High Frequency Quoting and Price Discovery in the Foreign Exchange Market

By

Hossein Jahanshahloo

Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds
Leeds University Business School
Centre for Advanced Studies in Finance

June, 2016

Intellectual Property Statement

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

The copy has been supplied with the understanding that it is copyright material and that no quotation from the thesis may be published without proper acknowledgment.

Acknowledgment

I would like to express my most sincere appreciation and thanks to my supervisors Professor Charlie X. Cai and Professor Kevin Keasey, who with their knowledge, patience, support, and wisdom guided and mentored me throughout the process of this PhD. They showed me the pathway to be a successful academic. I also would like to express my appreciation and thanks to Ms. Michelle Dickson who always supported me in every stage of this PhD process, her role in this process cannot be emphasised enough, by words.

I would like to express my appreciation to Dr. Shima Amini and Dr. Konstantinos Bozos for all their help and guidance during my MSc that was the pathway to this PhD. I am grateful to my colleagues in the Centre for Advance Studies in Finance (CASIF), Dr. Ian Clacher, and Dr. Timothy King who accompanied me in this journey. I gratefully acknowledge the financial support that I received during the last year of my PhD from CASIF. I thank participants in the Accounting and Finance Division Seminar Series for their useful feedback and comments.

I would like to express my warmest and most sincere appreciation to my beloved parents Farideh and Gholamreza whom without their love, sacrifices, financial, and moral support this PhD process would not have been possible. My special thanks to my sisters Laala, Hale, Hoda, and Ghazaal who always supported me and gave me energy and strength despite the thousands of kilometres distance.

Finally, I am sincerely grateful to my beloved and caring wife Laima who without her partnership, love, support, care and patience this journey would not have been possible. Words cannot express the extent that I appreciate everyone who helped me through the process of this PhD.

Abstract

This thesis studies the process of price discovery in the FX market via three empirical chapters. In the presence of high frequency trading and its expansion in the FX market, the first empirical chapter contributes to the literature by analysing how high frequency quoting affects price discovery in the foreign exchange market. It finds that while an increase in dealers' quotation speed is positively associated with short-term (within 1 minute) price discovery, this is not the case for longer-term (1-day) price discovery. These results cast doubt on the overall benefit of high frequency activities for long term price discovery in the foreign exchange market.

The second empirical chapter studies the impact of economist affiliation, quoting speed, and the geographical proximity on dealers' contribution to price discovery around macroeconomic news announcements. The findings show that dealers with affiliated economists have higher contribution to price discovery and their contribution increases by increases in the research scope of their affiliated economists. The locality of dealers and economists to news sources is also found to create an information advantage for dealers.

In the presence of the manipulation of the World Markets/Reuters benchmark in the foreign exchange market, regulators need a robust and timely methodology that identifies potential manipulation in order to better direct their limited resources towards more targeted in-depth investigation. The third empirical chapter of this thesis develops a manipulation index (ManIx) which captures the potential manipulation intention of dealers during the fixing period through a unique algorithm and simulation. The application of this model is able to identify banks that are prone to potential manipulative behaviour. The results concerning the identified banks are supported by verification of these bank with disclosure of regulatory investigations. Overall, ManIx offers a decision support tool to both regulators and banks to monitor market participants for manipulative behaviour.

Table of Contents

List of Tables, Figures, and Equations

Tables

Figures

Equations

List of Abbreviations

AT	Algorithmic Trading
ATs	Algorithmic Traders
BIS	Bank for International Settlements
CFTC	Commodity and Future Trading Commission
CME	Chicago Mercantile Exchange
DBMS	Database Management System
DOJ	Department of Justice (U.S.)
DOT	Designated Order Turnaround
EBS	Electronic Broking System
ECB	European Central Bank
FCA	Financial Conduct Authority
FED	Federal reserve (U.S.)
FINMA	Swiss Financial Market Supervisory Authority
FSB	Financial Stability Board
FX	Foreign Exchange [Market]
HFQ	High Frequency Quoting
HFQs	High Frequency Quoters
HFT	High Frequency Trading
HFTs	High Frequency Traders
LSE	London Stock Exchange
MiFiD	Markets in Financial Instruments Directive
NASDAQ	National Association of Securities Dealers Automated Quotations
NYDFS	New York Department of Financial Services

NYSE	New York Stock Exchange
OCC	Office of the Comptroller of the Currency
Regulation ATS	Regulation Alternative Trading System
Regulation FD	Regulation Fair Disclosure
Regulation NMS	Regulation National Market System
SEC	Securities and Exchange Commission
TSE	Tokyo Stock Exchange
U.K.	United Kingdom (of Great Britain and Northern Ireland)
U.S.	United States (of America)
WM Company	World Market Company
WM/R Fix	World Market / Reuters Fix Rate
WPC	Weighted Price Contribution

Chapter 1. Introduction

"Welcome to the world where every millisecond counts"

(Perez, 2011)

1.1. Introduction

The foreign exchange (FX) market is the biggest and arguably the most important financial market in the world with a daily turnover of $5.3 trillion (BIS, 2013). The FX market is a secondary underlying market for primary investment markets and affects almost every aspect of a country's economy such as output, employment, inflation, cost of imports and exports, commodity prices, and capital flow (King et al., 2011; BIS, 2011). In recent years, advances in computing and telecommunication technologies have paved the way for the emergence and expansion of new highly sophisticated and extremely fast market players know as High Frequency Traders (HFTs). Nowadays, HFTs account for more than 40% of the FX market and over 70% of the equity markets trading volumes (Hoffmann, 2014; Zhang, 2010).

The pervasiveness of HFTs in financial markets has attracted the attention of regulators, academics, and practitioners regarding their potential negative impact on the quality of financial markets (Conrad et al., 2015). The impact of HFTs on equity market functions such as liquidity, volatility, price efficiency, and the price discovery process has been extensively studied, although, there is a lack of study on the impact of these new market players on the functioning of the FX market (see chapter 2 for a survey on the existing

studies). Because the FX market is a decentralised, over the counter, geographically dispersed, quote driven, and 24/7 market (FSB, 2014) and is fundamentally different from equity markets, expansion of the findings regarding the impact of HFT on equity markets to the FX requires further examination. There are two reasons for the lack of studies on the impact of HFT in the FX market, the first is the lack of reliable data and the second is difficulties in identifying HFTs (BIS, 2011). Due to the characteristics of the FX market, collection and construction of a reliable dataset is difficult; however, in recent years, the expansion of electronic trading platforms in the FX market has reduced the complication and complexity of data collection processes and the identification of market participants.

This thesis strives to fill some of the gaps regarding the impact of these new market players, High Frequency Quoters (HFQs[1]), in the FX market literature and regulatory framework via three empirical chapters. The first empirical chapter examines how HFQs impact overall long-term and short-term price discovery process in the FX market. Since one of the main driving forces behind exchange rate movements is macroeconomic news, the second empirical chapters examines how information collection sources such as economists and dealers' quoting speed impact their contribution to price discovery. Finally, the third chapter develops an algorithm for identifying market participants who disrupt the price discovery of the WM/R fix rate, that is arguably the most important benchmark in the FX market.

The rest of this chapter is structured as follows. Section 1.2 discusses the research questions and contributions of this thesis and further explains the three empirical chapters briefly and section 1.3 concludes.

[1] Because the FX market is a quote driven market and market makers disseminate quotes to initiate a trade, in this thesis, high frequency traders and high frequency quoters are used interchangeably, in the context of the FX market.

1.2. Research Questions and Contributions

1.2.1. Quote Dataset

As stated above there are two reasons for a lack of studies regarding the impact of HFQs on the FX market. First the lack of reliable data and second, identifying market participants. The first contribution of this thesis is construction of a unique real time tick-by-tick bid and ask Quote Dataset that includes the identification of market participants and their locations and is accurate to the millisecond. The data in this dataset are collected from Thomson Reuters Eikon, one the most prominent FX trading platforms in the inter-dealer market. The high frequency and real time nature of the Quote Dataset makes it suitable for studying high frequency quoting. The existence of market makers' identification and locations in the Quote Dataset allows close observation of individual market participants' behaviour. Therefore, this dataset overcomes the existing barriers in studying High Frequency Quoting (HFQ) in the FX market and allows the investigation of many unexplored areas in this field.

The Inclusion of the identification and location of individual market participants allows an examination of individual market players' quoting speed (the most prominent feature of HFQs) and its impact on price discovery in the first empirical chapter (chapter 4). The location and identification of market players in the Quote Dataset also allows for construction of the link between market makers and their affiliated economists and subsequently studying the impact of affiliated economists, geographical proximity, and quoting speed on price discovery around macroeconomic news announcements in the second empirical chapter (chapter 5). Finally, the identification of individual market participants facilitates close observation of individual market players' quoting behaviour around the WM/R fixing windows that leads to the design, implementation, and test of an algorithm for identifying manipulators of the most prominent FX benchmark, in the third

empirical chapter (chapter 6). These three empirical chapters are a small portion of the unexplored areas in high frequency studies in the FX market that are facilitated by the construction of the Quote Dataset. This dataset could be used for future research to explore many of the unexplored areas in the FX market.

The Quote Dataset spans 286 days from April 22nd, 2013 to March 27th, 2014. Excluding Saturdays and Sundays the Quote Dataset includes 236 days and 98,860,278 quotes from the EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs. These currency pairs are the most liquid currency pairs in the world and their constructing currencies, Euro, British Pound, U.S. Dollar, and Japanese Yen, account for 77.7% of the overall FX turnover. In total, there are 94 dealers active in 49 cities and 44 countries, from all the six continents, forming 109 dealer-locations.

The Quote Dataset is unique in its kind in the scope and scale of its coverage. The last similar dataset to the Quote Dataset is HFDF93 that has been used in studying the FX market for more than 20 years. Research continued using HFDF93 up to recently such as, Chelley-Steeley and Tsorakidisb, (2013). The HFDF93 dataset include quotes from three currency pairs, USD/DEM, USD/JPY, and DEM-JPY, from 1992 to 1993. Although HFDF93 had contributed to the field of FX market microstructure for 2 decades, the FX market has significantly changed in both structure and nature in the last 20 years. The Quote Dataset constructed as a part of this thesis, therefore, also allows future research to study the current market microstructure of the FX market. In order to make this dataset available for future research the construction and collection method of the Quote Dataset is explained in chapter 3.

1.2.2. High Frequency Quoting and Price Discovery in the FX Market

As mentioned above the innovations in financial markets has given rise to new highly sophisticated market players known as high frequency traders. There is a growing concern

within market participants and regulators regarding the negative impact of HFTs on the functioning of financial markets. The first empirical chapter of this thesis (chapter 4) contributes to this debate by evaluating the impact of market participants' quotation speed on price discovery in the FX market. In other words, chapter 4 examines the applicability of the extension of findings in equity markets on the impact of HFTs on price discovery. Findings from this analysis allow market participants and regulators to have a better understanding of the role that a market player's quoting speed has on FX market quality. This chapter, to the best of my knowledge, is the first investigation on the impact of High Frequency Quoting (HFQ) of price discovery in the FX market.

The dataset used for the empirical study of chapter 4 is a subset of the Quote Dataset that was introduced in section 1.2.1 and is explained in more detail in chapter 3. Because price discovery is a continuous process and the goal of chapter 4 is to observe this process at the highest frequency possible, two conditions are imposed on the Quote Dataset, in order to be used for chapter 4's empirical work. First, the dataset of chapter 4 includes merely the days where there is no interruption in the data collection, and second, market makers' repetitive quotes[2] are removed since they do not contain any new information. This dataset spans from April 23rd, 2013 to March 11th, 2014 and includes 115 trading days and 39,250,175 quotes from 92 dealers in 6 continents, 42 countries, and 49 cities, which form 104 dealer-locations.

In order to measure market participants' contribution to price discovery, the Weighted Price Contribution of Barclay and Warner (1993) is used. This model measures the cumulative contribution of a market participant to the total price movement in the market. Following Pascual and Pascual-Fuster's (2014) findings that bid and ask quote are not equally informative, the bid and ask price discovery contribution for dealers is calculated separately.

[2] A repetitive quote from a dealer is a quote where its ask and bid prices are equal to those of the previous quotes of the dealer.

Market makers' contribution to price discovery is calculated in the two time horizons of 1-minute and 1-day. The 1-minute time horizon is used as a proxy for short-term or market price discovery and the 1-day time horizon is used as a proxy for long-term price discovery. In order to examine the impact of dealers' speed on their contribution to price discovery, a speed measure is based on the tick frequency measure proposed by Guillaume et al., (1997). In addition, due to the strong inventory control effect of FX dealers (Lyons 1995) that leads to one sided trading of market maker (Harris, 2003, p280), the observable intention, quoting aggressiveness, and spread widening measures are constructed to quantify dealers' quoting behaviour.

Chapter 4's findings shows that an increase in the quoting speed of dealers positively impacts their ability in predicting short-term price movements (contributing to short-term market price discovery), while it has no impact on their contribution to long-term price discovery. This discrepancy between the impact of speed on short-term and long-term price discovery is consistent with the fact that an increase in dealers' speed increases their price discovery volatility, thus undermining their contribution to long-term price discovery.

The contribution of the empirical work in chapter 4 is twofold. First, these findings strongly support the short-termism of FX market participants. In other words, the results show that market makers mainly focus on short-term value rather than long-term value. The short-termism of market participants could lead to lower concentration and attention to fundamental information regarding an asset and consequently impair the price discovery process, causes market overreaction, and reduces market efficiency (Froot et al., 1992; Menkoff, 2001; Zhang, 2010; Vives, 1995). Second, chapter 4's results also contribute to the regulatory debates regarding the impact of HFTs on financial markets. While the speed of market participants allows them to better predict the short-term price movements in the market, the lack of relationship between speed and long-term price discovery raises concerns regarding the potential negative impact of increasing speed in the FX market. The regulatory

implication of these findings suggests that the speed arms race of market participants might be a social waste, since it does not impact the most important function of financial markets long-term information discovery. In addition, the strong relationship between speed of market participants and price discovery volatility lends supports to criticism that HFT could increase market volatility.

1.2.3. Do Economists Add value to the FX?

Analyst affiliation and the geographical proximity of market makers and analysts to a firm is found to play an important role in information advantage, competitive advantage, and the contribution of dealers to price discovery, in equity markets. It is found that dealers with affiliated analysts have higher a contribution to price discovery and they are more informed than dealers without analyst affiliation (Madureira and Underwood, 2008). Empirical studies show that local market makers and analysts possess an information advantage over non-local market makers and analysts (Berger et al., 2009; Bae et al., 2008; Annand et al., 2011; Bolliger, 2004; Schultz, 2003; Kedia and Zhou, 2011). However, to the best of my knowledge, there is no similar study in the FX market that evaluates the impact of economist affiliation on market makers' contribution to price discovery. Due to fundamental and structural differences in information transparency (i.e., private information in equity markets) and information transfer medium (i.e., the centralised exchanges in equity markets) between equity and the FX markets, the validity and expansion of these findings in equity markets to the FX market require further examination. Furthermore, macroeconomic news and firm specific news have exhaustively different scopes and scales. While firm specific news is to do with the future cash flow of a company and impacts merely the equity price of the company, macroeconomic news is regarding the whole state of a country's economy and impacts every financial market and aspect of a country's economy.

The second empirical chapter of this thesis (chapter 5) for the first time, to the best of my knowledge, studies the impact of economist affiliation on the contribution of market makers to price discovery around macroeconomic news announcements. This chapter examines whether market makers with affiliated economists systematically are more informed than dealers without economist affiliation. Furthermore, in the presence of HFTs and their increasing share from the FX market (Rime and Schrimpf, 2013) and HFTs' ability in reading and reacting to macroeconomic news before others (Groß-Klußmann and Hautsch, 2011; Scholtus et al., 2014; Biais et al., 2015; Martinez and Rosu, 2013), in addition to early access of HFTs to some of the macroeconomic news announcements (Mullins et al., 2013; Goldstein et al., 2014), quoting speed of market participants is also studied. Finally, the impact of the geographical proximity of dealers, affiliated economists, and macroeconomic news sources to each other and their interactions on the information advantage of market makers is also examined. The answer to these questions not only show how price discovery happens around macroeconomic news announcements, but also answers what role geographical proximity plays in this process.

The dataset used for the empirical analysis of chapter 5 consists of four sections of quote, macroeconomic news, economist forecasts, and economist geographical information datasets. The existence of identification in the Quote Dataset allows the construction of a link between dealers and their affiliated economist and the macroeconomic news that their affiliated economists have forecasted. The Quote Dataset used in this chapter is a subset of the Quote Dataset explained in section 1.2.1 and chapter 3. The macroeconomic news announcements dataset, economist forecasts dataset, and economists' geographical information are collected from Bloomberg. The collection procedure of these datasets are also explained in chapter 3 and summary statistics and characteristics of these datasets are presented in chapter 5.

The methodology used in chapter 5 is analogous to that in chapter 4 regarding the calculation of market makers' contribution to price discovery and their quoting speed, however, with a different time frame of study. The time frames of study in chapter 4 are 1-minute and 1-day, while that of chapter 5 is a 4-minute window around macroeconomic news announcements. The geographical proximity of dealers, economists, and macroeconomic news sources to each other is calculated as the weighted average of their geographical proximity to each other, weighted by the number of news items released from each constructing zone of a currency pair. Finally, the impact of the above mentioned variables on the contribution of market makers to price discovery is measured.

The findings regarding the impact of economist affiliation on market makers' information advantage shows that economist affiliation not only creates an information advantage for market makers, but also increases in the scope of economists' research regarding a country's economy, increases the dealers' information advantage level. Furthermore, market makers' quoting speed also plays an important and significant role in dealers' contribution to price discovery. These results depict two main points, first, the impact of information collection sources (i.e., economists or analysts) on their affiliated market maker is independent of market structure and information medium transparency and structure. Second, the speed of market participants plays an important role in their contribution to price discovery, since it allows them to react to news quickly and incorporate new information into prices before slower traders. Findings regarding the geographical proximities illustrate the importance and limitation of locality of economists and market makers to macroeconomic news sources and each other. Locality of market makers and their affiliated economists to the country of macroeconomic news announcements creates an information advantage for market makers. Interestingly the results show the limitation of information availability from one geographical proximity. In other words, the results show

that there is a limitation to the amount of information that can be accessed from the same location, independent of its quality.

The contribution of chapter 5 is threefold. First, it shows the importance and impact of information collection sources and their geographical location on information quality, and the information advantages of market makers. Chapter 5 illustrates the interaction between geographical proximity of dealers, economists, and macroeconomic news sources and how they impact market makers' information content. However, it should be added here that since the results show that affiliated economists' research scope directly impacts the level of dealers' information advantage, and there is no evidence of privileged access to public information, there is no concern regarding market fairness and a regulation such as Regulation FD regarding this matter does not seem necessary. Second, it shows that the advantage of economists' forecasts is limited only to dealers with affiliated economists and illustrates the difference in information distribution mechanisms between FX and equity markets. Third it sheds light on the role of the market maker's quoting speed on the price discovery process around macroeconomic news announcements that also has policy implications. The importance of market makers' quotation speed and the ability of fast market makers in reacting to macroeconomic news, before others, suggest that selling early access to macroeconomic news announcements creates an unfair market environment and could impose significant adverse selection costs on slower market participants.

1.2.4. Monitoring the Foreign Exchange Rate Benchmark Fix

On 12th June 2013, three reporters from Bloomberg reported that FX traders had been manipulating the most important benchmark of the FX market, known as WM/R fix rate, for years. The breaking of this news triggered more than 20 investigations in many countries and led to the highest amount of fines ever imposed on banks in recent history[3].

[3] The collection of the fines and law suit settlements exceeds $11.8 billion.

The reason for such a large scale investigation and fines is that WM/R affects $3.6 trillion of assets including pension funds, multinational companies, and almost any entity with global investment and transactions. In other words, the WM/R fix rate impacts upon the resource allocation of economic agents who are involved in any form of global investment, thus can be extremely costly to society. This scandal raised strong concerns regarding the functioning of the FX market and the need for regulatory oversight of this widely unregulated market.

In the era of algorithmic and high frequency trading, the challenge that regulators face is the design of a monitoring system that can oversee such trading activities in a cost effective manner, and provides a timely warning signal that prompts further investigation. Chapter 6 of this thesis (third empirical chapter) for the first time designs, implements, and tests an algorithm for identification of WM/R fix rate manipulators, called Manipulation Index or ManIx. It is designed to identify the market participants who strategically and systematically place their quotes in order to manipulate the WM/R fix rate. ManIx consists of two phases of identification and statistical verification that is based on bootstrap methodology. It is implemented on a subset of the Quote Dataset that includes merely the quotes from WM/R fixing window that is a 60-second window centred at 4pm G.M.T. and spans from April 22nd, 2013 to March 27th, 2014. ManIx identifies 17 out of 69 dealer-locations in the dataset and 8 of them have been investigated by regulators or sued by their clients and investors. Among these banks 4 of them account for 68% of the fines imposed by regulators. These findings confirm the ability of the ManIx in capturing the abnormal behaviour of market participants around the WM/R fixing window and its applicability for regulators and market participants.

The contribution of Chapter 6 to the regulatory framework and academic literature is threefold. First, it designs a timely monitoring system that addresses the challenge of monitoring the unregulated FX market. Second, it contributes to the new debate on the response of regulators to the rapid changes in financial technology. Finally, chapter 6

demonstrate the usefulness of using quote data for identifying potential misbehaviour in the FX market.

1.3. Conclusion

Overall, this thesis attempts to address three main questions regarding the price discovery process in the FX market. First, what impact the quoting speed of market participants has on the long-term and short-term price discovery process of the FX market. Second, how the affiliation with economists impacts market makers' information advantage and how the geographical proximity of economists, dealers, and macroeconomic news sources to each other affects the market makers' contribution to the price discovery. Third, and finally, how the manipulators of the WM/R fix rate could be identified.

Chapter 2. Literature Review

2.1. Introduction

This chapter surveys the existing literature on high frequency trading, price discovery, and some of the factors affecting the information advantage of market makers and their contribution to price discovery in both equity and the FX markets. All the literature surveyed in this chapter regarding the impact of high frequency trading on financial markets (except the work of Chaboud et al., 2014) is focused on equity markets. Therefore, it should not come as a surprise that even though this thesis studies the impact of high frequency quoting on the *FX market*, the overwhelming majority of the literature presented here is with regards to equity markets. Since, the findings of the researches on equity markets cannot uncritically be applied to the FX market due to the significant differences between the nature, market structure, regulation, and price discovery process between the FX and equity markets (Booth, 1984; King et al., 2013; Osler et al., 2011; Harris, 2003), the lack of study of the impact of these new highly sophisticated and fast traders on the FX market is one of the main motivations of this thesis.

Two out of three empirical chapters of this thesis, chapter 4 and 5, are based on similar studies in the equity markets and therefore, the related literature regarding these two chapters are surveyed in this chapter. However, due to the absence of any academic literature, regulatory document, or previous study related to the third empirical chapter (Chapter 6), no literature regarding this chapter is surveyed.

This chapter is structured as follow. Section 2.2 surveys the past literature on market microstructure studies in the FX market and discusses the broad categories of financial markets with the focus Over-The-Counter (OTC), regulated market, order driven and quote driven markets. Section 2.3 defines high frequency trading, explains its expansion and gives a brief history on the emergence of high frequency trading in financial markets. Section 2.4, surveys the empirical and theoretical studies on the impact of high frequency trading on liquidity, volatility, transaction and adverse selection cost, social welfare and fairness, and price discovery and price efficiency. Section 2.5, reviews the current literature on price discovery and information advantage sources of market makers around macroeconomic news announcements. Section 2.6 reviews the existing price discovery models and discusses the reasons for the choice of Weighted Price Contribution (WPC) model. Section 2.7 concludes the overall theoretical and empirical findings of the surveyed literature and sets out the main questions that the consequent empirical work will focus on and are unsolved to date.

2.2. The FX Market

2.2.1. Emergence of FX Market Microstructure

After the abandonment of fixed exchange rates in the 1970s, researchers had little evidence to guide the development of exchange-rate models. In the 1990s, in response to the disappointing performance of macro-based exchange rate models, FX market microstructure emerged. Researchers in the FX market microstructure take a macroeconomic approach to understand the mechanics of exchange rate determination. Early microstructure researchers conducted their studies by directly observing the trading process in the market and engaging with FX dealers (King et a., 2013) reasoning that "economists cannot just rely on assumptions and hypotheses about how speculators and other market agents may operate in theory, but should examine how they work in practice, by first-hand study of such markets"

(Goodhart, 1988, p.438). The progress of FX market microstructure research was slow until the mid-1990s when electronic trading platforms emerged and generated large and accurate trading records[4]. These observation directed researchers to the features of the FX market, such as trading flow and private information[5], which had been considered irrelevant previously.

Order flow in the FX market is defined as the net of buyer-initiated and seller-initiated orders and quantifies the net buying pressure (Evans and Lyons, 2002). "A central hypothesis of the foreign exchange market microstructure literature is that order flow allows the wider market to learn about the private information and trading strategies of better informed participants and therefore represents the conduit through which information becomes embedded within market prices" (p.584). Large banks who can observe the order flow on a real-time basis, can use the information embedded in order flow to inform their trading decisions (Sager and Taylor, 2008)[6]. Cheung and Chinn (2001) surveyed FX traders in the U.S. and report that traders believe that a large customer base and consequently better information are the sources of large players' competitive advantage in the market. Evans and Lyons (2002) show that the order flow can explain 60% of the variation in Deutsche Mark/Dollar log price changes.

There are two different approaches in the literature regarding the quantification of order flow. Evan and Lyons (2002) define order flow as the difference between the number of buy-initiated and sell-initiated trades, while Berger et al., (2008) define order flow as the difference between the volume of buyer and seller initiated trades. Although, Berger et al.,

[4] In the late-1990s the FX market evolved by increases in automated trading and the emergence of new electronic trading technologies that increased transparency and transaction speed and reduced transaction cost (King et a., 2013).For further details on electronic platforms, geography and composition of currency trading, and players in the FX market see King et al. (2012) and chapter 3 section 3.3.

[5] For further review of the literature on order flow and private information see Cheung and Chinn (2001).

[6] Sager and Taylor's (2008) findings, however, challenges the value of the information that can be obtained from commercial available order flow datasets that are published with the minimum lag of 1 day. They show that these datasets do not improve the quality of the exchange rate forecasts.

(2008) argue that the order flow measure based on the volume term is superior to the order flow quantified from number of traders (such as the order flow that is measured from quote data rather than trade data), Love and Payne (2008) show that differentiating buyer-initiated from seller-initiated trading interest explains price variations better than the difference between buy and sell quantities.

2.2.2. Key Players in the FX Market

Any investigation of a market begins by determining the key players and the structure of that market. The FX market is a two layers market that is divided into the wholesale or inter-dealer market and the customer-dealer or retail market (King et a., 2013). The customer-dealer and inter-dealer sections of the FX market account for 25% and 75% of the trading volumes in this market, respectively (Danielsson and Payne, 2002). The inter-dealer market segment is divided into two segments of direct and indirect inter-dealer trades. Direct inter dealer trade consists of telephone and D2000-1 based trades and indirect inter-dealer trade consists of voice brokered trade and electronically brokered trade such as EBS and D2000-2 (Danielsson and Payne, 2002). Therefore, it can be concluded that the dealers are the main players in the FX market and the inter-dealer market accounts for the overwhelming majority of the trading activities in this market. The focus of this thesis is on the inter-dealer segment of the FX market and strives to examine the impact of new highly sophisticated market participants' behaviour in the FX market on this market quality.

2.2.3. The Difference between the FX and Equity Markets

As mentioned in the introduction of this chapter there are fundamental differences between the FX and equity markets that introduce some challenges in applying the findings in equity markets to the FX market. This section points out these differences.

2.2.3.1 Market Structure

Equity and FX markets have fundamentally differences market structures. Equity markets are regulated[7] and organised markets where publically listed companies are traded and have a specific market place such as NYSE, LSE, and TSE and are mainly order driven markets (Maxwell, 1994, p.41; Harris, 2003, p.34 and p.58). The FX market, on the other hand, is a market that currencies are purchased now for delivery in two days (Maxwell, 1994, p.193) and is a geographically dispersed, decentralised, OTC, quote driven (dealer) (FSB, 2014) and unregulated market. Primary suppliers of equity securities are public corporations who use equity markets to raise capital for financing their operations (Maxwell, 1994, p.252), while the sole suppliers of currencies are central banks and governments (Harris, 2003, p.39). Although both equity and FX markets are used by short-term speculators, equity markets are mainly used by investors while the FX market is mainly used by asset exchangers. For instance, in the U.S. 20% of national wealth is invested in equity markets, while less than 1% of it is in the FX market (Harris, 2003, p.33 and p.45).

Equity markets are usually order driven markets where trades are arranged by matching buy and sell orders according to a set of rules[8] (Harris, 2003, p. 34). In order driven markets traders can offer or take liquidity. "Traders who offer liquidity indicate the terms at which they will trade. Traders who take liquidity accept those terms" (Harris, 2003, p.94-95). On the other hand the FX market is a quote driven market, where dealers are involved in every trade and anyone who wants to trade must trade with a dealer. In these markets dealers are sole providers of liquidity and only dealers set the prices. In dealer markets, dealers also frequently trade among themselves, however, the public cannot trade directly with each other (Harris, 2003, p. 92-93). Dealer markets are made up of a large number of market makers

[7] For a list of the U.S. federal security laws see Gitman et al., (2011) page 49 and for regulatory bodies see Harris (2003) page 62.
[8] For order precedence rules see Harris (2003) chapter 6.

who are linked together via a mass telecommunications network and there is no centralised trading floor (Gitman et al., 2011, p.41; Maxwell, 1994, p.41). Market participants in the FX market are located in the major commercial and investment banks around the world (Hillier et al., 2010, p. 847). Some brokers and data providers organise markets in the currencies and traders use these services in order to lower the cost of searching for liquidity (Harris, 2003, p. 58).

2.2.3.2. Price Discovery

One of the other differences between the FX and equity markets is the process of price discovery in these markets. The process of price discovery in the FX market is typically assumed to be based on the mechanism outlined by Glosten and Milgrom (1985) that focuses on the adverse selection cost faced by uninformed dealers. The Glosten and Milgrom (1985) framework suggests that dealers, in order to protect themselves from losing to informed traders, quote prices that reflect the customer's expected information. In other words, their framework implies spreads are positively correlated with trade size (Osler et al., 2011). This is found to be valid in the U.S. stock markets (see Bernhardt and Hughson, 2002; Peterson and Sirri, 2003), however, Osler et al., (2011) argue that Glosten and Milgrom's (1985) model does not apply to the FX market. The authors find that spreads quoted to customers in the FX market do not follow the behaviour predicted by the adverse selection cost model. They conclude that the "standard adverse selection model does not adequately describe the price discovery process in FX" (p. 1715). They explain that the difference between the mechanisms of spread determination can be either due to the fact that dealers may narrow their spreads to attract informed customers in order to extract information from their trades or the transitory market power theory of Green et al., (2007). Green et al., (2007) argue that if a dealer knows that a customer might have a higher liquidity search cost per share and the

customer is not in a position to monitor the dealer's execution quality, the dealer might take advantage of this situation by quoting wider spread.

2.3. High Frequency Trading, Definition, Expansion, and History

High Frequency Trading (HFT) is a subset of Algorithmic Trading (AT), where computers monitor markets and manage the trading process at high frequency, focused on market making (Chaboud et al., 2014; Cole and Smart, 2013). HFT is a relatively new term that is not yet clearly defined and usually refers to proprietary professional traders for whom their trading strategies generate a large number of trades on a daily basis. The characteristics of High Frequency Traders (HFTs) are: "(1) The use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders; (2) use of co-location services and individual data feeds offered by exchanges and others to minimise network and other types of latencies; (3) very short time frames for establishing and liquidating positions; (4) the submission of numerous orders that are cancelled shortly after submission; and (5) ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night)" (SEC, 2010, p. 3606).

These characteristics of HFTs are not merely a definition and the existing literature confirms the truth of them. HFT relies on extremely fast speed (O'Hara, 2015) in that the time needed for execution of HFT strategies is measured in milliseconds (King et al., 2011). The fact that HFTs spend considerable resources to gain a few milliseconds of speed advantage suggests that there are large payoffs for being faster than others (Hoffmann, 2014). Speed is so essential for high frequency trading firms that they set up (co-locate) their server as geographically close as possible to electronic platforms to reduce transmission time (Detrixhe et al., 2014; King et al., 2011). The emergence of co-location by itself, on the other hand, has increased HFT activities (Frino et al., 2014). HFTs are usually on the passive side of the market and rely on complex algorithms for the execution of a vast amount of orders

in a very small time frame[9] and short holding periods. HFTs compete on the basis of speed for an average estimated net profit margin of 0.1 cents per share traded, in the U.S. equity markets, that requires extremely fast and high volume turnover to cover fixed costs. (Hagströmer and Nordén, 2013; Goldstein et al., 2014; BIS, 2011). HFTs use sophisticated algorithms to submit and cancel orders rapidly and frequently in order to execute their trades quickly (Goldstein et al., 2014; Chordia et al., 2013) and keep their inventories close to zero (Jovanovic and Menkveld, 2012; Menkveld, 2013). Due to the short holding period and high turnover of HFTs they are mainly active in mostly liquid assets (BIS, 2011)

Computerised trading dates back to 1998, however, its expansion started after the introduction of regulation Alternative Trading System (Regulation ATS; Reg ATS) in 2000, including electronic exchanges and the Regulation National Market System (Regulation NMS; Reg NMS) in 2007 in the U.S. and MiFiD in 2007 in Europe. Decimalisation, automation of electronic limit order books, Reg NMS, and Reg AT have paved the way of HFT in recent years. Regulation ATS in 2000 facilitated the entrance of a variety of non-exchange competitors while Regulation NMS in 2007 laid the road map for a market composed of multiple linked trading venues via rules over access and trade priority. In Europe MiFiD in 2007 had a similar impact on allowing new competition and trading venues. The result of these regulations was the fragmentation of markets in the U.S. and Europe with the dispersion of trading across a variety of exchanges and markets (O'Hara, 2015; Goldstein et al., 2014; Carrion, 2013).

Shortly after its appearance in equity markets, HFT emerged in the FX market in early 2000. The emergence of HFT in the FX was facilitated by the wider use of electronic

[9] Characteristics of HFTs are the same in both equity and the FX market and thus HFTs are mainly active in the most liquid currency pairs. As a result, more sophisticated HFT players in the FX market are mainly active on EBS and Reuter trading platforms that are currently the predominant source of interbank liquidity in the FX market. However, these platforms traditionally have much larger minimum trade size requirements. The minimum normal trade size on these platforms is 1,000,000 units of the base currency. Since this minimum trade size is too big for HFT purposes some platforms such as EBS in 2010, have launched new services that allows trader to trade smaller quantities (i.e., 100,000 units of base currency) (BIS, 2011).

trading platforms in the FX market. Some of the HFTs in the FX market evolved from HFTs in equity markets. Some equity hedge funds began to implement their algorithms that were developed for equity markets in the FX market and take advantage of very deep liquidity, broad participation, ease of access and arbitrage opportunities in the FX market. Other firms originating from equity markets, started by implementing pure latency models, and exploiting arbitrage opportunities in the FX market. Other HFTs have been developed by existing FX specialists that have decided to move into the HFT in the FX market. Some banks also conducted some HFT in proprietary trading, however, they are not prominent players in this area. These banks do not perceive HFT as a prominent trend for their business and rather see HFT as a way to keep up with technology in the FX market. HFTs' firms mainly focus their trading activities in FX on inter-dealer electronic platforms such as EBS and Reuters, both based in London, and multi-bank ECNs such as Currenex, Hotspot FX and FXall. HFT firms are also active on CME for trades involving FX futures (BIS, 2011).

Estimates of HFT activity in different markets varies (Carrion, 2013). The share of HFT in all equity trades in the U.S. at the beginning of the 2000s was merely 10% and grew to almost 50% of trading volume by late 2012 and between 40% and 60% of trading activities across all the U.S. financial markets for stocks, options and currencies (Goldstein et al., 2014). Zhang (2010) estimates that HFT accounts for more than 70% of dollar trading volume of U.S. capital markets. Hagströmer and Nordén, (2013) estimate that HFT market making accounts for 63% to 72% of trading volume and 81% to 86% of limit order traffic in NASDAQ-OMX Stockholm. Identified groups of HFT account for 68.3% of the dollar trading volume of a sample of NASDAQ listed firms (Carrion, 2013). In late 2012, HFT accounted for almost 45%, 40%, and 12% of equity trading volume in the European Union, Japan, and the rest of Asia, respectively (Popper, 2012a).

However, in recent years the profitability and volume of HFT are declining. HFT's trading volume has shrunk from six billion shares, 61% of trading volume, in 2009 to three

billion shares, 51% of volume, in 2012 (Popper, 2012b). Rosenblatt Securities brokerage firm estimate that the total profit was at most $1.25 billion in 2012, that is 35% less than that of 2011 and 74% lower than its peak of approximately $4.9 billion in 2009 (Goldstein et al., 2014). The reason for this reduction in profit of high frequency trading firms is the increase in costs of rights and hardware to maintain co-location. In addition, high data connection streams have become much more expensive than they were in 2008–2009. Many HFT firms, in order to keep up with their competitors, feel the pressure to obtain new technologies (Goldstein et al., 2014). These have led to suggestions that some HFT firms have been reducing their staff or completely closing down operations (Popper, 2012b).

Despite the shrinking share of HFTs in equity markets the FX market has observed an impressive increase in the share of HFT in recent years. HFTs share in the spot FX market has increased from 3% to 40% in the last decade according to an estimate from Boston-based Research firm Aite Group (Hoffmann, 2014). HFTs accounted for 35% of spot FX volume in October 2013 up from 9% in October 2008 and around 30% to 35% of transactions on EBS platform are high-frequency driven (Detrixhe et al., 2014).

2.4. Impact of HFTs on Financial Markets

Some believe that HFT is simply faster trading and thus HFTs' strategies are not new and therefore nothing has changed in the economics of the market (Chordia et al., 2013). For instance, Mendkveld (2013) examines one large high frequency trader in Chi-X market and concludes that HFTs are simply the fast version of traditional market makers[10]. On the other hand, others argue that there are two main differences between computer and human traders. First, computers process and act on information faster than humans and second, there is a higher correlation between computers' trading strategies than those of humans

[10] However, there is no agreement about how much of this market making is "true" market making (BIS, 2011).

(Chaboud et al., 2014). The higher speed and high correlation in trading strategies of computers could induce short-termism in the market that could push prices away from fundamental value (Froot et al., 1992).

Overall, there are two different views regarding the impact of HFT on financial markets. The advocates of HFT ague that HFTs have taken over the market-making function and benefit the markets by adding to price discovery and liquidity and reduced arbitrage opportunities, thus making prices more efficient. However, opponents of HFT argue that since HFTs do not have affirmative obligation, similar to traditional market makers, there are concerns that they can exit the market at will and cause disruption to the functioning of markets. They argue that HFTs' liquidity provision is unreliable and is outweighed by disruptive practices such as order spoofing, predatory trading, herding, or overloading the market infrastructure with excessive messages (Carrion, 2013; Hoffmann, 2014).

2.4.1. Liquidity

Empirical studies find that computerised trading causally improves market liquidity (Hoffmann, 2014; Hasbrouck and Saar, 2013; Castura et al., 2010). Hasbrouck and Saar (2013) find that HFT improves liquidity by reducing the bid-ask spread and increasing displayed depth in the limit order book. Brogaard et al., (2014) find that HFTs provide liquidity in volatile and stressful days and around macroeconomic news announcements. Carrion, (2013) shows that spreads are wider when HFTs provide liquidity and tighter when they consume liquidity. In other words, HFTs are liquidity providers when it is scarce and consume liquidity when it is plentiful, which means they add to market liquidity (Carrion, 2013; Hendershott and Riordan, 2011). Hendershott et al., (2011) find that AT improves standard measures of liquidity, namely quoted and effective spread in NYSE. Castura et al., (2010) find that HFT has increased the liquidity at the inside.

However, as explained above, HFTs do not have any affirmative obligation to provide liquidity at all times, similar to traditional market makers. This creates the fear that in challenging and unfavourable conditions they withdraw from the market as market makers. For instance, Anand and Venkataraman (2013) state that external liquidity providers (analogues to HFT market makers) exited from Toronto Stock Exchange when faced with unfavourable conditions. Kirilenko et al., (2011) finds that although HFTs did not cause the Flash Crash on May 6, 2010, they exacerbated the conditions by reducing their market presence when faced with challenging conditions.

One of the differences between the activity of ATs in equity and FX markets, despite the structural difference between these two markets, is the inexistence of rebate for liquidity provision in the FX market (Chaboud et al., 2014). Due to this difference, findings regarding the impact of ATs and HFTs on liquidity are contrary. Although BIS (2011) argues that HFT has benefited the FX by distributing liquidity across the decentralised market, Chaboud et al., (2014) finds that during the minute following the U.S. non-farm payrolls announcement, when volatility is high, the share of AT liquidity provision reduces more than that of human traders. In other words, when the FX market is volatile ATs reduce their liquidity provision.

2.4.2. Volatility

Volatility is the other important measure of market quality that is directly influenced by liquidity. Based on the empirical studies above it is reasonable to assume that HFTs have also reduced financial market volatility. However, the findings regarding price volatility are mixed (Hoffmann, 2014). Hasbrouck and Saar (2013) find that HFT has reduced short-term volatility. Castura et al., (2010) argue that there is no evidence that the increase in the HFT activity ratio to total market ratio has increased short-term volatility. Hagströmer and Norden (2013) conclude that HFTs mitigate intraday price volatility. However, Zhang (2010) finds that HFT "is positively correlated with stock price volatility after controlling for firm

fundamental volatility and other exogenous determinants of volatility". In the FX market, Chaboud et al., (2014) find no evidence that AT increases FX volatility and state that there is some evidence that AT might have reduced the volatility slightly.

2.4.3. Transaction and Adverse Selection Costs

One of the frequently argued impacts of HFTs on the financial markets is the costs that they impose on long-term investors and slow traders such as transaction cost and adverse selection cost. Theoretical models of Biais et al., (2015) and Martinez and Rosu (2013) suggest that fast traders impose adverse selection costs to slower traders by obtaining information before slow traders. Hagströmer and Nordén, (2013) state that in modern market making anyone who is unable to adjust his posted orders quickly in response to new information in the market, will be picked off by competitors. Brogaard et al., (2014) show that HFTs impose adverse selection costs on other investors. However, the authors state that since HFTs trade against the transitory pricing error, they reduce long-term investors' trading costs. Conrad et al., (2015) find that high frequency quotation activity is correlated with lower transaction costs. Castura et al., (2010) argues that reduction in the bid and ask spread over previous years has benefited all investors regarding the total cost of trading. Malinova et al., (2013) show that the reduction of HFTs' message traffic causes an increase in spreads and an increase in the trading costs of retail and other traders. In the FX market, Chaboud et al., (2014) explain that since the portion of FX market that they study is a wholesale market, the adverse selection cost imposed by AT is potentially smaller than it is in the equity market (Chaboud et al., 2014). Overall, "adverse selection today has taken on a different shape. In a high speed, co-located world, being informed means seeing and acting on market prices sooner than competitors. Today, it pays to be faster than the average bear, not smarter. To be uninformed is to be slow" (Haldane, 2011, p.4 as cited in O'Hara, 2015).

2.4.4. Fairness and Social Welfare

An import question that arises is the impact of HFTs on fairness and the social welfare of financial markets due to the imposed adverse selection costs by HFTs. SEC (2010, p. 3605) raises the question, "Is it necessary or economically feasible for long-term investors to expend resources on the very fastest and most highly sophisticated systems or otherwise obtain access to these systems? If not, does the fact that professional traders likely always will be able to trade faster than long-term investors render the equity markets unfair for these investors?".

