
British American Tobacco PLC	-0.190	-2.498	-0.141	-1.201	-0.203	-1.435	-0.122	-0.782	-0.228	-1.370	-0.176	-1.012	-0.229	-1.227	-0.118	-0.581	-0.193	-0.894	-0.240	-0.975
British Land Company PLC	-0.012	-0.129	0.090	0.698	0.050	0.332	-0.058	-0.340	-0.249	-1.300	-0.284	-1.255	-0.318	-1.373	-0.110	-0.447	-0.066	-0.253	0.006	0.021
British Sky Broadcasting Group PLC	0.256	1.872	0.239	1.332	0.217	1.007	0.242	1.089	0.162	0.649	0.080	0.309	0.005	0.018	-0.019	-0.068	-0.107	-0.361	-0.002	-0.008
BT Group PLC	0.030	0.283	0.111	0.826	0.063	0.397	0.173	0.931	-0.079	-0.353	-0.157	-0.586	-0.160	-0.545	-0.119	-0.368	-0.150	-0.497	0.078	0.241
Bunzl PLC	0.172	1.753	0.275	1.925	0.217	1.219	0.286	1.541	0.125	0.594	0.151	0.646	0.105	0.451	0.077	0.320	0.209	0.828	0.179	0.719
Cable & Wireless PLC	-0.031	-0.194	0.091	0.410	0.341	1.079	0.304	0.782	0.317	0.716	-0.110	-0.228	-0.209	-0.390	-0.049	-0.091	-0.032	-0.058	-0.425	-0.618
Cadbury PLC	-0.063	-0.712	-0.047	-0.368	-0.065	-0.402	-0.043	-0.248	-0.159	-0.814	-0.154	-0.703	-0.195	-0.851	-0.060	-0.246	-0.058	-0.240	-0.092	-0.349
Cairn Energy PLC	0.099	0.622	0.161	0.584	0.614	1.681	0.579	1.457	0.522	1.237	0.413	0.894	0.430	0.870	0.407	0.751	0.331	0.593	0.143	0.245
The Capita Group PLC	0.191	1.444	0.127	0.690	0.209	1.014	0.155	0.561	0.059	0.193	-0.232	-0.632	-0.403	-1.016	-0.339	-0.869	-0.370	-0.931	-0.421	-0.969
Carnival PLC	0.129	1.159	0.245	1.630	0.143	0.781	0.250	1.212	0.143	0.649	0.024	0.097	-0.258	-0.977	-0.250	-0.893	-0.261	-0.879	-0.283	-0.856
Centrica PLC	0.043	0.430	0.098	0.676	0.275	1.533	0.305	1.489	0.101	0.445	0.196	0.840	0.150	0.591	0.219	0.888	0.282	1.095	0.457	1.715
Cobham PLC	0.029	0.328	0.126	0.959	0.008	0.046	-0.061	-0.305	-0.097	-0.446	-0.017	-0.067	0.097	0.325	0.144	0.465	0.159	0.483	0.117	0.339
Compass Group PLC	0.001	0.004	0.058	0.269	-0.094	-0.359	0.185	0.561	-0.076	-0.225	-0.158	-0.408	-0.205	-0.550	-0.141	-0.361	-0.126	-0.306	0.102	0.264
Diageo PLC	0.099	1.369	0.197	1.901	0.143	1.142	0.226	1.461	0.164	0.993	-0.002	-0.014	-0.120	-0.742	-0.039	-0.236	-0.069	-0.381	-0.080	-0.406
First Group PLC	0.168	1.410	0.349	2.459	0.413	2.579	0.479	2.565	0.507	2.389	0.338	1.503	0.117	0.495	0.253	0.966	0.268	0.973	0.338	1.190
Friends Provident PLC	0.174	1.272	0.157	0.872	0.096	0.410	0.138	0.519	0.212	0.724	0.052	0.162	-0.116	-0.346	-0.076	-0.200	0.125	0.326	0.162	0.380
G4S PLC	0.056	0.429	0.050	0.290	-0.028	-0.131	0.228	0.990	0.150	0.636	0.430	1.613	0.328	1.156	0.279	0.930	0.327	1.033	0.358	1.038
Glaxosmithkline PLC	0.095	0.963	0.217	1.547	0.275	1.558	0.342	1.622	0.148	0.647	0.112	0.448	0.084	0.331	0.113	0.470	0.078	0.303	0.157	0.560
Hbos PLC	0.033	0.366	-0.042	-0.279	0.002	0.012	0.077	0.394	0.090	0.445	0.038	0.170	-0.165	-0.682	-0.060	-0.241	-0.004	-0.014	0.106	0.368
HSBC Holdings PLC	0.018	0.335	0.114	1.275	0.104	0.915	0.171	1.267	0.157	1.075	0.168	1.049	0.134	0.834	0.119	0.666	0.185	0.968	0.147	0.731
Icap PLC	0.165	1.405	0.224	1.381	0.359	1.897	0.309	1.425	0.280	1.169	0.203	0.727	0.080	0.259	0.008	0.028	0.106	0.323	-0.108	-0.307
Imperial Tobacco Group PLC	-0.096	-1.144	-0.064	-0.551	-0.122	-0.987	-0.137	-0.997	-0.208	-1.323	-0.153	-0.949	-0.147	-0.822	-0.205	-1.081	-0.136	-0.662	-0.124	-0.518
International Power PLC	0.476	2.523	0.820	3.281	0.878	3.112	1.046	3.317	0.940	2.962	1.029	3.045	0.965	2.659	1.049	2.555	0.803	1.929	0.894	2.012
Invensys PLC	0.145	0.465	0.182	0.439	0.205	0.413	0.379	0.594	0.682	1.037	0.670	0.852	0.804	0.966	0.570	0.662	0.583	0.666	0.933	0.993
Johnson Matthey PLC	0.164	1.653	0.352	2.696	0.249	1.733	0.322	1.708	0.261	1.338	0.274	1.355	0.101	0.458	0.209	0.866	0.190	0.746	0.373	1.369
Kingfisher PLC	0.004	0.033	0.148	1.013	-0.004	-0.026	0.093	0.505	-0.059	-0.267	-0.082	-0.332	-0.224	-0.837	-0.017	-0.058	0.048	0.160	-0.174	-0.546
Land Securities Group PLC	-0.050	-0.627	0.043	0.359	0.000	0.000	-0.129	-0.683	-0.160	-0.794	-0.216	-0.990	-0.257	-1.103	-0.114	-0.453	-0.048	-0.187	0.149	0.557
Legal & General Group PLC	0.118	0.893	0.296	1.681	0.211	0.926	0.188	0.825	0.084	0.348	0.083	0.312	-0.059	-0.203	-0.084	-0.255	-0.039	-0.110	0.181	0.477
Liberty International PLC	0.000	-0.002	0.082	0.980	-0.077	-0.742	-0.094	-0.703	-0.157	-1.103	-0.217	-1.327	-0.232	-1.304	-0.148	-0.761	-0.036	-0.174	-0.026	-0.121
Lloyds TSB Group PLC	0.164	1.633	0.246	1.645	0.181	0.912	0.096	0.409	-0.010	-0.042	-0.172	-0.588	-0.302	-1.011	-0.239	-0.761	-0.225	-0.682	-0.017	-0.045
London Stock Exchange Group PLC	0.262	2.496	0.385	2.390	0.376	2.018	0.453	1.969	0.395	1.505	0.306	1.124	0.456	1.561	0.438	1.392	0.259	0.752	0.136	0.379

Lonmin PLC	-0.056	-0.363	0.163	0.820	0.056	0.239	0.104	0.402	-0.118	-0.421	-0.168	-0.544	-0.250	-0.732	-0.138	-0.387	-0.200	-0.497	-0.205	-0.498
Man Group PLC	0.081	0.728	0.285	1.812	0.206	1.120	0.247	1.057	0.141	0.520	0.065	0.221	-0.230	-0.748	0.029	0.089	0.014	0.041	0.008	0.022
Marks & Spencer Group PLC	0.019	0.116	0.235	0.678	0.273	0.670	0.495	1.136	0.436	0.959	0.280	0.617	0.320	0.676	0.455	0.935	0.499	1.002	0.509	0.986
National Grid PLC	0.123	1.599	0.254	2.337	0.208	1.604	0.215	1.507	0.149	0.979	0.200	1.255	0.209	1.190	0.206	1.139	0.142	0.743	0.263	1.280
Next PLC	0.208	2.157	0.313	2.401	0.177	1.060	0.176	0.907	0.049	0.237	0.000	0.001	0.007	0.029	0.199	0.764	0.047	0.166	0.003	0.010
Old Mutual PLC	0.090	0.735	0.317	1.855	0.158	0.818	0.310	1.293	-0.001	-0.005	-0.013	-0.045	0.020	0.068	0.328	1.071	0.333	1.008	0.336	0.904
Pearson PLC	0.102	1.013	0.246	1.574	0.121	0.608	0.217	0.966	0.075	0.317	-0.192	-0.668	-0.265	-0.873	-0.090	-0.292	-0.001	-0.004	0.045	0.143
Prudential PLC	0.218	1.509	0.389	1.864	0.185	0.673	0.318	1.086	0.283	0.860	0.178	0.468	0.140	0.352	0.150	0.349	0.290	0.632	0.484	0.982
Reckitt Benckiser PLC	0.073	0.806	0.070	0.573	-0.020	-0.138	-0.114	-0.659	-0.245	-1.301	-0.132	-0.585	-0.173	-0.691	-0.016	-0.062	0.099	0.355	0.026	0.100
Reed Elsevier PLC	0.165	1.589	0.172	1.179	0.163	0.966	0.208	1.102	0.220	1.146	0.051	0.256	-0.014	-0.062	0.029	0.123	-0.031	-0.123	0.069	0.256
Rexam PLC	0.227	2.586	0.186	1.651	0.202	1.551	0.059	0.394	-0.064	-0.366	-0.068	-0.350	-0.101	-0.496	-0.192	-0.867	-0.177	-0.777	-0.145	-0.604
Rio Tinto PLC	0.101	0.815	0.412	2.465	0.329	1.653	0.382	1.555	0.097	0.374	0.103	0.356	-0.134	-0.418	0.057	0.175	-0.031	-0.090	-0.044	-0.128
Rolls-Royce Group PLC	0.045	0.315	0.258	1.145	0.255	0.791	0.222	0.629	0.054	0.149	-0.032	-0.078	-0.338	-0.750	0.042	0.089	0.155	0.308	0.174	0.335
Royal Bank Of Scotland Group PLC	0.031	0.350	0.006	0.046	-0.113	-0.641	-0.086	-0.437	-0.137	-0.614	-0.067	-0.254	-0.244	-0.898	-0.226	-0.823	-0.210	-0.730	-0.131	-0.418
Royal Dutch Shell PLC	0.090	1.034	0.061	0.451	0.045	0.269	0.194	0.994	-0.018	-0.082	0.042	0.175	-0.148	-0.627	-0.127	-0.521	-0.198	-0.805	-0.168	-0.624
RSA Insurance Group PLC	0.044	0.257	0.038	0.146	0.091	0.256	-0.317	-0.770	-0.623	-1.373	-0.626	-1.271	-0.919	-1.820	-0.584	-1.038	-0.481	-0.858	-0.385	-0.639
Sabmiller PLC	0.030	0.330	0.122	0.925	0.046	0.280	0.090	0.451	-0.034	-0.167	-0.019	-0.088	-0.084	-0.362	0.111	0.458	0.084	0.331	0.110	0.383
The Sage Group PLC	0.048	0.315	0.048	0.221	0.081	0.307	0.107	0.368	-0.039	-0.130	-0.214	-0.614	-0.440	-1.225	-0.235	-0.616	-0.204	-0.515	-0.261	-0.642
Sainsbury (J) PLC	0.030	0.283	0.085	0.642	0.015	0.091	-0.018	-0.096	-0.196	-0.835	-0.202	-0.743	-0.206	-0.736	-0.240	-0.774	-0.195	-0.617	-0.123	-0.379
Schroders PLC	0.152	1.180	0.373	2.262	0.235	1.025	0.281	1.024	0.106	0.352	-0.017	-0.051	-0.113	-0.333	-0.008	-0.021	0.078	0.209	-0.081	-0.204
Scottish & Southern Energy PLC	0.009	0.119	0.089	0.818	0.083	0.618	0.054	0.394	-0.083	-0.621	0.026	0.173	0.029	0.183	0.152	0.924	0.198	1.200	0.284	1.643
Severn Trent PLC	0.018	0.207	0.071	0.561	-0.037	-0.228	-0.158	-0.861	-0.307	-1.539	-0.227	-1.110	-0.125	-0.542	-0.201	-0.831	-0.088	-0.366	-0.081	-0.331
Shire PLC	-0.044	-0.333	0.090	0.410	-0.147	-0.616	-0.262	-0.955	-0.338	-1.127	-0.325	-0.918	-0.432	-1.123	-0.224	-0.577	-0.257	-0.655	-0.403	-0.963
Smith & Nephew PLC	0.155	1.293	0.304	2.110	0.323	1.881	0.336	1.742	0.304	1.448	0.489	2.090	0.373	1.445	0.285	1.071	0.322	1.120	0.378	1.251
Smiths Group PLC	0.078	0.866	0.318	2.509	0.286	1.704	0.333	1.728	0.283	1.382	0.263	1.134	0.064	0.261	0.096	0.413	0.128	0.507	0.194	0.750
Stagecoach Group PLC	-0.006	-0.022	-0.177	-0.511	-0.371	-0.983	-0.109	-0.266	-0.307	-0.696	-0.520	-1.097	-0.390	-0.677	-0.455	-0.724	-0.636	-0.948	-0.536	-0.788
Standard Chartered PLC	0.189	1.879	0.280	1.961	0.418	2.078	0.432	2.015	0.441	1.921	0.526	2.086	0.461	1.724	0.494	1.782	0.598	2.064	0.619	1.993
Tesco PLC	0.060	0.650	0.136	1.057	0.166	1.142	0.090	0.561	0.068	0.359	-0.007	-0.031	-0.107	-0.470	0.252	1.087	0.249	1.055	0.291	1.234
Thomson Reuters PLC	0.318	1.770	0.415	1.665	0.292	0.913	0.186	0.532	0.321	0.777	-0.031	-0.067	-0.192	-0.407	0.371	0.680	0.274	0.502	0.388	0.721
TUI Travel PLC	0.043	0.330	0.141	0.619	0.133	0.537	0.085	0.334	0.016	0.056	0.191	0.614	0.062	0.183	0.225	0.615	0.142	0.355	0.167	0.387
Unilever PLC	0.022	0.245	-0.006	-0.047	-0.058	-0.362	0.046	0.263	-0.063	-0.337	-0.048	-0.242	-0.148	-0.717	-0.101	-0.407	-0.137	-0.510	-0.108	-0.391
United Utilities Group PLC	-0.021	-0.298	0.047	0.479	0.040	0.348	-0.091	-0.686	-0.152	-1.059	-0.043	-0.244	-0.109	-0.600	-0.011	-0.061	0.020	0.090	-0.137	-0.632
Vodafone Group PLC	-0.001	-0.010	-0.165	-1.094	-0.216	-0.891	-0.245	-0.942	-0.279	-0.982	-0.548	-1.697	-0.542	-1.519	-0.545	-1.397	-0.459	-1.187	-0.430	-1.069
Whitbread PLC	0.126	1.389	0.254	2.030	0.220	1.432	0.252	1.356	0.058	0.299	0.169	0.690	0.110	0.418	0.185	0.676	0.242	0.873	0.160	0.566
Wolseley PLC	0.163	1.666	0.346	2.493	0.232	1.436	0.299	1.742	0.328	1.697	0.379	1.606	0.041	0.135	0.208	0.668	0.190	0.627	0.128	0.368
Wood Group (John) PLC	0.103	0.682	0.109	0.451	0.156	0.622	0.208	0.752	0.244	0.898	0.175	0.604	0.009	0.028	0.242	0.669	0.394	1.066	0.546	1.354
WPP Group PLC	0.291	2.469	0.357	2.203	0.317	1.513	0.349	1.395	0.258	1.063	0.138	0.522	-0.032	-0.117	0.118	0.371	0.149	0.475	0.198	0.632
Xstrata PLC	0.359	2.416	0.632	3.718	0.596	3.050	0.700	2.982	0.619	2.366	0.635	2.262	0.378	1.236	0.620	1.964	0.621	1.859	0.748	2.168
3I Group PLC	0.092	0.799	0.172	1.080	0.042	0.215	0.046	0.212	-0.086	-0.351	-0.152	-0.507	-0.313	-0.969	-0.191	-0.586	-0.224	-0.658	-0.182	-0.501

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Lev" customers on future UK stock market changes at individual stock levels ("Lev" for leveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-40: Longer Horizon Effects of "Lev" Order Flows on the UK Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Company	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**	**Corp**	**t-Stats**
3M Company	0.085	1.579	0.083	1.183	0.150	1.535	0.189	1.759	0.227	1.787	0.201	1.761	0.273	2.081	0.237	1.615	0.191	1.186	0.088	0.488
AT & T Inc	0.040	0.448	-0.066	-0.527	0.098	0.662	0.157	0.890	0.204	1.046	0.164	0.873	0.183	0.915	0.141	0.682	0.107	0.479	0.008	0.032
Alcoa Incorporated	0.115	1.165	-0.140	-0.935	-0.099	-0.559	-0.072	-0.352	-0.056	-0.245	-0.167	-0.714	-0.058	-0.230	-0.090	-0.330	-0.063	-0.204	-0.241	-0.708
American Express Company	0.111	1.530	0.034	0.358	0.153	1.278	0.190	1.370	0.219	1.340	0.217	1.293	0.335	1.754	0.264	1.275	0.276	1.341	0.271	1.267
Bank Of America Corp.	0.045	0.874	0.015	0.220	0.070	0.808	0.135	1.310	0.189	1.616	0.193	1.581	0.245	1.792	0.275	1.669	0.269	1.662	0.255	1.521
The Boeing Company	0.068	0.957	-0.069	-0.733	-0.044	-0.307	-0.058	-0.335	-0.006	-0.034	-0.178	-1.044	-0.120	-0.646	-0.105	-0.504	-0.193	-0.877	-0.179	-0.792
Caterpillar Inc	0.130	1.508	0.098	0.788	0.295	1.850	0.351	2.058	0.463	2.433	0.247	1.443	0.362	1.807	0.368	1.576	0.322	1.282	0.281	1.060
Chevron Corp.	0.105	1.447	0.110	1.130	0.224	2.036	0.232	1.891	0.234	1.657	0.170	1.456	0.251	1.816	0.432	2.622	0.388	2.187	0.377	1.986
Citigroup Inc	0.082	1.076	0.027	0.261	0.106	0.925	0.230	1.760	0.214	1.469	0.237	1.690	0.309	1.882	0.367	1.815	0.361	1.742	0.364	1.638
The Coca Cola Company	0.031	0.571	-0.001	-0.014	-0.010	-0.095	0.021	0.197	0.096	0.820	0.065	0.584	0.086	0.666	0.019	0.122	0.027	0.151	0.006	0.033
EI Du Pont De Nemours	0.158	2.463	0.156	1.673	0.199	1.806	0.268	2.104	0.180	1.275	0.016	0.118	0.163	1.113	0.136	0.768	0.147	0.725	0.182	0.816
Exxon Mobil Corp.	0.124	1.634	0.124	1.243	0.224	1.992	0.261	2.136	0.275	1.939	0.169	1.357	0.266	1.854	0.350	2.150	0.254	1.463	0.270	1.470
General Electric Company	0.116	1.747	0.078	0.799	0.157	1.268	0.197	1.475	0.285	1.968	0.174	1.177	0.293	1.816	0.388	2.099	0.366	1.837	0.352	1.719
General Motors Corp.	0.080	0.814	0.193	1.250	0.514	2.648	0.613	2.482	0.665	2.286	0.651	2.320	0.749	2.423	0.427	1.107	0.349	0.904	0.232	0.583
Hewlett-Packard Company	0.091	0.864	0.057	0.385	0.147	0.812	0.166	0.786	0.259	1.122	0.119	0.505	0.180	0.719	0.339	1.210	0.185	0.608	0.124	0.375
Home Depot Inc	0.184	2.284	0.121	1.152	0.193	1.531	0.235	1.286	0.329	1.721	0.289	1.620	0.461	2.207	0.487	2.006	0.508	1.824	0.508	1.706
Intel Corp.	0.205	1.876	0.136	0.940	0.251	1.332	0.352	1.740	0.342	1.581	0.361	1.768	0.527	2.265	0.432	1.639	0.416	1.433	0.266	0.873
International Business Machines	0.100	1.280	0.013	0.124	0.161	1.161	0.175	1.112	0.178	0.991	0.235	1.370	0.323	1.607	0.291	1.147	0.251	0.915	0.275	0.886
JP Morgan Chase & Company	0.125	1.597	-0.017	-0.155	0.120	0.846	0.206	1.261	0.272	1.353	0.302	1.370	0.396	1.749	0.384	1.559	0.376	1.371	0.462	1.558
Johnson & Johnson	0.070	1.366	0.083	1.277	0.168	1.966	0.227	2.248	0.280	2.582	0.197	2.017	0.265	2.547	0.208	1.651	0.241	1.819	0.281	2.054
Kraft Foods Inc	0.030	0.496	-0.027	-0.378	-0.023	-0.264	-0.067	-0.665	0.035	0.303	0.016	0.142	0.050	0.417	0.127	0.869	0.058	0.381	0.135	0.841
McDonalds Corp.	0.063	0.810	0.032	0.277	-0.015	-0.102	0.147	0.914	0.397	2.024	0.313	1.499	0.371	1.655	0.451	1.730	0.411	1.555	0.532	1.895
Merck & Company Inc	0.123	1.408	0.042	0.331	0.119	0.709	0.159	0.887	0.270	1.315	0.298	1.524	0.426	1.900	0.544	2.140	0.512	1.834	0.561	1.877
Microsoft Corp.	0.182	2.590	0.136	1.429	0.124	1.035	0.152	1.156	0.230	1.544	0.214	1.420	0.378	2.251	0.305	1.688	0.256	1.264	0.210	0.974
Pfizer Inc	0.176	2.655	0.124	1.115	0.078	0.512	0.168	1.030	0.199	1.166	0.026	0.152	0.198	1.095	0.221	1.086	0.175	0.834	0.282	1.250
The Procter & Gamble Company	0.087	1.695	0.098	1.439	0.107	1.406	0.137	1.588	0.188	2.099	0.084	1.015	0.158	1.587	0.164	1.399	0.218	1.759	0.251	1.969
United Technologies Corp.	0.073	1.010	-0.019	-0.200	0.089	0.623	0.075	0.461	0.068	0.400	-0.012	-0.075	0.043	0.240	0.191	1.016	0.145	0.732	0.156	0.799
Verizon Communications	0.051	0.701	-0.161	-1.511	-0.063	-0.503	-0.017	-0.107	0.008	0.042	-0.024	-0.130	0.006	0.031	-0.055	-0.280	-0.172	-0.834	-0.161	-0.692
Wal Mart Stores Inc	0.122	1.950	0.037	0.450	0.136	1.364	0.218	1.816	0.210	1.527	0.199	1.578	0.314	2.243	0.192	1.186	0.128	0.727	0.094	0.494
The Walt Disney Company	0.118	1.511	0.048	0.403	0.087	0.545	0.110	0.632	0.098	0.488	0.129	0.692	0.227	1.070	0.349	1.460	0.360	1.412	0.407	1.466

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Corp" customers on future US stock market changes at individual stock levels ("Corp" for commercial corporations) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-41: Longer Horizon Effects of "Corp" Order Flows on the US Stock Market

Company	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats	Unlev	t-Stats
3M Company	-0.138	-1.410	-0.201	-1.570	-0.185	-1.319	-0.057	-0.348	0.096	0.471	0.255	1.393	0.134	0.658	0.248	0.988	0.126	0.486	0.228	0.776
AT & T Inc	-0.370	-2.202	-0.220	-0.911	-0.225	-0.701	-0.076	-0.211	-0.088	-0.230	0.525	1.528	0.134	0.343	0.503	1.316	0.204	0.519	0.143	0.333
Alcoa Incorporated	-0.325	-1.627	-0.578	-2.143	-0.435	-1.322	-0.131	-0.406	-0.043	-0.116	0.531	1.437	0.215	0.543	0.559	1.037	0.463	0.923	0.426	0.784
American Express Company	-0.176	-1.192	-0.234	-1.308	0.025	0.124	0.144	0.582	0.124	0.403	0.325	0.901	0.122	0.356	0.368	0.924	0.350	0.916	0.331	0.859
Bank Of America Corp.	-0.231	-2.437	-0.394	-2.900	-0.177	-1.126	-0.089	-0.444	-0.045	-0.192	0.209	0.745	-0.040	-0.150	0.264	0.772	0.218	0.728	0.355	1.211
The Boeing Company	-0.215	-1.368	-0.539	-2.752	-0.393	-1.809	-0.214	-0.802	-0.070	-0.197	0.315	0.986	0.137	0.403	0.244	0.643	0.333	0.809	0.266	0.632
Caterpillar Inc	-0.290	-2.160	-0.502	-2.362	-0.354	-1.368	-0.175	-0.563	-0.145	-0.413	0.034	0.104	-0.262	-0.749	0.013	0.026	0.011	0.022	0.193	0.359
Chevron Corp.	-0.240	-1.799	-0.249	-1.489	-0.170	-0.976	-0.120	-0.749	-0.302	-1.642	-0.063	-0.312	-0.280	-1.289	-0.287	-1.161	-0.428	-1.777	-0.391	-1.485
Citigroup Inc	-0.206	-1.525	-0.490	-2.496	-0.282	-1.417	-0.090	-0.378	-0.172	-0.553	0.010	0.031	-0.193	-0.578	0.177	0.422	0.119	0.290	0.250	0.554
The Coca Cola Company	-0.067	-0.606	-0.135	-0.785	-0.169	-0.797	-0.099	-0.393	-0.039	-0.124	0.000	-0.002	-0.077	-0.260	-0.157	-0.497	-0.207	-0.627	-0.222	-0.661
EI Du Pont De Nemours	-0.275	-2.123	-0.446	-2.149	-0.256	-1.180	-0.058	-0.233	-0.012	-0.038	0.414	1.416	0.151	0.468	0.223	0.575	0.044	0.113	0.081	0.178
Exxon Mobil Corp.	-0.138	-1.129	-0.214	-1.209	-0.128	-0.762	-0.042	-0.220	-0.145	-0.681	0.048	0.201	-0.072	-0.318	-0.002	-0.007	-0.205	-0.763	-0.206	-0.716
General Electric Company	-0.209	-1.531	-0.255	-1.189	-0.171	-0.716	-0.025	-0.090	0.084	0.244	0.323	0.979	0.108	0.317	0.292	0.685	0.072	0.186	0.222	0.559
General Motors Corp.	-0.553	-3.337	-0.940	-3.612	-0.851	-2.833	-0.642	-1.666	-0.378	-0.777	0.238	0.528	-0.307	-0.622	0.249	0.392	0.115	0.197	0.376	0.604
Hewlett-Packard Company	-0.089	-0.401	-0.582	-1.882	-0.496	-1.185	-0.586	-1.443	-0.360	-0.728	-0.191	-0.472	-0.294	-0.581	-0.007	-0.011	-0.133	-0.214	-0.040	-0.063
Home Depot Inc	-0.412	-2.761	-0.611	-2.757	-0.734	-2.359	-0.550	-1.718	-0.221	-0.636	-0.009	-0.024	-0.402	-1.000	-0.333	-0.696	-0.314	-0.738	-0.075	-0.178
Intel Corp.	-0.462	-2.493	-0.754	-2.472	-0.620	-1.665	-0.376	-1.066	-0.323	-0.754	0.108	0.288	-0.295	-0.712	-0.027	-0.051	0.026	0.047	0.210	0.366
International Business Machines	-0.228	-1.874	-0.310	-1.771	-0.246	-1.104	0.016	0.069	-0.060	-0.227	0.015	0.061	-0.246	-0.895	0.111	0.297	0.056	0.148	0.293	0.728
JP Morgan Chase & Company	-0.344	-2.028	-0.507	-2.060	-0.462	-1.689	-0.201	-0.581	-0.521	-1.333	0.010	0.026	-0.344	-0.849	0.136	0.230	0.045	0.077	0.220	0.357
Johnson & Johnson	-0.045	-0.346	-0.162	-0.839	0.001	0.003	0.004	0.015	-0.080	-0.303	0.063	0.323	0.021	0.086	0.042	0.167	-0.109	-0.390	-0.038	-0.136
Kraft Foods Inc	-0.182	-1.244	-0.025	-0.141	-0.220	-1.057	-0.514	-1.267	-0.539	-1.121	-0.027	-0.076	-0.190	-0.475	0.079	0.166	-0.195	-0.409	-0.228	-0.469
McDonalds Corp.	-0.275	-1.746	-0.394	-1.961	-0.573	-2.199	-0.694	-2.196	-0.532	-1.491	-0.256	-0.675	-0.530	-1.305	-0.140	-0.266	-0.445	-0.920	-0.654	-1.177
Merck & Company Inc	0.051	0.287	-0.119	-0.456	-0.068	-0.263	0.299	1.019	0.313	0.916	0.135	0.391	0.185	0.472	0.670	1.616	0.369	0.837	0.281	0.550
Microsoft Corp.	-0.222	-1.481	-0.476	-2.323	-0.343	-1.210	-0.045	-0.158	-0.082	-0.243	0.088	0.314	-0.125	-0.356	0.177	0.457	0.231	0.574	0.241	0.606
Pfizer Inc	-0.054	-0.408	-0.375	-1.894	-0.366	-1.718	-0.013	-0.052	0.023	0.086	0.057	0.203	0.002	0.008	0.420	1.214	0.219	0.586	0.021	0.053
The Procter & Gamble Company	-0.066	-0.754	-0.054	-0.386	0.003	0.024	0.089	0.583	0.063	0.362	0.125	0.743	0.064	0.357	0.046	0.229	0.019	0.094	-0.012	-0.058
United Technologies Corp.	-0.323	-2.652	-0.400	-2.311	-0.266	-1.344	-0.068	-0.279	-0.041	-0.134	0.327	1.106	0.045	0.149	-0.045	-0.133	-0.002	-0.007	0.047	0.144
Verizon Communications	-0.212	-1.498	-0.223	-1.175	-0.184	-0.654	0.131	0.365	0.166	0.437	0.457	1.195	0.250	0.613	0.442	0.997	0.428	0.899	0.600	1.243
Wal Mart Stores Inc	-0.327	-2.638	-0.344	-2.079	-0.268	-1.538	-0.050	-0.253	0.100	0.452	0.411	1.729	0.137	0.523	0.425	1.493	0.208	0.721	0.317	1.046
The Walt Disney Company	-0.074	-0.434	-0.533	-2.163	-0.373	-1.104	-0.259	-0.653	-0.241	-0.549	-0.264	-0.690	-0.346	-0.885	-0.016	-0.036	-0.057	-0.134	0.181	0.391

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Unlev" customers on future US stock market changes at individual stock levels ("Unlev" for unleveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-42: Longer Horizon Effects of "Unlev" Order Flows on the US Stock Market

	t+1		t+2		t+3		t+4		t+5		t+6		t+7		t+8		t+9		t+10	
Company	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**	**Lev**	**t-Stats**
3M Company	-0.096	-1.038	-0.133	-0.995	-0.221	-1.462	-0.301	-1.847	-0.268	-1.512	-0.276	-1.486	-0.375	-1.900	-0.208	-1.065	-0.261	-1.200	-0.342	-1.469
AT & T Inc	0.022	0.171	0.108	0.687	0.207	1.064	0.004	0.020	-0.094	-0.362	-0.130	-0.448	-0.063	-0.218	-0.046	-0.156	-0.165	-0.499	-0.132	-0.373
Alcoa Incorporated	-0.010	-0.080	-0.104	-0.589	-0.041	-0.189	-0.137	-0.556	-0.229	-0.840	-0.259	-0.883	-0.344	-1.033	-0.299	-0.849	-0.297	-0.764	-0.247	-0.584
American Express Company	-0.049	-0.459	-0.048	-0.376	0.132	0.844	0.203	1.190	0.054	0.267	-0.004	-0.018	-0.095	-0.396	-0.004	-0.015	0.030	0.111	0.075	0.255
Bank Of America Corp.	-0.028	-0.407	-0.028	-0.284	0.061	0.481	0.047	0.328	0.014	0.081	-0.019	-0.117	-0.063	-0.351	-0.084	-0.458	-0.024	-0.121	-0.075	-0.372
The Boeing Company	0.121	1.129	0.330	2.497	0.287	1.717	0.203	0.991	0.308	1.469	0.177	0.837	0.167	0.652	0.061	0.208	-0.004	-0.013	0.230	0.747
Caterpillar Inc	0.055	0.498	-0.059	-0.427	-0.143	-0.719	-0.008	-0.024	-0.061	-0.199	-0.206	-0.636	-0.221	-0.662	-0.128	-0.353	-0.071	-0.199	-0.139	-0.369
Chevron Corp.	-0.160	-1.313	-0.203	-1.517	0.017	0.094	-0.169	-0.817	-0.166	-0.847	-0.183	-0.898	-0.235	-1.067	-0.210	-0.835	-0.307	-1.253	-0.251	-1.003
Citigroup Inc	-0.103	-1.027	-0.022	-0.188	0.127	0.814	0.098	0.539	0.035	0.167	0.032	0.153	0.010	0.046	-0.054	-0.228	-0.056	-0.217	-0.053	-0.191
The Coca Cola Company	0.019	0.260	0.068	0.626	0.044	0.370	0.109	0.802	0.031	0.202	0.004	0.023	-0.026	-0.143	0.028	0.140	-0.005	-0.024	0.040	0.179
EI Du Pont De Nemours	0.052	0.671	0.013	0.103	0.062	0.412	-0.051	-0.289	-0.212	-1.020	-0.298	-1.267	-0.442	-1.704	-0.347	-1.260	-0.412	-1.370	-0.365	-1.160
Exxon Mobil Corp.	0.021	0.185	-0.031	-0.231	0.076	0.424	0.003	0.013	-0.081	-0.418	-0.146	-0.712	-0.157	-0.701	-0.150	-0.602	-0.200	-0.805	-0.178	-0.692
General Electric Company	0.085	0.982	0.110	0.900	0.238	1.610	0.152	0.896	0.102	0.511	0.031	0.148	-0.170	-0.786	-0.146	-0.619	-0.156	-0.624	-0.240	-0.866
General Motors Corp.	0.059	0.358	0.359	1.825	0.411	1.748	0.217	0.748	-0.007	-0.024	-0.049	-0.141	-0.178	-0.444	0.244	0.531	0.280	0.578	0.210	0.419
Hewlett-Packard Company	0.114	0.854	-0.094	-0.567	-0.037	-0.166	-0.044	-0.184	-0.271	-1.003	-0.182	-0.631	0.021	0.064	0.166	0.472	-0.039	-0.105	-0.044	-0.112
Home Depot Inc	0.001	0.008	-0.111	-0.722	-0.057	-0.317	-0.149	-0.713	-0.176	-0.708	-0.225	-0.832	-0.181	-0.617	0.012	0.036	-0.181	-0.519	-0.173	-0.446
Intel Corp.	-0.044	-0.342	0.069	0.393	-0.102	-0.464	-0.051	-0.186	-0.296	-1.056	-0.616	-1.964	-0.583	-1.779	-0.553	-1.546	-0.556	-1.448	-0.473	-1.143
International Business Machines	-0.166	-2.011	-0.118	-0.981	-0.100	-0.652	-0.203	-1.085	-0.226	-1.054	-0.180	-0.751	-0.329	-1.200	-0.260	-0.936	-0.198	-0.621	-0.201	-0.561
JP Morgan Chase & Company	-0.032	-0.322	0.047	0.331	0.114	0.607	0.005	0.024	0.035	0.144	-0.098	-0.384	-0.142	-0.479	-0.248	-0.808	-0.156	-0.455	-0.141	-0.371
Johnson & Johnson	-0.107	-1.285	-0.129	-1.219	-0.143	-1.175	-0.287	-2.084	-0.291	-1.843	-0.288	-1.814	-0.352	-2.160	-0.280	-1.468	-0.324	-1.657	-0.256	-1.249
Kraft Foods Inc	0.151	1.420	0.127	0.794	0.187	1.158	0.217	1.224	0.087	0.471	0.173	0.875	0.097	0.450	0.168	0.735	0.134	0.576	0.075	0.296
McDonalds Corp.	0.223	1.542	0.115	0.555	0.463	1.968	0.507	1.946	0.322	1.126	0.124	0.423	0.218	0.667	0.159	0.461	0.127	0.372	0.168	0.436
Merck & Company Inc	-0.122	-1.236	0.000	-0.003	0.059	0.320	0.048	0.221	-0.023	-0.097	-0.113	-0.441	-0.040	-0.136	-0.072	-0.196	-0.065	-0.165	0.144	0.346
Microsoft Corp.	0.044	0.512	0.023	0.196	0.074	0.536	0.025	0.150	-0.044	-0.226	-0.059	-0.287	-0.041	-0.189	-0.014	-0.059	-0.155	-0.580	-0.061	-0.209
Pfizer Inc	-0.224	-2.288	-0.240	-1.612	-0.013	-0.052	0.135	0.435	0.043	0.130	-0.015	-0.045	-0.033	-0.087	0.064	0.168	0.099	0.260	0.114	0.297
The Procter & Gamble Company	-0.001	-0.019	-0.028	-0.323	0.015	0.138	0.050	0.379	-0.070	-0.553	-0.169	-1.344	-0.226	-1.592	-0.192	-1.240	-0.227	-1.346	-0.142	-0.794
United Technologies Corp.	0.000	0.000	-0.039	-0.347	-0.110	-0.752	-0.160	-1.006	-0.209	-1.095	-0.286	-1.370	-0.348	-1.667	-0.360	-1.640	-0.363	-1.536	-0.271	-1.034
Verizon Communications	-0.005	-0.041	-0.013	-0.096	0.055	0.325	-0.087	-0.438	-0.224	-0.897	-0.278	-0.976	-0.262	-0.888	-0.283	-1.031	-0.393	-1.157	-0.394	-1.100
Wal Mart Stores Inc	-0.010	-0.133	0.056	0.499	0.156	1.208	0.156	1.020	0.117	0.663	0.155	0.816	0.194	0.918	0.246	0.988	0.243	0.919	0.148	0.526
The Walt Disney Company	-0.139	-1.097	-0.169	-0.893	-0.310	-1.333	-0.425	-1.794	-0.503	-2.021	-0.487	-1.907	-0.530	-1.818	-0.430	-1.405	-0.607	-1.920	-0.625	-1.847

Notes: In the regression $R^{S}_{t,t+m} = C + \gamma R^{S}_{t} + \lambda R^{FX}_{t} + \sum_{i=1}^{4} \beta_i OF^{FX}_{t,i} + \varepsilon$, the table reports effects of order flows from "Lev" customers on future US stock market changes at individual stock levels ("Lev" for leveraged financial institutions) over m-day horizons from 1-day to 10-day. Red shaded cell stands for positive statistically significant coefficients, while blue shaded cell stands for negative statistically significant coefficients. The significance level here means 10% or better. R^2 is up to 5%.

Table 2-43: Longer Horizon Effects of "Lev" Order Flows on the US Stock Market

3 High Frequency Pure-FX and Cross-Market Order Flow Analysis

3.1 Introduction

In chapter 2, using daily customer order flows, we suggest that foreign exchange order flows have forecasting power for stock market returns and impacts from different groups of customers are distinctly different. We see clear patterns in our results in chapter 2 using daily order flows in the foreign exchange market: corporate order flows have positive effects on future stock market fluctuations, while order flows from unleveraged financial institutions have negative effects on future stock market changes. Furthermore, effects from foreign exchange order flows can last for several days in stock markets, order flows from corporate customers have longer impacts on future stock market changes than those from financial customers, especially for the US stock market. Based on findings with daily currency order flows in chapter 2, we suggest that the information conveyed in currency orders is one of the driving forces in changes in stock markets, because (i) coefficients for the UK market and the US market are both positive (negative) for order flows from corporate (financial) customers, (ii) it is unlikely that corporations are moving capital in order to invest in the stock market, and (iii) it is a cross market relationship between foreign exchange and stock markets, the relationship between foreign exchange order flows from corporate customers at day t and stock market returns at day t+1 is not caused by foreign currency buying pressure at day t. We conclude that at least a part of the private information conveyed in foreign exchange order flows is valuable also for stock markets.

However, the empirical findings of daily or weekly data do not always hold in intra-day analysis. To further confirm our findings in chapter 2, in this chapter we apply similar linear regression models to investigate whether the relationships between currency order flows and changes in foreign exchange and stock markets still hold over short-lived periods. We believe some information different from those found in daily frequency currency orders can be hidden in high frequency order flows in the foreign exchange market. The different sets of information might be due to different properties between daily and high frequency order flows which originates from the different trading mechanisms and styles of different market participants, in several ways:

1) Opposite orders from same groups of customers can be smoothed out throughout the day, while the tick-by-tick data, provided by a leading European bank, record every executed trade in the foreign exchange market through the bank and contain all the potential information in the market including noises;
2) Heterogeneity might be more intensive at high frequencies than at a daily frequency because expectations from investors within the same category in the long run could converge to similar levels;
3) Some open positions which are created in the morning might be closed out before the end of the day as required, according to the firm's investment philosophy and trading strategies;
4) Other unexpected and undesired orders which are corrected later, and possible intra-day irrational trading activities can be magnified in the process of high frequency trading in one day.

So this kind of high frequency orders can not be observed at a daily frequency, and intra-day orders have more noises than the aggregated daily order flows.

To the best of our knowledge, no much literature has gone very deep into this tick-by-tick type of order flows data, and the closest paper we find is Osler and Vandrovych (2009): they use executed contingent orders (stop-loss and take-profit orders) in the foreign exchange market to investigate the relationships between currency orders and exchange rate changes at different frequencies of 5-minute, 10-minute, 30-minute up to several hours, and they find positive results especially for currency orders from customers like hedge funds. In this chapter, with similar disaggregated high frequency currency order flows data, because we don't know at which frequency it contains the most powerful and intensive information, and also we don't know how long this kind of information can last and then disappear in the foreign exchange market, we test the hypothesized relationships at all possible frequencies from 1-minute to 30-minute, and use heat maps to observe the potential patterns in our findings. Compared to Osler and Vandrovych (2009), our research covers all frequencies higher than 30-minute, and in addition to the contemporaneous relationship we also test the forecasting power from currency order flows. We believe our methodology can give us a bigger picture of the effects of currency order flows on exchange rate returns.

More interestingly, similar to chapter 2, we also test the cross market relationships between the two different financial markets at high frequencies from 1-minute to 30-minute. To the best of our knowledge, no one has done anything about cross market relationships over such high frequencies. Due to the access to this very rare and unique set of tick-by-tick high frequency currency order flows data, not only we can test the explaining and forecasting power of order flows for exchange rate dynamics at high frequencies from 1-minute to 30-minute, we also can re-confirm our findings about cross market relationships found at a daily frequency in chapter 2 at higher frequencies.

As an empirical study of "pure FX" correlations between currency order flows and exchange rate dynamics, and the cross market short-run correlations between the foreign exchange market and the US stock market, this chapter contributes to the foreign exchange market and the stock market microstructure literature in several ways:

1) In this chapter we perform high frequency analysis on foreign exchange order flows. Many studies which use intraday order flows mainly focus on their feature as a vehicle to transfer macroeconomic news, with either inter-dealer order flows or customer order flows (see Evans and Lyons (2005b, 2007), among others). The length of our data implies that we can not check the news impact over a long period of time, however, we will investigate the effects of foreign exchange order flows on intra-day exchange rate changes, which complements the daily analysis in chapter 2.
2) Moreover, the unique set of currency order flows data used in this chapter is broken into four categories based on the orders' initiators, including customers and inter-dealers such as corporate customers, financial institutions, internal units, and inter-bank counterparties. The grouping orders make it available to compare the naturally heterogeneity in high frequency order flows analysis to the daily results in chapter 2. This will further confirm the heterogeneity in the

foreign exchange market at high frequencies, which is rarely investigated in previous literature. For example, Osler and Vandrovych (2009) suggest that, compared to other categories of customers, only hedge funds have private information which is gradually reflected into prices in the foreign exchange market.

3) Like in chapter 2, we also investigate the contemporaneous relationship between foreign exchange and stock markets as well as the forecasting power of foreign exchange order flows for stock market changes at high frequencies. To make the comparison consistent, we focus on order flows of corporate customers and financial customers in this chapter as well. Some papers suggest the existence of impacts of foreign exchange order flows on stock market at daily or weekly frequencies (Francis et al. (2006), Dunne et al. (2006)), however, to the best of our knowledge, no one has examined this at ultra high frequencies before.

The remainder of the chapter is organized as follows. In section 3.2, we provide a brief literature review. The high frequency foreign exchange order flows with exchange rates and stock prices data are presented in section 3.3. Section 3.4 describes the methodologies in detail and the hypotheses tested. The empirical findings will be discussed in section 3.5, and section 3.6 concludes.

3.2 Literature Review

In chapter 2, we suggest that although there is no forecasting power from foreign exchange order flows for exchange rate changes at a daily frequency, the effect of foreign exchange order flows on future stock market returns is strong. In this chapter, besides examining the well-established relationship between order flows and exchange rate, we also investigate the short-lived effects of foreign exchange order flows on stock market changes at frequencies from 1-minute to 30-minute. Due to the similarities between chapter 2 and chapter 3, here we only give a brief literature review, focusing on the high frequency aspect of the foreign exchange microstructure.

Market participants generally differ in their estimates of fundamental value of prices, because often they rely on different set of data or they have heterogeneous interpretations on even same set of information. Markets aggregate data from many sources to produce prices that typically estimate fundamental values more accurately than any individual investor can. This determines a long process of trading in the foreign exchange market, and then the possible predictability of order flows which carry information during the trading process. Evans and Lyons (2005b) examine the effects of news on transactions in different groups of customers in the foreign exchange market, and they find arrival of news generate subsequent changes in their trading behaviors which will last for days. They provide strong evidence that investors in the foreign exchange market are not responding to news instantaneously, and there is a clear existence of gradual learning process in the market. The theory is consistent with our findings in chapter 2; the effects of order flows on stock market returns will be felt for several days. In this chapter, we will check for similar effects at higher frequencies.

High frequency analysis is not usual because so little data is available. The traditionally low frequency data are used for testing macroeconomic models, while high frequency data have opened great possibilities to test market microstructure models. Even just finding the empirical facts which are buried in the high frequency data is recognized important. For example, Andersen, Bollerslev, Diebold and Labys (2003b) explore in detail the distributional properties of volatility computed from DEM/USD and

USD/JPY high frequency data over 10 years. Also see Zhou (1993) for the heteroskedasticity and Guillaume et al. (1997) for both volatility and heteroskedasticity characteristics in the market by using high frequency data.

Most of the papers in foreign exchange microstructure use low frequency data (most often daily or weekly data). Recent studies with high frequency tick-by-tick data often focus on order flow as a vehicle for macroeconomic news, and investigate the effects of news on the patterns after releases of the public information, in terms of exchange rates as well as foreign exchange order flows. High frequency analysis of news on exchange rates has been done by many. For example, Almeida, Goodhart and Payne (1998) examine the changes of DEM/USD exchange rate after releases of macroeconomic news in Germany and US, and they find the impact is significant up to tens of minutes. Also see Andersen et al. (2003a). All of the studies suggest that during the gradual process of trading in the foreign exchange market, to some extent the effects of order flows on exchange rate changes exist at high frequencies. Evans and Lyons (2008) use 4 months of tick-by-tick DEM/USD order flows data, and using five-minute frequency analysis they suggest that when news arrives, the following order flow is more important in exchange rate determination and the exchange rate can be forecasted by inter-dealer order flow in the foreign exchange market. Love and Payne (2008) analyze the number of trades as “proxy” of order flows over a period of 10 months and they also suggest the news is transmitted into prices via order flows but will be impounded into the market price faster than those suggested by Evans and Lyons (2008).

Another important related paper is Osler and Vandrovych (2009). This study examines all the executed price-contingent orders (stop-loss and take-profit orders) placed at the Royal Bank of Scotland from 10 different categories of counterparties (6 from customers, 4 from inter-dealers) over 16 months in 2001 and 2002. The authors document that there are connections between foreign exchange order flows and exchange rate changes at high frequencies. They also suggest that the leveraged financial institutions such as hedge funds are better informed than other customers, while the inter-dealers are even better through observations of orders placed by customers. The heterogeneity often observed at low frequencies in the foreign exchange market is still present at high frequencies.

In chapter 2, we find supportive evidence that foreign exchange order flows have forecasting power on stock market prices up to 10 days ahead. This can not only be explained by natural barriers between the two financial markets, because nowadays the mobility of funds across different markets, especially within developed countries, is very smooth and fast. In this chapter we will check if the cross market effects still exist at very short horizons.

A sizable body of literature investigates the contemporaneous relations between foreign exchange and stock markets. Early empirical studies mainly focus on the return spillovers between the two different financial markets and the results are very mixed. Jorian (1991), Bartov and Bodnar (1994) are among those which fail to find significant contemporaneous relationship between the foreign exchange market and the stock market. On the other hand, Ajayi and Mougoue (1996) find significant short-run and long-run feedback relations between the two markets for eight industrial economies. They show that increases in stock prices have a negative short-run effect on the local currency and long-run positive effect, while the appreciation of the local currency have positive short-run and long-run effects on the stock prices. Andersen, Bollerslev, Diebold and Vega (2007) also find important links between the foreign exchange market and the US stock market, even after controlling for the effects of macroeconomic announcements. Also see He and Ng (1998), Granger, Huang and Yang (2000), among many others with supportive evidence of cross market effects.

In addition to the return or volatility spillovers between the two markets, the results in chapter 2 also give us more evidence of cross market links, by relying on low frequency foreign exchange customer order flows data. Very few studies investigate the relationship between foreign exchange and stock markets with order flows data as additional variables. The paper by Francis, Hasan and Hunter (2006) is one of these studies which weigh on the role of currency order flows when dealing with relations between the two markets. Another related work is Dunne, Hau and Moore (2006), in which they obtain a structural relationship between exchange rates, stock market returns and the corresponding stock market order flows and foreign exchange order flows, between US and France. Both Dunne, et al. (2006) and Francis et al. (2006) check the impact of foreign exchange order flows on exchange rate changes, while Albuquerque, Francisco and Marques (2008) test the relations in the opposite way, order flows in stock markets on exchange rate determination. More details of these papers can be found in chapter 2.

All of the work on cross market effects performed up to now including chapter 2 uses daily order flows data over relative longer horizons. With the unique set of ultra high frequency data in this chapter, as complement to chapter 2, the high frequency analysis on the relations between the foreign exchange market and the stock market will provide more evidence how the trading happens across different markets and how the pricing of information evolves with time.

3.3 High Frequency Data

There are three main parts of our data in this chapter. The first and the most important is ultra high frequency tick-by-tick EURUSD order flow, which is provided by a leading European commercial bank. The second component of our data is the high frequency prices of exchange rate EURUSD, including both trade price for this specific bank and the matched market clearing price from EBS. This tick-by-tick data set opens the way for studying the foreign exchange market at different horizons, in this chapter from 1-minute to 30-minute. The last component of our data is stock market prices, including tick-by-tick quotes and transacted trades of listed companies in DOW 30 as well as ETFs (Exchange Traded Funds) tracking S&P 500 sectors and major US indices, such as Dow 30 and S&P 500. The ultra high frequency equity data are collected from TAQ (Trades and Quotes) database in WRDS (Wharton Research Data Services). More details of data used in this chapter are described separately in the following subsections.

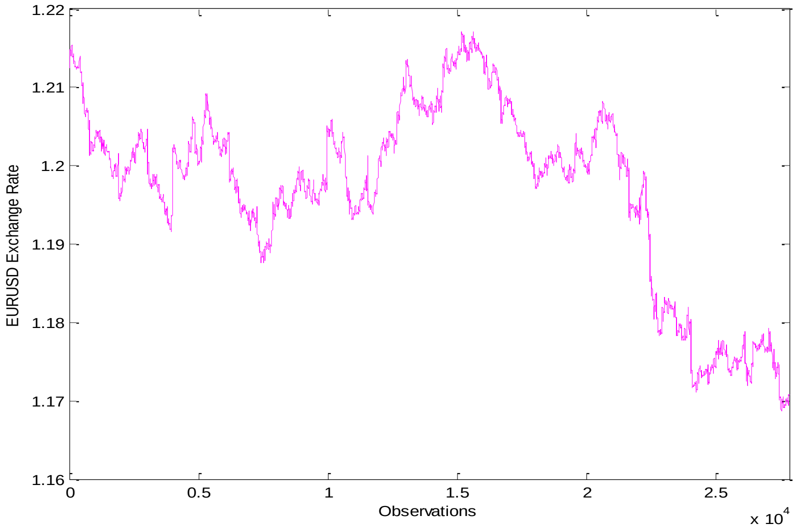
3.3.1 Foreign Exchange Market

Data Descriptions

High frequency data is direct information from markets. One logical unit of information is called a tick. The tick-by-tick high frequency Euro-Dollar (denoted as EURUSD afterwards) order flows data used in this chapter is provided by a leading European commercial bank that wishes to remain anonymous. The order flows data records every trade initiated by the bank's counterparties over 25 trading days from 10/OCT/2005 to 11/NOV/2005 and includes both customer orders and inter-dealer orders. With every deal there is a date and a time attached, which shows the transaction time of every trade, and it is irregularly spaced. Our data set also includes a "bought or sold" indicator for each trade, which allows us to sign trades for measuring order flows: indicating buying from the counterparty with a positive sign, otherwise selling with a negative sign. The transaction price from the bank and the market clearing price from EBS are also provided, together with the size of each deal. The customers and inter-dealers trading with the bank are identified by a code, although we do not have access to the identification of every counterparty, we can break the order flows data into four categories: financial customers, corporate customers, internal units, and inter-bank counterparties.

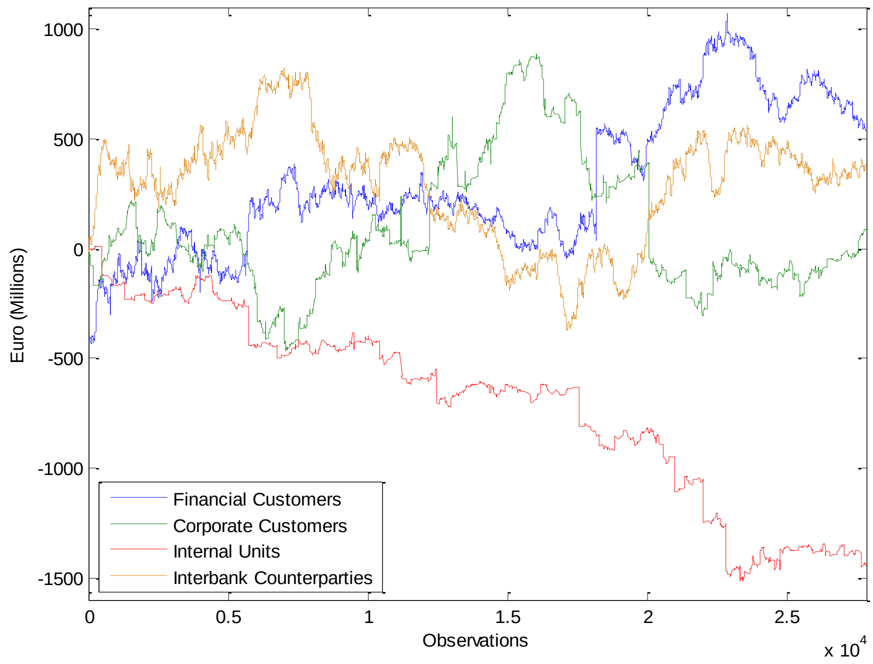
Data Filters & Data Statistics

Our order flow and price data are drawn from time-stamped, tick-by-tick transactions in the largest spot market, and some data errors or invalid records are inevitable. After excluding any "suspicious" entries, such as trades with a rate far away from the price range during a period of time, we have 27,830 transactions over 25 trading days with daily trading hours from around 7:30am to 17:00pm.



