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# Asset Pricing in the Foreign Exchange Market

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# Abstract

The exchange rate is one of the most vital components in any economic and investment decision. With the increase in globalisation, there is a concomitant increase in the exchange rate risk in any global investment decision. This Ph.D. thesis examines asset pricing in the foreign exchange market in various dimensions, introduces new techniques for performance measurement and information flow, and attempts to explain the carry trade in the foreign exchange market. The economic significance of empirical exchange rates models in a portfolio-based framework was examined, using a thirty-year time series of five exchange rates. The forecast performances were evaluated in mean-variance and performance index (indices of acceptability) to compare the fundamental exchange rate models with a benchmark random walk model. The parameters were computed using advanced computational finance and econometric techniques. The performance measurements obtained from mean-variance by various models were compared using the Sharpe ratio. It was concluded that the structural model, although unable to beat the random walk model, did not perform worse than the forecasts obtained from the benchmark model. The results from the *indices of acceptability* evaluation indicate that one-month ahead forecasts obtained from the monetary model of the exchange rate performed better than the benchmark model.

Furthermore, the information flow in the foreign exchange market was examined by evaluating the relationship between volatility and the customers' trading activity. An attempt was made to explain the relationship between volatility and customer order flows in a portfolio-based framework with unique aggregate and disaggregate customer order-flow data from the Union Bank of Switzerland (UBS). This was the largest private dataset used to-date in a study of the foreign exchange market. The relationship was found to be robust; that is, the order flow is one of the main sources for transmitting private information to the foreign exchange market. This relationship holds across all the currencies and in various volatility estimates. This study is the first in the foreign exchange market in the aforementioned setup, and robustly elucidates the cited relationship in the foreign exchange market. The results give significant support to information being asymmetric across classes of customers

and that private information is transmitted to the foreign exchange market by the trading behaviour of informed customers. Moreover, the volatility patterns in the foreign exchange market are significantly and substantially affected by the customer order flows. The size of the trade impact on volatility in a portfolio-based approach was also examined and it was found that the large sales are more influential trades on volatility in the foreign exchange market. In addition, to study the subsequent volatility, there was an examination of two existing hypotheses; i.e., the *liquidity-driven-trade-hypothesis* (positive subsequent relationship), and the *information-driven-trade-hypothesis* (negative subsequent relationship.) Both phenomena were found to exist, depending on the economic condition of the market.

Finally, an explanation was given for the existence and identification of the *carry trade* in the foreign exchange market. When an investor borrows from a low interest-rate currency and invests in a higher interest-rate currency, zero-investment portfolio, this trading strategy is called carry trade strategy. Again, a novel data set provided by the UBS was examined to establish a relationship between the ordering patterns of informed customers and the carry trade. The forward discount bias and the carry trade were studied using theories of microstructure finance and the consumption-based asset-pricing model in a portfolio-based framework. The microstructure approach is the standard model of Evans and Lyons (2002). It was found that the order flow significantly explained the excess return in the carry trade, implying that informed customers knew about the carry trade opportunities in the market and reorganised their portfolios in order to realise these gains. Volatility and customer order flows were also examined, using a GMM approach, as a global innovation factor, and it was found that both variables significantly explained the cross-section of carry returns in the foreign exchange market.

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# Declaration

"I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution."

Signature: ________________

Name: Muhammad Kaleem

# Chapter 1.

# Introduction

The economic and business decision-making processes, in today's highly globalised world, involve consideration of various key economic and financial components. These include e-commerce, financial linkages and trade as well as the foreign exchange rate, which is arguably the most significant of the four. Indeed the exchange rate is vitally important when formulating economic policies for economies, corporations and individual investors. As a consequence of Globalisation, there has been a relaxation in trade barriers as well as a fall in transportation and transaction costs. In turn this has led to a geographical separation of the production and the consumption of commodities. Another affect of Globalisation, moreover, is that economies have become interdependent. Therefore, a boom or recession in one country can lead to the same in another country as a result of this high level of economic integration.

In the 1950s and 1960s investors viewed the exchange rate as a regular component in the formulation of policies involving macroeconomics and international trade. Yet more recently the importance of the exchange rate has become much more pervasive: Every economic decision, such as the regulation of money markets, stock markets, imports and exports, industrial competitiveness, foreign investments and so forth, requires an extensive risk assessment of the underlying foreign exchange. Therefore, in reflection of this growing importance, the author of this thesis has selected "Asset Pricing in the Foreign Exchange Market" as the topic for this research thesis.

Forecasting exchange rates and assessing the foreign exchange risk when making an investment decision is an integral feature associated with fluctuations of the exchange rate. Thus this thesis will empirically examine the forecasting ability, volatility, and profitability aspects of the various exchange rate models in the foreign exchange market. This will be done via utilisation of newly developed techniques in econometrics, computational finance, and microstructure finance. The main content of this thesis will be divided into four main sections: The succeeding chapter, Chapter 2, will review the existing theoretical and empirical literature with regards to the exchange rate models, profitability and volatility in the foreign exchange market. It will also explore the impact of economic variables (both micro and macro), the economic evaluation of exchange models as well as the role of customer order flows and consumption-based asset pricing in the foreign exchange market. This literature review will be followed by three empirical chapters, and the final chapter will offer a conclusion. The empirical chapters address the following three questions:

1 Is the foreign exchange market efficient and can the forecasts of structural models outperform the naive random-walk model?

2 Can the volatility trend in the foreign exchange market be predicted with the help of microstructure theories using a private data set?

3 Can the carry trade in the foreign exchange market be explained by order-flows and volatility?

Finding answers to the first of these questions would reduce the foreign exchange risk and enable policymakers and investors to make more efficient and profitable decisions. Economic theories affirm that exchange rates should follow a set of underlying economic fundamentals. Empirical studies, however, suggest that the exchange rate between two economies with approximately similar interest and inflation rates follows a random walk.[1] There are number of empirical methods that estimate the exchange rate

[1] See Meese and Rogoff (1983).

forecast, based on certain economic fundamentals. These fundamentals have been studied extensively in the literature of empirical finance from both short term and long term perspectives. The long-term forecasts found that the exchange rate does follow economic fundamentals, whereas, in the short-term, forecasting has been more challenging. A number of studies found that the exchange rate models, which attempt to explain the moments in the exchange rate with the help of economic fundamentals, were outperformed by a naive random walk model.[2] A vast number of studies on the relationship between the exchange rate and economic fundamentals conclude that exchange rates are unpredictable, especially in the short run. Nonetheless, others concluded that exchange rates follow economic fundamentals but at longer horizons.

In this thesis the forecasting ability and accuracy of the empirical exchange rate models are studied within a statistical framework. They are also explored in terms of the economic value of the forecast, using recent techniques of *Bayesian econometrics* and *computational finance*. The general conclusion regarding the unpredictability of exchange rates via economic fundamental models is driven by studies that compared the forecasts by a statistical measure in order to evaluate the model's performance. However, fewer studies have been done on the exchange rate forecasting abilities of fundamental models using the economic value of the forecasts. The first empirical section of this thesis, Chapter 3, on the *Economic Significance of Empirical Exchange Rate Models*, is intended to fill this gap and examine the economic performance of the fundamental exchange rate models in economic terms. The performances of the forecasts are evaluated within a market participant decision-making context;

[2]See Meese and Rogoff (1983), Diebold (1988), Engel and Hamilton (1990) and Diebold and Nason (1990).

the participant maximises their profits using mean variance, and an index of acceptability methodologies. The return and risk of the underlying assets are the pre-requisites for the computation of mean variance and the index of acceptability methodologies. These returns, and standard deviations are computed using techniques of economic fundamental models empirically examined using linear regression, Bayesian linear regression, and Bayesian GARCH. The forecast from the fundamental models of the exchange rate is ranked together with a naive random walk model, taken as a benchmark model. The performance of the forecast are evaluated and measured on the portfolio's *theta*, that is, the Sharpe ratio, and the new performance measures proposed by Cherny and Madan (2009), i.e., the *index of acceptability*. These new measures are appropriate for non-Gaussian distributions, and include complete distribution of returns in order to evaluate the performance of the portfolio. The extension of the indices of acceptability approach of Cherny and Madan (2009) to portfolio analysis, and more generally, to monetary economics appear to be a relatively new development.

The second empirical chapter addresses the relationship between volatility and the customers' ordering behaviour. Volatility is the most vital component in finance. Indeed it is incorporated into virtually all decision-making processes including: risk assessment and management, asset pricing, asset allocation and market efficiency tests, amongst many others. Volatility has also been studied extensively in the literature together within several dimensions and clusters. Volatility in the foreign exchange market can change a profitable deal into a loss. Numerous studies that have attempted to discover the relationship between volatility and macroeconomic variables generally concluded that a large amount of volatility could not be explained by the underlying economic variables. This could be due to the fact that the underlying asset has been mispriced. Researchers have studied various factors in order to trace the unexplained volatility including macroeconomic variables, financial leverage, economic activities and trading volumes. Studies such as that by Schwert (1989) found that a significant portion of the volatility in the underlying asset was explained by trading activity. The relationship between trading activity and volatility is found to be positive and robust. Although this has not been supported by any fundamental economic theory. Studies have used a number of economic models, including a *mixture of distribution models*, to explain this relationship.[3]

The volume-volatility relationship has been studied extensively in the Stock Market, Bond Market, and Option's Market. Yet there is no such study that examines this relationship in the Foreign Exchange Market. The overarching aim of this thesis then will be to plug this gap in the literature by examining this relationship in the context of the Foreign Exchange Market by reference to *Microstructure Finance* theories. This research area will employ a private data set for disaggregate and aggregate customer order flows provided by the Union Bank of Switzerland (UBS). This is the largest data set with which to evaluate the volatility and customer order flow relationship. The first section of Chapter 4 examines the various dimensions of the relationship between the customer order flow and volatility. The second section examines volatility in a portfolio-based framework. Furthermore it looks at the *asymmetric volatility effect* in the Foreign Exchange Market. Basically, an attempt was made to examine the private information transmission mechanism in the foreign exchange market, on the assumption that customers possess private information. For this the model from the microstructure finance theories was used. In

[3]Detail of these models are provided in Chapter 4.

order to address the relationship between the order flow and the volatility the models of Schwert (1990) and Jones *et al.* (1994) were utilised. These are considered to be the customary models for testing this relationship.

Traditional economic theories do not incorporate trading activity into assessment models. Rather this gap is filled by the theories of microstructure finance. If it is assumed that the customer order flow facilitates the evolution of economic fundamentals in the foreign exchange market then a robust and positive relationship between the volatility and customer order flow should be expected. Hence, if customer order flows are used as a proxy for economic fundamentals, then the moment in the exchange rate can be anticipated by the buying and selling behaviour of the customers. This relationship helps to explain the contemporaneous persistent trends in the market if one group of customers (supposed to have better information) holds a long (short) position, relative to an underlying benchmark model position, implying that the market will be rising (plunging) and a positive (negative) order-flows is expected. In contrast to this microstructure phenomenon, traditional economic theories and the efficient market hypothesis do not incorporate any information regarding the order-flow/trading activity in the models. This hypothesis suggests that the information in the Foreign Exchange Market is asymmetric and allows price and volatility discovery for the less-informed customers through following the informed customers (information transmission mechanism). Most of the studies in this research area used inter-dealer order-flows, which appear to be less important because customers are likely to be better informed. Thus they are likely to be more significant in shaping the trends than the dealers. Investment banks monitor order-flows on a real time basis in order to make well-informed decisions. Whereas other market participants may not be able to monitor live information as it is privately owned information.

The motivation for this study is to establish the relationship between the exchange rate and volatility in order to facilitate the decision-making process in the financial markets.

The third empirical chapter of this thesis addresses the relationship between the profitability of the carry trade and customer order flows. As per the uncovered interest-rate parity condition the forward exchange rate should be an unbiased predictor of the future spot exchange rate. In reality, however, there is always a difference between the forward exchange rate and the future spot exchange rate. Several studies concluded that the forward exchange rate depreciates when the higher interest rate currencies systematically appreciate.[4] This phenomena is normally referred to as *Forward Discount Unbiasedness* (FDU) or *Forward Discount Puzzle* in the literature of international empirical finance.

The deviation of the uncovered interest-rate parity condition from fundamentals provides an opportunity for investors to make higher profits. This is done by borrowing from a low interest rate currency and investing in a higher interest rate currency. Thus, they would be able to make a positive profit from the interest rate differential alone, with no investment associated with these portfolios. This trading strategy is referred to as the *Carry Trade* and is an active research area for academics. In this thesis, the reason for the existences of forward discount un-biasedness and the profitability of the carry trade in the Foreign Exchange Market is studied. The thesis will make use of a unique weekly dataset provided by the UBS (a private dataset not available to the general public or through payment). This study is divided into two sections: The first section explores the

[4]See Bilson (1981); Fama (1984); Froot and Frankel (1989); Burnside *et al.* (2007*a*).

relationship between the carry trade returns, and the customer order flows in a portfolio-based framework, from an investors perspective: While the second section uses the consumption-based asset-pricing model to explore global foreign exchange (FX) customer order-flows and volatility innovations. Currently there are no studies addressing these relationships. Therefore this dissertation will fill a significant gap in empirical finance literature.

The next chapter of this dissertation reviews the existing literature in order to explain the relevant theoretical background, empirical evidence, and methodological issues. The focus of Chapter 3 is the economic significance of the empirical exchange-rate models: While Chapter 4 concerns customer order flows and volatility in the Foreign Exchange Market. The carry trade and asset pricing are addressed in Chapter 5, and the conclusion is presented in Chapter 6.

# Chapter 2.

# Literature Review

This chapter reviews the existing theoretical and empirical literature on exchange rates models, returns and volatility in the foreign exchange markets.[1] The scope of this literature review extends to other factors that also influence exchange rates such as macro- and microeconomic components, and customer order-flows. Furthermore it discusses the existing research on asset pricing, including microstructure theories, the economic evaluation of the existing empirical exchange rate models and the introduction of new performance measure.[2] The general aim of this chapter is to review the existing research in order to answer the following questions: -

1 Is the foreign exchange market efficient and can the forecasts of the structural models outperform the naive random-walk model?

2 Can the volatility trend in the foreign exchange market be predicted with the help of microstructure theories using a private data set?

3 Can the carry trade in the foreign exchange market be explained by order-flows and volatility?

These questions are extremely important from the perspective of investors and policy makers. Identifying a structural exchange rate model that is successful in its class of models, while explaining the exchange rate movement would make it possible for policy makers to influence the exchange rate and reduce the associated uncertainty. Furthermore, if a trend were deduced from the ordering behaviour of customers, then it would enable market participants to make better-informed decisions. Finally, market participants can maximise the wealth of their portfolios by relying

[1]Also referred to as fundamental/structural models.

[2]In Chapter 3 this thesis introduces a new performance measure in foreign exchange market, named *Indices of Acceptability*.

on the factors that tend to explain the changes in the carry trade portfolios.

Firstly, there will be an empirical discussion on the importance of foreign exchange to the decision making process of individuals, firms and the overall economy. Previously, academics and market participants perceived exchange rates as a single isolated component contributing to the formulation of international trade and macroeconomic policy in general. Yet more recently exchange rates have been viewed as a vitally important consideration of economic decisions regarding a variety of matters including domestic economies, money markets, stock markets, industrial competitiveness, imports and exports and many others. This augmented importance associated with exchange rates can be partly attributed to the globalisation of modern business, developments in the economic integration, a considerable increase in the magnitude of the growth in global trade relative to national economies, and the impact of e-commerce.[3]

In the last two decades, several books have been dedicated to the subject of exchange rates. Indeed this research area is no longer of exclusive interest to traders and economic specialists but an integral concern of all Economists and business actors. Many economic theories have been criticised because they have ignored the role of the exchange rate.[4] Exchange rates are highly volatile which makes them an important factor.[5] Their role is crucial in any economic and/or business transaction because they have the ability to convert a captivating investment project into a liability on the balance sheet of the original investor. The aim of this thesis is to enable market participants to have a better understanding of

[3]Specifically the European Union, the largest economic integrations between independent nations.
[4]See Madsen (2012)
[5]The underlying intuition behind the importance of volatility in the exchange rates is simple: exchange-rate risk reduces the gains to international trade and increases transaction costs.

the performance of structural exchange-rate models. The role of private information and the trade direction in the foreign exchange markets, plus explaining the missing link between the carry trade and the exchange rate order flow, in order to maximise their stakes in the decision making process.

In recent decades forecasting exchange rates, in both the short and the long term has become an increasingly challenging area for academic researchers. In this period, they have faced difficulty when fixing floating exchange rates to economic fundamentals such as interest rates, money supply, imports and exports as well as outputs. Theories of exchange rates assert that they should follow a set of underlying economic fundamentals. However, empirical studies suggest that the exchange rate between two economies, with approximately analogous interest and inflation rates, follows a random walk.[6] Several studies have attempted to test this relationship and found that the results of exchange rate models that were subject to economic fundamentals were outperformed by a random walk model.[7]

Meese and Rogoff (1983) drew the following conclusion on exchange rate structural models and random walk models:

> "A random walk model would have predicted major-country exchange rates during the recent floating-rate period as well as any of our candidate models."

[6] See Meese and Rogoff (1983).

[7] See Meese and Rogoff (1983), Diebold (1988), Engel and Hamilton (1990) and Diebold and Nason (1990).

## 2.1. Early Studies on the Exchange Rate

### 2.1.1. Exchange Rate and Parity Conditions

In the Sixteenth Century scholars of Spain's Salamanca School first introduced the concept of *purchasing power parity* (PPP) (see James *et al.*, 2012). Later, classical Economists *John Stuart Mill, Viscount Goschen, Alfred Marshall* and *Ludwig von Mises* discussed this concept in their works. *Gustav Cassel*, a Swedish Economist, upgraded the concept of PPP and introduced its specific terminology (Cassel, 1918).[8] PPP is one of the earliest theories, which states that identical products and services across different countries should be priced the same when expressed in a common currency. In other words the purchasing power of the common currency would be the same for all countries. Cassel's studies gained considerable importance after the First World War in the determination of various exchange rates, particularly in respect to Britain's decision.[9] (Officer, 1976)

The *Law of One Price* (LOOP) is the main governing fundamental that addresses the determination of the exchange rate under PPP theory. This law states that the prices of goods across countries should be equal to each other when they are denominated in a common currency: On the assumption that the goods are homogeneous, there are normal trading costs, no capital inflows and that the operation takes place in a perfect competitive market.

In the 1970s and 1980s, PPP was perceived by researchers as a theory of exchange rate determination for both long and short run conditions.

[8] See Pilbeam (2006) and Copeland (2008)

[9] E.g., Britain's attempted to reinstate the pre-war rate with the dollar in 1925.

Moreover it was viewed as a condition of efficient arbitrage in assets or goods markets (Officer, 1976; Frenkel, 1976, 1978). Subsequently, this consensus has shifted radically. In the early 1970s, this seemed to favour the presence of a reasonable, steady exchange rate (see e.g., Gailliot, 1970; Friedman and Schwartz, 1971). In the same decade the monetary approach to the exchange rate prevailed, assuming continuous existence of PPP (see e.g., Frenkel, 1976, 1978). In the mid- to the late 1970s, real exchange rates were in high turbulence: There was the start of the departure of exchange rates from the PPP concept, which was referred to as the *collapse* of PPP; (Frenkel, 1981*a*).

In the 1980s, researchers were unable to reject the random walk behaviour hypothesis in the movement of the real exchange rate. This lead to a deterioration in confidence in PPP. Afterward the view was taken that PPP is of little use in empirical studies and that exchange rate movements are eminently unsteady (Dornbusch, 1989).[10]

Currently, researchers test co-integration between the relative prices and the nominal exchange rate by testing mean reversion over the long horizon in PPP, stationary in the real exchange rate, and the residual of an equation.[11,12] Preliminary studies on co-integration concluded that there was a significant failure of the mean reversion for the recent float (Taylor, 1988; Mark, 1995). Conversely, some of the researchers found some evidence in favour of mean reversion. The main studies include

[10] See Adler and Lehmann (1983)

[11] Mean reversion is a theory which suggests the asset prices eventually revert back towards the mean. The mean on which the prices return can be historical or any other relevant mean such as industry average etc.

[12] Any time series will be stationary if the mean, variance, autocorrelation, etc. of the time series are constant over time. Most of the econometric measures are based on the assumption that the financial time series can be transformed to stationary (i.e., *stationarised*) through the use of mathematical transformations.

Taylor (1988), for the inter-war float; Myles *et al.* (1989), for the Canadian and U.S. float, and; Choudhry *et al.* (1991), for the exchange rate for high inflation countries. During the 1990s, studies on long run PPP between industrialised countries concluded in its favour.[13] Many researchers debated over the limitation of the data period. Indeed they questioned whether the float would be able to produce a relative strength of statistical test power for the real exchange rate mobility (Frankel, 1990).

Some researchers succeeded in rejecting the random walk hypothesis for the movement in the real exchange rate by increasing the power of the tests.[14] They utilised refined econometric techniques, such as pooling the data in a system of univariate auto-regression, and by using the Dickey and Fuller Statistics (Abuaf and Jorion, 1990).[15] The fractional integration technique was applied by Diebold *et al.* (1991) to data of the $19^{th}$ century and they found supporting evidence of long run PPP.[16] Lothian and Taylor (1996) deployed data for two centuries, ending in 1990 for the sterling-franc and the sterling-dollar: They found significant evidence of mean reversion of the real exchange rate towards PPP. Flood and Taylor (1996) utilised panel data from twenty-one industrialised countries during a floating exchange rate period. They then regressed exchange rate average movement of five, ten and twenty years against the average inflation differential of the U.S., and found robust evidence for the mean reversion of the real exchange rate towards PPP.

[13] See MacDonald and Taylor (1991)and Cheung Kon *et al.* (1993)

[14] The random walk hypothesis states that the movements in the exchange rate have the same distribution but are independent from each other, and therefore, no past movement or trend can predict any future movement of exchange rate.

[15] The DickeyFuller test examines the existence of a unit root in an autoregressive model.

[16] Fractional Integration is a technique which comprises a stationary process, in a broader class, under the alternative hypothesis.

### 2.1.2. Early Studies on Random Walk and Market Efficiency

According to the Efficient Market Hypothesis (EMH), asset prices should reflect all relevant information available to market participants at a given point in time.[17] This implies that market participants include all the underlying relevant information in order to set the spot exchange rate. Hence making it impossible for them to use arbitrage or make any abnormal *ex-ante* profit. In an efficient market hypothesis academics are interested in tracking the relevant information and the market prices of underlying assets at a given point in time. Empirically, the EMH interests researchers because of two key concerns: first, how quickly the new information is incorporated into the price of the underlying asset and, secondly, the relevance of the information to the foreign exchange. To test the EMH, various methods have been proposed by researchers. The most commonly-of these is to test if the forward exchange rate predicts the future spot rate. If the outcome is that it over- or under- predicts the future exchange spot rate then it is concluded that the foreign exchange market is not efficient. The *Rational Expectation Hypothesis* (REH) is one of the key hypotheses for testing the EMH.[18] According to the REH, market participants base their belief on or have good knowledge of the underlying economic model and assume that the model does not consistently over- or under- predict the future exchange rate.

[17] As per Fama (1970) in which prices always *fully reflect* available information.

[18] The *rational expectation hypothesis* states that market participants make decision on the basis of their future expectations about the market, based on their past experience and beliefs. Furthermore, it states that the future performance is strongly influenced by the current expectations. However, there is also much criticism of the practical implication of this hypothesis.

Early research based on EMH was conducted by Levich (1976) and Frankel (1982*a*). They tested market efficiency in the following model:

$$s_{t+1} = \beta_1 + \beta_2 f_t + \mu_{t+1}, \tag{2.1}$$

The above test implies that, under the assumption that the foreign exchange market is efficient, all relevant information is incorporated into the underlying currency: Then the forward rate should be an unbiased predictor of the future spot rate i.e., $s_{t+1} = f_t$, given that there is no risk premium. Therefore, the intercept term in equation 2.1 should be equal to zero i.e. $\beta_1 \approx 0$. If $\beta_1 \not\approx 0$ in equation 2.1 then this implies that the future spot exchange rate is systematically under- or over- predicted by the forward exchange rate. Therefore proving an opportunity for the market participant to make systematic profits. If the forward exchange rate in the above equation 2.1, on average, correctly explains the changes in the future spot exchange rate, then the $\beta_2 \approx 1$. $\mu$ is the noise term. It is normally distributed $\mathbb{N}(0, 1)$ and possesses the properties of classical ordinary least square regression.

Early research on the efficiency of the foreign exchange markets includes Poole (1967), who tested the random walk model. Poole (1967) concluded that the model does not hold in the sample data under examination. Furthermore, he added that this conclusion does not imply that the REH is invalid, because the serial dependency of some of the costs (transaction and carrying) is consistent with the hypothesis. Nevertheless, a random walk in the exchange rate is only implied if the differential of the nominal interest rate is correspondingly equal to a constant. Cumby and Obstfeld (1981) studied the random walks in the exchange rates. They tested for the randomness of deviations of the exchange rates from the uncovered interest rate parity condition and rejected its existence.[19] Despite this, Mussa (1984) stated that, over the recent float, the major nominal exchange rate time series are exceptionally difficult to differentiate empirically from a random walks.

Levich (1976) tested the joint hypothesis for the Pound, French Franc and the Deutschmark from March 1973 to March 1978.[20] Moreover, Frankel (1982*a*) studied the same exchange rates from June 1973 to July 1979. The results of both studies supported the joint hypothesis of no premium and the efficiency of the foreign exchange market hypothesis. In both of these studies, the coefficients are statistically significant and the $R^2$ for both of the studies are high. The results imply that there is no risk premium in the foreign exchange market. Later studies by the Hansen and Hodrick (1980); Meese and Singleton (1982) and Cumby and Obstfeld (1984) criticised this joint hypothesis by Levich (1976) and, later, Frankel (1982*a*). The main criticism was about the modelling technique, as, if the exchange rate follows a non-stationary process then the Levich (1976) and Frankel (1982*a*) regression model is inappropriate.[21] Later researchers de-trended the data in order to estimate unbiased coefficients in a stationary environment. Cumby and Obstfeld (1984) estimated the following regression model, adjusted for the trend:

$$(s_{t+1} - s_t) = \beta_1 + \beta_2(f_t - s_t) + \mu_{t+1}, \tag{2.2}$$

[19]The uncovered interest rate parity condition is discussed in the section 2.1.3.

[20]The joint hypothesis is the simultaneous testing of the relationship between the observable variable (interest rates) and how the market forms expectation about the said variable. Discussed in detail in section 2.1.3.

[21]This non-stationary process is the presence of trends; such as appreciation and depreciation in the underlying exchange rate.

The empirical results of the above equation 2.2 provided further support of the hypothesis. The results indicate that on average, the depreciation (appreciation) in $(f_t - s_t)$ would result in appreciation (depreciation) in $(s_{t+1} - s_t)$.

In equation 2.2, $\beta$ should be equal to one, if market participants have rational expectations and risk neutrality. The rational expectation forecast error $\mu_{t+k}$ should be uncorrelated to the information available at time $t+1$. A large number of studies are performed to test the above relationship, including, more pairs of currencies and different time scales. The results are not in-compliance with the theory of the efficient market hypothesis. Fama (1984) applied various models to measure the variations in the expected spot rate and the premium. Based on market participants rationality and risk neutrality, and given that the foreign exchange market is efficient, he concluded that:

> "(a) Most of the variation in the forward rates is variation in the premium, and (b) the premium and expected future spot rate components of forward rates are negatively correlated."

### 2.1.3. Parity Conditions and Market Efficiency

In a risk-neutral and rational market, the expected foreign exchange returns from holding one currency $(X)$ and investing it in debt instruments or converting it $(X)$ into another currency $(Y)$ and investing it into debt instruments of the same currency $(Y + i)$, while at the same time purchasing future contracts for the reversion to the base currency $(X)$ at maturation, should be offset by investing in debt instruments of the first currency $(X)$. This condition is called uncovered interest rate parity condition (UIRP), and is a keystone for examining the efficiency of foreign exchange markets.

$$\triangle s^{e}_{t+k} = i_t - i^{*}_t \tag{2.3}$$

where $s$ is the log of spot exchange rate, $i$ and $i^*$ are the domestic and foreign nominal interest rates[22] and $e$ denotes market expectations, at time $t$, for $k$ periods.

The greatest obstacle in testing the uncovered interest rate parity condition (UIRP) is represented by the unobservable qualities of the variables in equation 2.3. The expected interest rate is not directly observable, and neither are the expectations of market participants. A number of proxy variables are substituted for the expected interest rates and the expectations of market participants. Therefore, if any observable and quantifiable substitute is allowed for the $\triangle s^e$ in equation 2.3, this will limit the testing of UIRP condition. Thus, in order to test the UIRP, it is necessary to solve a joint hypothesis problem.

The joint hypothesis problem can be understood by considering the following example. Assuming that the market expects that the exchange rate will remain unchanged over the next period: That is, $\triangle s^e = 0$, substituting this into equation 2.3 would give the following result:

$$i = i^*$$

The deviation in the exchange rate implies that either the UIRP condition does not hold, or the expectations formed by the market participants

[22]Interest rate assumed to be on identical securities.

are irrational. Therefore, it is necessary to test theories about interest rates and market expectations simultaneously and hence, the underlying issue can be resolved by the testing of a joint hypothesis.