Since speed is a source of market power, it allows fast traders to impose adverse selection costs on other market participants and thus ignites a costly arms race that degrades social welfare (Hoffmann, 2014). HFTs reduce welfare when they impose adverse selection cost on other investors, by picking of their quote at "superhuman speed that anyway would have been revealed to investors anyway at a lower frequency" and HFTs might be engaged in a socially wasteful arms race (Menkveld, 2014). If the HFTs' main goal is to be faster than competitor HFTs on a publically observed signal, they overinvest in technology relative to social optimum (Goldstein et al., 2014). However, Biais et al, (2015, p. 295) notes that "with stochastic news arrivals, fast trading can be socially useful because it reduces the delay until the asset can be reallocated in response to news".

2.4.5. Price Discovery and Price Efficiency

Financial markets have two important functions, price discovery and liquidity (O'Hara, 2003). Therefore, informativeness of price and incorporation of new information into prices are important functions of financial markets. The impact of HFTs on them should be examined. The majority of empirical studies on the impact of HFT on financial markets have studied this function and the majority of them find that HFTs add to price discovery and price efficiency of financial markets. However, some other studies raise concerns

regarding the short-termism of HFTs and the correlation between their strategies that cause HFTs to react similarly, which, as a result, leads to an overreaction to the same news and consequent price discovery distortion.

It is found that ATs add to price efficiency by placing more efficient quotes that incorporate new information quickly, thus preventing arbitrage opportunities and demanding liquidity to move the prices towards the efficient price (Hendershott and Riordan, 2011; Hoffmann, 2014). Brogaard et al., (2014) find that HFTs add to price discovery and facilitate price efficiency by trading in the opposite direction of pricing errors and in the direction of permanent price changes. The authors, similar to Hendershott and Riordan (2011), find that this is done via liquidity demanding orders of HFTs. They find that HFTs' trading direction is correlated with "macroeconomic news announcements, market-wide price movements, and limit order book imbalances" (p. 2267). Carrion (2013) find that information from order flow is more efficiently incorporated in prices on the days that HFT activity is high. Castura et al., (2010) find that there is an overall improvement in price efficiency of the U.S. equity markets over time and the growth of HFT has lowered mean reversion and increased price efficiency.

In the FX market, Chaboud et al., (2014) study the frequency of triangular arbitrage opportunities in the EUR/USD, USD/JPY, and EUR/JPY currency pairs. They state that the existence of triangular arbitrage opportunities provides the clear evidence on informationally inefficiency of prices in the FX market. They find that expansion of AT in the FX market coincided with a considerable reduction in triangular arbitrage opportunities, increase in price efficiency by reduction in autocorrelation of high-frequency returns, and increased the price discovery process speed. Overall, they conclude that AT has added to the efficiency of the price discovery process in the FX market.

Contrary to the studies above, Zhang (2010) studies the impact of HFTs on the U.S. capital markets and finds that HFT impairs the price discovery process. He finds that HFT hinders market ability in incorporating information about firm fundamentals into prices because HFTs overreact to fundamental news and this overreaction is almost completely reversed later on, suggesting that HFT pushes prices away from fundamental value. He concludes that HFT has harmful effects on U.S. capital markets.

Contrary to Chaboud et al., (2014) who state that the correlation between ATs trading strategies does not push prices away from fundamental value, Kozhan and Tham (2012) who study triangular arbitrage opportunities in EUR/USD, GBP/USD and EUR/GBP, argue to the contrary. They argue that in contrast to the common notion of competition that it improves price efficiency, competition among arbitrageurs could limit efficiency. They argue that computers entering the same trade at the same time causes a crowding effect and deviates prices from their fundamental value. Their finding is consistent with the theoretical model of Froot et al., (1992) who show that markets, where market participants concentrate on short-term information[11], are less efficient in pricing than markets with long-term investors, due to concentration of short-term investors on information unrelated to fundamentals.

The existence of short-termism and deviation of prices from fundamental value in the FX market is well documented and argued. O'Hara (2015, p. 263) argues that "In the high frequency world, it is not clear that information-based trading necessarily is based on fundamental information". Gençay and Gradojevic, (2013) state that large volatility in the exchange rate cannot be explained by slow-moving macroeconomic variables. Cheung and

[11] Scholtus et al., (2014) finds that in the case of co-location, a round trip for HFTs could be completed within 100 microseconds that is equivalent to 0.1 millisecond or 0.0001 second. It takes at least 5 seconds to read the previous sentence, during which an HFT could have completed 50,000 round trips equivalent to 100,000 trades. It takes 100 milliseconds to blink during which an HFT can complete 1,000 round trips equivalent to 2,000 trades.

Chinn, (1999) find that the deviation of exchange rates from their fundamental value in the short-term is due to excess speculation and price manipulation. Evans and Lyons (2002) show that the order flow in a short horizon might be unrelated to existing fundamental macroeconomic news.

Two reasons are given for the short-termism of market participants in the FX market, inventory effect and trading strategies. In the FX market, the general preference of dealers is to complete their roundtrip and have zero inventories, thus after each trade with a customer they usually pass their accumulated inventory rapidly to another dealer. If the second dealer passes his position to another dealer, in order to maintain a zero inventory, a process known as "hot potato trading" is formed. The transfer of the position from a dealer to another dealer is continued until a dealer passes this position onto one of his customers (Lyons, 1995; Bjønnes and Rime, 2005; Lyons 1997; King et al., 2011) This dealers' intention for passing on inventory imbalance has informational effects on the exchange rates (Jong et al., 2001). On the other hand, some suggest that chartist behaviour of traders (i.e., technical traders) who act on unrelated information to fundamental value of an asset might explain some of the large movements and the overshooting of exchange rates (Ehrmann and Fratzscher, 2005).

2.5. Macroeconomic News Announcements and Price Discovery

There is perhaps no question more central to economics than how markets arrive at prices (Andersen et al., 2007). Empirical studies show that exchange rates are driven by new information arriving about fundamentals that are macroeconomic news announcements (King et al., 2011; Scholtus et al., 2014; Gençay and Gradojevic, 2013)[12]. Although prior to

[12] Savaser (2011) studies the impact of scheduled macroeconomic news announcements by using customer price-contingent orders and his results imply "that there may be a component of the news response that purely reflects institutional feature such as order types and not necessarily the content of the public information itself" (p. 107).

the 1990s exchange rates models using monthly or quarterly macroeconomic data could not explain the exchange rates movement (Payne, 2003), recent studies show that exchange rates incorporate new macroeconomic information almost instantaneously. Andersen et al., (2007) study the impact of real time U.S. macroeconomic news on GBP/USD, USD/JPY, and EUR/USD future contracts and find that macroeconomic news produces a conditional mean jump, therefore, exchange rate dynamics are linked to fundamental news. Evans and Lyons, (2008) show that macroeconomic news arrival accounts for more than 30%[13] of the DM/USD (Deutschmark / Dollar) exchange rate and is immediately and directly incorporated into prices. Ederington and Lee, (1995) study interest rate and FX futures markets from 1988 to 1992 and find that price changes as a result of macroeconomic news announcements starts within 10 seconds and "basically [completes] within 40 seconds of release" (p. 117). They find that prices adjust to macroeconomic news in a series of numerous small, but rapid, price changes. Cheung and Chinn, (1999), survey U.S. FX traders and found that macroeconomic news is quickly incorporated into the exchange rate. Carlson and Lo (2006) observe that the full impact of a news announcement from the Bundesbank (German Central Bank), in 1997, hits the DM/USD market 35 seconds after its release.

Equity markets, as well as the FX market, demonstrate a rapid and almost instantaneous response to the release of macroeconomic news. Scholtus et al., (2014) find that the speed of trading strategies based on U.S. macroeconomic news, on the S&P 500 ETF, is crucially important and that a delay of 300 milliseconds significantly reduces the performance of news-based trading strategies. They state that the current round trip time of an HFT in the case of co-location is less than 100 microseconds that combined with machine readable news feed is clearly unbeatable by human speed. Chordia et al., (2015) studies the impact of 15 types of macroeconomic news announcements on the stock index ETF, and

[13] They identify three sources of currency price variation, macroeconomic news arrival, direct impact of macroeconomic news on order flow, and order flow unrelated to fundamentals.

future and find trading activities intensify within a quarter second after a news release and prices start reacting within a tenth of a second and fully respond to macroeconomic surprises within five seconds. They argue through one channel that HFTs and ATs are perceived to profit is a rapid reaction to the public information released due to their technological advantage.

These empirical studies mentioned above, show three important aspects of price discovery around macroeconomic news announcements in financial markets. First, in the FX market macroeconomic news announcements are one of the most prominent driving forces behind exchange rate determination. Second, in both the FX and equity markets macroeconomic news announcements are incorporated in prices almost instantaneously. Third, by looking at the timeline of studies in the FX market, it can be vividly observed that throughout the time of advancements in technology and the increases in speed of the FX market and market participants, the speed of price discovery in the FX has increased dramatically. These findings are in line with Martinez and Rosu's (2013) statement that HFTs as strategic informed traders react to new information immediately and ensure that it is incorporated into prices instantaneously.

2.5.1. Price Discovery and Information Advantage

2.5.1.1. Equity Markets

In the equity markets fundamental information regarding a firm are news such as earnings announcement (Abarbanell and Bushee, 1997). Therefore, the private information in equity markets is considered to be advanced knowledge of a firm's cash flows (Green, 2004) which determines the change in fundamental value of a company. Private information possessed by market participants can be observed from their trading activities (Green, 2004). For instance, Koski and Michaely (2000) observe that larger than usual impacts of trading activities before a dividend announcement on prices is a sign of having possession of private

information by some of the market participants. Therefore, if having prior information gives the market makers the added advantage and enables them to incorporate new information into their prices, the market maker should have a higher contribution to price discovery than others (Madureira and Underwood, 2008). In other words, systematically higher contributions of some dealers to price discovery, than others, could be due to their information advantage.

The sources of the market makers' information advantage in equity markets could be due to analysts coverage (analyst affiliation), geographic location, or through their participation in underwriting syndicates (Schultz, 2003). Madureira and Underwood, (2008) study the interaction between market making and analyst affiliation on price discovery and find that market makers with affiliated analysts contribute more to the price discovery process than market makers without affiliated analysts. Anand et al., (2011) find that the local market makers spend more time at the inside bid and ask quotes and initiate larger changes in the quotes than non-local market makers. In addition, their average information share is almost twice that of non-local market makers. Market makers relocating farther away from the firms headquarters experience a reduction in their contribution to the price discovery process. These results suggest geographically proximate (local) market makers possess an information advantage over non-local market makers. Kedia and Zhou (2011) show that firms' stocks that are traded by local dealers, exhibit lower quoted and an effective spread and also more informative prices. Bolliger (2004) finds that there is more advantage for local brokerage house in Europe over foreign brokerage houses. The studies mentioned above demonstrate the importance of having analyst affiliation and geographical proximity of market makers as part of their information advantage.

Although analyst affiliation is found to improve the information advantage of market makers, not all analysts have the same accuracy. Financial analysts and brokerage houses compete for forecast accuracy that is one of their most important dimensions (Bae et al.,

2008). An analyst's ability in forecasting earnings more accurately than statistical models (Brown and Rozeff, 1978 and Bradshaw et al., 2012) and the profitability of his recommendations (Womack, 1996 and Jegadeesh et al., 2004) could be due to skilful processing of public information or their superior access to companies' management through visits to company headquarters, investor office meetings, and broker-hosted investor conferences. Access to a firm's management is found to be an important source of an analyst's informational advantage (Green et al., 2014). Green et al., (2014) examine whether access of analysts to a firm's management at broker-hosted conferences impacts on the informativeness of research by analysts. They find that "analyst recommendation changes have larger immediate price impacts when the analyst's firm has a conference-hosting relationship with the company" (p. 239). They argue that analysts' access to management remains a prominent source of informational advantage.

In addition to access to management, the geographical proximity of an analyst is also found to have a prominent impact on their forecast accuracy. Geographically proximate analysts are more accurate in their forecast and their forecast revisions impact on prices more than other analysts. These findings suggest that geographically proximate analysts possess an information advantage over others, which leads to their higher performance (Malloy, 2005). The geography of economists forecasting ECB monetary policies matters for their forecasts' accuracy (Berger et al., 2009). Using a sample of 32 countries Bae et al., (2008) find an economically and statistically significant local analyst advantage even after controlling for firm and analyst characteristics. In addition, they find that analysts have lower forecast errors for the local stocks that they follow than that of foreign stocks.

Berger et al., (2009) argues that financial analysts benefit from geographical proximity due to similarities in culture, language, closeness to local market conditions in which firms operate, and potentially better links to decision makers. Bae et al., (2008) believes that local

advantage could be due to an analyst's relationship and personal connections with firm representatives and their ability to observe what goes on in firms directly. The authors state that alternatively, local analysts could speak directly with employees, customers, and competitors.

2.5.1.2. The FX Market

In the FX markets the fundamental value of a currency is partly determined by macroeconomic variables. Because all market participants in the FX market have access to the same public information, the existence of private information has often been denied (Jong et al., 2001; Ito et al., 1998; Gençay and Gradojevic, 2013). However, empirical studies such as Ito et al., (1998) do not support this perception regarding the FX market and find evidence to the contrary. They argue that the view that FX traders' exclusive information source is public information or the view that all market participants interpret public news the same need to be relaxed. They explain that relaxing this view is eased by recognising that private information can be price relevant without being related to any fundamental information. Evans and Lyons (2012) show that private information obtained from trading customer order flow can predict exchange rates as well as macroeconomic news. Similar to Ito et al., (1998), Kim and Verrecchia (1994, 1997) argue that information asymmetry after public information release might increase by the different abilities of market participants in interpreting news. In other words, he argues that information content and the information advantage of market participants is affected by the way that they interpret the same macroeconomic news.

The impact of the market makers' locality on their information advantage has also been found to be a source of information advantage for FX market makers. Gençay and Gradojevic, (2013) state that FX traders' location might offer a temporary informational advantage. They explain that local advantage (region-specific private information) could arise

from the local knowledge that non-local traders might not be able to obtain. "With regard to the USD/JPY currency pair, Japanese banks receive FX orders from the largest Japanese corporations and this may offer a temporary informational advantage" (p. 92). They find that 5% to 25% of variation in exchange rates is due to region-specific private information. Jong et al., (2001) find a prominent but not exclusive role of German banks in price discovery of DM/USD. Covrig and Melvin (2002) studied USD/JPY markets and identified a period of high concentration of informed traders in Tokyo. They demonstrate that Japanese quotes lead the rest of the market in these periods. They find that Japanese quotes contribution to price discovery, in the aforementioned period, to the rest of the world is 5 to 12 percentage points higher. They believe that Japanese traders have more information about the USD/JPY currency pair than the rest of the market. The price leadership of Deutsche Bank prior to the German central bank interventions (Peiers, 1997) or price leadership of Japanese banks in the Yen market (Ito et al., 1998) are some of the examples regarding information asymmetry in the FX market due to region-specific private information.

Overall, although the geographical proximity of a dealer to a country and the dealer's order flow are found to be the source of private information, no study has ever examined the role of the dealer's geographical proximity to macroeconomic news origin and the dealers' affiliation with the economist (for forecasting macroeconomic variables) on dealers' information content and advantage. Furthermore, as different interpretations of public information is also found to be a source of information asymmetry, no study has ever examined the impact of the economist affiliation on the contribution of market makers to the price discovery in the FX market. Consequently, no study was found to examine how affiliated economists' geographical proximity affects the information content of their dealer.

2.6. Choice of Price Discovery Model

In order to measure markets or market participants' contribution to the price discovery process three models of Information Share (IS) by Hasbrouck (1995), Component Share (CS) by Gonzalo and Granger (1995), and Weighted Price Contribution (WPC) by Barclay and Warner (1993) are widely used in the literature. Due to the limitations and complication of using IS and CS in high frequency studies this thesis utilises the WPC model. This section explains each model and discusses the reasons behind the choice of WPC, its advantages over IS and CS models, WPC's suitability for high frequency microstructure studies, and the complications and limitations that prevent usage of IS and CS in market microstructure high frequency studies.

The IS model is suggested by Hasbrouck (1995) and is an economic approach based on an implicit unobservable efficient price common to all markets. Hasbrouck (1995) defines information share associated with a particular market as the proportional contribution of that market's innovations to the innovation in the common efficient price. The common factor is the implicit efficient price of the security, which is defined statistically as the random-walk component of the prices from the diverse markets. The innovation variance in this random walk is a measure of the information intensity of the efficient price process. The IS model enables measurement of lead and lag relation between the quote revisions of individual banks, such as to identify price leaders in the market. The CS model complements the IS model and provides a different view of the price discovery process between markets and focuses on the components of the common factor and the error correction process. (Bailiea et al, 2002; Korczak and Phylaktis, 2010; Yan and Zivot, 2010; Jong, et al, 2001).

Although IS and CS are closely related and both models use the vector error correction model (VECM) as their basis, they have different points of view on price discovery. The major difference between the two models is the role of the variance of the

innovations. Only IS takes into account the variability of the innovations in each market's price, while the CS model ignores the variance of the innovation and is concerned with only the error correction process. For instance, assume a security is traded in two markets, A and B and the price of this asset in cointegrated and highly correlated in both markets. Assume that the first market's price responds to deviations from the second market's price described by the error correction term, but the second market does not respond to deviations from the first market. According to the Gonzalo and Granger model price discovery only occurs in the second market while, the Hasbrouck metric suggests that both markets contribute to price discovery because of the high correlation between the two markets. In other words, the CS model completely ignores a market's reaction to new information, thus the IS model is a more adequate measure of the amount of information generated by each market or market participant (Jong, et al, 2001; Bailiea et al, 2002; Korczak and Phylaktis, 2010; Yan and Zivot, 2010). Since the goal of this thesis is to examine the role of individual market participants and their contribution to price discovery, the CS model is not an appropriate model for this thesis's empirical studies.

However, despite the advantage of IS over CS, this model also is not an appropriate choice for studying irregularly time spaced high frequency data and studying individual market participants contribution to price discovery. Similar to most econometric models that have been designed based on the equidistant observations (Zebedee, 2001), the IS model requires regularly spaced data (Kehrle and Peter, 2013). One of the fundamental characteristics of high frequency data in the FX market is that trades and quotes can occur at varying time intervals (i.e., not equally spaced) (Goodhart and O'Hara, 1997). Since, lag structure analyses such as the IS model are based on the implicit assumption of a constant discount parameter and they are designed for regular intervals and high frequency data is observed at irregular intervals, use of these models with high frequency irregularly spaced data might not be correct (Zebedee, 2001; Jong and Nijman, 1997). In addition, because not

all dealers update their quotes at equal frequency, and the IS model requires significant time variation, use of IS at market maker level[14] is not possible (Anand et al., 2011)[15].

Finally, the main drawback of the IS model is that it does not provide a unique measure of information share and its output is a range between upper and lower bounds for a market or market participant's information share. Depending on the sample frequency and number of information sources this range can vary significantly. This range is generally small when the number of information sources are small and the differences among them are large, however, the range diverges considerably when there are more than two information sources. In addition, estimation of IS based on high frequency sampling might be distorted by transitory frictions and misrepresent which market moves first in response to new information. Thus, determining the leading market or market participant is rather vague (Kehrle and Peter, 2013; Frijns and Schotman, 2009; Yan and Zivot, 2010). Due to reasons specified above, since the empirical studies of this thesis are based on high frequency and irregularly spaced data and the observation of individual market participants contribution to price discovery, the use of the IS model is not appropriate[16].

On the other hand, the WPC model does not encounter any of the aforementioned issues regarding the IS and CS models and their usage at high frequency. WPC is a non-parametric measure of price discovery (Wang, 2014) and is not based on any assumption regarding the distribution of prices and regularity of observations' interval. WPC's output is a unique number for the contribution of each market or market participant to price discovery

[14] Assuming each market maker as a separate market.
[15] In order to address this issue Anand et al., (2011) use the WPC model.
[16] One method for converting irregularly spaced data to equally spaced data is sampling the data at an arbitrary frequency (for instance see Kehrle and Peter, 2013; Korczak and Phylaktis, 2010), however, this method induces two main issues in the data. First, if the chosen interval is very small and the trading is not frequent, there will be many intervals with no new information and heteroscedasticity of a specific form and non-synchronous trading problem will be introduced into the data (Engle and Russel, 1998; Jong and Nijman, 1997). Second, the arbitrary choice of sampling frequency will induce imputation bias (Jong and Nijman, 1997) which means that the behaviour of some market participants and their role in the price discovery process could partly or completely be ignored.

in a given time period, calculated as a weighted sum of dealers' contribution to price discovery during the given time period. (Barclay and Hendershott, 2003; Madureira and Underwood, 2008; Anand et al., 2011)[17]. The WPC model is explained and discussed extensively in section 4.3.1.

2.7. Conclusion

Algorithmic and high frequency traders, new players in financial markets, emerged as a result of advances in technology and the increase in speed of financial markets. HFTs share of trading volume in financial markets increased from 10% to 70% in the U.S. equity markets. However, in recent years, their share of trading has reduced in the equity markets while the FX market has observed an increase in the share of HFT. Nowadays, they account for more than 40% of trades in the $5.3 trillion dollar a day FX market.

The studies surveyed here evaluated the impact of HFT on the quality of financial markets in five main areas; liquidity, volatility, transaction and adverse selection costs, social welfare and fairness, and price discovery and price efficiency. The empirical studies on the impact of HFT on the liquidity of equity markets is in favour of HFTs and finds that they significantly improve equity market liquidity. However, the fear of HFTs exiting the market in challenging conditions is shown to be true, and it can cause serious damage to market stability and resilience in volatile and unstable market conditions. Regarding the impact of HFT on price volatility in equity markets, the empirical findings are mixed. While some argue HFT has not increased volatility in equity markets, some suggest HFT is positively correlated with stock price volatility. In addition, no evidence is found that AT increases short-term price volatility in the FX market. The emergence of HFT in financial markets undoubtedly has imposed adverse selection costs on slower traders as shown by theoretical and empirical

[17] For examples and applicability of the WPC model usage in the FX market see Ligon and Liu (2013) and Wang (2014).

studies in both equity and the FX markets. The imposing of adverse selection costs on slower traders by HFTs could ignite (might already have ignited) a socially wasteful arms race. Regarding the transaction costs, findings show mixed results. While some show a considerable reduction in the cost of trading, others find to the contrary.

Similarly to the impact of HFTs on other markets' functions, the findings regarding their impact on price discovery and efficiency are mix. Some find that HFTs speed up the price discovery by quickly incorporating news information into prices, reducing arbitrage opportunities and making price formation more efficient by reducing autocorrelation. Other research groups argue that due to similarities and the correlation of HFT strategies and their short trading and holding period, HFTs concentrate on information unrelated to fundamental and push prices away from fundamental value due to crowding effect or herding on the same information.

In the FX markets, macroeconomic news is one of the main driving forces behind exchange rate movements and the price discovery process. However, although the existence of private information regarding public information is mainly denied in the FX markets, it was shown that different interpretations of the same macroeconomic news or customers' order flow can create an information asymmetry amongst market makers. In equity markets, analyst affiliation and the geographical location of analyst and market makers are found to be the source of information advantage regarding firms' fundamental information. However, in the FX market, except some studies on the region-specific information asymmetry, no study was found to examine the role economist affiliation and geographical location of economists and market makers (to the macroeconomic news source and each other) in the information content of the dealers.

This thesis strives to fill the gap in the existing literature by examining three questions regarding the price discovery process in the FX market. As mentioned in the introduction of

this chapter, the overwhelming majority of the studies on the impact of HFT and AT are conducted on equity markets and because the findings of these studies cannot uncritically be applied to the FX market, further examination is needed to evaluate the impact of these new market participants on the FX market. In addition, although the words HFT and AT imply the high speed of these market participants, no study, to the best of my knowledge, has examined the impact of HFTs and ATs' speed on financial markets. This thesis, first, evaluates the impact of market participants' speed on price discovery in the long and short-term in the FX market (Chapter 4). It is important to understand how the ever increasing speed of market participants, affects market quality. The answer to this question can determine whether the phenomenon of HFT is an arms race with no social benefit or the contrary.

Second, the existing literature in equity markets shows the positive impact of geographical proximity of market makers and analysts to a firm's location and affiliation of analysts with market makers on market maker's information advantage. However, such a study has not been conducted regarding the impact of economist affiliation with market makers and their geographical proximity to macroeconomic news sources in the FX market. In addition to fundamental differences between the FX and equity markets, the scope and scale of firm-specific news and a country's macroeconomic news are exhaustively different. This is the motivation for the second empirical chapter (chapter 5) of this thesis. The examination of this question deepens our understanding of the factors that affect market participants' information advantage and impact of information creation sources considering the different structure of equity and the FX markets. Finally, this thesis by using its unique Quote Dataset for the very first time designs, implements, and tests an algorithm to identify the dealers that exhibit manipulative behaviour around the WM/R fix rate (Chapter 6). The answers to the aforementioned questions above, in addition to their regulatory implications,

allow us to better understand the impact that HFT and AT have on the quality of the biggest financial market in the world.

Chapter 3. Data Description

"Our ability to analyse the working of markets is limited by the availability of relevant data"

(Goodhart and O'Hara, 1997)

3.1. Introduction

This chapter explains the two main datasets that are used in this thesis. Since both datasets are unique, the collection procedures of them are also explained, for future researches' use. The core dataset for empirical analysis of this thesis is the quote database, collected from Thomson Reuter Eikon. The main feature that makes the Quote Dataset unique, is that it includes the identity and location of dealers, who disseminate the quotes and includes quotes from EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs. The second dataset is the macroeconomic news announcement dataset that is collected from Bloomberg and contains the news that affects these six currency pairs from the United Kingdom (U.K.), the United States (U.S.), Eurozone countries, and Japan.

Since each empirical chapter utilises a portion of the Quote Dataset, this chapter explains the entire Quote Dataset and sub-datasets that are used in each empirical chapter are explained in more detail in each chapter. The first empirical chapter, chapter 4, utilises merely the days that there has been no interruption in data streaming, since the continuity of prices for studying the price discovery process is a necessity. The second and third empirical chapters, chapters 5 and 6, utilise a smaller subset of the Quote Dataset, due to the nature of their research questions. Chapter 5 utilises the quotes within the 4-minute window around

the macroeconomic news announcements and chapter 6 examines the quotes merely within the 60 seconds time frame around the WM/R fixing windows. Regarding the macroeconomic news announcement dataset, the collection procedure is presented here and more detailed characteristics of the dataset that is used for empirical work of this thesis is presented in chapter 5.

The rest of this chapter is organised as follows. Section 3.2 gives a brief background on the emergence and expansion of electronic trading platforms in the FX market and section 3.3 introduces the FX market, its characteristics, and use of indicative quotes in studying this market. Section 3.4 explains the collection procedure of the quote and macroeconomic news datasets. Section 3.5 describes the Quote Dataset summary statistics and section 3.6 concludes.

3.2. Emergence of Electronic Trading Platforms in the FX Market

The usage of communication technology for integrating financial markets goes back to 1840 when the use of telegraph facilitated exchanges to integrate into national networks and attract investors from around the world. Commenced establishing a telegraph line between New York and London decreased the delay between the exchanges from 5 days to 20 minutes and with further improvements later this delay was reduced to 30 seconds by the First World War. Establishment of these links meant that different stocks could be traded around the world which meant the facilitation of the capital flow from around the globe (Michi, 2010).

The first electronic equity market, NASDAQ, an electronic alternative to over-the-counter stock exchanges, was launched on February 8, 1971. This was followed by the launch of the fully automated Designated Order Turnaround (DOT) system on March 1, 1976 by the NYSE to route smaller orders electronically. The DOT was able to handle limit orders,

basket trades, and other type of market orders. On April 21, 1999 the regulation of Alternative Trading System (ATS) became effective and contained all the systems that SEC previously had called proprietary trading systems, broker-dealer trading systems, and Electronic Communication Networks (ECN). On October 9, 2002 Tradebot System Inc., for the first time traded more than 100 million shares in a single day. March 30, 2007 Chi-X Europe was launched (Perez, 2011).

The growth of electronic trading platforms was not limited to equity markets and also expanded to the FX market. The first multi-bank platform in the FX market was Currenex that was launched in 1999, by providing quotes from different FX dealers on a single page. This platform increased transparency, decreased transaction costs and attracted a growing customer base. In response to this new competition, top FX dealers launched proprietary single-bank trading platforms for their customers, such as BARX in 2001 by Barclays, Autobahn by Deutsche Bank in 2002, and Velocity by Citigroup in 2006. According to BIS average trading volume on single-bank trading systems has doubled over the time horizon of 2007 to 2010. Electronic trading and electronic brokering are transforming the FX markets by reducing transaction costs and increasing market liquidity and have paved the way for algorithmic trading. There are three types of ECNs in FX market, electronic broking systems (such as EBS and Thomson Reuters Matching), multi-bank trading systems (such as Currenex, FXall, and Hostspot FX), and single-bank trading systems (King and Rime, 2010). The emergence of ECNs in the FX market paved the way for high frequency and algorithmic trades in the FX market. Larger and more sophisticated HFT players tend to trade on EBS and Thomson Reuters which are the main source of interbank liquidity and very few HFTs trade on single-bank platforms, since HFT needs a diverse information-rich environment (BIS, 2011).

3.3. The FX market, A Quote Driven Market

The FX market is a geographically dispersed, decentralised, quote driven, and primarily over the counter market (FSB, 2014). Due to this attribute, there is not a single database that contains all the transactions conducted in this market. However, active dealers in the FX market disseminate the price that they are willing to trade on, in the form of indicative data (Goodhart and O'Hara, 1997). Indicative quotes are disseminated on different platforms with the most important one being Thomson Reuters (Martens and Kofman, 1998). More than 50% of all the electronic trading in the foreign exchange market occurs on the Reuters platform (Risk, 2011) and the majority of the main players in the FX market disseminate their indicative quotes on this platform.

In recent years, advances in communication technology have contributed to the integration of the FX market and enabled customers to access multi-pricing sources simultaneously. This has led to an increased share of electronic trading in the FX market, with 90% of the trades in the FX spot market being conducted via electronic platforms (FSB, 2014). Though the overwhelming majority of the FX market trades occur on electronic platforms, there is not a single database that includes all the trades in this market. However, the vast majority of transactions in the FX market, conducted on an electronic platform, originate from a quote in two ways. First, a customer asks for a quote from a dealer or multiple dealers, simultaneously, for ask and bid prices for a specific size and subsequently accepts the desired side. Second, dealers stream a series of quotes, with predefined sizes. A trader could accept either side of a quote (ask or bid) and conduct a transaction (RBS Market Place, 2014a; 2014b). In either of the situations, a quote disseminated by a dealer is displayed on multiple electronic platforms, while a transaction is recorded merely on a single platform. Furthermore, a quote is disseminated with the identity of the market maker, while transaction data do not include any identity information due to privacy reasons.

Many studies evaluated the quality and information content of indicative and transaction data in order to evaluate whether indicative data is an adequate dataset to be used in studying foreign exchange market microstructure. Phylaktis and Chen (2009) compare tick-by-tick matched, four month of Reuters' high frequency indicative quotes with D2000-1 transaction data for DEM/USD and GBP/USD. By using different information measures, they found that tick-by-tick indicative data are not inferior in terms of quality of information and contains higher information content than transaction data. In addition, they found that indicative data has the same effect on order flow as transaction data. They found that transaction data lag 5 to 10 minutes behind indicative data. They argue this result shows that indicative data have the predominant role in incorporating fundamental information into the prices.

Goodhart and O'Hara (1997) believe that indicative quotes illustrate traders' heterogeneous price interpretation better than transaction data. They explain that transaction price depends on the agreement of both counterparties while indicative quotes can be updated instantly. They add that studies using transaction data can lead to biased results because it ignores the informational content of non-trading intervals. Transaction prices are subject to bid and ask bounces, a source of transitory volatility. In addition, quotes are regarded as active between revisions and can be updated in the absence of trade. On the other hand, because bid and ask can be picked up in response to new public information, there is a strong motivation in keeping them updated, hence, they reflect currently available information better than transaction prices (Hasbrouck, 2007). The other advantage of indicative quotes over transaction data is the comprehensiveness of them. Transaction data in the FX market are collected from the platforms that the transactions are conducted on; hence if there are any other transactions on any other platforms, they are not recorded in transaction data. However, although some of the dealers cannot be traded with on multi

bank dealing platforms such as Thomson Reuters or EBS, they report their transaction to these platforms as an indicative quote.

Based on the aforementioned reasons, a comprehensive set of quotes with the identity of their disseminators, is the most appropriate, available dataset to study the FX market, should the behaviour of individual dealers be the focus of the analysis. Since the aim of this thesis is to evaluate and study the impact of market participants on price discovery, a dataset with the identity of market participants allows for closer observation of market participants and their impact on the price discovery process.

3.4. Data Collection Procedure

As mentioned in the introduction of this chapter, the datasets used in this thesis are unique in their kind. The uniqueness of these datasets are mainly due to the complex collection process. This section explains how the data collection process for quote and macroeconomic news datasets are designed and implemented.

3.4.1. The Quote Data Collection Procedure

The Quote Dataset is a live capture of ask and bid prices of EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs from the Thomson Reuter Eikon platform. Although the quotes, with dealers' identity, is streamed on the Thomson Reuter Eikon platform, collecting this data in a historical format from this platform is not possible. However, the quote data can be downloaded as they arrive to the Thomson Reuter Eikon platform via its Excel add-in. This is the reason that the data used in this thesis spans merely through a part of the life span of this research. The quote data collection procedure consists of 4 sections, streaming the quotes in an Excel sheet, capturing the quotes and storing them in the temporary database, sorting and organising quotes into

an intermediary database, validating and cleaning the quotes and storing them in the final database.

In order to capture the stream of quotes data from the Thomson Reuter Eikon platform, the live stream of quotes for each currency pair is streamed in a separate sheet via the Thomson Reuter Eikon Excel add-in. Each quote then is download into a temporary database, as soon as it arrives. The reason for streaming each currency pair in a separate sheet is that the download event in each sheet is triggered by the arrival of a new quote. Since different currency pairs have different frequency of quote arrival, capturing their stream in separate sheets prevents capture of redundant and repetitive quotes. For each quote, the name and location of the disseminating dealer, ask price, bid price, and the timestamp of the quote accurate to a millisecond is captured. While capturing each quote, after each refresh, the new quote is sent to a Database Management Software (DBMS) to be saved in an intermediary table. At the end of each week, when the market is not active, the saved quotes in the intermediary table are sorted by their date and time of their dissemination and saved in the final table.

3.4.2. Macroeconomic News Dataset Collection Procedure

The macroeconomic news database is collected from the Bloomberg platform and includes three sub-datasets, macroeconomic news announcements, economists' forecasts, and geographical information of economists and firms. The macroeconomic news announcements are retrieved from ECO (Economic Calendar) page and geographical information on economists and firms are collected from BIO page (People Profile) and each firm description page, respectively. These two datasets are collected manually, however, manual collection of economists' forecast is extremely time consuming and because it requires repetition of 6 steps for 3,321 times, it might induce some errors and inaccuracies in the final dataset. In order to explain the collection of economists' forecasts, the procedure

for manual collection of economists' forecasts for one macroeconomic news item will be explained.

As explained, the list of macroeconomic news is collected from the ECO page for the U.K., the U.S., Eurozone member countries, and Japan. The collection of economists' forecasts for each of the macroeconomic news in this list starts from the ECOS (Economist Estimate) page in Bloomberg. On the top right hand side of the page the intended macroeconomic news identifier (ticker) is entered. Then the start and end date of the existing economists' forecasts is entered. Then the export option from the page is selected to export the obtained economists' forecasts into an excel file. In the pop-up excel export page, the option for downloading all the available economists' forecasts is selected and the file is downloaded. The excel file downloaded regarding the macroeconomic news includes the name of the ticker, name of the economist and his/her firm, date of the forecast release, and the forecasts' value[18]. The obtained excel file is transposed[19] and imported into the DBMS. The automation of the economists' forecasts download process, explained above, follows the same procedure, while the process is done by software developed for this research.

3.5. The Quote Dataset Description and Summary Statistics

3.5.1. Quote Dissemination

The Quote Dataset includes quotes from EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs. These six currency pairs are constructed from Euro (EUR), British Pound (GBP), U.S. Dollar (USD), and Japanese Yen (JPY) that account for 77.7% of the overall $5.3 trillion a day turnover in the FX market

[18] Economists' forecasts for each macroeconomic news item is downloadable only in separate files. Therefore, overall there are 3,321 excel files, one for each macroeconomic news item.
[19] The excel file presents the data in column format that is not an adequate format for merging this data with macroeconomic news dataset.

(BIS, 2013). Table 3.1 reports the summary statistics of the average number of quotes per minute for each currency pair. The data presented here excludes Saturdays and Sundays.

[Table 3.1 Here]

EUR/GBP and GBP/JPY have the lowest and highest average number of quotes per minute and also total number of quotes. Overall, there are 236 days from April 22nd 2013 to March 27th, 2014, 286 including Saturdays and Sundays, and 98,860,278 quotes in the Quote Dataset with 53.51 quote per currency per minute, on average. In other words, on average almost 321 new quotes have disseminated in these six currency pairs, per minute. These statistics demonstrate the high frequency nature of this dataset and the FX market. Figure 3.1 visualises this data that is also summarised in table 3.1. Similar to table statistics, GBP/JPY always has the highest number of quotes per minute within the six currency pairs. Although, on average, EUR/GBP has the lowest number of quotes, between 08:00 and 15:00 its quote frequency passes that of USD/JPY.

Figure 3.1. Average Number of Quotes per Minute

This figure illustrates the average number of quotes per minute in each currency pair from 00:00 to 23:59.

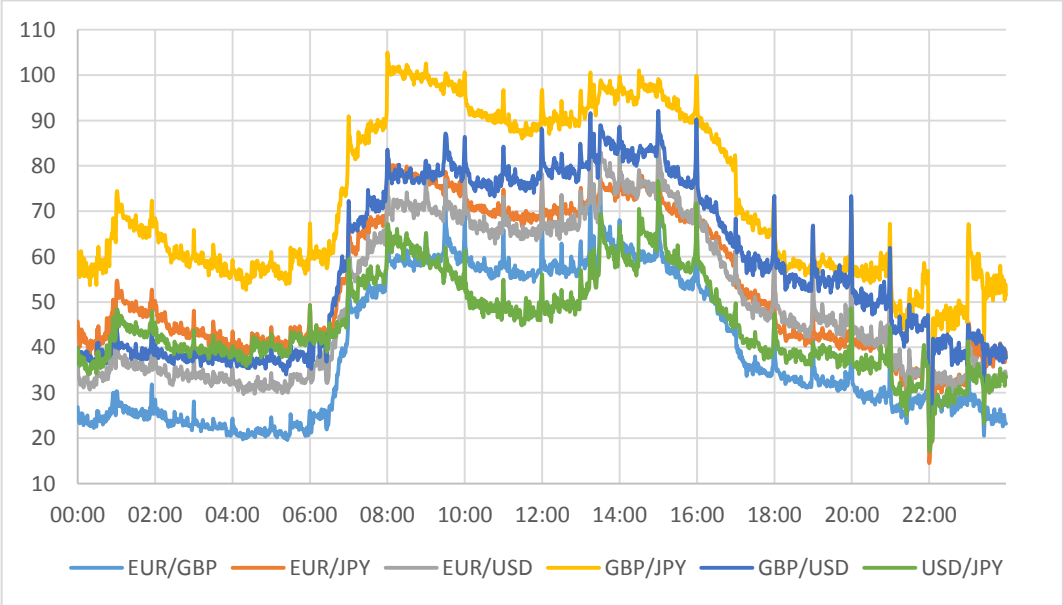


Figure 3.1 illustrates the market activity at different times of the day. There is a similar pattern between all currency pairs that is a significant increase from 08:00 and a considerable drop after 16:30. These are exactly the U.K. (London Stock Exchange) equity market working hours. This shows the importance of the U.K's role in the FX market. The Foreign Exchange Joint Standing Committee of the Bank of England (2014) reports the average daily turnover of the U.K. foreign exchange market in October 2013 was $2.236 trillion that is 42% of the FX market average daily turnover reported by BIS in 2013[20]. There is another peak around 14:30 which is consistent with the New York Stock Exchange (NYSE) opening time and a considerable drop after NYSE closing at 21:00. The interesting point regarding this figure is the spikes at the beginning of every hour specifically the one at 16:00. The spike at every hour might be due to the release of WM/R fix at every hour (World Market Company, 2015) and the biggest spike at 16:00 is the 4'o clock WM/R fixing that is the one of the most important benchmarks in the FX market and is studied in chapter 6. Furthermore, while after 20:00 there is a downward trend in non-Japanese Yen currency pairs, an opposite trend is observed in Japanese Yen currency pairs. This is consistent with the opening of the Japanese financial markets.

3.5.2. Dealers and their Geographical Distribution

This section explains the geographical distribution of dealers and how they are spread around the world. In this thesis every dealer-location is identified as a separate market maker based on their name and location. For instance, the Royal Bank of Scotland (RBS) that is active in London and New York, each of its trading branches is identified as a distinct dealer. For each currency pair information on the number of dealers, locations, and dealer-locations

[20] London's traditional dominance in FX grew out of the United Kingdom's worldwide economic dominance in the nineteenth century. It remains secure at the beginning of the twenty-first century because of its geographic location: London's morning session overlaps with Asian trading and its afternoon session overlaps with New York trading. (King et al., 2011)

are presented separately. The statistics presented here help to understand the global dispersion and decentralised nature of the FX market.

[Table 3.2 Here]

Table 3.2 demonstrates the geographical dispersion of dealers in each currency pair. EUR/USD and GBP/USD currency pairs have the highest number of dealers' concentration who are active in all six continents[21]. The lowest concentration of dealers and geographical dispersion is in the EUR/GBP currency pair, with only 44 dealer-locations in 22 countries. The highest concentration of dealer-locations is in Europe and Asia where 80% of market makers are located, while merely 8% of the market makers are located in South America, Africa, and Australia. Overall, in the Quote Dataset, there are 94 dealers active in 49 cities and 44 countries, from all the six continents, forming 109 dealer-locations. Since these six currency pairs are constructed from the four most traded currencies in the world, it should not come as a surprise that dealers all over the world are actively trading. In Africa, Asia, Europe, North and South America dealers are active in 2, 15, 21, 2, and 2 countries, respectively.

The question that arises here is whether the quote distribution follows the same pattern of geographical dispersion. The last row of table 3.3 shows the average number of quotes per dealer in each continent. Table 3.3 shows that although the number of dealers in Europe is almost 5 times more than that of North America, dealers in Europe have disseminated almost 2 times more quote than dealers in North America. Dealers in North America, on average, have the highest quoting frequency followed by dealers in Africa and Europe. Based on information in tables 3.3 and 3.2 it is concluded that the quoting quantity is not perfectly correlated with the number of dealers. In other words, different dealers

[21] In table 3.2, GFX (Global Foreign Exchange) is the locations code used by Thomson Reuter Eikon that refers to dealers who disseminate their quotes from multiple locations.

exhibit different quoting frequency and sheer number of dealers cannot be used as the proxy for quantifying quote quantity.

[Table 3.3 Here]

3.6. Conclusion

This chapter provided an over view of the data that is used in this thesis. It introduced the FX market and its characteristics, and explained the decentralised nature of the FX market and how this feature induces difficulties in collecting data. In order to address this issue, a unique quote dataset from the Thomson Reuter Eikon platform was collected. The main features of this dataset is that it included the identity and location of dealers and was accurate to milliseconds. These two features make this dataset an adequate data for studying the impact of high frequency trading on the FX market. The inclusion of identification and location of dealers in the Quote Dataset allows for the close observation of individual market participants on the price discovery process in the FX market.