Notes: The figure shows the price of the EURUSD exchange rate. The sample period is from 10/Oct/2005 to 11/Nov/2005 (27830 observations).

Figure 3-1: EURUSD EBS Exchange Rate



Notes: The figure shows the accumulation of EURUSD order flows from different customers: financial customers, corporate customers, internal units and interbank counterparties. The sample period is from 10/Oct/2005 to 11/Nov/2005 (27830 observations).

Figure 3-2: EURUSD Cumulative Order Flows by Counterparty Type

Figures 3-1 and 3-2 show a big picture of order flows as well as exchange rates in our data set. We do not observe clear contemporaneous relationship between exchange rate and order flows from any category of counterparties, but we see different ways of accumulating orders over time for each category.

The following table 3-1 compares the number of trades as well as trading volume for each category of the leading European commercial bank's counterparties.

	Financials	Corporates	Internal	Interbank	Total
Transactions	8898	2584	1905	14443	27830
Per Day	355.92	103.36	76.20	577.72	1113.20
Percent by Trades	**31.97%**	**9.28%**	**6.85%**	**51.90%**	100.00%
Net Order Flow	534.84	88.00	-1445.38	384.02	-438.52
Volume	34555.07	18479.44	8927.6	37123.33	100085.44
Mean	3.88	7.54	4.69	2.57	3.60
Standard Dev.	9.48	14.97	12.63	4.00	8.42
Median	2.00	2.52	2.00	1.00	2.00
Minimum	0.50	0.50	0.50	0.50	0.50
Maximum	500.00	228.64	220.00	137.28	500.00
Percent by Volume	**34.53%**	**18.46%**	**8.92%**	**37.09%**	100.00%

Notes: The table reports summary statistics for EURUSD order flows from all groups of customers. All numbers about volume are in Million Euros. The sample period is 10/Oct/2005 to 11/Nov/2005.

Table 3-1: Summary Statistics of EURUSD Order Flows by Counterparty Type

We notice that in terms of number of transactions, interbank counterparties initiate more than half of the trades. The share of orders initiated by commercial corporations is less than 10% of the number of total trades. However, in terms of trading volume, the corporations' share is nearly doubled (from 9.28% to 18.46%), while the share of interbank counterparties drops from 51.9% to 37.09%. The proportion of orders triggered by financial customers are similar in two ways of calculating market shares (31.97% and 34.53%), while internal units always have the lowest trading activities (6.85% and 8.92%). From the standard deviations, we also notice that the trading size is most volatile in orders initiated by corporations and internal customers, while the order size is relative stable from interbank counterparties.

High frequency tick-by-tick data means a very large amount of data. The number of observations in one single day of a liquid market is equivalent to the number of daily data over 30 years. Because we investigate the foreign exchange market changes at frequencies from 1-minute to 30-minute, the raw time series are not suitable to work with, due to the irregular spaces of timestamps. We need to filter the raw data into a new set of data with 1-minute intervals. The order flows data for each category is addition of each trade during that 1-minute period, and the transaction exchange rate is the price of the last execution over that 1-minute interval. We can also use the matched EBS database to determine the last price in the interval.

The following table 3-2 shows correlations between orders from different types of counterparties based on 1-minute frequency data.

	Financials	Corporates	Internal	Interbank	Total
Financials	1.000				
Corporates	-0.016	1.000			
Internal	0.005	0.006	1.000		
Interbank	0.261	-0.005	0.042	1.000	
Total	0.573	0.544	0.370	0.631	1.000

Notes: The table reports correlations of EURUSD 1-minute order flows between different groups of counterparties. The sample period is 10/Oct/2005 to 11/Nov/2005.

Table 3-2: Correlations between Categories based on 1-Minute Frequency Data

We find that there are only tiny correlations between any two categories out of commercial corporations, financial institutions, internal units and interbank counterparties, except for that between financial customers and interbank counterparties. The lack of correlations in our order flows data lead to good regression models with fewer misspecifications, when we deal with order flows together.

When performing regressions in "pure foreign exchange" environment (i.e. only considering order flows and exchange rates), all data (from 7:30am to 17:00pm London time for every day) can be used as sample period. After filtering data to frequencies from 1-minute to 30-minute, we get 511 observations (8 and a half hours) for every day and then 12775 observations in total over all horizons.

3.3.2 Stock Market

Data Descriptions

An Exchange Traded Fund (ETF) is an investment vehicle traded on stock exchanges, which is very liquid due to low costs, tax efficiency, diversification, and stock-like features. The first of these, S&P 500 ETF (denoted as SPY, known as SPDR: S&P Depositary Receipts), began trading in 1993 and is now the largest ETF in the world.

Following SPY's success, in 1998, the "Dow Diamond" (denoted as DIA) was introduced tracking the Dow Jones Industrials Average (DOW 30).

In addition to the two ETFs that mirror broad indices, we also collect high frequency data for sector ETFs that break the index S&P 500 into nine components, XLB, XLE, XLF, XLI, XLK, XLP, XLU, XLV, and XLY. Together with 30 individual stocks listed in the DOW 30, we have 41 series of high frequency data in the US stock market, listed in the following table 3-3,

Codes	Company/Sector/Index
SPY	S&P 500
DIA	Dow Jones 30
XLB	Basic Industries
XLE	Energy
XLF	Financial
XLI	Industrial
XLK	Technologies
XLP	Consumer Staples
XLU	Utilities
XLV	Consumer Services
XLY	Cyclical/Transportation
AA	Alcoa Inc
AXP	American Express
BA	Boeing Co
BAC	Bank of America
C	Citigroup Inc
CAT	Caterpillar Inc
CVX	Chevron Corp
DD	DuPont
DIS	Walt Disney Co
GE	General Electric
GM	General Motor
HD	Home Depot
HPQ	Hewlett-Packard
IBM	IBM
INTC	Intel Corp
JNJ	Johnson & Johnson
JPM	JPMorgan Chase
KFT	Kraft Foods Inc
KO	Coca-Cola Co
MCD	Mcdonalds Corp
MMM	3M Co
MRK	Merck & Co
MSFT	Microsoft
PFE	Pfizer Inc
PG	Procter & Gamble
T	At & T
UTX	United Tech Corp
VZ	Verizon Communications
WMT	Wal-Mart Stores
XOM	ExxonMobil

Notes: The table lists the market, sector ETFs and individual stocks employed in this chapter.

Table 3-3: List of US stocks and ETFs

Data Filters & Data Statistics

The tick-by-tick stock market data is over 25 trading days, ranging from 10/OCT/2005 to 11/NOV/2005, with daily open times from 9:30am to 16:00pm, New York Time. The 30 stocks listed in DOW 30 are very liquid, and there is always trading in every minute throughout the day. For ETFs, especially for some sector ETFs, the number of transactions is lower. The following table lists the average trading times for each of the ETF used in this chapter.

Codes	Company/Sector/Index	Trades per Day	Trades per Minute
SPY	S&P 500	89920	231
DIA	Dow Jones 30	12249	31
XLB	Basic Industries	5794	15
XLE	Energy	49739	128
XLF	Financial	39005	100
XLI	Industrial	951	2
XLK	Technologies	3453	9
XLP	Consumer Staples	3550	9
XLU	Utilities	6635	17
XLV	Consumer Services	2948	8
XLY	Cyclical/Transportation	848	2

Notes: The table reports the number of trades for ETFs (per day and per minute).

Table 3-4: Average Turnover for ETFs

FX conterparty	Trades per Day	Trades per Minute
Financials	356	0.6
Corporate	103	0.2
Internal	76	0.1
Interbank	578	1.0

Notes: The table reports the number of trades for order flows from different counterparties (per day and per minute).

Table 3-5: Average Turnover for Foreign Exchange Orders

As noted, the trading frequency is highest for S&P 500 ETF, while the DOW 30 ETF is also very liquid. Some sector ETFs such as XLI and XLY are relatively thin, but they are still trading more times every day than our foreign exchange order flows data (less than 600 times for each of the four categories of counterparties).

Another problem worth pointing out is, when handling foreign exchange order flows together with US stock market data, time difference between US and UK needs careful attention, especially since the data set used crosses the time point where both US and UK switch off Daytime Saving Time (the end of October or the start of November). Unlike in "pure foreign exchange" environment (8 and a half hours data for each day), when considering the cross market effects, due to the time difference, the length of overlapping data between the two markets which is available to use is much shorter. The overlapping interval is only from 14:30pm to approximately 5:00pm London time (9:30am to 12:00pm New York time), shown in the following figure.

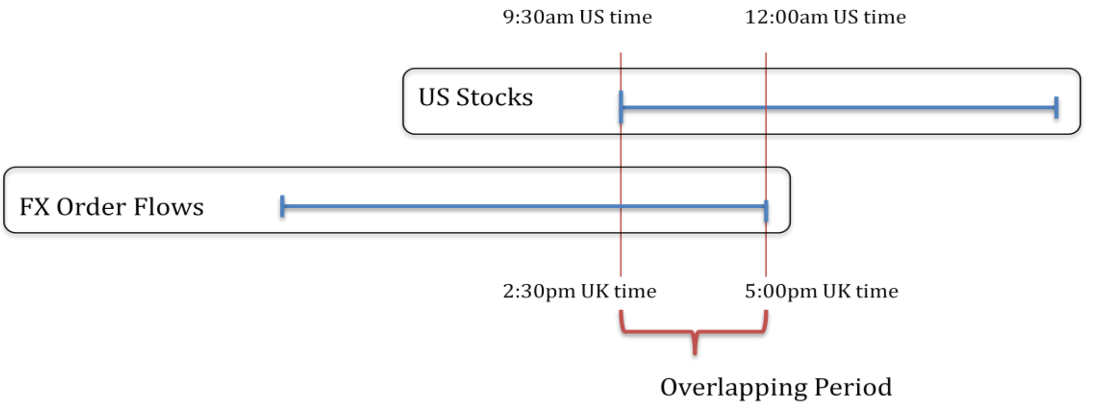


Figure 3-3: Overlapping Period between UK and US Markets

After filtering, our data set at frequencies from 1-minute to 30-minute have 121 observations for each day (3025 observations for all 25 days).

3.4 Hypotheses & Methodology

To get a big picture how order flows evolve over time minute by minute in the foreign exchange market and the stock market, we examine the impact of cumulative order flows over 1- to 30 -minute on the returns over 1- to 30-minute horizons, by testing both contemporaneous relations as well as the forecasting power from order flows on exchange rate returns as well as stock market returns. The development of hypotheses tested in this chapter is very much like that in chapter 2. We start with the following three hypotheses about foreign exchange order flows and fluctuations of the EURUSD exchange rate.

Hypothesis 1: EURUSD order flows are contemporaneously correlated to changes in the EURUSD exchange rate.

Hypothesis 2: EURUSD order flows have forecasting power for changes in EURUSD.

Hypothesis 3: correlations between EURUSD order flows from different groups of counterparties and EURUSD changes are significantly different.

We consider the effect of foreign exchange orders aggregated over i minutes on the returns over an i-minute horizon, in the "contemporaneous model. In the "forecasting model", we test the effects of cumulated order flows over i minutes on exchange rate returns over k-minute horizons, in which i and k are both from 1 to 30. All regression models are estimated by using Ordinary Least Square but correcting the coefficient variance/covariance matrix for autocorrelation and heteroskedasticity by using the Newey-West method. In the "forecasting model", we also include lagged dependent variables on the right hand side of the equation.

The regressions models are as follows,

$$R^{FX}_{t,t+i} = C + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$$

Notes: use intraday data from **7:30am to 5:00pm** for each of 25 days.

$$R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$$

Notes: use intraday data from **7:30am to 5:00pm** for each of 25 days.

In the "contemporaneous model", we regress exchange rate returns on concurrent foreign exchange order flows from four different groups (m=1 to 4) over i-minute horizons (i=1 to 30). In the "forecasting model", i and k can be any number between 1 and 30 to get a thorough picture of the evolution of information conveyed in high frequency foreign exchange order flows. For example, when i=3 and k=5, the "forecasting model" means we use the foreign exchange order flows over last 3 minutes to forecast the exchange rate returns over next 5 minutes, after controlling for the last 3-minute exchange rate return. In the regressions, m stands for 4 different types of counterparties when trading with the major European commercial bank, i.e. m = 1 for financial customers, 2 for commercial corporations, 3 for internal transaction within the bank, and 4 for interbank counterparties. C is the constant in both models.

We also need to point out that when analyzing order flows or exchange rate returns longer than 1 minute, we use overlapping orders or returns to increase the observations in the regression models. We use the overlapping return as an example to clarify this issue in the following figure 3-4,

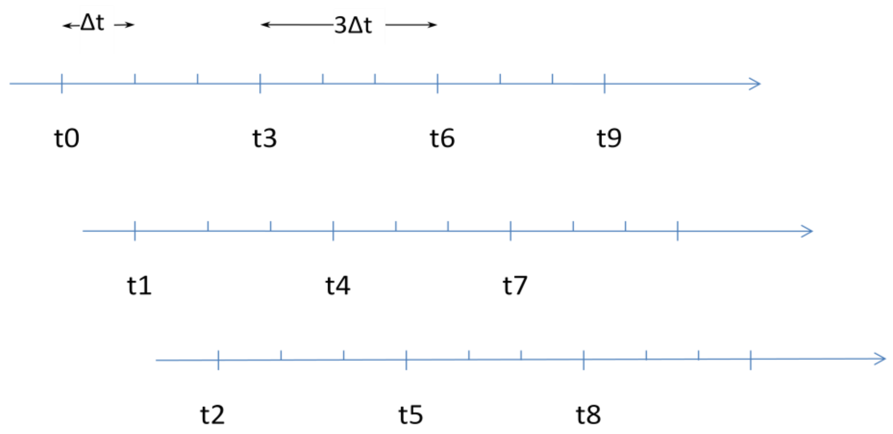


Figure 3-4: Overlapping Returns

Figure 3-4 shows that, for example, when we get the series of 3-minute returns, at each 1-minute point of time, the return is recorded as the addition of returns of the previous 3 minutes, i.e. the 3-minute return at t6 is the return from t3 to t6, the 3-minute return at t7 is the return from t4 to t7, and the 3-minute return at t8 is the return from t5 to t8. The increasing number of observations is compromised by the increasing dependence of neighboring returns with the use of overlapping methods. Thus, however, a gain in statistical significance is not obvious. See Müller (1993).

We now turn our attention to the next hypotheses about cross market effects between foreign exchange order flows and stock market returns at high frequencies, paralleling the daily frequency analysis in chapter 2.

Hypothesis 4: EURUSD order flows have contemporaneous effects on movements of US stock market indices, sector indices, and individual stocks.

Hypothesis 5: EURUSD order flows have forecasting power for movements of US stock market indices and sector indices, and individual stocks.

Hypothesis 6: EURUSD order flows from different groups of counterparties have different impacts on stock markets.

The regressions models are as follows,

$$R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta mOF^{FX}_{t,t+i} + \varepsilon$$

Notes: use intraday data from **2:30pm to 5:00pm** for each of 25 days.

$$R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta mOF^{FX}_{t-i,t} + \varepsilon$$

Notes: use intraday data from **2:30pm to 5:00pm** for each of 25 days.

In the "contemporaneous model", we regress stock market returns R^S over i-minute period on concurrent exchange returns and the foreign exchange order flows OF^{FX} from four categories of counterparties (m=1 to 4), in which m = 1 for financial customers, 2 for commercial corporations, 3 for internal transaction within the bank, and 4 for interbank counterparties. In the "forecasting model", we regress stock market returns R^S over k-minute period on lagged stock market returns over i-minute period, lagged exchange rate returns over i-minute period, and the four groups of order flows when m is from 1 to 4. C is the constant in both models.

3.5 Empirical Findings

In this section, we empirically test the hypotheses listed in the previous section, regarding the effects of foreign exchange order flows on exchange rate changes as well as the short-lived cross market high frequency changes between foreign exchange order flows and stock market returns at market, sector and individual company levels.

3.5.1 Foreign Exchange Market Findings

We start by investigating the contemporaneous relations between foreign exchange order flows and exchange rate returns at frequencies from 1-minute to 30-minute, which is **Hypothesis 1** as noted before. The following two tables show the relationships based on both market exchange rate (matched EBS market rate) and transaction rate (bank's trade price).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
OF1	beta	-0.004	-0.003	-0.002	-0.002	-0.002	-0.003	-0.004	-0.004	-0.006	-0.007	-0.009	-0.011	-0.013	-0.014	-0.015
OF2	beta	0.002	0.002	0.003	0.003	0.003	0.004	0.005	0.005	0.005	0.006	0.007	0.008	0.008	0.009	0.009
OF3	beta	-0.006	-0.012	-0.020	-0.027	-0.031	-0.036	-0.039	-0.043	-0.046	-0.049	-0.051	-0.054	-0.057	-0.059	-0.061
OF4	beta	-0.011	-0.017	-0.021	-0.023	-0.024	-0.025	-0.025	-0.026	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027	-0.027
C	beta	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003
OF1	t-stats	-1.323	-0.665	-0.305	-0.304	-0.242	-0.417	-0.436	-0.488	-0.637	-0.763	-0.953	-1.128	-1.245	-1.366	-1.446
OF2	t-stats	1.152	0.994	1.024	0.837	0.870	0.974	1.036	1.104	1.101	1.170	1.320	1.412	1.497	1.552	1.592
OF3	t-stats	-2.065	-2.780	-3.911	-4.395	-4.608	-4.776	-4.885	-5.124	-5.283	-5.428	-5.546	-5.685	-5.800	-5.925	-6.039
OF4	t-stats	-3.188	-3.939	-3.930	-3.831	-3.940	-3.832	-3.803	-3.828	-3.833	-3.821	-3.740	-3.590	-3.504	-3.489	-3.464
C	t-stats	-0.562	-0.715	-0.841	-0.931	-1.006	-1.057	-1.113	-1.154	-1.187	-1.211	-1.234	-1.260	-1.293	-1.342	-1.393

		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
OF1	beta	-0.015	-0.015	-0.016	-0.017	-0.017	-0.018	-0.018	-0.018	-0.018	-0.018	-0.017	-0.017	-0.017	-0.017	-0.017
OF2	beta	0.009	0.010	0.010	0.011	0.011	0.012	0.012	0.013	0.014	0.014	0.014	0.014	0.015	0.015	0.015
OF3	beta	-0.062	-0.063	-0.063	-0.064	-0.065	-0.066	-0.066	-0.066	-0.067	-0.067	-0.068	-0.069	-0.069	-0.069	-0.068
OF4	beta	-0.028	-0.029	-0.029	-0.029	-0.030	-0.030	-0.030	-0.030	-0.031	-0.031	-0.031	-0.032	-0.032	-0.033	-0.033
C	beta	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006	-0.006
OF1	t-stats	-1.453	-1.479	-1.533	-1.578	-1.626	-1.667	-1.669	-1.685	-1.668	-1.667	-1.658	-1.668	-1.657	-1.629	-1.596
OF2	t-stats	1.670	1.735	1.818	1.899	1.955	2.010	2.096	2.194	2.259	2.290	2.286	2.325	2.357	2.348	2.376
OF3	t-stats	-6.180	-6.284	-6.333	-6.369	-6.421	-6.434	-6.402	-6.368	-6.355	-6.345	-6.335	-6.340	-6.337	-6.217	-6.095
OF4	t-stats	-3.503	-3.526	-3.511	-3.508	-3.510	-3.527	-3.531	-3.513	-3.526	-3.542	-3.555	-3.571	-3.594	-3.624	-3.647
C	t-stats	-1.443	-1.486	-1.530	-1.575	-1.630	-1.678	-1.725	-1.750	-1.785	-1.818	-1.854	-1.880	-1.896	-1.910	-1.959

Table 3-6: Regression results in "contemporaneous model" based on market price

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
OF1	beta	0.009	0.003	-0.002	-0.006	-0.010	-0.015	-0.013	-0.012	-0.011	-0.010	-0.012	-0.013	-0.014	-0.016	-0.017
OF2	beta	-0.002	0.001	0.001	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.005	-0.002	-0.001	0.000	0.000	0.001
OF3	beta	-0.012	0.009	0.006	0.003	-0.001	-0.013	-0.022	-0.027	-0.031	-0.033	-0.036	-0.038	-0.039	-0.046	-0.052
OF4	beta	-0.013	-0.020	-0.021	-0.021	-0.025	-0.026	-0.030	-0.030	-0.030	-0.030	-0.030	-0.029	-0.027	-0.026	-0.026
C	beta	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
OF1	t-stats	0.884	0.319	-0.173	-0.627	-0.932	-1.346	-1.226	-1.106	-1.035	-0.994	-1.123	-1.251	-1.314	-1.467	-1.621
OF2	t-stats	-0.241	0.135	0.108	-0.630	-0.658	-0.724	-0.713	-0.710	-0.692	-0.601	-0.238	-0.205	-0.046	0.066	0.185
OF3	t-stats	-1.644	0.387	0.221	0.106	-0.034	-0.450	-0.851	-1.207	-1.486	-1.747	-1.973	-2.169	-2.313	-2.781	-3.149
OF4	t-stats	-2.061	-3.333	-3.152	-2.937	-3.393	-3.262	-3.385	-3.376	-3.333	-3.432	-3.351	-3.217	-3.019	-2.895	-2.871
C	t-stats	-0.386	-0.392	-0.421	-0.432	-0.480	-0.559	-0.640	-0.683	-0.689	-0.688	-0.690	-0.675	-0.686	-0.772	-0.839

		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
OF1	beta	-0.019	-0.021	-0.023	-0.023	-0.024	-0.024	-0.024	-0.023	-0.023	-0.023	-0.023	-0.023	-0.023	-0.023	-0.023
OF2	beta	0.002	0.003	0.004	0.005	0.006	0.007	0.009	0.009	0.010	0.010	0.010	0.010	0.010	0.010	0.011
OF3	beta	-0.056	-0.061	-0.063	-0.065	-0.066	-0.067	-0.067	-0.068	-0.069	-0.069	-0.069	-0.071	-0.071	-0.070	-0.072
OF4	beta	-0.026	-0.028	-0.028	-0.029	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.029	-0.030	-0.031	-0.032
C	beta	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.005
OF1	t-stats	-1.752	-1.901	-2.043	-2.104	-2.143	-2.159	-2.150	-2.150	-2.136	-2.090	-2.097	-2.137	-2.181	-2.177	-2.183
OF2	t-stats	0.343	0.417	0.597	0.684	0.877	1.083	1.280	1.396	1.481	1.495	1.557	1.580	1.563	1.582	1.611
OF3	t-stats	-3.424	-3.626	-3.849	-4.040	-4.213	-4.306	-4.395	-4.516	-4.610	-4.675	-4.777	-4.832	-4.779	-4.667	-4.683
OF4	t-stats	-2.852	-3.020	-3.054	-3.081	-3.038	-3.021	-2.963	-2.945	-2.984	-3.049	-3.042	-3.121	-3.175	-3.304	-3.426
C	t-stats	-0.905	-0.965	-0.968	-1.007	-1.064	-1.109	-1.174	-1.198	-1.248	-1.295	-1.347	-1.396	-1.376	-1.406	-1.493

Table 3-7: Regression results in "contemporaneous model" based on transaction price

Notes: Red shaded cell means positive effects at the 10% significance level; while blue shaded cell means negative effects at the 10% significance level. The first row stands for the frequency of i-minute in the model of $R^{FX}_{t,t+i} = C + \beta m \sum_{m=1}^{4} OF^{FX}_{t,t+i} + \varepsilon$. OF1 is order flows from "financials", OF2 is "corporates", OF3 is "internal", and OF4 is "interbank". C is the constant. Beta stands for the coefficient estimates of the corresponding independent variables and t-stats is t-statistics of the estimates. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 based on market price is less than 1%, while R^2 based on transaction price is up to 11%. Detailed R^2 for each regression can be provided upon request.

From tables 3-6 and 3-7, we see clear contemporaneous relationship between foreign exchange order flows and exchange rate. Order flows from other dealers are significant at all frequencies from 1-minute to 30-minute, possibly showing their dominant force when determining the price in the market and on our bank's price setting. We also notice that at high frequencies, order flows from corporations are positively correlated with exchange rate changes, while order flows from other type of counterparties (financials, internal, and interbank) are negatively correlated with exchange rate changes, which is opposite with what we find in chapter 2 at a daily frequency as well as many other related studies using daily order flows data, such as Evans and Lyons (2002a).

We investigate the forecasting power of order flows for exchange rate changes in the following, i.e. **Hypothesis 2**: EURUSD order flows have forecasting power for changes in EURUSD and **Hypothesis 3**: correlations between EURUSD order flows from different groups of counterparties and EURUSD changes are significantly different.

Based on the "forecasting model" $R_{t,t+k}^{FX} = C + \gamma R_{t-i,t}^{FX} + \sum_{m=1}^{4} \beta m OF_{t-i,t}^{FX} + \varepsilon$, we get the following tables of results. Here we only show t-statistics to simplify the reporting of our findings, and the coefficients of estimates can be found in the appendices as heatmaps (normally less than 0.1% of change in exchange rate with 1 billion Euro into the market).

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.12	-0.07	-0.61	-0.20	-1.38	-1.23	-1.65	-1.68	-1.63	-1.89	-2.12	-1.97	-2.36	-2.01	-1.42	-1.41	-1.60	-1.38	-1.50	-1.48	-1.16	-1.37	-1.10	-1.15	-1.03	-1.01	-0.59	-0.54	-0.51	-0.57
2	-0.10	-1.13	-0.98	-1.36	-1.81	-1.87	-2.02	-1.94	-2.01	-2.25	-2.30	-2.43	-2.46	-1.97	-1.66	-1.73	-1.70	-1.64	-1.68	-1.50	-1.43	-1.40	-1.30	-1.26	-1.18	-0.94	-0.70	-0.65	-0.66	-0.62
3	-0.70	-1.01	-1.43	-1.55	-1.97	-1.98	-2.01	-2.04	-2.15	-2.27	-2.45	-2.43	-2.24	-1.89	-1.73	-1.68	-1.69	-1.64	-1.55	-1.50	-1.36	-1.36	-1.24	-1.20	-0.99	-0.81	-0.63	-0.61	-0.56	-0.57
4	-0.38	-1.41	-1.57	-1.76	-2.02	-1.98	-2.07	-2.13	-2.17	-2.38	-2.43	-2.25	-2.10	-1.87	-1.67	-1.71	-1.70	-1.57	-1.55	-1.43	-1.35	-1.32	-1.26	-1.10	-0.93	-0.77	-0.64	-0.58	-0.55	-0.54
5	-1.49	-1.83	-1.99	-2.03	-2.14	-2.15	-2.23	-2.23	-2.36	-2.46	-2.37	-2.20	-2.09	-1.84	-1.74	-1.75	-1.66	-1.59	-1.51	-1.44	-1.34	-1.34	-1.18	-1.04	-0.88	-0.76	-0.61	-0.57	-0.54	-0.57
6	-1.36	-1.93	-2.02	-2.00	-2.15	-2.18	-2.22	-2.30	-2.35	-2.31	-2.21	-2.08	-1.93	-1.77	-1.67	-1.60	-1.57	-1.46	-1.41	-1.32	-1.25	-1.16	-1.01	-0.88	-0.74	-0.61	-0.49	-0.45	-0.43	-0.51
7	-1.81	-2.09	-2.07	-2.09	-2.25	-2.22	-2.33	-2.34	-2.26	-2.20	-2.12	-1.95	-1.87	-1.71	-1.56	-1.54	-1.46	-1.38	-1.31	-1.25	-1.10	-1.01	-0.87	-0.76	-0.61	-0.50	-0.40	-0.36	-0.39	-0.47
8	-1.80	-2.00	-2.10	-2.15	-2.24	-2.31	-2.34	-2.22	-2.13	-2.09	-1.96	-1.85	-1.76	-1.56	-1.46	-1.40	-1.35	-1.25	-1.21	-1.08	-0.94	-0.85	-0.72	-0.59	-0.47	-0.37	-0.28	-0.30	-0.32	-0.41
9	-1.72	-2.05	-2.17	-2.16	-2.34	-2.31	-2.21	-2.09	-2.02	-1.92	-1.84	-1.73	-1.59	-1.45	-1.32	-1.28	-1.21	-1.14	-1.04	-0.91	-0.77	-0.68	-0.55	-0.44	-0.33	-0.24	-0.20	-0.21	-0.22	-0.31
10	-1.93	-2.23	-2.23	-2.31	-2.37	-2.19	-2.07	-1.98	-1.85	-1.80	-1.71	-1.55	-1.46	-1.29	-1.19	-1.14	-1.09	-0.97	-0.86	-0.74	-0.61	-0.50	-0.39	-0.29	-0.19	-0.15	-0.11	-0.11	-0.12	-0.19
11	-2.08	-2.21	-2.34	-2.29	-2.18	-2.01	-1.93	-1.79	-1.72	-1.65	-1.52	-1.41	-1.29	-1.15	-1.05	-1.02	-0.91	-0.79	-0.68	-0.56	-0.42	-0.33	-0.22	-0.14	-0.08	-0.05	0.00	0.00	0.01	-0.03
12	-1.91	-2.30	-2.27	-2.02	-1.95	-1.84	-1.71	-1.64	-1.57	-1.45	-1.37	-1.23	-1.14	-1.01	-0.92	-0.84	-0.74	-0.61	-0.51	-0.37	-0.24	-0.16	-0.07	-0.02	0.03	0.08	0.12	0.13	0.16	0.10
13	-2.30	-2.29	-2.00	-1.81	-1.80	-1.65	-1.60	-1.52	-1.40	-1.33	-1.22	-1.11	-1.01	-0.90	-0.77	-0.69	-0.58	-0.46	-0.34	-0.22	-0.10	-0.03	0.03	0.08	0.13	0.17	0.23	0.26	0.27	0.22
14	-1.89	-1.72	-1.61	-1.56	-1.51	-1.46	-1.42	-1.30	-1.24	-1.15	-1.06	-0.95	-0.88	-0.72	-0.59	-0.51	-0.40	-0.26	-0.16	-0.04	0.07	0.11	0.16	0.22	0.27	0.32	0.39	0.40	0.41	0.36
15	-1.23	-1.41	-1.45	-1.35	-1.40	-1.34	-1.26	-1.19	-1.10	-1.04	-0.94	-0.86	-0.74	-0.58	-0.45	-0.36	-0.24	-0.11	-0.01	0.10	0.17	0.21	0.28	0.32	0.38	0.45	0.49	0.51	0.53	0.48
16	-1.29	-1.49	-1.39	-1.38	-1.40	-1.29	-1.24	-1.14	-1.07	-0.99	-0.92	-0.78	-0.66	-0.49	-0.36	-0.26	-0.15	-0.03	0.07	0.14	0.22	0.27	0.32	0.38	0.45	0.50	0.56	0.58	0.59	0.56
17	-1.41	-1.39	-1.42	-1.37	-1.33	-1.26	-1.18	-1.10	-1.02	-0.96	-0.83	-0.69	-0.56	-0.39	-0.25	-0.16	-0.05	0.07	0.13	0.20	0.29	0.32	0.39	0.46	0.52	0.58	0.63	0.65	0.68	0.64
18	-1.10	-1.37	-1.37	-1.26	-1.27	-1.17	-1.11	-1.03	-0.96	-0.85	-0.72	-0.58	-0.44	-0.27	-0.13	-0.04	0.06	0.14	0.20	0.28	0.35	0.40	0.48	0.54	0.61	0.66	0.72	0.74	0.77	0.73
19	-1.37	-1.45	-1.32	-1.27	-1.23	-1.15	-1.08	-1.00	-0.89	-0.77	-0.63	-0.48	-0.34	-0.17	-0.04	0.04	0.11	0.19	0.26	0.33	0.42	0.48	0.54	0.61	0.67	0.73	0.79	0.82	0.84	0.76
20	-1.28	-1.26	-1.24	-1.15	-1.14	-1.05	-1.00	-0.88	-0.76	-0.63	-0.50	-0.34	-0.21	-0.05	0.07	0.13	0.19	0.29	0.34	0.42	0.52	0.57	0.65	0.70	0.77	0.83	0.89	0.91	0.89	0.81
21	-0.96	-1.17	-1.10	-1.05	-1.04	-0.97	-0.86	-0.74	-0.62	-0.49	-0.36	-0.21	-0.08	0.07	0.16	0.23	0.31	0.38	0.45	0.54	0.63	0.69	0.77	0.82	0.89	0.95	1.01	0.99	0.96	0.87
22	-1.10	-1.13	-1.08	-1.01	-1.02	-0.87	-0.77	-0.64	-0.52	-0.39	-0.27	-0.12	0.00	0.11	0.22	0.29	0.36	0.44	0.52	0.60	0.70	0.77	0.85	0.91	0.98	1.03	1.05	1.02	0.98	0.90
23	-0.88	-1.04	-0.99	-0.95	-0.88	-0.76	-0.65	-0.52	-0.40	-0.29	-0.16	-0.03	0.06	0.19	0.30	0.36	0.44	0.54	0.60	0.69	0.80	0.86	0.95	1.02	1.07	1.09	1.09	1.05	1.03	0.97
24	-0.88	-0.98	-0.97	-0.84	-0.79	-0.65	-0.55	-0.42	-0.31	-0.19	-0.08	0.01	0.11	0.25	0.35	0.42	0.51	0.60	0.67	0.77	0.87	0.95	1.03	1.09	1.11	1.12	1.11	1.08	1.07	1.01
25	-0.79	-0.96	-0.84	-0.74	-0.68	-0.55	-0.45	-0.33	-0.22	-0.11	-0.04	0.07	0.18	0.30	0.41	0.49	0.57	0.66	0.75	0.85	0.96	1.03	1.11	1.13	1.14	1.13	1.14	1.13	1.12	1.08
26	-0.83	-0.82	-0.74	-0.63	-0.58	-0.45	-0.36	-0.24	-0.14	-0.08	0.01	0.13	0.22	0.35	0.47	0.54	0.63	0.74	0.82	0.93	1.03	1.10	1.14	1.15	1.15	1.16	1.18	1.17	1.18	1.12
27	-0.52	-0.66	-0.58	-0.50	-0.46	-0.35	-0.26	-0.15	-0.10	-0.01	0.09	0.19	0.29	0.43	0.54	0.62	0.71	0.82	0.91	1.02	1.11	1.15	1.18	1.17	1.19	1.21	1.23	1.24	1.23	1.16
28	-0.51	-0.59	-0.52	-0.43	-0.40	-0.29	-0.21	-0.15	-0.07	0.03	0.11	0.22	0.34	0.46	0.58	0.67	0.76	0.87	0.97	1.07	1.13	1.15	1.17	1.18	1.21	1.23	1.27	1.26	1.25	1.16
29	-0.38	-0.50	-0.44	-0.38	-0.34	-0.24	-0.21	-0.13	-0.03	0.05	0.14	0.27	0.36	0.50	0.62	0.71	0.81	0.93	1.01	1.08	1.13	1.14	1.17	1.20	1.23	1.27	1.29	1.28	1.25	1.13
30	-0.36	-0.46	-0.42	-0.34	-0.31	-0.27	-0.21	-0.11	-0.03	0.06	0.17	0.28	0.39	0.54	0.66	0.75	0.86	0.97	1.02	1.07	1.11	1.13	1.17	1.20	1.25	1.27	1.29	1.27	1.21	1.09

Table 3-8: t-statistics for “financials” in “forecasting model” based on market price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 1%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.24	1.54	0.57	0.70	0.66	0.27	0.10	0.46	1.26	1.39	1.56	1.41	1.19	1.25	1.28	1.42	1.66	1.97	2.05	2.00	2.11	1.92	1.65	1.39	1.17	1.57	1.41	1.07	1.12	1.17
2	1.52	0.76	0.39	0.44	0.20	-0.09	0.04	0.71	1.22	1.36	1.37	1.15	1.07	1.14	1.24	1.44	1.76	1.97	1.98	2.04	2.00	1.77	1.49	1.23	1.33	1.46	1.19	1.05	1.09	1.03
3	0.48	0.35	0.09	-0.02	-0.25	-0.26	0.21	0.74	1.16	1.21	1.12	1.00	0.96	1.07	1.24	1.53	1.79	1.92	1.99	1.97	1.85	1.60	1.32	1.29	1.31	1.27	1.11	1.03	0.99	0.96
4	0.60	0.35	-0.05	-0.21	-0.23	0.09	0.51	0.99	1.28	1.22	1.16	1.07	1.09	1.25	1.50	1.75	1.93	2.08	2.07	1.97	1.80	1.55	1.45	1.38	1.29	1.27	1.16	1.04	1.03	1.04
5	0.49	0.07	-0.32	-0.26	0.04	0.34	0.74	1.17	1.32	1.27	1.28	1.26	1.33	1.56	1.78	1.95	2.13	2.19	2.11	2.00	1.81	1.70	1.57	1.45	1.38	1.37	1.22	1.15	1.17	1.15
6	0.08	-0.26	-0.36	0.02	0.31	0.60	0.96	1.24	1.38	1.39	1.43	1.46	1.60	1.81	1.97	2.15	2.24	2.22	2.12	1.98	1.91	1.77	1.61	1.51	1.46	1.40	1.30	1.27	1.25	1.16
7	-0.18	-0.17	0.07	0.41	0.67	0.92	1.15	1.41	1.58	1.60	1.67	1.77	1.91	2.07	2.23	2.33	2.34	2.28	2.15	2.09	2.00	1.83	1.68	1.60	1.51	1.48	1.41	1.35	1.28	1.17
8	0.21	0.51	0.60	0.87	1.08	1.18	1.39	1.65	1.81	1.85	1.97	2.06	2.16	2.33	2.41	2.43	2.40	2.31	2.25	2.18	2.04	1.89	1.76	1.65	1.59	1.57	1.49	1.38	1.30	1.19
9	1.01	1.00	0.99	1.21	1.25	1.35	1.58	1.82	1.99	2.08	2.18	2.25	2.37	2.47	2.48	2.45	2.39	2.37	2.30	2.18	2.05	1.92	1.78	1.69	1.64	1.61	1.48	1.37	1.28	1.17
10	1.13	1.10	1.09	1.17	1.24	1.38	1.60	1.85	2.06	2.14	2.23	2.32	2.38	2.42	2.39	2.34	2.34	2.31	2.20	2.09	1.99	1.85	1.73	1.66	1.61	1.53	1.41	1.30	1.21	1.13
11	1.23	1.20	1.03	1.15	1.27	1.42	1.66	1.96	2.16	2.22	2.32	2.37	2.37	2.36	2.31	2.32	2.31	2.23	2.14	2.05	1.93	1.81	1.71	1.64	1.55	1.46	1.34	1.23	1.17	1.13
12	1.28	1.04	0.97	1.16	1.30	1.49	1.78	2.06	2.24	2.32	2.37	2.36	2.32	2.29	2.30	2.29	2.24	2.18	2.10	2.00	1.89	1.79	1.69	1.58	1.48	1.40	1.28	1.20	1.17	1.14
13	0.96	0.95	0.99	1.20	1.39	1.64	1.91	2.16	2.35	2.39	2.38	2.33	2.27	2.29	2.28	2.24	2.20	2.15	2.05	1.97	1.88	1.77	1.64	1.52	1.42	1.33	1.24	1.20	1.18	1.13
14	1.11	1.14	1.16	1.40	1.63	1.85	2.09	2.34	2.47	2.44	2.39	2.31	2.30	2.31	2.26	2.23	2.19	2.13	2.05	1.98	1.88	1.74	1.60	1.48	1.38	1.32	1.26	1.22	1.19	1.11
15	1.30	1.29	1.35	1.64	1.84	2.03	2.26	2.44	2.50	2.43	2.36	2.33	2.31	2.28	2.24	2.21	2.16	2.11	2.05	1.96	1.84	1.69	1.55	1.43	1.36	1.33	1.28	1.23	1.17	1.10
16	1.40	1.47	1.61	1.85	2.02	2.20	2.37	2.47	2.48	2.39	2.38	2.34	2.28	2.25	2.22	2.17	2.14	2.10	2.02	1.91	1.78	1.63	1.48	1.39	1.35	1.33	1.27	1.19	1.14	1.08
17	1.64	1.77	1.84	2.03	2.20	2.31	2.39	2.45	2.44	2.41	2.38	2.31	2.26	2.24	2.19	2.15	2.13	2.08	1.97	1.85	1.72	1.57	1.45	1.39	1.36	1.32	1.23	1.17	1.13	1.08
18	1.96	1.96	1.97	2.18	2.26	2.30	2.35	2.39	2.43	2.39	2.33	2.26	2.22	2.18	2.15	2.12	2.09	2.00	1.89	1.77	1.64	1.51	1.43	1.38	1.33	1.27	1.19	1.14	1.11	1.08
19	1.99	1.98	2.06	2.18	2.20	2.21	2.24	2.35	2.38	2.31	2.26	2.20	2.14	2.12	2.10	2.06	1.99	1.90	1.79	1.67	1.56	1.47	1.40	1.33	1.26	1.21	1.15	1.10	1.09	1.05
20	2.03	2.11	2.08	2.11	2.11	2.10	2.21	2.29	2.29	2.24	2.19	2.11	2.07	2.06	2.03	1.96	1.88	1.79	1.68	1.59	1.51	1.43	1.34	1.25	1.19	1.15	1.10	1.07	1.05	1.02
21	2.22	2.10	1.97	2.00	1.97	2.05	2.14	2.19	2.21	2.16	2.10	2.04	2.01	1.99	1.92	1.84	1.77	1.68	1.59	1.53	1.46	1.37	1.26	1.19	1.14	1.11	1.07	1.04	1.02	0.97
22	2.03	1.86	1.77	1.80	1.88	1.95	2.01	2.08	2.11	2.04	2.00	1.96	1.92	1.86	1.78	1.71	1.64	1.57	1.52	1.47	1.38	1.27	1.18	1.11	1.07	1.06	1.02	0.99	0.95	0.91
23	1.75	1.67	1.57	1.73	1.80	1.84	1.92	2.00	2.00	1.96	1.93	1.88	1.79	1.73	1.66	1.58	1.54	1.51	1.46	1.40	1.29	1.19	1.11	1.06	1.03	1.01	0.98	0.93	0.90	0.87
24	1.68	1.54	1.60	1.72	1.74	1.79	1.87	1.92	1.94	1.92	1.87	1.78	1.69	1.63	1.55	1.51	1.49	1.47	1.41	1.32	1.23	1.14	1.07	1.03	1.01	0.99	0.93	0.90	0.88	0.84
25	1.51	1.61	1.60	1.66	1.70	1.76	1.80	1.87	1.91	1.87	1.78	1.68	1.59	1.53	1.48	1.47	1.46	1.42	1.34	1.27	1.19	1.11	1.05	1.01	0.99	0.95	0.91	0.88	0.85	0.82
26	1.82	1.72	1.61	1.68	1.71	1.71	1.78	1.87	1.89	1.80	1.71	1.60	1.51	1.48	1.46	1.45	1.43	1.36	1.30	1.23	1.17	1.10	1.04	1.01	0.96	0.94	0.90	0.87	0.85	0.79
27	1.72	1.57	1.52	1.60	1.59	1.64	1.73	1.80	1.77	1.68	1.59	1.49	1.43	1.42	1.41	1.39	1.34	1.29	1.24	1.19	1.14	1.07	1.02	0.96	0.93	0.92	0.87	0.84	0.81	0.74
28	1.53	1.49	1.46	1.48	1.52	1.60	1.67	1.68	1.66	1.57	1.48	1.41	1.38	1.38	1.36	1.31	1.28	1.24	1.20	1.17	1.11	1.06	0.98	0.94	0.91	0.89	0.85	0.81	0.76	0.69
29	1.56	1.49	1.38	1.46	1.53	1.58	1.58	1.60	1.57	1.48	1.42	1.38	1.36	1.34	1.29	1.26	1.24	1.22	1.19	1.16	1.11	1.03	0.97	0.93	0.90	0.88	0.83	0.77	0.72	0.63
30	1.54	1.36	1.33	1.45	1.49	1.47	1.48	1.49	1.45	1.40	1.38	1.34	1.30	1.26	1.23	1.21	1.21	1.20	1.17	1.14	1.07	1.01	0.96	0.91	0.89	0.85	0.79	0.73	0.65	0.58

Table 3-9: t-statistics for “corporates” in “forecasting model” based on market price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 1%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-1.18	-1.82	-1.92	-1.20	-1.02	-1.30	-1.39	-1.24	-1.36	-1.21	-1.52	-1.02	-0.86	-0.82	-1.09	-1.07	-0.57	-0.57	-0.46	0.07	0.30	0.15	0.07	-0.37	-0.21	-0.23	0.23	0.26	0.31	0.97
2	-1.81	-2.17	-1.61	-1.03	-1.06	-1.25	-1.15	-1.10	-1.08	-1.23	-1.11	-0.75	-0.66	-0.77	-0.91	-0.64	-0.38	-0.33	0.00	0.40	0.45	0.35	0.08	-0.05	0.03	0.25	0.49	0.54	0.98	1.31
3	-1.98	-1.67	-1.10	-0.82	-0.91	-0.92	-0.91	-0.82	-0.99	-0.87	-0.77	-0.49	-0.54	-0.62	-0.53	-0.35	-0.14	0.08	0.38	0.62	0.65	0.42	0.32	0.22	0.44	0.59	0.77	1.11	1.42	1.63
4	-1.27	-1.13	-0.86	-0.72	-0.67	-0.72	-0.68	-0.76	-0.70	-0.62	-0.53	-0.40	-0.44	-0.36	-0.30	-0.14	0.17	0.40	0.60	0.78	0.68	0.58	0.50	0.55	0.72	0.85	1.22	1.49	1.70	1.74
5	-1.12	-1.17	-0.95	-0.68	-0.65	-0.66	-0.75	-0.64	-0.60	-0.52	-0.51	-0.40	-0.32	-0.25	-0.18	0.08	0.39	0.55	0.70	0.76	0.74	0.66	0.69	0.74	0.90	1.20	1.51	1.70	1.78	1.74
6	-1.31	-1.32	-0.94	-0.73	-0.66	-0.78	-0.69	-0.60	-0.55	-0.54	-0.53	-0.34	-0.26	-0.18	0.00	0.28	0.52	0.65	0.70	0.80	0.79	0.81	0.85	0.90	1.21	1.47	1.71	1.79	1.79	1.72
7	-1.41	-1.19	-0.93	-0.71	-0.78	-0.70	-0.64	-0.54	-0.55	-0.54	-0.44	-0.26	-0.18	0.00	0.22	0.44	0.64	0.68	0.77	0.87	0.94	0.96	1.01	1.22	1.49	1.69	1.83	1.84	1.81	1.74
8	-1.13	-1.09	-0.83	-0.79	-0.66	-0.62	-0.54	-0.50	-0.51	-0.42	-0.31	-0.14	0.03	0.24	0.41	0.60	0.71	0.79	0.87	1.03	1.10	1.14	1.33	1.52	1.74	1.86	1.93	1.91	1.89	1.84
9	-1.20	-1.09	-1.00	-0.72	-0.63	-0.57	-0.54	-0.51	-0.42	-0.32	-0.22	0.04	0.25	0.42	0.55	0.65	0.79	0.86	1.01	1.16	1.24	1.41	1.58	1.73	1.87	1.93	1.97	1.95	1.95	1.87
10	-1.13	-1.27	-0.90	-0.68	-0.57	-0.56	-0.54	-0.41	-0.31	-0.22	-0.03	0.26	0.42	0.57	0.62	0.74	0.87	1.00	1.14	1.30	1.50	1.66	1.79	1.88	1.96	1.98	2.02	2.02	1.99	1.90
11	-1.44	-1.15	-0.88	-0.63	-0.58	-0.58	-0.46	-0.31	-0.23	-0.04	0.18	0.43	0.57	0.63	0.71	0.83	1.01	1.14	1.29	1.56	1.75	1.87	1.95	1.98	2.03	2.06	2.10	2.07	2.02	1.96
12	-0.91	-0.91	-0.66	-0.52	-0.50	-0.40	-0.28	-0.15	0.03	0.25	0.43	0.64	0.70	0.79	0.86	1.03	1.21	1.35	1.60	1.86	2.02	2.09	2.11	2.11	2.16	2.19	2.20	2.15	2.12	2.03
13	-1.05	-0.92	-0.73	-0.59	-0.45	-0.32	-0.21	0.02	0.24	0.42	0.57	0.70	0.78	0.87	1.00	1.16	1.35	1.60	1.84	2.06	2.17	2.18	2.18	2.18	2.23	2.23	2.23	2.20	2.15	2.09
14	-0.92	-0.93	-0.76	-0.48	-0.32	-0.22	0.00	0.26	0.44	0.59	0.66	0.81	0.89	1.03	1.16	1.33	1.62	1.86	2.06	2.23	2.28	2.27	2.27	2.27	2.30	2.28	2.30	2.25	2.23	2.17
15	-1.03	-1.00	-0.63	-0.34	-0.21	0.00	0.25	0.47	0.62	0.68	0.77	0.92	1.05	1.19	1.33	1.60	1.88	2.08	2.23	2.35	2.37	2.36	2.36	2.34	2.34	2.35	2.34	2.32	2.31	2.27
16	-1.22	-0.79	-0.43	-0.23	0.02	0.25	0.46	0.67	0.72	0.80	0.89	1.10	1.20	1.34	1.58	1.72	1.96	2.12	2.25	2.34	2.36	2.35	2.22	2.19	2.23	2.22	2.26	2.25	2.27	2.30
17	-0.63	-0.39	-0.22	0.10	0.35	0.52	0.71	0.82	0.88	0.96	1.11	1.27	1.38	1.63	1.74	1.82	2.01	2.15	2.25	2.34	2.36	2.22	2.07	2.08	2.09	2.13	2.18	2.22	2.30	2.39
18	-0.48	-0.38	0.01	0.34	0.54	0.71	0.79	0.92	0.98	1.12	1.23	1.40	1.62	1.73	1.78	1.81	1.99	2.10	2.21	2.29	2.17	2.02	1.91	1.91	1.97	2.02	2.10	2.20	2.35	2.46
19	-0.56	-0.12	0.27	0.54	0.73	0.77	0.88	1.00	1.13	1.23	1.35	1.63	1.70	1.75	1.76	1.79	1.94	2.05	2.16	2.09	1.97	1.86	1.75	1.79	1.86	1.94	2.09	2.24	2.41	2.53
20	0.00	0.32	0.58	0.80	0.83	0.90	1.00	1.19	1.27	1.38	1.61	1.74	1.75	1.76	1.76	1.77	1.91	2.03	1.99	1.92	1.83	1.72	1.66	1.70	1.80	1.94	2.13	2.30	2.48	2.59
21	0.26	0.44	0.70	0.75	0.84	0.91	1.09	1.24	1.33	1.57	1.65	1.72	1.70	1.71	1.69	1.72	1.87	1.84	1.80	1.76	1.67	1.61	1.56	1.64	1.79	1.98	2.19	2.36	2.52	2.62
22	0.23	0.47	0.53	0.68	0.77	0.95	1.09	1.25	1.49	1.57	1.60	1.63	1.62	1.61	1.62	1.66	1.67	1.64	1.63	1.58	1.54	1.50	1.49	1.62	1.82	2.02	2.23	2.39	2.54	2.63
23	0.29	0.24	0.44	0.62	0.82	0.95	1.11	1.43	1.50	1.52	1.52	1.55	1.52	1.54	1.57	1.48	1.49	1.48	1.47	1.46	1.44	1.43	1.48	1.65	1.86	2.07	2.27	2.42	2.55	2.69
24	-0.08	0.18	0.41	0.71	0.85	1.00	1.32	1.45	1.46	1.45	1.45	1.46	1.46	1.49	1.40	1.32	1.35	1.34	1.36	1.37	1.38	1.43	1.52	1.71	1.93	2.12	2.30	2.44	2.61	2.70
25	0.19	0.34	0.67	0.86	1.00	1.31	1.42	1.46	1.43	1.42	1.40	1.44	1.45	1.36	1.26	1.22	1.24	1.27	1.30	1.34	1.40	1.49	1.60	1.79	2.00	2.18	2.35	2.52	2.65	2.75
26	0.22	0.58	0.77	0.97	1.30	1.37	1.39	1.41	1.38	1.35	1.36	1.40	1.29	1.21	1.15	1.11	1.16	1.20	1.26	1.34	1.44	1.55	1.67	1.85	2.04	2.22	2.42	2.55	2.69	2.80
27	0.63	0.70	0.90	1.31	1.35	1.33	1.32	1.34	1.30	1.30	1.32	1.24	1.14	1.10	1.04	1.03	1.09	1.16	1.26	1.39	1.51	1.63	1.74	1.91	2.09	2.29	2.45	2.60	2.75	2.88
28	0.49	0.69	1.20	1.27	1.23	1.20	1.20	1.21	1.21	1.23	1.13	1.06	1.00	0.96	0.94	0.94	1.04	1.14	1.29	1.43	1.56	1.66	1.77	1.94	2.15	2.31	2.48	2.63	2.80	2.91
29	0.60	1.19	1.19	1.16	1.11	1.10	1.09	1.13	1.14	1.05	0.96	0.93	0.87	0.86	0.86	0.89	1.02	1.17	1.33	1.48	1.60	1.70	1.80	1.99	2.16	2.34	2.52	2.69	2.84	2.93
30	1.34	1.09	1.02	1.00	0.98	0.97	1.00	1.06	0.95	0.87	0.82	0.80	0.77	0.78	0.81	0.88	1.05	1.22	1.38	1.52	1.63	1.73	1.86	2.01	2.19	2.37	2.57	2.72	2.85	2.94