Furthermore, regression based analyses are performed by researchers to test foreign exchange market efficiency of spot and forward exchange rate in context of the parity condition. As discussed earlier, forward rate is the expected yield for an exchange of currency at a particular time in the future. The margin between the current spot rate and the current forward rate of that maturity is the forward premium.[23] If this is equal to the differential of the interest rates of foreign and domestic currency, then this condition is called Covered Interest Rate Parity.

$$(i - i_t^*) = (f_t^{(k)} - s_t)$$
$$(i - i_t^*) - (f_t^{(k)} - s_t) = 0$$

where $f_t^{(k)}$ is the forward rate for the maturity of $k$ periods at time $t$, $i_t$ is the nominal interest rates (foreign and domestic) and $s_t$ is the spot exchange rate at time $t$.

If market participants are rational, then any difference between the change in the expected and actual exchange rate will be due to the forecast error of the rational expectations of market participants. Therefore, the uncovered interest rate parity condition can be regressed by defining an error term in the regression for the rational expectation forecast error.

$$\triangle s_{t+k} = \alpha + \beta(f_t^{(k)} - s_t) + \mu_{t+k} \tag{2.4}$$

[23]Some authors refer to forward premium when the returns are positive and to forward discount when the returns are negative.

where $f_t^{(k)}$ is the forward rate for the maturity of $k$ periods at time $t$, $i_t$ is the nominal interest rates (foreign and domestic) and $s_t$ is the spot exchange rate at time $t$ and $\mu_{t+k}$ is the error term.

The interest rate parity condition was tested by Frenkel and Levich (1975, 1977), who tested exchange rates of the 1970s, after adjusting them for transaction cost, and using Treasury Bill discount rates. They found significant departures from the covered interest rate parity condition, as few deviations were found when Euro-deposit rates were used. Clinton (1988) provides evidence for the existence of the covered interest rate parity condition during the recent float for major exchange rates. Contemporaneously sampled, high quality, high frequency data were used by Taylor (1987, 1988), in his studies on Euro deposit rates; he found few profitable departures from the covered interest rate parity.

### 2.1.4. Forward Discount Bias and Early Regressions

If all relevant is information incorporated in the underlying security and given no risk premium, then the $\beta$ in equation 2.4, i.e., $\triangle s_{t+k} = \alpha + \beta(f_t^{(k)} - s_t) + \mu_{t+k}$, should be 1, i.e., $\beta = 1$. Froot and Thaler (1990) studied the exchange rates against the U.S. dollar and found that the estimates for the slope were generally nearer to minus unity instead of plus unity.[24] If it is assumed that the foreign exchange market is efficient and participants are risk neutral and rational, then the forward discount functions as an unbiased estimate of the future exchange rate. A great number of empirical studies present evidence of forward discount bias and the rejection of the joint hypothesis. Hodrick (1992) concluded that the forward premium does not anticipate the path of the spot exchange rate

[24]This is referred to as the *forward discount puzzle* in the literature of empirical finance.

change; however, technically, this result is ambiguous because the constant term in the regression was ignored. The negativity of the '$\beta$' implies that the more the premium on holding the foreign currency in the forward market, the less anticipation there is of the home currency depreciating.

Frenkel (1976), among others, carried out a regression-based study on the efficiency of the foreign exchange market by taking the log of the spot exchange rate as response and the log of forward exchange rate as stimuli, and the regression slope $\beta$ was found near to one i.e., $\beta \approx 1$. One of the criticisms of Frenkel (1976) was that the data series were non-stationary and basic regression analysis for this type of relationships was invalid.

The problems with the regression model presented in equation 2.4 can be further understood by decomposing the error term of this model in the following equation:

$$\triangle s_{t+k} = \alpha + \beta f_t^{(k)} + \mu'_{t+k} \tag{2.5}$$

Under the null hypothesis, the $\beta = 1$, in the regression model, is explained in equation 2.4. The error term in equation 2.5, $\mu'_{t+k}$ may be rewritten as $[(1-\beta)s_t + \mu'_{t+k}]$. Putting this in equation 2.5 will give the following equation:

$$\triangle s_{t+k} = \alpha + \beta f_t^{(k)} + [(1-\beta)s_t + \mu'_{t+k}] \tag{2.6}$$

In equation 2.6 the spot exchange rate is non-stationary; therefore, the variance of the spot exchange rate will intrinsically be very high. Whereas the ordinary least estimate (OLS) in the regression relationship reduces the residual variance. Therefore, when OLS follows equation 2.4, instead of explaining the true value of the slope, it will force the value towards unity.

The most basic fact regarding exchange rates is that they are volatile. Therefore, it is extremely difficult to differentiate the movements of exchange rates from the basic random walk model. In a foreign exchange market, regardless of its efficiency, if it is assumed that the exchange rate follows a random walk, then the predicted value of the slope in equation 2.6 should be equal to zero. Furthermore, assuming that the exchange rate follows a random walk, then by combining the random walk and efficiency hypotheses implies that $f_t^{(k)} = s_{t+k}^e = s_t$, therefore, the slope should be equal to zero and in this case the '$\beta$' is unidentifiable. Practically, even under these assumptions, $(f_t^{(k)} - s_t)$ would not be equal to zero unless a measurement error was made.

Hence, the regression model present in the equation 2.6 is confused by the random walk behaviour of the exchange rate. To overcome these problems while testing the efficient market hypothesis, researchers tested the orthogonality of the rational forecasting error of the forward rate, by $\beta = 1$ in equation 2.6 and testing the following regression with the null hypothesis $\rho = 0$:

$$\triangle s_{t+k} - f_t^{(k)} = \rho I_t + \mu_{t+k} \tag{2.7}$$

Where $f_t^{(k)}$ is the forward rate for maturity of $k$ periods at time $t$, $s_t$ is the spot exchange rate at time $t$, $\mu$ is the error term and $\rho I_t$ is the vector of variables comprising information at the given point in time $t$.

Orthogonality tests such as that in equation 2.7 using the vector of the lag forecast of the underlying exchange-rate i.e., $I_t$ in equation 2.7, normally reject the efficient market hypothesis (with the assumption of risk neutrality and market participants rationality); furthermore, if additional information is incorporated into the vector $I_t$ in equation 2.7 then stronger rejections are usually obtained (Hansen and Hodrick, 1980).[25]

Since the 1970s, the field of econometrics has flourished, and enabled researchers in empirical finance to use sophisticated techniques to test foreign exchange market efficiency. Therefore, early studies on foreign exchange market efficiency, linear regressions of uncovered interest rate parity and testing of simple random walk in the spot rate, became, more elaborate in the context of forward contracts due to the advances of econometric tools that used sampled data (Hansen and Hodrick, 1980). Generally, greater sophistication in econometrics facilitated the production of firm empirical evidence opposing the efficient market hypothesis with no risk premium.

[25]Multidimensional models. When performing statistical analysis, independent variables that affect a particular dependent variable are said to be orthogonal if they are uncorrelated, since the covariance forms an inner product. In this case the same results are obtained for the effect of any of the independent variables upon the dependent variable, regardless of whether one models the effects of the variables individually with simple regression or simultaneously with multiple regression. If correlation is present, the factors are not orthogonal and different results are obtained by the two methods. This usage arises from the fact that if cantered (by subtracting the expected value (the mean)), uncorrelated variables are orthogonal in the geometric sense discussed above, both as observed data (i.e. vectors) and as random variables (i.e. density functions). One econometric formalism that is an alternative to the maximum likelihood framework, the Generalized Method of Moments, relies on orthogonality conditions. In particular, the Ordinary Least Squares estimator may be easily derived from an orthogonality condition between the explanatory variables and model residuals.

### 2.1.5. Parity Conditions, Risk Premia and Expectations

Hence, based on the above discussion, it can be concluded that the departure of the efficient foreign exchange market hypothesis may be due to irrational behaviour of market participants or to the risk aversion behaviour, or both. If the risk averseness of market participants in the foreign exchange market is assumed, then participants will require a higher interest differential for bearing the risk of holding foreign currency. This will result in the distortion of the uncovered interest rate parity condition by a risk premium $RP_t$. Accordingly, market participants will only be interested if they expect the cost of holding foreign currency to be equal to the expected return from holding it, plus a risk premium.

$$i_t - i_t^* = \triangle s_{t+k}^e + RP_t \tag{2.8}$$

Furthermore, if the risk premium is dynamic and correlated with the interest rate differential or the forward premium $RP$, then this premium would be the test of efficiency stated in equation 2.8 (Fama, 1984). This fundamental investor behaviour influenced researchers to find reliable models that account for the assumption of rational expectations and the existence of the risk premium $RP$. Considering the theoretical relationship between the risk and the second moment of the exchange rate, researchers looked at risk premium $RP$ as a function of the variance of forecast or the variance of exchange rate movements (Frankel, 1982$a$; Domowitz and Hakkio, 1985; Giovannini and Jorion, 1989).[26]

[26] The second moment in financial economics is the square of the draw of the expected value of a random variable. i.e., the second moment is $EV^2$. It is the same as ‘un-centred second moment’ and differentiated from the variance which is the ‘cantered second moment’.

A number of researchers also studied the other risk premium models such as the latent variables formulations model.[27] For instance, Hansen and Hodrick (1983) concluded that the model's results were generally mixed and failed the robustness test when examined for a different time period and data set. Another study, by Lewis (1989*b*), on the risk premium model, included the degree of risk aversion of the market participants, and concluded that these models cannot significantly explain the changes in the forward exchange rate.

Another possible reason for the rejection of the efficient foreign exchange market is that the error in the rational expectation component in the joint hypothesis suggests the *peso problem*;[28] Bilson (1981) suggested inefficient information processing, while Lewis (1989*b*) studied the regime shifts, or rational bubbles in order to explain the rejection of the EMH. Furthermore, the peso problem also produces noticeable evidence of non-zero excess returns from forward speculation. Similar to the peso problem, rational bubbles may also emanate as non-zero return, despite the participants' risk neutrality.

A number of empirical studies have been carried out with larger, but different, sample periods and exchange rates, reaching the same conclusion by rejecting the EMH in the foreign exchange markets. The rational bubble and the peso problem generate the same problem while studying the forward discount bias, which is that the uncovered interest rate parity

[27]Latent response can be understood in contrast of *manifest response*. Suppose $X$ is a random variable representing a binary response coded zero and one, then $X$ would be called the manifest response. In contrast if there is an unobservable continuous random variable $Y$ which can take any value in a given threshold $z$, then $Y$ is the latent response.

[28]The Peso Problem is a situation in which market participants tie a small probability that the economic fundamentals will change largely, which is not true in the sample, resulting in bringing out a skew in the distribution of the forecast error.

$\beta$ estimated are generally negative and are near to minus instead of plus unity.[29] Lewis (1989*b*) conducted a study on learning in the U.S. money supply process and the early 1980s dollar appreciation and discovered a consistent error in the forward rate, which eludes to the fact that market participants cannot forever be learning about the absolute regime shift. The peso problem is based on the phenomenon of a small sample and it is unable to explain the empirical result, which is why the estimates for the slopes are negative. One of the basic problems which may lead to the rejection of the efficient foreign exchange market hypothesis (assuming rational and risk-neutral market participants) is that while testing one part of the joint hypothesis, it is automatically assumed that the other part holds and vice versa. For example, in searching for a stable risk premium model from the extensive literature under discussion, ia suitable model would be one that is stable for the risk premium but with the assumption of rational expectations and vice versa. A number of researchers tested the joint hypothesis by examining each component (e.g., Froot and Frankel, 1989; Takagi, 1991). The majority reached the same conclusion that the departures of the risk aversions and rational expectations lead to the rejection of the efficient market hypothesis.

### 2.1.6. EMH and Alternate Tests

As per the *efficient market hypothesis* (EMH), the forward rate of any currency pair should include all the relevant information in pricing the future expected spot exchange rate. The researcher included an additional variable in equation 2.1, if it is assumed that this improves the significance

[29] A foreign exchange market bubble is an economic bubble occurring in FX markets. The bubble is the phenomenon where the market participants over value the currency prices, above their economic/fundamental value.

of the estimates, and concluded that the forward exchange rate does not contain all the relevant information about the future spot exchange rate. The researcher used the following equation in order to test the above stated hypothesis, the lag of the former exchange rate in the following equation was included.

$$s_{t+1} = \beta + \beta_2 f_t + \beta_3 f_{t-1} + \mu_{t+1},$$

As per the efficient market hypothesis (EMH) any variable, including the previous period's forward exchange rate, in principal, should not contain any additional information that improves the forecasting of the future exchange rate. Researchers such as Edwards (1983) used pound-U.S. dollar, lira-U.S. dollar, Deutschmark-U.S. dollar, and French franc-U.S. dollar, for a sample period from July 1973 to September 1979, to test the above equation and found that the forward exchange rate lagged coefficient was statistically insignificant. This suggests that the previous period forward exchange rate does not improve or provide any additional information about the future spot exchange rate; hence, Edwards (1983) supports the efficient market hypothesis.

Furthermore, researchers also studied the regression error term between the expected and the actual future exchange rate. If the foreign exchange market holds the efficient market hypothesis then predicting the error on the basis of information available at time $t$ is not possible. Researchers used the following equation to examine the error term:

$$\mu_{t+1} = \beta + \beta_2 I_t + \nu_{t+1}$$

where $\mu_{t+1}$ is the error forecast, that is $s_t + 1 - f_t$, $I_t$ is the vector of information available at time $t$ and $\nu_t$ is a random error term with a normal distribution, $\mathbb{N}(0,1)$, with the mean is equal to 0 and variance equal to 1.

Again, if it is assumed that the foreign exchange market holds the efficient market hypothesis then the slope coefficient $\beta_2$ should be equal to 0, i.e., $\beta_2 = 0$. No information at time $t$, such as the current spot exchange rate $s_t$ or the previous period spot exchange rate $s_{t-1}$ or the forward lagged exchange rate $f_{t-1}$ or any other relevant variable at time $t$, could be used in order to predict the future error term. Using these types of models, normally known as orthogonal models, assumes that market participant incorporates all the relevant information in forecasting/predicting the futures spot exchange rate, and to avoid predictable forecast errors.

Furthermore, researchers used various traditional tests, in order to examine the efficient market hypothesis, in the foreign exchange market. One of the empirical test involves using alternative proxy variables for the future expected exchange rate $\mathbb{E}s_{t+1}$. In addition, as econometric techniques improved, more sophisticated estimation techniques were used by researchers, namely Clarida and Taylor (1997); Clarida *et al.* (2003) and Sweeney (2012).

Clarida and Taylor (1997) used a time series of forward exchange rates, with intervals of 4, 13, 26 and 52 weeks, and managed to beat a naive random walk model in a linear econometric framework; the results were 40% better then the predictions of the random walk model. Furthermore, Clarida *et al.* (2003) used the same interval series but examined them with the nonlinear modelling techniques and again they concluded that the forecast from the non-linear model was better than the forecast of the random walk, even in the short run, by 27-31% over the horizon of 4 weeks and 68% at 52 weeks over the 5 week horizon; the forecast performance increased as the forecast horizon increased.

## 2.2. Empirical Evidence for Exchange Rate Models

### 2.2.1. Empirical Testing of the Monetary Class of Models

Frenkel (1976) studied the exchange rate of the German Mark-U.S. dollar for the 1920s (the German hyperinflation period) and found strong evidence in favour of the monetary model (flexible price). Furthermore, researchers such as Bilson (1978); Dornbusch (1979) studied data, up to the 1970s, by estimating the model using data of the recent float for the major exchange rates, and all found strong evidence for the flexible price monetary model. Moreover, the flexible price monetary model's empirical performance began deteriorating and became ineffecient of providing a meaningful estimation of the movements in the exchange rates (Frankel and Jeffrey, 1993). The flexible price monetary model performed poorly in estimating the dollar-Mark rate and often produced coefficients implying that during the period when the German money supply increased there was an appreciation of the currency. Some researchers attributed this to the misspecification of the econometric model, while others argued that the substantial surpluses and deficits in the current account for the period under consideration generated significant wealth effects which are not properly addressed by the monetary model (Frankel, 1982*b*; Frankel and Jeffrey, 1993). Furthermore, researchers such as Driskill (1981) studied beyond 1970 and still found favourable results for the data covering the period 1973 to 1977 for the Swiss franc-U.S. dollar, while Backus (1984) studied the U.S. dollar-Canadian dollar exchange rate data for the period 1971 to 1980 and found little evidence supporting the flexible price monetary model.

Many researchers, such as Meese and Rogoff (1988) and Edison and Pauls (1993), further worked on monetary models concluded that the failures of the test resulted from the omission of the variables that are the key determinants of the equilibrium of real exchange rate or risk premium (Edison and Pauls, 1993). Band-spectral regression techniques are used by Baxter (1994), who found a significant positive correlation between the real exchange rate and real interest rate differentials on frequencies between six to thirty-two quarters and *trend* on frequencies of more than forty-two quarters.

During the 1990s, MacDonald and Taylor (1993), in an influential paper, studied a number of exchange rates by deploying dynamic modelling techniques and multivariate co-integration analysis and found supportive evidence of the monetary model for the exchange rate equilibrium; this equilibrium is where the exchange rate converges.

Taylor (1995) suggested that the effectiveness of the co-integration techniques proposed by the study, as discussed above, are very subjective because the robustness of these studies across various exchange rates and sample periods has not been examined. Flood and Rose (1995) studied the high volatility of exchange rates under floating exchange rates, and argued that any proposed exchange rate model should include underlying economic fundamental variables that are as volatile as the exchange rate during a floating exchange rate regime.

The authors named above find small differences in the volatility of economic fundamentals, as suggested by the sticky-price monetary model and the flexible price monetary model across different nominal exchange rate regimes for a number of OECD countries exchange rates. Baxter and Stockman (1989) studied a number of macroeconomic aggregates for 49 countries in a time series over the post-war period. Although, their study found that the real exchange rate under flexible exchange rates was more volatile than under the nominal exchange rate system. Baxter and Stockman (1989) also found no systematic differences in the behaviour of macroeconomic aggregates under alternative exchange rate arrangements. It can be concluded that there are speculative forces at work in the foreign exchange market, which cannot be explained by the normal basic fundamentals of the macroeconomics (Taylor, 1995).

### 2.2.2. Empirical Testing of Portfolio Balance Model

In the literature, fewer empirical studies have been performed on the portfolio balance model than on the monetary models of exchange rate determination. Most probably, this is because of the problems faced by researchers while converting the financial data of the real world into the portfolio balance model. Researchers faced many methodological issues such as the selection of the non-monetary assets for inclusion in the model and ensuring the availability of the data on a bilateral basis. Researchers such as Branson *et al.* (1977) studied many major exchange rates using the reduced form of the portfolio balance model that is logically a new version of the business model version, in order to determine the exchange-rate by deploying a cumulated stock of foreign asset current accounts. For the 1970s float, it was found that the estimates for the coefficients were poor and frequently insignificant and there were constant problems of residual autocorrelation. Another reason was the inadequate substitutability of domestic assets with the foreign assets assumption in the portfolio balance model. This corresponds to the assumption that the disparity between the interest rate differentials (domestic and foreign) and expected appreciation are due to the existence of a risk premium, and the portfolio business model expresses the risk premium as a function of the relative debt (between foreign and domestic) outstanding. Therefore, another substitute for testing portfolio balance model is the testing of indirect relationships for the portfolio balance model.

Domínguez and Frankel (1993) studied the effectiveness of the portfolio balance model in the determination of the exchange rate, for U.S. dollar-Swiss franc and U.S. dollar-Mark for the period of the 1980s. They attempted to measure the risk premium by using survey data in a modified portfolio balance model. They demonstrated that the resulting empirical model complied with the portfolio balance model, they basically introduced a further assumption, in the context of the investor, of mean variance optimisation. Domínguez and Frankel's (1993) study is also consistent with the empirical studies testing exchange market efficiency in the foreign exchange market, that is, the significant existence of the non-rational expectations and foreign exchange risk premia.

### 2.2.3. Testing Equilibrium and Liquidity Models

When preparing an equilibrium model to be specified and tested, it is necessary to make a set of assumptions, like a specific utility function or uniform preferences, which are not relevant in the real world.[30] Although the estimates derived from the models are valid. Therefore, the researchers peruse the study of equilibrium model in a broad sense, instead of some specific impression of the exchange rate behaviours of equilibrium models.

Fundamental facts regarding the recent float of exchange rates include the significant correlation of the change in the nominal and real exchange rates and high volatility in the real exchange rate, and that both lack the characteristic of strong mean reversion. Both equilibrium and sticky-price monetary model have the potential of explaining the variability in the nominal and real exchange rate in addition to the variability in the relative price. Researchers, when testing the equilibrium model, argued that the difficulty faced in rejecting the non-stationary hypothesis of the real exchange rate is evidence in support of the equilibrium model and again in negation of the sticky-price model.

Stockman (1987) argued that there were two assumptions when describing the consistency in nominal and real exchange rates within the framework of sticky price models over the recent float. The first is that the variation in the nominal exchange rate arises largely because of the constant real disturbances, and second is that they are due to the implausibly sluggish price. However, equilibrium models are not affected by

[30]The utility function is expressed mathematically as a function of real goods consumption (in basic units; such as kilogram, litres, and so forth).

consistency in the nominal and the real exchange rate movements.

Neutrality of the exchange rate with respect to the exchange rate regime is one of the testable areas of the simplest equilibrium model. The reason for this is that real variable such as technology and taste determine the real exchange rate, and this behaviour is not bounded by whether the exchange rate is pegged or allowed to float freely. Major exchange rate movements during the recent float are observed to be more volatile.

Stockman (1983) studied 38 countries, covering various sample periods and concluded that volatility seems to be higher under a normal exchange rate regime.[31][32] Nevertheless, the results are not sufficiently significant to reject the simplest equilibrium model.[33] Stockman (1983) also added that regime neutrality assumptions are excessively restrictive when presented in a fully specified equilibrium model. These assumptions include: no real effect of inflation, completely flexible prices, Ricardian equivalence, no wealth-distribution effects of nominal price changes, identical sets of government policies under different exchange-rate systems, and no real effects of changes in the level of the money supply.footnoteRicardian equivalence, (also known as the Barro-Ricardo equivalence proposition) is an economic theory which proposes that when the government tends to stimulate demand by increasing expenditure (debt finance) the demand remains unchanged. This effect is because that the public know that this debt will be paid in future from taxes and therefore they anticipate that the tax rate will be higher in the next periods. Therefore, the public will save excess money in order to adjust consumption against high taxes in the

[31] Including those countries, whose currencies remained pegged to the dollar after 1973.
[32] See Mussa (1986); Baxter and Stockman (1989)
[33] Those countries that experience greater real disturbances are more likely to adopt a flexible exchange rate system.

future. On the grounds that all these assumptions are very unlikely to be met in practice. Therefore, Stockman (1983) suggested the development of the equilibrium model with the provision of these assumptions and rejected the simplest class of equilibrium. Stockman (1983) observed that those countries, which used a fixed exchange-rate mechanism instead of a floating one, tend to establish efficient controls on capital flows of trade in order to manage the losses of foreign reserves. Hence, any disturbance that could shift the preference of domestic goods towards foreign goods will increase the chances that the country will introduce trade or capital restrictions that will result in raising the prices of domestic goods relative to the prices of foreign goods.

Inter-temporal substitution, stimulating the demand of domestic goods, will facilitate the offsetting of the direct effect of disturbances, which may raise the prices of foreign goods and result in the reduction of real exchange rate movement.[34] Hence, pegged exchange rate countries will experience lower volatility in real exchange rate than countries with flexible exchange rate mechanisms.

Eichenbaum and Evans (1995) and Grilli and Roubini (1992) studied the implication of the liquidity models for the U.S. and G-7 countries respectively. The results of these studies suggest that unanticipated monetary contractions will result in a domestic currency appreciation and an increase in domestic interest rates in both real and nominal terms. This is concluded by the most equilibrium models in which nominal shock may not affect real variables, including liquidity models with the cash in

[34]Intertemporal substitution is an economic decision in which the consumer foregoes the current consumption and saves in order to consume in the future; or, in technical terms, the process of maximising the utility by resource allocation across time.

advance constraint. Although liquidity models and sticky price monetary models are seems to be equivalent in the context discussed above, generally, the simplest equilibrium models are rejected by the empirical evidence.

The empirical evidence on exchange rate models is relatively mixed, due to the fact that some researchers conducted empirical tests using different exchange rates for different periods with various time intervals, within a given model. Therefore, some researchers found evidence in support of the underlying model, whereas others were unable to interpret their results in favour of exchange rate models' having any ability to forecast the future exchange rate. In well-known studies, by Frankel (1984) and Frankel and Jeffrey (1993), modified the monetary model of exchange rate determination, and replaced the interest rate differential $i - i^*$ with price inflation expectation differential i.e., $pe - pe^*$, put these together with the characteristics of portfolio balance model, and produced the following model:

$$\begin{aligned} s = \frac{-\alpha}{\Theta\beta + 1} + \frac{1}{1 + 1/\Theta\beta}(m - m*) - \frac{\eta}{1 + 1/\Theta\beta}(y - y*) \\ + \frac{\sigma + 1/\Theta}{1 + 1/\Theta\beta}(pe - pe*) - \frac{1}{\Theta - 1/\Theta\beta}(i - i*) + \frac{1}{\Theta\beta + 1}(b - f) \end{aligned} \tag{2.9}$$

This so-called fully flexible price monetarist version hypothesises that the parameters $\Theta$ and $\beta$ approach infinity, and this infinitely leads to the above equation 2.9 that is the flexible price monetary equation. However, researchers in favour of the sticky price monetarist model suggests that parameter $\Theta$ is less than infinity, while $\beta$ is infinite, which implies that the above equation 2.9 will result in the real interest rate differential equation. Researchers also suggest that in the sticky price portfolio balance model the parameters $\beta$ and $\Theta$ are less than infinite; thus, in relative terms, the bond supply has an impact on the exchange rate, based on the sticky price portfolio model. The above equation can be modified into the following version so that it can be regressed against the exchange rate.

$$s = \beta + \beta_2(m - m*) + \beta_3(y - y*) + \beta_4(i - i*) + \beta_5(pe - pe*) + \beta_6(b - f) + \mu_t \tag{2.10}$$

Frankel and Jeffrey (1993) used the above equation in a study of a sample period from January 1974 to September 1978 using monthly data, and studied the dollar-Mark with the above regression model. The same research set-up was also used by Pilbeam (1991), who studied the Frankel and Jeffrey (1993) equation for USD-GBP for a sample period from January 1973 to December 1984. Both studies showed incorrect parameter signs. The conclusions of both of the studies imply that the empirical relation between interest rates and price expectations is not clear-cut for either exchange rate for the stated periods.

## 2.3. Exchange Rate Determination: Other Techniques

### 2.3.1. Exchange Rate Models: A Forecasting Analysis

Based on the coefficients obtained from Equation 2.10, it cannot be concluded that the model performance from a class of exchange rate models proved unsuccessful for forecasting purposes. The seminal work of Meese and Rogoff (1983) is the most important piece of research in the context of the evaluation of exchange rate models. Meese and Rogoff (1983) examined the forecast ability in a statistical framework and compared the forecast with the naive random walk model. Pilbeam (1991) replicated the Meese and Rogoff (1983) study for the USD-GBP exchange rate. He examined three exchange rate models, i.e., the flexible price monetary models, the real interest rate model, and the sticky price portfolio balance model, in order to forecast, using Frankel and Jeffrey's (1993) equation to estimate the exchange rate. Pilbeam (1991) examined the forecast performance of the exchange rate models on the short horizon, one period ahead, using a quarterly dataset from January 1979 to March 1988. A rolling regression technique was used; this re-estimates the parameter for each time period $t$, to forecast the exchange rate at $t + 1$. The forecasts of the model is evaluated in the widely-used statistical measure of root mean squared errors.[35] The studies concluded that on the basis of root mean squared error, a naive random walk model has superior forecasting power to the exchange rate fundamental models.

Many researchers including Meese and Rogoff (1983); Backus (1984); Frankel (1984) and Pilbeam (1991) studied various exchange rates coupled with various sample durations and horizons. Yet they were unsuccessful in their attempts to produce a better forecast from the exchange rate model rather than those produced by naive random walk models. However, some of the researchers managed to beat the random walk model. These included MacDonald and Taylor (1994), who outperformed a random walk model by monetary model forecasting using Mark-dollar parity. They used relatively sophisticated dynamic specification of the econometric model. Although they managed to obtain a better forecast, the margin is relatively small and these results could be affected by time specific or sophisticated econometric techniques. Various reasons have been given by researchers

[35] $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}}$

to explain the failures of the exchange rate model. These include the complex dynamics of monetary and fiscal policy and their interaction with the macroeconomic policies across countries. As per the EMH, if new information arrives between time $t$ and $t+1$, which would transform the expectation about the future rate. One of the most important reasons specified by researchers is that great change in the financial structure of international finance, performance, and interaction of economies, could cause considerable disturbance to exchange rate.

