# ESSAY ON INTERNATIONAL ECONOMICS

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Dedicated to mummy and daddy

This thesis should appeal to several audiences. The literature reviews and empirical examinations will aid economists and academic researchers in navigating the literature and will be valuable for their work. Practitioners and forecasters at central banks and commercial companies are likewise interested in learning which predictors, models, and approaches accurately estimate currency rates. Policymakers, for whom the success of policy choices depends heavily on accurate projections, should also be interested in our review of the current state of the research. Lastly, the regular coverage of exchange rate predictions in the media suggests that this study might be applicable outside academic and policy circles.

This thesis studies two aspects of international economics: international finance and international trade, and it is organised as follows: Part I provides an in-depth description of the background research that formed the basis for this thesis. Part II consists of three empirically-based original chapters that are independent of one another and each make a unique contribution to the international economics literature. In the Appendix, more technical theories, such as machine learning and decomposition analysis, are described in greater detail.

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## ACRONYMS

| | |
|---|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| AR | Auto Regressive |
| ARIMA | Auto Regressive Moving Average |
| BEER | Behavioural Equilibrium Exchange Rate |
| BMS | Buying Minus Sell |
| BK | Baxter-King Filter |
| BW | Butterworth |
| CAPM | Capital Asset Pricing Model |
| CES | Constant Elasticity of Substitution |
| CF | Christiano-Fitzgerald Filter |
| CPI | Consumer Price Index |
| DSGE | Dynamic Stochastic General Equilibrium |
| ECB | European Central Bank |
| EU | European Union |
| FX | FOREX/Foreign Exchange Market |
| GDP | Gross Domestic Product |
| HO | Heckscher-Ohlin |
| HP | Hodrick-Prescott Filter |
| IR | Interest Rate |
| LSTM | Long-Short Term Memory |
| MA | Moving Average |
| MAPE | Mean Absolute Percentage Error |
| MSE | Mean Squared Error |
| NARX | Non-Linear AutoRegressive with eXogenuos Inputs |
| NMT | Neural Microstructure Technique |

| | |
|---|---|
| NN | Neural Network |
| OLS | Ordinary Least Squares |
| PCA | Principal Component Approach |
| PIN | Probability of Informed Trading |
| PPP | Purchasing Power Parity |
| REER | Real Effective Exchange Rates |
| RMSFE | Root Mean Squared Forecast Error |
| RNN | Recurrent Neural Network |
| RW | Random Walk |
| SMA | Simmetric Moving Average |
| SO | Sortino Ratio |
| SR | Sharpe Ratio |
| SWIFT | Society for Worldwide Interbank Financial Telecommunications |
| ToT | Term of Trade |
| UIP | Uncovered Interest Parity |
| USA | United States of America |
| VECM | Vector Error Correction Model |
| WTO | World Trade Organization |

# 1 INTRODUCTION TO THE THESIS

Multiple audiences should find this theory compelling. The literature reviews and empirical analysis will be helpful to economists and academic researchers in their work and in navigating the literature. The best predictors, models, and methodologies for estimating currency rates are of interest to practitioners and forecasters in central banks and commercial organisations. Our analysis of the status of the research should also be interesting to policymakers, for whom the effectiveness of policy decisions strongly rests on accurate estimates. Last but not least, given how frequently exchange rate forecasts are covered in the media, this study may have relevance outside of the realms of academia and public policy.

International economics has always been significant; each century presents its own unique economic and political issues and challenges, and each century introduces new instruments and methodologies; the $21^{st}$ century is no exception. This is a period of global financial crisis, economic turmoil in many developed nations, rising trade barriers, currency crises, Brexit, COVID-19, climate change, and most recently, the Ukrainian-Russian conflict. All of these issues have presented challenges for policymakers and business leaders involved in international trade and finance. Corporate managers, central bankers, and students must be interested in the intricate interrelationships between trade policies, central bank activities, and changes in government spending and taxation on interest rates, prices, exchange rates, and economic activity. However, this is also the time when machine learning, high-frequency data, and complex computers can be relied upon to provide assistance. The renewed interest in econometrics among academics has endowed researchers with new methodologies and the exponential sophistication of computers, allowing us to perform intensive computations in a very short amount of time and acquire a large quantity of data with high frequency.

International economics focuses on seven interrelated topics: (1) the gains of trade, (2) the structure of trade, (3) protectionism, (4) the balance of payments, (5) the determination of exchange rates, (6) international policy coordination, and (7) the international capital market. Because people are motivated and behave in the same ways while transacting internationally as they do domestically, international economists use the same standard tools and techniques to study international commerce as they do to study domestic trade.

Economic interactions between independent nations provide unique challenges, and these are the kinds of questions that international economics seeks to answer.

This thesis studies two aspects of international economics: international finance and international trade, and it is organised as follows: Part I provides an in-depth description of the background research that formed the basis for this thesis. Part II consists of three empirically-based original chapters that are independent of one another and each make a unique contribution to the international economics literature. In Part III's Appendix, more technical theories, such as machine learning and decomposition analysis, are described in greater detail.

*Summary of the Essays*

Chapter 2 explains the context of the study. In this chapter, we discuss the concepts of international economics, international finance, and international trade, paying special attention to the two approaches—the microstructure approach and the gravity model—that were utilised in the production of this thesis.

Chapter 3 focuses on non-linear forecasts to test exchange rate models by examining microstructure and order flow and comparing the new model to the random walk benchmark. The basic hypothesis is that if order flow includes heterogeneous beliefs and the information contained in them, heterogeneous customer order flow can have forecasting power for exchange rates. We agree with the literature that suggests FX traders utilising order flow data should emphasise client group flow as opposed to overall flow. Using statistical and economic evaluation, we quantify the effect that the key micro-level price determinants—order flows—play when information is released to all market players. We find that order flow with non-linear consideration led to substantial and statistically significant improvements over the random walk model, and order flow is a potent predictor of the exchange rate movement in an out-of-sample exercise based on economic value criteria such as the Sharpe ratio. Disaggregated information is essential for order flows and future returns from end-users, given that future order flows differ by customer group. As a result of their FX focus, financial clients have more information.

In Chapter 4, the portfolio technique that we introduce to the FX microstructure literature and that has proven beneficial in cross-sectional FX asset pricing research offers a straightforward and intuitive method for estimating the economic value of order flow. Most crucially, it facilitates research into the understudied subject of whether customer order flow captures risk premia in currency markets.

Finally, an empirical study is presented in Chapter 5 to confirm that shifts in the real exchange rate, broken down into its permanent and temporary components, cause shifts in the volume of bilateral trades. The findings imply that the mismeasurement of the real exchange rate is to blame for the lack of conclusive findings in the vast existing literature and that once speculative fluctuations and unobservable shocks driven by the real exchange rate are removed, the true relationship between these variables can be established.

# Part I

# BACKGROUD OF THE STUDY

# 2

# REVIEW OF INTERNATIONAL ECONOMICS

The purpose of this section is to introduce the general concepts of International Economics with particular attention to the two main methods used in this thesis, namely the Microstructure Theory and the Gravity Model.

The theory of the international economy can be divided into two broad sub-fields: the study of international finance and the study of international trade. Along with the tactics for managing currency risk, understanding the influence that changes in currency have on the cost of a company's products is an essential issue that managers and other decision-makers in organisations need to grasp. In open economy macroeconomics, the assessment of the level of national production serves as the major emphasis, in addition to the calculation of the general price level. After that, it analyses the impact that changes in the money supply, tax rates, and government expenditures have had on interest rates, exchange rates, the level of national production, and the general price level of goods and services. Companies that operate on a global scale, importing raw materials from other countries, producing sections of their products in other countries, and competing in the global market, are required to have an understanding of how these trends will affect their operations.

The study of international trade investigates the impact that trade has on national economies. There is a general agreement that a nation will prosper as a result of participation in international commerce; nevertheless, certain groups within the nation will prosper while others will suffer losses. Concerns about the effects that international trade has on the distribution of income lead governments to enact trade policies that aim to protect industries and workers that are harmed due to the competition from imports, as well as other policies that aim to promote exports. These policies are often called "protectionism." From a purely economic point of view, some local firms will find themselves in direct competition with international enterprises, while other domestic companies will find an opportunity in expanding their customer base in other nations. Every company that participates in international commerce is exposed to both dangers and possibilities. It is very necessary for business managers to get a basic understanding of the foundation of trade as well as the pattern of commerce. They must also be aware of the effects that national trade policies and international trade agreements have on their expenditures, receipts, and earnings.

## 2.1 INTERNATIONAL FINANCE

The FOREX/Foreign Exchange Market (FX), also known as the forex market, is a worldwide decentralised market where currencies and other financial products denominated in other currencies may be bought and sold. According to the data provided by the Bank for International Settlements, the daily average value of transactions involving foreign currencies was around 7.5 trillion in 2022, a volume that is 30 times greater than daily global Gross Domestic Product (GDP). The dollar is used in 90% of global FX transactions, with the euro, the yen, and the pound following as the most traded currencies. London is the location where one-third of all of these agreements are finalised, followed by New York, Singapore, Hong Kong, and Tokyo. Consumers, companies, investors, speculators, commercial and investment banks, currency dealers and brokers, and central banks are the most prominent players in the foreign exchange market. On the market for foreign exchange, only a minuscule portion of transactions involve the actual swapping of one currency for another. The most frequent method of settlement used by commercial banks, as well as FX brokers and dealers, is the sending and receiving of electronic balance transfers. On the foreign currency market, the players with the most significant impact are commercial banks. The customers the banks serve in the business sector are the primary driving force behind their involvement in this area. Another characteristic of this market for the exchange of currencies is the presence of banks as participants in the market. Interbank trading takes place on the wholesale market, which is also the location of currency exchanges. There are around 20 large banks that take part in interbank trade[1].

Exchange brokers, as opposed to FX dealers, function in the foreign currency market as intermediaries between buyers and sellers and collect a fee for their services. FX dealers are directly involved in the transaction between buyers and sellers. Data on exchange rates may be obtained by foreign currency dealers from major commercial information sources such as Thomson Reuters and Bloomberg. After that, dealers may get in contact with one another to negotiate agreements and get realistic price estimates. More than 11,000 banks and broker-dealers located in over 200 countries are electronically connected through SWIFT[2]. After the confirmation of the contract, dollar transactions are considered complete, and depending on the currency that was transacted, the payments are transferred by either CHIPS or the TARGET2 system (Trans-European Automated Real-time Gross Settlement Express Transfer). Foreign Exchange Instruments are:spot

1 Citi, JPMorgan, UBS, Bank of America Merrill Lynch, Deutsche Bank, HSBC, Barclays, Goldman Sachs, Standard Chartered, and BNP Paribas are some of the most famous FX dealers in terms of market share

2 Society for Worldwide Interbank Financial Telecommunications (SWIFT) is a communications network that conducts more than 15 million transactions on a daily basis

contracts [3]; forward contracts[4]; futures contracts[5]; swaps[6];options[7].

Analysis of exchange rate behaviour in both an academic and a practical setting has received a substantial amount of attention within the context of the study of international market environments. This attention has been paid to both aspects of the topic. The behaviour of exchange rates can be most accurately characterised as a random walk, according to the conclusions of the study report conducted by Meese and Rogoff (1983) as well as those of subsequent research.

However, these studies have produced conflicting findings and continue to struggle with the challenge of forecasting exchange rates in a way that is more accurate than a simple random walk model. The dynamics of exchange rates, spanning from univariate to macro-fundamental implications, have been investigated in depth in the research that is considered to be the mainstream. This seemingly puzzling phenomena, which Obstfeld and Taylor (1997) have named the "exchange rate disconnection dilemma", is considered as among the most critical problems in the open macroeconomics literature. Some authors as Dumas (1992), investigate the price deviations away from parity and modelled the behaviour of the band of inactive regime. This was done on the basis of the idea that pricing to market with nominal limits generates erratic variances in real exchange rates, and this was the reasoning behind why this was done. Depending whether or not there is a difference in price and variance of price in excess of trade cost, which provides an arbitrage opportunity, these give different non-linear specifications for the series. The presence or absence of an arbitrage opportunity is what determines whether or not this can be done. For example, Dumas (1992) develops a model in order to assess the costs that are associated with arbitrage trades that lead in

3 On the spot market, currencies are exchanged for immediate delivery, which occurs around two days after a transaction is completed.

4 Forward contracts are made to purchase or sell currency for future delivery at a rate known as the forward rate, which is determined today in the forward market. Forward contracts may be used to buy or sell foreign exchange.

5 A futures contract is an agreement made by two parties that they will deliver currencies to each other at some future date at a preset exchange rate. This promise is made by the parties holding the futures contract. Futures contracts are standardised agreements that are bound to expire on certain calendar dates and that may be exchanged on regulated futures exchanges.

6 A swap is a type of financial transaction that includes the buying and selling of the same currency in two different time periods. Corporations make use of these contracts in order to cut the expenses of the many transactions involved in foreign currency trading.

7 A person who owns an option contract has the authority to purchase or sell a defined quantity of a currency at a price that has been predetermined at any point during a given period of time. The owner of an option has the right, but not the responsibility, to purchase a certain amount of a foreign currency at a certain time. On the other hand, the owner of a put option has the right to sell a certain amount of a foreign currency at a particular price. The price at which the option may be purchased or sold is referred to as the "strike price."

departures from the law of one price. The researchers Sercu, Uppal, and Van Hulle (1995) investigate the fluctuation of nominal exchange rates inside a band that surrounds the value of the Purchasing Power Parity (PPP). They explain why there exist slope coefficients that are less than one, which get closer to one under hyperination or with low-frequency data in regression tests of purchasing power parity. Alternately, Berka (2005) investigates resilience and deviations from purchasing power parity as a consequence of heterogeneous shipping costs in a dynamic general equilibrium framework with arbitrage trade. To accomplish this, he makes use of a framework known as dynamic general equilibrium.

Changes in the values of a variety of basic factors are often interpreted to be the cause of developments in exchange rates. This is a point of view that is quite reasonable to hold in the longer term. Empirical studies, on the other hand, often reveal that there is only a limited association between the changes of exchange rates and other economic indicators over the short term. This might be due to the fact that the values of exchange rates, along with the prices of other assets, are primarily driven by the expectations that market participants have about the development of fundamental factors in the future. However, standard models of exchange rates do not account for these forecasts in a way that is realistically thorough and comprehensive. In addition, these models abstract the mechanisms of price generation that are widely used by market makers on markets for foreign currency.

Traditional exchange rate models, which are focused on the longer-term interaction between several basic factors, such as the relative price level, productivity, interest rates, and current account balances, are unable to provide an appropriate explanation for the majority of short-term changes in exchange rates. This conclusion has been proven as a robust empirical event in exchange rate research time and time again by a broad range of approaches. This has typically taken place without calling into account the longer-term relationships that exist between exchange rates and basic data. Providing an explanation for short-term changes in exchange rates is consequently something that continues to be difficult to do, both in theory and in reality.

If we use the asset price approach of exchange rate theory to try to solve this problem, we are making the assumption that expectations are the most important part of the model. According to this framework, the exchange rate is the present value of discounted current and expected future fundamental variables. Under these conditions, however, market participants put a lot larger weight on their predictions for the establishment of prices than they do on the values that are now in effect. According to this concept, expectations, and therefore also exchange rates, are altered in response to the appearance of fresh information; nevertheless, this might lead to issues.

In empirical studies, it has been found that news is readily available to the public accounts for no more than five percent of the evolution of exchange rates. Because of this, private information, or information that is only accessible to a limited number of market participants, is often considered to be a primary factor in the genesis of exchange rate fluctuations. This might very well involve evaluations of the economy, analyses of the nation, and the use of charting methods by professional investors.

Different points of view and methods of investigation have informed the development of a great number of models that attempt to simulate the behaviour of the exchange rate. Historically, macroeconomic models have had a preeminent position in the field of study pertaining to currency exchange markets. These have included, for instance, the early model of PPP[8] and the subsequent models, such as the balance of payment flow approach[9], the flexible-price monetary model[10], the sticky-price monetary model[11], and the productivity-based model[12]. On the other hand, macroeconomic models have been found wanting by empirical study in significant ways. There is not much data to back them up, and most of the time the evidence implies that macro models are not much better than a basic random walk model when it comes to understanding and predicting the volatility in exchange rate.

Meese and Rogoff (1983) compare the flexible-price monetary model, the sticky-price monetary model, and the sticky-price model that incorporates the current account to a random walk model. They do this in order to test the out-of-sample predictive accuracy for the dollar/pound, dollar/mark, dollar/yen, and a weighted dollar-based exchange rate. Flexible-price monetary models assume that prices are allowed to fluctuate over time. They come to the conclusion that the capacity to make accurate predictions possessed by the three models being evaluated cannot compete with that of the random walk model. In addition to PPP and the sticky-price monetary model, Cheung, Chinn, and Pascual (2003) conduct a similar test based on three models: interest rate parity, productivity-based model, and a composite specification. These models are evaluated using a variety of criteria such as Mean Squared Error (MSE), direction of change, and consistency. All of the examined models are discovered to not necessarily be more effective than the random walk model. This is due to the fact that these models may perform well in a currency pair according to one criteria, but they may perform badly in a different currency pair

8 Cassel (1918)
9 Kouri (1977)
10 Bilson (1978)
11 Dornbusch (1976), Frankel (1979)
12 Dornbusch (1976)

according to another criterion.

The inadequacy of the macroeconomic model to describe the movement of the exchange rate, particularly the short-run dynamic, has prompted economists to explore other approaches to examine the behaviour of the exchange rate. In particular, the short-run dynamic has been the focus of this branch of search. One strategy that has garnered significant attention is one that concentrates on the granular details of the currency exchange market.

The idea of order flow is essential to the micro viewpoint, which was first designed for the purpose of analysing the equities market. For instance, the groundbreaking study that was conducted by Evans and Lyons (2002a) shown that the micro variable order flow might have an effect on the movement of the exchange rate. They developed a hybrid model that incorporates both macro variables and micro variables – more particularly, interest rate difference and order flow – and discovered that order flow can explain more than sixty percent of daily fluctuations in USD/DEM and forty percent of daily movements in USD/JPY. Following that, a large number of scholars shifted their attention to the study of microstructure, particularly the order flow. This strategy has shown promising results over the last several years because to the fact that it takes into account the influence of the market transaction process on the setting of exchange rates, something that is absent from macro models. However, its performance is hindered by the stringent needs for high frequency transaction data that it has, particularly in the developing countries. In point of fact, it has been plagued by a number of deficiencies in this respect up to this point, one of which is an absence of specific data on the dealings of dealers. This situation has significantly improved in recent years, ever since the introduction of the availability of tick-by-tick data as a result of the fast growth of the internet and technologies associated to it. As a direct consequence of this, a significant amount of progress has been made in the investigation of the microstructure of currency exchange markets.

The microstructure method was able to make its way as a supplementary model to the standard models as a result of the pioneering investigations conducted by Evans and Lyons (2002a). A better grasp of the link between fundamentals and exchange rates is another benefit that may be gained by using this approach.

Canonical rational-expectation equilibrium is a model that was developed by Grossman and Stiglitz (1980). According to this model, the information that is currently available cannot be perfectly reflected into price because, if it did, those who spent resources to obtain it would receive no compensation. This leads to the conclusion that an efficient market from the perspective of information cannot be achieved[13]. If prices represent all of the information that is available to educate traders, then no trader would pay the cost to become informed since he could just acquire the knowledge from the price instead of paying the cost. However, it is undeniable that if no one produced information, then prices would reflect the absence of knowledge, and it would be financially beneficial to generate information. Due to the fact that prices convey information along with some noise, which encourages traders to obtain the information, prices cannot be completely effective in this manner. The concept of rational efficient markets acknowledges the fact that investors would not rationally undertake the expenditures of acquiring information unless they expect to be rewarded by better gross returns in comparison to the cost-free option of accepting the market price. In addition, more contemporary theorists have recognised that when it is difficult to ascertain the stock's underlying worth, as is the case with common stock, and when there are trading expenses involved, there is even more space for price to diverge from value.

Since the players in macroeconomic theory are assumed to be rational and the market is assumed to be flawless, there is no need for transactions to take place at intermediate levels since a shift in demand results in a new equilibrium. Order flow does not play a part in this scenario; but, if we remove one of the assumptions, order flow becomes a means through which information about the market may be sent. Order flow is often regarded as a reliable measure of the purchasing pressure or selling pressure that is currently being exerted on a certain currency. Order flow will notify the participant in the transaction of the market-clearing exchange rate if any of the two assumptions underlying the macroeconomics method are shown to be incorrect. Marker makers have access to confidential information since the price and amount of every client transaction are only known to the market maker who conducted the trade. They are the only ones who are aware of the size and the course of the transaction that was started by their clients. Nevertheless, throughout the process of interdealer trading, every market maker is exposed to indirect indications of the client transactions conducted by other market makers and is given information about the predominant buying or selling pressure. In this manner, the originally confidential information on client trades is progressively divulged to the active market makers so that they may become aware of it in part. The information will also be included into the exchange rate at the same time as it is integrated into the rate. Order flow has the potential to be instructive, since confidential information could be concealed behind the transactions of consumers. On the foreign currency markets, essential knowledge on the progression of future exchange rates can seldom be kept secret for an extended length of time (one exception is the order flow resulting

13 Sewell (2001)

from central bank intervention, which is a typical example of flows carrying private information).

*Understanding Order Flows*

It is essential to have an understanding of order flow in order to fully comprehend how the microstructure approach works. The microstructure approach to exchange rate theory is an expansion of the traditional asset price technique. This approach takes into account, on one hand, the practical dominance of player heterogeneity in the foreign currency market and, on the other hand, asymmetric information patterns. This results in the establishment of a two-stage process, the first of which involves the acquisition of macroeconomic information via the order flow of market makers and the second of which involves the exchange rate's subsequent incorporation of that information. To be more specific: in the first stage of this paradigm, market makers receive orders from consumers who may – intentionally or unconsciously – have a greater grasp of the fundamental factors that drive exchange rate growth. In other words, the model operates on the assumption that customers have access to more accurate information. After then, the market makers who participate in the interbank trading will pass on their balances in accordance with the purchase and sell orders of their clients. As a general rule, in contrast to trading conducted with individual customers, the trading conducted between banks is anticipated to become a significant amount more open as a direct consequence of the growth of computerised trading platforms. As a consequence of this, market makers are able to establish prices that are similar to one another in the model that is being discussed. These prices are based on the usual market-wide order flow.

Order flow is the amount of transactions that are actually signed; it is a measurement of the transactions that take place. Order flow is a term that refers to the interaction that takes place between the market depth and market orders. The total amount of limit buy and sell orders that are put at any moment is what is meant to be understood as the depth of the market. It is also sometimes referred to as "the book", "limit orders" or "passive orders".

The party that is the starting side in the deal is the one that signs the document. Order flow may be quantified as the total number of signed orders that were either started by the buyer or the seller during a period of time. If the total is negative (positive), it indicates that there is a net amount of selling (buying) pressure during the time. An electronic book serves as a repository for all of the limit orders placed. The most competitive orders in the book are used to establish the best bid and offer prices that are currently accessible. The limit orders are the part of any transaction that is considered to be passive; these orders are what create the flow of signed orders. Order flow, as it is used in microstructure finance, is a variation of "excess demand" in economics.

Kyle (1985) employs a dynamic model of insider trading to investigate the informative volume of prices, it provides a theoretical framework for determining bid-ask spreads and "market impact" of trades. His approach takes into account three different types of agents that are dealing with a single hazardous asset: 1) a market maker, who sets prices efficiently conditional on information he has about the quantities trades by others; 2) a "noise" trader, who trades randomly and provides a veil which hides their trading from the market; and 3) an insider, who has exclusive access to a private observation. A limiting model of continuous trading is created when the same time delay between actions is decreased until it reaches zero. In this state of equilibrium, the prices follow a Brownian motion, the depth of the market remains constant throughout time, and all confidential information is included into the prices by the time trading comes to a close.

An alternate microstructure model was established by Glosten and Milgrom (1985), and it is often used to the analysis of trade and the creation of prices. A market maker in their model would publish bid and ask prices, which indicate the prices at which he is prepared to purchase and sell shares from transactions. The market maker is in the position of not knowing the identity of the trader who submitted the trade request when that request is received by the market maker at a given moment in time. The trade request may have originated from an informed trader or a uniformed trader. By requesting a higher price when he sells a share as opposed to when he buys a share, the market maker in the sequential-trade model prevents himself from suffering a loss at the hands of a knowledgeable trader. The bid-ask spread is the measure of illiquidity in the model, and it refers to the difference in price that may be found between the two values.

A simultaneous-trade model of the spot foreign currency market that generates hot-potato trading was developed by Lyons (2006)[14]. To begin, risk-averse dealers accept client orders that are not widely viewable. These orders may or may not be fulfilled. After then, dealers do business with one another. Therefore, each dealer acts as an intermediary for the transactions of his clients and any information that may be included within. Then, this information will be exposed in the price, based on the information that is included in interdealer deals. Lyons demonstrates that engaging in hot-potato trading limits the amount of information that is exchanged during interdealer

14 Hot-potato trading is a term that refers to the repeated passing of inventory imbalances between dealers

exchanges, which results in prices that are less informative. He presented a graphic that illustrates (Figure 1) the two steps that are involved in the processing of information. The first stage consists of market participants who are not dealers doing fundamental research or making observations (mutual funds, hedge funds, individuals with special information, etc.). The dealer's analysis of the findings of the first-stage study is the focus of the second stage. Monitoring the order flow contributes to the dealer's perception of the market. This interpretation is used to determine the pricing that dealers charge.

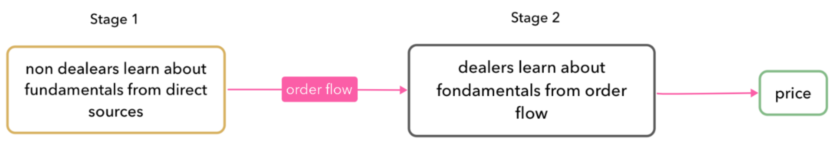



Figure 1: Lyons' two stages of information processing diagram

Because it comprises the trades of people who analyse fundamentals, order flow is a source of information about the underlying market fundamentals. It functions as a transmission mechanism in this regard. When using a typical microstructure model, the dealer does not get any further knowledge about the fundamentals beyond what is obtained via the order flow. Because the information that is being learnt is not readily available to the general public, these models necessitate the dependency of the dealer on learning from order flow. When information is readily available to the public, there is no need for dealers to learn from order flow. In actual fact, certain information pertinent to foreign exchange is available to the public while other information is not; hence, learning from order flow may be very essential. Information flow is able to aggregate macroeconomic information in theory for two reasons: (i) various interpretations of the news, and (ii) different expectations about future fundamentals.

The information role that transactions play is a crucial component of the microstructure method. In conventional models, macroeconomic news are disclosed to the public and may therefore be reflected immediately in pricing. Order flow plays no part in these models, thus there is no need to account for it. Within the framework of the asset method, the equations for determining the exchange rate have the form:

$$\Delta P_t = f(i, m, z) + \epsilon_t \tag{1}$$

The actual and historical values of nominal interest rates, both domestic and international, money supply, and other macroeconomic factors are included among the driving variables in the function denoted by the notation $f(i, m, z)$. It is assumed that changes in these publicly available information factors would influence pricing, whereas order flow has no effect whatsoever. In the event that order flow was shown to have an influence on prices, such price effects would be absorbed by the residual. $\epsilon_t$.

Within the microstructure approach, equations of exchange rate determination are derived from the optimisation problem faced by the actual price setters. These models are variations on the following specification:

$$\Delta P_t = g(X, I, Z) + \epsilon_t \tag{2}$$

The order flow $X$ (which is signed to denote direction), a measure of dealer net position (or inventory) $I$, and other micro determinants $Z$ are the driving variables in the function $g(\cdot)$. In this particular instance, the residual, denoted by $\epsilon_t$, is the inverse of the residual that is calculated by the asset approach equation. This is because the $\epsilon_t$ value incorporates any price changes that are the result of the asset approach's public information variable.

To establish a link between the micro and macro approaches Lyons, 2006 investigates equations with components from both approaches:

$$\Delta P_t = f(i, m, z) + g(X, I, Z) + \epsilon_t \tag{3}$$

Through the use of time-aggregated measures of order flow, it is possible to estimate the values of these equations at the frequencies that correspond to the asset method. The time aggregated measures of $X$ cover far longer periods of time than the measurements that are generally used in empirical microstructure. The estimates of this equation demonstrate that time-aggregated order flow has a much greater capacity for explanatory power than macro factors.

*Review of Microstructure Approach*

Over the last four decades, there has been significant expansion in the market microstructure. In particular, the decades of the 1970s and 1980s saw the development and the presentation of a significant number of the most influential ideas in the field of microstructure. The term microstructure is often credited to Garman (1976), who used it as the title of a paper analysing inventory costs and market making.

There are a few different generic studies that look at the microstructure of the market. O'Hara (1995) is the primary source that is used when discussing the theory of market microstructure. The works of Madhavan (2000) and Biais, Glosten, and Spatt (2005) are examples of generic survey research. Shephard (2005)'s research is an investigation that focuses on the volatility of asset values, and on the stochastic volatility in particular. Lyons (2001) focuses on the microstructure of the foreign exchange market, which is a market in where the majority of trading takes place on an over-the-counter basis away from exchanges.

The authoritative reference for a practical explanation of how securities markets function, Harris (2003) offers a comprehensive look at trading procedures across a wide range of asset classes across the world. A more practitioner-oriented perspective on the analysis of high-frequency data is provided by Gençay et al. (2001), who place a focus on the study of data pertaining to the foreign exchange markets. Roll (1984) makes the distinction between the underlying value of a security and the market prices that are seen in the market, which may vary from the fundamental value owing to differences in market organisation and the trading process. His model assumes that asset prices would follow a random walk and that traders will be uniform in their behaviour. A further collection of models that are highly essential to consider enables heterogeneous traders to participate in the market in a sequential and independent fashion. Glosten and Milgrom (1985) offered an early example of one of these models.

The topic of informed trading is explored in several theoretical studies. Easley, O'Hara, and Saar (2001) discover that following a stock split, there is an increase in the amount of knowledgeable trading. Easley, O'Hara, and Paperman (1998) investigate whether or not there is a substantial connection between foreign analyst coverage and educated trading, but they are unable to uncover such a connection. The anonymous automated Xetra[15] market is contrasted with the non-anonymous trading floor of the Frankfurt Stock Exchange by Grammig, Schiereck, and Theissen (2001). They come to the conclusion that there is a far less amount of information-based trading on the floor. Price responses to the announcement of a cross-listing have been shown to be typically favourable. Notable theoretical models of trading in a context with numerous markets have been provided and debated, among others, by Chowdhry and Nanda (1991), Biais (1993), Madhavan (1995) and Frutos and Manzano (2002). But the studies that cover the greatest ground are those done by Miller (1999) and Foerster and Karolyi (1999). A set of publications written by Easley (1996), defined an empirical approach that may be used to examine the amount of informed trading that occurs in a market. This model, which is called theProbability of Informed Trading (PIN), is based on the sequential trading model that Glosten and Milgrom (1985) developed. The PIN model has been used to investigate a wide range of concerns pertaining to monetary matters. Within the Fama and French (1992) asset pricing paradigm, Easley, Hvidkjaer, and O'Hara (2002) discover that there is a substantial positive association between

15 Xetra is the reference market for exchange trading in German shares ans also the European market leader in exchange traded funds (ETs)

informed trading, as assessed by PIN, and the predicted returns of a stock. This relation is found to be statistically significant. Theirs findings are used by Duarte and Young (2009), who then disassemble the PIN into its component parts of illiquidity and asymmetric information. They come to the conclusion that illiquidity has a price, but information does not.

In the early days of empirical research on multi-market trading, arbitrage, and price discovery, researchers relied on low-frequency daily data. Wang, Rui, and Firth (2002) investigate the price and volatility of the markets in London and Hong Kong. According to their findings, both markets have an impact on the returns and volatility of assets. The opening and closing prices of Japanese firms that are cross-listed in New York are analysed in Lau and Diltz (1994)'s research paper. They come to the conclusion that the price of these equities is affected by both markets in some way. Kim, Szakmary, and Mathur (2000) take into account both the current exchange rate and the index of the market in the United States for a selection of equities originating from five distinct markets. They come to the conclusion that the price of these cross-listed equities is affected not just by the exchange rate but also by the market in the United States. The research conducted by Hauser, Tanchuma, and Yaari (1998) and Lieberman, Ben-Zion, and Hauser (1999) on Israeli equities that are traded in New York reveals that pricing is most of the time efficient, meaning that there are no arbitrage gains in the majority of instances. In addition, they find that the home market is the most important factor in price discovery.

Researchers are able to investigate the price of a stock when it is concurrently traded on two or more exchanges since high frequency data is readily available. One of the very first studies to make use of high frequency data was carried out by Alhaj-Yaseen, Lam, and Barkoulas (2014). After doing an analysis on Nokia, the most liquid stock on the Finnish market, they came to the conclusion that the New York market is the most important one for price discovery. Phylaktis and Korczak (2007) and Pascual, Pascual-Fuster, and Climent (2006) do research on Spanish and United Kingdom equities, respectively, that are cross-listed in the United States. Sapp (2002) investigates the foreign currency market as well as the roles that five significant banks play as dealers in what is primarily an over-the-counter market. An over-the-counter market is one that does not operate within the boundaries of a centralised exchange. Menkveld, Koopman, and Lucas (2007) analyse price discovery for Dutch equities that are cross-listed in the United States. Rather than concentrating just on the simultaneous trading hours of the two exchanges, they look at the full combined trading day and use state-space approaches in their research. According to the findings of Ding, Harris, Ding et al. (1999), the majority of pricing for a Malaysian firm that is also cross-listed in Singapore takes place in the company's home market. A detailed investigation on the process of price discovery was carried out by Grammig, Schlag, and Melvin (2004) for cross-listed equities from Canada, Germany, France, and the United Kingdom that were traded on the NYSE. Using data from 1999, they discover that the home exchange predominates in most cases, but that there is a significant amount of variation amongst businesses. Eun and Sabherwal (2003) conducted research on the process of price discovery for Canadian equities that are also cross-listed in New York. They uncover enormous disparities in the proportions of price discovery shares.

There is no connection between the foreign exchange market and the other subsets of the economy in any of the theoretical models of the FX market's microstructure, such as the Evans-Lyons model. When viewed from the perspective of the model, shocks that have an effect on the fundamentals as well as the order flow are regarded to be exogenous. The conventional macroeconomic models, on the other hand, are unable to recreate a variety of actual data about the evolution of exchange rates.

The integration of the two methodologies makes it possible to construct macro models with exchange rate dynamics that are more reflective of the actual world. On the other hand, they are also able to carry out tasks that are often carried out by broad macro models, such as policy simulations, forecasting, welfare analysis, and so on. When seen through this lens, the research that Bacchetta and Wincoop (2004) conducted may be regarded as innovative and groundbreaking. They begin with a two-country model that is based on the monetary approach (i.e. money market equilibrium, purchasing power parity, and uncovered interest rate parity), but at the same time, they deny the concept of the homogeneity of economic agents and assume that investors have access to a variety of pieces of information. This is because they begin with a model that is based on the monetary approach for both countries. The model is able to represent the relationships between the order flow and the exchange rate, which arise as a result of the microstructure. Although the model has not been validated using real-world data, it has been shown to be capable of accurately recreating a variety of stylised features including exchange rates, fundamentals, and order flow. According to the model, there is not a significant correlation between changes in the fundamentals and movements in the short-term or medium-term exchange rate. On the other hand, the value of the exchange rate is ultimately determined by the fundamentals throughout the course of time. Everything here is consistent with the findings obtained from real data. In a similar vein, the exchange rate is not a very accurate indicator of the future developments of fundamentals, and the movement of the exchange rate and order flow are strongly correlated with one another.

Evans and Lyons (2007) also attempted to develop a hybrid model that included components of microstructure. Their dynamic model varies from the framework of typical macro models, and it also has the capability of explaining a number of stylised facts and problems (as Bacchetta and Wincoop model can). Among them are the facts that the volatility of the foreign exchange market is much greater in comparison to that of the fundamentals and that the order flow can better explain swings in exchange rates than the fundamentals can. When it comes to studying the factors that go into determining exchange rates, which are, in essence, prices, researchers in this discipline employ a microeconomics approach. They examine the nature of equilibrium as well as the agents that trade currencies, the incentives and constraints that arise from the institutional structure of trading, and the nature of the trading institutions themselves. The microstructure has consistently shown positive findings in the empirical area ever since it was introduced.

Chinn and Moore (2011) presented their proposal for a hybrid exchange rate model. Because the variables in the monetary model are only accessible at monthly or lower frequencies, the researchers decided to utilise monthly data over a period of eight years. They began with the premise that earlier studies were based on daily data sets collected over short time periods (a few months). They were able to include both the Evan-Lyons model and the monetary model into a hybrid general specification as a result of having access to this "new" data-set, utilising a flow of order (monthly buyer-initiated trades net of seller-initiated trades, in millions of base currency). They make the data more consistent by transforming the order flow variable inputs into each equation in a comparable fashion. They focus on the fact that order flow has the ability to explain the macroeconomically significant monthly frequency; they demonstrate that a hybrid model that combines the monetary model with the Evans-Lyons model creates a whole; and they demonstrate that the hybrid model outperforms both the monetary model and a random walk in a straightforward forecasting exercise.

The macro-based model studies show evidence that long-run or lower frequency movement in exchange rates are connected with the conventional macro fundamentals. On the other hand, the shorter run movement is poorly understood. Sarno and Schmeling (2014) investigates the fundamental that influences exchange rate. It would seem that the fundamentals of the future matter a great deal for determining the present exchange rate. They have findings that are consistent with the theory that volatility in exchange rates impact future economic fundamentals. However, their findings could also be interpreted as suggesting that a depreciation in the value of the currency leads to an increase in both net export and output. This would be consistent with the present value model, which links exchange rates to macroeconomic variables via an expectation mechanism. In a broader sense, the fundamentals that are taken into account are endogenously determined combined with exchange rates that are in equilibrium. This finding is compatible with numerous other hypotheses about the determination of exchange rates. According to the findings, nominal macro fundamentals (such as CPI inflation, money growth, and GDP growth) seem to have the strongest relationship with currency exchange rates.

The real macro aggregates, such as real production and real money, do not have a direct and relevant link to present exchange rates. As a result, it seems that the real macro aggregates do not play a significant role in the setting of exchange rates. Several studies have shown that foreign exchange returns may be significantly influenced by certain aspects of order flow[16]. Evans and Lyons contend that gradual learning in the foreign currency market may create both explanatory power and forecasting power in order flow. Their argument is based on the fact that gradual learning occurs over time. According to a research published in 2005[17], if it is true that order flow is a carrier of information then it should be feasible to estimate exchange rates by utilising order flow aggregates . They also discovered that order flow is superior to random walk in terms of forecasting in the short run. Danielsson and Payne (2012) discovered that order flow is superior to random walk at high frequency for all four currencies that they investigate and at longer frequencies for the two currency pairs that have the most liquidity. While Rime, Sarno, and Sojli (2010) demonstrate that order flow not only outperforms random walk, but also yields Shape ratios that are greater than one, these results are in contrast to their earlier findings. Adding financial order flow to a forecasting model that already incorporates macroeconomic fundamentals and commodity prices increases the model's ability to anticipate movements in Canadian dollar; they discover that a large percentage of order flow variance can be explained using macro news, and order flow appears to aggregate changes in expectations about fundamentals; this may compliments the evidence that macro information influences financial markets. In 2010, King et.al.[18] are of the opinion that present and future exchange rates are not the result of a random walk but are, at the very least, indirectly affected by the fundamentals of the economy.

16 Evans and Lyons (2002b); Evans and Lyons (2005) and King, Sarno, and Sojli (2010)
17 Evans and Lyons (2005)
18 King, Sarno, and Sojli (2010)

Market makers do not know the current underlying value that the exchange rate is based on since there is often a delay in the delivery of economic data. This delay makes it impossible for market makers to make accurate predictions. This is because it takes such a long time to publish economic statistics, which is the root cause of the problem. On the other hand, it is plausible to presume that market makers take into account the cumulative order flow, and that this is subsequently reflected in the changes in market prices. This is because the accumulated order flow affects market makers directly. This is also the case in circumstances in which one's expectations play a substantial part in the process of deciding the exchange rate. In addition, the consistent order flow that emerges as a consequence of interbank trade undoubtedly plays a significant role in the explanation of the day-to-day shifts in the movements of currency rates.

In spite of the inconsistencies between the theoretical model and the empirical data, the price-setting patterns of the market maker demonstrate that order flow simulates private knowledge and forecasts of the fundamental exchange rate value on opaque marketplaces with players who have varied amounts of information about the market. In spite of the fact that it has been shown that the order flow of a market maker should not be treated as an unambiguous indicator of fundamental value, the value of current and anticipated fundamental elements will ultimately be reflected in the exchange rate orders made by customers. It makes no difference whether particular customers actually identify the information that pertains to their orders or not; the value of this data remains the same either way. The order flow comprises information that is not available in any other manner at that moment on the current and projected condition of the economy since the essential facts have not yet been revealed. This information relates to the present status of the economy. This information is included into the order flow as part of the process. As a consequence of this, it has the possibility of becoming a valuable leading indicator.

In reaction to changes in the market circumstances, prices are not immediately updated; rather, only the difference between bid and ask is altered. This is due to the relatively idiosyncratic nature of the individual order flow, which means that a market maker will only ever obtain a proportion of client orders on the market. As a result of this, a market maker will only ever get a percentage of client orders on the market. In the end, there is always a chance that an arbitrage will be carried out using a rate that is significantly distinct from that of another market marker. As a result, movements in the exchange rate don't typically become visible until after all market makers have released their net positions from client trading to the transparent interbank market and the order flow for the entire market can be viewed by all parties involved. This is because the interbank market is a market that is open to the public.

The microstructure approach to currency exchange rates may be broken down into DL and ML models, with each category being determined by the composition of order flow. DL models provide an emphasis on the factors that impact the pricing behaviour of individual market players, such as dealers, and as a result integrate microvariables such as order flow and inventory with exchange market quotations. The majority of the time, DL models are lifted straight from the somewhat more mature field of equities market research. The model developed by Madhavan and Smidt (1993) combines the concepts of asymmetric information (information impact), as well as inventory control (inventory effect). The demand from knowledgeable dealers is a reflection of the information effect, and it is this demand that is related to trade volume. The Madhavan and Smidt model is expanded upon by Lyons (1995), who introduces the concept of market-wide order flow and enables dealers to exercise control over inventory via outgoing and brokered trade. He investigates the mark/dollar market and tests the null hypothesis while permitting a variety of inventory management approaches. The results show that the information effect and the inventory effect both have substantial effects, hence it is not possible to reject the null hypothesis. As a result, he draws the conclusion that the model that was tested suggests that inbound order flow is indicative of market-wide order flow.

The indicator model proposed by Huang and Stoll (1997b) is yet another kind of microstructure model. This model gets its name from the fact that the information cost is influenced by the direction of trade rather than trading volume. Ding (2006) approaches the task of developing a microstructure model for the foreign exchange market from a unique perspective. The model relaxes the assumption of equal pricing, which is derived from the concept of no arbitrage, and mixes client trade and interbank trade as the same inbound trading process. This allows the model to more accurately reflect market conditions. However, there have been reports that utilising the incoming transaction request as the only source of order flow is problematic. Romeu (2005) reexamines the conclusion reached by Lyons (1995) using the same dataset. The test demonstrates that the DL model is unstable and identifies two structural cracks in the estimation of Lyons' data. As a consequence of this, the data are partitioned into three sub-samples based on the two splits, and it is discovered that the DL model was incorrectly set. In the meanwhile, it has been shown that the sub-samples do not concurrently support both the inventory effect and the information effect. In order to investigate the connection between dealer behaviour and the determination of exchange rates, both the Madhavan and Smidt (1993) model as well as the Huang and

Stoll (1997a) model are used. According to the model developed by Madhavan and Smidt, there is no evidence to support the inventory effect or the information impact that was anticipated by Lyons (1995). The test result of Huang and Stoll's model reveals, on the other hand, that incoming order flow is characterised by a significant information impact. Quote shading is the only method available for controlling inventory if we assume that the dealer only gets orders that are placed with them. The dealer has to make the pricing more appealing in order to attract more buyer- (seller-) initiated orders and reduce (raise) the quantity of inventory that he maintains. Additionally, he needs to drop (increase) his market quotations. On the other hand, due to the multi-structure of the foreign currency market, dealer behaviour is much more diverse, and there is a large variety of inventory management methods available to choose from. As a result, the fundamental assumptions of the DL model, which are that the market is straightforward and that there are few ways to regulate inventories, are problematic.

On the other hand, the ML model, which investigates how market-wide exchange rates are established, has been shown to be more effective via empirical research. Evans and Lyons (2002) developed a model that bridges the gap between macrostructure and microstructure models by enhancing conventional macro variables with order flow. This model has received a lot of attention and is widely discussed. The foreign exchange market is developed into a multi structure, which includes both the consumer market and the interbank market. It is permissible for dealers to trade in a variety of styles, including incoming orders, outgoing orders, client orders, limit orders, and market orders. These styles are referred to collectively as "orders." The model is highly good in tracking the daily movement of exchange rates between the yen and the dollar (over 40% of the time) and between the mark and the USD (over 60% of the time). Its reliability has been shown by extensive testing with a variety of monetary systems and frequency ranges (for examples, see Payne (2003), Froot and Ramadorai (2005), and Breedon and Vitale (2010). This work makes an effort to reconnect the DL and ML models that have been previously separated. As a result, it creates a model that is more comprehensive in nature than the ones developed by Evans and Lyons (2002a) or Ding (2006).

The inventory models centre their attention on the fleeting price change in the vicinity of a constant predicted future reward. In this instance, order flow has an effect on pricing since it has an effect on dealer stocks. The inventory models provide a solution to the challenge that the dealer has while trying to manage inventory on both sides of the market. Due to the fact that order flows are not synchronised, dealers face the risk of either running out of cash, which would result in bankruptcy, or running out of inventory, which would result in failure. The Walrasian framework, according to which a lower (or higher) price drives (or diminishes) demand, is the foundation for risk-neutral models[19]. These models show that rational dealers who are trying to maximise their earnings need to set a particular bid/ask spread and adjust its size in order to maintain preferred inventory levels.

Risk aversion is a notion that describes an individual's reluctance to pick a deal that has an unknown payout rather than a bargain that has a guaranteed return, notwithstanding the possibility that it would be lower. The bid/ask spread is the result of Stoll's (1978) model, and it has a linear dependence on the risk aversion of the dealer as well as the volatility of the asset.

In the multi-period model, the optimum spread narrows because the risk of holding inventory decreases as trade comes to a conclusion. This is because the model takes into account many periods of time. The spread narrows as a result of the increased number of accounting dealers since the risk is distributed more evenly among them. The goal of the information models' point of view is to explain permanent price adjustment in the direction of a change predicted in future reward, and order flow is what causes this price adjustment in relation to future payout.

## 2.2 INTERNATIONAL TRADES

The amount of international commerce has increased steadily during the past three hundred years, with the exception of the Great Depression and the years between the two World Wars. Between 1945 and 1980, there was an explosion in the volume of international trade that had never been seen before. The Great Depression, the two world wars, the dropping of trade barriers, and the precipitous decline in the cost of transportation were the main causes of this. During this time, developing and industrialised nations traded manufactured goods for agricultural and commodity exports from rising nations. These exports were exchanged for manufactured commodities by these countries. Beginning in the 1980s, several developing countries increased their participation in the international economy. Numerous other nations have entered the manufacturing sector since China became a major supplier of textiles and clothing. Malaysia, Turkey, Mexico, South Korea, Indonesia, and Thailand are a few examples of these nations. Global corporations began moving their operations there, and as a result, they began outsourcing part of their

19 Garman (1976)

manufacturing jobs to the locals. To take advantage of the lower labour costs and lower skill requirements in emerging nations, American corporations began outsourcing the manufacturing of commodities like apparel, shoes, and toys there.