One of the contributions of this thesis to the market microstructure field is the construction of the Quote Dataset that allows the studying of the constantly changing FX market. Such a comprehensive database of this scale has never been used in any academic research. The last known similar dataset (much smaller in size) is the HFDF93, which has been used in academic research for the past two decades. HFDF93 contains data in three currency pairs, USD/DEM, USD/JPY, and DEM-JPY from 1992 to 1993 - see Peiers (1997); Herbst et al., (1997); Hafner (1998); Jong, et al (2001); Franke et al., (2004); Wu (2007); Lanne and Vesala (2010); and Chelley-Steeley and Tsorakidisb (2013).

Tables

Table 3.1. Summary statistics of Number of Quotes per Minute

This table reports the summary statistics of the captured quotes in the Quote Dataset per minute for each currency pair. Column N reports the number of minutes and the remaining statistics include the minimum (Min), first quartile (Q1), median, mean, third quartile (Q3), maximum (Max), and standard deviation (S.D.) for each currency pair per day. These statistics are calculated based on the average number of quotes in each minute from 00:00[22] to 23:59.

Currency	N	Total	Min	Q1	Median	Mean	Q3	Max	S.D.
EUR/GBP	1440	12,245,621	17.15	25.33	33.27	39.84	57.00	76.73	15.64
EUR/JPY	1440	16,795,194	14.48	41.74	48.61	54.34	69.84	82.77	15.26
EUR/USD	1440	15,593,208	25.91	34.31	46.29	50.70	67.17	87.31	16.49
GBP/JPY	1440	22,340,181	20.66	57.71	65.81	72.72	90.62	104.99	17.96
GBP/USD	1440	17,966,522	24.20	39.28	55.65	58.15	76.93	92.13	17.91
USD/JPY	1440	13,919,552	17.18	38.19	42.66	45.31	53.32	76.75	10.18
Total	8640	98,860,278	14.48	38.34	51.70	53.51	67.17	104.99	18.93

[22] All the times in this thesis are GMT times.

Table 3.2 Geographical Distribution of Dealers

This table shows where dealers in each currency are located and illustrates their geographical dispersion. Column Dealer shows the distinct number of dealers in a currency pair without considering their location. Columns city and country depict the distinct number of cities and countries that dealers in each country are located in, respectively. Column Dealer-Location shows the total number of dealers identified based on their name and location. The rest of the columns show the name of the continents and total number of dealer-locations in those continents. GFX is the location code used by Thomson Reuter Eikon that refers to dealers who disseminate their quotes from multiple locations.

Currency	Dealer	City	Country	Dealer – Location	Africa	Asia	Australia	Europe	GFX	North America	South America
EUR/GBP	41	24	22	44	1	0	3	34	3	3	0
EUR/JPY	46	25	23	50	0	7	2	34	3	4	0
EUR/USD	77	45	42	88	2	26	3	42	4	9	2
GBP/JPY	46	25	23	50	0	7	2	34	3	4	0
GBP/USD	65	37	34	72	2	22	3	32	4	8	1
USD/JPY	60	30	33	69	1	28	3	26	4	7	0
Total	94	49	44	109	3	37	4	50	4	9	2

Table 3.3 Geographical Distribution of Quotes

This table depicts the geographical distribution of quotes in each continent for all the six currency pairs. Each column shows the name of the continent and the total number of quotes disseminated from that continent. The last row, average per dealer, shows the average number of quotes per dealer in each continent.

Currency	Africa	Asia	Australia	Europe	GFX	North America	South America
EUR/GBP	0	37,823	110,270	9,011,184	57,754	3,028,590	0
EUR/JPY	0	688,607	75,898	10,770,303	45,208	5,215,178	0
EUR/USD	29,542	2,830,577	61,172	8,649,319	114,951	3,905,776	1,871
GBP/JPY	0	927,621	97,013	13,943,370	55,772	7,316,405	0
GBP/USD	3,572,450	2,173,100	67,660	7,457,973	48,070	4,620,395	26,874
USD/JPY	171	2,731,906	73,086	6,830,225	12,560	4,271,604	0
Total	3,602,163	9,389,634	485,099	56,662,374	334,315	28,357,948	28,745
Average per Dealer	1,200,721	253,774	121,275	1,133,247	83,579	3,150,883	14,373

Chapter 4. HFQ and Price Discovery in the FX Market

4.1. Introduction

The development of the financial markets is deeply influenced by and reliant on innovations in information technology. Over the past three decades high frequency traders (HFTs) have entered the financial markets and have been shown to improve price discovery and reduce transaction costs[23]. Nonetheless, there is heightened concern amongst financial organizations (see a survey of 700 organizations reviewed in the Financial Times by Shorter and Miller, 2014) and regulators that high frequency trading is having a negative effect on market efficiency[24]. Almost all the focus so far has been on equity and derivative markets as summarised in a congressional research report by Shorter and Miller (2014). However, the recent scandal concerning the manipulation of the FX benchmark rate has led to concerns as to the lack of regulatory oversight in the FX market. This chapter contributes to the extant debate on HFT and FX market regulation by analysing how the speed of dealers' quotation updates affects their contribution to price discovery in the foreign exchange (FX) market.

[23] Hagströmer and Norden (2013) conclude that HFTs mitigate intraday price volatility. Malinova et al., (2013) show that the reduction of HFTs' message traffic causes an increase in spreads and an increase in the trading costs of retail and other traders. Brogaard et al., (2014) find that HFTs add to price discovery by trading in the direction of permanent price movement and in the opposite direction to transitory price errors. Chaboud et al., (2014) evaluate the effect of algorithm trades on quality measures of price discovery, autocorrelation and arbitrage opportunities in the FX market and find that algorithm trades add to price discovery quality.

[24] On June 5, 2014 the SEC's chair Mary Jo White announced that in response to concerns over "aggressive, destabilizing trading strategies in vulnerable market conditions," the agency was pursuing several HFT-related reform proposals, including requiring unregistered HFT firms to register with the agency (SEC, 2014). Similar requirement was introduced in Europe through the Markets in Financial Instruments Directive II (MiFID II) in 2014. Firms will have to become authorised to continue to trade using a HFT technique.

To examine the effect of speed on price discovery in the FX market, a subset of the Quote Dataset that was introduced in chapter 3 is used in this chapter. Overall, there are 53,702,925 quotes between April 23, 2013 and March 11, 2014 from 92 dealers that are active in 6 continents, 42 countries and 49 cities, which yield the total number of 104 dealer-locations[25]. Such a unique dataset allows addressing the question of whether the quoting frequency (Speed) of market participants contributes to the price discovery process. Dealers' contribution to the price discovery process is calculated by the Barclay and Warner (1993) Weighted Price Contribution (WPC) model. It captures the accumulated percentage price movement generated by a given dealer's quotes to the overall price movement in the measured time horizons. Price discovery is studied within two time horizons, one minute and daily, to examine whether speed plays a similar role in the price discovery of different horizons.

The daily horizon is used to proxy for long-term price discovery, whereas the minute horizon is used to proxy for short-term price discovery. The fundamental (long term) value of an asset is defined as the value of the asset in the distant future. Distant future refers to a time horizon where there is a considerable number of transaction and quote changes (Lehmann, 2002). Given the large volume of transactions in the foreign exchange market, a daily time horizon meets the criterion of an adequate time interval for examining long-term price discovery. Long-term value is different from short-term value by the noise imbedded in the short-term value (Harris, 2003, p 223). Therefore, even if markets process information quickly ("information efficiency") in the short term, the processed information may not be directly related to fundamental (long term) values (Cunningham, 1994).

[25] Since in this chapter is a subset of the quote dataset and includes only the days that there has been no interruption in data capture, 2 dealers and 5 dealer-locations are omitted from the original quote dataset due to the implementation of continuity condition of data capture. See footnote 16 for further discussion.

While this chapter's findings show that dealers using higher frequency quotes are more successful in predicting short-term price movements (contributing to short-term market price discovery), no relationship between the speed of dealers and their impact on long-term price discovery is found. Furthermore, it will be shown that this discrepancy in the role of speed in short and long-term price discovery is reconciled by the fact that higher speed quotations increase the *volatility* of the dealers' intraday *price discovery* and, therefore, undermine their contribution to long-term price discovery. The main results are robust to further controls of dealers' quoting behaviour, including net buy-sell intention and quote aggressiveness.

The contribution of this chapter to the existing literature is that it offers, to the best of my knowledge, the first investigation of the effect of High Frequency Quoting (HFQ) on price discovery in the FX market. Building on the existing literature, this chapter's findings, regarding the impact of market participants' speed on price discovery, strongly support short-termism in the FX markets, with dealers focusing more on short-term rather than long-term value (Harris, 2003 p.286). Froot et al's, (1992), theoretical model suggests that short-term investors concentrate on short-time information and pay less attention to fundamentals. Market participants concentrate on short-term rather than fundamental information, distort the price discovery process and cause market overreaction (Menkoff, 2001). Zhang (2010) argues that the practice of focusing on the short-term rather than fundamental information makes markets less efficient. He finds HFTs hinder price discovery, confirming Vives' (1995) findings that short-term investors could impair information efficiency. Therefore, the results highlight the fact that while high frequency activities (either trading or quotation) contribute to very short-term price discovery, this is not the case across the longer term.

This chapter's findings also contribute to the regulatory debate on HFT activities. While this chapter's findings lend support to the use of technology as a means to improve the prediction of short time price movements, the lack of association between speed and

longer term price discovery raises important concerns about the potential downside of increasing speed in the FX market. The implication of these findings suggests that the arms race in trading technology is potentially a social waste. While the first movers who invest in the technology would benefit from their investment, these 'technological innovations' in the trading industry do not produce social benefit as they do not enhance the key function of financial markets: long term information discovery. Furthermore, the finding of the strong association between quote speed and price discovery volatility provides support to the criticism that HFT could exacerbate market volatility as highlighted in Shorter and Miller (2014).

The rest of this chapter is structured as follows. Section 4.2 explains attributes of the Quote Dataset. Section 4.3 presents the key definitions of price discovery and quotation speed measurements. Section 4.4 presents the findings regarding the impact of HFQ on price discovery and section 4.5 offers conclusions.

4.2. Data

This chapter's sample period spans from April 23, 2013 until March 11, 2014 and includes quotes from the Thomson Reuters' platform in six currency pairs: EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY. Each record contains the identity and location of the dealer, bid and ask prices, and the time of the quote dissemination accurate to the millisecond. The Quote Dataset contains 92 dealers, bank and non-banks, from 6 continents, 42 countries, and 49 cities. The initial dataset of 286 days was reduced to 236 days after removing holidays, Saturdays, Sundays, and after removing the days with problems in capturing the data this number reduced to 115 days[26].

[26] The quote dataset is the capture of the live stream of data from the Thomson Reuters FX screen. Due to the live nature of data capture activity there are some days in the dataset that have not been captured completely. Following Evans and Lyons, (2008) the Quote Dataset includes only the days where there is no interruption in the data collection. This is important because the price discovery process is a continuous process and the goal is to observe the impact of every single quote on overall price discovery. In order to avoid any discrepancies in

Overall, there are 53,702,925 quotes from the 104 dealer-locations in the six currency pairs. The data on dealers, their location and the currencies that they are active in, can be seen in Appendix I. The location Global Forex (GFX) in Appendix I, refers to Global Forex dealers who are active from multiple locations throughout the globe. Dealers in EUR/GBP, EUR/JPY, and GBP/JPY are active in Asia, Australia, Europe, and North America, whereas dealers in USD/JPY are active in Australia, Europe, and North America. Dealers in EUR/USD and GBP/USD are active across all the six continents. In addition, GFX dealers are active in all six currency pairs.

In order to study the impact of dealers on the price discovery process the repetitive quotes are removed since they do not contain new pricing information (see Dacorogna et al., 2001, p86)[27]. After controlling for repetitive quotes the dataset contains 39,250,175 quotes for all the six currency pairs.

Table 4.1 reports the descriptive statistics of the dataset. EUR/USD has the highest concentration of dealers and is the most globally spread traded currency pair, whereas GBP/JPY has the highest number of quotes. In terms of the return characteristics, during this period the GBP strengthened against all currencies while the Euro was the second strongest. On the opposite side, the U.S. is the weakest against all currencies and the JPY is the second weakest. Regarding volatility, the USD/JPY has the highest volatility while the EUR/GBP has the lowest.

[Table 4.1 here]

the data, these days have been removed from the sample. In the remaining days from Monday to Thursday all the 1440 minutes and on Fridays all the 1320 minutes of market activity are captured. On Fridays, the FX market is active for only 22 hours, from 00:00 to 22:00, GMT time (Mancini et al., 2013). In addition, following Chen and Gau (2014) Saturdays and Sundays are also removed "to prevent the empirical analysis confounding by thin trading activities" (pp. 196).

[27] Repetitive quotes are the quotes disseminated by a dealer that have the same ask and bid prices as their previous quote.

4.3. Methodology

4.3.1. Contribution to Price Discovery

In order to calculate each dealer's contribution to price discovery, the Barclay and Warner (1993) WPC model is used. The intuition behind the method is to capture the proportion of contribution to price discovery in a given horizon by measuring the cumulated price movement that is accompanied by a dealer's quote in relation to the total price movement in the measurement horizon. For example, Madureira and Underwood (2008) use this model to study the contribution of NASDAQ market makers to price discovery. For the formal definition of WPC, Cai et al. (2015) starting with the following:

$$PD_{j,t} = \frac{\sum_{i=1}^{N_t} \Delta P_i \times D_j}{\sum_{i=1}^{N_t} \Delta P_i} * \frac{\left|\sum_{i=1}^{N_t} \Delta P_i\right|}{\sum_{t=1}^{T}\left|\sum_{i=1}^{N_t} \Delta P_i\right|} \quad (1)$$

$$Where\ \Delta P_i = Ln(P_i) - Ln(P_{i-1})$$

Where $PD_{j,t}$ is the contribution of dealer *j* at time *t*, N_t is the number of quotes disseminated by all dealers at time *t*. D_j is a dummy variable equal to 1 if price P_i is disseminated by dealer *j* and zero otherwise. T is the total number of periods in the whole sample. The first fraction on the right hand side measures the distortion or contribution of an agent to price discovery in a sub period. The second fraction weights the first fraction relative to the total price movement in the whole sample period. The reason for the weighting is because when the price movement of a given period ($\sum_{i=1}^{N_t} \Delta P_i$) is close to zero, it would inflate the value of the contribution measure in the first fraction. To mitigate this problem, following Barclay and Warner (1993) the price discovery is weighted by the absolute total cumulative price change ($\left|\sum_{i=1}^{N_t} \Delta P_i\right|$).

The price discovery across two distinctly different time horizons are examined: by the minute and daily. Given the high liquidity and fast pace of the FX market, the view is

taken that a one-minute price movement is a measure of short-term price discovery and a daily price movement is a measure of 'long-term' price discovery.

In addition, the price discovery in bid and ask prices are studied separately due to the following reasons. Stoll (1978) points out that dealers use asymmetric bid and ask quotes to maintain their target inventory level. Indeed, Bessembinder (1994) shows that dealers' quotes are sensitive to their inventory holding cost. Hasbrouck (1995) points out it is useful to analyse the bid and ask separately in order to model the buy-initiated and sell-initiated traders. Hasbrouck (2007, p.46) also argues that bid and ask prices are not set symmetrically around the efficient price. Harris (2003, p.284) explains that though dealers quote on both sides, the ones who want to trade merely on one-side use asymmetric aggressive bid and ask quotes. More recent studies also provide evidence pointing out the importance of recognizing such an asymmetry. In equity market research, Pascual and Pascual-Fuster (2014) study 10 years of data for 84 listed companies and find that ask and bid quotes are not equally informative in the short-run. They conclude that any assumption on equal informativeness for ask and bid quotes is not supportable and the use of mid-point prices might lead to a significant loss of information concerning the price discovery process. In studying the FX market between 2004 and 2005, Chen and Gau (2014) find bid and ask quotes make different contributions to price discovery in EUR/USD.

4.3.2. Measuring Quotation Speed

In order to capture the quoting frequency of dealers, *Speed* measure is constructed based on the tick frequency measure proposed by Guillaume et al., (1997). They define tick frequency as the number of quotes disseminated in a time horizon and suggest calculation of tick frequency disaggregated by banks and their locations. The main issue of this method is the assumption of equal activity time of market participants; dealers' active time matters especially when the intention is to differentiate dealers who disseminate quotes at a much

higher speed than others. Based on this assumption, two dealers who disseminated the same amount of quotes have the same tick frequency. For instance, assuming an extreme scenario that two dealers have disseminated a total 25 non-repetitive quotes in one-minute measurement period, then they would have the same tick-frequency. However, suppose further that one dealer has disseminated all quotes in 1 second and another dealer in 60 seconds, the tick-frequency defined above fails to distinguish their difference in quotation speeds.

This issue of tick frequency is addressed by embedding the activity time of a dealer in a time horizon, into its definition and to call this measure, *Speed*. Speed is defined as the number of quotes divided by the total activity time. Therefore, for any given minute, the speed of a dealer is defined as the average normalised number of quotes disseminated during a dealer's active time and its unit of measurement is *quotes per minute*. The speed measure is intentionally designed to capture high-speed traders who may not be active for a long period. This measure is formulated as below,

$$Speed_{i,t} = \begin{cases} \frac{60000}{S_{i,t}} \times N\{x(\tau_k)|\tau_k \in [S_{i,t_s}, S_{i,t_f}]\}, & N\{x(\tau_k)\} > 1 \\ 1, & N\{x(\tau_k)\} = 1 \end{cases} \quad (2)$$

$$where\ S_{i,t} = S_{i,t_f} - S_{i,t_s} \quad (3)$$

Where $\{\tau_k\}$ is the sequence of the tick recording times that is unequally spaced, $x(\tau_k)$ is the price at time τ_k. $N(\{x(\tau_k)\})$ is the counting function that captures the number of quotes disseminated by dealer *i* at time $S_{i,t}$. Where $S_{i,t}$ is the activity time, the time difference between the last and first quote disseminated by dealer *i*, measured in milliseconds, in minute *t*. S_{i,t_f} and S_{i,t_s} are the clock time of the last and first quotes disseminated by dealer *i* in the minute *t*, respectively. The multiplier of 60,000 is used to normalise the speed measure

to per minute[28]. Since $S_{i,t}$ of the speed formula will be zero for the dealers with merely one quote in a minute, in order to include these observations in the analysis, their activity time as the whole one minute, 60000 milliseconds, is assumed that yields the speed of 1 for these dealers in those minutes. In a sense, the speed measures capture the upper limit of the number of quotes (maximum number of quotes) a dealer could have disseminated, should the dealer have been active for the whole one minute.

4.3.3. Additional Quotation Characteristics

In order to analyse the impact of dealers' speed on price discovery, other characteristics that need to be controlled for are discussed below.

4.3.3.1. Dealers' Observable Intention

A dealer must accommodate the random arrival of buy and sell orders that are sensitive to his posted quotes, in a way to maintain his/her inventory target level. As a result, after every trade, the dealer updates his/her beliefs and posts new quotes (Hasbrouck, 2007, p.47). Dealers actively control their inventory by setting prices to induce movement toward desired inventory levels (Madhavan and Smidt, 1993). In the event of excess inventory, a dealer increases his/her ask and bid prices and vice versa in the case of inventory shortage (Manaster and Mann, 1996). A dealer's intention to long or short the base currency is tried to be deduced from the quote updates. Dealers can update their quotes in a number of combinations that affect only bid, ask or both sides. Table 4.2 reports the eight possible combinations of a dealer's actions in comparison with his/her latest quotes.

A dealer's intention is indicated by B and S for Buying and Selling the base currency, respectively. Dealers use the strategy of keeping the ask or bid price static and moving the other, when they want only one side of their quotes to be hit (Harris, 2003, p280). For

[28] There are 60,000 milliseconds in 1 minute

example, with an intention to buy, a dealer can post a more competitive bid (**B**↑) and/or a less competitive ask (**A**↑) and vice versa (Muller and Sgier, 1992 as cited in Guillaume et al., 1997).

[Table 4.2 here]

Love and Payne (2008) show that differentiating buyer-initiated from seller-initiated trading interest explains price variations better than the difference between buy and sell quantities. Following their method, a buy-sell trading interest measure is constructed by subtracting the number of sell-initiated quotes from buy-initiated quotes for a given dealer in the time horizon.

$$BS_{j,t} = \sum_{i=2}^{NQ_{j,t}} (D_{B_i} - D_{S_i}) \quad (4)$$

Where $BS_{j,t}$ is the net buy-sell interests for dealer *j* at time *t*, D_B and D_S are dummy variables equal to one when the intention of the dealer for disseminating quote *i* is to buy and sell the base currency, respectively. The reason that the sigma index starts at 2 is that in order to calculate a dealer's intention, quote i should be compared to quote i-1, hence, no intention can be interpreted from a dealer's first quote in a day. A positive sign of BS shows that the dealer was an intended net buyer in time *t* and a negative sign means the dealer was an intended net seller in time *t*.

In Table 4.2, W represents the time that a dealer widens his/her spread by reducing the bid and increasing the ask price. This is mainly driven by the increased uncertainty of the market's condition or any other reason that the dealer is not willing to trade. N represents that the dealer wants to return to the market and signals this to their customers by narrowing their bid-ask spread. Although there is no direct observable intention from these two types of quotes, they do capture the dealer's willingness to do business. Therefore, a measure is constructed by counting the net number of times the dealer increases the bid-ask spread as

$$WN_{j,t} = \sum_{i=2}^{NQ_{j,t}} (D_{W_i} - D_{N_i}) \quad (5)$$

Where $WN_{j,t}$ is the net number of times that the dealer j increases his bid-ask spread at time t, D_N and D_W are dummy variables equal to one when the dealer increases or decreases the spread in quote i, respectively. A higher value for this measure, the less willing is the dealer to provide liquidity.

4.3.3.2. Quote Aggressiveness Measure

When dealers update their quotes, in addition to the direction, they also have a choice of the size of the changes. A larger size in the change of their quotes signifies a more aggressive attitude in their quotation. Therefore, quotation aggressiveness is quantified by the portion of a dealer's quotes that has been changed by more than one pip with the exception of EUR/JPY and GBP/JPY for which two and three pips are used, respectively. These thresholds of aggressiveness are chosen because, on average, more than 70% of ask and bid price movements are realised within these price movements.

Accordingly, a dealer's quotation update, the change in the price of the latest quote in comparison to the previous quote, is categorised into five groups: very negative, negative, unchanged, positive and very positive. The reason that ask or bid prices may be unchanged is that the dealer only updates one side of his/her quotes.

$$p_{vp_{i,t}} = N(\{\Delta_{p_{i,t}} \mid \Delta_{p_{i,t}} > AG_T\}) \quad (6)$$

$$p_{vn_{i,t}} = N(\{\Delta_{p_{i,t}} \mid \Delta_{p_{i,t}} < AG_T \times -1\}) \quad (7)$$

$$Where\ \Delta_{p_{i,t}} = p_{i,t} - p_{i,t-1} \quad (8)$$

Where $p_{vp_{i,t}}$ and $p_{vn_{i,t}}$ are the number of times that dealer i has increased and decreased his/her quotes more than aggressiveness, respectively. For ask and bid p is replaced

with *a* and *b*, respectively. N is the total number of quotes disseminated in time *t* and AG_T is the aggressiveness threshold. $p_{i,t}$ is the ask or bid price disseminated by dealer *i* at time *t*. The point that should be mentioned here is that $\Delta_{p_{i,t}}$ is calculated continuously throughout the day and not every minute. In other words, in order to calculate each price change, $\Delta_{p_{i,t}}$, each price is compared to the previous price, from the beginning to the end of a day. The aggressiveness measure is defined separately for bid and ask, as follows:

$$AG_{Ask_{i,t}} = \frac{a_{vp\,i,t} + a_{vn\,i,t}}{N\{x(\tau_k)|\tau_k \in [S_{i,t_s}, S_{i,t_f}]\}} \quad (9)$$

$$AG_{Bid_{i,t}} = \frac{b_{vp_{i,t}} + b_{vn_{i,t}}}{N\{x(\tau_k)|\tau_k \in [S_{i,t_s}, S_{i,t_f}]\}} \quad (10)$$

Where AG_{Ask} and AG_{Bid} are the aggressiveness measures of ask and bid of dealer *i* in time *t*, respectively. The higher the measure, the more aggressive the dealer is in moving his/her quotes.

4.4. Results and Discussion

In this section, the results of this chapter's empirical analysis on the impact of speed on price discovery are presented.

4.4.1. Summary Statistics

In this section, the basic summary statistics of the speed and other quoting characteristic measures is reported. For the speed measure, Table 4.3 Panel A reports the summary statistics by dealer-minute. It illustrates a similarity in the mean and standard deviation of all currency pairs, except for the GBP/JPY, demonstrating the analogousness of market participants' speed characteristic. On average, the number of quotations for dealers in one minute is approximately 5 to 6 quotes. There are large extremes in dealer-minutes as

shown in the Max column. These speeds lend support to the high frequency nature of dealers in the FX market.

When speed measures are considered at the dealer level, in Panel B, the different speed characteristic of market participants in GBP/JPY is observable via their average speed of 46.1 quotes per minute in comparison to those of other currency pairs varying between 4.76 and 5.69. These figures report a significantly higher speed of GBP/JPY market participants than those of other currency pairs[29]. Furthermore, even the lowest average speed of 4.76 quotes per minute by a dealer, in EUR/GBP, considering the number of dealers, 42, in that currency pair, is further evidence of the high frequency nature of the currency market. The fastest Dealers' average speed in all currency pairs varies from 16 up to 344 quotes per minute, demonstrated by the maximum column in Table 4.3.

[Table 4.3 here]

The nature of the aggressive quoting behaviour among market participants is illustrated in Table 4.4. The use of aggressive quoting averages from 19% to 33% across the different currency pairs. Although there is a consonant homogeny between the bid and ask aggressive quoting of all currency pairs, GBP/JPY, again, is an exception, with a six percentage difference between bid and ask aggressive quoting, re-demonstrating the difference in the nature of this currency pair in the quoting characteristics of its market participants.

[Table 4.4 here]

In terms of dealers' buy-sell intention of trades, Table 4.5 reports the proportions of quote updates, on currency level, in each of the eight categories of bid and ask tick

[29] This difference in market participants' speed characteristic is due to the extremely active and volatile nature of GBP/JPY currency pair - in some cases its price can change up to 350 pips in a single trading day (FXDD, 2013).

movement, defined in Table 4.2. With the exception of GBP/JPY, the most frequent techniques of price movement are those with simultaneous and unidirectional movements of ask and bid (i.e. **A↑B↑** and **A↓B↓** cells). Using these classifications, measure of Buy–Sell intention (BS) can be further derived. Table 4.6, panel A, shows that the majority of the differences between buy and sell intended quotes are negligible. Zero medians and symmetries in the first and third quartiles are consistent with the overall symmetrical pattern of the B and S cells in Table 4.5. This suggests that, in general, dealers are interested in market making and completing their round trip. However, there are some extreme values at the two tails of the distribution, demonstrated by maximum and minimum values. These extreme values are caused by large imbalances in buy-sell orders and consequently push the prices up or down, thus are of great prominence in the price discovery process. In some cases, large imbalances in buy-sell orders are driven by news such as macroeconomic news announcement[30]. The relationship between these order imbalances and price discovery will help with understanding how dealers adjust them to facilitate price discovery.

[Tables 4.5 and 4.6 here]

Another set of statistics that can be derived from the Table 4.5 classification is the net number of times that dealers widen their spreads (WN), measured by subtraction of W cell value from N cell value. The results in Table 4.6 panel B depict that the imbalance between W and N only exists in less than half of the dealer-minute observations (the imbalance measure is zero in the first and third quartiles). A lower range and variance in panel B, than those in panel A, in conjunction with the results in Table 4.5, is further evidence

[30] Market and stock returns are significantly affected by order imbalance size (Chordia et al., 2002; Chan and Fong, 2000; Blume Et al., 1989). Berger et al., (2008) report a substantial association between interdealer order flow and exchange rate returns at horizons ranging from 1 min to two weeks. Evans and Lyons (2008) argue that macroeconomic news can affect currency prices directly and indirectly via order flow. They find that macroeconomic news announcements account for 30% of daily price movements.

of the dominance of Buy and Sell initiated quotes over widening and narrowing spread quotes.

4.4.2. Regression Analysis

In this section, the effect of dealers' speed on their contribution to price discovery after controlling for other quotation characteristics is evaluated with the following specification.

$$\mathrm{PD}_{i,t} = \alpha + \beta_1 Speed_{i,t} + \beta_2 AG_{i,t} + \beta_3 Speed_{i,t} * AG_{i,t} + \beta_4 BS_{i,t} + \beta_5 WN_{i,t} + \beta_6 AT_{i,t} + \varepsilon \quad (11)$$

Where $PD_{i,t}$ is the price discovery contribution of dealer i in time t, $Speed_{i,t}$, $AG_{i,t}$, $BS_{i,t}$, $WN_{i,t}$, and $AT_{i,t}$ are quote speed measure, measure of aggressiveness, net buying intention, net number of times that the dealer increased his/her spread and activity time (measured in seconds) of dealer i at time t, respectively. For ask and bid minute regressions, models 1 and 2 (Ask-Minute and Bid-Minute models) in table 4.7, each of these variables are calculated for each dealer in each minute[31], however for bid and ask daily regressions, models 3 and 4 (Ask-Day and Bid-Day models) in table 4.7, independent variables, for each dealer, are calculated as the daily average of minute independent variables[32]. . How often and how much a quote changes are the two choices that dealers make that will affect how quick and aggressive their quote will be. In this chapter's analysis, the possible interaction between these two measures is further examined (Speed and AG).

[31] This means that on a minute basis independent variables vary from one minute to another and consequently the same holds for independent variables on a daily basis.

[32] The correlation matrixes of model 11 for ask and bid price discovery on a minute and daily basis are reported in tables 4.10 and 4.11, respectively. The magnitude of correlation coefficients in table 4.11 shows that regarding models 3 and 4 in table 4.7 there are no concerns regarding the existence of multicollinearity and its impact on the results except the correlation between AT and BS. In order to address this issue, first, the Variance Inflation Factor (VIF) of models 3 and 4 is examined and the correlation between AT and BS does not raise any issue in this sense. Second, models 3 and 4 are re-run once without AT, once without BS and the results are consistent with the results reported for models 3 and 4 in table 4.7. However, the results are not reported here.

In model (11), it is recognised that not all dealers are homogenous specifically in relation to their size that might affect their speed and order flow. However, it is not possible to control for dealers' size, since many of the dealers in the Quote Dataset are private companies and no information could be collected regarding their sizes. However, this concern is addressed in model (11) by controlling for BS (as the proxy for order flow) and Speed.

The other point that should be mentioned here is regarding the use of panel data for model (11). Although the data structure is similar to that of a panel data, due to two limitations panel data analysis cannot be used here. First, the data does not meet the condition of a panel data structure that requires the same dealer to be present in most of the time periods (Pindado, 2014). The structure of the data is extremely unbalanced, in the sense that the presence of dealers in each time period is neither continuous nor consistent. For instance, a dealer might be active for a while and then stop his activity for a period and then continue his trading activity again and so on. Second, the other element of the data that is not consistent with panel data structure is the number of dealers and time periods. For the GMM model to work N (number of dealers) should be large relative to T (time) (Smith and Fuertes, 2016), while it is the opposite in this case. For EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY there are 42, 48, 81, 48, 66, and 63 dealer-locations in this chapter's quote dataset, respectively. While the number of time periods for these currency pairs and dealer-locations are 162412, 162917, 162669, 162683, 162919, and 162550, respectively. Due to these two reasons the use of panel data for model (11) is not appropriate.

Table 4.7 presents the pool regression results for all currencies and Table 4.8 reports the breakdown of each currency.[33] For the short-term price discovery, Models 1 and 2 (Ask-

[33] As the basic statistics show the average statistics of speed varies significantly from one currency to another. In order to ensure comparability in the pool regressions, the speed measure is normalised in each currency pair by dividing each observation's speed to the average speed of the currency pair, realised by averaging the speed

Minute and Bid-Minute models) in table 4.7 demonstrate that speeds are significantly and positively associated with the contribution to price discovery. This finding is consistent with the findings in the HFT literature regarding equity (Brogaard et al., 2014 and algorithmic trading in the FX markets Chaboud et al., 2014) that HFT can predict short-term price movements more than the other types of dealers.

Interestingly, it shows that an increase in aggressive quoting reduces dealers' contribution to price discovery. In other words, quotes with a larger tick size are normally in the wrong direction in terms of the overall price movement within a minute time horizon. Furthermore, the coefficients for the interaction term between Speed and AG show that when speed is combined with aggressive quotes it reduces the contribution to price discovery. Therefore, it further confirms the negative effect of aggressiveness on short-term price discovery.

[Table 4.7 Here]

Regarding the other quotation characteristics, dealers' net buying intentions have asymmetric effects on ask and bid price discovery. Specifically, dealers' net buying intention reduces their quotes' contributions to the ask (sell) price discovery, while it increases their contributions to the bid (buy) price discovery. In other words, this finding suggests that dealers focus on one side of the market and make a better price discovery contribution on the side they intended to do business with.

In general, quotations that increase spreads make the quotes less informative; this is shown by the negative signs for the WN coefficients, it is significant in the case of the ask regression (Model 1). This is consistent with dealers widening their spreads to reflect uncertainty in the market (Mcinish and Wood, 1992). Finally, the regression controls for the

of all market participants in a currency pair. Doing so makes different currency pairs' speed comparable by converting the mean speed of each currency pair to one.

length of time that a dealer is active during those minutes and shows that the activity time's coefficients are positive and highly significant.

Now the price discovery in the longer term with a daily measure of price discovery in Models 3 and 4 (Ask-Day and Bid-Day models) are presented. In this regression, the dependent variables are dealers' contribution to daily price discovery. For the independent variables, the daily average of the minute measures are used to capture dealers' quotation characteristics[34]. Table 4.7 shows that dealers' quotation characteristics bear little relationship with their contribution to the long-term price discovery. In general, none of the quoting characteristics and speed coefficients are statistically significant, thus, it is concluded that there is no relationship between the speed of a market participant and his/her contribution to the long-term price discovery of a currency pair. Overall, the regression analysis demonstrates that dealers with higher quotation speeds contribute significantly to the short-term price discovery but not to the long-term price discovery.

In order to explore the potential differences among the currency pairs, separate regressions for each currency pair is run and reported in Table 4.8 (minute data).[35] In Table 4.8, the same model as in Table 4.7 is estimated for each currency. In this context, the speed measure is the raw unstandardized measure. It can be seen that the main results hold for all currency pairs; specifically, the speed coefficients are all positive and significant.

[Table 4.8 Here]

[34] This construction of the daily variable is to maintain comparability of dealers' characteristics across the minute and daily regressions. In other words, a dealer that is characterised as HFQ in minute data will also be placed in a similar relative position in terms of quote speed. For other quotation characteristics such as aggressiveness, buy intention and increase in spread (WN), calculating them on a daily basis is also explored. The difference of these measures to the minute average is that it takes a whole day of data as a session of calculation. Some of the intraday differences will be smoothed out in these calculations. Nevertheless, the daily analysis with variables that are constructed at a daily level is run and the main results are consistent with the finding presented here.

[35] Since the daily regression results for each currency are consistent with the pool regression in table 4.7, they are not reported.

Overall, the finding of speed increasing the short-term contribution to price discovery is consistent with Brogaard et al., (2014) who show that HFT plays a role in price discovery across very short time intervals. However, it is found that a dealer's speed does not play any role in longer-term price discovery, which contrasts with the Brogaard et al., (2014) finding regarding the positive role of HFTs in the fundamental price discovery in equity markets. This presents an interesting puzzle in terms of reconciling the role of speed in short and long-term price discovery; how a dealer with a high-speed quotation can positively contribute to minute price discovery but not to a daily overall price discovery? The answer lies in that the minute price movement is not always in line with the daily price movement. Therefore, correctly predicting movements by the minute will not automatically lead to a correct prediction of daily price movements. The high-speed dealer's ability to predict a short-term price movement is likely to be transitional in the daily context and, therefore, higher speed dealing will be associated with higher price discovery volatility.

[Table 4.9 Here]

Table 4.9 reports the regression of the speed measure and intraday price discovery volatility. The volatility of price discovery is measured by the standard deviation of the minute price discovery measure for each dealer daily. The other variables are defined in a similar manner to the daily regression in Table 4.7. The results in Table 4.9 demonstrate a strong contrast to those in Table 4.7. It shows that dealers' quoting characteristics affect the volatility of their contribution to price discovery. Higher speed dealers will have larger intraday volatility in their price discovery. It confirms that this increased volatility in the intraday price discovery could be the reason for the weak association between speed and longer-term price discovery.

4.5. Conclusions

This chapter studies the effect of speed on price discovery in the FX market. While there is a large amount of emerging literature on high frequency trading in equity markets, less attention has been given to the effect of increasing speed in the FX market. A unique dataset is utilised containing quotes from 92 dealers and 42 countries around the globe time stamped to a millisecond. Using the Weighted Price Contribution (WPC) model of Barclay and Warner (1993) the contribution of HFQs on price discovery is studied in the short-term (by the minute) and across longer-term horizons (daily), while controlling for their quoting behaviour. The findings demonstrate that an increase in a dealer's speed is associated with an increase in their contribution to short-term price discovery, while speed does not play a role in longer-term price discovery.

This study provides further evidence to the literature regarding the relationship between speed and price discovery in the context of the FX market. The finding of the overall lack of speed's connection with longer-term price discovery echoes the concerns in the literature and by regulators regarding the high frequency traders' negative potential impact on market efficiency.

Tables

Table 4.1 Dataset Descriptive Statistics

This table reports the descriptive statistics of the Quote Dataset. The Dealer-location column depicts the number of active dealer-locations in each currency pair. The Number of Quotes column shows the number of non-repetitive quotes in each currency pair. The Countries and Cities columns report the number of countries and cities that a dealer in a respective currency pair are active in. Return Mean and Return Volatility are the average return and return volatility of each currency pair on a daily basis, respectively, throughout the whole sample period between April 22nd, 2013 and March 11th, 2014. These values are calculated by using mid-point price. Returns are multiplied by 10,000.

Currency Pair	Dealer-location	Number of Quotes	Countries	Cities	Return Mean	Return Volatility
EUR/GBP	42	4,368,448	18	24	-0.97	38.78
EUR/JPY	48	6,678,068	20	25	4.35	59.30
EUR/USD	81	5,903,200	36	42	2.63	40.89
GBP/JPY	48	9,695,802	20	26	5.43	63.57
GBP/USD	66	7,386,862	29	35	3.70	44.74
USD/JPY	63	5,143,583	26	29	1.84	65.91
SUM	104	39,175,963				

Table 4.2 Observable Intention of a Dealer

This table demonstrates how a dealer's observable intention is calculated. In order to calculate this measure, every quote from a dealer is compared with their last quote. A=, A↓, and A↑, represent no, upward, and downward movement in the ask price, respectively, and B=, B↓, and B↑ are defined similarly for the bid price. Based on the movement of the dealer's ask or bid price and following the table, the intention of the dealer is defined. B and S demonstrate whether the dealer's intention is to buy or sell the base currency, respectively. W represents the time that the dealer increases his/her spread by reducing bid and increasing ask. N represents the times that the dealer wants to return to the market by reducing the ask price and increasing the bid price.

	B↑	**B↓**	**B=**
A↑	**B**	**W**	**B**
A↓	**N**	**S**	**S**
A=	**B**	**S**	

Table 4.3 Speed Summary Statistics

This table represents the summary statistics of speed by dealer-minute (Panel A) and by dealers' average speed (Panel B) in each currency pair. Mean is the average of the average speed measured in the minute interval, Q1, median, and Q3 represent the first, second, and third quartiles of the average speed of dealers. STD is the standard deviation of the distribution and Obs is number of observations in each currency pair.

Panel A. dealer-minute

Currency	Mean	Min	Q1	Median	Q3	Max	SD	Obs
EUR/GBP	5.5307	1	1	3.5232	6.0226	12000	49.7393	1,830,167
EUR/JPY	5.7237	1	1	4.0917	6.3093	8000	32.4979	2,374,201
EUR/USD	5.7051	1	1	3.7572	6.1000	12000	45.8481	2,370,469
GBP/JPY	25.9290	1	2.9873	5.9653	9.6192	24000	131.0243	2,509,818
GBP/USD	5.7064	1	1	4.0001	6.5271	4000	12.3898	2,386,649
JPY/USD	5.4993	1	1	3.9650	6.0309	12000	43.3301	2,130,738

Panel B. dealer average

Currency	Mean	Min	Q1	Median	Q3	Max	SD	Obs
EUR/GBP	4.7605	1	1.9323	3.5183	5.6376	27.0725	4.6206	42
EUR/JPY	5.6938	1	1.9037	3.7281	5.7848	47.6894	7.9272	48
EUR/USD	5.5309	1	1.6373	4.0899	7.8516	41.7500	5.9437	81
GBP/JPY	46.1040	9.4998	16.9577	31.4674	56.7749	344.1269	52.8312	48
GBP/USD	4.8180	1	1.5529	3.6427	7.0006	16.2247	4.0204	66
USD/JPY	4.9503	1	1.2177	3.2597	6.5363	27.7658	5.0306	63
ALL	10.8164	1	1.8889	4.3033	9.9703	344.1269	24.5908	348

Table 4.4 Dealers' Aggressiveness

Panel A and B report the aggressiveness measure of ask and bid, respectively. It measures the proportion of quotes that move in steps that are larger than the aggressive thresholds (for EUR/GBP, EUR/USD, GBP/USD, and USD/JPY is 1 pip, for EUR/JPY and GBP/JPY are 2 and 3 pips, respectively). The table reports the summary statistics of dealer-minute observations for each currency.

Panel A. Ask Aggressiveness

Currency	Mean	Min	Q1	Median	Q3	Max	STD	Obs
EUR/GBP	0.1957	0	0	0	0.3333	1	0.3492	1,830,167
EUR/JPY	0.1963	0	0	0	0.3333	1	0.3406	2,374,201
EUR/USD	0.2517	0	0	0	0.5000	1	0.3809	2,370,469
GBP/JPY	0.2849	0	0	0.1667	0.5000	1	0.3380	2,509,818
GBP/USD	0.3288	0	0	0.1111	0.5333	1	0.3958	2,386,649
USD/JPY	0.2592	0	0	0	0.5000	1	0.3830	2,130,738

Panel B. Bid Aggressiveness

Currency	Mean	Min	Q1	Median	Q3	Max	STD	Obs
EUR/GBP	0.1963	0	0	0	0.3333	1	0.3496	1,830,167
EUR/JPY	0.1873	0	0	0	0.2857	1	0.3344	2,374,201
EUR/USD	0.2462	0	0	0	0.5000	1	0.3782	2,370,469
GBP/JPY	0.2262	0	0	0	0.4000	1	0.3166	2,509,818
GBP/USD	0.3226	0	0	0.0435	0.5000	1	0.3950	2,386,649
USD/JPY	0.2598	0	0	0	0.5000	1	0.3833	2,130,738

Table 4.5 Dealers' Quoting Intention

This table reports the mean of dealers quoting behaviour measures classified by the way they update their quotes. B and S demonstrate whether the dealer's intention is to buy or sell the base currency, respectively. W represents the time that dealers increase their spreads by reducing bid and increasing ask. N represent the times that dealers reduce their spreads by reducing the ask price and increasing the bid price. The sample period is between April 22nd, 2013 and March 11th, 2014.