### 2.3.2. The *News* Approach to Modelling Exchange Rates

The fundamental models of the ex- change rate determination, in terms of forecasting, did not perform well empirically. Whereas, researchers have been successful in the modelling of exchange rate behaviour in the context of the *news* approach. One of the most important aspects of the news approach is that it combines the *efficient market hypothesis* with exchange rate determination models. It has been suggested that the best way to model exchange rate movements is by assuming that the foreign exchange market is fully efficient and EMH completely holds; this assumption entirely eliminates the possibilities of all *ex ante* profit opportunities. Therefore, any movement in the exchange rate can be attributed to the arrival of news/information. Pioneering work on the *news* models was conducted by Dornbusch *et al.* (1980) and Frenkel (1981*b*), who modelled the exchange rates using different approaches, but results from both of their studies support the great impact of *news*.

The *news* approach theory is underpinned by the EMH. Assuming that the foreign exchange market accords with the efficient market hypothesis, then the *news* modeling hypothesis states that the forward exchange rate should be equal to the future spot exchange rate and all the information is embedded into the spot exchange rate in real-time, with no risk premium, and then any change in the exchange rate is due to the arrival of new information. Alternatively, it could be said that any change in the exchange rate price is due to the fact that there is an unexpected change in the underlying economic fundamentals. This can be modelled as below:

$$s_t - f_{t/t-1} = \beta + \beta_2 uX_t + \beta_3 uY_t + \beta_4 uZ_t + \mu_t \tag{2.11}$$

where, $s_t$ is the log of the spot exchange rate at time $t$, $f_{t/t-1}$ is the log of the forward exchange rate for a time $t$ at time $t-1$, $X$, $Y$ and $Z$ are the log of unexpected changes in the underlying economic fundamentals.

The main problem in the *news* model presented in equation 2.11 that is faced by the researchers is to compute the unexpected change in the underlying economic fundamentals. This issue was resolved by the expected change in the underlying fundamentals. They already knew the actual change; therefore, any difference between the expected change and the actual change is the unexpected component. Alternatively, the expected spot rate (forward exchange rate at time $t$) is given by the forward exchange rate in the previous period. Hence, the unexpected component can be computed by subtracting the expected spot rate from the actual sport rate, and the difference will be the unexpected component of the news.

Furthermore, while testing this *news* phenomena, the researcher first needs to identify what $X, Y$ and $Z$, the underlying economic fundamental variables, are. This provides an opportunity for the researcher to select a set of variables from the exchange rate model he is interested in testing. Therefore, theoretically, the *news* approach is capable of incorporating all of the exchange rate determination models. Another constraint in testing the *news* model is defining the proxies for the unexpected change. This constraint has been overcome by researchers using publicly available forecasts, as used by Dornbusch *et al.* (1980), who used six-month OECD[36] forecasts of the expected economic growth rate and current account balance, from which they computed the expected component. The expected component can also be computed using econometric techniques such as regression and auto-regression, but these econometric techniques are not very popular because the expectations depend on defining a good model to forecast the underlying economic fundamental variable X.

The results of the seminal studies of the Dornbusch *et al.* (1980) and Frenkel (1981*b*) are in support of the *news* approach. Basically, they found that any unexpected change in the underlying economic fundamentals leads to an unexpected change in the exchange rate; the coefficients of this relationship are significant and have the correct signs. However, the selection of the economic fundamentals was not based on any of the traditional exchange rate models. Edwards (1982) studied the *news* approach in a real interest rate differential model; the regression model is as below:

$$s_t = \beta_1 f_{t/t-1} + \beta_2(um - um^*)_t + \beta_3(uy - uy^*)_t + \beta_4(ui - ui^*)_t + \mu_t$$

where $f_{t/ti1}$ is the one period ahead forward exchange rate at time $t-1$, $um$ is the log of an expected change in money supply, $uy$ is the change in income, $ui$ is the unexpected change in domestic real interest rate. The

[36]OECD stands for Organisation for Economic Cooperation and Development. It is an international economic organisation comprising of 34 countries in order to stimulate economic growth and global trade. It was established in 1961.

asterisk denotes the foreign country.

The results of Edwards (1982)' study were in general support of the *news* approach, but there were a few discrepancies such as incorrect signs for the unexpected changes in the real interest rate differential and they were not statistically significant. MacDonald (1983) studied the news model using six exchange rates against the U.S. dollar for a sample period starting from the $1^{st}$ quarter of 1972 to the $4^{th}$ quarter of 1979. MacDonald (1983) found that the unexpected change in the monetary fundamentals were statistically significant in explaining the unexpected change in the exchange rate but sometimes gave the wrong sign. Furthermore, Edwards (1982) and MacDonald (1983) found that in some cases the regression coefficients were significant, when the lagged news term was used in order to explain the unexpected change in the exchange rate. This implies the weak form of the efficient market hypothesis in that the new information is not immediately incorporated into the exchange rate.

Recent studies on the *news* approach include Ehrmann and Fratzscher (2005), who studied the impact of news on the dollar-Deutsch mark for a sample period from January 1993 to February 2003. They used a money market survey on the expected announcements for 25 economic factors and subtracted them from the actual change to obtain the un- expected component. With the help of these 25 proxies they managed to ex- plain 73% of the change in the exchange rate movements. They suggested that when testing the *news* model, it was important to use real-time data, because the revised data is typically published/released months after the real announcement. They also observed that the impact of news on the exchange rate varies according to the condition of the market at the time of announcement, finding that in times of high volatility the announcement of news has a greater impact on the underlying exchange rate.

Predominantly, the *news* models of exchange rate determination which managed to blend with the fundamental model of exchange rate determination together with the efficient market hypothesis, provided a better explanation for the changes in the exchange rate. The stand alone results of either the fundamental exchange rate models and market efficient hypothesis demonstrate little empirical evidence in support of the model and hypothesis. Whereas, when combined together, the results, to a certain degree provide some empirical support.

### 2.3.3. The Predictability of Exchange Rate Movements

As discussed in the previous section, the fundamental models of the exchange rate determination failed to predict the exchange rate movement, particularly in the short run; therefore, the relatively recent literature has focused more on the prediction of exchange-rate movements over the short horizons. One of the most important research papers on the predictive ability of the exchange rate over long horizon, was that of Mark (1995). He deployed the following model to estimate the parameters, in order to forecast the exchange rate over various horizons:

$$s_{t+k} - s_t = \alpha_k + \beta_k(z_t - s_t) + \mu_{t+k} \tag{2.12}$$

where $s_{t+k}$ is the $k$-step ahead exchange rate forecast, $s_t$ is the spot exchange rate, $z_t$ is the underlying fundamental variable significant for exchange rate determination, for example:

$$z_t = [(m - m^*) - \eta(y - y^*)]$$

where $m$ is the money supply, $y$ is the national income, and $*$ denotes the foreign country. This equation is from the monetary model of exchange rate determination, as in this equation $\eta$ imposes the restriction that income elasticity of money demand symbol is equal to unity. Yet this term can removed, and $\mu$ is the error term (random and normally distributed).

If it is assumed that the equation above represents the economic fundamentals and then one should expect that $\beta$ in the equation 2.12 should be greater than 0 ($\beta > 0$) and statistically significant, and, inline with the underlying hypothesis, the value of the $\beta$ should increases as the time horizon increases. However, if the $\beta$ in equation 2.12 is equal to 0 i.e. ($\beta = 0$), then this means there is mean reversion in the exchange rate, and this mean reversion is unrelated to the economic fundamentals. Furthermore, it can be noted in the above equation that the log of economic fundamentals is utilised in order to predict the future exchange rate over $k$ periods, therefore, the error correction methodology is applied. Mark (1995) studied the Canadian dollar, Deutschmark, Yen and Swiss franc for quarterly sampled data, for a period from the $2^{nd}$ quarter of 1973 to the $4^{th}$ quarter of 1991, against the U.S. dollar, using 1, 4, 8, 12, and 16 quarter ahead forecasts.

Mark (1995) found that the estimates of $\beta$ in the equation 2.12, for all exchange rates, are greater than 0 and increases as the time horizon increases $k$. In addition, the explanatory power of the model increases with the time horizon, $R^2$. One of the main drawbacks of the Mark's

(1995) study is that the coefficients are not statistically different from 0. Mark (1995) justified this by sating that the insignificant coefficients may be caused by the small sample size. However, regarding the forecast, Mark (1995) managed to beat the naive random walk model using the forecast of the Deutschmark, yen and Swiss franc over a horizon of four years, utilising the monetary fundamental model, although, in the case of the Canadian dollar, the random walk model still managed to outperform the monetary fundamental model. Mark (1995) also concluded that the economic fundamental models of exchange rate determination perform better in supplying the forecast of the future exchange rate.

Furthermore, in a similar set-up, Mark and Sul (2001) studied quarterly data for a period from the $1^{st}$ quarter of 1973 to the $1^{st}$ quarter of 1997 for a 19-country exchange rate panel. They found evidence in favour of the monetary model of exchange rate determination in the long run. Moreover they suggested that the monetary models of exchange rate determination perform better than purchasing power parity modelling, particularly in a long horizon set-up. Mark and Sul (2001) demonstrated that out of sample forecasts of the monetary model were better than the random walk model, with a one period ahead forecast. Although the improvement was very marginal, 13 out of 18 currencies reflected this improvement. In addition, the purchasing power parity forecasts for the period ahead show precisely the same marginal improvement over a random walk model. The forecasts of the monetary model of exchange rate determination clearly outperform the forecast of the naive random walk model. Over a 16th quarter investment horizon, the monetary model decisively beat the naive random walk model in 17 out of 18 currencies. Critically, success over the random walk model is only valid if either the Swiss franc or the U.S.

dollar is used as *numeraire* currency.[37] Conversely, if the Japanese yen is taken as the numeraire currency, the random walk model outperforms the monetary model of exchange rate determination over the quarterly investment horizon, as well as beating the PPP and the monetary model of exchange rate over a 16 quarters horizon. Another criticism, made by Faust *et al.* (2003), is that, if the original release date of the underlying economic fundamentals are used, rather than the fully revised dates (which are not available to the market participants at the time $t$), then the results of Mark (1995) show deterioration, particularly for the Deutschmark and the yen against the U.S. dollar. Faust *et al.* (2003) also demonstrated that the forecasts of the exchange rate deteriorate using real-time data rather than published/ex post data, and almost all of the studies regarding exchange rate forecasts before Faust *et al.* (2003) used ex post published data.

A further comprehensive study was conducted by Groen (2000), who used pooled-panel and cross-sectional data for a sample period from the $1^{st}$ quarter of 1973 to the $4^{th}$ quarter of 1994, for a group of 14 countries using the following monetary model:

$$\overline{\triangle s_t} = \beta + \beta_1 \overline{\triangle m_t} + \beta_2 \overline{\triangle y_t} + \mu_t \tag{2.13}$$

where $\overline{\triangle s_t}$ is the $1^{st}$ difference of spot exchange rate and $\overline{\triangle s_t}$ and $\overline{\triangle m_t}$ is the differential of money and income $\mu_t$ is the random error term.

Using the cross-sectional data analysis techniques Groen (2000) estimates Equation 2.13. Equation 2.13 is the average change in the exchange

[37] *Numeraire* represents a unit of account. It is a term of French origin normally refers to *money*, *coinage* or *face value*. The basic concept of *numeraire* is usually applied to a single good. That good becomes a base unit, then other goods are valued against the base/*numeraire* good. Normally money serves as a *numeraire* good.

rate $s_t$ related to average differential money supply $m_t$ and the average differential change in the real income $y_t$, using either the Deutschmark or the U.S. dollar as numeraire currency, and provides long-run support for the monetary model. The result of Groen's 2000's supports the monetary model forecast in the long run. The results of the cross-sectional estimate show that the long-term prediction of the exchange rate by the monetary model perform very well; the coefficients are in line with the existing theory that the $\beta_1$ coefficient estimate is statistically significant, and equal to 1 and $\beta_2$ is negative, as predicted by many monetary models. Both estimation techniques, pooled and cross-sectional models, demonstrate a good long-term predictive ability, and explanatory power of the models are very good, $R^2$.

In addition, another notable research paper in the same vein was produced by Rapach and Wohar (2002). They took a somewhat different approach to that of Mark (1995), and studied the forecasting ability of the exchange-rate monetary model using 14 currencies against U.S. dollars, using long-term data in order to support the validity of the exchange rate monetary models for a sample period from 1880 to 1995. In general, their results supported the monetary class of exchange rate determination model for Spain, France, Netherlands, and Italy, whereas, a moderate support was found for Portugal, Finland, and Belgium, and weak support for the Swiss franc. However, this extensive study failed to provide any support for countries such as Denmark, Canada, Norway, Australia, Sweden and the UK. One of the main criticisms of Rapach and Wohar (2002) is that the long horizon includes various exchange-rate regimes, i.e., the gold standard, the Bretton Woods agreement and the recent float. The estimation model is given below:

$$s_t = \beta + \beta_1(m_t - m_t^*) + \beta_2(y_t - y_t^*) + \mu_t$$

As discussed above, the monetary differential coefficient should be equal to 1, $\beta_1 = 1$, and the coefficients for the income differential should be equal to -1, $\beta_1 = 1$. The result of the study, in terms of coefficients, varies and does not follow the underlying theory's suggested coefficients.

Other studies on the predictive ability of the monetary models of exchange rate determination includes Kilian (1999) and Kilian and Taylor (2003), who used long run regression-based models and found mixed results. Later studies, using a simple PPP fundamental model that allows non-linearity (as in Mark (1995)) gave robust results that support the longer predictive ability of the nominal exchange rate and suggest that PPP holds valuable information to predict long-term exchange rates. Kilian and Taylor (2003) argued that the monetary models of the exchange rate are based on linearity between the macroeconomic fundamentals and exchange rate, and suggested that there could be a non-linear relationship between the economic fundamentals and exchange rates. Kilian and Taylor's (2003) model allows for the a non-linear adjustment mechanism for the exchange rate to deviate from its PPP path. They studied a number of bilateral exchange rates using quarterly data and found that the random walk model was beatable over a horizon of 2 to 3 years, but that it was not beatable in the short run, normally for a period 6 months or less, as suggested by Meese and Rogoff (1983).

Based on the above empirical evidence, using sophisticated econometric techniques, it can be concluded that exchange rates are predictable over the long horizon using monetary fundamental models, whereas it is very difficult to outperform a naive random walk model over the short horizon with a fundamental model of exchange determination, such as a monetary model. Even for the medium term, the results are mixed and predictions from fundamental models cannot become a ‘stylised fact’. However, these studies demonstrate that economic fundamentals provide better forecasts of the exchange rate over long horizons.

### 2.3.4. Alternative Approach to Modelling Exchange Rates: The Role of Chartists and Fundamentalists

Due to the poor performance of exchange rate determination models in forecasting exchange rate that could materially contribute to the policy makers’ and market participants’ decision making process, researchers such as Goodhart (1988); Allen and Taylor (1990); De Grauwe (1990); Pilbeam (1995) studied the different approaches opted for by market participants, including the *fundamentalists* and *chartists*. These researchers studied the role played by these two groups, in order to establish the efficiency of these techniques in exchange rate determination.

The group of market participants referred to as *chartists* examine a variety of charts related to the exchange rate, and claim that they successfully predict the future pattern of the underlying exchange rate. The *chartists’* analysis resembles an art rather than a scientific examination. *Chartists* claim that the future exchange rate is predictable on the basis that specific patterns of the underlying fundaments repeat themselves and correct recognition of the relevant patterns in the charts leads to a successful prediction of the asset under consideration. These specific patterns are named by the chartists and Feeny (1989) provided a comprehensive study of these pattern terminologies, which include *ascending triangle*, *triple bottom*, *double top*, and *head and shoulder*. *Chartists* rely on recent past behaviour of the *economic fundamentals*, which include interest rate, money supply, national income and the exchange rate itself. There has been a great deal of criticism of the chartist approach in the literature of empirical finance and chartists are also referred to *non-fundamentalists*.

Unlike *chartists*, *fundamentalists* believe that the foreign exchange market is efficient and that the efficient market hypothesis holds; therefore, examining past information is of no use. Hence, *fundamentalists* suggest that the best way to predict the future spot exchange rate is to study the prospects of the underlying economic fundamentals such as the prospects of balance of payments, inflation rate, future interest rate, etc. Basically, *fundamentalists* study the prospective development of the underlying economic fundamentals. Frankel and Froot (1990) studied the *fundamentalist* and *chartist* approaches to decision making and argued that in times of certainty, or less volatility in the foreign exchange market, the *chartist* approach overcomes the *fundamentalist* approach, whereas in periods of high volatility or uncertainty in the foreign exchange market, the *fundamental* approach is the dominant approach in the determination of the exchange rate.

A number of researchers have studied the *fundamentalist* and *chartist* approaches and arrived at mixed results, favouring both approaches. Allen and Taylor (1989) and Allen and Taylor (1990) conducted a thorough survey of *chartists* in the London foreign exchange market and found that most traders utilise the *chartist* approach to forecast the exchange rate in the short and medium runs, while the *fundamentalist* approach is used to forecast the exchange rate in the long run. They collected data from *chartists* each Tuesday for one week ahead forecast of the U.S. dollar-yen, U.S. dollar-mark and sterling-U.S. dollar, from June 1988 to March 1989. They found that *chartists* normally under-predicted the rising market and over-predicted a falling market. Another important feature of *chartists* observed by Allen and Taylor (1990) was elasticity; they reported that the elasticity of the forecast was less than 1%, and that if the market rose/fell by 1%, the following period forecast rose/fell by less than 1%. They also reported that one of the *chartists*[38] in the London foreign exchange market managed to outperform the random walk model. However, Allen and Taylor (1990) found that, in general, the forecasts of the *chartists* were worse than the forecast from a random walk model. They concluded that the forecasts of the *chartists* did not outperform the fundamental exchange rate determination models in the long-run.

Another aspect of forecasts is to evaluate them in economic terms, to assess the profitability of the forecasts obtained from the *fundamentalist* and *chartists* approaches. One study examining the economic evaluation of the *chartist*, *fundamentalist* and *simpleton* approaches in the context of the relative investment performance was conducted by Pilbeam (1995), using quarterly data from January 1973 to December 1994. *Chartists* were classified into three traders' groups, each using a different approach in forecasting the exchange rate, but generally all of these three approaches involved reading and interpreting past charts. Similar to the *chartists* the *fundamentalist* investors were classified into three groups, each using a different *fundamentalist* exchange rate determination models; the flexible price model, Frankel's sticky-price monetary model, and the portfolio

[38] Allen and Taylor (1990) called the *chartists* by the code name *Mr. M.*

balance model. Finally, the *simpletons* were also grouped into three investment categories. The *simpletons*' groups used simple investment assessment techniques, when making decisions about their investments. One of the groups place their investments into the currency that had showed highest returns in the previous quarter; the second group placed all of their investment into foreign exchange and left it there to earn an interest rate adjusted for the appreciation or depreciation of the underlying currency; and the third group of *simpleton* investors believed that the foreign exchange market followed a random walk and invested their funds in the high interest rate currency because they believed that, on average, no profit can be made on the movement of exchange rate. The results of the Pilbeam's (1995) study were unable to make a clear distinction between any of the models based on profitability and statistically, they were unable to reject the hypothesis that the return from all the three methodologies were equal. Although there were differences among the annual yields, it was not possible to differentiate them from each other.

Further, the *filter rule* is another approach used by market participants and testing the profitability of the *filter rule* is an alternative approach to testing market efficiency. The *filter rule* is a technical approach to trading in which a market participant buys and sells currency only if exchange rate movements of the underlying currency[39] retrogress by a least acceptable percentage. According to the theory of market efficiency, if a foreign exchange market is efficient and follows the conditions of uncovered interest rate parity, any profit should be eliminated by the cost if a *filter rule* strategy is adopted. Studies such as those of Dooley and Shafer (1984) and Levich *et al.* (1993), show evidence for the profitability

[39]This movement can be in either direction; if the price is going up then the market participant will take a long position (for only a certain percentage) and a short position if the market is going down.

of the *filter rule*; however, these studies do not indicate that when the filter rule is applied, riskiness in the substantial sub-period losses are not incorporated. Moreover, indirect findings on filter rule profitability were made by Engel and Hamilton (1990), who studied the dollar trend from the beginning of the 1970s until the end of the 1980s. They found consecutive large trends, which are susceptible to mechanical trading rules.[40] More recently, Sweeney (2012) studied the *filter rule* approach in a Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT), using U.S. dollar-Deutsche mark exchange rate. He found that the foreign exchange market was inefficient and demonstrated that an investment strategy using filter rule outperformed the naive random walk model.

## 2.4. Exchange Rate Determination: Recent Studies

### 2.4.1. Economic Fundamentals and Exchange Rates

For a vast period of time researchers in international finance have desired to formulate a model that forecasts the exchange rate, incorporating the conditions economic fundamentals. As discussed earlier, the majority of the empirical literature concludes that any model built for the estimation of the exchange rate cannot outperform basic random walk models. Some researchers conclude that the in the long run, economic fundamentals and exchange rates fluctuate together.[41] The perception regarding exchange rate predictability in international finance is that exchange rates are unpredictable. As discussed above, the empirical literature argues that the forward exchange rate contains valu- able information for the estimation

[40]Trends followed by the market participants using the trading rule.
[41]E.g., Mark (1995) and Mark and Sul (2001)

of real exchange rates. The uncovered interest parity (UIP) condition, involves a relationship be- tween the forward and spot exchange rates. The theory of UPI advocates that the change in the future exchange rate is perfectly and positively related to the forward premium. In contrast, empirical studies on this relationship find a negative relationship instead of the positive relationship dictated by the theory of uncovered interest rate parity. Furthermore, researchers such as Backus *et al.* (1993) and Backus *et al.* (2001). (2001) who studied this relationship, found evidence to support the predictability of exchange rates and concluded that the findings of a negative relationship in the earlier empirical literature were due to the forward premium often producing exchange rate predictability. Moreover, researchers concluded that the interest rate and the term structure of the forward exchange rate contained vital information for the estimation of the spot exchange rate.

The vast majority of the academic literature focuses on statistical measures of the accuracy of the exchange rate forecasting, while only a small proportion addresses the evaluation of the economic significance of exchange rate predictability.

The empirical literature to date on the economic significance of exchange rate predictability comprises only few papers, such as those of West *et al.* (1993), who conducted a study on utility-based evaluation of exchange rate volatility; Abhyankar *et al.* (2005), who also utilised a utility-based framework for the evaluation of exchange rate volatility to study long-run exchange rate predictability; and more recently, Della Corte *et al.* (2009) who comprehensively studied the short horizon predictive ability of the monetary models of exchange rate determination on monthly exchange rate with any portfolio-based approach using various measures for the returns and volatility. They found statistically significant evidence in favour of the monetary model, which they then compared with the benchmark random walk, and their findings supported the idea that exchange rates were predictable.

### 2.4.2. Microstructure Approach and Exchange Rate

Due to the poor performance of exchange rate determination model, researchers have suggested that the massive trading volume of the exchange rate could be the problem with the fundamental approach to determining the exchange rate. The traditional models of exchange determination do not account for any trading activity, mainly because trading is awarded no role in mapping macroeconomic variables when determining the exchange rate. A new approach was suggested, i.e., the micro-structure approach, the main difference of which to the fundamental-based approach is relaxing the underlying assumptions regarding information, players and institutions. The microstructure approach relaxes the efficient market hypothesis assumption, recognising that not all the information regarding the exchange rate is publicly available, and classifying market participants into various groups. It is argued that the trading mechanism is different and affects the prices. Flood and Taylor (1996) concluded that:

> “given the exhaustive interrogation of the macro fundamentals in this respect over the last 20 years, it would seem that our understanding of the short run behaviour of exchange rates is unlikely to be further enhanced by further examination of macro fundamentals. And it is in this context the new work on

> the microstructure of the foreign exchange market seems both warranted and promising."

The term *microstructure* is defined by O'Hara (1995) as the process and outcomes of exchanging assets under explicit trading rules. Two variables play a vital role in microstructure finance: order flow and spreads. The order flow is different from the volume, in that it is a signed transaction, and also referred to as excess demand. Microstructure theorists claim that the order flow conveys information about fundamentals from non-dealers to dealers, because the non-dealers/customers are the ones who analyse fundamentals. The second variable of the microstructure approach is the spread, as micro-structure theorists argue that this plays an important role in the determination of the exchange rate because market participants are intensely concerned with the management of trading cost.

The researcher argues that the implications of microstructure should be long-lived, that is when the order flow conveys information, the effect on the price and volatility should be long-lived. This is in line with the underlying fundamental theories that any new information will be permanently incorporated into the underlying asset price, whereas any pricing error will be temporary (French and Roll (1986), Hasbrouck (1991*b*)). In the foreign exchange market, Evans (1997), Evans and Lyons (2002), Rime (2000) and Payne (2003) demonstrated that the order flow has a significant effect on the exchange rate and that effect was long-lived. Thus, it can be argued that the implications of microstructure being long-lived is the most fundamental in terms of information transmission.

Microstructure finance tools have been used extensively by researchers in order to explain the crisis of 1987 (see Grossman, 1988; Gennotte and

Leland, 1990; Jacklin *et al.*, 1992; Romer, 1993). These researchers try to explain the stock market crisis of 1987 by relaxing all three of the underlying assumptions explained above. Basically, they try to answer three questions: i) what the information structure was at the time of the crash; ii) the extent of the heterogeneity of the market participants; and, iii) what the role of the institution in the crash was. These researchers successfully explained the crisis of 1987 with the help of microstructure finance theories.

Various methodologies have been utilised in the aforementioned studies by researchers in order to generate the evidence that supports the information mechanism of order flows. These studies addressed the effect of order flows on price and volatility and produced similar robust results. The use of a methodology that utilises the order flow to explain changes in the price is very common in the empirical finance literature, which also distinguishes between transitory effect or permitted effects on price.[42] Any permanent change in the price means that the change is due to the new information regarding the underlying fundamentals. This identification of pricing error as opposed to permanent effect was introduced by French and Roll (1986), who studied information arrival and volatility in stock returns. One of the other techniques used to segregate pricing error and permanent effect is to estimate the vector auto-regression model and test for innovations in order flow that have a long-term effect on price (Hasbrouck, 1991*a*). These identifications were studied by Evans and Lyons (2002) and Payne (2003) in the foreign exchange market and they concluded that the order flow innovation will indeed have a longer impact on foreign exchange prices.

[42]See French and Roll (1986)

Another method for evaluating the impact of order flow and the persistence in stock price has been applied in the foreign exchange market. This method includes studying the aggregate order flow to explain the price movements. Basically, this method aggregates all the transaction overtime and examines the impact on price, rather than asking whether an individual class of customer influences price. Studies such as those of Rime (2000) and Evans and Lyons (2002) applied this aggregate transaction technique in the foreign exchange market and found that the order flow does remain robustly related to changes in foreign exchange prices.

Another dimension of studying the micro-structure finance is to show that the order flow provides information on price volatility over the period the trade has taken place. It is well established that order flows contain private information and this private information is transmitted to the foreign exchange market using order flows. Andersen and Andersen and Bollerslev (1998) examined the volatility in a flexible framework, which was also applied by Cai *et al.* (2001) and Dominguez and Panthaki (2006). The main aim of the Andersen and Andersen and Bollerslev (1998) study was to capture the impact of news on the volatility of the daily exchange rate, controlling the noise for systematic intra-day patterns in the volatility. They found that news has a robust and direct impact on the volatility in the foreign exchange market. The theory of microstructure finance considers order flow as a measure of private information transmission into the foreign exchange market. The arrival of news, private and public information, was studied by DeGennaro and Shrieves (1997), Cai *et al.* (2001) and Bauwens *et al.* (2005).

### 2.4.3. Common Risk Factors and Foreign Exchange Market

As discussed in the previous section, there is a large body of literature, including the work of Hansen and Hodrick (1980) and Fama (1984), which documents the failure of uncovered interest parity. These studies concluded that an interest rate that is higher than usual leads to the appreciation of the underlying currency and foreign exchange market participants earn more profit by holding debt instruments from the currencies whose interest rates are generally higher than usual (see Cochrane, 2001). Therefore, market participants are always interested in knowing which currencies reflects an interest rate that is higher than usual in order to optimise their portfolios. Bansal and Dahlquist (2000) studied a large number of currencies and they found that country-specific attributes are very important in understanding the cross-sectional variations in currency risk-premia.

A number of studies have examined this phenomena by building portfolios of positions in currency forward contracts, arranged according to the forward discount (e.g., Lustig *et al.* (2011) used T-bills). Studies based on the failure of the UIP can be broadly classified into two main categories. The first attempts to understand the predictability of the exchange rate using the standard asset pricing framework based on systematic risk.[43] Backus *et al.* (2001) conducted the seminal work in this category and provided the empirical evidence that common factors do indeed account for the forward premium in the foreign exchange market. The second category of studies is based on the non-risk explanation of the failure of the UIP condition.