Table 3-10: t-statistics for "internal" in "forecasting model" based on market price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 1%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.41	-0.64	-1.16	-1.26	-1.25	-0.94	-0.67	-0.28	-0.21	0.12	0.26	0.34	0.14	0.21	0.01	-0.05	0.21	0.04	0.21	0.29	0.25	0.64	0.63	0.73	0.97	0.84	0.60	0.67	0.73	0.80
2	-0.65	-1.42	-1.66	-1.58	-1.33	-0.97	-0.56	-0.29	-0.07	0.17	0.29	0.22	0.15	0.09	-0.06	0.05	0.11	0.12	0.25	0.29	0.47	0.66	0.70	0.87	0.94	0.75	0.67	0.74	0.81	0.84
3	-1.18	-1.65	-1.61	-1.38	-1.07	-0.62	-0.31	-0.01	0.19	0.38	0.38	0.36	0.23	0.16	0.15	0.17	0.28	0.32	0.41	0.58	0.69	0.85	0.95	1.03	0.99	0.89	0.85	0.93	0.98	0.92
4	-1.20	-1.55	-1.37	-1.05	-0.65	-0.28	0.04	0.30	0.47	0.54	0.55	0.47	0.35	0.36	0.32	0.40	0.51	0.54	0.71	0.82	0.93	1.12	1.18	1.17	1.15	1.08	1.09	1.14	1.12	1.05
5	-1.20	-1.33	-1.08	-0.65	-0.32	0.05	0.33	0.54	0.60	0.67	0.62	0.55	0.51	0.49	0.50	0.61	0.69	0.80	0.92	1.04	1.18	1.31	1.32	1.32	1.31	1.29	1.28	1.28	1.24	1.16
6	-0.92	-1.00	-0.63	-0.29	0.05	0.37	0.60	0.70	0.76	0.76	0.70	0.69	0.63	0.65	0.70	0.79	0.93	1.01	1.12	1.26	1.37	1.45	1.46	1.46	1.48	1.45	1.41	1.38	1.33	1.22
7	-0.66	-0.57	-0.30	0.05	0.33	0.60	0.72	0.81	0.81	0.80	0.79	0.75	0.74	0.79	0.83	0.97	1.09	1.16	1.31	1.42	1.48	1.55	1.57	1.59	1.60	1.54	1.48	1.44	1.36	1.27
8	-0.20	-0.25	0.03	0.33	0.57	0.72	0.83	0.87	0.84	0.88	0.84	0.84	0.86	0.90	1.00	1.11	1.22	1.33	1.44	1.51	1.57	1.64	1.67	1.68	1.66	1.59	1.52	1.45	1.39	1.31
9	-0.09	-0.02	0.23	0.51	0.62	0.77	0.82	0.84	0.87	0.87	0.88	0.91	0.92	1.02	1.09	1.20	1.33	1.42	1.49	1.56	1.62	1.70	1.72	1.70	1.66	1.58	1.49	1.44	1.38	1.31
10	0.21	0.20	0.42	0.55	0.67	0.76	0.79	0.86	0.86	0.90	0.94	0.97	1.03	1.11	1.18	1.31	1.42	1.47	1.54	1.61	1.68	1.75	1.73	1.70	1.65	1.55	1.48	1.43	1.38	1.33
11	0.32	0.32	0.39	0.55	0.61	0.68	0.78	0.82	0.86	0.93	0.96	1.04	1.09	1.17	1.26	1.37	1.45	1.50	1.58	1.66	1.71	1.75	1.72	1.68	1.61	1.53	1.45	1.41	1.38	1.33
12	0.44	0.23	0.36	0.45	0.51	0.66	0.73	0.81	0.89	0.95	1.03	1.09	1.14	1.24	1.32	1.40	1.48	1.54	1.62	1.69	1.72	1.73	1.70	1.63	1.58	1.49	1.43	1.41	1.37	1.30
13	0.16	0.14	0.21	0.32	0.47	0.59	0.70	0.82	0.90	1.01	1.08	1.14	1.21	1.29	1.35	1.42	1.50	1.57	1.65	1.68	1.70	1.70	1.64	1.59	1.53	1.46	1.42	1.39	1.33	1.23
14	0.26	0.08	0.15	0.35	0.46	0.62	0.76	0.88	1.00	1.10	1.16	1.24	1.30	1.36	1.41	1.49	1.58	1.63	1.68	1.70	1.70	1.68	1.63	1.58	1.53	1.48	1.43	1.37	1.30	1.21
15	0.06	-0.03	0.18	0.33	0.49	0.68	0.81	0.98	1.08	1.18	1.26	1.32	1.35	1.41	1.47	1.55	1.63	1.66	1.69	1.70	1.68	1.67	1.62	1.57	1.54	1.48	1.41	1.34	1.27	1.20
16	0.02	0.10	0.23	0.42	0.60	0.77	0.96	1.10	1.19	1.30	1.37	1.41	1.43	1.50	1.56	1.63	1.67	1.69	1.71	1.70	1.68	1.67	1.62	1.59	1.55	1.47	1.39	1.32	1.27	1.19
17	0.29	0.20	0.36	0.57	0.72	0.95	1.10	1.23	1.34	1.43	1.47	1.50	1.53	1.60	1.65	1.68	1.72	1.72	1.72	1.72	1.70	1.68	1.65	1.61	1.55	1.46	1.37	1.33	1.27	1.20
18	0.23	0.27	0.47	0.66	0.88	1.06	1.21	1.35	1.45	1.51	1.54	1.58	1.62	1.67	1.68	1.71	1.73	1.72	1.72	1.71	1.69	1.69	1.65	1.59	1.51	1.42	1.36	1.30	1.25	1.19
19	0.41	0.45	0.61	0.87	1.03	1.20	1.35	1.47	1.54	1.59	1.62	1.67	1.69	1.71	1.72	1.73	1.73	1.72	1.72	1.71	1.71	1.69	1.63	1.55	1.48	1.41	1.34	1.29	1.25	1.19
20	0.58	0.58	0.82	1.01	1.15	1.33	1.46	1.55	1.61	1.66	1.70	1.72	1.72	1.73	1.73	1.72	1.73	1.71	1.70	1.71	1.70	1.67	1.58	1.51	1.46	1.38	1.32	1.27	1.23	1.17
21	0.66	0.79	0.93	1.11	1.27	1.42	1.52	1.60	1.66	1.72	1.74	1.74	1.72	1.73	1.70	1.71	1.71	1.69	1.70	1.70	1.66	1.61	1.54	1.48	1.42	1.36	1.30	1.26	1.21	1.16
22	1.01	0.91	1.04	1.24	1.36	1.48	1.57	1.65	1.72	1.76	1.75	1.74	1.72	1.70	1.69	1.70	1.69	1.69	1.69	1.66	1.61	1.56	1.51	1.45	1.40	1.34	1.28	1.24	1.20	1.15
23	0.90	0.89	1.09	1.26	1.36	1.47	1.56	1.66	1.71	1.73	1.72	1.70	1.66	1.65	1.64	1.64	1.65	1.64	1.62	1.58	1.53	1.51	1.45	1.40	1.35	1.29	1.24	1.20	1.17	1.11
24	1.00	1.05	1.18	1.30	1.38	1.50	1.61	1.68	1.70	1.71	1.69	1.65	1.62	1.62	1.60	1.62	1.63	1.60	1.56	1.52	1.50	1.46	1.41	1.37	1.32	1.27	1.21	1.18	1.14	1.09
25	1.19	1.11	1.19	1.31	1.40	1.53	1.62	1.66	1.67	1.67	1.63	1.61	1.59	1.58	1.58	1.59	1.58	1.53	1.49	1.48	1.44	1.42	1.38	1.33	1.29	1.24	1.19	1.15	1.12	1.07
26	1.13	1.04	1.14	1.28	1.40	1.52	1.57	1.60	1.61	1.59	1.57	1.56	1.53	1.54	1.53	1.52	1.49	1.44	1.44	1.41	1.39	1.37	1.33	1.28	1.25	1.20	1.15	1.11	1.08	1.04
27	1.05	1.00	1.12	1.31	1.39	1.47	1.51	1.54	1.53	1.53	1.52	1.49	1.48	1.49	1.46	1.43	1.40	1.39	1.37	1.35	1.34	1.32	1.28	1.24	1.21	1.16	1.11	1.08	1.05	1.01
28	1.06	1.03	1.19	1.32	1.37	1.43	1.47	1.47	1.48	1.48	1.46	1.45	1.44	1.42	1.38	1.36	1.35	1.33	1.32	1.31	1.29	1.28	1.25	1.21	1.18	1.13	1.08	1.05	1.02	0.99
29	1.09	1.13	1.21	1.28	1.31	1.37	1.38	1.40	1.42	1.42	1.41	1.40	1.36	1.33	1.29	1.30	1.29	1.27	1.27	1.26	1.25	1.24	1.21	1.17	1.14	1.09	1.05	1.02	0.98	0.94
30	1.25	1.15	1.15	1.21	1.24	1.27	1.30	1.34	1.34	1.36	1.35	1.32	1.27	1.24	1.23	1.23	1.23	1.23	1.22	1.22	1.21	1.20	1.17	1.13	1.10	1.06	1.02	0.98	0.93	0.92

Table 3-11: t-statistics for "interbank" in "forecasting model" based on market price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 1%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.49	0.84	1.24	0.68	1.29	1.48	1.98	2.16	2.01	1.36	1.19	1.45	1.23	1.14	1.16	1.14	0.98	1.30	1.08	1.33	1.33	1.32	1.34	1.22	1.19	1.27	1.25	1.21	1.21	1.39
2	0.61	0.55	0.53	0.67	1.16	1.58	1.97	1.96	1.51	1.03	1.10	1.12	0.96	0.92	0.90	0.82	0.93	0.98	1.01	1.15	1.15	1.16	1.13	1.06	1.10	1.13	1.11	1.10	1.24	1.15
3	1.01	0.51	0.80	0.98	1.56	1.93	2.12	1.81	1.39	1.16	1.11	1.10	0.98	0.93	0.87	0.94	0.95	1.08	1.11	1.21	1.22	1.20	1.16	1.15	1.16	1.17	1.16	1.26	1.30	1.13
4	0.54	0.66	0.99	1.32	1.83	2.04	1.94	1.59	1.35	1.09	1.03	1.03	0.92	0.85	0.90	0.90	0.99	1.11	1.13	1.21	1.19	1.17	1.17	1.16	1.16	1.18	1.25	1.28	1.24	1.17
5	1.15	1.17	1.60	1.86	2.18	2.08	1.87	1.63	1.34	1.10	1.05	1.02	0.91	0.93	0.92	0.99	1.07	1.16	1.18	1.22	1.20	1.21	1.20	1.18	1.20	1.28	1.31	1.27	1.27	1.21
6	1.37	1.62	1.99	2.09	2.09	1.88	1.76	1.47	1.21	1.01	0.95	0.90	0.87	0.85	0.91	0.98	1.05	1.13	1.12	1.16	1.17	1.17	1.16	1.15	1.22	1.26	1.23	1.23	1.24	1.19
7	1.93	2.03	2.19	1.97	1.86	1.76	1.57	1.31	1.09	0.90	0.82	0.85	0.79	0.82	0.89	0.95	1.02	1.07	1.06	1.12	1.12	1.12	1.12	1.17	1.21	1.19	1.19	1.20	1.22	1.18
8	2.15	2.01	1.84	1.60	1.64	1.49	1.33	1.12	0.91	0.73	0.73	0.72	0.73	0.77	0.83	0.89	0.93	0.98	1.00	1.05	1.05	1.06	1.11	1.13	1.12	1.14	1.15	1.16	1.19	1.13
9	1.92	1.49	1.36	1.34	1.33	1.22	1.10	0.91	0.71	0.61	0.59	0.64	0.66	0.71	0.76	0.80	0.84	0.90	0.93	0.97	0.98	1.04	1.07	1.04	1.06	1.08	1.10	1.13	1.14	1.07
10	1.23	0.99	1.14	1.08	1.09	1.02	0.90	0.72	0.61	0.50	0.53	0.60	0.62	0.66	0.70	0.73	0.79	0.85	0.87	0.91	0.97	1.01	0.99	1.00	1.02	1.05	1.08	1.09	1.08	1.01
11	1.00	1.03	1.05	0.99	1.01	0.93	0.80	0.70	0.57	0.52	0.56	0.63	0.64	0.66	0.69	0.74	0.79	0.85	0.87	0.96	1.00	0.99	0.99	1.00	1.03	1.07	1.08	1.07	1.07	0.99
12	1.28	1.04	1.03	0.97	0.97	0.87	0.82	0.69	0.62	0.58	0.62	0.67	0.66	0.68	0.72	0.77	0.82	0.87	0.94	1.00	1.00	1.01	1.02	1.03	1.07	1.09	1.08	1.08	1.06	0.99
13	0.98	0.84	0.89	0.83	0.82	0.81	0.73	0.67	0.62	0.59	0.62	0.66	0.65	0.68	0.72	0.76	0.81	0.91	0.95	0.97	0.99	1.01	1.02	1.05	1.07	1.07	1.07	1.05	1.04	0.98
14	0.85	0.77	0.81	0.74	0.81	0.76	0.74	0.71	0.66	0.63	0.64	0.68	0.68	0.72	0.76	0.80	0.89	0.96	0.96	1.00	1.02	1.04	1.07	1.08	1.08	1.09	1.07	1.06	1.05	1.01
15	0.86	0.73	0.74	0.78	0.79	0.79	0.81	0.77	0.72	0.67	0.68	0.73	0.73	0.77	0.81	0.89	0.95	0.98	1.00	1.04	1.07	1.10	1.11	1.10	1.10	1.09	1.08	1.07	1.08	1.05
16	0.76	0.64	0.79	0.75	0.82	0.86	0.86	0.82	0.76	0.70	0.73	0.78	0.79	0.82	0.90	0.94	0.96	1.01	1.04	1.08	1.12	1.13	1.11	1.11	1.10	1.09	1.08	1.10	1.12	1.10
17	0.72	0.77	0.80	0.83	0.92	0.94	0.93	0.87	0.81	0.77	0.80	0.85	0.85	0.93	0.97	0.97	1.01	1.06	1.09	1.15	1.16	1.15	1.14	1.11	1.11	1.11	1.12	1.15	1.16	1.14
18	0.99	0.79	0.90	0.94	1.00	1.01	0.98	0.92	0.87	0.84	0.87	0.91	0.96	1.00	1.00	1.02	1.06	1.11	1.15	1.19	1.18	1.17	1.14	1.13	1.13	1.15	1.17	1.19	1.20	1.17
19	0.77	0.80	0.95	0.98	1.03	1.01	0.99	0.95	0.91	0.88	0.91	0.99	1.01	1.00	1.02	1.05	1.10	1.16	1.18	1.19	1.19	1.16	1.14	1.13	1.16	1.18	1.20	1.22	1.23	1.19
20	0.99	0.99	1.07	1.07	1.08	1.06	1.06	1.03	0.99	0.95	1.02	1.07	1.04	1.06	1.08	1.11	1.17	1.21	1.21	1.22	1.20	1.18	1.16	1.17	1.20	1.22	1.24	1.25	1.25	1.19
21	1.12	1.05	1.11	1.06	1.08	1.09	1.10	1.07	1.03	1.04	1.08	1.08	1.07	1.09	1.12	1.16	1.20	1.21	1.21	1.21	1.19	1.17	1.18	1.19	1.21	1.23	1.24	1.25	1.22	1.18
22	1.10	1.03	1.06	1.03	1.09	1.12	1.13	1.09	1.10	1.08	1.07	1.08	1.08	1.11	1.15	1.17	1.18	1.20	1.18	1.18	1.17	1.17	1.17	1.18	1.20	1.22	1.22	1.20	1.20	1.15
23	1.06	0.98	1.03	1.06	1.13	1.16	1.16	1.18	1.15	1.07	1.07	1.09	1.09	1.13	1.16	1.15	1.16	1.16	1.15	1.16	1.16	1.17	1.17	1.17	1.20	1.20	1.19	1.19	1.17	1.11
24	1.01	0.97	1.09	1.13	1.20	1.21	1.27	1.24	1.14	1.08	1.08	1.10	1.12	1.14	1.14	1.13	1.13	1.14	1.13	1.16	1.16	1.16	1.16	1.17	1.19	1.17	1.17	1.16	1.14	1.08
25	1.03	1.08	1.20	1.22	1.26	1.34	1.34	1.24	1.17	1.10	1.11	1.14	1.14	1.13	1.13	1.11	1.11	1.12	1.14	1.16	1.16	1.16	1.17	1.17	1.16	1.16	1.15	1.13	1.11	1.07
26	1.22	1.23	1.31	1.30	1.40	1.42	1.33	1.26	1.18	1.12	1.14	1.15	1.12	1.11	1.09	1.08	1.08	1.12	1.13	1.15	1.15	1.16	1.16	1.14	1.14	1.13	1.11	1.10	1.08	1.05
27	1.31	1.25	1.32	1.40	1.44	1.35	1.30	1.23	1.16	1.13	1.12	1.11	1.08	1.06	1.04	1.04	1.07	1.09	1.11	1.13	1.14	1.14	1.11	1.11	1.11	1.09	1.08	1.07	1.06	1.03
28	1.29	1.23	1.42	1.42	1.35	1.30	1.25	1.20	1.16	1.11	1.07	1.06	1.03	1.01	1.00	1.02	1.04	1.08	1.09	1.12	1.12	1.10	1.09	1.08	1.07	1.06	1.05	1.04	1.04	1.02
29	1.24	1.39	1.46	1.33	1.29	1.25	1.21	1.18	1.12	1.04	1.00	0.98	0.95	0.94	0.96	0.96	0.99	1.03	1.05	1.06	1.04	1.04	1.01	1.00	1.00	0.99	0.99	0.99	1.00	0.98
30	1.57	1.46	1.34	1.25	1.24	1.23	1.21	1.15	1.06	0.98	0.93	0.92	0.90	0.91	0.92	0.93	0.96	1.01	1.01	0.99	0.99	0.97	0.94	0.93	0.93	0.94	0.94	0.95	0.96	0.93

Table 3-12: t-statistics for "lagged exchange rate return" in "forecasting model" based on market price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 1%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.04	-0.86	-0.78	-0.45	-1.20	-0.65	-1.19	-1.09	-0.46	-0.89	-1.18	-1.02	-1.21	-1.85	-2.18	-1.96	-2.49	-1.86	-1.73	-0.90	-1.11	-1.08	-1.22	-0.63	-1.26	-1.18	-1.26	-1.43	-1.50	-0.65
2	-0.89	-1.45	-1.02	-1.22	-1.39	-1.21	-1.57	-1.10	-0.91	-1.28	-1.37	-1.39	-1.84	-2.34	-2.37	-2.56	-2.53	-2.10	-1.73	-1.21	-1.32	-1.41	-1.12	-1.14	-1.43	-1.47	-1.53	-1.68	-1.26	-0.81
3	-1.04	-1.16	-1.29	-1.19	-1.42	-1.35	-1.31	-1.05	-1.07	-1.25	-1.45	-1.63	-2.08	-2.35	-2.62	-2.49	-2.41	-1.88	-1.61	-1.23	-1.38	-1.19	-1.23	-1.21	-1.47	-1.52	-1.60	-1.39	-1.10	-0.65
4	-0.97	-1.48	-1.32	-1.33	-1.58	-1.31	-1.32	-1.23	-1.16	-1.41	-1.71	-1.98	-2.30	-2.67	-2.65	-2.54	-2.34	-1.89	-1.67	-1.41	-1.32	-1.37	-1.40	-1.41	-1.62	-1.70	-1.51	-1.35	-1.03	-0.46
5	-1.66	-1.72	-1.61	-1.64	-1.63	-1.39	-1.47	-1.30	-1.34	-1.66	-2.00	-2.20	-2.60	-2.70	-2.67	-2.47	-2.28	-1.90	-1.76	-1.38	-1.46	-1.50	-1.55	-1.59	-1.80	-1.65	-1.51	-1.29	-0.84	-0.56
6	-1.49	-1.70	-1.70	-1.53	-1.55	-1.36	-1.36	-1.29	-1.42	-1.79	-2.09	-2.41	-2.56	-2.64	-2.49	-2.29	-2.11	-1.79	-1.51	-1.32	-1.40	-1.46	-1.53	-1.60	-1.60	-1.49	-1.30	-0.96	-0.69	-0.32
7	-1.69	-1.86	-1.60	-1.48	-1.54	-1.31	-1.37	-1.38	-1.59	-1.91	-2.27	-2.36	-2.49	-2.41	-2.30	-2.13	-1.99	-1.57	-1.45	-1.30	-1.39	-1.48	-1.57	-1.46	-1.47	-1.30	-1.01	-0.82	-0.48	-0.25
8	-1.58	-1.50	-1.38	-1.37	-1.38	-1.23	-1.36	-1.46	-1.65	-2.04	-2.19	-2.27	-2.24	-2.18	-2.09	-1.96	-1.71	-1.43	-1.34	-1.23	-1.35	-1.45	-1.37	-1.29	-1.23	-0.97	-0.81	-0.55	-0.31	-0.15
9	-1.19	-1.34	-1.31	-1.26	-1.39	-1.32	-1.51	-1.60	-1.87	-2.06	-2.18	-2.11	-2.10	-2.06	-1.99	-1.77	-1.63	-1.39	-1.31	-1.25	-1.36	-1.30	-1.25	-1.09	-0.95	-0.81	-0.59	-0.42	-0.22	-0.06
10	-1.34	-1.46	-1.36	-1.41	-1.59	-1.59	-1.74	-1.93	-1.99	-2.14	-2.12	-2.06	-2.06	-2.04	-1.89	-1.77	-1.64	-1.43	-1.39	-1.34	-1.30	-1.26	-1.13	-0.91	-0.87	-0.68	-0.54	-0.39	-0.19	-0.15
11	-1.43	-1.50	-1.54	-1.63	-1.85	-1.83	-2.07	-2.06	-2.10	-2.09	-2.08	-2.04	-2.06	-1.95	-1.90	-1.80	-1.67	-1.50	-1.46	-1.28	-1.25	-1.14	-0.95	-0.83	-0.74	-0.61	-0.50	-0.36	-0.26	-0.16
12	-1.47	-1.70	-1.75	-1.87	-2.04	-2.14	-2.17	-2.17	-2.05	-2.05	-2.05	-2.04	-1.96	-1.95	-1.91	-1.81	-1.72	-1.56	-1.40	-1.24	-1.14	-0.97	-0.87	-0.70	-0.66	-0.56	-0.45	-0.40	-0.24	-0.15
13	-1.72	-1.98	-2.04	-2.06	-2.34	-2.26	-2.28	-2.13	-2.03	-2.05	-2.07	-1.97	-1.99	-1.98	-1.93	-1.86	-1.77	-1.50	-1.36	-1.15	-0.98	-0.90	-0.75	-0.63	-0.62	-0.52	-0.50	-0.38	-0.23	-0.13
14	-1.98	-2.23	-2.20	-2.32	-2.41	-2.33	-2.22	-2.07	-2.01	-2.05	-1.99	-1.97	-1.99	-1.97	-1.95	-1.87	-1.67	-1.43	-1.23	-0.96	-0.89	-0.76	-0.65	-0.56	-0.55	-0.53	-0.44	-0.34	-0.18	0.00
15	-2.18	-2.30	-2.42	-2.34	-2.42	-2.22	-2.11	-2.01	-1.98	-1.93	-1.96	-1.95	-1.96	-1.96	-1.93	-1.75	-1.58	-1.29	-1.03	-0.85	-0.72	-0.63	-0.56	-0.47	-0.53	-0.45	-0.38	-0.26	-0.02	0.09
16	-2.15	-2.47	-2.37	-2.31	-2.26	-2.07	-2.01	-1.94	-1.83	-1.87	-1.90	-1.88	-1.92	-1.91	-1.78	-1.63	-1.40	-1.06	-0.88	-0.65	-0.57	-0.51	-0.44	-0.43	-0.43	-0.36	-0.27	-0.07	0.10	0.29
17	-2.50	-2.46	-2.37	-2.16	-2.12	-1.97	-1.94	-1.78	-1.76	-1.82	-1.84	-1.85	-1.87	-1.76	-1.66	-1.45	-1.17	-0.91	-0.69	-0.50	-0.44	-0.39	-0.40	-0.33	-0.34	-0.24	-0.08	0.05	0.30	0.35
18	-2.17	-2.27	-2.05	-1.91	-1.92	-1.80	-1.69	-1.64	-1.64	-1.69	-1.74	-1.74	-1.67	-1.59	-1.43	-1.18	-0.97	-0.66	-0.49	-0.32	-0.28	-0.31	-0.25	-0.19	-0.17	-0.01	0.09	0.30	0.40	0.48
19	-2.19	-2.05	-1.89	-1.83	-1.86	-1.65	-1.66	-1.61	-1.60	-1.68	-1.72	-1.62	-1.57	-1.43	-1.22	-1.04	-0.79	-0.52	-0.37	-0.23	-0.25	-0.22	-0.18	-0.09	0.00	0.10	0.28	0.34	0.48	0.52
20	-1.79	-1.78	-1.73	-1.74	-1.68	-1.59	-1.60	-1.54	-1.57	-1.65	-1.58	-1.50	-1.39	-1.20	-1.07	-0.85	-0.64	-0.39	-0.26	-0.19	-0.16	-0.13	-0.06	0.09	0.12	0.30	0.33	0.43	0.53	0.50
21	-1.84	-1.89	-1.86	-1.75	-1.80	-1.68	-1.67	-1.64	-1.66	-1.62	-1.57	-1.43	-1.26	-1.14	-0.97	-0.77	-0.58	-0.35	-0.29	-0.17	-0.14	-0.09	0.05	0.15	0.25	0.29	0.37	0.43	0.46	0.48
22	-1.95	-2.01	-1.83	-1.85	-1.88	-1.74	-1.76	-1.72	-1.62	-1.60	-1.48	-1.28	-1.19	-1.03	-0.88	-0.71	-0.53	-0.38	-0.27	-0.15	-0.10	0.03	0.12	0.29	0.26	0.34	0.37	0.37	0.44	0.45
23	-2.02	-1.93	-1.91	-1.91	-1.91	-1.81	-1.82	-1.66	-1.58	-1.49	-1.32	-1.20	-1.06	-0.92	-0.80	-0.65	-0.55	-0.34	-0.23	-0.09	0.03	0.10	0.27	0.31	0.32	0.36	0.32	0.37	0.44	0.51
24	-1.82	-1.95	-1.93	-1.83	-1.90	-1.80	-1.69	-1.56	-1.45	-1.30	-1.20	-1.05	-0.93	-0.82	-0.72	-0.64	-0.48	-0.29	-0.16	0.05	0.12	0.27	0.30	0.38	0.36	0.33	0.34	0.38	0.52	0.58
25	-2.04	-2.10	-1.94	-1.90	-1.95	-1.73	-1.64	-1.47	-1.29	-1.23	-1.09	-0.96	-0.87	-0.78	-0.75	-0.62	-0.47	-0.26	-0.06	0.10	0.25	0.26	0.34	0.38	0.29	0.31	0.32	0.43	0.57	0.64
26	-2.06	-1.99	-1.92	-1.88	-1.80	-1.61	-1.49	-1.26	-1.17	-1.06	-0.95	-0.84	-0.78	-0.76	-0.68	-0.56	-0.39	-0.11	0.04	0.27	0.29	0.34	0.38	0.36	0.32	0.33	0.41	0.52	0.67	0.70
27	-1.88	-1.95	-1.89	-1.72	-1.68	-1.46	-1.26	-1.12	-0.99	-0.91	-0.82	-0.74	-0.76	-0.68	-0.61	-0.47	-0.23	-0.01	0.21	0.32	0.38	0.40	0.37	0.39	0.34	0.43	0.51	0.62	0.73	0.75
28	-2.04	-2.06	-1.81	-1.69	-1.59	-1.29	-1.19	-1.00	-0.89	-0.84	-0.78	-0.78	-0.73	-0.66	-0.58	-0.39	-0.20	0.10	0.21	0.36	0.38	0.33	0.35	0.37	0.39	0.48	0.57	0.65	0.75	0.76
29	-2.03	-1.83	-1.65	-1.50	-1.32	-1.12	-0.98	-0.82	-0.74	-0.71	-0.74	-0.67	-0.63	-0.56	-0.43	-0.27	-0.01	0.18	0.32	0.42	0.38	0.38	0.39	0.47	0.50	0.59	0.65	0.71	0.81	0.79
30	-1.68	-1.62	-1.42	-1.21	-1.14	-0.89	-0.79	-0.66	-0.61	-0.67	-0.63	-0.57	-0.52	-0.40	-0.31	-0.08	0.06	0.28	0.39	0.42	0.42	0.42	0.50	0.58	0.62	0.67	0.72	0.79	0.84	0.85

Table 3-13: t-statistics for “financials” in “forecasting model” based on transaction price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 11%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.67	1.43	-1.15	0.49	0.27	0.54	0.40	0.45	1.21	0.93	0.73	1.37	1.92	2.02	2.11	2.46	2.57	2.71	3.25	3.22	3.25	1.69	1.76	1.06	1.79	1.56	1.16	1.46	1.25	1.59
2	1.43	-0.60	-1.04	0.25	0.28	0.38	0.34	0.83	1.16	0.83	1.14	1.75	2.11	2.28	2.41	2.67	2.81	3.19	3.43	3.50	2.72	1.82	1.49	1.69	1.80	1.42	1.38	1.39	1.49	1.48
3	-1.00	-1.01	-1.43	-0.14	-0.16	-0.05	0.27	0.56	0.66	0.74	1.19	1.67	2.06	2.22	2.34	2.56	2.89	3.16	3.41	2.92	2.27	1.39	1.54	1.45	1.40	1.23	1.12	1.30	1.21	1.06
4	-0.03	-0.22	-0.49	0.29	0.28	0.58	0.74	0.87	1.17	1.39	1.71	2.12	2.44	2.62	2.75	3.09	3.31	3.54	3.31	2.86	2.20	1.85	1.79	1.61	1.65	1.46	1.50	1.49	1.34	1.36
5	-0.24	-0.23	-0.54	0.22	0.43	0.66	0.72	1.06	1.46	1.68	2.06	2.43	2.75	2.90	3.13	3.38	3.62	3.46	3.20	2.69	2.37	1.95	1.79	1.73	1.70	1.65	1.55	1.47	1.44	1.52
6	-0.10	-0.22	-0.49	0.41	0.55	0.68	0.95	1.40	1.78	2.05	2.38	2.72	3.00	3.23	3.39	3.65	3.56	3.37	3.03	2.79	2.41	1.96	1.90	1.78	1.86	1.69	1.54	1.56	1.58	1.59
7	-0.23	-0.26	-0.27	0.49	0.55	0.88	1.24	1.67	2.07	2.30	2.61	2.92	3.26	3.46	3.64	3.60	3.47	3.21	3.07	2.77	2.35	2.01	1.91	1.90	1.86	1.66	1.60	1.66	1.64	1.60
8	-0.19	0.05	-0.09	0.52	0.77	1.20	1.55	2.02	2.37	2.57	2.85	3.20	3.50	3.71	3.62	3.54	3.33	3.24	3.05	2.70	2.37	2.03	2.02	1.92	1.83	1.71	1.70	1.71	1.65	1.66
9	0.22	0.23	-0.03	0.74	1.08	1.50	1.89	2.30	2.61	2.80	3.12	3.43	3.73	3.68	3.56	3.40	3.34	3.20	2.95	2.67	2.34	2.11	2.02	1.88	1.85	1.78	1.74	1.72	1.70	1.65
10	0.14	0.07	0.09	0.94	1.28	1.74	2.08	2.45	2.74	2.98	3.28	3.59	3.63	3.56	3.37	3.35	3.23	3.04	2.84	2.55	2.33	2.05	1.92	1.84	1.86	1.76	1.69	1.70	1.63	1.34
11	0.20	0.45	0.59	1.26	1.63	2.04	2.34	2.68	3.01	3.25	3.53	3.60	3.61	3.47	3.42	3.32	3.14	2.99	2.78	2.60	2.33	2.03	1.96	1.92	1.91	1.79	1.76	1.72	1.44	1.25
12	0.65	0.93	0.95	1.60	1.93	2.27	2.56	2.94	3.25	3.48	3.52	3.56	3.49	3.46	3.35	3.20	3.06	2.89	2.77	2.53	2.26	2.03	1.99	1.93	1.89	1.81	1.74	1.50	1.31	1.17
13	1.01	1.18	1.27	1.85	2.13	2.47	2.81	3.18	3.47	3.48	3.49	3.45	3.49	3.40	3.25	3.12	2.96	2.87	2.70	2.45	2.23	2.05	1.99	1.90	1.89	1.77	1.50	1.35	1.20	1.03
14	1.08	1.37	1.43	1.96	2.24	2.64	2.97	3.33	3.40	3.38	3.32	3.38	3.35	3.22	3.10	2.95	2.87	2.73	2.55	2.36	2.18	1.99	1.90	1.85	1.80	1.49	1.31	1.19	1.02	0.83
15	1.33	1.54	1.56	2.09	2.44	2.84	3.16	3.29	3.32	3.23	3.28	3.28	3.21	3.10	2.95	2.88	2.75	2.60	2.48	2.33	2.14	1.92	1.86	1.77	1.54	1.32	1.17	1.03	0.84	0.69
16	1.44	1.63	1.71	2.32	2.69	3.07	3.15	3.24	3.20	3.22	3.20	3.15	3.09	2.96	2.90	2.77	2.63	2.53	2.44	2.27	2.06	1.88	1.78	1.51	1.36	1.17	1.01	0.85	0.69	0.56
17	1.46	1.73	1.94	2.54	2.89	3.00	3.05	3.07	3.15	3.09	3.02	3.00	2.92	2.86	2.74	2.61	2.52	2.45	2.35	2.17	1.99	1.78	1.51	1.32	1.20	0.99	0.81	0.68	0.54	0.40
18	1.72	2.10	2.31	2.81	2.87	2.95	2.94	3.07	3.07	2.97	2.93	2.88	2.88	2.76	2.64	2.55	2.49	2.41	2.29	2.14	1.92	1.55	1.35	1.19	1.05	0.82	0.67	0.56	0.41	0.44
19	2.04	2.40	2.56	2.70	2.73	2.75	2.87	2.92	2.88	2.82	2.75	2.79	2.72	2.60	2.52	2.47	2.39	2.30	2.20	2.02	1.64	1.35	1.18	1.00	0.84	0.65	0.52	0.39	0.41	0.45
20	2.27	2.60	2.32	2.48	2.44	2.63	2.67	2.68	2.69	2.61	2.63	2.61	2.54	2.46	2.42	2.35	2.26	2.19	2.06	1.71	1.42	1.16	0.97	0.78	0.65	0.48	0.33	0.37	0.41	0.47
21	2.39	2.18	1.96	2.12	2.28	2.38	2.40	2.46	2.45	2.47	2.44	2.41	2.38	2.35	2.29	2.20	2.14	2.03	1.74	1.47	1.21	0.93	0.73	0.57	0.46	0.28	0.30	0.36	0.41	0.45
22	1.72	1.71	1.50	1.97	2.02	2.10	2.18	2.23	2.32	2.28	2.24	2.27	2.28	2.22	2.15	2.09	1.98	1.71	1.49	1.27	0.99	0.70	0.53	0.39	0.27	0.25	0.29	0.36	0.39	0.43
23	1.74	1.60	1.64	1.93	1.93	2.06	2.11	2.25	2.27	2.22	2.22	2.27	2.26	2.18	2.13	2.02	1.75	1.55	1.37	1.11	0.82	0.57	0.42	0.26	0.30	0.30	0.35	0.41	0.43	0.48
24	1.59	1.77	1.59	1.84	1.90	2.00	2.15	2.21	2.20	2.20	2.23	2.26	2.22	2.16	2.07	1.79	1.58	1.42	1.21	0.94	0.69	0.46	0.30	0.30	0.35	0.36	0.40	0.45	0.48	0.51
25	1.88	1.76	1.54	1.84	1.87	2.06	2.13	2.16	2.21	2.23	2.24	2.24	2.22	2.12	1.85	1.63	1.47	1.27	1.05	0.82	0.59	0.35	0.34	0.36	0.43	0.42	0.45	0.51	0.52	0.57
26	1.67	1.53	1.40	1.73	1.87	1.98	2.03	2.11	2.18	2.18	2.16	2.18	2.10	1.83	1.63	1.46	1.26	1.06	0.87	0.66	0.42	0.35	0.36	0.39	0.44	0.42	0.46	0.50	0.55	0.57
27	1.58	1.54	1.41	1.83	1.87	1.95	2.05	2.14	2.18	2.15	2.15	2.11	1.86	1.65	1.50	1.29	1.08	0.91	0.75	0.53	0.46	0.40	0.42	0.44	0.48	0.48	0.50	0.56	0.58	0.56
28	1.65	1.56	1.58	1.84	1.85	1.98	2.09	2.16	2.16	2.16	2.09	1.87	1.70	1.53	1.34	1.12	0.95	0.80	0.62	0.57	0.52	0.47	0.48	0.49	0.54	0.52	0.56	0.61	0.57	0.55
29	1.64	1.75	1.59	1.82	1.88	2.02	2.10	2.13	2.16	2.08	1.84	1.69	1.55	1.35	1.16	0.97	0.82	0.66	0.65	0.62	0.58	0.52	0.52	0.54	0.57	0.57	0.60	0.59	0.56	0.51
30	1.94	1.78	1.57	1.86	1.92	2.03	2.07	2.13	2.09	1.82	1.66	1.55	1.37	1.17	1.00	0.84	0.68	0.69	0.70	0.68	0.63	0.56	0.57	0.57	0.63	0.61	0.58	0.57	0.52	0.48

Table 3-14: t-statistics for "corporates" in "forecasting model" based on transaction price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 11%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.74	0.58	0.57	0.36	-2.80	-2.89	-3.38	-2.66	-3.05	-2.66	-2.83	-2.89	-3.10	-2.78	-3.19	-3.00	-2.63	-2.97	-2.70	-1.92	-1.81	-1.97	-1.68	-1.32	-1.55	-0.91	-0.52	-0.62	-1.70	-1.55
2	0.63	0.47	0.31	-1.28	-2.78	-2.93	-2.72	-2.73	-2.76	-2.61	-2.70	-2.82	-2.83	-2.85	-3.00	-2.84	-2.94	-2.96	-2.46	-1.97	-1.96	-1.98	-1.70	-1.58	-1.44	-1.07	-0.94	-1.45	-1.89	-1.88
3	0.53	0.24	-1.10	-2.89	-2.59	-2.54	-2.53	-2.43	-2.47	-2.40	-2.51	-2.53	-2.62	-2.67	-2.71	-2.77	-2.76	-2.55	-2.20	-1.96	-1.91	-1.82	-1.67	-1.47	-1.32	-1.14	-1.34	-1.65	-1.93	-1.51
4	0.31	-1.01	-2.54	-2.91	-2.43	-2.47	-2.40	-2.35	-2.38	-2.38	-2.43	-2.49	-2.59	-2.59	-2.69	-2.72	-2.55	-2.34	-2.14	-1.94	-1.82	-1.77	-1.58	-1.39	-1.31	-1.38	-1.53	-1.78	-1.63	-1.41
5	-0.75	-2.15	-2.56	-2.59	-2.33	-2.32	-2.28	-2.24	-2.31	-2.29	-2.35	-2.44	-2.50	-2.55	-2.62	-2.53	-2.34	-2.22	-2.05	-1.82	-1.74	-1.64	-1.45	-1.33	-1.41	-1.47	-1.62	-1.53	-1.48	-1.33
6	-1.11	-2.45	-2.68	-2.75	-2.40	-2.40	-2.37	-2.38	-2.41	-2.42	-2.52	-2.58	-2.67	-2.70	-2.65	-2.49	-2.36	-2.21	-1.97	-1.78	-1.65	-1.50	-1.36	-1.37	-1.45	-1.54	-1.40	-1.39	-1.35	-1.16
7	-1.25	-2.53	-2.83	-2.79	-2.44	-2.43	-2.45	-2.42	-2.48	-2.53	-2.60	-2.67	-2.76	-2.66	-2.55	-2.45	-2.29	-2.07	-1.88	-1.64	-1.47	-1.38	-1.35	-1.36	-1.47	-1.30	-1.23	-1.23	-1.15	-0.98
8	-1.30	-2.69	-2.85	-2.81	-2.45	-2.50	-2.49	-2.48	-2.58	-2.61	-2.68	-2.75	-2.71	-2.56	-2.51	-2.39	-2.16	-1.98	-1.75	-1.48	-1.36	-1.38	-1.35	-1.39	-1.25	-1.14	-1.10	-1.06	-0.98	-0.87
9	-1.56	-2.82	-2.93	-2.84	-2.55	-2.55	-2.57	-2.61	-2.67	-2.70	-2.77	-2.72	-2.63	-2.53	-2.46	-2.28	-2.09	-1.87	-1.61	-1.40	-1.38	-1.40	-1.40	-1.20	-1.13	-1.05	-0.96	-0.93	-0.91	-0.88
10	-1.59	-2.84	-2.89	-2.88	-2.55	-2.58	-2.65	-2.66	-2.72	-2.75	-2.70	-2.59	-2.56	-2.45	-2.32	-2.17	-1.96	-1.70	-1.50	-1.39	-1.36	-1.40	-1.19	-1.06	-1.00	-0.88	-0.81	-0.83	-0.88	-0.90
11	-1.74	-2.90	-3.03	-2.92	-2.62	-2.70	-2.75	-2.77	-2.82	-2.74	-2.63	-2.58	-2.53	-2.36	-2.26	-2.08	-1.83	-1.62	-1.52	-1.41	-1.41	-1.24	-1.08	-0.97	-0.88	-0.78	-0.76	-0.84	-0.93	-0.92
12	-1.81	-3.06	-3.07	-2.99	-2.73	-2.79	-2.84	-2.85	-2.79	-2.65	-2.60	-2.53	-2.43	-2.28	-2.15	-1.93	-1.73	-1.62	-1.51	-1.43	-1.22	-1.11	-0.97	-0.83	-0.75	-0.71	-0.75	-0.87	-0.92	-0.94
13	-2.03	-3.15	-3.16	-3.10	-2.82	-2.87	-2.92	-2.82	-2.70	-2.62	-2.56	-2.42	-2.34	-2.17	-2.00	-1.83	-1.73	-1.61	-1.53	-1.25	-1.10	-1.01	-0.85	-0.71	-0.69	-0.71	-0.79	-0.88	-0.95	-0.95
14	-2.20	-3.35	-3.37	-3.25	-2.95	-3.02	-2.97	-2.82	-2.76	-2.67	-2.53	-2.43	-2.32	-2.11	-1.97	-1.90	-1.78	-1.69	-1.42	-1.20	-1.07	-0.95	-0.79	-0.72	-0.75	-0.81	-0.86	-0.97	-1.01	-1.02
15	-2.47	-3.64	-3.56	-3.42	-3.11	-3.08	-2.97	-2.88	-2.80	-2.64	-2.54	-2.41	-2.25	-2.08	-2.03	-1.95	-1.86	-1.59	-1.37	-1.17	-1.01	-0.90	-0.80	-0.78	-0.86	-0.89	-0.96	-1.04	-1.08	-1.04
16	-2.78	-3.78	-3.70	-3.51	-3.11	-3.04	-3.01	-2.89	-2.76	-2.63	-2.50	-2.31	-2.24	-2.15	-2.09	-2.07	-1.80	-1.59	-1.38	-1.16	-1.01	-0.94	-0.94	-0.95	-1.00	-1.06	-1.10	-1.18	-1.16	-1.08
17	-2.85	-3.83	-3.69	-3.39	-3.00	-3.00	-2.93	-2.77	-2.68	-2.52	-2.34	-2.24	-2.24	-2.14	-2.15	-1.95	-1.74	-1.53	-1.32	-1.10	-0.99	-1.03	-1.05	-1.03	-1.11	-1.14	-1.18	-1.21	-1.15	-1.03
18	-2.95	-3.81	-3.52	-3.24	-2.95	-2.90	-2.79	-2.66	-2.54	-2.34	-2.25	-2.22	-2.20	-2.16	-2.00	-1.85	-1.65	-1.43	-1.22	-1.05	-1.04	-1.10	-1.08	-1.10	-1.15	-1.18	-1.17	-1.16	-1.07	-0.91
19	-2.92	-3.56	-3.32	-3.16	-2.85	-2.76	-2.68	-2.52	-2.36	-2.24	-2.22	-2.17	-2.22	-2.02	-1.90	-1.75	-1.53	-1.31	-1.15	-1.08	-1.09	-1.12	-1.13	-1.12	-1.17	-1.16	-1.12	-1.08	-0.94	-0.76
20	-2.73	-3.36	-3.24	-3.08	-2.75	-2.69	-2.58	-2.37	-2.27	-2.22	-2.18	-2.20	-2.08	-1.91	-1.80	-1.64	-1.42	-1.25	-1.19	-1.14	-1.12	-1.17	-1.15	-1.14	-1.16	-1.11	-1.04	-0.95	-0.81	-0.67
21	-2.74	-3.45	-3.28	-3.06	-2.75	-2.66	-2.50	-2.36	-2.32	-2.25	-2.28	-2.12	-2.02	-1.86	-1.74	-1.57	-1.40	-1.32	-1.28	-1.20	-1.21	-1.23	-1.21	-1.17	-1.14	-1.07	-0.95	-0.86	-0.75	-0.56
22	-2.87	-3.51	-3.25	-3.07	-2.73	-2.60	-2.50	-2.42	-2.36	-2.36	-2.20	-2.08	-2.00	-1.82	-1.68	-1.57	-1.48	-1.42	-1.36	-1.31	-1.29	-1.30	-1.25	-1.16	-1.12	-1.00	-0.87	-0.81	-0.65	-0.48
23	-2.87	-3.37	-3.21	-2.99	-2.63	-2.56	-2.52	-2.43	-2.44	-2.26	-2.14	-2.03	-1.92	-1.73	-1.65	-1.62	-1.56	-1.47	-1.43	-1.35	-1.33	-1.31	-1.22	-1.12	-1.03	-0.89	-0.80	-0.69	-0.55	-0.38
24	-2.68	-3.33	-3.11	-2.88	-2.60	-2.58	-2.54	-2.52	-2.35	-2.20	-2.08	-1.98	-1.84	-1.71	-1.70	-1.69	-1.60	-1.54	-1.46	-1.38	-1.33	-1.28	-1.17	-1.02	-0.92	-0.82	-0.68	-0.59	-0.45	-0.26
25	-2.83	-3.30	-3.06	-2.88	-2.67	-2.63	-2.65	-2.46	-2.32	-2.18	-2.07	-1.93	-1.85	-1.79	-1.80	-1.76	-1.69	-1.59	-1.52	-1.41	-1.33	-1.26	-1.10	-0.95	-0.88	-0.73	-0.61	-0.51	-0.36	-0.18
26	-2.70	-3.20	-3.02	-2.92	-2.69	-2.72	-2.57	-2.41	-2.28	-2.15	-2.00	-1.92	-1.91	-1.87	-1.85	-1.83	-1.73	-1.63	-1.53	-1.40	-1.30	-1.18	-1.02	-0.90	-0.78	-0.65	-0.53	-0.42	-0.26	-0.05
27	-2.80	-3.26	-3.13	-2.98	-2.82	-2.68	-2.57	-2.40	-2.27	-2.10	-2.01	-2.00	-2.01	-1.94	-1.94	-1.88	-1.78	-1.66	-1.53	-1.38	-1.24	-1.11	-0.99	-0.81	-0.71	-0.58	-0.45	-0.34	-0.15	0.05
28	-2.88	-3.44	-3.25	-3.15	-2.81	-2.71	-2.59	-2.43	-2.26	-2.14	-2.12	-2.13	-2.11	-2.05	-2.03	-2.00	-1.87	-1.71	-1.55	-1.35	-1.20	-1.11	-0.93	-0.78	-0.67	-0.55	-0.39	-0.25	-0.08	0.09
29	-3.01	-3.47	-3.35	-3.06	-2.77	-2.66	-2.54	-2.35	-2.22	-2.18	-2.19	-2.16	-2.15	-2.08	-2.08	-1.99	-1.84	-1.65	-1.46	-1.26	-1.14	-1.00	-0.84	-0.68	-0.59	-0.44	-0.25	-0.12	0.02	0.12
30	-2.95	-3.50	-3.20	-2.98	-2.69	-2.59	-2.44	-2.29	-2.25	-2.23	-2.20	-2.19	-2.17	-2.12	-2.06	-1.95	-1.76	-1.54	-1.35	-1.19	-1.02	-0.90	-0.73	-0.58	-0.46	-0.28	-0.11	-0.01	0.07	0.21

Table 3-15: t-statistics for "internal" in "forecasting model" based on transaction price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 11%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-0.47	-0.56	-1.77	-2.10	-1.33	-1.61	-1.27	-1.12	-1.42	-0.26	-0.32	-0.16	-0.17	-0.18	0.55	-0.55	-0.06	0.24	0.10	-0.11	0.51	0.41	0.47	0.32	1.00	-0.40	-0.35	-0.28	-0.15	0.28
2	-1.00	-1.95	-2.61	-2.06	-1.87	-1.86	-1.74	-1.81	-1.23	-0.67	-0.60	-0.50	-0.50	-0.08	-0.32	-0.61	-0.17	-0.09	-0.30	-0.07	0.18	0.14	0.14	0.46	0.06	-0.65	-0.58	-0.48	-0.18	0.05
3	-2.35	-2.86	-2.26	-2.15	-1.89	-2.00	-2.04	-1.52	-1.19	-0.71	-0.66	-0.59	-0.29	-0.45	-0.41	-0.48	-0.24	-0.25	-0.16	-0.06	0.14	0.08	0.36	0.04	-0.20	-0.67	-0.57	-0.35	-0.15	0.24
4	-2.83	-2.28	-2.17	-2.00	-1.86	-2.04	-1.58	-1.19	-0.86	-0.49	-0.46	-0.18	-0.31	-0.27	-0.15	-0.25	-0.11	0.07	0.10	0.21	0.34	0.50	0.29	0.09	-0.09	-0.42	-0.22	-0.07	0.27	0.33
5	-2.17	-2.19	-2.04	-2.00	-1.90	-1.66	-1.20	-0.76	-0.51	-0.23	0.00	-0.09	-0.07	0.04	0.09	-0.04	0.24	0.35	0.40	0.48	0.77	0.55	0.44	0.26	0.13	-0.05	0.10	0.38	0.46	0.64
6	-2.42	-2.23	-2.13	-2.15	-1.68	-1.40	-0.86	-0.48	-0.26	0.14	0.05	0.09	0.18	0.23	0.24	0.26	0.47	0.59	0.63	0.85	0.79	0.64	0.53	0.39	0.37	0.21	0.48	0.54	0.71	0.83
7	-2.34	-2.24	-2.21	-1.89	-1.41	-1.03	-0.55	-0.22	0.11	0.19	0.22	0.32	0.35	0.37	0.49	0.47	0.68	0.78	0.95	0.87	0.86	0.72	0.63	0.59	0.56	0.55	0.63	0.76	0.89	1.02
8	-2.39	-2.37	-1.94	-1.70	-1.16	-0.81	-0.37	0.07	0.11	0.28	0.37	0.42	0.43	0.56	0.62	0.62	0.81	1.02	0.93	0.90	0.87	0.75	0.75	0.71	0.80	0.65	0.80	0.88	1.02	1.09
9	-2.56	-2.04	-1.78	-1.51	-1.02	-0.67	-0.13	0.03	0.18	0.39	0.43	0.47	0.59	0.67	0.74	0.74	1.01	0.99	0.94	0.88	0.87	0.83	0.82	0.90	0.85	0.78	0.90	1.00	1.07	0.98
10	-1.97	-1.77	-1.53	-1.34	-0.88	-0.42	-0.15	0.10	0.29	0.45	0.48	0.62	0.68	0.78	0.85	0.95	1.00	1.01	0.92	0.89	0.94	0.89	0.99	0.94	0.97	0.88	1.01	1.05	0.98	0.93
11	-2.08	-1.74	-1.53	-1.35	-0.76	-0.55	-0.19	0.12	0.28	0.43	0.56	0.65	0.72	0.82	0.98	0.87	0.95	0.92	0.85	0.88	0.92	0.98	0.96	0.98	0.99	0.92	1.00	0.90	0.87	0.81
12	-1.82	-1.61	-1.46	-1.14	-0.81	-0.50	-0.08	0.18	0.31	0.56	0.64	0.75	0.82	1.00	0.96	0.89	0.92	0.91	0.90	0.92	1.06	1.01	1.05	1.05	1.07	0.96	0.91	0.85	0.80	0.77
13	-1.79	-1.60	-1.26	-1.20	-0.76	-0.38	-0.03	0.20	0.45	0.63	0.73	0.84	0.99	0.98	0.97	0.86	0.90	0.94	0.93	1.05	1.07	1.08	1.10	1.11	1.09	0.87	0.85	0.78	0.75	0.74
14	-1.78	-1.34	-1.35	-1.15	-0.66	-0.33	-0.01	0.33	0.51	0.71	0.81	0.99	0.95	0.96	0.93	0.83	0.92	0.95	1.04	1.05	1.13	1.12	1.15	1.13	0.99	0.81	0.78	0.72	0.71	0.68
15	-1.39	-1.47	-1.31	-1.05	-0.62	-0.33	0.11	0.38	0.57	0.77	0.94	0.94	0.92	0.91	0.88	0.85	0.92	1.05	1.03	1.10	1.15	1.15	1.15	1.02	0.91	0.73	0.71	0.68	0.65	0.61
16	-1.95	-1.65	-1.35	-1.11	-0.72	-0.30	0.06	0.35	0.55	0.82	0.81	0.82	0.79	0.78	0.81	0.76	0.93	0.95	0.99	1.04	1.11	1.08	0.96	0.86	0.75	0.59	0.60	0.55	0.51	0.48
17	-1.81	-1.45	-1.25	-1.08	-0.56	-0.22	0.15	0.44	0.70	0.78	0.79	0.78	0.74	0.79	0.80	0.84	0.91	0.99	1.01	1.07	1.10	0.96	0.88	0.78	0.68	0.54	0.53	0.47	0.44	0.42
18	-1.61	-1.39	-1.25	-0.94	-0.50	-0.15	0.22	0.58	0.64	0.75	0.72	0.72	0.74	0.77	0.87	0.82	0.93	1.00	1.03	1.06	0.98	0.86	0.78	0.68	0.61	0.46	0.44	0.38	0.36	0.39
19	-1.67	-1.48	-1.15	-0.94	-0.48	-0.12	0.32	0.47	0.56	0.63	0.62	0.68	0.68	0.79	0.80	0.80	0.90	0.98	0.98	0.90	0.85	0.73	0.65	0.59	0.50	0.34	0.32	0.28	0.30	0.31
20	-1.71	-1.28	-1.09	-0.88	-0.42	0.02	0.24	0.42	0.49	0.57	0.61	0.65	0.73	0.76	0.82	0.81	0.92	0.96	0.86	0.79	0.74	0.63	0.58	0.50	0.40	0.25	0.24	0.24	0.25	0.24
21	-1.41	-1.21	-1.04	-0.83	-0.28	-0.07	0.18	0.34	0.42	0.56	0.58	0.70	0.71	0.78	0.83	0.84	0.92	0.85	0.77	0.70	0.65	0.57	0.51	0.41	0.32	0.18	0.22	0.20	0.19	0.23
22	-1.56	-1.29	-1.10	-0.77	-0.46	-0.20	0.04	0.21	0.35	0.47	0.59	0.63	0.68	0.75	0.82	0.80	0.77	0.72	0.63	0.57	0.55	0.45	0.38	0.29	0.21	0.12	0.14	0.11	0.15	0.20
23	-1.54	-1.29	-0.96	-0.90	-0.54	-0.30	-0.06	0.18	0.30	0.51	0.54	0.63	0.68	0.77	0.80	0.68	0.67	0.61	0.53	0.49	0.46	0.35	0.29	0.20	0.17	0.07	0.07	0.09	0.13	0.16
24	-1.55	-1.12	-1.13	-1.01	-0.67	-0.43	-0.12	0.10	0.33	0.45	0.53	0.61	0.68	0.74	0.68	0.58	0.55	0.51	0.44	0.40	0.35	0.25	0.19	0.16	0.12	0.00	0.05	0.07	0.09	0.10
25	-1.31	-1.35	-1.28	-1.15	-0.81	-0.49	-0.21	0.12	0.26	0.43	0.50	0.59	0.64	0.61	0.56	0.45	0.44	0.41	0.34	0.28	0.24	0.15	0.15	0.10	0.04	-0.03	0.02	0.01	0.02	0.05
26	-1.74	-1.67	-1.53	-1.37	-0.94	-0.64	-0.25	-0.01	0.19	0.35	0.45	0.52	0.46	0.44	0.39	0.30	0.31	0.27	0.18	0.13	0.10	0.06	0.05	-0.01	-0.03	-0.09	-0.07	-0.08	-0.05	0.04
27	-1.87	-1.69	-1.55	-1.30	-0.91	-0.52	-0.23	0.07	0.26	0.44	0.50	0.46	0.42	0.40	0.35	0.28	0.27	0.22	0.14	0.10	0.12	0.07	0.03	0.02	0.00	-0.08	-0.07	-0.06	0.02	0.06
28	-1.90	-1.75	-1.50	-1.31	-0.81	-0.53	-0.17	0.10	0.30	0.45	0.40	0.38	0.33	0.32	0.29	0.19	0.18	0.14	0.08	0.09	0.10	0.03	0.04	0.02	-0.01	-0.11	-0.07	-0.01	0.01	0.03
29	-1.99	-1.69	-1.51	-1.20	-0.83	-0.47	-0.15	0.15	0.32	0.35	0.31	0.29	0.25	0.25	0.20	0.11	0.10	0.08	0.07	0.06	0.05	0.03	0.04	0.01	-0.04	-0.11	-0.03	-0.03	-0.02	0.00
30	-1.84	-1.67	-1.36	-1.20	-0.75	-0.42	-0.08	0.18	0.23	0.27	0.24	0.21	0.19	0.17	0.14	0.05	0.06	0.09	0.05	0.03	0.06	0.04	0.04	0.00	-0.03	-0.05	-0.03	-0.04	-0.04	0.00