Programming, software development, chip design, and financial analysis are just some of the high-skilled jobs that many companies increasingly outsource to employees in other countries. Other high-skilled jobs include biomedical engineering and medical imaging. The European Union (EU) is the main exporter among all nations in the world, accounting for 35% of global exports of agricultural commodities. After comes China, Brazil, Canada, and the United States of America. Additionally, the EU dominates the global market for the export of energy, minerals, and cars. China, Japan, South Korea, and the EU are now the top four exporters of iron and steel in the world. The export of textiles, clothing, and office and communication technology are all areas in which China dominates the worldwide market. The United States of America (USA), EU, Japan, and Canada are the top five exporters of vehicles in the world. A significant portion of global commerce can be broken down into the following categories: transportation, travel, communications, construction, insurance, finance, and information technology, as well as other commercial services such as operational leasing, technical and professional services, cultural and recreational services, and other fields that are comparable.[20]

Mercantilism was the preeminent theory of international commerce throughout the seventeenth and eighteenth centuries. Mercantilists believed that countries should try to maximise their profit from trade. According to this school of thought, the wealth of a nation could be determined by the quantity of gold and silver that it had. Mercantilists held the belief that exporting goods would result in an increase in the amount of gold and silver entering a country, while importing goods would result in an increase in the amount of gold and silver leaving the country. Therefore, in order to boost a nation's overall income, that nation should work to expand its exports while simultaneously cutting down on its imports. The mercantilist ideology held that international commerce was a zero-sum game, meaning that the success of one nation could only come at the cost of another. On the basis of this mercantilist ideology, governments implemented a wide range of levies and other limitations on imports, in addition to offering financial incentives and other forms of support for exports. Individual corporations were also granted exclusive rights by governments to participate in commercial activity.

A new kind of mercantilism has surfaced in modern times, one in which the collection of gold is substituted with the creation of employment. The so-called neo-mercantilists are of the opinion that

20 Source: World Trade Organization (WTO)

exports create employment whereas imports are responsible for the loss of jobs in the home economy. Therefore, a rise in both the number of jobs and the national revenue will result from a trade surplus. They believe that free trade is a zero-sum game and encourage the government to establish policies that aggressively boost exports and prohibit imports. This viewpoint is similar to that of the mercantilists.

Some philosophers and political economists, including as David Hume, Adam Smith, and David Ricardo, started to criticise the idea of mercantilism in the latter half of the eighteenth century and the early part of the nineteenth century. Hume proposed that an increase in the nation's money supply was caused by a trade surplus in addition to the accumulation of gold and silver. The rise in the amount of money in circulation would eventually result in an increase in the cost of consumer products. The increased cost of commodities would make it more costly to ship goods overseas while simultaneously lowering the cost of importing goods, which would result in a reduction in exports, an increase in imports, and the elimination of the trade surplus.

Smith (1776) published the book "An Inquiry into the Nature and Causes of the Wealth of Nations" where he criticises mercantilism and maintains that the wealth of a nation does not increase by accumulating gold and silver, but rather by the number of goods and services available for consumption through trade. In his words, if a foreign country can supply us with a commodity cheaper than we ourselves can make it, better buy it of them with some part of the produce of our own industry, employed in a way in which we have some advantage. Smith maintained that each country has an absolute advantage in the production of a product, that is, if a worker can produce more units of a product than another country. Then each country can specialise in the production of that product and exchange it with the product that it has a comparative disadvantage.

Ricardo (1817), posed the same question and in his book "Principles of Political Economy and Taxation" he wrote:

> *"It will appear . . . that a country possessing very considerable advantages in machinery and skill, and which may, therefore, be enabled to manufacture commodities with much less labour than her neighbours, may, in return for such commodities, import a portion of its corn required for it consumption, even if its land were more fertile, and corn could be grown with less labour than in a country from which it was imported".*

He demonstrated that mutually beneficial trade is still possible if instead of comparing productivity across countries, we compare the opportunity costs of producing each product in each country. Opportunity cost is the amount of a unit of product X that must be given up in order to produce a unit of product Y. If a country can produce a product at a lower opportunity cost, then it has a comparative advantage in the production of that product. Ricardo's insights are used to construct models based on the following assumptions: a) there are only two countries and two products; b) labour is the only factor of production, and each country has a fixed amount of labour that is fully employed; c) labour can work in both industries and can easily move between industries; d) countries may have different technologies, but firms in each country use the same technology to produce the two products; e) there are constant returns to scale, which means that an increase in the number of workers by a certain percentage leads to an equal percentage increase in the level of output; f) there is perfect competition in the market, which means there are many small-sized firms producing an identical product. The price of the product is equal to the extra cost of hiring the labour; g) there are no barriers to trade and no transportation costs.

Smith and Ricardo simply assumed that comparative advantage was due to different labour productivity yet did not explain the causes of comparative advantage. In the early 1930s two economists, Eli Heckscher and Bertil Ohlin, developed a new model that explained comparative advantage. Heckscher-Ohlin (HO) model has been considered important to international trade for decades since it was first proposed. It is one of the theoretical constructs that has had the most substantial influence on international economics. This model lays an emphasis on the inequalities that exist between countries in terms of the relative factor endowments they possess, as well as the differences that exist between commodities in terms of the intensities with which they utilise these components. It provides an emphasis on the interaction that happens between the ratios in which they are employed in the manufacture of a range of various sorts of commodities. In general, countries have an inclination to export those commodities that demand a considerable amount of the materials with which they are abundantly supplied. The model shows how the relative availability of components of production (resources) and the technology (how the item or service is produced) impact a nation's comparative advantage. The theory of factor-proportions is the term given to this specific model.

According to the Heckscher-Ohlin thesis, nations with high incomes, like as the United States and Japan, who have an excess of capital, will be exporters of relatively capital-intensive items, such as machinery, precision equipment, and chemicals. Conversely, nations with lower middle incomes, like Bangladesh and Vietnam, will export labour-intensive items, such apparel, toys, and sports equipment, because of their plentiful labour supply.

In the framework of monopolistic competition, there are two distinct types of trade that may be distinguished. The trading of distinct items back and forth inside an industry is referred to as intra-industry trade, while the trading of the wares produced by one industry in exchange for those produced by another industry is referred to as inter-industry trade. While trade inside an industry demonstrates economies of scale, trading across industries illustrates comparative advantages. Trade inside an industry does not have the same significant influence on the distribution of income as trade between industries does. Inter-industry trade, which refers to trade in products from different industries, such as aircraft and apparel, or wheat and oil, is explained by trade models that are based on comparative advantage. These models are due to differences in productivity or factor endowments that exist between industries. However, the vast majority of the trade in goods that takes place between industrialised nations takes the form of intra-industry trade. This refers to the exchange of items that are comparable to one another, such as apples for apples or shoes for shoes. Because these nations have similar relative factor endowments and the items that are exchanged have comparable factor intensities, the Heckscher-Ohlin model is unable to adequately describe the pattern of trade that exists between them.

Krugman (1979) adheres to the monopolistic competition model proposed by Dixit and Stiglitz (1975). According to this model, a consumer's utility is positively related to several varieties of manufactured products, and each variety is produced subject to the increasing returns to scale that result when an element of fixed costs is added to labour costs that are proportional to outputs. In his paper, he assumed that every country produces many variants of a single type of good. However, from another paper of 1980[21], he allowed for each country to produce two types of products, with many variants of each type. This allowed for the introduction of elements of inter-sectoral trade. Helpman (1987) conducted a groundbreaking paper that challenged the monopolistic competition model for the very first time using real data. He demonstrated that the model's primary assumptions were compatible with manufactured trade between advanced industrial nations.

A new set of models known as New Trade Theory has been developed to explain the pattern of trades[22]. In order to explain international commerce, traditional trade models depended on differences in productivity, such as the Ricardian model of comparative advantage, or models that concentrate on variations in factor endowment, such as the Heckscher–Ohlin model. The premise of constant returns to scale was modified by new trade theorists, who demonstrated that growing returns may drive trade flows between comparable nations even in the absence of disparities in productivity or factor endowments.

21 Krugman (1980)
22 Krugman (1983) and Helpman (1999).

Countries that are completely comparable to one another nonetheless have a reason to trade with one another due to the growing returns to scale. Economies of scale may be achieved in certain sectors when industries in specific nations focus their attention on producing different targeted items. Following this, countries will trade these specialised items with one another; each nation will specialise in a certain industry or kind of product. Because of trade, the nations are able to take advantage of bigger economies of scale. These models rely on economies of scale and imperfect competition as their foundations. When there is an increase in output or scale of production, there may be opportunities for cost savings that are referred to as "economies of scale." These cost savings are estimated by dividing the entire cost of production by the total output generated. Internal economies of scale and external economies of scale are the two types of economies of scale.

In the twenty-first century, many of the controversial issues that Ricardo brought up are still very much a part of the conversation. His creative thoughts and unconventional suggestions are still relevant in the contemporary economic systems (Peach, 2007; King, 2013). In addition to this, we are now seeing the resurgence of the Ricardian trade theory, which is being driven primarily by the contributions of Eaton and Kortum (2002). The Eaton-Kortum model may be thought of as a form of Ricardian many nations, many excellent trade models with bilateral trade costs. The "new trade" notion may be explained and modelled in a number of different ways[23].

The novel notion, on the other hand, is a probabilistic model with two parameters that determines the inputs that are necessary for the production of each item. To analyse the consequences of trade openness and liberalisation on the vast margins of trade is one of the most impressive capabilities that the model has, and it is also one of its most noteworthy aspects.

The role of corporations in commerce is on the increase. Several different economists have established a relationship between firm-level and aggregate data, which makes it possible to do a general equilibrium analysis of the impact of aggregate shocks on individual businesses[24]. The growth of commerce across industries and the increasing technical sophistication of multinational corporations are the two elements that are now defining the international trade landscape[25]

23 Alvarez and Lucas (2007), Naito (2017)
24 Eaton, Kortum, and Kramarz (2022)
25 Melitz and Trefler (2012)

*Gravity Model as Measure of International Trade*

In 1687, Isaac Newton presented his law of universal gravitation, which provided the inspiration for the gravity. Newton postulated that the force of attraction between any two particles in space would be directly related to the product of their masses and inversely related to the square of the distance between them. In that context, an early coherent formulation was the 1885 publication of Regenstein's article titled "The Laws of Migration". He made an effort to clarify that migratory currents are propelled by the "absorption of centre of trade and industry" but diminish with increasing geographical distance. Following this, two important notions for the development of trade theories were presented, the "Linder hypothesis" (1961)[26] and the "Factors-price equalisation"[27]. The gravity model has historically relied heavily on intuitive notions of which factors are most likely to affect trade. In its earliest appearance the Gravity Model was a-theoretical, examples include Ravenstein, 1885 and Tinberger, 1962, who employs gravity studies to explore immigration and trade flows respectively. Under the assumptions of product differentiation by place of origin and Costant Elasticity of Substitution (CES), Anderson, 1979 is the first to propose a theoretical economic underpinning for the gravity equation.

The gravity model is the primary method that is used to correlate various trade obstacles and associated costs. According to the findings of research, trade costs are a cause of comparative advantage or disadvantage because of the way they influence trade[28]. Additionally, there has been a revival of interest in the theory and use of gravity in recent years. The gravity model has been used in the writing of hundreds of academic articles and books to investigate and quantify the impacts of a wide variety of factors that influence international commerce. In the research that has been done up to this point, a wide variety of models have been developed to account for the different kinds of data and approaches to estimate. For instance, given the availability of panel data, the dynamic gravity model is suggested as a possible solution[29].

In addition, Head and Mayer (2014) investigated the estimating processes, technical problems, and theoretical implications of the gravity model. They defined the success of the gravity model as a "workhorse, toolbox, and cookbook." As a consequence of the earlier research, the

26 Linder (1961)
27 Samuelson (1948) and Samuelson (1949)
28 McGowan and Milner (2011)
29 Olivero and Yotov (2012)

model is in no sense an intellectual "orphan," but rather it is now related to the diverse family of economic theory[30].

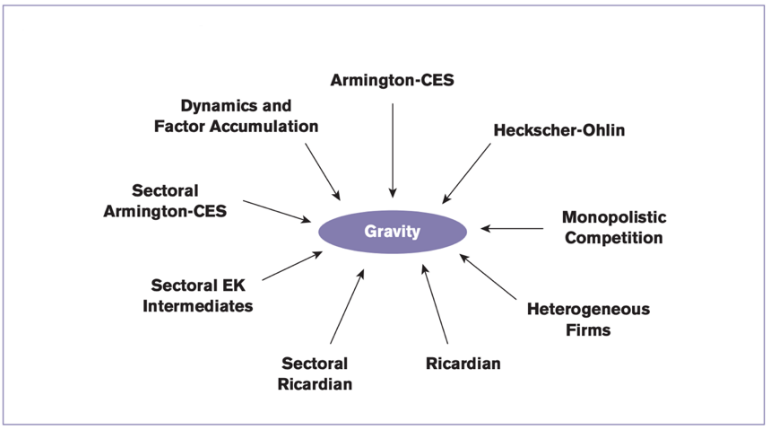



Figure 2: Gravity model's strong theoretical foundations. Source: WTO

The figure 2 shows the gravity model foundations. The benefits derived from trade are unaffected by a variety of alternative microfoundations, such as a single economy model with monopolistic competition, a Herckshe-Ohilin framework, a Ricardian framework, entry of heterogeneous firms, selection into markets, a sectoral Armington model, a sectoral ricardian model, a sectoral input-output linkages gravity model, and a dynamic framework with asset accumulation.

The first economist to provide the theoretical economic basis for the gravity equation was Anderson. He was also the first person to use the term "gravity equation." The work that he did was predicated on the assumptions of product differentiation determined by location of origin and Constant Elasticity of Substitution (CES) spending. The Armington idea, which served as the basis for Anderson's most important work, was the impetus behind it. Anderson was able to include the product differentiation strategy into his research by establishing the gravity equation, which accounted for the incorporation of income concerns. This allowed him to do the analysis. Early on in his career, Bergstrand[31] is responsible for the publication of a number of works that have since been deemed to be among the very best in the subject of gravity literature. He was the second author to offer the micro-economic foundation for the gravity model, and he did it as part of the gravity model. He created a link between the two, placing more of an emphasis on the supply side of the economy, as well as between trade theory and bilateral commerce. Specifically, he was referring to the supply side of the economy. During this time span, there have been many writers who have made substantial contributions to

30 Anderson and Wincoop (2003); Anderson, Larch, and Yotov (2017); Anderson (2004); Feenstra, Markusen, and Rose (2001); Rubinstein, Helpman, and Melitz (2008a); Bergstrand (1985); Shahriar et al. (2019)

31 Bergstrand (1985); Bergstrand (1990); Bergstrand (1989)

the extension of trade theory. These writers include Brakman, Garretsen, and Marrewijk (2009); Helpman and Krugman (1985); Helpman (1984); Krugman and Obstfeld (2002) and Rubinstein, Helpman, and Melitz (2008b).

Helpman (1987) drew a relationship between the monopolistic competition model and the gravity model by using research that were done on eighteen different industrial nations. This had the immediate effect of laying the financial groundwork for the gravity technique, which was in the process of being developed.

According to Deardorff (1998), the gravity model is suitable for use in conjunction with a diverse range of economic models. The HO model, the growing returns to scales model, the Ricardian model, and a great many additional models are examples of this kind of model. Evenett and Keller (2002) found that the success of the gravity equation can be adequately explained with only two fundamental hypotheses—namely, the HO model and expanding returns to scale—and that this is sufficient.

In the meantime, McCallum (1995) published an important study that evaluated the impact of national boundaries on the regional trade patterns between Canada and the United States. He did this by applying the gravity equation to analyse data on interprovincial and international trade that was conducted by Canadian provinces during the years 1988-1990. He found that commerce between Canadian provinces was more than 20 times bigger compared to trade between Canadian provinces and states in the United States. This finding was made in comparison to trade between Canadian provinces and states in the United States. Since the publishing of the foundational works of McCallum (1995) and Helliwell (1997), economists have pondered the notion that boundaries may induce customers to prefer things that are produced locally. As a direct consequence of this, the so-called "border effect" has become one of the phenomena that has garnered the most attention in recent years[32].

The issue of border effects, often known as the "McCullum Border Puzzle" in the academic community, has been the focus of a considerable deal of study and writing over the years. An investigation of the impact that borders have on the wide and intense margins of commerce was carried out by Cheong, Kwak, and Tang (2015). This was done in an effort to discover a solution to the challenge that is posed by the separation in distance.

Anderson and Wincoop (2003) proposed a solution to the McCallum border problem. Their findings suggest that McCallum's calculations of the gravity equation are flawed due to an omitted variable bias. With McCallum's own data in hand, Anderson and van Wincoop were able to verify their own points; they then enhanced McCallum's model by including the many resistance aspects, and applied

32 Carter (2017); Feenstra (2002); and Magerman, Studnicka, and Van Hove (2015)

this revised model to the solution of the notorious McCallum border problem. Due to the exclusion of the multilateral components, they conclude that all of the coefficients are skewed. Fixed effects models allow for unobserved or mis-specified factors that simultaneously explain trade volume between two countries[33]. The fixed effects are also used to estimate the trade effects of currency unions[34]; or to estimate the effects of borders on trade[35], or to calculate the cost of protection[36].

According to Anderson and Yotov (2016), there are at least five noteworthy considerations that may explain the gravity model's tremendous success and widespread appeal:

- The trade gravity model is rather intuitive. The gravity model of trade predicts that international trade (gravitational force) between two nations (objects) is directly related to the product of their sizes (masses) and inversely related to trade frictions (the square of the distance between them).

- one of the most attractive properties of the gravity model is its predictive power. Empirical gravity equations of trade flows consistently deliver a remarkable fit of between 60 and 90 percent with aggregate data as well as with sectoral data for both goods and services. High explanatory power with $R^2$ between 0.65 and 0.95;

- The gravity model of trade is a structural model supported by sound theoretical premises. Due to this trait, the gravity framework is well suited for hypothetical research, such as measuring the consequences of trade policy.

- The gravity model offers a realistic environment of general equilibrium that allows several nations, different industries, and even enterprises. As a result, the gravity framework may be used to account for the likelihood that markets (sectors, nations, etc.) are interconnected and that changes in trade policy in one market would cause ripple effects throughout the rest of the world.

- The gravity setup is a highly flexible structure that may be used into a broad range of general equilibrium models in order to examine the relationships between trade and labour markets, investment, the environment, etc.

The ability of the gravity model to make accurate predictions is one of the model's most compelling selling points. The empirical character of gravity equations of trade flows has continuously delivered a

33 Matyas (1997), Bayoumi and Eichengreen (1996), Coughlin and Wall (2002)
34 Glick and Rose (2002), Pakko and Wall (2001)
35 Millimet and Osang (2007)
36 Wall(1990)

fantastic match between 60 and 90 percent with aggregate data as well as sectoral data for both commodities and services[37].

The most influential structural gravity theories in economics are those from Eaton and Kortum (2002), who derived gravity on the supply side as a Ricardian structure with intermediate goods, and Anderson and Wincoop (2003), who popularised the Armington - CES model of Anderson (1979) and emphasises the importance of the general equilibrium effects of trade costs. Arkolakis, Costinot, and Rodríguez-Clare (2012) demonstrate that a large class of models generate isomorphic gravity equations which preserves the gains from trade.

Theories that might integrate the gravity equation were developed because of the model's stability and its capacity to explain bilateral trade flows. In the field of international trade theory, the gravity model has become the go-to tool, notably for predicting the effect of policy shifts on trade costs. The model's adaptability allows for a variety of factors, such as cultural and political distance between trade nations, to be considered "distance." Impacts on trade flows from Britain's withdrawal from the European Union (Brexit) have been predicted using the theoretical framework offered by the Gravity model.

The general formulation of the gravity model is the following:

$$X_{i,j} = GS_i M_j \phi_{i,j} \tag{4}$$

where $X_{i,j}$ is the monetary value of exports from country $i$ to country $j$; $S_i$ is the economic mass of the importer; $M_j$ is the economic mass of exporter; $G$ is a variable that does not depend on $i$ or $j$ (for example the global level of liberalisation); and finally $\phi_{i,j}$ is the inverse of bilateral costs.

The gravity equation relates the natural logarithm of the monetary value of trade between two countries to log of their respective GDPs, and trade term between them. The standard procedure for estimating a gravity equation is to take the natural logarithm of all the variables in order to obtain a log-linear equation that can be estimated through an Ordinary Least Squares (OLS).

The model can be written as follow:

$$\ln X_{i,j} = \beta_0 + \beta_1 \ln GDP_i + \beta_2 \ln GDP_j + \beta_3 \ln \tau_{i,j} + \varepsilon_{i,j} \tag{5}$$

where $X_{i,j}$ indicates exports from country $i$ to country $j$; $GDP_i$ and $GDP_j$ indicates each country's gross domestic product; $\tau_{i,j}$ represents trade costs between the two countries; and $\varepsilon_{i,j}$ is the error term.

Grouping terms together for exporters and importers allow us us to rewrite the gravity model equation as follows:

$$\log X_{i,j} = C + F_i + F_j + (1 - \sigma)[\log \tau_{i,j}] \tag{6}$$

37 Bergeijk and Brakman (2010)

The first term, $C = -\log Y$, is a regression constant. In terms of the theory, it is equal to world GDP, but for estimation purposes it can be captured as a coefficient multiplied by a constant term, since it is constant across all exporters and importers. The term, $F_i = \log Yi - \log \Pi_j$, is a full set of exporter fixed effects. By fixed effects, we mean dummy variables equal to unity each time a particular exporter appears in the dataset. We take the same approach on the importer side, specifying a full set of importer fixed effects $Fj = \log Y_j - \log P_j$. According to the panel data literature, this method accounts for all unobserved heterogeneity sources that are constant for a particular exporter across all importers and for a given importer across all exporters. The theory gives a solid justification for such a strategy, since the GDP and international resistance terms meet these conditions. The estimation of models with fixed effects is easy. Since the fixed effects are essentially dummy variables for each importer and exporter, all that is required is it to build the dummies and then add them as explanatory variables to the model.

In the gravity model, zero trade flows are a major issue. The zero logarithm is undefined. In order to solve the issue of zero flows in trade data-sets, truncations and filtering techniques are suggested in the literature. There are various biases and difficulties with these estimating methods. Information loss is a major concern. This occurs as a result of the inefficiency of estimate methods. The exclusion of data may result in biassed estimations[38].

Westerlund and Wilhelmsson (2011) noted in their work that the absence of trade flows results in sample selection bias. In the estimate of gravity model for commodity or sectoral trade, the occurrence of 'zero' is a prevalent concern[39]. Nonetheless, a panel data model allows for the recognition of how significant variables change over time and the identification of particular time or country effects. Therefore, there should be a greater emphasis on methodological enhancements with the goal of embracing dynamic panel data approaches.

38 Baldwin and Harrigan (2011); Burger, Linders, and Oort (2009); Martin and Pham (2015)

39 Burger, Linders, and Oort (2009); Martin and Pham (2015)

# Part II

# EMPIRICAL STUDIES

# 3 NON-LINEAR FORECAST USING MACHINE LEARNING MODELS

This chapter evaluates the performance of a new forecasting model compared to a random walk benchmark. The empirical findings provide the following conclusions. Empirical data suggests that the microstructure order flow models discussed earlier exhibit more economic value compared to a basic random walk model, particularly when analysing a portfolio of currencies. The findings of this evaluation indicate that the proposed forecasting model outperforms the random walk model in terms of forecasting accuracy. According to the authors, the primary focus for foreign exchange (FX) traders should be on the flow of different customer groups rather than solely considering the overall order flow. Asset managers exhibit superior predictive capabilities compared to other clients. The study additionally takes into account non-linearities within the microstructure framework, underscoring the necessity for non-linear data. This study evaluates the economic significance of exchange rate forecasts, specifically highlighting the considerable economic value of microstructure order flow in the context of dynamic portfolio allocation. The order flow from customers is an informative indicator of future excess returns, and there are significant disparities across various end-user categories. Both asset managers and hedge funds are significant players in foreign exchange markets, and their order flows significantly and favourably anticipate currency excess returns.

This chapter also makes a valuable contribution to the existing body of literature concerning the prediction of low-frequency data, highlighting the limitations of current methodologies for unconditional forecasting due to linearity and the large amounts of data needed. Deep neural networks, characterised by their lack of constraint to a specific functional form, can be considered a promising approach for improving prediction accuracy in scenarios with limited data availability. The utilisation of artificial intelligence in the field of economics has witnessed significant growth; however, there remains a dearth of scholarly investigations pertaining to the application of Artificial Intelligence (AI) in macroeconomic finance or the analysis of low-frequency data.

## 3.1 INTRODUCTION AND MOTIVATION

The process of forecasting the evolution of exchange rates is a challenging endeavour, but it is an essential component of economic research. Researchers have spent a significant amount of time trying to develop an accurate theoretical model of the dynamics of exchange rates, but they have been unsuccessful. In spite of this, they have continued their efforts. There is a general agreement among economists that models that depend on macroeconomic data to forecast the exchange rate have a lower degree of accuracy compared to models that are based on a simple Random Walk (RW). In recent decades, an increasing number of scholars have looked at the concept of market microstructure as a means of gaining accurate insight into the structure of exchange rates. This strategy involves examining the movement of exchange rates on specific markets in order to get a better understanding of the functioning of the markets. There has been a significant amount of debate regarding the use of microstructure models with the purpose of gaining a better understanding of the effect that changes in microstructure have on the behaviour of currencies. In this regard,Evans and Lyons (2005), Evans and Lyons (2002b) and Sager and Taylor (2008) think that these models are useful tools for understanding how the performance of exchange rates might be affected by changes in microstructure, and they prove that these models are actually helpful. Microstructure models are not always able to reliably reflect the behaviour of exchange rates, according to these researchers. The performance of order flow models is superior to that of a straightforward random walk based on sample forecasts.

According to the findings of the research conducted by Evans and Lyons (2005), order flow is a major element that affects exchange rates, and it may be used to anticipate exchange rates in the future. However, there is little evidence from real-world experiments to support the hypothesis that market orders result in more effective markets. In fact, Sager and Taylor (2008) discovered, via the use of market data and interdealer orders, that the markets are not necessarily more efficient than they might be. Researchers interested in market microstructure have been looking at the link between order flow and exchange rates in a variety of different market settings. Some scholars feel that the degree of this link is dependent on the present circumstances of the market, while other scientists think that the association is impacted more by releases of macroeconomic news. For instance, Love and Payne (2008) conducted research on the effect of order flow on the transmission of information about published macroeconomic fundamentals. They found that information that is issued contemporaneously is partly impounded into prices through the microstructure order flow. Nevertheless, it is abundantly evident that the predictions of rational agents are not being met by the events that are taking place.

Other researchers show that economic news influences exchange rates in two distinct ways: directly, as in a standard macroeconomic model, and indirectly, through orders. The former procedure was illustrated by Bacchetta and Van Wincoop (2006), while the latter was illustrated by Rime, Sarno, and Sojli (2010). One way to look at the flow of orders in the market is as a random variable that helps map information that has been floating about the market into price discovery. Order flow in the foreign exchange market is made up of a variety of market players, each of whom has their own unique risk-return expectations and informational asymmetry. As a result, the order flow from customers is the major source of the confidential information that is used to forecast upcoming shifts in the basic drivers of exchange rates. Despite the fact that the microstructure models provide some helpful insights into the foreign exchange market, there are still certain issues that have not been satisfactorily resolved. When the information is published openly and concurrently to all market players, microstructure models have proven effective in making out-of-sample projections. However, since the status of the economy may take some time to affect the exchange rate, a model that uses a delayed order flow may be able to more accurately anticipate the exchange rate[1]. When forming their expectations for the new equilibrium exchange rate, many market players use both public and private information. Expectations about the new exchange rate are generated as a result of a mix of macroeconomic factors and elements pertaining to market microstructure.

Guresen, Kayakutlu, and Daim (2011) provides evidence that solutions based on Neural Network (NN) perform better than those based on other statistical and mathematical methods. Within the realm of forecasting issues, neural networks provide a model of prediction that is both general and specific at the same time. These models are data-driven, and as a result, they are able to produce nonlinear models without requiring any previous information about the functional forms.Because of this finding, there are now more opportunities than ever before to enhance the precision and effectiveness of machine learning systems. Neural networks might be able to provide the universality of the forecasting model in the category of forecasting issues. Due to their ability to self-train and their qualities, neural networks are able to accurately capture the dynamics of nonlinearities and the complex elements of financial data. This is useful because it makes it possible to do an analysis of financial data that is both more accurate and up-to-date. They also have the ability to learn and generalise information. Approaches that are not smooth, such as those that rely on

1 Sager and Taylor (2008)

assumptions about normality, linearity, and variable independence, might be less dependable than those that employ NNs.

The analysis contained in this chapter focuses on evaluating the performance of empirical exchange rate models relative to the random walk benchmark. In addition, we contribute to that part of the literature that suggests that the most relevant information for FX traders with access to order flow information is not necessarily the total of order flow but rather the flow of different customer groups, finding that asset managers own the better predictive power among all the customers[2]. What does matter for the relationship between end-user order flows and future returns is disaggregated data since the information content of flows for the future varies across customer groups. In particular, financial customers are those who exhibit superior information, and this is not surprising considering the specific FX core nature of this group. We find the most informative are asset managers, followed by hedge funds, while corporations and private clients generate negative spreads.

### 3.1.1 *Research Contributions*

*Why Forecast Exchange Rate is Important?*

It is crucial to have the capacity to correctly foresee expected future market movement in order to successfully influence the decision-making process for hedging, and as a result, it is essential to have a method of forecasting that can be trusted. The alternative is to base decisions on information that is either incomplete, irrelevant, or otherwise misinterpreted, which does not fit under any reasonable hedging technique. An approach to forecasting exchange rates that is both relatively new and one that requires a large amount of processing power has been utilised in an effort to anticipate the future price of exchange rates. In the following discussion, we will outline the components that, when combined, make this piece of study a noteworthy addition to the area.

*Econometric Contribution*

The goal of this chapter is to estimate the log returns of time series of exchange rates using a novel model called the Neural Microstructure Technique (NMT). This approach is interdisciplinary, combining machine learning with finance, and it ends in a new model. In particular, we combine the microstructure approach to exchange rates with the Artificial Neural Network (ANN) forecasting ability in order to test whether the new method can outperform traditional methods in predicting customer order flow. It is difficult to forecast the future path of the exchange rate because of the inconsistency of the macroeconomic fundamentals and the heterogeneity of the agents. I provide

2 see an example Figure 5

evidence to support the claim that the model discussed in this chapter is capable of adequately explaining the observed pattern.

The proposed model successfully handles the issue of vanishing gradients, making it extremely adaptable to a variety of practical issues. Long-short-term memory (LSTM) is a type of recurrent neural network (RNN) that has the capacity to learn what information should be stored and what should be deleted. Through the incorporation of exogenous factors and the facilitation of the inclusion of fundamentals, this method worsens the problem of instability. In this work, the time series forecasting model incorporates exogenous data in the form of client order flow. We next evaluate if adding this data improves the model's ability to predict outcomes. This model can forecast macroeconomic time series by incorporating a wide variety of fundamental components as necessary because of its distinctive feature of including exogenous variables. Despite the fact that earlier studies have attempted to forecast exchange rates using the acRNN and others have used intuition based on microstructure, the combination of these elements in this study allows it to significantly advance the area.

*Economic Contribution*

According to the findings of this research, microstructure variables and non-linear models are able to give superior out-of-sample predictions compared to a random walk model. There is a substantial volume of published research on the effect that order flow has on forecasting future currency prices, yet not a single one of these studies uses deep learning techniques to study the question. The purpose of the model is to study the role that order flow that is segmented into customer groups plays in the process of predicting currencies. This makes it possible to contribute to the building of a bridge between research on foreign exchange microstructure and the cross-sectional pricing of currency assets. The portfolio technique is one that we use, and it offers a straightforward and easy-to-understand method of estimating the economic worth of order flow for the purpose of predicting exchange rates.

The support provided by the informational content of asset manager order flow, specifically, and financial institution order flow, more broadly, might be valuable to practitioners seeking arbitrage possibilities. Order flow trading involves monitoring market orders that are pending execution. Based on this particular strategy, price variations occur as a result of imbalances within the market, and it is possible to forecast forthcoming price changes by employing this methodology. By employing order flow analysis, it is possible to anticipate the occurrence of market order imbalances at a future price level. The levels of supply and demand serve as indicators of market imbalance. By employing the order flow trading method, one may forecast market price fluctuations just by examining market orders. The order book, which encompasses a comprehensive list of pending orders, holds significant importance for order flow traders as it serves as a vital instrument for their trading activities.

*Low-frequency data* Further, we investigate the use of deep neural networks (which are not tied to any particular functional form) to improve the accuracy of predictions with a small amount of data. The traditional methods for unconditional forecasting are not useful for making accurate predictions about the future in this context. This is because models are inherently linear and need a lot of data. There have been several studies on finance using machine learning techniques, and despite the fact that the use of artificial intelligence in economics is quickly expanding, the literature is lacking in macroeconomic finance and/or low-frequency data. Bayesian analysis, Dynamic Stochastic General Equilibrium (DSGE) models, as well as textual analysis, are the primary areas of concentration in low-frequency research.

### 3.1.2 *Outline of the Chapter*

This chapter is organised as follows: First, in Section 3.2, we conduct a literature survey in order to find the main challenges in the research area, formulate a hypothesis, and design and develop a research strategy. Then, collect the required data, and in the section on empirical analysis paragraph 3.4 is described as we carried out necessary pre-processing steps. Then, conduct exploratory analysis in order to better understand the behaviour of the data and to design the analysis method. After that, create multiple sub-datasets using different combinations of independent attributes as well as based on a number of lags. With each of these datasets, train the LSTM based multi-step forecasting models. Then compare the forecasting performances among these models using different evaluation matrices and comment on the economic performance of the results. Finally, in the conclusions 3.5 we discuss the advantages and disadvantages of the proposed method and make suggestions for future work.

## 3.2 REVIEWS OF THE RELATED RESEARCH

The forecaster will choose an information set to base their projections in order to forecast the currency exchange rate. A wide range of variables, such as interest rates, inflation, current account deficits, governmental debts, terms of trade, political stability, and economic performance, all have an impact on the exchange values of different currencies [3].

3 MacDonald (2000)

Before 1970, the use of the products market was by far the most common method for anticipating currency exchange rates. This required keeping track of the pricing of items that were being exchanged between nations. This model helps to comprehend how an increase in exports can lead to a surplus for a nation, which will cause the currency to appreciate as a consequence of the surplus. It is possible by linking currency movements to import and export levels. The study makes the assumption that domestic and foreign bonds are equivalent in every way, and that the equilibrium of the money market is sufficient information for establishing short-run exchange rates.

In the latter part of the 1970s, the asset market method, which is based on the demand for money resulting from the buying and selling of assets such as bonds and stock, started to gain acceptance. These writers concentrate on portfolio balance under the assumption that domestic and foreign bonds are unsatisfactory replacements for one another[4]. Studies that concentrate on understanding or predicting exchange rates using standard macroeconomic fundamentals (such as the money supply or investment portfolios) are widespread. During this time period, only a small number of studies attempted to compare the two approaches, and those that did so encountered a number of obstacles as a result of the distinct approaches and data that had evolved over time. Since that time, the major macroeconomic variables-based models in the foreign currency market have depended on three essential assumptions. These assumptions are that all of the information is public, that agents are homogeneous, and that the structure of the market does not matter.

It is not obvious why exchange rates don't always move in a consistent manner, yet macroeconomic indicators like the GDP in classic monetary models are not susceptible to long-term or severe situations. For example, the GDP does not always grow in the same direction. It has been hypothesised by some economists that the reason for this is shifts in inflation rates; however, these theories do not always hold [5]. When modelling the nominal exchange rate using the macro fundamentals based method, there is a chance of excessive exchange rate swings in comparison to the fundamentals because of this element of the technique.

*Fundamental Approach*

The literature has spent a significant amount of time investigating the link between currency exchange rates and the fundamentals of an economy, with a particular emphasis on how the nominal exchange rate might deviate from its true value. The nominal exchange rate is given by forward looking expectations, in the monetary context, can be a parsimonious set of fundamentals, comprising the money supply

4 Backus (1984), Campbell and Clarida (1987) and Meese and Rogoff (1983)
5 Meese and Rogoff (1983); Frankel and Rose (1995); Cheung, Chinn, and Pascual (2003); Sarno and Valente (2009)

and output, but it can also include a broader set of fundamentals such as net foreign assets or trade balance. Future exchange rate changes are a function of the gap between the current exchange rate and the expected current fundamentals.

According to Meese and Rogoff (1983), who were leaders in this area of the literature, models that depend on fixed exchange rates don't explain much of currency changes over short time periods, and they can't exceed a basic model that assumes a random walk in terms of accuracy. They looked at three distinct currency pairs and found that the random walk model outperformed for all of them when evaluated over a length of six and twelve months, but it performed better for just two of the currency pairs when examined over a period of one month. Following this, a large number of studies have claimed to have uncovered the success of a range of fundamental-based exchange rate models spanning a variety of historical periods; nevertheless, the success of the models has not been demonstrated to be long-lasting. Frankel and Rose (1995) reached the opinion that the Meese and Rogoff analysis of short time horizons has not been sufficiently rejected or explained. This was the result that they got to after doing their research. Cheung, Chinn, and Pascual (2003) came to the conclusion that not a single model exhibited a consistent level of performance after conducting a reevaluation of the capability of a group of macroeconomic fundamentals-based models developed in the 1990s to make accurate forecasts. These models were established in an effort to accurately predict the state of the economy. Some models may perform better than others at specific time horizons for specific currency pairings; however, models that are a suitable fit for one exchange rate may be unable to estimate another exchange rate. This can happen when the models are compared to each other using the same currency pairings and time horizons. Often a concern is model consistency, and the effectiveness of a model may be contingent on the kind of money or the time period being modelled. Even if favourable findings are obtained from one model, this does not ensure that other models will also yield positive results; this is because there is no way to account for all possible variables.

It is a common knowledge that the efficacy of macroeconomic variables based exchange rate models seems to improve with bigger data sets and more complex econometrics techniques over horizons of more than one year. This is the case regardless of the length of time being analysed. When the performance is assessed, this is the situation that arises. The association between changes in fundamental data and variations in exchange rates, on the other hand, may only be shown empirically after a considerable length of time has elapsed since the correlation was first hypothesised. Mark (1995) arrived to the conclusion that variations in the market for foreign currencies are predictable, and that the results had statistical significance. He found that the bias-adjusted slope coefficient and $R^2$ increase with the forecast horizon, and that out-of-sample predictions often perform better than the random walk. These conclusions were drawn on the basis of the finding that the slope coefficient is influenced by the time horizon of the prediction. However, there is widespread scepticism over the extent to which models are applicable to time periods that extend beyond a single year. Kilian (1999) found that the model did not show any evidence of being predictable after using the bootstrapping procedure to the data set that was reported in Mark (1995).

Engel and West (2005) show that if the fundamentals follow I(1) are a random walk, then the discounting factor is very close to 1. Because of this, the study based on fundamentals cannot provide more accurate forecasts than the random walk model of exchange rates. In particular, they find very little evidence that the exchange rate can be described by the observable fundamentals. Additionally, they concur with the findings of earlier research that there is a role for unseen fundamentals including real shocks and risk premium. It would seem that this at least partially explains why making predictions based on fundamentals may be challenging.

*Microstructure Approach*

Due to the absence of relevant variables in models that are based on macroeconomic fundamentals, research in the microstructure approach has become more prevalent. According to the researchers, changes in the exchange rate must have a significant correlation with news about future fundamentals. This finding is compatible with the investigation of market microstructure. In an environment where there is a variety of information available on the market and where typical macro factors are taken into account in structural exchange rate models, macro fundamentals are unable to operate as information aggregators that lead to price discovery. Order flow is seen as a random variable by microstructure models, and it is used to translate heterogeneous and dispersed information into price discovery. Therefore, order flow in the microstructural approach constitutes the missing connection between changes in exchange rates and changes in economic circumstances. This is in contrast to macro-based exchange rate models, which focus on exchange rates as a whole.

According to Rogoff (1999b) the failure of basic analysis may be ascribed to three primary issues. He is of the opinion that standard economic models do not adequately take into account all of the elements that might be contributing to the movement of currency exchange rates. It is necessary to update earlier models whenever new information is obtained since the underlying assumptions and concepts that are utilised in such models may not always be valid. The failings of certain of the models that are based on macroeconomics may be partially attributed to the three causes. Because they do not take into account the dynamics of the market and the process of buying and selling, the fundamentals of macroeconomic indicators, such as inflation rates, interest rates, and so on, are unable to always accurately predict short-term changes.

Neither the fluctuations in currency exchange rates nor the diffuse participation in FX trading can be well explained by conventional economic theories. The microstructure approach is providing first insights. The market microstructure theory is a framework for analysing the dynamics at play when various asset classes are exchanged in accordance with predetermined norms[6]. In contrast to the standard asset approach, the microstructure method does not assume that all relevant information is readily accessible to all market participants, that all assets are highly differentiated, or that market mechanisms have a substantial impact on asset prices. Information is scattered and asymmetrically dispersed in the market, and the market microstructure method aggregates this information into prices. The role of trade in the creation of prices is also investigated. In the microstructure method, order flow is used to represent dealers' access to data about transactions. In recent years, several empirical studies' results have corroborated the function of order flows in affecting currency exchange rates. However, most macroeconomic exchange rate models ignore several elements that are genuinely crucial in influencing exchange rates[7]. Traditional exchange rate models do not account for the fact that the order flow in the stock market has a significant effect on stock prices.

The future dynamics of prices in micro-exchange rate agreements are heavily influenced by the order flow of a certain asset. Microstructure research has shown how distinct sets of participants may obtain different information, contrary to the "weak form" of an efficient market theory, which is supported by standard technical analysis. Customers' willingness to pay for a product or service is affected by a number of factors, one of which is the price. In the context of the microstructure, practitioners are referring to well-informed trades when they describe order flow. Order flow data has been analysed as a possible predictor of future prices because of their nature as forecasters of future exchange rates. Order flows are the sum of all completed transactions; they are the gold standard for measuring business activity. They has been demonstrated by several studies to be an excellent indicator of future occurrences. There is evidence that order flow data can be used to accurately anticipate daily fluctuations in currency exchange rates. The reason that order flow should be able to anticipate exchange rate returns if it represents diverse ideas about the status of the economy and if currency markets don't learn or-

6 Market Microstructure Theory, O'Hara (1995)

7 Evans and Lyons (2002a), Evans and Lyons (2002b), Evans and Lyons (2005), Rime (2000), Payne (2003), Marsh and O'Rourke (2005), Froot and Ramadorai (2005), Osler and Vandrovych (2009), and many others

der flow in real time. These findings lend credence to a hypothesis put out by Bacchetta and Van Wincoop (2006) and Evans and Lyons (2008). When both the mark/dollar and yen/dollar exchange rates are taken into account, Evans and Lyons (2002b) find that the order flow is much better explained. Explanatory power ranges from 0.00% to 68%, according to this expansion of the empirical research conducted by Evans and Lyons (2002a). Further, they state that the order flow model outperforms a random walk model in terms of out-of-sample predictive power. As with Evans and Lyons' findings, Killeen, Lyons, and Moore (2001) note that the order flow model has substantial explanatory power. Given that it presupposes perfect foresight, Payne (2003) argue that the aforementioned model is not very useful in reality. The authors demonstrate this using central bank order flow for Swiss franc/dollar for the sample period 1986–1995, and they find that despite a high contemporaneous connection between inter-dealer order flow and exchange rate returns, the predictive potential of this relationship is weak. In a comprehensive empirical research, Sager and Taylor (2008) go more into this topic. To paraphrase their argument, they claim that there is a lag between when news is made public and when prices adjust, proposing the so-called publication lag model. Through extensive empirical testing, they demonstrate that the lagged order flow model provides little insight into the data and cannot compete with a basic random walk model when trying to predict future exchange rates. Furthermore, they provide enough proof of a Granger-causal link running from exchange rate returns to order volume from customers. Engel and West (2005) found some empirical support for the inverse relationship among fundamentals and exchange rate, arguing that exchange rates may aid in forecasting fundamentals.

Cerrato, Sarantis, and Saunders (2011) utilise weekly customer order flow for nine of the most liquid currencies to examine the in-sample and out-of-sample forecasting capabilities of the order flow models. The in-sample findings with the contemporaneous order flow model are highly supportive of this model, while the aggregate results are consistent with Sager and Taylor (2008). Using disaggregate data seems to boost the in-sample and out-of-sample forecasting capabilities of the order flow model, which may be overly restricted when dealing with weekly data.

Evans and Lyons demonstrate, in a series of studies published between 2002 and 2008, that order flow contemporaneously explains a considerable amount of the high-frequency fluctuation in exchange rates. Order flow appears to aggregate changes in expectations about fundamentals; this may supplement the findings that macro information impacts exchange rate at high frequency[8], and it may antici-

8 Andersen et al. (2003)

pate exchange rate returns over long horizons. When compared to the news approach, the quality of the regression of higher-frequency exchange rates is much enhanced when the order flow is included into the equation. This improvement may be attributed to the fact that the order flow is included in the equation. This is because, when the microstructure technique is used, order flow works as a leading indicator by amassing knowledge on fundamental facts far in advance of their release. When the economic figures are released, it should not come as a surprise since the information is constantly included into the price of the exchange rate while the market process that was just described is taking place. In addition, empirical investigations have demonstrated that the connection between order flow and exchange rate in interbank trading is extremely high only on a contemporaneous basis, and that order flow in customer trading delivers a noisy signal of the market-wide order flow. This is due to the fact that the order flow generated by client trading provides a signal that is not indicative of the market as a whole. Accordingly, it would seem that the use of order flow can only be advantageous for forecasting exchange rates to a limited degree, at least when seen from the perspective of the typical market maker.

Several studies appear to imply that there exist information asymmetries in the foreign exchange market; hence, order flow has the potential to be informative. Ito, Lyons, and Melvin (1997) discover that when trading is introduced during the lunch hour, volatility increases by a factor of two. It would seem that the information from order flow is gradually incorporated into the price rather than the immediate price adjustment process that would be the case if the efficient market theory were true.

When calculating exchange rates, it is common practise not to take into consideration the order flow that is employed in trading. This is owing to the fact that the mechanics of transactions that take place inside markets are not well understood. The micro approach to currency exchange examines how the orders that are made in a particular asset will influence the price dynamics in the days and weeks to come. Traditional technical analysis lends credence to the "weak version" of the efficient market hypothesis. However, research into market microstructure has shown that diverse groups of participants have access to a variety of information. There are a number of different elements that go into determining the cost of this item, some of which are more significant than others. Order flow is what microstructuralists mean when they speak about informed transactions when they talk about order flow. This indicates that all of the essential data has been compiled and is ready for use, making it possible for transactions to go easily and without hitch. It is possible to forecast future prices by looking at the orders of currencies. Data on order flow, it has been discovered by researchers, may be put to use in the production of reliable forecasts. The total value of all transactions that have been completed in a certain amount of time is shown as a line graph in the order flow chart.

According to the findings of some researchers, order flow has a high degree of predictive capacity. This is proved by Rime, Sarno, and Sojli (2010), who make use of order flow in order to anticipate daily fluctuations in exchange rates. They believe that order flow should be able to provide forecasting power for exchange rate returns if it reflects different beliefs about the current and future state of the economy, and if the currency market does not immediately discover order flow. These findings are in line with previously proposed hypotheses, such as those put out by Bacchetta and Van Wincoop (2006) and Evans and Lyons (2008). Prices in the market may be affected by a wide variety of variables, including the regulations that traders are adhering to, the various sorts of investors that are active, and the structure of the markets itself. Each and every one of them plays a significant part in both the theoretical models and the practical implementations. Glosten and Milgrom (1985) contributed significantly to the development of the theoretical foundation for microstructure analysis. Since quite some time ago, the equities and bond markets have both made substantial use of one sub-field of economics known as market microstructure. The foreign exchange market has seen a steady introduction of market microstructure since the middle of the 1990s, in part owing to the increased accessibility of order flow data. Evans and Lyons (2002a) is one of the numerous research that finds that order flow may explain more than 60 percent of fluctuations in exchange rates. According to Gehrig and Menkhoff (2004), there are many aspects that play a significant role in trading, including order flow, fundamental analysis, and technical analysis. Up to two thirds of all public information is transferred via the order flow, while the order flow itself protects the confidentiality of any information that may be considered sensitive.

Traditional macroeconomic variable-based models may have an issue that might be helped by microstructure approaches to exchange rates, which is that certain assumptions may not always hold true over time[9]. Lyons (2001) notes that traders in the foreign exchange market utilise information that is distinct from the information that is used in models of exchange rates that are based on macroeconomic data. The microstructure approach modifies three of the most fundamental assumptions found in traditional macroeconomic models. These assumptions are that a) all consumers act rationally, b) all information relevant to foreign exchange is publicly available, and c) all trading mechanisms affect prices in the same way.