[43] (See Backus *et al.*, 2001; Harvey *et al.*, 2002; Alvarez *et al.*, 2009; Verdelhan, 2010; Viceira *et al.*, 2009)

Recent contributions on the failure of the uncovered interest rate parity condition have used fully-specified dynamic asset pricing models. These models specify a complete description of preferences and endowments. Studies using dynamic asset pricing models include those of Lustig *et al.* (2011) and Banti *et al.* (2012). Lustig *et al.* (2011) identified a slope in the exchange rate, finding that currencies with higher interest rates tend to fall on the identified slope, as compared to currencies with low interest rate loadings. The cross-section of the slope factor accounts for variations in the access return between the high and low interest rate currencies. They also confirm these findings with a no-arbitrage model of interest rates with two factors, one global and one country specific. They also concluded that the slope factor model identifies shocks in the currency market, that is, those shocks that are related to global equity market volatility. Banti *et al.* (2012) constructed a unique measure of global liquidity risk using institutional investors' order flow for a dataset of 20 U.S. dollar exchange rates. They demonstrated that the liquidity measure is a common factor in liquidity across currencies. They concluded that this liquidity factor is priced in the cross-section of currency returns, and they computed that approximately 4.7% of that risk in the foreign exchange market accounts for the liquidity risk.

## 2.5. Conclusion

Theoretically exchange rate models have performed very well over the last few decades, whereas the empirical analysis of these theories have been notoriously unrewarding, in particular in determining the exchange rate in the short-run. The failures of the exchange rate determination model suggest problems with econometric estimation techniques. However, recently with the help of new econometric techniques, the problem of estimation has been overcome to a certain extent in the long run, but still these sophisticated econometric techniques remain unable to predict the relationship between the exchange rate and economic fundamentals in the short-run.

There have been many studies on foreign exchange market efficiency with no risk premium, and uncovered interest rate parity in the short-run, with the empirical results of these studies rejecting the efficient market hypothesis (EMH). Therefore, the monetary models, which are based on the EMH and no risk premium assumptions, have been negatively affected by these findings. However, although the portfolio balance model accounted for the existence of risk premium and the departure from the uncovered interest rate parity condition, there is little empirical evidence to support the portfolio balance model against the monetary fundamental models. Empirical explanations of the risk premium in the fundamental models of exchange rate determination model have failed. The consensus that has been built regarding the exchange rate determination theories and models is that they provide incomplete explanations and that the movements in the exchange rate in the medium and short runs cannot be forecasted.

The empirical rejection of the exchange rate determination models does not necessarily mean that they are wrong. Merely the models of exchange rate determination are unable to account for all of the complexities of the exchange rate determination theories. Therefore, policy makers and market participants should not wholly ignore the limitations of the models nor should they rely completely on one exchange rate determination theory.

To date, the exchange rate determination in the medium and short-run remain unsolved. Whereas the theoretical aspects of modelling the exchange rate in the long-run have been proven successful. Recent research has also studied the various groups of market participants those who use diverse methods in order to forecast exchange rates. For example, *chartists*, *fundamentalists*, and *simpletons* have been shown to use various techniques to insights into the working of the foreign exchange market. More recently, studies using sophisticated modelling, asset pricing and portfolio management techniques have managed to beat the random walk models in terms of the economic value of the forecasts obtained from the fundamental models of exchange rate determination.

# Chapter 3.

# Economic Significance of Empirical Exchange Rate Models

This chapter examines the in-sample and out-of-sample performance of three structural Monetary Fundamental models of exchange rates. In particular it compares their forecasting performance, defined as their predictive ability from in an economic rather than a statistical capacity, to that of a Simple Random Walk Model. This is done using recent techniques in *Bayesian econometrics* and *computational finance*.

The breakdown of the Bretton Woods system in the early 1970's motivated Economists to consider the problem of forecasting exchange rates, in both the short and long term. Various theoretical models, which link exchange rates to economic fundamentals such as interest rates, money supply, trade balances, and output have been developed. Yet numerous empirical studies, including the seminal paper by Meese and Rogoff (1983), show that these models have not been able to outperform a bench- mark Random Walk Model. The study by Meese and Rogoff (1983) have encouraged many researchers to study exchange rate forecasting but they do not provide a consensus in favour of one specific structural model (see, for example, Diebold and Nason, 1990; Engel and Hamilton, 1990; West *et al.*, 1993).

Indeed, Meese and Rogoff (1983) reach the following conclusion on the relationship between exchange rates and economic fundamentals:

> "A random walk would have predicted major country exchange rates during the recent floating rate period as well as any of our candidate models."

Follow-up research mostly supports Meese and Rogoff (1983) and concludes that exchange rates are largely unpredictable. However, the majority of academic literature cited earlier (apart from West *et al.*, 1993) focused on the statistical measures of the accuracy of exchange rate forecasting. Empirical models may be statistically relevant. Yet they may not be appropriate for use as decision support tools, by investors or corporate treasurers. Therefore, a second line of research, beginning with West *et al.* (1993), has focused on finding empirical evidence in support of structural models when used for asset allocation and portfolio management (see Abhyankar *et al.*, 2005; Della Corte *et al.*, 2009).

This second line of research has produced empirical evidence that structural models perform better (both in-sample and out-of-sample) than a Simple Random Walk Model. However this must be treated tentatively due to the sensitive performance measures used. The most common measure has been the Sharpe Ratio.[1] These have limited validity, as a performance measure, if i) portfolio returns are not normally distributed (see Goetzmann *et al.*, 2007); ii) portfolios are dynamically adjusted (see Marquering and Verbeek, 2004; Han, 2006; Della Corte *et al.*, 2009).

This chapter utilises a new set of performance measures, termed *indices of acceptability* (Cherny and Madan (2009)) for assessing the performance of a portfolio. Such measures are entirely valid when returns are not normally distributed. They are computed after shocking (or *distorting*) portfolio returns using some appropriate distortion functions. These measures are used to evaluate the portfolios after using different econometric methodologies (specifically Bayesian Linear Regression and Bayesian GARCH) to compute the mean and variance of exchange rate returns. This represents both an important departure from and a significant con-

[1] Della Corte *et al.* (2009) is a notable exception

tribution to the literature cited earlier.

The forecasts are evaluated, moreover, after employing a trading strategy, which dynamically rebalances the portfolios. This is consistent with market practice and with Abhyankar *et al.* (2005). As these authors discuss the possibility that the results in the extant literature may be impaired by only considering static portfolio strategies when computing asset allocations.

Finally, in comparison to the ones used in Della Corte *et al.* (2009), the dataset and performance measures used here will be extended, in terms of the currencies considered as well as the time span of the data. The aim, therefore, is to illuminate whether the results in Della Corte *et al.* (2009) are driven by the sample selection, time-span of the data and/or performance measures used. A *mean-variance criterion* and new performance measures (indices of acceptability) are used. It will be concluded that monetary fundamental models of exchange rates have good forecasting power compared with a simple random walk model, when the economic significance of the forecasts are the basis for comparison and when used with the new performance measures.

## 3.1. Theoretical Background, Empirical Evidence and Methodological Issues

### 3.1.1. Economic Fundamentals and Exchange Rate: Theoretical Background

Various models, such as structural models, purchasing power parity (PPP) and portfolio balance models have been proposed to link exchange rates to economic fundamentals. Structural monetary models are based on the idea that increasing the home country (domestic) money supply would increase the spending of home country residents, which would, in turn, drive up domestic price levels.[2] This will result in a depreciation of the home currency in order to prevent the rise of cheaper imports into the home country.

Asterisks are used to denote foreign quantities. Let $M_0^{d*}$ be the demand (the superscript $d$ is for *demand*) for money in the foreign country, $Y^*$ be foreign income and $P^*$ be the foreign price level. The foreign demand for money $M_0^{d*}$ is proportional to foreign nominal income $P^*Y^*$:

$$M_0^{d*} = kP^*Y^*,$$

for some constant of proportionality $k$. Similarly, $M_0^d = kPY$ is the domestic demand for money. Let $M_0^{s*}$ (respectively, $M_0^s$) be the initial money stock of the foreign (respectively, domestic) country (the superscript $s$ is for *stock*). Setting the demand for money in each country equal to supply, $M_0^{d*} = M_0^{s*}$, $M_0^d = M_0^s$ and dividing to eliminate $k$, we have:

$$\frac{M_0^s}{M_0^{s*}} = \frac{PY}{P^*Y^*}$$

[2]See West *et al.* (1993); Abhyankar *et al.* (2005); Della Corte *et al.* (2009).

Under purchasing power parity, the level of prices, when converted to a common currency, will be the same in every country, i.e. $P = P^*Z$, where $Z$ is the exchange rate expressed as the domestic price of the foreign currency. Hence,

$$\frac{M_0^s}{M_0^{s*}} = Z\frac{Y}{Y^*} \Rightarrow Z = \frac{M_0^s/M_0^{s*}}{Y/Y^*}.$$

Denoting by small letters logs of quantities denoted by capital letters gives:

$$z_t = (m_t - m_t^*) - (y_t - y_t^*). \tag{3.1}$$

The structural monetary model of exchange rates in equation 3.1 states that the log of the exchange rate is the log of the relative money stock minus the log of relative real demand. Therefore, anything that tends to increase (decrease) the foreign money stock relative to the domestic, or shrink (expand) foreign demand for money relative to the domestic, will cause the foreign currency to depreciate, i.e., will cause $z_t$ to rise. An increase in the foreign money supply or a decrease in the domestic money supply will lead to the depreciation (appreciation) of the foreign (domestic) currency in the same proportion. Similarly, a rise (fall) in domestic real income will lead, *ceteris paribus*, to an appreciation (depreciation) of the home currency. Moreover, relative real income determines the demand for relative money between countries. Therefore, an increase (decrease) in domestic income has the same impact as a fall (rise) in foreign income. Monetary fundamental (or structural) models of exchange rates are frequently used in the literature on exchange rate forecasting.[3] Consider the following

[3]See, for example West *et al.* (1993) Mark (1995) Mark and Sul (2001) Abhyankar *et al.* (2005) and Della Corte *et al.* (2009).

model:

$$x_t = z_t - s_t \tag{3.2}$$

In equation 3.2, $z$ measures the *disequilibrium* of the economic fundamentals between the domestic and the foreign country. It can, therefore, be interpreted as the relative velocity between the two countries, while $x$ is the gap between nominal exchange rates and economic fundamentals. The larger the gap $x$, the further the exchange rate is away from the level suggested by economic fundamentals and the further it will have to move in the future in order to converge towards its long-run equilibrium level. In this case, $z$ describes this convergence at time $t$.

In this chapter, equation 3.2 is used as the basic underlying model relating exchange rate predictability to economic fundamentals. This structural monetary model is widely accepted in the empirical finance literature.[4] Three versions of this monetary model are considered here.[5]

According to the *Efficient Market Hypothesis* (EMH) asset prices should reflect all the information available at that given point in time. Closely related to this is the notion that asset prices should follow a random and unpredictable path, i.e., a random walk. Applying this to a time series of spot exchange rates, the following can be written:

$$s_t - s_{t-1} \equiv \Delta s_t = \mu_t \tag{3.3}$$

[4] See, for example, West *et al.* (1993); Mark (1995); Abhyankar *et al.* (2005); Della Corte *et al.* (2009).

[5] These versions of the monetary models are based on the monetary model presented in equation 3.4. The details of these three versions are presented in section 3.1.3, on *conditional mean & conditional volatility.*

where $\mu_t$ is noise.

Here, the random walk model in equation 3.3 is used as a benchmark for calculating one-month forward forecasts of exchange rates in order to compare these with forecasts based on the monetary models. Many papers, in particular Meese and Rogoff (1983), find that exchange rates are unpredictable and follow a random walk - especially in the short term. However, most of this literature is based on evaluating out-of-sample forecasts with statistical performance measures such as *root mean square error*. The present author argues that it is more pertinent to evaluate these forecasts based on their economic value - in other words, whether investors or corporate treasurers can use the forecasts as a decision-support tool. The following section addresses the empirical literature on the predictability of exchange rates and the economic value of these forecasts.

### 3.1.2. Empirical Evidence for the Economic Significance of the Exchange Rate Forecasts

Cornell (1977), Mussa (1979) and Frenkel (1981*b*), according to whom exchange rates are unpredictable.[6] In response to this Meese and Rogoff (1983) investigated the forecasting power of structural exchange rate models. They used observations from March 1973 to June 1981 for the dollar/yen, dollar/pound, dollar/mark and a traded-weighted dollar exchange rate. Their forecasts were mainly assessed in terms of root-mean-square error (RMSE), after using univariate and multivariate time series models.[7] They found that forecasts from a simple random walk model

[6]Mussa (1979) stated that "The natural logarithm of the spot exchange rate follows approximately a random walk," and concluded that the correlation found between the exchange rate and the economic fundamental in-sample tests are likely to be unstable in the long run.

[7]Unconstrained Vector Auto Regression

have lower RMSEs than a variety of univariate and multivariate models and concluded that:

> "We find that a random walk model performs as well as any estimated model at one- to twelve-month horizons"(Meese and Rogoff, 1983)

Some potential reasons for the failure of the structural models could be that they did not account for non-linearities, sampling error or simultaneous equation bias. This led researchers to conduct further studies but with little avail. Diebold (1988), for example, studied seven nominal dollar spot rates and found little evidence of linearities, whereas he found strong evidence in all exchange rate returns of auto-regressive conditional heteroskedasticity. Diebold and Nason (1990) used non-parametric techniques to forecast the spot exchange rates for ten major currencies against the U.S. dollar for the period after the 1973 float.[8] However, these techniques were not able to do better in terms of forecasting power than a simple random walk model. Engel and Hamilton (1990) studied the Deutschemark, the French Franc, and the British Pound from 1984 to 1988, using quarterly data. However, again, they found that their model was outperformed by a simple random walk model in the case of 4-quarter forecasts for the Deutschemark and French Franc.

More recently, Clarida *et al.* (2003) set up a three-regime Markov-switching vector equilibrium correction model for the spot exchange rate and the term structure of forward interest rates. They did this using weekly data for four major dollar exchange rates. They found that non-linearities in exchange rate dynamics and the term structure of forward premia played a significant role in predicting future rates. Clarida *et al.*

[8] in-sample and out-of-sample nonparametric forecasts.

(2003) used weekly observations for Euro-deposit rates for Germany, Japan and the U.S. from February 1982 to December 2000. This was done within a Markov- switching model framework, focusing on the out-of-sample forecast of the term structure of interest rates, and found robust evidence of asymmetries and nonlinearities in them. These are adjusted by a multivariate asymmetric two-regime Markov-switching model. They found that the term structure of interest rates contains significant information in out-of-sample forecasting.

The vast majority of the academic literature cited above focuses on statistical measures of the accuracy of exchange rate forecasting. Whereas only a small proportion evaluates the economic significance of the exchange rate predictability. Indeed, even when an empirical model is statistically appropriate for forecasting use, this does not mean that investors can employ it for asset allocation or portfolio management. West *et al.* (1993) focused on evaluating the economic performance of the forecasts as opposed to the statistical significance. They evaluated (weekly) out-of-sample exchange rate volatility for the Canadian Dollar, French Franc, Deutschemark, Japanese Yen, and British Pound from 1973 to 1989, as well as Euro-deposits from 1981 to 1989. They used mean-variance criteria based on the expected mean and volatility from a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model and reported some evidence in favour of structural models.

Abhyankar *et al.* (2005) investigated the forecasting ability of structural models over a long time span using Bayesian econometric models. Based on 10-year forecast horizons and using data covering a significant proportion of the period of floating exchange rates, January 1977 to December 2000, for the Canadian Dollar, Japanese Yen and British Pound vis-à-vis the U.S. Dollar. They found that, depending upon the assumed level of the risk of the representative agent in the market, the predictability varied substantially. Their main interest was the out-of-sample predictability measured on the basis of the economic value of the optimal allocation of a portfolio constructed from exchange rate forecasts. They concluded that the allocations based on structural models performed better than those based on a random walk model. Della Corte *et al.* (2009) used 15 different exchange rates models under the assumption of constant, time-dependent and stochastic volatility. After using Bayesian Linear Regression, Bayesian GARCH and Bayesian Stochastic Volatility models, they reported vigorous evidence of the predictability of structural models compared to a random walk model.

### 3.1.3. Methodological Issues and Econometric Framework

This chapter will reflect the main literature cited earlier: Four competing models will be used to assess the forecasting ability, conditional on a set of economic fundamentals, of exchange rates. These models include a simple random walk model and three monetary fundamental models. Beginning with the structural model in equation 3.2, the model is written as

$$\triangle s_t = \beta_1 + \beta_2 x_{t-1} + \mu_t \qquad \mu_t = \sigma_t \varepsilon_t \qquad \varepsilon_t \sim NID(0,1) \tag{3.4}$$

where $\beta_1$ and $\beta_2$ are the parameters to be estimated.

#### Conditional *Mean* and Conditional *Variance*

To compute the mean-variance optimal portfolios and indices of acceptability, one-month ahead forecasts of conditional mean and conditional variances are required. A Bayesian Linear Regression computes the conditional mean and variance while Bayesian GARCH (1,1) models compute the conditional time varying variances. The conditional mean is obtained by using the four exchange rate models.

The conditional mean specifications of exchange rate return are obtained with the regression model presented in equation 3.4 estimates for the five exchange rates. The first model is the random walk model (which sets $\beta = 0$). This model has been the standard benchmark in the literature on exchange rate predictability since the work of Meese and Rogoff (1983).

The random walk is calculated by using equation 3.3, i.e., $\Delta s_t = s_t - s_{t-1}$ and $s_{t-1}$ is set to be $x_t$ in equation 3.4. In a simple random walk model, $\beta_2 = 0$ is set. The purpose of considering the random walk (RW) model is, of course, to give a benchmark with no predictive ability in exchange rate returns.

Following Della Corte *et al.* (2009), three monetary fundamental models are also considered: Monetary Fundamental I (abbreviated to MF I) uses the model in equation 3.4 and sets the $x$ as in equation 3.2.

The other two models are termed Monetary Fundamental II (MF II) and Monetary Fundamental III (MF III). The second monetary model estimates are obtained from the OLS regression.

$$s_t = c_0 + c_1 z_t + \pi_t \tag{3.5}$$

where $\pi_t$ is an error term. The error term is the deterministic component in the deviation of the exchange rate from its fundamentals (economic fundamentals) and set $x_t = \pi_t$.

The third monetary model, i.e. Monetary Fundamental III (MF III), is obtained from the following regression equation:

$$s_t = c_0 + c_1 t + c_2 z_t + \pi_t \tag{3.6}$$

where $x_t = -\pi_t^*$ in equation 3.6, $\pi_t^*$ denotes the estimated residuals and $t$ is a time-trend.[9] Therefore, MF II adjusts the deviation of the nominal exchange rate from the Monetary Fundamentals $z_t$ by including an intercept, while MF III includes an intercept and a time-trend.[10] The descriptive statistics of the models are presented in Table 3.2.

To compute the mean-variance optimal portfolios and the indices of acceptability the conditional mean and variance are required. These are obtained by performing Bayesian regressions and the parameters are then applied to predict one month ahead return. Moreover, Bayesian Linear Regression assumes constant variance over the time period i.e. $v_t^2 = v^2$. Therefore, the conditional volatility obtained from the Bayesian Linear Regression remains constant over time.

Following West *et al.* (1993) and Della Corte *et al.* (2009), the conditional variance is modelled using a simple GARCH(1,1) model (Bollerslev,

[9]The trend creates a series that begins at zero in the first observation of the sample, and increases by one for each subsequent observation, up through the last observation.
[10]As discussed in Della Corte *et al.* (2009), the motivation for using MF II and MF III comes from the empirical evidence showing that cointegration between nominal exchange rates and fundamentals can only be found after correcting the model for deterministic components.

1986; Engle, 1982):

$$\sigma^2_{t|t-1} = \omega + \alpha_m u^2_{t-1} + \beta\sigma^2_{t-1|t-2} \tag{3.7}$$

The economic performance of the four models (MF I, MF II, MF III and a simple random walk (RW)) is evaluated on the basis of mean-variance and the index of acceptability. The next two sub-sections outline this criteria.

**Investment Decision: *Mean-Variance***

A mean-variance approach is taken to determine the optimal allocation of funds between a (foreign exchange rate) risky asset and a (domestic) risk-free asset. The strategy used is dynamic and revised monthly. A representative investor whose utility function is exponential with coefficient of absolute risk aversion $\gamma$ is considered. Therefore, the utility of the end-of-month wealth is given by

$$U(W) = -\exp(-\gamma W), \qquad \gamma > 0$$

where $W$ are the possible wealth outcomes at the end of the time period.

The expected portfolio return is given by:

$$\mu = w'E(r)$$

where $w$ is the vector of portfolio weights and $r$ is the vector of returns from the two classes of assets, while the portfolio variance is:

$$\sigma^2 = w'Vw$$

where $V$ is the covariance matrix of the asset returns.

Assuming that returns follow a normal distribution with a mean $\mu$ and a standard deviation $\sigma$, the certainty equivalent $CE$ of the investment can be given by:

$$CE = \mu - \frac{1}{2}\gamma\sigma^2$$

The optimal (in the sense of maximising the certainty equivalent CE) allocation for an investor with an exponential utility function can be obtained from the optimisation:

$$\max_{w} \left\{ w'E(r) - \frac{1}{2}\gamma w'Vw \right\} \tag{3.8}$$

The Sharpe Ratio SR, used as a measure to rank portfolio performance, is defined as:

$$SR = \frac{E(r_x) - Rf}{\sigma_x} \tag{3.9}$$

where $E(r_x)$ (respectively, $\sigma_x$) is the expected return (respectively, standard deviation) of portfolio $x$, $Rf$ is the risk free return.

**Performance: *Index of Acceptability***

Aside from the issue of static versus dynamic portfolio strategies, as portfolios have normally distributed returns, Sharpe Ratios are a valid logical measure for ranking their relative performance. However, when returns follow general (i.e., non-normal) distributions, Sharpe Ratios lead to unsatisfactory *paradoxes*. This renders them unsuitable for ranking relative portfolio performances or more generally, for ranking investment opportunities. Specifically, for general distributions of returns, Sharpe

Ratios are inconsistent with both no arbitrage and second order stochastic dominance.[11]

This led Cherny and Madan (2009) to introduce what they termed *indices of acceptability*. Essentially, these are a class of performance measures which satisfy a series of properties, including consistency with no arbitrage and second order stochastic dominance. Such properties allow for a consistent and logical way of comparing the performance of different portfolios even when the returns on the portfolios are not approximated by a normal distribution. Thus they overcome the limitations of Sharpe ratios. The approach has already been used in asset pricing theory and in corporate finance.[12] In this chapter, this novel approach is extended to measure the economic performance of the dynamically re-balanced portfolio. To the best of this authors knowledge the extension of the *indices of acceptability* approach, of Cherny and Madan (2009), to portfolio analysis, and more generally to monetary economics, is a new development.

It is outside the scope of this thesis to describe the Cherny and Madan (2009) approach in full; therefore only a brief outline of it is given. The objective of an index of acceptability is to give a performance measure or relative ranking, which describes whether and by how much a return on a portfolio is *acceptable* to a liquid financial market. Given a portfolio return $X$, modelled as a random cash flow with the end of period distribution function $F_X(X)$, it is considered *acceptable* at a given level $\mu$ if the following

[11]For more background and some specific illustrative examples, see Cherny and Madan (2009); Bernardo and Ledoit (2000); Goetzmann *et al.* (2007); Cerny (2003).

[12]In Pricing Theory to price and optimally hedge complex contingent claims, see Madan (2010) and in corporate finance (to price corporate securities), see Madan and Schoutens (2011).

condition is satisfied:

$$E(\mu, X) \geq 0 \text{ where } E(\mu, X) = \int_{-\infty}^{\infty} xd(\Psi_{\mu}(F_X(x))) \tag{3.10}$$

where $\Psi_{\mu}(F_X)$ is termed a distortion function and is parameterised by some constant $\mu$. It should be noted that in the special case that $\Psi_{\mu}(F_X) = F_X(X)$, then $E(\mu, X)$ in equation 3.10, is simply the expected value of $X$ (i.e., the expected portfolio return). In contrast, if the distortion function $\Psi_{\mu}(F_X)$ is concave, the effect is to re-weight losses upwards when $F_X(X)$ is near zero and discounts gains when $F_X(X)$ is near unity. This is intuitively consistent with the behaviour of risk-averse agents. Cherny and Madan (2009) consider four different concave distortion functions. This leads to four *indices of acceptability* labelled MINVAR, MAXVAR, MAXMINVAR and MINMAXVAR. Each of these indices of acceptability, will now be considered in turn.

The first index is called MINVAR and is defined by choosing:

$$\Psi_x(y) = 1 - (1 - y)^{\mu_1 + 1}, \quad \mu_1 \in \mathbf{R}_+, \quad y \in [0, 1] \tag{3.11}$$

The intuition behind MINVAR is two-fold.[13] Firstly, the condition $E(\mu_1, X) \geq 0$ is tantamount to saying that the expectation computed using the minimum of $(\mu_1 + 1)$ draws from the distribution of the portfolio return $X$ is still positive. The intuition here is that even using the worst case of $(\mu_1 + 1)$ draw is still an acceptable investment opportunity or portfolio return. Secondly, Cherny and Madan (2009) also show that large gains are discounted to zero while large losses are exaggerated by a factor $(\mu_1 + 1)$. This points to a possible disadvantage of MINVAR, as one would

[13]See section 3.8 of Cherny and Madan (2009), for full details.

possibly wish large losses to be exaggerated to infinity and not by a factor that is a fixed constant.

The second index is called MAXVAR and, in contrast, it does exaggerate large losses to infinity. MAXVAR is defined by choosing:

$$\Psi_x(y) = y^{\frac{1}{\mu_2+1}}, \quad \mu_2 \in \mathbf{R}_+, \quad y \in [0,1] \tag{3.12}$$

For MAXVAR, large losses are exaggerated to infinity but large gains are discounted by a maximum proportional factor of $(\mu_2 + 1)$. This points to a possible disadvantage of MAXVAR, as one would possibly wish large gains to be discounted to zero.

This leads to the consideration of the third and fourth indices, termed MAXMINVAR and MINMAXVAR. Both of these indices discount large gains to zero and simultaneously exaggerate large losses to infinity.

Specifically, MAXMINVAR is defined by choosing:

$$\Psi_x(y) = (1 - (1 - y^{\mu_3+1})^{\frac{1}{\mu_3+1}}, \quad \mu_3 \in \mathbf{R}_+, \quad y \in [0,1] \tag{3.13}$$

while MINMAXVAR is defined by choosing:

$$\Psi_x(y) = 1 - (1 - y^{\frac{1}{\mu_4+1}})^{\mu_4+1}, \quad \mu_4 \in \mathbf{R}_+, \quad y \in [0,1] \tag{3.14}$$

All four indices of acceptability produce valid logical measures for ranking portfolio performance: The larger the index of acceptability, the better the portfolio performance. Portfolio returns that are not acceptable at a given level $\mu$ (where $\mu \in \{\mu_1, \mu_2, \mu_3, \mu_4\}$) are assigned an index of acceptability identically equal to zero.

Finally, one additional advantage of *indices of acceptability* is that they are intuitively consistent with the notion of risk-aversion and with classical ideas of utility functions. Yet they do not actually require the specification of a particular utility function. This is useful because corporate treasurers and portfolio managers are not typically acting on their own personal account and hence a personalised utility function may not be appropriate. Instead, indices of acceptability attempt to de-personalise portfolio selection and to measure the acceptability of portfolio returns to a wide range of agents who collectively constitute some section of the market (or a large sub-section of it).[14]

**Estimation and Forecasting: Bayesian Method**

Bayesian methods are used to estimate the parameters of the models discussed in Section 3. In the literature, Bayesian methods have been used by various authors including; Kandel and Stambaugh (1996), West *et al.* (1993), Abhyankar *et al.* (2005) and Della Corte *et al.* (2009), to assess some aspect of of exchange rate forecasts.[15]

The next section of this chapter explains the data set and the interpretation of the results.

[14]See Cherny and Madan (2009) for more details.
[15]A detailed discussion of the algorithms used in this chapter are provided in the Appendix.

## 3.2. Data and Results

### 3.2.1. Data Description

The empirical dataset which is used consists of industrial production, money supply and spot (end of month) exchange rates for the UK, Germany, Japan, Australia and Canada, all relative to the U.S. dollar.[16] Monthly observations, from January 1980 to December 2009, (i.e., 360 observations) are used. The spot exchange rates are taken from Bloomberg. The Euro-rate is used as a proxy for the Deutschemark after the introduction of the Euro in January 1999. The descriptive statistics for the (log) spot exchange rates, industrial production and money supply are presented in Table 3.1. The Jarque-Bera statistics indicate that the null hypothesis of normally distributed exchange rate returns is rejected with $100(1 - 0.04) = 96\%$ confidence for AUDUSD and at confidence levels well in excess of 99.9% for GBPUSD, for DEM/EURUSD and for JPYUSD.

The variables of interest are logarithmically transformed, prior to beginning the empirical analysis: From the raw data to time series of $s_t$ as the natural logarithm of spot rate, $m_t$ as the money supply of domestic currency, $m_t^*$ as the money supply of foreign currency, $y_t$ as the national income of domestic country and $y_t^*$ as the national income of the foreign country.[17] Rates on one-month U.S. certificates of deposit (CD) are taken to be the risk-free interest-rate. These data are obtained from Data-stream.

[16]Industrial production rather than GDP has been used since the latter is not typically available on a monthly basis. Della Corte *et al.* (2009) note that the correlation between the quarterly industrial production index and GDP over the time period they consider is more than 0.95.