Table 3-16: t-statistics for "interbank" in "forecasting model" based on transaction price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R_{t,t+k}^{FX} = C + \gamma R_{t-i,t}^{FX} + \sum_{m=1}^{4} \beta m OF_{t-i,t}^{FX} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 11%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-4.80	-6.25	-5.22	-8.89	-11.9	-12.2	-10.8	-12.7	-13.4	-13.8	-13.6	-13.3	-13.7	-11.5	-14.0	-14.5	-14.4	-13.9	-14.4	-13.3	-13.4	-14.3	-13.4	-10.8	-12.9	-12.7	-10.7	-14.1	-13.7	-13.8
2	-4.33	-4.44	-7.53	-9.29	-9.53	-9.86	-10.8	-10.8	-11.1	-11.0	-10.2	-10.9	-10.7	-10.1	-11.5	-11.9	-11.5	-11.6	-11.3	-11.0	-11.1	-11.4	-9.90	-9.57	-10.2	-9.20	-10.1	-11.2	-10.9	-11.0
3	-3.75	-6.16	-7.50	-8.58	-9.09	-9.45	-9.68	-9.52	-9.69	-9.24	-9.33	-9.17	-9.48	-9.37	-10.3	-10.3	-10.3	-10.1	-9.85	-9.92	-9.90	-9.48	-8.86	-8.48	-8.32	-8.88	-9.22	-9.75	-9.62	-9.61
4	-5.00	-7.45	-8.18	-7.99	-8.92	-9.11	-9.23	-9.11	-9.12	-9.16	-8.86	-9.00	-9.33	-9.31	-9.74	-9.96	-9.88	-9.57	-9.58	-9.61	-9.15	-9.06	-8.41	-7.79	-8.54	-8.76	-8.94	-9.36	-9.14	-9.18
5	-5.34	-6.74	-7.62	-7.73	-7.95	-8.08	-8.20	-7.69	-8.01	-7.77	-7.70	-7.98	-8.33	-8.17	-8.71	-8.81	-8.60	-8.50	-8.53	-8.40	-8.07	-7.83	-7.01	-7.19	-7.61	-7.73	-7.92	-8.15	-8.01	-8.08
6	-5.06	-6.76	-7.35	-7.22	-7.40	-7.49	-7.51	-7.31	-7.35	-7.28	-7.34	-7.59	-7.71	-7.75	-8.14	-8.09	-8.05	-7.95	-7.86	-7.76	-7.35	-6.87	-6.74	-6.77	-7.08	-7.23	-7.41	-7.52	-7.42	-7.47
7	-5.05	-7.02	-7.21	-6.98	-7.06	-7.04	-7.21	-6.87	-6.99	-7.02	-7.11	-7.19	-7.45	-7.46	-7.66	-7.73	-7.66	-7.44	-7.45	-7.24	-6.63	-6.69	-6.47	-6.47	-6.79	-6.94	-6.99	-7.13	-7.04	-7.01
8	-5.38	-6.59	-6.67	-6.54	-6.39	-6.55	-6.58	-6.31	-6.48	-6.57	-6.55	-6.77	-6.97	-6.87	-7.15	-7.18	-6.99	-6.88	-6.82	-6.39	-6.26	-6.20	-6.00	-6.05	-6.35	-6.39	-6.45	-6.59	-6.46	-6.44
9	-5.10	-6.39	-6.33	-6.17	-6.19	-6.20	-6.28	-6.13	-6.31	-6.27	-6.37	-6.52	-6.56	-6.57	-6.79	-6.68	-6.59	-6.42	-6.17	-6.13	-5.93	-5.86	-5.73	-5.82	-6.00	-6.05	-6.12	-6.19	-6.09	-6.10
10	-5.15	-6.09	-5.86	-5.96	-5.85	-5.91	-6.02	-5.94	-6.01	-6.10	-6.14	-6.15	-6.28	-6.26	-6.34	-6.32	-6.18	-5.86	-5.94	-5.83	-5.63	-5.62	-5.54	-5.54	-5.72	-5.78	-5.78	-5.87	-5.79	-5.81
11	-4.93	-5.65	-5.71	-5.66	-5.64	-5.72	-5.87	-5.72	-5.89	-5.91	-5.86	-5.95	-6.03	-5.91	-6.04	-5.97	-5.68	-5.68	-5.69	-5.57	-5.43	-5.45	-5.30	-5.32	-5.51	-5.50	-5.52	-5.61	-5.55	-5.56
12	-4.78	-5.64	-5.55	-5.57	-5.57	-5.69	-5.74	-5.71	-5.79	-5.73	-5.75	-5.80	-5.80	-5.73	-5.79	-5.59	-5.60	-5.54	-5.53	-5.45	-5.36	-5.31	-5.19	-5.22	-5.34	-5.35	-5.38	-5.47	-5.40	-5.43
13	-4.90	-5.65	-5.62	-5.56	-5.63	-5.65	-5.79	-5.68	-5.70	-5.71	-5.68	-5.69	-5.69	-5.58	-5.49	-5.58	-5.53	-5.45	-5.48	-5.44	-5.28	-5.25	-5.15	-5.13	-5.27	-5.28	-5.31	-5.39	-5.34	-5.32
14	-4.74	-5.59	-5.54	-5.52	-5.50	-5.63	-5.66	-5.52	-5.60	-5.57	-5.54	-5.53	-5.50	-5.26	-5.41	-5.43	-5.37	-5.33	-5.41	-5.30	-5.15	-5.13	-4.98	-4.97	-5.11	-5.13	-5.14	-5.25	-5.14	-5.00
15	-4.97	-5.69	-5.68	-5.55	-5.64	-5.62	-5.63	-5.57	-5.60	-5.58	-5.52	-5.46	-5.29	-5.29	-5.39	-5.41	-5.38	-5.39	-5.39	-5.29	-5.16	-5.09	-4.96	-4.96	-5.11	-5.10	-5.15	-5.19	-4.98	-5.00
16	-4.85	-5.73	-5.64	-5.55	-5.50	-5.52	-5.60	-5.51	-5.60	-5.53	-5.43	-5.24	-5.31	-5.26	-5.34	-5.39	-5.42	-5.35	-5.36	-5.27	-5.08	-5.03	-4.92	-4.93	-5.04	-5.07	-5.07	-5.00	-4.95	-4.92
17	-4.94	-5.67	-5.60	-5.36	-5.36	-5.45	-5.48	-5.49	-5.50	-5.39	-5.18	-5.22	-5.24	-5.17	-5.28	-5.39	-5.33	-5.28	-5.29	-5.15	-4.97	-4.95	-4.84	-4.82	-4.97	-4.95	-4.84	-4.93	-4.83	-4.90
18	-4.81	-5.57	-5.35	-5.19	-5.27	-5.29	-5.45	-5.36	-5.34	-5.13	-5.14	-5.12	-5.10	-5.08	-5.26	-5.28	-5.24	-5.19	-5.15	-5.02	-4.87	-4.85	-4.72	-4.74	-4.84	-4.72	-4.75	-4.79	-4.81	-4.80
19	-4.81	-5.40	-5.24	-5.15	-5.16	-5.33	-5.35	-5.24	-5.14	-5.14	-5.09	-5.04	-5.08	-5.13	-5.21	-5.24	-5.21	-5.10	-5.07	-4.97	-4.82	-4.77	-4.69	-4.66	-4.66	-4.68	-4.66	-4.81	-4.74	-4.79
20	-4.73	-5.26	-5.16	-5.07	-5.26	-5.26	-5.25	-5.09	-5.11	-5.05	-4.98	-4.98	-5.08	-5.03	-5.14	-5.18	-5.09	-5.00	-4.99	-4.89	-4.72	-4.71	-4.58	-4.46	-4.59	-4.57	-4.65	-4.72	-4.72	-4.79
21	-4.67	-5.35	-5.25	-5.33	-5.34	-5.31	-5.22	-5.17	-5.13	-5.05	-5.02	-5.07	-5.08	-5.06	-5.17	-5.15	-5.07	-5.01	-5.00	-4.87	-4.74	-4.69	-4.47	-4.49	-4.57	-4.64	-4.64	-4.77	-4.79	-4.81
22	-4.70	-5.37	-5.50	-5.36	-5.35	-5.26	-5.25	-5.16	-5.10	-5.06	-5.08	-5.06	-5.11	-5.09	-5.13	-5.12	-5.07	-5.00	-4.97	-4.88	-4.71	-4.57	-4.48	-4.45	-4.63	-4.62	-4.68	-4.84	-4.80	-4.82
23	-4.71	-5.54	-5.50	-5.30	-5.26	-5.23	-5.17	-5.06	-5.05	-5.07	-5.02	-5.03	-5.07	-4.98	-5.04	-5.05	-5.01	-4.91	-4.92	-4.78	-4.54	-4.53	-4.39	-4.45	-4.55	-4.60	-4.69	-4.79	-4.75	-4.80
24	-4.64	-5.54	-5.48	-5.23	-5.22	-5.14	-5.07	-5.02	-5.05	-5.01	-5.00	-5.02	-4.99	-4.92	-4.98	-4.99	-4.92	-4.87	-4.83	-4.62	-4.50	-4.44	-4.40	-4.39	-4.54	-4.61	-4.65	-4.74	-4.73	-4.71
25	-4.74	-5.42	-5.36	-5.08	-5.03	-4.96	-4.96	-4.95	-4.93	-4.93	-4.93	-4.89	-4.89	-4.83	-4.88	-4.86	-4.84	-4.74	-4.63	-4.55	-4.39	-4.42	-4.31	-4.34	-4.52	-4.54	-4.57	-4.69	-4.61	-4.59
26	-4.72	-5.56	-5.29	-4.99	-4.93	-4.91	-4.94	-4.89	-4.91	-4.92	-4.85	-4.83	-4.83	-4.77	-4.79	-4.81	-4.75	-4.58	-4.60	-4.47	-4.40	-4.36	-4.29	-4.36	-4.47	-4.50	-4.55	-4.60	-4.51	-4.49
27	-5.03	-5.48	-5.20	-4.91	-4.91	-4.91	-4.92	-4.90	-4.91	-4.85	-4.81	-4.79	-4.78	-4.69	-4.76	-4.73	-4.59	-4.56	-4.53	-4.49	-4.35	-4.35	-4.33	-4.33	-4.45	-4.48	-4.47	-4.51	-4.43	-4.38
28	-4.71	-5.21	-5.04	-4.88	-4.90	-4.89	-4.93	-4.93	-4.88	-4.84	-4.79	-4.77	-4.73	-4.68	-4.77	-4.81	-4.75	-4.65	-4.59	-4.48	-4.38	-4.42	-4.33	-4.35	-4.48	-4.45	-4.43	-4.47	-4.38	-4.33
29	-4.59	-5.11	-5.01	-4.86	-4.88	-4.89	-4.95	-4.87	-4.83	-4.79	-4.74	-4.68	-4.68	-4.65	-4.75	-4.74	-4.67	-4.55	-4.52	-4.46	-4.40	-4.38	-4.30	-4.33	-4.39	-4.36	-4.34	-4.38	-4.27	-4.23
30	-4.55	-5.12	-4.97	-4.87	-4.92	-4.95	-4.92	-4.85	-4.80	-4.76	-4.68	-4.65	-4.68	-4.66	-4.71	-4.69	-4.60	-4.51	-4.53	-4.51	-4.39	-4.38	-4.32	-4.28	-4.34	-4.30	-4.28	-4.31	-4.20	-4.19

Table 3-17: t-statistics for “lagged exchange rate return” in “forecasting model” based on transaction price

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used. R^2 is up to 11%. Detailed R^2 for each regression can be provided upon request.

As noted before, in this chapter, we investigate the explaining and forecasting power of currency order flows at high frequencies using a very unique set of tick-by-tick data. In the previous tables, the "warm" (red, orange, yellow) color shade in the table stands for positive effect of order flows on exchange rates, with more statistical significance lying in warmer colors; while the "cold" (blue, green) color shade means negative effect, with more significance lying in colder colors. Like in the "contemporaneous model", here we clearly see there is a pattern of effects on the foreign exchange market from order flows over time, after controlling for the lagged exchange rate returns. As discussed in chapter 2, we suggest there is information content in order flows in the foreign exchange market. In the following, we will try to suggest some explanations on our high frequency results, which are different from but connected with daily frequency findings.

Based on our findings at both daily (chapter 2) and high frequencies (chapter 3), especially the signs of coefficients of currency order flows from corporate customers, we can draw the following graph.

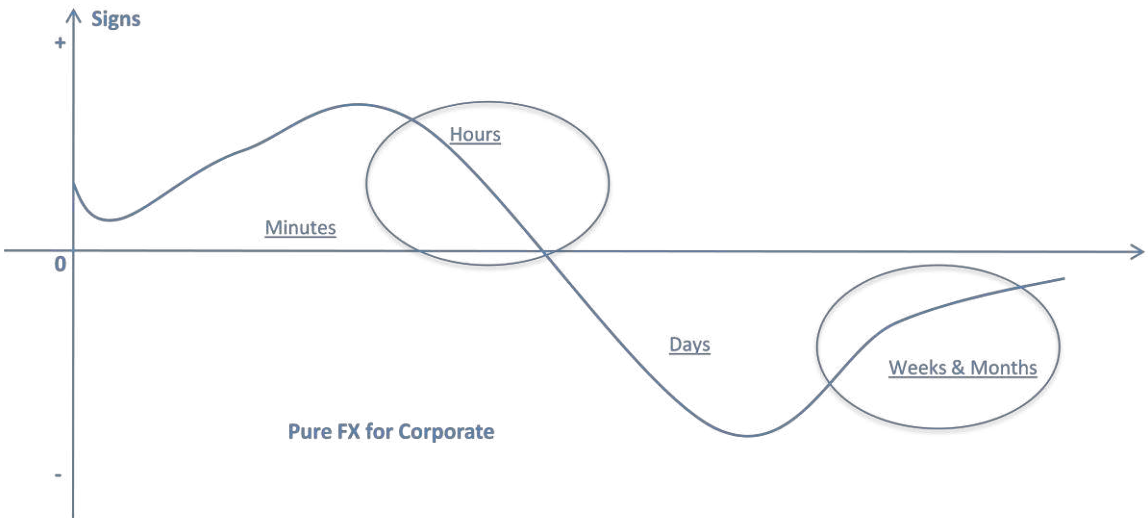


Figure 3-5: "Pure FX" for corporate: relationship between corporate currency orders and currency movements

From the above graph (figure 3-5), we can roughly see the changes in the coefficients, i.e. the impacts of currency order flows from corporate customers on exchange rate changes, at frequencies from 1 minute up to several months. In chapter 2, we find a negative but insignificant contemporaneous relationship between daily currency orders from corporate customers and exchange rate changes; while in chapter 3, we find statistically significant coefficients at high frequencies all from 1-minute to 30-minute, which are all positive, with ups and downs shown in the graph, but then will tend to approach to 0 from positive numbers. We only have results for frequencies higher than 30-minute and around 1-day, and the signs and trends of coefficients at frequencies from 30-minute to 1-day and lower than 1-day, are simulated based on hypothetic smoothness of the curves (circled in the graph).

As discussed by many others, corporate customers are believed to be passively buying and selling currencies, and then the positive effects can not be explained by price pressure. Although we only test impacts within the first 30 minutes after orders are executed, they are very strong, and then there must be something going on over this period of time, for corporate customers. We will try to understand more about these findings later.

We have to note that there are two main drawbacks if we combine both daily and high frequency results to draw these graphs: 1) currency pair is changed, because we use GBPUSD for the daily analysis, while we use EURUSD for the high frequency analysis; 2) we focus on unleveraged financial institutions for daily analysis, while for high frequency analysis the data from leveraged and unleveraged financial clients are as a whole set; 3) based on the positive results, at a daily frequency we use contemporaneous findings, while at high frequencies we use forecasting findings to draw the graph (for “cross market” figures, we use forecasting findings for all frequencies). So when explaining the our findings, especially when comparing daily and high frequency results, we need to bear this in mind, although we believe to some extent it’s meaningful to consider them together because we only focus on trends of changes in coefficients.

Similar to corporate customers, we draw the changes in impacts of currency orders from financial customers in the following graph,

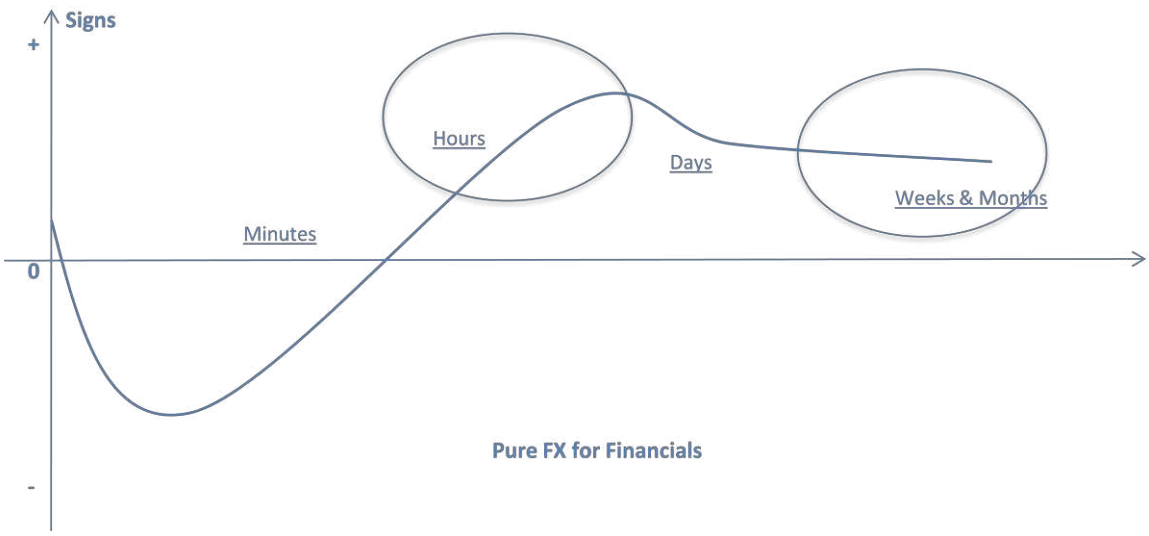


Figure 3-6: "Pure FX" for financial: relationship between financial currency orders and currency movements

From the above graph (figure 3-6), we can roughly see the changes in the coefficients, i.e. the impacts of currency order flows on the exchange rate changes, at frequencies from 1 minute up to several months. In chapter 2, we find a very strong contemporaneous relationship between daily currency orders from financial customers and exchange rate changes, which are positive; while in chapter 3, we find the coefficients at high frequencies from 1-minute to 30-minute are mixed: at 1-minute, it's positive, and then all negative but will tend to approach to 0 from negative numbers. Still, the simulated curves are circled in the graph.

The standing alone positive coefficient on the left end of the curve means that impacts of financial orders in the foreign exchange market on exchange rate changes in the next 1 minute are positive, which can be explained as pure price pressure. When more orders follow, over time the impacts will go negative and this can not be only explained by price pressure. More importantly, as discussed before, the negative coefficients at high frequencies less than 15-minute are against findings from many previous studies including Evans and Lyons (2002a, 2002b). However, with the accumulation of orders and the increase in return horizons, the effect of order flows from "financial" customers is turning positive, although it is not statistically significant. In the graph, we can tell this tendency to go positive (with lower frequencies) is in line with the positive relationship for financial customers in daily frequency analysis in Evans and Lyons

(2006), Reitz et al. (2007), among many others. To the best of our knowledge, we do not find many studies reporting coefficient estimates of high frequency order flows, but in Osler and Vandrovych (2009), they show different signs which also are opposite to those daily analysis. For example, at 5-minute frequency, the sign of institutional investors is negative, and the sign of large corporations is positive while that of middle-market corporations is negative (although most of them are not statistically significant).

Because we use heat maps to demonstrate the effects of currency order flows in the foreign exchange market, we can investigate the impact horizons. Impact periods are different for the two customers: corporate customers seem have longer effects on future exchange rates than financial customers (see table 3-8 and table 3-9). In chapter 2, we suggest that information relevant for stock market conveyed in order flows from commercial corporations is aggregated slower than that from financial institutions. If our hypothesis "information conveyed in foreign exchange order flows is relevant for stock markets which are related to macroeconomics" holds, the high frequency order flows related to equity markets may show similar pace when aggregating information (i.e. "corporate" customers have longer effects than "financial" customers).

We use two sets of exchange rates in our research, one is the rate used by the data provider, a leading European bank, and the rate is the one at which specific orders are executed (called "bank rate" or "trade rate"). The other price is the market rate, which is the matched rate from the EBS platform (called "market rate"). The interesting part we need to point out is the different results between "market" and "trade" prices (in "corporate", "financial", "internal", "interbank", and "lagged exchange rate", see tables 3-8 to 3-17). We suggest that the major European commercial bank may usually continuously adjust its quotes to attract more customers when optimizing its inventories, because we see strong impacts from lagged bank rate but little from lagged market rate, and also larger significance of effects in all "corporate", "financial", "internal" and "interbank" order flows when using "transaction" prices. And also regarding the whole explanatory power of our models, R^2 based on trade price (from 3% to 11%) is much larger than that based on EBS market price (less than 1%).

Last but not least, we underline our findings again. In the above tables 3-8 to 3-17, we clearly see forecasting power of order flows from different types of customers, and the magnitudes are up to 0.3% of change in exchange rate by 1 billion Euro into the market. The difference among all customers indicates there is clear heterogeneity among various customers in the foreign exchange market at high frequencies, too. The clear existence of forecasting power of order flows for exchange rate changes at high frequencies partly explain why we do not find any forecasting power in the foreign exchange market using daily frequency data in chapter 1: the information buried in order flows can only last for minutes and will dissipate by the end of each trading day.

Up to now, based on the currency order flows' strong explaining and forecasting power in the foreign exchange market, we suggest there must be something going on and there possibly exist information content in such orders. In graphs 3-5 and 3-6, if the right end of the curve can stay at this level away from zero, we can suggest that there exist information in the set of currency order flows. But what is the nature of the information? Like in chapter 2, we also do the cross market analysis between currency orders and stock market dynamics at high frequencies, in the following section.

3.5.2 Cross Market Findings (Market Level)

In chapter 2, we find that there is significant forecasting power of foreign exchange order flows for US stock market returns. With some cross market studies have been done at daily frequencies (Evans and Lyons (2002b), Francis et al. (2006), Dunne et al. (2006), Albuquerque et al. (2008)), we first investigate the concurrent impacts of foreign exchange order flows on stock market changes at high frequencies from 1-minute to 30-minute, i.e. **Hypothesis 4**: EURUSD order flows have contemporaneous effects on changes in the US stock market at market, sector and individual stock levels, at high frequencies.

We start with the two ETFs tracking stock market indices, SPY (S&P 500) and DIA (DOW 30). According to the "contemporaneous model" discussed in previous sections, i.e. $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$, we get the results in the following tables (based on market exchange rate, while the results based on transaction exchange rate are available upon request).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
OF1	beta	0.005	0.008	0.009	0.007	0.005	0.004	0.004	0.004	0.004	0.004	0.004	0.005	0.005	0.004	0.005
OF2	beta	0.002	0.015	0.023	0.029	0.037	0.035	0.033	0.030	0.027	0.026	0.025	0.025	0.023	0.023	0.023
OF3	beta	0.001	0.016	0.026	0.026	0.030	0.023	0.022	0.024	0.021	0.020	0.019	0.016	0.010	0.008	0.007
OF4	beta	-0.003	-0.009	-0.008	-0.002	0.002	0.005	0.007	0.008	0.007	0.005	0.000	-0.002	-0.005	-0.006	-0.010
C	beta	-0.001	-0.001	-0.001	-0.002	-0.002	-0.003	-0.003	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.005	-0.006
Rfx	beta	0.040	0.028	0.021	0.038	0.052	0.063	0.077	0.086	0.098	0.111	0.115	0.118	0.120	0.121	0.125
OF1	t-stats	0.853	1.407	1.200	0.912	0.634	0.499	0.450	0.495	0.467	0.542	0.547	0.585	0.571	0.560	0.652
OF2	t-stats	0.212	1.133	1.497	1.680	1.926	1.595	1.324	1.163	1.008	0.950	0.913	0.880	0.782	0.762	0.737
OF3	t-stats	0.065	0.703	0.929	0.820	0.793	0.561	0.510	0.530	0.457	0.425	0.377	0.322	0.188	0.156	0.130
OF4	t-stats	-0.202	-0.508	-0.462	-0.135	0.095	0.261	0.366	0.370	0.308	0.198	-0.006	-0.092	-0.183	-0.236	-0.357
C	t-stats	-0.916	-0.908	-0.832	-0.871	-0.843	-0.845	-0.861	-0.852	-0.879	-0.889	-0.866	-0.860	-0.879	-0.892	-0.913
Rfx	t-stats	1.451	0.777	0.456	0.725	0.930	1.043	1.247	1.398	1.603	1.808	1.864	1.909	1.941	1.939	2.007

		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
OF1	beta	0.005	0.005	0.005	0.006	0.006	0.006	0.007	0.007	0.007	0.007	0.008	0.009	0.010	0.011	0.012
OF2	beta	0.022	0.021	0.019	0.018	0.016	0.013	0.009	0.004	0.001	-0.001	-0.003	-0.003	-0.004	-0.006	-0.009
OF3	beta	0.005	-0.001	-0.008	-0.011	-0.020	-0.031	-0.045	-0.058	-0.066	-0.074	-0.079	-0.082	-0.083	-0.086	-0.091
OF4	beta	-0.016	-0.020	-0.023	-0.024	-0.025	-0.027	-0.029	-0.032	-0.032	-0.033	-0.031	-0.028	-0.024	-0.023	-0.022
C	beta	-0.006	-0.007	-0.007	-0.008	-0.009	-0.009	-0.010	-0.011	-0.012	-0.012	-0.013	-0.013	-0.013	-0.013	-0.013
Rfx	beta	0.132	0.147	0.163	0.179	0.190	0.203	0.211	0.219	0.228	0.235	0.241	0.247	0.254	0.259	0.263
OF1	t-stats	0.669	0.699	0.703	0.712	0.714	0.746	0.768	0.774	0.769	0.749	0.812	0.901	0.971	1.016	1.037
OF2	t-stats	0.686	0.646	0.584	0.543	0.483	0.392	0.282	0.139	0.049	-0.044	-0.088	-0.119	-0.148	-0.206	-0.320
OF3	t-stats	0.090	-0.020	-0.148	-0.197	-0.360	-0.553	-0.789	-1.023	-1.159	-1.306	-1.386	-1.433	-1.444	-1.502	-1.602
OF4	t-stats	-0.585	-0.731	-0.811	-0.831	-0.883	-0.927	-1.014	-1.126	-1.149	-1.184	-1.124	-1.018	-0.907	-0.848	-0.830
C	t-stats	-0.931	-0.982	-1.043	-1.088	-1.126	-1.185	-1.257	-1.337	-1.397	-1.443	-1.484	-1.514	-1.511	-1.490	-1.465
Rfx	t-stats	2.101	2.307	2.537	2.766	2.897	3.067	3.128	3.179	3.280	3.346	3.416	3.489	3.602	3.698	3.761

Table 3-18: "SPY" Regression results in "cross market contemporaneous model"

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
OF1	beta	0.007	0.008	0.008	0.007	0.007	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.004	0.005
OF2	beta	0.003	0.009	0.017	0.021	0.032	0.033	0.032	0.030	0.027	0.022	0.019	0.018	0.016	0.014	0.014
OF3	beta	0.016	0.023	0.032	0.039	0.048	0.041	0.042	0.048	0.051	0.049	0.048	0.045	0.041	0.034	0.033
OF4	beta	0.004	-0.012	-0.009	-0.003	0.001	0.003	0.003	0.002	0.001	-0.003	-0.008	-0.011	-0.015	-0.017	-0.021
C	beta	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
Rfx	beta	0.037	0.019	0.006	0.018	0.032	0.035	0.047	0.055	0.072	0.087	0.097	0.103	0.109	0.111	0.116
OF1	t-stats	1.550	1.650	1.296	1.014	0.943	0.808	0.689	0.663	0.659	0.647	0.643	0.631	0.543	0.518	0.572
OF2	t-stats	0.370	0.633	1.070	1.200	1.601	1.589	1.377	1.197	1.024	0.828	0.693	0.636	0.539	0.464	0.443
OF3	t-stats	1.032	1.168	1.339	1.380	1.438	1.127	1.108	1.185	1.214	1.140	1.079	0.994	0.870	0.715	0.666
OF4	t-stats	0.297	-0.845	-0.614	-0.217	0.083	0.154	0.174	0.118	0.054	-0.128	-0.343	-0.484	-0.623	-0.719	-0.841
C	t-stats	-0.388	-0.291	-0.188	-0.202	-0.145	-0.134	-0.113	-0.057	-0.019	0.018	0.071	0.098	0.131	0.129	0.146
Rfx	t-stats	1.508	0.624	0.152	0.398	0.609	0.630	0.821	0.951	1.241	1.499	1.653	1.755	1.859	1.864	1.954

		16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
OF1	beta	0.005	0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.004	0.005	0.005
OF2	beta	0.012	0.012	0.011	0.010	0.008	0.004	0.001	-0.004	-0.006	-0.009	-0.009	-0.010	-0.010	-0.011	-0.013
OF3	beta	0.030	0.026	0.021	0.018	0.010	-0.001	-0.012	-0.024	-0.033	-0.040	-0.045	-0.047	-0.047	-0.048	-0.053
OF4	beta	-0.026	-0.029	-0.031	-0.032	-0.033	-0.036	-0.038	-0.041	-0.041	-0.042	-0.041	-0.039	-0.036	-0.034	-0.033
C	beta	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	0.000	0.000
Rfx	beta	0.122	0.133	0.148	0.163	0.172	0.185	0.194	0.202	0.212	0.219	0.225	0.231	0.238	0.244	0.248
OF1	t-stats	0.545	0.529	0.476	0.402	0.358	0.350	0.345	0.315	0.289	0.260	0.294	0.348	0.386	0.413	0.408
OF2	t-stats	0.381	0.368	0.322	0.287	0.234	0.133	0.029	-0.108	-0.195	-0.279	-0.297	-0.322	-0.354	-0.384	-0.445
OF3	t-stats	0.606	0.519	0.414	0.363	0.191	-0.013	-0.239	-0.483	-0.643	-0.792	-0.876	-0.907	-0.896	-0.927	-1.001
OF4	t-stats	-1.061	-1.162	-1.200	-1.248	-1.304	-1.385	-1.473	-1.593	-1.611	-1.667	-1.639	-1.551	-1.455	-1.364	-1.330
C	t-stats	0.156	0.138	0.112	0.105	0.104	0.076	0.037	-0.009	-0.049	-0.068	-0.087	-0.085	-0.069	-0.034	0.012
Rfx	t-stats	2.027	2.173	2.407	2.616	2.723	2.901	2.989	3.049	3.151	3.207	3.266	3.325	3.429	3.510	3.568

Table 3-19: "DIA" Regression results in "cross market contemporaneous model"

Notes: Red shaded cell means positive effects at the 10% significance level; while blue shaded cell means negative effects at the 10% significance level. The first row stands for the frequency of i-minute in the model of $R^{FX}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \beta m \sum_{m=1}^{4} OF^{FX}_{t,t+i} + \varepsilon$. OF1 is order flows from "financials", OF2 is "corporates", OF3 is "internal", and OF4 is "interbank". C is the constant. Beta stands for the coefficient estimates of the corresponding independent variables and t-stats is t-statistics of the estimates. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

From the tables, we see no contemporaneous relationship between foreign exchange order flows and stock market changes, which is in line with the findings in chapter 2 at a daily frequency. All but one coefficients of order flows are insignificant, and there is no consistency in "signs" for every category of the bank's counterparties. However, there is clear contemporaneous relationship between exchange rate returns and stock market returns, over horizons longer than 10 minutes, which is consistent with many previous studies about "returns spillover" between different markets (see Ajayi and Mougoue (1996), Andersen et al. (2007)).

We next investigate the forecasting power of order flows for stock market changes, i.e. **Hypothesis 5**: EURUSD order flows have forecasting power for changes in the US stock market; **Hypothesis 6**: EURUSD order flows from different groups of counterparties have different impacts on stock markets. In the following tables, we only show t-statistics for all the coefficients to simplify the reporting of our results, in the "forecasting model", $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.11	0.93	0.43	-0.42	-0.40	-0.41	0.29	0.41	0.73	0.47	0.72	-0.01	-0.15	1.08	0.35	0.09	0.03	0.31	-0.10	0.23	0.24	0.28	-0.08	-0.14	-0.50	-0.29	-0.39	-0.57	-0.62	-0.35
2	1.02	0.67	-0.33	-0.77	-0.74	-0.29	0.25	0.57	0.59	0.53	0.26	-0.30	0.39	0.62	0.08	-0.11	0.04	-0.04	-0.02	0.18	0.21	0.05	-0.22	-0.46	-0.51	-0.43	-0.57	-0.71	-0.58	-0.01
3	0.56	-0.29	-1.16	-1.31	-0.87	-0.38	0.30	0.36	0.50	0.06	-0.23	-0.12	0.04	0.11	-0.32	-0.31	-0.37	-0.19	-0.15	0.04	-0.08	-0.27	-0.63	-0.71	-0.78	-0.76	-0.86	-0.82	-0.42	-0.24
4	-0.24	-0.77	-1.34	-1.08	-0.62	0.02	0.32	0.46	0.27	-0.17	0.04	-0.17	-0.15	-0.12	-0.35	-0.49	-0.35	-0.19	-0.14	-0.09	-0.24	-0.50	-0.71	-0.80	-0.89	-0.90	-0.86	-0.60	-0.46	-0.10
5	-0.32	-0.72	-0.90	-0.63	-0.04	0.23	0.54	0.34	0.14	0.11	0.01	-0.29	-0.30	-0.19	-0.52	-0.48	-0.33	-0.19	-0.23	-0.22	-0.43	-0.59	-0.78	-0.91	-1.00	-0.91	-0.68	-0.61	-0.32	-0.18
6	-0.20	-0.22	-0.39	-0.02	0.18	0.49	0.44	0.22	0.35	0.06	-0.13	-0.42	-0.34	-0.39	-0.53	-0.47	-0.33	-0.28	-0.36	-0.42	-0.55	-0.70	-0.91	-1.06	-1.05	-0.79	-0.72	-0.50	-0.38	-0.28
7	0.34	0.19	0.17	0.12	0.40	0.36	0.28	0.40	0.27	-0.12	-0.32	-0.49	-0.55	-0.45	-0.56	-0.47	-0.41	-0.40	-0.52	-0.53	-0.67	-0.87	-1.09	-1.13	-0.95	-0.84	-0.61	-0.53	-0.46	-0.42
8	0.52	0.54	0.14	0.24	0.18	0.10	0.37	0.23	0.00	-0.39	-0.48	-0.75	-0.66	-0.54	-0.61	-0.59	-0.57	-0.60	-0.67	-0.69	-0.88	-1.09	-1.21	-1.09	-1.03	-0.77	-0.67	-0.63	-0.60	-0.55
9	0.84	0.40	0.19	-0.08	-0.14	0.14	0.13	-0.11	-0.37	-0.62	-0.82	-0.93	-0.82	-0.68	-0.79	-0.81	-0.83	-0.81	-0.89	-0.97	-1.18	-1.29	-1.23	-1.20	-0.98	-0.85	-0.79	-0.78	-0.74	-0.70
10	0.24	0.22	-0.42	-0.61	-0.25	-0.24	-0.33	-0.59	-0.70	-1.01	-1.06	-1.14	-1.01	-0.92	-1.06	-1.12	-1.09	-1.08	-1.21	-1.32	-1.42	-1.35	-1.36	-1.16	-1.06	-0.96	-0.93	-0.91	-0.88	-0.85
11	0.63	-0.08	-0.68	-0.43	-0.41	-0.51	-0.63	-0.74	-0.96	-1.12	-1.16	-1.20	-1.12	-1.07	-1.24	-1.25	-1.24	-1.29	-1.44	-1.46	-1.39	-1.40	-1.24	-1.16	-1.09	-1.04	-1.00	-0.99	-0.97	-0.97
12	-0.31	-0.72	-0.64	-0.74	-0.81	-0.88	-0.84	-1.05	-1.12	-1.25	-1.26	-1.33	-1.28	-1.27	-1.40	-1.42	-1.46	-1.55	-1.61	-1.47	-1.47	-1.31	-1.26	-1.21	-1.17	-1.11	-1.08	-1.08	-1.09	-1.13
13	-0.43	-0.13	-0.62	-0.84	-0.92	-0.85	-0.95	-1.02	-1.08	-1.19	-1.22	-1.33	-1.32	-1.29	-1.42	-1.50	-1.59	-1.60	-1.51	-1.45	-1.29	-1.25	-1.23	-1.22	-1.18	-1.14	-1.12	-1.15	-1.20	-1.27
14	0.58	-0.07	-0.71	-0.95	-0.86	-0.95	-0.93	-0.99	-1.02	-1.18	-1.27	-1.41	-1.39	-1.36	-1.55	-1.67	-1.69	-1.55	-1.55	-1.34	-1.29	-1.27	-1.28	-1.26	-1.24	-1.21	-1.21	-1.28	-1.36	-1.39
15	-0.25	-0.76	-1.16	-1.13	-1.19	-1.13	-1.08	-1.11	-1.18	-1.37	-1.48	-1.59	-1.56	-1.60	-1.83	-1.89	-1.77	-1.72	-1.56	-1.44	-1.41	-1.42	-1.40	-1.38	-1.36	-1.35	-1.40	-1.48	-1.52	-1.54
16	-0.61	-0.96	-1.06	-1.26	-1.20	-1.13	-1.07	-1.15	-1.28	-1.48	-1.55	-1.65	-1.68	-1.77	-1.94	-1.88	-1.84	-1.63	-1.57	-1.49	-1.49	-1.47	-1.46	-1.46	-1.46	-1.49	-1.55	-1.60	-1.62	-1.64
17	-0.69	-0.69	-1.14	-1.22	-1.16	-1.06	-1.08	-1.23	-1.37	-1.54	-1.59	-1.75	-1.84	-1.88	-1.92	-1.93	-1.73	-1.62	-1.59	-1.54	-1.53	-1.52	-1.53	-1.54	-1.59	-1.64	-1.66	-1.69	-1.71	-1.74
18	-0.09	-0.78	-1.07	-1.16	-1.08	-1.07	-1.15	-1.31	-1.41	-1.57	-1.68	-1.89	-1.94	-1.87	-1.97	-1.81	-1.71	-1.64	-1.64	-1.58	-1.58	-1.59	-1.62	-1.68	-1.75	-1.76	-1.77	-1.80	-1.82	-1.84
19	-0.78	-0.95	-1.20	-1.22	-1.22	-1.27	-1.35	-1.45	-1.54	-1.76	-1.92	-2.09	-2.02	-2.01	-1.94	-1.86	-1.80	-1.75	-1.73	-1.69	-1.69	-1.71	-1.79	-1.86	-1.89	-1.88	-1.89	-1.92	-1.94	-1.94
20	-0.43	-0.79	-1.03	-1.18	-1.29	-1.35	-1.38	-1.48	-1.64	-1.92	-2.04	-2.07	-2.05	-1.88	-1.88	-1.84	-1.81	-1.76	-1.76	-1.73	-1.76	-1.83	-1.93	-1.97	-1.98	-1.97	-1.98	-2.01	-2.01	-1.99
21	-0.48	-0.73	-1.12	-1.36	-1.46	-1.46	-1.48	-1.63	-1.85	-2.07	-2.05	-2.12	-1.92	-1.84	-1.87	-1.86	-1.82	-1.81	-1.81	-1.81	-1.89	-1.98	-2.04	-2.06	-2.07	-2.07	-2.07	-2.08	-2.06	-2.02
22	-0.38	-0.81	-1.33	-1.54	-1.55	-1.54	-1.61	-1.81	-1.98	-2.04	-2.08	-1.96	-1.86	-1.81	-1.86	-1.85	-1.84	-1.82	-1.86	-1.92	-2.02	-2.08	-2.12	-2.14	-2.15	-2.14	-2.12	-2.11	-2.08	-2.06
23	-0.62	-1.13	-1.54	-1.65	-1.64	-1.68	-1.79	-1.96	-1.95	-2.07	-1.92	-1.89	-1.83	-1.81	-1.85	-1.87	-1.86	-1.88	-1.98	-2.07	-2.13	-2.16	-2.20	-2.22	-2.22	-2.19	-2.16	-2.13	-2.11	-2.08
24	-0.97	-1.25	-1.55	-1.66	-1.73	-1.82	-1.89	-1.89	-1.96	-1.88	-1.83	-1.84	-1.81	-1.78	-1.85	-1.87	-1.90	-1.99	-2.12	-2.17	-2.20	-2.23	-2.26	-2.27	-2.25	-2.20	-2.15	-2.14	-2.12	-2.08
25	-0.87	-1.09	-1.45	-1.69	-1.79	-1.83	-1.73	-1.82	-1.69	-1.71	-1.71	-1.75	-1.72	-1.73	-1.80	-1.86	-1.97	-2.10	-2.19	-2.21	-2.24	-2.27	-2.29	-2.28	-2.24	-2.17	-2.14	-2.12	-2.09	-2.07
26	-0.76	-1.15	-1.61	-1.87	-1.99	-1.99	-1.90	-1.91	-1.78	-1.78	-1.76	-1.80	-1.75	-1.73	-1.79	-1.86	-1.99	-2.11	-2.18	-2.20	-2.25	-2.27	-2.27	-2.24	-2.19	-2.13	-2.09	-2.06	-2.05	-2.04
27	-0.97	-1.44	-1.88	-2.11	-2.19	-2.19	-2.02	-2.04	-1.89	-1.88	-1.84	-1.85	-1.77	-1.74	-1.81	-1.91	-2.02	-2.10	-2.18	-2.21	-2.24	-2.24	-2.23	-2.18	-2.15	-2.08	-2.04	-2.03	-2.02	-2.02
28	-1.27	-1.70	-2.09	-2.26	-2.34	-2.26	-2.11	-2.10	-1.95	-1.92	-1.86	-1.84	-1.75	-1.73	-1.83	-1.90	-1.99	-2.08	-2.16	-2.18	-2.19	-2.17	-2.14	-2.11	-2.06	-2.00	-1.97	-1.97	-1.98	-1.99
29	-1.48	-1.88	-2.21	-2.38	-2.38	-2.31	-2.16	-2.14	-1.98	-1.93	-1.84	-1.81	-1.73	-1.74	-1.81	-1.86	-1.95	-2.05	-2.13	-2.13	-2.11	-2.08	-2.06	-2.02	-1.98	-1.93	-1.91	-1.93	-1.95	-1.97
30	-1.65	-1.99	-2.33	-2.40	-2.41	-2.34	-2.19	-2.15	-1.97	-1.89	-1.80	-1.77	-1.73	-1.72	-1.78	-1.83	-1.93	-2.02	-2.07	-2.05	-2.02	-2.00	-1.97	-1.94	-1.91	-1.88	-1.88	-1.91	-1.95	-1.95

Table 3-20: t-statistics for “financials” in “forecasting model” for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.88	2.37	2.08	2.25	2.00	2.07	2.02	2.05	2.60	2.23	1.76	1.27	1.44	1.53	1.65	1.66	1.41	1.33	1.39	1.89	2.00	1.76	1.98	1.68	2.22	2.65	2.91	2.52	1.77	1.97
2	2.42	2.41	2.30	2.18	2.08	2.02	1.93	2.22	2.26	1.73	1.22	1.09	1.22	1.28	1.32	1.17	1.01	1.00	1.30	1.61	1.55	1.55	1.48	1.58	2.14	2.51	2.45	1.82	1.52	1.71
3	2.01	1.99	1.44	1.47	1.54	1.57	1.75	1.67	1.52	0.99	0.75	0.69	0.79	0.88	0.80	0.71	0.66	0.83	1.08	1.23	1.32	1.15	1.30	1.53	2.04	2.14	1.80	1.42	1.24	1.48
4	1.90	1.28	1.05	1.17	1.26	1.49	1.40	1.21	0.93	0.61	0.45	0.42	0.53	0.52	0.48	0.44	0.53	0.70	0.84	1.07	1.00	1.03	1.25	1.52	1.78	1.62	1.41	1.15	1.09	1.31
5	0.97	0.90	0.85	1.00	1.24	1.22	1.03	0.72	0.56	0.31	0.20	0.20	0.23	0.25	0.24	0.32	0.43	0.52	0.73	0.79	0.86	0.98	1.24	1.34	1.36	1.27	1.12	0.96	0.95	1.15
6	1.02	0.97	0.92	1.17	1.14	1.04	0.73	0.51	0.37	0.17	0.10	0.05	0.10	0.12	0.20	0.29	0.34	0.50	0.57	0.74	0.88	1.05	1.18	1.09	1.15	1.09	1.02	0.91	0.90	1.06
7	1.05	1.00	1.07	1.06	0.94	0.72	0.48	0.30	0.17	0.03	-0.09	-0.10	-0.04	0.07	0.16	0.20	0.32	0.36	0.52	0.74	0.92	0.99	0.94	0.89	0.96	0.96	0.92	0.83	0.81	0.99
8	1.12	1.22	0.96	0.88	0.64	0.51	0.29	0.12	0.03	-0.16	-0.22	-0.23	-0.09	0.03	0.07	0.18	0.19	0.33	0.54	0.79	0.88	0.78	0.77	0.73	0.84	0.86	0.83	0.73	0.76	0.92
9	1.42	1.02	0.75	0.54	0.41	0.30	0.10	-0.05	-0.19	-0.32	-0.38	-0.29	-0.15	-0.08	0.03	0.04	0.14	0.32	0.56	0.72	0.66	0.60	0.60	0.60	0.73	0.74	0.69	0.65	0.68	0.83
10	0.81	0.59	0.27	0.23	0.13	0.04	-0.12	-0.31	-0.40	-0.51	-0.46	-0.37	-0.27	-0.14	-0.13	-0.03	0.12	0.33	0.48	0.50	0.48	0.43	0.47	0.49	0.61	0.60	0.60	0.57	0.60	0.77
11	0.67	0.30	0.16	0.12	0.01	-0.07	-0.29	-0.42	-0.50	-0.52	-0.46	-0.41	-0.25	-0.22	-0.13	0.02	0.20	0.32	0.35	0.40	0.39	0.38	0.44	0.46	0.55	0.58	0.58	0.55	0.60	0.76
12	0.17	0.11	0.04	-0.04	-0.16	-0.27	-0.41	-0.53	-0.52	-0.51	-0.50	-0.40	-0.32	-0.21	-0.08	0.10	0.20	0.20	0.26	0.33	0.36	0.36	0.42	0.44	0.56	0.59	0.60	0.58	0.62	0.79
13	0.27	0.15	0.01	-0.10	-0.27	-0.31	-0.44	-0.47	-0.44	-0.48	-0.41	-0.39	-0.24	-0.09	0.07	0.16	0.14	0.18	0.25	0.36	0.40	0.41	0.47	0.52	0.63	0.67	0.69	0.66	0.72	0.90
14	0.25	0.05	-0.09	-0.24	-0.33	-0.37	-0.41	-0.42	-0.43	-0.40	-0.43	-0.32	-0.14	0.03	0.11	0.08	0.10	0.15	0.26	0.37	0.42	0.43	0.52	0.57	0.68	0.74	0.74	0.74	0.81	0.94
15	0.07	-0.11	-0.27	-0.34	-0.43	-0.37	-0.39	-0.43	-0.37	-0.44	-0.38	-0.23	-0.02	0.06	0.03	0.04	0.06	0.15	0.26	0.38	0.42	0.47	0.56	0.61	0.74	0.77	0.79	0.81	0.84	1.01
16	0.02	-0.23	-0.24	-0.32	-0.33	-0.27	-0.32	-0.33	-0.37	-0.35	-0.23	-0.07	0.04	0.02	0.01	0.00	0.07	0.15	0.26	0.38	0.46	0.52	0.61	0.68	0.79	0.83	0.87	0.84	0.91	1.05
17	-0.34	-0.27	-0.28	-0.28	-0.28	-0.25	-0.27	-0.37	-0.31	-0.23	-0.11	-0.03	-0.02	-0.02	-0.04	-0.02	0.05	0.14	0.25	0.41	0.49	0.55	0.67	0.72	0.84	0.91	0.90	0.92	0.97	1.07
18	-0.09	-0.21	-0.17	-0.21	-0.25	-0.16	-0.28	-0.27	-0.16	-0.07	-0.01	-0.04	-0.01	-0.03	-0.03	0.00	0.07	0.15	0.30	0.46	0.55	0.64	0.74	0.81	0.94	0.95	1.00	1.01	1.02	1.10
19	-0.30	-0.23	-0.23	-0.28	-0.23	-0.25	-0.24	-0.17	-0.05	-0.02	-0.07	-0.07	-0.06	-0.07	-0.06	-0.02	0.04	0.17	0.32	0.48	0.61	0.68	0.79	0.87	0.94	1.01	1.05	1.03	1.03	1.17
20	-0.11	-0.18	-0.22	-0.18	-0.26	-0.15	-0.09	0.00	0.04	-0.04	-0.06	-0.08	-0.05	-0.06	-0.04	-0.01	0.10	0.23	0.38	0.57	0.68	0.77	0.88	0.91	1.03	1.09	1.10	1.06	1.12	1.24
21	-0.23	-0.26	-0.19	-0.27	-0.20	-0.03	0.04	0.06	-0.01	-0.07	-0.11	-0.11	-0.08	-0.07	-0.06	0.02	0.13	0.27	0.45	0.62	0.74	0.83	0.90	0.98	1.09	1.12	1.10	1.12	1.17	1.30
22	-0.30	-0.16	-0.26	-0.18	-0.03	0.13	0.13	0.03	-0.01	-0.10	-0.13	-0.13	-0.08	-0.07	-0.01	0.08	0.20	0.37	0.53	0.71	0.83	0.87	0.98	1.05	1.13	1.14	1.18	1.20	1.25	1.36
23	-0.13	-0.15	-0.05	0.06	0.20	0.28	0.16	0.05	-0.01	-0.08	-0.09	-0.08	-0.03	0.02	0.08	0.19	0.34	0.49	0.66	0.83	0.89	0.99	1.10	1.14	1.20	1.28	1.31	1.32	1.37	1.46
24	-0.29	0.05	0.18	0.29	0.33	0.27	0.15	0.03	-0.01	-0.06	-0.05	-0.03	0.06	0.10	0.18	0.32	0.46	0.61	0.77	0.89	1.01	1.10	1.18	1.21	1.33	1.40	1.43	1.43	1.46	1.53
25	0.23	0.44	0.49	0.45	0.35	0.29	0.15	0.05	0.03	0.00	0.01	0.07	0.15	0.21	0.33	0.46	0.59	0.74	0.85	1.02	1.13	1.20	1.26	1.36	1.47	1.53	1.55	1.54	1.54	1.61
26	0.41	0.56	0.48	0.31	0.20	0.14	0.05	-0.02	-0.01	-0.03	0.02	0.08	0.19	0.29	0.40	0.54	0.67	0.76	0.93	1.09	1.18	1.23	1.36	1.44	1.55	1.59	1.60	1.57	1.58	1.66
27	0.50	0.47	0.26	0.09	0.00	0.00	-0.05	-0.09	-0.07	-0.05	0.02	0.11	0.26	0.36	0.49	0.62	0.70	0.85	1.01	1.15	1.23	1.34	1.46	1.53	1.62	1.65	1.64	1.61	1.63	1.68
28	0.27	0.12	-0.02	-0.16	-0.17	-0.12	-0.14	-0.16	-0.09	-0.04	0.05	0.18	0.32	0.46	0.57	0.65	0.79	0.94	1.08	1.21	1.35	1.46	1.56	1.62	1.69	1.71	1.69	1.68	1.66	1.67
29	-0.15	-0.17	-0.25	-0.30	-0.23	-0.16	-0.18	-0.15	-0.06	0.00	0.14	0.25	0.42	0.54	0.60	0.72	0.86	0.98	1.11	1.31	1.44	1.54	1.63	1.68	1.73	1.74	1.73	1.69	1.64	1.67
30	-0.28	-0.25	-0.26	-0.24	-0.16	-0.11	-0.10	-0.06	0.04	0.14	0.27	0.40	0.54	0.61	0.71	0.82	0.93	1.05	1.24	1.43	1.55	1.64	1.71	1.73	1.78	1.79	1.75	1.68	1.65	1.68