The differences between microstructure approaches to exchange rates and classic macro-based models may be summarised by the

9 Rogoff (1999a)

three relaxations of the traditional macro-based models. Abandoning those assumptions, we have that some market players do hold private information which cannot be accessible by others; that heterogeneous investors do not respond to the same information in the same way; and that information flows do not effect the price instantly and they will be completely reflected into the market in a slow manner.

The market for foreign exchange is one of a kind due to the fact that it has a variety of market structures that influence how it acts. These structures consist of interest rates, supply and demand dynamics, as well as potential for arbitrage. The price of various foreign currencies is determined together by these variables. The foreign exchange market has two stages: an inter-dealer market and a dealer-customer market. Customers go via dealers when buying and selling assets in the market, while dealers make use of liquidity in order to fulfil the requirements of customers. In the inter-dealer market, traders will work together to rid themselves of any unexpected positions by trading with one another. The foreign exchange market is an international network consisting of consumers and dealers who engage in the computerised trading of assets and currencies. Instead of taking place on a real trading floor, transactions take place on electronic trading platforms. There are a few factors that, when combined, can lead to a low degree of transparency that exists in the market for foreign exchange. These factors include a combination of investors with low and high levels of transparency, a trading process that is slow, and trading rules that vary depending on the market. Order flows represent the most significant component to consider when attempting to understand the market's behaviour, however a number of other variables may have an effect on exchange rates. This is due to the fact that orders are frequently the earliest indicator of price changes and may contribute to the maintenance of stable market conditions.

*Non-linearities*

According to Cerrato, Kim, and MacDonald (2015), the presence of nonlinearities is what causes the conflicting and sometimes inconclusive results that this methodology has produced. As a result, nonlinearities in a microstructure model should be taken into account because they can cause unexpected changes. In general, despite the promising results that some research based on order flow analysis has yielded, this technique has offered up conflicting and sometimes inconclusive results. With the assistance of various machine learning strategies in particular, there is the possibility for advancement to be made in the process of resolving the problem of non linearity. In point of fact, Recurrent Neural Networks have been used in the search for a forecasting model that is superior to that of a random walk. Due to the fact that an RNN was developed specifically to make use of sequential information, it is capable of performing the identical duties for each and every component that makes up a sequence. This makes it possible for the outcome to be independent of the calculations that came before it.

Although the prediction of time series has often been done under the premise of linearity, which has promoted the research and use of linear models such as autoregressive Auto Regressive (AR) models, Moving Average (MA) and Auto Regressive Moving Average (ARIMA) models, it has turned out that time series, such as exchange rates, frequently have an unknown non-linear structure. This has encouraged the study and use of linear models. The use of mathematical models as a tool for forecasting is very beneficial; yet, these models are not perfect and cannot always anticipate everything accurately owing to the large number of diverse input elements. Predicting exchange rates remains a challenging endeavour due to the fact that they are impacted by a wide variety of economic, political, and even geopolitical variables that are closely associated with one another. They also feature significant levels of volatility, intricacy, and noise, all of which may be traced back to a nebulous market process that generates daily observations. In recent years, machine learning has gotten more popular, and it is now often used to make predictions about time series in a variety of different industries. The use of neural network models to forecast currency exchange rates has been demonstrated to be beneficial by a number of different studies. Because of the data-driven nature of these models, it is possible to demonstrate the validity of nonlinear models without having previous knowledge of the functional form. Due to the fact that NNs are capable of self-training and possessing certain qualities, they are able to correctly recognise the dynamics and intricacies of financial data. In addition to this, they have the potential to generalise procedures that are predicated on stringent assumptions like normalcy, linearity, and independence.

*Model instability*

In the existence of the role of macro fundamentals, one of the consequences of both methods to the microstructure is that a macro variable will include pertinent common knowledge, which will then be incorporated into a currency of any microstructure role.

Evans and Lyons (2002a), Evans and Lyons (2008), and Love and Payne (2008) all took a similar but slightly different approach when they tried to clarify the relationship between the release of economic news and the order flow. They also attempted to provide empirical evidence that macro news triggers trading that reveals dispersed information, which in turn affects currency prices. Order flow is connected to macroeconomic news in this context; nevertheless, the explanatory power is either not recorded or proven to be lower than what the model implies. According to Rime, Sarno, and Sojli (2010) hypothesis, the heterogeneous interpretation of macroeconomic news may lead market makers to make different inferences, and the order flow will gradually incorporate this information. Additionally, the authors hypothesise that the order flow will incorporate this information. The findings from the computed coefficients are statistically significant at the 10% level, which suggests that news is a substantial factor in order flow. However, they highlight that the sign of the link between news and order flow is unclear since it relies on how much the exchange rate changes immediately in reaction to the news. This makes the sign of the relation between news and order flow confusing. They do this by using a Probit model in order to conduct an empirical investigation into the relevance of the association between cumulative order flow and macroeconomic news. With the use of this model, they were able to locate a coefficient for macroeconomic news that was appropriately signed and statistically significant. Note that the new equilibrium price is determined by the order flow, which represents the many ways in which the news might be interpreted, but the portion of the news that is already common knowledge directly influences the exchange rate by moving where the equilibrium price lies. Rime et al. suggest a direct and an indirect specifications model on the basis of this discovery.

Both of the models discussed above provide evidence that fluctuations in the exchange rate are linked to both order flow and macroeconomic fundamentals. Direct links are found in the traditional theory of the foreign exchange rate, while indirect links are found in the microstructure approach to the foreign exchange rate. If this is the case, then the diverse perception of market information has a direct impact on the asset price. This is the case if order flows completely include macroeconomic news, as is assumed by usual microstructure techniques. However, as shown in the study of Love and Payne (2008), if the order flows partially reflect heterogeneous interpretations of macroeconomic news, the indirect specification model of Rime, Sarno, and Sojli (2010) specifies the effects between news and order flows. This model was developed by these three researchers. This modelling technique has the potential to provide some explanation for the relationship between fundamentals of the macro economy and exchange rates, which was investigated by Bacchetta and Van Wincoop (2006) and Evans and Lyons (2008). It is important to keep in mind that the discovery of strong explanatory power for macroeconomic news on the exchange rate does not always mean that order flow information is superfluous. The model's ability to explain phenomena is given a major boost when order flow is included into it.

*Deep Learning in Economics*

Estimation methods such as neural networks and deep learning have garnered a growing amount of interest among economists. Even while the present state of theoretical findings is limited, what we do know shows that some neural networks have many desirable qualities with regularly used estimators, such as sieve estimators[10]. For the

10 Chen (2007)

purpose of constructing functions from covariates, neural networks make use of nonlinear transformations of affine combinations.
These nonlinear transformations, which are called activation functions, play a significant role in both theoretical and practical applications and are referred to as such. Stinchcombe and White (1989) and Chen and White (1999), provide results for single hidden layer neural networks with smooth activation functions, and Chen (2007) presents results for deep neural networks with piece wise linear activation functions. These results can be found in the current theoretical literature[11]. However, practitioners have conducted research on a wide range of neural network topologies and discovered that increasing the network's depth delivers advantages in terms of both accuracy and generalisability[12].

Figure 3 from Herbrich et al. (1999) illustrates the most prevalent economic uses of neural networks. Starting with Rumelhart, Hinton, and Williams (1986) and the use of backpropagation to neural network learning, economists began using machine learning as a tool since neural networks for classification and regression can be readily applied to economic issues. Principal applications in economics include the categorisation of economic agents, the modelling of bounded rational economic agents, and prediction of time series.

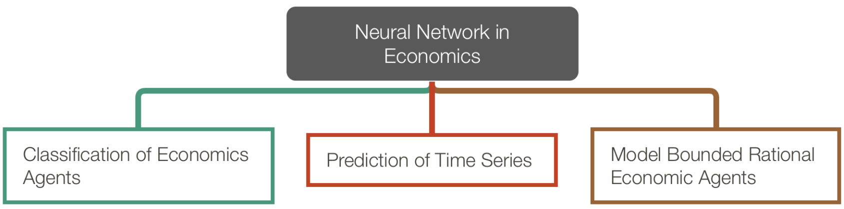



Figure 3: Major Applications of Neural Networks in Economics

The topic of forecasting time series in financial markets is likely where neural networks have found the most use in economics, and one of the primary uses of these systems is in the capital markets. In most cases, linear models of financial time series (such as exchange rates or stock exchange series) have a poor performance, and linear univariate models regularly produce evidence for a random walk[13]. This has been considered as evidence in support of the efficient market theory, in which efficiency refers to the fact that the market completely and accurately reflects all relevant information in establishing security prices[14]. However, this premise is not usually accepted, and as a result, one of the strategies that is often pursued is to attempt to

11 Farrell, Liang, and Misra (2019)
12 Telgarsky (2016), and Safran and Shamir (2017)
13 see, for example, the debate in Meese and Rogoff (1983) or Lee et al., 1993
14 Fama (1970) or Malkiel (1992)

employ nonlinear models in order to enhance the fit, and therefore, the prediction[15].

Neural Networks are adaptable functional forms that enable the approximation of any continuous function, even nonlinear ones. As a result, it is reasonable to anticipate that they will provide efficient nonlinear models for financial time series, which will therefore make it possible to make more accurate forecasts. White (1988) is one of the first researchers to utilise Neural Networks in the capital markets. He used a two-layer neural network to analyse a series of length 1000 IBM equities. His goal was not to make predictions, but rather to examine the validity of the efficient market theory. Because he was unable to locate any evidence to the contrary, he believes that a random walk is still the most effective model for a financial market. However, since the network that was employed in his research was not very complex, a number of writers questioned the reliability of White's findings. A neural network was proposed as the fundamental component of an expert system by Bosarge (1993). He discovered major nonlinearities in a variety of time series, including the S&P 500, Crude Oil, Yen/Dollar, Eurodollar, and the Nikkei-index, and as a result, he was able to significantly increase the quality of the prediction. Similar findings have also been reported by Wong (1990), Tsibouris and Zeidenberg (1995), Refenes (1995), Hiemstra (1996), or Haefke and Helmenstein (1996).

Results by other authors go in the other direction, Hill et al. (1994) present inconsistent evidence as to the predicting outcomes of Neural Networks, despite the fact that they performed "as well as (and sometimes better than)" statistical approaches. This conclusion was reached after conducting a study of the literature. In a study titled "Comparing Feedforward and Recurrent Neural Networks as Prediction Tools for Different Currency Exchange Rates," written by Kuan and Liu (1995), the authors reveal mixed data when comparing the two types of neural networks. The same may be said for Verkooijen (1996), who used a Neural Network to relate financial time series to basic factors such as GDP or trade balance. Chatfield (1993) cautioned against making direct comparisons between Neural Networks and linear prediction techniques due to the fact that, in many cases, the linear approaches that were used seemed to be incorrect. The fact that there are no objective guidelines to choose the appropriate dimension (i.e. the number of hidden layers or neurons) of the Neural Network, which is a problem that was referred to earlier as the model selection problem, appears to be a major obstacle in the implementation of Neural Networks as tools for prediction. This issue is known as the model selection problem. Although implementations often relate to rules of thumb and to a trial-and-error technique, systematic ways have been offered. One example of such a method is the Sup-

15 Engle (1982), Granger and Hallman (1991), or Brock, Hsieh, and LeBaron (1991)

port Vector method [16]. As a consequence of this, and as a general outcome, it would seem that Neural Networks have the potential to be used as tools for predicting. The ability to accurately forecast nonlinear time series is one of its many strengths. However, further findings are required before these tools can be considered credible instruments for the "everyday-forecaster." Examples of applications of time series prediction in disciplines other than finance include those by Franses and Draisma (1997) or Swanson and White (1997) for macroeconomic variables, Church and Curram (1996) for consumers' expenditures, or Kaastra and Boyd (1995) for agricultural economics.

## 3.3 THEORETICAL FRAMEWORK

A forecast represents an expectation about a future value or values of a variable. The expectation is constructed using an information set used by the forecaster, there are two approaches to forecast exchange rate: fundamental and technical. The ability to forecast future FX market movements requires the correct interpretation and evaluation of a number of issues.

Technical analysis care little for fundamental factors, instead focusing on the extrapolation, understanding and measurement of past price trends. Many refers to technical analysis as an art rather than a science, which in many respects confirms its position as a polar opposite to fundamental analysis, which centres on factual analysis of economics and other relevant determinants.

Whereas technical analysis involves poring over charts to identify patterns or trends, fundamentals analysis involves poring over economic data, reports and news headlines, and nowadays even social media posts. Fundamental analysis is a way of looking at the forex market by analysing economic, social, and political forces that may affect currency prices.

*Fundamental Analysis*

The Fundamental approach is based on a wide range of data regarded as fundamental economic variables that determine exchange rates. These fundamental economic variables are taken from economic models. Usually included variables are gross national product, consumption, trade balance, inflation rates, interest rates, unemployment, productivity indexes, etc. In general, the fundamental forecast is based on structural equilibrium models. These models are then modified to take into account statistical characteristics of the data and the experience of the forecasters. A fundamental approach incorporates a wide range of data considered to be "fundamental" in determining exchange rates. Factors including political and financial considerations,

16 for more discussions see Kuan and Liu (1995), Weigend, Huberman, and Rumelhart (1990), or Anders and Korn (1999)

statistics economics, multi-asset analysis and supply and demand are used to determine the underlying impact on price movement and how expected changes in these variables could impact price moving forward. Fundamental analysis is widely reported in the media and one will often read commentary centred on confidence indicators, production data, inflation, interest rates, and labour numbers. The analysis then regresses the data using sophisticated models to make projection on how actual and anticipated changes in these variables could impact on price. Often one is looking at the impact divergence between corresponding dataset in order to determine the likely impact on future exchange rate volatility. Furthermore, implied volatility distribution by the options market will often provide confirmation or a contrary outlook on forecasting by leveraging price prediction available in that market. Traders tend to focus on the most important macroeconomic readings that affects the market and provide more volatility. The effect on the market highly depends on the comparison between the actual reading of the macroeconomic reading and the market consensus, where the bigger the difference, the bigger is the effect on the market.

Other macroeconomic data, one of the most important factors in fundamental analysis is the monetary policy carried out by central banks. Interest rates, open market operations and central banks interventions influence market conditions and are closely monitored by financial analysts and traders alike. Fundamentalist also consider outside influences that could affect an instrument's value or price movement. Natural disasters, such as floating or earthquakes can also have a major impact on the fundamentals strength of an asset. The various fundamental factors can be grouped into two categories: quantitative and qualitative. The quantitative relates to information that can be shown in numbers and amounts; qualitative relates to the nature or standards of something, rather than its quantities. It is related to things that are more subjective and unable to quantify. Among the common indicators used for fundamental analysis: unemployment rate, interest rates, new building permits, change in the GDP, income and wages, Consumer Price Index (CPI), inflation, balance of trade, corporate profits.

*Technical Analysis*

Technical analysis predicts price movements and future trend expectations by studying charts of past market action. In other words, its focus is on the effect of movement on price by utilising pattern recognition, mathematical modelling and analytical theory. The technical analysis focuses on a smaller (compared to fundamental) subset of the available data. In general, it is based on price information. The analysis is "technical" in the sense that it does not rely on fundamental analysis of the underlying economic determinants of exchange rates or asset prices, but only on extrapolations of past price trends.

This kind of analysis looks for the repetition of specific price patterns, major trends and critical or turning points. These turning points are used to generate trading signals: buy and sell signals. Among the most popular technical models are simple and rely on moving average, filters or momentum indicators.

The three key principles of technical analysis are:

1. market action: market action "discounts" everything that is already known about the market or underlying asset/financial instrument. In other words, an asset's price history incorporates all the relevant information, so there is no need to forecast on research asset "fundamentals". Indeed, technical purists do not even look at fundamentals, except through the prism on prices, which reflect fundamentals before those variables are fully observable. Presaging finding by Engel and West (2005), Murphy (1986) claims that asset price changes often precede observe changes in fundamentals.

2. asset prices move in trends: this is essential to the success of technical analysis because trends imply predictability and enable traders to profits by buying (selling) assets when the price is rising (falling). This is captured in the technicians' mantra "the trend is your friend".

3. history repeats itself: technicians believe that market is fractal and patterns repeat over different time frames. Asset traders will tend to react in a similar way when confronted by similar conditions. This implies that asset price patterns will tend to repeat themselves.

Using these three principles, technical analysis attempt to identify trends and reversals of trends. These methods are explicitly extrapolating; that is, they infer future price changes from those of the recent past. Technicians argue that formal methods of detecting trends are necessary because prices move up and down around the primary or long-term trend. That is, technical indicators can be constructed with data over multiple time frames, from intraday to daily or multi year horizons. Technicians may consider patterns over these multiple time frames, placing increased emphasis on the signals from longer horizons.

Volume frequently plays a role in technical analysis, in particular in the stock market, but foreign exchange markets are decentralised; there are no comprehensive indicators of volume. For this reason, technicians in FX markets sometimes use proxies for total volume, such as volume measures from futures markets IMM Commitment of Trades or screen-based tick counts, or proprietary data from market-makers banks).

There are many types of technical analysis and many way to map current and past price and volume data into trading decision. Broadly speaking, technician have traditionally employed two types of analysis to distinguish trends from shorter-run fluctuations and to identify reversal: charting and mechanical (or indicators) methods.

Practitioners use structural models to generate equilibrium exchange rates. The equilibrium exchange rates can be used for projections or to generate trading signals. A trading signal can be generated every time there is a significant difference between the expected foreign exchange rate and the actual rate; the technician then, decides if the difference between the expected foreign exchange rate and the actual rate is due to a mispricing or a heightened risk premium. If the practitioner decides the difference is due to mispricing then a buy or sell signal is generated.

*Order Flows Analysis*

It is usual practise, when determining exchange rates, to ignore the order flow used in trading. This is due to the fact that the mechanics of transactions occurring inside markets are poorly understood. The micro approach to currency exchange investigates how orders placed in a specific asset may impact the price dynamics over the course of the following days and weeks. The "weak variant" of the efficient market theory is supported by conventional technical analysis. However, market microstructure research has shown that varied participant groups have access to a range of information. The price of an item is determined by a variety of distinct factors, some of which are more relevant than others. When microstructuralists discuss informed transactions, they are referring to order flow. This signifies that all required data has been gathered and it is available to use, allowing transactions to proceed without difficulty. It is feasible to predict future prices based on the relative positions of currencies. Researchers have found that order flow data may be used to the generation of accurate projections. In the order flow chart, a line graph depicts the total value of all completed transactions during a specified time period. Certain studies have determined that order flow has a high degree of predicting ability. The microstructure theory presents a diverse explanation for how the order flow conveys information about fundamentals by using the trading mechanism. This explanation is the microstructure theory's most important contribution. Order flow transforms into a transmission gear that makes it easier to aggregate information on price dispersion, such as diverse interpretations of the news, changes in anticipation, and shocks to hedging. Despite the fact that order flow is the primary variable used for explanation in microstructure-based models of exchange rates, it is not the primary reason why exchange rates move in the way that they do. Order flows simply send individual bits of information on basic factors that determine the exchange rate, and this information is then aggregated by the market. The empirical evidence demonstrates that there is a correlation between order flow and exchange rate[17].

The function of customer order flow is essential in the majority of models based on the microstructure theory. It is via the customer orders that the confidential information is sent to the market makers and is then included into the pricing. In addition to being emphasised in theory, the significance of customer order flow was also brought up in the survey that was based on a questionnaire and was conducted by Cheung and Chinn (1999) and Gehrig and Menkhoff (2004). According to the findings of these research, the majority of traders in the foreign exchange market place a high value on client order flow as a source of information before deciding whether to purchase or sell. Several studies have shown that the influence of macroeconomic data on the currency exchange rate is not just direct, as it would be in a typical macro model, but also indirect, as it would be via order flow[18].

### 3.3.1 *The Proposed Method*

The approach that is being presented here is a hybrid system that is based on both machine learning and trading. In this chapter, we test a novel model that we suggest to improve the instability problem, the test takes place out of the sample exercise.

Because traditional neural networks only take in new information in the form of a standalone vector, they do not have any concept of memory, which prevents them from being able to successfully complete tasks that need memory. Using a basic feedback-type method as a solution for the neurons in the network was one of the early approaches that was taken to solve this problem. The output of the network was looped back into the network so that it could provide context for the most recent inputs that were analysed as part of this tactic. They were referred to by their true name, which was "Recurrent Neural Networks."(Recurrent Neural Network (RNN)s). Despite the fact that these RNNs did function to some extent, their major flaw was that any extensive usage of them resulted in an issue known as the Vanishing Gradient Problem. This was a huge drawback. The phenomenon known as vanishing gradient occurs when it is unclear how much weight to give to inputs that occurred in the past. When you start multiplying previous outputs by new outputs, the resulting values become unmeasurably small. This is because the value of multiplication for sigmoid layers, which range from 0 to 1, is always $<1$, and as a result, the values become far too small for networks to learn from them. We will not go into detail on the problem of vanishing

17 Evans and Lyons (2002b); Killeen, Lyons, and Moore (2001)
18 Rime, Sarno, and Sojli (2010)

gradients any further, but enough it to state that RNNs are not well suited for most real-world issues because of this difficulty. As a result, it was necessary to find another approach to the problem of context memory.

Long-Short-Term Memory (Long-Short Term Memory (LSTM)) neural networks were able to overcome the aforementioned issue. LSTM neurons, much like RNN neurons, maintain a context of memory inside its pipeline. This enables them to solve sequential and temporal issues without the vanishing gradient problem hindering their performance. It is a kind of RNN capable of learning what information to keep and what not to keep. The Long Short-Term Memory (LSTM) model it is a subcategory of the deep learning category and it is well suited for solving issues involving sequences that include autocorrelations. It makes use of memory blocks, also known as cells, that are located in the hidden layer and that are linked in a circular fashion. The memory blocks are the ones in charge of remembering things, and there are three main methods, called gates, that are used to make changes to the memory. The forget gate is in charge of erasing information from the current state of the cell; the input gate is in charge of adding information to the current state of the cell; and lastly, the output gate is in charge of determining which of the following hidden states should be chosen.

In this research, we make use of a multi-step recurrent LSTM forecasting, which not only considers the present state of the recurrent output layer but also the order in which inputs come in from the outside environment. In addition to this, we will investigate whether or not the addition of a market microstructure component, such as order flow, to a collection of weekly observations and the use of an machine learning approach can better explain fluctuations in exchange rates than a random walk model does. So, we incorporate exogenous information, represented by customer order flow, in the time series forecasting and check if this improves the performance of the prediction. This will be done by determining whether or not the random walk model is the best fit for the data.

Our empirical analysis is based on predictive regressions for exchange rate returns, many of which are nested and motivated by Engel and West (2005) present value model. The predictive regressions have the same linear structure:

$$r_{t+1} = \Delta s_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{7}$$

where $\Delta s_{t+1} = s_{t+1} - s_t$ is the logarithm change at weekly frequency for exchange rate $i$ at time $t+1$; $X_t$ is the predictive variable, $\alpha$ and $\beta$ are constant parameters to be estimated and $\varepsilon_{t+1}$ is the error term.

The main difference between the regressions is how it is expressed the predictive variable $X_t$ used to estimate exchange rate returns.

We only utilise order flow information that is readily accessible on the day of the prediction. The primary focus of this research is on making predictions that are one step ahead of current conditions for all of the out of sampling frequencies and exchange rates. The capacity to estimate the order flow of customers, segmented into its many categories (such as asset managers, hedge funds, corporate clients, and private clients), is the primary emphasis here.

The aggregated model relies on all four customer order flows, and the independent variable $X_t$ of equation Equation 7 will be equal to $[x_t^{am} + x_t^{hf} + x_t^{co} + x_t^{pc}]$, whereas the disaggregated or individual model evaluates the order flows of each of the four clients independently.

These regressions will determine whether there is predictive information in customer order flow and the extent to which different customer groups provide different information.

Following the Guo and Lin (2018)'s model, we assume to have $N-1$ exogenous time series and a target series $y$ of lenght $T$, where $y = [y_1, ...., y_T]$ and $y \in \mathbb{R}^T$. By stacking exogenous variables and target series, we define a multi-variable input sequence as $X - t = \{x_1, ....x_T\}$, where $x_t = [x_t^1, ..., x_t^{N-1}, y_t] \in \mathbb{R}^N$ is the multi-variable input at time step $t$ and $x_t^n \in \mathbb{R}$ is the observayion of $n$-th exogenous time series at time $t$. Given $X_T$, we aim to learn a non-linear mapping to predict the next value of the time series, namely $\hat{y}_{T+1} = F(X_T)$. Model $F(\cdot)$ should be interpreted in the sense that we can understand which exogenous variables are crucial for the forecasting.

With the input $X_t$ equal $\{x_t^i, ..., x_{t+n}^i\} = \{orderflow\}$ the final Deep Microstructure Algorithm will have the following steps:

- data spitting to 70% for training, 30% for testing;
- train NN model;
- predict the exchange rate with NN;
- add the predicted price to the dataset $X_t^{i,new} = \{x_t^{am}, x_t^{hf}, x_t^{co}, x_t^{pc}\}$;
- train LSTM with $X_t^{i,new}$;
- validate the model with 20% testing.

### 3.3.2 *Traditional Methods*

Since Meese and Rogoff (1983) pioneering work, the random walk model has been the benchmark by which to evaluate the accuracy of future exchange rate predictions. The RW model encapsulates the consensus among academics studying international finance that exchange rates are very volatile and provides the theoretical underpinnings for the popular carry trade strategy. The Random walk with drift model sets β=0 and serves as a standard against which the predictive regressions conditioned on order flow will be evaluated.

Purchasing Power Parity (PPP) states that national price level should be equal when expressed in a common currency and it is typically though of a long-run condition rather than holding at each point in time[19]. The PPP model hypothesis is that $X_t = p_t - p_t^* - s_t$, where $X_t$ is the cost of the good X at time t, s is the exchange rate of currency 1 to currency 2; $p_t$ is the cost of good X in currency 1 and $p_t^*$ is the cost of good X in currency 2.

The Uncovered Interest Parity (UIP) is the cornerstone condition for the FX market efficiency. It is based on the condition: $X_t = i_t - i_t^*$. Assuming risk neutrality and rational expectations, it implies that $\alpha = 0$ and $\beta = 1$, it also implies that the error term is serially uncorrelated. However, numerous empirical studies consistently reject the UIP condition[20]. As a results, it is a stylised fact that estimates of β tend to be closer to minus unity than plus unity. This is commonly referred to as the "forward premium puzzle", which implies that high-interest currencies tend to appreciate rather that depreciate and forms the basis of the widely used carry trade strategy in active currency management.

### 3.3.3 *Forecast Evaluation*

Two error measurement are utilised. For each evaluation of the training convergence of the neural prediction we use the root mean squared error:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathtt{target}_i - \mathtt{out}_i)^2} \tag{8}$$

where $\mathtt{target}_i$ is the desired value and $\mathtt{out}_i$ is the predicted value and N is the number of training pairs. The ratio Root Mean Squared Forecast Error (RMSFE) versus random walk may be used to assess out of sample predictions given four forecasts: the basic random walk forecast, the LSTM forecast, the UIP and the PPP.

For the evaluation of the quality of the predictions, we use the standard Mean Absolute Percentage Error (MAPE), this shows the average deviation of the prediction from the actual value in percentage:

19 Rogoff (1996) and Taylor and Taylor (2004)
20 Hodrick (1989); Engel (1996)

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\text{target}_i - \text{out}_i}{\text{target}_i}\right| \tag{9}$$

To get a single MAPE score we simply take an average of MAPE scores across all predicted time steps.

### 3.3.4 *Economic Interpretation*

Given that transactions record data about customers, it is reasonable to employ a trading technique in assessing individual's ability to foresee consumer order flow. This is because transactions reveal information about customers. We compare these approaches based on the returns they generate. In this way we are able to assess the worth of conditioning on different types of client order flow and to quantify the economic benefits of doing so. Keep in mind that all interactions between dealer and customer are strictly confidential, and that the dealer is the only one who knows the nature of the client's transactions in real time. Therefore, even though order flows from customers may be used as a predictor of future foreign currency excess returns, this information is not widely available to market participants. Knowing this, we want to use a trading technique as a means of determining whether or not dealers are provided with predictive information through client order flows.

After the best network has been chosen, the findings are applied to a portfolio strategy, and the portfolio's value is calculated. The network's efficiency in making predictions over a period of time equal to that of the test set is then evaluated in terms of the portfolio's performance over the same period of time.

When evaluating the overall quality of various portfolios, it is common practise to analyse and compare the risk and return statistics of the investments held over a certain period of time. This is done in order to facilitate the construction of an investment portfolio. Moreover, a predictive portfolio selection model for short-term investment methods requires a system that can make accurate predictions about the future returns of stocks and the risks that are connected with those returns. We use LSTM so that we may produce accurate projections about the future stock return of the currency rate.

Therefore, to predict stock return $\hat{R}$ at time $t+1$, the return data of $R_{t-1}, \ldots, R_t$ are used.

Each period the investor has two stages. First, the investor makes a prediction for the next period of exchange rate returns using the LSTM model. Then, constantly rebalances the portfolio depending on the predictions of each model. Specifically, we examine the performance of dynamically rebalanced portfolios based on NMT in comparison to the random walk benchmark. In this scenario, the investor obtains predictions of exchange rate returns for the subsequent period by applying neural network conditioning to order flow data available at the time of the forecast. The investor selects investment weights using the maximum expected return technique with an annual goal volatility of $\sigma_p^*$=10% and a relative risk aversion coefficient of $\gamma$=6[21].

### 3.3.5 *Performance Measures*

We evaluate the performance of exchange rates models using the most commonly used measures that is Sharpe Ratio (SR) and Sortino Ratio (SO). The realised SR is equal to the average excess return of a portfolio divided by the standard deviation of the portfolio returns.

$$SR = \frac{E[R_p - r_f]}{\sigma_p} \tag{10}$$

with $R_p$ being return of portfolio, $R_f$ being risk-free rate and $\sigma_p$ being standard deviation of the portfolio's excess return. The SO is equal to the average excess return divided by the standard deviation of the negative returns:

$$SO = \frac{R_p - r_f}{\sigma_d} \tag{11}$$

$\sigma_d$ is the "downside standard deviation" equal to the standard deviation of solely the investment's or portfolio's negative returns, i.e. the downside deviation.

We compare the performance of the exchange rate model conditioning on order flow to the benchmark RW computing the difference between the portfolio returns of the order flow strategy with the benchmark RW.

### 3.3.6 *Robustness*

A Non-Linear AutoRegressive with eXogenuos Inputs (NARX) is employed at weekly frequency for G10 exchange rate forecasting exercise. In this research exchange rates and order flows are selected as input variables in the network modelling. Given the output time series to predict $y(t)$ and the exogenous inputs $X(t)$, the model generates target and features as:

$$y_{t+1} = y_t, y_{t-1}, \ldots, y_{t-p-1}, X_{t-d-1}, \ldots, X_{t-d-q+1} + \epsilon_t \tag{12}$$

Where $y$ is the variable to be forecasted one step-ahead; $X$ are the exogenous variables (order flows), $p$ is the autoregressive order, $q$ is

21 these decisions are supported by several empirical research

the exogenous input order, d is the exogenous delay. In a standard NARX network, we have a two-layer feed-forward network, with a sigmoid transfer function in the hidden layer and non-linear transfer function in the output of the NARX model $y(t)$ is fed back to the input of the network through delays.

## 3.4 EMPIRICAL ANALYSIS

In this study seven years of historical data are analysed to target exchange rates. The inputs are order flows and current exchange rates and the output are future exchange rates.

### 3.4.1 *Dataset Description*

Throughout the entirety of this chapter, statistics are drawn from two different sources: order flow from USB for the nine pair of currencies and weekly nominal foreign exchange rates supplied from Reuters. Both sets of information are presented on a weekly basis and cover the span from November 2, 2001 to November 23, 2007 for a total of 317 observations.

The exchange rates were sourced from Thomson Reuters, who derived their information from DataStream. They are the closing spots rates from WM/Reuters, which were given by Reuters at about 16 GMT. A positive coefficient indicates dollar buying or euro selling and vice versa; an increase in the rate represents a weakening of the euro, whereas a decline in this rate represents a strengthening of euro against US dollar. The exchange rate is defined as the price in US dollars of one unit of the Euro.

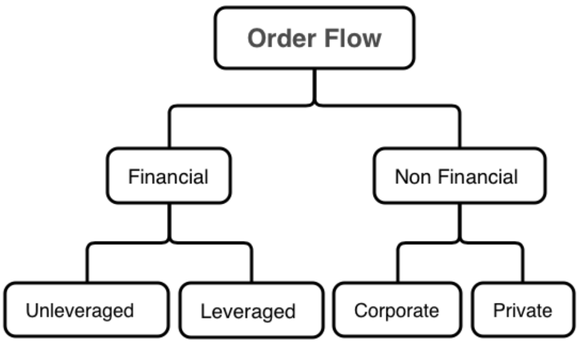



Figure 4: Order Flows Composition

Figure 4 illustrates the classification of order flows into two categories: financial and non-financial end customers. The financial clientele include those with and without leverage. Real money investors, such as mutual funds and pension funds, comprise the asset managers group of the unleveraged financial division. Hedge funds are unregulated firms that comprise highly leveraged traders and short-term asset managers that are not included in the asset management group; these clients belong to the leveraged financial sector. The corporate section consists of non-financial firms that import or export goods and services internationally or have a global supply chain. It also covers the treasury units of big non-financial organisations, except those following a highly leveraged investing strategy, which are categorised as hedge funds. Private consumers are the final section of non-financial customers. They trade largely for financial reasons and with their own funds. It comprises affluent consumers with more than $3 million in investable liquid assets.

### 3.4.2 *Data Manipulation*

To get started with training a neural network, we must first model the data so that the network can learn from a historical series of values. Both the input and output data of a neural network are treated beforehand. Since the input series were scaled using the same technique, the network output was likewise scaled. Therefore, when the neural network computations are complete, a reverse scaling method is applied to the output data, thereby unscaling the result. Because of the need to normalise the data, we divide the order flows by their standard deviation to get rid of the absolute order flow size disparity across currencies. The range of the data has been standardised to $[-1, 1]$.

After being normalised, the data are split up into two primary collections of information. The first data set is designated for the purpose of model selection, which includes the functional approximation of neural network input/output mapping for expected value estimation as well as the selection of stochastic process for asset returns. As a consequence of this, the initial data set will serve as both the training set and the validation set. The final evaluation of the neural network's predicted performance is carried out with the assistance of the second data set. It is also the set that the overall model will examine in order to determine whether or not it is capable of generating extra return on the market.

Exchange rates is converted by taking logs returns calculated as:

$$r_t = \ln(s_t) - \ln(s_{t-1}) \tag{13}$$

As $s_t$ is the FX spot rate of the US dollar versus a foreign currency. The data must also be transformed into a stationary format, which may be accomplished by calculating the difference between any two numbers in the series. As its name implies, differencing is a technique used to strip time series data of its temporal components. The difference can be used in place of the raw numbers to facilitate modelling, and the resulting model is more accurate in predicting future outcomes.

Lastly, LSTM requires a supervised learning environment for optimal performance. In other words, if you have X and want to forecast Y, we apply a lag to the series, wherein the input is the value at time $(t-k)$ and the output is the value at time $t$ for a $k-step$ delayed dataset.

With time series data, such as exchange rates, the sequence of the observations does have a relevance, which is not the case with most analyses, where data-sets for training and testing are picked at random. I used the first 70% of the data as a training set and the latter 30% for validation.

Next, we normalise the input data $x$ to the range of the activation function, just as we would with any other neural network model. The activation function used by default is a sigmoid function with parameters in the range [-1,1]. Keep in mind that the minimum and maximum values from the training dataset are the scaling parameters used to normalise the testing and training sets, as well as the projected values. This eliminates any potential bias in the model due to extreme values in the test data. Predicted values are finally converted back to their original scale.

### 3.4.3 *Descriptive Statistics*

Descriptive data regarding total flows of money is provided in the Table 2 (in billion USD). The mean flow is little more than one billion US dollars, while the standard deviation is almost two and a half billion US dollars. The fact that the minimum flow is in the negative indicates that there are times when the outflows are greater than the inflows. The European Union currency (EUR), the Japanese yen (JPY), and the Swiss franc (CHF) have the highest average and median weekly order flows, while the pair EUR/USD has the highest average weekly flow in absolute value. This is because customers sold an average of 69 million EUR against USD each trading week. When compared to the entire volume of trading that takes place each day on the foreign exchange market, the majority of transactions involve very tiny sums of money.

The results of weekly order flow series are highly surprising when compared to the order flow data from the past. The order flow series exhibit a significant kurtosis, which is mostly caused by some days with extraordinarily high or low order flows on each side of the distribution. This is because there is very little relationship between the flows that occur throughout various weeks. The order flow standard deviation has a pattern that is easy to recognise and may be seen. The volume of money coming into and out of large currencies is far greater than the volume of money flowing into and out of smaller currencies, which leads to greater fluctuations in exchange rates. This is because a much higher volume of trade takes place in large currencies than in lesser ones. According to the information that is shown in this table, each of the four customers has average flows that are rather close to being equal to zero. Because of this, there is not a major difference in the amounts of money that are moved into and out of the various currencies. Hedge funds are subject to the largest level of volatility with regard to their flows, followed by asset managers, individual clients, and businesses. Table 3 also displays the descriptive statistics for the major client types. The table reveals that asset managers have the highest volatility, followed by hedge funds, private consumers, and corporations.

Table 4 provides information on the relationships that exist between all of the different variables. They show that correlation is quite low in every case; for instance, the correlation between the order flows of diverse customer groups is virtually completely uncorrelated. For example, the correlation between order flow in asset management and hedge funds is only 0.3 percent on average across currencies, and the connection between asset managers and hedge funds is only 11 percent, despite the fact that this pair has the highest correlation in absolute terms. Another example is that the correlation between order flow in asset management and hedge funds is only 0.3 percent on average across currencies. It is hard to make an accurate prediction of how much money a certain group of customers would spend based on the amount of money spent by another group due to the fact that different types of customers have distinctive patterns of expenditure. In terms of the flows of customers, there is a positive auto correlation between them on average 11, despite the fact that the size of this auto correlation is fairly low, which is also the case for aggregate flows. This is because of the fact that there is a positive auto correlation between the flows of customers and aggregate flows. This is crucial when taking into mind the market microstructure literature, which lays a focus on unexpected order flow as a component that is vital to the process of determining prices. This highlights the significance of the element in question.

Finally, Table 5 we report results from Cerrato, Kim, and MacDonald (2015) showing evidence of non-linearities for six aggregate order flows and the majority of the disaggregated data. These results corroborate the appropriateness of a non-linear model.

### 3.4.4 *Results*

The process of forecasting and optimising portfolios is done out-of-sample. The results of the out-of-sample predictions that were produced in two stages. The first stage involved determining parameters for the first 70% of data, and the second stage involved updating those estimates consecutively for the rest of the out-of-sample time. We begin by estimating the predictive regressions for the first time period spanning November 2001 to November 2005, and then we iteratively re-estimate these regressions up to the conclusion of the whole example in November 2007. Each out-of-sample prediction is conditional on the information that is currently available at the time that the forecast is being made. That is to say, the core of a recurrent neural network is a recursive process that, in order to arrive at an accurate prediction at any point in time, solely depends on the input that was provided up to the point when the prediction is being made. The model is then continually re-estimated as the date on which predictions are conditioned moves forward through the data set. When evaluating the effectiveness of the models, we pay particular attention to the realised excess portfolio returns as well as the descriptive statistics associated with them, including the Sharpe Ratio (SR) and the Sortino Ratio (SO).

The results for monthly rebalancing are in Table 6. To begin, order flow models does not demonstrate a significant better performance than the random walk benchmark. These findings were achieved by analysing the market as a whole. These results are in line with the findings of the vast bulk of the empirical research that has been carried out in this area. According to Cerrato, Sarantis, and Saunders (2011) and Cerrato, Kim, and MacDonald (2015), the research evidence presented in this chapter prove that the aggregated order flow model offers little evidence of its capacity ability to produce realistic projections. This is demonstrated by the fact that the model's ability to make accurate forecasts is not truly demonstrated in this section.

However, according to Evans and Lyons (2002b), the use of aggregate customer order flow data may be the reason why researchers have not been able to successfully acquire findings that are generally supportive of the major concepts offered in the market microstructure literature. These findings are consistent with what Evans and Lyons (2005) have found, and they indicate that the use of such information could be the reason why researchers have not been successful in gaining conclusions that are generally supportive of the key ideas stated. On the other hand, owing to the fact that the client sector of the foreign exchange market is comprised of a diverse group of individuals, different clients on the market are likely to react to news in a number of different ways. According to Sager and Taylor (2008), having a grasp of the various sorts of customers that are prevalent in the market at any given moment as well as the manner in which these customers purchase and sell and interact with the wider market should aid in having an understanding of the process of an exchange rate at a specific period of time.

Asset manager has a Sharpe ratio of 0.71, making it the most successful model (compared to 0.24 for RW). The SR for the hedge funds clients is 0.59, while the SR for the corporation model is 0.52. The private customers flow is the only form of order flow that has a negative Sharpe ratio. Because of this, we are aware that the asset manager and hedge funds order flows, in particular, show substantial out-of-sample predictive ability. This demonstrates that it is essential to take into account the heterogeneity in customer order flow.

In comparison to the performance of the aggregate order flow model, the performance of the disaggregated predictive regression is much better. To put it another way, we may make economic advantages by using the predictive knowledge of each individual client order flow in isolation and leveraging that information. For example, asset managers are major investors with a long-term outlook, which may explain the extraordinarily high performance of the asset managers monthly order flow. To avoid a dramatic shift in the asset's price, it's likely that experienced traders would rather trade gradually, invisibly interspersing their transactions among those of others who are unaware. When it comes down to it, asset managers could hold large roles that need a lot of downtime. As a result, given the greater regularity with which asset managers order flow occurs monthly is the best time to collect data on its predictability. At the other hand, there is evidence that private traders often make mistakes in terms of both timing and direction. That private customers are often seen as liquidity providers, who are less sophisticated than asset managers and hedge funds, may help to explain this conclusion.

*Economic Interpretation*

After demonstrating that customer order flow can accurately forecast future events, the next step is to investigate the degree to which this predictive information is connected to knowledge about the economy that is readily accessible to the public. Rewording, we want to know whether the flow of client orders for currencies is driven by macroeconomic information. We provide an answer to this issue by constructing a structure that is built on trading methods that condition on order flow and on the macroeconomic models. In particular, we look at whether the excess portfolio returns that are produced by strategies that are dependent on order flow have any correlation with the excess portfolio returns that are produced by other strategies. The order strategies invest in the G10 currencies by conditioning on the order flow of asset managers (AM), hedge funds (HF), corporates (CO) and private clients (PC). The macroeconomic information strategies are the following: the random walk (RW), uncovered interest parity (UIP) and Purchasing power parity (PPP). The Machine Learning strategies are: long-short term memory (LSTM) and Non-Linear AutoRegressive with eXogenuos Inputs (NARX). Finally, take into account that all predictions of macroeconomic variables are developed using data that is currently accessible to market participants in real time.

Following this, we publish the results (Table 7) of an out-of-sample test of predictability against the null hypothesis of the RW in order to evaluate the analytical performance of the empirical exchange rate models. We are primarily concerned in the $R^2$. It worth to mention that when conducting out-of-sample predictive regressions, it is essential to keep in mind that a lack of statistical significance does not always indicate a lack of economic relevance. Campbell and Thompson (2008) demonstrate that even a very modest amount of $R^2$ may result in significant economic rewards for investors. They show, via the use of a mean-variance framework, that a reasonable approach to measure the size of $R^2$ is to compare it to the square of the Sharpe ratio. When the predictive factors are taken into account, an increase in the anticipated return may be achieved proportionally even with a relatively low R-squared value.

In this study, we discover that a combination of macroeconomic techniques accounts for a significant portion of the excess profits provided by order flow methods. The most important findings are summed up here. The coefficient of determination ($R^2$) varies between 16.1% (AM) to 39.4% (CO). When compared to CO and PC, AM and HF have a smaller $R^2$, suggesting that these trading methods are less reliant on macroeconomic data. It is important to note that the betas for the macroeconomic strategies, with few exceptions, tend to be positive but negligible. The alphas are marginally positive for AM, HF, and CO, and slightly negative for PC.

*Robustness*

As robustness we employ a Non-linear AutoRegressive with eXogenous inputs (NARX) model which is a variant of Recurrent Network[22] that has been successfully utilised in time series prediction problems. RNN family networks allow a weighted feedback connection between layers of neurons and thereby making it suitable for time series analysis by allowing lagged values of variables to be considered in the model. It has the power to predict the current value of a time series based on historical values of the series plus the historical values of multiple exogenous time series, like an ARIMA with exogenous factors. It tries to train a one-step ahead prediction model and make multi step prediction recursively given the future exogenous inputs.

*Summary of Results*

These results allow us to draw the following conclusions from the aforementioned empirical findings. There is empirical evidence that

22 Gao and Meng (2005) and Lin et al. (1996)

the microstructure order flow models introduced above have more economic value than a simple random walk model when a portfolio of currencies is considered.

Collectively, these findings suggest that certain combinations of macroeconomic information may account for the observed differences in trading strategies conditioned on client order flow. Further evidence that customer order flow does not include any information independent of macroeconomic news is the lack of a substantial (positive) alpha. Therefore, we conclude that order flow is linked macroeconomic information but provides no extra information beyond what is already readily accessible to the public. It is not surprising that order flow from financial end customers are more informative and produce better prediction than non-financial end customers. The use of information derived from asset manager order flow as well as order flow originating from financial institutions has the potential to aid practitioners in identifying opportunities for arbitrage. Order flow trading involves monitoring pending market orders for execution. Based on this methodology, price fluctuations arise due to market imbalances, and by employing this approach, one may anticipate forthcoming price fluctuations. The use of order flow analysis can aid in the detection of potential market order imbalances at future price levels. The application of the order flow trading strategy allows for the prediction of future market price variations by only analysing market orders. The market exhibits an imbalance through the manifestation of varying amounts of supply and demand. The order book, including a comprehensive compilation of pending orders, holds significant value for order flow traders as an essential instrument in their trading toolkit.

## 3.5 CONCLUSIONS

This chapter examines how well a new way to generate predictions works by comparing it to a random walk measure. Based on the results of this study, it looks like the suggested forecasting model is more accurate than the random walk model. Moreover, we find that order flow trading, derived from asset managers and financial institutions, can help practitioners identify arbitrage opportunities. This approach monitors pending market orders, detecting potential imbalances and predicting future price fluctuations. The order book, including a comprehensive compilation of pending orders, is an essential tool for order flow traders.

The authors say that foreign exchange (FX) traders should pay more attention to the flow of different customer groups than to the flow of orders as a whole. Asset managers are better than other clients at figuring out what will happen in the future. The study also looks at nonlinearities in the structural system. This shows how important it is to have nonlinear data. This study looks at how important predictions of exchange rates are to the business as a whole. It shows, in particular, how important microstructure order flow is in a dynamic portfolio allocation setting. The flow of orders from customers is a good sign of coming extra profits, and there are big differences between the different types of end users. Asset managers and hedge funds are both big players in the foreign exchange market, and the way their orders move is a good sign of currency excess returns. This chapter also adds something useful to the study that has already been done on predicting low-frequency data. It shows how linearity and the need for a lot of data make it hard to use current methods to make predictions that are always true. Deep neural networks, which don't have to work in a certain way, could be a good way to improve the accuracy of predictions when there isn't enough data. AI's use in economics has grown a lot, but there aren't many research studies on how AI can be used in macroeconomic finance or to look at low-frequency data.

Are exchange rates predictable? It depends. In fact, it depends on the choice of predictor, forecast horizon, sample period, model, and forecast evaluation model. Many highly correlated economic, political, and even psychological factors have an impact on exchange rates. These factors interact in a very complex fashion, and the theory of exchange rate determination is in an unsatisfactory state, so predicting exchange rate movements is still a problematic task. From a theoretical point of view, the debates between the traditional flow approach and the modern asset-market approach have seen the victory of the latter. However, from an empirical point of view, the forecasting ability of the theoretical models remains very poor. Moreover, even with the use of sophisticated techniques, such as time-varying coefficients, the forecasts are only marginally better than a naïve random walk model. In fact, Meese and Rogoff (1983) showed that the out-of-sample performance of many structural and time series models is not better than that of a simple random walk model. Their findings discouraged many researchers in the area since the superiority of the random walk means the unpredictability of the foreign exchange rate.