[17]The U.S. being taken as the home (domestic) country

**Table 3.1.:** Descriptive statistics of *industrial production*, *money supply* and *FX return*

| | Industrial Production[a] | | | | | | Money Supply[b] | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Statistics | AUSTRALIA | CANADA | GERMANY | JAPAN | UK | US | AUSTRALIA | CANADA | GERMANY | JAPAN | UK | US |
| Mean | 4.44 | 4.51 | 4.52 | 4.51 | 4.51 | 4.37 | 5.61 | 11.75 | 6.86 | 6.16 | 6.28 | 8.23 |
| Median | 4.45 | 4.57 | 4.53 | 4.55 | 4.53 | 4.38 | 5.64 | 11.67 | 7.11 | 6.27 | 6.34 | 8.16 |
| Maximum | 4.72 | 4.83 | 4.75 | 4.72 | 4.65 | 4.72 | 7.08 | 13.07 | 7.23 | 6.60 | 7.63 | 9.05 |
| Minimum | 4.01 | 4.03 | 4.32 | 4.19 | 4.26 | 3.96 | 4.05 | 10.42 | 5.96 | 5.25 | 4.56 | 7.30 |
| Std. Dev. | 0.20 | 0.19 | 0.09 | 0.14 | 0.11 | 0.24 | 0.82 | 0.76 | 0.44 | 0.40 | 0.81 | 0.46 |
| Skewness | -0.29 | -0.47 | 0.24 | -0.89 | -0.75 | -0.10 | -0.12 | -0.11 | -0.69 | -0.81 | -0.35 | -0.07 |
| Kurtosis | 1.85 | 2.29 | 3.02 | 2.75 | 2.31 | -1.46 | 2.08 | 1.96 | 1.80 | 2.38 | 2.18 | 2.17 |
| Jarque-Bera | 25.04 | 20.68 | 3.47 | 48.76 | 40.43 | 25.24 | 13.62 | 16.90 | 50.60 | 45.06 | 17.29 | 10.51 |
| Probability | 0.00 | 0.00 | 0.18 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| Observations | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 | 360 |

| | FX Return[c] | | | | |
|---|---|---|---|---|---|
| Statistics | AUD/USD | GBP/USD | CAD/USD | DEM/USD | JYP/USD |
| Mean | -0.28 | 0.51 | -0.25 | -0.35 | -4.91 |
| Median | -0.28 | 0.49 | -0.25 | -0.47 | -4.81 |
| Maximum | 0.17 | 0.89 | 0.05 | 0.46 | -4.43 |
| Minimum | -0.72 | 0.08 | -0.47 | -1.20 | -5.62 |
| Std. Dev. | 0.19 | 0.13 | 0.11 | 0.43 | 0.30 |
| Skewness | 0.29 | 0.32 | 0.07 | 0.21 | -0.93 |
| Kurtosis | 3.30 | 3.74 | 2.53 | 1.97 | 2.62 |
| Jarque-Bera | 6.20 | 14.25 | 3.66 | 18.67 | 53.72 |
| Probability | 0.04 | 0.00 | 0.16 | 0.00 | 0.00 |
| Observations | 360 | 360 | 360 | 360 | 360 |

[a] Note: The (log) industrial production is taken as proxy to income of Australia, Canada, Japan, UK and U.S.*, U.S. as domestic country, plotted in the time series from January 1980 to December 2009.
[b] Note: The (log) money supplies are taken from the Bloomberg terminal.
[c] Note: The descriptive statistics of (log) exchange rates AUD/USD, CAD/USD, DEM (EURO)/USD, GBP/USD and JPY/USD from January 1980 to December 2009.

**Table 3.2.:** Descriptive statistics of *Monetary Fundamental I, II and III*

| | Monetary Fundamental I[a] | | | | | Monetary Fundamental II[b] | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Statistics | AUSTRALIA | CANADA | GERMANY | JAPAN | UK | AUSTRALIA | CANADA | GERMANY | JAPAN | UK |
| Mean | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.08 | -0.06 | -0.23 | -0.18 | 0.01 |
| Median | 7.62 | 9.64 | -15.62 | -10.08 | -5.66 | -0.06 | -0.42 | -12.70 | 5.30 | -1.75 |
| Maximum | 68.84 | 63.79 | 114.87 | 83.14 | 104.01 | 37.86 | 32.09 | 91.54 | 71.93 | 39.23 |
| Minimum | -89.73 | -83.43 | -85.62 | -60.71 | -91.58 | -37.50 | -20.77 | -71.64 | -63.33 | -42.44 |
| Std. Dev. | 35.87 | 36.63 | 55.7 | 38.10 | 51.16 | 16.62 | 10.84 | 41.40 | 27.80 | 13.15 |
| Skewness | -0.52 | -0.24 | 0.40 | 0.72 | 0.15 | 0.09 | 0.32 | 0.64 | -0.34 | 0.39 |
| Kurtosis | 2.72 | 2.34 | 1.76 | 2.34 | 2.06 | 2.64 | 2.78 | 2.32 | 2.94 | 3.82 |
| Jarque-Bera | 17.12 | 10.09 | 32.88 | 37.86 | 14.51 | 2.40 | 6.70 | 31.10 | 7.04 | 19.10 |
| Probability | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.30 | 0.04 | 0.00 | 0.03 | 0.00 |
| Observations | 359 | 359 | 359 | 359 | 359 | 359 | 359 | 359 | 359 | 359 |

| | Monetary Fundamental III[c] | | | | |
|---|---|---|---|---|---|
| Statistics | AUSTRALIA | CANADA | GERMANY | JAPAN | UK |
| Mean | -0.09 | -0.05 | 0.02 | -0.03 | 0.01 |
| Median | -0.60 | -2.55 | 0.77 | -2.63 | -1.74 |
| Maximum | 37.25 | 31.23 | 47.77 | 42.55 | 39.21 |
| Minimum | -37.29 | -19.68 | -43.41 | -34.98 | -42.58 |
| Std. Dev. | 16.51 | 10.24 | 15.59 | 17.01 | 13.15 |
| Skewness | 0.16 | 0.45 | -0.02 | 0.25 | 0.37 |
| Kurtosis | 2.53 | 2.77 | 4.06 | 2.10 | 3.81 |
| Jarque-Bera | 4.72 | 13.04 | 16.91 | 15.90 | 18.17 |
| Probability | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 359 | 359 | 359 | 359 | 359 |

[a] Note: The descriptive statistics of the Monetary Fundamental model I, explained in equation 3.4 i.e. $\triangle s_t = \beta_1 + \beta_2 x_{t-1} + \mu_t$ and setting $x_t = z_t - s_t$.
[b] Note: The descriptive statistics of the Monetary Fundamental model II, explained in equation 3.5 i.e. $s_t = c_0 + c_1 z_t + \pi_t$ and setting $x_t = \pi_t$.
[c] Note: The descriptive statistics of the Monetary Fundamental model III, explained in equation 3.6 i.e. $s_t = c_0 + c_1 t + c_2 z_t + \pi_t$ and setting $x_t = -\pi_t$.

Two assessment criteria, *mean-variance* and *Index of Acceptability* are applied to measure the economic significance of the exchange rate forecast. For each, an investor is considered who, on a monthly basis, splits her wealth between a (foreign exchange rate) risky asset and a (domestic) risk-free asset. The investor makes their asset allocation on the basis of the volatility and expected return. The changing monthly forecasts of volatility from each model will lead to different wealth allocations and, therefore, to different portfolio performances.

## 3.3. Results

### 3.3.1. Statistical Measure

Before evaluating model forecasts based on their economic performance, an assessment based on statistical criteria is performed. In order to understand the relationship between the five exchange rates and Monetary Fundamentals. The *Ordinary Least Squares* method is used to obtain the parameters. The regression equation used is as follows:

$$\Delta s_{t+k} = \alpha + \beta_k x_t + \varepsilon_{t+k}$$

The RMSE ratio between the structural models and the random walk model estimation results are reported (see Table 3.3). These results are in line with the existing literature except for the UK when out-of-sample forecasts are considered. Based on statistical measures of performance, the random walk model appears to perform as well as, if not better, than the structural models.

**Table 3.3.:** RMSE ratio between the structural and Random Walk models

| | Australia | Canada | Germany | Japan | UK |
|---|---|---|---|---|---|
| in-sample | 0.95 | 1.00 | 1.00 | 1.00 | 1.01 |
| out-of-sample | 1.12 | 1.25 | 1.22 | 1.00 | 0.81 |

This table presents the ratios of RMSE between the structural and random walk model. A value greater than or equal to one represents better performance of the random walk model.

It should be noted that, for *in-sample* forecasting, all the observations are used to calculate the forecast volatility, whereas for *out-of-sample*, the data are split into two halves (180 observations each). The first half is used to estimate the parameters and then these are used to forecast the second half observations. The forecasts are compared with the benchmark of the random walk model.

### 3.3.2. Bayesian Linear Regression

In order to compute the optimal portfolio weights held by the investor each month, estimates of the conditional mean and variance are required. The former is calculated from the Random Walk and structural models described in equations 3.3, 3.4, 3.5 and 3.6. The latter is calculated from either Bayesian Linear Regression or from Bayesian GARCH (equation 3.7). The Bayesian Linear Regression model assumes constant variance over the regression horizon whereas the Bayesian GARCH model estimates time varying volatility for a forecast of one-month ahead. This sub-section contains a brief description of the Bayesian Linear Regression algorithm (detailed in A.1).

There are 360 observations, conducted monthly for 30 years. The parameters of interests are contained in a set $\theta = \{\theta_1, \theta_2\}$, where $\theta_1 = \{\alpha, \beta\}$ and $\theta_2 = \{h\}$ where $h$ is the error precision defined by $h = \frac{1}{\sigma^2}$. Normal priors are assumed for $\theta_1 = \{\alpha, \beta\}$, with zero mean and variance one. Prior gamma $\left(\frac{\nu}{2}, \frac{2s^{-2}}{\underline{\nu}}\right)$ is assumed for $\theta_2 = \{h\}$ with mean and degree of freedom $\underline{\nu} = 2$.

**Table 3.4.:** Log likelihood of the models

| | UK | Germany | Japan | Canada | Australia |
|---|---|---|---|---|---|
| | | | in-sample | | |
| RW | -912 | -1064 | -952 | -751 | -934 |
| MF 1 | -921 | -1068 | -955 | -757 | -941 |
| MF 2 | -914 | -1068 | -956 | -756 | -938 |
| MF 3 | -914 | -1060 | -955 | -755 | -938 |
| | | | out-of-sample | | |
| RW | -488 | -477 | -479 | -306 | -455 |
| MF 1 | -495 | -482 | -484 | -312 | -460 |
| MF 2 | -491 | -481 | -483 | -310 | -458 |
| MF 3 | -491 | -476 | -483 | -311 | -458 |

This table represents the loglkelihood computed by $p(y, x|\beta, \sigma^2, \lambda) = p(y|x, \beta, \sigma^2)p(x|\lambda)$, for in-sample and out-of-sample.

**Table 3.5.:** Bayesian linear regression results (*in-sample* & *out-of-sample*)

| | Monetary Fundamental I | | | Monetary Fundamental II | | | Monetary Fundamental III | | | Random Walk | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ |
| UK | -0.10*** (0.16) (0.00) | 0.00*** (0.00) (0.01) | 0.11 (0.02) | -0.09*** (0.16) (0.00) | -0.04*** (0.01) (0.04) | 0.11 (0.02) | -0.09*** (0.16) (0.00) | -0.04*** (0.01) (0.04) | 0.11 (0.02) | 1.39*** (0.58) (0.00) | -2.94*** (1.11) (0.00) | 0.11 (0.02) |
| Germany | 0.26*** (0.24) (0.00) | 0.00*** (0.00) (0.01) | 0.05 (0.02) | 0.26*** (0.24) (0.00) | 0.00*** (0.01) (0.02) | 0.05 (0.02) | 0.26*** (0.24) (0.00) | -0.06*** (0.02) (0.05) | 0.05 (0.02) | 0.18*** (0.31) (0.00) | -0.22*** (0.56) (0.00) | 0.05 (0.02) |
| Japan | 0.28*** (0.18) (0.00) | 0.01*** (0.00) (0.01) | 0.09 (0.02) | 0.27*** (0.18) (0.00) | -0.01*** (0.01) (0.02) | 0.09 (0.02) | 0.28*** (0.18) (0.00) | -0.02*** (0.01) (0.03) | 0.09 (0.02) | -2.58*** (2.18) (0.01) | -0.58*** (0.44) (0.00) | 0.09 (0.02) |
| Canada | 0.03*** (0.10) (0.00) | 0.00*** (0.00) (0.01) | 0.27 (0.04) | 0.02*** (0.10) (0.00) | -0.01*** (0.01) (0.03) | 0.27 (0.04) | 0.02*** (0.10) (0.00) | -0.01*** (0.01) (0.03) | 0.27 (0.04) | -0.22*** (0.23) (0.00) | -0.99*** (0.84) (0.00) | 0.27 (0.04) |
| Australia | -0.06*** (0.17) (0.00) | 0.00*** (0.00) (0.02) | 0.10 (0.02) | -0.06*** (0.17) (0.00) | -0.02*** (0.01) (0.03) | 0.10 (0.02) | -0.06*** (0.17) (0.00) | -0.02*** (0.01) (0.03) | 0.10 (0.02) | -0.56*** (0.30) (0.00) | -1.79*** (0.87) (0.00) | 0.10 (0.02) |
| | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ | $\alpha$ | $\beta$ | $h$ |
| UK | -0.36*** (0.44) (0.00) | 0.00*** (0.01) (0.00) | 0.08 (0.03) | -0.20*** (0.26) (0.00) | -0.04*** (0.02) (0.05) | 0.08 (0.03) | -0.19*** (0.26) (0.00) | -0.04*** (0.02) (0.05) | 0.08 (0.03) | 1.29*** (0.80) (0.00) | -2.99*** (1.50) (0.00) | 0.08 (0.03) |
| Germany | -0.11*** (0.39) (0.00) | 0.00*** (0.01) (0.00) | 0.09 (0.03) | -0.28*** (0.45) (0.00) | -0.01*** (0.01) (0.00) | 0.09 (0.03) | 0.09*** (0.24) (0.00) | -0.05*** (0.01) (0.05) | 0.10 (0.03) | -0.39*** (0.77) (0.00) | -0.70*** (1.07) (0.00) | 0.09 (0.03) |
| Japan | 0.43*** (0.31) (0.00) | 0.00*** (0.01) (0.02) | 0.09 (0.03) | 0.46*** (0.28) (0.00) | 0.00*** (0.01) (0.03) | 0.09 (0.03) | 0.55*** (0.25) (0.00) | -0.01*** (0.01) (0.04) | 0.09 (0.03) | -0.53*** (2.59) (0.01) | -0.20*** (0.51) (0.00) | 0.09 (0.03) |
| Canada | -0.10*** (0.19) (0.00) | 0.00*** (0.01) (0.02) | 0.59 (0.08) | -0.09*** (0.10) (0.00) | -0.01*** (0.02) (0.05) | 0.60 (0.08) | -0.11*** (0.10) (0.00) | 0.00*** (0.01) (0.04) | 0.59 (0.08) | -0.27*** (0.24) (0.00) | -0.69*** (0.98) (0.00) | 0.59 (0.08) |
| Australia | -0.53*** (0.41) (0.00) | 0.01*** (0.01) (0.00) | 0.12 (0.04) | -0.19*** (0.22) (0.00) | -0.03*** (0.01) (0.05) | 0.12 (0.04) | -0.19*** (0.22) (0.00) | -0.03*** (0.02) (0.05) | 0.12 (0.04) | -0.58*** (0.32) (0.00) | -1.85*** (1.16) (0.00) | 0.12 (0.04) |

The first half of the table presents in-sample and second half presents out-of-sample Bayesian MCMC estimates of the posterior means of the in-sample Linear Regression, for the USD/GBP, DEM/USD, JPY/USD, AUD/USD and CAD/USD monthly percent FX returns using equation $y_i = \beta_1 + \beta_2 x_i + \varepsilon_i$. $h$ is the error precision i.e., $h = \sigma^{-2}$ The MCMC chain runs for 10,000 iterations after an initial burn-in of 1,000 iterations. The numbers in parenthesis indicates standard deviation and the Numerical Standard Error (NSE) respectively. The superscripts *, ** and *** indicate that the 90%, 95% and 99% highest posterior density (HPD) regions, respectively, do not contain zero. The HPD region for each MCMC parameter estimate is the shortest interval that contains 95% of the posterior distribution.

The log-likelihood of the models is calculated by using the following equation:

$$\log l = \sum_{t=1}^{t} \log f(\triangle s_t | \sigma_t, \theta)$$

The log-likelihood results are presented in Table 3.4. These show that the monetary models perform no worse than the Random Walk model. The regression results are presented in Table 3.5.

The regression coefficients, presented in Table 3.5 and obtained from equation 3.5, can be interpreted as follows: If explanatory variable $x$ is increased by one unit, the spot exchange rate is increased by $\beta_1 + \beta_2 x$. The numbers in parenthesis are the numerical standard errors (NSE) of the Monte Carlo estimation (calculated as is explained in Appendix A.1).

Table 3.5 shows that the estimations of the Monetary Fundamental models are a little more accurate than the Random Walk model in the sense that the latter has larger numerical standard errors. The estimated parameters are, generally, statistically significant. Thus overall, Monetary Fundamental models perform no worse than the random walk model. This is evident if the error precision is considered $h$.

However, the root-mean-square errors (table 3.6) are substantially of the same order of magnitude across the different models. In summary the results in Tables 3.5 and 3.6 reiterate the previous results and are in line with the extant empirical literature: Structural models do not appear to be better than a simple Random Walk model when statistical measures are used as the basis for comparison.

**Table 3.6.:** RMSE ratio between the structural and Random Walk model

| | Monetary Fundamental I | | | | | Monetary Fundamental II | | | | | Monetary Fundamental III | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Australia | Canada | Germany | Japan | UK | Australia | Canada | Germany | Japan | UK | Australia | Canada | Germany | Japan | UK |
| | One Month | | | | | One Month | | | | | One Month | | | | |
| In-Sample | 1.01 | 1.00 | 1.00 | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 1.02 |
| Out-of-Sample | 1.02 | 1.00 | 1.00 | 1.00 | 1.04 | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 1.01 |
| | Three Month | | | | | Three Month | | | | | Three Month | | | | |
| In-Sample | 1.02 | 1.00 | 1.00 | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 1.03 |
| out-of-sample | 1.03 | 1.00 | 0.99 | 1.00 | 1.04 | 0.99 | 1.01 | 1.00 | 1.00 | 1.00 | 0.99 | 0.98 | 1.00 | 1.00 | 1.00 |
| | Six Month | | | | | Six Month | | | | | Six Month | | | | |
| In-Sample | 1.02 | 1.00 | 1.00 | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 1.03 |
| Out-of-Sample | 1.03 | 1.00 | 0.99 | 1.00 | 1.04 | 1.00 | 1.01 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 1.00 | 1.00 | 1.01 |

Note: This table presents the ratios of RMSE between the Monetary Fundamental model I and random walk model, a value greater than or equal to one represents the better performance for the random walk model.

### 3.3.3. Bayesian GARCH

In this section, the Bayesian GARCH model is briefly outlined (detailed in Appendix A.2). The GARCH error parameter $\alpha$ measures the reaction of conditional volatility to market shocks. When $\alpha$ is relatively large (e.g. above 0.1) then volatility is very sensitive to market events. The GARCH lag parameter $\beta$ measures the persistence in conditional volatility irrespective of anything happening in the market. When $\beta$ is relatively large (e.g., about 0.9) then volatility takes a long time to die out following a crisis in the market. The sum of $\alpha + \beta$ determines the rate of convergence of the conditional volatility to the long-term average level. When $\alpha + \beta$ is relatively large (e.g., above 0.99) then the term structure of the volatility forecast from the GARCH model is relatively flat. The GARCH constant parameter $\omega$, together with sum $\alpha + \beta$, determines the level of the long-term average volatility, i.e., the unconditional volatility in the GARCH model. When $\frac{\omega}{1-(\alpha+\beta)}$ is relatively large (its magnitude is related to the magnitude of the squared returns) then the long-term volatility in the market is relatively high.

The results for the Bayesian GARCH model are shown in Table 3.7.[18] It is found that in all four exchange rate forecasting models, except the random walk model for DEM and the Monetary Fundamental model I for JPY, $\alpha$ is greater than 0.1. This suggests that these exchange rates are very sensitive to market events. The values of $\beta$ suggests that the market effect does not take long to disappear for all of the exchange rates. The estimates for $\omega$, $\alpha$ and $\beta$ are used to estimate the advanced month forecast of the variance in equation 3.7.

[18]GARCH values are obtained by the bayesGARCH function of R language provided by Ardia and Hoogerheide (2010).

**Table 3.7.:** Bayesian GARCH estimations

| | | Monetary Fundamental I | | | | Monetary Fundamental II | | | | Monetary Fundamental III | | | | Random Walk | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | NSE | SE | Mean | SD | NSE | SE | Mean | SD | NSE | SE | Mean | SD | NSE | SE |
| GBPUSD | $\omega$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | $\alpha$ | 0.59 | 0.17 | 0.00 | 0.02 | 1.05 | 0.13 | 0.00 | 0.01 | 1.03 | 0.12 | 0.00 | 0.01 | 1.02 | 0.12 | 0.00 | 0.01 |
| | $\beta$ | 0.19 | 0.15 | 0.00 | 0.02 | 0.06 | 0.05 | 0.00 | 0.00 | 0.06 | 0.05 | 0.00 | 0.00 | 0.05 | 0.05 | 0.00 | 0.00 |
| | $\nu$ | 219.3 | 136.8 | 2.16 | 16.67 | 12.51 | 3.75 | 0.06 | 0.43 | 13.86 | 3.93 | 0.06 | 0.42 | 15.37 | 5.01 | 0.08 | 0.56 |
| DEMUSD | $\omega$ | 0.03 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | $\alpha$ | 0.34 | 0.21 | 0.00 | 0.01 | 1.17 | 0.15 | 0.00 | 0.01 | 0.99 | 0.13 | 0.00 | 0.01 | 0.76 | 0.10 | 0.00 | 0.01 |
| | $\beta$ | 0.20 | 0.14 | 0.00 | 0.02 | 0.08 | 0.07 | 0.00 | 0.00 | 0.04 | 0.04 | 0.00 | 0.00 | 0.09 | 0.07 | 0.00 | 0.00 |
| | $\nu$ | 210.38 | 130.27 | 2.06 | 17.43 | 8.51 | 1.43 | 0.02 | 0.12 | 13.34 | 3.98 | 0.06 | 0.43 | 189.6 | 95.46 | 1.51 | 12.24 |
| JPYUSD | $\omega$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | $\alpha$ | 1.06 | 0.13 | 0.00 | 0.01 | 0.92 | 0.12 | 0.00 | 0.01 | 1.04 | 0.12 | 0.00 | 0.01 | 0.76 | 0.10 | 0.00 | 0.01 |
| | $\beta$ | 0.07 | 0.06 | 0.00 | 0.00 | 0.07 | 0.06 | 0.00 | 0.00 | 0.04 | 0.04 | 0.00 | 0.00 | 0.06 | 0.06 | 0.00 | 0.00 |
| | $\nu$ | 11.43 | 2.51 | 0.04 | 0.24 | 24.31 | 19.48 | 0.31 | 3.01 | 19.56 | 10.15 | 0.16 | 1.47 | 114.96 | 95.05 | 1.50 | 13.39 |
| AUDUSD | $\omega$ | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| | $\alpha$ | 0.67 | 0.04 | 0.00 | 0.00 | 0.92 | 0.40 | 0.01 | 0.00 | 0.78 | 0.10 | 0.00 | 0.00 | 0.70 | 0.23 | 0.00 | 0.03 |
| | $\beta$ | 0.02 | 0.02 | 0.00 | 0.00 | 0.04 | 0.04 | 0.00 | 0.00 | 0.06 | 0.05 | 0.00 | 0.00 | 0.02 | 0.02 | 0.00 | 0.00 |
| | $\nu$ | 5.35 | 1.02 | 0.02 | 0.11 | 8.54 | 2.49 | 0.04 | 0.27 | 129.2 | 100 | 1.58 | 12.65 | 8.98 | 2.50 | 0.04 | 0.26 |
| CADUSD | $\omega$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | $\alpha$ | 0.50 | 0.18 | 0.00 | 0.01 | 1.01 | 0.13 | 0.00 | 0.01 | 0.92 | 0.10 | 0.00 | 0.00 | 0.99 | 0.13 | 0.00 | 0.01 |
| | $\beta$ | 0.17 | 0.14 | 0.00 | 0.01 | 0.03 | 0.03 | 0.00 | 0.00 | 0.04 | 0.03 | 0.00 | 0.00 | 0.06 | 0.05 | 0.00 | 0.00 |
| | $\nu$ | 182.8 | 94.18 | 1.49 | 11.55 | 35.29 | 31.26 | 0.49 | 4.39 | 151.9 | 118.6 | 1.88 | 16.31 | 15.08 | 5.78 | 0.09 | 0.73 |

The table presents the MCMC GARCH estimates, for the GBP/USD, DEM/USD, JPY/USD, AUD/USD and CAD/USD monthly percent FX returns using equation $\hat{\sigma}^2_{T+S+1} = \hat{\omega} + (\hat{\alpha} + \hat{\beta})\sigma^2_{T+S}$. The returns are obtained from the Monetary Fundamental II model. The MCMC chain runs for 2,000 iterations after an initial burn-in of 1,000 iterations. The numbers under the column (NSE) represents Numerical Standard Error.

### 3.3.4. Investment Decision: Mean-Variance Analysis

The statistical evaluation of a model provides important information about the empirical validity of that model. However, it says little about whether the same model can be used profitably to exploit investment opportunities. The recent contributions of Abhyankar *et al.* (2005) and Della Corte *et al.* (2009) have begun to address this issue.

Beginning with the mean-variance approach discussed earlier, the aim is to maximise the certainty equivalent of the utility of an investor conditional on the proposed models. A simple dynamic trading strategy is implemented, where a domestic (U.S.) investor, will invest in a portfolio consisting of two assets: a (foreign exchange rate) risky asset and a (domestic) risk-free asset, which is taken to be a one-month certificate of deposit denominated in U.S. dollars. Thus, the only risk involved is the currency risk.

The out-of-sample predictability of the competing models are compared. Specifically, the variance is analysed in two different ways: Firstly, the case where the variance is constant (Bayesian Linear Regression) is considered. Secondly, the case where it is assumed that the variance is time varying is considered. Furthermore, the one month ahead forecast of variance is estimated using Bayesian GARCH. The risk aversion coefficient $\gamma$ (defined in section 3.1.3) equal to 20 is set.[19] The out-of-sample forecasts are based on a recursive approach where at the end of each month new sets of weights are determined based on the portfolio expected return. Thus, the portfolios are dynamically rebalanced according to the new computed

[19] Different values for the risk aversion coefficient are also considered but the results were qualitatively the same.

weights.

Tables 3.8 and 3.9 show the average optimal portfolio weights. It should be stressed that these are average weights; the actual weights change dynamically through time. Table 3.8 shows the in-sample and out-of-sample results based on Bayesian Linear Regression. The results from the GARCH model are reported in Table 3.9. The columns labelled Portfolio Mean and Portfolio Sigma denote the return and risk (standard deviation) respectively.

Taking Table 3.8 as an example, in the case of GBPUSD, the monetary fundamental II model (in-sample) suggests that, on average through time, about 29.9% of the principal should be invested in the (foreign exchange) risky asset. Moreover it indicates that on average through time, about 70.1% should be in the (domestic) risk-free asset. On the whole it appears that structural models tend to allocate a larger proportion of wealth to the risky asset than the Random Walk model does.