Table 3-21: t-statistics for “corporates” in “forecasting model” for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.30	-0.30	-0.44	-0.68	-1.30	-1.58	-1.48	-1.60	-1.44	-1.34	-1.31	-1.43	-0.92	-1.10	-1.07	-1.28	-1.31	-1.46	-1.33	-1.40	-1.48	-1.21	-1.17	-1.25	-1.36	-1.62	-1.53	-1.80	-2.01	-1.87
2	-0.36	-0.59	-0.69	-1.08	-1.64	-1.60	-1.54	-1.57	-1.62	-1.47	-1.70	-1.67	-1.36	-1.55	-1.68	-1.71	-1.75	-1.91	-1.99	-1.98	-1.92	-1.65	-1.75	-1.83	-2.04	-2.05	-2.12	-2.42	-2.48	-2.45
3	-0.28	-0.58	-0.91	-1.35	-1.59	-1.54	-1.46	-1.58	-1.53	-1.63	-1.68	-1.69	-1.54	-1.81	-1.82	-1.87	-1.94	-2.20	-2.23	-2.13	-2.00	-1.90	-1.98	-2.16	-2.18	-2.29	-2.44	-2.60	-2.68	-2.72
4	-0.40	-0.92	-1.21	-1.38	-1.56	-1.44	-1.47	-1.51	-1.67	-1.67	-1.74	-1.83	-1.82	-1.98	-2.00	-2.08	-2.27	-2.43	-2.37	-2.21	-2.18	-2.10	-2.25	-2.27	-2.36	-2.53	-2.60	-2.76	-2.88	-2.89
5	-0.88	-1.24	-1.23	-1.36	-1.45	-1.45	-1.41	-1.65	-1.70	-1.71	-1.85	-2.04	-1.96	-2.10	-2.16	-2.35	-2.46	-2.51	-2.39	-2.35	-2.31	-2.30	-2.32	-2.42	-2.57	-2.66	-2.73	-2.90	-2.99	-2.99
6	-1.03	-1.08	-1.11	-1.21	-1.40	-1.33	-1.51	-1.63	-1.68	-1.76	-1.98	-2.08	-2.01	-2.17	-2.34	-2.46	-2.48	-2.45	-2.43	-2.38	-2.40	-2.30	-2.39	-2.55	-2.63	-2.73	-2.82	-2.96	-3.02	-3.01
7	-0.65	-0.86	-0.90	-1.16	-1.26	-1.43	-1.48	-1.58	-1.69	-1.87	-2.01	-2.11	-2.08	-2.33	-2.44	-2.47	-2.42	-2.47	-2.44	-2.45	-2.37	-2.35	-2.50	-2.61	-2.68	-2.79	-2.86	-2.98	-3.03	-2.97
8	-0.54	-0.75	-0.90	-1.04	-1.37	-1.36	-1.42	-1.58	-1.81	-1.91	-2.06	-2.20	-2.27	-2.47	-2.50	-2.46	-2.50	-2.53	-2.55	-2.46	-2.45	-2.51	-2.60	-2.72	-2.80	-2.88	-2.94	-3.04	-3.03	-3.00
9	-0.39	-0.81	-0.80	-1.22	-1.33	-1.35	-1.49	-1.78	-1.93	-2.04	-2.25	-2.48	-2.52	-2.62	-2.57	-2.63	-2.64	-2.69	-2.62	-2.60	-2.65	-2.67	-2.77	-2.90	-2.94	-3.02	-3.06	-3.09	-3.11	-3.02
10	-0.62	-0.75	-1.05	-1.21	-1.34	-1.44	-1.70	-1.92	-2.08	-2.25	-2.53	-2.74	-2.69	-2.70	-2.75	-2.78	-2.82	-2.78	-2.77	-2.82	-2.81	-2.84	-2.95	-3.04	-3.08	-3.14	-3.12	-3.17	-3.14	-3.01
11	-0.38	-1.00	-1.01	-1.20	-1.42	-1.65	-1.85	-2.07	-2.27	-2.52	-2.77	-2.88	-2.75	-2.85	-2.88	-2.93	-2.88	-2.90	-2.96	-2.95	-2.95	-3.00	-3.07	-3.15	-3.18	-3.19	-3.20	-3.21	-3.14	-3.00
12	-1.09	-1.10	-1.10	-1.37	-1.73	-1.90	-2.08	-2.34	-2.60	-2.83	-2.98	-3.00	-2.96	-3.02	-3.07	-3.02	-3.03	-3.12	-3.13	-3.12	-3.13	-3.15	-3.22	-3.28	-3.27	-3.31	-3.27	-3.23	-3.16	-3.03
13	-0.63	-0.88	-1.04	-1.46	-1.77	-1.91	-2.15	-2.49	-2.74	-2.87	-2.94	-3.06	-2.99	-3.09	-3.05	-3.07	-3.16	-3.20	-3.22	-3.22	-3.19	-3.20	-3.25	-3.27	-3.30	-3.29	-3.21	-3.16	-3.10	-3.00
14	-0.69	-1.01	-1.30	-1.62	-1.87	-2.09	-2.42	-2.75	-2.89	-2.94	-3.11	-3.20	-3.17	-3.18	-3.21	-3.31	-3.34	-3.39	-3.40	-3.35	-3.30	-3.30	-3.31	-3.37	-3.35	-3.29	-3.21	-3.17	-3.13	-3.04
15	-0.95	-1.39	-1.50	-1.75	-2.10	-2.39	-2.69	-2.91	-2.97	-3.12	-3.25	-3.37	-3.24	-3.31	-3.42	-3.46	-3.51	-3.55	-3.52	-3.45	-3.39	-3.36	-3.40	-3.41	-3.34	-3.27	-3.19	-3.18	-3.15	-2.99
16	-1.34	-1.50	-1.53	-1.91	-2.33	-2.60	-2.79	-2.94	-3.10	-3.22	-3.38	-3.40	-3.33	-3.48	-3.53	-3.59	-3.64	-3.64	-3.59	-3.51	-3.41	-3.42	-3.41	-3.37	-3.29	-3.23	-3.18	-3.18	-3.08	-2.93
17	-1.37	-1.45	-1.70	-2.20	-2.58	-2.72	-2.83	-3.07	-3.20	-3.33	-3.38	-3.44	-3.49	-3.61	-3.69	-3.75	-3.75	-3.73	-3.66	-3.55	-3.55	-3.50	-3.44	-3.37	-3.29	-3.25	-3.19	-3.13	-3.02	-2.86
18	-1.24	-1.69	-2.06	-2.49	-2.71	-2.75	-2.97	-3.16	-3.29	-3.32	-3.42	-3.58	-3.62	-3.77	-3.86	-3.87	-3.84	-3.80	-3.70	-3.68	-3.62	-3.50	-3.41	-3.36	-3.30	-3.25	-3.14	-3.06	-2.95	-2.79
19	-1.81	-2.23	-2.44	-2.68	-2.78	-2.93	-3.10	-3.28	-3.31	-3.38	-3.59	-3.72	-3.79	-3.94	-3.97	-3.95	-3.90	-3.82	-3.81	-3.73	-3.60	-3.46	-3.39	-3.35	-3.29	-3.19	-3.06	-2.98	-2.87	-2.64
20	-2.18	-2.49	-2.49	-2.63	-2.87	-2.99	-3.13	-3.23	-3.30	-3.49	-3.66	-3.83	-3.89	-3.99	-3.99	-3.95	-3.86	-3.88	-3.82	-3.67	-3.51	-3.38	-3.33	-3.30	-3.18	-3.07	-2.94	-2.86	-2.68	-2.48
21	-2.33	-2.36	-2.30	-2.62	-2.83	-2.92	-2.98	-3.12	-3.32	-3.47	-3.69	-3.85	-3.86	-3.92	-3.91	-3.84	-3.86	-3.81	-3.67	-3.50	-3.37	-3.27	-3.22	-3.13	-3.01	-2.89	-2.77	-2.63	-2.47	-2.25
22	-1.98	-2.01	-2.23	-2.52	-2.71	-2.73	-2.85	-3.11	-3.28	-3.49	-3.70	-3.81	-3.79	-3.83	-3.78	-3.82	-3.78	-3.66	-3.50	-3.35	-3.25	-3.15	-3.05	-2.95	-2.82	-2.72	-2.54	-2.42	-2.25	-2.07
23	-1.70	-2.07	-2.20	-2.48	-2.58	-2.66	-2.91	-3.15	-3.36	-3.56	-3.70	-3.77	-3.73	-3.73	-3.81	-3.79	-3.67	-3.52	-3.39	-3.27	-3.17	-3.02	-2.90	-2.80	-2.68	-2.52	-2.36	-2.23	-2.09	-1.91
24	-2.07	-2.16	-2.25	-2.41	-2.58	-2.78	-3.00	-3.27	-3.46	-3.58	-3.68	-3.72	-3.64	-3.76	-3.77	-3.67	-3.52	-3.41	-3.31	-3.19	-3.04	-2.88	-2.76	-2.66	-2.48	-2.34	-2.18	-2.07	-1.94	-1.79
25	-1.88	-2.06	-2.06	-2.34	-2.64	-2.83	-3.08	-3.33	-3.44	-3.52	-3.59	-3.59	-3.64	-3.69	-3.61	-3.49	-3.37	-3.29	-3.20	-3.03	-2.87	-2.71	-2.60	-2.45	-2.29	-2.15	-2.01	-1.91	-1.80	-1.66
26	-1.89	-1.90	-2.05	-2.47	-2.74	-2.98	-3.20	-3.37	-3.42	-3.47	-3.48	-3.61	-3.59	-3.55	-3.45	-3.35	-3.26	-3.19	-3.04	-2.88	-2.71	-2.56	-2.40	-2.26	-2.11	-1.99	-1.86	-1.79	-1.68	-1.55
27	-1.62	-1.89	-2.22	-2.61	-2.93	-3.11	-3.24	-3.35	-3.37	-3.37	-3.50	-3.55	-3.44	-3.38	-3.29	-3.23	-3.15	-3.02	-2.88	-2.71	-2.56	-2.36	-2.21	-2.08	-1.95	-1.84	-1.74	-1.67	-1.57	-1.45
28	-1.86	-2.27	-2.46	-2.88	-3.13	-3.19	-3.25	-3.32	-3.29	-3.40	-3.46	-3.42	-3.29	-3.24	-3.19	-3.13	-3.00	-2.87	-2.72	-2.57	-2.36	-2.18	-2.03	-1.93	-1.81	-1.72	-1.63	-1.57	-1.48	-1.37
29	-2.34	-2.49	-2.68	-3.04	-3.14	-3.14	-3.17	-3.20	-3.29	-3.33	-3.30	-3.23	-3.12	-3.11	-3.07	-2.96	-2.84	-2.70	-2.57	-2.36	-2.17	-1.99	-1.87	-1.77	-1.68	-1.60	-1.51	-1.46	-1.38	-1.27
30	-2.25	-2.55	-2.72	-2.92	-2.98	-2.96	-2.97	-3.12	-3.14	-3.10	-3.05	-3.01	-2.95	-2.95	-2.86	-2.76	-2.63	-2.51	-2.33	-2.14	-1.95	-1.80	-1.69	-1.63	-1.55	-1.47	-1.39	-1.35	-1.27	-1.16

Table 3-22: t-statistics for "internal" in "forecasting model" for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-0.01	-1.08	-0.32	-0.39	0.06	0.27	0.20	0.07	-0.26	-0.68	-0.68	-0.72	-0.86	-1.46	-1.97	-1.85	-1.52	-1.34	-1.47	-1.15	-1.14	-0.99	-0.72	-0.73	-0.36	-0.19	0.02	-0.06	-0.35	-0.31
2	-0.97	-0.76	-0.31	-0.07	0.25	0.31	0.18	-0.11	-0.49	-0.78	-0.83	-0.92	-1.31	-1.90	-2.11	-1.87	-1.61	-1.59	-1.45	-1.26	-1.17	-0.94	-0.82	-0.62	-0.33	-0.11	-0.07	-0.31	-0.44	-0.46
3	-0.09	-0.25	0.22	0.40	0.52	0.48	0.18	-0.20	-0.51	-0.77	-0.85	-1.14	-1.63	-2.02	-2.03	-1.81	-1.67	-1.50	-1.38	-1.18	-1.02	-0.89	-0.65	-0.45	-0.16	-0.08	-0.20	-0.34	-0.46	-0.37
4	-0.17	-0.07	0.30	0.36	0.42	0.26	-0.10	-0.43	-0.73	-0.96	-1.22	-1.63	-1.99	-2.17	-2.13	-1.98	-1.75	-1.61	-1.46	-1.21	-1.09	-0.85	-0.61	-0.40	-0.22	-0.28	-0.34	-0.48	-0.50	-0.40
5	0.14	0.16	0.35	0.37	0.28	0.00	-0.30	-0.63	-0.88	-1.25	-1.62	-1.95	-2.13	-2.24	-2.22	-2.00	-1.81	-1.64	-1.43	-1.23	-1.00	-0.76	-0.51	-0.38	-0.35	-0.37	-0.44	-0.49	-0.49	-0.39
6	0.15	0.02	0.19	0.08	-0.16	-0.35	-0.64	-0.92	-1.29	-1.73	-2.02	-2.20	-2.29	-2.40	-2.30	-2.11	-1.90	-1.66	-1.49	-1.18	-0.95	-0.70	-0.52	-0.53	-0.47	-0.50	-0.48	-0.52	-0.52	-0.48
7	-0.16	-0.17	-0.11	-0.38	-0.52	-0.70	-0.95	-1.33	-1.76	-2.14	-2.30	-2.40	-2.51	-2.51	-2.42	-2.20	-1.93	-1.73	-1.45	-1.14	-0.89	-0.72	-0.66	-0.63	-0.59	-0.55	-0.53	-0.56	-0.60	-0.57
8	-0.08	-0.29	-0.48	-0.62	-0.75	-0.91	-1.27	-1.72	-2.09	-2.35	-2.45	-2.57	-2.57	-2.58	-2.46	-2.17	-1.93	-1.63	-1.35	-1.03	-0.84	-0.78	-0.70	-0.69	-0.59	-0.54	-0.52	-0.59	-0.64	-0.57
9	-0.36	-0.77	-0.77	-0.90	-1.00	-1.28	-1.71	-2.12	-2.37	-2.57	-2.69	-2.72	-2.73	-2.70	-2.50	-2.23	-1.89	-1.58	-1.28	-1.04	-0.95	-0.86	-0.80	-0.73	-0.63	-0.59	-0.62	-0.68	-0.69	-0.61
10	-0.97	-1.04	-1.01	-1.09	-1.35	-1.72	-2.09	-2.40	-2.58	-2.80	-2.84	-2.88	-2.83	-2.72	-2.53	-2.17	-1.82	-1.51	-1.27	-1.13	-1.01	-0.93	-0.82	-0.75	-0.66	-0.67	-0.69	-0.73	-0.73	-0.64
11	-0.90	-1.09	-1.07	-1.36	-1.70	-2.02	-2.32	-2.54	-2.76	-2.91	-2.94	-2.93	-2.80	-2.70	-2.42	-2.05	-1.70	-1.44	-1.30	-1.13	-1.04	-0.92	-0.81	-0.75	-0.70	-0.71	-0.71	-0.74	-0.73	-0.65
12	-1.09	-1.22	-1.43	-1.80	-2.07	-2.29	-2.49	-2.74	-2.90	-3.03	-3.02	-2.92	-2.80	-2.59	-2.30	-1.93	-1.64	-1.48	-1.31	-1.16	-1.02	-0.90	-0.80	-0.78	-0.74	-0.72	-0.71	-0.73	-0.73	-0.66
13	-1.13	-1.63	-1.89	-2.15	-2.32	-2.42	-2.66	-2.84	-2.98	-3.07	-2.95	-2.87	-2.65	-2.43	-2.13	-1.84	-1.64	-1.46	-1.32	-1.12	-0.98	-0.87	-0.80	-0.78	-0.72	-0.70	-0.69	-0.71	-0.72	-0.67
14	-1.83	-2.20	-2.27	-2.38	-2.42	-2.58	-2.74	-2.90	-3.00	-2.98	-2.89	-2.71	-2.48	-2.25	-2.03	-1.83	-1.61	-1.45	-1.27	-1.07	-0.93	-0.86	-0.80	-0.75	-0.69	-0.66	-0.66	-0.69	-0.71	-0.66
15	-2.20	-2.35	-2.30	-2.33	-2.46	-2.56	-2.71	-2.84	-2.84	-2.85	-2.67	-2.46	-2.21	-2.07	-1.93	-1.72	-1.53	-1.33	-1.15	-0.96	-0.87	-0.80	-0.71	-0.67	-0.59	-0.58	-0.58	-0.63	-0.65	-0.56
16	-2.13	-2.24	-2.10	-2.28	-2.37	-2.48	-2.61	-2.66	-2.69	-2.60	-2.37	-2.15	-1.99	-1.94	-1.78	-1.60	-1.37	-1.18	-1.00	-0.87	-0.78	-0.68	-0.60	-0.54	-0.47	-0.47	-0.50	-0.55	-0.53	-0.46
17	-2.06	-2.03	-2.11	-2.25	-2.34	-2.42	-2.47	-2.56	-2.49	-2.35	-2.10	-1.95	-1.89	-1.81	-1.68	-1.47	-1.24	-1.06	-0.93	-0.79	-0.69	-0.60	-0.50	-0.45	-0.39	-0.41	-0.44	-0.46	-0.45	-0.40
18	-1.78	-2.08	-2.11	-2.25	-2.29	-2.28	-2.36	-2.32	-2.21	-2.05	-1.87	-1.82	-1.74	-1.71	-1.56	-1.33	-1.11	-0.98	-0.85	-0.70	-0.60	-0.49	-0.40	-0.37	-0.34	-0.36	-0.36	-0.38	-0.39	-0.37
19	-2.14	-2.20	-2.22	-2.29	-2.22	-2.24	-2.18	-2.09	-1.95	-1.87	-1.80	-1.73	-1.68	-1.61	-1.44	-1.20	-1.05	-0.90	-0.76	-0.61	-0.49	-0.39	-0.33	-0.33	-0.30	-0.29	-0.29	-0.33	-0.37	-0.26
20	-2.00	-2.17	-2.13	-2.10	-2.08	-1.97	-1.86	-1.75	-1.70	-1.74	-1.64	-1.61	-1.53	-1.44	-1.27	-1.10	-0.93	-0.78	-0.64	-0.47	-0.37	-0.30	-0.27	-0.27	-0.22	-0.21	-0.22	-0.29	-0.24	-0.14
21	-2.04	-2.06	-1.92	-1.92	-1.78	-1.63	-1.53	-1.50	-1.57	-1.59	-1.56	-1.49	-1.40	-1.30	-1.17	-0.99	-0.81	-0.66	-0.49	-0.35	-0.28	-0.25	-0.22	-0.20	-0.14	-0.15	-0.20	-0.19	-0.14	-0.01
22	-1.85	-1.73	-1.69	-1.56	-1.38	-1.26	-1.25	-1.34	-1.39	-1.48	-1.42	-1.35	-1.25	-1.18	-1.03	-0.83	-0.66	-0.47	-0.34	-0.23	-0.21	-0.18	-0.13	-0.10	-0.06	-0.11	-0.08	-0.07	0.01	0.06
23	-1.43	-1.48	-1.24	-1.10	-0.99	-0.98	-1.07	-1.18	-1.29	-1.35	-1.27	-1.19	-1.12	-1.04	-0.88	-0.68	-0.47	-0.33	-0.23	-0.17	-0.15	-0.10	-0.04	-0.02	-0.02	0.01	0.03	0.07	0.07	0.13
24	-1.36	-1.04	-0.81	-0.74	-0.75	-0.86	-0.97	-1.13	-1.22	-1.24	-1.16	-1.11	-1.02	-0.92	-0.76	-0.53	-0.36	-0.25	-0.20	-0.15	-0.10	-0.03	0.01	-0.01	0.07	0.09	0.13	0.11	0.12	0.15
25	-0.60	-0.53	-0.43	-0.52	-0.67	-0.79	-0.96	-1.08	-1.14	-1.16	-1.10	-1.02	-0.91	-0.82	-0.62	-0.43	-0.30	-0.24	-0.19	-0.11	-0.05	0.00	0.01	0.07	0.14	0.18	0.16	0.14	0.13	0.12
26	-0.39	-0.39	-0.45	-0.65	-0.77	-0.95	-1.05	-1.13	-1.17	-1.20	-1.12	-1.01	-0.91	-0.77	-0.60	-0.44	-0.35	-0.29	-0.21	-0.12	-0.07	-0.06	0.03	0.08	0.17	0.14	0.13	0.09	0.04	0.04
27	-0.31	-0.50	-0.65	-0.81	-0.99	-1.08	-1.14	-1.20	-1.25	-1.26	-1.14	-1.04	-0.88	-0.76	-0.62	-0.51	-0.42	-0.33	-0.24	-0.15	-0.13	-0.04	0.05	0.12	0.14	0.11	0.08	0.00	-0.04	-0.06
28	-0.56	-0.79	-0.86	-1.06	-1.13	-1.18	-1.22	-1.29	-1.30	-1.27	-1.16	-1.00	-0.87	-0.77	-0.67	-0.56	-0.44	-0.34	-0.26	-0.20	-0.10	-0.01	0.09	0.10	0.12	0.08	0.01	-0.06	-0.13	-0.15
29	-0.86	-0.95	-1.07	-1.16	-1.18	-1.23	-1.27	-1.30	-1.28	-1.26	-1.09	-0.96	-0.85	-0.80	-0.71	-0.57	-0.44	-0.34	-0.30	-0.16	-0.07	0.05	0.08	0.09	0.09	0.01	-0.06	-0.14	-0.21	-0.20
30	-0.85	-1.10	-1.08	-1.13	-1.15	-1.21	-1.23	-1.22	-1.21	-1.13	-1.00	-0.90	-0.85	-0.80	-0.68	-0.53	-0.41	-0.35	-0.22	-0.10	0.02	0.06	0.10	0.09	0.05	-0.03	-0.12	-0.21	-0.25	-0.23

Table 3-23: t-statistics for “interbank” in “forecasting model” for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.38	1.32	0.75	0.19	0.57	0.54	1.10	1.17	1.53	1.40	1.57	1.16	1.74	1.63	1.89	1.86	1.87	2.02	1.71	1.70	1.88	1.79	1.80	1.71	1.62	1.60	1.80	1.81	1.97	1.77
2	0.83	1.04	0.36	0.08	0.41	0.53	1.06	1.29	1.55	1.37	1.26	1.18	1.40	1.51	1.80	1.93	1.97	2.00	1.72	1.76	1.85	1.86	1.75	1.71	1.57	1.65	1.75	1.81	1.80	1.77
3	1.12	1.00	0.42	0.25	0.58	0.78	1.28	1.46	1.59	1.29	1.34	1.21	1.49	1.69	1.96	2.07	2.05	2.01	1.85	1.86	1.98	1.90	1.82	1.71	1.69	1.72	1.84	1.81	1.86	1.77
4	0.93	0.91	0.50	0.40	0.74	1.03	1.46	1.55	1.51	1.39	1.35	1.35	1.70	1.92	2.14	2.20	2.14	2.13	1.99	2.03	2.06	1.99	1.87	1.85	1.83	1.89	1.92	1.94	1.91	1.85
5	1.00	1.01	0.69	0.65	1.04	1.29	1.58	1.52	1.60	1.43	1.48	1.59	1.94	2.12	2.27	2.27	2.25	2.22	2.13	2.11	2.13	2.02	1.99	1.97	1.98	1.98	2.04	2.01	1.99	1.97
6	1.10	1.14	0.89	0.92	1.28	1.43	1.53	1.57	1.58	1.49	1.66	1.82	2.12	2.24	2.32	2.36	2.33	2.33	2.20	2.17	2.14	2.09	2.06	2.07	2.03	2.06	2.07	2.04	2.05	2.13
7	1.19	1.32	1.15	1.15	1.43	1.40	1.58	1.57	1.64	1.68	1.89	2.02	2.27	2.33	2.43	2.46	2.44	2.39	2.27	2.19	2.22	2.18	2.17	2.14	2.14	2.13	2.14	2.14	2.23	2.24
8	1.43	1.65	1.45	1.36	1.43	1.50	1.62	1.65	1.82	1.91	2.08	2.17	2.35	2.43	2.51	2.55	2.48	2.44	2.28	2.26	2.28	2.25	2.20	2.20	2.16	2.16	2.20	2.28	2.30	2.26
9	1.81	1.92	1.62	1.33	1.52	1.52	1.67	1.82	2.03	2.09	2.21	2.24	2.44	2.50	2.60	2.58	2.51	2.43	2.33	2.31	2.34	2.27	2.25	2.21	2.19	2.22	2.34	2.35	2.32	2.25
10	1.96	1.95	1.41	1.31	1.45	1.51	1.78	1.97	2.12	2.15	2.22	2.28	2.44	2.51	2.55	2.53	2.43	2.40	2.31	2.30	2.29	2.26	2.21	2.18	2.19	2.29	2.35	2.31	2.25	2.20
11	1.79	1.55	1.28	1.17	1.40	1.61	1.91	2.07	2.19	2.17	2.25	2.29	2.46	2.48	2.52	2.47	2.42	2.40	2.33	2.27	2.30	2.23	2.19	2.19	2.27	2.32	2.32	2.25	2.22	2.23
12	1.23	1.50	1.21	1.23	1.59	1.81	2.08	2.19	2.26	2.25	2.31	2.35	2.47	2.50	2.50	2.50	2.47	2.45	2.34	2.32	2.31	2.25	2.24	2.32	2.34	2.33	2.31	2.27	2.28	2.27
13	1.67	1.69	1.50	1.64	1.98	2.13	2.33	2.37	2.44	2.41	2.47	2.46	2.57	2.56	2.61	2.62	2.58	2.52	2.43	2.38	2.38	2.35	2.41	2.43	2.40	2.37	2.36	2.37	2.35	2.33
14	1.61	1.86	1.86	1.99	2.27	2.34	2.46	2.51	2.54	2.51	2.53	2.52	2.59	2.62	2.67	2.67	2.60	2.55	2.44	2.40	2.42	2.47	2.48	2.45	2.39	2.37	2.40	2.39	2.36	2.37
15	1.99	2.33	2.29	2.30	2.49	2.48	2.61	2.61	2.64	2.58	2.60	2.55	2.66	2.70	2.74	2.70	2.64	2.57	2.47	2.45	2.55	2.55	2.51	2.46	2.41	2.43	2.44	2.41	2.42	2.40
16	2.43	2.71	2.53	2.45	2.55	2.56	2.65	2.66	2.66	2.60	2.59	2.59	2.71	2.73	2.73	2.71	2.63	2.57	2.50	2.56	2.60	2.56	2.49	2.45	2.44	2.45	2.45	2.45	2.43	2.40
17	2.62	2.78	2.52	2.36	2.50	2.49	2.60	2.59	2.60	2.53	2.57	2.59	2.69	2.68	2.69	2.65	2.59	2.57	2.58	2.58	2.57	2.50	2.45	2.45	2.43	2.43	2.46	2.44	2.41	2.39
18	2.60	2.69	2.36	2.27	2.39	2.42	2.51	2.52	2.53	2.51	2.57	2.59	2.65	2.65	2.64	2.62	2.59	2.65	2.61	2.56	2.53	2.47	2.47	2.46	2.43	2.46	2.47	2.44	2.41	2.39
19	2.44	2.50	2.28	2.20	2.34	2.34	2.45	2.46	2.52	2.52	2.57	2.54	2.61	2.59	2.60	2.61	2.66	2.66	2.58	2.51	2.49	2.48	2.46	2.44	2.45	2.46	2.46	2.43	2.41	2.40
20	2.30	2.48	2.29	2.23	2.31	2.33	2.43	2.49	2.57	2.55	2.56	2.54	2.58	2.58	2.62	2.71	2.71	2.65	2.55	2.50	2.52	2.50	2.48	2.49	2.48	2.47	2.47	2.45	2.44	2.44
21	2.38	2.54	2.36	2.23	2.31	2.32	2.47	2.55	2.60	2.55	2.55	2.51	2.58	2.61	2.73	2.76	2.69	2.62	2.52	2.52	2.53	2.50	2.50	2.49	2.47	2.46	2.47	2.46	2.45	2.43
22	2.44	2.60	2.33	2.24	2.29	2.35	2.53	2.57	2.58	2.53	2.52	2.50	2.60	2.71	2.77	2.74	2.65	2.59	2.54	2.52	2.52	2.52	2.50	2.48	2.45	2.45	2.47	2.47	2.43	2.42
23	2.51	2.51	2.29	2.20	2.31	2.41	2.54	2.55	2.57	2.50	2.50	2.52	2.69	2.75	2.74	2.69	2.62	2.60	2.54	2.51	2.54	2.52	2.48	2.45	2.43	2.44	2.47	2.43	2.42	2.42
24	2.26	2.40	2.19	2.19	2.36	2.40	2.50	2.52	2.51	2.46	2.50	2.59	2.71	2.70	2.67	2.63	2.60	2.58	2.51	2.52	2.52	2.48	2.44	2.42	2.41	2.42	2.41	2.40	2.39	2.39
25	2.39	2.40	2.28	2.32	2.40	2.42	2.51	2.48	2.49	2.48	2.60	2.64	2.69	2.66	2.64	2.64	2.61	2.57	2.53	2.51	2.50	2.46	2.42	2.40	2.39	2.38	2.39	2.38	2.38	2.36
26	2.27	2.47	2.40	2.35	2.41	2.42	2.45	2.45	2.51	2.59	2.65	2.62	2.64	2.62	2.65	2.65	2.60	2.59	2.53	2.49	2.47	2.43	2.40	2.39	2.35	2.36	2.38	2.37	2.35	2.31
27	2.50	2.71	2.47	2.39	2.43	2.39	2.45	2.50	2.65	2.66	2.64	2.58	2.61	2.63	2.65	2.65	2.63	2.59	2.50	2.46	2.44	2.41	2.39	2.34	2.33	2.34	2.36	2.34	2.30	2.26
28	2.72	2.69	2.44	2.36	2.36	2.34	2.47	2.61	2.70	2.63	2.59	2.53	2.61	2.63	2.64	2.66	2.61	2.55	2.47	2.43	2.42	2.39	2.34	2.32	2.30	2.32	2.33	2.28	2.24	2.23
29	2.47	2.52	2.31	2.18	2.23	2.30	2.54	2.62	2.61	2.53	2.50	2.50	2.57	2.58	2.62	2.62	2.56	2.50	2.42	2.39	2.38	2.33	2.30	2.28	2.27	2.28	2.26	2.22	2.20	2.17
30	2.43	2.47	2.20	2.12	2.26	2.45	2.61	2.58	2.55	2.48	2.49	2.49	2.55	2.59	2.61	2.59	2.53	2.47	2.40	2.37	2.34	2.31	2.28	2.26	2.24	2.23	2.21	2.19	2.16	2.12

Table 3-24: t-statistics for “lagged exchange rate” in “forecasting model” for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-1.40	-2.74	-2.92	-3.41	-3.54	-3.31	-2.49	-3.00	-2.96	-3.05	-2.66	-2.26	-2.08	-1.52	-1.95	-2.70	-2.64	-2.67	-2.71	-2.65	-2.53	-2.60	-2.40	-1.71	-2.20	-2.40	-2.62	-3.09	-2.91	-3.19
2	-2.52	-3.09	-3.25	-3.50	-3.31	-2.77	-2.63	-2.95	-2.93	-2.77	-2.39	-2.09	-1.73	-1.69	-2.32	-2.63	-2.56	-2.61	-2.60	-2.52	-2.48	-2.39	-1.91	-1.81	-2.16	-2.40	-2.80	-2.92	-2.96	-3.25
3	-2.56	-3.19	-3.14	-3.15	-2.70	-2.50	-2.49	-2.72	-2.54	-2.31	-1.99	-1.58	-1.52	-1.82	-2.22	-2.42	-2.40	-2.41	-2.38	-2.35	-2.25	-1.92	-1.78	-1.78	-2.14	-2.49	-2.67	-2.86	-2.98	-3.11
4	-3.04	-3.35	-3.09	-2.73	-2.53	-2.46	-2.44	-2.46	-2.24	-2.00	-1.56	-1.34	-1.57	-1.79	-2.10	-2.28	-2.24	-2.23	-2.22	-2.15	-1.89	-1.79	-1.74	-1.84	-2.29	-2.50	-2.73	-2.93	-2.96	-2.99
5	-3.14	-3.14	-2.54	-2.46	-2.39	-2.28	-2.13	-2.06	-1.84	-1.47	-1.21	-1.29	-1.45	-1.64	-1.91	-2.05	-2.00	-2.00	-1.96	-1.74	-1.67	-1.64	-1.69	-1.93	-2.24	-2.48	-2.71	-2.83	-2.79	-2.85
6	-2.75	-2.41	-2.24	-2.34	-2.24	-2.02	-1.81	-1.72	-1.39	-1.17	-1.19	-1.23	-1.38	-1.56	-1.78	-1.90	-1.87	-1.82	-1.65	-1.60	-1.60	-1.67	-1.85	-2.00	-2.33	-2.57	-2.73	-2.78	-2.78	-2.80
7	-1.96	-2.23	-2.22	-2.30	-2.08	-1.80	-1.57	-1.33	-1.15	-1.18	-1.16	-1.18	-1.31	-1.48	-1.67	-1.77	-1.70	-1.53	-1.49	-1.52	-1.60	-1.80	-1.90	-2.08	-2.40	-2.58	-2.67	-2.74	-2.72	-2.57
8	-2.44	-2.60	-2.44	-2.33	-2.04	-1.71	-1.33	-1.24	-1.30	-1.28	-1.24	-1.25	-1.36	-1.50	-1.66	-1.72	-1.54	-1.50	-1.54	-1.62	-1.81	-1.93	-2.06	-2.25	-2.51	-2.61	-2.72	-2.76	-2.59	-2.40
9	-2.58	-2.60	-2.29	-2.16	-1.85	-1.35	-1.15	-1.29	-1.30	-1.26	-1.22	-1.23	-1.31	-1.43	-1.54	-1.49	-1.44	-1.47	-1.56	-1.75	-1.87	-2.02	-2.16	-2.31	-2.50	-2.61	-2.70	-2.60	-2.38	-2.25
10	-2.45	-2.30	-1.97	-1.83	-1.39	-1.10	-1.18	-1.28	-1.25	-1.21	-1.17	-1.16	-1.22	-1.30	-1.31	-1.37	-1.39	-1.47	-1.67	-1.79	-1.94	-2.11	-2.22	-2.31	-2.50	-2.59	-2.53	-2.39	-2.24	-2.08
11	-2.02	-1.98	-1.64	-1.34	-1.12	-1.14	-1.17	-1.24	-1.21	-1.17	-1.11	-1.08	-1.11	-1.09	-1.20	-1.34	-1.41	-1.61	-1.75	-1.90	-2.06	-2.18	-2.24	-2.33	-2.51	-2.46	-2.36	-2.27	-2.09	-1.93
12	-1.91	-1.78	-1.22	-1.17	-1.28	-1.23	-1.22	-1.26	-1.24	-1.19	-1.11	-1.04	-0.98	-1.06	-1.22	-1.40	-1.58	-1.73	-1.90	-2.06	-2.18	-2.26	-2.32	-2.42	-2.47	-2.38	-2.33	-2.19	-2.00	-1.88
13	-1.64	-1.28	-1.06	-1.40	-1.40	-1.31	-1.27	-1.31	-1.28	-1.21	-1.10	-0.94	-0.98	-1.11	-1.30	-1.58	-1.71	-1.88	-2.06	-2.19	-2.27	-2.36	-2.43	-2.41	-2.41	-2.36	-2.26	-2.11	-1.96	-1.88
14	-0.99	-1.12	-1.37	-1.59	-1.55	-1.45	-1.38	-1.39	-1.35	-1.24	-1.05	-0.99	-1.07	-1.23	-1.53	-1.77	-1.92	-2.10	-2.25	-2.33	-2.42	-2.52	-2.48	-2.42	-2.44	-2.35	-2.24	-2.13	-2.01	-1.91
15	-1.34	-1.90	-1.87	-1.98	-1.90	-1.74	-1.63	-1.62	-1.51	-1.32	-1.22	-1.20	-1.30	-1.57	-1.83	-2.08	-2.24	-2.38	-2.47	-2.55	-2.65	-2.63	-2.55	-2.52	-2.49	-2.39	-2.31	-2.24	-2.09	-2.01
16	-2.34	-2.42	-2.24	-2.30	-2.18	-1.98	-1.85	-1.76	-1.56	-1.46	-1.42	-1.42	-1.63	-1.86	-2.12	-2.37	-2.49	-2.58	-2.67	-2.76	-2.74	-2.68	-2.61	-2.54	-2.49	-2.42	-2.38	-2.28	-2.16	-2.08
17	-2.22	-2.33	-2.26	-2.33	-2.20	-2.00	-1.82	-1.64	-1.56	-1.53	-1.51	-1.62	-1.80	-2.04	-2.30	-2.51	-2.57	-2.67	-2.78	-2.76	-2.71	-2.67	-2.57	-2.48	-2.47	-2.44	-2.38	-2.30	-2.19	-2.07
18	-2.21	-2.39	-2.31	-2.38	-2.24	-1.98	-1.72	-1.65	-1.63	-1.64	-1.74	-1.82	-2.00	-2.24	-2.46	-2.60	-2.69	-2.79	-2.79	-2.73	-2.72	-2.65	-2.54	-2.50	-2.52	-2.46	-2.42	-2.35	-2.20	-2.05
19	-2.31	-2.39	-2.30	-2.38	-2.17	-1.83	-1.70	-1.69	-1.71	-1.84	-1.91	-2.00	-2.18	-2.37	-2.53	-2.68	-2.77	-2.77	-2.73	-2.71	-2.66	-2.59	-2.53	-2.51	-2.50	-2.47	-2.43	-2.34	-2.14	-2.05
20	-2.17	-2.33	-2.29	-2.31	-2.02	-1.83	-1.76	-1.80	-1.94	-2.05	-2.14	-2.22	-2.35	-2.48	-2.64	-2.81	-2.79	-2.75	-2.74	-2.69	-2.63	-2.59	-2.56	-2.51	-2.52	-2.49	-2.42	-2.28	-2.16	-2.02
21	-2.19	-2.37	-2.23	-2.18	-2.04	-1.91	-1.88	-2.06	-2.18	-2.29	-2.36	-2.40	-2.46	-2.60	-2.77	-2.82	-2.76	-2.77	-2.71	-2.65	-2.62	-2.61	-2.55	-2.52	-2.52	-2.46	-2.35	-2.27	-2.10	-1.96
22	-2.23	-2.25	-2.05	-2.19	-2.11	-2.04	-2.15	-2.30	-2.42	-2.51	-2.54	-2.51	-2.58	-2.72	-2.78	-2.79	-2.77	-2.74	-2.68	-2.65	-2.65	-2.61	-2.56	-2.52	-2.49	-2.38	-2.33	-2.22	-2.04	-1.93
23	-1.95	-1.99	-2.05	-2.26	-2.25	-2.33	-2.40	-2.56	-2.65	-2.70	-2.66	-2.64	-2.72	-2.75	-2.77	-2.81	-2.75	-2.71	-2.69	-2.69	-2.64	-2.61	-2.56	-2.48	-2.40	-2.36	-2.26	-2.14	-2.00	-1.90
24	-1.76	-2.11	-2.22	-2.46	-2.60	-2.63	-2.71	-2.83	-2.86	-2.84	-2.81	-2.80	-2.76	-2.75	-2.81	-2.81	-2.74	-2.73	-2.74	-2.70	-2.66	-2.62	-2.53	-2.42	-2.40	-2.31	-2.21	-2.12	-1.99	-1.92
25	-2.19	-2.44	-2.50	-2.90	-2.95	-2.98	-3.02	-3.06	-3.03	-3.01	-2.99	-2.86	-2.78	-2.81	-2.82	-2.81	-2.78	-2.80	-2.76	-2.73	-2.69	-2.61	-2.48	-2.42	-2.35	-2.26	-2.18	-2.10	-2.01	-1.93
26	-2.31	-2.60	-2.88	-3.20	-3.24	-3.22	-3.17	-3.15	-3.15	-3.14	-2.97	-2.81	-2.78	-2.77	-2.76	-2.81	-2.81	-2.79	-2.77	-2.73	-2.65	-2.53	-2.46	-2.36	-2.28	-2.21	-2.15	-2.11	-2.00	-1.92
27	-2.52	-3.10	-3.18	-3.48	-3.48	-3.36	-3.26	-3.28	-3.28	-3.12	-2.92	-2.81	-2.74	-2.72	-2.78	-2.86	-2.83	-2.81	-2.78	-2.70	-2.59	-2.53	-2.41	-2.30	-2.25	-2.19	-2.16	-2.10	-1.99	-1.92
28	-3.12	-3.35	-3.38	-3.66	-3.55	-3.39	-3.32	-3.34	-3.19	-3.00	-2.87	-2.71	-2.66	-2.71	-2.79	-2.85	-2.82	-2.80	-2.73	-2.61	-2.56	-2.45	-2.33	-2.24	-2.19	-2.17	-2.12	-2.06	-1.96	-1.91
29	-2.98	-3.28	-3.33	-3.53	-3.39	-3.29	-3.25	-3.12	-2.94	-2.84	-2.67	-2.53	-2.55	-2.63	-2.69	-2.75	-2.73	-2.68	-2.57	-2.51	-2.41	-2.29	-2.20	-2.12	-2.11	-2.07	-2.02	-1.98	-1.89	-1.82
30	-3.01	-3.32	-3.25	-3.39	-3.34	-3.26	-3.06	-2.90	-2.81	-2.66	-2.52	-2.45	-2.50	-2.55	-2.62	-2.68	-2.62	-2.53	-2.49	-2.38	-2.27	-2.17	-2.09	-2.05	-2.02	-1.98	-1.95	-1.91	-1.81	-1.75

Table 3-25: t-statistics for “lagged stock market return” in “forecasting model” for SPY

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.68	0.88	0.30	0.35	0.33	-0.14	0.12	0.50	0.47	0.48	0.49	-0.07	0.16	0.70	0.27	-0.12	-0.16	-0.03	-0.25	0.12	0.07	0.22	-0.07	-0.13	-0.30	-0.20	-0.61	-0.65	-0.95	-0.53
2	0.93	0.39	-0.15	-0.09	-0.37	-0.51	0.07	0.32	0.31	0.30	-0.04	-0.29	0.19	0.24	-0.28	-0.51	-0.40	-0.43	-0.28	-0.08	0.00	-0.07	-0.30	-0.43	-0.45	-0.59	-0.84	-1.04	-0.98	-0.46
3	0.38	-0.16	-0.74	-0.91	-0.97	-0.58	-0.04	0.15	0.16	-0.17	-0.38	-0.34	-0.21	-0.36	-0.77	-0.84	-0.83	-0.58	-0.46	-0.21	-0.28	-0.38	-0.65	-0.70	-0.88	-0.99	-1.30	-1.25	-0.96	-0.80
4	0.33	-0.15	-0.96	-0.91	-0.52	-0.18	0.10	0.24	-0.02	-0.24	-0.19	-0.40	-0.43	-0.57	-0.82	-0.96	-0.73	-0.55	-0.38	-0.28	-0.38	-0.51	-0.69	-0.86	-1.01	-1.20	-1.29	-1.07	-1.01	-0.63
5	0.38	-0.36	-0.93	-0.48	-0.16	-0.04	0.18	0.03	-0.14	-0.16	-0.36	-0.67	-0.70	-0.75	-1.04	-0.96	-0.76	-0.54	-0.49	-0.43	-0.55	-0.62	-0.89	-1.06	-1.26	-1.28	-1.21	-1.17	-0.89	-0.71
6	-0.05	-0.45	-0.54	-0.19	-0.08	0.03	-0.06	-0.13	-0.13	-0.38	-0.67	-0.94	-0.92	-1.03	-1.10	-1.02	-0.77	-0.67	-0.65	-0.63	-0.70	-0.87	-1.12	-1.36	-1.42	-1.31	-1.37	-1.13	-1.00	-0.87
7	0.17	0.09	-0.08	-0.01	0.09	-0.12	-0.13	-0.04	-0.24	-0.58	-0.86	-1.06	-1.11	-1.06	-1.11	-0.95	-0.81	-0.76	-0.76	-0.70	-0.87	-1.05	-1.38	-1.48	-1.41	-1.42	-1.27	-1.18	-1.08	-1.06
8	0.61	0.35	0.05	0.14	-0.05	-0.20	-0.04	-0.16	-0.46	-0.80	-1.02	-1.26	-1.16	-1.08	-1.04	-0.98	-0.89	-0.85	-0.82	-0.86	-1.05	-1.31	-1.51	-1.49	-1.52	-1.34	-1.31	-1.24	-1.25	-1.25
9	0.55	0.21	0.00	-0.22	-0.33	-0.28	-0.33	-0.54	-0.87	-1.13	-1.38	-1.47	-1.35	-1.19	-1.22	-1.20	-1.13	-1.05	-1.10	-1.17	-1.44	-1.57	-1.63	-1.70	-1.52	-1.46	-1.43	-1.46	-1.47	-1.50
10	0.35	0.15	-0.47	-0.56	-0.44	-0.60	-0.72	-0.95	-1.19	-1.49	-1.59	-1.66	-1.46	-1.39	-1.47	-1.45	-1.33	-1.34	-1.43	-1.57	-1.70	-1.70	-1.82	-1.67	-1.61	-1.55	-1.61	-1.64	-1.69	-1.72
11	0.51	-0.21	-0.71	-0.53	-0.65	-0.91	-1.03	-1.19	-1.48	-1.65	-1.72	-1.70	-1.59	-1.56	-1.63	-1.57	-1.53	-1.59	-1.73	-1.75	-1.76	-1.84	-1.75	-1.71	-1.65	-1.69	-1.75	-1.82	-1.86	-1.88
12	-0.33	-0.70	-0.81	-0.89	-1.11	-1.29	-1.34	-1.55	-1.70	-1.81	-1.81	-1.85	-1.77	-1.75	-1.79	-1.80	-1.81	-1.92	-1.95	-1.85	-1.92	-1.79	-1.80	-1.76	-1.79	-1.83	-1.92	-1.98	-2.01	-2.08
13	-0.22	-0.26	-0.77	-1.04	-1.23	-1.35	-1.48	-1.57	-1.70	-1.74	-1.78	-1.87	-1.80	-1.75	-1.85	-1.92	-2.00	-2.00	-1.91	-1.90	-1.77	-1.76	-1.77	-1.83	-1.88	-1.96	-2.04	-2.10	-2.17	-2.24
14	0.31	-0.33	-1.01	-1.23	-1.34	-1.55	-1.56	-1.62	-1.66	-1.76	-1.86	-1.95	-1.88	-1.88	-2.04	-2.16	-2.13	-2.03	-2.04	-1.83	-1.81	-1.80	-1.89	-1.95	-2.04	-2.11	-2.18	-2.27	-2.34	-2.39
15	-0.35	-0.96	-1.44	-1.50	-1.68	-1.74	-1.72	-1.68	-1.79	-1.94	-2.03	-2.10	-2.06	-2.14	-2.34	-2.37	-2.24	-2.23	-2.06	-1.96	-1.94	-2.00	-2.08	-2.16	-2.23	-2.28	-2.38	-2.46	-2.50	-2.56
16	-0.75	-1.18	-1.48	-1.66	-1.71	-1.75	-1.65	-1.69	-1.85	-1.99	-2.04	-2.16	-2.19	-2.32	-2.44	-2.39	-2.35	-2.16	-2.10	-2.02	-2.08	-2.13	-2.24	-2.31	-2.36	-2.44	-2.53	-2.58	-2.63	-2.68
17	-0.83	-1.05	-1.56	-1.62	-1.67	-1.63	-1.62	-1.72	-1.88	-1.98	-2.07	-2.24	-2.33	-2.40	-2.43	-2.46	-2.24	-2.17	-2.12	-2.11	-2.19	-2.27	-2.37	-2.42	-2.50	-2.57	-2.64	-2.69	-2.73	-2.78
18	-0.47	-1.13	-1.50	-1.56	-1.52	-1.60	-1.66	-1.75	-1.87	-2.00	-2.16	-2.40	-2.42	-2.41	-2.52	-2.36	-2.24	-2.18	-2.21	-2.23	-2.33	-2.40	-2.49	-2.58	-2.65	-2.69	-2.76	-2.81	-2.85	-2.90
19	-0.92	-1.24	-1.59	-1.51	-1.59	-1.74	-1.78	-1.82	-1.97	-2.19	-2.41	-2.57	-2.51	-2.56	-2.47	-2.40	-2.30	-2.32	-2.36	-2.41	-2.49	-2.55	-2.67	-2.75	-2.78	-2.83	-2.90	-2.95	-2.98	-3.00
20	-0.67	-1.13	-1.34	-1.44	-1.64	-1.78	-1.76	-1.85	-2.09	-2.38	-2.51	-2.57	-2.58	-2.43	-2.43	-2.37	-2.36	-2.41	-2.50	-2.53	-2.60	-2.70	-2.81	-2.86	-2.90	-2.95	-3.01	-3.06	-3.06	-3.05
21	-0.74	-0.91	-1.35	-1.58	-1.75	-1.80	-1.84	-2.02	-2.32	-2.51	-2.54	-2.65	-2.45	-2.40	-2.40	-2.44	-2.46	-2.55	-2.62	-2.64	-2.75	-2.85	-2.92	-2.97	-3.01	-3.05	-3.11	-3.12	-3.10	-3.08
22	-0.37	-0.90	-1.53	-1.69	-1.75	-1.86	-1.99	-2.21	-2.41	-2.48	-2.59	-2.48	-2.39	-2.34	-2.43	-2.49	-2.57	-2.64	-2.70	-2.78	-2.89	-2.94	-3.02	-3.06	-3.10	-3.14	-3.16	-3.15	-3.12	-3.10
23	-0.71	-1.30	-1.73	-1.76	-1.87	-2.07	-2.23	-2.36	-2.42	-2.57	-2.44	-2.44	-2.36	-2.41	-2.51	-2.64	-2.69	-2.75	-2.87	-2.95	-3.01	-3.06	-3.13	-3.17	-3.20	-3.20	-3.21	-3.19	-3.17	-3.14
24	-1.05	-1.36	-1.64	-1.78	-2.00	-2.23	-2.29	-2.31	-2.47	-2.36	-2.35	-2.35	-2.37	-2.44	-2.61	-2.71	-2.77	-2.89	-3.01	-3.05	-3.10	-3.15	-3.21	-3.24	-3.23	-3.22	-3.21	-3.21	-3.18	-3.17
25	-0.85	-1.05	-1.54	-1.84	-2.10	-2.22	-2.16	-2.29	-2.19	-2.21	-2.21	-2.31	-2.36	-2.50	-2.64	-2.75	-2.87	-3.01	-3.08	-3.11	-3.17	-3.21	-3.26	-3.25	-3.22	-3.20	-3.20	-3.19	-3.18	-3.19
26	-0.57	-1.01	-1.65	-2.06	-2.26	-2.33	-2.26	-2.33	-2.23	-2.24	-2.23	-2.31	-2.36	-2.46	-2.60	-2.75	-2.88	-3.00	-3.07	-3.11	-3.16	-3.19	-3.22	-3.19	-3.15	-3.13	-3.12	-3.12	-3.14	-3.14
27	-0.74	-1.34	-2.05	-2.33	-2.47	-2.50	-2.37	-2.44	-2.32	-2.33	-2.29	-2.36	-2.37	-2.46	-2.63	-2.80	-2.91	-3.02	-3.09	-3.13	-3.16	-3.16	-3.18	-3.14	-3.11	-3.08	-3.08	-3.11	-3.11	-3.10
28	-1.12	-1.76	-2.28	-2.48	-2.60	-2.57	-2.44	-2.49	-2.38	-2.35	-2.32	-2.34	-2.34	-2.47	-2.66	-2.80	-2.90	-3.00	-3.08	-3.10	-3.10	-3.09	-3.09	-3.06	-3.02	-3.00	-3.03	-3.04	-3.04	-3.06
29	-1.54	-1.97	-2.39	-2.57	-2.62	-2.59	-2.46	-2.52	-2.38	-2.36	-2.29	-2.30	-2.34	-2.49	-2.65	-2.78	-2.88	-2.98	-3.04	-3.03	-3.02	-3.00	-3.00	-2.97	-2.94	-2.95	-2.97	-2.98	-3.01	-3.02
30	-1.53	-1.99	-2.42	-2.52	-2.58	-2.56	-2.46	-2.48	-2.34	-2.29	-2.22	-2.28	-2.35	-2.47	-2.63	-2.75	-2.85	-2.93	-2.96	-2.94	-2.91	-2.90	-2.90	-2.88	-2.88	-2.88	-2.90	-2.95	-2.96	-2.97