Quantitative research methods are largely used in this chapter. More specifically, we use a deductive method. In order to identify the main challenges, generate hypotheses and designs, and plan a research approach, we begin by reviewing the relevant literature. The next step is to gather the essential information and do any preliminary processing that is called for. Then, conduct exploratory analysis in order to better understand the behaviour of the data and to design the analysis method; in particular, assess the presence of nonlinearities. After that, create multiple sub-datasets using different combinations of independent attributes as well as based on a number of lags. With each of these datasets, train LSTM based multi-step forecasting models. Then compare the forecasting performances among these models using different evaluation matrices.

This chapter makes several contributions to the literature on exchange rate forecasting. In order to properly influence the decision-making process for hedging, it is vital to accurately predict future market movements; hence, a reliable forecasting approach is needed. Although prior research has tried to forecast future exchange rates using RNNs and others have used the microstructure method conceptually, the combination of both components offers a substantial addition to the area. The objective of this chapter is to integrate the microstructure approach to exchange rates with the ANN forecasting capability in order to determine if the new technique outperforms conventional approaches in anticipating customer order flow. It is difficult to predict the future course of the exchange rate due to the inconsistency of macroeconomic fundamentals and the heterogeneity of agents. We provide evidence to support the assertion that this chapter's model is capable of appropriately describing the observed pattern. Microstructure variables and non-linear models are able to provide more accurate out-of-sample predictions than a random walk model, according to the results of this study.

There is a large amount of published research on the impact of order flow on projecting future currency values, yet not a single one of these studies employs deep learning methods to investigate the issue. The goal of the model is to investigate the role that segmented client order flow plays in the process of currency forecasting. This enables the construction of a bridge between studies on foreign exchange microstructure and the cross-sectional pricing of currency assets. We use the portfolio strategy, which provides a clear and simple way for assessing the economic value of order flow, in order to forecast exchange rates. We focus on initiating customer trades and consider nonlinearities (Table 5). In a microstructure context, Yang and Gradojevic (2006) highlights the necessity of embodying information in a non-linear way. The assessment of the economic value of exchange rate forecasts shows that the ability to predict the microstructure order flow has a lot of economic value in a dynamic portfolio allocation context and that non-linear models do better than the simple random walk model. We have determined that the order flow from customers is an informative indicator of future excess returns and that there are significant disparities across the various categories of end-users. Both asset managers and hedge funds are categories of end-users that are significant players in the foreign exchange markets, so it is legitimate to consider both sets of customers to be "informed" market participants. In accordance with this preconceived notion, our research reveals that the order flows of both groups considerably exceed the favourable anticipated currency excess returns.

A final contribution to this chapter is a contribution to the literature on predicting low-frequency data. Due to the inherent linearity of models and the vast quantities of data needed, the present methodologies for unconditional forecasting are not well suited for producing reliable future predictions. Investigate the use of deep neural networks, which are not bound to a certain functional form, as a viable method for enhancing prediction accuracy with little data. There has been much research on finance, but very little on macroeconomic finance or with low-frequency data. Despite the rapidly rising application of artificial intelligence in economics, this is the case. In low-frequency research, Bayesian analysis, DSGE models, and textual analysis are the key areas of focus.

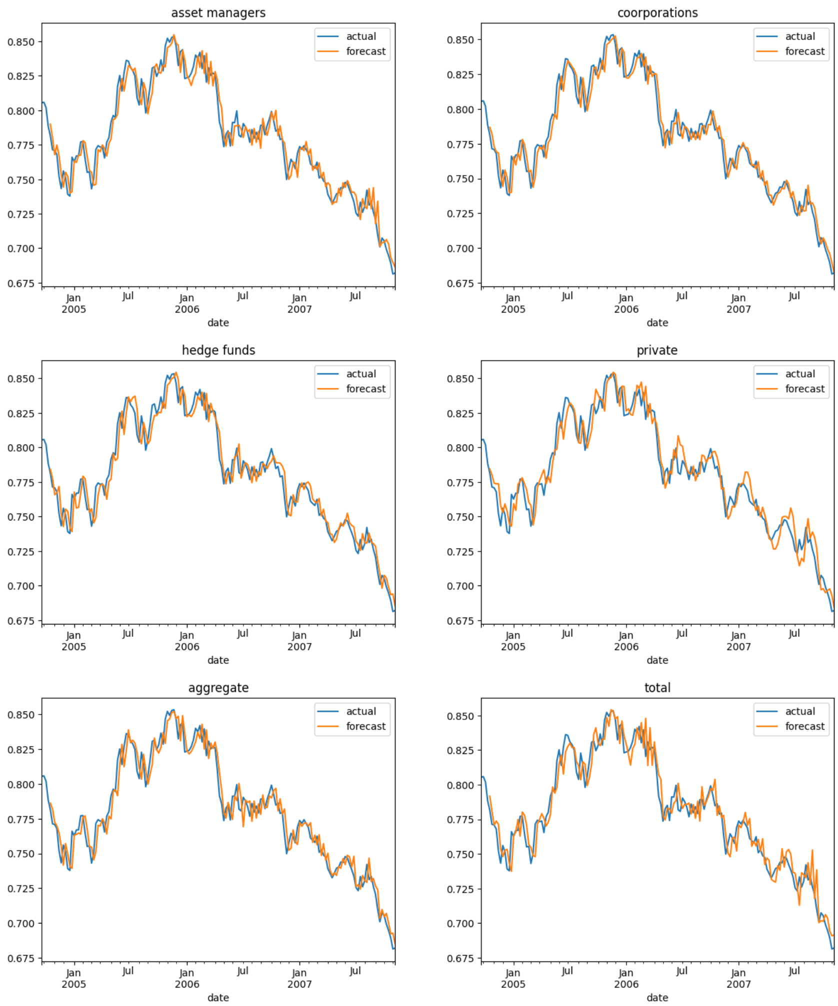
*What Machine Learning Cannot Do*

Machine learning has great potential for improving risk premium measurement, which is fundamentally a problem of prediction. It amounts to best approximating the conditional expectation $E(r_{i,t+1}|F_t)$, where $r_{i,t+1}$ is an asset's return in excess of the risk-free rate, and $F_t$ is the true and unobservable information set of market participants. This is a domain in which machine learning algorithms excel. But these improved predictions are only measurements. The measurements do not tell us about economic mechanisms or equilibria. Machine learning methods, on their own, do not identify deep fundamental associations among asset prices and conditioning variables. When the objective is to understand economic mechanisms, machine learning may still be useful. It requires an economist to add structure to build a hypothesised mechanism into the estimation problem and decide how to introduce a machine learning algorithm subject to this structure. A nascent literature has begun to make progress in marrying machine learning with equilibrium asset pricing[23] and this remains an exciting direction for future research.

23 Fang and Taylor (2021) Gu, Kelly, and Xiu (2018)

## 3.6 FIGURES AND TABLES

Figure 5: Forecasts using NNs




The graphs represent an example of results for euro/dollar forecasting with LSTM using different customer order flow as exogenous variables. The blue line represents the actual series, whereas the orange shows the forecasted series.

Table 1: UBS Market Share

| | Overall Market | | Real Money | | Leveraged Funds | | Non-financial Corporations | |
|---|---|---|---|---|---|---|---|---|
| | share(%) | rank | share(%) | rank | share(%) | rank | share(%) | rank |
| 2001 | 3.55 | 7 | 3.11 | 8 | - | - | - | - |
| 2002 | 10.96 | 2 | 10.77 | 2 | - | - | - | - |
| 2003 | 11.53 | 1 | 11.25 | 1 | 13.03 | 1 | 6.38 | 4 |
| 2004 | 12.36 | 1 | 11.32 | 2 | 11.7 | 2 | 7.16 | 3 |
| 2005 | 12.47 | 2 | 11.6 | 1 | 8.57 | 3 | 8.41 | 3 |
| 2006 | 22.5 | 1 | 11.35 | 2 | 5.23 | 7 | 6.38 | 4 |
| 2007 | 14.85 | 2 | 13.73 | 1 | 5.9 | 6 | 5.65 | 6 |
| 2008 | 15.8 | 2 | 9.07 | 2 | 7.53 | 4 | 5.13 | 5 |
| 2009 | 14.58 | 2 | 10.96 | 2 | 6.94 | 4 | 7.43 | 5 |
| 2010 | 11.3 | 2 | 9.39 | 2 | 14.63 | 2 | 4.93 | 9 |
| 2011 | 10.59 | 3 | 9.02 | 2 | 8.21 | 4 | 3.98 | 9 |

The table displays the overall market share and the market share by customer type for UBS. The rank is with respect to the top 10 global leaders in the FX market from 2001 to 2011 based on the Euromoney annual survey. The market shares by customer type (available from 2003 for all customer types) are presented for real money, leveraged funds and non-financial corporations. Source: Euromoney

Table 2: Summary Statistics of FX Returns(%) Log Returns

| | **Mean** | **Median** | **Sdev** | **Skewness** | **Kurtosis** | **Variance** | **AC(1)** | **PAC(2)** |
|---|---|---|---|---|---|---|---|---|
| AUD | -0.00172 | -0.00331 | 0.01402 | 0.62911 | 3.65437 | 0.00024 | 0.04676 | -0.07347 |
| CAD | -0.00151 | -0.00215 | 0.01018 | 0.25878 | 3.19437 | 0.00010 | 0.0568 | -0.0315 |
| CHF | -0.00124 | -0.00145 | 0.01332 | 0.19670 | 2.70669 | 0.00018 | -0.0215 | -0.0803 |
| EUR | -0.00157 | -0.00239 | 0.01215 | 0.43748 | 2.95118 | 0.00015 | -0.0307 | -0.0654 |
| GBP | -0.00109 | -0.00179 | 0.01142 | 0.25597 | 2.89850 | 0.00013 | 0.0120 | -0.0611 |
| JPY | -0.00037 | -0.00004 | 0.01298 | -0.36637 | 3.36298 | 0.00017 | -0.0256 | -0.0111 |
| NOK | -0.00155 | -0.00262 | 0.01506 | 0.40433 | 3.18808 | 0.00023 | -0.0133 | -0.0721 |
| NZD | -0.00191 | -0.00454 | 0.01646 | 0.73687 | 4.11230 | 0.00027 | -0.0339 | -0.0308 |
| SEK | -0.00166 | -0.00304 | 0.01380 | 0.30742 | 2.94978 | 0.00019 | 0.0244 | -0.0800 |

The table displays the descriptive statistics for logs returns for G10 currencies.

Table 3: Summary Statistics of Order Flow Data

| | | Mean | Median | Sdev | Skewness | Kurtosis | Variance | AC(1) | PAC(2) |
|---|---|---|---|---|---|---|---|---|---|
| | Aggregate | -0.0002 | -0.0029 | 0.0757 | 0.8727 | 8.9394 | 0.0057 | 0.0318 | 0.0557 |
| | Asset Manager | -0.0048 | 0.00090 | 0.2009 | -0.2121 | 7.4012 | 0.0404 | 0.0436 | 0.0375 |
| AUD | Corporate | -0.0151 | -0.0000 | 0.1013 | -3.9485 | 30.0414 | 0.0103 | 0.4586 | 0.0221 |
| | Hedge Funds | 0.0161 | -0.0076 | 0.2020 | 0.4950 | 10.4027 | 0.0408 | -0.0429 | -0.0447 |
| | Private Clients | 0.0031 | 0.0039 | 0.1037 | 0.4014 | 7.3016 | 0.0108 | 0.2218 | 0.0790 |
| | Aggregate | -0.00396 | -0.00325 | 0.06305 | 0.91397 | 12.24130 | 0.00398 | -0.0303 | -0.0204 |
| | Asset Manager | 0.00804 | 0.00280 | 0.18513 | 1.67000 | 16.19112 | 0.03427 | -0.0388 | -0.0045 |
| CAD | Corporate | -0.02582 | -0.01693 | 0.07612 | -1.95573 | 16.62938 | 0.00579 | 0.1753 | 0.0986 |
| | Hedge Funds | -0.00062 | 0.00663 | 0.18728 | -0.31535 | 5.53089 | 0.03508 | 0.0622 | 0.0145 |
| | Private Clients | 0.00257 | 0.00079 | 0.06600 | 0.61764 | 9.17516 | 0.00436 | 0.0726 | 0.1170 |
| | Aggregate | -0.03227 | -0.01541 | 0.18797 | -0.35568 | 5.77141 | 0.03533 | 0.0373 | 0.1702 |
| | Asset Manager | -0.06079 | -0.03768 | 0.50172 | -0.02819 | 7.22015 | 0.25173 | 0.0782 | 0.0321 |
| CHF | Corporate | 0.00005 | 0.01159 | 0.42199 | 1.98181 | 22.73535 | 0.17807 | 0.2193 | -0.0581 |
| | Hedge Funds | -0.08669 | -0.04354 | 0.55484 | -0.63391 | 5.10036 | 0.30785 | 0.0570 | 0.0846 |
| | Private Clients | 0.01836 | 0.03233 | 0.23730 | -0.15069 | 4.50699 | 0.05631 | -0.0491 | -0.0509 |
| | Aggregate | 0.06940 | 0.04889 | 0.36661 | 0.94222 | 13.94816 | 0.13440 | 0.0399 | 0.0384 |
| | Asset Manager | -0.04542 | -0.02679 | 0.94911 | 0.17667 | 5.62748 | 0.90080 | -0.0028 | 0.1014 |
| EUR | Corporate | 0.19168 | 0.15513 | 0.46056 | 0.75123 | 7.09845 | 0.21212 | 0.1858 | 0.0952 |
| | Hedge Funds | 0.19867 | 0.18219 | 0.91559 | 0.33271 | 4.49345 | 0.83830 | 0.0293 | 0.0241 |
| | Private Clients | -0.06734 | -0.04342 | 0.58533 | -0.13889 | 8.04165 | 0.34261 | -0.0483 | -0.0605 |
| | Aggregate | -0.00124 | 0.00709 | 0.20206 | -3.95498 | 36.94534 | 0.04083 | 0.3244 | -0.0433 |
| | Asset Manager | -0.04455 | 0.00751 | 0.66915 | -3.92982 | 30.76291 | 0.44776 | 0.3731 | -0.0891 |
| GBP | Corporate | 0.01049 | 0.00305 | 0.19076 | -0.40147 | 9.52645 | 0.03639 | 0.0035 | 0.0855 |
| | Hedge Funds | 0.02474 | 0.02185 | 0.39840 | -1.12310 | 12.86177 | 0.15872 | 0.0035 | 0.1177 |
| | Private Clients | 0.00436 | -0.00730 | 0.24005 | 1.12087 | 10.67230 | 0.05762 | -0.0298 | -0.1284 |
| | Aggregate | -0.05996 | -0.05318 | 0.20667 | 0.79627 | 13.64040 | 0.04271 | -0.0031 | 0.0471 |
| | Asset Manager | -0.09848 | -0.06688 | 0.63593 | 0.70659 | 12.67411 | 0.40441 | 0.0660 | 0.0546 |
| JPY | Corporate | -0.04847 | -0.04506 | 0.14596 | -0.57927 | 5.97117 | 0.02130 | 0.0375 | -0.0082 |
| | Hedge Funds | -0.07834 | -0.04995 | 0.58368 | -0.85056 | 6.43238 | 0.34068 | 0.1723 | -0.0208 |
| | Private Clients | -0.01454 | -0.03163 | 0.23784 | 0.42159 | 5.52182 | 0.05657 | -0.0839 | -0.0886 |
| | Aggregate | 0.00243 | 0.00046 | 0.02759 | 0.88700 | 10.09427 | 0.00076 | -0.0306 | 0.0882 |
| | Asset Manager | 0.00364 | 0.00012 | 0.08156 | 0.10952 | 15.18677 | 0.00665 | -0.1278 | -0.0631 |
| NOK | Corporate | -0.00433 | 0.00002 | 0.02428 | -1.21830 | 15.77784 | 0.00059 | -0.0609 | 0.0978 |
| | Hedge Funds | 0.00777 | 0.00047 | 0.06336 | 0.59437 | 8.21670 | 0.00402 | -0.0993 | -0.0469 |
| | Private Clients | 0.00264 | -0.00031 | 0.02968 | 2.59192 | 20.96558 | 0.00088 | -0.0872 | -0.0088 |
| | Aggregate | 0.00345 | 0.00104 | 0.02866 | 1.31330 | 16.07718 | 0.00082 | 0.0476 | -0.0223 |
| | Asset Manager | -0.00070 | 0.00087 | 0.07335 | 0.09756 | 32.03473 | 0.00538 | 0.1034 | 0.0697 |
| NZD | Corporate | 0.00516 | 0.00402 | 0.02023 | 0.39899 | 11.70160 | 0.00041 | 0.0387 | -0.0833 |
| | Hedge Funds | 0.00779 | 0.00000 | 0.07064 | 1.51756 | 10.81871 | 0.00499 | 0.1332 | -0.0046 |
| | Private Clients | 0.00155 | 0.00020 | 0.03924 | 2.59077 | 38.70732 | 0.00154 | -0.1363 | -0.2117 |
| | Aggregate | -0.00180 | -0.00390 | 0.03651 | 1.58324 | 11.27828 | 0.00133 | 0.2115 | -0.0839 |
| | Asset Manager | -0.00383 | -0.00293 | 0.11421 | 0.45716 | 8.55221 | 0.01304 | 0.1229 | -0.1565 |
| SEK | Corporate | -0.01308 | -0.00815 | 0.04698 | 0.05436 | 6.63722 | 0.00221 | 0.1806 | 0.1315 |
| | Hedge Funds | 0.00818 | 0.00073 | 0.08054 | 1.04046 | 7.57237 | 0.00649 | 0.0346 | -0.0724 |
| | Private Clients | 0.00153 | 0.00035 | 0.02422 | 2.60272 | 33.96088 | 0.00059 | -0.0056 | -0.1983 |
| | Asset Manager | -0.0274 | -0.0136 | 0.3790 | -0.1059 | 15.0723 | 0.2338 | 0.1384 | 0.1385 |
| | Corporate | 0.0112 | 0.0115 | 0.1654 | -0.5463 | 14.0132 | 0.0519 | 0.1397 | 0.1401 |
| Clients | Hedge Funds | 0.0108 | 0.0123 | 0.3396 | 0.1175 | 7.9366 | 0.1930 | -0.0531 | -0.0531 |
| | Private Clients | -0.0053 | -0.0050 | 0.1737 | 1.1175 | 15.4286 | 0.0590 | -0.0047 | -0.0047 |

This table displays descriptive statistics for the major customer types. The table reveals that asset managers have the highest volatility, followed by hedge funds, private consumers, and corporations.

Table 4: Cross Correlations

Panel A

| | AM/CO | AM/HF | AM/PC | HF/CO | HF/PC | CO/PC |
|---|---|---|---|---|---|---|
| AUD | 0.0185 | 0.0924 | -0.1334 | -0.0277 | -0.3163 | 0.0178 |
| CAD | -0.0827 | -0.0571 | -0.1862 | -0.0670 | -0.1456 | 0.0447 |
| CHF | -0.2515 | 0.0469 | -0.1744 | -0.2438 | -0.1285 | 0.2061 |
| EUR | -0.0479 | 0.0094 | -0.0731 | 0.0377 | -0.1349 | 0.1412 |
| GBP | -0.1580 | 0.2596 | -0.2031 | -0.2427 | -0.0964 | 0.0210 |
| JPY | -0.1656 | 0.0246 | -0.2406 | 0.0754 | -0.2729 | 0.1236 |
| NOK | -0.1052 | -0.0123 | 0.0701 | 0.0235 | 0.0393 | 0.0206 |
| NZD | -0.0595 | -0.0001 | 0.0868 | 0.0213 | 0.0120 | 0.2333 |
| SEK | 0.1753 | -0.0896 | -0.1461 | -0.0893 | 0.2059 | -0.2402 |

Panel B

| | Asset Manager | Corporations | Hedge Funds | Private Clients |
|---|---|---|---|---|
| Asset Manager | 1.000 | -0.075 | 0.030 | -0.109 |
| Corporations | 0.075 | 1.000 | -0.057 | 0.063 |
| Hedge Funds | 0.030 | -0.057 | 1.000 | -0.093 |
| Private Clients | -0.109 | 0.063 | -0.093 | 1.000 |

The table reports the cross-correlations coefficient between flows of customers groups for nine currencies. Order flow is defined as the difference between the value of buyer-initiated and seller-initiated transaction for the foreign currency so that a positive (negative) order flow implies net foreign currency purchase (sales). Order flows are billions of US dollar and are classified into four customer segments: asset managers; hedge funds, corporate and private clients. The sample period comprises weekly observations from November 2001 to November 2007. Exchange rates are from DataStream while customer order flows are proprietary data from USB.

Table 5: Linearity Test

| | Aggregate | Asset Manager | Corporation | Hedge Funds | Private Clients |
|---|---|---|---|---|---|
| AUD | 3.725 | 9.074[1] | 64.932[1] | 2.875 | 23.236[1] |
| CAD | 3.939 | 13.249[1] | 1.689 | 4.705[1] | 5.471[1] |
| CHF | 10.885[1] | 5.943[1] | 17.234[1] | 5.669[1] | 0.073 |
| EUR | 10.198[1] | 4.022 | 1.713 | 4.794[1] | 0.161 |
| GBP | 13.046[1] | 32.893[1] | 6.698[1] | 1.518 | 3.789 |
| JPY | 4.393 | 2.022 | 1.002 | 10.517[1] | 11.476[1] |
| NOK | 22.766[1] | 1.818 | 2.147 | 0.645 | 17.980[1] |
| NZD | 36.289[1] | 7.843[1] | 32.099[1] | 18.601[1] | 3.631 |
| SEK | 15.545[1] | 8.687[1] | 13.278[1] | 0.083 | 3.802 |

Linearity test to the aggregate and disaggregate order flows, results from Cerrato, Kim, and MacDonald, 2015. [1] denotes the 10% significance level.

Table 6: Out-of-sample predictive ability of Order Flow

| Predictive Ability of Order Flow | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $r_p$% | $\sigma_p$% | skew | kurt | $\rho_p$ | SR | SO |
| RW | 4.9 | 12.4 | -0.21 | 0.55 | 0.20 | 0.24 | 0.29 |
| AM | 12.4 | 12.3 | 0.07 | 0.56 | 0.17 | 0.71 | 1.33 |
| HF | 11.1 | 13.4 | -0.27 | 0.66 | 0.14 | 0.59 | 0.89 |
| CO | 11.0 | 14.9 | -0.22 | 0.55 | 0.33 | 0.52 | 0.83 |
| PC | -5.0 | 13.4 | 0.01 | 3.45 | 0.38 | -0.33 | -0.37 |
| AGG | 7.7 | 11.2 | -2.0 | 3.14 | 0.02 | 0.22 | 0.28 |

The table reports the out-of-sample economic value of the predictive ability of order flow. The results are based on dynamic asset allocation strategies investing in the G10 currencies with monthly rebalancing. The benchmark strategy is the naive random walk (RW) model. The strategies condition on lagged currency order flow, which is classified into four customer segments: asset managers (AM), hedge funds (HF), corporate (CO) and private clients (PC) and aggregate customer order flows. Using the exchange rate forecasts from each model, a US investor builds a maximum expected return strategy subject to a target volatility $\delta_p = 10\%$ and proportional endogenous transaction costs. The strategy invests in a domestic bond and nine foreign bonds and is rebalanced monthly. For each strategy, we report the annualised mean (rp), annualised volatility (p), skewness (skew), excess kurtosis (Kurt), annualised Sharpe ratio (SR), annualised Sortino ratio (SO)

Table 7: Predictive Regressions

| | $\alpha$ | $\beta_{RW}$ | $\beta_{PPP}$ | $\beta_{UIP}$ | $\beta_{LSTM}$ | $\beta_{NARX}$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| Asset Manager | 0.040 | 0.111 | 0.412 | -0.242 | 0.1240 | 0.1240 | 16.1 |
| | (0.052) | (1.222) | (1.444) | (0.162) | (0.182) | (0.116) | |
| Hedge Funds | 0.0211 | 0.299 | -0.621 | 0.316 | 0.323 | 0.285 | 22.3 |
| | (0.033) | (0.147) | (1.559) | (0.160) | (0.153) | (0.022) | |
| Corporation | 0.032 | 0.352 | 2.210 | 0.185 | 0.311 | 0.287 | 39.4 |
| | (0.049) | (0.139) | (0.969) | (0.126) | (0.150) | (0.154) | |
| Private Clients | -0.085 | 0.738 | 1.936 | 0.137 | 0.697 | 0.850 | 27.1 |
| | (0.053) | (0.234) | (1.046) | (0.226) | (0.204) | (0.432) | |

The table presents regression results on the relation between portfolio excess returns generated by conditioning out-of-sample on order flow and monthly portfolio excess returns by conditioning out-of-sample on macroeconomic information. The order flow strategies invest in the G10 currencies by conditioning on the order flow of asset managers (AM), hedge funds (HF), corporates (CO) and private clients (PC). The strategies are the following: the random walk (RW), uncovered interest parity (UIP) purchasing power parity (PPP), long short term memory (LSTM), narx (NARX). All strategies are implemented out of sample for the period of November 2001 to November 2007. Results suggest that asset manager and hedge funds are less reliant on macroeconomic data. There is empirical evidence that the microstructure order flow models have more economic value than a simple random walk when a portfolio of currencies is considered. There is also evidence that order flow are linked to macroeconomic information, but does not provide any extra information.

# 4 SYSTEMIC RISK ON FOREIGN EXCHANGE MARKET

This chapter is mainly empirical in nature. We examine what the data tells us about the role of customer order flow. Using the standard analytical framework of the FX microstructure, based on Evans and Lyons (2002), we test if order flow helps explain exchange rate fluctuations. We also identify the typical market roles of different customer types. Liquidity risk is a significant factor in the foreign exchange market, as it rewards investors for exposure to liquidity risk. Differentiation in how liquidity risk is priced affects the behaviour of specific FX returns in a way that is economically important. This is because spot trading's liquidity makes it possible to build profitable trading strategies that involve borrowing in some currencies and lending in others. These liquidity-based methods, similar to carry trades, choose borrowing and lending currencies based on indicators of spot trading liquidity rather than interest rates.

The study uses a data set to analyse the underlying economic foundation of the bond between order flow and exchange rates. The data is segmented into different client groups, each with a different set of information. The portfolio technique is used to investigate whether customer order flow incorporates risk premia in the currency market related to factors such as systematic volatility, liquidity default, or macro risk. The study examines the potential addition of a risk premium to the exchange rates of the most frequently traded currencies.

The liquidity of different currencies is determined by defining it as the expected return reversal associated with order flow. The stock market also shows a considerable component of commonality in currency liquidity, with dealers' inventory management limits and preferences being key channels contributing to price establishment. The annualised liquidity risk premium is estimated to be around 2.43 percent for the aggregate scenario and 2.34 percent if a dollar risk-free element is included. Corporations exhibit the highest liquidity risk premium, with individual consumers coming in third with a risk premium of 0.8 percent. The hypothesis that liquidity risk is a price driver in the FX market for this specific class of consumers is erroneous due to the asset manager's presentation of a negative liquidity risk factor.

## 4.1 INTRODUCTION AND MOTIVATION

In this chapter, we examine what the data tells us about the role of customer order flow in systemic liquidity risk. Inspired by Banti, Phylaktis, and Sarno (2011) and using a standard analytical framework of the FX microstructure, based on Evans and Lyons (2002a), we test if order flow helps explain exchange rate fluctuations. We also identify the typical market roles of different customer types.

The foreign currency (FX) market is the deepest financial market in the world, as measured by the average daily trading volume, which will be over 7.5 trillion in 2022. The foreign exchange market is considered to be quite liquid; however, its liquidity is not particularly well known because of the low openness of the market, the variety of players, and the decentralised dealership structure[1]. Both the global financial crisis of 2007 and research on currency crashes have brought to light how vital liquidity is to the foreign exchange market.

The foreign exchange markets are widely used to finance short-term money market positions. A decrease in foreign exchange liquidity will have an effect on financing costs, raise rollover risks, and make it more difficult to hedge. A multitude of arbitrage schemes, such as triangle arbitrage, exploiting deviations from covered interest rate parity, or price mismatching between multiple listed equity shares and American depository receipts, all rely heavily on foreign exchange rates as a key component. As a result, liquidity in the foreign exchange market is essential for arbitrage trading, which maintains prices that are aligned with underlying values and promotes market efficiency[2].

Traditional macroeconomic theories postulate that the underlying fundamentals of macroeconomics are responsible for the fluctuations in exchange rates. The models used to predict the exchange rate take into account a wide range of macroeconomic variables, such as money supply, interest rate, and capital movement. The value of the currency exchange rate is thought to be affected by these elements in a way that is hard to properly predict. Several prominent macroeconomic models focus on monetary matters, such as the money supply and the lending practises of financial institutions. However, there are models that focus on how a family's assets and obligations affect the family's financial picture as a whole. Explanatory variables in these models include money supply, total income, interest rate, and domestic and overseas portfolio holdings. These variables may play a key role in explaining economic downturns and recoveries.

In a macroeconomic perspective, it is assumed that the exchange rate instantly reflects any new information regarding the value of the currency, independent of the method of trading. As a result, the trad-

1 Lyons (2001)
2 Shleifer and Vishny (1997)

ing process is disregarded by the macro approach when it comes to setting the exchange rate. Some financial experts argue that standard macroeconomic models do not adequately account for crucial empirical elements of exchange rate evolution. Exchange rate volatility and the ratio of currency traded to output are two examples. Since these models rely on too many simplistic assumptions, their predictions of future exchange rate behaviour are generally inaccurate. Long time periods are required to establish a connection between these variables[3]. The ability of macroeconomic models to predict future exchange rates is shown to be no better than that of a random walk, according to a large body of research [4].

After discovering that traditional structural models are unable to adequately explain and forecast exchange rates, researchers turned their attention to more recent lines of inquiry that focused on the implications of using a standard present value approach to asset pricing and a microstructure approach to the foreign exchange market. The microstructure approach is a relatively recent school of thought in the field of economics. This school of thought attempts to explain the enigma of the macroeconomic exchange rate by using the technique of microstructure. It aims to shed light on the many elements that contribute to the formation of currency values. For a considerable amount of time, specialists in the field of foreign currencies have been engaged in heated debates over the issues of how exchange rates will develop and what measures authorities should take to maintain stability. The decisions that central banks make on monetary policy are not made in a sterile environment. Researchers have spent a significant amount of time and effort trying to construct a theoretical model of the dynamics of exchange rates that is both viable and experimentally applicable.

Despite the common notion that the forex market is very liquid at all times, we find that the liquidities of various currencies fluctuate significantly throughout sections. Our analysis shows that there is a lot of evidence for a significant liquidity commonality, which we define as a strong correlation between changes in FX rate liquidity over time. This would suggest that broad shocks to the forex market, rather than changes in individual FX rates, are the key drivers of liquidity in the forex market. Moreover, we find that the EUR/USD exchange rate, which is one of the most liquid in the world, has low liquidity sensitivity relative to the whole FX market. To the contrary, less liquid foreign exchange prices are more stable.

*Why Liquidity is Important*

One consequence of the universality of foreign exchange liquidity is that the availability of liquidity for a certain FX rate may have beneficial knock-on effects on other currencies. Generally speaking, this is

3 Meese and Rogoff (1983); Frankel and Rose (1995)
4 Mark (1995)

seen as positive by central banks. Consider the role that high-interest-rate currencies play in the carry trade unwinding process. A central bank's injection of liquidity in its own currency may help reduce liquidity restrictions in other investment currencies and moderate the sharp appreciation (depreciation) of other financing (investment) currencies. Further, the available empirical data on liquidity spirals implies that monetary measures designed to ease limitations in the finance market may also increase liquidity in the foreign currency market, which would benefit all exchange rates.

This is the implication of the potential benefits of these measures for increasing liquidity in the foreign currency market. But too much cash on hand might be dangerous. Excessive liquidity in one currency tends to flow into other currencies, particularly those used for international transactions, and this trend is expected to persist. Sufficient liquidity in a risk-taking and carry-trade-friendly climate may stimulate speculative trading.

### 4.1.1 *Research Contributions*

We want to know whether the risk of global liquidity is reflected in currency exchange rates and, if so, which types of clients—asset managers, businesses, hedge funds, and individual clients—have the most impact on liquidity.

When we examine the characteristics of each currency liquidity indicator separately, we find that they are closely related, indicating that they all share a component. The existence of a common component supports the idea that shocks to the foreign exchange market as a whole have a more significant impact on liquidity than any one currency. Then, we utilise an index of global FX liquidity innovation called unexpected liquidity, created by Banti, Phylaktis, and Sarno (2011), to demonstrate that it accounts for a significant portion of the variance in liquidity across different currencies.

Next, we consider the question from the point of view of a US investor: do innovations in FX market liquidity impact the volatility of exchange rates? Paraphrasing, we look at the possibility of a systemic liquidity premium in the foreign exchange market. In order to estimate systemic liquidity risk as the covariance of exchange rate returns and innovations in global liquidity risk, we employ standard empirical asset pricing tests and the portfolio construction techniques first applied to FX data by Lustig and Verdelhan (2007)[5], thereby iden-

5 According to Lustig and Verdelhan (2007), the additional returns obtained from borrowing US dollars and investing in foreign currency serve as a form of compensation for US investors who are exposed to higher levels of risk associated with US consumption growth. However, it is worth noting that the stochastic discount factor associated with their benchmark model exhibits a lack of correlation with the returns under investigation. Therefore, it is not possible to reject the null hypothesis

tifying a liquidity risk premium. By using these techniques, we may account for the shared component of excess returns due to systemic liquidity risk, thereby removing currency-specific sources of returns. Indicators from the field of empirical asset pricing point to the existence of a statistically and economically substantial risk premium related to global FX liquidity risk, with an annualised rate of about 4.7 percent. After controlling for other common risk factors in FX asset pricing analysis, the market price of liquidity risk is still statistically significant.

### 4.1.2 *Outline of the Chapter*

The chapter is composed as follows: in Section 4.2 we discuss the literature review. In Section Section 4.3 we define liquidity and the different methodologies to measure it. The empirical analysis is in Section 4.4, along with the description and manipulation of the data set (Section 4.4.2; also in Section 4.4.1 we introduce the methodology used in this chapter. In Section 4.4.3 we describe the results obtained; and finally in Section 4.5 there are the conclusions.

## 4.2 REVIEWS OF THE RELATED RESEARCH

In his book *"The General Theory of Employment, Interest and Money"*, Schumpeter and Keynes (1936) argue that when aggregate demand is too low, wages will fall and unemployment will increase. In Keynesian economics, there are three reasons why people might want to hold money: the transaction motive, which is considered interest-inelastic, the precautionary motive, which is considered to be motivated by fear of future events, and the speculative motive, which is motivate by the expectation of future prices.

In the transactionary demand motive, people prefer to be able to easily transfer money between different accounts for day-to-day expenses. The amount of liquidity desired depends on the level of income. Higher incomes require more money to spend, which in turn affects the amount of liquidity available. The precautionary demand for liquidity is the demand for cash to cover unforeseen expenditures, such as an accident or health emergency. As people earn more money, they increasingly want cash that is backed by the government. The speculative demand for bonds is the demand to take advantage of future changes in interest rates or bond prices. Speculative demand

that their model does not account for any of the cross-sectional variation in expected returns. Based on the aforementioned discovery and additional supporting evidence, Burnside (2011) asserts that the enigma surrounding the forward premium puzzle persists.

can be thought of as a type of demand that is based on expectations of future changes in prices, rather than actual changes in prices.

According to Keynes, the higher the rate of interest, the lower the speculative demand for money. If interest rates were lowered, people would want to borrow more money to invest in stocks, because that would make those stocks more valuable. This would create a huge amount of speculative demand for money, which would lead to even more interest rate decreases and a spiralling cycle of ever more speculative investment. The interest rate is determined by the intersection of the supply of money (which is assumed to be fixed by the monetary authorities) and the demand for money (which is based on people's desires for liquidity).

One of the key streams of the finance literature that receives a significant amount of attention from scholars is concerned with liquidity and the challenges that are linked with it. There have been several research conducted over the course of the last four decades that centre on this topic[6].

Liquidity is an important part of the functioning of financial markets. The term liquidity has various meanings in the economics and finance literature, for example, the Concise Desk Book of Business Finance (Moffat, 1975) defines liquidity as:

> *"the desire on the part of the general public to hold their idle funds in the form of money rather than in interest-earning form"*.

One of the most widely acknowledged definitions of liquidity was developed by Liu (2006). In specifically, liquid stocks are those that are able to trade in a high volume fast at a cheap cost and with little affect on the stock's price. This definition reveals four aspects of stock liquidity: trading quantity, trading speed, trading costs, and price impact. Trading quantity refers to the amount of a security that can be traded at a given cost; trading speed refers to how quickly a given quantity of a security can be traded at (how easy it is to trade a security of a given quantity with minimum impact on price). This definition reflects five key qualities of a liquid market[7]: tightness (low transaction costs)[8], immediacy (speed of execution)[9], depth

6 Some examples of these studies are Amihud and Mendelson, 1986a; Eleswarapu and Reinganum, 1993; Vayanos, 1998; Chordia, Subrahmanyam, and Anshuman, 2001; Amihud, 2002; Vayanos, 2004; Acharya and Pedersen, 2005; and Hasbrouck, 2005

7 Black (1971); Sarr and Lybek, 2002; Harris, 2003; Amihud and Mendelson, 2012

8 such as the difference between buy and sell prices, like bid ask spread in quote-drive markets, as well as implicit costs

9 this reflects, among other things, the efficiency of the trading, clearing, and settlement system

(abundant orders)[10], breadth (many orders of various sizes)[11], and resiliency (quickly correcting order imbalances)[12].

In addition, a number of metrics are developed and used to determine a security's liquidity. Each metric reflects many elements of stock liquidity. For instance, Roll (1984)'s effective bid–ask spread metric implicitly reflects the transaction cost component of liquidity. In contrast, the illiquidity ratio of Amihud (2002) and the return to turnover ratio of Florackis, Gregoriou, and Kostakis (2011) are based on the price effect dimension. In addition, Liu (2006) proposes a multiple dimension-based metric, namely the turnover-adjusted zero daily trading volume number. Despite the fact that they concentrate on various elements of liquidity, these metrics are closely connected (Goyenko, Holden, and Trzcinka (2009) and Fong, Holden, and Trzcinka (2017) among others).

On the basis of data frequency, liquidity proxies may be divided into high-frequency (intraday) and low-frequency (daily) estimates. High-frequency liquidity metrics are produced from intraday data, whereas low-frequency liquidity proxies are mostly derived from daily stock return and volume data.

High-frequency liquidity proxies consist of intraday transactions; the data samples are often quite big, requiring sophisticated computer programming and processing capacity to analyse. Consequently, high-frequency measurements are mostly used for U.S. markets[13].

Low-frequency liquidity measures are often used due to the following benefits. First, it is readily accessible and available not just for big markets such as the U.S. and U.K. equities markets, but also for many smaller stock exchanges, such as developing economies. As a consequence, researchers may acquire data from several nations over extended time periods, therefore enhancing study in the field of liquidity. In addition, these measurements are very effective in capturing the intraday liquidity benchmarks. In fact, Goyenko, Holden, and Trzcinka (2009) discover a considerable association between 0s by Lesmond, Ogden, and Trzcinka (2015), return to volume ratio of Amihud (2002), and intraday benchmarks when comparing a broad variety of low-frequency liquidity metrics to high-frequency benchmarks.

The bid-ask spread, turnover, and the Amihud (2002) ratio are all standard indicators, but other indicators are being developed as well, such as the price impact ratio developed by Florackis, Gregoriou, and Kostakis (2011) and the free-float-adjusted price impact ratio devel-

10 either actual or easily uncovered of potential buyers and sellers, both above and below the price at which a security now trades

11 orders are both numerous and large in volume with minimal impact on prices

12 new orders runs quickly to correct order imbalances, which tend to move prices away from what is warranted by fundamentals

13 Huang and Stoll (1997b) and Hasbrouck (2009)

oped by Karim and Bin (2016). Regardless of these advantages, there are also drawbacks to using low frequency data to generate liquidity gauges. For instance, while the illiquidity ratio proposed by Amihud is better than most other metrics at capturing liquidity[14], it fails to account for days without trade, which may provide relevant information about illiquidity. And because continuous stock trading is assumed while the market is open, high-low spread may be used to capture the transaction costs dimension proposed by Corwin and Schultz (2012). As a result, the high-low spread is less reliable when put into reality than it would be if this assumption were true. To this end, it is necessary to get a deeper familiarity with the current liquidity measures in use in order to effectively put them to use.

It is well acknowledged that liquidity is an important quality of capital assets, and it has a significant bearing on the values of such assets [15]. Previous research has looked at the connection between high liquidity and high stock returns from two different angles.

The initial line of inquiry in this area of study is concerned with determining whether or not the degree of liquidity possessed by a security acts as a factor in determining the returns that are anticipated from investment in that asset. Investors take on more risk when purchasing illiquid equities but are rewarded with larger returns on their investments. This relationship to predicted stock returns is supported by data from a great number of research. For instance, Amihud and Mendelson (1986a) demonstrate that the illiquidity cost, also known as the bid–ask spread, has a positive correlation with the anticipated returns on assets when the spread is used as a liquidity proxy. Using the turnover ratio and trading volume, respectively, as measures of liquidity, Brennan, Chordia, and Subrahmanyam (1998) provide evidence that liquidity has a negative correlation with required asset returns when focusing on U.S. equities. This evidence shows that liquidity has a negative correlation with required asset returns. Bekaert, Harvey, and Lundblad (2007) found a similar correlation in developing markets, confirming this association there as well. On the other hand, there are empirical investigations that present evidence that contradicts itself. According to the findings of Bekaert and colleagues, turnover does not substantially predict future return. Eleswarapu and Reinganum (1993) show evidence of seasonality by proving that bid–ask spread and average returns are positively connected to each other only in the month of January. In the meanwhile, Hasbrouck (2009) provides a novel method for estimating the trading effective cost based on daily closing prices. The author examines the link between their cost measure and stock returns and finds conflicting results. In specifically, they show that effective cost has a positive

14 Goyenko, Holden, and Trzcinka (2009)
15 Amihud and Mendelson (1991)

link with stock returns, with the highest relationship happening in the month of January.

The second stream, that studies the connection between high liquidity and high stock returns, investigates whether or not stock returns are influenced by systemic risk associated with liquidity. When determining the value of assets, liquidity is seen as a significant risk element. The stock with the greater predicted return is the one whose returns are more susceptible to changes in the market's liquidity. This second link to stock returns has also been thoroughly investigated in several previous research. For example, Pastor and Stambaugh (2003) present a market-wide liquidity and demonstrate that the expected returns of stock are correlated with the sensitivities of returns to fluctuations in aggregate liquidity. They say this correlation exists because expected returns are sensitive to changes in aggregate liquidity. According to their findings, the difference between the annualised average returns of stocks that are very sensitive to changes in liquidity and those that are less sensitive is 7.5 percent. It was shown by Acharya and Pedersen (2005) that liquidity is a component that is valued in the cross section of stock returns. They propose a new version of the Capital Asset Pricing Model (CAPM) that takes liquidity into account and they claim that it is superior to the traditional CAPM.

In conclusion, each and every low-frequency liquidity measure often comes with its own set of benefits as well as drawbacks. For example, some proxies, such as the high–low spread developed by Corwin and Schultz (2012) and the Closing Percent Quoted Spread developed by Chung and Zhang (2014), are effective in estimating the bid–ask spread, but they are unable to capture the essence of long-run financial stability. As a direct consequence of this fact, future suggested approximations of liquidity make an effort to ameliorate the deficiencies shown by earlier measurements. The AR spread developed by Abdi and Ranaldo (2017) makes an adjustment for nontrading times, as opposed to Corwin and Schultz (2012), and it does not depend on bid–ask bounces to capture the effective spread in the same way as Roll (1984)'s method does. In addition, Karim and Bin (2016)'s free-float–adjusted price effect ratio takes into account the public free-float component, which improves the predictive potential of price impact when compared to other price impact ratios, such as Amihud (2002)'s illiquidity ratio. Low-frequency measures of liquidity are very popular in both research and practise due to the ease with which they can be calculated and the data that is readily available. However, as compared to high-frequency liquidity metrics that are generated using intraday data, there are still certain restrictions to consider. As a result, experts are still looking for the most accurate indicator of low-frequency liquidity[16].

## 4.3 THEORETICAL FRAMEWORK

### 4.3.1 *Measures of Liquidity*

Liquidity measure can be classified into four categories: price impact and return reversal; transaction costs; price dispersion; econometric techniques.

*Price Impact and Return Reversal*

The price impact of a trade, as discussed in Kyle (1985)'s work, pertains to the extent to which the exchange rate is influenced by a specific order flow. There is a positive correlation between the magnitude of price impact and the subsequent movement of the exchange rate, indicating a decrease in market liquidity. Furthermore, in the case of an illiquid currency, a portion of the price impact is transitory. This occurs when the net buying or selling pressure causes the currency to experience excessive appreciation or depreciation. However, this deviation from the fundamental value is subsequently corrected, as indicated by Campbell and Clarida (1987). Here, to explain the price impact and return reversal, we follow the terminology of Mancini, Ranaldo, and Wrampelmeyer (2013), and for each currency, let $r_{t_i}, v_{b,t_i}$, and $v_{s,t_i}$ be the log exchange rate return between $t_{i-1}$ and $t_i$, the volume of buyer-initiated trades, and the volume of seller-initiated trades at time ti during day t, respectively. Then, price impact and return reversal can be modelled as:

$$r_{t_i} = \vartheta_t + \varphi_t(\upsilon_{b,t_i} - \upsilon_{s,t_1}) + \sum_{k=1}^{K} \gamma_{t,k}(\upsilon_{b,t_{i-k}} - \upsilon_{s,t_{i-k}}) + \varepsilon_{t_i}. \quad (14)$$

Every day, the liquidity aspects of price effect and return reversal can be calculated by estimating the parameter vector $\theta_t = [\vartheta_t \;\; \varphi_t \;\; \gamma_{t,1} \ldots \gamma_{t,K}]$. Due to net buying pressure, it is assumed that a trade with $L^{(pi)} = \varphi_t$ will raise the price. $L^{(rr)} = \gamma_t = \sum_{k=1}^{K} \gamma_{t,k}$ is a measure of the general return reversal, which is supposed to be negative[17].

It is important to acknowledge that Equation 14 aligns with contemporary theoretical models pertaining to limit order books. In its study, Rosu (2009) presents a dynamic model that posits a relationship between asset liquidity and two key market indicators: bid-ask spreads and price impact. The model predicts that assets with higher levels

16 Le and Gregoriou (2020)

17 The presence of a positive contemporaneous correlation between stock returns and volatility estimates will give rise to a negative bias. The presence of contemporaneous order flow leads to a simultaneous increase in the value of the currency due to a net demand effect, denoted as $\beta > 0$. However, this appreciation is somewhat counteracted by delayed order traffic. $\gamma < 0$

of liquidity tend to display narrower spreads and experience lower price impact. According to Foucault, Kadan, and Kandel (2005), the rapid recovery of prices from overshooting resulting from a market order is contingent upon the resilience, or liquidity, of the market[18].

*Transaction Cost*

The trading cost, also known as transaction cost, pertains to the expenses incurred in the process of executing a trade. A market can be deemed to possess liquidity when the relative quoted bid-ask spread, denoted as $L^{ba}$ is low:

$$L^{(ba)} = (P^A - P^B)/P^M, \tag{15}$$

The symbols $P^A$, $P^B$, and $P^M$ represent the ask, bid, and mid quotes, respectively. In practise, it is important to note that trades may not invariably occur at the bid or ask quotes that are publicly displayed. On the contrary, transactions often occur at more favourable prices.

*Price Dispersion*

According to Stoll (1978), when major dealers possess unwanted inventories, their significance in offering liquidity becomes more pronounced as volatility increases. According to Chordia, Roll, and Subrahmanyam (2000), when volatility is high, there is typically a decrease in liquidity. In this context, the measure of intraday price dispersion, denoted as $L^{(pd)}$, can serve as an indicator of illiquidity.

*Other Econometric Techniques*

Other econometric techniques are used in some liquid studies to separate the impact of anticipated trading volumes from that are unanticipated and which may carry new information. The expected volumes are usually estimated by fitting an auto regressive moving average (ARMA) model of volumes traded.