### 3.3.5. Sharpe Ratio

It can be noticed that optimal weights from structural models are sometimes of opposite sign compared to optimal weights from the Random Walk model as noted by Abhyankar *et al.* (2005). The change in sign suggests that the Random Walk model may indicate shorting an asset when structural models indicate the opposite. Overall, there is evidence suggesting that the Monetary Fundamental models (particularly II and III) perform better than a simple random walk model. This result also holds in the case of out-of-sample forecasts and seems to be stronger when

**Table 3.8.:** Mean-variance analysis results (Bayesian linear regression) (*in and out-of-sample*)

| | | FX | R$f$ | Mean | Sigma | SR | FX | R$f$ | Mean | Sigma | SR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | in-sample | | | | | out-of-sample | | | | |
| Monetary Fundamental I | UK | -1.000 | 2.000 | 0.217 | 0.338 | 0.462 | 1.187 | -0.187 | 0.246 | 0.533 | 0.420 |
| | Germany | 2.000 | -1.000 | 0.460 | 0.436 | 0.914 | -0.313 | 1.313 | 0.463 | 0.400 | 0.197 |
| | Japan | 1.229 | -0.229 | 0.569 | 0.486 | 0.951 | -0.313 | 1.313 | 0.359 | 0.399 | 0.858 |
| | Canada | 0.249 | 0.751 | 0.218 | 0.746 | 0.220 | 1.187 | -0.187 | 0.549 | 1.020 | 0.573 |
| | Australia | -1.000 | 2.000 | 0.178 | 0.322 | 0.362 | -0.313 | 1.313 | 0.253 | 0.420 | 0.484 |
| Monetary Fundamental II | UK | 0.299 | 0.701 | 0.617 | 0.503 | 1.173 | -0.313 | 1.313 | 0.637 | 0.390 | 1.880 |
| | Germany | 1.656 | -0.656 | 0.477 | 0.398 | 0.997 | 0.194 | 0.806 | 0.428 | 0.451 | 0.942 |
| | Japan | 1.732 | -0.732 | 0.533 | 0.547 | 0.850 | -0.053 | 1.053 | 0.573 | 0.425 | 1.521 |
| | Canada | 0.349 | 0.651 | 0.198 | 0.756 | 0.198 | 1.187 | -0.187 | 0.606 | 1.019 | 0.611 |
| | Australia | 0.098 | 0.902 | 0.502 | 0.457 | 0.978 | 0.408 | 0.592 | 0.314 | 0.501 | 0.591 |
| Monetary Fundamental III | UK | 0.257 | 0.743 | 0.624 | 0.507 | 1.170 | 0.215 | 0.785 | 0.496 | 0.443 | 1.125 |
| | Germany | 0.877 | 0.123 | 1.163 | 0.392 | 2.735 | 0.194 | 0.806 | 0.428 | 0.451 | 0.939 |
| | Japan | 1.095 | -0.095 | 0.656 | 0.500 | 1.105 | 0.450 | 0.550 | 0.599 | 0.475 | 1.178 |
| | Canada | 0.508 | 0.492 | 0.223 | 0.786 | 0.229 | 1.187 | -0.187 | 0.795 | 1.021 | 0.732 |
| | Australia | -0.020 | 1.020 | 0.422 | 0.398 | 0.949 | -0.313 | 1.313 | 0.260 | 0.420 | 0.504 |
| Random Walk | UK | 0.081 | 0.919 | 0.455 | 0.477 | 0.887 | 0.240 | 0.760 | 0.510 | 0.445 | 1.156 |
| | Germany | 2.000 | -1.000 | 0.460 | 0.436 | 0.917 | -0.003 | 1.003 | 0.372 | 0.437 | 0.830 |
| | Japan | 1.958 | -0.958 | 0.510 | 0.577 | 0.775 | -0.204 | 1.204 | 0.400 | 0.410 | 0.992 |
| | Canada | 0.324 | 0.676 | 0.200 | 0.753 | 0.199 | 1.187 | -0.187 | 0.649 | 1.019 | 0.639 |
| | Australia | -0.045 | 1.045 | 0.422 | 0.459 | 0.801 | 0.307 | 0.693 | 0.440 | 0.462 | 0.881 |

Note: This table shows the proportion of the portfolio which is invested, on average, between the foreign exchange instrument and risk-free investment, volatility based on the Bayesian Regression for in-sample and out-of-sample data, followed by the portfolio return, risk and Sharpe ratios respectively.

**Table 3.9.:** Mean-variance analysis results (GARCH)

| | | FX | R$f$ | Mean | Sigma | SR |
|---|---|---|---|---|---|---|
| Monetary Fundamental I | UK | -0.490 | 1.490 | 0.137 | 0.125 | 0.614 |
| | Germany | 1.002 | -0.002 | 0.261 | 0.452 | 0.442 |
| | Japan | 0.590 | 0.410 | 0.310 | 0.424 | 0.527 |
| | Canada | 0.141 | 0.859 | 0.139 | 0.258 | 0.297 |
| | Australia | -0.479 | 1.479 | 0.117 | 0.109 | 0.515 |
| Monetary Fundamental II | UK | 0.161 | 0.839 | 0.337 | 0.479 | 0.552 |
| | Germany | 0.818 | 0.182 | 0.266 | 0.327 | 0.665 |
| | Japan | 0.847 | 0.153 | 0.293 | 0.411 | 0.533 |
| | Canada | 0.185 | 0.815 | 0.129 | 0.246 | 0.284 |
| | Australia | 0.065 | 0.935 | 0.280 | 0.399 | 0.520 |
| Monetary Fundamental III | UK | 0.140 | 0.860 | 0.341 | 0.477 | 0.559 |
| | Germany | 0.446 | 0.554 | 0.613 | 0.634 | 0.711 |
| | Japan | 0.545 | 0.455 | 0.358 | 0.434 | 0.627 |
| | Canada | 0.269 | 0.731 | 0.142 | 0.257 | 0.311 |
| | Australia | -0.019 | 1.019 | 0.243 | 0.341 | 0.546 |
| Random Walk | UK | 0.052 | 0.948 | 0.257 | 0.390 | 0.500 |
| | Germany | 0.996 | 0.004 | 0.260 | 0.361 | 0.562 |
| | Japan | 0.967 | 0.033 | 0.283 | 0.411 | 0.520 |
| | Canada | 0.173 | 0.827 | 0.130 | 0.246 | 0.288 |
| | Australia | 0.004 | 0.996 | 0.238 | 0.355 | 0.467 |

Note: This table shows the proportion of the portfolio which is invested, on average, between the foreign exchange instrument and risk-free investment, volatility based on the Bayesian GARCH for in-sample and out-of-sample data, followed by the portfolio return, risk and Sharpe ratios respectively.

returns are modelled using a GARCH process (see Table 3.9). This may suggest that, in modelling portfolio returns, allowing for GARCH processes may be important. However, the results thus far are based on the use of Sharpe Ratios. Due to the various criticisms that Sharpe Ratios have received these results should be treated tentatively.[20] This is especially necessary with the ranking of non-normal portfolio return distributions and dynamic portfolio strategies. This leads to the consideration of indices of acceptability for ranking portfolio performance.

### 3.3.6. Investment Decision: Indices of Acceptability

With regard to indices of acceptability, the results are reported in Table 3.10 for in-sample and out-of-sample.

The results in Table 3.10 confirm the results shown in 3.8 and 3.9 and suggest that monetary models for the exchange rate (specifically MFII and MFIII) perform better than the Random Walk Model. For example, in-sample results (Table 3.10) show that Monetary Fundamental III (MFIII) has a higher index of acceptability, for all four indices and for all five exchange rates, than that of the Random Walk Model. The margin of out-performance is greatest for GBPUSD, DEM/EURUSD and JPYUSD. These (from Table 3.1) are the three exchange rates for which the Jarque-Bera statistics indicate the greatest departure from normally distributed exchange rate returns. The JPYUSD and DEM/EURUSD show the highest indices of acceptability. Different values of levels $\mu$ ranging from 0.2 to 2 with an increment of 0.2 were considered. The results are shown in the figures 3.1 and 3.1 for MINMAXVAR and MAXMINVAR.

[20]See, for example Cherny and Madan (2009); Bernardo and Ledoit (2000).

**Table 3.10.:** Index of Acceptability (*in and out-of-sample*)

| | | MINVAR | MAXVAR | MINMAXVAR | MAXMINVAR | MINVAR | MAXVAR | MINMAXVAR | MAXMINVAR |
|---|---|---|---|---|---|---|---|---|---|
| Monetary Fundamental I | UK | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Germany | 0.170 | 0.168 | 0.107 | 0.154 | 0.159 | 0.163 | 0.104 | 0.148 |
| | Japan | 0.195 | 0.189 | 0.112 | 0.165 | 0.032 | 0.034 | 0.023 | 0.033 |
| | Canada | 0.037 | 0.037 | 0.023 | 0.034 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Australia | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Monetary Fundamental II | UK | 0.100 | 0.104 | 0.070 | 0.097 | 0.050 | 0.340 | 0.050 | 0.022 |
| | Germany | 0.168 | 0.171 | 0.114 | 0.097 | 0.095 | 0.099 | 0.066 | 0.093 |
| | Japan | 0.187 | 0.187 | 0.121 | 0.172 | 0.077 | 0.078 | 0.049 | 0.069 |
| | Canada | 0.037 | 0.038 | 0.026 | 0.038 | 0.012 | 0.011 | 0.000 | 0.033 |
| | Australia | 0.083 | 0.083 | 0.052 | 0.074 | 0.000 | 0.027 | 0.025 | 0.000 |
| Monetary Fundamental III | UK | 0.111 | 0.105 | 0.057 | 0.083 | 0.070 | 0.080 | 0.090 | 0.020 |
| | Germany | 0.313 | 0.308 | 0.186 | 0.266 | 0.022 | 0.012 | 0.013 | 0.219 |
| | Japan | 0.213 | 0.206 | 0.119 | 0.176 | 0.049 | 0.052 | 0.037 | 0.051 |
| | Canada | 0.045 | 0.046 | 0.030 | 0.043 | 0.005 | 0.005 | 0.003 | 0.004 |
| | Australia | 0.066 | 0.069 | 0.046 | 0.065 | 0.044 | 0.032 | 0.022 | 0.000 |
| Random Walk | UK | 0.007 | 0.066 | 0.039 | 0.057 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Germany | 0.172 | 0.169 | 0.103 | 0.151 | 0.113 | 0.121 | 0.084 | 0.118 |
| | Japan | 0.188 | 0.185 | 0.113 | 0.164 | 0.100 | 0.112 | 0.064 | 0.093 |
| | Canada | 0.039 | 0.038 | 0.023 | 0.034 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Australia | 0.060 | 0.063 | 0.037 | 0.053 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: The different columns of the table represent different measures for the index. The rows represent the models and the corresponding. $\mu_3$ (MAXMINVAR), $\mu_4$ (MINMAXVAR), $\mu_1$ (MINVAR) and $\mu_2$ (MAXVAR) are set $\mu$ equal to 0.2.

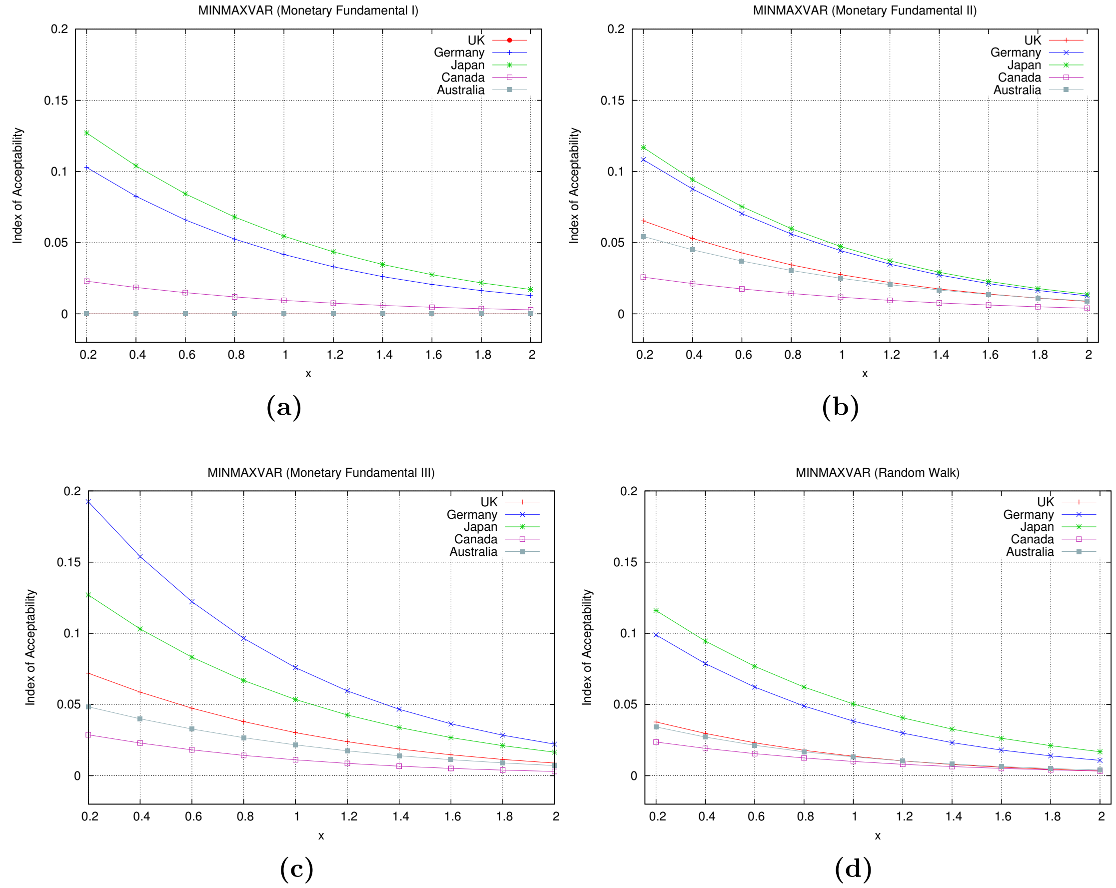


**Figure 3.1.:** Note: Graphs from (a) to (d) depicts the index of acceptability for MINMAXVAR on the $y$ axis across the variable $\mu$ on $x$ axis from 0.2 to 2.0 for Monetary Fundamental I, II, III and Random Walk models, respectively.

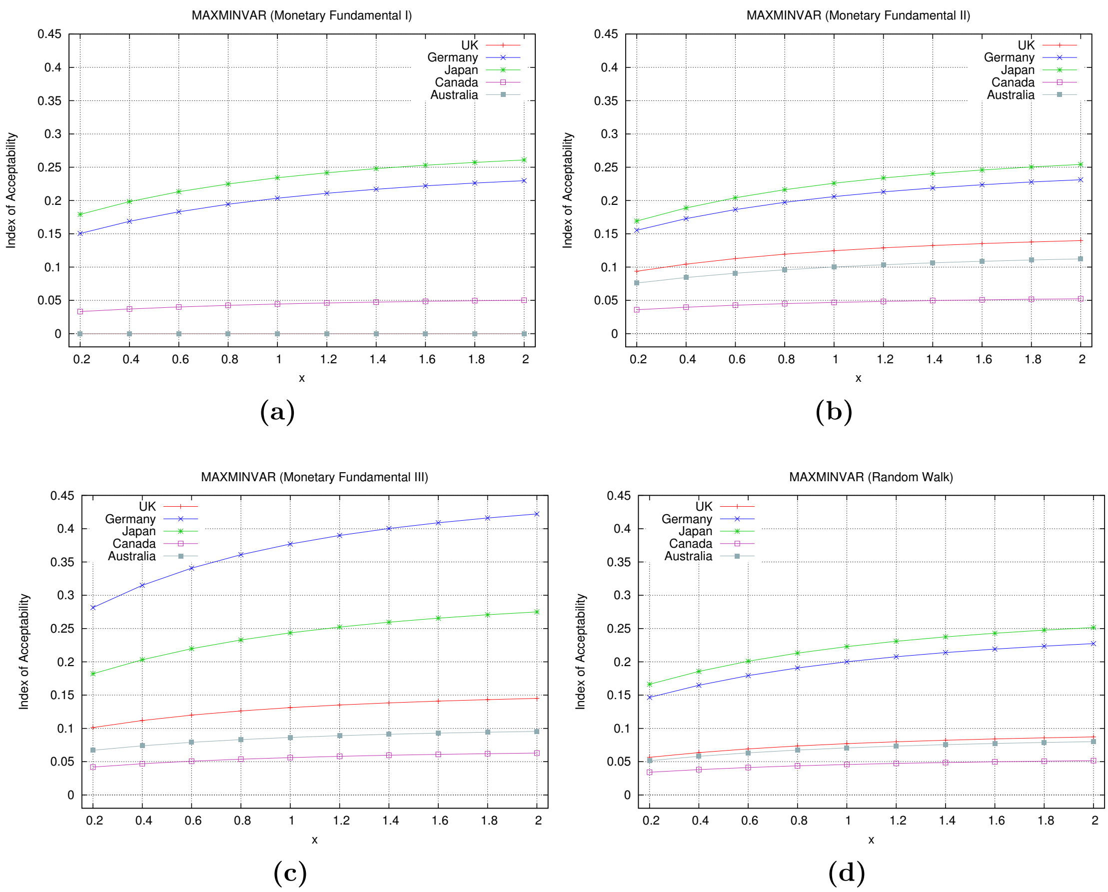


**Figure 3.2.:** Note: Graphs from (a) to (d) depicts the index of acceptability for MAXMINVAR on the $y$ axis across the variable $\mu$ on $x$ axis from 0.2 to 2.0 for Monetary Fundamental I, II, III and Random Walk models, respectively.

The MAXMINVAR acceptability index increases as the level of $\mu_3$ increases whilst the MINMAXVAR index decreases as the level of $\mu_4$ increases. The figures confirm the results in Table 3.10: Forecasts obtained from the Monetary Fundamental models perform better than the forecasts obtained from the Random Walk Model. In particular, it can be noticed that MF II and MF III, i.e., those considering deterministic trends in the model, perform best. These results are true for a wide range of values of $\mu_3$ and $\mu_4$.

## 3.4. Robustness Tests

This section presents some robustness tests to support the empirical results. All the tests presented above are re-ran after excluding the 2008-2009 financial crisis period. Thus, the empirical results refer to the period January 1980 to December 2007.

### 3.4.1. Statistical Analysis: Bayesian Linear Regression.

This sub-section begins with the statistical analysis (in-sample and out-of-sample) of the models discussed above and the use of Bayesian Linear Regression. The results are reported in the Tables below.

There seems to be more evidence favouring the Monetary Fundamental III model over a Simple Random Walk Model. The full analysis is not reported but the overall results are similar to the ones for the full sample. The economic evaluation of the models will now be discussed. The log likelihoods of the Bayesian Linear Regression are presented in Table 3.11.

**Table 3.11.:** Log Likelihood of the Models

| | UK | Germany | Japan | Canada | Australia |
|---|---|---|---|---|---|
| | | | in-sample | | |
| RW | -842 | -838 | -838 | -834 | -842 |
| MF 1 | -986 | -986 | -979 | -981 | -986 |
| MF 2 | -877 | -877 | -877 | -873 | -877 |
| MF 3 | -622 | -623 | -623 | -618 | -622 |
| | | | out-of-sample | | |
| RW | -459 | -457 | -457 | -453 | -459 |
| MF 1 | -445 | -445 | -441 | -440 | -445 |
| MF 2 | -447 | -447 | -447 | -443 | -447 |
| MF 3 | -287 | -286 | -286 | -282 | -287 |

This table represents the loglkelihood computed by $p(y, x|\beta, \sigma^2, \lambda) = p(y|x, \beta, \sigma^2)p(x|\lambda)$, for in-sample and out-of-sample.

### 3.4.2. Economic Analysis: Mean-Variance Approach.

Table 3.12 shows the (in-sample and out-of-sample) results from the mean-variance approach.

Overall, these results of Table 3.12 are in line with those presented earlier and show that Monetary Fundamental models do better than a Random Walk Model when the economic significance of the model forecasts is considered. A GARCH model has also been considered as before and the results remain substantially unchanged.

**Table 3.12.:** Mean-variance analysis results (Bayesian Linear Regression) (*in and out-of-sample*)

| | FX | R$f$ | Mean | Sigma | SR | FX | R$f$ | Mean | Sigma | SR | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | UK | 0.18 | 0.82 | 0.42 | 0.49 | 0.77 | -0.41 | 1.41 | 0.50 | 0.40 | 1.47 |
| | Germany | 1.79 | -0.79 | 0.46 | 0.43 | 0.95 | -0.41 | 1.41 | 0.54 | 0.40 | 1.52 |
| Monetary Fundamental I | Japan | 1.47 | -0.47 | 0.40 | 0.54 | 0.62 | 0.94 | 0.06 | 0.32 | 0.54 | 0.53 |
| | Canada | 0.04 | 0.96 | 0.17 | 0.84 | 0.18 | -0.03 | 1.03 | 0.20 | 0.72 | 0.30 |
| | Australia | -0.12 | 1.12 | 0.39 | 0.49 | 0.69 | -0.41 | 1.41 | 0.70 | 0.43 | 1.78 |
| | UK | -0.46 | 1.46 | 0.22 | 0.42 | 0.43 | -0.06 | 1.06 | 0.32 | 0.43 | 0.73 |
| | Germany | 1.79 | -0.79 | 0.46 | 0.43 | 0.93 | 0.05 | 0.95 | 0.24 | 0.45 | 0.49 |
| Monetary Fundamental II | Japan | 0.63 | 0.37 | 0.52 | 0.43 | 0.93 | 0.94 | 0.06 | 0.54 | 0.54 | 0.91 |
| | Canada | 0.12 | 0.89 | 0.27 | 0.87 | 0.29 | 0.44 | 0.56 | 0.28 | 0.84 | 0.36 |
| | Australia | -0.95 | 1.95 | 0.23 | 0.37 | 0.45 | -0.04 | 1.04 | 0.39 | 0.47 | 0.77 |
| | UK | 0.33 | 0.67 | 0.50 | 0.52 | 0.90 | -0.05 | 1.05 | 0.32 | 0.44 | 0.72 |
| | Germany | 1.53 | -0.53 | 0.54 | 0.40 | 1.17 | 0.22 | 0.78 | 0.49 | 0.47 | 1.00 |
| Monetary Fundamental III | Japan | 1.03 | -0.03 | 0.54 | 0.48 | 0.91 | 0.91 | 0.09 | 0.61 | 0.54 | 1.03 |
| | Canada | -0.41 | 1.41 | 0.14 | 0.75 | 0.14 | 0.08 | 0.92 | 0.23 | 0.75 | 0.33 |
| | Australia | 0.04 | 0.96 | 0.39 | 0.50 | 0.67 | 0.00 | 1.00 | 0.38 | 0.48 | 0.76 |
| | UK | 0.31 | 0.69 | 0.50 | 0.51 | 0.89 | -0.21 | 1.21 | 0.31 | 0.42 | 0.73 |
| | Germany | 0.78 | 0.22 | 1.10 | 0.40 | 2.57 | -0.41 | 1.41 | 0.40 | 0.40 | 1.06 |
| Random Walk | Japan | 0.85 | 0.15 | 0.51 | 0.49 | 0.86 | 0.94 | 0.06 | 0.52 | 0.54 | 0.86 |
| | Canada | -0.13 | 1.13 | 0.15 | 0.81 | 0.15 | 0.10 | 0.90 | 0.22 | 0.75 | 0.32 |
| | Australia | -0.07 | 1.07 | 0.30 | 0.48 | 0.53 | 0.08 | 0.92 | 0.30 | 0.48 | 0.54 |

Note: This table represents that how much proportion of the investment will be invested between the foreign exchange instrument (assumption of one foreign exchange asset at a time) and risk-free investment, volatility based on the Bayesian Regression for out-of-sample data, followed by the portfolio return, risk and Sharpe ratios respectively.

### 3.4.3. Economic Analysis: Acceptability Index

In this section, the empirical results obtained earlier by using the indices of acceptability are further assessed. To make sure that the previous results are not affected by the choice of the parameters $\mu_1, \mu_2, \mu_3$ and $\mu_4$, different values to those used in the previous section are considered.

The results in Table 3.13 are in line with the results from the full sample and show empirical support for the Monetary Fundamental models (specifically MFII and MFIII). In particular, the out-of-sample results in Table 3.13 are compared. It should be noted that in Table 3.12, where Sharpe ratios are considered, MFII and MFIII generally perform better than the Random Walk Model. However, this is not actually true for every individual entry in the table. In contrast in Table 3.13, where indices of acceptability are considered, MFII and MFIII out-perform the Random Walk Model in every single entry for all indices of acceptability. The margin of out-performance is particularly large for DEM/EURUSD and JPYUSD. These as observed earlier (see Table 3.1), are the exchange rates for which the Jarque-Bera statistics indicate the greatest departure from normally-distributed exchange rate returns.

## 3.5. Conclusion

This chapter assesses the forecasting performance of widely used Monetary Fundamental models of exchange rates. Supporting evidence was found by evaluating the economic significance of their forecasting ability. Specifically, the performance of portfolios, consisting of a risky asset (foreign exchange rate) and a risk-free (domestic) asset, constructed using model predictions

**Table 3.13.:** Index of Acceptability (*in and out-of-sample*)

| | | MINVAR | MAXVAR | MINMAXVAR | MAXMINVAR | MINVAR | MAXVAR | MINMAXVAR | MAXMINVAR |
|---|---|---|---|---|---|---|---|---|---|
| Monetary Fundamental I | UK | 0.012 | 0.013 | 0.006 | 0.013 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Germany | 0.187 | 0.119 | 0.081 | 0.184 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Japan | 0.181 | 0.183 | 0.079 | 0.176 | 0.148 | 0.150 | 0.058 | 0.138 |
| | Canada | 0.041 | 0.042 | 0.018 | 0.041 | 0.015 | 0.016 | 0.006 | 0.014 |
| | Australia | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Monetary Fundamental II | UK | 0.108 | 0.108 | 0.041 | 0.010 | 0.041 | 0.042 | 0.015 | 0.037 |
| | Germany | 0.218 | 0.217 | 0.086 | 0.206 | 0.029 | 0.032 | 0.012 | 0.026 |
| | Japan | 0.200 | 0.205 | 0.090 | 0.199 | 0.314 | 0.332 | 0.139 | 0.326 |
| | Canada | 0.021 | 0.020 | 0.008 | 0.019 | 0.082 | 0.086 | 0.036 | 0.081 |
| | Australia | 0.063 | 0.066 | 0.030 | 0.066 | 0.073 | 0.077 | 0.031 | 0.071 |
| Monetary Fundamental III | UK | 0.106 | 0.107 | 0.004 | 0.009 | 0.043 | 0.042 | 0.012 | 0.034 |
| | Germany | 0.326 | 0.340 | 0.153 | 0.337 | 0.189 | 0.200 | 0.084 | 0.183 |
| | Japan | 0.175 | 0.177 | 0.074 | 0.172 | 0.38 | 0.390 | 0.151 | 0.369 |
| | Canada | 0.024 | 0.025 | 0.011 | 0.024 | 0.035 | 0.036 | 0.013 | 0.033 |
| | Australia | 0.038 | 0.004 | 0.018 | 0.004 | 0.069 | 0.072 | 0.026 | 0.068 |
| Random Walk | UK | 0.008 | 0.009 | 0.003 | 0.008 | 0.015 | 0.016 | 0.006 | 0.015 |
| | Germany | 0.190 | 0.188 | 0.107 | 0.179 | 0.000 | 0.000 | 0.000 | 0.000 |
| | Japan | 0.162 | 0.163 | 0.067 | 0.156 | 0.299 | 0.310 | 0.120 | 0.290 |
| | Canada | 0.028 | 0.030 | 0.013 | 0.028 | 0.030 | 0.032 | 0.013 | 0.032 |
| | Australia | 0.054 | 0.054 | 0.002 | 0.050 | 0.068 | 0.070 | 0.002 | 0.059 |

Note: The different columns of the table represent different measures for the index. The rows represent the models and the corresponding. $\mu_3$ (MAXMINVAR), $\mu_4$ (MINMAXVAR), $\mu_1$ (MINVAR) and $\mu_2$ (MAXVAR) are set equal to 0.2.

were compared. New measures, most notably, indices of acceptability were used to evaluate portfolio performance that are robust to non-normally distributed portfolio returns. It was found that structural models perform better than Random Walk Models in generating profitable trading signals. This conclusion is particularly important because, while it is in line with Della Corte *et al.* (2009), it is in contrast to the majority of papers in the extent literature, which have evaluated predictive ability based on purely statistical measures.

# Chapter 4.

# The Impact of Customer Order Flow on Volatility in the Foreign Exchange Market

## 4.1. Introduction

The concept of *volatility* and its various impetuses are fundamental to the study of finance. Indeed it is integral to every decision in finance including portfolio management, risk assessment, measurement, asset pricing, and market efficiency tests. Hence, volatility is studied thoroughly along several dimensions in the empirical finance literature: Within which volatility clustering is widely studied.[1] This particular type of volatility has been comprehensively documented in the both Autoregressive Conditional Heteroskedasticity (ARCH) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, as presented by Engle (1982) and Bollerslev (1986), respectively. Many studies have attempted to establish the relationship between volatility and macroeconomic variables: The majority of them concluding that a substantial amount of volatility cannot be explained by a change in such fundamentals. It can, therefore, be deduced that unexplained volatility comes from the mispricing of underlying assets.[2] Despite these conclusions, researchers such as Schwert (1989) have continued to study the relationship between macroeconomic volatility and principles such as stock market volatility, financial leverage, economic activity and trading volume.[3] Schwert (1989) also studied variations in the volatility of the stock market and, in contrast, concluded that a significant part of volatility is explained by trading activity. Studies like Cerrato *et al.* (2011), furthermore, noted a positive contemporaneous relationship between price volatility and trading volume. Studies on the relationship

[1] Volatility clustering is studied extensively in the financial markets. It can be defined as in a time series of stock returns. It is observed that there is high variance for extended periods followed by low variance. (e.g., the daily returns variance can be high one period, and low in the next.) Therefore, the above noted phenomenon makes the i.i.d. model of returns less desirable. The volatility clustering behaviour is usually approached by ARCH-type modelling.

[2] See LeRoy and Porter (1981); Shiller (1981); Roll (1984, 1988); Cutler *et al.* (1989)

[3] The negative relationship between order-flow and subsequent volatility usually referred to as the *liquidity-driven-trade* hypothesis

between volatility and stock returns argue that the volatility is negatively correlated in the lagged return, normally referred to as *asymmetric volatility effect*.[4] These relationships are found to be robust at various return intervals.