Table 3-26: t-statistics for "financials" in "forecasting model" for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.79	2.47	1.81	2.61	2.75	2.44	2.59	2.59	2.86	2.27	2.12	1.63	1.51	1.85	1.79	1.83	1.67	1.57	1.61	1.88	1.79	1.91	2.06	1.89	2.40	2.75	2.89	2.67	2.27	2.14
2	2.57	2.21	2.35	2.76	2.71	2.50	2.50	2.56	2.34	1.96	1.59	1.28	1.39	1.51	1.51	1.44	1.31	1.25	1.42	1.52	1.53	1.68	1.66	1.82	2.32	2.59	2.55	2.21	1.95	1.92
3	1.85	2.05	2.14	2.05	2.13	2.02	2.10	1.80	1.64	1.22	0.94	0.88	0.92	1.11	1.05	0.97	0.92	0.98	1.10	1.22	1.35	1.33	1.51	1.75	2.17	2.25	2.10	1.81	1.64	1.71
4	2.12	2.07	1.75	1.72	1.80	1.80	1.59	1.39	1.10	0.75	0.65	0.58	0.70	0.80	0.74	0.71	0.75	0.79	0.92	1.11	1.11	1.25	1.49	1.72	1.96	1.93	1.77	1.55	1.49	1.63
5	2.06	1.62	1.49	1.51	1.60	1.36	1.21	0.90	0.62	0.43	0.35	0.37	0.44	0.51	0.48	0.52	0.56	0.63	0.81	0.88	1.01	1.20	1.45	1.57	1.69	1.62	1.48	1.36	1.39	1.46
6	1.36	1.29	1.26	1.31	1.16	1.01	0.75	0.45	0.29	0.14	0.15	0.15	0.21	0.27	0.31	0.35	0.41	0.53	0.61	0.79	0.97	1.18	1.33	1.36	1.42	1.37	1.30	1.26	1.24	1.29
7	1.36	1.31	1.25	1.05	0.96	0.70	0.41	0.21	0.06	0.01	0.00	0.00	0.05	0.17	0.20	0.26	0.37	0.41	0.58	0.80	1.00	1.13	1.18	1.18	1.24	1.24	1.23	1.15	1.13	1.21
8	1.41	1.32	0.98	0.89	0.67	0.40	0.20	0.01	-0.06	-0.14	-0.15	-0.15	-0.04	0.06	0.12	0.23	0.26	0.39	0.61	0.84	0.96	1.01	1.04	1.03	1.12	1.17	1.12	1.04	1.06	1.14
9	1.35	0.94	0.76	0.54	0.32	0.16	-0.03	-0.15	-0.25	-0.32	-0.33	-0.27	-0.17	-0.05	0.05	0.10	0.22	0.39	0.62	0.78	0.83	0.85	0.87	0.89	1.03	1.03	0.98	0.94	0.97	1.03
10	0.78	0.72	0.42	0.22	0.10	-0.05	-0.17	-0.31	-0.41	-0.47	-0.42	-0.36	-0.25	-0.08	-0.05	0.08	0.25	0.43	0.59	0.68	0.71	0.73	0.78	0.85	0.93	0.92	0.90	0.88	0.89	0.97
11	0.93	0.56	0.26	0.15	0.01	-0.08	-0.23	-0.37	-0.47	-0.48	-0.43	-0.37	-0.21	-0.12	0.00	0.16	0.35	0.46	0.56	0.63	0.66	0.70	0.79	0.82	0.89	0.90	0.90	0.86	0.89	0.97
12	0.34	0.14	0.01	-0.13	-0.23	-0.30	-0.43	-0.55	-0.59	-0.58	-0.51	-0.40	-0.31	-0.14	0.02	0.21	0.32	0.38	0.46	0.53	0.58	0.66	0.72	0.75	0.84	0.87	0.85	0.83	0.86	0.93
13	0.11	0.06	-0.13	-0.24	-0.32	-0.39	-0.51	-0.57	-0.60	-0.57	-0.46	-0.42	-0.25	-0.04	0.13	0.24	0.30	0.35	0.42	0.52	0.62	0.66	0.73	0.78	0.87	0.89	0.89	0.87	0.88	0.99
14	0.20	-0.03	-0.18	-0.28	-0.37	-0.44	-0.51	-0.57	-0.57	-0.49	-0.46	-0.33	-0.13	0.09	0.19	0.25	0.29	0.33	0.43	0.57	0.63	0.69	0.77	0.83	0.91	0.94	0.93	0.90	0.96	1.02
15	-0.07	-0.16	-0.27	-0.37	-0.47	-0.48	-0.55	-0.56	-0.51	-0.52	-0.39	-0.22	-0.01	0.12	0.17	0.22	0.26	0.32	0.46	0.57	0.63	0.71	0.80	0.85	0.94	0.96	0.94	0.95	0.97	1.06
16	0.03	-0.10	-0.20	-0.33	-0.41	-0.43	-0.46	-0.45	-0.48	-0.39	-0.22	-0.06	0.07	0.15	0.17	0.19	0.27	0.36	0.46	0.58	0.67	0.75	0.83	0.90	0.98	0.99	1.00	0.98	1.02	1.08
17	-0.08	-0.15	-0.25	-0.38	-0.44	-0.40	-0.41	-0.46	-0.40	-0.26	-0.08	-0.01	0.07	0.13	0.13	0.17	0.28	0.34	0.45	0.59	0.69	0.77	0.87	0.93	1.00	1.04	1.02	1.03	1.05	1.09
18	-0.06	-0.22	-0.31	-0.46	-0.43	-0.37	-0.43	-0.39	-0.26	-0.12	-0.01	0.01	0.07	0.09	0.11	0.19	0.25	0.34	0.46	0.62	0.71	0.81	0.90	0.96	1.05	1.07	1.08	1.07	1.08	1.12
19	-0.28	-0.34	-0.46	-0.49	-0.42	-0.42	-0.38	-0.27	-0.13	-0.06	-0.01	0.00	0.03	0.06	0.11	0.16	0.24	0.34	0.49	0.63	0.75	0.84	0.92	0.99	1.06	1.10	1.11	1.09	1.10	1.20
20	-0.28	-0.42	-0.40	-0.40	-0.41	-0.31	-0.20	-0.08	-0.03	-0.02	0.02	0.00	0.03	0.10	0.12	0.18	0.28	0.40	0.53	0.70	0.81	0.89	0.99	1.03	1.12	1.15	1.14	1.13	1.20	1.27
21	-0.47	-0.36	-0.32	-0.40	-0.30	-0.12	-0.02	0.01	0.00	0.00	-0.01	-0.01	0.06	0.10	0.14	0.22	0.34	0.44	0.60	0.76	0.85	0.95	1.02	1.09	1.16	1.18	1.18	1.22	1.25	1.32
22	-0.23	-0.17	-0.29	-0.23	-0.05	0.11	0.12	0.09	0.06	0.01	0.01	0.04	0.08	0.15	0.21	0.31	0.41	0.55	0.70	0.84	0.94	1.01	1.10	1.16	1.22	1.24	1.29	1.30	1.33	1.38
23	-0.18	-0.15	-0.06	0.04	0.21	0.26	0.22	0.14	0.07	0.03	0.09	0.10	0.16	0.23	0.31	0.39	0.52	0.64	0.77	0.91	0.99	1.08	1.16	1.20	1.27	1.35	1.37	1.37	1.39	1.43
24	-0.21	0.12	0.25	0.32	0.37	0.36	0.26	0.16	0.09	0.11	0.14	0.17	0.24	0.32	0.39	0.51	0.62	0.72	0.85	0.96	1.06	1.14	1.20	1.26	1.38	1.43	1.45	1.44	1.44	1.48
25	0.30	0.54	0.58	0.49	0.46	0.40	0.27	0.18	0.18	0.17	0.22	0.25	0.34	0.41	0.51	0.60	0.70	0.80	0.91	1.04	1.13	1.20	1.27	1.38	1.47	1.52	1.52	1.49	1.50	1.53
26	0.56	0.74	0.60	0.45	0.38	0.29	0.20	0.16	0.14	0.17	0.23	0.29	0.37	0.47	0.56	0.64	0.74	0.82	0.95	1.07	1.14	1.22	1.35	1.43	1.51	1.55	1.53	1.52	1.51	1.55
27	0.69	0.63	0.47	0.30	0.19	0.16	0.14	0.09	0.11	0.14	0.23	0.29	0.41	0.51	0.59	0.67	0.75	0.85	0.97	1.08	1.17	1.30	1.40	1.47	1.54	1.56	1.55	1.52	1.53	1.54
28	0.42	0.40	0.24	0.05	0.03	0.08	0.05	0.04	0.07	0.14	0.23	0.33	0.45	0.55	0.62	0.68	0.78	0.87	0.98	1.11	1.25	1.35	1.44	1.50	1.56	1.58	1.55	1.54	1.53	1.52
29	0.21	0.17	0.01	-0.09	0.00	0.04	0.03	0.03	0.10	0.16	0.29	0.38	0.48	0.57	0.62	0.69	0.79	0.87	0.99	1.17	1.28	1.38	1.46	1.50	1.55	1.56	1.55	1.51	1.48	1.50
30	-0.01	-0.04	-0.08	-0.04	0.02	0.07	0.05	0.10	0.16	0.26	0.37	0.43	0.52	0.59	0.65	0.72	0.80	0.89	1.06	1.21	1.32	1.41	1.47	1.50	1.53	1.55	1.51	1.47	1.46	1.44

Table 3-27: t-statistics for "corporates" in "forecasting model" for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-0.21	-0.46	-0.25	-0.85	-0.99	-1.31	-1.01	-1.37	-1.26	-1.22	-1.04	-1.35	-1.25	-1.15	-1.04	-1.22	-1.24	-1.25	-1.40	-1.32	-1.30	-1.07	-1.23	-1.19	-1.33	-1.43	-1.40	-1.80	-1.91	-1.70
2	-0.41	-0.23	-0.56	-1.02	-1.18	-1.12	-1.05	-1.41	-1.46	-1.23	-1.40	-1.68	-1.57	-1.55	-1.59	-1.63	-1.61	-1.78	-2.00	-1.86	-1.73	-1.58	-1.77	-1.81	-1.94	-1.83	-2.00	-2.35	-2.36	-2.24
3	-0.05	-0.47	-0.81	-1.18	-1.11	-1.13	-1.19	-1.51	-1.38	-1.44	-1.62	-1.78	-1.75	-1.81	-1.77	-1.79	-1.90	-2.12	-2.22	-2.03	-1.92	-1.87	-2.06	-2.12	-2.08	-2.14	-2.33	-2.54	-2.53	-2.48
4	-0.64	-0.89	-1.10	-1.23	-1.22	-1.27	-1.41	-1.53	-1.64	-1.73	-1.87	-2.05	-2.07	-2.05	-2.01	-2.12	-2.29	-2.41	-2.40	-2.23	-2.18	-2.17	-2.33	-2.25	-2.33	-2.42	-2.54	-2.69	-2.71	-2.69
5	-0.82	-0.99	-0.97	-1.16	-1.21	-1.35	-1.33	-1.66	-1.79	-1.84	-2.00	-2.19	-2.16	-2.13	-2.19	-2.36	-2.45	-2.46	-2.44	-2.35	-2.33	-2.32	-2.33	-2.38	-2.50	-2.53	-2.61	-2.75	-2.79	-2.79
6	-0.88	-0.77	-0.88	-1.16	-1.30	-1.27	-1.49	-1.80	-1.89	-1.97	-2.13	-2.25	-2.21	-2.27	-2.40	-2.49	-2.48	-2.48	-2.51	-2.45	-2.42	-2.31	-2.43	-2.53	-2.60	-2.61	-2.69	-2.83	-2.88	-2.81
7	-0.43	-0.61	-0.85	-1.24	-1.21	-1.42	-1.64	-1.88	-1.97	-2.08	-2.19	-2.29	-2.33	-2.45	-2.51	-2.51	-2.49	-2.54	-2.58	-2.52	-2.39	-2.40	-2.55	-2.61	-2.65	-2.67	-2.75	-2.90	-2.88	-2.81
8	-0.49	-0.71	-1.03	-1.19	-1.41	-1.58	-1.73	-1.99	-2.14	-2.17	-2.31	-2.47	-2.57	-2.64	-2.61	-2.60	-2.64	-2.69	-2.73	-2.57	-2.53	-2.59	-2.71	-2.75	-2.79	-2.81	-2.90	-2.97	-2.94	-2.90
9	-0.55	-0.90	-0.95	-1.40	-1.56	-1.66	-1.85	-2.16	-2.24	-2.31	-2.52	-2.76	-2.81	-2.78	-2.73	-2.78	-2.81	-2.85	-2.79	-2.72	-2.74	-2.77	-2.87	-2.91	-2.94	-2.98	-3.00	-3.05	-3.04	-2.95
10	-0.74	-0.76	-1.16	-1.52	-1.63	-1.77	-2.02	-2.27	-2.37	-2.53	-2.81	-3.00	-2.94	-2.89	-2.91	-2.97	-2.98	-2.92	-2.94	-2.93	-2.91	-2.94	-3.03	-3.06	-3.10	-3.08	-3.09	-3.15	-3.09	-2.94
11	-0.36	-0.98	-1.27	-1.57	-1.72	-1.95	-2.14	-2.39	-2.59	-2.82	-3.04	-3.11	-3.04	-3.05	-3.09	-3.11	-3.02	-3.05	-3.12	-3.08	-3.06	-3.09	-3.16	-3.21	-3.19	-3.17	-3.19	-3.21	-3.09	-2.96
12	-1.12	-1.36	-1.50	-1.81	-2.06	-2.21	-2.40	-2.74	-2.99	-3.16	-3.26	-3.31	-3.29	-3.31	-3.31	-3.22	-3.22	-3.30	-3.33	-3.29	-3.25	-3.27	-3.36	-3.34	-3.32	-3.31	-3.29	-3.24	-3.15	-3.03
13	-1.15	-1.29	-1.51	-1.94	-2.14	-2.28	-2.59	-3.00	-3.20	-3.25	-3.33	-3.45	-3.44	-3.44	-3.34	-3.35	-3.41	-3.45	-3.48	-3.42	-3.37	-3.41	-3.42	-3.41	-3.40	-3.36	-3.27	-3.24	-3.16	-3.09
14	-0.96	-1.27	-1.63	-1.99	-2.18	-2.46	-2.85	-3.21	-3.29	-3.33	-3.48	-3.61	-3.59	-3.48	-3.49	-3.56	-3.59	-3.62	-3.63	-3.55	-3.52	-3.48	-3.50	-3.50	-3.47	-3.36	-3.30	-3.26	-3.22	-3.17
15	-1.24	-1.64	-1.84	-2.17	-2.52	-2.86	-3.18	-3.39	-3.45	-3.56	-3.70	-3.80	-3.66	-3.66	-3.73	-3.76	-3.78	-3.79	-3.79	-3.72	-3.62	-3.59	-3.62	-3.58	-3.48	-3.39	-3.33	-3.34	-3.31	-3.20
16	-1.54	-1.72	-1.90	-2.43	-2.84	-3.12	-3.29	-3.49	-3.63	-3.73	-3.84	-3.83	-3.80	-3.86	-3.89	-3.91	-3.92	-3.92	-3.92	-3.78	-3.69	-3.69	-3.67	-3.56	-3.48	-3.39	-3.38	-3.39	-3.32	-3.21
17	-1.71	-1.77	-2.25	-2.86	-3.14	-3.25	-3.40	-3.66	-3.78	-3.84	-3.84	-3.92	-3.98	-4.03	-4.05	-4.07	-4.05	-4.07	-3.99	-3.87	-3.84	-3.77	-3.69	-3.59	-3.50	-3.46	-3.43	-3.41	-3.34	-3.20
18	-1.62	-2.17	-2.68	-3.14	-3.24	-3.33	-3.56	-3.79	-3.85	-3.80	-3.89	-4.06	-4.12	-4.17	-4.18	-4.17	-4.17	-4.10	-4.04	-3.99	-3.90	-3.75	-3.68	-3.59	-3.54	-3.49	-3.42	-3.40	-3.29	-3.14
19	-2.44	-2.78	-3.08	-3.31	-3.38	-3.52	-3.71	-3.87	-3.83	-3.88	-4.05	-4.20	-4.26	-4.29	-4.27	-4.27	-4.18	-4.14	-4.14	-4.03	-3.85	-3.73	-3.66	-3.62	-3.56	-3.46	-3.40	-3.34	-3.23	-3.02
20	-2.69	-2.95	-3.02	-3.26	-3.43	-3.54	-3.67	-3.73	-3.79	-3.93	-4.09	-4.25	-4.28	-4.28	-4.27	-4.20	-4.13	-4.16	-4.11	-3.91	-3.76	-3.64	-3.63	-3.57	-3.47	-3.38	-3.29	-3.22	-3.04	-2.84
21	-2.82	-2.74	-2.88	-3.24	-3.38	-3.42	-3.44	-3.59	-3.76	-3.90	-4.07	-4.19	-4.20	-4.21	-4.13	-4.08	-4.09	-4.06	-3.92	-3.75	-3.62	-3.55	-3.52	-3.43	-3.34	-3.22	-3.12	-3.00	-2.83	-2.64
22	-2.36	-2.51	-2.86	-3.18	-3.24	-3.18	-3.31	-3.58	-3.74	-3.89	-4.04	-4.13	-4.15	-4.07	-4.02	-4.05	-4.00	-3.87	-3.76	-3.61	-3.53	-3.45	-3.39	-3.30	-3.18	-3.06	-2.90	-2.78	-2.64	-2.47
23	-2.42	-2.67	-2.88	-3.11	-3.05	-3.11	-3.36	-3.62	-3.79	-3.91	-4.01	-4.11	-4.04	-4.00	-4.03	-4.00	-3.86	-3.76	-3.66	-3.57	-3.47	-3.36	-3.30	-3.18	-3.05	-2.88	-2.73	-2.63	-2.49	-2.32
24	-2.65	-2.66	-2.77	-2.87	-2.95	-3.14	-3.38	-3.65	-3.78	-3.85	-3.96	-3.96	-3.92	-3.97	-3.94	-3.82	-3.70	-3.63	-3.58	-3.47	-3.34	-3.24	-3.15	-3.03	-2.84	-2.67	-2.55	-2.46	-2.33	-2.19
25	-2.45	-2.44	-2.46	-2.75	-2.97	-3.16	-3.40	-3.62	-3.70	-3.78	-3.79	-3.83	-3.88	-3.86	-3.74	-3.65	-3.56	-3.53	-3.48	-3.33	-3.22	-3.09	-2.99	-2.81	-2.64	-2.50	-2.38	-2.30	-2.20	-2.07
26	-2.22	-2.06	-2.34	-2.79	-3.02	-3.21	-3.40	-3.57	-3.64	-3.63	-3.66	-3.78	-3.77	-3.65	-3.56	-3.49	-3.45	-3.41	-3.32	-3.20	-3.06	-2.92	-2.76	-2.60	-2.45	-2.33	-2.21	-2.16	-2.07	-1.95
27	-1.79	-2.06	-2.54	-2.96	-3.17	-3.28	-3.41	-3.56	-3.53	-3.54	-3.65	-3.69	-3.59	-3.50	-3.42	-3.40	-3.35	-3.28	-3.20	-3.05	-2.90	-2.72	-2.58	-2.44	-2.31	-2.18	-2.11	-2.06	-1.97	-1.84
28	-2.19	-2.54	-2.88	-3.26	-3.36	-3.37	-3.47	-3.51	-3.51	-3.58	-3.62	-3.56	-3.47	-3.40	-3.38	-3.35	-3.26	-3.20	-3.10	-2.94	-2.73	-2.56	-2.44	-2.31	-2.19	-2.10	-2.02	-1.98	-1.88	-1.77
29	-2.72	-2.81	-3.10	-3.35	-3.35	-3.35	-3.35	-3.42	-3.48	-3.49	-3.43	-3.40	-3.34	-3.32	-3.28	-3.22	-3.15	-3.06	-2.95	-2.74	-2.55	-2.40	-2.29	-2.17	-2.08	-1.99	-1.92	-1.87	-1.79	-1.69
30	-2.68	-2.88	-3.04	-3.19	-3.20	-3.12	-3.16	-3.30	-3.31	-3.23	-3.20	-3.21	-3.20	-3.18	-3.11	-3.07	-2.98	-2.88	-2.72	-2.52	-2.36	-2.23	-2.12	-2.04	-1.96	-1.87	-1.80	-1.76	-1.69	-1.61

Table 3-28: t-statistics for "internal" in "forecasting model" for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-1.13	-1.17	-0.39	-0.77	-0.73	-0.35	-0.10	-0.24	-0.65	-0.97	-1.13	-1.27	-1.30	-1.95	-2.21	-1.87	-1.35	-1.65	-1.60	-1.47	-1.37	-1.17	-0.86	-0.99	-0.68	-0.27	-0.21	-0.18	-0.38	-0.42
2	-1.10	-0.38	-0.29	-0.44	-0.27	0.05	0.09	-0.29	-0.69	-0.98	-1.20	-1.32	-1.68	-2.17	-2.12	-1.66	-1.54	-1.70	-1.56	-1.43	-1.26	-0.98	-0.91	-0.79	-0.39	-0.15	-0.14	-0.28	-0.39	-0.38
3	-0.23	-0.21	-0.10	-0.13	0.06	0.20	-0.02	-0.43	-0.80	-1.13	-1.31	-1.64	-2.02	-2.23	-1.97	-1.76	-1.66	-1.69	-1.57	-1.38	-1.14	-1.01	-0.80	-0.56	-0.27	-0.12	-0.23	-0.32	-0.38	-0.35
4	-0.57	-0.37	-0.16	-0.12	-0.02	-0.10	-0.36	-0.75	-1.13	-1.42	-1.76	-2.13	-2.32	-2.26	-2.15	-1.98	-1.83	-1.84	-1.66	-1.40	-1.25	-1.01	-0.73	-0.52	-0.31	-0.30	-0.36	-0.42	-0.46	-0.33
5	-0.46	-0.20	-0.01	-0.03	-0.15	-0.31	-0.57	-0.98	-1.32	-1.74	-2.12	-2.34	-2.30	-2.32	-2.24	-2.04	-1.90	-1.83	-1.59	-1.41	-1.16	-0.86	-0.61	-0.47	-0.38	-0.36	-0.40	-0.44	-0.38	-0.31
6	-0.36	-0.21	-0.10	-0.35	-0.58	-0.69	-1.00	-1.35	-1.80	-2.23	-2.45	-2.46	-2.47	-2.49	-2.37	-2.19	-2.01	-1.85	-1.66	-1.38	-1.07	-0.81	-0.61	-0.56	-0.48	-0.45	-0.46	-0.43	-0.42	-0.39
7	-0.47	-0.33	-0.47	-0.80	-0.94	-1.12	-1.38	-1.83	-2.30	-2.58	-2.63	-2.68	-2.68	-2.65	-2.53	-2.29	-2.04	-1.93	-1.64	-1.30	-1.02	-0.81	-0.71	-0.66	-0.57	-0.52	-0.47	-0.47	-0.49	-0.46
8	-0.43	-0.61	-0.86	-1.07	-1.26	-1.41	-1.79	-2.26	-2.60	-2.72	-2.79	-2.83	-2.79	-2.75	-2.57	-2.27	-2.06	-1.84	-1.50	-1.19	-0.95	-0.83	-0.73	-0.68	-0.58	-0.47	-0.46	-0.49	-0.51	-0.46
9	-0.92	-1.11	-1.18	-1.44	-1.60	-1.88	-2.28	-2.64	-2.82	-2.96	-3.04	-3.04	-2.98	-2.87	-2.62	-2.35	-2.04	-1.76	-1.45	-1.18	-1.02	-0.90	-0.80	-0.73	-0.58	-0.52	-0.54	-0.56	-0.56	-0.51
10	-1.30	-1.28	-1.44	-1.68	-1.99	-2.31	-2.59	-2.80	-3.00	-3.16	-3.19	-3.18	-3.05	-2.87	-2.65	-2.29	-1.92	-1.66	-1.40	-1.20	-1.04	-0.92	-0.81	-0.69	-0.58	-0.55	-0.57	-0.58	-0.58	-0.51
11	-1.30	-1.46	-1.60	-2.03	-2.37	-2.55	-2.70	-2.93	-3.16	-3.28	-3.28	-3.20	-2.99	-2.84	-2.53	-2.11	-1.78	-1.57	-1.36	-1.17	-1.02	-0.89	-0.73	-0.66	-0.59	-0.56	-0.57	-0.58	-0.55	-0.50
12	-1.65	-1.70	-2.05	-2.49	-2.67	-2.70	-2.87	-3.12	-3.31	-3.39	-3.33	-3.17	-2.98	-2.73	-2.37	-1.99	-1.70	-1.55	-1.34	-1.16	-1.00	-0.83	-0.71	-0.66	-0.60	-0.56	-0.57	-0.56	-0.55	-0.54
13	-1.74	-2.12	-2.46	-2.70	-2.72	-2.78	-2.98	-3.20	-3.36	-3.37	-3.22	-3.10	-2.82	-2.52	-2.18	-1.87	-1.64	-1.49	-1.30	-1.11	-0.90	-0.76	-0.68	-0.64	-0.57	-0.53	-0.52	-0.52	-0.55	-0.52
14	-2.38	-2.59	-2.63	-2.69	-2.76	-2.86	-3.03	-3.21	-3.29	-3.22	-3.11	-2.90	-2.57	-2.30	-2.04	-1.78	-1.56	-1.42	-1.23	-0.98	-0.82	-0.72	-0.64	-0.59	-0.52	-0.47	-0.47	-0.51	-0.52	-0.50
15	-2.60	-2.48	-2.41	-2.57	-2.71	-2.81	-2.95	-3.07	-3.08	-3.05	-2.85	-2.56	-2.27	-2.07	-1.86	-1.62	-1.41	-1.27	-1.03	-0.83	-0.71	-0.61	-0.53	-0.47	-0.39	-0.35	-0.40	-0.43	-0.44	-0.39
16	-2.22	-2.11	-2.21	-2.47	-2.63	-2.71	-2.80	-2.85	-2.90	-2.78	-2.48	-2.24	-2.02	-1.88	-1.67	-1.45	-1.24	-1.05	-0.86	-0.70	-0.58	-0.48	-0.40	-0.32	-0.25	-0.26	-0.30	-0.33	-0.31	-0.28
17	-1.97	-2.06	-2.25	-2.54	-2.65	-2.66	-2.68	-2.77	-2.72	-2.49	-2.23	-2.04	-1.88	-1.74	-1.55	-1.33	-1.06	-0.92	-0.77	-0.61	-0.50	-0.39	-0.29	-0.23	-0.20	-0.20	-0.25	-0.25	-0.25	-0.24
18	-2.17	-2.27	-2.46	-2.67	-2.67	-2.59	-2.65	-2.62	-2.45	-2.25	-2.05	-1.92	-1.77	-1.65	-1.46	-1.18	-0.96	-0.86	-0.70	-0.55	-0.43	-0.30	-0.22	-0.20	-0.17	-0.18	-0.19	-0.21	-0.22	-0.21
19	-2.35	-2.42	-2.56	-2.63	-2.54	-2.52	-2.46	-2.31	-2.18	-2.05	-1.91	-1.78	-1.65	-1.53	-1.27	-1.03	-0.85	-0.75	-0.60	-0.45	-0.29	-0.19	-0.16	-0.15	-0.12	-0.10	-0.12	-0.16	-0.17	-0.09
20	-2.47	-2.46	-2.44	-2.43	-2.42	-2.28	-2.09	-1.98	-1.93	-1.86	-1.73	-1.63	-1.50	-1.32	-1.10	-0.91	-0.74	-0.63	-0.48	-0.30	-0.18	-0.12	-0.10	-0.09	-0.04	-0.03	-0.07	-0.10	-0.04	0.03
21	-2.42	-2.19	-2.14	-2.21	-2.10	-1.84	-1.73	-1.69	-1.72	-1.67	-1.59	-1.48	-1.28	-1.14	-0.96	-0.77	-0.59	-0.49	-0.30	-0.17	-0.10	-0.06	-0.04	-0.01	0.04	0.03	-0.01	0.01	0.07	0.15
22	-2.05	-1.82	-1.93	-1.87	-1.63	-1.46	-1.43	-1.46	-1.51	-1.50	-1.43	-1.26	-1.11	-0.99	-0.80	-0.60	-0.43	-0.28	-0.14	-0.06	-0.02	0.01	0.06	0.09	0.11	0.09	0.12	0.13	0.20	0.23
23	-1.73	-1.68	-1.57	-1.38	-1.25	-1.18	-1.21	-1.29	-1.37	-1.38	-1.23	-1.10	-0.96	-0.85	-0.65	-0.46	-0.25	-0.15	-0.07	-0.02	0.02	0.08	0.12	0.13	0.15	0.20	0.21	0.24	0.25	0.27
24	-1.77	-1.33	-1.08	-1.02	-1.01	-1.01	-1.09	-1.20	-1.29	-1.21	-1.10	-0.99	-0.86	-0.73	-0.55	-0.31	-0.15	-0.12	-0.05	-0.01	0.05	0.12	0.14	0.15	0.23	0.26	0.28	0.26	0.27	0.27
25	-1.13	-0.69	-0.67	-0.77	-0.85	-0.90	-1.02	-1.13	-1.13	-1.10	-1.00	-0.90	-0.75	-0.64	-0.40	-0.22	-0.12	-0.10	-0.05	0.03	0.09	0.13	0.16	0.23	0.30	0.34	0.31	0.28	0.26	0.22
26	-0.58	-0.45	-0.59	-0.78	-0.88	-0.97	-1.08	-1.08	-1.12	-1.09	-0.99	-0.87	-0.74	-0.56	-0.37	-0.25	-0.16	-0.15	-0.07	0.01	0.05	0.10	0.19	0.25	0.32	0.31	0.27	0.22	0.17	0.15
27	-0.61	-0.61	-0.78	-0.95	-1.08	-1.14	-1.12	-1.17	-1.20	-1.17	-1.05	-0.93	-0.72	-0.58	-0.46	-0.35	-0.27	-0.22	-0.13	-0.07	-0.01	0.09	0.17	0.24	0.26	0.24	0.18	0.10	0.07	0.04
28	-0.82	-0.83	-0.95	-1.16	-1.24	-1.17	-1.20	-1.23	-1.26	-1.20	-1.09	-0.89	-0.73	-0.64	-0.54	-0.43	-0.32	-0.26	-0.19	-0.12	0.00	0.10	0.18	0.20	0.22	0.18	0.08	0.02	-0.02	-0.05
29	-1.01	-0.96	-1.13	-1.28	-1.22	-1.21	-1.23	-1.26	-1.25	-1.21	-1.02	-0.87	-0.77	-0.71	-0.60	-0.46	-0.34	-0.30	-0.23	-0.09	0.02	0.13	0.16	0.17	0.16	0.09	0.01	-0.06	-0.11	-0.11
30	-1.05	-1.11	-1.21	-1.18	-1.20	-1.18	-1.21	-1.21	-1.21	-1.09	-0.95	-0.88	-0.81	-0.74	-0.60	-0.46	-0.36	-0.31	-0.17	-0.05	0.07	0.12	0.15	0.13	0.09	0.03	-0.06	-0.13	-0.15	-0.16

Table 3-29: t-statistics for "interbank" in "forecasting model" for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.30	1.11	0.66	0.34	-0.05	0.03	0.37	0.56	0.92	0.84	0.70	0.68	0.92	0.96	1.14	1.11	1.20	1.39	0.88	0.95	1.23	1.34	1.18	1.25	1.13	1.28	1.34	1.28	1.46	1.24
2	0.70	0.67	0.07	-0.18	-0.26	-0.02	0.43	0.76	0.95	0.76	0.64	0.67	0.71	0.85	1.10	1.16	1.30	1.37	1.02	1.18	1.41	1.37	1.23	1.32	1.20	1.33	1.33	1.35	1.30	1.25
3	0.82	0.48	-0.09	-0.16	-0.07	0.27	0.76	0.95	0.99	0.82	0.77	0.72	0.84	1.05	1.26	1.34	1.41	1.42	1.27	1.43	1.52	1.45	1.38	1.40	1.34	1.40	1.44	1.34	1.36	1.32
4	0.56	0.29	-0.05	-0.02	0.18	0.62	0.97	1.03	1.02	0.91	0.81	0.85	1.06	1.27	1.46	1.50	1.52	1.61	1.52	1.57	1.63	1.58	1.48	1.54	1.47	1.56	1.51	1.46	1.46	1.43
5	0.46	0.37	0.15	0.28	0.57	0.89	1.08	1.10	1.12	0.96	0.95	1.09	1.30	1.48	1.62	1.62	1.70	1.79	1.65	1.68	1.74	1.66	1.61	1.64	1.63	1.63	1.61	1.57	1.56	1.57
6	0.66	0.60	0.50	0.68	0.88	1.04	1.15	1.18	1.15	1.07	1.17	1.32	1.51	1.63	1.73	1.79	1.88	1.90	1.76	1.79	1.80	1.76	1.70	1.75	1.67	1.70	1.67	1.63	1.65	1.68
7	0.83	0.90	0.88	0.97	1.02	1.10	1.22	1.20	1.22	1.25	1.37	1.52	1.67	1.75	1.89	1.96	1.99	1.98	1.87	1.85	1.89	1.84	1.81	1.80	1.76	1.78	1.76	1.74	1.78	1.79
8	1.22	1.31	1.16	1.10	1.09	1.17	1.25	1.27	1.38	1.45	1.54	1.66	1.76	1.89	2.03	2.05	2.05	2.05	1.91	1.93	1.95	1.92	1.83	1.84	1.80	1.82	1.84	1.84	1.86	1.83
9	1.57	1.47	1.19	1.09	1.10	1.15	1.26	1.38	1.52	1.58	1.65	1.72	1.87	2.00	2.08	2.08	2.09	2.06	1.95	1.95	1.99	1.91	1.85	1.86	1.83	1.88	1.90	1.90	1.87	1.85
10	1.55	1.32	1.02	0.98	0.99	1.09	1.31	1.45	1.56	1.61	1.64	1.76	1.90	1.97	2.03	2.04	2.01	2.01	1.91	1.93	1.92	1.86	1.81	1.82	1.82	1.88	1.90	1.85	1.84	1.83
11	1.27	1.10	0.87	0.85	0.95	1.16	1.40	1.54	1.63	1.63	1.71	1.83	1.91	1.96	2.03	2.02	2.02	2.01	1.94	1.90	1.90	1.85	1.80	1.84	1.86	1.90	1.88	1.85	1.85	1.88
12	1.14	1.06	0.86	0.93	1.14	1.34	1.56	1.66	1.71	1.75	1.83	1.89	1.95	2.01	2.06	2.07	2.06	2.08	1.94	1.93	1.93	1.88	1.86	1.92	1.92	1.93	1.92	1.90	1.93	1.94
13	1.22	1.12	1.03	1.22	1.39	1.56	1.73	1.78	1.85	1.89	1.91	1.95	2.01	2.05	2.12	2.12	2.13	2.08	1.97	1.96	1.96	1.95	1.95	1.99	1.95	1.97	1.97	1.98	1.99	1.99
14	1.25	1.34	1.38	1.51	1.65	1.76	1.86	1.93	2.00	1.98	1.99	2.02	2.06	2.11	2.17	2.18	2.14	2.10	2.00	1.98	2.02	2.02	2.01	2.01	1.98	2.00	2.02	2.02	2.02	2.03
15	1.65	1.76	1.73	1.78	1.85	1.89	2.03	2.09	2.10	2.06	2.06	2.07	2.13	2.17	2.24	2.19	2.16	2.12	2.02	2.04	2.09	2.09	2.04	2.05	2.02	2.07	2.08	2.06	2.07	2.07
16	2.01	2.03	1.91	1.90	1.92	2.00	2.14	2.13	2.13	2.10	2.09	2.13	2.17	2.23	2.23	2.19	2.16	2.13	2.07	2.11	2.14	2.10	2.06	2.07	2.07	2.10	2.10	2.09	2.09	2.09
17	2.10	2.07	1.89	1.84	1.93	2.02	2.10	2.10	2.11	2.08	2.10	2.14	2.19	2.18	2.19	2.17	2.14	2.15	2.11	2.13	2.13	2.09	2.05	2.09	2.08	2.10	2.12	2.10	2.09	2.09
18	2.13	2.03	1.82	1.85	1.94	1.99	2.07	2.09	2.10	2.11	2.13	2.17	2.16	2.17	2.19	2.16	2.17	2.20	2.15	2.13	2.13	2.10	2.09	2.12	2.10	2.15	2.15	2.12	2.12	2.13
19	2.00	1.91	1.81	1.87	1.90	1.95	2.05	2.07	2.12	2.13	2.15	2.13	2.12	2.13	2.15	2.17	2.21	2.22	2.13	2.12	2.11	2.12	2.10	2.12	2.12	2.15	2.15	2.13	2.14	2.17
20	1.98	1.98	1.95	1.90	1.92	1.98	2.07	2.13	2.17	2.17	2.13	2.11	2.11	2.13	2.18	2.22	2.24	2.21	2.13	2.12	2.16	2.15	2.12	2.16	2.15	2.17	2.17	2.17	2.20	2.25
21	2.11	2.15	1.98	1.92	1.93	1.99	2.12	2.17	2.20	2.14	2.10	2.09	2.10	2.15	2.23	2.25	2.23	2.21	2.12	2.14	2.17	2.15	2.14	2.17	2.15	2.18	2.19	2.21	2.25	2.28
22	2.36	2.16	1.98	1.92	1.94	2.04	2.16	2.17	2.16	2.10	2.07	2.07	2.12	2.19	2.25	2.23	2.21	2.18	2.14	2.15	2.16	2.16	2.14	2.16	2.14	2.19	2.22	2.25	2.27	2.30
23	2.11	2.00	1.86	1.84	1.92	2.03	2.11	2.09	2.07	2.03	2.01	2.04	2.12	2.19	2.19	2.18	2.16	2.17	2.12	2.12	2.15	2.13	2.10	2.12	2.12	2.19	2.23	2.24	2.26	2.30
24	2.03	1.93	1.82	1.87	1.95	2.02	2.06	2.03	2.02	1.99	2.00	2.07	2.13	2.14	2.16	2.14	2.17	2.17	2.11	2.12	2.13	2.11	2.08	2.12	2.14	2.20	2.23	2.24	2.27	2.30
25	2.02	1.93	1.90	1.94	1.96	1.97	2.00	1.98	1.98	1.99	2.03	2.08	2.09	2.11	2.13	2.15	2.16	2.15	2.11	2.10	2.11	2.09	2.08	2.12	2.15	2.20	2.23	2.24	2.26	2.27
26	2.03	2.06	2.01	1.96	1.93	1.93	1.96	1.94	2.00	2.04	2.06	2.06	2.08	2.10	2.16	2.17	2.17	2.17	2.11	2.10	2.10	2.10	2.10	2.15	2.16	2.21	2.24	2.25	2.25	2.25
27	2.23	2.19	2.01	1.91	1.88	1.88	1.92	1.97	2.05	2.07	2.04	2.05	2.06	2.11	2.16	2.16	2.17	2.16	2.09	2.08	2.09	2.10	2.11	2.14	2.15	2.21	2.24	2.23	2.22	2.23
28	2.29	2.10	1.88	1.81	1.78	1.80	1.92	2.00	2.07	2.03	2.02	2.01	2.06	2.11	2.15	2.16	2.16	2.13	2.07	2.06	2.10	2.10	2.10	2.13	2.15	2.20	2.21	2.19	2.19	2.21
29	2.05	1.87	1.71	1.67	1.66	1.77	1.94	2.00	2.01	1.98	1.96	2.00	2.05	2.09	2.14	2.14	2.13	2.11	2.05	2.07	2.10	2.10	2.09	2.13	2.14	2.17	2.17	2.16	2.17	2.17
30	1.92	1.79	1.64	1.61	1.70	1.86	2.00	1.99	2.00	1.96	1.98	2.02	2.06	2.11	2.14	2.14	2.13	2.13	2.09	2.10	2.12	2.11	2.11	2.14	2.13	2.15	2.16	2.16	2.16	2.14

Table 3-30: t-statistics for "lagged exchange rate" in "forecasting model" for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	-3.92	-2.77	-2.71	-2.78	-3.00	-2.40	-1.72	-1.84	-1.85	-1.97	-1.51	-1.74	-1.50	-1.31	-1.44	-2.18	-2.00	-2.30	-2.24	-1.97	-1.87	-1.94	-2.00	-1.76	-1.60	-1.83	-2.15	-2.57	-2.32	-2.55
2	-2.64	-1.89	-1.92	-2.14	-1.90	-1.17	-0.95	-1.08	-1.21	-1.06	-1.07	-1.08	-0.89	-0.88	-1.36	-1.63	-1.69	-1.80	-1.66	-1.50	-1.45	-1.48	-1.37	-1.17	-1.19	-1.50	-1.93	-2.01	-1.99	-2.24
3	-2.44	-1.88	-1.94	-1.79	-1.32	-0.89	-0.78	-0.94	-0.85	-0.93	-0.82	-0.77	-0.70	-1.00	-1.25	-1.55	-1.56	-1.57	-1.46	-1.33	-1.33	-1.26	-1.13	-1.09	-1.25	-1.64	-1.83	-1.95	-2.01	-2.08
4	-2.36	-1.95	-1.67	-1.28	-0.98	-0.70	-0.69	-0.68	-0.77	-0.73	-0.58	-0.57	-0.77	-0.94	-1.24	-1.47	-1.42	-1.40	-1.32	-1.25	-1.19	-1.10	-1.07	-1.18	-1.45	-1.67	-1.89	-2.03	-1.99	-2.02
5	-2.49	-1.68	-1.20	-0.98	-0.80	-0.55	-0.43	-0.55	-0.54	-0.43	-0.37	-0.59	-0.67	-0.92	-1.16	-1.29	-1.24	-1.22	-1.18	-1.07	-0.99	-0.99	-1.09	-1.30	-1.46	-1.69	-1.91	-1.95	-1.90	-1.97
6	-1.92	-1.04	-0.83	-0.76	-0.59	-0.29	-0.31	-0.34	-0.27	-0.23	-0.39	-0.51	-0.69	-0.89	-1.04	-1.14	-1.09	-1.09	-1.01	-0.91	-0.91	-1.03	-1.21	-1.33	-1.52	-1.75	-1.87	-1.91	-1.89	-1.93
7	-1.42	-0.86	-0.80	-0.68	-0.44	-0.29	-0.23	-0.17	-0.18	-0.35	-0.40	-0.60	-0.74	-0.88	-0.98	-1.07	-1.05	-1.00	-0.91	-0.88	-1.00	-1.19	-1.30	-1.44	-1.62	-1.77	-1.87	-1.93	-1.90	-1.87
8	-1.57	-1.08	-0.89	-0.65	-0.54	-0.31	-0.15	-0.18	-0.38	-0.44	-0.58	-0.73	-0.81	-0.91	-1.00	-1.10	-1.03	-0.97	-0.96	-1.03	-1.20	-1.31	-1.44	-1.58	-1.69	-1.81	-1.92	-1.96	-1.88	-1.81
9	-1.76	-1.13	-0.82	-0.72	-0.54	-0.19	-0.13	-0.32	-0.41	-0.57	-0.67	-0.75	-0.78	-0.88	-0.99	-1.04	-0.96	-0.96	-1.05	-1.16	-1.27	-1.40	-1.52	-1.60	-1.69	-1.82	-1.91	-1.89	-1.78	-1.73
10	-1.63	-0.90	-0.75	-0.58	-0.29	-0.10	-0.22	-0.32	-0.49	-0.60	-0.64	-0.68	-0.72	-0.83	-0.89	-0.92	-0.91	-1.01	-1.13	-1.20	-1.32	-1.46	-1.52	-1.58	-1.68	-1.78	-1.82	-1.77	-1.68	-1.55
11	-1.33	-0.88	-0.62	-0.31	-0.19	-0.20	-0.22	-0.41	-0.53	-0.59	-0.58	-0.65	-0.69	-0.76	-0.79	-0.91	-0.98	-1.12	-1.19	-1.27	-1.39	-1.47	-1.51	-1.59	-1.66	-1.71	-1.73	-1.69	-1.53	-1.41
12	-1.51	-0.86	-0.43	-0.32	-0.39	-0.26	-0.38	-0.51	-0.58	-0.57	-0.61	-0.67	-0.67	-0.70	-0.81	-0.98	-1.09	-1.19	-1.28	-1.37	-1.44	-1.50	-1.56	-1.61	-1.65	-1.68	-1.70	-1.59	-1.44	-1.38
13	-1.27	-0.48	-0.36	-0.48	-0.40	-0.38	-0.44	-0.52	-0.54	-0.58	-0.62	-0.63	-0.60	-0.71	-0.86	-1.07	-1.15	-1.26	-1.36	-1.40	-1.46	-1.53	-1.58	-1.61	-1.61	-1.65	-1.59	-1.49	-1.39	-1.35
14	-0.79	-0.48	-0.66	-0.58	-0.61	-0.54	-0.54	-0.56	-0.63	-0.67	-0.66	-0.64	-0.69	-0.84	-1.04	-1.21	-1.30	-1.41	-1.46	-1.49	-1.57	-1.62	-1.65	-1.65	-1.66	-1.62	-1.57	-1.52	-1.43	-1.41
15	-1.28	-1.18	-1.00	-0.98	-0.93	-0.77	-0.70	-0.77	-0.82	-0.83	-0.78	-0.83	-0.91	-1.10	-1.26	-1.44	-1.53	-1.58	-1.61	-1.65	-1.71	-1.75	-1.75	-1.75	-1.68	-1.64	-1.63	-1.60	-1.52	-1.51
16	-1.97	-1.39	-1.30	-1.21	-1.09	-0.86	-0.86	-0.92	-0.93	-0.90	-0.94	-1.02	-1.14	-1.30	-1.47	-1.64	-1.67	-1.70	-1.75	-1.77	-1.80	-1.81	-1.81	-1.73	-1.65	-1.66	-1.67	-1.65	-1.58	-1.55
17	-1.53	-1.37	-1.28	-1.16	-0.99	-0.87	-0.86	-0.88	-0.88	-0.94	-1.01	-1.14	-1.23	-1.40	-1.56	-1.68	-1.69	-1.75	-1.77	-1.78	-1.78	-1.80	-1.72	-1.65	-1.63	-1.66	-1.69	-1.67	-1.59	-1.53
18	-1.94	-1.57	-1.39	-1.17	-1.10	-0.96	-0.92	-0.91	-0.99	-1.09	-1.20	-1.29	-1.39	-1.56	-1.66	-1.75	-1.79	-1.83	-1.83	-1.81	-1.84	-1.78	-1.71	-1.70	-1.69	-1.74	-1.77	-1.74	-1.63	-1.56
19	-1.90	-1.45	-1.21	-1.14	-1.07	-0.90	-0.84	-0.91	-1.04	-1.19	-1.27	-1.36	-1.46	-1.57	-1.64	-1.76	-1.79	-1.81	-1.79	-1.79	-1.74	-1.70	-1.69	-1.69	-1.70	-1.75	-1.77	-1.71	-1.60	-1.56
20	-1.71	-1.25	-1.22	-1.14	-1.03	-0.86	-0.89	-1.01	-1.19	-1.30	-1.39	-1.49	-1.52	-1.60	-1.70	-1.80	-1.81	-1.80	-1.80	-1.73	-1.70	-1.71	-1.71	-1.72	-1.73	-1.76	-1.75	-1.69	-1.60	-1.53
21	-1.47	-1.32	-1.26	-1.13	-1.01	-0.94	-1.01	-1.20	-1.33	-1.45	-1.53	-1.56	-1.57	-1.67	-1.76	-1.84	-1.81	-1.83	-1.75	-1.70	-1.71	-1.73	-1.75	-1.76	-1.75	-1.75	-1.73	-1.70	-1.58	-1.50
22	-1.86	-1.49	-1.33	-1.17	-1.15	-1.12	-1.25	-1.38	-1.52	-1.63	-1.65	-1.66	-1.68	-1.77	-1.84	-1.88	-1.88	-1.81	-1.76	-1.74	-1.76	-1.79	-1.80	-1.79	-1.76	-1.75	-1.75	-1.69	-1.57	-1.49
23	-1.74	-1.37	-1.23	-1.22	-1.25	-1.31	-1.38	-1.52	-1.66	-1.70	-1.70	-1.73	-1.75	-1.81	-1.84	-1.90	-1.82	-1.77	-1.76	-1.76	-1.78	-1.81	-1.80	-1.76	-1.72	-1.73	-1.70	-1.64	-1.52	-1.45
24	-1.61	-1.25	-1.29	-1.35	-1.46	-1.45	-1.53	-1.67	-1.73	-1.76	-1.78	-1.80	-1.79	-1.82	-1.87	-1.85	-1.79	-1.79	-1.79	-1.80	-1.82	-1.81	-1.78	-1.73	-1.71	-1.70	-1.67	-1.60	-1.49	-1.47
25	-1.59	-1.43	-1.51	-1.63	-1.65	-1.63	-1.70	-1.76	-1.81	-1.86	-1.86	-1.85	-1.81	-1.86	-1.82	-1.82	-1.81	-1.82	-1.83	-1.83	-1.83	-1.79	-1.76	-1.72	-1.68	-1.66	-1.62	-1.56	-1.50	-1.45
26	-1.96	-1.76	-1.89	-1.88	-1.86	-1.84	-1.81	-1.86	-1.93	-1.96	-1.92	-1.87	-1.86	-1.82	-1.81	-1.86	-1.87	-1.89	-1.89	-1.87	-1.84	-1.81	-1.78	-1.73	-1.67	-1.65	-1.62	-1.60	-1.51	-1.47
27	-2.21	-2.11	-2.05	-2.02	-2.02	-1.87	-1.85	-1.94	-1.99	-1.97	-1.89	-1.88	-1.78	-1.78	-1.83	-1.90	-1.91	-1.93	-1.92	-1.87	-1.84	-1.81	-1.77	-1.70	-1.64	-1.62	-1.63	-1.59	-1.51	-1.45
28	-2.49	-2.16	-2.10	-2.09	-1.97	-1.84	-1.88	-1.94	-1.95	-1.89	-1.86	-1.74	-1.70	-1.77	-1.84	-1.92	-1.93	-1.93	-1.89	-1.84	-1.82	-1.77	-1.71	-1.64	-1.58	-1.61	-1.59	-1.55	-1.45	-1.41
29	-2.27	-2.03	-2.04	-1.90	-1.80	-1.78	-1.81	-1.83	-1.79	-1.79	-1.66	-1.61	-1.64	-1.73	-1.81	-1.89	-1.89	-1.87	-1.84	-1.79	-1.74	-1.67	-1.62	-1.55	-1.54	-1.53	-1.52	-1.47	-1.39	-1.35
30	-2.33	-2.12	-1.92	-1.81	-1.83	-1.78	-1.76	-1.73	-1.74	-1.63	-1.57	-1.60	-1.65	-1.75	-1.83	-1.89	-1.87	-1.85	-1.83	-1.75	-1.68	-1.62	-1.56	-1.53	-1.48	-1.49	-1.46	-1.42	-1.34	-1.30

Table 3-31: t-statistics for “lagged stock market return” in “forecasting model” for DIA

Notes: The table reports t-statistics of corresponding coefficient estimates in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. The horizontal axis stands for the exchange rate return over k-minute horizon; the vertical axis stands for cumulative foreign exchange order flows through the i-minute period. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used. R^2 is up to 6%. Detailed R^2 for each regression can be provided upon request.

From the results of SPY and DIA (two market level ETFs), We can clearly see there is a pattern of effects on the equity market from foreign exchange order flows over time, even after controlling for lagged exchange rate and stock market returns. The findings are consistent for the two index-tracking ETFs. Like in the "pure FX" part, we also draw two graphs (graph 3-7 and 3-8) to show the changes in coefficients, based on both daily (chapter 2) and high frequency (chapter 3) results.

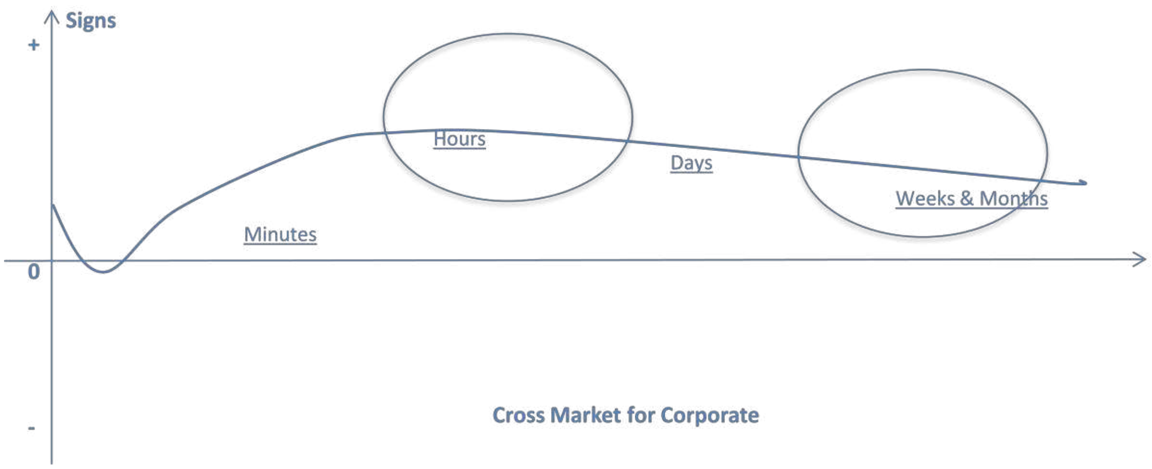


Figure 3-7: "Cross market" for corporate: relationship between corporate currency orders and currency movements

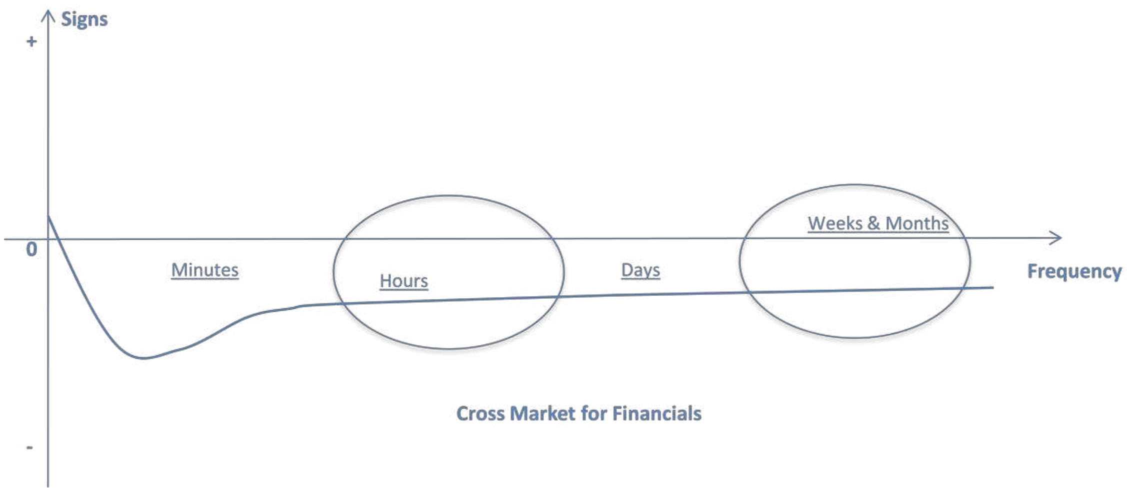


Figure 3-8: "Cross market" for financial: relationship between corporate currency orders and currency movements

From the above two graphs (figure 3-7 and figure 3-8), we can see the changes in the coefficients, i.e. the impacts of currency order flows on stock market dynamics, at frequencies from 1 minute up to several months. In chapter 2, we find very significant and positive (negative) forecasting power of daily currency orders from corporate (financial) customers for stock market changes; while in chapter 3, we also find generally significant coefficients at high frequencies from 1-minute to 30-minute, which are almost all positive (negative) for corporate (financial) customers. Similar to the "pure FX" part, we only have results for frequencies higher than 30-minute and daily up to 10 days (2 weeks), and the signs and trends of coefficients at frequencies from 30-minute to 1-day and lower than 2-week, are simulated based on hypothetic smoothness of the curves (circled in the graphs). According to our hypothesis in chapter 2, if we find strong links between stock market changes and currency order flows, we suggest that something is going on between the two financial markets, and there possibly exist some stock market relevant information content in the foreign exchange order flows, which are related to macroeconomic fundamentals.

Together with the graphs and our cross market high frequency results, we have the following findings and suggest the following conclusions.

1) Compared to the findings in the "contemporaneous model", where order flows play no role in explaining concurrent stock market changes at market level (consistent with daily results at market level in chapter 2), there are strong relationships between foreign exchange order flows and future stock market returns in the "forecasting model", after controlling for lagged exchange rate and stock market returns. In addition to the findings at a daily frequency in chapter 2, we suggest the effects of foreign exchange order flows on stock market changes at high frequencies still hold to some extent, and the effects from both corporate and financial customers are consistent with the daily results (chapter 2). As discussed in chapter 2, we suggest there is information content in order flows in the foreign exchange market and the information is relevant for stock markets, which are related to macroeconomics and global economic information. For example, corporate customers know the underlying economic health based on

their cash flows across the borders. As discussed in chapter 2, if they buy more home currencies (here Euro), it means more sales in foreign countries and good economy, and then the stock market will go up. We believe this is a gradual process and can be observed at both daily and high frequencies, as found in chapter 2 and chapter 3.

2) The effect of “corporate” order flows on stock market changes is mainly positive (“warm” color dominates in table 3-21 for SPY and table 3-27 for DIA), while that of “financial” orders is mainly negative (“cold” color dominates in table 3-20 for SPY and table 3-26 for DIA), at high frequencies. In “pure exchange rate environment”, foreign exchange order flows from “corporate” customers have longer effects than those from “financial” customers; however, in “cross market environment”, there is no clear difference between these two, at high frequencies. As noted in chapter 2, the effects of daily foreign exchange order flows from corporations are longer than those from financial institutions. It might suggest that information relevant for stock markets in foreign exchange order flows from both “corporate” and “financial” customers are continuously reflected into the market intraday, however, the effects of commercial order flows are fully priced into the market several days longer than those of financial order flows. By any means, we suggest the lasting effects of currency orders mean some existence of information content.

3) Similar to findings in “pure foreign exchange environment”, magnitudes of coefficients for all the four categories of order flows indicate that up to 0.5% of changes when 1 billion Euro into the market, except for that of “internal” order flows, which is even up to 3% (matched with magnitudes of lagged exchange rates and larger than that of lagged stock market returns). For R^2 in the regressions, at high frequencies up to approximately 6% of variations of market level equity returns can be explained by foreign exchange order flows with lagged exchange rate and stock market returns.

4) Moreover, the impacts of order flows from “internal” and “interbank” counterparties on stock market returns are both negative. The effects of order flows from “internal” units on stock market changes at market level are very strong, and we suspect that the “internal” unit might be stock market trading related desks in the bank, which search for investment opportunities in the international equity markets. From table 3-15 to table 3-26, we notice the

different pattern of effects of order flows from different counterparties, because the significance and sign of coefficients from different counterparties change with aggregation of orders and minutes over time. The clear difference in terms of “signs” and “patterns” between different customers and “interbank” counterparties further suggest the heterogeneity in the foreign exchange market, at high frequencies. All the properties endorse the possible information content in currency order flows, due to different trading styles and investment philosophy among various market participants.