More sophisticated econometric techniques are also used to take account of the fact that once price volatility starts, it will take some times for all the market participants o come to agreement on equilibrium prices. This results in volatility persistence, which can be captured by auto regressive conditional heteroskedasticity (ARCH) and generalised autoregressive conditional heteroskedasticity (GARCH) type models. All liquidity measures presented above capture different aspects of liquidity. Averaging and Principal Component Approach (PCA) are methodologies to extract common information across these measure[19]

*Averaging*

An estimate for market-wide liquidity is computed as simply as cross-sectional average of liquidity at the individual exchange rate level, following Chordia, Roll, and Subrahmanyam (2000) and Pastor

18 Mancini, Ranaldo, and Wrampelmeyer (2013)

19 Mancini, Ranaldo, and Wrampelmeyer (2013) employed these methods to to investigate commonality in FX liquidity

and Stambaugh (2003) that the use for determining aggregate liquidity in equity markets.

Given a measure of liquidity daily market-wide liquidity $L^{(.)}_{M,t}$, can be computed as follow:

$$L^{(.)}_{M,t} = \frac{1}{N}\sum_{j=1}^{N} L^{(.)}_{j,t} \tag{16}$$

where N is the number of exchange rate and $L^{(.)}_{j,t}$ is the liquidity of exchange rate j on day t. Therefore, it is excluded the currency pairs with the highest and lowest value for $L^{(.)}_{j,t}$ in the computation of $L^{(.)}_{M,t}$.

*Principal Component Approach*

Other authors[20] rely on the principal component approach to extract market wide liquidity. PCA can be interpreted as liquidity factors for an individual exchange rate.

For each exchange rate, a given liquidity measure is standardised by the time-series mean and standard deviation of the average of the liquidity measure obtained from the cross-sectional of exchange rates. Then, the first three principal component across exchange rates are extracted for each liquidity measure, with the first principal component representing the market wide-liquidity. To formally test for commonality, Mancini, Ranaldo, and Wrampelmeyer (2013) regress for each exchange rate, the time series of daily liquidity measure $L^{(.)}_{j,t}$ with $t = 1, .., T$ on the first three principal component.

## 4.4 EMPIRICAL ANALYSIS

### 4.4.1 *Methodology*

The purpose of this chapter is to explore how different customer groups can affect liquidity. By the end of this chapter, readers should have a good understanding of how different customer groups can influence liquidity in different ways. To answer this question, we follow Banti, Phylaktis, and Sarno (2011) and we use portfolio analysis to simulate the returns of foreign exchange trading. We use simulations to study order flow and liquidity, and then organise currencies into portfolios based on their sensitivity to these factors. The liquidity measure assesses how easily it is to buy or sell an asset without affecting its price.

We divide currency into different categories based on how easily they can be exchanged for other currencies. Several studies have

20 Hasbrouck and Seppi (2001), Korajczyk and Sadka (2008)

found that the order of transactions is a strong predictor of foreign exchange (FX) returns[21].

Kyle (1985) run a regression to see if there is a relationship between changes in the exchange rate and incoming orders. He finds that there is a positive relationship between the two, meaning that inventory control and the informational asymmetry channel are both affecting the exchange rate. To calculate the liquidity sensitivity of a security using Kyle's model, it is needed to understand the intuition behind Evans and Lyons (2002b)'s paper. The impact that order flow has on exchange rates can be explained by the information discovery process of the dealer. The dealer keeps track of their quotes and makes changes to them based on what their clients and other dealers are ordering.

We use the Evans-Lyons' regression to predict log returns for every currency and every week of the dataset. This equation shows how a currency's value changes with its order flow from different customer groups. It shows how the value of a currency is affected by the buying and selling activity of different market participants. In this case, we refer to liquidity as the impact of trades on prices. In general, trades have more of an impact when markets are less liquid, other things being equal (Evans and Lyons, 2002b).

Kyle's $\lambda$ measures the price impact of aggregate orders that are driven by private information and noise from insiders and trades respectively. We use Kyle's model of market depth $\beta$ to measure the market volatility.

$$r_{i,t} = \alpha_i + \beta_i^c \Delta x_{i,t}^c + \epsilon_{i,t} \tag{17}$$

where $r_{i,t}$ is the log return of the currency $i$ at time $t$, calculated as in Equation 13; and $x_{i,t}^c$ is the contemporaneous order flow of currency $i$ at time $t$ from customer group $c$ (asset manager, corporations, hedge funds, private clients).

We, then, calculated a series of monthly regressions to estimate a time series of $\beta$s based on Equation 17 and we use the estimated $\beta$ as measure of liquidity, equal to $L_{j,t} = \hat{\beta}_{j,t}$.

The more liquid the market is, the lower the impact of individual transactions on exchange rate prices. Since, in this chapter the regression includes actual order flow, in order to estimate liquidity no other proxies are required, but $\beta$s[22].

*Estimation of Common Liquidity*

Demand- and supply- side variables may also assist to explain temporal and cross-sectional fluctuations in the liquidity of currencies. The demand-side approach ties liquidity similarity to foreign investors'

21 Evans and Lyons (2002a), Breedon and Ranaldo (2012), and Cerrato, Sarantis, and Saunders (2011) among many

22 We expect to find a positive coefficient associated with contemporaneous order flow $\Delta x_{i,t}$. A positive order flow causes the currency to appreciate, which leads to an increase in the exchange rate quoted as US dollar versus the foreign currency

linked trading activity. Co-movements may thus be explained by investors' preferred habitats[23], which stem from essential institutional qualities such as sovereign credit risk (as evaluated via credit ratings), central bank transparency, and independence[24]. On the supply side, liquidity spiral dynamics apply to multiple-asset setups as well. Kyle and Xiong (2001) demonstrate that if financial intermediaries providing liquidity in two markets incur trading losses in one market, they may decrease liquidity supply in both sectors. Cespa and Foucault (2014) demonstrate that financing restrictions for traders in one market may spread to other assets and reduce market liquidity.

While the aforementioned research gives assistance on identifying some potential causes of FX liquidity and its commonality, it is hard to procure empirical elements that distinguish supply-side from demand-side forms of liquidity, and causal inference is contingent on the validity of identifying assumptions. Nevertheless, in the spirit of the above mentioned models, we examine the existence of commonality.

We create a time-series of market-wide liquidity which reflects the commonality of liquidity across exchange rates. This allows us to test for commonality in the FX market[25]. Formally, systematic liquidity based on liquidity measure L is estimated as:

$$L^J_m = \frac{1}{N}\sum_{j=1}^{N} L_{j,m} \tag{18}$$

where the subscript $m$ refers to the monthly frequency of the series. The systematic liquidity is estimated by excluding the highest and lowest values for $L_{j,m}$ in the computation. This makes the common liquidity less influenced by extreme currency pairs.

Pastor and Stambaugh (2003) looked at how changes in liquidity (the availability of cash and other assets) affects asset prices. Investors seem to price risk into their investment decisions by considering changes in liquidity. They suggest a way to account for the reversal of expected returns that can result from changed prices as a result of completed transactions. This rule is based on the theory that when liquidity is low, returns usually reverse quickly.

We calculate the average liquidity level for each currency by averaging the individual weekly liquidity measures $DL_m$. According to Pastor and Stambaugh (2003), and Mancini, Ranaldo, and Wrampelmeyer (2013) posit that, corporate insiders tend to trade their stock before bad news is announced to the public:

$$DL_{i,m} = (L_{i,m} - L_{i,m-1}) \tag{19}$$

23 Barberis, Shleifer, and Wurgler (2005)
24 Dincer and Eichengreen (2014)
25 Mancini, Ranaldo, and Wrampelmeyer (2013)

$$DL_m = \frac{1}{N}\sum_{1}^{N} DL_{i,m} \tag{20}$$

To isolate the effects of liquidity innovations, we use an AR(1) model to predict the unexpected component of the common liquidity measure $(DL_w^C)$. This residual is then used to identify any autocorrelation in the individual liquidity series:

$$DL_m = \rho_0 + \rho_1 DL_{m-1} + \varepsilon_m \tag{21}$$

We compute the regression for every currency and every typology of customer present in my dataset and set $DL_w^C = \hat{\varepsilon}_w$ accordingly.

Following Chordia, Roll, and Subrahmanyam (2000), after controlling for global FX liquidity risk, to find that the individual liquidity measure $\beta$ is a good proxy for systematic liquidity across currencies. This may suggests that our measure captures the true underlying liquidity of a currency, and also confirms the extensive literature that gives to $\beta$s the role of liquidity proxy:

$$DL_{i,w} = \delta_{0i} + \delta_{1i} DL_w^C + \epsilon_{i,w} \tag{22}$$

with $DL_{i,w}$ being the individual weekly liquidity and $DL_w^C$ the residual obtained from equation (21).

If there is a statistically significant of $\delta_1$ difference in liquidity levels between different currencies, that may be indicative of a link between global FX liquidity risk and fluctuations in liquidity within individual currencies. Changes in liquidity in one currency can have an impact on global FX liquidity risk. This is because FX liquidity is closely related to the availability of funds to buy and sell currencies. The regression is estimated using Ordinary Least Squares (OLS) and the standard errors are adjusted to account for the method proposed by Newey and West (1987).

*Portfolio Analysis*

When investors are exposed to liquidity risk, they require a higher return in order to compensate for the increased risk. This is because liquidity risk is the fear that an investment will not be able to be sold at a desired time and could become worthless. Investors tend to require a higher return in order to reduce their exposure to this type of risk. The sensitivity of global liquidity to changes in interest rates is estimated using regression analysis. Changes in global liquidity may have a significant impact on returns earned on investments. The ability of investors to sell and purchase assets quickly and easily affects the prices at which assets are traded and the returns that can be earned on those investments. The sensitivity of each return on global liquidity is estimated as:

$$r_{i,m} = \sigma_{0i} + \sigma_{1i} DL_m^C + \varepsilon_{i,m} \tag{23}$$

The currencies are sorted according to the sensitivity to global liquidity risk $\sigma_1$, with the most liquid currencies at the top of the list. In order to compute liquidity betas, we introduce a liquidity risk factor that penalises currencies that are more difficult to liquidate, relative to currencies that are easier to liquidate, this allows to capture the risk associated with changes in liquidity. Changes in liquidity can be a risk to an investment. This is because an increase in the number of buyers or sellers of a security can cause the price of the security to change, which could affect the profitability of the investment. Additionally, changes in liquidity can also create uncertainty about the future price of a security, which could lead to a loss in investment.

*Liquidity Sorted Portfolio*

We study how global liquidity risks are reflected in foreign exchange returns by dividing order flows into three portfolios according to estimated sensitivities and rebalancing these portfolios annually. We anticipate that portfolios with the greatest excess return will be most vulnerable to liquidity risk. The analysis begins in January 2002 and covers the period until November 2007. We create a portfolio that includes currencies with less sensitivity and currencies with greater sensitivity. Each portfolio is evaluated based on its excess returns relative to the returns of the other two portfolios. To calculate the liquidity measure for each currency, the coefficient associated with the order flow is estimated from regression analysis (17) of past data. The monthly series of common liquidity is calculated at the end of each year according to the equations (19) − (21). This information provides a valuable resource for assessing the financial health of the company. The sensitivity of each currency's return to global liquidity risk is estimated by regressing monthly returns on a global liquidity risk measure estimated at each year-end.

At this point, currencies are sorted according to their sensitivity to global liquidity risk according to the estimated parameter $\sigma_i$, which captures the sensitivity to global liquidity risk. This parameter is based on a variety of factors, including the size and health of a country's economy, trade openness, and the level of foreign reserves. At the end of each year, four portfolios are constructed, each with five currencies that are equally weighted. This is based on the ranking of these currencies. This ranking provides a detailed and vivid picture of the four portfolios, which are truly remarkable in their diversity and quantity.

*Client Sorted Portfolio*

To get a better understanding of customer types, another set of portfolios has been created. We created three portfolios for each customer, each containing four currencies. Currencies are calculated according to their liquidity and riskiness from the equations (19) − (21), with a parameter that captures sensitivity to global liquidity risk calculated using regression:

$$r_{i,m} = \sigma_{0i} + \sigma_{1i} DL_m^{client} + \varepsilon_{i,m} \tag{24}$$

where $r_{i,m}$ is the monthly logarithmic exchange rate return calculated using the equation (13) and $DL_m^{client}$ is the residual of the calculated AR(1) model for each model for each client group: asset manager, corporations, hedge funds and private.

At this point, following the same steps we used for aggregated order flow analysis, three portfolios are constructed for each client group. Therefore, the first portfolio contains currencies with different levels of sensitivity, the second portfolio is more balanced, and the last portfolio is designed to be the most sensitive to liquidity. The portfolios are rebalanced every year, and the excess return for each currency is calculated using the Equation 26. All currencies are weighted equally. We compared the excess return of portfolios expecting a higher return from that portfolio more sensitive to liquidity.

*Cross-sectional Analysis*

To measure the risk of systematic liquidity problems, a benchmark study is conducted of Fama and MacBeth. This analysis reveals whether the risk is priced in. We begin by examining how sensitive a portfolio's excess return is to global liquidity. We examine monthly excess returns for three portfolios to gain insight into which portfolios are performing best and we measure global liquidity by looking at the unexpected component of common liquidity $(DL_m^c)$. Finally, we consider additional dollar risk factor, which is the cross-sectional average of the portfolio excess returns. Then, we plot the cross-sectional effect of FX excess return sensitivity at each point in time as follows:

$$er_{j,m} = \beta_j^{liq} \lambda^{liq} + \beta_j^{ave} \lambda^{ave} + \varepsilon_{j,m} \tag{25}$$

where $\lambda_m$ is the market price of a particular risk factor (either liquidity factor or dollar risk factor) at time m.

Both the aggregated and the disaggregated order flows go through this process. This indicates that each order is either for the entire value of the security being exchanged or for a particular amount of the security. The average of the calculated risk coefficients at each time point is the market price of risk. This also holds true for incorrect pricing. Market prices are anticipated to reflect liquidity risk and to factor this risk into their calculations. Furthermore, it is unlikely that the presence of a further risk factor will significantly affect these findings. To confirm the theory that liquidity risk is a priced component in the FX market, the market price $\lambda_m$ should be positive and substantial; moreover, the existence of an additional risk factor should not materially impact the results.

### 4.4.2 *Data Manipulation*

The data set utilised for this study includes USB client order data, weekly nominal exchange rates, and one-month forward exchange rates from February 11, 2001 to November 23, 2007. The following are the currencies: Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), Australian Dollar (AUD), New Zealand Dollar (NZD), British Pound (GBP), Japanese Yen (JPY), Norwegian Krone (NOK), and Swedish Krone (SEK) are the most traded currencies. Foreign exchange rates are usually presented in US dollars. A positive coefficient implies that the dealer is selling or purchasing foreign currency. The rate will rise when the value of the foreign currency falls. A reduction in the exchange rate indicates that the foreign currency has appreciated in value relative to the US dollar. To approximate the risk-free rate, we use the three-month LIBOR rate obtained from Bloomberg. Because all rates are expressed in foreign currency per US dollar, a positive coefficient signifies dollar purchasing (foreign currency selling), and the rate will rise as the foreign currency falls in value. On the contrary, a decrease in this rate indicates that the foreign currency is rising relative to the US dollar. Table 2 displays descriptive statistics for this dataset. We use log differenced rates since exchange rates are determined to be I(1).

*Order Flow* The primary emphasis is on the order flow coming from individual retail investors rather than banks or other types of organisations. The microstructure of flows seems to indicate that the information included in flows originates not from trade between banks but rather from trading with consumers. This is significant because it indicates that banks will have a greater chance of having access to the information they need to make informed decisions on lending and other activities. UBS is the market leader in foreign exchange on a worldwide scale, and the company conducts transactions with four distinct customer groups on a weekly basis. These customer groups include asset managers, hedge funds, businesses, and individual customers.

The data on order flow reveals some interesting and useful information about the activities of the various parties in the market. The real money investors that make up the asset management sector of the market include pension funds and mutual funds, among other types of funds. These investors have a tendency to be more cautious, and they want both growth and stability from the investments they make. The asset managers sector does not include hedge funds since they are considered highly leveraged traders and short-term asset managers rather than asset managers. In contrast to asset managers, hedge funds are not subject to any regulations. Businesses that either bring in or bring out products and services from other countries, as well as those with international supply chains, are included in the corporate sector of the economy. This sector is very important to the economy as a whole since it serves to make international trade and commerce easier to carry out across countries. Treasury divisions of big non-financial firms are included in the corporate sector, with the exception of corporations that pursue highly leveraged investing strategies and are thus categorised as hedge funds. These corporations fall into the latter category. This last category covers affluent private customers who have investable liquid assets totalling more than three million dollars in the United States. Customers that trade privately do so for their own personal financial advantage and use their own funds.

As can be seen in table 1, UBS maintained a dominant position among the top 10 foreign exchange dealers worldwide from the years 2001 through 2011. This is based on the results of the yearly study conducted by Euromoney, which rates dealers according to the sort of consumer they serve. According to the data shown in the table, UBS has consistently ranked as one of the most successful dealers across all of the market's end-user categories. This indicates that they are able to supply their customers with a diverse selection of goods and services, as well as modify their offers to cater to the requirements that are unique to each individual customer. Because of this, they are an excellent option for investors of all stripes, whether they individual or institutional. It is essential to have significant institutions actively participating in the market so that pricing may be established. This is because there are very few competitors in the market. The significant market relevance of UBS's client groups is shown by the tight alignment between the asset management (AM), hedge fund (HF), and corporate (CO) sectors of UBS and the real money, leveraged funds, and non-financial companies groups of the Euromoney survey.

The table reveals that UBS is one of the top two banks for trading with asset managers, one of the top five banks for hedge funds, and one of the top ten banks for non-financial businesses. In addition, UBS is one of the top two banks for trading with hedge funds. It is estimated that a daily transaction of around $4.7 trillion dollars takes place in the foreign currency markets. With a market share that comes close to 10%, UBS is recognised as one of the most successful financial organisations in the world. It generates a daily turnover of more over $400 billion, which is equivalent to more than $8 trillion each month.

The following is an example of how the data on the order flow are gathered and organised. Each transaction that is booked by UBS at any of its offices anywhere in the globe is assigned a client type as it is being recorded. At the conclusion of each business day, the sum of all of the transactions completed that day for each client category is determined. The order flow is the value difference between the buy orders and the sell orders for foreign currency that were started by a certain set of UBS clients. If the individual who initiated the transaction is purchasing foreign currency, then the transaction is recorded as a positive, but if they are selling it, then it is recorded as a negative. Therefore, a positive order flow suggests that there is net demand for foreign currency, while a negative order flow shows that there is net supply of foreign currency.

*Spot Exchange Rate*

The order flow data that we use for the empirical study are updated every week with the spot exchange rates and future rates that are provided by Reuters and can be accessed via Datastream.

The FX spot exchange rates of the US dollar over nine different currencies are used to generate the log returns, and these data may be accessed from DataStream for the period of time covering November 2001 through November 2007. They are the closing spots rates from WM/Reuters, which were given by Reuters at about 16 GMT. The formula for calculating log-exchange rate returns is as in Equation 13. A positive exchange rate return equates to a foreign currency appreciation. A positive connection between order flow and exchange rate returns indicates that net purchasing pressure in the currency market (against the US dollar) is connected with an appreciation of the foreign currency (against the US dollar) and vice versa (in almost all currencies, a negative association exists between corporate and private clientele).

*One-Month Forward Exchange Rate*

The sample period for the portfolio analysis and asset pricing exercise is from November 2001 to November 2007. This allows for a rich examination of market trends and behaviours over this six-year time span. We compute currency excess returns by taking the natural logarithm of the one-month forward exchange rate and subtracting the natural logarithm of the spot rate at time t+1. We obtain one-month forward exchange rate from DataStream provided by WM/Reuters, and FX excess returns are calculated in the following way:

$$er_t = \ln(S_{t+1}) - \ln(F_t) \tag{26}$$

where $S_{t+1}$ is the spot rate at time t+1 and $F_t$ is one-month forward exchange rate.

### 4.4.3 *Results*

Results of descriptive statistics and preliminary analysis are reported in Table 2 and Table 4 and described in Section 3.4.3

The findings of estimating Evans-Lyons' regression 17 for order flow are shown in Table 8. This regression examines the relationship between FX returns and contemporaneous order flow. We estimate this model by utilising data from each week of the sample's corresponding months. OLS was used to do the estimate, and Newey and West (1987)'s method was used in order to determine standard errors. For asset managers and hedge funds, we discovered a positive coefficient related with contemporaneous order flow across all currencies. On the other hand, companies and individual customers offer few instances of the opposite phenomenon.

The corresponding P-value is statistically significant at <0.01 for all of the currencies, which indicates that the model explains a large amount of variation in the outcome variable; however, when we investigated the clients, we discovered that in 67% of the instances, a high P-value was present. A time series of monthly $\beta$s values for each currency is obtained by running the same regression for each month that is included in the sample period. These series stand in for a proxy for the liquidity of the currencies that were taken into consideration.

*Commonality*

Following the methodology of Banti, Phylaktis, and Sarno (2011), we will now analyse whether or not there is any similarity. Then, using from Equation 19 to Equation 21, we develop a common liquidity measure. The proxy $DL_{cm}$ that we get as a consequence represents the innovation in common liquidity across currencies, and the findings are shown in table Table 9. The proxy $DL_{cm}$ has a mean that is equal to -0.0032, a standard deviation that is equal to 0.9776, and an auto correlation that is about -0.489. If the coefficient were to have a statistically significant value, it would suggest that changes in the liquidity of specific currencies are connected to global FX liquidity risk.

The purpose of running Regression 22 is to explore whether or not the proxy is able to capture systematic liquidity across currency pairs. If the value of the coefficient $\delta$ is found to be statistically significant, this would suggest that changes in the liquidity of specific currencies are connected to global FX liquidity risk. The findings, which are presented in Table 9, lend credence to the idea that commonalities do exist, in particular for private clients and corporations. In point of fact, the coefficients associated with these types of customers are statistically significant, whereas the coefficients for asset managers and hedge funds are not. This suggests that private clients and corporations do share some characteristics in common. Also, 69% of the regressions have an $R^2$ that is greater than 5%; as a result, it is possible to deduce that the common liquidity proxy explains a portion of the movement in individual currencies' liquidity, particularly for private clients and corporation. This is the case because private clients and corporation are the two groups that have the highest $R^2$ values.

*Aggregated Liquidity Sorted Portofolios*

We divide order flows into three portfolios $(P_1, \cdots, P_3)$ based on their sensitivity to liquidity using Equation 23 and then calculate portfolio excess returns (on spot exchange rate changes) over the following year to see whether the liquidity risk premium is priced in FX. This is how portfolios are rebalanced annually. By calculating the return of a portfolio short in the foreign exchange basket and a portfolio long in the currency basket $P_j - P_i$, we can cancel out the dollar component, making the long-short portfolio dollar-neutral.

All year-end currency portfolios have been sorted using the $\sigma_1$ parameter. Each portfolio's excess return is derived from the sum of the excess returns of the four equally weighted currencies, and an excess return series is generated for each portfolio by connecting the excess returns computed in successive years. The first portfolio contains the least sensitive currency along with the three most sensitive ones; the second portfolio is the most well-rounded option, as it also includes the two most sensitive currencies along with the two least sensitive ones; and the third portfolio contains the three least sensitive currencies along with the most sensitive one. According to Banti, Phylaktis, and Sarno (2011), NOK and NZD are the most common less sensitive currencies found in portfolios, whereas EUR and CHF are the most sensitive. Descriptive data for all three portfolios and the Buying Minus Less (BMS) portfolio, which is long in the less volatile portfolio and short in the more volatile portfolio, are shown in Table 10. As expected, the portfolio with the more liquidity-sensitive currencies performs better (Figure 6). All of these early findings are consistent with those found by Banti, Phylaktis, and Sarno (2011), who performed the same experiment with aggregate only order flow using Pastor and Stambaugh (2003)'s liquidity proxy.

Data from a Fama-MacBeth-based cross-sectional pricing study is shown in Equation 25. This analysis checks whether the global liquidity risk component is priced in the cross-section of currency excess returns. Results just considering liquidity risk are provided in panel A, where we find that the $\lambda$ coefficient for systematic liquidity risk is positive and statistically significant and where we estimate a liquidity risk premium of about 2.43 percent each year. Results from a Fama-Macbeth analysis containing the dollar risk are shown in Panel B, where AVE showed the dollar risk factor derived as the mean of the cross-sectional portfolios' monthly returns; in this scenario, the $\lambda$ linked with the systematic liquidity risk stays statistically meaningful and does not alter substantially in monetary terms.

*Costumer Based Liquidity Sorted Portfolios*

Descriptive data for client liquidity-sorted portfolios are shown in Table 12. For the purpose of determining the liquidity sensitivity, we first derive a measure of general liquidity from equation Equation 25. `Portfolio1` consists of three relatively insensitive stocks and one relatively sensitive stock, whereas `Portfolio2` consists of three relatively insensitive stocks and one somewhat sensitive stock. Even with this kind of portfolio, it is still easy to see that the customer with the greatest sensitivity to liquidity gets the highest returns. The findings provide credence to the idea that there is a universal liquidity risk premium across all client types. The most common currencies in customer-based portfolios are less volatile than others. This is true across the board: NOK and NZD for asset managers; NZD and NOK for companies; NOK and NOK for hedge funds; SEK and CAD for individual customers. While EUR and GBP are most common in the most volatile portfolios for asset managers, EUR and CHF are most common for companies, EUR, GBP, and JPY are most common for hedge funds, and EUR and CHF are most common for individual customers.

The Fama-MacBeth study findings for the four client types are shown in Table 13. This analysis reports my testing of whether the global liquidity risk component is priced in the cross-section of currencies' excess returns. Liquidity risk premiums are estimated to be 1.6% for businesses, 1.4% for hedge funds, 0.80% for private customers, and -1.10% for asset managers, whose coefficient $\lambda$, which represent the market price of a particular risk factor, is positive and statistically significant.

*Summary of Results*

Liquidity risk is significant, according to the analysis's principal conclusion. To be more specific, we demonstrate that the betas on one or more of the liquidity risk variables, as well as the risk premia on the foreign currencies, reward investors for exposure to liquidity risk. This observation has an impact on risk premia for significant currency pairings that are frequently believed to trade in highly liquid markets. We also demonstrate that differences in liquidity risk pricing have economically significant effects on the behaviour of specific FX returns.

The results shown above demonstrate that this is because spot trading's liquidity enables the development of profitable trading strategies that involve borrowing in some currencies and lending in others. Akin to the carry trade, these liquidity-based methods choose borrowing and lending currencies based on indicators of spot trading liquidity rather than interest rates. We contend that these methods are successful because the forward market fails to account for information about the likely future behaviour of spot rates that is embedded in the liquidity of spot trade. In particular, the structure of limit orders will shift to reflect the perceived increased risk of providing liquidity as spot traders' anxiety about a foreign currency fall grows. Since the prices of forward contracts are calculated by adding forward or swap points to the best limit prices, these fluctuations are only partly represented in these quotes. It is important to note that unlike liquidity circumstances in spot currency trading, money market conditions dictate forward points.

In this chapter, we make use of a data set that was developed specifically for the purpose of analysing the underlying economic foundation of the bind that exists between order flow and exchange rates. The aim of this chapter is to examine the tie that exists between order flow and exchange rates. The data on the order flow has been segmented into a few different client groups, each of which is likely to hold a different set of information than the other categories.

The portfolio technique is being used in this scenario; it has been shown to be helpful in research that cross-sectionally prices foreign exchange assets. This makes it easier to investigate the topic of whether or not customer order flow incorporates risk premia in the currency market related to factors such as systematic volatility, liquidity default, or macro risk; as well as variances between the various categories of customers. We investigate the potential that a risk premium may be added to the exchange rates of the currencies that are exchanged the most often. To be more explicit, we look at the prospect of a risk premium being added to the classification of currencies according to the degree to which customers are concerned about their access to liquidity.

Particularly, we analyse the liquidity of the foreign exchange market for nine distinct US dollar exchange rates over a period of seven years using order flow data from a large custodial bank. We determine the liquidity of different currencies by defining it as the expected return reversal associated with order flow. This allows us to compare the liquidity of different currencies.

Concerning the stock market, we discover a considerable component of commonality in currency liquidity. This finding is in line with the research that identifies dealers' inventory management limits and preferences as key channels that contribute to the establishment of prices[26]. In other words, the behaviour of the dealers towards orders received for different currencies is driven, at least partially, by inventory constraints. Even if the orders are for different currencies, this remains the case. In addition, the need for financing has an effect on the availability of liquidity in each and every currency that an investor trades in, which helps to explain why these two sets of situations are so comparable to one another.

We estimate that the annualised liquidity risk premium is somewhere in the region of 2.43% for the aggregate scenario and 2.34% if a dollar risk-free element is included; both of these values are statistically and economically significant. When we do the same research on the disaggregated typology of portfolios, we discover that corporations exhibit the highest liquidity risk premium, which is equal to 1.60 percentage points. Individual consumers come in third with a risk premium of 0.8%, behind hedge funds in second place with a risk premium of 1.41%. The hypothesis that liquidity risk is a price driver in the FX market for this specific class of consumers is demonstrated to be erroneous as a result of the asset manager's presentation

26 Mancini, Ranaldo, and Wrampelmeyer (2013); Banti, Phylaktis, and Sarno (2011)

of a negative liquidity risk factor ($\lambda$) equal to -1.06%.

## 4.5 CONCLUSIONS

Since the beginning of research on market microstructure, it has been understood that liquidity is not a single variable but rather a multi-faceted notion that cannot be reduced to a single number. Alternative measures that have been considered in the research include the price-impact of order flow, which has been discussed in Kyle (1985), Evans and Lyons (2002a), Evans and Lyons (2002b), and Banti, Phylaktis, and Sarno (2011); return reversal, which has been discussed in Campbell, Grossman, and Wang (1993),Pastor and Stambaugh (2003), and Mancini, Ranaldo, and Wrampelmeyer (2013); and price dispersion, which has been discussed in Chordia, Subrahmanyam, and Anshuman (2001). We evaluate the liquidity of specific currencies by defining it as the expected return reversal linked to order flow. This allows us to calculate individual liquidity metrics. As for the stock market, we discover the existence of a large common element in liquidity between exchange rates, which is in line with the research that identifies the dealers' inventory management restrictions and preferences as significant channels affecting price construction. In other words, we find that there is a significant commonality in liquidity between currencies. In particular, the traders' reaction to new orders of various currencies is governed, at least in part, by inventory concerns. This is the case even when the orders are for different currencies. The need that traders have for appropriate capital and liquidity is another factor that contributes to this parallelism, which may be explained. In this respect, the supply of liquidity in each and all of the exchange rates at which an investor trades is impacted if there is a change in the financing circumstances.

In spite of the widespread belief that the foreign exchange market is always very liquid, our research reveals a large amount of cross-sectional variance in the liquidities of different currencies. Our investigation uncovered a variety of data suggesting the existence of a robust consistency in liquidity, which manifests itself as significant co-movements in the FX rate liquidity across time. This indicates that shocks that influence the foreign exchange market as a whole, rather than specific FX rates, are the primary drivers of the liquidity of the foreign exchange market. Additionally, we discover that more liquid currency exchange rates, such as EUR/USD, tend to have lower liquidity sensitivity relative to market-wide FX liquidity and vice versa.

In this particular piece of research, we emphasise the unexpected part of the overall FX aggregate liquidity, often known as the global FX liquidity risk. In this regard, the most important addition that the study makes is the discovery and assessment of a systematic liquidity risk premium. This premium considerably explains part of the cross-sectional volatility in FX excess returns, and it is the primary focus of the paper. In the event of a liquidity risk premium in the foreign exchange market, an investor will need a larger return to justify holding a currency that is more susceptible to innovations in the liquidity market. It would seem that market-wide liquidity is a state variable that plays a significant role in the pricing of exchange rates. Our investigation reveals that predicted returns are connected, in a cross-sectional manner, to the sensitivity of the returns to innovations. Those currency exchange rates that are much more sensitive to fluctuations in liquidity often have significantly larger anticipated returns. The liquidity measure developed by Pastor and Stambaugh and used in this investigation is characterised by a substantial degree of consistency across rates, supporting the theory that liquidity is a price constant variable.

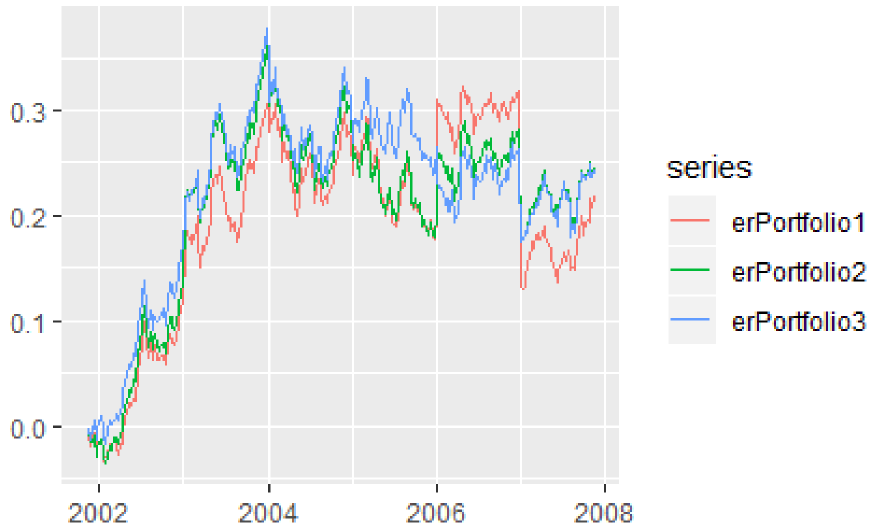
The portfolio approach employed here has been shown to be useful in cross-sectional FX asset pricing studies. This helps in studying the question of whether or not customer order flow captures risk premia in the currency market associated with things like systematic volatility, liquidity default, or macro risk, and variation between different types of customers. We study the possibility of a risk premium being assigned to the exchange rates of the currencies that are the most actively traded. More specifically, we investigate the possibility of a risk premium being linked to the sorting of currencies based on the liquidity sensitivity of clients. From the point of view of an investor in the United States, we classify currencies into one of four portfolios according to their historical sensitivity to liquidity. When we compare the returns of the different portfolios, we discover that the portfolios that include the currencies with the highest sensitivity have the highest overall returns. The greater a currency's sensitivity to shifts in liquidity, the larger the premium associated with holding that currency will be.

Our discoveries are based on the fact that it is possible to build trading strategies that involve buying some currencies and selling others, relying on the liquidity of spot trading. These liquidity-based techniques are very similar to those that define the carry trade; the main difference is that rather than relying on interest rates to determine which currencies to borrow and lend, these strategies utilise measurements of the liquidity of spot trading instead. In our opinion, the reason why these tactics are successful is due to the fact that the liquidity of exchange rates contains information about the behaviour of exchange rates in the future that has not yet been absorbed into pricing. Particularly as the fear of a foreign currency collapse increases among spot traders, there will be adjustments to the structure of limit orders that represent the projected increased risk of providing liquidity. These changes will take place when a foreign currency crash is expected to happen. Prices only reflect some of these changes because of how quickly they were implemented. When we use conventional approaches to valuing assets, we reach an annualised liquidity risk premium of around 4.7 percent. This premium is statistically and economically significant.

In this chapter, we make use of a data set that is well suited for analysing the fundamental economic foundation of the relationship that exists between order flow and exchange rates. The data on the order flow has been broken down into several client categories, all of which are likely to have different kinds of information stored in their profiles. By using a distinct proprietary data set for order flow that was segmented according to the kind of client, we were able to produce empirical evidence that demonstrated the amount of the liquidity risk premium had significantly risen for corporations. In fact, when we perform the same analysis on the disaggregated typology of portfolios, we discover that corporations present the highest liquidity risk premium, which is equal to 1.60 percent. This is followed by hedge funds, which have a risk premium of 1.41 percent, and private clients, who have a risk premium of 0.81 percent. The asset manager gives a negative $\lambda$ (-1.06%), which disproves the notion that liquidity risk is a pricing element in the foreign exchange market for this particular class of customers.

## 4.6 FIGURES AND TABLES

Figure 6: Annualised Portfolio's Returns




The figure shows results from portfolio analysis, where currencies are sorted according to their sensitivity to global liquidity $\sigma_1$. Each portfolio's excess return is derived from the sum of the excess returns of the four equally weighted currencies, and an excess return series is generated for each portfolio by connecting the excess returns computed in successive years. The first portfolio contains the least sensitive currency along with the three most sensitive ones; the second portfolio is the most well-rounded option, as it also includes the two most sensitive currencies along with the two least sensitive ones; and the third portfolio contains the three least sensitive currencies along with the most sensitive one.

Table 8: Regression of Returns of Order Flow

| Currency | Clients | β | t | $R^2$ | Obs | P > \|t\| |
|---|---|---|---|---|---|---|
| AUD | Asset Managers | 0.0218 | (5.84) | 0.098 | 316 | 0.000 |
| | Corporation | -0.0068 | (-0.87) | 0.002 | 316 | 0.384 |
| | Hedge Funds | 0.0164 | (4.33) | 0.056 | 316 | 0.000 |
| | Private Clients | -0.0323 | (-4.38) | 0.058 | 316 | 0.000 |
| CAD | Asset Managers | 0.0086 | (2.81) | 0.025 | 316 | 0.005 |
| | Corporation | 0.0067 | (0.89) | 0.003 | 316 | 0.372 |
| | Hedge Funds | 0.0059 | (1.93) | 0.012 | 316 | 0.054 |
| | Private Clients | -0.0624 | (-7.86) | 0.164 | 316 | 0.000 |
| CHF | Asset Managers | 0.0053 | (3.64) | 0.040 | 316 | 0.000 |
| | Corporation | -0.0093 | (-5.46) | 0.087 | 316 | 0.000 |
| | Hedge Funds | 0.0072 | (5.55) | 0.089 | 316 | 0.000 |
| | Private Clients | -0.0284 | (-10.41) | 0.256 | 316 | 0.000 |
| EUR | Asset Managers | 0.0030 | (4.24) | 0.054 | 316 | 0.000 |
| | Corporation | -0.0018 | (-1.23) | 0.005 | 316 | 0.221 |
| | Hedge Funds | 0.0040 | (5.66) | 0.093 | 316 | 0.000 |
| | Private Clients | -0.0103 | (-10.19) | 0.249 | 316 | 0.000 |
| GBP | Asset Managers | 0.0036 | (3.81) | 0.044 | 316 | 0.000 |
| | Corporation | -0.0035 | (-1.03) | 0.003 | 316 | 0.302 |
| | Hedge Funds | 0.0085 | (5.54) | 0.089 | 316 | 0.000 |
| | Private Clients | -0.0227 | (-9.62) | 0.228 | 316 | 0.000 |
| JPY | Asset Managers | 0.0060 | (5.48) | 0.087 | 316 | 0.000 |
| | Corporation | -0.0187 | (-3.81) | 0.044 | 316 | 0.000 |
| | Hedge Funds | 0.0071 | (6.01) | 0.103 | 316 | 0.000 |
| | Private Clients | -0.0290 | (-11.13) | 0.283 | 316 | 0.000 |
| NOK | Asset Managers | 0.0095 | (0.91) | 0.003 | 316 | 0.362 |
| | Corporation | -0.0272 | (-0.78) | 0.002 | 316 | 0.436 |
| | Hedge Funds | 0.0222 | (1.66) | 0.009 | 316 | 0.097 |
| | Private Clients | 0.0640 | (2.26) | 0.016 | 316 | 0.025 |
| NZD | Asset Managers | 0.0417 | (3.36) | 0.035 | 316 | 0.001 |
| | Corporation | 0.0449 | (0.98) | 0.003 | 316 | 0.327 |
| | Hedge Funds | 0.0845 | (6.91) | 0.132 | 316 | 0.000 |
| | Private Clients | -0.0589 | (-2.52) | 0.020 | 316 | 0.012 |
| SEK | Asset Managers | -0.0098 | (-1.45) | 0.007 | 316 | 0.147 |
| | Corporation | -0.0591 | (-3.64) | 0.041 | 316 | 0.000 |
| | Hedge Funds | 0.0248 | (2.60) | 0.021 | 316 | 0.010 |
| | Private Clients | 0.0677 | (2.12) | 0.014 | 316 | 0.034 |

This table shows findings of estimating Evans-Lyons regression $r_{i,t} = \alpha_i + \beta_i^c \Delta x_{i,t}^c + \epsilon_{i,t}$ where β measure the market volatility; $ri_t$ is the log return of the currency i at time t, and $x_{i,t}^c$ is the contemporaneous order flow of currency i at time t from customer group c (asset manager, corporations, hedge funds, private clients). This regression examines the relationship between FX returns and contemporaneous order flow.

Table 9: Liquidity Commonality

| | | $\delta_1$ | Std. Err. | t | P > \|t\| | [95%Conf.Interval] | | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| AUD | AM | 0.1146 | 0.0690 | -2.18 | 0.033 | -0.2880 | -0.0125 | 0.064 |
| | CO | -2.2457 | 0.1942 | -2.75 | 0.008 | -0.9224 | -0.1475 | 0.099 |
| | HF | -0.0085 | 0.0171 | -0.50 | 0.618 | -0.0426 | 0.0255 | 0.004 |
| | PC | -0.0227 | 0.0555 | -0.41 | 0.684 | -0.1333 | 0.0880 | 0.002 |
| CAD | AM | -0.0771 | 0.0704 | -1.09 | 0.277 | -0.2175 | 0.0634 | 0.017 |
| | CO | 0.0379 | 0.1039 | 0.37 | 0.716 | -0.1693 | 0.2452 | 0.002 |
| | HF | 0.0052 | 0.0037 | 1.39 | 0.169 | -0.0023 | 0.0126 | 0.027 |
| | PC | 0.0859 | 0.0744 | 1.15 | 0.252 | -0.0626 | 0.2344 | 0.019 |
| CHF | AM | 0.0852 | 0.0329 | 2.59 | 0.012 | 0.0196 | 0.1509 | 0.089 |
| | CO | 0.0099 | 0.0271 | 0.37 | 0.716 | -0.0441 | 0.0639 | 0.002 |
| | HF | -0.0008 | 0.0015 | -0.54 | 0.593 | -0.0037 | 0.0021 | 0.004 |
| | PC | -0.0031 | 0.0169 | -0.19 | 0.853 | -0.0369 | 0.0305 | 0.001 |
| EUR | AM | 0.0387 | 0.0122 | 3.18 | 0.002 | 0.0145 | 0.0630 | 0.128 |
| | CO | 0.0222 | 0.0276 | 0.81 | 0.423 | -0.0328 | 0.0773 | 0.009 |
| | HF | -0.0014 | 0.0007 | -2.04 | 0.046 | -0.0028 | -0.0003 | 0.057 |
| | PC | 0.0020 | 0.0054 | 0.36 | 0.718 | -0.0088 | 0.0128 | 0.002 |
| GBP | AM | 0.0533 | 0.0234 | 2.27 | 0.026 | 0.0065 | 0.1000 | 0.070 |
| | CO | 0.0699 | 0.0471 | 1.49 | 0.142 | -0.0240 | 0.1638 | 0.031 |
| | HF | 0.0011 | 0.0035 | 0.31 | 0.759 | -0.0059 | 0.0081 | 0.001 |
| | PC | 0.0090 | 0.0162 | 0.55 | 0.583 | -0.0235 | 0.0414 | 0.004 |
| JPY | AM | 0.0188 | 0.0218 | 0.86 | 0.390 | -0.0246 | 0.0622 | 0.011 |
| | CO | -0.0228 | 0.0902 | -0.25 | 0.801 | -0.2027 | 0.1571 | 0.001 |
| | HF | -0.0001 | 0.0011 | -0.01 | 0.989 | -0.0022 | 0.0022 | 0.0000 |
| | PC | -0.1072 | 0.0476 | -2.27 | 0.026 | -0.2013 | -0.0131 | 0.070 |
| NOK | AM | 3.8208 | 0.4002 | 9.55 | 0.000 | 3.0225 | 4.6191 | 0.569 |
| | CO | 2.1029 | 0.5679 | 3.70 | 0.000 | 0.9700 | 3.2359 | 0.166 |
| | HF | 9.0094 | 1.0945 | 8.23 | 0.000 | 6.8260 | 11.1929 | 0.496 |
| | PC | 2.3851 | 0.6749 | 3.53 | 0.001 | 1.0387 | 3.7316 | 0.153 |
| NZD | AM | 5.1465 | 0.8779 | 5.86 | 0.000 | 3.3951 | 6.8979 | 0.332 |
| | CO | 2.7784 | 1.0901 | 2.55 | 0.013 | 0.6038 | 4.9530 | 0.086 |
| | HF | 0.0082 | 0.0199 | 0.41 | 0.684 | -0.0316 | 0.0479 | 0.002 |
| | PC | 1.2696 | 0.2754 | 4.61 | 0.000 | 0.7202 | 1.8190 | 0.236 |
| SEK | AM | 0.0640 | 0.1715 | 0.37 | 0.710 | -0.2783 | 0.4062 | 0.002 |
| | CO | 4.5365 | 1.1753 | 3.86 | 0.000 | 2.1918 | 6.8811 | 0.178 |
| | HF | -0.0131 | 0.0179 | -0.73 | 0.469 | -0.0488 | 0.0227 | 0.008 |
| | PC | 5.3815 | 0.9025 | 5.96 | 0.000 | 3.5811 | 7.1819 | 0.340 |

This table shows results from $DL_{i,w} = \delta_{0i} + \delta_{1i} DL^C_w + \epsilon_{i,w}$ with $DL_{i,w}$ being the individual weekly liquidity and $DL^C_w$ the residual. If the value of $\delta_1$ is statistically significant, this may be indicative of a link between global FX liquidity risk and fluctuation in liquidity within individual currencies. This regression is estimated using OLS and standard errors are adjusted by Newey and West (1987)

Table 10: Descriptive Statistics of the Aggregate Order Flow Portfolios

| Portfolio | 1 | 2 | 3 | BMS |
|---|---|---|---|---|
| mean | 0.0163 | 0.0173 | 0.0184 | 0.0182 |
| median | 0.0176 | 0.0195 | 0.0201 | 0.0200 |
| st. dev. | 0.0078 | 0.0075 | 0.0072 | 0.0075 |
| sharpe ratio | 0.1425 | 0.1509 | 0.1692 | 0.1510 |
| st.error | 0.0004 | 0.0004 | 0.0004 | 0.0004 |

This table reports descriptive statistics from $r_{i,m} = \sigma_{0i} + \sigma_{1i} DL_m^C + \varepsilon_{i,m}$ for the three portfolios and the Buying Minus Sell (BMS) portfolio, which is long in the less volatile portfolio and short in the more volatile portfolio. Order flow are sorted into portfolios based on their sensitivity to liquidity $\sigma_1$ and then calculate portfolio excess return over the following year and then portfolio are rebalanced annually. Portfolio 1 represents the portfolio more sensitive to liquidity, Portfolio 3 is the portfolio less sensitive to liquidity. Each portfolio is evaluated based on its excess returns of the other two portfolios; the sensitivity of each currency's return to global liquidity risk is estimated by regressing monthly returns on global liquidity risk measure estimated at each year-end.

Table 11: Results from Cross Sectional Pricing Analysis

| | LIQ | costant | $\chi^2$ | std.err. |
|---|---|---|---|---|
| $\lambda$ | 0.0243 | - | 0.0384 | 0.0585 |
| t-stat | (4.98) | | | |
| | LIQ | AVE | $\chi^2$ | std.err. |
| $\lambda$ | 0.0234 | 0.0124 | 0.0347 | 0.0574 |
| t-stat | (4.88) | (2.32) | | |

This table reports results from Fama-MacBeth based cross-section pricing study: $er_{j,m} = \beta_j^{liq}\lambda^{liq} + \beta_j^{ave}\lambda^{ave} + \varepsilon_{j,m}$ where $\lambda_m$ is the market price of a particular risk factor at time $m$. This analysis verify if the global liquidity risk component is priced in the cross-section of currency excess returns. Results just considering liquidity risk are provided in panel A, while results from a Fama-Macbeth analysis containing the dollar risk are shown on panel B, where AVE shows the dollar risk factor derived as the mean of the cross-sectional portfolios' monthly returns.