EUR/GBP				EUR/JPY			
	B↑	**B↓**	**B=**		**B↑**	**B↓**	**B=**
A↑	28.63%^{B}	3.79%^{W}	8.67%^{B}	**A↑**	40.20%^{B}	2.37%^{W}	3.63%^{B}
A↓	**3.62%**^{N}	29.20%^{S}	8.73%^{S}	**A↓**	**2.40%**^{N}	40.47%^{S}	3.76%^{S}
A=	8.68%^{B}	8.68%^{S}		**A=**	3.60%^{B}	3.57%^{S}	
EUR/USD				**GBP/JPY**			
	B↑	**B↓**	**B=**		**B↑**	**B↓**	**B=**
A↑	32.55%^{B}	1.98%^{W}	7.78%^{B}	**A↑**	19.01%^{B}	22.10%^{W}	4.73%^{B}
A↓	**1.92%**^{N}	32.47%^{S}	7.94%^{S}	**A↓**	**21.96%**^{N}	19.12%^{S}	4.85%^{S}
A=	7.64%^{B}	7.72%^{S}		**A=**	4.16%^{B}	4.08%^{S}	
GBP/USD				**USD/JPY**			
	B↑	**B↓**	**B=**		**B↑**	**B↓**	**B=**
A↑	30.79%^{B}	5.36%^{W}	7.23%^{B}	**A↑**	37.37%^{B}	1.73%^{W}	5.46%^{B}
A↓	**5.35%**^{N}	30.86%^{S}	7.33%^{S}	**A↓**	**1.76%**^{N}	36.93%^{S}	5.61%^{S}
A=	6.59%^{B}	6.50%^{S}		**A=**	5.56%^{B}	5.57%^{S}	

Table 4.6 Buy-Sell Intention and Widen Spread

Buy intention is the net buying intention of the dealer calculated as the number of long minus the number of short quotations (B-S in Table 4.2 classifications). Widen spread is the number of times when dealers increase their spread minus the number of times they reduce their spread (W-N in Table 4.2 classifications).

Panel A. Buy-Sell Intention

Currency	Mean	Min	Q1	Median	Q3	Max	STD	Obs
EUR/GBP	-0.0149	-23	-1	0	1	19	1.1701	1,830,167
EUR/JPY	-0.0106	-17	-1	0	1	18	1.4111	2,374,201
EUR/USD	-0.0039	-18	-1	0	1	18	1.3131	2,370,469
GBP/JPY	-0.0058	-13	-1	0	1	11	1.3131	2,509,818
GBP/USD	-0.0023	-17	-1	0	1	16	1.3560	2,386,649
USD/JPY	0.0068	-15	-1	0	1	13	1.3415	2,130,738

Panel B. Widen Spread

Currency	Mean	Min	Q1	Median	Q3	Max	STD	Obs
EUR/GBP	0.0040	-7	0	0	0	20	0.3051	1,830,167
EUR/JPY	-0.0008	-4	0	0	0	5	0.2676	2,374,201
EUR/USD	0.0014	-4	0	0	0	4	0.2373	2,370,469
GBP/JPY	0.0054	-8	0	0	0	7	0.7689	2,509,818
GBP/USD	0.0003	-7	0	0	0	7	0.3791	2,386,649
USD/JPY	-0.0007	-4	0	0	0	4	0.2063	2,130,738

Table 4.7 Speed Measure and Price Discovery across Short and Long Term Horizons

This table reports the results of the following regression analyses:

$$PD = \alpha + \beta_1 Speed + \beta_2 AG + \beta_3 Speed * AG + \beta_4 BS + \beta_5 WN + \beta_6 AT + \varepsilon$$

Where PD is the price discovery measure for ask and bid; the price discovery measures are measured for each dealer in minute intervals for models 1 and 2 and in daily intervals for models 3 and 4. The pool regression for all six currency pairs is reported. Speed is the average speed of quotation update for a given dealer and is normalised by dividing by the average speed in each currency pair. BS is the net buying intention of the dealer; WN is net number of times when dealers increase their spread; AG is the measure of aggressiveness that measures the proportion of quotes that move in steps that are larger than the aggressive thresholds; AT is the active time measured in seconds. Number of observations reports the number of dealer-minutes or dealer days in the sample. All of these quotation characteristics are calculated in minute intervals and in the daily regression the average of all minute observations in a day for a given dealer is used. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively. Robust standard errors are reported in parentheses.

	Model (1)	Model (2)	Model (3)	Model (4)
VARIABLES	Ask-Minute	Bid-Minute	Ask-Day	Bid-Day
Speed	0.0001***	0.000104***	8.639	4.238
	(6.96e-06)	(7.21e-06)	(28.08)	(27.56)
AG	-0.00195***	-0.00250***	-111.4	22.03
	(8.10e-05)	(7.30e-05)	(141.5)	(86.30)
Speed*AG	-0.000118***	-0.000156***	-7.155	-5.974
	(1.32e-05)	(1.49e-05)	(46.94)	(46.15)
BS	-0.00176***	0.00183***	-10.99	0.614
	(3.94e-05)	(3.47e-05)	(47.19)	(41.18)
WN	-0.000633***	4.14e-05	-48.86	31.99
	(9.37e-05)	(8.51e-05)	(137.9)	(83.37)
AT	0.000187***	0.000161***	-0.784	-0.00341
	(2.29e-06)	(1.90e-06)	(4.924)	(2.466)
Constant	0.00183***	0.00258***	68.09	-12.11
	(4.41e-05)	(3.93e-05)	(81.31)	(57.79)
Observations	10,966,743	10,883,018	22,436	22,374
R-squared	0.001	0.002		
F-Statistics	0	0	0.747	1

Table 4.8 Speed Measure and Price Discovery of Ask and Bid on a Minute Basis by Currency

This table reports the results of the following regression analyses:

$$PD = \alpha + \beta_1 Speed + \beta_2 AG + \beta_3 Speed * AG + \beta_4 BS + \beta_5 WN + \beta_6 AT + \varepsilon$$

where PD is the price discovery measure for ask and bid for Panels A and B respectively; Speed is the average speed of quotation updates for a given dealer; BS is the net buying intention of the dealer; WN is net number of times when dealers increase their spread; AG is the measure of aggressiveness that measures the proportion of quotes that move in steps that are larger than the aggressive thresholds; AT is the active time measured in seconds. Number of observations reports the number of dealer-minutes in the sample. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively. Robust standard errors are reported in parentheses.

Panel A Ask Price Discovery

Variables	EUR/GBP	EUR/JPY	EUR/USD	GBP/JPY	GBP/USD	USD/JPY
Speed	9.63e-06***	1.68e-05***	1.90e-05***	6.31e-06***	0.000103***	1.41e-05***
	(1.92e-06)	(2.53e-06)	(2.82e-06)	(4.01e-07)	(7.60e-06)	(2.44e-06)
AG	-0.00244***	-0.000490**	-0.00345***	0.000334**	-0.00194***	-0.00168***
	(0.000367)	(0.000230)	(0.000171)	(0.000143)	(0.000167)	(0.000172)
Speed*AG	-9.98e-06**	-8.41e-06	-3.35e-05***	-1.95e-07	-0.000462***	-1.60e-05***
	(4.30e-06)	(6.09e-06)	(5.70e-06)	(1.48e-06)	(2.85e-05)	(3.73e-06)
BS	-0.00439***	-0.000194*	-0.00206***	-0.00104***	-0.000611***	-0.00402***
	(0.000180)	(9.99e-05)	(0.000104)	(5.04e-05)	(8.45e-05)	(8.59e-05)
WN	-0.00213***	-0.00167***	-0.00149***	-0.000180**	-0.000819***	-0.00187***
	(0.000792)	(0.000432)	(0.000319)	(9.10e-05)	(0.000262)	(0.000368)
AT	0.000243***	0.000209***	0.000197***	0.000213***	0.000127***	0.000217***
	(1.07e-05)	(6.55e-06)	(5.59e-06)	(3.03e-06)	(4.35e-06)	(5.28e-06)
Constant	0.00301***	-8.68e-05	0.00265***	-0.00115***	0.00341***	0.00212***
	(0.000150)	(0.000125)	(9.40e-05)	(7.23e-05)	(9.98e-05)	(9.83e-05)
Observations	1,410,555	2,045,277	1,776,238	2,182,885	1,879,238	1,672,550
R-squared	0.002	0.001	0.002	0.003	0.001	0.004

Panel B. Bid Price Discovery

Variables	EUR/GBP	EUR/JPY	EUR/USD	GBP/JPY	GBP/USD	USD/JPY
Speed	7.89e-06***	1.80e-05***	1.94e-05***	6.64e-06***	8.94e-05***	1.79e-05***
	(1.84e-06)	(2.82e-06)	(2.69e-06)	(4.06e-07)	(6.83e-06)	(3.11e-06)
AG	-0.00568***	-0.00109***	-0.00321***	-0.000942***	-0.00136***	-0.00225***
	(0.000300)	(0.000187)	(0.000163)	(0.000139)	(0.000157)	(0.000165)
Speed*AG	-1.58e-05***	-3.07e-5***	-2.18e-05***	-4.48e-06***	-0.000433***	-2.34e-05***
	(4.30e-06)	(6.85e-06)	(5.52e-06)	(1.54e-06)	(2.75e-05)	(5.12e-06)
BS	0.00473***	0.00150***	0.00131***	0.000451***	0.000938***	0.00367***
	(0.000160)	(7.82e-05)	(9.75e-05)	(4.37e-05)	(7.89e-05)	(7.97e-05)
WN	0.00115*	0.00421***	-0.00172***	-0.000167**	-0.000889***	-0.00191***
	(0.000688)	(0.000404)	(0.000316)	(8.14e-05)	(0.000256)	(0.000358)
AT	0.000181***	0.000139***	0.000182***	0.000210***	0.000127***	0.000197***
	(8.51e-06)	(4.81e-06)	(4.92e-06)	(2.71e-06)	(4.04e-06)	(4.83e-06)
Constant	0.00496***	0.00178***	0.00288***	-0.000706***	0.00327***	0.00260***
	(0.000124)	(0.000101)	(8.74e-05)	(6.45e-05)	(9.33e-05)	(9.58e-05)
Observations	1,407,722	2,016,780	1,765,786	2,163,922	1,859,611	1,669,197
R-squared	0.002	0.001	0.002	0.004	0.001	0.004

Table 4.9 Speed Measure and Intraday Price Discovery Volatility

This table reports the results of the following regression analyses:

$$SDPD = \alpha + \beta_1 Speed + \beta_2 AG + \beta_3 Speed * AG + \beta_4 BS + \beta_5 WN + \beta_6 AT + \varepsilon$$

Where SDPD is the daily standard deviation of the price discovery measure at minutely interval for ask and bid. The pool regression for all six currency pairs is reported. Speed is the average speed of quotation update for a given dealer and is normalised via dividing by the average speed in each currency pair. BS is the net buying intention of the dealer; WN is net number of times when dealers increase their spread; AG is the measure of aggressiveness that measures the proportion of quotes that move in steps that are larger than the aggressive thresholds; AT is the active time measured in seconds. Number of observations reports the number of dealer days in the sample. All of these quotation characteristics are the average of all minute observations in a day for a given dealer. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively. Robust standard errors are reported in parentheses.

Variables	SD - PDA	SD - PDB
Speed	0.00866***	0.00831***
	(0.00103)	(0.000727)
AG	0.0406***	0.00713***
	(0.00414)	(0.00168)
Speed*AG	-0.00891**	-0.0133***
	(0.00398)	(0.00131)
BS	0.00703***	0.0120***
	(0.000820)	(0.000713)
WN	-0.0641***	-0.0321***
	(0.00266)	(0.00156)
AT	0.00277***	0.00129***
	(7.92e-05)	(4.22e-05)
Constant	0.0192***	0.0344***
	(0.00158)	(0.000919)
Observations	22,409	22,347
R-squared	0.403	0.411

Table 4.10 Correlation Matrix of Table 4.7 Regressions (Models 1 and 2)

This table reports the correlation matrix of models 1 and 2 in table 4.7 to address the concerns regarding the existence of high correlations and possible consequent multicollinearity. The magnitude of correlation coefficients in table 4.10 shows that regarding models 1 and 2 in table 4.7 there are no concerns regarding the existence of multicollinearity and its impact on the results. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Panel A. Correlation Matrix from Model 1 in Table 4.7

	PDA	Speed	AG	BS	WN	AT
PDA	1					
Speed	0.0033***	1				
AG	-0.0096***	-0.0184***	1			
BS	-0.0196***	-0.0015***	0.0004	1		
WN	-0.002***	0.0013***	0.0041***	-0.0079***	1	
AT	0.0306***	-0.0036***	-0.115***	-0.0062***	0.0031***	1

Panel B. Correlation Matrix from Model 2 in Table 4.7

	PDB	Speed	AG	BS	WN	AT
PDB	1					
Speed	0.0035***	1				
AG	-0.0129***	-0.0205***	1			
BS	0.0233***	-0.0017***	-0.0002	1		
WN	0	0.0016***	0.0028***	-0.0098***	1	
AT	0.0307***	-0.0034***	-0.1309***	-0.0064***	0.0027***	1

Table 4.11 Correlation Matrix of Table 4.7 Regressions (Models 3 and 4)

This table reports the correlation matrix of models 3 and 4 in table 4.7 to address the concerns regarding the existence of high correlations and possible consequent multicollinearity. The magnitude of correlation coefficients in table 4.11 shows that regarding models 3 and 4 in table 4.7 there are no concerns regarding the existence of multicollinearity and its impact on the results except the correlation between AT and BS. In order to address this issue, first the Variance Inflation Factor (VIF) of models 3 and 4 is examined and the correlation between AT and BS does not raise any issue this sense. Second, the models 3 and 4 are re-run once without AT, once without BS and the results are consistent with results reported from models 3 and 4 in table 4.7. However, the results are not reported here. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Panel A. Correlation Matrix from Model 3 in Table 4.7

	PDA	Speed	AG	BS	WN	AT
PDA	1					
Speed	0.0016	1				
AG	-0.0044	-0.1647***	1			
BS	-0.0021	0.2761***	-0.4052***	1		
WN	-0.0052	0.065***	-0.0431***	0.1943***	1	
AT	-0.0028	0.2054***	-0.4857***	0.7138***	0.4524***	1

Panel B. Correlation Matrix from Model 4 in Table 4.7

	PDB	Speed	AG	BS	WN	AT
PDB	1					
Speed	0.0009	1				
AG	0.0003	-0.1637***	1			
BS	0.0007	0.2754***	-0.4043***	1		
WN	0.0029	0.0654***	-0.0434***	0.1953***	1	
AT	0.0011	0.2047***	-0.4846***	0.7136***	0.4531***	1

Appendix I

This table depicts the active dealers in each continent and the currency pair that they are active in. A blank cell in front of each dealer's name means the dealer is not active in the respective currency pair. Check mark in the cells in front of a dealer's name shows that the dealer is active in the respective currency pair. The location GFX refers to Global Forex and is used for the dealers who conduct their market activities from multiple location throughout the globe.

Panel A. Active Dealers in Africa

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ABSA BANK	SOUTH AFRICA	JOHANNESBURG			√			
NEDBANK	SOUTH AFRICA	JOHANNESBURG					√	

Panel B. Active Dealers in Asia

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ABU DHABI ISLAMIC BANK	UNITED ARAB EMIRATES	ABU DHABI			√		√	√
AFFIN BANK	MALAYSIA	KUALA LUMPUR			√		√	√
AHLI BANK OMAN	OMAN	MUSCAT			√			√
AM BANK	MALAYSIA	KUALA LUMPUR						√
ASYA KATILIM BANKASI A.S	TURKEY	ISTANBUL			√		√	
BANK DHOFAR SAOG	OMAN	MUSCAT			√		√	√
BANK MUSCAT	SAUDI ARABIA	RIYADH			√		√	
BANK OF CHINA INTERNATIONAL LTD	HONG KONG	HONG KONG			√		√	√
BANK OF COMMUNICATION	CHINA	SHANGHAI	√	√		√	√	√
BANK OF TOKYO-MITSUBISHI UFJ	JAPAN	TOKYO		√	√	√	√	√
BANK OF TOKYO-MITSUBISHI UFJ	MALAYSIA	KUALA LUMPUR						√
COMMERCIAL BANK OF KUWAIT	KUWAIT	SAFAT			√		√	√
CREDIT AGRICOLE CORPORATE AND INVESTMENT BANK	HONG KONG	HONG KONG					√	√
DBS BANK	HONG KONG	HONG KONG			√			√
ESKAN BANK	BAHRAIN	MANAMA						√
INDUSTRIAL AND COMMERCIAL BANK OF CHINA	HONG KONG	HONG KONG			√		√	√
ING BANK	TURKEY	ISTANBUL					√	
KASPI BANK	KAZAKHSTAN	ALMATY			√		√	√
KUWAIT FINANCE HOUSE	KUWAIT	SAFAT					√	√
MIZUHO CORPORATE BANK	SINGAPORE	SINGAPORE		√	√	√		√
MIZUHO CORPORATE BANK	HONG KONG	HONG KONG		√	√	√		√
MIZUHO CORPORATE BANK	JAPAN	TOKYO			√		√	√
NATIONAL BANK OF KUWAIT	KUWAIT	SAFAT			√		√	√
NATIONAL BANK OF OMAN	OMAN	MUSCAT			√		√	√
NOMURA SECURITIES	JAPAN	TOKYO		√		√		

NORTHERN TRUST	SINGAPORE	SINGAPORE			√			
OMAN ARAB BANK	OMAN	MUSCAT			√			√
PROMSVYAZ BANK	RUSSIA	MOSCOW			√			
QATAR ISLAMIC BANK	QATAR	DOHA			√			
SKANDINAVISKA ENSKILDA BANK	SINGAPORE	SINGAPORE		√		√		√
STANDARD CHARTED BANK	MALAYSIA	KUALA LUMPUR						√
TOKYO FOREX	JAPAN	TOKYO		√	√	√		√
UAE EXCHANGE	UNITED ARAB EMIRATES	ABU DHABI			√		√	√
UNITED OVERSEAS BANK	HONG KONG	HONG KONG			√		√	√
YAPI KREDI BANK	TURKEY	ISTANBUL					√	

Panel C. Active Dealers in Australia

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
LLOYDS BANK	AUSTRALIA	SYDNEY	√					
NATIONAL AUSTRALIA BANK	AUSTRALIA	MELBOURNE	√	√	√	√	√	√
WESTPAC BANK	AUSTRALIA	SYDNEY	√	√	√	√	√	√

Panel D. Active Dealers in Europe

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ALLIED IRISH	IRELAND	DUBLIN	√	√	√	√	√	√
BANCA AKROS	ITALY	MILAN	√	√	√	√	√	√
BANCA MONTE DEI PASCHI DI SIENA	ITALY	MILAN	√	√	√	√		
Banco Commercial Portuguese SA	PORTUGAL	LISBON		√		√		
BANCO DE SABADELL	SPAIN	SABADELL	√	√	√	√		
BANCO POPOLARE	ITALY	BERGAMO	√	√	√	√	√	
BANCPOST SA	ROMANIA	BUCHAREST					√	
BANK BPH SA	POLAND	WARSAW	√		√		√	√
CAIXA GERAL DE DEPOSITOS	PORTUGAL	LISBON	√	√	√	√	√	
CANADIAN IMPERIAL BANK OF COMMERCE CIBC	CANADA	TORONTO	√	√	√	√	√	
CITIBANK	CZECH REPUBLIC	PRAGUE			√			
COMMERZBANK	GERMANY	FRANKFURT	√	√	√	√	√	√
COMMONWEALTH BANK OF AUSTRALIA	UNITED KINGDOM	LONDON						√
DANSKE BANK	DENMARK	COPENHAGEN K	√	√	√	√	√	√
DEN NORSKE BANK	NORWAY	OSLO			√		√	√
DIE ERSTE OESTERR. SPAR-CASSE BANK	AUSTRIA	VIENNA			√			√
HSBC	UNITED KINGDOM	LONDON			√		√	
I.C.M. INVESTMENTBANK AG	ITALY	MILAN			√			
INDUSTRIAL AND COMMERCIAL BANK OF CHINA	UNITED KINGDOM	LONDON			√			
ING BANK	UKRAINE	KIEV			√			

INTESA SANPAOLO BANK	ITALY	MILAN	√	√	√	√	√	
INTESA SANPAOLO BANK	ALBANIA	TIRANA			√			
LANDESBANK BADEN-WÜRTTEMBERG	GERMANY	STUTTGART	√	√	√	√	√	
NATIONAL BANK OF GREECE	GREECE	ATHENS	√	√		√		
NORDEA BANK	DENMARK	COPENHAGEN C	√	√	√	√	√	√
OSCHAD BANK	UKRAINE	KIEV					√	
OTP BANK	SLOVAKIA	BRATISLAVA	√	√		√		
PIRAEUS BANK	GREECE	ATHENS	√	√	√	√		
PRAVEXBANK	UKRAINE	KIEV			√			
RABO BANK FINANCIAL GLOBAL MARKET	UNITED KINGDOM	LONDON	√	√	√	√	√	√
RAIFFEISEN BANK	CZECH REPUBLIC	PRAGUE			√			
RAIFFEISEN BANK	ALBANIA	TIRANA			√			
RBS	UNITED KINGDOM	LONDON	√	√	√	√	√	√
SANTANDER	SPAIN	MADRID	√	√		√	√	
SKANDINAVISKA ENSKILDA BANK	SWEDEN	STOCKHOLM	√	√	√	√	√	√
SOCIETE GENERALE	FRANCE	PARIS	√	√	√	√		√
TATRA BANK	SLOVAKIA	BRATISLAVA	√	√		√		√
UBS	SWITZERLAND	ZURICH	√	√	√	√	√	√
WGZ BANK	GERMANY	DÜSSELDORF	√	√	√	√	√	
WINDSOR BROKERS	CYPRUS	LIMASSOL	√	√	√	√	√	√
ZUERCHER KANTONALBANK	SWITZERLAND	ZURICH	√	√	√	√	√	√

Panel E. Active Dealers in Global Forex

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
AUSTRALIA AND NEW ZEALAND BANKING GROUP	Australia	GLOBAL FOREX	√	√	√	√	√	√
BANQUE INTERNATIONALE A LUXEMBOURG	Luxembourg	GLOBAL FOREX	√	√	√	√	√	√
BARCLAYS	United Kingdom	GLOBAL FOREX	√	√		√	√	√
DEUTSCHE BANK	Germany	GLOBAL FOREX	√	√	√	√	√	√
GOLDMAN SACHS U.K.	United Kingdom	GLOBAL FOREX	√	√	√	√	√	√
HSBC	United Kingdom	GLOBAL FOREX	√	√	√	√	√	√
HSBC NEW YORK	United States	GLOBAL FOREX	√	√	√	√	√	√
KBC	Belgium	GLOBAL FOREX	√	√	√	√	√	√
NATIONAL AUSTRALIA BANK	Australia	GLOBAL FOREX			√		√	√
NEDBANK	South Africa	GLOBAL FOREX			√		√	√
SOCIETE GENERALE	France	GLOBAL FOREX	√	√	√	√	√	√

Panel F. Active Dealers in North America

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
RADA FOREX	UNITED STATES OF AMERICA	NEW YORK		√	√	√	√	√

BANK OF MONTREAL-BANQUE DE MONTREAL	CANADA	MONTREAL			√		√	√
Brown Brothers Harriman & Co	UNITED STATES OF AMERICA	NEW YORK		√	√	√	√	√
COMMONWEALTH BANK OF AUSTRALIA	UNITED STATES OF AMERICA	NEW YORK			√		√	√
RBS	UNITED STATES OF AMERICA	NEW YORK	√	√	√	√	√	√
ROYAL BANK OF CANADA	CANADA	TORONTO			√			
SKANDINAVISKA ENSKILDA BANK	UNITED STATES OF AMERICA	NEW YORK	√		√		√	
THE BANK OF NEW YORK MELLON	UNITED STATES OF AMERICA	NEW YORK			√		√	√

Panel G. Active Dealers in South America

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
BANCO CENTRAL DEL ECUADOR	ECUADOR	QUITO			√			
INTERCAM BANK	MEXICO	MEXICO CITY			√		√	

Chapter 5. Do Economists Add Value to the FX market?

5.1. Introduction

This chapter, for the first time, investigates the impact of economist affiliation, geographical proximity, and speed on price discovery of market makers in the foreign exchange (FX) market. Prior literature provides some evidence on the importance of access to analyst research and its consequent information advantage in equity markets. Schultz (2003) finds that the knowledge embedded in a research division is valuable to the market making section of the same bank. Li and Heidle (2004), Michaely and Womack (1999), and Chung and Cho (2005) show information share between affiliated market makers and their analysts. Chung and Cho (2005) show that analysts and market makers work as a team to benefit the company[36]. The collaboration between market makers and analysts is expected to increase information and competitive advantages of market makers due to the access of analysts to management of a firm, connection with a firm's representative, observation of a firms' input and output, the ability to speak with clients, customers, or employees (Berger et al., 2009; Bae et al., 2008; Green et al., 2014). This expectation is consistent with Green's (2006) findings which provide evidence on the value of early access to stock recommendation and incorporation of analysts' recommendations to market makers' trading activities. Madureira and Underwood (2008) demonstrate the information advantage of market makers because

[36] Chung and Cho state that analysts are hired by Brokerage firms to track and make buy and sell recommendations. See Li and Heidle (2004) and Michaely and Womack (1999) for the collaboration between affiliated analysts and market makers.

of their affiliation with analysts and show that affiliated market makers contribute more to price discovery and are more likely to be informed than are market makers without analyst affiliation. However, due to fundamental differences in the information transparency, information distribution medium, and scope of macroeconomic and firm specific news, the role of analysts and economists exhibits fundamental differences. Therefore, an expansion of the findings on the impact of an analyst's affiliation on market makers' activities in equity markets to the impact of economists' affiliation on dealers in FX market requires more critical examination.

The differences in the informational transparency and information distribution mediums between the FX and equity markets originate from the difference in the nature of private information and structure of these markets, respectively. The information advantage of analysts in equity markets is found to be, partially, due to private information, access to different sets of information, and access to management by analysts following a company (Chen and Matsomoto, 2006; Alford and Berger, 1999; Chen and Jiang, 2006; Green et al., 2014). However, no such private and privileged information access is reported regarding macroeconomic news of a country. This is the reason for the statement above regarding the difference in information transparency between firm specific and macroeconomic news announcements. In addition, equity markets are centralised exchange traded markets while the FX market is a geographically dispersed, decentralised, quote driven, and primarily over the counter market (FSB, 2014). There is also a considerable difference between the scope and scale of firm specific news and macroeconomic news. Firm specific news is only regarding a firm and mainly concerns its future cash flow while macroeconomic news is is regarding the whole economy state of a country and concerns every aspect of a country's economy. These differences between the equity and the FX market create two structurally different information distribution mediums between the two markets.

This chapter builds on the existing literature on analyst affiliation with market makers in equity markets and expands it to economists' affiliation with market makers in the FX market. It is examined whether affiliated economists create an information advantage for their dealer organisation. An affiliated economist is defined as an economist who is employed in a dealer market making arm or any of the dealer's subsidiaries. A dealers' contribution to price discovery is measured by the Weighted Price Contribution (WPC) model of Barclays and Warner (1993) within a four-minute window around macroeconomic news announcements and it is examined as to whether affiliated dealers systematically exhibit a higher contribution to price discovery. However, nowadays with the increase in the presence of algorithmic and high frequency traders in the FX markets (Rime and Schrimpf, 2013), their contribution to price discovery around macroeconomic news announcements (Brogaard et al., 2014), the ability of machines in reading and interpreting macroeconomic news announcements (Groß-Klußmann and Hautsch, 2011) reacting to news before humans (Scholtus et al., 2014; Biais et al., 2015; Martinez and Rosu, 2013), and even the early access of HFT to some of the macroeconomic news announcements[37] (Mullins et al., 2013; Goldstein et al., 2014), a dealers quoting speed is also studied.

The dataset that is used for this chapter's empirical work consists of four sections: quotes obtained from Thomson Reuters, macroeconomic news announcements, economists' forecasts, and economists' personal information obtained from Bloomberg. The Quote Dataset that is used here is a subset of the Quote Dataset[38] explained in chapter 3 and includes merely the days that there has been no interruption in the collection of data[39]. The

[37] A new industry has emerged to deliver machine readable news and financial information to hedge funds, ATs, and HFTs within milliseconds such as Reuters NewsScope Sentiment Engine (Chordia et al., 2015; Groß-Klußmann and Hautsch, 2011). This has gone even further by controversial practices such as selling early access, by 2 seconds, to University of Michigan's Consumer Sentiment Index, by Reuters, to HFTs (Mullins et al., 2013; Goldstein et al., 2014). However, despite the legality of this practice Reuters agreed to end selling this early access upon the request of the New York attorney general (Chordia et al., 2015).

[38] Although the quote dataset that is used here is a subset of the quote dataset, explained in chapter 3, in this chapter it is referred to, as quote dataset.

[39] Similar to chapter 4, Saturdays and Sundays are removed.

Quote Dataset spans from April 23rd, 2013 to March 11th, 2014. The most prominent feature of this dataset is that it includes the name and the location of quote disseminators, which allows this research to construct the link between dealers and their affiliated economists. The macroeconomic news announcements dataset includes all the macroeconomic news announcements from the United Kingdom, the United States, Japan, Eurozone, and Eurozone countries. Economists' forecast and economist information datasets include all the existing forecasts for the all the released macroeconomic news and geographical locations of all forecasters, respectively.

The empirical results show, despite the illustrated differences between the FX and equity markets, that the empirical analysis results are analogous to those regarding the analyst affiliation in equity markets. The results show that dealers with affiliated economists have a higher contribution to price discovery that supports the information advantage hypothesis created by affiliated economists. However, as mentioned above, there is a difference in the scope of firm specific and macroeconomic news that is also reflected in the results. This chapter's findings depict that the scope of affiliated economists' research is more important than merely having affiliated economists. The results show that the increase in the number of forecasts by a dealer's affiliated economists increases the dealer's contribution to the price discovery. This finding shows that the collection of information regarding the wider aspect of a country's economic condition creates a higher information advantage for affiliated dealers. Since the definition of affiliated economists includes economists who are employed in a dealer market making arm or any of the dealer's subsidiaries, this finding shows that different sections of a dealer organisation work as a team to benefit the market making activities of a dealer's organisation. This chapter's findings, in conjunction with the prior findings in equity markets, is consistent with the positive impact of information collection sources on the market makers' information quality and information advantage is independent of the information medium transparency and market structure.

Studies in equity markets show that the analyst's benefit is not limited to their affiliated organisation and expands to benefiting the rest of the market. Bernnan et al. (1993) find the increase in the number of analysts following a stock coincides with a faster reaction of the stock to common information, which means an increase in the pace of the price discovery process. Following Bernnan et al.'s (1993) findings in equity markets, the existence of the same relationship in the FX market is also examined between the total numbers of forecasts, by affiliated and non-affiliated economists, and the information distribution quality and price discovery process in the market. This is done to isolate the impact of the economist affiliation and control for the possible impact of all economists' forecasts on a dealer's contribution to the price discovery. The results show that the total number of forecasts regarding a set of macroeconomic news has no impact on the information quality of market participants or the price discovery process. This is one of the other differences between the price discovery process in equity and the FX market that illustrates the difference in information distribution mechanisms between the two markets.

The findings regarding the impact of market makers' quoting speed on their contribution to price discovery depict a positive and significant role of speed in dealers' contribution to price discovery. Having a quoting speed which is equivalent to an average speed of the market participants in a currency pair increases a dealer's contribution to a price discovery of ask and bid by 2.7 and 2.1 times more than an increase of 1 affiliated forecast, respectively. This finding depicts the importance and significance of market makers quoting speed on their information advantage, which is supported by the arguments that the higher speed of market participants allows them to react faster to public information and consequently have a higher contribution to price discovery (Biais et al., 2015; Martinez and Rosu, 2013). However, the significant impact of speed on market participants' information advantage in conjunction with early access of HFTs to some of the macroeconomic news

announcements raises a concern regarding the negative impact that it could have on the fairness of the FX market and the costs that it could impose on slower market participants.

Although an analyst's affiliation creates an information advantage, not all analysts create the same level of information advantage for their dealers. One of the factors that is found to have a prominent impact on analysts' performance is their geographical proximity. The geographical proximity of analysts to a firm is expected to increase their forecast quality due to similarities in culture, language, and closeness to local market conditions in which firms operate (Berger et al., 2009). In addition, Bae et al., (2008) find that local analysts, on average, have followed a firm for half a year longer, thus it is expected their higher experience regarding a firm increases their forecasting quality. These expectations are consistent with Malloy's (2005) finding that geographically proximate analysts have a higher forecast accuracy than their distant counterparts. He argues that abnormal returns around large forecast revisions by local analysts demonstrates the higher impact of them on stock prices. Bae et al., (2008) by studying the sample of 32 countries, find that local analysts are more accurate and call this a local analyst advantage. Orpurt (2002) as cited in Malloy (2005) finds that analysts located in Germany outperform foreign analysts in forecasting earnings of German firms. Chang (2002) as cited in Malloy (2005) studies Taiwanese markets and finds that foreign analysts with a research group in the country outperform both local and other foreign analysts without such arrangements. Kedia and Zhou (2011) and Anand et al., (2011) find that local market makers possess information advantages. These findings show that an analyst's performance and a market maker's information, as a result of locality is influenced by geographical tripartite proximity of analysts, market makers, and the firm's headquarter's country.

This chapter further evaluates the validity of these findings in the FX and examines whether the location of the market makers, economists, and the macroeconomic news releasing countries have any impact on a dealer's information advantage. One of the

innovative approaches of this chapter is the division of the geographical proximity factor into three subsections and studying their interaction with each other at the same time. the geographical proximity factor is divided into the geographical proximity of a dealer and his affiliated economists to the country of the macroeconomic news origin, and the geographical proximity of a dealer to his affiliated economists. The geographical proximity of a dealer to the country of news origin is the only location factor that is common between affiliated and non-affiliated dealers. The findings suggest that the geographical proximity of the dealers and the country of macroeconomic news origin has a significant impact on dealers' contribution to price discovery and information advantage[40] and this impact is up to 15 times more than the effect of the affiliated economist forecast.

For dealers with affiliated economists, the geographical proximity of their affiliated economists to the country of macroeconomic news origin also has a positive impact on a dealer's contribution to the price discovery. An increase in the number of news items that are released from the same country that affiliated economists of a dealer are located, increases a dealer's contribution to price discovery. The results also show that dealers or affiliated economists who are local to macroeconomic news sources are significantly more informed than dealers or affiliated economists who are not local to macroeconomic news sources. These findings suggest that the geographical proximity of an economist to the country of macroeconomic news origin is an important factor in the quality of his forecast and consequently in the quality of information that the economist generates for his dealer. Interestingly, the findings in this chapter also illustrate that the information set that is collected by dealers and their affiliated economists, who are located in the same geographical location, has a lower impact on dealers information advantage than the dealers and affiliated economists who are positioned in different locations. This is independent of the quality of

[40] This finding is not new in the FX market. Previous studies in the FX market have also found the importance of region-specific information advantage. For further discussion, see section 5.5.1.

the information set. However, in the presence of the information transfer medium that have reached the speed of light, one could expect that the geographical distance plays no role in the information transfer rate. Similar to the findings in the equity markets, these results are interpreted not only as the prominent role of geographical proximity, but also as the familiarity of the economist with the economy of the countries that they are located in, and the collection of information that is not accessible by non-local economists or dealers.

This chapter's contribution to the literature is threefold. First, it demonstrates that the information collection sources, such as analysts or economists, create information advantages for their affiliated market makers and this added value is independent of the market structure or the information medium transparency. The geographical proximity of dealers, economists, and the macroeconomic news source, to each other and their interactions, were also found to have an important impact on the dealers' contribution to price discovery. Second, it is shown that the benefit of the information advantage of economists' forecasts is merely limited to their affiliated dealers and the increase in the number of economists following macroeconomic news does not benefit the price discovery process in the market. This finding illustrates the difference in the information distribution mechanism between FX and equity markets. In this sense the FX market is different from equity markets. Third, the results show the positive and the significant role of quoting speeds on the market participants' information advantage around macroeconomic news announcements. This finding has an important regulatory implication that selling early access of macroeconomic news announcements to HFTs creates an unfair market environment and can be costly for slower traders. In addition, since the results show that dealers' information content is directly affected by the scope of their economists' research and because there is no privileged access to public information, the imposition of a regulation similar to the Regulation Fair Disclosure is not necessary in this context.

The rest of this chapter is structured as follows. Section 5.2 discusses the dealers, macroeconomic news, economists' forecast, and economists' information datasets that are used in this research. Section 5.3 explains the methodology and variables construction. Section 5.4 presents and discusses the results of the empirical analyses and section 5.5 concludes.

5.2. Data

In this section the dataset that facilitates this research, it characteristics, properties, and statistics are presented. This chapter's dataset consists of four sections, quote data, macroeconomic news announcements, economists' forecasts, and economists' location. The quote database is a live capture of the multi-contributor tick-by-tick ask and bid quotes that contains the names and location of the disseminator dealers, which allows construction of the link between economists, dealers, and macroeconomic news announcements. The Quote database includes the six cross rates of four currencies, Euro, British Pound, Japanese Yen, and the U.S. Dollar. These four currencies form EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs.

The macroeconomic news announcements, economist forecasts, and economist locations are collected from Bloomberg. Since the six currency pairs are constructed from four zones, the macroeconomic news announcements from these zones on the existing days in the quote database are collected. Each macroeconomic news announcement contains the country, date and time[41] of release, news identifier ticker, the actual value of the news, and the Relevance Index (henceforth R-Index). The economist forecast dataset includes the name of the economists, if available, forecaster organisation, forecasted value, and forecasted news ticker. Overall, there are 3255 news announcements from the U.S., the U.K., the Eurozone,

[41] Macroeconomic news announcement dataset is merely accurate to a minute.

and Japan (651, 419, 1714, and 471 macroeconomic news announcements, respectively). Following Madureira and Underwood (2008) only the macroeconomic news that at least one dealer with an affiliated economist who has been active in trading within the 4-minute window are studied[42]. Any macroeconomic news announcements that do not meet this condition are removed. There are 1571 news announcements that meet this criteria, 298 from the U.K., 466 from the U.S., 186 from Japan, and 621 from the Eurozone and Eurozone member countries. Out of 18 Eurozone members between 2013 and 2014[43], the macroeconomic news from Austria, Cyprus, Malta, Portugal, Netherlands, and Slovakia, with 38, 31, 6, 89, 98, and 97 news items, respectively, have not been forecasted by any of the affiliated economists[44].

The final piece of the dataset is the information of economists which contains information on their location and their employer. In some cases, the name of the economist or the group of economists who forecasted a piece of news is not reported and merely the name of the organisation is reported. The piece of news that does not contain the economist' name have been released without the economist's name for as long as the forecast series existed. These forecasts are therefore institutional forecasts rather than an individual economist forecast. In these cases, the location of the economists is assumed to be the location of the forecasting organisation.

[42] Madureira and Underwood (2008) limit their dataset to the stocks that are covered by at least one affiliated and at least one non-affiliated market maker. However, in this dataset all the news that have at least one affiliated market maker have more than one non-affiliated market maker. That is the reason that the condition of at least one non-affiliated economist is not emphasised.

[43] Although there are 19 Eurozone member states, Lithuania joined the Eurozone in 2015 that is after the scope of this study. This is the reason for mentioning 18 Eurozone members rather than 19.

[44] In the rest of this chapter macroeconomic news refers to the macroeconomic news that have been forecasted by at least one affiliated economist, unless stated otherwise.

5.2.1. Macroeconomic News Announcements and Coverage by Economists

[Table 5.1 here]

Table 5.1 reports the summary statistics for macroeconomic news announcements by individual countries[45] in each zone, and their coverage by dealers and economists. There are 15 countries, 12 from the Eurozone in addition to the U.K., the U.S. and Japan. Column News depicts the number of distinct macroeconomic news types that are covered with at least one affiliated economist from each country. The numbers after "/" in this column shows the total number of news items that exists in the database but do not meet the requirement of having at least one affiliated economist. A similar interpretation of numbers after "/" holds for other columns. Column #MENA depicts the total number of macroeconomic news announcements from each country which are forecasted by at least one affiliated economist.

Columns News and MENA show the prominence of macroeconomic news, regarding a country and the influence of that country's economy on the exchange rate fluctuation for a dealer's perspective. These columns show how often and how many types of macroeconomic news items are covered by affiliated economists. Column News shows that for the U.S., U.K., and Japan that are the sole countries affecting their currencies, 83%, 69%, and 61% of the news types are covered by at least one affiliated economist. However, the story is both similar and different regarding the Eurozone countries. 82%, 77%, 76%, 65%, 53%, 42% of the news regarding the most important countries in Eurozone, namely France, Eurozone[46], Germany, Finland, Italy, and Greece[47] are covered by at least one affiliate economists, respectively. While these numbers for smaller and less influential

[45] The complete list of macroeconomic news from each country is reported in appendix III.
[46] Eurozone news are the macroeconomic news that are released by EU organisations, regarding the whole Eurozone economy.
[47] Although Greece has one of the smallest economies in the Eurozone, its financial instability and debt problems have significantly influenced the Euro (€).

countries in the Euro varies from 7% to 28%. Similarly, column MENA shows the number of news announcements and the same interpretation that was mentioned for column News holds for this column.

Columns Events and Days show the number of news announcement sessions and days, respectively. The combination of these two columns with column MENA demonstrate the density and frequency of news announcements. The number of days divided by events shows the average number of different sessions of news announcements that existed on each day. The number of events divided by MENA depicts how many news were released, on average, per event. For instance, on average, there are almost two sessions of news announcements regarding the U.S. economy, that on average around 2.5 news items are released in each event. Numbers after "/" show that on average there are almost 3 events per day, however, affiliated economists whose affiliated dealers are trading around these news items, are not interested in forecasting all of them.

The column TF demonstrates the total number of forecasts regarding a country and column AF shows how many of the existing forecasts are estimated by affiliated economists. Columns LAF shows how many of the forecasts in column AF are estimated by the economists who are located in the country. Overall, there are 42,087 forecasts regarding these 15 countries, 7,197 (17.10%) of them are from affiliated economists. Interestingly, 3,974 (55.22%) of affiliated forecasts are estimated by economists or organisations that are located in the country for which they forecast its macroeconomic news. These numbers demonstrate, that although the usage of affiliated economists by dealers is not considerable, a considerable portion of affiliated economists' forecasts are estimated by affiliated economists who are located in the country in which they forecast news. In other words, these numbers show that more than half of the affiliated forecasts are estimated by ***local*** affiliated economists. This suggests that dealers who have economist affiliation are aware of the importance of locality.

The Dealer column demonstrates the number of dealers in affected currency pairs, who have been active around the news announcements of the country, out of the total number of dealers in the affected currency pairs. For instance, Belgium news (Belgium is a member of the Eurozone) affects EUR/GBP, EUR/JPY, and EUR/USD. In these three currency pairs, out of 74 distinct dealer-locations active, 50 of them have been active around the Belgium news announcements. In table 5.1, column FDelaer (11th column) shows the number of dealer-locations whom their affiliated economists have forecasted the country's news and LDealer show how many of those dealer-locations are located in the countries that their affiliated economists have forecasted their news. A point that should be mentioned here is that LDealer and #LAF are independent and the locality of a dealer does not mean that his affiliated economists are local, and vice versa.

Overall, there are 349 macroeconomic news types[48] by these 15 countries that are released in 640 sessions of news announcement and 113 days, which are forecasted by at least one affiliated economist. The news announcements span from 00:05 to 23:50 GMT.

5.2.2. Events, Quotes, News, and Dealer Coverage

Each macroeconomic news announcement from each country affects three currency pairs, from the studied currency pairs, while at the same time these three currency pairs are also affected by a news release from the opposite currencies, if any. For instance, a new announcement from the U.K. affects EUR/GBP, GBP/JPY, and GBP/USD if there is any news announcement from Eurozone, Japan, and/or the U.S., at the same time of the day, these currency pairs would also react to that news. Therefore, in order to accommodate these circumstances an ***event***, for a currency pair, is defined as a time frame that includes news from one or both of the quote and base currencies at *the same date and time*. Therefore, the

[48] The same macroeconomic news in different countries are considered different. For instance, GDP announcement in the UK and Japan are counted as two different types of news.

number of events in a currency pair is always smaller or equal to the number of events in its constructing zones. For instance, in table 5.2, panel A shows that there are 149 events affecting the GBP/JPY currency pair that is exactly equal to the summation of events (shown in table 5.1 by column Event) in the U.K. and Japan, which shows none of the events in these two zones were simultaneous. On the other hand, there are 356 events in the EUR/GBP which is less than the summation of events in the U.K. and Eurozone, demonstrating that in 24 cases the news announcements in the Eurozone, the U.K., or both were simultaneous. For instance, in the case of the EUR/GBP, 24 of the events within the Eurozone member countries were simultaneous.