5) The lagged exchange rate has significantly positive impacts on the stock market changes, while the lagged stock market return has significantly negative impacts on the stock market changes, at market level. This cross market “return spillovers” has borne out in many previous studies (see Ajayi and Mougoue (1996), Andersen et al. (2007), among many others). The strong impacts from these two market returns indicates more important roles that foreign exchange order flows are playing in determining stock market changes.

Up to now, we discussed the changes of effects of currency order flows on both exchange rate and stock market changes at both daily and high frequencies, and we suggest similar interpretations for all frequencies, because trading over time from clients is in a gradual manner, and then the embedded information can be similar for both daily and high frequencies, although there maybe some noises in our intra-day order flows. In the following section, we will test the cross market relationships at sector and individual stock levels.

3.5.3 Cross Market Findings (Sector and Individual Stock Levels)

Now we turn our attention to the relationship between high frequency foreign exchange order flows and sector level equity returns. We consider 9 sector ETFs which track major S&P 500 sector indices (details of the ETFs are listed in section 3.3).

Similar to market level cross market effects, we perform regression analysis as the following two models (“contemporaneous” and “forecasting” respectively),

$$R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$$

$$R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$$

In the following we report our findings in figures. In the “contemporaneous model”, we plot the coefficients of estimates and t-statistics for all the four groups of foreign exchange order flows with lagged exchange rate returns, separately (5 coefficients and t-statistics for OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, and Rfx: exchange rate returns). In the “forecasting model”, we draw heatmaps of the coefficients and t-statistics for the four categories of order flows with lagged exchange rate and stock market returns, separately (6 coefficients and t-statistics for OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, Rfx: lagged exchange rate returns, and Rdow: lagged stock market returns). Intraday data from 2:30pm to 5:00pm (the overlapping period) for 25 days are used.