The view of a robust relationship between price volatility and trading volume exists regardless of any underlying economic justification. Several researchers have examined this perception using theoretical models including a mixture of distribution models.[5] Yet despite these attempts there is still no consensus about the forces, which drive the volatility-volume relationship. Researchers have decomposed volume into two separate components; the size of the transaction and the number of the transactions. This implies that volatility in the financial market is positively affected either by the size of the trade or the number of transactions. Whereas early theoretical models suggested that the size of the trade does not impact on the volume-volatility relationship. However, studies have also suggested that the informed investor prefers large transaction at any given price.[6] Studies have also found that the trade size is positively related to volatility (see Easley and O'Hara, 1987; Chan and Fong, 2000; Lee and Yi, 2001).

The above hypotheses have been studied thoroughly in the stock, bond and option markets. Whereas there are no studies addressing this area of research in the context of the foreign exchange market. Even though, the foreign exchange market is the the largest and most liquid. Thus it is the intention of this study to fill this research void by examining the relationship between the customer order-flow and volatility within the

[4]See Christie (1982); French *et al.* (1987); Glosten *et al.* (1993); Graham and Harvey (2001)

[5]Such as Epps and Epps (1976); Tauchen and Pitts (1983); Harris (1986), and asymmetric information or subsequent volatility models, such as Kyle (1985), and Admati and Pfleiderer (1988)

[6]See Grundy and McNichols (1989); Holthausen and Verrecchia (1990); Kim and Verrecchia (1994)

context of the foreign exchange market. Volatility will be measured using a unique data set along with various other quantitative techniques.

Firstly, this study will provide an overview of the fundamental, technical and microstructure studies and existing literature in the context of the exchange rate movements, volatilities, and order-flows. This study will employ disaggregated and aggregated customer order-flow data provided by the Union Bank of Switzerland (UBS), for nine eminently traded foreign exchange instruments. The data comprises of the trade size of the transaction. This is a private dataset and unavailable for public or commercial means. This dataset is believed to be the largest utilised to investigate this topic. The first section will evaluate the relationship between order-flows and volatility with various dimensions in a portfolio based framework. Secondly, the *asymmetries volatility effect* is scrutinised: The foundation of the hypothesis is to examine the transmission mechanism of private information to the market, presuming that private information leads to volatility and subsequent volatilities. These questions will be answered by reference to models of the microstructure theories of the foreign exchange. The models of Schwert (1990) and Jones *et al.* (1994) are the standard models for testing the volatility - order-flow relationship. Therefore these will be employed in this thesis.

The motivation for this research is that order-flow addresses two important features in the study of the foreign exchange market. Firstly, the theoretical relationship aspects of the non-economic variables and the market: Fundamentally, the transmission mechanism of both public and private information into the markets via order-flow. Secondly most trading in the financial markets is now driven by algorithmic trading.

Hence, customer order-flow is an essential variables contemplated in the algorithmic trading models.[7] This study will help programmers to develop the algorithms for automated trading in order to maximise profits. Furthermore, another unique point of this study is that order-flows will be classified into four customer categories; (*Asset Management* (AM), *Corporate* (C), *Hedge Fund* (HF) and *Private Customer* (PC)). This will reveal further information about the behaviour of each category of customer.[8] The customer order-flows, furthermore, are examined in aggregate and disaggregate form. Again in order to acquire a more in-depth knowledge about their impact of order-flow on volatility in the foreign exchange market.

Presuming that the customer order-flow facilitates the evolution of economic fundamentals into the financial markets, and also there is a statistically significant correlation between the order-flows and the volatility. Then the customer order-flows as a proxy for economic fundamentals can anticipate the movement in the exchange rates and volatility. This relationship helps to explain the contemporaneous trends in the market if one group of customers, supposedly better informed, holds a long (short) position, relative to an underlying benchmark model position. Thus implying that the market will be rising (plunging) and positive (negative) order-flows are expected. Contrary to this, traditional economic theories, the efficient market hypothesis, do not incorporate any information regarding the order-flow/trading activity into the models. This hypothesis suggests that the information in the foreign exchange market is asymmetric and allows price and volatility discovery for the less informed customers by following the informed customers (information transmission mechanism).

[7] Computer programs track information according to the algorithm and makes decision about buying and selling.

[8] Therefore, hereafter, the order-flows are customers' order-flow.

Most of the studies in this research area used inter-dealer order-flows, which seem less important because the customers are likely to be better informed and more pertinent in shaping the trends than the dealers are. Investment banks monitor order-flows on a real time basis in order to make well-informed decisions. Other market participants may not be able to monitor live information, because it is privately owned.

## 4.2. Economic Theory, Literature Review, and Methodological Issues

### 4.2.1. Economic Theory

Exchange rate analysis and forecasting are underpinned by firstly, the economic fundamentals that the exchange follows, and secondly, the technical analysis which forecasts asset attributes according to past data. After the Bretton Woods Agreement in August 1971 fundamental analysis dominated the exchange market.[9] The influential research of Meese and Rogoff (1983) on the performance of fundamental models found that they were outperformed by naive random walk models, particularly in the short run:

> "The out-of-sample failure of the estimated univariate time series models and the vector auto-regression suggests that major-country exchange rates are well-approximated by a random walk model (without drift). Of course, as long as the exchange rate does not exactly follow a random walk, we would expect one of the estimated time series models to prevail in a large enough sample."

[9]See *About the IMF: History: The end of the Bretton Woods System (1972–81)* (n.d.)

Mark (1995) analysed the relationship between the long horizon nominal exchange rate and fundamentals. His exchange rate projections, however, were based on 1, 4, 8, 12, and 16 quarters and he found that the economic fundamental forecasting effectiveness increases as the forecast horizon increases. The better performance of long horizon predictably was found for both in and out-of-sample forecasts. Chinn and Meese (1995) and Chen and Mark (1996) also validated these results, finding that the forecasts of nominal exchange rate returns, based on the monetary fundamentals, are robust in the long horizon. Mark and Sul (2001) conducted studies using panel data of 19 countries' exchange rates against the US dollar from 1973:Q1 to1997:Q1. The regression estimates for the panel data were found to increase the predictive ability of economic fundamentals. Lastly, Engel *et al.* (2008), using panel data regression and error correction techniques, concluded that the evidence was in the favour of monetary models of the exchange rate over the long horizon.

The *microstructure* finance field has their own analysis method that deals with factors that are not accounted for within the confines of fundamental and technical analysis. Whereas fundamental analysis holds the hypothesis that all the market participants share and believe the same information set, microstructure analysis assumes that market participants use different information sets. Therefore, microstructure finance attempts to measure the beliefs of market participants; Order-flow is among the information sets that are eminently influential to foreign exchange asset pricing and volatility. Fundamental and technical analysis differ in terms of research design: While microstructure analysis differs in the variables (information set) of market participants.

Customer order-flow is the primary source of private information and the information transmission mechanism in the foreign exchange market.[10] Researchers believe that private information leads to change in asset prices and volatility in the foreign exchange markets (Jansen *et al.*, 2003; Evans and Lyons, 2004, 2006). Another important characteristic of the order-flow is that it contains vital information about the decision-making process of well-informed participants; like response to return and risk. Moreover the shifts in the strategic response, of well-informed participants, to the various issues of risk leads to deviate prices at a distance from its fundamentals (Lyons *et al.*, 2001; Dominguez and Panthaki, 2006). Furthermore, any change in the underlying variables of foreign exchange asset pricing and volatility will dominate the change in the strategic investment reallocation. This reallocation of the portfolio eventually leads to transactions (order-flows) in the market.[11] Many researchers have studied the impact of order-flows on asset pricing yet most only focused on inter-dealer order-flows rather than customer order-flows. Thus customer order-flows, rather than inter-dealer order-flows are considered to be the main source of private information (Evans and Lyons, 2006).

The relationship between the return and order-flow has been the focus of much research, including Evans and Lyons (2002, 2007); Cerrato *et al.* (2011). These studies found significant evidence that order-flows account for a substantial portion of the movement in the FX spot rate. Empirically, order-flows have more predictive power than economic fundamentals, and approximately 40-70% of the changes in asset prices are explained by the customer order-flow.[12] These researchers also concluded that the order-

[10]See Lyons (1995); Ito *et al.* (1998); Rime (2002); Evans and Lyons (2004); Bjonnes and Rime (2005)

[11]This reallocation is supposed to be domestic and internationally. Change in the international assets leads to the change in hedge ratio.

[12]See Payne (2003); Evans and Lyons (2002)

flow performs better at the short horizons, usually of 12 months or less: Whereas, economic fundamentals are better at long horizons forecasts. Furthermore, order-flows are also related to news that is relevant to the decision-making process of well-informed participants (Lyons *et al.*, 2001; Evans and Lyons, 2004; Dominguez and Panthaki, 2006). In summary order-flows do contain private information that affects the prices in foreign exchange markets Thus providing motivation for researchers to discover whether this information also influences the volatility in the market.

### 4.2.2. Literature Review

The existence of a positive relationship between the advent of information and volatility is a stylised fact within the empirical finance literature (Sarno and Taylor, 2002). Such information is further classified into public and private categories, and research has found that public information is not the only information driving volatility in the foreign exchange markets. It appears that private information also plays a vital role in defining volatility trends.[13] As discussed in section 4.2.1, order-flow is amongst the set of microstructure variables that transmits private information into the market.

### 4.2.3. Relationship between Order-flow/Volume and Volatility in the Equity Market

Clark (1973) conducted pioneering work on the relationship between volatility and volume using *mixture of distributions* models. Tauchen and Pitts (1983) found evidence of a relationship between volatility in the daily stock price change and trading volume in the speculative market, through

[13]See Melvin and Yin (2000); Andersen *et al.* (2003)

studying joint probability distribution of intraday trading volume and price changes. Andersen (1996) developed an empirical volatility-volume model from the framework of microstructure finance using a modified version of the Mixture of Distribution Hypothesis (MDH): The dynamics of the information were driven by stochastic volatility and the standard ARCH specification process. Andersen (1996) studied the daily data of five stocks from 1973-1991 and found news transmission evidence in the volatility via volume. All the models account for volatility and the trading volume in a joint process of information arrival. Therefore, any persistence in the news arrival process leads to a persistence in the trading volume and volatility. However, in practice, the persistence of volatility estimated by these models has been considerably out-performed by the simple univariate time-series models. Liesenfeld (2001) modified the existing mixture models in order to incorporate the latent information that influences the impact of information on volatility in the volume-volatility relationship.

There are fewer studies which address the relationship between volume and stock volatility than those which compare the return versus volume relationship. The studies assessing the relationship of stock volatility and trading volume are mainly statistical. Initial studies on this relationship include Morgan's (1976), ground-breaking evidence that the variance of the stock return is not constant and is correlated with trading volume as proxy of private information of the underlying share. Lamoureux and Lastrapes (1990) introduced the Autoregressive Conditional Heteroskedasticity (ARCH), time varying volatility, for daily trading volume as a proxy of the private information arrival time. They concluded that the volatility of the stock returns is not constant through time, and that it is correlated with the trading volume. Gallant *et al.* (1992) also studied the relationship of stock volatility and trading volume, and found a positive correlation between conditional volatility and volume. Although, there are several studies addressing the volume-volatility relationship, there is no fundamental consensus among researchers about the impetus of the volatility-volume relationship. The researchers decomposed volume into two components, size of the transaction and the number of the transaction. Fundamentally, this infers that either the size of the trade or the number of the transactions drives volatility in the financial market. Early theoretical models suggested that the size of the trade does not impact on the volume-volatility relation. In contrast, studies have also suggested that informed investors prefer large transactions at any given price.[14] Hence, it was also found that the trade size is positively related to the volatility.

Schwert (1990) provided an unprecedented research design in addressing the volatility and trading activity relationship. He studied daily data from over a century in order to analyse the crash of 1987 in the context of the volatility-volume relationship. He used various volatility measures, including implied volatility and the absolute residual method of volatility measure. Jones *et al.* (1994) studied the volatility-volume relationship, for the Stock Market, based on the Schwert (1990) model. They further classified trading activity into the number of transactions and size of transactions, and found that the number of trades is more informative in explaining volatility.

### 4.2.4. The Relationship Between Order-flow/Volume and Volatility in the Foreign Exchange Market

Andersen *et al.* (2003) examined the impact of announcements on exchange rate return and volatility. They revealed that the news affects

[14] See Grundy and McNichols (1989); Holthausen and Verrecchia (1990); Kim and Verrecchia (1994)

the volatility, but with asymmetric response patterns. Some studies also looked at the economic fundamentals and the aggregation of the news from the newswire agencies, and found that volatility is positively related to the arrival of the news.[15] These studies capture only public announcements and completely ignore the possible impact of private information. One of the main reservations about the existence of private information in the foreign exchange market is the nature and origin of private information. One possible explanation of the private information notion is that central banks possess an information advantage by exercising monetary policy. Studies based on asymmetric information in the foreign exchange markets confirm that its existence is accepted by traders. The difference in the information sets provides an advantage to the substantial traders (Cheung and Chinn, 2001). Furthermore, some studies demonstrated that the information in the foreign exchange market is asymmetric across geographical areas. Hence, it gives an advantage to traders according to the proximity of the information (Goodhart, 1988; Covrig and Melvin, 2002). The above facts show the presence of asymmetric and private information: The next significant question regards the identification and filtration of such information in the markets.[16]

DeGennaro and Shrieves (1997) studied the role of public and private information on volatility in the foreign exchange market. They obtained the volatility from the GARCH framework, and decomposed the ten-minute quote arrival rate into public and private information for the yen/dollar, by setting the expected and shock component from the quotes. Cai *et al.* (2001) employed the approach of the realised volatility measure of Andersen and Bollerslev (1998). They studied the weekly data for

[15] E.g., Melvin and Yin (2000); Bauwens *et al.* (2006)
[16] Discussed in detail in section 4.2.1.

changes in the foreign exchange positions of large US investors for the yen/dollar, and news announcements of macro-economic variables. A positive relationship between the announcements of the news and volatility in the foreign exchange market was found. Bauwens *et al.* (2005) studied the euro/dollar rate obtaining the volatility measure from the EGARCH specification on a time scale of five minutes. They also decomposed the quotes into expected and unexpected components, following DeGennaro and Shrieves (1997), and found a positive relationship, similar to previous studies. More recent research by Frommel *et al.* (2008) explored the links between volatility, order-flow and news. They studied high frequency data for the banks over four months, classified the transactions size and found that volatility in the foreign exchange market reflects the announcement of the news and order-flow movements.

### 4.2.5. Asymmetric Impact of Customer Order-flow on Subsequent Volatility

Campbell *et al.* (1993) studied the relationship between aggregate trading volume in the equity market and serial correlation in daily stock returns. The authors found that the first-order autocorrelation of daily returns tends to decline with increasing trading volume. They introduced the *liquidity-driven trade hypothesis*. This asserts that if *non-informational* or *liquidity* traders start to sell their portfolios in order to raise funds to invest in alternative markets, then informed investors will start to invest in-turn to accommodate the selling pressure. As these informed investors are risk averse, they demand compensation in the form of higher prospective returns. This implies that initial returns will be negative but will become positive in subsequent periods. Hence, Campbell *et al.*'s (1993) model suggests that if the market experiences high trading volume, the reversal in returns will lead to higher return volatility. Thus trading volume and subsequent volatilities are positively related. In this thesis, a positive correlation between trading volume and subsequent volatility is referred to as the *liquidity-driven trade hypothesis*. Conrad *et al.* (1994) studied the relationship between trading volume and subsequent returns for individual stocks, focusing on short time-horizons. They discovered that the auto-covariance differs in both magnitude and sign according to the trading volume. Stocks facing high transaction volumes experience price reversals or negative auto-covariance. Conversely stocks facing low transaction volumes experience positive auto-covariance in returns, as is consistent with Campbell *et al.*'s (1993) and Conrad *et al.*'s (1994) results.

Wang (1994) conducted a study on the relationship between asset prices and trading volume based on heterogeneity. The heterogeneity derives from asymmetric information and investment opportunities. In contrast to the *liquidity-driven trade hypothesis* of Campbell *et al.* (1993), Wang (1994) introduces the *information-driven trade hypothesis* where trading volume and subsequent volatilities are negatively related. This is because if informed investors have better, perhaps private, information and they start to sell on the basis of their (adverse) information, then the negative return, in the current period, will be followed by another negative return, in the subsequent period, when the news will be public.[17]

[17] The seminal work on the information driven trade hypothesis was presented byKyle (1985). Kyle (1985) developed various models for insiders/informed traders and empirically many studies attempted to estimate the magnitude of the trades based on some superior information. Insider trading/information driven trade can be explained in a situation where the investor trades on the basis of some superior/private information that is not available publicly. Although, insider-trading is illegal, somehow, some institutions by default contain some private information, like central bank deciding the monetary policy as they know in advance the next period's interest-rate before the dissemination of the announcement news.

The information driven trading probability (PIN) was first measured by Easley *et al.* (1996), who proposed a model that is normally used by estimating the PIN; this model is based on the imbalance of order flow. However, this model is not meant purely to estimate the magnitude of the

Since the signs of the return of these two periods are the same, high order-flows will lead to lower subsequent volatility. Hence, trading volume and subsequent volatilities are negatively related. Kim and Verrecchia (1994) empirically examined the *information-driven trade hypothesis* and found support for it. Connolly and Stivers (2003) document substantial momentum in subsequent weekly stock returns when the current week has substantially high trading volume, or vice versa. This is further evidence for the *information-driven trade hypothesis*. The Llorente *et al.* (2002) study is also based on Wang (1994) and concludes that what they term the *hedging trade* generates negatively autocorrelated returns (as with the *liquidity-driven trade hypothesis*), whereas *speculative trades* generate positively autocorrelated returns (as with the *information-driven trade hypothesis*). These conclusions are also supported by the model's predictions. The two contrasting hypotheses are summarised in Table 4.1.

**Table 4.1.:** Summary of subsequent volatility hypothesis

| Hypothesis | Motivation | Sign | Coefficient |
|---|---|---|---|
| Liquidity-Driven-Trade hypothesis | Exogenous investment opportunities | Positive | $\hat{\beta}_i OF_{i,t-1}$ |
| Information-Driven-Trade hypothesis | Unfavourable private information | Negative | $\hat{\beta}_i OF_{i,t-1}$ |

This table explains the two hypotheses relating customer order-flow to subsequent volatility.

The two hypotheses, therefore, provide opposing views: The *liquidity-driven trade hypothesis* (*information-driven trade hypothesis*) suggests that trading volume and subsequent volatilities are negatively (positively)

insider trading/information driven trading; generally, this model was meant to capture the trade by informed investors; informed means skilled in analysing the public news (see Vega (2006)). Another important behaviour of informal traders is that they often try to hide their superior information, and try to act as ordinary market participants; therefore, medium-sized trades are most likely to be significant/robust in the empirical studies, this is consistent with the findings of this research (see Lee and Yi (2001); Barclay *et al.* (2003); Brunnermeier and Pedersen (2005); Boehmer (2005); Anand *et al.* (2005))

correlated. In this thesis, the two hypotheses are examined in the context of the foreign exchange market, with the help of a private data set, in order to analyse, which one of these two hypotheses dominates in the foreign exchange market.

Avramov *et al.* (2006) studied the asymmetric impact of order-flow on the daily volatility of individual stock returns. Considering a variety of measures of volatility, they tested two hypotheses, the first, that the asymmetry is due to the leverage effect, and the second, that it is due to time-varying expected returns. The results were mixed; the leverage effect may be valid at low frequencies but is unlikely to be relevant at higher frequencies (for example, with daily data): While they also found strong evidence that selling activity is the source of the asymmetric impact of order-flow on volatility. In this thesis, a modified version of the Avramov *et al.* (2006) methodology is employed to study the asymmetric impact of customer order-flows.

### 4.2.6. Methodological Issues

This section attempts to develop empirical methodologies in order to examine the relationship between customer order-flows (both contemporaneous and lagged) and volatility (both current and future). The analysis has three layers: the first computes volatility from daily returns; the second examines the relationship between customer order- flows and volatility and; the third examines the relationship between order- flows and future volatility (to look for asymmetric effects). Although various measures have been used previously, including implied volatility and conditional volatility, the ubiquitous way to measure volatility is from the time-series of return.[18]

**Computation of weekly returns**

The weekly log spot FX return $r_{i,t}$ of foreign currency $i$ is calculated from:

$$r_{i,t} = ln[s_{i,t}] - ln[s_{i,t-1}], \tag{4.1}$$

where $s_{i,t}$ is the log of the spot price of the foreign currency $i$ against the domestic currency at week $t$. The descriptive statistics are presented in table 4.5.

**Absolute Return Residuals**

A variant[19] of the model developed by Schwert (1990) and Jones *et al.* (1994) is used. The following equation, which regresses weekly returns on their own seven lags, is considered:

$$r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}, \tag{4.2}$$

where $r_{i,t}$ is the weekly return of foreign currency $i$ obtained from equation 4.1, $r_{i,t-j}$, $j = 1, \ldots, 7$ are the seven lags of the weekly returns (thus, each estimation uses data spanning 49 days), $\hat{\beta}_0$ (the intercept) and $\hat{\beta}_j$, $j = 1, \ldots, 7$ are coefficients to be estimated and $\hat{\epsilon}_{i,t}$ is the error term

[18] See Schwert (1990); Jones *et al.* (1994); Wang (1994); Chan and Fong (2000)

[19] Stock markets operate five days a week and are subject to the Monday effect, in that trading volumes and returns are usually higher on Mondays. Therefore, Schwert (1990) and Jones *et al.* (1994) introduce a dummy variable to account for this effect. Foreign exchange markets operate 24 hours a day and are more global in nature. Therefore, for simplicity, day-of-the-week is not taken as a dummy variable.

(noise). The estimated volatility is set equal to the absolute value of the error term i.e. $|\hat{\epsilon}_{i,t}|$.

**Realised Volatility**

It is found that the precise estimates of volatility can be measured by summing up the squared daily high-frequency returns (see Andersen *et al.*, 2001). Volatility is the measure of dispersion/variation of the foreign exchange instrument return from its mean. In simple terms, if it is assumed that an asset return mean is 0% and availability in the mean time is 10% (-10%; +10%) then the asset return could be a maximum of a 10% gain or a 10% loss. If it is assumed that the volatility is normally distributed, then it can be said that ±10% is the one standard deviation from the mean; that is 68.3%, plus ±20% is the two standard deviation probability from the mean and ±30% is the standard deviation and the probability of 99.7%. Realised volatility is basically the volatility of the foreign exchange prices for a series overlooking the historical path of the underlying financial instrument. The most commonly used historical estimate for volatility is a standard deviation. Thus the realised volatility is given by the equation (4.3).

An estimation was also made of the realised volatility $\sigma_i$, computed daily over $n$ number of days, of the log of the spot price $s_{i,j}$, at time $j$, of foreign currency $i$ against the U.S. dollar via:

$$\sigma_i = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(r_{i,k} - \bar{r})^2} \quad \text{where } \bar{r} = \frac{1}{n}\sum_{j=1}^{n} r_{i,j}, \text{ and } r_{i,j} = \frac{s_{i,j}}{s_{i,j-1}}. \tag{4.3}$$

The annualised realised volatility $\sigma_{a,i} = \sigma_i \times \sqrt{h}$, where $h = 365$. In the analysis, $n = 30$ was set. The descriptive statistics of the historical realised volatilities are in Table 4.5.

**Implied Volatility**

The Black and Scholes (1973) implied volatilities of each currency pair are obtained from Bloomberg and they correspond to the prices of at-the-money-forward options with one-month maturity. For the descriptive statistics of the implied volatilities see Table 4.4.

**Conditional (GARCH (1,1)) Volatility**

Another model was applied for capturing the volatility, that is, the Generalised Autoregressive Conditional Heteroskedasticity GARCH (1,1) (GARCH (1,1)) which was developed by Bollerslev (1986). This model is a generalisation of the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982).

A GARCH (1,1) (Engle, 1982; Bollerslev, 1986) model for volatility is estimated using the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \sigma_{t-1}^2, \tag{4.4}$$

where $\mu_t$ denotes the conditional mean and $\sigma_t^2$ the conditional variance at time $t$. The conditional variance depends on the one-period lagged squared error term and the conditional variance. The conditional mean ($\mu$) is the unexpected return or market shock and follows a conditional normal process with zero expected return and follows a time varying conditional variance.[20] The descriptive statistics of the GARCH (1,1) volatilities are in Table 4.5.

## 4.3. Data, Econometric Framework and Results

The foreign exchange rate data obtained from Bloomberg are expressed as the number of units of domestic currency (for GBPUSD, this is USD) per unit of foreign currency (for GBPUSD, this is GBP). The first-named currency in a pair is always the foreign currency. The order-flow data for each pair is in billions of the domestic currency: For example, EURUSD is expressed in billion of dollars and the USDJPY is expressed in billion of Japanese yen. Order flows reflect this same convention - a positive order-flow represents the buying of domestic currency (and hence, sales of the foreign currency). The customer order-flow dataset that will be examined here was provided by UBS (Union Bank of Switzerland). It covers from the $2^{nd}$ November 2001 to $11^{th}$ November 2011.

UBS assembled the dataset in the following fashion. Each spot foreign exchange transaction carried out by UBS with one of its clients is recorded along the following dimensions: size (in billions of domestic currency), currency pair (e.g., GBPUSD or AUDUSD), direction (sale or purchase) and the classification of the client. The client classifications are *Asset Manager* (AM, representing *real* investment funds), *Corporate* (C), *Hedge Fund* (HF, representing *leveraged* investment funds) and *Private Customer* (PC). UBS sums up the transactions that have occurred during each week. They also exclude order-flows that are greater in magnitude than three standard deviations from the mean. Their rationale for this is that these

[20]The market shock or excess return is taken as the mean deviation defined in equation 4.1.

very large transactions are invariably large-scale cross-border mergers and acquisitions and that they have the impact of skewing the data. The removal of these large transactions from the dataset is positive to the analysis process. This is because market participants are very well aware of these transactions and so they can adjust their portfolios in advance.

The dataset gives both net and gross order-flow. The gross order-flow indicates that, for example, in a given week, there were purchases of USD against GBP of 2.9 billion USD and sales of USD against GBP of 2.2 billion USD. The corresponding net order-flow is simply +0.7 billion USD. The dataset also provides what is termed disaggregate and aggregate order-flow. The disaggregate order-flow is the order-flow for each of the four client classifications. The aggregate order-flow sums up the four separate disaggregate order-flows. The aggregate order-flow dataset is available in both net and gross forms. However, the disaggregate dataset is only available in net form. Disaggregate order-flow data are available for twelve exchange rates: EURUSD, USDJPY, EURJPY, GBPUSD, EURGBP, USDCHF, EURCHF, AUDUSD, NZDUSD, USDCAD, EURSEK and EURNOK. Aggregate order-flow data are available for twenty exchange rates, which are the twelve above plus USDMXN, USDSGD, USDHKD, USDTRY, EURHUF, EURPLN, EURCZK and EURSKK.

The UBS dataset gives substantial novelty and value. It is, as far as the researcher is aware, the largest dataset ever used in relation to volatility and order-flows in the foreign exchange market. Plus, as it is not publicly available, it provides a unique research opportunity. The vast time period (over a decade) and the number of exchange rates (up to twenty) distinguishes this dataset from those used in previous studies which use much smaller variables.[21] Furthermore, UBS is one of the most active participants in the foreign exchange market with a market share greater than 10%. Most research related to order-flows in the foreign exchange markets considers inter-dealer order-flows rather than considering customer orders flows,. The implicit hypothesis is that dealers trading between each other gradually reveal their customer order-flows to the market. In practice, the trading volume also increases as dealers *pass-the-parcel* (the *hot potato* effect). Unlike some previous studies (e.g., Rime et al., 2010) that used only the sign or direction of the order-flow, here both the sign and the magnitude (monetary value) are looked at. Finally, disaggregate order-flows are considered, distinguishing between client classifications, as well as aggregate order-flows. The summary statistics of the disaggregate and aggregate customer order flow data are presented in Tables (4.2) and (4.3), respectively.