[Table 5.2 Here]

Table 5.2, panel A reports the summary statistics of quotes, dealers, and news. There are 83 distinct dealers active around macroeconomic news announcements in these six currency pairs with the EUR/USD having the highest number of active dealers, 61, and the EUR/GBP with the lowest number of active dealers, 39. On average the GBP/USD and the USD/JPY have the highest and lowest average number of quotes around macroeconomic news announcements, with 291 and 191 quotes in the 4-minute period, respectively. Even the lowest quoting frequency average of 191 quotes in the 4-minute period demonstrates the high frequency nature of the Quote Dataset. There are 115 days from April 23, 2013 to March 11, 2014 in the quote database. Overall, within the 4-minute window, there are 427,971 non-repetitive [49]quotes in the quote database from 72 dealers who are active in 6 continents, 35 countries and 41 cities, which yields the total number of 83 dealer-locations. The reason for the difference between number of dealers and locations between this chapter's dataset and the original Quote Dataset, explained in chapter 3, is due to two conditions that are imposed on this chapter's dataset. First, as explained in chapter 4 section

[49] Repetitive quotes of a dealer are removed, since they do not contain any new information.

2, only the days that there has been no interruption in capturing the dataset are studied. Second, this chapter only examines a four-minute window around macroeconomic news announcements and not all dealers have been active within this four-minute time frame. See appendix I for further information on dealers, their location, and the currencies that they are active in, around macroeconomic news announcements.

The reason for choosing to study a 4-minute time frame around macroeconomic news announcements is to achieve the longest time frame possible while being able to isolate dealers' responses to individual events. The length of the time frame is important because if it is too short, the slower market players who cannot react and adjust their quotes to macroeconomic news quickly will be omitted from the sample study. This induces a sample bias that affects the accuracy of the study's result. If the length of the time is too long, the time frames that the impact of macroeconomic news are studied will overlap with each other. This overlap does not allow us to study the isolated impact of a news announcement. For instance, consider that the time frame of study is 10 minutes and there are two macroeconomic news announcements that are 4 minutes apart. The time frame of study for the first (second) macroeconomic news would include the second (first) news announcement. In this situation, it will not be possible to distinguish a dealer's response to the different news items. The 4-minute time frame is the longest time frame that none of 1571 macroeconomic news study windows overlap. The question that arises here is whether a 4-minute time frame windows is enough for the macroeconomic news to be incorporated into prices. As the review of empirical studies in section 2.5 illustrated, the incorporation of macroeconomic news into prices in the current FX market speed is almost instantaneous.

Panel B in table 5.2, depicts the summary statistics of macroeconomic news announcements and dealers with affiliated economists per event. There are 1842 events affecting theses six currency pairs. EUR/USD is affected by the highest number of events, 462, and GBP/JPY is affected by the lowest, 149. EUR/USD is affected by the highest

number of macroeconomic news announcements, 1087, and GBP/JPY is affected by the lowest number of news announcements, 187. On average, there are close to 3 macroeconomic news announcements per event, in each of the currency pairs with the maximum of 13 news announcements per event.

The right hand side of panel B shows the summary statistics of the percentage of dealers with affiliated economists per event. On average, in these six currency pairs, 20% of the dealers in each event have affiliated economists, with dealers in EUR/JPY and GBP/USD having the lowest (13.37%) and highest (24.10%) percentage of dealers with an economist affiliation. Overall, the distribution of dealers with affiliated economists in each event is similar for all the six currency pairs.

5.3. Methodology

The construction and calculation of models and variables that are used for the empirical analysis of this chapter will be explained.

5.3.1. Event

As mentioned before, an event is the unit of measurement for price discovery around macroeconomic news announcements. For instance, considering that the GBP/USD currency pair is affected by news from its two constructing zones, zone 1 that is the U.K. and zone 2 that is the U.S. Assume that at 13:30 (GMT) there has been some macroeconomic news announcements regarding the U.K. and the U.S. economy. In this situation, the GBP/USD currency pair is affected by all the news items at exactly the same time. The set of these news items at the same time is called an event and the price discovery within its time frame is calculated. In other words, an event is a 4-minute window that there can be one or more news items from one or both of the constructing zones of a currency pair at *exactly* the same time. All the variables that are listed below, except the price discovery contribution, are

calculated assuming that the news and forecasts are regarding merely one of the constructing zones of a currency pair. Subsequently, the construction of the variables for events where there is a news item from both constructing zones of a currency pair is explained.

5.3.2. Contribution to Price Discovery and Quoting Speed and Behaviour

The contribution of dealers to the price discovery process and their quoting behaviour (BS, AG, WN, and AT) are calculated similarly to section 4.2. The only difference is that in chapter 4 the time frame of study was in 1 minute or 1 day while in this chapter the time frame of study is a 4-minute window around macroeconomic news announcements. The 4-minute window is constructed from 90 seconds before the macroeconomic news announcement, 60 seconds of the macroeconomic news minute, and 90 seconds after the macroeconomic news announcement. The reason that a symmetric 2-minute window around the announcement time is not assumed is that the macroeconomic news dataset is accurate merely to a minute. Therefore, a 90-second symmetric window around the macroeconomic news time is assumed. Assuming the time frame as such induces an imbalance in the time frame before and after announcements, the news announcement is not exactly centred in the middle of the time frame. However, because of the limitation of macroeconomic announcement data that is reported only to the minute, this issue cannot be addressed directly except through the construction of a time frame of study as long as possible to accommodate the maximum participation of market participants in the time frame of study.

The only point that should be recalled here is that since the speed in different currency pairs has different characteristics (as was mentioned section 4.3.2.) in order to ensure comparability in the pool regressions, the speed measure in each currency pair is normalised by dividing each observation's speed by the average speed of the currency pair, realised by averaging the speed of all market participants in a currency pair. Doing so makes

different currency pairs' speeds comparable by converting the mean speed of each currency pair to one.

5.3.3. Affiliated Forecasts – AF

Affiliated Forecasts (AF) is the number of forecasts that are estimated by a dealer's affiliated economists in an event. This number is not necessarily equal to the number of macroeconomic news forecasted or the number of economists. The reason is that on some occasions, one macroeconomic news item is forecasted by more than one affiliated economist, or more than one economist forecasted a macroeconomic news item as a group. AF is calculated on the total number of forecasts estimated by affiliated economists of a dealer in an event. Therefore, affiliated forecasts can be formulated as below.

$$AF_{i,j,z_1} = \sum_{n=1}^{N_{j,z_1}} D_n \qquad (1)$$

Where $AF_{i,j,z1}$ is the number of affiliated forecasts by the dealer *i*'s affiliated economists regarding the macroeconomic news announcements in event *j* regarding the constructing zone 1 of the currency pair. $N_{j,z1}$ is the total number of forecasts released by all economists for the news in event *j* regarding the first constructing zone of the currency pair. D_n is the dummy variable equal to 1 if forecast *n* belongs to dealer *i* and zero otherwise. In the event that a dealer's affiliated economists have forecasted news items regarding both constructing zones of a currency pair, AF is calculated as the summation of AF for each constructing zone and formulated as follows.

$$AF_{i,j} = AF_{j,i,z_1} + AF_{j,i,z_2} \qquad (2)$$

5.3.4. Geographical Proximity of Dealers, Economists, and News Sources

In all the three measures of distance, DN, EN, and DE, the aim for quantifying the geographical proximity of dealers, economist, and news sources is more than just a physical and geographical distance. The geographical proximity of dealers, economist, and news sources, in addition to physical distance also demonstrates the locality and familiarity of them. For instance, these location variables allows us to observe whether there is any difference between a dealer who is located in Germany and a dealer who is located in France, regarding a news item that is released in Germany. Similarly, it can be observed whether the location of an affiliated economist in Germany and forecasting German related economic news adds more to his affiliated dealer than that of an affiliated economist in France, forecasting the same news.

The point that should be mentioned here is that since Eurozone macroeconomic news announcements are regarding all 18 member states[50], no market maker or economist is assumed to be local. The robustness of this assumption is addressed in section 5.4.4.

5.3.4.1. Geographical Proximity of Dealers to News Source (DN)

DN quantifies the geographical proximity of a dealer's location and that of news sources. DN quantifies what percentage of the macroeconomic news that is announced in an event is disseminated from the country that the dealer is located in. This variable is calculated for all the dealers, since it is independent of having an affiliated economist. Since there can be more than one news item in an event, the DN variable is the percentage of the news items which are disseminated from the same country that the dealer is located in. DN is quantified as follows.

[50] The number of Eurozone member states in 2014. In 2015 it reached 19 when Lithuania joined Eurozone.

$$DN_{i,j,z_1} = \frac{1}{N_{j,z_1}} \sum_{k=1}^{N_{j,z_1}} D(D_i, NS_k) \quad (3)$$

Where $DN_{i,j,z1}$ is the percentage of the news item, regarding the construction zone 1 of the currency pair, which are released from the same country as that of dealer *i* in event *j*. $N_{j,z1}$ is the number of news items in event *j* constructing zone 1 of the currency pair. NS_k and D_i are the locations of macroeconomic news source *k* and dealer *i*, and D (D_i, NS_k) is a function that returns 1 if the macroeconomic news source *k* and dealer *i* are located in the same country and zero if the macroeconomic news source *k* and dealer *i* are located in different countries. In an event where there is macroeconomic news from both constructing zone of a currency pair, DN is formulated as follows.

$$DN_{i,j} = \frac{\sum_{k=1}^{N_{j,z_1}} D(D_i, NS_k) + \sum_{k=1}^{N_{j,z_2}} D(D_i, NS_k)}{N_{j,z_1} + N_{j,z_2}} \quad (4)$$

5.3.4.2. The Geographical Proximity of Economists to News Sources (EN)

EN quantifies the geographical proximity of a dealer's affiliated economists' locations and the news source locations. However, as is obvious from its definition, this variable is exclusive only for dealers with an affiliated economist. Since there can be more than one news item in an event or more than one affiliated economist that could forecast the same news, or the combination of both, EN is formulated as follows.

$$EN_{i,j,z_1} = \frac{1}{N_{i,j,z_1}} \sum_{n=1}^{N_{i,j,z_1}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, NS_n) \quad (5)$$

Where $EN_{i,j,z1}$ is the percentage of the news items that are released from the same geographical proximity of the affiliated economists of dealer *i* who forecasted the news in event *j*, regarding the constructing zone 1 of the currency pair. $N_{i,j,z1}$ is the number of

forecasts by dealer *i*'s affiliated economists. L_n is the *distinct* number of locations of dealer *i*'s affiliated economists who have estimated forecast *n* regarding constructing zone 1 of the currency pair. L_k is the *k*th member of affiliated economists array of distinct location of dealer *i* who estimated forecast *n*. NS_n is the macroeconomic news source for the forecast *n*. D (L_k, NS_n) is a function that returns 1 if the macroeconomic news source *n* and *k*th location are located in the same country and zero otherwise.

The reason for considering the distinct locations of economists is to eliminate double calculation. For instance, consider a group of 3 economists, two of them are located in the U.S. and one of them is located in the U.K. In this scenario, economists are located in two countries not three. In the case of a news release from both constructing zones of a currency pair and the forecast of news by a dealer's affiliated economist, EN value for a dealer in an event is calculated as follows.

$$EN_{i,j} = \frac{\sum_{n=1}^{N_{i,j,z_1}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, NS_n) + \sum_{n=1}^{N_{i,j,z_2}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, NS_n)}{N_{i,j,z_1} + N_{i,j,z_2}} \qquad (6)$$

5.3.4.3. The Geographical Proximity of Dealers to Economists (DE)

DE is the geographical proximity of an affiliated economist to his dealer. In each event, there could be more than one news announcement. In addition, for every news announcement there could be forecasts from more than one economist. Therefore, DE is formulated as follows. In this formula all the variables are the same as DN, with the only difference being that a news source is replaced by the dealer. In other words, DE calculates the percentage of the news forecasts by a dealer's affiliated economists who are located in the same country as that of the dealer.

$$DE_{i,j,z_1} = \frac{1}{N_{i,j,z_1}} \sum_{n=1}^{N_{i,j,z_1}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, D_i) \quad (7)$$

In the case of news announcements from both constructing zones of a currency pair and the forecast of both constructing zone news by a dealer's affiliated economists, DR for a dealer is calculated as follows.

$$DE_{i,j} = \frac{\sum_{n=1}^{N_{i,j,z_1}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, D_i) + \sum_{n=1}^{N_{i,j,z_2}} \frac{1}{L_n} \sum_{k=1}^{L_n} D(L_k, D_i)}{N_{i,j,z_1} + N_{i,j,z_2}} \quad (8)$$

5.3.5. R-Index – R

R-Index or Relevance Score, as stated by Bloomberg is "the number of alerts that are set for the corresponding economic event relative to all alerts set for all events in the selected country/alert type, with each bar indicating a higher percentile range". In other words, R-Index demonstrates the relative popularity of events in the selected calendar (Bloomberg Terminal Documentation[51]). Since there could be more than one news item in an event, the average value of the R-Index of all released news in that event is considered as the R value of that event. Thus, the R-Index is formulated as follows.

$$R_{j,z_1} = \frac{1}{N_{j,z_1}} \sum_{n=1}^{N_{j,z_1}} R_n \quad (9)$$

Where $R_{j,z1}$ is the corresponding R-Index for event *j* regarding the constructing zone 1 of the currency pair, $N_{j,z1}$ is the total number of news, and R is the relative score for news *n*. Since, in an event there can be more than one macroeconomic news from one or both constructing zones of a currency pair, R is defined for such an event as the weighted average

[51] This documentation is only accessible via Bloomberg Terminals.

of Rs for each constructing zone of the currency pair and is formulated as follows, where R_j is the corresponding R value of event *j*.

$$R_j = \frac{\sum_{n=1}^{N_{j,z_1}} R_n + \sum_{n=1}^{N_{j,z_2}} R_n}{N_{j,z_1} + N_{j,z_2}} \quad (10)$$

5.4. Results and Discussion

In this section the results of the empirical analysis on the impact of economist affiliation, geographical proximity, and speed on the information advantage of market makers are presented. First, the results of univariate tests and subsequently the results of the regression analysis are reported.

5.4.1. Economist Affiliation, Local Market Makers, Speed, and Price Discovery

[Table 5.3 Here]

5.4.1.1. Univariate Tests

Table 5.3 panel A, depicts the result of the T-Test on dealers' price discovery and quoting behaviour between affiliated and non-affiliated dealers. These results show the differences in five categories of speed, buy-sell intention, activity time, number of quotes, and contribution to price discovery[52]. On average, the speed of dealers with affiliated economists is 10.5% higher than the average speed of all dealers and that of dealers without an affiliated economist is 2.6% lower. In other words, dealers with affiliated economists, on average, have a significantly higher speed than dealers without affiliated economists and this difference is statically significant.

[52] The terms Speed, NQ, AG, BS, AT, and PD, used in table 5.3, are the same as defined and used in chapter 4.

The Activity Time (AT) of dealers with affiliated economists is two seconds shorter than dealers with no affiliated economists. This shortage of activity time does not translate to a lower number of quotes, because dealers with affiliated economists have a higher quoting speed that compensates this shortage in activity time. Dealers with an affiliated economist disseminate almost 2 quotes more than that of dealers without an affiliated economist. In addition, the lower activity time of dealers with economist affiliation could be due to their higher information advantage and faster reaction to news (speed) that allows them to bring their price to an efficient level quicker than dealers without an economist affiliation.

The other significant difference between dealers with and without affiliated economists is their intention to buy or sell. The intention of dealers with an affiliated economist for disseminating quotes on average is to buy while that of dealers with no affiliated economists is to sell. The point here is not whether the buy or sell intention is correct. This difference in the quoting intentions of dealers with and without economist affiliation illustrates their different perception of market movement direction.

The univariate test of the contribution to price discovery shows that dealers with affiliated economists have a higher contribution to the price discovery of ask than dealers with no economist affiliation. However, their contribution to the price discovery of bids, although higher, is not statistically different. This point, as mentioned in chapter 4, further lends support to the different behaviour of ask and bid price discovery and the factors that affect them. The reason and interpretation of the significant (insignificant) difference of the price discovery of ask (bid) is explained in the next section, section 5.4.1.2, in conjunction with the regression results. Finally, the aggressiveness of dealers for both bid and ask prices are considerably similar, which shows having or not having affiliation with an economist does not affect a dealer's aggressiveness quoting.

Results of univariate tests in this section demonstrated different behaviour characteristics between dealers with and without affiliated economists. The next section shows how these differences impact on the dealers' information quality.

5.4.1.2. Regression Results

This section reports the findings of evaluating the impact of the economist affiliation and the geographical proximity of the dealers to the macroeconomic news sources on the price discovery of dealers while controlling for the total number of economists, dealers' quoting speed and behaviour, and macroeconomic news popularity as specified below.

$$PD = \alpha + \beta_1 AF_{i,t} + \beta_2 TF_t + \beta_3 R_t + \beta_4 DN_{i,t} + \beta_5 Speed_{i,t} + \beta_6 AG_{i,t} + \beta_7 BS_{i,t} + \beta_8 WN_{i,t} + \beta_9 AT_{i,t} + \varepsilon \quad (11)$$

Where PD is the contribution of a dealer to the price discovery of bid and ask separately. AF is the number of forecasts estimated by the dealer's affiliated economists in an event, TF is the total number of forecasts by all economists in the market in an event. Speed, AG, BS, WN, and AT are measures to quantify quoting characteristic of the dealer exactly as explained in section 4.2, and R is the relative index that demonstrates the popularity of the released news in an event. DN is the geographical proximity of the Dealer's location to the macroeconomic news sources[53].

Table 5.3, panel B, reports the regression results of model (11) for the price discovery of the ask and bid for all currency pairs. The first observation from these results is the different behaviour of the price discovery of ask and bids that leads to the different impacts of the independent variables on them. The systematic difference between the ask and bid quotes informativeness is also reported by Pascual and Pascual-Fuster, (2014) who show that

[53] The correlation matrixes of model 11 for ask and bid price discovery is reported in table 5.6. The magnitude of correlation coefficients in table 5.6 shows that regarding model 11 there are no concerns regarding the existence of multicollinearity and its impact on the results It should also be added here that the reason for not using panel data model rather than OLS regression for model 11 is exactly similar to the reason mentioned in section 4.4.2.

the ask and bid in the short-run might not be equally informative. The authors explain that in the presence of a substantial order imbalance the ask and bid prices have different behaviour[54].

5.4.1.2.1 Market Makers' Affiliation with Economists

The first variable that is examined in model (11) is ***AF*** that measures the impact of the number of forecasts by affiliated economists of a dealer on his contribution to price discovery (information advantage hypothesis). Positive and statistically significant coefficients of AF for both price discoveries of ask and bid shows that the increase in the number of forecasts by dealers' affiliated economists, if any, increases a dealer's contribution to price discovery. This impact is almost equal for the ask and bid price discovery. AF shows that the widening of the research scope of a dealers' affiliated economists regarding the macroeconomic news affecting a currency pair, increases the dealer's information advantage relative to other dealers with no or a lower number of forecasts. The results in the previous section showed that there is no statistically significant difference between the bid price discovery of dealers with and without affiliated economists. The insignificant difference in a univariate test in conjunction with the significance of AF for the price discovery of both the bid and ask show that it is not the sheer factor of having an affiliated economist that impacts on the dealer's contribution to price discovery. The scope of a dealer's affiliated economists' focus on a country's macroeconomic conditions is more important that only having affiliated economists. The finding also has a regulatory implication. This finding shows that the economist affiliation and scope of the economists' research creates an information advantage for dealers. Since there is no private and privileged access to macroeconomic news, there is no necessity for the imposition of regulations analogous to the regulation Fair Disclosure

[54] Macroeconomic news announcements could induce extreme price changes to the prices that are the result or cause of excessive buy or sell pressure on the market.

(Regulation FD) in the FX market. In other words, the regulatory implication of this finding is no regulation.

The significant impact of the economist affiliation, AF, on the price discovery is consistent with Madureira and Underwood, (2008) and Schultz, (2003) findings that market makers with an analyst affiliation contribute more to the price discovery and have an information advantage over market makers without an analyst affiliation. Madureira and Underwood (2008) state that, however, the unaffiliated market makers should not be assumed uninformed since they "could obtain valuable information about future prices from observing the order flow of their customers" (p. 110). The authors argue that therefore market makers for a given stock consist of some "relatively informed" and some "relatively uninformed" market makers. The same argument holds in the context of FX market and currency. Therefore, it can be concluded that market makers with analyst affiliation are relatively *more informed* than unaffiliated market makers and this by no means suggests that unaffiliated market makers are uninformed, since the order flow information could give them valuable information about future price movements.

This result also illustrates the existence of the similar relationship between market makers, in the FX, and their affiliated economists that exists in equity markets. In the equity markets, it is found that market makers and their affiliated economists share information to benefit the company (Li and Heidle, 2004; Michaely and Womack, 1999; Chung and Cho, 2005) and this information is incorporated in market makers' trading activity (Green, 2006). The significant impact of affiliated forecasts, AF, on a dealer's contribution to the price discovery is consistent with marker makers in the FX and their affiliated economists sharing information and this information being incorporated in the market makers' quotes. Overall, the result regarding the impact of AF on a dealer's contribution to price discovery demonstrates that information collection sources create an information advantage for their market makers and this impact is independent of the market structure and the information

transfer medium. However, the difference between economists and analysts' research is the scope of their research and information collection. Vividly a country economy scale and scope is larger than that of a firm. Therefore, the information advantage creation of economists for their affiliated market maker is affected by the scope and scale of their research.

5.4.1.2.2. The Locality of Market Makers

The other factor that impacts on a dealer's contribution to the price discovery which is examined is the role of the geographical proximity of market makers to the macroeconomic news sources. Model (11) evaluates whether a dealer's geographical proximity to the sources of the macroeconomic news announcements play any role in their contribution to price discovery. This is measured by the ***DN*** variable in model (11) that measures the percentage of the macroeconomic news that is announced from the country where a dealer is located. On average only 10% of the dealer-events are local to the sources of macroeconomic news announcements, as reported in panel C of table 5.3. The value of zero for the third quartile of the DN variable shows that more than 75% of the dealer-events are not located (even partially) in the countries of the macroeconomic news sources. To be exact only 9.83% of dealer-events are partially or fully located in the countries of the macroeconomic news source.

The impact of the location variable (DN) on the price discovery of ask and bid is different in both impact size and significance. While the geographical proximity is significantly positive for the price discovery of ask, it does not play a significant role on price discovery of bid. The DN variable shows that the geographical proximity of dealers to the news source increases their information advantage significantly. In other words, local dealers know more about the economic condition of the country they are located in, than non-local dealers. The impact of the complete locality of a dealer to the macroeconomic news source (DN equal to 100%) on his information advantage is almost 15 times more than the increase

of one forecast by their affiliated economists. These results illustrate the significant and important impact of the geographical proximity of dealers to sources of macroeconomic news announcements, however, the location of a dealer in a country is random while having an affiliated economist is not. This finding further lends support to the existence of region-specific private information in the FX market (Gençay and Gradojevic, 2013) such as price leadership of German and Japanese banks in DM/USD and USD/JPY, respectively (Peiers, 1997; Ito, 1998). The locality of market makers is also found to be a source of information advantage in equity markets (Annand et al., 2011; Bolliger, 2004; Schultz, 2003). Gençay and Gradojevic, (2013) explain that any region-specific information advantage of FX traders might be due to local knowledge that non-local traders are not able to access.

5.4.1.2.3. Quoting Speed

The other important element that is of the interest in this chapter is market makers' quoting speed, and its impact on a dealer's contribution to price discovery. This is a prominent factor because quoting speed of a dealer could affect his ability in adjusting his quotes in times whenthey are on the wrong side of the market before anyone can capitalise on it or when new information emerges in the market. On the other hand, nowadays macroeconomic news is released in formats that are understandable for computers (Groß-Klußmann and Hautsch, 2011) and some macroeconomic news items are released to HFTs before other market participants (Mullins et al., 2013; Goldstein et al., 2014). Clearly, if news is read by algorithms, they are reacted on, by algorithms. A speed variable examines whether there is any relationship between market participants quoting speed and their ability in reacting to macroeconomic news announcements and incorporating news information into their quotes.

Positive, significant, and considerably larger than affiliated forecasts impact of the speed variable on the dealers' contribution to price discovery demonstrates the prominent

impact of speed on dealers' information advantage. Having a speed equal to the average speed of all market participants has 2.7 and 2.1 times higher impact on the dealer's contribution to the price discovery of ask and bid, respectively, than an increase of 1 affiliated forecast. However, in interpreting the speed result a point should be mentioned regarding the impact of speed on a dealer's contribution to the price discovery. As panel C of table 5.3 shows the quoting speed of half of the market participants is almost 33% lower than the average quoting speed. The reason, as can be deduced from the third quartile and the maximum value of the speed, is the existence of the some market participants with extreme quoting speeds that are up to ***125*** times faster than the average speed. In other words, although the results demonstrated the significantly positive impact of an economist affiliation on market makers' information advantage and contribution to price discovery, its impact on the dealers' information advantage is minute relative to that of speed.

This result illustrates the importance of quoting frequency and information interpretation speed on a dealers' contribution to price discovery. In other words, although economist affiliation improves a dealer's contribution to price discovery, high frequency traders do it better. This finding follows Biais et al's., (2015) and Martinez and Rosu's (2013) arguments about speed advantage of ATs, over humans, that allows them to react more quickly to public information (such as macroeconomic news) and thus contributes to price discovery. However, this finding also has an important policy implication. The significant contribution of quoting speed of market participants on the contribution to price discovery demonstrates that early access of HFTs to some of the macroeconomic news announcements creates an unfair market environment for slower market participants and can impose a significant adverse selection cost on them.

5.4.1.2.4. Other Variables

Now the effect of all economists' forecasts on the contribution of all dealers to the price discovery is considered. This impact is quantified by variable ***TF*** in model (11). Macroeconomic news is forecasted by different entities such as banks, financial analysis and research companies, broker-dealers, investment managements firms, FX trading platforms, universities and many others. The question here is whether the release of these forecasts to the market adds to the contribution of all dealers to the price discovery of affected currency pairs. The answer is that it does not. The increase in the number of economists following macroeconomic news does not have any impact on information distribution and the price discovery process in the market. This is one of the differences between the findings of this chapter and findings in equity markets (Bernnan et al., 1993) that further magnifies the difference between an information transfer medium and information distribution mechanism in equity and FX markets.

In studying a dealer's contribution to price discovery and the affecting factors on his information advantage, the popularity of news by market participants was also controlled for. This was done by using the Bloomberg Relative Index, demonstrated by variable R in model (11). The assumption behind the use of R was to evaluate whether the interest of market participants to a specific set of news impacts a dealer's contribution to price discovery. In other words, the question here is whether the interest of market participants to a set of news will affect a dealer's information collection and consequently his information advantage. Table 5.3 panel B shows that the popularity of news plays no role in a dealer's contribution to price discovery. Therefore, it can be concluded that after controlling for other variables, the popularity of news does not have any impact on the information collection and the information quality of dealers. The rest of the control variables, AG, BS, WN, and AT are as expected and reported in chapter 4.

5.4.2. Location, and Affiliation on Quoting Behaviour and Information Content

The geographical proximity of dealers and analysts on their information advantage is well documented in equity markets. In this section the results of the analysis regarding the impact of affiliated economist's geographical proximity to dealers and news sources on the dealers' contribution to price discovery via model (12) is reported.

$$PD = \alpha + \beta_1 AF + \beta_2 EN + \beta_3 DN + \beta_4 DE + \beta_5 R + \varepsilon \qquad (12)$$

In model (12), PD is replaced by the dealers' contribution to the price discovery of ask and bid, AF is the number of forecasts by the dealer's affiliated economists. EN (DE) is the geographical proximity of economists (dealers) to the news source (economist). The results of these analyses are reported in table 5.4 panel A. It should be stressed here that model (12) is conducted only on dealers with affiliated economists. Therefore, all the results presented and explained in this section only concern dealers with affiliated economists. It means the analysis presented in this section explores the impact of studied factors on the information advantage creation of dealers with economist affiliation.

[Table 5.4 Here]

The geographical proximity of a dealer's affiliated economists and dealers to each other and to the macroeconomic news sources play a prominent role in their quotes' information content. These three points, EN, DE, and DNs, can be positioned in three formations. First, when they are completely apart from each other (i.e., all are located in different countries). Second, when two of them are overlapping and one is separate from the other two (i.e., two points in one country and one in another country). Third, when these three points completely overlap on each other in the same country. The question that will be addressed here is how the location and position of these three geographical factors, economists, dealers, and news sources interact with each other and what the impact of this interaction is on a dealer's information advantage. In order to address this question, first EN

and DN variables are separately examined and subsequently their interaction with each other via DE, is explained.

5.4.2.1. The Locality of Economists to Macroeconomic News Sources

The first element of geographical proximity that is studied is EN, which quantifies the geographical proximity of a dealer's affiliated economists' locations and the news source. EN measures what percentage of news that affiliated economists of a dealer have forecasted are released from the same country that they are located in. The results show that the increase in EN significantly increases the dealers' contribution to the price discovery of ask and bid. In other words, EN shows that the dealers with affiliated economists who are local to the source of a news release have a higher information advantage than dealers with non-local affiliated economists. This finding is similar to the information advantage of analysts due to their locality in the equity markets where it is found that local analysts have higher forecasting accuracy than that of non-local analysts (Malloy, 2005; Bae et al., 2008). The importance of locality also holds for forecasting monetary policies (Berger et al., 2009).

The geographical proximity of dealers to macroeconomic news sources was shown to have a significant impact on their contribution to price discoveries. Similarly, the geographical proximity of a dealer's affiliated economists has also considerable impact on the dealer's contribution to price discovery and this impact is considerably higher than the impact of an affiliated economist's research scope. Although the physical location of a market maker can be assumed random, the positioning of affiliated economists is not. This finding has an implication for market makers in positioning their affiliated economists in the country in which they research their macroeconomic news announcements. Although the summary statistics of EN in table 5.4 panel B shows on average 42% of the dealers' affiliated economists are located in the country that they research its macroeconomic news, EN's

summary statistics show that this average is extremely influenced by the left skewness of the EN distribution.

An interesting question is the reasons behind analysts' information advantage due to their locality. Four reasons are found from the literature, however, testing these reason in this context is not possible either due to the short time period of this study or inapplicability of these reason to the FX market. First it is found that quality of information disclosure by firms affects analyst performance (Bae et al., 2008). However, since the countries for which macroeconomic news are studied here are amongst the most developed and open economies, this reason seems unlikely to be the force behind local advantage for forecasting macroeconomic news. Second, access to management of a firm, connection with a firm's representative, observation of a firms' input and output, the ability to speak with clients, customers, or employees are also found to be an important information advantage source for local analysts (Berger et al., 2009; Bae et al., 2008; Green et al., 2014). There is no need to explain that none of these factor is valid regarding a country's macroeconomic news.

Third, Berger et al., (2009) argues that financial analysts benefit from geographical proximity due to similarities in culture, language, and closeness to local market condition in which firms operate. Fourth, Bae et al., (2008) find that local analysts, on average, have followed a firm for half a year longer[55]. These last two argument are very probably scenarios that seem valid in the context of a country's macroeconomic news. It can be argued that local analysts and economists learn how to interpret the news and data based on their familiarity and experience with the local environment. Familiarity and experience of an economist might affect his ability in interpreting public information that is found to be the source of information asymmetry around public information announcements (Ito et al., 1998; Kim and Verrecchia, 1994 and 1997).

[55] This research dataset merely contains 113 days of data for macroeconomic news announcement that makes it extremely short for testing this hypothesis.

5.4.2.2. Locality of Dealers to Macroeconomic News Sources and its Implication

The second element of geographical proximity that is evaluated in model (12) is the locality of dealers and macroeconomic news sources. Model (11)'s results showed that the increase in the number of news released from a dealer's country of location, increases their contribution to price discovery of ask. The same result is found here, however, in this case, it is significant for both price discoveries of ask and bid, however, with different magnitude. Interestingly, the locality of a dealer's impact on his contribution to bid (ask) price discovery is larger (smaller) than that of the locality of their affiliated economists to macroeconomic news source. This finding shows that the geographical proximity of a dealer or affiliated economist to a news source are neither superior nor inferior to each other in terms of the information advantage creation that has implications for market makers. Model (11)'s results showed that the location of the market maker has a considerably important impact on their information advantage. The results here show that although a dealer's location is fixed, dealers can create almost the same level of information advantage by hiring local economists.

5.4.2.3. The Locality of Dealers and Their Affiliated Economists

Until now, it was shown that the location of dealers and affiliated economists in the country of the macroeconomic news origin, increases the dealers information advantage. The question that arises here is how these two geographical proximities interact with each other and the news source location. For instance, do the dealers and their affiliated economists which are located in the same country as the news source have dramatically higher information advantages than others? Do the dealers and their affiliated economists who are located in the same country, which is not the country of the news origin, have a different information set than dealers and affiliated economists who are located in different countries? These questions can be answered by studying DN, EN, and DE, side-by-side. DE shows

that the location of dealers and their affiliated economists in the same country reduces a dealer's contribution to the price discovery.

However, the interpretation of DE becomes meaningful when it is done side by side with EN and DN. The negative sign of DE for the price discovery of ask and bid means, although there is an increase in DN and/or EN, increase in a dealer's information quality, location of both economists and the dealer in the country of news origin does not yield a higher contribution to price discovery, equal to the linear summation of their coefficients. Variable DE states that the benefit or caveats of a dealer's geographical proximity on price discovery is non-linear relationship. This nonlinear relationship shows that there is a limit on the quality of the information that can be collected by dealers or their affiliated economists from the same location. In other words, although the locality of dealers and economists enables them to collect and interpret higher quality information than non-local dealers and economists, there is a limit on the quality of information, even if this information is the best available. The explanation of DE, until now, was concerned with the locality of dealers and/or their affiliated economist to news sources, and the impact of the location of both of them in the news source country. However, as table 5.4 panel B shows, this is not always the case. Only 16% of dealers and 42% of affiliated economists are local to the news that are released and they forecast, respectively. The question that arises here is whether the location of economists and dealers in the same country, where it is not the country of news origin, has any impact on a dealer's information quality. The short answer is yes. Although the position of a dealer and/or his affiliated economists who are in locations other than that of the news source reduces a dealer's information quality, relative to local dealers, in the case that a dealer and his economists are in different locations, they will have access to a different set of information. Again, the same principal of information quality limitation, holds here. When a dealer and his affiliated economists are not located in the country of the macroeconomic news origin but in the same country, there is a certain amount of

information that they can collect. Their location in different countries, even if not the country of the news origin, allows them to have access to different and a wider set of information. In other words, there is a limit on the quality of information that can be accessed from the same location. The best set of information can be collected when a dealer and his affiliated economists are located in the country of news origin, and the lower quality set of information is collected when a dealer and his affiliated economists are located in the same country that is not the country of news origin.

The combination of these three variables, EN, DN, and DE, illustrates that dealers and their affiliated economists which are both located in the same country as that of macroeconomic news sources, have the highest contribution to price discovery. While dealers who neither they nor their affiliated economists are located in the news source geographical proximity and they are both located in the same country, have the lowest contribution to price discovery, within dealers with affiliated economists.

5.4.3. Contradiction to Previous Findings in Chapter 4?

This chapter showed that speed has an important and significant impact on the contribution of dealers to price discovery around macroeconomic news announcements. In addition, in the introduction and literature review chapter (section 2.5), it was argued that macroeconomic news is one of the main driving forces behind price changes and are linked to fundamental information regarding exchange rates. The question that arises here is are these findings in contradiction to the findings in chapter 4 that "*increase in a dealer's speed is associated with increase in their contribution to short-term price discovery, while speed does not play a role in fundamental, longer-term, price discovery*"? The simple answer is NO. Although it was explained that macroeconomic news announcements and price changes as a result of them are linked to fundamental information, they do not explain ALL the variation in price changes. Evan and Lyons (2008) show that macroeconomic news announcements account for around 30%

of the DM/USD exchange rate variation. Ito et al., (1998) argue that the view that the FX traders' exclusive source of information is public information should be relaxed. If macroeconomic news announcements were to be the only force behind the exchange rate variations or the only source of information in the FX, and because the incorporation of macroeconomic news in prices is almost instantaneous, one should have observed no price change (i.e., a flat line) between macroeconomic news announcements. Therefore, the findings in this chapter are not contrary to the findings of chapter 4.

5.4.4. Locality to The Eurozone

The final point that should be clarified here is the way that locality is considered regarding the Eurozone macroeconomic news. Eurozone macroeconomic news announcements are regarding the whole dispersed Eurozone member states' economic condition and not a single country. Because this news is regarding all 18 countries, no market maker or economists are assumed local. However, the question that arises here is the robustness of this assumption. In order to address this concern, the same analysis is repeated. If the assumption of the locality of market makers and economists located in the Eurozone as non-local is wrong, an increase in explanatory power of the model and the coefficient of the locality variables should be observed. However, as table 5.5 depicts it is not the case in any of the models and in all the cases there is a reduction in size and significance of all the location variables. Therefore, these results are consistent with the alternative assumption that is the non-locality of economists and market makers to the Eurozone macroeconomic news .

[Table 5.5 Here]

The point that should be considered here is, when market makers and economists who are located in the Eurozone member state countries are assumed local to the Eurozone macroeconomic news, they are also local to each other if they are both located in Eurozone member state countries.

5.5. Conclusion

This chapter examined the impact of the economist affiliation, geographical proximity, and quoting speed of the market participants on their contribution to price discoveries of ask and bid. Although these factor are extensively studied in equity markets, due to the differences in the information transfer medium, information distribution mechanism, and the scope of macroeconomic and firm specific news, the expansion of findings in the equity market to the FX market requires further verification. Despite the overall similarities in findings regarding the impact of the economists' affiliation and geographical proximity in the FX market to those of the equity markets, some differences exist in the findings. Analogous to equity markets, the results show that the market makers with economist affiliation have a higher contribution to price discovery than market makers without economist affiliation. This finding suggests that a positive impact of information collection sources on their affiliated market maker is independent of the market structure and information transparency medium. The difference between the findings in this chapter and similar studies in the equity market is that the level of information advantage of market makers, with affiliated economists, is significantly affected by the scope of affiliated economists' research regarding a country's macroeconomic news. The regulatory implication of this finding is that since the information content of market makers is influenced by the scope of the affiliated economists' research scope and there is no private access to macroeconomic news, no regulatory action similar to Reg FD is required in the context of macroeconomic news, at least in the FX markets.

The findings regarding the quotation speed of market makers are exhaustively similar to those of the equity markets. The results demonstrate that high speed market participants have a higher contribution to price discovery and the impact of a dealers' quoting speed on the price discovery is considerably higher than that of economist affiliation. This finding also

has a regulatory implication. Considering the importance of market participants quoting speed on their price discovery and importance of macroeconomic news in the FX market, allowing HFQs to have early access to macroeconomic news announcements could impose adverse selection costs on slower traders.

Finally, this chapter examines the impact of the geographical proximity of market makers, affiliated economists, and macroeconomic news sources to each other. The findings depict the significant and positive impact of the geographical proximity of market makers and their affiliated economists to macroeconomic news sources on market makers' information quality. Interestingly, the examination of the geographical proximity of market makers and their affiliated economists to each other revealed the position of the market makers and their affiliated economists in the same location imposes limitations on the quality of the information that they have access to.

Tables

Table 5.1 Countries Macroeconomic News Announcements and Coverage by Dealers and Economists

This table demonstrates the summary statistics about countries macroeconomic news announcement, that is covered by at least one affiliated economist, and dealers and economists activity around them. Columns **Country** and **Zone** show the country that macroeconomic news has been released from and the currency zone, respectively. **#News** column depicts the number of distinct macroeconomic news from each country (/the total number of distinct news). It is also known as the ticker of the macroeconomic news. **#MENA** is the total number of macroeconomic news announcement released by the corresponding country (/the total number of announcement). **#Events** and **#Days** columns show the number of the announcement sessions and days (/the total number of distinct announcement days and session), respectively. **#TF**, **#AF**, and **#LAF** show the total number of forecasts in the whole market, number of affiliated forecasts, and number of local affiliated forecasts, respectively. **#Dealers** depicts the number of dealers (/all the dealers) who traded around the news announcements in the affected currencies. **#Fdealer (#LDealer)** refers to number of dealers (local dealers) who them or their subsidiaries have forecasted the news regarding a country and have been active in trading around those macroeconomic news announcements. **The number of local economists for the Eurozone is calculated based on the number of economists who are located in the Eurozone countries, however, in empirical analysis no economist or dealer is assumed to be local to Eurozone macroeconomic news.

Zone	Country	#News	#MENA	#Events	#Days	#TF	#AF	#LAF	#Dealers	#FDealer	#LDealer
Eurozone	Belgium	1/9	6/41	6/35	6/33	81	10	0	50/74	2	0
	Estonia	3/17	10/73	8/41	8/29	40	19	10	44/74	4	0
	*Eurozone***	30/39	147/205	65/87	53/66	4,192	717	248	64/74	25	9
	Finland	13/17	36/74	28/50	27/48	84	38	36	57/74	2	0
	France	28/34	117/163	58/69	52/60	1,456	326	0	67/74	11	2
	Germany	35/54	184/246	74/92	64/68	4,252	784	291	67/74	16	4
	Greece	3/7	6/34	5/30	5/29	21	7	6	49/74	2	1
	Ireland	4/21	4/89	1/32	1/30	10	6	4	36/74	2	1
	Italy	18/34	72/161	41/87	37/63	779	167	33	63/74	7	1
	Latvia	4/19	7/78	3/49	3/42	32	13	3	44/74	3	0
	Slovenia	1/13	1/63	1/33	1/33	5	1	0	29/74	2	0
	Spain	8/28	31/128	10/68	10/54	314	76	0	52/74	7	0
U.K.	U.K.	59/85	298/419	80/136	68/89	5,691	1,461	1,152	62/66	21	6
Japan	Japan	46/75	186/471	69/189	56/95	3,867	384	197	44/62	9	1
U.S.	U.S.	96/116	466/651	191/285	100/104	21,263	3,188	1,994	65/77	19	1
Total		**349/568**	**1571/2897**	**640/1302**	**113/115**	**42,087**	**7,197**	**3,974**	**83**		

Table 5.2 Quoting and News Summary Statistics

This table reports the quotes and news summary statistics of all currency pairs. **Panel A** reports the summary statistics of number of quotes in the 4 minute windows, 90 seconds before, 60 seconds within, and 90 seconds after each event. **#Events** demonstrates the number of macroeconomic news announcements affecting each currency pair and is the number of news release session, based on the intersection of the news release time, in the base and quote currency. **#Dealers** columns depicts the number of dealers in each currency pair that have traded within the sample window. Column **Total** depicts the total number of quotes in each currency pair within the 4-minute time frame of study. **Panel B** reports the summary statistics of news announcements affecting each currency pair from both base and quote currency zones, calculated based on the number of news per event. **#News** is the total number of distinct news, also known as news ticker, affecting the currency pair, from both base and quote currency zones. **#MENA** is the number of macroeconomic news announcements affecting the currency pair. Right hand side table in panel B reports the summary statistics of percentage of dealers with affiliated economists per event for each currency pair.