Table 12: Descriptive Statistics of the Customers Based Portfolios

| *Asset Managers* | *1* | *2* | *3* | *BMS* |
|---|---|---|---|---|
| mean | 0.0191 | 0.0194 | 0.0195 | 0.0195 |
| median | 0.0180 | 0.0207 | 0.0208 | 0.0208 |
| st dev | 0.0089 | 0.0084 | 0.0081 | 0.0081 |
| sharpe ratio | 0.1611 | 0.1714 | 0.1736 | 0.1663 |
| *Corporations* | | | | |
| mean | -0.0150 | 0.0175 | 0.0197 | 0.0020 |
| median | -0.0153 | 0.0187 | 0.0203 | 0.0204 |
| st dev | 0.0081 | 0.0079 | 0.0082 | 0.0080 |
| sharpe ratio | -0.2384 | 0.1504 | 0.1592 | 0.1511 |
| *Hedge Funds* | | | | |
| mean | 0.0193 | 0.0221 | 0.0221 | 0.0220 |
| median | 0.0168 | 0.0247 | 0.0246 | 0.0246 |
| st dev | 0.0246 | 0.0091 | 0.0090 | 0.0091 |
| sharpe ratio | 0.1385 | 0.1710 | 0.1737 | 0.1547 |
| *Private Clients* | | | | |
| mean | 0.0215 | 0.0215 | 0.0215 | 0.0215 |
| median | 0.0235 | 0.0236 | 0.0231 | 0.0240 |
| st dev | 0.0099 | 0.0100 | 0.0101 | 0.0101 |
| sharpe ratio | 0.1562 | 0.1514 | 0.1622 | 0.1585 |

This table reports descriptive statistics from $r_{i,m} = \sigma_{0i} + \sigma_{1i} DL^{C}_{m} + \varepsilon_{i,m}$ (Equation 23) for the three portfolios and the BMS portfolio, which is long in the less volatile portfolio and short in the more volatile portfolio. Order flow are sorted into portfolios based on their sensitivity to liquidity $\sigma_1$ and then calculate portfolio excess return over the following year and then portfolio are rebalanced annually. Portfolio 1 represents the portfolio more sensitive to liquidity, Portfolio 3 is the portfolio less sensitive to liquidity. Each portfolio is evaluated based on its excess returns of the other two portfolios; the sensitivity of each currency's return to global liquidity risk is estimated by regressing monthly returns on global liquidity risk measure estimated at each year-end.

Table 13: Results from Cross Sectional Pricing Analysis

| *Asset Manager* | LIQ | constant | $\chi^2$ | std.error |
|---|---|---|---|---|
| $\lambda$ | -0.0106 | - | 0.0386 | 0.0037 |
| t-stat | -0.69 | | | |
| *Corporation* | LIQ | constant | $\chi^2$ | std.error |
| $\lambda$ | 0.0160 | - | 0.0387 | 0.0026 |
| t-stat | 1.32 | | | |
| *Hedge Funds* | LIQ | constant | $\chi^2$ | std.error |
| $\lambda$ | 0.0141 | - | 0.0384 | 0.0020 |
| t-stat | 1.07 | | | |
| *Private Clients* | LIQ | constant | $\chi^2$ | std.error |
| $\lambda$ | 0.0081 | - | 0.0387 | 0.072 |
| t-stat | 0.85 | | | |

This table reports results from Fama-MacBeth based cross-section pricing study: $er_{j,m} = \beta_j^{liq}\lambda^{liq} + \beta_j^{ave}\lambda^{ave} + \varepsilon_{j,m}$ where $\lambda_m$ is the market price of a particular risk factor at time $m$. This analysis verify if the global liquidity risk component is priced in the cross-section of currency excess returns.

# 5

# THE ROLE OF DECOMPOSED EXCHANGE RATES IN INTERNATIONAL TRADES

This chapter aims to increase the literature on the role of exchange rates in international trade. The primary goal is to study the permanent component of the exchange rate. The study addresses the issue of inconclusive findings by claiming that the failure of previous studies was due to a misunderstanding of measuring exchange rates. The direction of the link between exchange rate and trade varies depending on the set of players considered. A gravity model investigation using various parameters revealed unfavourable conclusions, suggesting that an increase in a country's export value leads to a decline in its currency rate. This is supported by the idea that the price elasticity of demand reduces imports. However, the gravity model is not immune to criticism, especially when complex hypotheses are tested, fixed effects are considered, and endogeneity is incorporated. When country-fixed effects are addressed, there is no significant difference in the findings, and when GDPs are considered as possible endogenous, the results show that if bias is caused by endogeneity, it is not as severe in the dataset. The endogeneity test does not reject the null hypothesis that the GDPs of the two countries are exogenous to the model.

We also make a contribution that is more econometric in nature. The analysis and examination of decomposed exchange rates have attracted significant interest and intellectual consideration. The distinct roles that permanent and temporary exchange rates play in facilitating trade flows are the subject of another study. The panel cointegration technique is employed to examine the outcomes of several decompositions. Based on the analysis, it is determined that the Christiano- Fitzgerald filter methodology is the most suitable approach for effectively separating exchange rate fluctuations into two economically relevant components. The Christiano-Fitzgerald filter methodology divides exchange rate changes into two main categories: permanent changes due to fundamental factors and temporary changes due to speculative shifts and unobservable shocks. This decomposition provides valuable information on the exchange rate and its relationship to fundamentals, allowing us to determine the economic logic behind various econometric approaches. The Christiano-Fitzgerald filter is the only econometric model that fulfils the assumption that the trend component reflects observable fundamentals. However, further research is needed to expand the study to include a wider group of countries and examine the responses of certain sectors to long-term currency value shifts. Also, coming up with an optimal filter that can separate a time series, like the exchange rate, into permanent and temporary parts and figuring out if the frequency of the dataset affects the choice of filter.

## 5.1 INTRODUCTION AND MOTIVATION

The world economy and international commerce have seen massive shifts in the last quarter of a century. Since the global financial crisis (GFC), the growth of international trade has slowed remarkably, and with the exception of an immediate recovery following the crisis, it has only gradually recovered since then. Several studies have been conducted to study its primary causes and determine if the phenomenon is caused by cyclical or structural reasons. In particular, the influence of exchange rates on trade, as well as the efficiency of monetary policies as a tool in balancing a nation's external position and the stability of its home economy, have been prominent topics of discussion in the academic literature.

This chapter's contribution to the existing body of research is an examination of the relationship between the real exchange rate and trade volume. More specifically, this chapter expands the body of research related to the portion of research that hypothesises that a decline in a nation's currency value will lead to an increase in that nation's exports. In addition, the purpose of this chapter is to narrow the gap that exists between trade and the connection between exchange rate misalignment. To do this, the chapter examines the elements of exchange rate movements and asserts that the extent to which exchange rates impact trade balances is dependent on the sources of exchange rate fluctuations. The empirical study explores how variations in trade volumes are caused by shifts in real exchange rates, which are broken down into permanent and temporary components. There is very little research that investigates the role of the decomposed real exchange rate on trade flows, but there is a lot of research that investigates the impact of exchange rate volatility on trade flows[1].•

Exchange rates are prices, which, according to conventional models, are dependent on both observable macroeconomic fundamentals as well as unobservable shocks. The interaction between currency rates and their elements is particularly complicated since exchange rates are an endogenous variable.

The exchange rate is embodied in a framework for asset prices by Engel and West (2005), who defines it as a weighted sum of observable fundamentals and unobservable shocks. This combination can be seen as a decomposition into a trend component and a cycle component, with the trend component being linked to the fundamentals

1 Krugman (1986); Clark (1973); De Grauwe (1998); Hooper and Kohlhagen (1978); Baron (1976)

of the macro-economy and the cycle component being linked to unobservable factors in the money market. In accordance with this definition, the first section of the chapter is devoted to analysing the decomposition of exchange rates into trends and cycles through the application of a variety of econometric approaches. This is followed by an in-depth examination of whether or not decomposing exchange rates into trends and cycles actually has the expected link with the fundamentals. A panel cointegration test is used to investigate the potential for a long-term connection between the many potential trend and cycle components and the fundamentals of the economy.

### 5.1.1 *Research Contributions*

*Econometric Contribution*

There is a gap in the literature as a result of the fact that no published paper has explicitly tested for the economic validity of the alternative methodologies and verified whether or not the new time series has the expected relationship with fundamentals, despite the fact that several papers use multiple detrending strategies to shape exchange rates into fundamentals and shocks. This decomposition gives important information on the exchange rate and its link to fundamentals since it takes into consideration the fact that the trend component is connected to the fundamentals that can be seen, while the cyclical component is tied to the shocks that cannot be observed. This lets us figure out the economic reasoning behind different econometric methods, and our research leads us to the conclusion that the Christiano-Fitzgerald filter is the only econometric model that meets our ex ante economic premise that the trend component represents observable fundamentals. This is a first step towards closing the gap in the professional agreement about which filter is the optimal choice.

*Economic Contribution*

In order to investigate the relationship between shifts in trade and exchange rate, a sample of G10 countries is used for the period from 1994 to 2006, and a gravity model is used with various fixed effects included to control for omitted variable bias and its associated endogeneity. Additionally, a real effective exchange rate is added to the model. This is done so that the results can be more accurately interpreted. The findings gained provide more evidence that a devaluation of a country's currency may have a beneficial effect on the trade flow of that country, leading to an increase in exports for the G10 nations. When we explore the link between currency exchange rates and EU nations, we also obtain the opposite findings. This leads us to believe that there must be other elements that impact currency exchange rates and commerce, and that these variables differ from country to country. The findings that are produced from this study are able to explain why the conclusions that have been found in the previous research are inclusive (for the mismeasurement) and diverse (for the heterogeneity of different countries).

### 5.1.2 *Outline of the Chapter*

The chapter is organised as follows: Section 5.2 discusses the previous literature review on decomposition methodologies and the literature review on international trade in general. In section 5.3, we describe the methodology used for this chapter. Section 5.4 analyses the results obtained by the decomposition of the real effective exchange rate using different filters, then compares them, and investigates the impact of the exchange rate on trade through empirical analysis. Making use of the decomposed exchange rate series, the impact of exchange rates on bilateral trade flows is empirically analysed using the Gravity Model in a panel setting. From this analysis, we want to find out whether the impact of currency depreciation on trade flows depends on the source and whether that change in exchange rather reflects a shift in trend or is just a transitory movement. Finally, in Section 5.5 we conclude.

## 5.2 REVIEWS OF THE RELATED RESEARCH

Since the establishment of the floating system in 1973, the subject of how the exchange rate impacts international commerce has been a recurring topic of discussion in the community of traders and policymakers. The vast majority of economic literature that has been written on the topic of the relationship between exchange rate and trade focuses on the effect that increased volatility of the exchange rate has on trade. However, when it comes to the question of the effects that exchange rate variability has on trade, the significant bundle of theoretical and empirical research that has been conducted is still relatively obscure. This idea is emphasised in a number of different surveys of the relevant research; for example, see McKenzie, 1999, Bahmani-Oskooee, Harvey, and Hegerty, 2013, Ozturk, 2006. Despite the fact that this subject has been thoroughly researched, the results that have been produced so far are vague and contradictory; nonetheless, one thing that is known for certain is that the influence of exchange rate on trade is very sensitive. There are just a few factors that are thought to be the cause of this sensitivity. In the first place, if on the one hand exchange rates are thought to be endogenous because of the way in which they interact with macroeconomic, financial, and trade determinants, on the other hand, currency movement is thought to be exogenous when it comes from the perspective of an individual trader. Misalignment imposes costs on the actual economy that are asymmetric across various economies, which is another crucial element to consider. In conclusion, the perspective of the exchange rate is that it acts as a transmission route for financial shocks to the actual economy as well as a vector for "monetary dumping" (Auboin and Ruta, 2013).

The fact that customers often utilise financial instruments in order to protect themselves against this risk is one reason why volatility alone is not a crucial element for international trade (Either, 1973). Additionally, the presence of fixed costs in exporting reduces the impact of volatility of currency rates on commerce. One critique of the use of volatility to examine the link between exchange rates and the volume of exports is that it is not a significant component for international trade[2]. These findings that there are no effects of volatility on trade are confirmed by a study that was carried out by UNCTAD[3]. In this study, they compare the results achieved from volatility with the results derived using exchange rate imbalance finding that currency misalignment instead has a significant effect on trade. They discover that a reduction in the value of the currency leads to an increase in exports and a decrease in imports.

Since the Great Financial Crisis, academic and policy discussions have shifted their emphasis from volatility to real exchange rate, paying particular attention to global macroeconomic imbalances, stagnant recovery, and the consequences of chronic currency misalignment. It is evident that volatility is not the proper option to examine the ultimate link between trade volume and exchange rate (WTO, 2011). It has been shown by Huchet and Korinek (2011) that trades are more sensitive to real exchange rates (RER) than it is to volatility, and the agricultural sector is especially susceptible to this.

A large body of further research investigates the link between the exchange rate and the trade balance by use the actual exchange rate rather than volatility, finding more encouraging findings. Hooy, Law, and Chan (2015), Thorbecke (2006), and Thorbecke and Kato (2012) all came to the conclusion that a devaluation of a currency has considerable beneficial impacts on exports and significant negative effects on imports[4]. Because of the influence of price elasticity of demand and changes in terms of trade, a depreciation would cause a rise in a country's exports while simultaneously causing imports to decrease. International Monetary Fund (2015a) provides evidence to support the deteriorating link between exchange rate and trade owing to global value chains for certain countries; they also discover that the increase in export is larger when the exporting nation has a weaker financial system, particularly in the event of banking crises.

2 Franke (1981)
3 Nicita (2013)
4 Appuhamilage and Alhayky (2010)

The Marshall-Lerner (ML) condition is defended by proponents of the theory that the ML condition is both a necessary and sufficient requirement for an improvement in the trade balance. This theory asserts that the demand elasticity only has an impact on the trade balance if the total of imports and exports is greater than one, and that this condition must be met for there to be a positive change in the trade balance. If the national currency is devalued, the shift in relative prices causes imports to become more costly and exports to become cheaper; nonetheless, Bahmani-Oskooee, 1985 establish that even when the ML condition is held, the trade balance continues to worsen.

As a result, attention shifted to the phenomenon known as the J-curve, which states that a decline in the value of the real exchange rate may be linked to a worsening of the trade balance's effect, followed by an improvement in that balance. This is due to the fact that businesses plan their import and export activities many months in advance, far in advance of any unforeseen changes that may occur. There will be an initial decrease in trade balance if there is an unexpected depreciation since it will cause the value of the pre-contracted amount of imports to increase (Junz and Rhomberg, 1973; Magee, 1973 and Magee, 1996). In a nutshell, while adjustments to exchange rates take place instantly in the event of an increase in the cost of imported goods, consumers and producers require some time to readjust to the new prices, which results in a time lag caused by the readjustment of domestic goods (if they are available) to take the place of the imported goods. If and when this occurs, a real exchange rate drop will result in an improvement in the trade balance in comparison to its level before the depreciation (Magee, 1973). The literature evaluation pertaining to the J-curve solely is very extensive, yet even in this particular instance, the findings are unclear and conflicting. The broad opinion is that the short-run reaction of trade balance on fluctuations in the exchange rate does not take a specific path, leaving the issue unresolved and producing findings that are distinctive to each nation. If, on the other hand, the research is conducted with a focus on bilateral trade rather than on aggregate data, the findings are more convincingly in favour of a positive association between the exchange rate and the trade balance (Rose and Yellen, 1989; Shirvani and Wilbratte, 1997). Finding variations in exchange rate elasticity that might help to understand the activity of comparative advantage commodities as opposed to comparative disadvantage commodities is the subject of some research, such as that conducted by Breuer and Clements, 2003. This kind of study examines the sensitivity of trade flows to changes in the exchange rate at the commodity level.

Concerns about high unemployment and a sluggish recovery from the Great Recession have increased sensitivity and vigilance toward nations that are thought to be "exporting" their way out of the crisis at the expense of their trading partners. This has strengthened the sensitivity and vigilance towards those nations. The level of the exchange rate thus became the focus of concern at this point in time. Misalignment is defined as an exchange rate value that is either above or below the equilibrium exchange rate. Exchange rates can move from their equilibrium level either as a direct result of an intentional intervention by the government in the form of currency manipulation or as an unintended side effect of macroeconomic policy. Eichengreen (2007) and Rodrik (2008) question whether or not economic policies can influence the real exchange rate. They find that the relative price of non-traded goods are not influenced from policy makers in the long-run. However, they also find that the level of exchange rate can be influenced by policy in the short or medium term. In addition, some studies have been conducted to investigate the effect that shifts in currency have on the expansion of exports. The nations that are included in each of these studies are chosen differently. Arslan and Wijnbergen (1993) focused on the function that the depreciation of the Turkish lira had in exports. Fang et al. (2006) investigates the effect of exchange rate devaluation on exports for Asian nations.

A number of recent studies examine the misalignment in the exchange rate, or the exchange rate that is either higher or lower than the rate at which it would be considered to be in equilibrium. Studies use a variety of methodologies, such as the internal-external balance approach, the behaviour approach, and the permanent equilibrium approach, in order to quantify the degree of misalignment. Some research[5] employ the concept of the equilibrium exchange rate, which is derived from the theoretical idea of the equilibrium exchange rate. They quantify the misalignment as the divergence from the equilibrium exchange rate, which is the level at which both internal (productivity theory presented by Balassa-Samuelson, 1964) and external (asset markets) markets in the economy are balanced. In addition, some research[6] regresses the real exchange rate on per-capita income, and the misalignment is defined as the difference between the actual values and the values that are fitted to the data.

In addition, research that investigate the connection between growth and currency exchange rates have shown the negative effects of undervaluing a currency on international commerce According to the findings of these research, economic growth may be improved by undervaluing the currency and increasing exports.

Other research has also investigated the influence of the currency exchange rate on disaggregated data by studying how businesses react to an increase or decrease in the value of their currency. Berman, Martin, and Mayer (2012), Chatterjee, Dix-Carneiro, and Vichyanond (2013), and Tang and Zhang (2012) each investigated how companies

5 Razin and Collins (1997); Ricci et al. (2008)
6 Rodrik (2008); Freund and Pierola (2012); Haddad and Pancaro (2010), Nicita, 2012

in France, China, and Brazil responded to fluctuations in their respective currencies. According to the findings of these studies, large and small businesses respond differently to fluctuations in the exchange rate. For example, the effect of a currency depreciation on large firms causes them to increase the markup, while the impact of a currency depreciation on small firms causes them to change their import prices. In addition, as major exporters account for a greater proportion of overall exports, the findings of these firm-level analyses indicate that the effect of depreciation on total trade flow will be relatively little.

*Decomposition of a Time Series*

Deconstructing the exchange rate has been done in a number of studies for a variety of reasons across the body of academic work. The majority of these studies focus on the determination of the equilibrium exchange rate and use the theoretical concept of the equilibrium exchange rate. Another approach that is used in the literature is the permanent equilibrium approach, which uses model-based methods to calculate the permanent component as an indicator of the equilibrium exchange rate.

Both theoretical inquiry and empirical applications have a long history of interest in the economic cycle. This interest has been around for quite some time. When doing empirical study on the economic cycle, the researcher is faced with the statistical challenge of determining how to best extract the cyclical component of the data, given that the majority of time series are characterised by both fluctuation and expansion. An extensive body of academic work has been done during the course of the economic cycle's empirical study. According to Burns and Mitchell (1946)'s definition a cycle is defined as follows:

> *"Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organise their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle"*

After seventy years, students and researchers are still confronted with the challenge of determining how to separate the cyclical element of an economic time series. Even though Bry and Boschan (1971) use a business-cycling dating algorithm to implement the Burns and Mitchell model with a judgement-free version, the insiders decided to deviate from the Burns and Mitchell (1946) model due to its complexity and the need for judgement evaluations. Researchers now focus on methods that are easier to apply rather than methods that make judgements. As a result, several methods have been developed for obtaining the business cycle from a selected time series; however, none of these methods produce results that are inferior to those produced by the others.

Calculating the length of the business cycle is difficult due to the fact that its movements are made up of both low frequency trends and high frequency random patterns. In order to address this problem, several approaches have been developed, each of which varies in how it deals with trends and noises and, as a consequence, produces a unique set of outcomes[7]. According to Canova (1998), the various techniques for subtracting do not estimate the same cyclical components. The conventional school of thought held that one could study the cyclical component and the trend component independently of one another due to the fact that the economic mechanism that underpinned short-term and long-term economic swings was relatively unlike. These decomposition approaches are usually ad-hoc in the view that the researcher demands simply that the detrending process yield a stable business-cycles component, but does not in any other way clearly describe the statistical properties of the business cycle. The use of two-sided moving averages, first-difference, the elimination of linear or quadratic time series, and the application of the most renowned Hodrick and Prescott (1997) filter are a few examples of procedures that are often used. Other approaches include: Butterworth (1930) filters are a kind of filter, and Gomez (2001) demonstrates that one may acquire an HP filter by treating it as a special instance of the broader category of Butterworth filters. Their characteristics are easily analysed in the frequency domain, which supplies a significant amount of information on the nature of the process being carried out. Gomez demonstrates further that Butterworth filters are capable of being interpreted in a model-based manner. It is possible to show, as a consequence of the link with Butterworth filters, that a model generating the estimate of an ideal band pass filter can be obtained as a limiting case. This is the primary benefit of this extended class of models; it makes it possible to extract smoother cycles than would be possible with other models.

Some works centre their attention on the problems that arise from the trends on long-run components in economic time series, studies that characterise trends in economic time series, and studies that characterise trends in economic data. An example of this approach may be seen in Nelson and Plosser (1982)'s research, which examines the use of both deterministic and stochastic trends. Geweke, Meese, and Dent (1983) concentrates on deflecting long-run links, whereas Nelson and Kang (1981), Nelson and Kang (1984) and Engle and Granger (1987) include long-run links in short-run dynamic interaction. Other publications, such as Nelson and Kang (1981 and 1984), centre on the econometric ramifications of mispecification in the model of the d component. On top of that, Nelson and Kang (1981) demonstrate that mis-specification in a model for the trend may have a significant impact on the predicted monetary values produced by an econometric

7 Estrella (2007)

model. If contemporary theories of economic behaviour are going to be validated by using these dynamic linkages, then accurate assessment of those dynamic interactions is essential.

In their study, Baxter and King (1999) separate business cycles with the use of a moving average approach. At the turn of the century, researchers have been concentrating their efforts on band pass filters that can strip signals of high-frequency as well as low-frequency components. In their research from 1999, Baxter and King explore the design of band-pass filters as well as their implementation in limited samples. In the time domain, their primary objective is to approach the ideal filter, which is a perfectly sharp band pass filter; Christiano and Fitzgerald (2003) also offer a revised BK filter proving its features when applied to US macroeconomic data.

The fact that the filters that are implicitly specified by the model are compatible with both each other and along with data is one of the appealing aspects of the model-based approach. In addition to this, they automatically adjust themselves to the beginning and end of the sample, and root mean square errors may be determined if the user so chooses. The models can also be used to gain insight into the more ad hoc filters that are used in business cycle analysis. These models can indicate when it might be appropriate to use these filters as well as when they can lead to serious distortions. These significant discrepancies have been recorded by Harvey and Jaeger (1993) for band pass filters and byCogley and Nason (1995) and Harvey and Jaeger (1993) for the Hodrick-Prescott filter.

In more recent times, Hamilton (2018) has harshly criticised the Hodrick-Prescott filter, which is often utilised. When used to a standard economic time series, he demonstrated that the HP filter produces false cycles and is affected by an end-of-sample bias. In addition to this, a smoothing parameter has to be set, which is often done in an ad hoc manner. In addition to this, Hamilton suggests a different filter that is based on a regression. The cyclical properties of the Hamilton filter and the Hodrick and Prescott (1999) filter are compared by Schüler (2018), who finds that the Hamilton filter produces more robust results. He also discovers that the Hamilton filter modifies the cyclical structure of a time series in its original form.

## 5.3 METHODOLOGY

There are several tools developed in the literature to extract the permanent component of a macroeconomic time series and none of them seems to stand up for their results. The filter chosen in this chapter are the most widely used by macroeconomists to decompose time-series into trend and cycle, and they are examples of band-pass, high-pass and low-pass filters. In this part of the chapter, the Behavioural Equilibrium Exchange Rate (BEER) is also introduced. This model, that is widely used in practice, is was developed in 1999 by Clark and MacDonald, and estimates the fair value of currencies according to short, medium and long-rum determinants. BEER is be used, in this contest, to compare different decomposition filters and evaluate which one has more economic sense, and use it in the second part of the empirical analysis in a gravity model exercise.

The gravity model is finally used to analyse the exchange rate and trade balance relationship. In the gravity model analysis is usually used the Real Effective Exchange Rates (REER) index. The real effective exchange rate aims to assess a country's price or cost competitiveness relative to its competitors in international markets. The REER is crucial because the ratio of the euro to the dollar would have a larger effect on the index's overall value if a robust economic tie between the United States and Europe occurs. As a consequence of this, a significant shift in the value of the euro relative to the dollar would have a more profound effect on the REER than would the relative strength of another currency with a lower weighting. The index's weightings would be weighted most heavily toward the countries that had the most extensive trade links. Those nations who have few other countries with which they trade will have a reduced influence on the overall basket of currencies.

When looking at the REER, economists are able to determine whether nations' economies have become less competitive in comparison to those of other countries. REER is also highly significant for determining the equilibrium of currency value as well as the flows of the trade balance and the factors that drive them.

### 5.3.1 *Behavioural Equilibrium Exchange Rate (BEER)*

Behavioural Equilibrium Exchange Rate is what we use in conjunction with a fixed-effect panel regression on G10 currencies to determine the fair value of REERs. Clark and MacDonald (1998) are the ones who developed the concept known as the Behavioural Equilibrium Exchange Rate, and since then, it has gained a lot of attention in the field of international economics. The primary focus of this method is on econometric analysis rather than economic analysis, which is what makes it so distinctive. After plugging in the set of factors that are anticipated to have an effect on the exchange rate, the equation is solved using either an error correction model or a vector error correction model. The real interest rate difference, the productivity differential which to capture the Balassa-Samuelson effect[8], the relative

8 The Balassa-Samuelson model is a theoretical construct used to analyse the properties of real exchange rates. It explains the consistent shifts in real exchange rates observed over time and across nations through analysing variations in total-factor

fiscal stance, and the cumulative current account balance are the most typical variables used in the study.

The case currency that we use in my regression is the US dollar, and the three macroeconomic variables used in this chapter are inflation, Term of Trade (ToT), and Interest Rate (IR). Using the US dollar as the case currency allows me to find the fair value of REERs. The formula for the reduce form equation that Clark and MacDonald (1999) proposed may be rewritten as follows:

$$e_t = \beta_1 Z_{1,t} + \beta_2 Z_{2,t} + \beta_3 Z_{3,t} + \tau T_t + \epsilon_t \tag{27}$$

where: $Z_{i,t}$s are vectors of economic fundamentals that are expected to have an effect on the exchange rate over the medium and long term respectively; $\beta 1$ and $\beta 2$ are vectors of reduced-form coefficients; T is a vector of transitory factors that influence the real exchange rate in the short run; $\tau$ is a vector of reduced form coefficients; and $\varepsilon$ is the noise in the model. For the purpose of conducting an analysis of this study and taking into consideration the fact that we are interested in modelling the medium-to-long term value of currencies, we combine $Z_1$ and $Z_2$, exclude the transitory matrix T, and ultimately rearrange the equation as follows:

$$e_t = \beta Z_t + \epsilon_t \tag{28}$$

We employ a technique called a panel fixed effect (FE) model to assess the "fair" values of various currencies. To approximate the long-run equilibrium relationship, the reduced-form equation that follows is employed (all logs except for the IR differential, which might be negative):

$$REER_{i,t} = \alpha_i + \beta_1 ToT_{i,t} + \beta_2 IR_{i,t} + \beta_3 inf_{i,t} + \epsilon_{i,t} \tag{29}$$

where $REER_{i,t}$ is the real effective exchange rate of country $i$ at time $t$, ToT is the terms of the trade differential between country $i$ and the US; IR is the interest rate differential; $inf$ is the inflation rate differential: and $\alpha_i$ is the country specific fixed effect which captures the time-invariant characteristic of each country; $\epsilon$ is the error term. A further stage in the expansion of the BEER methodology is the development of statistical approaches that could discriminate between the permanent and transient impact of variables[9]. This is accomplished as part of the BEER methodology. Regardless this method models a time-varying RER it "places even less normative structure on the

productivities across different sectors of the economy. The underlying mechanisms that propel this model are straightforward; a spike in productivity growth within sectors that engage in trade leads to a corresponding rise in local input costs, subsequently affecting the prices of goods that are not subject to trade. The phenomenon of traded-goods prices being balanced across economies produces an increase in the local price level, resulting in a real exchange rate appreciation.

9 Gonzalo and Granger (1995)

model and its consumption." It is feasible for the model to incorporate a large number of major macro variables. Some examples of these would include the actual price of oil, terms of trade, and net foreign assets. It is predicted that all of these factors would have an effect on the real exchange rate. According to Duval (2001), the primary benefit of this method is that it is able to flexibly adapt to the level of long-term equilibrium, and it also records for the Balassa-Samuelson effect. This is a significant benefit that comes with using this model. The use of the permanent component is utilised by the PEER in order to provide a measure of balance. This approach takes into explicit account the potential that a number of the significant variables are linked via a cointegrating relationship.

It is possible to arrive at a permanent equilibrium exchange rate by first splitting the real exchange rate into components that are permanent $q_t^P$ and transitory $q_t^T$respectively. The equilibrium then becomes the permanent component, which is defined as:

$$q_t = q_t^P + q_t^T \tag{30}$$

This approach provides a smoother equilibrium exchange rate than BEER, and it is easier to read. It is based on the decomposition of an actual real exchange rate into its permanent and transitory components, and then utilising the permanent component as a measure of equilibrium exchange rate.

The Gonzalo-Granger approach was used by Clark and MacDonald (2000) to decompose the BEER data, and they described the PEER as a result of this. Gonzalo and Granger (1995) demonstrate that the common factor can be estimated if it is assumed that it is a linear combination of the series that are in discussion and if it is further presumed that the residuals from this method do not have a permanent effect on the series that are in question. These two assumptions are necessary for the estimation of the common factor. They demonstrate that the linear combination may be calculated from a Vector Error Correction Model (VECM), and since this method accounts for any non-stationarity, it makes statistical inferences about the common variables easier to make. The term "cointegration" refers to the equilibrium of given variables over the long run. When a shock happens in the progression of a variable, there is a process known as vector error correction that explains the rate at which the variable will adapt in order to return to the equilibrium state.

Let us consider a vector of variables $X_t$ with one cointegration vector ($X_t$ is a $n \times 1$ matrix and the matrix $\pi$ is of rank 1). We can define the orthogonal complements $\alpha_\perp$ and $\beta_\perp$ as complements of $\alpha$ and $\beta$ respectively ($\alpha$ and $\beta$ are the matrices of the Granger decomposition of the matrix $\pi$):

$$\alpha_\perp = (I - \alpha(\alpha^{'}\alpha)^{-1}\alpha^{'}) \qquad \beta_\perp = (I - \beta(\beta^{'}\beta)^{-1}\beta^{'})t \tag{31}$$

It holds that $\alpha_{\perp}^{'}\alpha = \beta_{\perp}^{'}\beta = 0$. Furthermore, it can be written:

$$X_t = \beta_{\perp}(\alpha_{\perp}^{'}\beta_{\perp})^{-1}\alpha_{\perp}^{'}X_t + \alpha(\beta^{'}\alpha)^{-1}\beta^{'}X_t \tag{32}$$

Gonzalo and Granger denominated the first and the second component of equation (32) permanent and transitory component respectively and showed that the transitory component has no effect on permanent (long-term) component.

### 5.3.2 *Gravity Model*

Initially, the gravity model was seen as an empirical one, without any grounding in trade theory, but the widespread adoption of the gravity model to explain patterns of trade has been seen by economists as a significant development on previous theoretical models. These include the Ricardian model, that explain trade patterns in terms of differences in the distribution of technology, and the Heckscher-Ohlin model that relies on differences in factor endowments among countries as the basis for trade. In these pre-gravity models the size of an economy was not considered significant. At its most basic, the intuitive gravity model takes the following log-linearized form:

$$\ln X_{i,j} = a_0 + a_1 \ln GDP_i + a_2 \ln GDP_j + a_3 \ln t_{i,j} + e_{i,j} \tag{33}$$

where $X_{i,j}$ indicates exports from country $i$ to country $j$; $GDP_i$ and $GDP_j$ indicates each country's gross domestic product; $t_{i,j}$ represents trade costs between the two countries; and $e_{i,j}$ is the error term.

Since the multilateral terms were not included, Anderson and van Wincoop (2003) discovered that the coefficients were biassed. Multilateral trade-resistance (MTR) is the phenomena wherein two countries that are surrounded by other large trading economies deal less with each other than if they were bordered by oceans or by deserts and mountains. Here is Anderson and van Wincoop's suggested gravity equation:

$$\ln X_{i,j} = a_0 + a_1 \ln GDP_i + a_2 \ln GDP_j + a_3 \ln t_{i,j} + a_4 \ln p_i + a_5 \ln P_j + e_{i,j} \tag{34}$$

where $t_{i,j}$ is the cost in $j$ of importing a good or a service from $i$; $p_i$ is the exporter's ease of market, or outward multilateral resistance. It captures the fact that exports from country $j$ depend on trade costs across all possible export markets. $P_j$ is the importer's ease of market, or inward multilateral resistance. It accurately represents the relationship between imports into nation $i$ from country $j$ and total trade costs of importing goods from all suppliers. If a nation is cut off from global trade, its $p_i$ and $P_j$ will be low.

For the panel data set, the basic gravity equation for the regression analysis of this chapter takes the following form:

$$\ln X_{i,j,t} = a_0 + a_1 \ln GDP_{i,t} + a_2 \ln GDP_{j,t} + a_3 \ln t_{i,j} + a_4 \ln PERM_{i,j,t} + a_5 \ln TEMP_{i,j,t} + a_6 \ln POP_{i,t} + a_7 POP_{j,t} + a_8 \ln LAND_{i,t} + a_9 \ln LAND_{j,t} + a_{10} CONT_{i,j,t} + a_{11} LANG_{i,j,t} + a_{12} COL_{i,j,t} + e_{i,j,t} \tag{35}$$

with $PERM_{i,j,t} = \frac{perm_{i,t}}{perm_{j,t}}$ is the ratio of the permanent component of nominal exchange rate decomposed; while $TEMP_{i,j,t} = \frac{temp_{i,t}}{temp_{j,t}}$ is the ratio of the temporary component of nominal exchange rate decomposed.

In the gravity model we an add as many variables as we think are useful for your analysis, as for example fixed effects. By fixed effects for exporter we mean a dummy variable that is equal to 1 each time a particular exporter appears in the dataset, using the same approach for importers and years. In terms of the panel data literature, this approach can be seen as accounting for all sources of unobserved heterogeneity that are constant for a given exporter across all importers, and constant for a given importers across all exporters. Additionally, this method can be understood as providing for all inputs of unobserved heterogeneity that are constant for a given exporter throughout all importers.

## 5.4 EMPIRICAL ANALYSIS

In this part, we will describe the data set that was used, as well as the results that were produced. I test the hypothesis that variations in the volume of trade are caused by the impacts of fluctuations in exchange rates. In order to accomplish this goal, many distinct models of exchange rate decomposition are evaluated, and a mechanism known as the Behavioural Equilibrium Exchange Rate has been implemented.

### 5.4.1 *Dataset Description*

*Decomposition Analysis*

Monthly effective real exchange rates taken from Bank for International Settlement database comprising 11 economies beginning from January 1994 are used to study the trade movements. For the purpose of this research the broad version has been chosen, that, on one side has less years of observation, but on the other owns more variable comprising all the EU countries. The BIS uses a deflator based on consumer price indices compared to a panel of 42 countries in order to construct the particular REER for the macroeconomic imbalance method (double export weights are used to calculate REERs, reflecting not only competition in the home markets of the various competitors, but also competition in export market elsewhere).

REER is published on a consistent basis by both the World Bank and the Bank for International Settlement. The Bank for International Settlement's monthly effective real exchange rates (REER) are used in this calculation. BIS provides Real Effective Exchange Rate, which reflects weighted average of bilateral real exchange rates with trading partners CPI based with the coverage of 61 countries for the broad index and 27 countries for the narrow index. The broad index covers 61 countries, while the narrow index covers 27 countries. My primary emphasis is on the ten most liquid currencies, which are the US Dollar (USD), the British Pound (GBP), the Japanese Yen (JPY), the Australian Dollar (AUD), the Canadian Dollar (CAD), the Norwegian Krone (NOK), and the Swedish Krona (SEK). We obtain panel dataset consisting of 892 observations, covering the years 1994 to 2006. The real effective exchange rate (REER) is the weighted average of a country's currency against an index of other currencies that is adjusted for inflation and trade weighted. In order to calculate the trade weight, a comparison of a country's trade deficit in relation to its primary trading partners is performed. This comparison is carried out between each of the currencies that are part of the index. The adjustment for inflation is determined by analysing the degree to which one currency's buying power differs from that of other currencies.

In addition to this, we utilise the spot exchange rate in comparison to USD. Note that an ECB currency technique has been used to calculate the Euro before to 1999. This approach followed the currency conversion rates that are shown in the Table 14.

In order to put the BEER analysis into practise, a few macroeconomic factors are selected. These variables are ones that, in addition to explaining economic intuition, are expected to have an impact on the exchange rate. The first macroeconomic variable that was used for this study and because of the frequency of the data was the interest rate that was consisting of 10-years government bonds in comparison to those of the United States. This variable was employed to grasp the impact of monetary policy discrepancy among countries. A currency with higher interest rates will tend to gain over the medium term as a result of the "carry trade effect" and the violation of the UIP theory. This is because high-interest-rate currencies attract foreign capital inflows, which will exert upward pressure on the currency.

Another macroeconomic variable that is useful for the purpose of this research is the consumer price index (CPI): a large increase in general prices is typically followed by a currency depreciation, as a higher CPI in a particular country will lead to capital outflow. This is because international investors will look for countries with higher real interest rates in countries where the CPI is relatively lower. Because of this, a growing spread ought to have an effect, both statistically and economically, on an exchange rate.

The terms of trade is the last variable that is utilised in the economic valuation of the decomposition procedures. This variable represents the development of the price of a country's exports and imports over time. This term could be interpreted as meaning that a nation that possesses a wealth of natural resources may be able to entice investors and experience a currency appreciation, but that nation may, in the long term, lose competitiveness as a result of a strong currency and might be pressured to devalue its currency in order to lend to important ways of pricing inflation and deflation in assets. If the REER were to go up, this would point to a significant gain in the value of the domestic currency.

*International Trade Analysis*

The following data, which cover the period from 1994 to 2006 and are employed in the empirical study, are used in order to analyse the link between international commerce and exchange rate.

- a series of permanent and temporary component of exchange rate obtained by decomposing REER with a Christiano-Fitzgerald filter for G10 currencies;
- bilateral exports from country i to country j: measures the total exports from country i to country j in current period USD. The variable is converted into real terms by export price indices[10];
- gross Domestic Product of country i and country j at purchaser's prices in millions of dollars[11];
- distance, between the country i and country j, calculated following the great circle formula, which uses latitude and longitude of a country's most important city (in terms of population) or its official capital in nautical miles[12];
- population of country i and j: total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship - except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. The values shown are midyear estimates[13];
- a dummy variable that takes the value 1 if exporter i and importer j are contiguous and 0 otherwise[14];

10 source: Direction of Trade Statistics IMF
11 source: World Development Indicators, WDI
12 source: Mayer and Zignago (2011) dataset
13 source: World Development Indicators, World Bank - WDI
14 source:Mayer and Zignago (2011) dataset

- a dummy variable that takes the value of 1 if i and j share a common official language and 0 otherwise[15];
- a dummy variable that is equal to 1 if the country pairs have the same currency and 0 otherwise.

### 5.4.2 *Results*

Results from the preliminary analysis, statistics, and robustness check are reported here, along with those from the decomposition analysis and the beer and gravity model. While we do discover a strong connection across trend filters, we find that correlations between exchange rates and cycle components are consistently modest in all the filters. However, the results of the preliminary analysis are insufficient to state categorically whether or not a filter has a connection to the fundamentals. The detrending of the currency exchange rate employs four distinct filters. We analyse the data using a BEER analysis to determine the nature of this relationship. With the help of the Gravity Model, we examine the relationship between currency fluctuations and international trade. To achieve this, we introduce a new variable (the permanent and temporary exchange rate) into the Gravity model and conduct a panel data analysis to determine the relevance of the long-term and short-term components. This investigation reveals that the long-term factor significantly affects international trade.

*Econometric Evaluation*

The cointegrating information in the data is used to decompose the observed actual exchange rate into two factors. The first component shows the equilibrium exchange rate (the fundamentals are at their equilibrium level) and the second component represents the departures from this equilibrium.

Figure 8 displays a comparison between the components arising from the filters that were employed and the genuine exchange rate for G10 countries during 1994-2016. The chart shows how the economic cycle component looks like when examined with the selected filters. The Butterworth and Hodrick-Prescott filters display more stable fluctuations, whereas the CF and BK filters display more volatile fluctuations that are more in line with the true REER. In contrast, the reliability of the component estimate is not shown in this investigation. A periodogram is helpful since it displays the spectral density function seen in figures Figure 12 to Figure 15 in the Appendix for all of the G10 currencies, broken down by filter type as follows: Baxter-King Filter (BK), Butterworth (BW), Christiano-Fitzgerald Filter (CF), and Hodrick-Prescott Filter (HP). Burn and Mitchell (1946) established typical values for the business-cycles component, and they

15 source: Mayer and Zignago (2011) dataset

are added to the graph as vertical lines at the natural frequencies. If the filter successfully filtered out all of the random cycles that were associated with the unwanted frequencies, the resulting periodogram would have a horizontal line with a minimum value of -6 outside of the range that was indicated by the vertical lines.

The filter's inability to selectively pass only stochastic cycles with frequencies within the predetermined band is shown by the fact that the periodogram takes values bigger than 6 outside of the permitted range. Graph analysis suggests that only the Christiano-Fitzgerald filters and the Baxter-King filter are useful. It's not unexpected that the CF filter, a variant of the BK filter, would provide similar findings to the BK filter, suggesting that the two filters are roughly equivalent. Also, for your convenience, we've included a Table 15 that displays our findings about the relationships between various filters. As was to be predicted, the data show a strong association between the REERs and the permanent component but no correlation at all with the temporary component.

Although several model-based approaches are used to dissect the real exchange rate, it remains unclear which decomposed series is best suited to examine the impact of the exchange rate on the real economy. This motivated an empirical test using a reduced form model [16]

*Unit Root and Cointegration Test*

Before continuing with more analysis it is imperative that I determine whether or not the variables are stationary by subjecting each variable to several iterations of an Augmented Dickey-Fuller (ADF) unit root test. Because the countries that make up the G10 may have certain characteristics, the findings may be influenced by cross-sectional correlations in real exchange rate. Because of this possibility, the results shown in Table 16 do not include the cross-sectional averages. In favour of the alternative hypothesis of the Fisher test, which states that certain panels are stationary, all of the tests provide a strong rejection of the null hypothesis, which states that the panels contain unit roots. However, if we do the tests on the first differenced series, we may reject the null hypothesis of a unit root. This is because doing so makes it impossible to reject the null hypothesis of a unit root for the majority of the instances (with strong levels of significance). As a result, our first step is to reach the conclusion that the variables are not stationary and integrated of order 1 (also known as I(1)), with the majority of the variables being integrated of order 0. Therefore, since non-stationarity is present, our OLS-FE regression ( Equation 29) will only produce consistent results if the non-stationary variables that are included are co-integrated. The purpose of this exercise is to de-

16 Clark and MacDonald (1998)

termine whether or not there is a linear combination between the following combinations:

$$e_{i,t} - (a_1 ToT_{i,t} + a_2 IR_{i,t} + a_3 inf_{i,t}) \tag{36}$$

is stationary (i.e. I(1)). When a time series is non-stationary, the cointegration test is used to establish whether or not the variables in the series have a stable connection over the long run. Pedroni was the one who invented the cointegration test (1995, 1999). With the null hypothesis that there is no cointegration, the panel cointegration test is simply a test of unit root in the estimated residuals of the panel. This test combines the statistics that were calculated for each nation in the panel, producing a test with high power.

On Table 16 are reported the results obtained from a cointegration test; the dataset here used is an I(1) series that wander over time, and a test of cointegration presents evidence that there is (or is not) a long run connection between these series even if they tend to deviate temporary to each other. All the tests are based of the following panel-data model for I(1) dependent variable $y_{it}$, where $i = 1, ..., N$ denotes the panel and $t = 1, ..., T_i$ denotes time:

$$y_{i,t} = x_{i,t}^{'}\beta_i + z_{i,t}^{'}\gamma_i + e_{i,t} \tag{37}$$

for each panel $i$, each of the covariates in $x_{it}$ is at least I(1) series. The test requires that the covariates are not cointegrated among themselves. $\beta_i$ is the cointegrating vector which may vary across panels, $\gamma_i$ is a vector of coefficients on $z_{it}$, the deterministic terms that control for panel-specific effects and linear time trends.

Pedroni's test has a null hypothesis that $y_{it}$ and $x_{it}$ are not cointegrated by testing that $e_t$ is nonstationary. Rejection of the null hypothesis implies that $e_{ij}$ is stationary and that the series $y_{it}$ and $x_{it}$ are cointegrated. The alternative hypothesis is that all the variables are cointegrated in all the panels.

The test statistics indicate that the null hypothesis that there is no cointegration for the Christiano-Fitzgerald, Butterworth, and Hodrick-Prescott filters is not true. Instead, they support the alternative hypothesis that the decomposed exchange rates, the interest rate differential, the terms of trades differential, and the inflation rate differential are all cointegrated in all of the panels. Cointegration indicates that the series move together in long-run equilibrium (although a group can wander arbitrarily). To adjust for serial correlation, each of the three statistics used a Barlett kernel with lags ranging from 0 to 3, depending on the variable. These lags were determined by Newey-West methods. The ADF (Augmented Dickey-Fuller) test, on the other hand, used a regression with only one additional lag in each of the cases.

The findings imply that the series of trend components produced by Butterworth, Hodrick-Prescott, and Christiano-Fitzgerald filters decomposition are cointegrated in the long run with the fundamentals; however, we only discover cointegration for Butterworth and Hodrick-Prescott for the cycle components. On the other hand, there isn't a particularly strong cointegration between these basics and other decomposing series of permanent components that make use of alternative approaches. It would be helpful to do more research in terms of cointegration, and we will construct an acceptable VEC model (Vector Error Correction Model). Because many economic time series seem to be 'first difference stationary,' with their levels displaying unit root or non-stationary behaviour, these models are utilised. VECM is used to prevent false regression, which is another reason why these models are used. When a shock occurs in the progression of a variable, the VEC model is used to define the rate at which the variable is able to change so that it may return to the equilibrium state. When two (or more) variables that are in no way connected to one another display significant coefficients when run together, this statistical phenomenon is known as spurious regression. The approach developed by Johansen is used in this context as a test for cointegration. The findings categorically refute the null hypothesis that none of the currencies are cointegrated, and they show that in the vast majority of instances, there are two cointegrating relationships. The VECM roots matrix is shown in Figure 9, which was created to assess the stability of the predicted VECm. The fact that none of the roots are equal to one demonstrates that the model is reliable. We also perform a test for serial correlation in the residuals using a Lagrange multiplier, and the results indicate that we are unable to reject the hypothesis that the residuals are normally distributed. In addition, it appears that there is no presence of most skewness and kurtosis in the errors. This conclusion is based on the fact that we found no evidence of serial correlation in the residuals.

We estimate the model in Equation 29 by using an OLS, and the results are reported on Table 18 (with the standard errors in parentheses). Based on these results, we are able to deduce that only the decomposed series resulting from the use of the Christiano-Fitzgerald filter presents a long-run relationship with all of the fundamentals. Therefore, at this point in time I am inclined to come to the conclusion that the CF filter need to be used in order to carry out an economically significant breakdown of exchange rate into permanent and transitory components.

The number of non-stationary components will always be less than the total number of series if there is a cointegrated connection between the variables. Because of this, we are now able to deduce the PEER by using the decomposed time series.