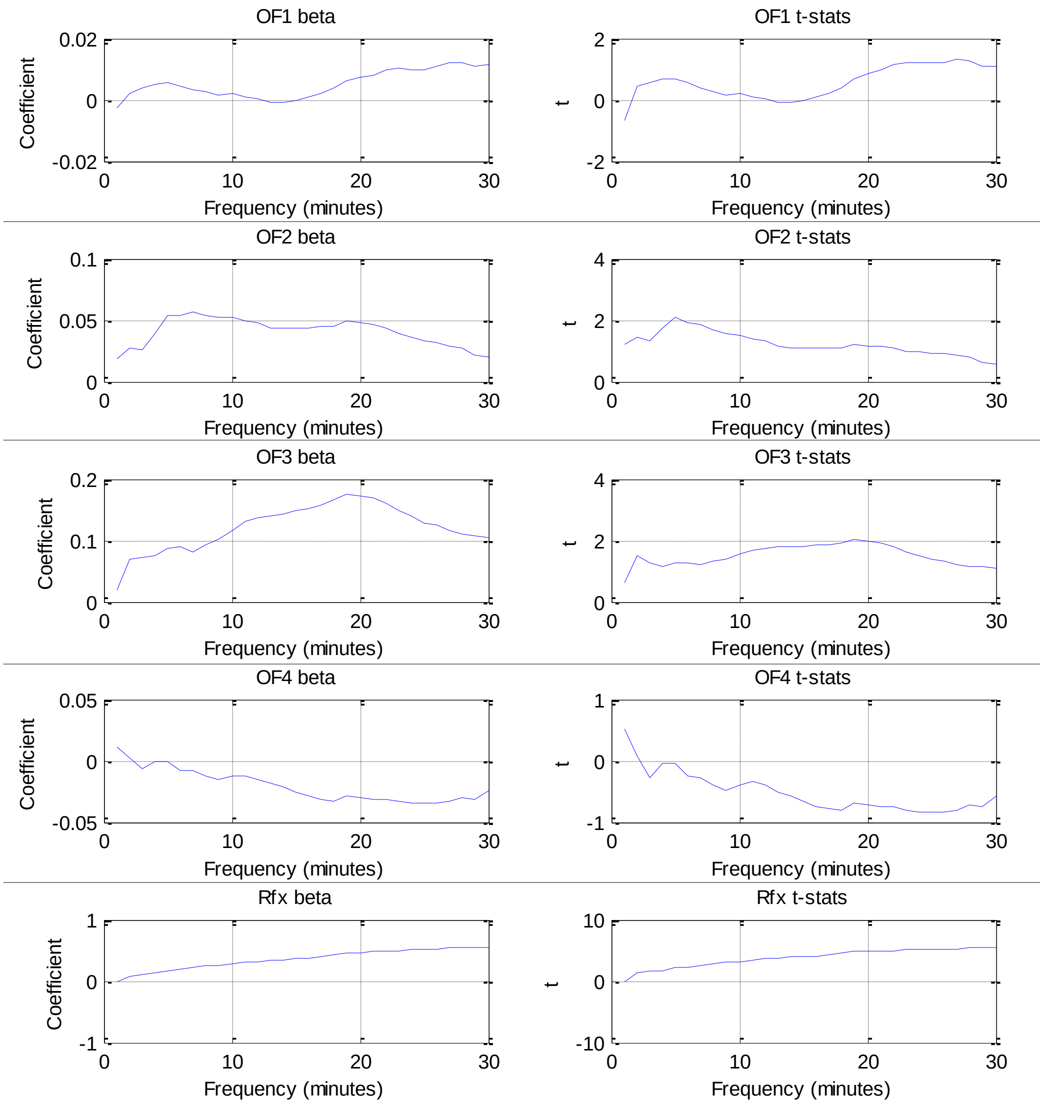


Figure 3-9: XLB contemporaneous

Notes: The figures show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

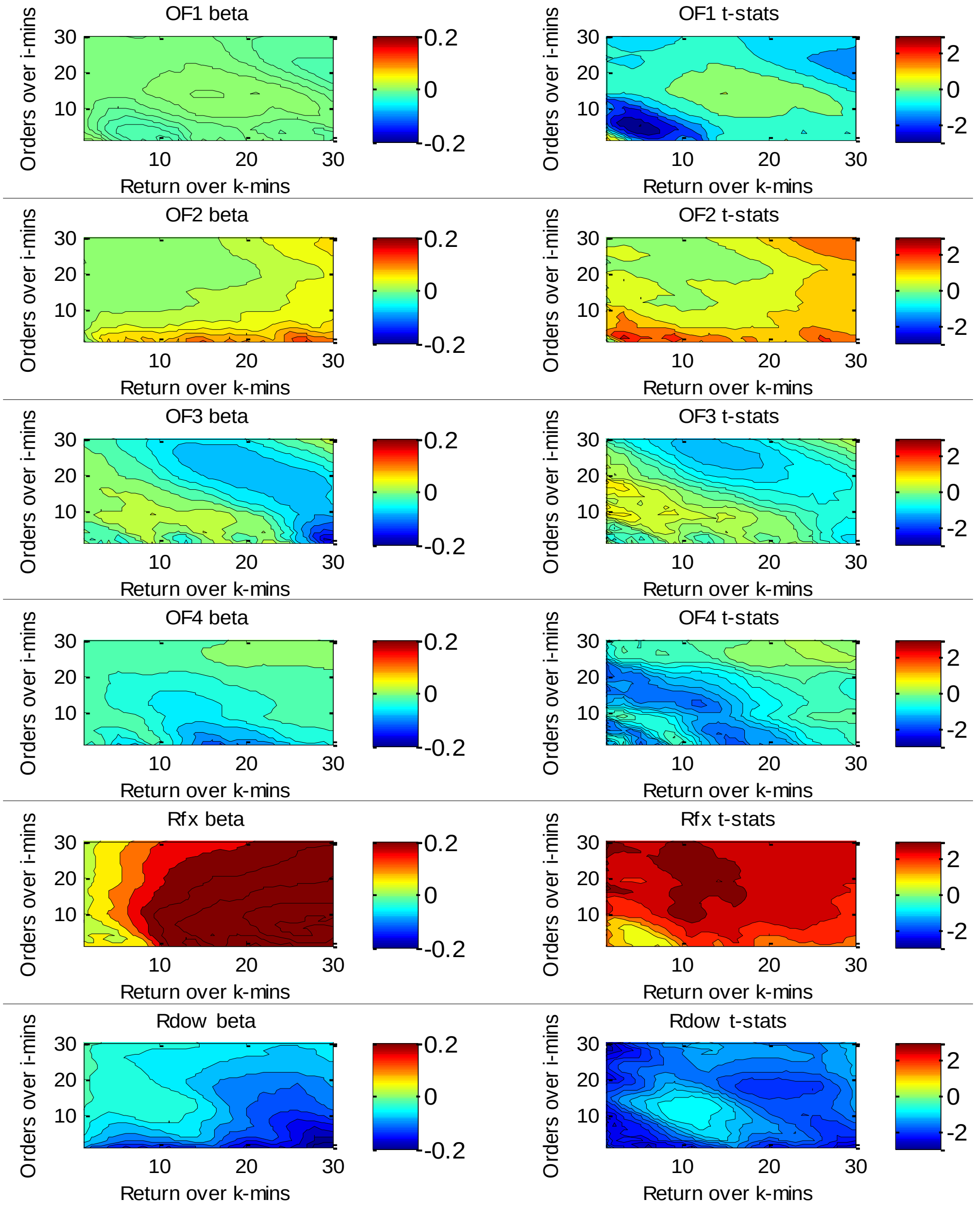


Figure 3-10: XLB forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

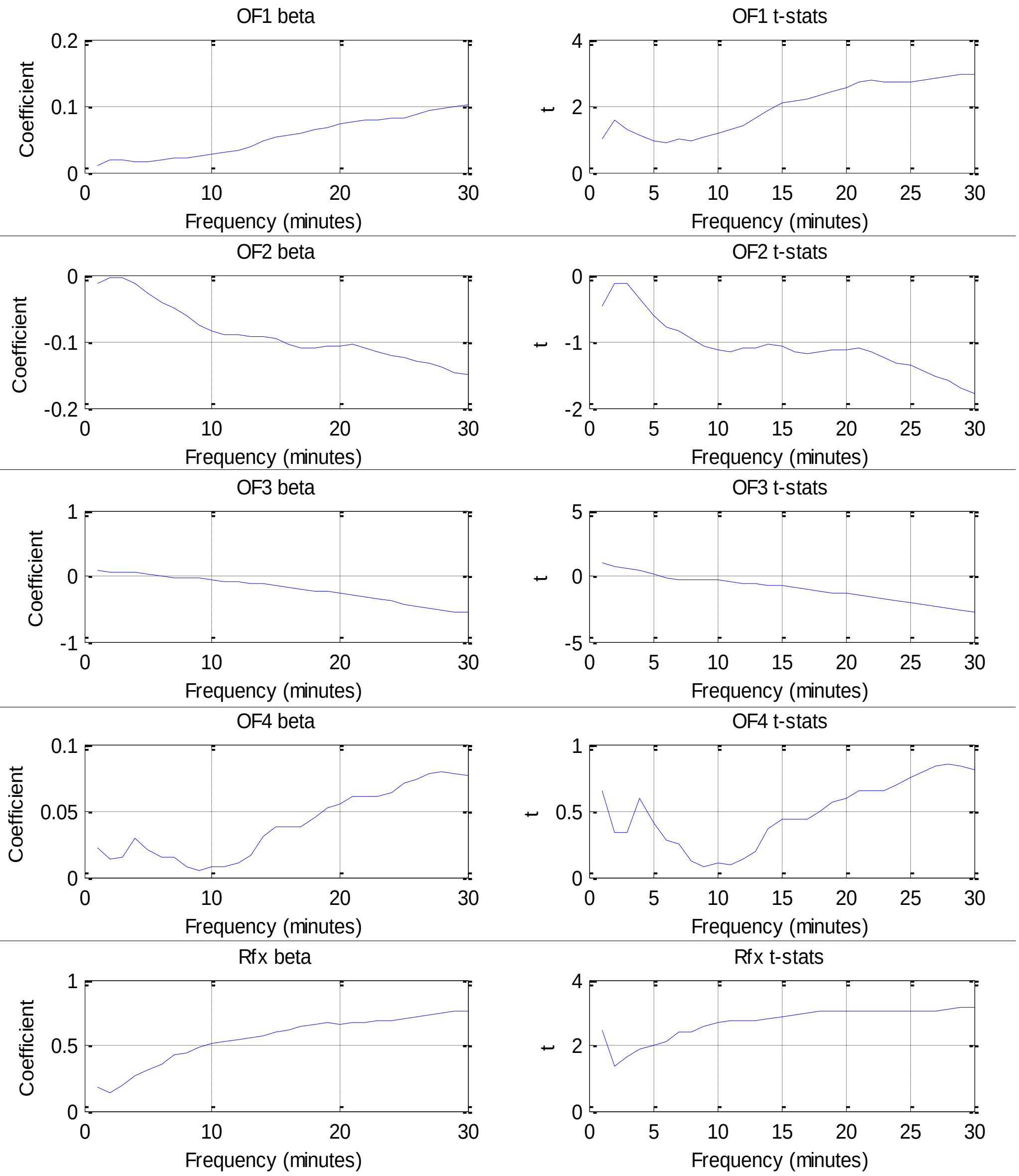


Figure 3-11: XLE contemporaneous

Notes: The figures show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

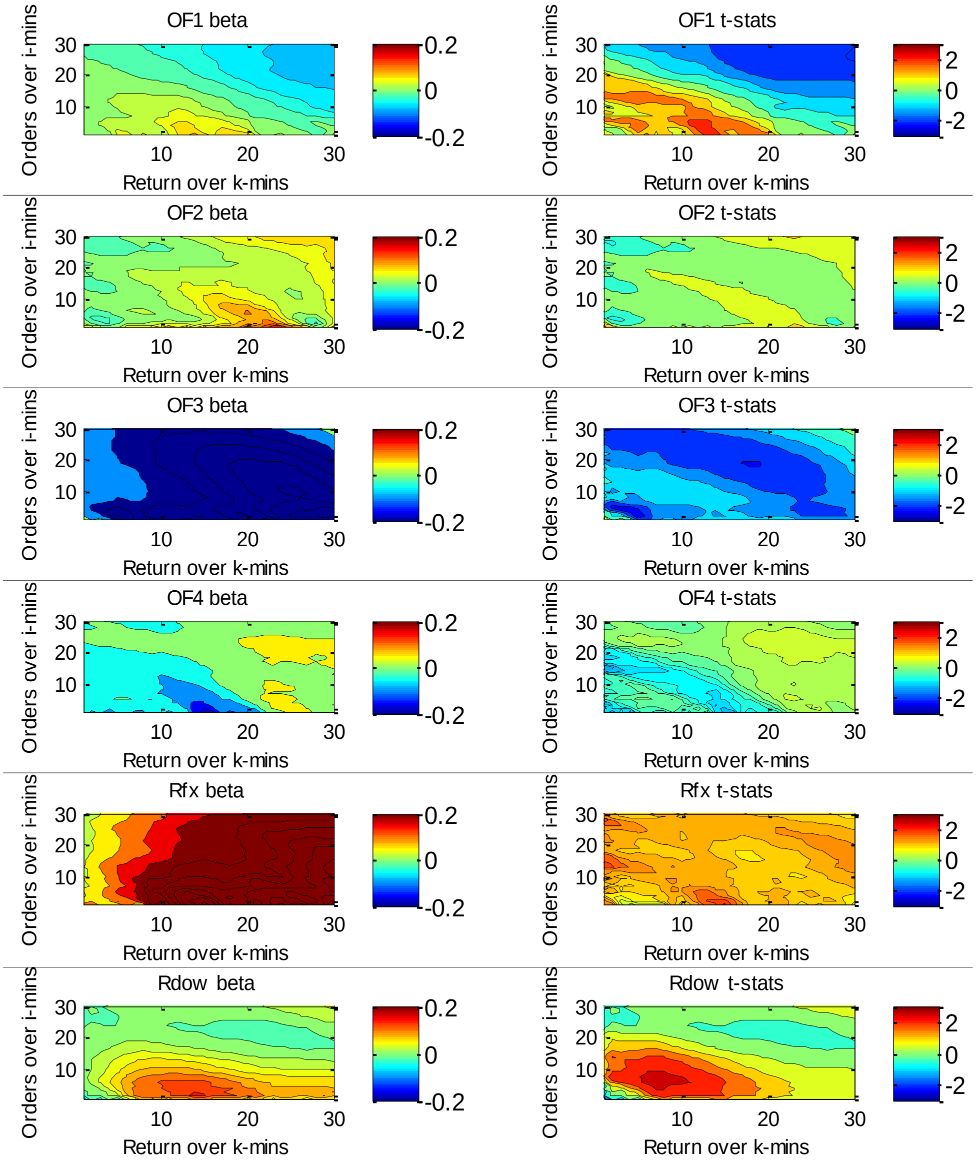


Figure 3-12: XLE forecasting

Notes: The heatmaps show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

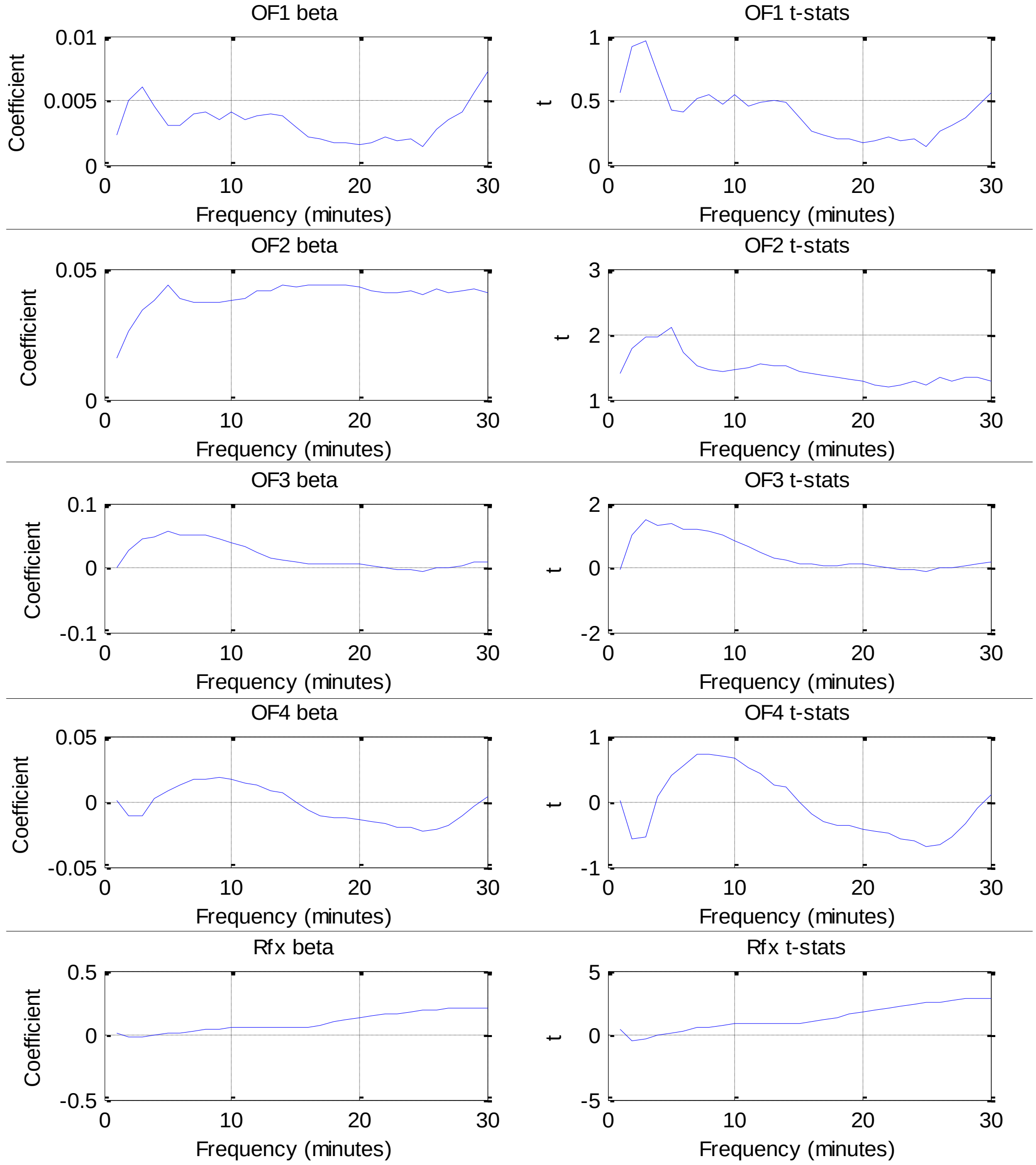


Figure 3-13: XLF contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

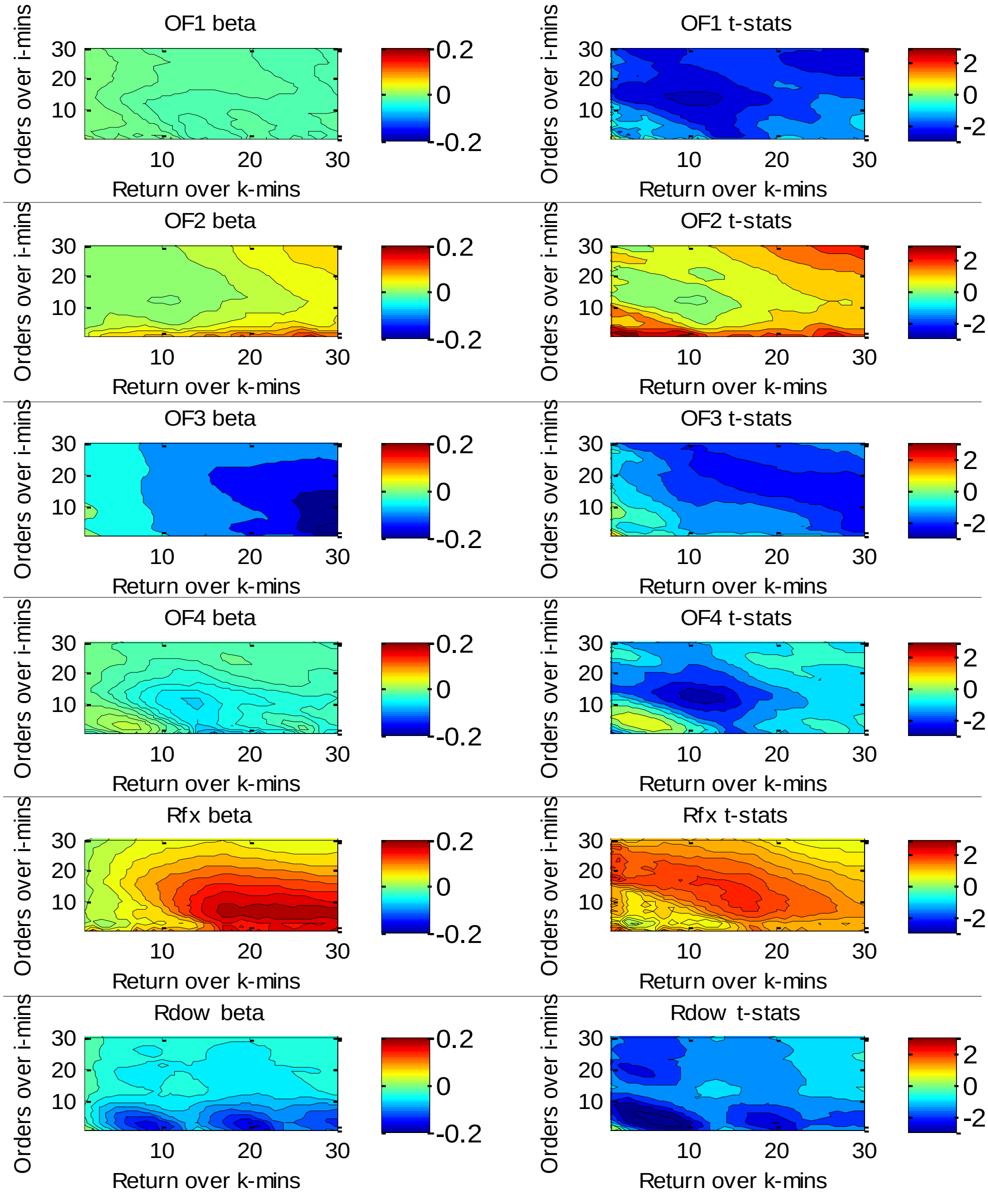


Figure 3-14: XLF forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

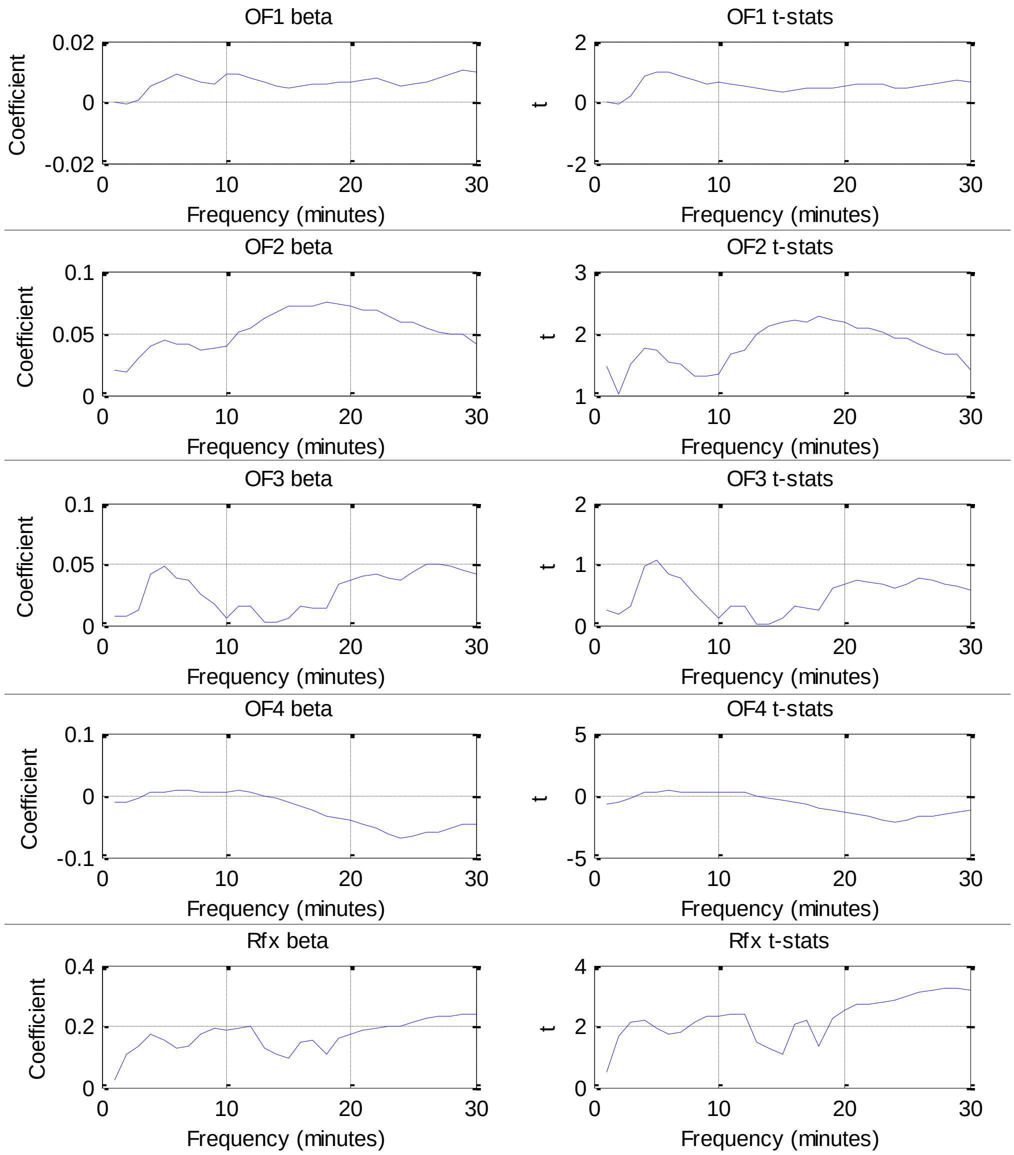


Figure 3-15: XLI contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

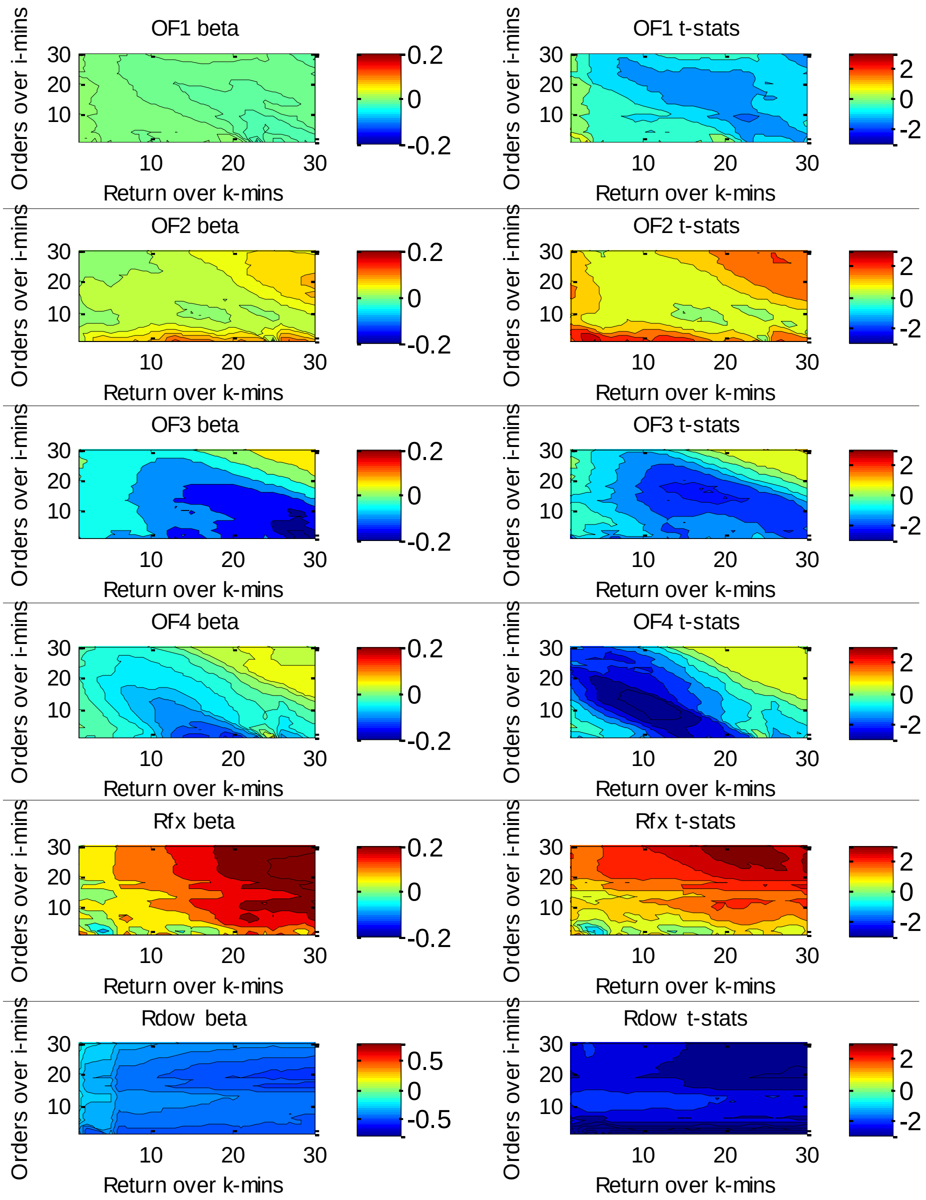


Figure 3-16: XLI forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

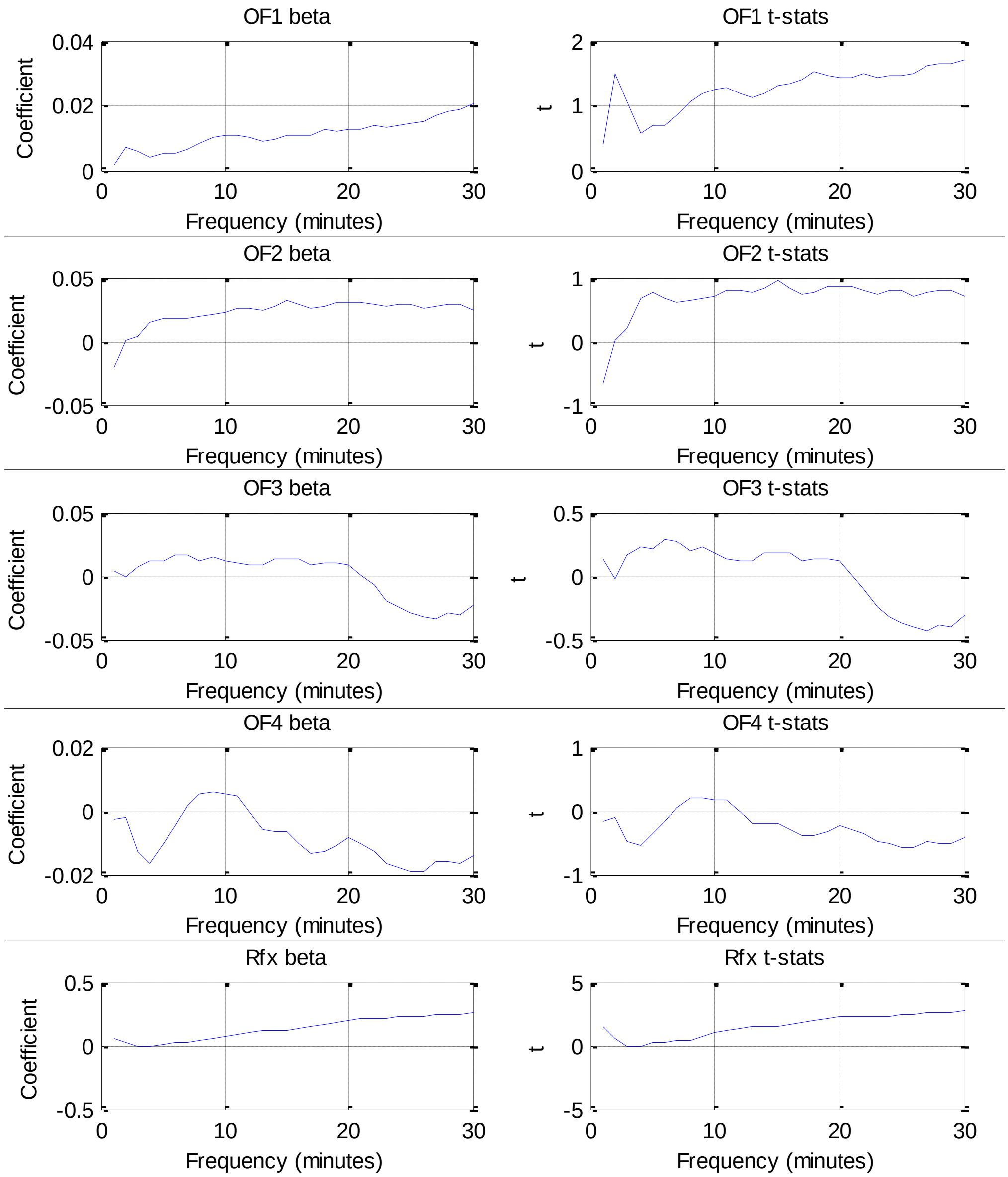


Figure 3-17: XLK contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

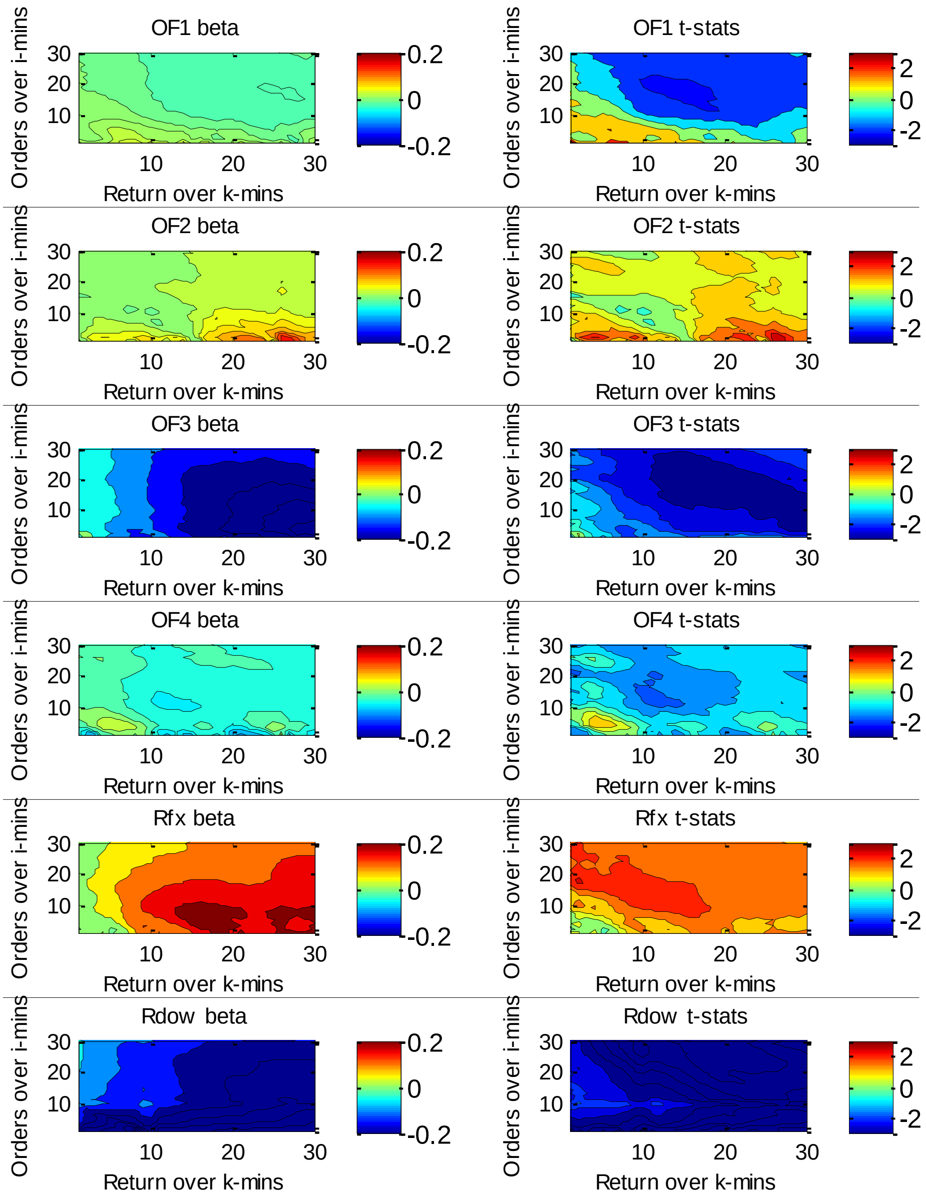


Figure 3-18: XLK forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

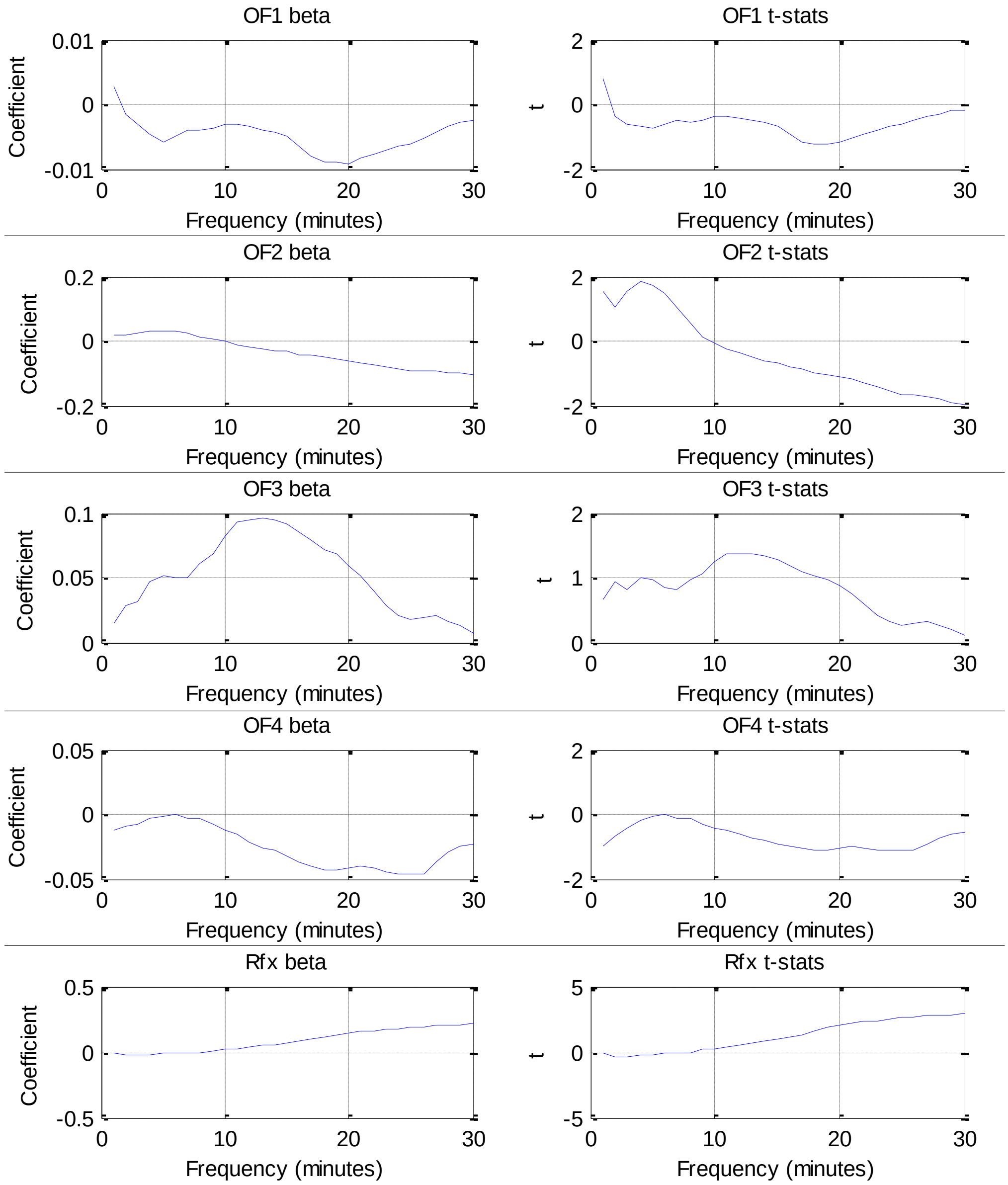


Figure 3-19: XLP contemporaneous

Notes: The figures show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

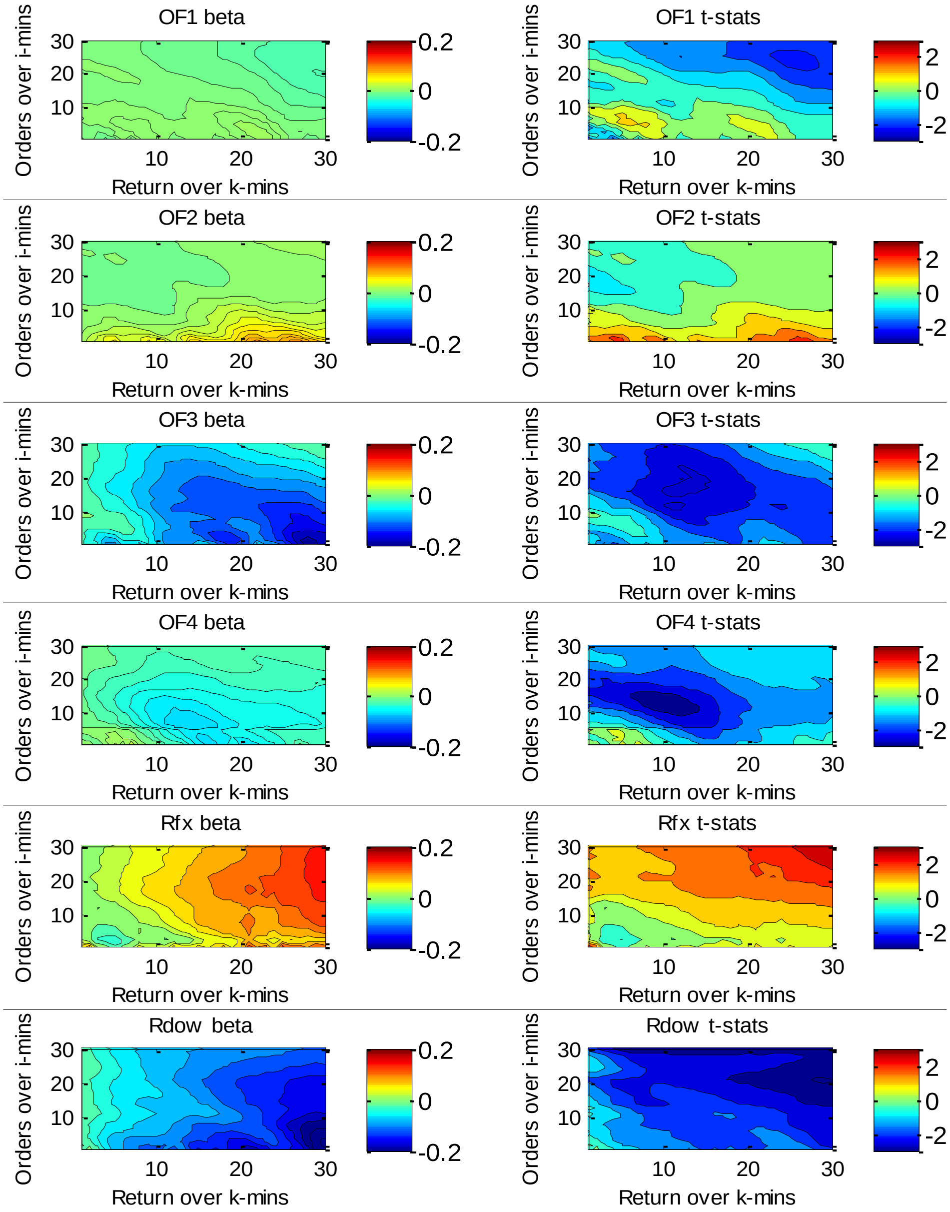


Figure 3-20: XLP forecasting

Notes: The heatmaps show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

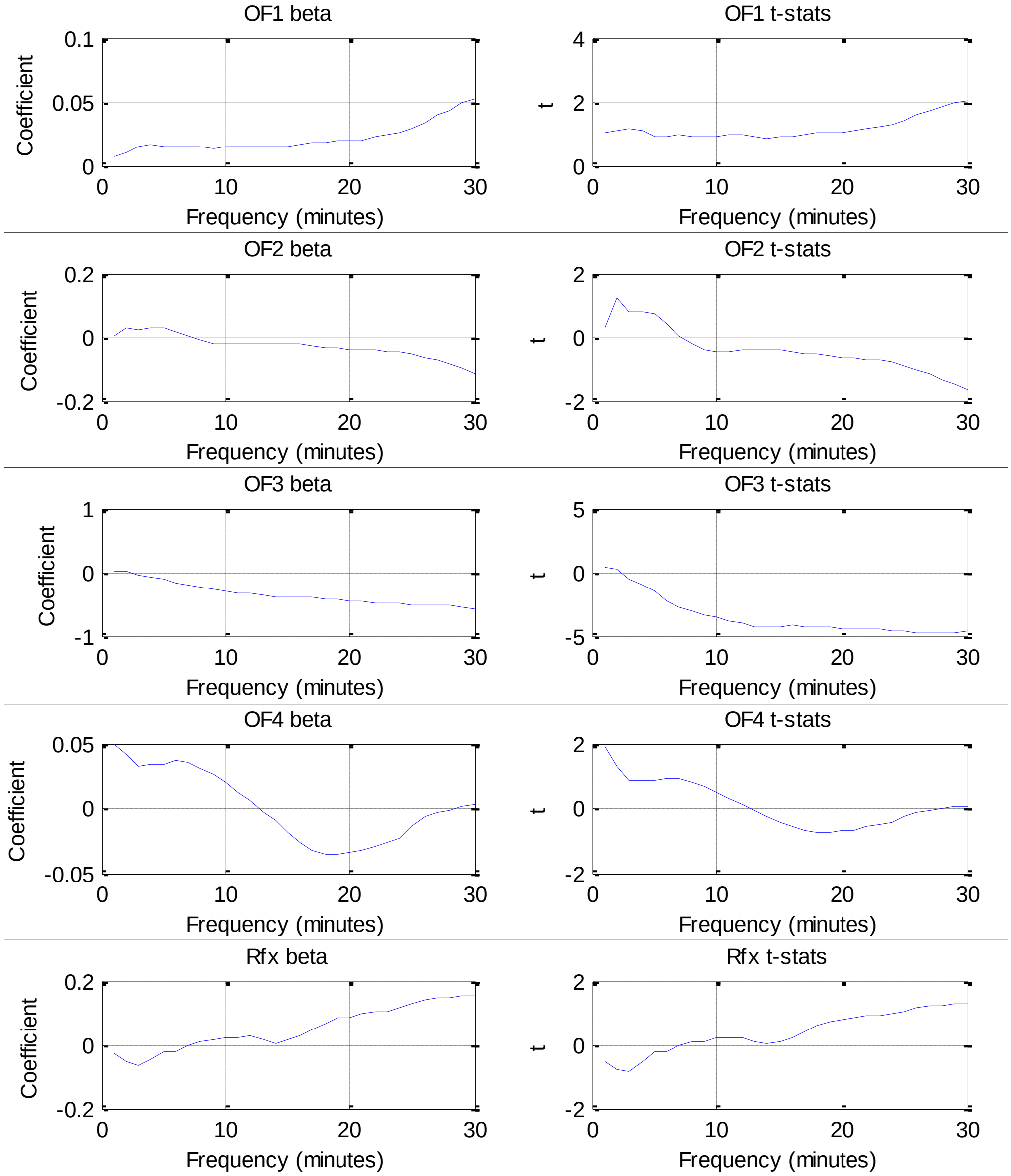


Figure 3-21: XLU contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

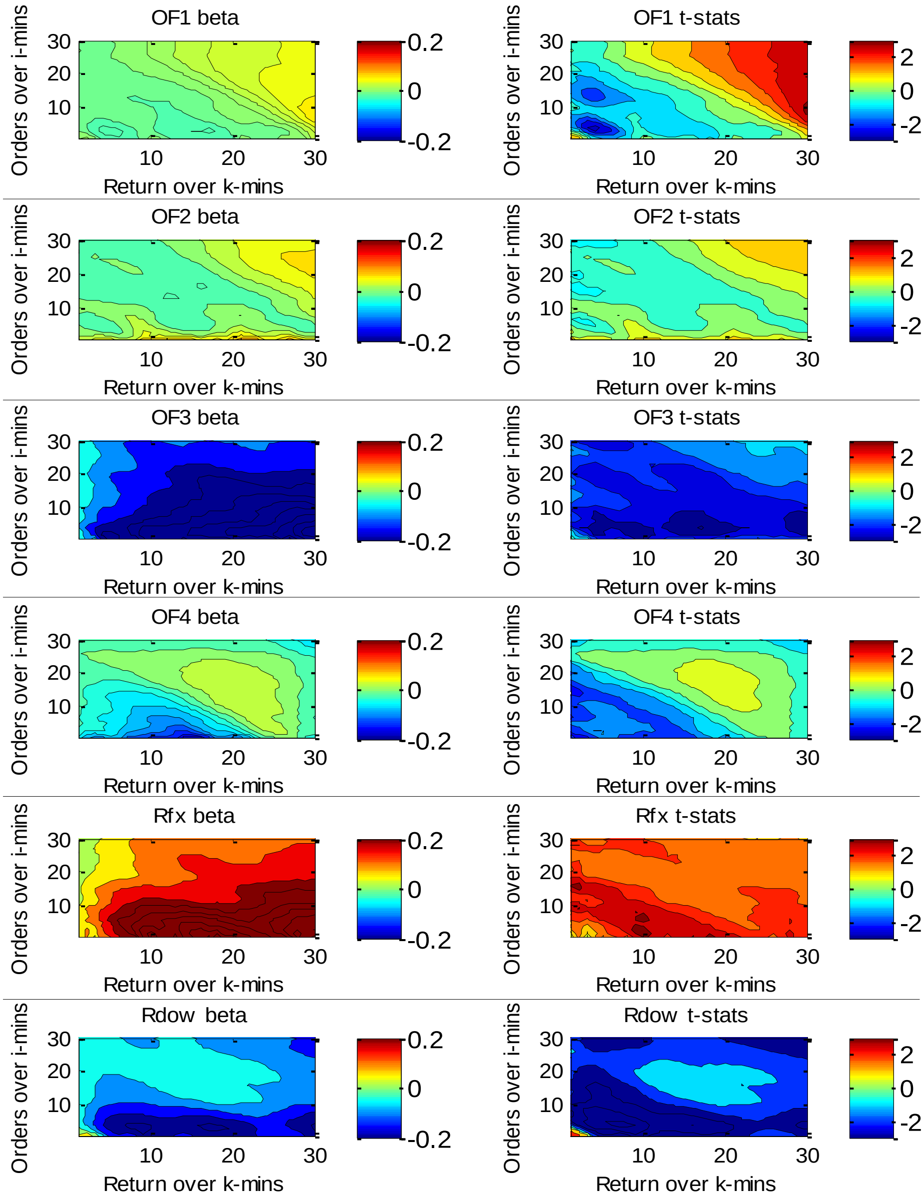


Figure 3-22: XLU forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

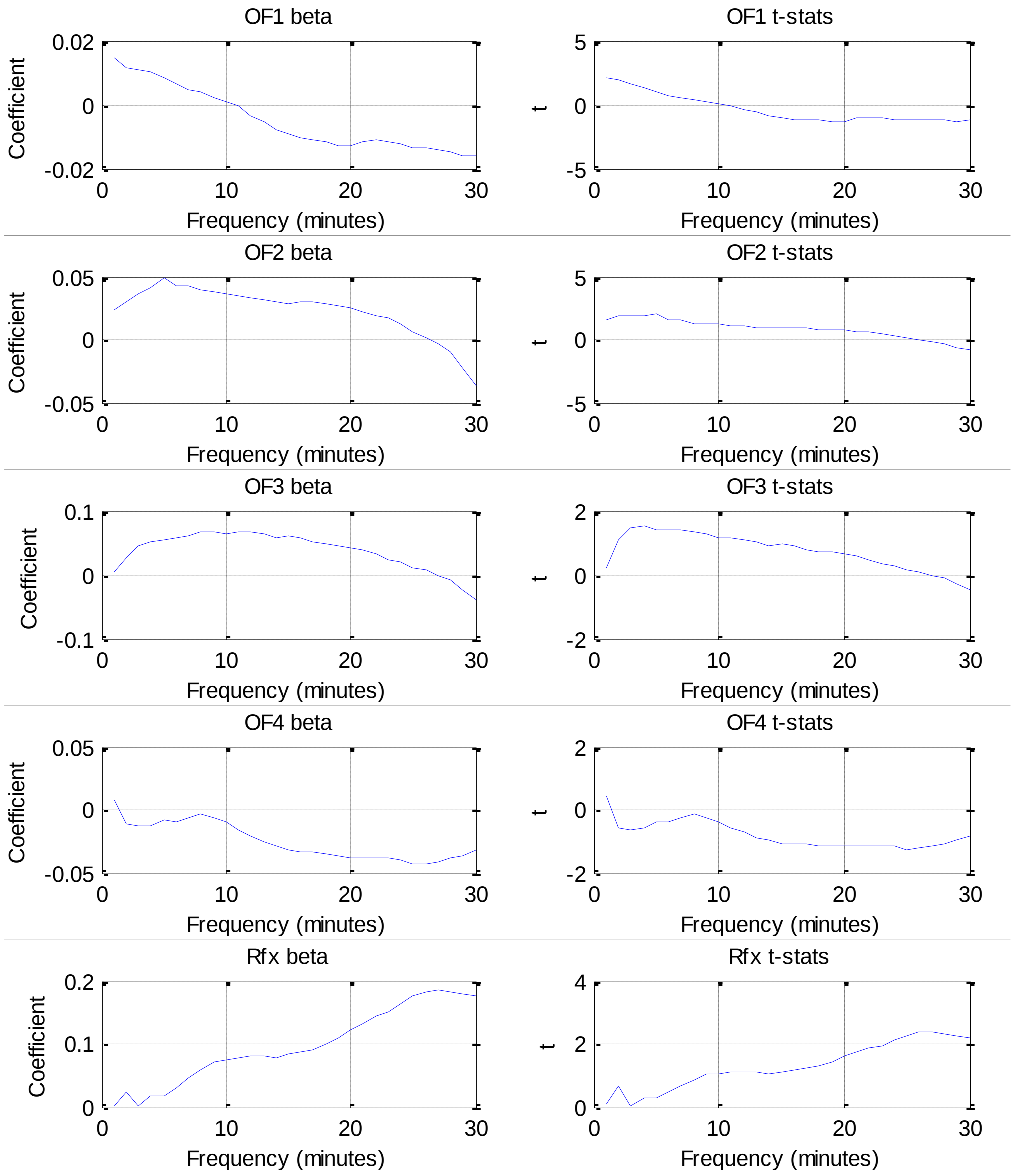


Figure 3-23: XLV contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

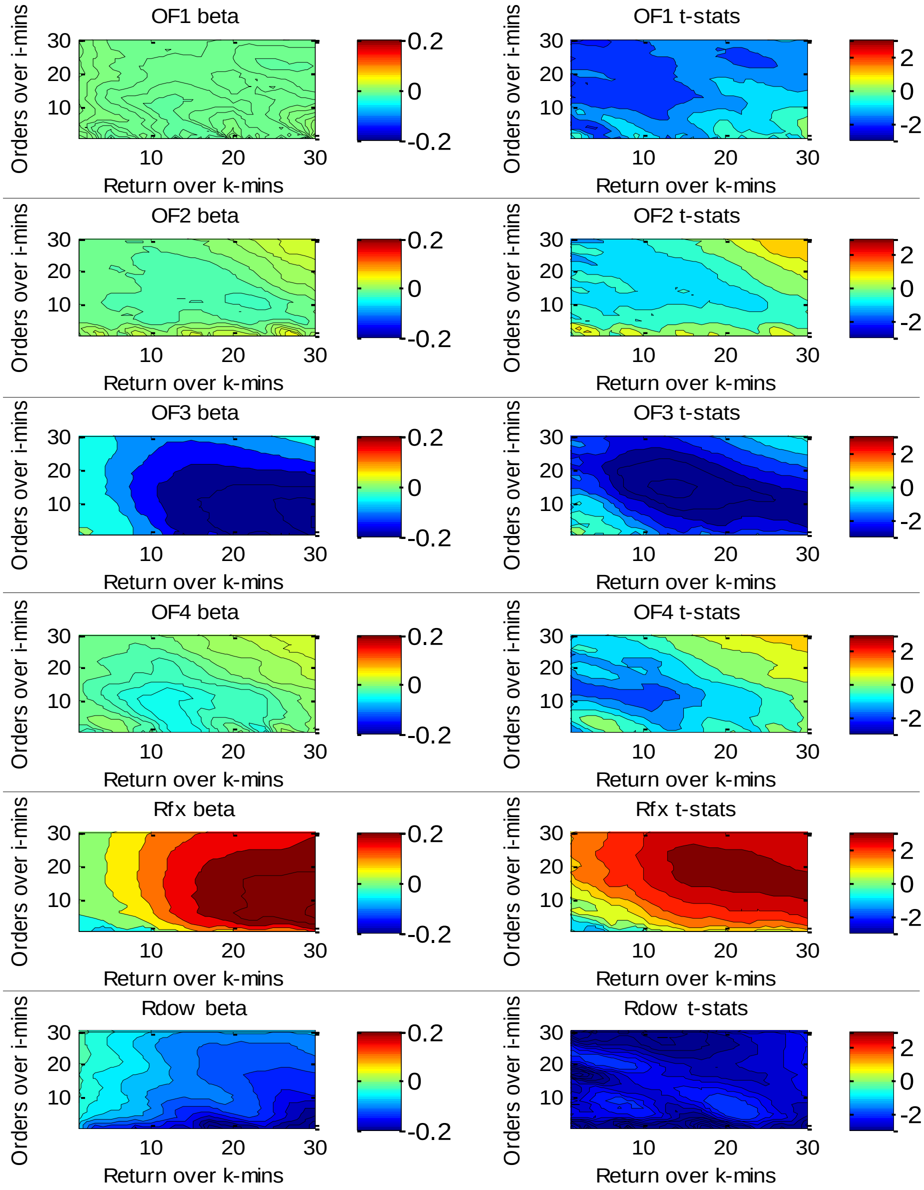


Figure 3-24: XLV forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

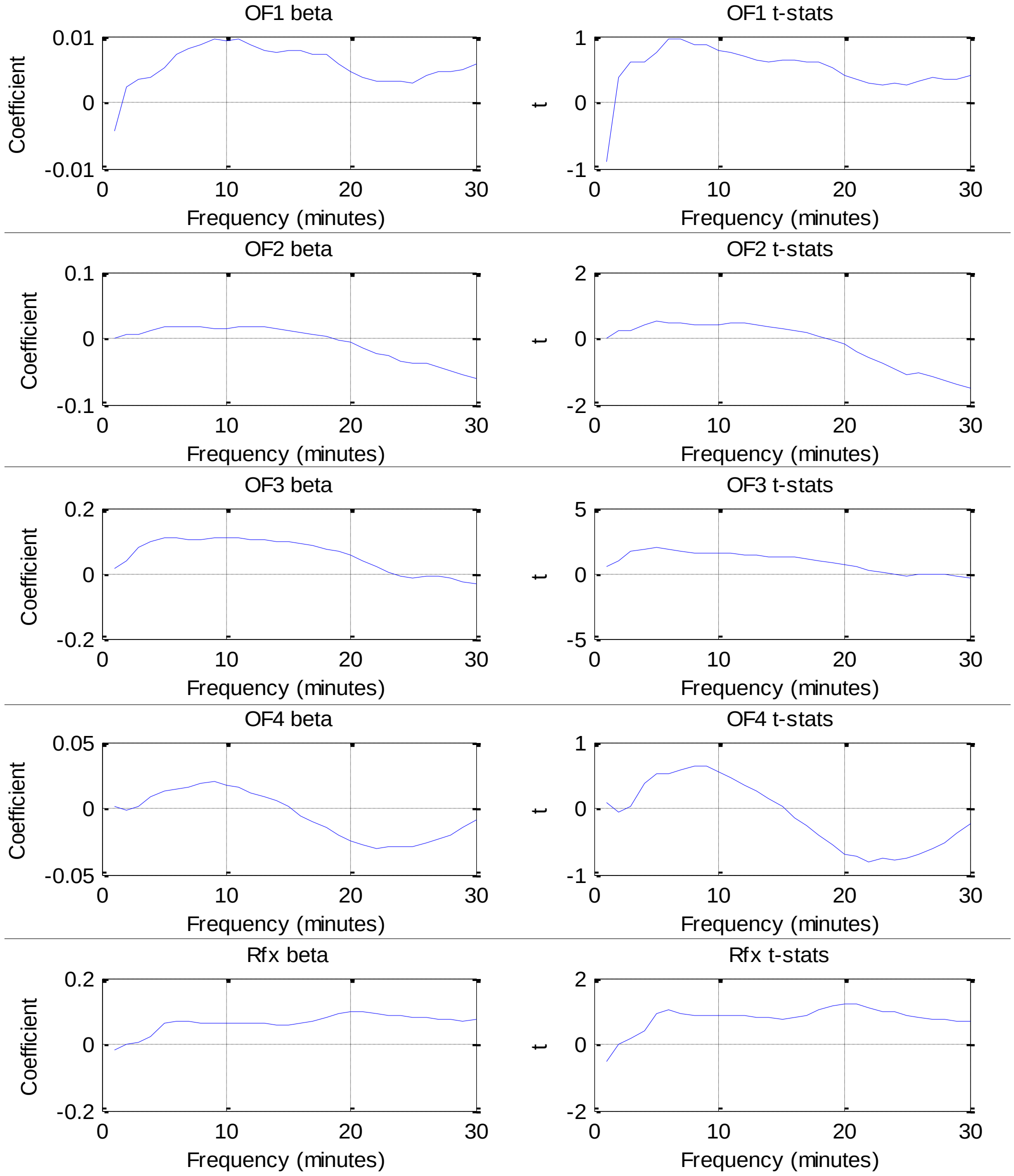


Figure 3-25: XLY contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

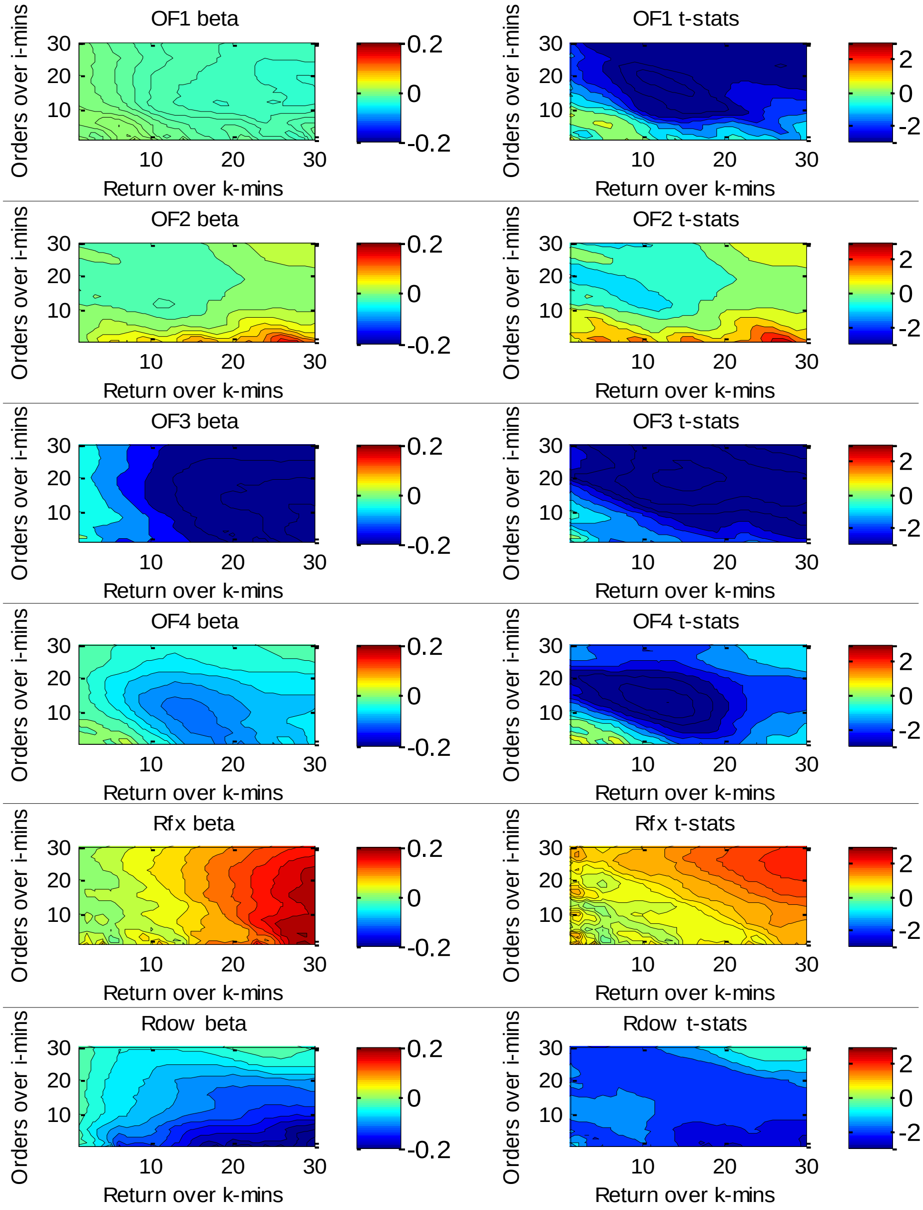


Figure 3-26: XLY forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

From previous figures of “contemporaneous” and “forecasting” sector ETFs results, we notice that the consistency and uniformity across different sectors loose a little in comparison to the results of market level ETFs (SPY and DIA), but still normally hold.

In “contemporaneous” results, similar to market level ETFs, there is strong contemporaneous relationship between exchange rate and sector level equity returns, especially at frequencies more than 10-minute. However, for some sector ETFs, at some frequencies there are also significant contemporaneous relationship between foreign exchange order flows and stock market returns (for market level ETFs, it is rare), although most of the relations are still statistically insignificant.

In “forecasting” results, we clearly see a pattern of effects from foreign exchange order flows on different sector level stock ETFs changes. We summarize major findings and highlight the difference between market level and sector level ETFs,

1) After controlling for lagged exchange rate and stock market returns, there are still significant effects from foreign exchange order flows on subsequent sector ETFs changes, at high frequencies.
2) Same as market level ETFs, heterogeneous effects across different groups of counterparties on sector ETFs changes still hold. Except for XLE (Energy sector) and XLU (Utility sector), where “financial” order flows have positive impacts on future stock market changes, in the other sector ETFs, “financial” order flows have negative impacts on future sector ETFs changes (“cold” color dominates). The consistency of effects from “corporate” order flows on stock market hold well for all the sector ETFs (“warm” color dominates), especially when the relationship is significant.
3) Effects of “internal” order flows are strongest in terms of magnitudes and t-statistics, which is consistent to results of market level ETFs. Magnitudes of “internal” order flows are up to 0.4% while other groups of order flows are mostly less than 0.05%, at any frequencies (we do not know exactly what “internal” has, but we suspect that stock market desks in the bank are covered in

this group). The different signs and magnitudes further confirm the heterogeneity in order flows initiated by different groups of counterparties.

4) Similar to market level ETFs, lagged exchange rate have positive effects on future stock market changes for all sector ETFs. Normally lagged sector ETFs returns forecast negative future stock market changes, except for XLE (Energy sector), which has a positive effect.

Finally, we also test the relationships between foreign exchange order flows and individual stocks changes at high frequencies. The consistency is weaker than those in market and sector ETFs. We suggest that the weaker links for individual stocks are due to the idiosyncratic characteristics in each individual company that foreign exchange order flows can not capture very well, at least at intraday level. The idiosyncratic company possibly contributes to that, the forecasting power of lagged exchange rate on individual stock changes is gone for half of the stocks considered. Another possible explanation for the weak link is because that the choice of individual stocks trading in the US stock market is much broader than that of sector and market tracking indices. More funds related to foreign exchange order flows flood into sector and market ETFs, rather than the 30 stocks listed in DOW 30.

We list selected coefficients and t-statistics of individual stock results in the appendices. Full results can be accessed online or downloaded at:

http://docs.google.com/leaf?id=0B2VOf-3UbWllNzRlZWIxZGItNDM3Zi00NzhkLWFkMGItYzMzMTNjNDUzN2Qy&hl=en_GB

3.6 Conclusions

In addition to the daily relationship between order flows in the foreign exchange market and exchange rate changes in many well-established papers (see Evans and Lyons (2002a), among many others), some studies also give evidence that foreign exchange order flows are correlated with exchange rate changes at high frequencies (see Love and Payne (2008), Osler and Vandrovych (2009), among others). Besides the relations in “pure exchange rate market”, the orders flows in one market also play an important role in the movements of other markets, and some studies document the evidence of the cross market effects from currency order flows at a daily frequency (e.g. Francis, Hasan and Hunter (2006), Dunne, Hau and Moore (2006), among others). However, to the best of our knowledge, no one has reported any effects of foreign exchange order flows on other market changes at high frequencies. In this chapter, we use a unique set of tick-by-tick foreign exchange order flows data including customer orders and inter-dealer orders to test the effects of order flows on stock market changes at frequencies from 1-minute to 30-minute, in addition to the dynamic relationship between currency order flows and exchange rate fluctuations at high frequencies.

We first suggest the following findings in “pure foreign exchange environment”,

1) We find impacts of foreign exchange order flows on contemporaneous and future exchange rate changes at high frequencies. Order flows from “corporates” are positively related to exchange rate changes, while order flows from “financials” are negatively “signed” (contradicts with published studies, e.g. Evans and Lyons (2006)), but will go positive when close to 30-minute frequency (then in line with daily relations between the two suggested by many other papers, such as Evans and Lyons (2006), Reitz et al. (2007)). The high frequency findings are consistent with Osler and Vandrovych (2009), which also suggest mixed signs for their 10 groups of counterparties at frequencies less than 30-minute (e.g. positive for large corporations; negative for institutional investors, broker-dealers and middle-cap corporations).

2) In addition to results of “corporate” and “financial” customers, we find that the effects of order flows from “internal” and “interbank” counterparties are mixed based on “market” or “transaction” prices used. The magnitudes of all the four groups of counterparties are similar (up to 0.3% of change in exchange rate when 1 billion Euro into the market) and the heterogeneity is holding well at high frequencies.
3) The clear existence of forecasting power from order flows on exchange rate changes at high frequencies partly explain why we do not find any forecasting power in the foreign exchange market by using daily frequency data in chapter 1: the information buried in order flows can only last for minutes and will dissipate by the end of each trading day.

We then suggest the findings in “cross market environment”,

4) We do not see clear contemporaneous relationship between foreign exchange order flows and stock market changes at high frequencies (consistent with daily results at market level in chapter 2), but we see the important role currency order flows are playing in forecasting the stock market returns over 1-minute to 30-minute horizons, after controlling for lagged exchange rate and stock market returns. The effects of order flows from “financial” customers are negative on stock market changes, while the effects of orders from “corporate” customers are positive on stock market changes, which further confirms our findings in chapter 2.
5) In “pure foreign exchange environment”, we notice that “corporate” order flows have longer effects on exchange rate than “financial” order flows, at high frequencies. While in “cross market environment”, there is no difference in effects between the two categories of currency order flows, at high frequencies. Together with the longer effects of daily (chapter 2) foreign exchange order flows from corporations on the US stock market (than financial institutions), we suggest that information relevant for stock markets in foreign exchange order flows from both “corporate” and “financial” customers are continuously reflected into the market intraday, however, the effects of commercial order flows are fully priced into the market several days longer than those of financial order flows.

6) The magnitudes of effects of different types of foreign exchange order flows on stock market changes are different from those in "pure exchange rate environment". The magnitudes of coefficients for all categories of order flows indicate that up to 0.5% of changes will be made when 1 billion Euro into the market, except for that of "internal" order flows, which is up to 3% (matched with magnitude of lagged exchange rate and equity returns). From the strong effects of order flows from "internal" units on stock market changes at high frequencies, we suspect that the "internal" might be desks related to stock market trading in the bank.
7) Moreover, we see clear "return spillovers" between the foreign exchange market and the stock market, that is, the lagged exchange rate has significantly positive impact on the stock market changes at market level (in line with Ajayi and Mougoue (1996), Andersen et al. (2007), among many others). We also find evidence that the lagged stock market returns mostly have significantly negative impacts on the subsequent stock market changes.

Appendices

1) We list two selected (AA and C) coefficients and t-statistics of individual stock results. Full results can be accessed online or downloaded at:

http://docs.google.com/leaf?id=0B2VOf-3UbWllNzRlZWIxZGItNDM3Zi00NzhkLWFkMGItYzMzMTNjNDUzN2Qy&hl=en_GB

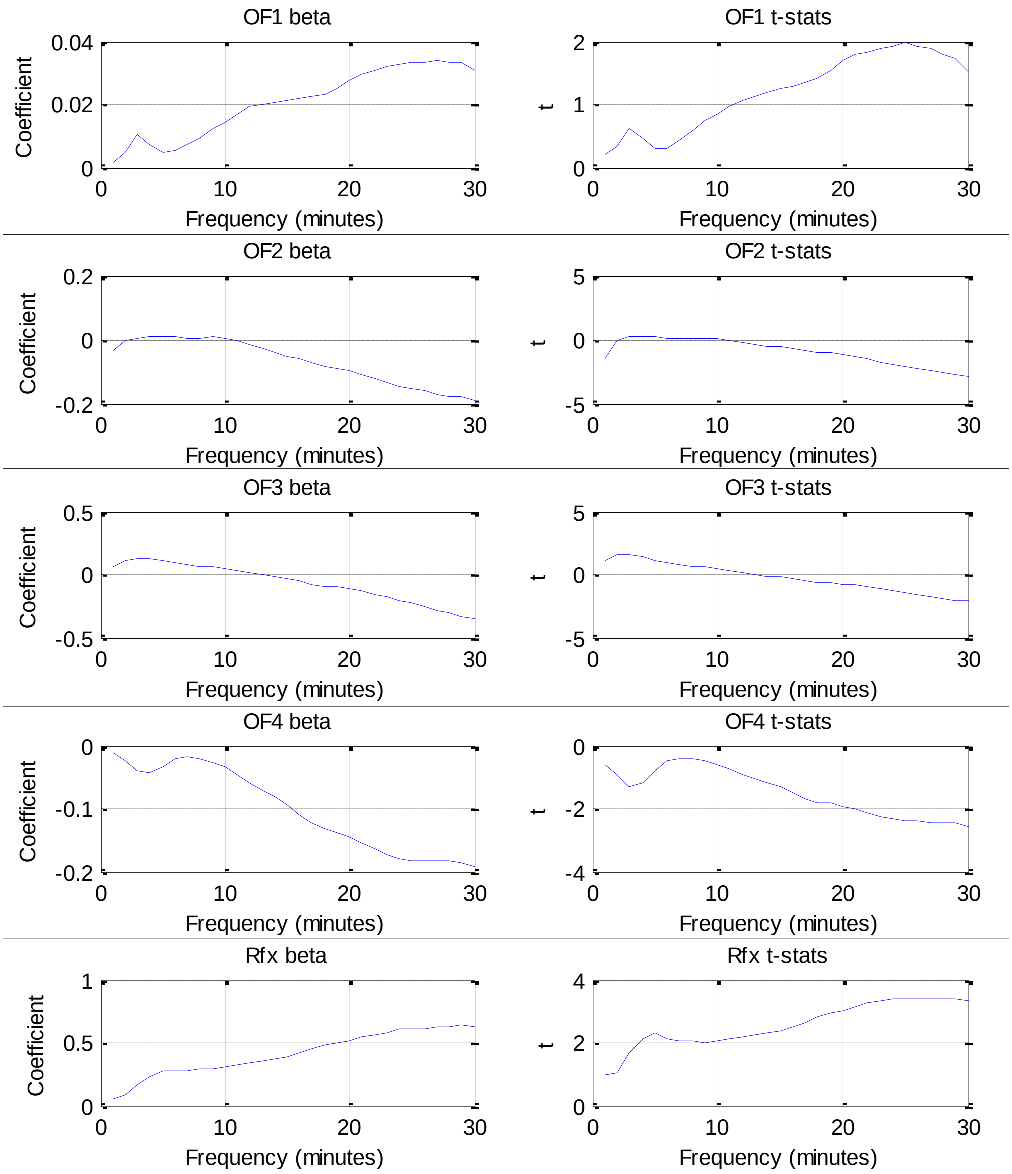


Figure 3-27: AA contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

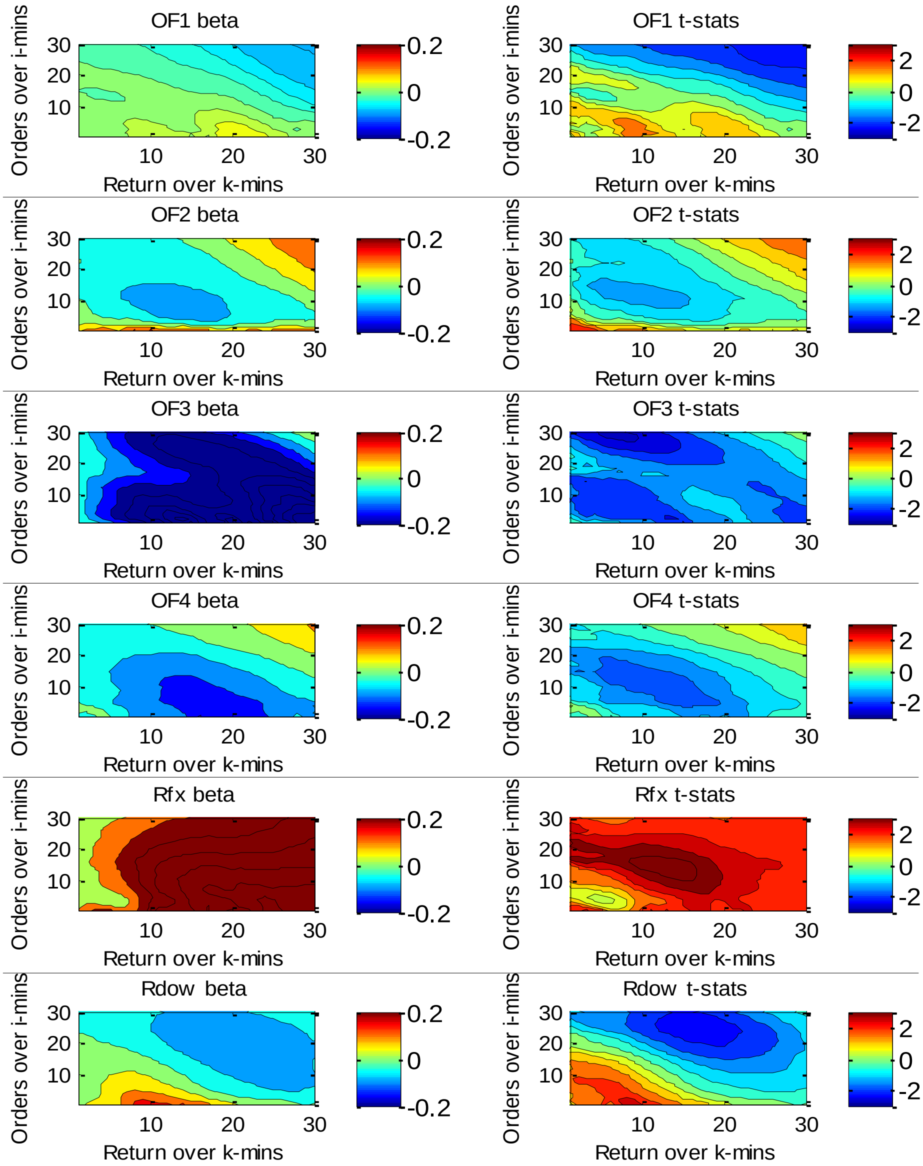


Figure 3-28: AA forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

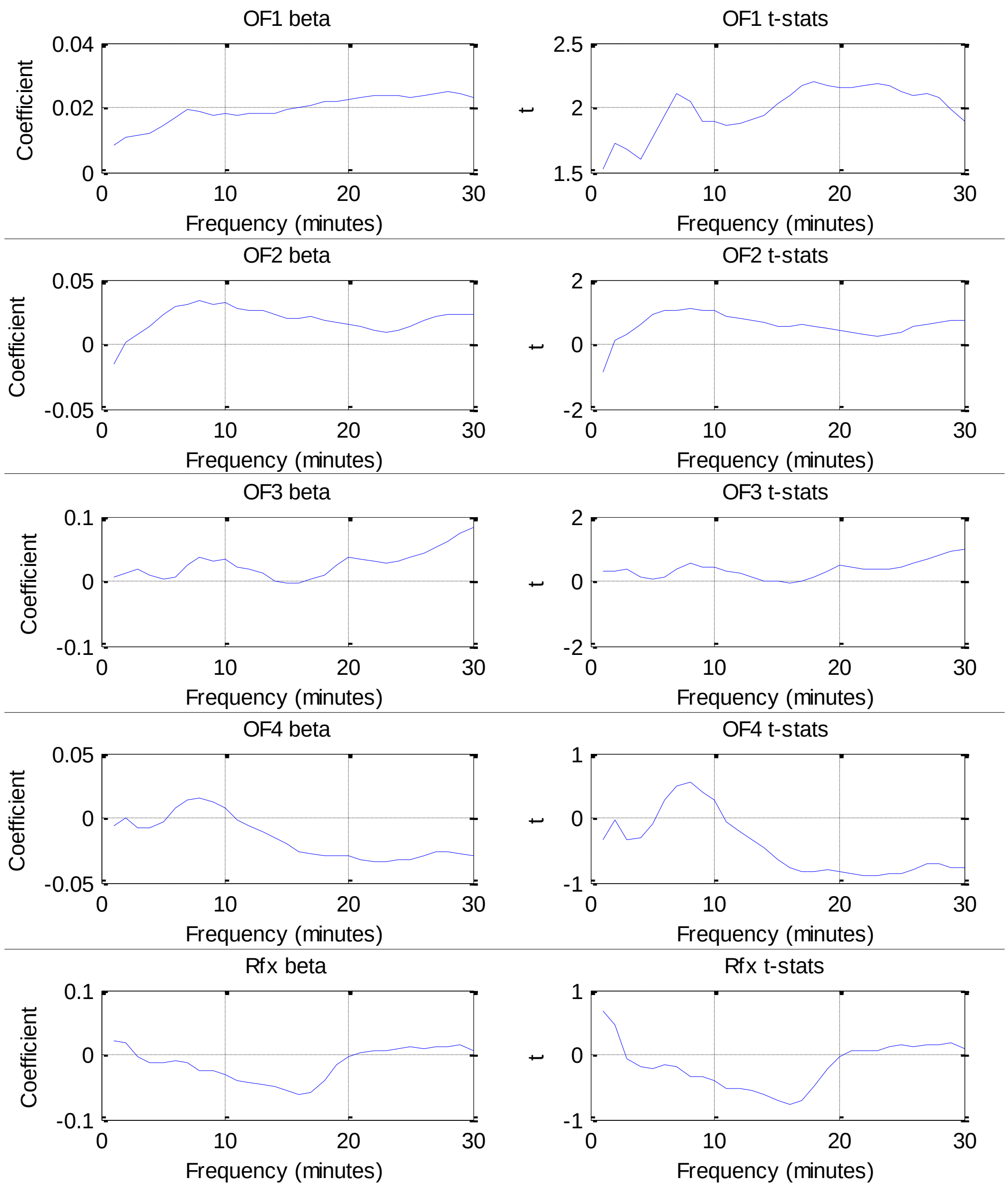


Figure 3-29: C contemporaneous

Notes: The figures show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", and Rfx: exchange rate returns) with t-statistics at high frequencies from 1-minute to 30-minute, in regression $R^{S}_{t,t+i} = C + \gamma R^{FX}_{t,t+i} + \sum_{m=1}^{4} \beta m OF^{FX}_{t,t+i} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

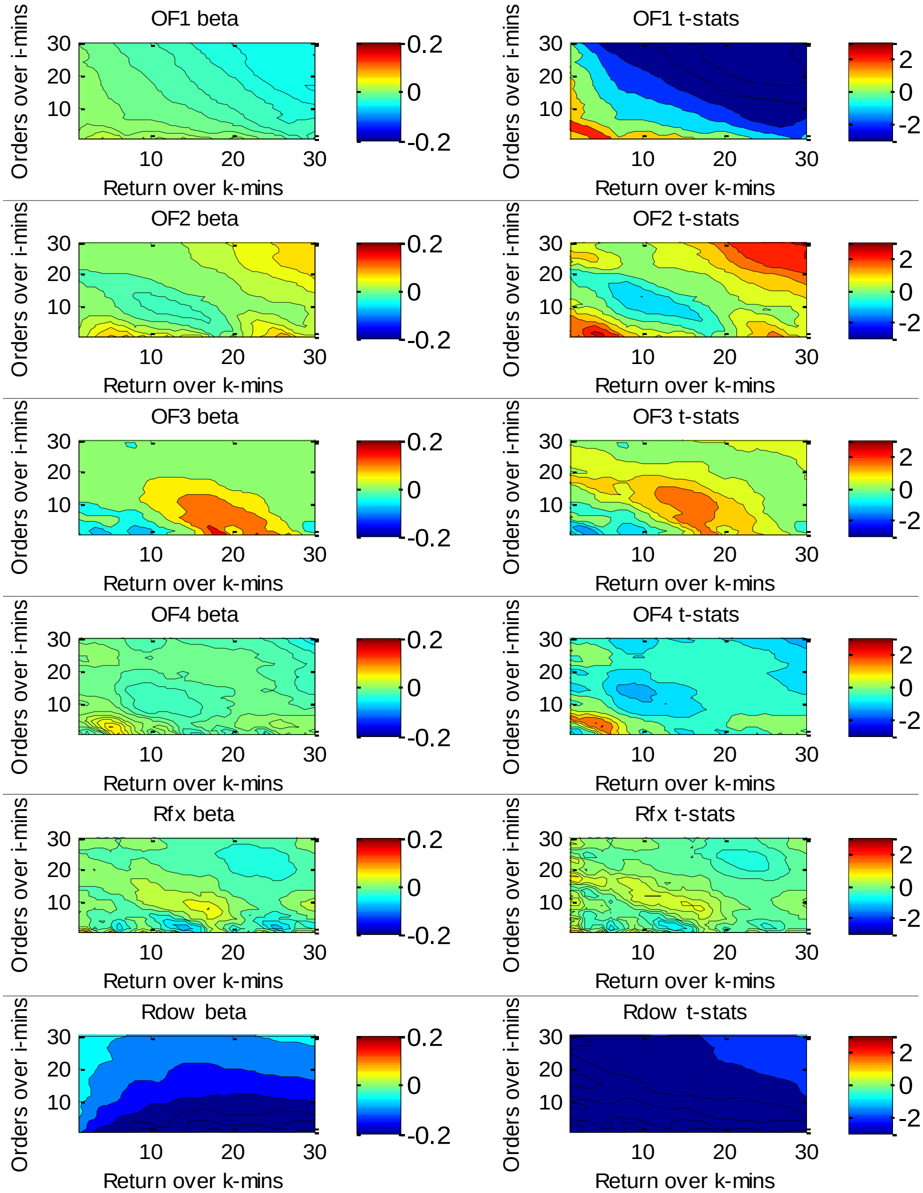


Figure 3-30: C forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

2) Heatmaps of results in the "pure foreign exchange environment", and SPY, DIA magnitudes of coefficients in the "cross market environment", in the forecasting models.

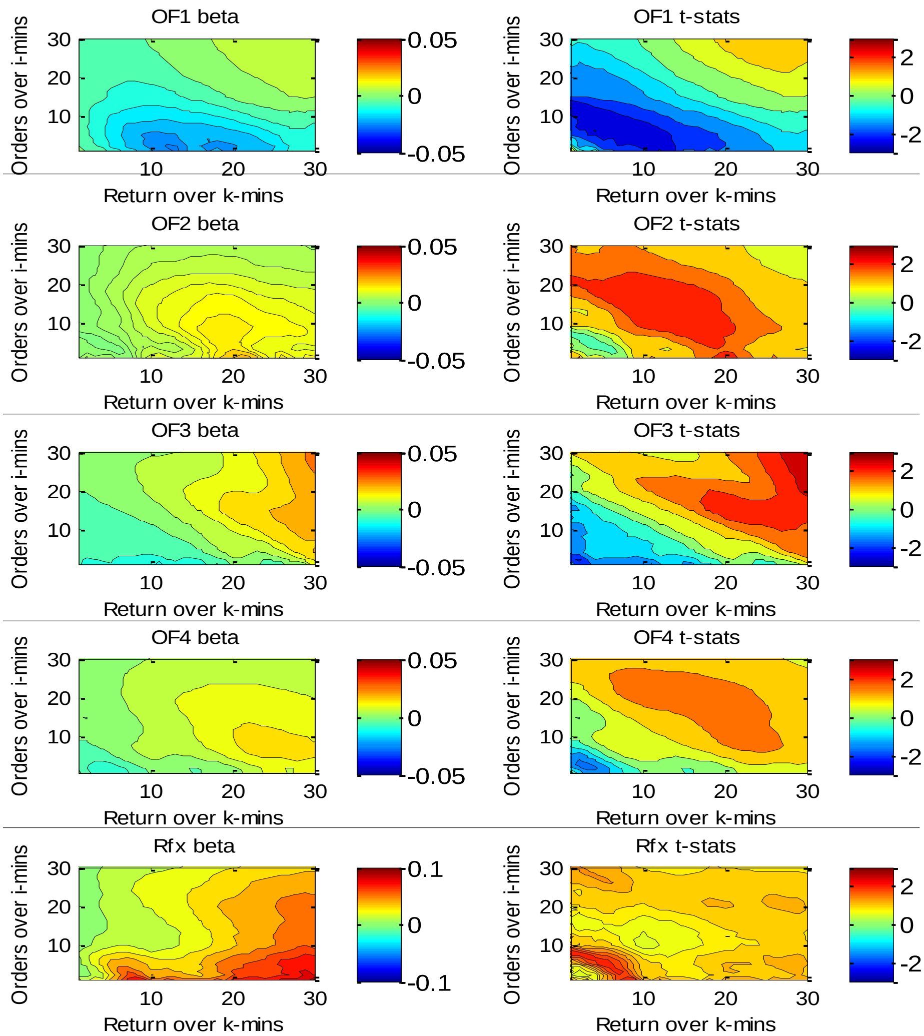


Figure 3-31: FX forecasting (Market rates)

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx: lagged EBS exchange rate returns) with t-statistics, in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used.

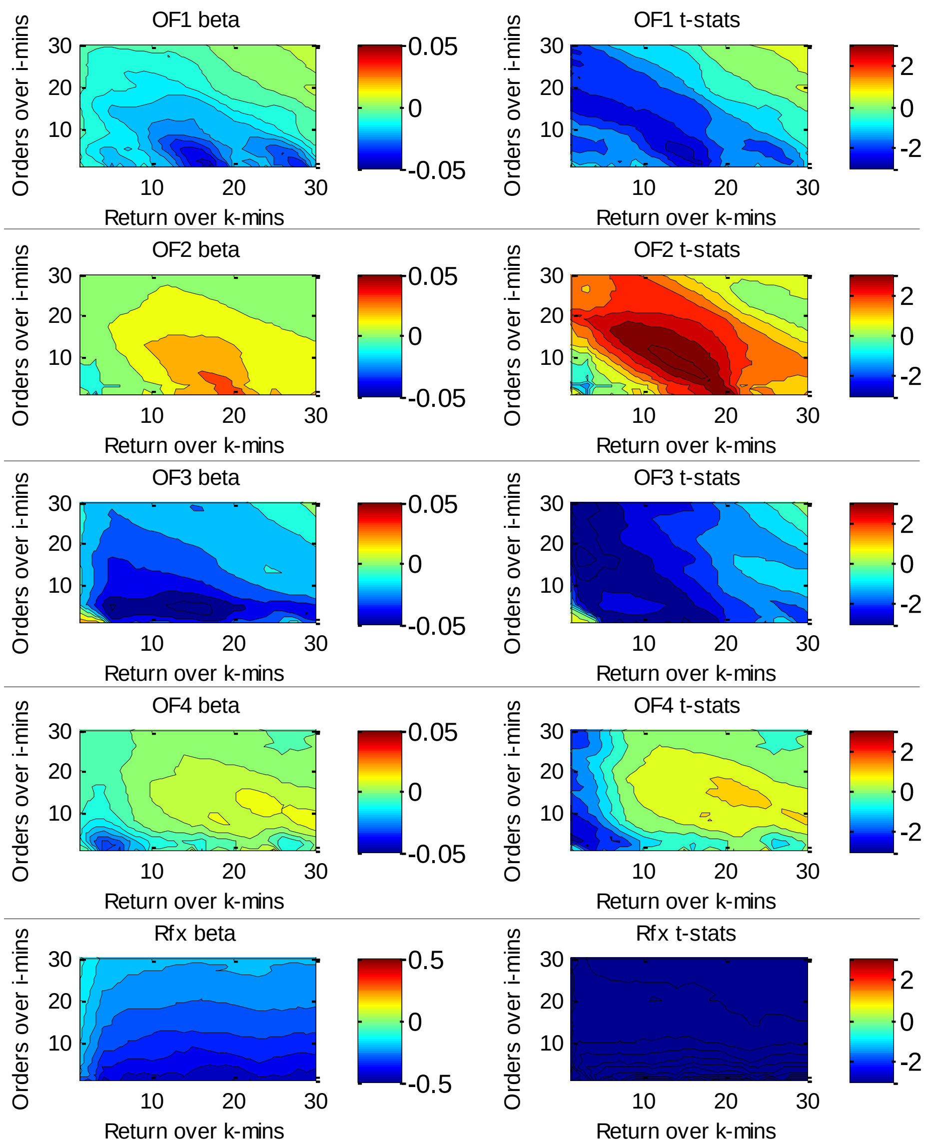


Figure 3-32: FX forecasting (Trade rates)

Notes: The heatmaps show coefficients estimates (OF1: “financials”, OF2: “corporates”, OF3: “internal”, OF4: “interbank”, Rfx: lagged bank exchange rate returns) with t-statistics, in regression $R^{FX}_{t,t+k} = C + \gamma R^{FX}_{t-i,t} + \sum_{m=1}^{4} \beta m OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 7:30am to 5:00pm for 25 days are used.

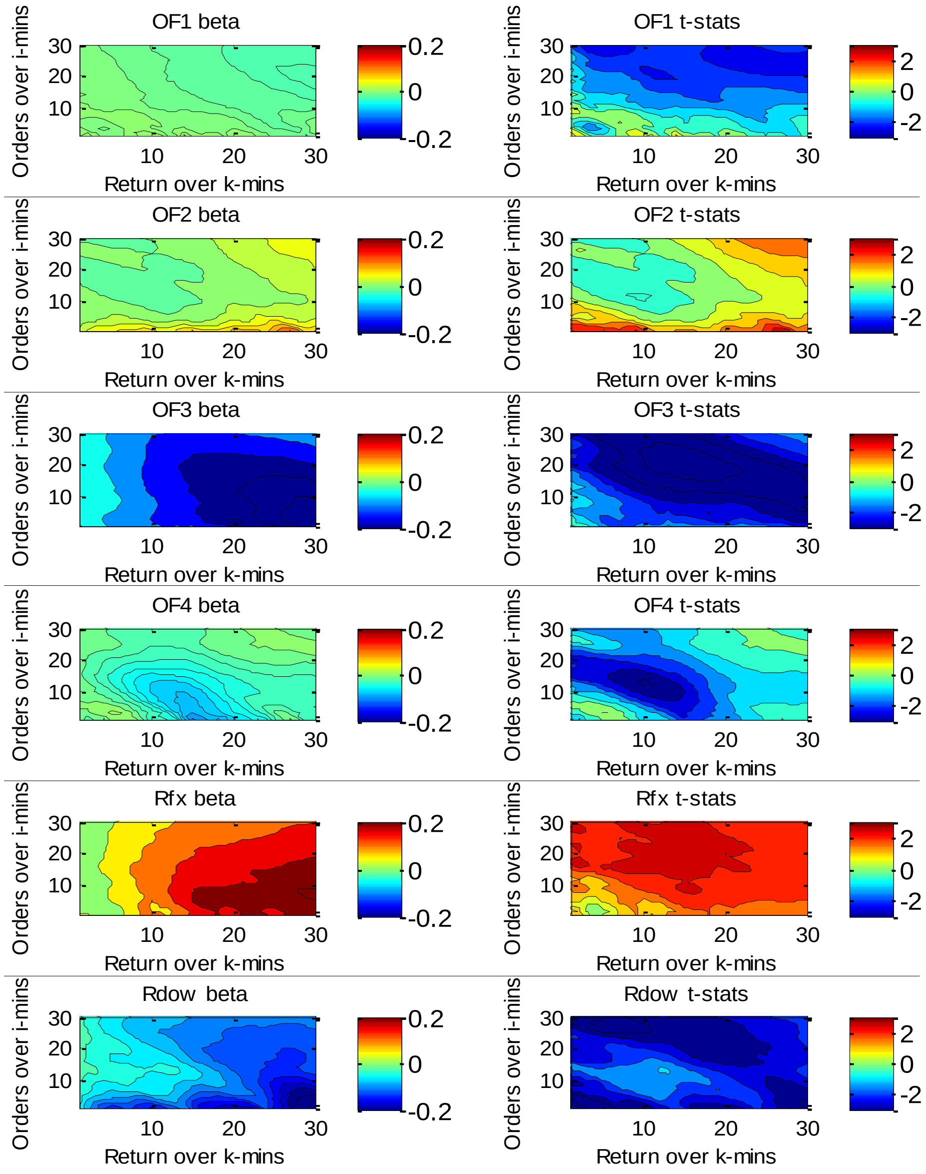


Figure 3-33: SPY forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

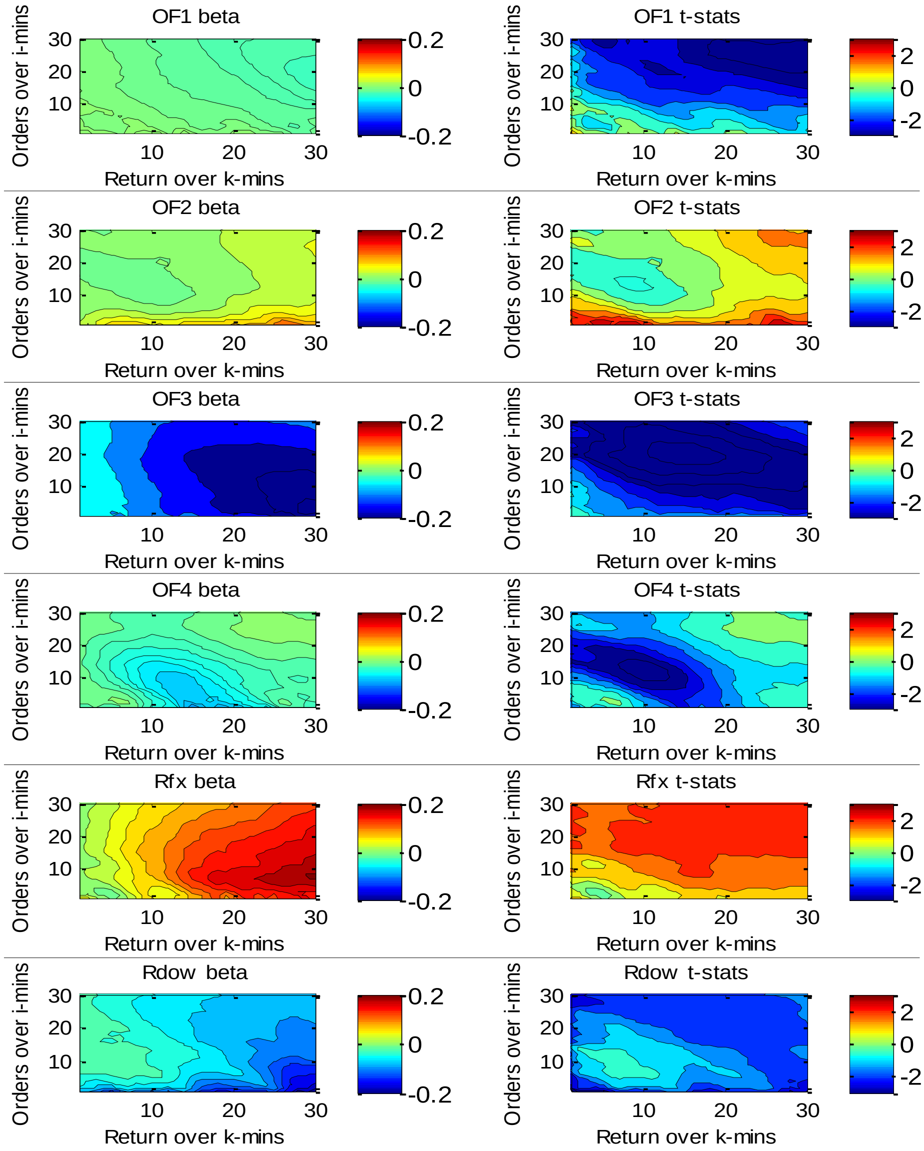


Figure 3-34: DIA forecasting

Notes: The heatmaps show coefficients estimates (OF1: "financials", OF2: "corporates", OF3: "internal", OF4: "interbank", Rfx and Rdow: lagged exchange rate stock market returns) with t-statistics, in regression $R^{S}_{t,t+k} = C + \alpha R^{S}_{t-i,t} + \gamma R^{FX}_{t-i,t} + \beta m \sum_{m=1}^{4} OF^{FX}_{t-i,t} + \varepsilon$. Warm color shaded cell means positive effects, while cold color shaded cell means negative effects. Intraday data from 2:30pm to 5:00pm for 25 days are used.

4 Conclusions

This thesis makes three contributions to foreign exchange microstructure research.

1) In chapter 1, we use genetic algorithms to investigate whether using technical analysis and order flows based trading strategies in the foreign exchange market is profitable, and whether the performance of technical trading can be improved by importing order flows as additional variables. To the best of our knowledge, only Bates et al. (2003) perform similar research before, however, our dataset is much longer (3.5 years vs. 10 months) and broader (6 vs. 3 exchange rates) than the ones used by them. Our findings suggest that there is no consistent forecasting power of foreign exchange order flows for exchange rate changes, which contradicts Bates et al. (2003), but is consistent with Chueng et al. (2005), suggesting possible uniqueness for each set of customer order flows data used in all the studies.
2) In chapter 2, using daily GBPUSD customer order flows provided by RBS, we find order flows from corporate customers have positive effects on future stock market changes, while order flows from unleveraged financial institutions have negative effects on future stock market changes. The "signs" of order flows from different groups of customers are systematically different for both UK and US. The cross market effects of order flows are partly consistent with findings in Francis et al. (2006) (using proxy variables to order flows) and Dunne et al. (2006) (only use brokered inter-dealer order flows over 1 year). However our findings on the heterogeneity of impacts are novel with longer truly transacted order flows data.
3) In chapter 3, using a unique set of tick-by-tick EURUSD order flows data obtained from a leading European commercial bank, we further confirm our findings in chapter 2. To the best of our knowledge, no one examines the cross market effects of foreign exchange order flows at intra-day frequencies. We find that order flows from financial customers have negative effects on concurrent and future exchange rate changes, while order flows from corporate customers have positive effects on exchange rate changes, at high frequencies ranging from 1-minute to 30-minute, which completely contradict our findings in chapter 2

and many well-documented papers, such as Evans and Lyons (2002a) using daily order flows (partly consistent with Osler and Vandrovych (2009)). More importantly, we provide more evidence on the cross effects of foreign exchange order flows at higher frequencies. Order flows from financial customers have negative effects on stock market changes and those from corporate customers have positive effects on stock market changes (consistent with findings in chapter 2 using daily order flows).

4) We suggest that the private information conveyed in foreign exchange order flows, is also of value to stock markets, suggesting at least some macroeconomic informational content.

The inconsistency of forecasting power of order flows across different periods for different exchange rates in chapter 1 suggest the possible structural breaks in our data, or customer order flows from one bank is not enough to explain exchange rate changes well. However, using tick-by-tick high frequency order flows data from another European bank, we find strong effects of the flows on exchange rate changes. This result might suggest why we do not find consistent forecasting power in the foreign exchange market using daily frequency data in chapter 1: the information buried in order flows can only last for minutes and will dissipate by the end of each trading day.

In the case of cross market effects of foreign exchange order flows on stock market changes discussed in chapter 2 and chapter 3, we hypothesize some explanations on that without using theoretical models to verify the interpretations.

For non-financial corporations, net buying of GBP or EUR and selling USD has positive forecasting power for stock market returns. Since (i) it is unlikely that corporations are moving capital in order to invest in the stock market, (ii) coefficients for the UK market and the US market are both positive (in chapter 2), and (iii) longer effects (up to 10 days) of order flows on US stock market changes are consistent across different companies and indices, the relationship between foreign exchange order flows from corporate customers at day t and stock market returns at day t+1 is not caused by foreign currency buying pressure at day t. Instead, we argue that the forecasting power of corporate foreign exchange order flows must be because of some information content. We hypothesise that corporate customers of the bank are mainly based in the UK. When the world economy is doing well, multi-national companies are selling more goods in the US and repatriate more foreign currencies back to UK, during which more GBP or EUR are converted from US Dollars. More sales of US Dollars then reflect the good future prospects of the world economy and stocks listed in both US and UK will rise in value. And also we know some big corporations have their own finance department and they will use the large amount of outstanding cash in hand to do investment to preserve the value of their assets. The other reason for the finance departments to be involved in buying and selling of currencies and stocks are due to active mergers and acquisitions especially over blossom business cycles.

For unleveraged financial institutions, when the world economy is going bad, clients of those mutual funds which are based in the UK will ask for redemptions of their funds. Assuming the bank services a client base that is UK oriented, this leads to the repatriation of money from abroad back to UK. The buying of GBP or EUR in exchange for US Dollars then takes place alongside sales of US and UK stocks. Foreign exchange flows into GBP or EUR from unleveraged funds forecast poor future stock market returns globally. Another possible explanation is called "risk on, risk off theme". When market is full of turbulences, investors will sell the risky assets and bring the overseas foreign currency denominated assets back to the UK. Before doing that the foreign currency will be converted to British pounds. This will contribute some to the negative relationships between buying of sterling and downward trends of global financial markets. Last but not least explanation is about portfolio balancing requirements. According to Hau and Rey (2006), many real money portfolio managers who hold internationally diversified stocks will rebalance the holdings, when foreign stock markets are volatile or when exchange rates are away from their expected values.

Taking together the findings provided in chapter 2 and chapter 3, we think information content is the best way to explain such a cross market relationship, and we suggest the private information which drives exchange rates also appears to be relevant for equity markets.

Finally we point out some refinements that can consolidate our findings and the some possible directions of further research.

- We suggest explanations on the heterogeneous effects based on the assumption that RBS customers are mainly located in London. If we know more details of the bank's customers, explanations will be more concrete. Also we can not rule out the possibility that both foreign exchange order flows and stock market returns are affected by an "omitted" variable, or the forecasting power of foreign exchange order flows for stock markets is only because the information aggregation process is slower than that in the foreign exchange market.
- When dealing with cross market effects, due to time difference between the UK and the US, the overlapping data is only 2.5 hours every day. Although we still have more than 3000 observations in the regression models, the conclusion will be better if we have more overlapping periods. For example, if we can find 24-hour trading futures data, it will be a plus; or if we can have access to some high frequency data in UK or European stock markets.
- In chapter 2 we use daily GBPUSD order flows data, while in chapter 3 the tick-by-tick data is EURUSD, which makes the comparison a little bit doubtful.
- In chapter 3 we only check the changes in the foreign exchange market and the stock market at frequencies from 1-minute to 30-minute. Maybe we can get a broader picture of how order flows carry information throughout the day by checking the dynamics at frequencies up to 60 minutes or 120 minutes, although in this way the observations will drop in "pure foreign exchange" regressions.

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