Panel A. Quotes Summary Statistics per Event

Currency	#Events	#Dealers	Min	Median	Mean	Max	S.D.	Total
EUR/GBP	356	39	33	193.5	195.38	347	62.55	69,554
EUR/JPY	344	44	36	230.5	218.58	340	63.61	75,192
EUR/USD	462	61	32	247	242.17	457	67.77	111,881
GBP/JPY	149	41	36	292	285.99	452	87.54	42,612
GBP/USD	271	52	70	295	291.38	475	62.25	78,963
JPY/USD	260	46	26	201.5	191.42	369	71.2	49,769
Total	1,842	83						427,971

Panel B. News Summary Statistics per Event

		News							% of Dealers with Affiliated Economists				
Currency	#Events	#News	#MENA	Min	Median	Mean	Max	S.D.	Min	Median	Mean	Max	S.D.
EUR/GBP	356	207	919	1	2	2.58	13	2.12	4%	18.18%	20.08%	59.09%	11.41%
EUR/JPY	344	194	807	1	2	2.35	11	1.62	3.70%	11.76%	13.37%	55.00%	8.11%
EUR/USD	462	244	1087	1	2	2.35	12	1.81	3.33%	18.78%	21.32%	54.55%	12.43%
GBP/JPY	149	105	484	1	2	3.25	13	2.76	4.17%	14.81%	15.81%	50.00%	9.18%
GBP/USD	271	155	764	1	2	2.82	13	2.59	3.45%	25.00%	24.10%	46.43%	10.38%
JPY/USD	260	142	652	1	2	2.51	12	2.1	4.35%	20.42%	20.36%	47.06%	11.02%
Total	1,842	349							3.33%	17.39%	19.42%	59.09%	11.31%

Table 5.3 Information Advantage and Economist Affiliation

This table illustrates the relationship between economist affiliation and dealers' information advantage. **Panel A** reports the univariate mean comparison test of affiliated and non-affiliated dealers. **Speed** is quoting frequency of dealers per minute. **AT** is the average activity time of dealers, measured in milliseconds and presented in seconds. **NQ** is the number of quotes disseminated by dealers. **AGA** and **AGB** are the percentage of aggressiveness quoting of ask and bid, respectively. **BS** is the buy-sell intention of a dealer and **WN** is the number of times that a dealer has increased his spread by moving ask and bid in opposite directions minus the number of times that they have reduced their spread by tightening both bid and ask. **PDA** and **PDB** are the price discovery of ask and bid, respectively, and are magnified by 100,000. **Panel B** reports the results of the regression on the impact of economic affiliation on price discovery. **AF** is the number of forecasts released by a dealer's affiliated economists, if any, and **TF** is the total number of forecast released by all the economist in the market. **DN** is the percentage of the news in an event that are released from the same country of the dealer's location. **R** is the average of the relevance index, a measure of relative popularity calculated by Bloomberg for each ticker news, in each event, presented in percentage. **Panel C** depicts the summary statistics of variables in panel B. *Numbers in parentheses are robust standard errors.* ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Panel A. Price Discovery, Quoting Behaviour, Characteristic, and Economist Affiliation

	Speed	AT	NQ	AGA	AGB	BS	PDA	PDB	Obs
Non-Affiliated	0.974	164.811	10.080	62.822%	62.519%	-0.042	12.671	14.363	32,781
Affiliated	1.105	162.831	11.970	63.477%	63.12%	0.015	29.011	22.493	8,130
Difference	-0.131***	1.98**	-1.890***	-0.655%	-0.6%	-0.057*	-16.34*	-8.13	

Panel B. Price Discovery and Number of Forecasts

	AF	TF	DN	R	Speed	AT	AG	BS	WN	Constant	Obs	R^2
PDA	3.590*	0.0381	0.533***	0.010	10.024***	0.118***	0.024	-1.559	8.160	-26.05*	37,711	0.002
	(1.907)	(0.036)	(0.136)	(0.163)	(3.123)	(0.043)	(0.103)	(1.954)	(8.084)	(14.76)		
PDB	3.378*	0.0462	0.142	-0.001	7.631***	0.160***	-0.032	3.556**	-12.36*	-22.50**	37,646	0.002
	(1.889)	(0.028)	(0.100)	(0.118)	(2.573)	(0.030)	(0.079)	(1.447)	(6.967)	(10.56)		

Panel C. Summary Statistics of Variables

	Obs	Min	Q1	Median	Mean	Q3	Max	S.D.
PDA	37,711	-8473.094	-175.250	0	15.973	187.621	8786.611	694.695
PDB	37,646	-5108.985	-152.420	0	15.996	173.468	8094.004	508.745
#AF	8,130	1	1	2	2.826	3	33	2.718
#TF	1,842	1	16	29	33.783	45	101	23.393
Speed	40,911	0.087	0.425	0.675	1.000	1.124	125.171	1.759
AGA	40,911	0	33.333%	66.667%	62.952%	100%	100%	36.208%
AGB	40,911	0	33.333%	66.667%	62.639%	100%	100%	36.225%
AT	40,911	0	120.869	185.625	164.417	217.800	239.951	68.903
R	1,842	0	41.18%	68.59%	57.44%	81.25%	98.41%	30.52%
DN	40,911	0	0	0	9.597%	0	100%	29.272%

Table 5.4 Affiliated Economist Characteristics and Dealers' Quoting Behaviour

This table illustrates the impact of geographical proximity of dealers, affiliated economists, and news origins on information advantage and quoting behaviour of dealers. **Panel A** reports the results of regression analysis based on model 12 and **panel B** reports the summary statistics of the variables. **PDA** and **PDB** are the price discovery of ask and bid, respectively. **AGA** and **AGB** are the percentage of aggressiveness quoting of ask and bid, respectively. **Speed** is quoting frequency of dealers per minute. **AT** is the average activity time of dealers, measured in milliseconds and presented in seconds. **AF** is the number of forecasts by affiliated economists of a dealer. **DN** is the percentage of the news in an event that are released from the country that the dealer is located in. **EN** is the percentage of the news that are released from the country that the affiliated economist is located in and the affiliated economist has forecasted the news. **DE** is the percentage of the times that the affiliated economists who forecasted the news in an event are located in the same country as that of their dealer. **R** is the average of relevance index, a measure of relative popularity calculated by Bloomberg for each ticker news, in each event, presented in percentage. Numbers in parentheses are robust standard error. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Panel A. Affiliated Economist Characteristic and Price Discovery

	#AF	DN	EN	DE	R	Constant	Obs	R^2
PDA	3.039	0.689**	0.751***	-0.533**	0.526	-42.27	7,620	0.005
	(2.418)	(0.275)	(0.182)	(0.253)	(0.382)	(29.24)		
PDB	5.501**	0.464**	0.257*	-0.312*	-0.125	6.807	7,561	0.003
	(2.586)	(0.211)	(0.140)	(0.180)	(0.321)	(25.13)		

Panel B. Summary Statistics of Variables

	Obs	Min	Q1	Median	Mean	Q3	Max	S.D.
PDA	7,620	-8473.094	-151.365	0	29.011	186.054	6936.200	715.816
PDB	7,561	-5108.985	-166.425	0	22.493	169.596	8094.004	557.961
DN	8,130	0	0	0	15.547%	0	100%	35.777%
EN	8,130	0	0	7.692%	41.606%	100%	100%	45.137%
DE	8,130	0	0	0	30.187%	50%	100%	40.222%

Table 5.5 Robustness Test of Locality of Economists and Dealers to Eurozone

This table replicates the results of table 5.3 panel B and Table 5.4 panel A and reports them in **Panels A** and **B**, respectively, however, with the assumption that economists and market makers who are located in Eurozone member state countries are local to Eurozone macroeconomic news announcements. **AF** is the number of forecasts released by a dealer's affiliated economists, if any, and **TF** is the total number of forecast released by all the economist in the market. **DN** is the percentage of the news in an event that are released from the same country of the dealer's location. **R-Index** is the average of relevance index, a measure of relative popularity calculated by Bloomberg for each ticker news, in each event, presented in percentage. **Speed** is quoting frequency of dealers per minute. **AT** is the average activity time of dealers, measured in milliseconds and presented in seconds. **AG** is the percentage of aggressiveness quoting of ask and bid. **BS** is the buy-sell intention of dealers and **WN** is the number of times that a dealer has increased his spread by moving ask and bid in opposite directions minus the number of times that they have reduced their spread by tightening both bid and ask. **PDA** and **PDB** are the price discovery of ask and bid, respectively, and are magnified by 100,000. Numbers in parentheses are robust standard error. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Panel A. Price Discovery and Number of Forecasts

	AF	TF	DN	R	Speed	AT	AG	BS	WN	Constant	Obs	R^2
PDA	3.610*	0.041	0.357***	-0.018	10.245***	0.122***	0.018	-1.568	8.061	-24.77*	37,711	0.002
	(1.923)	(0.036)	(0.122)	(0.163)	(3.149)	(0.043)	(0.103)	(1.955)	(8.086)	(14.80)		
PDB	3.525*	0.047	0.003	-0.002	7.803***	0.162***	-0.035	3.552**	-12.388*	-21.60*	37,646	0.002
	(1.897)	(0.028)	(0.083)	(0.118)	(2.603)	(0.030)	(0.079)	(1.447)	(6.966)	(10.55)		

Panel B. Affiliated Economist Characteristic and Price Discovery

	#AF	DN	EN	DE	R	Constant	Obs	R^2
PDA	3.360	0.498**	0.644***	-0.607**	0.426	-32.13	7,620	0.004
	(2.408)	(0.227)	(0.178)	(0.253)	(0.380)	(29.02)		
PDB	5.379**	0.203	0.430**	-0.236	-0.163	10.80	7,561	0.003
	(2.599)	(0.172)	(0.178)	(0.185)	(0.320)	(24.87)		

Table 5.6 Correlation Matrix of Table 5.3 Regression Model 11

This table reports the correlation matrix of model 11 in table 5.3 to address the concerns regarding the existence of high correlations and possible consequent multicollinearity. The magnitude of correlation coefficients in table 5.6 shows that regarding model 11 there are no concerns regarding the existence of multicollinearity and its impact on the results. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively

Panel A. Correlation Matrix from Model 11 in Table 5.3 for Price Discovery of Ask (PDA)

	PDA	AF	TF	DN	R	Speed	AT	AGA	BS	WN
PDA	1									
AF	0.0135***	1								
TF	0.0099*	0.3708***	1							
DN	0.026***	0.0732***	0.0463***	1						
R	0.001	-0.008	0.0036	-0.0019	1					
Speed	0.0294***	0.038***	0.0183***	0.0793***	0.0157***	1				
AT	0.0159***	0.0315***	0.0362***	0.0518***	0.0255***	0.1033***	1			
AGA	-0.0028	0.0225***	0.1053***	-0.0384***	0.0008	-0.1036***	-0.0936***	1		
BS	0.2347	0.0135***	0.0381***	-0.0018	-0.0165***	-0.0018	-0.0091*	0.021***	1	
WN	0.1765	0.004	0.0234***	-0.0047	0.0012	-0.007	0.003	0.0062	-0.0105**	1

Panel B. Correlation Matrix from Model 11 in Table 5.3 for Price Discovery of Bid (PDB)

	PDB	AF	TF	DN	R	Speed	AT	AGB	BS	WN
PDB	1									
AF	0.0166***	1								
TF	0.0137***	0.3714***	1							
DN	0.0128**	0.0738***	0.0458***	1						
R	0.0006	-0.0081	0.0026	-0.0025	1					
Speed	0.03***	0.0402***	0.0197***	0.0835***	0.0176***	1				
AT	0.0254***	0.0314***	0.036***	0.0516***	0.0312***	0.1113***	1			
AGB	-0.0061	0.0217***	0.1012***	-0.0377***	0.0128	-0.108***	-0.1004***	1		
BS	0.0195***	0.0151***	0.041***	-0.0013	-0.0187***	-0.0022	-0.0102**	0.0222***	1	
WN	-0.0144***	0.0056	0.0235***	-0.0032	-0.0011	-0.0056	0.0039	0.0061	-0.0112**	1

Appendix I

This appendix lists the geographical information of dealers who have been active around macroeconomic news announcements and the currency pairs that they have been active in.

Panel A. Africa

Contributor	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
NEDBANK	South Africa	Johannesburg					√	
NEDBANK	South Africa	Global Forex			√		√	√

Panel B. Asia

Contributor	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ADIB	U.A.E	Abu Dhabi			√			
AHLI BK OMAN	Oman	Muscat			√			
BANK ASYA	Turkey	Istanbul			√		√	
BANK DHOFAR	Oman	Muscat			√			
BANK MUSCAT	Oman	Muscat			√		√	
BANK OF COMM	Hong Kong	Hong Kong	√	√		√	√	√
BK OF CHINA	Hong Kong	Hong Kong			√		√	√
BTM	Japan	Tokyo		√	√	√	√	√
COMM BK KW	Kuwait	Safat			√		√	√
DBS HONGKONG	Hong Kong	HONG KONG			√			√
HLAL	U.A.E	Abu Dhabi			√		√	
ICBC	Hong Kong	Hong Kong			√		√	√
ING BANK	Turkey	Istanbul					√	
KASPI BANK	Kazakhstan	Almaty			√		√	√
MIZUHO	Hong Kong	Hong Kong		√	√	√		√
MIZUHO	Singapore	Singapore		√		√		√
MIZUHO	Japan	Tokyo						√
NAT BK OMAN	Oman	Muscat			√		√	√
NOMURA SEC	Japan	Tokyo		√				
PROMSVYAZ BK	Russia	Moscow			√			
QIB	Qatar	Doha			√			
SEB	Singapore	Singapore		√		√		√
TKFX UH	Japan	Tokyo		√	√	√		√
UOB	Hong Kong	Hong Kong						√
YAPI KREDI	Turkey	Istanbul					√	

Panel C. Australia								
Contributor	**Country**	**City**	**€/£**	**€/¥**	**€/$**	**£/¥**	**£/$**	**$/¥**
ANZ	Australia	Global Forex	√	√	√	√	√	√
LLOYDS	Australia	Sydney	√					
NAB	Australia	Global Forex			√			√
WESTPAC	Australia	Sydney	√	√	√	√	√	√
Panel D. Europe								
Contributor	**Country**	**City**	**€/£**	**€/¥**	**€/$**	**£/¥**	**£/$**	**$/¥**
ALLIED IRISH	Ireland	Dublin	√	√	√	√	√	√
BANCA AKROS	Italy	Milan	√	√	√	√	√	√
BANCPOST	Romania	Bucharest					√	
BANK BPH	Poland	Warsaw	√		√		√	√
BARCLAYS	United Kingdom	Global Forex	√	√		√	√	√
BCOPOPOLARE	Italy	Bergamo	√	√	√	√	√	
BCP	Portugal	Lisbon		√		√		
CAIXA GERAL	Portugal	Lisbon	√	√	√	√	√	
CBA	United Kingdom	London						√
CIBC	Canada	Toronto	√	√	√	√	√	
CITIBANK	Czech Republic	Prague			√			
Commerzbank	Germany	Frankfurt	√	√	√	√	√	√
DANSKE BANK	Denmark	Copenhagen	√	√	√	√	√	√
DEUTSCHE BANK	Germany	Global Forex	√	√	√	√	√	√
DEXLUX	Luxembourg	Global Forex	√	√	√		√	√
DNB BANK	Norway	Oslo					√	√
ERSTE BANK	Austria	Vienna			√			√
GSUK	United Kingdom	Global Forex	√	√	√	√	√	√
HSBC	United Kingdom	Global Forex	√	√	√	√	√	√
HSBC	United Kingdom	London			√		√	
ICBC	United Kingdom	London			√			
ICM	Italy	Milan			√			
ING BANK	Ukraine	Kiev			√			
INTESA	Italy	Milan	√	√	√	√	√	
KBC	Belgium	Global Forex	√	√	√	√	√	√
LBBW	Germany	Stuttgart	√	√	√	√	√	
MONTE PASCHI	Italy	Milan	√	√	√	√		
NAT B GREECE	Greece	Athens	√	√		√		
NORDEA	Denmark	Copenhagen	√	√	√	√	√	√
PIRAEUS BANK	Greece	Athens	√	√	√	√		
RABOBANK	United Kingdom	London	√	√	√	√	√	√
RBS	United Kingdom	London	√	√	√	√	√	√

SABADELL	Spain	Sabadell	√	√	√	√		
SANTANDER	Spain	Madrid	√	√		√	√	
SEB	Sweden	Stockholm	√	√		√		√
SOC GENERALE	France	Global Forex	√	√	√	√	√	√
SOC GENERALE	France	Paris	√	√	√	√		√
TATRA BANKA	Slovakia	Bratislava	√	√				
UBS	Switzerland	Zurich	√	√	√	√	√	√
WGZ BANK	Germany	Düsseldorf	√	√	√	√	√	
ZUERCHER KB	Switzerland	Zurich	√	√	√	√	√	√
Panel E. America								
Contributor	**Country**	**City**	**€/£**	**€/¥**	**€/$**	**£/¥**	**£/$**	**$/¥**
BK MONTREAL	Canada	Montreal			√		√	√
BNY Mellon	United States	New York			√		√	√
BROWN BROS	United States	New York		√	√	√	√	√
CBA	United States	New York			√		√	√
HSBC	United States	Global Forex	√	√	√	√	√	
RADA FOREX	United States	New York					√	√
RBS	United States	New York	√	√	√	√	√	√
SEB	United States	New York	√				√	
INTERCAM	Mexico	Mexico City			√		√	

Appendix II

This table reports dealers and the countries that they have affiliated economists regarding their macroeconomic news. The countries' abbreviations are as follows, Belgium **BEL**, Estonia **EST**, Finland **FIN**, France **FRA**, Germany **DEU**, Greece **GRC**, Ireland **IRL**, Italy **ITA**, Japan **JPN**, Latvia **LVA**, Slovenia **SVN**, Spain **ESP**, United Kingdom **UK**, and United States of America **USA**.

Dealer	BEL	EST	EU	FIN	FRA	DEU	GRC	IRL	IT	JPN	LVA	SVN	ESP	UK	USA	Total
Allied Irish			√					√						√		**3**
Barclays			√		√	√	√	√	√	√			√	√	√	**10**
Citibank			√		√	√			√				√		√	**6**
Commerzbank	√		√			√								√	√	**5**
Danske Bank		√	√	√	√	√			√		√		√	√	√	**10**
DBS			√													**1**
Deutsche Bank			√			√			√					√	√	**5**
Goldman Sachs			√							√			√	√	√	**5**
HSBC			√		√	√				√				√	√	**6**
ING Bank														√	√	**2**
Intesa	√		√		√	√			√				√	√	√	**8**
LBBW			√			√								√	√	**4**
Lloyds			√			√								√		**3**
Mizuho										√					√	**2**
N.B. of GREECE			√													**1**
Nomura Security						√										**1**
Nordea		√	√	√							√					**4**
Piraeus Bank							√									**1**
Rabobank			√		√									√		**3**
RBS			√		√					√		√		√	√	**6**
Santander						√								√	√	**3**
SEB		√	√								√			√		**4**
Societe Generale			√		√	√			√	√			√	√	√	**8**
UBS			√							√				√	√	**4**
Westpac			√			√								√	√	**4**
WGZ			√			√										**2**
Total	**2**	**3**	**21**	**2**	**8**	**14**	**2**	**2**	**6**	**7**	**3**	**1**	**6**	**18**	**16**	**111**

Chapter 6. Monitoring the Foreign Exchange Rate Benchmark Fix

6.1. Introduction

This paper, for the first time, proposes a method for monitoring the behaviour of market participants in the foreign exchange (FX) market around the WMR fixing window. The FX market is a decentralised market with dealers spread across the globe conducting trades 24 hours a day. The around the clock trading poses a challenge to determining a daily closing price. Such a concept is needed for any entity that holds multi-currency portfolios in order to evaluate the value and performance of their holdings. The World Market Company (WM) in conjunction with Thomson Reuters launched the Closing Spot Rate Service, also known as the WMR Fix Rate or London Close, in January 1994. The WMR Fix Rate "has become a de facto standard for the closing spot rate" (FCA, 2014b, p.27). Given the importance of this fix rate for a whole range of financial instruments and contracts, it has been a shock to the financial system and regulators to find out that the fix rate has been subject to manipulation[56]. The widespread scandal concerning the manipulation has led to

[56] On June 12, 2013, Bloomberg news reported that traders in five banks manipulated the fix rate affecting $3,600,000,000,000 assets "in funds including pension and savings accounts that track global indexes" (Vaughan et al., 2013; http://www.bloomberg.com/news/articles/2013-06-11/traders-said-to-rig-currency-rates-to-profit-off-clients). The breaking of this news triggered 20 investigations in 10 countries and the European Union resulting in $9,900,000,000 fines as of May 20, 2015 (Bloomberg Visual Data, 2015).

heightened concerns as to the lack of regulatory oversight and weaknesses in the design of the FX market.

Given the manipulation issue and the near impossibility of switching the FX market to a regulated exchange in the near future, the priority is to understand what has gone wrong with the current system and how regulators can act in a more timely and informed manner as suggested in the Financial Stability Board 2014 report. To date the focus of the regulatory investigations and media attention has been on tracking trading activities for potential manipulation and collusive behaviour (FCA, 2014a; 2014b; 2014c; 2014d; Finch and Vaughan, 2014). It is, however, costly for regulators to investigate and, therefore, effectively identifying potential investigation targets is itself an important task. Given the rise of algorithmic and high-frequency trading within this market[57], the challenge facing regulators is the design of a method that can monitor such trading activities in a cost effective manner and provide a *timely warning* signal that prompts further investigation. This chapter aims to fill this void by exploring the possibility of developing a monitoring system that can detect abnormal market behaviour.

The FX market is predominantly a quote driven market[58]. Understanding the quoting behaviour of dealers is essential for examining the price discovery process of the market. Practically monitoring *traders*' transaction behaviour through publicly available data is extremely difficult given that transaction data are disclosed without any identity information. It is even more difficult for the FX market given its decentralised nature causes a dispersion of trades across different platforms and markets. In contrast, *dealers*' quotes are disseminated in real time (with identity) across a relatively few, large platforms. Among these platforms,

[57] The Bank for International Settlement's estimates the share of automated spot trading in the FX market is 24.7% of $4.124 billion (BIS, 2011). Rime and Schrimpf (2013) report that "EBS estimates that around 30%-35% of volume on its trading platform is HFT-driven." Page 40.
[58] See section 6.2.1 for further discussion of the quote driven nature of the FX market.

Thomson Reuters is by far the largest and most comprehensive[59]. This chapter accordingly collects and constructs a unique tick-by-tick dataset from the Thomson Reuters platform that contains dealers' high frequency bid and ask quotes. The most prominent feature of this dataset is that the identity and location of the quote disseminators are recorded that allows close observation of how individual dealers contribute to price discovery around the WMR fixing at 4 o'clock (henceforth the Fix). The final dataset spans from 22nd April 2013 to 27th March 2014 and contains 109,474 quotes from EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY. These currencies are the most traded, liquid, and important currency pairs in the FX market, forming 77.7% of the $5.3 trillion a day FX trades (BIS, 2013).

The analysis of the abnormal behaviour of dealers is started by understanding their "manipulative" objective functions when participating in the fixing process. The WMR benchmark fixing process is based on the median of the trade/quote prices within one minute centred at 4pm London time. The fix price, calculated by WM, is the outcome of the median of the snapshots of ask and bid prices, independently. Over the fixing window the actual trades executed, and the bid and offer rates are sampled every second by WM. Where trade data are available, they will be used to generate bid and ask prices by applying the bid-ask spread at the time of the trade captured. For example, a public buy trade will be traded at the ask price; this trade price minus the bid-ask spread will produce the bid price at the time of the captured trade. The captured market data are subject to currency specific systematic tolerance checks that will identify outlying data. When the trade data are not sufficient or unavailable, quoted bid and ask data are used in the pool of calculation. After the finalization of the data capture, the medians of bid and ask prices are calculated and

[59] Although the Electronic Broker System (EBS) is known as the main venue for the price discovery of the Euro and Yen (Cabrera et al., 2009), Thomson Reuters matches all the venues that are providing liquidity in the EBS (Thomson Reuters, 2014). Therefore, this dataset contains all the disseminated quotes from all the liquidity providers from Thomson Reuters and EBS.

subsequently the mid-rate is formed based on these bid and ask medians. Finally, to obtain the bid and offer price from the mid-rate, a minimum standard spread is applied to the mid-rate to calculate the new bid and ask price (World Market Company, 2015). Therefore, these medians are the most prominent and fundamental elements in constructing the fix price. This chapter conjectures that the manipulation of these medians is likely to lead to the manipulation of the fix price.

One of the reasons for the emergence and attractiveness of manipulating the fix rate is the process, at which trading at the fix price occurs, that allows firms to front-run their clients' orders. Prior to the determination of the fix rate, clients place orders (with a predetermined currency, volume and direction) with a firm. The firm, by agreeing to transact with clients at the fix rate, that is yet to be determined, exposes itself to price movements at the fix. "A firm with net client orders to buy currency at the fix rate will make a profit if the average rate at which the firm buys the currency in the market is lower than the fix rate at which it sells to its clients. Similarly, a firm with net client orders to sell currency at the fix rate will make a profit if the average rate at which it sells the currency in the market is higher than the fix rate at which it buys from its clients" (FCA, 2015, p.7).

Receiving a client order before 4 p.m. gives banks a window of opportunity to adjust their positions and manipulate the fix rate to boost their profits. In order to manipulate the fix rate, traders concentrate their orders moments before and during the fixing window, and this allows them to push the rate in their desired direction. When traders received a large order they adjusted their positions with the knowledge that their clients' trade could move the market, otherwise they may have lost money for their banks. For instance, when a trader with more than a decade of experience received an order at 3:30 p.m. to sell €1 billion and buy Swiss francs he stated he had two objectives - first to sell his own euros at a higher price, and second to move the rate lower so as to enable the buying of euros more cheaply from

his client. A simple 2 basis points movement in the fix price would lead to a 200,000 francs ($216,000) profit (Vaughan et al., 2013). In addition, since the fix rate is calculated on the median of trades during the fixing window, placing a number of small trades has a higher impact than a large one. Therefore, in order to maximise their profits, traders break their transactions into smaller trades in order to put the highest possible pressure on the fix rate (Vaughan et al., 2013)[60].

The procedure of capturing potential manipulation behaviour is achieved in two phases. First, in the identification phase, those quotes updates that are *strategically* and *systematically* contributing to moving the current median (the median before the quote) towards the final median (the realised median of the quotes during the fixing period) are identified. The idea is that before every quote update, a dealer examines the distribution of the quotes posted since the fixing window started and makes a decision of a quote update so that it will move the median in the intended direction[61]. The number of such identified quote actions are counted for each dealer and create a daily measure that is referred to as the ManIx (the method is described in detail in Section 6.3).

The second phase is statistical verification. The ManIx measure is, therefore, intended to capture a specific type of quoting behaviour that is in line with the manipulation motive. However, it is possible that a dealer has a high ManIx by a random coincidence of when they post their quotes. In order to determine that the ManIx score for individual banks is capturing the strategic and systematic behaviour of dealers, the significance of the ManIx score through bootstrap simulations is examined. In simulations, for a given fixing period, only one aspect of the dealers' quotes, the timing, is changed. In other words, all dealers'

[60] Although no direct evidence of increases in transactions during the fixing exists, from the Quotation Database, it can be seen that the numbers of quotes during the one minute of the fixing window are about 40% to 90% more than other non-fixing minute averages for the six currency pairs.

[61] It is difficult to observe dealers' real intentions. In practice, this chapter uses the observed final median as a measure of dealers' manipulation targets. This design captures only successful manipulative attempts. In other words, this approach is a conservative estimate of the true manipulation in the market.

number of quotes and the quote movements, relative to the previous quote in the fixing window, are maintained while randomizing the sequence of their quotes in the fixing window. Such a design randomises the dealers' quotes with respect to the current median. If dealers' quotes are *not* conditional on the median of the quotes before their quotes, their ManIx measured from their realised quote should not be significantly different from the mean ManIx measure constructed from these bootstrap simulations[62]. A significant realised ManIx compared to the bootstrap distribution would suggest that the realised ManIx is most likely to be due to systematic and strategic behaviour.

17 out of 69 dealer-locations in the Quote Dataset are identified that have at least one realised ManIx score that is significant at the 5% level when compared to the simulated scores. In order to verify the effectiveness of this model in capturing realised manipulation, an extensive search of regulatory investigations and press releases for a full list of banks that have been investigated, is conducted. This is a full survey of the FX fixing scandal. The findings show that by mid December 2015, there are nine banks that have been investigated or sued by their investors and many cases are still on going. These investigations have led to a total of more than $11.8 billion of fines across the globe – the scale of these fines imposed by regulatory sanction and investor class actions is unprecedented. In addition, more than 40 traders have been fired, suspended, put on leave, or resigned since the start of the investigations (see section 6.4.2 for detailed discussions).

When the identified list with the investigation list is compared, it is found that eight dealer-locations among the top identified banks sorted by the number of significant ManIx, have been either fined by regulators or have internal investigations. Among these banks, four banks that have been heavily fined by regulators are identified that account for 68% ($8

[62] Such a bootstrap design also has the important benefit of controlling for a size effect as is discussed later in the methodology session.

billion) of the total fines imposed by regulators and through court settlements. This confirms the power of the ManIx in capturing the abnormal behaviour of banks that is of interest to regulators.

One interesting question to ask is what has happened to the quotation behaviour of dealers after the breakout of the sandal and especially the regulatory investigations. To this end, an out of sample test is performed by applying the ManIx model to March 2016 when the new longer fixing window has been implemented by WM. The results show that ManIx demonstrates a decrease in its frequency of occurrence by more than 4 times on average compared to the 2013-14 period, which suggests an overall improvement in the quality of the 'fixing environment' after the investigations. Nevertheless, there are still some signs of significant ManIx that may be worth close monitoring by regulators.

One of the important insights of the regulatory investigations is that the manipulators are not acting alone and collude via the sharing of information through chat rooms (Finch and Vaughan, 2014; Ahmed, 2014). Directly detecting and investigating such networks requires special access to information that is deemed to be private and confidential. Although ManIx is designed to capture the abnormal behaviour of individual dealers, it is possible to use it to infer potential collusion through coordinated manipulation. To quantify the potential extent of collusion, the coincidences of banks that have abnormal behaviour in the same fixing period is mapped. In other words, by counting the number of days that two banks have a significant ManIx score in the same currency pairs, it is possible to identify potential collusion networks. The analysis identifies that some networks exist that are of potential interest to regulators - there is, of course, a lack of public information to verify these findings at this stage. This analysis illustrates the potential application of ManIx in a network analysis context.

This research contributes to the regulatory framework and academic literature in the following ways. First, the challenge of monitoring the unregulated FX market through an algorithm that can serve as an automated *timely warning* system to regulators and banks is addressed. Warning systems are usually methods for forecasting crises (Geng et al., 2015; Savona, 2014; Sevim et al., 2014). These warning systems are designed to predict undesirable events in the future. However, such a philosophy does not hold for regulatory investigation purposes. This is because misconduct cannot be accused before such behaviour has occurred. The FX fix scandals have sparked not only the need for closer regulatory oversight but also more internal controls. The ManIx approach provides an important toolkit to regulators and banks to monitor the activities during such a key trading period – the Fix price period[63].

Second, and more generally, this study contributes to the new debate on the response of regulators to the rapid changes in financial technology. The availability of big-data and high speed computing could create a new generation of regulatory technology; referred to as RegTech in a report by the UK Government (Government Office for Science, 2015). This chapter demonstrates, in the context of the FX market, that it is feasible to design an automated early warning/monitoring system[64]. This study also provides a first demonstration that by reverse engineering, it is possible to design a monitoring system for a fixing price process.

Finally, this study highlights the potential of quote data in demonstrating potential misbehaviour in the FX market. This chapter shows how market monitoring is implementable by using quote data. Dealers who have manipulation intentions should have

[63] Although this chapter takes great comfort that the banks identified via its methodology are close to the regulatory investigations' findings, it recognises that there may be false positives in its test. Not all of the identified banks have been investigated by the regulators. Whether or not these are false positive will only be found if regulators initiate investigations and release their findings.

[64] "In response to the rapidly changing financial landscape the FCA set up Project Innovate and so regulators are working to keep up with new business models entering the financial system" (Government Office for Science, 2015, p.47).

a cohesive strategy in both their trading and quoting, since most transactions originate from a quote[65]. This chapter identifies potential manipulation behaviour in the quote data that affects the quality of the WMR Fix price.

The rest of this chapter is structured as follows. Section 6.2 discusses the background and motivation of this chapter and explains the structure of the FX market and the dataset that is used for the empirical analysis of this chapter. Section 6.3 explains the ManIx methodology and its identification and statistical verification phases. Section 6.4 presents the results of implementing ManIx and compares the findings of ManIx by media reports and regulatory investigation findings and section 6.5 draws conclusion of the chapter.

6.2. Background, Motivation and Data

6.2.1. The Forex Market – A Quote Driven Market

The FX market is a geographically dispersed, decentralised, quote driven, and primarily over the counter market (FSB, 2014). Due to these attributes, there is not a single database that contains all the transactions conducted in this market. However, active dealers in the FX market disseminate the price that they are willing to trade on, in the form of indicative data (Goodhart and O'Hara, 1997). Indicative quotes are disseminated on different platforms with the most important one being Thomson Reuters (Martens and Kofman, 1998); more than 50% of all the electronic trading in the foreign exchange market occurs on the Reuters platform (Risk, 2011) and the majority of the main players in the FX market disseminate their indicative quotes on this platform.

In recent years, advances in communication technology have contributed to the integration of the FX market and enabled customers to access multi-pricing sources

[65] See section 6.2.1. for further details

simultaneously. This has led to an increased share of electronic trading in the FX market, with 90% of the trades in the FX spot market being conducted via electronic platforms. Though the overwhelming majority of the FX market trades occur on electronic platforms, there is not a single database that includes all the trades in this market. However, the vast majority of transactions in the FX market, conducted on an electronic platform, originate from a quote in two ways. First, a customer asks for a quote from a dealer or multiple dealers, simultaneously, for ask and bid prices for a specific size and subsequently accepts the desired side. Second, dealers stream a series of quotes, with predefined sizes. A trader could accept either side of a quote (ask or bid) and conduct a transaction (RBS Market Place, 2014a; 2014b). In either of the situations, a quote disseminated by a dealer is displayed on multiple electronic platforms, while a transaction is recorded merely on a single platform. Furthermore, a quote is disseminated with the identity of the disseminator, while transaction data do not include any identity information due to privacy reasons.

Based on the aforementioned reasons, a comprehensive set of quotes with the identity of their disseminators, is the most adequate, available dataset to study the FX market, should the behaviour of individual dealers be the focus of the analysis.

6.2.2. The WMR Benchmark

In 1990 the World Markets (WM) Company, a small actuarial firm in Edinburgh, needed a single exchange rate for valuing the international portfolio of its pension fund clients. Until then a closing rate, published by Financial Times the following morning, was being used. The WM Company proposed their idea of producing a "carefully defined, cleaned, and screened benchmark" with Reuters (Willson-Taylor, 2013, p.2). The FX Fix rate was introduced by the WM Company by using a Reuters' data feed in 1994 (World Market Company, 2015). The daily Fix rate produced by WM/Reuters at 4pm London time, also known as WMR Fix rate or London closing rate, "is by far the dominant benchmark being

used, not just in FX, but also as a key input in multi-currency equity, bond, and credit indices" (FSB, 2014, p.1). Due to the prominence of this benchmark and in response to the recent scandal in the FX Fix rate, HM Treasury in the UK has brought WMR and six other benchmarks "into the regulatory perimeter [to] enable close and continuous supervision by the UK regulators, as well as providing specific powers of enforcement against those that manipulate these benchmarks" (HM Treasury, 2015, p.6)[66].

The Fix rate is used in a variety of financial benchmarks and by a majority of investment entities that invest globally such as asset managers (including ETFs and corporate end users), non-financial corporates, and index providers (FSB, 2014). The main cause behind the emergence of the Fix rate manipulation problem is the way it is being used. Due to the growth in demand for trading at a fix rate and a consequent increase in competition from banks for this business, FX dealers have increasingly agreed to buy from or sell to their clients at the mid-point fix price, rather than applying the spread. Dealers receive orders from their clients ahead and within the Fix rate window and guarantee to buy or sell at the yet unknown mid-point Fix price. In order to manage the risk of trading at the mid-point Fix rate, dealers attempt to manage their risk by trading before and around the fixing window. It is clear that the larger the size of a dealer's clientele, the easier it will be for the dealer to 'predict' the direction of the price movement.

The WMR Fix rate manipulation scandal that unfolded in 2014 shook the foundation of many banks. These investigations have resulted in the largest ever fines imposed by regulators on a group of banks (Ring and Vaughan, 2014). The Bank of England fired its chief currency dealer, Martin Mallett, because of his failure to inform his superiors of the practice of sharing clients' information by traders (Vaughan and Hamilton, 2014). There have

[66] Explanatory memorandum to the Financial Services and Markets Act 2000 (regulated activities) (amendment) order 2015 no. 369, section 2, by HM treasury.

been many investigations and law suits since 2014. More details of these investigations are discussed in section 6.4.

6.2.3. Data

This chapter starts investigating WM/R fix rate manipulation by using a subset of the Quote Dataset explained in chapter 3. This subset includes merely the quotes, in the six currency pairs, around WM/R fixing window. Recall that the Quote Dataset contains quotes from EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY. The dataset spans from April 22nd, 2013 to March 27th 2014. There are 92 dealers from 6 continents, 42 countries and 49 cities that form 104 dealer-locations – of which 69 are active around the fixing window. There are two reasons for the difference between the number of dealers and locations in this chapter's dataset in comparison to the original Quote Dataset, explained in chapter 3. First, this chapter's quote dataset includes only the days that there has been no interruption in capturing the data around WM/R fix rate. Second, not all dealers have been active around the WM/R fix rate.

Table 6.1 reports the descriptive statistics of the Quote Dataset of the one-minute fixing window: from 15:59:30.000 to 16:00:30.000. It contains 225 days with 109,474 quotes in total for all the six currency pairs. GBP/JPY is the most active currency with an average of 102 quotes per day, while USD/JPY is the least active with an average of 72 quotes per day. It suggests that for all currency pairs more than one quote per second is disseminated.

[Table 6.1 Here]

For dealer information, the Dealers/Locations column depicts the total number of unique dealers/locations in the Quote Dataset. The reason for distinguishing between the branches of the same dealers in different locations is due to their different characteristics. For instance, the Royal Bank of Scotland has two branches, one in New York and one in

London. The London branch is active from 8am to 4pm GMT time while the one in New York is active around the clock. In total, there are 69 unique dealer/locations across 37 cities in the Quote Dataset. For more information regarding the dealers, their locations, and the currency pairs they are active in, see the appendix.

6.3. The Manipulation Intention Index (ManIx)

To search and identify the potentially manipulative behaviour of market participants, it is begun by analysing the objective of manipulative behaviour. It is noted that the outcome of the manipulation is influenced by the fixing methodology. In order to calculate the fix price, WM Company captures snapshots of trades/quotes, for 60 seconds centred at 4pm GMT, at the interval of one second. Then after validation of the captured snapshots the medians of bid and ask prices are calculated and the minimum standard spread is applied to produce the final fix price[67] (WM Company, 2015). Thus, a market participant who wishes to manipulate the fix rate should do so by manipulating the median price, since it is the most prominent element of the fix price calculation process.

The proposed method for identifying manipulative behaviour consists of two phases, identification and statistical verification. The first phase, identification, identifies those quote updates that contributed to the movement of the current median towards the final median, where the current median is the median of the quotes since the start of the fixing period up to the current quote. The idea behind this phase is that for every quote update, if a dealer has manipulation intention, the dealer strives to move the median towards the intended

[67] "WM performs tolerance checks at the time the data are sourced and again after the calculation of the benchmark is complete. This may result in some captured data being excluded from the fix calculation." (World Market Company, 2015, p.6). Though the mid-price Fix rate is the most common form of use, the Fix rate is published as bid and ask prices. As a result, in this methodology the bid and ask quotes separately are examined to analyze the behavior of dealers.

direction. The second phase, statistical verification, determines whether the realised measures of manipulation intention are statistically significant.

6.3.1. The Identification Phase

This chapter's proposed methodology identifies those quote updates that are contributing to the movement of the current median towards the final median, where the current median is the median of the quotes since the start of the fixing period up to the current quote. The idea behind this methodology is that for every quote update, if a dealer has manipulation intention, the dealer strives to move the median in the intended direction. For successful manipulations, the realised medians would be a good proxy for dealers' manipulation targets. This methodology determines whether a set of quotes, disseminated by a dealer is placed strategically to move the Fix price. Specifically, two conditions should be met to classify each quote as a Potentially Manipulative Quote (PMQ):

$$IF \begin{cases} S(F_m - C_m) * S(P_t - C_m) = 1 \\ \textbf{\textit{and}} \\ S(F_m - C_m) * S(P_t - P_{t-1}) = 1 \end{cases} \Rightarrow PMQ = 1, otherwise\ PMQ = 0 \qquad (1)$$

Where F_m, C_m, P_t, and P_{t-1} are the final median, current median, the quote price[68] at time t, and quote price at time t-1, respectively; final and current medians are the final median of the price in the fixing windows and the median up to the current quote, respectively; S(x) is the sign of x and is equal to +1, 0, and -1 when x is positive, zero, and negative, respectively. If PMQ is equal to 1 it means that the quote could potentially be manipulative and otherwise, if zero. By definition, the PMQ for the first quote is zero, since there is no activity before it in the fixing window to compare it with. It should be mentioned that equation (1) does not take into account the magnitude of price change that could also be a source of price manipulation.

[68] F_m, C_m, P_t, and P_{t-1} refer to both ask and bid prices.

Equation (1) states that a potentially manipulative quote is a quote that meets two conditions. First, the sign of the difference between the final and current median is equal to the sign of the difference between current price and the current median, it is called the location condition. This suggests that the new quoted price will move the current median towards the final median. Second, the sign of the difference between the final and current median is equal to the sign of the difference between the current price and the previous price, it is called the direction condition. This suggests that the direction of the latest quote is in the same direction as the intended median movement. The reason for this second condition is to capture a strong form of manipulative behaviour. For example, when quoting to move the median down, a down tick quote is more likely to be so when the resulting latest quote is at a lower level for others to follow[69]. To put it simply, equation (1) determines whether the current quote is moving the price towards the final median.

The final step of the identification phase is constructing the ManIx score for a given fixing session. In order to do so, the PMQ score of each dealer is aggregated in each fixing daily. Thus, the ManIx score is formulated as below:

$$ManIx_{i,j} = \sum_{k=1}^{n} PMQ_k * D_i \qquad (2)$$

Where $ManIx_{i,j}$ is the aggregated PMQ score for dealer *i* in day *j*, n is the number of all quotes in the fixing window *j*, and $ManIx_k$ is the ManIx score for quote *k*. D_i is a dummy variable equal to 1 when quote *k* belongs to dealer *i* and 0 otherwise.

[69] It is possible to quote a price lower than the current median while higher than the last quote price. Such a quote would be a less effective manipulation than a down tick quote (a quote that has a quote price lower than the previous quote price).

6.3.2. The Statistical Verification Phase

The aim of this research is to develop a framework and a methodology that can identify manipulative behaviour within the WMR fixing window. This methodology, ManIx, identifies which quotes strategically contribute to the final realization of the Fix rate. Such behaviour, per se, is not necessarily a sign of manipulative behaviour since it could be just a coincidence that the quote meets the specified condition. Strategically placing quotes in order to move it in a dealer's desired direction and successfully doing so is a manipulative behaviour. The question that needs addressing is how to differentiate the random from the systematic strategic behaviour of a dealer. To this end, a bootstrap test for the ManIx statistics is designed.