*International Trades Analysis*

It is feasible to validate the notion that there is a clear positive strong link between trade and GDPs by examining the correlations among the variables presented in Table 19. This data lends credence to the widespread perception that larger nations often engage in a greater volume of commerce. On the other hand, we discover a robust inverse association between trade and distance, which lends credence to the idea that nation pairings that are geographically more away tend to engage in less commerce. A graphical representation of the same data is shown in Figure 7, which illustrates findings based on the explanatory variable of the combined economic mass of nations exporting and importing goods. The scatter plot demonstrates a positive association between the two variables, which is consistent with the findings of the study; however, the plot presented in figure 5 demonstrates a negative relation between trade and distance, which is consistent with the theory. Both figures present their results using the same methodology that was used for Figure 7. Even in this specific instance, the visual data backs up the fundamental gravitational understanding that the greater the distance between nation pairings, the lower the volume of commerce that occurs between them. Bigger nations trade more, while greater remote countries trade less. Correlations between transactions, GDPs, distance, and REERs are also provided in panel C of Table 19, which may be found further down the page. Based on the findings I have, I anticipate discovering a positive value of REER when I do an exercise using a gravity model. The gravity model is estimated using OLS conduct using the robust option, which gives standard errors that are robust to arbitrary patterns of heteroskedasticity in the data. In this way, it is possible to fix violations of the homoskedasticity OLS assumption. After checking the relationship between variables using correlations and scatter plot analysis, the model is estimated using OLS conduct using the robust option.

Table 20 contains the findings that were obtained by OLS estimation on the basic gravity model. Other factors, such as population, contiguity, common language, common currency, and RTA are included as variables in the model, as described in the paragraph that accompanied the dataset. There is evidence from the literature on gravity that each of these elements may explain a major influence on trade flows. The findings of an OLS with the estimate limited to European Union nations

If we add actual exchange rates as an independent variable in the study, the model fits the data much better, with an $R^2$ of 0.89 (the global average is approximately 0.67). This indicates that the exchange rate is a significant component that helps influence international flows. The fact that the F-test is highly statistically significant and rejects the hypothesis that all of the coefficients are jointly zero at the 1% level is another another signal that the model is working well.

Now, let's take a closer look at the calculated coefficients as well as the values that correlate to them. Taking the GDP terms into consideration first, we find that both importer and exporter GDP have a positive association with trade (as was to be expected): a one percent increase in importer or exported GDP tends to increase trade by about 0.55 and 0.60 respectively, and this effect is statistically significant (P value less than 0.01) Because GDP coefficients in the research on trade are typically quite near to one, I decided to do an experiment to see whether this is, in fact, the case. The results provide strong evidence against the equality null hypothesis; specifically, the p-value of the F-statistic is less than $0.01, which indicates that the hypothesis may be rejected with a probability of one hundred percent. The same method may also be used to test the compound hypothesis that historical and cultural connection do not important for trades. This hypothesis states that the coefficient on all such variables is jointly equal to zero. This hypothesis can be examined by using the same method. The null hypothesis may be rejected with high confidence, just as it was in the earlier test, since the P-value associated with the F-test is less than $0.01, which indicates that the null hypothesis can be rejected with confidence at the 10% level. As a consequence of these data, we have come to the conclusion that historical connections and cultural ties are essential factors that determine commerce. On the other hand, the coefficient on distance is negative and statistically significant at the level of one percent, which indicates that a rise in the distance of one percent is followed by a reduction in trade of around sixty-eight percent. The following variables all have coefficients that have a positive sign, and they all reach the threshold of statistical significance required to be considered significant. The use of a common language is a promising indicator, since its presence will lead to a rise in the volume of commerce between the two countries.

Another important category of variables is that which is denoted by policy variables; these variables can play a significant part in international flows, and they can also be incorporated into the calculation of the gravity model's parameters; an illustration of this type of analysis is provided by the Regional Trade Agreements. The World Trade Organization (WTO) describes RTAs as "regional trade agreements" that are made between two or more nations. Free trade agreements and customs unions are included in this category. This variable was included in the analysis so that we could use it as a measure of the restrictiveness of policies. These measures, which include measures of exporter and importer policies, give us an idea of the degree to which restrictiveness matters as a factor in determining the pattern of trades.

The impact of economies of scale may be somewhat approximated by looking at population numbers. A nation that has a big population may more readily specialise in a broad variety of goods and, as a consequence, may be less reliant on international commerce, which may result in a negative coefficient for the economy. Alternately, a favourable influence on export may transpire as a consequence of the variable in the event that demand-related elements predominate. In the case of the G10 nations, population, regardless of whether it is positive or substantial, has a very little effect in international commerce.

In Table 21, column 2, you'll find the results for the gravity model combined with the exchange rate, which support all of the earlier findings. The presence of exchange rates on the regression is statistically significant and positive, which means that a depreciation of the currency of nation I will boost its own exports, which will be around $1.41 in this particular instance.

The REER impact on trade is positive and significant at the level of 1%, which suggests that the bigger the export volume is in relation to trading partners, the weaker the currency of the exporting nation is. On average, an increase in export volume of 1.41 percent is caused by a depreciation of an export's real effective exchange rate (REER) by one percent. When the lagging version of the exchange rate is taken into account, the influence of this factor on the expansion of exports is rendered meaningless and its magnitude is reduced so drastically that it becomes even negative. This would imply that the effect of currency depreciation is stronger in the same year but decreases over the course of time. In light of the extended time span, 1994–2006, it is fascinating to examine the various time slots and periods individually (the long time period considered all together could obscure some features). The findings of the gravity model for the time periods 1994-1998, 1999-2002, and 2003-2006 are reported in Table 22, which may be seen below. The findings back up the conclusions drawn from the more comprehensive study. must take note of the lack of a single currency in column 1, which is caused by the fact that the G10 nations did not adopt a common currency (the Euro) until 1999. The primary purpose of this study is to investigate whether or not there is a correlation between two-way commerce and either the permanent or the temporary component of the exchange rate. The findings are summarised in the table below. Utilising the panel data methodology of fixed effects estimate is one method that may be used in the process of consistently estimating the theoretical gravity model. In order to account for fixed effects, an importer/exporter dummy has been included in the analysis. This dummy is assigned to the value 1 if a certain exporter is present in the dataset (exp=1). Because of this, there is one dummy for the United Kingdom acting as an exporter, another for the United States of America, etc., and the same for the importer dummy, describing a whole set of importers' fixed effects. This method can be interpreted, in terms of the panel data literature, as accounting for all sources of unobserved heterogeneity that are constant for a given exporter across all importers and constant for a given importer across all exporters. Additionally, this method accounts for all sources of unobserved heterogeneity that are constant for a given exporter across all importers. The results of the OLS estimate of the gravity model with country fixed effects are shown in Table 24. When the results obtained with the gravity model with fixed effects are compared, it is possible to notice that the model's explanatory power is greater once the fixed effects are included. This confirms all of the earlier findings concerning the role that REER and decomposed REER play in international trade. This shift is not significant due to the fact that a huge number of new factors have been included in the model; nonetheless, it does show the important role played by variables such as multilateral resistance in the process of explaining observed on findings.

The time-varying importer and exporter fixed effects are accounted for in the expanded form of the gravity model, which is the reason why the findings derived from this version of the model are deemed to be more reliable. The REER impacts are positive and significant at the $1 level for the examination of the period 1994–2006; this suggests that the weaker the currency of a country's exports, the lower the volume of those exports for that country. A depreciation of the exporter's REER of one percent results in a decline in export volume of around two and a half percent in the same year on average. According to exchange rate fixed effect estimators, there is less significance, which indicates that the impacts of exchange rates on commerce vary across nations but do not vary over time.

### 5.4.3 *Economic Interpretation*

To do a panel data analysis, we extract the permanent and temporary components and add them to the Gravity Model as a new variable. No temporary component is found to have a significant impact on exports across all of the models included in this analysis. Since the cyclical component of the exchange rate is the transient component of the exchange rate, and since they reflect transitory changes in the exchange rate, the impact of these movements on the real economy (that is, the flow of international trade) will be minimal. This means that trade contracts will not reflect any fluctuations in the actual exchange rate that occur over very short periods of time. Since these changes are short-lived and have no long-term impact on price levels, they will not influence how businesses and consumers react to movements in the exchange rate. There would be consequences for the general price level and the decisions taken by both consumers and producers if the change in the exchange rate was followed by a comparable change in the trend.

On the other hand, we find that the real exchange rate's permanent component has a significant, considerable, and robust positive relationship with bilateral exports. Inconclusive results have been found in studies examining the correlation between commerce and currency rates. Further, the proper link between these variables may be determined if speculative fluctuations in the actual exchange rate are ruled out. Thus, a shift in the real exchange rate will impact trade volume in a manner determined by the cause of the movement in the real exchange rate. To further establish the validity of the results, we replicate them using a second group of countries, this time the European Union. The temporary element is negligible even under these conditions, whereas the permanent one is strong and crucial. This conclusion adds weight to the argument that the trend real exchange rate component has a stronger relationship to bilateral flow than the cycle components do to trade. A negative effect of trend components on trade suggests that the influence of exchange rates on trade differs between countries. This is so even though the EU and G10 groups of nations are not identical; they each comprise countries with unique features.

## 5.5 CONCLUSIONS

In spite of the vast amount of research that has been carried out on the subject of the relationship between exchange rates and international trade, the findings have not been conclusive, and the nature of the connection between these two factors is still unclear, with no discernible trend. This is because there is no clear pattern that can be seen in the relationship between these two factors.

This chapter's objective is to provide a contribution to the growing body of research that acknowledges the role that currency exchange rates play, even if just a minor one, in influencing the flow of money across international boundaries. The results of an investigation into the relevance of the influence of exchange rates using a gravity model with a range of parameters have shown that the conclusions are unfavourable. According to the findings provided in this chapter, an increase in the value of a country's exports will be followed by a decline in the rate of that country's currency. These findings are supported by the intuitive idea that a reduction in imports will occur because of the impact of price elasticity on demand. Additionally, it is essential to be aware that, despite the fact that the gravity model is a helpful place to start researching international business, it is not immune to criticism. This is especially true when complex hypotheses are tested, fixed effects are taken into consideration, and endogeneity is incorporated into the analysis. When country-fixed effects are addressed, there is no significant difference in the findings that are obtained; when GDPs are considered as a possible endogenous variable, the results show that if there is any bias caused by the endogeneity, this isn't quite as severe in the dataset as one would anticipate it to be; alternatively, there is no significant difference in the results produced when country-fixed effects are not considered. Even when the model is improved, the original intuition continues to be accurate. It is possible to draw the conclusion that endogeneity is not a significant problem with the GDPs in this dataset; even after the model is improved, the initial intuition continues to be accurate. These results are supported even more by the fact that the endogeneity test does not reject the null hypothesis that the GDPs of the two countries are in fact exogenous to the model.

*Summary of Findings*

Decomposed exchange rates have garnered a great deal of attention and thought. Extra research is being carried out using both permanent and temporary exchange rates with the purpose of finding the specific function that each plays in the flow of trades. Using the panel cointegration method, the results of the different decompositions are compared, and it is decided that the Christiano-Fitzgerald filter method should be used to split changes in the exchange rate into two parts that are important from an economic point of view.

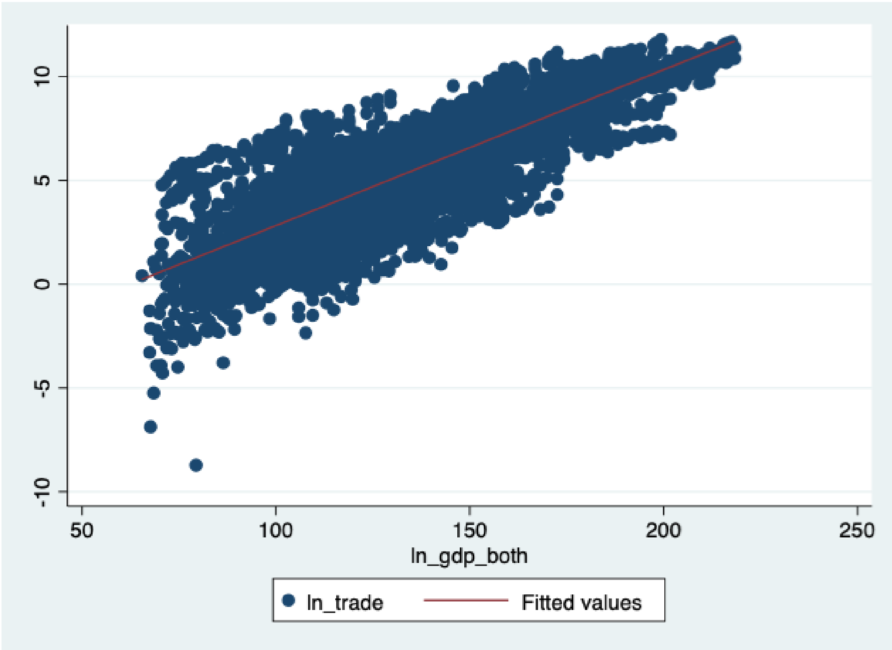
The breaking down of fluctuations in currency rates into two distinct categories: the first category, which is called permanent, comprises movements that are caused by fundamental factors. The second of these components is called temporary, and it comprises movements that are attributable to speculative shifts and reflect shocks that are unobservable. Because it takes into account the fact that the trend component is tied to the fundamentals that can be seen but the cyclical component is tied to the shocks that cannot be observed, this decomposition provides useful information on the exchange rate and its relationship to the fundamentals. For this, we are able to determine the economic logic that lies behind various econometric approaches, finding that the Christiano-Fitzgerald filter is the only econometric model that fulfils our ex ante economic assumption that the trend component reflects observable fundamentals.

Moving on to the relationship between currency rates and trades, the findings support the idea that the differences are caused by wrong measurements of the exchange rate. This is because they show that changes in the exchange rate have different effects on the trade balance depending on where the changes come from. The results point to the inaccurate assessment of the actual exchange rate as the underlying cause of the conflicting findings in the link between trade and currency rates. The proper link between these variables may be determined if speculative fluctuations and unobservable shock-driven effects are removed. Therefore, whether or not a variation in the real exchange rate reflects a shift in trend or is only a transient fluctuation impacts the effect on trade volume. For the reason that any of these outcomes is possible after a movement in the actual exchange rate. This discovery is especially significant because, via deconstruction, I am able to account for the ambiguous results of prior studies that attempted to explain the relationship between exchange rates and trade. Further, for the goal of producing a policy recommendation in the case of a movement in the currency, it is vital to find the explanation behind these movements in order to assess whether or not this shift in the monetary system would have an impact on the volume of trade. Next, we repeat the methodology with a different set of observations and discover that, despite the fact that the permanent component of the exchange rate is still highly significant, the effect of the exchange rate on trade in the case of European nations is the opposite of what was anticipated; thereby, a decline in the temporary component of the exchange rate results in a reduction in bilateral trade. These results indicate that contradictory conclusions may be drawn from the research literature, suggesting that a third or more variables must influence the function that exchange rates play in international commerce.

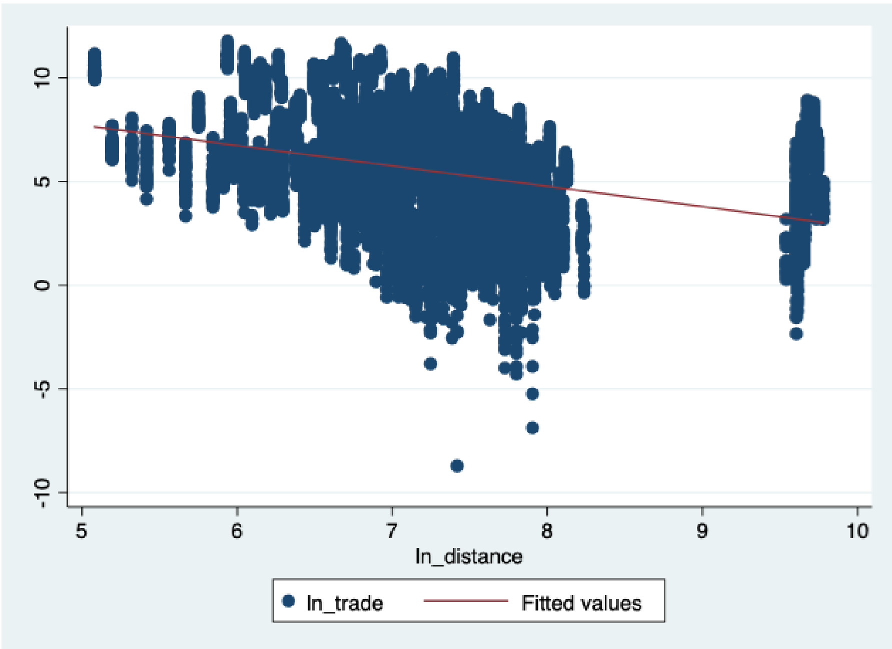
*Summarising* In conclusion, this chapter sets out to increase the volume of literature that points to the exchange rate as a crucial factor in international trade. Studying the role of the exchange rate's permanent component is a primary goal of this investigation. Using deconstructed exchange rates, we are able to address the issue of inconclusive findings. We achieve this by claiming that the failure of the prior study was due to a misunderstanding of how to measure the actual exchange rate and by adding that the speculative component does not need to be included in order to determine the true nature of the connection between the two variables. The issue of ambiguous findings is therefore resolved. Furthermore, we determine that the direction of the link between the exchange rate and trade varies depending on the set of players that is considered, isolating the origin of the issue of the contradicting results. There are, however, a few questions that still need exploring. To start, the research conducted here could be extended to include a wider and more complex group of countries to validate (or refute) the hypothesis that the impact of a change in the real exchange rate on the volume of trade is conditional on the factors that cause changes in the real exchange rate. Because the data is so widely available, it would be fascinating to expand this study to a more granular dataset in order to examine the responses of certain sectors to long-term shifts in the value of the currency. Finally, assuming there is no ideal decomposition technique since the choice of the filter is fully dependent on the kind of data that we use, it would be interesting to define a single "optimal" filter that is able to decompose economically into permanent and temporary components of a time series represented in this case by the exchange rate and to validate if the frequency of the dataset affects the choice of filter.

## 5.6 figures and tables

Figure 7: Distance and GDP



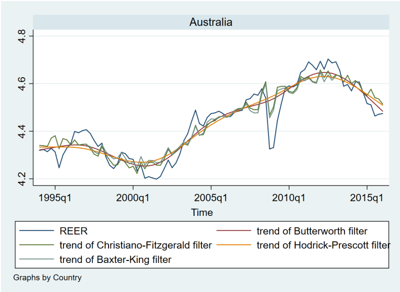

(a) Scatter plot and line of best fit for trade versus combined GDPs for EU countries



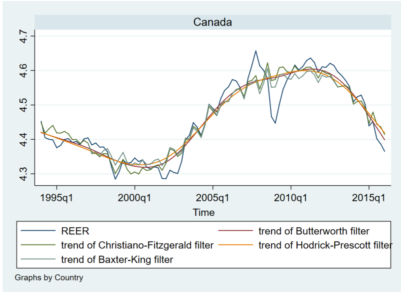

(b) Scatter plot and line of best fit for trade versus distance for EU countries

This figures shows the relationship between GDP and trade for EU countries in panel (a). In panel (b) the plot shows the the fit for trade and distance for EU countries.

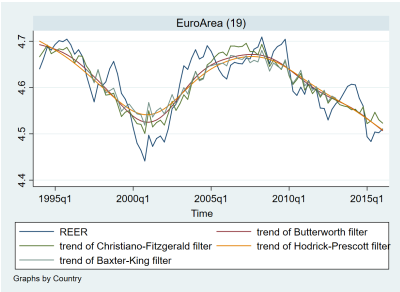
Figure 8: Filters Comparison



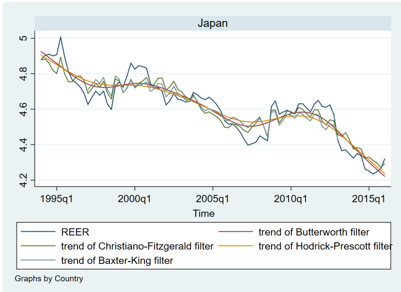

(a) Australia



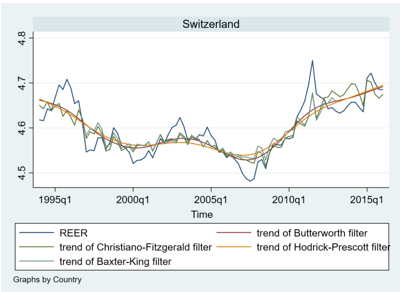

(b) Canada



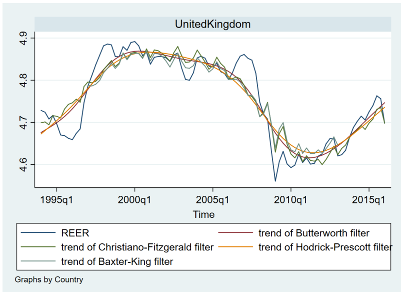

(c) Euro Zone



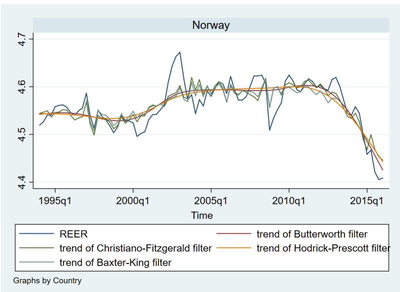

(d) Japan



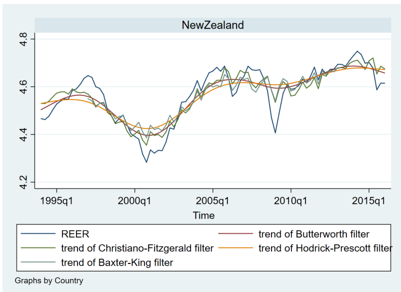

(e) Switzeland



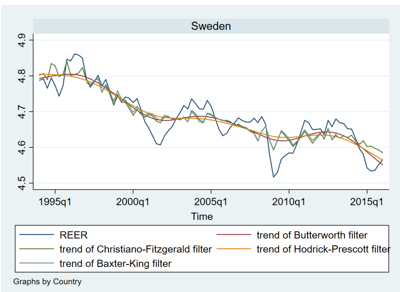

(f) United Kingdom



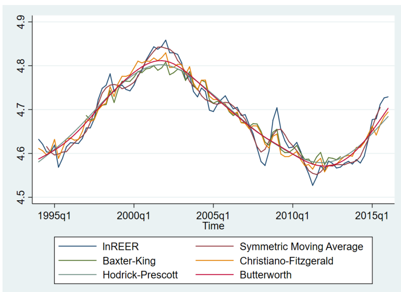

(g) Norway




(h) New Zeland




(i) Sweden

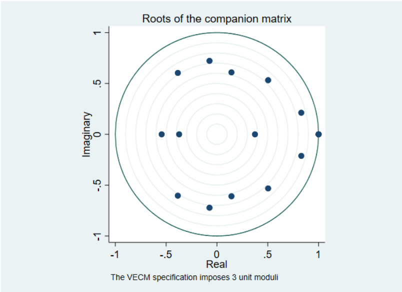



(j) United States

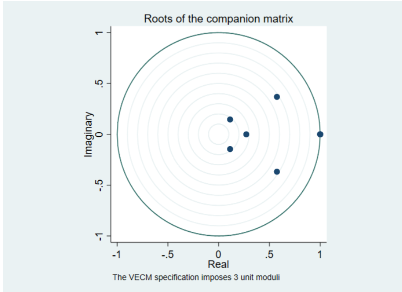


These graphs display a comparison between the components arising from the filters that were employed and the genuine exchange rate for G10 countries during 1994-2016.

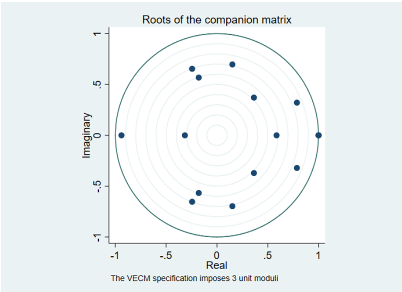
Figure 9: Vector Error Correction Mode



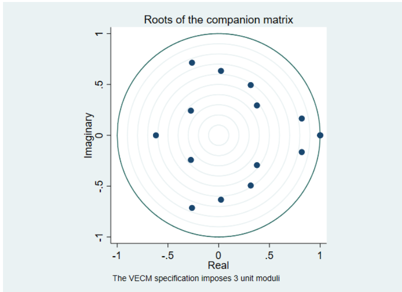

(a) Australia



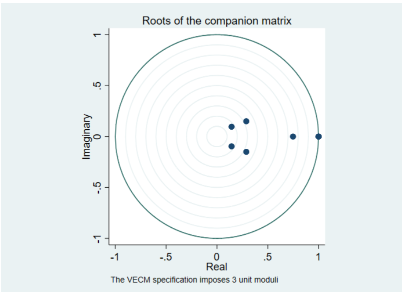

(b) Canada



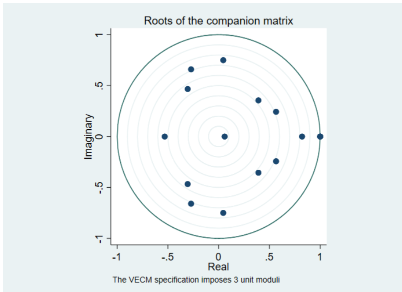

(c) Australia



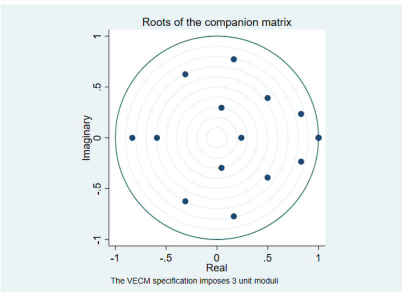

(d) Canada



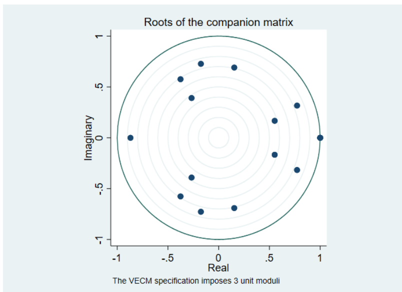

(e) New Zeland



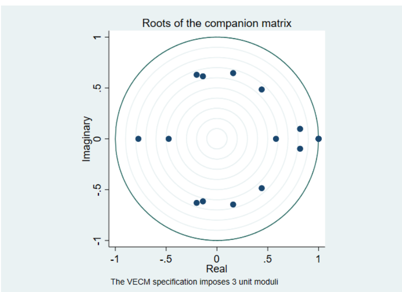

(f) Norway



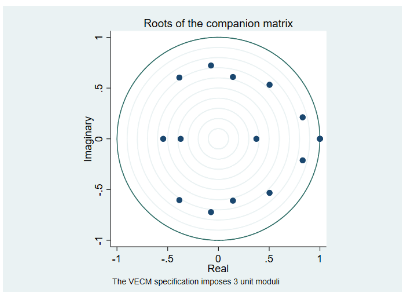

(g) Sweden




(h) Switzerland




(i) United Kingdom




(j) United States

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The figures show the VECM roots matrix, which was created to assess the stability of the predicted VECm. A Lagrange multiplier is performed to test for serial correlation in the residuals.

Table 14: Euro Conversion Rates

| **Currency** | **Weight** (%) | **Units of national currency for 1€** |
|---|---|---|
| Deutsche Mark | 34.66 | 1.95583 |
| French Franc | 17.83 | 6.55957 |
| Italian Lira | 14.34 | 1936.27 |
| Dutch Guilder | 9.19 | 2.20371 |
| Belgium Franc | 8.01 | 40.3399 |
| Spanish Peseta | 4.95 | 166.386 |
| Irish Punt | 3.75 | 0.787564 |
| Finnish Mark | 3.27 | 5.94573 |
| Austrian Shilling | 2.91 | 13.7603 |
| Portuguese Escudo | 1.08 | 200.482 |

The table shows the Euro conversion rates for units of national currencies for 1 Euro as calculated by European Central Bank (ECB). Source: ECB

Table 15: Cross Correlation Matrix

| cycle | REER | BW | HP | CF | BK |
|---|---|---|---|---|---|
| REER | 1.000 | | | | |
| BW | 0.406 | 1.000 | | | |
| HP | 0.439 | 0.987 | 1.000 | | |
| CF | 0.339 | 0.894 | 0.890 | 1.000 | |
| BK | 0.454 | 0.910 | 0.934 | 0.948 | 1.000 |
| trend | REER | BW | HP | CF | BK |
| REER | 1.000 | | | | |
| BW | 0.952 | 1.000 | | | |
| HP | 0.937 | 0.997 | 1.000 | | |
| CF | 0.956 | 0.990 | 0.986 | 1.000 | |
| BK | 0.950 | 0.990 | 0.990 | 0.995 | 1.000 |

This table shows the correlations between the permanent (or cycle) or and temporary (or trend) components of REER using different filters. Filters tested are Butterworth, Hodrick-Prescott, Christiano-Fitzgerald and Baxter-King. The sample spans the period November 2001 – November 2007

Table 16: Pedroni's Panel Cointegration Test

| | Cycle Component | | | |
|---|---|---|---|---|
| | BW | CF | HP | BK |
| Group ρ | -4.505*** | 2.187* | -2.926*** | 1.138 |
| Group t PP | -4.918*** | 1.635 | -3.484*** | 0.716 |
| Group t ADF | -4.287*** | -5.411*** | -2.712*** | -2.305 ** |
| | Trend Component | | | |
| Group ρ | 3.372*** | 0.104** | 3.2457*** | -1.043 |
| Group t PP | 4.753*** | -0.310** | 4.5449*** | -2.063* |
| Group t ADF | 6.230*** | -0.706** | 5.6122*** | -2.422* |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows the panel cointegration statistics result to test the relationship between the fundamentals in the economy and the exchange rate components that are decomposed by six different methods. On the table are reported Modified Phillips-Perron, Phillips-Perron and Augmented Dickey-Fuller t results.

Table 17: Kao's Panel Cointegration Test and Westerlund Cointegration Test

| | Cycle Component | | | | | |
|---|---|---|---|---|---|---|
| | BW | CF | HP | TR | BK | HM |
| DF ρ* | -24.072*** | -9.078*** | -16.634*** | -6.322*** | -10.765*** | -3.970*** |
| DF t* | -8.738*** | -6.306*** | -6.668*** | -2.490** | -4.237*** | -1.504 |
| ADF | -9.841*** | -15.119*** | -8.310*** | -15.217*** | -9.811*** | -7.483*** |
| DF ρ | -23.918*** | -6.494*** | -16.455*** | -2.854** | -7.113*** | -0.909 |
| DF t | -8.731*** | -6.106*** | -6.653*** | -1.775* | -3.848*** | -0.476 |
| Variance ratio | -2.690*** | -2.346** | -2.655*** | -2.534** | -2.719*** | -1.927* |
| | Trend Component | | | | | |
| DF ρ* | -1.343 | -8.411*** | -2.664* | -3.625*** | -2.916*** | -10.155*** |
| DF t* | -0.606 | -6.206*** | -1.184 | -2.348* | -0.843*** | -6.930*** |
| ADF | -2.101 | -14.286*** | -2.167 | -0.638 | -0.919*** | -6.757*** |
| DF ρ | 1.036 | -6.449*** | 0.307 | -8.823*** | -2.916*** | -10.155*** |
| DF t | 0.863 | -6.007*** | 0.081 | -4.003*** | -0.843*** | -6.930*** |
| Variance ratio | -0.344 | -2.386** | 0.010 | -0.481 | -0.9604 | -1.5342 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows the panel cointegration statistics result to test the relationship between the fundamentals in the economy and the exchange rate components that are decomposed by six different methods. On the table are reported the Modified Dickey-Fuller, the Dickey-Fuller, the Augmented Dickey-Fuller, the Unadjusted modified Dickey-Fuller and the Unadjusted Dickey-Fuller test results. Also, the variance ratio results are reported results from Westernlund test

Table 18: BEER results table

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\ln(e)$ | REER | $BW_{cycle}$ | $CF_{cycle}$ | $HP_{cycle}$ | $BK_{cycle}$ | $BW_{trend}$ | $CF_{trend}$ | $HP_{trend}$ | $BK_{trend}$ |
| IR Diff | 4.271*** | 0.842* | 0.300 | 0.0569 | 0.362 | 0.446 | 0.542 | 0.786** | 0.480 | -0.00828 |
| | (0.541) | (0.364) | (0.191) | (0.190) | (0.217) | (0.308) | (0.279) | (0.294) | (0.259) | (0.374) |
| Infl Diff | -1.058*** | 0.313*** | -0.00796 | 0.0185 | -0.0117 | -0.0973** | 0.321*** | 0.295*** | 0.325*** | 0.198*** |
| | (0.0604) | (0.0407) | (0.0213) | (0.0213) | (0.0243) | (0.0364) | (0.0312) | (0.0328) | (0.0290) | (0.0443) |
| ToT Diff | 0.613*** | 0.439*** | 0.0218* | 0.0243* | 0.0283* | 0.0360** | 0.418*** | 0.415*** | 0.411*** | 0.392*** |
| | (0.0292) | (0.0197) | (0.0103) | (0.0103) | (0.0117) | (0.0136) | (0.0151) | (0.0159) | (0.0140) | (0.0165) |
| Constant | -0.165*** | 4.578*** | 0.00306 | 0.00539 | 0.00428 | 0.00590 | 4.575*** | 4.572*** | 4.573*** | 4.561*** |
| | (0.0169) | (0.0113) | (0.00594) | (0.00593) | (0.00677) | (0.00783) | (0.00869) | (0.00914) | (0.00808) | (0.00952) |
| Obsevations | 797 | 797 | 797 | 797 | 797 | 585 | 797 | 797 | 797 | 585 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows results from Equation 29 $REER_{i,t} = \alpha_i + \beta_1 ToT_{i,t} + \beta_2 IR_{i,t} + \beta_3 inf_{i,t} + \epsilon_{i,t}$ using an OLS and standard error in parentheses. Results exchange rate decomposed into cycle and trend using the decomposition methods discuss througout the thesis.

Table 19: Correlations - Gravity Model

Panel A - World

| | trade | distance | $GDP_i$ | $GDP_j$ |
|---|---|---|---|---|
| trade | 1.000 | | | |
| distance | -0.192 | 1.000 | | |
| $GDP_i$ | 0.391 | 0.072 | 1.000 | |
| $GDP_j$ | 0.475 | 0.117 | -0.118 | 1.000 |

Panel B - EU countries

| | | | | |
|---|---|---|---|---|
| trade | 1.000 | | | |
| distance | -0.334 | 1.000 | | |
| $GDP_i$ | 0.542 | 0.058 | 1.000 | |
| $GDP_j$ | 0.641 | 0.058 | -0.009 | 1.000 |

Panel C - G10 countries

| | | | | |
|---|---|---|---|---|
| trade | 1.000 | | | |
| distance | -0.326 | 1.000 | | |
| $GDP_i$ | 0.373 | 0.358 | 1.000 | |
| $GDP_j$ | 0.388 | 0.358 | -0.078 | 1.000 |

The table shows correlations between trade and distance and GDPs for world (Panel A), Europe Union Countries (Panel B) and G10 countries (Panel C).

Table 20: OLS

| | ols | ols DUM |
|---|---|---|
| (Intercept) | 4.56* | |
| | (0.01) | |
| IRDiff | 0.27 | −0.01 |
| | (0.37) | (0.37) |
| InflDiff | 0.63* | 0.20* |
| | (0.06) | (0.04) |
| ToTDiff | 0.02* | 0.39* |
| | (0.01) | (0.02) |
| factor(countries)1 | | 4.56* |
| | | (0.01) |
| factor(countries)2 | | 4.45* |
| | | (0.01) |
| factor(countries)3 | | 4.57* |
| | | (0.01) |
| factor(countries)4 | | 4.47* |
| | | (0.01) |
| factor(countries)5 | | 3.59* |
| | | (0.04) |
| factor(countries)6 | | 4.53* |
| | | (0.01) |
| factor(countries)7 | | 4.61* |
| | | (0.01) |
| factor(countries)8 | | 4.51* |
| | | (0.01) |
| factor(countries)9 | | 4.76* |
| | | (0.01) |
| N | 797 | 585 |
| $R^2$ | 0.15 | 1.00 |
| adj. $R^2$ | 0.15 | 1.00 |
| Resid. sd | 0.13 | 0.05 |

Standard errors in parentheses

* $p < 0.05$

This table shows findings obtained running a gravity model as explain in Equation 34 estimated using OLS conduct using the option, which gives standard errors that are robust to arbitrary patter of heteroskedasticity OLS assumption.

Table 21: Pooled OLS

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | trade | trade | trade | trade |
| distance | -0.680*** | -0.680*** | -0.683*** | -0.681*** |
| | (-20.60) | (-20.75) | (-20.67) | (-20.45) |
| GDPexp | 0.604*** | 0.593*** | 0.596*** | 0.597*** |
| | (27.30) | (26.83) | (26.78) | (26.57) |
| GDPimp | 0.547*** | 0.558*** | 0.555*** | 0.554*** |
| | (24.73) | (25.24) | (24.98) | (24.67) |
| POPexp | 0.00405*** | 0.00403*** | 0.00398*** | 0.00400*** |
| | (12.32) | (12.34) | (12.13) | (12.08) |
| POPimp | 0.00525*** | 0.00528*** | 0.00530*** | 0.00535*** |
| | (15.98) | (16.17) | (16.20) | (16.17) |
| contiguity | 0.266*** | 0.266*** | 0.268*** | 0.268*** |
| | (5.99) | (6.04) | (6.03) | (5.95) |
| language | 0.136*** | 0.135*** | 0.132*** | 0.128*** |
| | (3.93) | (3.94) | (3.81) | (3.68) |
| currency | 0.356*** | 0.356*** | 0.351*** | 0.350*** |
| | (8.65) | (8.72) | (8.53) | (8.42) |
| RTA | 0.468*** | 0.468*** | 0.461*** | 0.469*** |
| | (6.45) | (6.49) | (6.33) | (6.39) |
| REER | | 1.406*** | 1.418*** | 1.479*** |
| | | (4.53) | (3.96) | (3.77) |
| L.REER | | | -0.106 | -0.0677 |
| | | | (-0.29) | (-0.18) |
| L2.REER | | | | -0.236 |
| | | | | (-0.63) |
| Constant | -2.500*** | -3.900*** | -3.785*** | -3.666*** |
| | (-5.14) | (-6.80) | (-6.36) | (-6.01) |
| Observations | 1429 | 1429 | 1417 | 1405 |
| R-squared | 0.890 | 0.892 | 0.892 | 0.891 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results from a pooled OLS are shown in this table, and exchange rates are included into the equation in column 2. Since exchange rates are statistically significant and have a positive effect on the regression, a decline in the value of the nation i's currency would increase that country's exports. When the lagged version of the exchange rate is taken into consideration (columns 3 and 4), this component's impact on the growth of exports turns meaningless and its size is diminished, turning it into a negative factor.

Table 22: Pooled OLS with different time specifications

| | (1) 1995 – 1998 | (2) 1999 – 2002 | (3) 2003 – 2006 |
|---|---|---|---|
| distance | -0.900*** | -0.889*** | -0.837*** |
| | (-36.38) | (-29.28) | (-25.93) |
| GDPexp | 0.632*** | 0.628*** | 0.578*** |
| | (15.76) | (13.17) | (11.26) |
| GDPimp | 0.594*** | 0.603*** | 0.575*** |
| | (14.84) | (12.65) | (11.21) |
| POPexp | 0.00428*** | 0.00364*** | 0.00361*** |
| | (7.10) | (5.11) | (5.09) |
| POPimp | 0.00474*** | 0.00510*** | 0.00514*** |
| | (7.87) | (7.14) | (7.24) |
| contiguity | 0.250** | 0.136 | 0.247* |
| | (3.29) | (1.44) | (2.45) |
| language | 0.0673 | 0.107 | 0.0922 |
| | (1.18) | (1.57) | (1.26) |
| currency | 0 | 0.330*** | 0.422*** |
| | (.) | (4.31) | (5.07) |
| REER | 1.695** | 1.870** | 1.742 |
| | (3.22) | (3.23) | (1.92) |
| Constant | -3.225*** | -3.493** | -2.831* |
| | (-3.50) | (-3.28) | (-2.10) |
| Observations | 439 | 330 | 330 |
| R-squared | 0.911 | 0.901 | 0.884 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows results from The table summarises the results of the gravity model for the years 1994 through 1998, 1999 through 2002, and 2003 through 2006. The results support the conclusions reached in the more thorough investigation. Observe that there isn't a single currency in column 1 since the G10 countries didn't adopt a single currency (the Euro) until 1999.

Table 23: OLS with decomposed REER using CF filter

| | (1) trade | (2) trade |
|---|---|---|
| distance | -0.680*** | -0.678*** |
| | (-20.75) | (-20.74) |
| GDPexp | 0.593*** | 0.592*** |
| | (26.83) | (26.88) |
| GDPimp | 0.558*** | 0.555*** |
| | (25.24) | (25.20) |
| POPimp | 0.0053*** | 0.0053*** |
| | (16.17) | (16.22) |
| POPexp | 0.0040*** | 0.0040*** |
| | (12.34) | (12.40) |
| contiguity | 0.266*** | 0.273*** |
| | (6.04) | (6.20) |
| language | 0.135*** | 0.133*** |
| | (3.94) | (3.88) |
| currency | 0.356*** | 0.360*** |
| | (8.72) | (8.83) |
| RTA | 0.468*** | 0.468*** |
| | (6.49) | (6.52) |
| REER | 1.406*** | |
| | (4.53) | |
| CFcycle | | 0.005 |
| | | (3.14) |
| CFtrend | | 1.444*** |
| | | (4.57) |
| Constant | -3.900*** | -3.913*** |
| | (-6.80) | (-6.80) |
| Observations | 1429 | 1429 |

*t* statistics in parentheses

Results shows results from an OLS where exchange rate are decomposed using Christiano - Fitzgerald method.

Table 24: Country Fixed Effects

| | (1) trade | (2) trade | (3) trade |
|---|---|---|---|
| distance | -0.643*** | -0.672*** | -0.670*** |
| | (-19.19) | (-20.00) | (-19.92) |
| GDPexp | 0.408*** | 0.328*** | 0.341*** |
| | (6.54) | (5.16) | (5.42) |
| GDPimp | 0.588*** | 0.616*** | 0.612*** |
| | (28.38) | (29.12) | (29.08) |
| POPimp | 0.00500*** | 0.00509*** | 0.00512*** |
| | (16.45) | (16.88) | (16.99) |
| POPexp | -0.00442 | -0.00518 | -0.00544 |
| | (-1.37) | (-1.62) | (-1.70) |
| contiguity | 0.223*** | 0.177*** | 0.183*** |
| | (5.22) | (4.12) | (4.24) |
| language | 0.259*** | 0.236*** | 0.231*** |
| | (7.75) | (7.09) | (6.92) |
| currency | 0.323*** | 0.305*** | 0.307*** |
| | (8.40) | (7.99) | (8.04) |
| RTA | 0.653*** | 0.669*** | 0.674*** |
| | (9.24) | (9.55) | (9.63) |
| CAN | 0.126 | 0.370*** | 0.369*** |
| | (1.44) | (3.77) | (3.75) |
| CHE | -0.515*** | -0.508*** | -0.509*** |
| | (-10.24) | (-10.20) | (-10.25) |
| DEU | 0.981*** | 1.169*** | 1.153*** |
| | (4.43) | (5.27) | (5.20) |
| FRA | 0.378* | 0.542*** | 0.527** |
| | (2.37) | (3.37) | (3.28) |
| GBR | 0.500** | 0.547*** | 0.531*** |
| | (3.16) | (3.49) | (3.39) |
| ITA | 0.347* | 0.515*** | 0.503** |
| | (2.28) | (3.34) | (3.27) |
| JPN | 1.729*** | 2.026*** | 2.013*** |
| | (4.95) | (5.79) | (5.74) |
| NLD | 0.121* | 0.147** | 0.140* |
| | (2.12) | (2.59) | (2.47) |
| SWE | -0.120* | -0.206*** | -0.216*** |
| | (-2.31) | (-3.82) | (-4.00) |
| USA | 2.775*** | 3.248*** | 3.268*** |
| | (3.42) | (4.01) | (4.03) |
| REER | | 2.198** | |
| | | (5.40) | |
| CFcycle | | | 0.004 |
| | | | (2.55) |
| CFtrend | | | 2.329** |
| | | | (5.44) |
| Constant | -0.745 | -2.075* | -2.337** |
| | (-0.92) | (-2.49) | (-2.75) |
| Observations | 1429 | 1429 | 1429 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In this table, the findings of the OLS estimate of the gravity model with country fixed effects are presented. Gravity model's explanatory power increases if the fixed effects are taken into account when the findings from the gravity model with fixed effects are compared. This supports every previous result about the function of REER and the decomposition of REER in international trade. Due to the large number of new components that have been incorporated into the model, this shift is not substantial, but it does highlight the crucial role that variables like multilateral resistance play in explaining the observed result.

Table 25: Robustness Check 1: Hodrick-Prescott filter

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | trade | trade | trade | trade |
| distance | -0.680*** | -0.678*** | -0.680*** | -0.681*** |
| | (-20.49) | (-20.46) | (-20.46) | (-20.48) |
| GDPexp | 0.593*** | 0.592*** | 0.593*** | 0.596*** |
| | (27.67) | (27.66) | (27.63) | (27.83) |
| GDPimp | 0.558*** | 0.555*** | 0.557*** | 0.555*** |
| | (24.69) | (24.68) | (24.66) | (24.59) |
| POPimp | 0.00528*** | 0.00528*** | 0.00531*** | 0.00533*** |
| | (17.08) | (17.27) | (17.17) | (17.20) |
| POPexp | 0.00403*** | 0.00404*** | 0.00403*** | 0.00399*** |
| | (11.06) | (11.09) | (11.04) | (10.94) |
| contiguity | 0.266*** | 0.273*** | 0.265*** | 0.266*** |
| | (6.56) | (6.73) | (6.54) | (6.55) |
| language | 0.135*** | 0.133*** | 0.135*** | 0.136*** |
| | (3.99) | (3.93) | (3.99) | (4.00) |
| currency | 0.356*** | 0.360*** | 0.357*** | 0.357*** |
| | (11.20) | (11.27) | (11.20) | (11.20) |
| RTA | 0.468*** | 0.468*** | 0.468*** | 0.466*** |
| | (6.28) | (6.31) | (6.28) | (6.25) |
| REER | 1.406*** | | | |
| | (4.02) | | | |
| CFcycle | | 0.005 | | |
| | | (3.14) | | |
| CFtrend | | 1.444*** | | |
| | | (4.57) | | |
| HPcycle | | | -0.000381 | |
| | | | (-0.71) | |
| HPtrend | | | 1.499*** | |
| | | | (4.08) | |
| HMLcycle | | | | -0.000571 |
| | | | | (-0.59) |
| HMLtrend | | | | 1.543*** |
| | | | | (4.09) |
| Constant | -3.900*** | -3.913*** | -3.974*** | -4.028*** |
| | (-6.24) | (-6.21) | (-6.24) | (-6.29) |
| Observations | 1429 | 1429 | 1429 | 1429 |

*t* statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

In this table, the findings of the OLS estimate of the gravity model with Hodrick-Prescott decomposition filter applied to exchange rates

Table 26: Robustness Check 2: Different countries EU

| | (1) | (2) | (3) |
|---|---|---|---|
| | trade | trade | trade |
| distance | -1.162[1] | -1.162[1] | -1.162[1] |
| | (-66.88) | (-67.05) | (-67.08) |
| GDPexp | 1.092[1] | 1.120[1] | 1.120[1] |
| | (88.90) | (89.27) | (89.68) |
| GDPimp | 0.836[1] | 0.809[1] | 0.807[1] |
| | (67.42) | (61.55) | (61.34) |
| POPimp | 0.000520 | 0.00112 | 0.00120 |
| | (0.71) | (1.53) | (1.63) |
| POPexp | -0.0101[1] | -0.0108[1] | -0.0108[1] |
| | (-14.49) | (-15.35) | (-15.35) |
| contiguity | 0.396[1] | 0.395[1] | 0.394[1] |
| | (9.64) | (9.70) | (9.68) |
| language | 0.686[1] | 0.686[1] | 0.685[1] |
| | (12.09) | (12.17) | (12.16) |
| currency | 0.146[1] | 0.146[1] | 0.144[1] |
| | (4.78) | (4.76) | (4.69) |
| RTA | -0.236[1] | -0.236[1] | -0.235[1] |
| | (-7.10) | (-7.15) | (-7.12) |
| REER | | -0.375[1] | |
| | | (-8.18) | |
| CFcycle | | | -0.000438 |
| | | | (-1.73) |
| CFtrend | | | -1.712[1] |
| | | | (-8.68) |
| Constant | -8.171[1] | -8.170[1] | -6.438[1] |
| | (-38.03) | (-38.12) | (-20.98) |
| Observations | 7622 | 7622 | 7622 |

*t* statistics in parentheses

[1] $p < 0.05$, [1] $p < 0.01$, [1] $p < 0.001$

In this table, the findings of the OLS estimate of the gravity model testing different EU countries.