Simulations are run that randomise dealers' quoting sequences while maintaining their quoting characteristics (size and direction of the tick movement). Maintaining the number of quotes and the size of tick movement in their quotes control for the potential size effect and information effect that may affect the calculation of ManIx. For example, for a dealer who quotes more often, then it is more likely that they will have a false positive ManIx by chance. Comparing the realised ManIx with a bootstrap simulation that maintains such a property will control for such a potential bias.

For each day, in each currency pair, 10,000 series of randomised quotes are generated. All of these randomised sequences have the same total price movement, and dealers maintain their number of quotes and the associated tick movements as the realised sequence in the fixing. The only thing that changes is the location of the dealers' quotes in the overall sequence. After generating these series, the simulated *PMQ* and *ManIx* scores for each dealer in that day are calculated.

The design of this verification is to differentiate a dealer's contribution to price discovery from manipulation. The simulated sequences will maintain the same level of

contribution to price discovery (the total number of ticks that a dealer would have moved the price) while the timing of the contribution is different. In these simulated sequences, there will be quotes that have ManIx equal to 1 but are due to randomness. The assumption is that if a dealer is making quotes to time the market so that the median will move in an intended direction, their realised ManIx for that fixing session will be at the right tail of the ManIx distribution generated from the 10,000 randomised quote sequences; otherwise, the realised ManIx will be indistinct from that of the randomised sequences.

To exemplify the process of the verification phase, consider the following example. Assume five quotes, Q1 to Q5, are disseminated by three dealers, A, B, and C and the sequence of the quotes is given in Table 6.2. Panel A, demonstrates the original quote series. The subscripts for a dealer demonstrate the sequence of price for that dealer. The randomised sequence starts by keeping the first quote the same as the original sequence, in order to maintain the start and finish prices for all the sequences to be the same as the original one. For instance, Panel B shows an illustration of the randomization process. Q1 to Q5 are randomised as Q1, Q5, Q2, Q3, and Q4. In order to rebuild the price series after randomization, the price change of the quote in the sequence is applied. For example, the second quote in the randomised series is Q5, which was B2 in the original quote. The corresponding price change for B2 was "-0.1". Therefore, the price in the randomised series will be the previous price plus the corresponding change, which is equal to 1.8 + (-0.1) = 1.7. Notice that the total contribution to price discovery of each dealer is maintained. For example, for dealer B their total contribution to price discovery is zero in both panels (0.1+(-0.1)=0). What is different is the timing of these contributions to the sequence. If the timing is strategic to manipulate the fixing, a randomization will remove this effect and, therefore, reduce the possibility of generating a positive ManIx signal in the randomization.

[Table 6.2 Here]

For each day, in each currency pair, 10,000 series of randomised quotes are generated. After generating these series, the *PMQ* score and *ManIx* score are calculated for each of the dealers in that day. To determine whether a dealer's quoting behaviour was a result of random or strategic quoting, it is identified where the original ManIx score lies within the simulated ManIx scores distribution. If the original ManIx score lies within the top 5% of the simulated ManIx score histogram, the behaviour of the dealer on that day is classified as **manipulative,** otherwise it is classified as random or **non-manipulative**.

[Figure 6.1 Here]

Figure 6.1 illustrates a simulation distribution for ask price of RBS (New York branch) on 21st June 2013 for the GBP/USD currency pair with the realised ManIx score of 17. Out of the 10,000 simulated ManIx scores, only 0.92% of them are larger or equal to the realised ManIx score by the dealer on the day. In other words, the original ManIx score, realised by the dealer, lies within the top 5% of the simulated ManIx distribution and, consequently, the dealer's ask quotes are identified as manipulative.

6.4. Results and Discussion

6.4.1. An Overview of Fix Rate Discovery

Table 6.3 reports the daily distribution of the average ManIx per quote. For each day, the average ManIx is calculated for each currency pair using all dealers' quotes. Such per quote averages give an idea of the frequency of quotes that are captured as potentially manipulative by the ManIx. Panel A shows that on average the number of quotes that are deemed to be manipulative range from 10 (10) to 22 (21) percent for the Ask (Bid) price. For instance, the daily mean of the average ManIx per quote is 0.1334 for EURGBP. This means

that on average, almost, 1 out of 7.5 quotes coincides with the potential manipulation definition[70].

[Table 6.3 Here]

6.4.2. ManIx and Regulatory Investigations

Table 6.4 reports the identified dealers with significant ManIx. If the realised ManIx score lies within the top 5% of the simulated ManIx score, the dealer's behaviour in that day is classified as manipulative, otherwise it is classified as random or non-manipulative. In terms of the EUR/GBP, EUR/JPY, EUR/USD, GBP/JPY, GBP/USD, and USD/JPY currency pairs the results identify 7, 6, 5, 6, 7, and 3 dealers, respectively, who their quoting behaviour is identified as potentially manipulative. The number of days that dealers have manipulated the market varies amongst the dealers[71]. In all the currency pairs, Barclays and the Royal Bank of Scotland, both London and New York branches, Rabobank, and Societe Generale demonstrate considerably greater manipulative behaviour than other dealers.

Table 6.4 provides a short list that can guide regulators in their potential investigations of manipulation. How can this list be verified and, therefore, provide evidence for the validity of the ManIx methodology? It is unlikely to be able to identify manipulation using publicly available data (even ex-post) as was discussed earlier and this is one of the motivations behind developing ManIx. The manipulative behaviour can only be identified and confirmed through detailed investigation with access to private trade and chat records. Such investigations are costly to both regulators and banks and, therefore, if ManIx can act as an effective monitoring system it will help direct the limited regulatory resource to more targeted investigations. To validate this measure, a table of banks that have been investigated and fined has been compiled.

[70] The division of 1 by 0.1334 yields 7.5, which means 1 quote out of 7.5 quotes contribute to Fix rate discovery.
[71] Note that only dealers that have at least one significant ManIx are included in the list.

[Table 6.4 Here]

Table 6.5 reports a collection of fines imposed on the banks following the investigations and law suits around the globe. It shows that most of the investigations have happened in the UK and U.S. The UK regulator, the Financial Conduct Authority (FCA) fined five banks $1.7 billion for manipulating the WMR benchmark in November 2014 and Barclays $441 in May 2015 (FCA, 2014e; 2015) [72]. The Swiss Financial Market Supervisory Authority (FINMA) imposed a $139 million fine on UBS bank for its FX manipulation (FINMA, 2014). In the U.S., the Commodity and Future Trading Commission (CFTC) fined five banks: Citibank, HSBC, JPMorgan, RBS, and UBS a total of $1.4 billion in November 2014 and Barclays for $400 million in May 2015 (CFTC, 2014; 2015). At the same time, the United States Office of the Comptroller of the Currency (OCC) fined BOA, Citi, and JP Morgan a total of $950 million for unsafe or unsound practices related to their foreign exchange (FX) trading businesses (OCC, 2014)

[Table 6.5 Here]

Subsequently, a second wave of investigation announcements were released in May, 2015. The Department of Justice (DOJ) fined Citibank, JP Morgan, Barclays, RBS, and UBS a total of $2.5 billion for conspiring to manipulate the price of U.S. dollars and euros exchanged in the foreign currency exchange (FX) spot market. (DOJ 2015). The Federal Reserve imposed a fine of $342 million on each of Citibank, Barclays, and UBS banks, a fine of $274 million on RBS and $205 million on BOA (FED, 2015). These fines are among the largest ever assessed by the Federal Reserve (FED 2015). Finally, the New York Department of Financial Services (NYDFS) imposed a $485 million fine on Barclays for its role in

[72] Although some examples of these banks' manipulations were published by the FCA, there is no comprehensive information on the currencies that they manipulated.

manipulation of WMR rate since the bank was chartered by the state of New York (NYDFS, 2015).

The regulatory investigations are being followed by lawsuits from investors against involved banks in WMR fix rate manipulation. In a lawsuit brought by the Scott and Scott law firm against involved banks: Barclays, RBS, and UBS settled with their investors for $384 million, $255 million, and $135 million, respectively (Kleinman, 2015; Kennedy, 2015). In addition, the Scott and Scott law firm brought a lawsuit against Societe Generale for its role in manipulating the WMR Fix rate (Voris, 2015). The litigation document released by Scott and Scott demonstrates the participation of Citibank, Barclays, RBS, UBS, and Societe Generale in chat rooms for manipulating the WMR fix rate (Scott and Scott, 2015, p. 43 and p.44). The litigation document on page 45 mentions that UBS, RBS, and Barclays with other banks, agreed to manipulate the GBP/USD currency pair, exactly as was identified in Table 6.4 (Scott and Scott, 2015, p. 45). In addition, on page 75 of the same document, the transcript of a chat between Citigroup and JP Morgan traders demonstrates their intention to manipulate the EUR/USD currency pair. Considering these settlements, the total amount of fines and settlements banks encountered by December 2015 reached $11.8 billion. In addition, more than 40 traders have been fired, suspended, put on leave, or resigned since the start of the investigations (McGeever, 2014).

Comparing the list of banks being fined by regulators to the identified list, there are two important observations. First, four out of the top five identified banks have been heavily fined by regulators. The exception is JP Morgan which is more active on the EBS platform and not featured in Thomson Reuter's database[73]. Economically, 68% ($8 billion) of the regulator fines are from the top 8 banks that have been identified by ManIx in Table 6.4. If

[73] Similarly, BoA and BNP Paribas are not in the quote dataset. These banks are more active in the EBS platform.

the regulators focused their investigations on the identified list, they would have covered the major suspects. Importantly, having such a monitoring system in place would speed up the response of investigators to potential manipulation as a timely signal would be generated by the ManIx. Second, although some banks were not investigated by regulators, they conducted their own internal investigations into the attempted manipulation of the WMR fix rates by their employees. In May 2014, Commerzbank AG, Germany's second largest lender, fired one FX trader and suspended another one on suspicions of the attempted manipulation of the Polish zloty's euro exchange rate (Schuetze and McGeever, 2014). Rabobank, which was fined $974 million during 2014 for manipulating interest rates, suspended two senior FX traders, Gary Andrews and Chris Twort, employees of the bank since 2004 and 2010, respectively (Gaal and Choudhury, 2014). The New York State regulator, subpoenaed Societe Generale in December 2014, a month after U.S., U.K. and Swiss regulators concluded their probe into the rigging of the FX rate (Saks-McLeod, 2015).

Overall, the media reports and regulatory findings discussed above confirm that the banks highlighted by this chapter's monitoring methodology have been investigated by regulators. This supports the notion that this monitoring methodology aligns with the actions of regulators and should provide value because of its time and cost effective design. This methodology, however, also signals potential manipulative behaviour by banks that have not been investigated. Whether these are false positives in this chapter's estimation or a lapse in regulatory activity is open to question and can only be clarified by further regulatory investigation in the future.

6.4.3. Out of sample test

One interesting question to ask is what has happened to the quotation behaviour of dealers after the breakout of the scandal and especially the regulatory investigations. Two main structural changes have taken place. First, from February 2015, the fixing period has

changed from 60 seconds to 300 seconds. Second, there are more dealers involved in the fixing window in 2016 than was the case for 2013 and 2014. To demonstrate the application in this new environment, Table 6.6 reports the results of ManIx for the period from the 2nd March to 30th March 2016.

[Table 6.6 Here]

Table 6.6 shows there are some significant results. Particularly, RBS and Rabobank have the highest number of significant days. In order to compare these results with those of 2013-14, since there are different number of days and dealers in the two periods, the total number of dealer-days is calculated for each currency pair for each period. By dividing the total number of identified events (significant ManIx) in each currency by the total number of dealer-days, the occurrence of the frequency of potential manipulative behaviour can be observed. By comparing the columns event per dealer-day (E/DD) in Table 6.7 it can be ascertained if the frequency has changed between the periods 2013-14 and March 2016.

[Table 6.7 Here]

Table 6.7 shows the results of comparing the frequency of potential manipulative behaviour by dealers in 2013-14 and 2016 periods. With the exceptions of the EUR/GBP and USD/JPY currency pairs, there is a reduction in the frequency of ManIx occurrence. After the change in the fix rate calculation and the exhaustive investigations by regulators, ManIx shows a decrease in its frequency of occurrence by more than 4 times on average. Nevertheless, there are still some signs of significant ManIx that may worth close monitoring by regulators.

6.4.4 Network Analyses – Signs of Collusion

One of the arguments for not regulating the FX market is that given its size and competition, it is less likely that any one bank can manipulate this market. Manipulating the

fix rate requires a considerable amount of capital and coordination between colluding traders. For example, some traders disclosed to Bloomberg news that they would need more than €200 million to have a possibility of moving the fix rate (Vaughan et al., 2013). Furthermore, the manipulation could "backfire" if another party enters the market with a large order in the opposite direction. Indeed, there is the suggestion that the manipulators are not acting alone and collude via the sharing of information through chatrooms (Ahmed, 2014; Finch and Vaughan, 2014). However, directly detecting and investigating such networks requires special access to information that is deemed to be private and confidential.

Three methods of collusion can be deduced from the regulators' findings (FCA, 2014d). First, traders transfer all of the orders to one trader who executes the orders in the collective desired direction. Second, traders transfer their orders to two or more traders and these traders join forces and third, trading with dealers out of the network by giving them orders to trade in the desired direction. Since in the first case scenario the manipulation is conducted merely by one dealer, it is not possible to identify the network of dealers behind the manipulation with the existing data. The second and third methods suggest that the collusion will have a trail of coordination in the trading activity. While the ManIx measure is designed to capture manipulative intention on a quote by quote basis, examining all dealers' quotes in the same fixing window will flag up potential collusion networks. To this end, network graphs of banks that have significant manipulative behaviour in a same fixing window are drawn.

When identifying the list of potential manipulative banks, a strong statistical criterion of 5% significance in identifying the significant ManIx is applied. This produces the short and focused list of banks in Table 6.4. However, in order to identify potential collusion effects, a more relaxed criterion of 10% significance is chosen when identifying individual significant ManIx. This follows the logic that when banks collude to achieve manipulation,

the act of manipulation will be less obvious in each individual bank. These network graphs are reported in Figure 6.2. Any two banks that have a significant ManIx on the same day for a given pair of currencies will have a connection value of one. All these connections are counted for all dealers in each fixing. The lines show the connections while the size of each node shows its prominence in the network.

The network analyses in Figure 6.2 demonstrate three features of such networks. First, there can be a large network of interconnected banks. For example, this is illustrated in Panels A, C and D. They show that a large number of banks are interconnected by their behaviour consistent with manipulation. For example, in Panel A for the EUR/GBP currency pair, there has been suspected collusion between four banks: Rabobank, Danske Bank, CIBC, and Barclays. Second, there can be more than one network identified. This is illustrated in Panels B, E and F. This fragmentation demonstrates that not all those identified as potential manipulators are connected. Finally, some banks are found to play a dominant role in the network. For example, Barclays has a centrality and a prominent role with the highest number of connecting banks in Panel A for the EUR/GBP currency pair. Similarly, RBS-NYC has played the central role in the EUR/JPY, EUR/USD and GBP/USD currency pairs, while RBS-LON plays the central role in the USD/JPY currency pair and WGZ-Bank plays the major role in the GBP/JPY currency pair.

[Figure 6.2 Here]

In the regulators' investigative findings (discussed in Section 6.4) the individual banks who manipulated the fix rate were identified. However, there was very little mention as to which banks colluded over which currencies. Therefore, verification of this chapter's findings in this section based on the regulators' findings or media reports is not possible. The only chatroom members identified by regulators are "The Cartel" chatroom that consisted of traders from JP Morgan, UBS, and Citigroup (Finch and Vaughan, 2014). However, this

chatroom was not the only existing network of manipulators and there existed different chatrooms with names such as "The A Team", "The 3 Musketeers", and "The Players" (Ahmed, 2014). The network analysis presented here is, however, a way to detect potential collusive behaviour and it could be a toolkit for regulators and banks to further target the investigation of collusion.

6.5. Conclusion

The WMR benchmark rate is important for a number of financial instruments and markets, and its seemingly extensive manipulation has given rise to a lot of regulatory 'interest'. The problem facing regulators in tackling this issue in a timely and effective manner is having data and a methodology that identifies potential manipulation as it progresses. In response to this issue a dataset based on quotes is constructed and an index (ManIx) is developed that is able to capture the intended manipulation of the benchmark rate. This chapter identifies banks that are prone to potential manipulative behaviour and uses ex post regulator investigation data to verify its findings. Essentially, this chapter provides a ***warning*** system that will help regulators and FX market participants to keep up with the speed and size of the FX market in order to conduct their monitoring and investigative activities.

The exercise of developing an automatic monitoring system is of great importance to regulators given the rapid increase of speed in the financial markets. Having an automatic monitoring system will help regulators to allocate their limited resources to timely investigations. This chapter demonstrates the feasibility of developing such a regulation technology and tests its effectiveness. The out of sample analysis provides some evidence of improvement in the fixing quality after the regulators' investigation and the adjustment of the fixing methodology. Nevertheless, there are still some signs of significant ManIx that may be worth close monitoring by regulators. The limitation of the current study is the

unavailability of transaction data with identity; however, such data can only be made available via requests from regulators. Finally, the application of this technology is not confined to foreign exchange rate fixing. For example, it can be applied to securities data to identify manipulation near the close of day trading. This is potentially important in days when the closing price has important implications for other markets such as derivative settlement or index membership.

Tables and Figures

Table 6.1 Dataset Summary Statistics

This table reports the descriptive statistics of the dataset of the one-minute fixing window: from 15:59:30.000 to 16:00:30.000. The Days column shows the number of days that the data was captured without any interruption. The Sum, Mean, Min, Max, and STD columns report the total, average, minimum, maximum and standard deviation of the number of quotes in the one-minute fixing window, respectively. The Dealers and Locations columns depict the total number of distinct dealers and locations that are active within the fixing window in the Quote Dataset, respectively. The Dealers/Locations column depicts the total number of unique dealers/location in the Quote Dataset.

Currency	Days	Sum	Mean	Min	Max	STD	Dealers	Locations	Dealers-Locations
EUR/GBP	212	16,156	76.21	48	122	13.28	36	22	38
EUR/JPY	216	16,825	77.89	55	108	10.76	33	21	34
EUR/USD	215	18,571	86.38	48	127	14.42	49	31	52
GBP/JPY	216	22,027	101.98	72	133	11.91	33	21	34
GBP/USD	224	20,672	92.29	44	144	16.14	44	28	47
USD/JPY	210	15,223	72.49	36	118	13.35	33	18	34
Total	**225**	**109,474**	**486.55**				**64**	**37**	**69**

Figure 6.1 Example of Statistical Verification through Bootstrapping

Figure 6.1 illustrates a simulation distribution for one dealer day for RBS New York. The realised ManIx for RBS New York on June 21st, 2013 is equal to 17, which lies within the top 5% of the bootstrapping distribution. Since this value stands at the top 5% of the bootstrapping, the behaviour of RBS New York on the day is classified as manipulative.

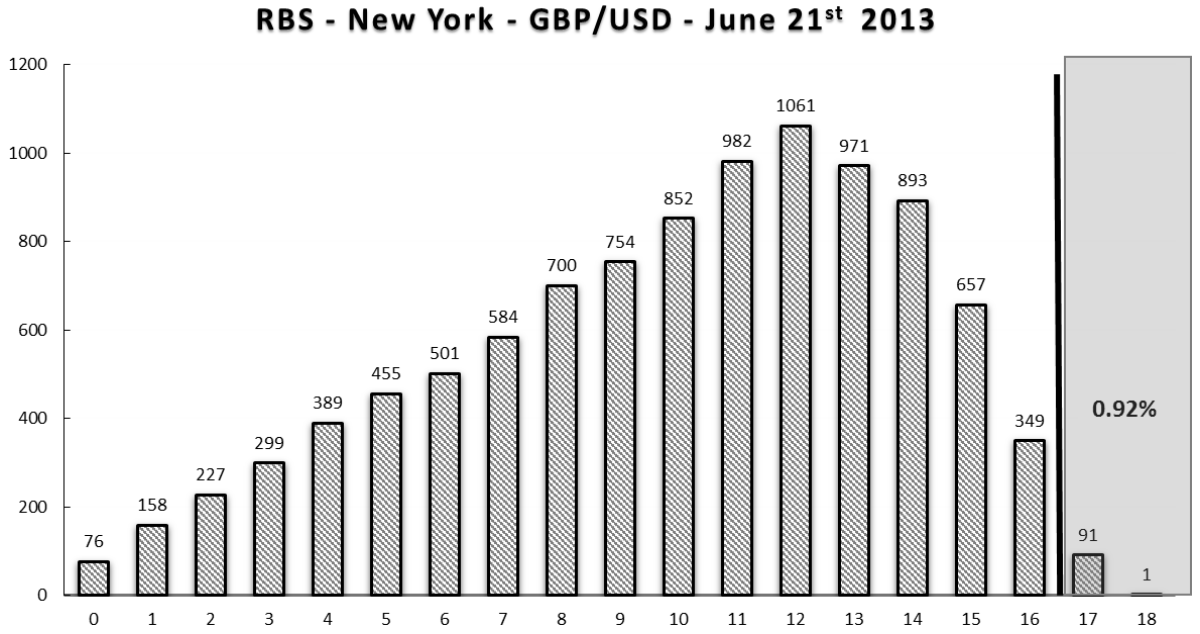


Table 6.2 Randomization process

This tables illustrates the process of price sequence randomisation before bootstrapping.

Panel A. Original Price Series					
Quote	**Q_1**	**Q_2**	**Q_3**	**Q_4**	**Q_5**
Price	1.8	1.9	2.1	1.7	1.6
Dealer	A_1	B_1	A_2	C_1	B_2
Change	0	0.1	0.2	-0.4	-0.1
Panel B. Randomised Price Series					
Quote	**Q_1**	**Q_5**	**Q_2**	**Q_3**	**Q_4**
Price	1.8	1.7	1.8	2.0	1.6
Dealer	A_1	B_2	B_1	A_2	C_1
Change	0	-0.1	0.1	0.2	-0.4

Table 6.3 ManIx Summary Statistics

This table reports the daily distribution of the average ManIx per quote. Column N represents the number of days available in the Quote Dataset for a currency pair. Mean, Median, Std Dev, Min, and Max represent the summary statistics.

		Average ManIx Ask					Average ManIx Bid				
Currency	**N**	**Mean**	**Median**	**Std Dev**	**Min**	**Max**	**Mean**	**Median**	**Std Dev**	**Min**	**Max**
EURGBP	212	0.1334	0.1343	0.1014	0	0.4111	0.1314	0.1149	0.0920	0	0.3623
EURJPY	216	0.2194	0.2298	0.1035	0	0.4247	0.2042	0.2051	0.0990	0	0.4267
EURUSD	215	0.1499	0.1429	0.0905	0	0.3697	0.1481	0.1481	0.0887	0	0.4118
GBPJPY	216	0.0971	0.0950	0.0384	0	0.2083	0.0954	0.0980	0.0371	0	0.1848
GBPUSD	224	0.2099	0.2215	0.0956	0	0.3910	0.1903	0.1971	0.0988	0	0.4235
JPYUSD	210	0.1456	0.1419	0.0808	0	0.3614	0.1479	0.1421	0.0894	0	0.3500

Table 6.4 Dealers with Manipulative (Significant Abnormal) Activities during Fixing

This table reports a list of dealer-locations that are identified by the simulations to have manipulative/significant-abnormal activity. If the realised ManIx score is significant at the 5% level given the simulated ManIx distribution from the 10,000 simulations, the dealer's behaviour in that day is classified as manipulative, otherwise it is classified as random or non-manipulative. This table reports the total number of days a dealer participates in the fixing and the number of days their ManIx measures are significant for the Bid and Ask prices. The shaded rows indicate banks that are featured in investigations that are summarised in Table 6.5.

		EUR/GBP			EUR/JPY			EUR/USD			GBP/JPY			GBP/USD			USD/JPY			Sum
Dealer	**Location**	C_{Total}	C_{Ask}	C_{Bid}	C_{Total}	C_{Ask}	C_{Bid}	C_{Total}	C_{Ask}	C_{Bid}	C_{Total}	C_{Ask}	C_{Bid}	C_{Total}	C_{Ask}	C_{Bid}	C_{Total}	C_{Ask}	C_{Bid}	
RBS	**NYC**	207	5	3	211	6	7	211	6	3	211	2	3	219	13	8	205	3	4	**63**
RBS	**LON**	196	4	5	198	4	4	198	1	9				203	11	10	197	2	5	**55**
BARCLAYS	**GFX**	212	0	2	194	2	2							223	0	1				**7**
RABOBANKGFM	**LON**	162	0	1	44	1	0										162	1	1	**4**
SOC GENERALE	**PAR**	200	1	0	215	0	2	211	0	1										**4**
WGZ BANK	DUS	115	0	1							117	1	1							**3**
BK MONTREAL	MON													29	1	1				**2**
CITIBANK	**PRG**							209	0	2										**2**
COMMERZBANK	**FFT**	211	1	0										223	1	0				**2**
KBC	GFX				159	2	0													**2**
UBS	**ZUR**													212	1	1				**2**
BANCA AKROS	MIL													150	1	0				**1**
BCP	LIS										207	0	1							**1**
CIBC	TOR										173	0	1							**1**
DANSKE BANK	COP										174	0	1							**1**
ICBC	LON							73	1	0										**1**
SEB	STO										189	0	1							**1**
Total			**11**	**12**		**15**	**15**		**8**	**15**		**3**	**8**		**28**	**21**		**6**	**10**	**152**

Table 6.5 Investigations, Law Suits and Fines

This table reports a collection of fines imposed on the banks following the investigations and law suits. The data are collected from various regulatory press releases and news disclosures. Since some investigations are still on going, this table covers all announcements up to December 2015. The fines are reported in millions of dollars. FCA: Financial Conduct Authority, FINMA: Swiss Financial Market Supervisory Authority, CFTC: Commodity Futures Trading Commission, OCC: office of the comptroller of the currency, DOJ: Department of Justice, Fed: Federal Reserve, N.Y.D.F.S: New York State Department of Financial Services, Scott + Scott: Scott and Scott LLP Law Firm. The shaded rows indicate banks that are identified in Table 6.4.

Country	U.K.	Swiss	United States of America						Total
Investigation	FCA	FINMA	CFTC	OCC	DOJ	Fed	N.Y.D.F.S	Scott + Scott	
Banks									
BARCLAYS	441		400		650	342	485	384	2,702
CITI	358		310	350	925	342			2,285
JP MORGAN	352		310	350	550	342		99.5	2,004
RBS	344		290		395	274		255	1,558
UBS	371	139	290		203	342		135	1,480
HSBC	343		275					285	903
BOA				250		205		180	635
BNP PARIBAS									
GOLDMAN SACHS								249	249
Total	2,209	139	1,875	950	2,723	1,847	485	1,588	11,816

Table 6.6 Dealers with Manipulative Activities during Fixing

This table reports a list of dealer-locations that are identified by the simulations to have manipulative/significant-abnormal activity in March 2016. If the realised ManIx score is significant at the 5% level given the simulated ManIx distribution from the 10,000 simulations, the dealer's behaviour in that day is classified as manipulative - otherwise it is classified as random or non-manipulative. This table reports the total number of days a dealer participates in the fixing and the number of days their ManIx measures are significant for the Bid and Ask prices. Columns CT, CA, and CB demonstrate the total number of days that a dealer has been active and total number of significant ManIx for ask and bid, respectively.

		EUR/GBP			EUR/JPY			EUR/USD			GBP/JPY			GBP/USD			USD/JPY			Sum
Dealer	**Location**	C_T	C_A	C_B	C_T	C_A	C_B	C_T	C_A	C_B	C_T	C_A	C_B	C_T	C_A	C_B	C_T	C_A	C_B	
RBS	**LON**	19	1	1	19	0	1										19	0	1	4
Rabobank	**LON**	18	0	2				19	0	1				18	0	1				4
Barclays	**LON**	20	0	1	20	1	0													2
BNY Mellon	**NYC**																18	1	0	1
Total		20	1	4	20	1	1	20	0	1	20	0	0	20	0	1	20	1	1	11

Table 6.7 Frequency of Manipulation Occurrence

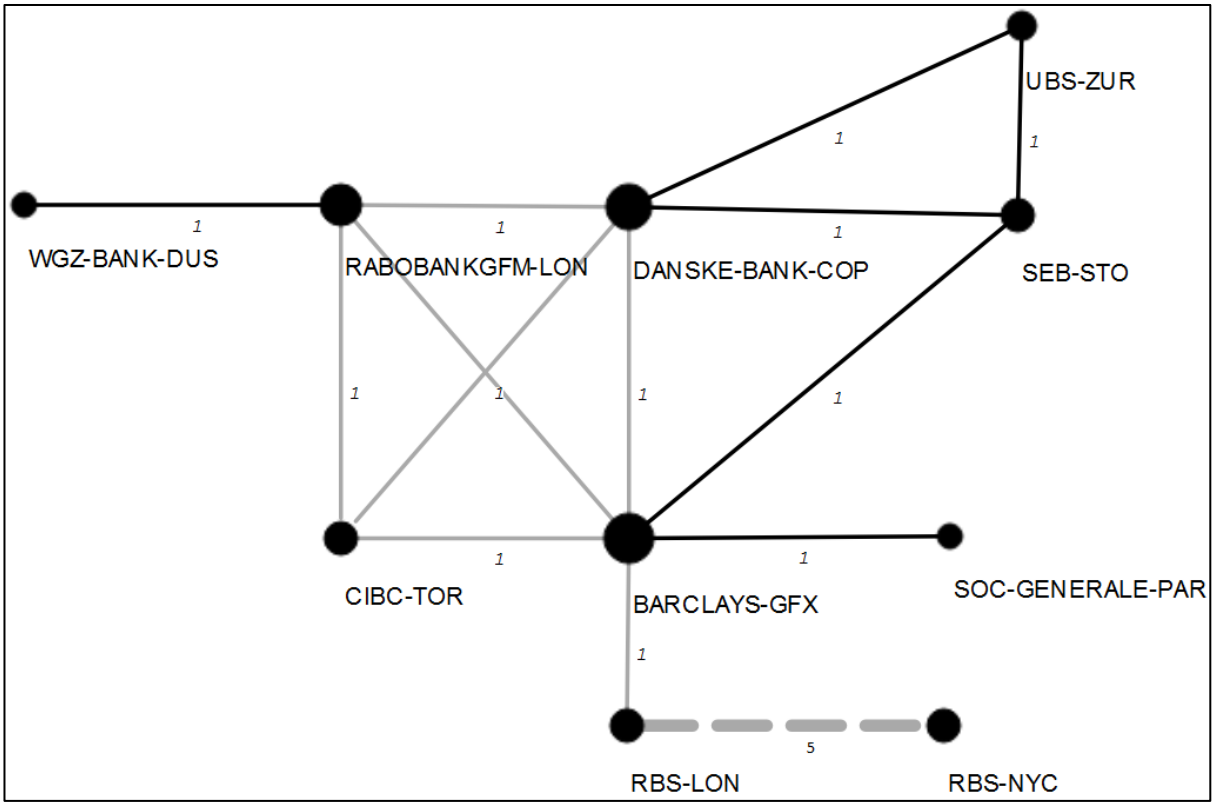
This table reports the frequency of the occurrence of significant ManIx for the 2013-14 and 2016 periods. The column Dealer-Day shows the total number of dealers who have been active in all days in a currency pair. The column Events reports the number of significant ManIx for both ask and bid. The column E/DD is the percentage of significant ManIx occurrence that has been calculated by dividing Events by Dealer-Day.

	2013-2014			2016		
Currency	**Dealer-Day**	**Events**	**E/DD**	**Dealer-Day**	**Events**	**E/DD**
EUR/GBP	3,982	23	0.58%	384	5	1.30%
EUR/JPY	3,895	30	0.77%	381	2	0.52%
EUR/USD	4,276	23	0.54%	415	1	0.24%
GBP/JPY	3,896	11	0.28%	381	0	0.00%
GBP/USD	4,653	49	1.05%	390	1	0.26%
USD/JPY	3,404	16	0.47%	317	2	0.63%
Total	**24,106**	**152.00**	**0.63%**	**7491.00**	**11.00**	**0.15%**

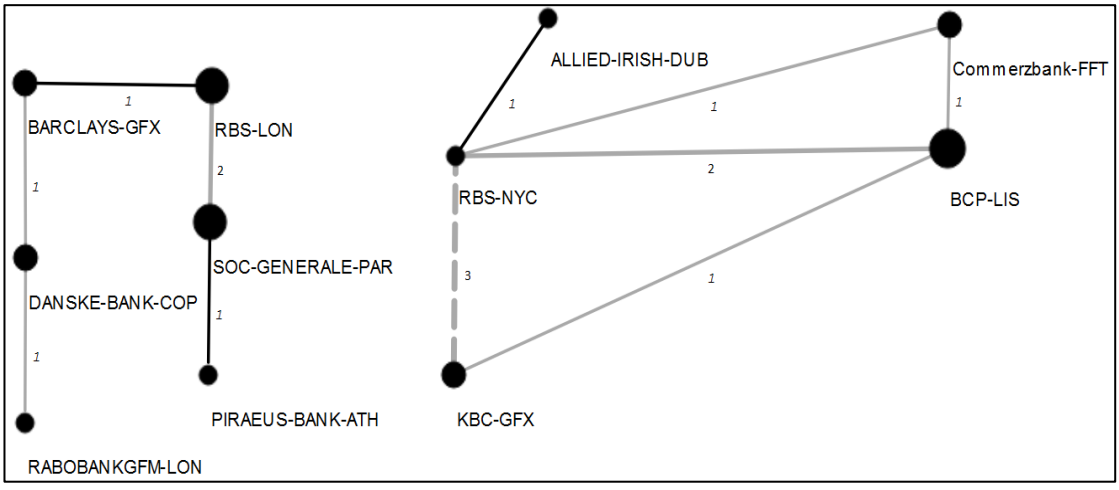
Figure 6.2 Manipulative Networks

This figure illustrates the identified network of manipulators for each of the six currency pairs. In order to identify the network of manipulators, the network connection and strength is determined by the number of the times that any two banks have a significant ManIx for a currency pair on a same day. The weight on each link demonstrates the number of days that a specific pair of dealers may have colluded together. The grey, black, and grey dashed lines illustrate collusion between dealers in manipulating bid, ask, and both bid and ask prices, respectively.

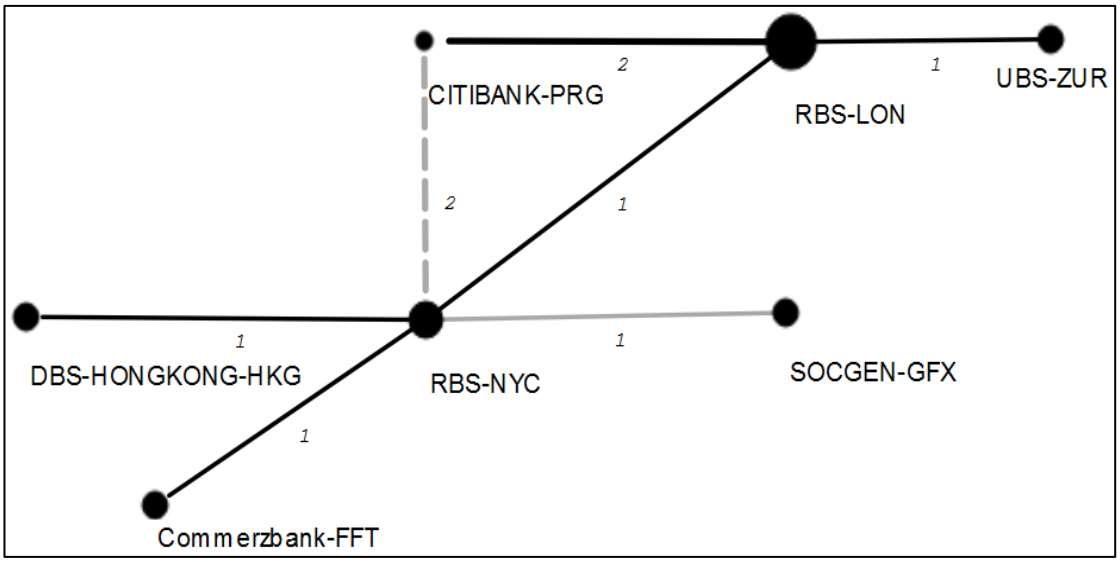
Panel A. EUR/GBP



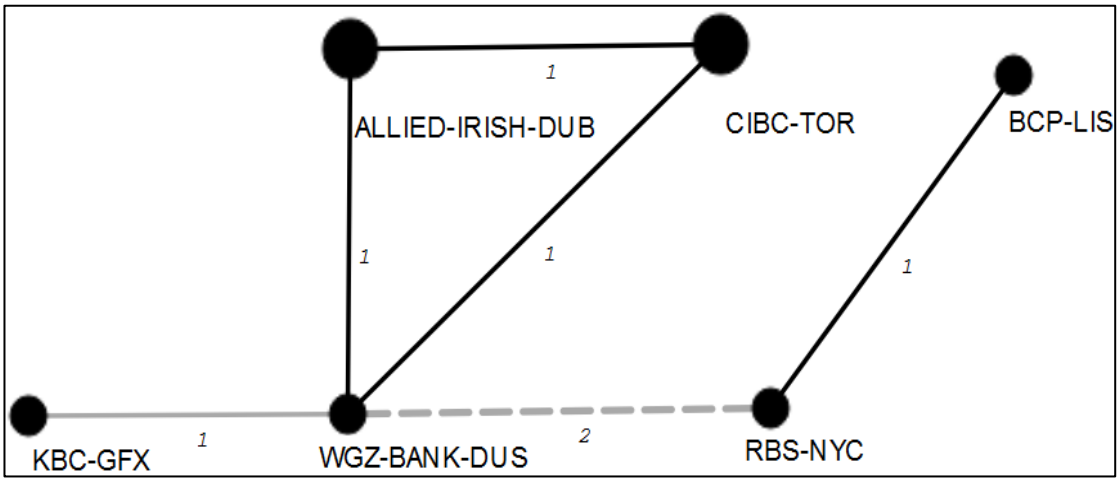
Panel B. EUR/JPY



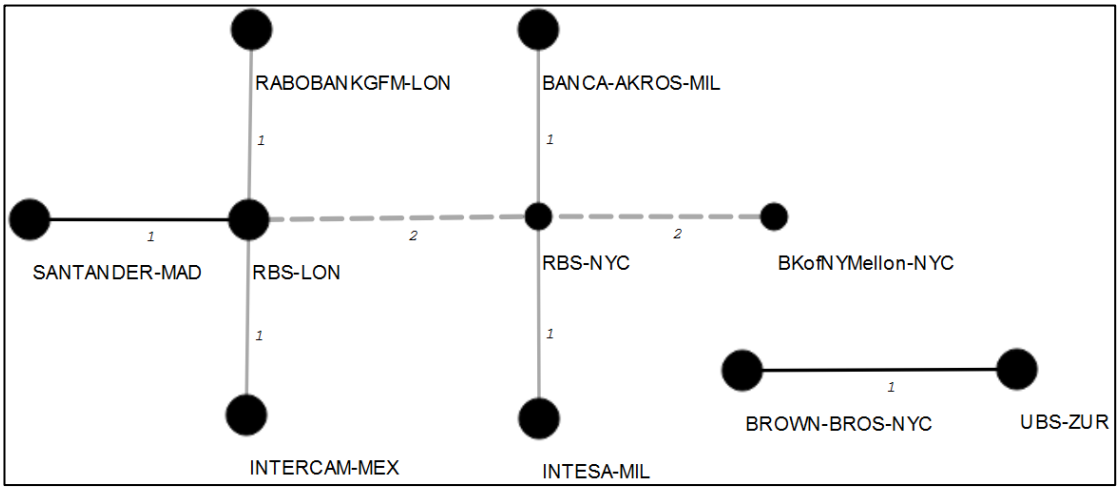
Panel C. EUR/USD



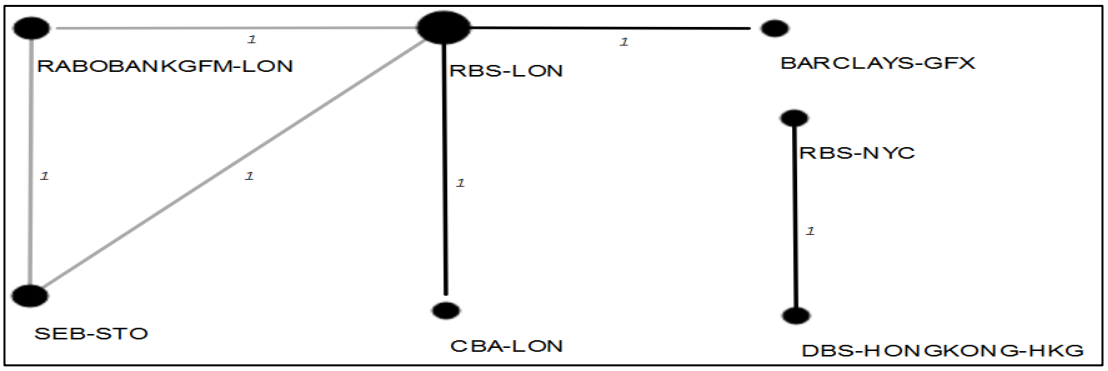
Panel D. GBP/JPY



Panel E. GBP/USD



Panel F: USD/JPY



Appendix I

This appendix reports the active dealers, their locations and the number of quotes during the fix

Panel A. Active Dealers in Africa

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ABSA BANK	SOUTH AFRICA	JOHANNESBURG			11			
NEDBANK	SOUTH AFRICA	JOHANNESBURG					2,522	

Panel B. Active Dealers in Asia

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
AL HILAL BANK	UAE	ABU DHABI			4		4	
ASYA KATILIM BANKASI A.S	TURKEY	ISTANBUL			53		59	
BANK MUSCAT	SAUDI ARABIA	RIYADH			8		5	
BANK OF COMMUNICATION	CHINA	SHANGHAI	41	44		57	41	43
INDUSTRIAL AND COMMERCIAL BANK OF CHINA	HONG KONG	HONG KONG			12		9	11
ING BANK	TURKEY	ISTANBUL					811	
KASPI BANK	KAZAKHSTAN	ALMATY			383		388	353
NATIONAL BANK OF OMAN	OMAN	MUSCAT			7		7	6
OMAN ARAB BANK	OMAN	MUSCAT			8			6
PROMSVYAZ BANK	RUSSIA	MOSCOW			14			
QATAR ISLAMIC BANK	QATAR	DOHA			497			
YAPI KREDI BANK	TURKEY	ISTANBUL			6		210	

Panel C. Active Dealers in Australia

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
LLOYDS BANK	AUSTRALIA	SYDNEY	45					
WESTPAC BANK	AUSTRALIA	SYDNEY	71	88	59	101	89	72

Panel D. Active Dealers with Multiple Location

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
AUSTRALIA AND NEW ZEALAND BANKING GROUP	GLOBAL FOREX	GLOBAL FOREX	1					
BANQUE INTERNATIONALE A LUXEMBOURG	GLOBAL FOREX	GLOBAL FOREX	3	2	1	2		
BARCLAYS	United Kingdom	GLOBAL FOREX	1,336	1,105		1,377	799	677
DEUTSCHE BANK AG LONDON	United Kingdom	GLOBAL FOREX	149	7	82	7	2	1
GOLDMAN SACHS INTERNATIONAL	GLOBAL FOREX	GLOBAL FOREX	15	7	5	8	6	2
HSBC	GLOBAL FOREX	GLOBAL FOREX	24		6		3	
HSBC BANK USA	GLOBAL FOREX	GLOBAL FOREX	11		2		1	
KBC GROUP	GLOBAL FOREX	GLOBAL FOREX	2	686		907	318	601

NATIONAL AUSTRALIA BANK	GLOBAL FOREX	GLOBAL FOREX			3			
NEDBANK	GLOBAL FOREX	GLOBAL FOREX			84		156	4
SOCIETE GENERALE	GLOBAL FOREX	GLOBAL FOREX	69		383		192	12
N/A	GLOBAL FOREX	GLOBAL FOREX	12	17		22		

Panel E. Active Dealers in America

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
BANK OF MONTREAL-BANQUE DE MONTREAL	CANADA	MONTREAL			54		107	56
Brown Brothers Harriman & Co	U.S.A	NEW YORK		311	291	407	289	288
RADA FOREX	U.S.A	NEW YORK		9		12	1	4
RBS	U.S.A	NEW YORK	4,045	4,244	4,426	6,078	4,460	4144
SKANDINAVISKA ENSKILDA BANK	U.S.A	NEW YORK	286				386	
THE BANK OF NEW YORK MELLON	U.S.A	NEW YORK			546		755	564
INTERCAM BANK	MEXICO	MEXICO CITY			4		236	

Panel F. Active Dealers in Europe

Name	Country	City	€/£	€/¥	€/$	£/¥	£/$	$/¥
ALLIED IRISH	IRELAND	DUBLIN	427	513	342	698	498	330
BANCA AKROS	ITALY	MILAN	217	224	116	284	265	259
BANCA MONTE DEI PASCHI DI SIENA	ITALY	MILAN	32	34	22	42		
BANCO COMMERCIAL PORTUGUES SA	PORTUGAL	LISBON		1,517		1,977		
BANCO DE SABADELL	SPAIN	SABADELL	244	257	172	324		
BANCO POPOLARE	ITALY	BERGAMO	252	259	148	318	210	
BANCPOST SA	ROMANIA	BUCHAREST					125	
BANK BPH SA	POLAND	WARSAW	58		61		74	63
CAIXA GERAL DE DEPOSITOS	PORTUGAL	LISBON	69	72		86	4	
CANADIAN IMPERIAL BANK OF COMMERCE CIBC	CANADA	TORONTO	402	501		646	572	
CITIBANK	CZECH REPUBLIC	PRAGUE			1,768			
COMMERZBANK	GERMANY	FRANKFURT	946	860	979	1,106	1,058	695
COMMONWEALTH BANK OF AUSTRALIA	UNITED KINGDOM	LONDON						1,491
DANSKE BANK	DENMARK	COPENHAGEN	781	696	328	884	347	268
DBS BANK	HONG KONG	HONG KONG			761			850
DEN NORSKE BANK	NORWAY	OSLO			1		9	13
DIE ERSTE OESTERR. SPAR-CASSE BANK	AUSTRIA	VIENNA			97			103
HSBC	UNITED KINGDOM	LONDON			313		50	

I.C.M. INVESTMENTBANK AG	ITALY	MILAN			140			
INDUSTRIAL AND COMMERCIAL BANK OF CHINA	UNITED KINGDOM	LONDON			261			
INTESA SANPAOLO BANK	ITALY	MILAN	347	342	324	423	340	
LANDESBANK BADEN-WÜRTTEMBERG	GERMANY	STUTTGART	101	107	95	142	106	
NORDEA BANK	DENMARK	COPENHAGEN	245	316	284	401	318	303
PALATINE BANK AND TRUST	FRANCE	PARIS	8	14	12	17	11	10
PIRAEUS BANK	GREECE	ATHENS	72	76	49	102		
RABO BANK FINANCIAL GLOBAL MARKET	UNITED KINGDOM	LONDON	816	133	562	181	587	603
RAIFFEISEN BANK	ALBANIA	TIRANA			24			
RBS	UNITED KINGDOM	LONDON	2,070	1,624	2,765	1,896	2,552	1,983
SANTANDER	SPAIN	MADRID	224	9		14	209	
SKANDINAVISKA ENSKILDA BANK	SWEDEN	STOCKHOLM	756	413		509		738
SOCIETE GENERALE	FRANCE	PARIS	576	857	677	1,088		264
UBS	SWITZERLAND	ZURICH	368	385	378	501	375	306
WGZ BANK	GERMANY	DÜSSELDORF	912	925	815	1,188	927	
ZUERCHER KANTONALBANK	SWITZERLAND	ZURICH	123	171	128	222	179	100

Chapter 7 Conclusion

7.1. Introduction

Advances in information technologies and the emergence of algorithmic and high frequency traders have dramatically changed the way that financial markets work. The emergence of HFTs, these new highly sophisticated and fast market players has raised concerns of regulators, academics, and practitioners regarding their potential negative impact on financial markets. Many studies have examined the impact of ATs and HFTs in financial markets, particularly in equity markets. However, there is a lack of study on the impact of HFTs and ATs on the FX market due to the lack of reliable data and difficulties in identifying market participants (BIS, 2011). Examining the impact of ATs and HFTs on this market is of great importance because the FX market is the biggest and arguably the most important financial market in the world, which impacts on almost every aspect a of country's economy. The first contribution of this thesis is the construction of a unique and comprehensive Quote Dataset that has two advantages over existing datasets. First, it includes the identity and location of market participants that addresses the issue of market participants' identification and second, it is accurate to the millisecond making it an adequate dataset for studying high frequency quoting.

This thesis attempts to explore the impact of HFTs on the price discovery process, one of the most prominent functions of financial markets, in the FX market. This is done through three empirical chapters. The first empirical chapter (chapter 4) studies the impact of the individual market participant's quoting speed on short-term and long-term price discovery. The second empirical chapter (chapter 5) examines the impact of economist affiliation, geographical proximity, and the quoting speed of a market participant on his contribution to price discovery around macroeconomic news announcements. Finally, the third empirical chapter (chapter 6) designs, implements, and tests an algorithm for identifying market participants who manipulate the WM/R fix rate that is one of the most important benchmarks in the FX.

This chapter is structured as follows. Section 7.2 summarises the findings of the three empirical chapters and explains their implications and section 7.3 discusses the limitations of this study and introduces some directions for future research in this field.

7.2. Summary of Findings and Regulatory Implications

7.2.1. High Frequency Quoting and Price Discovery

The first empirical chapter of this thesis (chapter 4) examines the impact of individual market participants' quoting speed on their contribution to price discovery. Two time horizons of 1-minute and 1-day are studied, where the 1-minute time horizon is used as a proxy for short-term or transitory price discovery and the 1-day time horizon is used as a proxy for long-term price discovery. In order to quantify the market participants' speed, a new measure of speed is defined, which in addition to the number of quotes disseminated by a dealer also controls for the time period that a market participant has been active. In addition, to control for a dealer's one-sided trading and inventory control three measures of buy-sell intention, widening spread, and quote aggressiveness are defined. Chapter 4's

findings show while the increase in quoting speed of market participants improves their ability in predicting short-term price movements (contributing to short-term market price discovery), there is no relationship between the quoting speed of dealers and their impact on long-term, price discovery.

This finding supports short-termism in the FX markets and shows that market players in the FX focus more on short-term information that could be unrelated to fundamentals rather than fundamental information. Theoretical and empirical studies explain that the concentration of market participants on short-term information rather than fundamental information distorts the price discovery process and makes markets less efficient (Froot et al., 1992; Menkoff, 2001; Zhang, 2010; Vives, 1995). The lack of relationship between market participants quoting speed and their contribution to long-term price discovery and strong evidence of short-termism in the FX market reflect the concerns of academics, practitioners, and regulators regarding the potential negative effects of HFTs on market efficiency. The regulatory implication of this finding suggests that the arms race in trading technology is potentially a social waste since it does not produce social benefit by having no impact on the long-term information discovery which is the key function of financial markets.

7.2.2. Do Economists Add Value to the FX?

Macroeconomic news announcements are one of the main driving forces behind exchange rate movements. Therefore, it is of a great importance to study the factors that impact market participants' contribution to price discovery around them. The second empirical chapter (chapter 5) of this thesis evaluates the impact of economist affiliation, geographical proximity, and quoting speed on the contribution of market participants to the price discovery in the FX market. Although previous studies have examined the impact of these three factors in equity markets, their findings cannot be extended to the FX market

due to the differences in the scope of macroeconomic and firm specific news, information transfer medium transparency, and market structure. Chapter 5's results show that, similar to equity markets, market makers with economist affiliation are more informed. However, the level of a market maker' information content is positively affected by the increase in the scope of his affiliated economists' research regarding a country's economic condition. This is one of the differences between FX and equity markets that arises from the difference in the scope of macroeconomic and firm specific news. Overall, the findings regarding the impact of the economists' affiliation demonstrate that the positive impact of information collection sources on market makers' information quality, is independent of the market structure and information transfer medium. The results regarding the quoting speed of market participants are similar to those in the equity markets. Chapter 5 also shows that the quoting speed of market participants significantly impacts on their contribution to price discovery and the size of this impact is considerably higher than that of having affiliated economists.

The geographical proximity factor is divided into three subsections of geographical proximity of dealers and affiliated economists to macroeconomist news sources and dealers and economist to each other. The findings depict that the geographical proximity of dealers and economists to macroeconomic news sources significantly and positively impacts on the market makers' contribution to price discovery, and this impact is considerably higher than that of speed and economist affiliation. However, it is also found that the position of market makers and their affiliated economists in the same country limits the amount of information that they can access and this is independent of the quality of information set. In other words, this finding shows that there is a limit to the amount of information that can be accessed from the same location, independent of the quality of information.

Chapter 5 also contributes to the regulatory debate in two ways. First, the findings in chapter 5 show that the market participants' quoting speed has a significantly positive impact on their information advantage. Therefore, early access of high speed market participants to macroeconomic news announcements could create an unfair market environment and impose significant adverse selection costs on slower traders. Second, the evidence presented in chapter 5 demonstrates that the information advantage of market makers with economist affiliation is dependent on the scope of their affiliated economists' research. Considering that there is no evidence of privileged access to macroeconomic news, the evidence suggests that there is no need for an imposition of regulations similar to Regulation FD regarding the macroeconomic news announcements, at least in the context of the FX market.

7.2.3. Monitoring the FX Rate Benchmark Fix

In light of the WM/R fix rate manipulation news, the trigger of 20 regulatory investigations and consequently the highest amount of fines on banks in history, the third empirical chapter of this thesis (chapter 6) focuses on the process of WM/R fix rate discovery and proposes a methodology to identify the manipulators of this rate. WM/R fix rate is one of the most prominent benchmarks in the FX market that affect $3.6 trillion of assets. Its manipulation impacts on almost every entity that is involved in international investment and transactions. The break of the WM/R fix rate manipulation news has been a shock to the financial system and regulators and raised concerns regarding the lack of regulatory oversight in the FX markets.

Given the rise of high frequency and algorithmic trading in the FX market and limited resources of regulators, the challenge that regulators face is the design of a method that in a timely manner can monitor market participants and provide a warning signal that prompts further investigation. Chapter 6 of this thesis designs, implements, and tests an algorithm for monitoring and identification of WM/R fix rate manipulators. This methodology that is

called manipulation index (ManIx) is designed by understanding a manipulator's objective function and consists of two phases of identification and verification. These two phases are designed to identify the market participants who systematically and strategically place their quotes to move the WM/R fix rate in their desired direction and differentiate such behaviour from the random process of price discovery. ManIx identifies 17 out of 69 dealers in the Quote Dataset, who were active within the WM/R fixing window. Out of these 17 dealers 8 of them have been investigated by regulators or sued by their clients and investors. 4 of the identified banks as manipulators account for 68% of the fines imposed by regulators. These findings demonstrated the ability of the ManIx in monitoring and identifying manipulative behaviour of market participants and its applicability for regulators and policy makers. Chapter 6's contribution to the existing academic literature and regulatory framework is threefold. First, it addresses the challenge of monitoring the unregulated FX market, second it contributes to the debate on the manner that regulators should respond to the new structural changes in financial markets and rapid changes in financial technology. Finally, chapter 6 illustrates how quote data could be useful for monitoring and identifying abnormal behaviour in the FX markets.

7.4. The Limitations of The Current Study & Future Research

Although this thesis research deepens the understanding of the price discovery process in the FX markets, it is not without its limitations. The first empirical chapter of this thesis contributed to the existing regulatory framework and academic literature by demonstrating the impact of a dealer's quoting speed on the price discovery process. The results of the first empirical study show that while the increase in the quoting speed of market participants increases their ability to forecast short-term price movements, there is no relationship between quoting speed and a dealer's contribution to long-term price discoveries. However, this research could benefit by combining its dataset with transaction data

(conditional on the inclusion of the traders' identity) to further examine the impact of order cancellation and messaging traffic on the price discovery process. It should be mentioned here that obtaining transaction data with the dealers' identity in order to be merged with the Quote Dataset could be difficult.

The second empirical chapter of this thesis studied the impact of economist affiliation, quoting speed, and geographical proximity of a dealer to economists and news sources on dealers' information content. The results show that the affiliation of a dealer with economists, particularly the increase in the scope of his affiliated economists' research, adds to the dealer's information content. The locality of affiliated economists and dealers are also found to have a significant impact on a dealer's information quality. There are some reasons given for the locality advantage in the context of equity markets, however, examining them in the context of the FX market requires a longer time series. A longer time series would allow a better examination of the locality advantage and the reasons behind it. Therefore, this research could benefit from a longer time series. Future research can also examine how affiliated economists gender, education, work experience, and age impacts on their dealer's behaviour. It is interesting to see how the affiliated economists' characteristics translates into a dealer's quoting behaviour, if any. This can further help in understanding better the FX market information transfer medium mechanisms.

Finally, the third empirical chapter of this thesis designs, tests, and implements an algorithm called ManIx for identifying market participants who systematically and strategically manipulated the WM/R fix rate. This algorithm contributes to the existing debate on the manner in which regulators should respond to new changes in financial markets. Regulators can use ManIx to monitor market participants and individual FX dealers could use ManIx to monitor their traders and entities who use their prime brokerage services. Future research could add to ManIx by adjusting the design of ManIx to verification phases

mentioned in the World Market Company's methodology documentation. The World Market Company mentions two phases of validation, while it does not explain explicitly how these validations work and what trades or quotes, if any, are affected by these validation phases. This adjustment, combined by using the exact data sources that WM/R uses, could significantly increase the accuracy of ManIx.

References

Abarbanell, J. S. & Bushee, B. J., 1997. Fundamental Analysis, Future Earnings, and Stock Prices. *Journal of Accounting Research,* **35**, 1-24.

Ahmed, K., 2014. *RBS boss admits – I cringed when I read forex chat room messages.* [Online] Available at: http://www.bbc.co.uk/news/business-30027544 [Accessed 25 May 2016].

Alford, A. W. & Berger, P. G., 1999. A Simultaneous Equations Analysis of Forecast Accuracy, Analyst Following, and Trading Volume. *Journal of Accounting, Auditing & Finance,* 14, 219-240.

Anand, A. , Gatchev, V. A., Madureira, L., Pirinsky, C. A., Underwood, S., 2011. Geographic proximity and price discovery: Evidence from NASDAQ. *Journal of Financial Markets,* **14**, 193-226.

Anand, A. & Venkataraman, K., 2013. *Should Exchanges impose Market Maker obligations?.*

Andersen, T. G., Bollerslev, T., Diebold, F. X. & Vega, C., 2007. Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics,* **73**, 251-277.

Bae, K.-H., Stulz, R. M. & Tan, H., 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics,* **88**, 581-606.

Baillie, R. T., Booth, G. G., Tse, Y. & Zabotina, T., 2002. Price discovery and common factor models. *Journal of Financial Markets,* **5**, 309-321.

Bank for International Settlements, 2011. *High-frequency trading in the foreign exchange market.*

Bank for International Settlements, 2013. *Triennial Central Bank Survey; Foreign exchange turnover in April 2013: preliminary global results.*

Barclay, M. J. & Warner, J. B., 1993. Stealth trading and volatility. *Journal of Financial Economics,* **34**, 281-305.

Barclay, M. J., Hendershott, T., 2003. Price discovery and trading after hours. *The Review of Financial Studies*, **16**, 1041-1073.

Berger, D. W., Chaboud, A. P., Chernenko, S. V., Howorka, E., Weight J. H., 2008. Order flow and exchange rate dynamics in electronic brokerage system data. *Journal of International Economics,* **75**, 93-109.

Berger, H., Ehrmann, M. & Fratzscher, M., 2009. Forecasting ECB monetary policy: Accuracy is a matter of geography. *European Economic Review,* **53**, 1028-1041.

Bessembinder, H., 1994. Bid-ask Spreads in the interbank foreign exchange markets. *Journal of Financial Economics,* 317-348.

Biais, B., Foucault, T. & Moinas, S., 2015. Equilibrium fast trading. *Journal of Financial Economics,* **116**, 292-313.

Bjønnes, G. H. & Rime, D., 2005. Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics,* **75**, 571-605.

Bloomberg Visual Data, 2015. *Forex Investigation a Global Affair.* [Online]
Available at: http://www.bloomberg.com/infographics/2014-08-13/forex-investigation-a-global-affair.html
[Accessed 25 May 2016].

Blume, M. E., Mackinlay, A. C. & Terker, B., 1989. Order Imbalances and Stock Price Movements on October 19 and 20, 1987. *The Journal of Finance,* **54**, 827-848.

Bolliger, G., 2004. The characteristics of individual analysts' forecasts in Europe. *Journal of Banking & Finance,* **28**, 2283-2309.

Booth, L. D., 1984. Bid-ask spreads in the market for forward exchange. *Journal of International Money and Finance,* **3**, 209-222.

Bradshaw, M. T., Drake, M. S., Myers, J. N. & Myers, L. A., 2012. A re-examination of analysts' superiority over time-series forecasts of annual earnings. *Review of Accounting Studies,* **17**, 944-968.

Brenhardt, D., Hughson, E., 2002. Intraday trade in dealership markets. *European Economic Review,* **46**, 1697-1732.

Brennan, M. J., Jegadeesh, N. & Swaminathan, B., 1993. Investment Analysis and the Adjustment of Stock Prices to Common Information. *Review of Financial Studies,* **6**, 799-824.

Brogaard, J., Hendershott, T. & Riordan, R., 2014. High-Frequency Trading and Price Discovery. *The Review of Financial Studies,* **27**, 2267-2306.

Brown, L. D. & Rozeff, M. S., 1978. The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings. *The Journal of Finance,* **33**, 1-16.

Cabrera, J., Wang, T. & Yang, J., 2009. Do futures lead price discovery in electronic foreign exchange markets?. *Journal of Futures Markets,* **29**, 137-156.

Cai, C. X., Harris, J. H., Hudson, R. S. & Keasey, K., 2015. Informed Trading and Market Structure. *European Financial Management*, **21**, 148-177.

Carlson, J. A. & Lo, M., 2006. One minute in the life of the DM/US$: Public news in an electronic market. *Journal of International Money and Finance,* **25**, 1090-1102.

Carrion, A., 2013. Very fast money: High-frequency trading on the NASDAQ. *Journal of Financial Markets,* **16**, 680-711.

Castura, J., Litzenberger, R., Gorelick, R. & Dwivedi, Y., 2010. *Market Efficiency and Microstructure Evolution in U.S Equity Market: A High Frequency Perspective,* RGM Advisors.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E. & Vega, C., 2014. Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market. *The Journal of Finance,* **69**, 2045-2084.

Chan, K. & Fong, W.-M., 2000. Trade size, order imbalance, and the volatility–volume relation. *Journal of Financial Economics,* **57**, 247-273.

Chelley-Steeley, P. L. & Tsorakidis, N., 2013. Bid-ask spread dynamics in foreign exchange markets. *International Review of Financial Analysis,* **29**, 119-131.

Chen, Q. & Jiang, W., 2006. Analysts' Weighting of Private and Public Information. *Review of Financial Studies,* **19**, 319-355.

Chen, S. & Matsumoto, D. A., 2006. Favorable versus Unfavorable Recommendations: The Impact on Analyst Access to Management-Provided Information. *Journal of Accounting Research,* **44**, 657-689.

Chen, Y.-L. & Gau, Y.-F., 2014. Asymmetric responses of ask and bid quotes to information in the foreign exchange market. *Journal of Banking and Finance,* January, **38**, 194-204.

Cheung, Y.-W. & Chinn, M. D., 1999. *Macroeconomic Implications of the Beliefs and Behavior of Foreign Exchange Traders,* IFM.

Chordia, T., Goyal, A., Lehmann, B. N. & Saar, G., 2013. High-frequency trading. *Journal of Financial Markets,* **16**, 637-645.

Chordia, T., Green, T. C. & Kottimukkalur, B., 2015. *Do High Frequency Traders Need to be Regulated? Evidence from Algorithmic Trading on Macro News.*

Chordia, T., Roll, R. & Subrahmanyam, A., 2002. Order imbalance, liquidity, and market returns. *Journal of Financial Economics,* **65**, 111-130.

Chung, K. H. & Cho, S.-Y., 2005. Security analysis and market making. *Journal of Financial Intermediation,* **14**, 114-141.

Cole, T. & Smart, J., 2013. *An Introduction to FX Algorithms.*

Commodity Futures Trading Commission , 2014. *CFTC Orders Five Banks to Pay over $1.4 Billion in Penalties for Attempted Manipulation of Foreign Exchange Benchmark Rates.* [Online]
Available at: http://www.cftc.gov/PressRoom/PressReleases/pr7056-14
[Accessed 25 May 2016].

Commodity Futures Trading Commission , 2015. *Barclays to Pay $400 Million Penalty to Settle CFTC Charges of Attempted Manipulation and False Reporting of Foreign Exchange Benchmark Rates.* [Online]
Available at: http://www.cftc.gov/PressRoom/PressReleases/pr7181-15
[Accessed 25 May 2016].

Conrad, J., Wahal, S. & Xiang, J., 2015. High-frequency quoting, trading, and the efficiency of prices. *Journal of Financial Economics,* **116**, 271-291.

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

Cunningham, L. A., 1994. Capital Market Theory, Mandatory Disclosure, and Price Discovery. *Washington and Lee Law Review,* **51**, 843-877.

Dacorogna, M. M. , Gencay, R., Muller, U., Olsen, R. B., Pictet, O. V., 2001. *An Introduction to High-Frequency Finance.* Academic Press.

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

Department of Justice, 2015. *Five Major Banks Agree to Parent-Level Guilty Pleas.* [Online] Available at: https://www.justice.gov/opa/pr/five-major-banks-agree-parent-level-guilty-pleas [Accessed 25 May 2016].

Detrixhe, J., Gammeltoft, N. & Mamudi, S., 2014. *High-Frequency Traders Chase Currencies.* [Online] Available at: http://www.bloomberg.com/news/articles/2014-04-02/high-frequency-traders-chase-currencies-as-stock-volume-recedes [Accessed 25 May 2016].

Ederington, L. H. & Lee, J. H., 1995. The Short-Run Dynamics of the Price Adjustment to New Information. *Journal of Financial and Quantitative Analysis,* **30**, 117-134.

Ehrmann, M. & Fratzscher, M., 2005. Exchange rates and fundamentals: new evidence from real-time data. *Journal of International Money and Finance,* **24**, 317-341.

Engle, R. f., Russel, J. r., 1998. Autoregressive Conditional Duration: a new model for irregularly spaced transaction data. *Econometrica*, **66**, 1127-1162.

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

Evans, M. D. & Lyons, R. K., 2008. How is macro news transmitted to exchange rates?. *Journal of Financial Economics,* **88**, 26-50.

Evans, M. D. & Lyons, R. K., 2012. Exchange Rate Fundamentals and Order Flow. *Quarterly Journal of Finance,* 02.

Federal Reserve, 2015. *Press Release.* [Online]
Available at:
http://www.federalreserve.gov/newsevents/press/enforcement/20150520a.htm
[Accessed 25 May 2016].

Financial Conduct Authority, 2014a. *Citibank Final Notice.*

Financial Conduct Authority, 2014b. *HSBC Final Notice.*

Financial Conduct Authority, 2014c. *Royal Bank of Scotland Plc Final Notice.*

Financial Conduct Authority, 2014d. *UBS AG Final Notice.*

Financial Conduct Authority, 2014e. *FCA fines five banks £1.1 billion for FX failings and announces industry-wide remediation programme.* [Online]
Available at: http://www.fca.org.uk/news/fca-fines-five-banks-for-fx-failings
[Accessed 25 May 2016].

Financial Conduct Authority, 2015. *Barclays Bank plc Final Notice.*

Financial Stability Board, 2014. *Foreign Exchange Benchmarks.*

Finch, G. & Vaughan, L., 2014. *Traders Boasted of Whacking FX Market.* [Online]
Available at: http://www.bloomberg.com/news/articles/2014-11-13/-cartell-chat-room-traders-boasted-of-whacking-fx-market
[Accessed 25 May 2016].

FINMA, 2014. *FINMA sanctions foreign exchange manipulation at UBS.* [Online]
Available at: https://www.finma.ch/en/news/2014/11/mm-ubs-devisenhandel-20141112/
[Accessed 25 May 2016].

Foreign Exchange Joint Standing Committee, 2014. *The Foreign Exchange Joint Standing Committee.* [Online]
Available at:
http://www.bankofengland.co.uk/markets/Documents/forex/fxjsc/fxturnresults140728.pdf
[Accessed 25 May 2016].

Franke, J., Neumann, M. H. & Stockis, J.-P., 2004. Bootstrapping nonparametric estimators of the volatility function. *Journal of Econometrics,* **118**, 189-218.

Frijns, B., & Schotman, P., 2009. Price discovery in tick time. *Journal of Empirical Finance,* **16**, 759-776.

Frino, A., Mollica, V. & Webb, R. I., 2014. The Impact of Co-Location of Securities Exchanges' and Traders' Computer Servers on Market Liquidity. *Journal of Futures Markets,* **34**, 20-33.

Froot, K. A., Scharfstein, D. S. & Stein, J. C., 1992. Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation. *The Journal of Finance,* September, **47**, 1461-1484.

FXDD Global, 2013. [Online]
Available at:
http://www.fxdd.com/fileadmin/user_upload/pdfs/mt/en/CurrencyPairguide.pdf
[Accessed 25 May 2016].

Gaal, M. V. & Choudhury, A., 2014. *Rabobank Suspends Two London Currency Traders After Probe.* [Online]
Available at: http://www.bloomberg.com/news/articles/2014-10-07/rabobank-suspends-two-london-currency-traders-after-probe
[Accessed 6 May 2015].

Gençay, R. & Gradojevic, N., 2013. Private information and its origins in an electronic foreign exchange market. *Economic Modelling,* **33**, 86-93.

Geng, R., Bose, I. & Chen, X., 2015. Prediction of financial distress: An empirical study of listed Chinese companies using data mining. *European Journal of Operational Research,* **241**, 236-247.

Gitman, L. J., Joehnk, M. D., Smart, S. B., 2011. *Fundamental of investing.* London: Pearson Publication.

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

Goldstein, M. A., Kumar, P. & Graves, F. C., 2014. Computerized and High-Frequency Trading. *Financial Review,* **49**, 177-202.

Gonzalo, J. & Granger, C., 1995. Estimation of Common Long-Memory Components in Cointegrated Systems. *Journal of Business & Economic Statistics,* **13**, 27-35.

Goodhart, C. A. & O'Hara, M., 1997. High frequency data in financial markets: Issues and applications. *Journal of Empirical Finance,* **4**, 73-114.

Goodhart, C. A., 1988. The foreign exchange market: a random walk with a Dragging Anchor. *Economica,* **55**, 437-460.

Government Office for Science, 2015. *Fin Tech Futures The UK as a World Leader in Financial Technologies.*

Green, T. C., 2004. Economic News and the Impact of Trading on Bond Prices. *The Journal of Finance,* **59**, 1201-1233.

Green, T. C., 2006. The value of client access to analyst recommendations. *Journal of Financial and Quantitative Analysis,* **41**, 1-24.

Green, R.C., Hollifield, B., Schurhoff, N., 2007. Financial intermediation and the costs of trading in an opaque market. *Review of Financial Studies,* **20**, 275-314.

Green, T. C., Jame, R., Markov, S. & Subasi, M., 2014. Access to management and the informativeness of analyst research. *Journal of Financial Economics,* **114**, 239-255.

Groß-Klußmann, A. & Hautsch, N., 2011. When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance,* **2**, 321-340.

Guillaume, D. M., Dacorogna, M. M., Dave, R. R., Muller, U. A., Olsen, R. B., Pictet, O. V., 1997. From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets. *Finance and Stochastics,* **1**, 95-129.

Hafner, C. M., 1998. Estimating high-frequency foreign exchange rate volatility with nonparametric ARCH models. *Journal of Statistical Planning and Inference,* **68**, 247-269.

Hagströmer, B. & Nordén, L., 2013. The diversity of high frequency traders. *Journal of Financial Markets,* November, **16**, 741-770.

Harris, L., 2003. *Trading and Exchanges; Market Microstructure for Practitioners.* New York: Oxford University Press.

Hasbrouck, J., 1995. One Security, Many Markets: Determining the Contributions to Price Discovery. *The Journal of Finance,* **50**, 1175-1199.

Hasbrouck, J., 2007. *Emprical Market Microstructure; The Institutions, Economics, and Econometrics of Securities Trading.* New York: Oxford University Press.

Hasbrouck, J. & Saar, G., 2013. Low-latency trading. *Journal of Financial Markets,* **16**, 646-679.

Hendershott, T., Jones, C. M. & Menkveld, A. J., 2011. Does Algorithmic Trading Improve Liquidity?. *The Journal of Finance,* **66**, 1-33.

Hendershott, T. & Riordan, R., 2011. *Algorithmic Trading and Information.*

Herbst, A. F., Smith, C. L. & Traichal, P. A., 1997. The existence of a numeraire currency in foreign exchange: Evidence from transaction spot rates for Japan, Germany, and the United States. *Global Finance Journal,* **8**, 181-197.

Hillier, D., Ross, S., Westerfield, R., Jaffe, J., Jordan, B., 2010. *Corporate Finance*. Maidenhead: McGraw-Hill.

HM Treasury, 2015. [Online] Available at: http://www.legislation.gov.uk/ukdsi/2015/9780111127629/pdfs/ukdsiem_9780111127629_en.pdf [Accessed 25 May 2016].

Hoffmann, P., 2014. A dynamic limit order market with fast and slow traders. *Journal of Financial Economics,* **113**, 156-169.

Ito, T., Lyons, R. K. & Melvin, M. T., 1998. Is There Private Information in the FX Market? The Tokyo Experiment. *The Journal of Finance,* **53**, 1111-1130.

Jegadeesh, N., Kim, J., Krische, S. D. & Lee, C. M. C., 2004. Analyzing the Analysts: When Do Recommendations Add Value? *The Journal of Finance,* **59**, 1083-1124.

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

Jong, F. d., Mahieu, R., Schotman, P. & Leeuwen, I. v., 2001. *Price Discovery on Foreign Exchange Markets with Differentially Informed Traders*.

Jovanovic, B. & Menkveld, A. J., 2012. *Middlemen in Limit Order Markets*.

Kedia, S. & Zhou, X., 2011. Local market makers, liquidity and market quality. *Journal of Financial Markets,* **14**, 540-567.

Kehrle, K., & Peter, F. J., 2013. Who moves first? An intensity-based measure for information flows across. *Journal of Banking and Finance,* **37**, 1629-1642.Kennedy,

J., 2015. *Forex Suit Adds Japanese, Canadian, French, UK Banks.* [Online]
Available at: http://www.law360.com/articles/686131/forex-suit-adds-japanese-canadian-french-uk-banks
[Accessed 25 May 2016].

Kim, O. & Verrecchia, R. E., 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics,* **17**, 41-67.

Kim, O. & Verrecchia, R. E., 1997. Pre-announcement and event-period private information. *Journal of Accounting and Economics,* **24**, 395-419.

King, M. R. & Rime, D., 2010. The $4 Trillion Question: What Explains FX Growth Since the 2007 Survey?. *BIS Quarterly Review,* 27 - 42.

King , M. R., Osler , C. . L. & Rime , D., 2011. *Foreign Exchange Market Structure, Players and Evolution.*King , M. R., Osler , C. . L. & Rime , D., 2013. The market microstructure approach to foreign exchange: looking back and looking forward. *Journal of International Money and Finance,* **38**, 95-119.

Kirilenko, A. A., Kyle, A. S., Samadi, M. & Tuzun, T., 2011. *The Flash Crash: High Frequency Trading in an Electronic Market.*

Kleinman, M., 2015. *UK Bank Trio Agree $924m Forex-Rigging Bill.* [Online]
Available at: http://news.sky.com/story/1574604/uk-bank-trio-agree-924m-forex-rigging-bill
[Accessed 25 May 2016].

Korczack, P. & Phylaktis, K., 2010. Related securities and price discovery: Evidence from NYSE-listed Non-U.S. stocks. *Journal of Empirical Finance,* **17**, 566-584.

Koski, J. L. & Michaely, R., 2000. Prices, Liquidity, and the Information Content of Trades. *Review of Financial Studies,* **13**, 659-696.

Kozhan, R. & Tham, W. W., 2012. Execution Risk in High-Frequency Arbitrage. *Management Science,* **58**, 2131-2149.

Lanne, M. & Vesala, T., 2010. The Effect of a Transaction Tax on Exchange Rate Volatility. *International Journal of Finance and Economics,* **15**, 123-133.

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

Li, X. & Heidle, H. G., 2004. *Information Leakage and Opportunistic Behavior Before Analyst Recommendations: An Analysis of the Quoting Behavior of Nasdaq Market Makers*.

Liong, J. A., Liu, H., 2013. The relation of trade size and price contribution in a traditional foreign exchange brokered market. *Pacific-Basin Finance Journal*, **21**, 1024-1045.

Love, R. & Payne, R., 2008. Macroeconomic News, Order Flows, and Exchange Rates. *Journal of Financial and Quantitative Analysis,* June, **43**, 467-488.

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

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

Madhavan , A. & Smidt, S., 1993. An Analysis of Changes in Specialist Inventories and Quotations. *The Journal of Finance,* **68**, p. 1595–1628.

Madureira, L. & Underwood, S., 2008. Information, sell-side research, and market making. *Journal of Financial Economics,* **90**, 105-126.

Malinova, K., Park, A. & Riordan, R., 2013. *Do Retail Traders Suffer from High Frequency Traders?*.

Malloy, C. J., 2005. The Geography of Equity Analysis. *The Journal of Finance,* **60**, 719-755.

Manaster , S. & Mann, S. C., 1996. Life in the Pits: Competitive Market Making and Inventory Control. *Review of Financial Studies,* **9**, 953-975.

Mancini, L., Ranaldo, A. & Wrampelmeyer, J., 2013. Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums. *The Journal of Finance,* **68**, 1805-1841.

Martens, M. & Kofman, P., 1998. The inefficiency of Reuters foreign exchange quotes. *Journal of Banking & Finance,* **22**, 347-366.

Martinez, V. H. & Rosu, I., 2013. *High frequency traders, news and volatility*.

Maxwell, C. E., 1994. *Financial markets and institutions the global view* . St. Paul: West Publishing Company.

McGeever, J., 2014. *Exclusive - FX chatrooms show traders shared order, price details: sources.* [Online]
Available at: http://uk.reuters.com/article/2014/06/19/uk-fx-investigation-idUKKBN0EU1GH20140619
[Accessed 25 May 2016].

Mcinish, T. H. & Wood, R. A., 1992. An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks. *The Journal of Finance,* **47**, 753-764.

Menkoff, L., 2001. Short-term Horizons in Foreign Exchange? Survey Evidence from Dealers and Fund Managers. *KYKLOS,* **54**, 27-48.

Menkveld, A. J., 2013. High frequency trading and the new market makers. *Journal of Financial Markets,* **16**, 712-740.

Menkveld, A. J., 2014. High-Frequency Traders and Market Structure. *Financial Review,* **49**, 333-344.

Michaely, R. & Womack, K. L., 1999. Conflict of Interest and the Credibility of Underwriter Analyst Recommendations. *The Review of Financial Studies,* **12**, 653-686.

Michie, R., 2010. *Regulated Exchange.* Oxford University Press.

Mullins, B., Rothfeld, M., McGinty, T. & Strasburg, J., 2013. *Traders Pay for an Early Peek at Key Data.* [Online]
Available at:
http://www.wsj.com/articles/SB10001424127887324682204578515963191421602
[Accessed 25 May 2016].

New York State Department of Financial Services, 2015. *Press Release.* [Online]
Available at: http://www.dfs.ny.gov/about/press/pr1505201.htm
[Accessed 25 May 2016].

O'Hara, M., 2015. High frequency market microstructure. *Journal of Financial Economics,* **116**, 257-270.

Office of the Comptroller of the Currency , 2014. *OCC Fines Three Banks $950 Million for FX Trading Improprieties.* [Online]
Available at: http://www.occ.treas.gov/news-issuances/news-releases/2014/nr-

occ-2014-157.html

[Accessed 25 May 2016].

O'Hara, M., 2003. Presidential Address: Liquidity and Price Discovery. *The Journal of Finance,* **58**, 1335-1354.

Osler, C. L., Mende, A., Menkhoff, L., 2011. Price discovery in currency markets. *Journal of International Money and Finance,* **30**, 1696-1718.

Pascual, R. & Pascual-Fuster, B., 2014. The relative contribution of ask and bid quotes to price discovery. *Journal of Financial Markets,* September, **20**, 129-150.

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

Peiers, B., 1997. Informed Traders, Intervention, and Price Leadership: A Deeper View of the Microstructure of the Foreign Exchange Market. *The Journal of Finance,* **52**, 1589-1614.

Perez, E., 2011. *The Speed Traders.* McGraw Hill.

Peterson, M. A., & Sirri, E.R., 2003. Order preferencing and market quality on U.S. equity exchanges. *Review of Financial Studies,* **16**, 385-415.

Phylaktis, K. & Chen, L., 2009. Price discovery in foreign exchange markets: A comparison of indicative and actual transaction prices. *Journal of Empirical Finance,* **16**, 640-654.

Pindado, J., 2014. Data management and panel data models.

Popper, N., 2012a. *Beyond Wall St., Curbs on High-Speed Trades Proceed.* [Online] Available at: http://www.nytimes.com/2012/09/27/business/beyond-wall-st-

curbs-on-high-speed-trading-advance.html?_r=0

[Accessed 25 May 2016].

Popper, N., 2012b. *High-Speed Trading No Longer Hurtling Forward.* [Online]

Available at: http://www.nytimes.com/2012/10/15/business/with-profits-dropping-high-speed-trading-cools-down.html?pagewanted=all&_r=0

[Accessed 25 May 2016].

RBS Market Place, 2014a. *RBS Market Place.* [Online]

Available at:

https://www.rbsm.com/psp/public/pagebuilder.aspx?page=rp8000&video=fx-quote

[Accessed 25 May 2016].

RBS Market Place, 2014b. *RBS Market Place.* [Online]

Available at:

https://www.rbsm.com/psp/public/pagebuilder.aspx?page=rp8000&video=fx-stream

[Accessed 25 May 2016].

Rime, D. & Schrimpf, A., 2013. *The anatomy of the global FX market through the lens of the 2013 Triennial Survey,* Bank For International Settlements.

Ring, S. & Vaughan, L., 2014. *Citigroup, JPMorgan Pay Most in $4.3 Billion FX Rig Cases.* [Online]

Available at: http://www.bloomberg.com/news/articles/2014-11-12/banks-to-pay-3-3-billion-in-fx-manipulation-probe

[Accessed 25 May 2016].

Risk, H., 2011. *Bloomberg challenges FX multi-dealer incumbents.* [Online]
Available at: http://www.euromoney.com/Article/2913198/Bloomberg-challenges-FX-multi-dealer-incumbents.html
[Accessed 25 May 2016].

Sager, M.., Taylor M. P., 2008. Commercially available order flow data and exchange rate movements: Caveat Emptor. *Journal of Money, Credit, and Banking,* **40**, 583-625.

Saks-McLeod, A., 2015. *New York State regulator investigates major banks for FX rigging.* [Online]
Available at: http://leaprate.com/2015/03/new-york-state-regulator-investigates-major-banks-for-fx-rigging/
[Accessed 15 March 2015].

Savaser, T., 2011. Exchange rate response to macronews: Through lens of microstructure. *Journal of International Financial Markets, Institution and Money,* **21**, 107-126.

Savona, R., 2014. Hedge fund systemic risk signals. *European Journal of Operational Research,* **236**, 282-291.

Scholtus, M., Dijk, D. v. & Frijns, B., 2014. Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking & Finance,* **38**, 89-105.

Schuetze, A. & McGeever, J., 2014. *Commerzbank fires one forex trader and suspends another - sources.* [Online]
Available at: http://uk.reuters.com/article/2014/05/21/uk-commerzbank-forex-idUKKBN0E111720140521
[Accessed 25 May 2015].

Schultz, P., 2003. Who makes markets. *Journal of Financial Markets,* **6**, 49-72.

Scott and Scott, 2015. *In re foreign exchange benchmark rates antitrust litigation.*. [Online]
Available at: https://www.scott-scott.com/73115redcomplaint.pdf
[Accessed 25 May 2016].

Securities and Exchange Commission, 2010. *17 CFR Part 242 Concept Release on Equity Market Structure; Proposed Rule.* [Online]
Available at: http://www.sec.gov/rules/concept/2010/34-61358fr.pdf
[Accessed 25 May 2016].

Securities and Exchange Commission, 2014. *Enhancing Our Equity Market Structure.*

Sevim, C. , Oztekin, A., Bali, O., Gumus, S., Guresen, E., 2014. Developing an early warning system to predict currency crises. *European Journal of Operational Research,* **237**, 1095-1104.

Shorter, G. & Miller, R. S., 2014. *High-Frequency Trading: Background, Concerns, and Regulatory Developments.*

Smith, R. P. & Fuertes, A., 2016. *Panel time-series.*

Stoll, H., 1978. The supply of dealer services in securities markets. *The Journal of Finance,* 33, 1133-1151.

Thomson Reuters, 2014. *Thomson Reuters Eikon For Foreign Exchange Professionals Who Seek More.* [Online]
Available at:
http://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/eikon-foreign-exchange.pdf
[Accessed 25 May 2016].

Vaughan, L., Finch, G. & Choudhury, A., 2013. *Traders Said to Rig Currency Rates to Profit Off Clients.* [Online]
Available at: http://www.bloomberg.com/news/articles/2013-06-11/traders-said-to-rig-currency-rates-to-profit-off-clients
[Accessed 25 May 2016].

Vaughan, L. & Hamilton, S., 2014. *BOE Chief FX Dealer Fired as Probe Faults Non-Escalation.* [Online]
Available at: http://www.bloomberg.com/news/articles/2014-11-12/boe-chief-currency-dealer-fired-after-not-reporting-risks
[Accessed 25 May 2016].

Vives, X., 1995. Short-term investment and the informational efficiency of the market. *The Review of Financial Studies,* **8**, 125-160.

Voris, B. V., 2015. *Standard Chartered, Societe Generale Added to Forex Lawsuit.* [Online]
Available at: http://www.bloomberg.com/news/articles/2015-08-01/standard-chartered-societe-generale-added-to-forex-lawsuit
[Accessed 25 May 2016].

Wang, J., 2014. Overnight price discovery and the internationalization of a currency: the case of the Korean won. *Pacific-Basin Financial Journal*, **29**, 86-95.

Willson-Taylor, S., 2013. *The story of the Fix. How we got here, how to fix the fix, and how not to have to use it (for trading) in the first place.* Molton Markets Inc.

Womack, K. L., 1996. Do Brokerage Analysts' Recommendations Have Investment Value?. *The Journal of Finance,* **51**, 137-167.

World Market Company, 2015. *WM/Reuters Spot and Forward Rates Methodology Guide.* [Online]
Available at: http://www.wmcompany.com/pdfs/WMReutersMethodology.pdf
[Accessed 1 April 2015].

Wu, M.-C., 2007. Phase correlation of foreign exchange time series. *Physica A,* **375**, 633-642.

Yan, B. C., Zivot, E., 2010. A structural analysis of price discovery measures. *Journal of Financial Markets*, **13**, 1-19.

Zebedee, A. A., 2001. The impact of a trade on national best bid and offer quotes: a new approach to modelling irregularly spaced data. *Journal of Multinational Financial Management*, **11**, 363-3863.

Zhang, F., 2010. *High-Frequency Trading, Stock Volatility, and Price Discovery*.