# 6 CONCLUSIONS TO THE THESIS

This thesis should be intriguing to a variety of readers. The literature reviews and empirical analysis will be beneficial to the work of academic researchers and economists, both of whom will find it easier to navigate the existing body of literature as a result. Learn which predictors, models, and methodologies successfully estimate currency rates so you may share this information with practitioners and forecasters at private businesses and central banks. Our analysis of the present level of research ought to also be of interest to policymakers, for whom the viability of policy decisions relies significantly on accurate estimates. In conclusion, the fact that exchange rate forecasts are often discussed in the media lends credence to the notion that this research may have applications outside the realm of academia and policy spheres.

Policymakers and business decision-makers who are involved in international trade and finance have been confronted with challenges as a result of the global financial crisis, the economic turbulence in many developed nations, the rising barriers to international commerce, currency crises, Brexit, COVID-19, and most recently the conflict between Ukraine and Russia, which is leading to an energy crisis. Corporate managers, central bankers, academics, and students should all be interested in the complex interrelationships between trade policies, the activities of central banks, and changes in government spending and taxation on interest rates, prices, and exchange rates. These interrelationships all have an effect on economic activity. International economists use the same conventional tools and methods for the study of international commerce as they do for the study of domestic trade. This is due to the fact that individuals are motivated in the same ways and behave in the same ways when dealing globally as they do when transacting domestically. The study of international economics aims to give explanations for concerns like these that arise as a result of the economic exchanges that take place between different sovereign states.

Within the scope of this thesis, two areas of international economics are investigated: finance and trade. The foreign currency market and the process by which exchange rates are determined are the primary focuses of the first two chapters of the thesis. The risk that comes with dealing with variations in exchange rates is one that managers and other decision-makers in businesses need to be aware of and prepared to deal with. Exchange rates are a significant component of international economics and play a vital role in the field. The breakdown of the Bretton Woods system, coupled with the introduction of generally floating exchange rates, ushered in a new era that was characterised by increased volatility and uncertainty regarding currency exchange rates. This new era began when the Bretton Woods system was completely dismantled. As a result of this growing volatility, economists have been searching for economic models that are able to accurately capture the behaviour of observed exchange rates.

In order to properly influence the decision-making process for hedging, it is required to accurately predict projected future market movements; hence, a reliable technique of forecasting is essential. The alternative is to make choices based on information that is either insufficient, irrelevant, or misinterpreted in some way, which is incompatible with any fair hedging method. Attempts have been made to predict the future price of exchange rates using a method that is both relatively new and computationally intensive. In the next section, we will describe the elements that, when combined, make this work an outstanding contribution to the field. After introducing the basic concepts of international economics in Chapter 2, in Chapter 3 we make use of the microstructure approach and adopt a specific kind of dataset that is ideally suited for investigating the underlying economic foundations of the link between order flow and exchange rates, and we evaluate the performance of exchange rate models in forecasting future prices. After assessing the presence of non-linearity in order flow, we employ a machine learning technique as a method of forecasting, finding that machine learning combined with the microstructure approach gives better results than the benchmark random walk. We also find that the relationship between end-user order flows and future returns exhibits better performance when disaggregated data is used. In particular, we find that asset managers are the group that performs better because they have superior information content compared to other kinds of customer order flow.

As a result of the universality of foreign exchange liquidity, the availability of liquidity for a particular FX rate may have positive repercussions for other currencies. Central banks generally view this positively. The injection of liquidity by a central bank into its own currency might help alleviate liquidity constraints in other investment currencies and temper the fast appreciation (depreciation) of other financing (investment) currencies. In addition, the existing empirical data on liquidity spirals suggests that monetary actions intended to alleviate constraints in the financial market may also improve liquidity in the foreign currency market, which would be advantageous for all exchange rates. This is the conclusion due to the possible benefits of these actions for enhancing liquidity on the foreign exchange market. However, having too much cash on hand might be risky. The tendency for excess liquidity in one currency to move into other currencies, particularly those used in international transactions, is anticipated to continue. Sufficient liquidity in an environment that encourages risk-taking and carry trades may drive speculative trading.

In Chapter 4 we find that liquidity matters, and we demonstrate that shocks that influence the foreign exchange market as a whole, rather than specific FX rates, are the primary drivers of the liquidity of the foreign exchange market; we also find that more liquid currency exchange rates, such as EUR/USD, tend to have lower liquidity sensitivity relative to market-wide FX liquidity and vice versa. This study focuses on global FX liquidity risk, which significantly explains a portion of the cross-sectional volatility in FX excess returns. Our analysis demonstrates a cross-sectional relationship between projected returns and the sensitivity of returns to innovations. Those currency exchange rates that are substantially more sensitive to variations in liquidity typically have far higher expected returns. The liquidity measure exhibits a high degree of consistency across rates, supporting the assumption that liquidity is a variable with a fixed price. We find that the premium associated with retaining a currency will be higher the greater its sensitivity to changes in liquidity. Our findings are predicated on the idea that it is feasible to construct trading strategies that include the purchase of some currencies and the sale of others, utilising the liquidity of spot trading. These liquidity-based tactics are very similar to those that characterise the carry trade, with the primary distinction being that rather than depending on interest rates to identify which currencies to borrow and lend, these strategies evaluate the liquidity of spot trading. We use a data set that is ideally suited for analysing the economic foundations of the link between order flow and exchange rates. The order flow data has been segmented into many customer groups, each of which is likely to have distinct types of information saved in their profiles. We were able to present empirical data demonstrating that the liquidity risk premium for firms had dramatically increased. In fact, when we conduct the same study on the disaggregated portfolio type, we find that companies have the largest liquidity risk premium. The asset manager's negative response disproves the concept that liquidity risk is a factor in pricing on the foreign exchange market for this class of consumers.

The contribution of Chapter 5 to the current body of knowledge is a study of the relationship between the real exchange rate and the trade volume. This chapter expands the body of knowledge relating to the component of the study that hypothesises that a drop in the value of a nation's currency will result in an increase in that nation's exports. In addition, the objective of this chapter is to bridge the gap between trade and the correlation between misaligned exchange rates.

In order to accomplish this, the chapter explores the components of exchange rate fluctuations and states that the amount to which exchange rates affect trade balance is based on the origins of exchange rate variations. The empirical study investigates the relationship between fluctuations in trade volumes and shifts in real exchange rates, which are split into permanent and transitory components. Very little research studies the impact of decomposing the actual exchange rate on trade flows, whereas a great deal of research investigates the effect of exchange rate volatility on trade flows.

# Part III

# APPENDIX

# A MACHINE LEARNING TECHNIQUES

RNN family networks have a weighted feedback link between each layer of neurons. This makes them good for time series analysis because the model can take into account values of variables that are lagging behind. This makes RNN family networks excellent for time series analysis. Here are two methods used in this thesis.

## A.1 LONG SHORT-TERM MEMORY - LSTM

The concept of long-short-term memory was first proposed by Hochreiter and Schmidhuber, 1997, and its primary purpose was to overcome the problem of long-term dependence. The ability to remember information for an extended period of time is essentially its natural behaviour. LSTM contains cells that ignore the noisy information that might confuse prediction systems and only maintain the crucial information that can then be transmitted to the hidden layers. This allows LSTM to perform better than other prediction approaches.

Long-Short-Term Memories (LSTMs) are a unique category of Recurrent Neural networks (RNNs) that have the ability to learn long-term dependencies. The vanishing gradient issue is a phenomenon that occurs when regular RNNs multiply relatively tiny weights several times over the course of several time steps. This results in gradients that progressively decrease until they reach zero. Memory blocks, also known as cells, are primarily what make up an LSTM network. These cells are coupled to one another through layers. The information in the cells is controlled by mechanisms called gates, and it is stored in the cell state as well as the hidden state. Activation functions are required for this information to be accessed (sigmoid or tanh are examples of activation functions). Values from 0 to 1 are generated by the sigmoid function or layer, with 0 signifying "nothing gets through" and 1 meaning "everything gets through." As a result, it is capable of adding new information to the cell state or removing old information, depending on the context.

The LSTM-based architecture is shown in Figure 10. A long short-term memory network maps a certain inputs sequence $x = (x_1, \ldots, x_T)$ to an output sequence $y = (y_i, \ldots, y_T)$ iteratively for $t = 1, \ldots, T$. In general, the gates take in, as input, the hidden states from previous time step $h_{t-1}$ and the current input $x_t$, and multiply them pointwise by weight matrices, $W$, and a bias $b$ is added to the product.

This method may be broken down into three distinct stages, which are as follows:

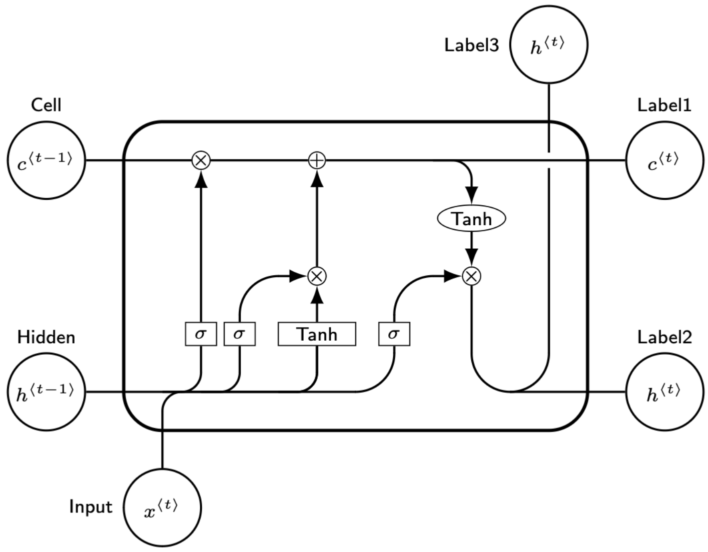



Figure 10: Long-Short Term Memory Diagram

1. in the Forget Gate the information that will be removed from the cell state is determined. The result is a value between 0 and 1, where 0 indicates "remove all" and 1 indicates "remember all" $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$;
2. in the Input Gate stage the Tanh activation layer will produce a vector of potential candidates as $C_t = tanh(W_c h_{t-1}[, x_t] + b_c$.

   The sigmoid layer generates an update filter in the following manner: $U_t = \sigma(W_u[h_{t-1}, x_t] + b_u$. Next, the old cell state $C_{t-1}$ is updated as $C_t = f_t * C_{t-1} + U_t * \hat{C}_t$.
3. during the stage of the Output Gate process, the sigmoid layer performs a filtering operation on the cell state that is going to output $O_t = \sigma(W_o[h_{t-1}, x_t] + b_o$. After that, the tanh function is used on the cell state $C_t$ in order to normalise the values to fall within the range $[-1, 1]$. In the end, in order to calculate the hidden $s_t$, the scaled cell state is multiplied by the filtered output to obtain the hidden state $h_t$ to be passed on to the next cell $h_t = O_t * tanh(C_t)$.

In order for LSTM to function properly, the data must be in a supervised learning setting. Specifically, work with a target variable Y and a predictor X. To do this, we create a k-step lagged dataset where the values at time$(t-k)$ serve as input and the value at time t serves as output.

## A.2 NON-LINEAR AUTOREGRESSIVE WITH EXOGENOUS INPUTS - NARX

The Non-Linear AutoRegressive with eXogenous Inputs neural network is a variation of the Recurrent Network that has been successfully exploited in time series prediction issues (Lin et al., 1996 Gao and Meng, 2005). It is comparable to an ARIMA model that contains exogenous components in the sense that it can estimate the present value of a time series based on the values that the series has experienced in the past in addition to the values that it has experienced in the past for a large number of other time series that are not endogenous. It conducts recursive multi-step predictions based on future exogenous inputs, and it works to train a model that can make predictions one step further in the future.

In a NARX network, the mathematical rules that govern the input output representation of nonlinear discrete time series are described by the following equation (we use the terminology of Liu et al., 2020):

$$\hat{y}_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-n_y}, \\ u_t, u_{t-1}, u_{t-2}, u_{t-3}, \dots, u_{t-n_u}) + \varepsilon_t \quad (38)$$

here $y_t$ and $\hat{y}_t$ are the desired and expected variables, respectively; $ut$ is the network's input variable; $n_u$ and $n_y$ are the corresponding time delays of the input and output variables, respectively; and $\varepsilon_t$ is the model error between the desired and predicted outcomes. According to the input variable $u_t$, the hidden layer output at time t is given by:

$$H_{it} = f_1[\sum_{r=0}^{n_u} w_{ir} u_{t-r} + \sum_{l=1}^{n_y} w_{il} y_{t-l} + a_i] \quad (39)$$

where $w_{ir}$ is the connection weight between the input neuron; $u_{t-r}$ and $i^{th}$ are hidden neuron; $w_{il}$ is the connection weight between the hidden neuron $i^{th}$ and output feedback neuron $y_{(t-l)}$; $a_i$ is the bias of the $i^{th}$ hidden neuron; and $f_1(\cdot)$ is the hidden layer activation function.

After summing all the predictions from the hidden layers, we get:

$$\hat{y}_t = f_2[\sum_{i=1}^{n_h} w_{ij} H_{i,t} + b_j] \quad (40)$$

where $w_{ji}$ is the connection weight between the hidden neuron $i^{th}$ and predicted $j^{th}$ output $n_h$; $b_j$ is the bias of the $j^{th}$ predicted output; $n_h$ is the number of hidden neurons; and $f_2(\cdot)$ is the output layer activation function.

When the subsequent value of the dependent output signal, $y(t)$, is regressed on both the prior values of the output signal as well as the previous values of an independent (exogenous) input signal.

NARX can takes copies from the output and input layers. Multiple levels of copies can be maintained such as time $t-1$, $t-2$, $t-3$ and so on. The general architecture of a NARX neural network is displayed in figure 11.

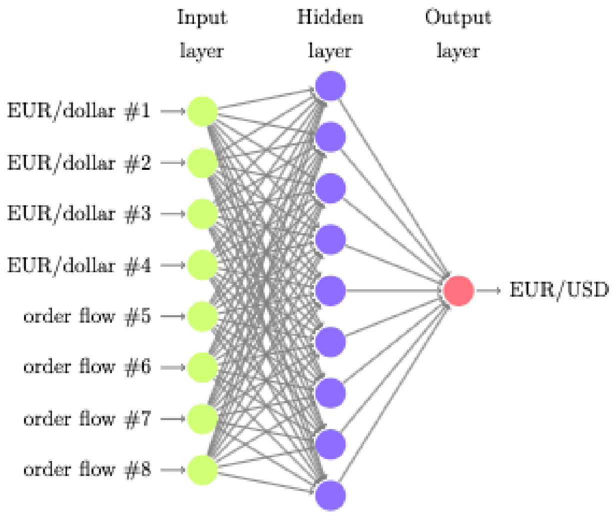



Figure 11: The architecture of the NARX network model

The NARX topology consists of 3 layers connected with each other:

- input layer $F_x$: the neural network receives its data in the input layer. For the purpose of this research inputs are the exogenous variables represented by order flows disaggregated by customer group.
- hidden layer $F_h$: is the place where the hidden correlations of the input and output data are captured. This allows the network to learn, adjust, and generalise from the data to the new input. As each input-output set is presented to the network, the internal mapping is recorded in the hidden layer.
- output layer $F_y$: after the training the network responds to the new input by producing an output that represents a forecast. During the training, the network collects the in-sample output values in the output layer.

The NARX network may be used in a wide variety of contexts. It is possible to utilise it as a predictor, which allows one to anticipate the subsequent value of the input signal. In nonlinear filtering, another use for this technique, the goal of which is to produce an output signal that is identical to the input but free of noise, it may also be utilised. The modelling of nonlinear dynamic systems is an additional significant application that demonstrates the usefulness of the NARX network.

# B
# DECOMPOSITION TECHNIQUES

Time series are often filtered in order to get rid of unfavourable attributes such as trends and seasonal components, or in order to assess components that are driven by stochastic cycle from a certain range of time. The time series filters separated a series called $y_t$ into its two components, which are as follows:

$$y_t = \tau_t + c_t \tag{41}$$

where $\tau_t$ is the trend component that it may be non-stationary and it may also contain a deterministic or a stochastic trend; and $c_t$ is the cyclical component, it is a stationary and it is driven by stochastic cycles within a specified range of periods.

In the frequency-domain method of analysing time series, both the time series ($yt$) and the auto covariance $gamma_i$ are determined at the frequencies $\omega \in [-\pi, \pi]$. Additionally, the spectral density function $fy(\omega)$ specifies the contribution of stochastic cycle at each frequency $omega$ relative to the variance of $y_t$, which is denote by $\sigma_y^2$. Both the variance and the auto-covariance may be represented by the following expressions:

$$\gamma_i = \int_{-\pi}^{+\pi} e^{i\omega j} fy(\omega) d\omega \tag{42}$$

where $i$ is the imaginary number $i = \sqrt{-1}$. Equation [42] implies that if $fy(\omega) = 0$ for $\omega \in [\omega_1, \omega_2]$, then the stochastic cycles at these frequencies contribute zero to the variance and autocovariance.

The primary objective of the filter is to change the original series into a new series denoted by $y_t^*$ in which the value of $fy_*(\omega)$ is set to zero for frequencies that are not desired and is set to the value of $fy(\omega)$ for frequencies that are desired (Wei 2006-282). It is possible to write the following into a filter for a time series:

$$y_t^* = \sum_{j=\infty}^{\infty} \alpha_j y_{t-j} = \alpha(L) y_t \tag{43}$$

where $y_t$ is an infinite long time series, $fy^*(\omega)$ is an espression able to underlie the impact of the filter on components of the time series at each frequency $\omega$:

$$fy^*(\omega) = |\alpha(e^{i\omega})|^2 fy(\omega) \tag{44}$$

where $\alpha_j$ are the weights of the filter and $|\alpha(e^i\omega)|$ is the gain of the filter. Additionally, $|\alpha(e^i\omega)|^2$ translates the original spectral density into the spectral density of the filtered series. The value $|\alpha(e^{i}\omega)|$ provides an interpretation of what the filter is doing, and we want the gain to be equal to zero for the frequencies that we do not want and equal to one for the frequencies that we do want. Based on this value, the filter will either pass or block the stochastic cycles that occur at the specified frequencies.

## B.1 SYMMETRIC MOVING AVERAGE

The Simmetric Moving Average (SMA) is the most fundamental and fundamentally sound way for estimating a cyclical component (the trend component can then be computed by the difference $\tau_t = y_t - c_t$), which allows for the trend component to be calculated (SMA). The time series $y_t$ that has the values $t \in [1, ..., T]$is transformed into the following:

$$y_t^* = \sum_{-q}^{+q} \alpha_j y_{t-j} \tag{45}$$

for each $t \in [q+1, ..., T-q]$ where $\alpha_{-j} = \alpha_j$ for $j \in [-q, ..., q]$ end $q$ is the order of the SMA filter. The series obtained will drop some observations and will have $T - 2q$ observations of the $T$ of the original series. The total of the weights in the SMA filter is zero, therefore both deterministic and stochastic trends are cancelled out[1].

## B.2 BAND-PASS FILTERS

Band-pass filters are able to pass frequencies within a given range while changing those outside of that range because of the addition of drift to a random walk process. They let random cycles of a certain frequency through while rejecting all others. In a band pass filter, only the frequencies between $[\omega 0, \omega 1]$ are let through, while all other frequencies are blocked. Some common instances of band-pass filters may be found in the works of Baxter and King (1999) and Christiano and Fitzgerald (2003), who designed a SMA filter with zero-sum coefficients. This kind of filters are designed to get as close as possible to the random-walk optimal filter under the assumption that it is a SMA filter with restrictions that sum to zero. This formula technically explains a random-walk process, where $y_t = y_{t-1} + \epsilon_t$ is a zero-mean stationary random variable due to the integrated structure of the process and the need for just a single differentiation to achieve stationary

1 Fuller (1996) and Baxter and King (1999)

behaviour. The results of combining a random walk method with drift are:

$$\tilde{y}_t = \mu + \tilde{y}_{t-1} + \epsilon_t \tag{46}$$

where $\epsilon_t$ a zero-mean stationary random variable.
Fuller (1996) and Baxter and King (1999) state that a SMA with zero-sum weights may eliminate both deterministic and stochastic trends of order 2 or less. This is due to the fact that the sum of the weights equals 0. Baxter and King (1999) devised a class of symmetric moving averages with coefficients that sum to zero and preserve the required cyclical component as closely as is technically practicable. These averages can be conceived of as keeping the cyclical component as closely as feasible. Since it is difficult to implement their ideal filter with the number of coefficients at their disposal, they devised a close approximation as an alternate. Using the following calculation, we can determine the cyclical component of the ideal band-pass filter of infinite order.

$$c_t = \sum_{-\infty}^{+\infty} b_j y_{t-j} \tag{47}$$

with $p_l$ and $p_h$ be the minimum and maximum period of the stochastic cycles of interest, and the weights $b_j$ in this calculation are given by:

$$b_j = \begin{cases} \pi^{-1}(\omega_h \omega_p), & \text{if } j = 0 \\ (j\pi)^{-1}\{\sin(j\omega h) - \sin(j\omega p)\}, & \text{if } j \neq 0 \end{cases} \tag{48}$$

where $\omega_p = 2\pi/p_p$ and $\omega_h = 2\pi/p_h$ are the lower and the higher cutoff frequencies respectively. An ideal band-pass filter for an infinite series would have a gain function of 1 for $\omega \in [\omega 0, \omega 1]$ and 0 for all other frequencies. This perfect band-pass filter happens to be a SMA filter with zero-sum coefficients.

They determine the coefficients of the ideal bank-pass filter to be those of a SMA filter with terms of $2q + 1$ that are as similar to those of the ideal filter as is achievable. The choice of q involves a trade-off: although bigger values of q bring the gain of the BK filter closer to the gain of the ideal filter, they also bring the number of missing observations in the filtered series up to a higher level.

Although the mathematics of the frequency-domain method for analysing time series is expressed in terms of stochastic cycles at frequencies $\omega \in [-\pi, \pi]$, actual work is often expressed in terms of periods p, where p is defined as $p = 2\pi/\omega$. The BK filter is a technique that is often used for research into business cycles among economists. Burns and Mitchell (1946) described business cycles as stochastic cycles in business data corresponding to duration between 1.5 and 8 years, scaled to the frequency of the dataset. Business cycles were scaled to the frequency of the dataset.

In spite of the fact that their technique was developed for non-stationary time series, they provide a version of the model that is stationary by just making a little adjustment to it. The imposition of the constraint that the filter coefficients should total to zero is what makes their approach relevant to non-stationary time series; removing this restriction results in a filter that can be used to stationary time series. In light of this, Baxter and King (1999) arrive to their estimation of $c_t$ via:

$$c_t = \sum_{j=-q}^{+q} \hat{b}_j y_{t-j} \tag{49}$$

where the coefficient $\hat{b}_j$ is equal to $\hat{b}_j = b_j - \bar{b}_q$, where $\hat{b}_{-j} = \hat{b}_j$ and $\bar{b}_q$ is the mean of the ideal coefficients truncated at $\pm q$:

$$\bar{b}_q = (2q+1)^{-1} \sum_{j=-q}^{q} b_j \tag{50}$$

if the time series is stationary, the BK filter sets the coefficients to the ideal coefficients, that is, $\hat{b}_j = b_j$. For these weights,$\hat{b}_j = \hat{b}_-j$, and although $\sum_{j=-\infty}^{\infty} \hat{b}_j \neq 0$.

Baxter and King (1999) reduced the error between the coefficients of their filter and the ideal band-pass filter, while Christiano and Fitzgerald (2003) minimised the mean squared error between the estimated component and the actual component, provided the raw series is a random-walk process. Christiano and Fitzgerald provide three important reasons for employing their filter: first the true dependence structure of the data affects which filter is optimal; also,many economic time series are well approximated by random-walk processes; and finally, their filter does a good job of passing through stochastic cycles of desired frequencies and blocking stochastic cycles from unwanted frequencies on a variety of processes that are close to being a random-walk process.

The ideal characteristics of the CF filter are obtained at the consequence of an extra variable that must be determined and a reduction in robustness. The best filter for a random walk is the CF filter. Their filter is asymmetric, and the coefficients do not add to zero. Using the asymmetric version of the CF filter, the formula for computing the value of the cyclical component $c_t$ for $t = 2, 3, ..., T-1$ may be expressed as follows:

$$c_t = b_0 y_t + \sum_{j=1}^{T-t-1} b_j y_{t+1} + \tilde{b}_{T-t} y_T + \sum_{j=1}^{T=2} b_j y_{t-j} + \tilde{b}_{t-1} y_1 \tag{51}$$

where $b_0, b_1 ...$ are the weights used by the ideal band-pass filter. $\tilde{b}_{T-t}$ and $\tilde{b}_{t-1}$ are linear functions of ideal weights used in this calculation.

The CF filter uses two different calculations for $\tilde{b}_t$ depending upon whether the series is assumed to be stationary or not.

For the nonstationary case with $1 < t < T$, Christiano and Fitzgerald (2003) set $\tilde{b}_{T-t}$ and $\tilde{b}_{t-1}$ to:

$$\tilde{b}_{T-t} = \frac{1}{2}b_0 + \sum_{j=1}^{T-t-1} b_j \qquad \tilde{b}_{T-1} = \frac{1}{2}b_0 + \sum_{j=1}^{T-2} b_j \tag{52}$$

which forces the weights to sum to zero. For the non-stationary case, when $t = 1$ on $t = T$, the two endpoints ($C_1$ and $C_T$) use only one modified weight, $\tilde{b}_{T-1}$:

$$c_1 = \frac{1}{2}b_0 y_1 + \sum_{j-1}^{T-2} b_j y_{T+1} + \tilde{b}_{T-1} y_T c_t = \frac{1}{2}b_0 y_T + \sum_{j-1}^{T-2} b_j y_{T-j} + \tilde{b}_{T-1} y_1 \tag{53}$$

The ideal qualities of the Cf filter are obtained at the expense of an extra parameter that must be determined and a reduction in robustness. The CF filter is best for random walk processes, but it is not symmetric, therefore it does not exclude second-order deterministic or integrated processes.

## B.3 HIGH-PASS FILTER

The high-pass filter blocks out frequencies and components that are below the cut-off frequency while allowing those that are above it to get through (lower than the cut-off frequency). The high-pass filters enable only the stochastic cycles that are at or above a certain frequency to get through, while they prevent the passage of stochastic cycles that have a lower frequency. For these filters, let the frequency $omega_0$ serve as the cut-off point, with the required frequencies falling exclusively between $omega_0$ and $\omega \geqslant \omega_0$.

In the literature, the Hodrick and Prescott (1997) filter is the one that is most often employed by macroeconomists to extract a stochastic trend that travels smoothly over time and is uncorrelated with the cycle. This filter is quite popular. The purpose of this filter is to generate a smoothed-curve representation of a time series, one that is more sensitive to long-term than to short-term variations. This representation will be obtained by applying the filter.

By making the further assumption that the sum of squares of the second difference of $x_t$ is relatively small, the assumption is made that the trend is continuous.

The trend estimate, in its initial form, is the outcome of an optimization problem that involves minimising ($y_t = \tau_t + c_t$) the distance between the trend and the original series while also minimising the curvature of the trend series:

$$\min_{\tau_t} \sum_{t=0}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} (T_{t+1} - 2\tau_t + \pi_{t-1})^2 \tag{54}$$

where T is the total number of samples and $\lambda$ is the parameter that adjusts for the amount of variation in the trend. When the value of $\lambda$ is increased, the penalty that is incurred for excessive swings in the secular component also rises, which results in a smoother trajectory for $x_t$. We begin by taking the initial $y_t$ series and decomposing it into two parts: the trend component, which we will refer to as $\tau_t$, and the cyclical component, which we will refer to as $c_t$. We do this in such a way that we minimise the gap between the trend and the original series while also minimising the curvature of the trend series. The value of the parameter known as lambda will determine how the two objectives will be prioritised. There is a solution to the optimisation issue, and that answer may be expressed by a linear transformation that is not reliant on y t.

According to Hodrick and Prescott, the filter is equipped with a trend-removal strategy that may be used on data that are generated by a diverse range of processes. This technique can be used to data. According to their interpretation, the method identified a pattern in the data, and the data were filtered by excluding the identified trend in the data. The parameter $\lambda$ determines how smoothly the trend moves, and the trend gets smoother as $\lambda \to \infty$ moves closer to infinity. The authors suggested that a value of 1600 be used for lambda while dealing with quarterly data. Based on a heuristic argument that specified values for the variance of the cyclical component and the variance of the second difference of the trend component, both of which were recorded at quarterly frequency, Hodrick-Prescott proposed that the smoothing parameter $\lambda$ should be set to 1600. This recommendation was based on the results of the study. According to the research on filters, the characteristics of the filter should be determined based on the cut off frequency (Pollock 2000, 324). This technique determines the filter parameters in such a way as to make the gain of the filter equal to 1/2 at the frequency at which it cuts off the signal. In order to use this approach to pick $\lambda$ at the cut-off frequency of 32 periods, you will need to solve the following equation: "begin-equation."

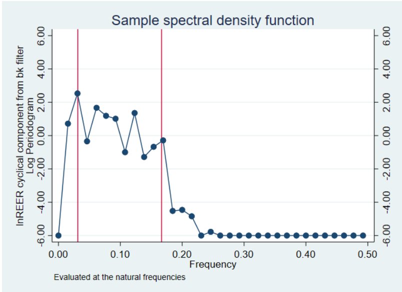
$$1/2 = \frac{4\lambda\{1 - \cos(2\pi(32))\}^2}{1 + 4\lambda\{1 - \cos(2\pi(32))\}^2} \tag{55}$$

Which results in the value of $\lambda \simeq 677.13$, which was used in the exercise. King and Rebelo (1993) demonstrated that eliminating a trend that was predicted using an HP filter is functionally identical to applying a high-pass filter. They demonstrated that this high-pass filter would render integrated processes of order 4 or lower stationary and determined the gain function of the filter. If the time series does not have a stationary pattern, then the HP filter may be an option.

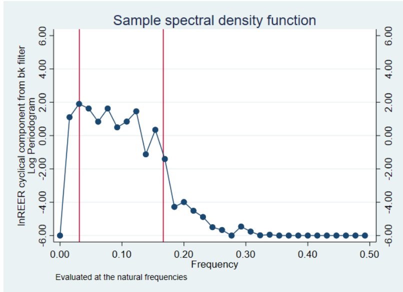
Because Butterworth filters are "maximally flat," they have been widely employed for a significant amount of time by engineers[2]. The gain functions of these filters are as near as they can go to being a flat line with a value of 0 for the undesirable periods and a value of 1 for the preferred times. Butterworth filters may be generated from certain axioms that identify features that we would want a filter to have. Although Butterworth and Baxter-King filters are similar in that they both have the qualities of symmetry and phase neutrality, the coefficients of Butterworth filters do not have to add up to zero in order for the filter to be considered valid. Pollock (2000) demonstrates that Butterworth filters have detrending features that are dependent on the parameters of the filter, despite the fact that the BK filter depends on the detrending properties of SMA filters with coefficients that total to zero. The high-pass Butterworth filter is implemented by ts-filter bw by the use of the computational approach that was developed by Pollock (2000). The cutoff period and the order of the filter, which is designated by the letter m, are the two parameters that are used with this filter. The cutoff period determines where the gain function will begin to filter out high-period (low-frequency) stochastic cycles, and the value of m determines the slope of the gain function for a certain cutoff period. The slope of the gain function at the cutoff point grows with the magnitude of the parameter m for any given cutoff period. The slope of the gain function at the cutoff period rises as the cutoff period becomes longer for a fixed value of the parameter m. Because of the instability in the calculation, we are unable to acquire a vertical slope at the cutoff frequency, which is the ideal. The cutoff time determines the value of m beyond which the calculation may no longer be trusted. According to Pollock (2000) the high-pass Butterworth filter is superior than the HP filter when it comes to predicting the cyclical components because of the increased flexibility that is created by the additional parameter. He demonstrates that the high-pass Butterworth filter is able to estimate the required components of the difference in order of a $d^{th}$ integrated process provided that $m \geqslant d$ is maintained.

2 Butterworth (1930)

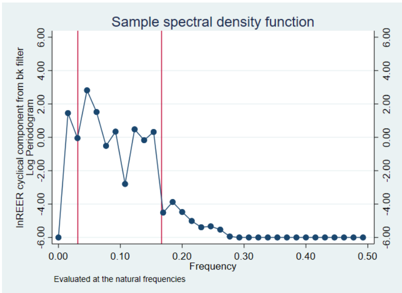
Figure 12: Baxter-King Filter Periodogram



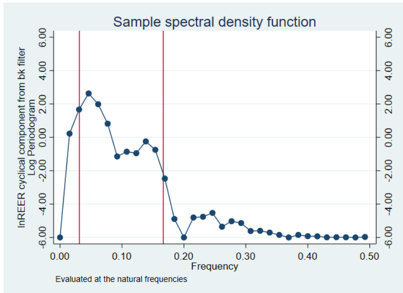

(a) Australia



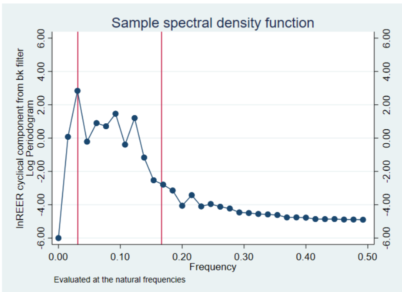

(b) Canada



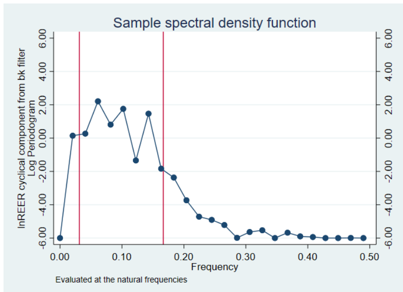

(c) Euro Zone



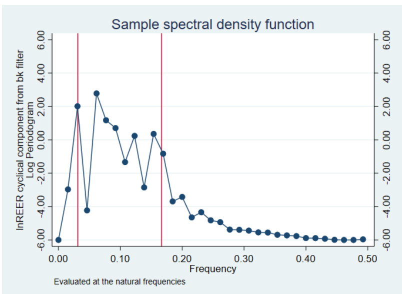

(d) Japan



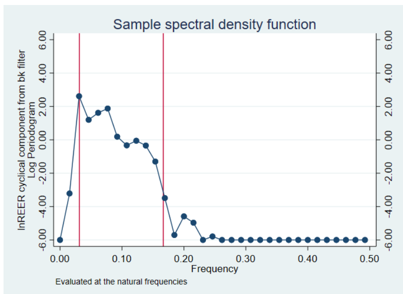

(e) New Zeland



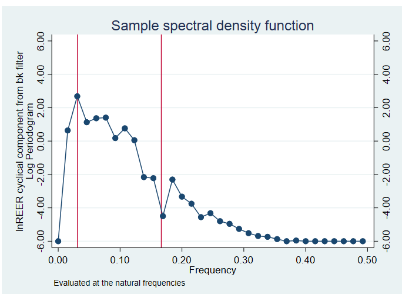

(f) Norway



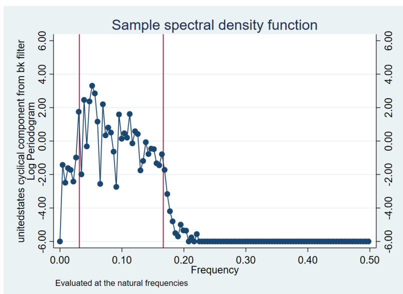

(g) Sweden




(h) Switzerland




(i) United Kingdom

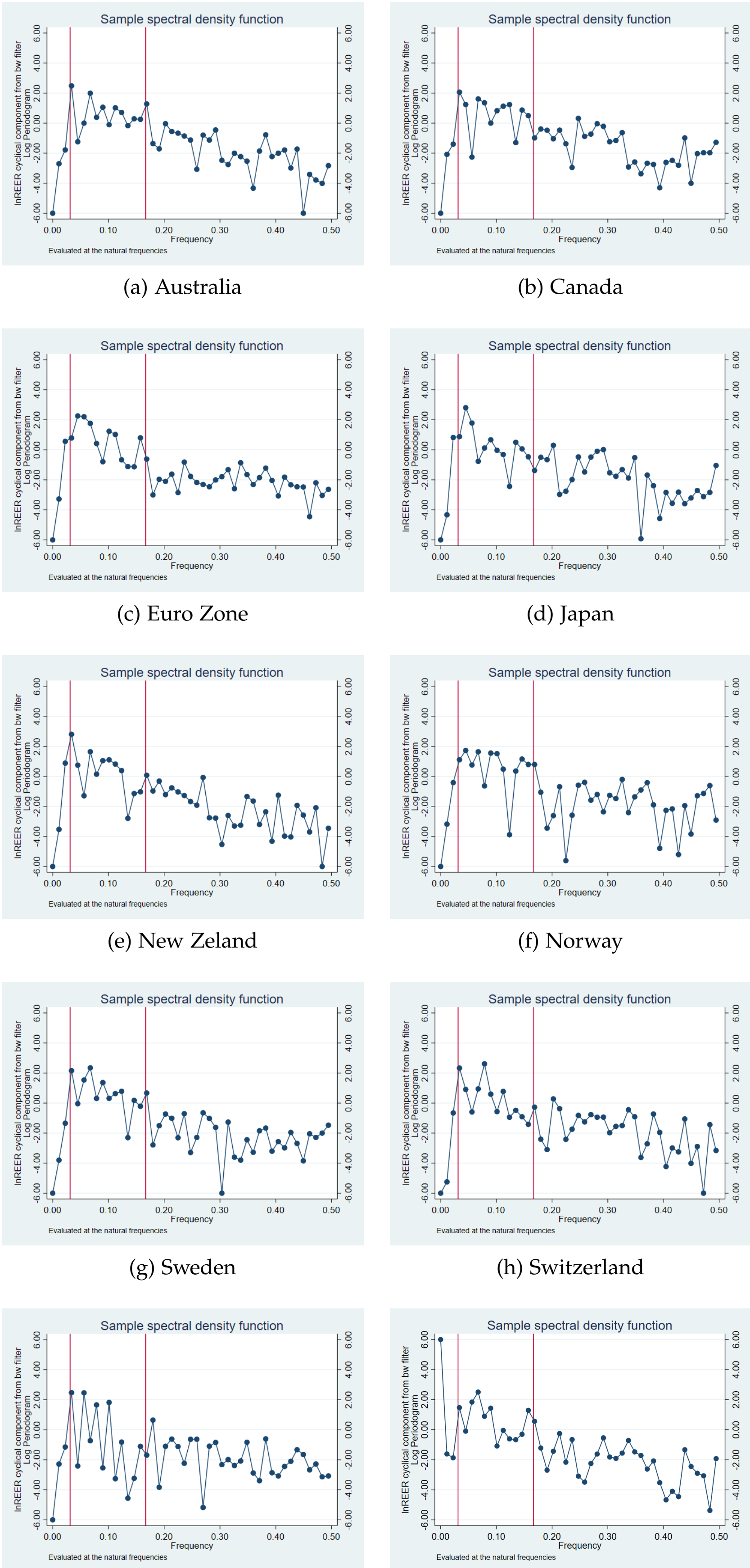



(j) United States



This figures show the periodgram for the G10 country for Baxter-King filter.

Figure 13: Butterworth Filter Periodogram




(a) Australia (b) Canada

(c) Euro Zone (d) Japan

(e) New Zeland (f) Norway

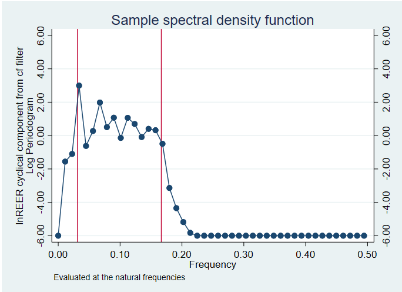
(g) Sweden (h) Switzerland

(i) United Kingdom (j) United States

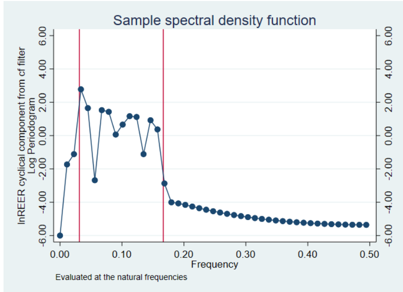


This figures show the periodgram for the G10 country for Butterworth filter.

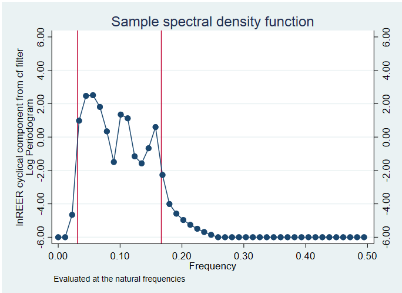
Figure 14: Christiano-Fitzgerald Filter Periodogram



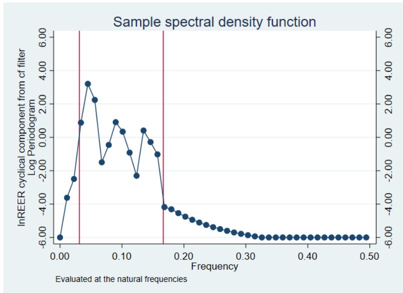

(a) Australia



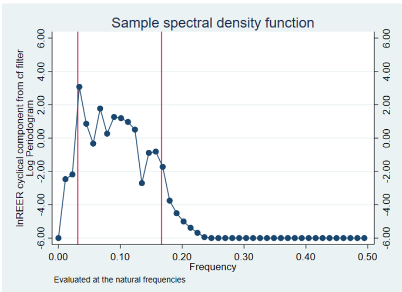

(b) Canada



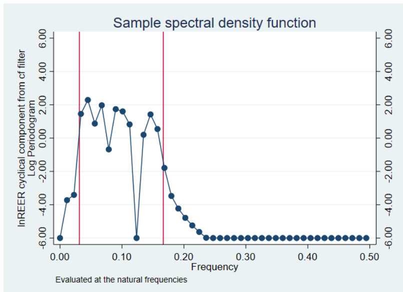

(c) Euro Zone



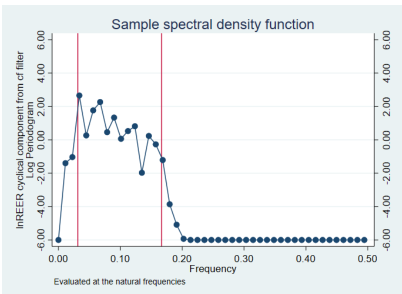

(d) Japan



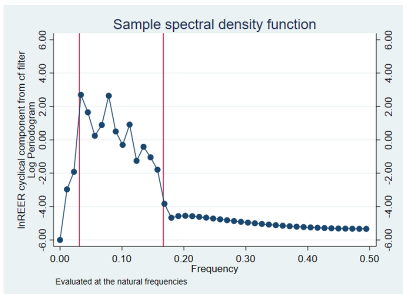

(e) New Zeland



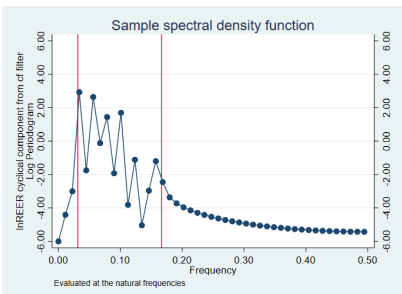

(f) Norway



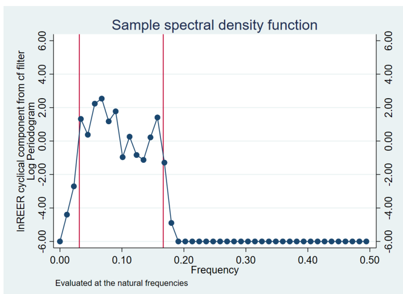

(g) Sweden




(h) Switzerland




(i) United Kingdom




(j) United States

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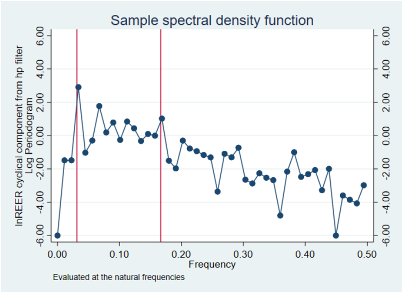
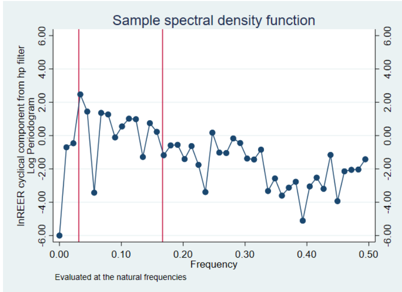
This figures show the periodgram for the G10 country for Christiano - Fitzgerald filter.

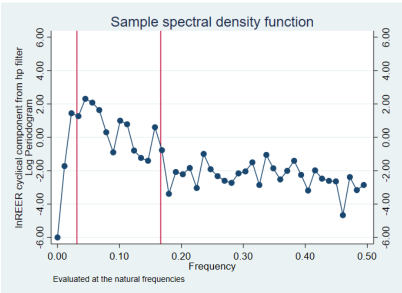
Figure 15: Hodrick-Prescott Filter Periodogram



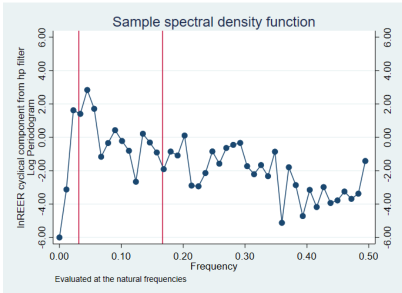

(a) Australia



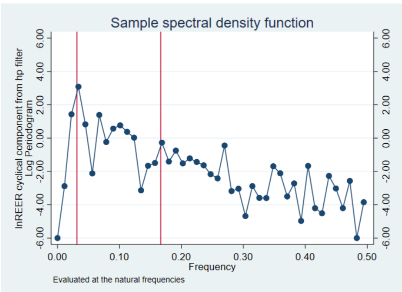

(b) Canada



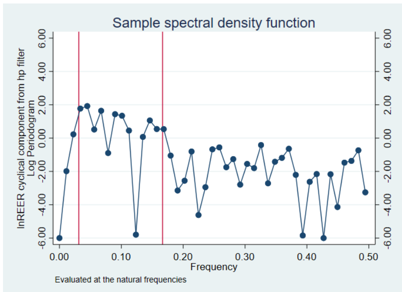

(c) Euro Zone



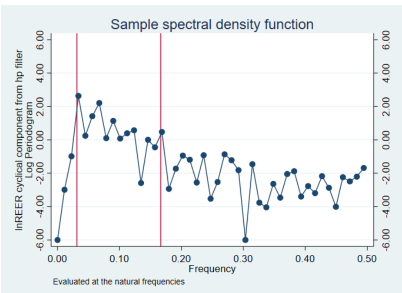

(d) Japan



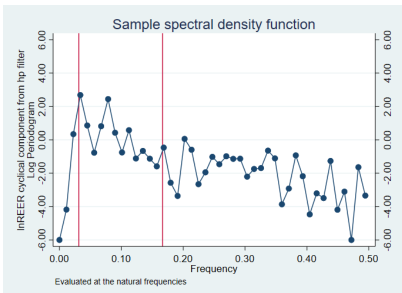

(e) New Zeland



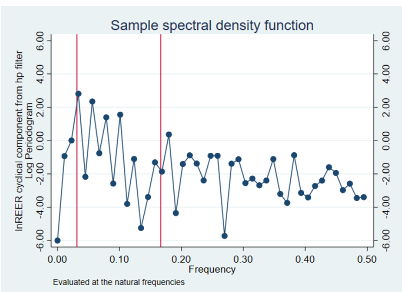

(f) Norway



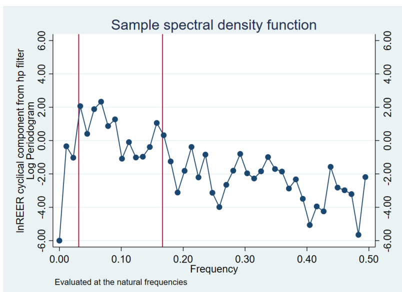

(g) Sweden




(h) Switzerland




(i) United Kingdom




(j) United States



This figures show the periodgram for the G10 country for Hodrick-Prescott filter.

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# DECLARATION

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