[21](see Carpenter and Wang, 2003; Evans and Lyons, 2005; Frommel *et al.*, 2008)

**Table 4.2.:** Summary statistics of net disaggregate customer order-flows

| | EURUSD | | | | USDJPY | | | | EURJPY | | | | GBPUSD | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC |
| Mean | -0.02 | -0.26 | -0.13 | 0.04 | -0.03 | -0.02 | -0.08 | -0.01 | 0.00 | -0.02 | -0.02 | 0.00 | 0.03 | -0.01 | -0.05 | 0.01 |
| St-Dev | 0.99 | 0.36 | 0.87 | 0.50 | 0.58 | 0.13 | 0.53 | 0.21 | 0.28 | 0.11 | 0.21 | 0.13 | 0.57 | 0.17 | 0.42 | 0.26 |
| Median | -0.02 | -0.24 | -0.11 | 0.03 | -0.05 | -0.02 | -0.07 | -0.01 | 0.00 | -0.01 | 0.00 | 0.00 | 0.01 | -0.01 | -0.03 | 0.01 |
| Min | -5.50 | -1.78 | -3.45 | -2.31 | -2.72 | -0.63 | -2.65 | -0.90 | -1.89 | -2.02 | -1.32 | -0.79 | -2.44 | -0.78 | -3.00 | -1.35 |
| Max | 5.75 | 1.63 | 3.74 | 2.53 | 2.85 | 0.48 | 2.01 | 0.86 | 1.67 | 0.32 | 0.72 | 0.63 | 4.89 | 1.27 | 3.18 | 1.25 |
| AR(1) | 0.05 | 0.19 | -0.06 | 0.02 | 0.13 | 0.03 | 0.18 | -0.04 | -0.02 | 0.04 | 0.02 | -0.08 | 0.23 | 0.05 | 0.11 | -0.04 |
| AR(1-7) | 0.08 | 0.14 | 0.05 | -0.02 | 0.03 | 0.03 | 0.00 | -0.05 | -0.02 | 0.10 | 0.06 | -0.11 | -0.02 | 0.12 | 0.00 | -0.03 |
| | EURGBP | | | | USDCHF | | | | EURCHF | | | | AUDUSD | | | |
| | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC |
| Mean | -0.04 | 0.03 | -0.03 | 0.00 | 0.02 | -0.04 | -0.03 | -0.03 | -0.02 | -0.01 | -0.02 | 0.01 | 0.00 | 0.01 | -0.02 | 0.00 |
| St-Dev | 0.31 | 0.15 | 0.17 | 0.07 | 0.41 | 0.26 | 0.40 | 0.20 | 0.35 | 0.31 | 0.46 | 0.14 | 0.28 | 0.10 | 0.29 | 0.16 |
| Median | -0.02 | 0.02 | -0.01 | 0.00 | 0.00 | -0.04 | -0.01 | -0.02 | 0.00 | 0.00 | -0.01 | 0.02 | 0.00 | 0.00 | 0.01 | 0.00 |
| Min | -1.71 | -0.74 | -0.99 | -0.31 | -1.79 | -1.28 | -1.94 | -1.36 | -2.46 | -1.44 | -2.82 | -1.30 | -1.34 | -0.32 | -1.28 | -1.15 |
| Max | 1.96 | 0.98 | 1.12 | 0.36 | 1.65 | 2.50 | 1.58 | 1.12 | 1.70 | 2.02 | 4.17 | 0.74 | 1.64 | 0.86 | 1.28 | 0.77 |
| AR(1) | 0.06 | 0.00 | 0.05 | 0.00 | 0.15 | 0.25 | 0.03 | -0.01 | 0.05 | 0.13 | 0.01 | 0.15 | 0.14 | 0.31 | 0.11 | 0.32 |
| AR(1-7) | 0.05 | 0.07 | -0.01 | -0.06 | 0.07 | 0.09 | 0.02 | -0.01 | 0.03 | 0.09 | 0.05 | 0.11 | -0.01 | 0.12 | 0.01 | 0.15 |
| | NZDUSD | | | | USDCAD | | | | EURSEK | | | | EURNOK | | | |
| | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC | AM | C | HF | PC |
| Mean | 0.00 | -0.01 | 0.00 | 0.00 | -0.01 | -0.01 | -0.01 | 0.00 | 0.00 | -0.01 | 0.01 | 0.00 | 0.01 | -0.01 | 0.00 | 0.00 |
| St-Dev | 0.11 | 0.02 | 0.10 | 0.04 | 0.29 | 0.09 | 0.21 | 0.11 | 0.13 | 0.04 | 0.11 | 0.03 | 0.11 | 0.03 | 0.09 | 0.04 |
| Median | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Min | -0.63 | -0.13 | -0.44 | -0.39 | -1.86 | -0.62 | -0.82 | -1.09 | -0.67 | -0.18 | -0.46 | -0.18 | -0.52 | -0.19 | -0.38 | -0.31 |
| Max | 0.61 | 0.12 | 0.49 | 0.26 | 1.47 | 0.69 | 0.73 | 0.61 | 0.67 | 0.21 | 0.55 | 0.24 | 0.56 | 0.14 | 0.38 | 0.31 |
| AR(1) | 0.10 | -0.03 | 0.04 | -0.02 | 0.10 | 0.20 | 0.10 | 0.06 | 0.06 | 0.16 | 0.11 | 0.02 | -0.13 | 0.11 | 0.00 | 0.08 |
| AR(1-7) | 0.08 | -0.08 | 0.02 | -0.08 | 0.07 | 0.10 | 0.02 | -0.19 | -0.08 | 0.12 | -0.06 | -0.21 | 0.05 | 0.08 | -0.05 | -0.09 |

Note: This table represents the summary statistics of the weekly net customer order-flows (Asset Manager (AM), Corporate (C), Hedge Fund (H), and Private Customer (PC)) of 524 weekly observations starting from 2 Nov 2001 to 11 Nov 2011. AR(1) is the first order autocorrelation, and AR(1-7) is the second order autocorrelation.

**Table 4.3.:** Summary statistics of aggregate customer order-flows

Gross aggregate customer order-flows

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 22.24 | 8.95 | 3.40 | 7.63 | 2.84 | 6.79 | 5.22 | 3.57 | 0.76 | 2.52 |
| St-Dev | 11.97 | 3.91 | 1.68 | 5.14 | 1.68 | 3.27 | 2.92 | 2.59 | 0.61 | 1.64 |
| Median | 18.68 | 7.88 | 3.23 | 6.87 | 2.46 | 5.38 | 4.43 | 2.60 | 0.66 | 2.11 |
| Min | 0.64 | 0.26 | 0.06 | 0.13 | 0.07 | 0.27 | 0.15 | 0.04 | 0.00 | 0.13 |
| Max | 84.44 | 25.92 | 12.25 | 50.7 | 11.55 | 24.79 | 19.72 | 11.69 | 3.17 | 12.3 |
| AR(1) | 0.77 | 0.58 | 0.65 | 0.64 | 0.62 | 0.72 | 0.69 | 0.85 | 0.82 | 0.60 |
| AR(1-7) | 0.71 | 0.49 | 0.53 | 0.57 | 0.59 | 0.63 | 0.58 | 0.80 | 0.76 | 0.56 |

| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.63 | 0.45 | 0.46 | 0.42 | 0.58 | 0.31 | 0.15 | 0.23 | 0.08 | 0.01 |
| St-Dev | 0.38 | 0.40 | 0.39 | 0.34 | 0.49 | 0.37 | 0.15 | 0.23 | 0.09 | 0.04 |
| Median | 0.57 | 0.34 | 0.36 | 0.35 | 0.46 | 0.20 | 0.11 | 0.17 | 0.05 | 0.00 |
| Min | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | -0.23 |
| Max | 2.97 | 3.09 | 2.22 | 1.79 | 2.54 | 2.11 | 0.96 | 1.67 | 0.71 | 0.48 |
| AR(1) | 0.53 | 0.72 | 0.71 | 0.61 | 0.77 | 0.78 | 0.63 | 0.71 | 0.55 | 0.42 |
| AR(1-7) | 0.48 | 0.66 | 0.64 | 0.56 | 0.72 | 0.69 | 0.58 | 0.62 | 0.52 | 0.35 |

Net aggregate customer order-flows

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | -0.38 | -0.15 | -0.05 | 0.00 | -0.03 | -0.08 | -0.04 | -0.01 | -0.01 | -0.03 |
| St-Dev | 1.38 | 0.81 | 0.40 | 0.76 | 0.39 | 0.61 | 0.63 | 0.42 | 0.15 | 0.34 |
| Median | -0.37 | -0.13 | -0.05 | -0.01 | -0.02 | -0.06 | -0.02 | -0.01 | 0.00 | -0.03 |
| Min | -5.84 | -4.16 | -2.08 | -4.94 | -2.53 | -3.38 | -3.7 | -1.79 | -0.75 | -2.01 |
| Max | 6.87 | 2.94 | 1.75 | 7.97 | 1.66 | 2.55 | 2.23 | 2.10 | 0.75 | 1.83 |
| AR(1) | 0.08 | 0.07 | -0.06 | 0.24 | 0.03 | 0.11 | 0.15 | 0.12 | 0.01 | 0.05 |
| AR(1-7) | 0.09 | 0.00 | -0.01 | -0.06 | 0.07 | 0.08 | 0.05 | 0.06 | -0.02 | 0.04 |

| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | -0.01 | 0.00 | 0.01 | 0.00 | -0.02 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 |
| St-Dev | 0.17 | 0.15 | 0.11 | 0.14 | 0.18 | 0.12 | 0.07 | 0.10 | 0.05 | 0.03 |
| Median | -0.01 | 0.00 | 0.00 | 0.00 | -0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Min | -0.60 | -0.82 | -0.49 | -0.65 | -1.12 | -0.70 | -0.35 | -0.44 | -0.23 | -0.39 |
| Max | 0.88 | 0.62 | 0.55 | 0.89 | 0.74 | 1.02 | 0.36 | 0.57 | 0.33 | 0.17 |
| AR(1) | 0.06 | -0.09 | -0.09 | 0.19 | 0.14 | 0.12 | 0.00 | 0.01 | 0.10 | -0.17 |
| AR(1-7) | -0.05 | 0.10 | -0.05 | 0.12 | 0.17 | 0.05 | 0.04 | 0.07 | -0.01 | 0.00 |

Note: This table represents the summary statistics of the weekly gross and net aggregate customer order-flows comprising of 524 weekly observations starting from 2 Nov 2001 to 11 Nov 2011. AR(1) is the first order autocorrelation, and AR(1-7) is the second order autocorrelation.

Transactions are classified according to their size so that this factor can be examined as to ascertain its impact on volatility. Then five portfolios based on sizes ranging from portfolio 1 to portfolio 5 are created. The sorted portfolios are rebalanced every week. For the case of aggregate customer order-flows (20 currency pairs are available), each of the 5 portfolios has trades for 4 currency pairs. In the case of disaggregate customer order-flows (for which 12 currency pairs are considered), the number of currency pairs in the portfolios is 2, 2, 4, 2, and 2. The aim is to investigate the impact of large, medium and small transactions on volatility in order to establish, for example, if large sales and purchases are indeed the trades that carry better (or private) information. The summary statistics of the portfolios for net and gross aggregate customer order-flow are in Table 4.4.

The summary statistics of the exchange rate returns are presented in Table 4.5. The mean returns over the time period considered are negative for half of the currency pairs, but with high levels of variability relative to the means. Row AR(1), the first order autocorrelation are uncorrelated $AR(1) \approxeq 0$ and AR(1-7) is the sum of the first seven autocorrelations, which on average will result in almost no autocorrelations, i.e., $AR(1-7) \approxeq 0$.

**Table 4.4.:** Summary statistics of aggregate net and gross customer order-flows portfolios

| | FX Order-Flow Net Portfolios Descriptive Statistics | | | | |
|---|---|---|---|---|---|
| | Portfolio '1' | Portfolio '2' | Portfolio '3' | Portfolio '4' | Portfolio '5' |
| Mean | -0.58 | -0.10 | -0.01 | 0.06 | 0.43 |
| St-Dev | 0.41 | 0.09 | 0.03 | 0.07 | 0.33 |
| Median | -0.49 | -0.08 | 0.00 | 0.05 | 0.35 |
| Min | -3.50 | -0.64 | -0.14 | -0.04 | 0.02 |
| Max | -0.03 | 0.01 | 0.13 | 0.48 | 2.56 |
| AR(1) | 0.29 | 0.33 | 0.18 | 0.24 | 0.25 |
| AR(1-7) | 0.25 | 0.35 | 0.14 | 0.17 | 0.14 |
| | FX Order-Flows Gross Portfolios Descriptive Statistics | | | | |
| | Portfolio '1' | Portfolio '2' | Portfolio '3' | Portfolio '4' | Portfolio '5' |
| Mean | 0.09 | 0.36 | 1.06 | 3.68 | 11.44 |
| St-Dev | 0.09 | 0.27 | 0.62 | 1.82 | 5.40 |
| Median | 0.09 | 0.31 | 1.00 | 3.31 | 9.99 |
| Min | 0.00 | 0.01 | 0.07 | 0.53 | 2.63 |
| Max | 0.44 | 1.42 | 4.65 | 12.87 | 42.34 |
| AR(1) | 0.80 | 0.86 | 0.78 | 0.78 | 0.77 |
| AR(1-7) | 0.72 | 0.79 | 0.74 | 0.70 | 0.70 |

Note: This table represents the summary statistics of the five FX aggregate net customer order-flow portfolios of twenty currencies consisting of 524 weekly observations from 2 Nov 2001 to 11 Nov 2011, classified into 5 portfolios from large sales to large purchases. The portfolios are constructed on an interval of 4, 4, 4, 4 and 4 observations ascending order-flows. The portfolios are rebalanced at each time $t$. Portfolios 1 & 5 represent the large sales and large purchases respectively, consisting of twenty currencies.

**Table 4.5.:** Summary statistics of FX spot return and FX implied volatility

FX Spot Return[a] Descriptive Statistics

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.08 | -0.09 | -0.01 | 0.02 | 0.06 | -0.11 | -0.03 | 0.13 | 0.12 | -0.09 |
| St-Dev | 1.44 | 1.46 | 1.71 | 1.40 | 1.22 | 1.58 | 0.93 | 2.00 | 2.01 | 1.40 |
| Median | 0.14 | -0.09 | 0.17 | 0.09 | 0.08 | -0.14 | -0.02 | 0.33 | 0.36 | -0.19 |
| Min | -6.05 | -7.52 | -13.32 | -8.35 | -7.50 | -6.41 | -4.27 | -18.52 | -10.78 | -5.22 |
| Max | 4.99 | 4.55 | 4.87 | 5.19 | 5.89 | 11.44 | 7.46 | 7.02 | 6.29 | 8.03 |
| AR(1) | 0.02 | -0.09 | -0.07 | -0.02 | -0.08 | -0.02 | -0.11 | -0.05 | -0.03 | 0.00 |
| AR(1-7) | 0.01 | 0.03 | 0.03 | -0.06 | -0.10 | 0.07 | -0.01 | 0.07 | 0.02 | -0.07 |
| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
| Mean | -0.01 | -0.01 | 0.07 | -0.07 | 0.00 | 0.02 | 0.04 | 0.03 | -0.05 | -0.07 |
| St-Dev | 0.97 | 1.05 | 1.49 | 0.72 | 0.08 | 2.11 | 1.34 | 1.46 | 0.95 | 0.56 |
| Median | 0.00 | -0.07 | -0.03 | -0.11 | 0.00 | -0.15 | -0.06 | -0.06 | -0.01 | 0.00 |
| Min | -4.45 | -4.52 | -5.65 | -2.48 | -0.60 | -9.56 | -6.69 | -8.27 | -4.88 | -2.70 |
| Max | 5.57 | 5.21 | 15.47 | 4.49 | 0.30 | 12.18 | 5.40 | 6.91 | 4.55 | 2.17 |
| AR(1) | -0.12 | -0.03 | -0.07 | 0.06 | 0.00 | -0.03 | -0.14 | -0.18 | -0.02 | -0.01 |
| AR(1-7) | 0.03 | 0.06 | 0.09 | 0.05 | 0.00 | 0.09 | 0.00 | 0.12 | -0.07 | 0.10 |

FX Implied Volatility[b] Descriptive Statistics

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 10.32 | 10.59 | 11.52 | 9.44 | 7.68 | 10.69 | 5.41 | 12.11 | 13.31 | 9.72 |
| St-Dev | 3.27 | 3.40 | 5.25 | 3.51 | 3.25 | 2.70 | 3.29 | 5.12 | 4.41 | 3.66 |
| Median | 9.82 | 9.84 | 9.95 | 8.40 | 7.06 | 10.45 | 4.04 | 10.79 | 11.88 | 8.75 |
| Min | 4.68 | 6.13 | 5.00 | 4.55 | 3.50 | 5.25 | 2.35 | 5.93 | 8.40 | 5.40 |
| Max | 27.00 | 35.53 | 45.88 | 28.5 | 22.5 | 24.55 | 22.93 | 45.00 | 40.00 | 28.25 |
| AR(1) | 0.95 | 0.90 | 0.95 | 0.96 | 0.97 | 0.92 | 0.95 | 0.95 | 0.94 | 0.97 |
| AR(1-7) | 0.93 | 0.89 | 0.92 | 0.95 | 0.96 | 0.88 | 0.92 | 0.92 | 0.92 | 0.95 |
| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
| Mean | 6.94 | 7.41 | 10.86 | 5.61 | 0.69 | 14.45 | 10.29 | 10.92 | 7.23 | 4.01 |
| St-Dev | 3.28 | 2.85 | 7.05 | 2.14 | 0.47 | 4.59 | 4.51 | 5.04 | 3.46 | 2.33 |
| Median | 5.95 | 6.74 | 9.21 | 5.10 | 0.60 | 14.73 | 9.10 | 9.90 | 6.25 | 5.00 |
| Min | 3.00 | 4.20 | 4.90 | 2.85 | 0.10 | 5.95 | 4.25 | 5.65 | 3.40 | 0.01 |
| Max | 19.56 | 22.75 | 71.43 | 14.44 | 5.00 | 49.77 | 40.00 | 37.00 | 26.79 | 9.00 |
| AR(1) | 0.97 | 0.96 | 0.90 | 0.95 | 0.84 | 0.91 | 0.95 | 0.96 | 0.97 | 0.98 |
| AR(1-7) | 0.95 | 0.92 | 0.85 | 0.90 | 0.72 | 0.83 | 0.91 | 0.94 | 0.94 | 0.97 |

Note: This table presents the summary statistics of the daily FX spot return and FX implied Black and Scholes (1973) volatility constructed from 524 weekly observations spanning 2 Nov 2001 to 11 Nov 2011. AR(1) is the first order autocorrelation, and AR(1-7) is the second order autocorrelation.

[a] T he FX spot returns are obtained from $r_{i,t} = ln[s_{i,t}] - ln[s_{i,t-1}]$

**Table 4.6.:** Summary statistics of FX realised and conditional volatility

FX Realised Volatility[a] Descriptive Statistics

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 9.51 | 10.04 | 10.59 | 9.26 | 7.08 | 10.60 | 4.18 | 12.37 | 13.16 | 9.20 |
| St-Dev | 3.33 | 3.56 | 5.60 | 4.12 | 3.64 | 3.23 | 2.41 | 7.66 | 6.12 | 4.17 |
| Median | 9.02 | 9.30 | 9.01 | 8.30 | 6.05 | 10.40 | 3.43 | 10.34 | 11.42 | 8.18 |
| Min | 3.92 | 3.25 | 3.28 | 2.85 | 2.67 | 5.02 | 1.48 | 4.72 | 5.67 | 3.60 |
| Max | 24.49 | 25.60 | 40.93 | 28.68 | 27.24 | 28.91 | 15.69 | 70.60 | 46.63 | 32.31 |
| AR(1) | 0.94 | 0.92 | 0.96 | 0.96 | 0.97 | 0.93 | 0.96 | 0.96 | 0.95 | 0.96 |
| AR(1-7) | 0.88 | 0.84 | 0.91 | 0.91 | 0.93 | 0.85 | 0.91 | 0.90 | 0.89 | 0.91 |

| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 5.88 | 6.77 | 8.41 | 4.73 | 0.37 | 14.61 | 8.66 | 9.49 | 6.49 | 4.01 |
| St-Dev | 3.76 | 3.28 | 6.14 | 1.87 | 0.38 | 7.86 | 5.31 | 4.92 | 3.63 | 2.33 |
| Median | 4.63 | 5.81 | 6.69 | 4.34 | 0.26 | 12.70 | 7.10 | 8.16 | 5.57 | 3.89 |
| Min | 1.57 | 2.85 | 2.34 | 1.63 | 0.03 | 3.40 | 1.91 | 3.28 | 1.92 | 0.00 |
| Max | 22.41 | 21.70 | 52.77 | 14.82 | 2.71 | 53.75 | 33.94 | 32.69 | 24.79 | 14.82 |
| AR(1) | 0.97 | 0.96 | 0.96 | 0.94 | 0.93 | 0.94 | 0.94 | 0.97 | 0.96 | 0.91 |
| AR(1-7) | 0.95 | 0.91 | 0.90 | 0.88 | 0.85 | 0.86 | 0.85 | 0.92 | 0.90 | 0.81 |

FX Conditional Volatility[b] Descriptive Statistics

| | EURUSD | USDJPY | EURJPY | GBPUSD | EURGBP | USDCHF | EURCHF | AUDUSD | NZDUSD | USDCAD |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 9.95 | 10.38 | 11.75 | 9.38 | 7.64 | 10.95 | 5.56 | 13.25 | 14.21 | 9.75 |
| St-Dev | 2.71 | 2.69 | 5.01 | 3.33 | 3.02 | 2.59 | 3.68 | 6.56 | 5.05 | 3.76 |
| Median | 9.65 | 9.69 | 10.85 | 8.46 | 7.33 | 10.64 | 4.05 | 11.93 | 13.00 | 8.97 |
| Min | 4.85 | 6.13 | 5.35 | 5.12 | 3.46 | 5.89 | 2.35 | 6.35 | 8.33 | 4.13 |
| Max | 22.36 | 23.28 | 42.35 | 24.00 | 24.01 | 25.29 | 32.86 | 61.42 | 38.43 | 29.66 |
| AR(1) | 0.97 | 0.93 | 0.93 | 0.98 | 0.98 | 0.92 | 0.95 | 0.95 | 0.92 | 0.97 |
| AR(1-7) | 0.94 | 0.88 | 0.88 | 0.96 | 0.96 | 0.88 | 0.89 | 0.91 | 0.88 | 0.95 |

| | EURSEK | EURNOK | USDMXN | USDSGD | USDHKD | USDTRY | EURHUF | EURPLN | EURCZK | EURSKK |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 6.42 | 8.06 | 9.33 | 5.08 | 0.49 | 16.51 | 10.03 | 10.06 | 6.76 | 4.06 |
| St-Dev | 3.12 | 6.35 | 5.18 | 1.71 | 0.30 | 8.37 | 4.16 | 4.01 | 2.89 | 2.26 |
| Median | 5.30 | 6.64 | 7.52 | 4.63 | 0.51 | 14.26 | 8.95 | 9.20 | 6.10 | 4.40 |
| Min | 2.68 | 4.35 | 4.32 | 2.72 | 0.06 | 5.72 | 4.35 | 4.51 | 3.21 | 0.66 |
| Max | 18.37 | 114.23 | 40.60 | 15.30 | 1.63 | 55.03 | 28.43 | 26.13 | 23.28 | 12.32 |
| AR(1) | 0.98 | 0.60 | 0.96 | 0.92 | 0.96 | 0.91 | 0.94 | 0.97 | 0.94 | 0.96 |
| AR(1-7) | 0.96 | 0.56 | 0.90 | 0.85 | 0.91 | 0.83 | 0.86 | 0.93 | 0.90 | 0.93 |

Note: This table represents the summary statistics of the daily underlying FX realised and conditional volatility consisting of 524 weekly observations from 2 Nov 2001 to 11 Nov 2011. AR(1) is the first order autocorrelation, and AR(1-7) is the second order autocorrelation.

[a] T he realised volatility is obtained from $\sigma_i = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(r_{i,k} - \bar{r})^2}$

[b] T he conditional volatility is obtained from $\sigma_t^2 = \alpha_0 + \alpha_1\mu_{t-1}^2 + \alpha_2\sigma_{t-1}^2$

In sub-sections 4.2.6, four different measures of volatility are presented; Absolute Return Residuals, Realised, Implied and Conditional (see equations 4.2, 4.3 and 4.4). The descriptive statistics for the four different measures of volatility are presented in Tables 4.5 and 4.6. Again columns AR(1) and AR(1-7) are the first order autocorrelation and the sum of 1-7 lags of the first order autocorrelation. The realised volatility (equation 4.3) is based on n = 30 daily returns. The descriptive statistics suggest that EURJPY, AUDUSD, NZDUSD, USDMXN and USDTRY have the highest volatilities among the set of currencies considered, the first order autocorrelation is positive and almost equal to one $AR(1) \approxeq 1$. Whereas, based on implied volatility, EURJPY, AUDUSD, NZDUSD, USDMXN, USDTRY, EURHUF and EURPLN have the highest volatilities and the first order autocorrelation is positive for AR(1) and AR(1-7). Hence, because of autocorrelation high $\bar{R}^2$ is expected in the estimated models. Finally, the conditional volatility that is obtained from the GARCH (1,1) model (equation 4.4) suggests that EURJPY, AUDUSD, NZDUSD, EURNOK, EURMXN, and USDTRY have the highest volatilities and the first order autocorrelation is positive for AR(1) and AR(1-7). Hence, because of autocorrelation high $\bar{R}^2$ is expected in the estimated models.

$\sigma_{i,t}$ is the volatility of the log of the spot price $s_{i,t}$, at time $t$, of foreign currency $i$ against the US dollar. While there are four different measures of volatility (Absolute Return Residuals, Realised Volatility, Implied Volatility and Conditional Volatility) generically denoted by $\sigma_{i,t}$. Therefore the $\sigma_{i,t}$ obtained is for four different methodologies.

An average volatility and an average customer order-flow across the different currency pairs are considered, i.e., are $N_{\text{ccy}} = 12$ currency pairs and an average volatility $\Sigma_t$ (for each of the four measures of volatility) and an average customer order-flow $OF_t$, across the 12 currency pairs, at each time $t$ are computed:

$$\Sigma_t \equiv \frac{1}{N_{\text{ccy}}} \sum_{i=1}^{N_{\text{ccy}}} \sigma_{i,t} \quad \text{and} \quad OF_t \equiv \frac{1}{N_{\text{ccy}}} \sum_{i=1}^{N_{\text{ccy}}} OF_{i,t}. \tag{4.5}$$

**Relationship between Customer Order-flows and Contemporaneous Volatility**

Four measures of volatility (Absolute Return Residuals, Realised Volatility, Implied Volatility and Conditional Volatility) are used. Each of these volatility measures is utilised to analyse a modified version of the model of Schwert (1990) and Jones *et al.* (1994) relating customer order-flow to volatility. In contrast to Schwert (1990) and Jones *et al.* (1994), weekly data are used. Hence, unlike the aforementioned authors, a day-of-the-week dummy variable term is not used and 7 lagged returns are used as opposed to their 12 lagged returns, to control for any serial dependence in weekly returns. Then the following model is estimated:

$$\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\eta}_t, \tag{4.6}$$

where $\hat{\eta}_t$ is the error term and where $\hat{\beta}_0$, $\hat{\beta}_j$, for $j = 1, \dots, 7$ and $\hat{\gamma}$ are coefficients to be estimated.

**Asymmetric Impact of Customer Order-Flows on Subsequent Volatility**

The asymmetric impact of customer order-flows on subsequent volatility are also considered. Similarly to the previous sub-section, the following modified version of the model of Schwert (1990) Jones *et al.* (1994) and

Avramov *et al.* (2006) is estimated.

$$\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\lambda} OF_{t-1} + \hat{\eta}_t, \tag{4.7}$$

where $\hat{\eta}_t$ is the error term and where $\hat{\beta}_0$, $\hat{\beta}_j$, for $j = 1, \ldots, 7$, $\hat{\gamma}$ and $\hat{\lambda}$ are coefficients to be estimated. $OF_t$ (respectively, $OF_{t-1}$) is the contemporaneous (respectively, lagged) aggregated customer order-flow, averaged across the $N_{\text{ccy}} = 12$ currency pairs. Again, four different measures of volatility are used.

### 4.3.1. Contemporaneous Relationship between Volatility and Disaggregate Customer Order-flows

In this subsection, the relationship between volatility and disaggregate customer order-flows is examined. Following Schwert (1990) and Jones *et al.* (1994), the following equation is estimated.

$$\sigma_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \sigma_{i,t-j} + \sum_{k=1}^{4} \hat{\gamma}_k OF_{k,i,t} + \hat{\eta}_{i,t}, \tag{4.8}$$

where $\hat{\eta}_{i,t}$ is the error term and where $\hat{\beta}_0$, $\hat{\beta}_j$, for $j = 1, \ldots, 7$ and $\hat{\gamma}_k$, for $k = 1, 2, 3, 4$, are coefficients to be estimated. $i$ denotes the foreign currency. $OF_{k,i,t}$ is the customer order-flow, at time $t$, for $k = 1, 2, 3, 4$ (the four client classifications). The model is estimated using ordinary least squares with Newey and West (1987) adjustment for the autocorrelation mentioned above.[22] The results of the estimation of equation 4.8 are presented in Table 4.7. The results are highly statistically significant with

[22]The Newey and West (1987) adjustment is used in econometrics for the estimation of covariance matrix of the regression models. The Newey and West (1987) adjustment is applied when the standard assumptions of regression analysis cannot be applied.

**Table 4.7.:** Estimation of the relationship between volatility and disaggregate customer order-flow across twelve currencies

| | Regression with individual currency[a] | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\lambda_{1(AM)}$ | $\lambda_{2(C)}$ | $\lambda_{3(HF)}$ | $\lambda_{4(PC)}$ | S.E. | D.W.[c] | $\bar{R}^2$ |
| EURUSD | 0.365***[b] | -0.140 | 0.420*** | -1.087*** | 1.377 | 2.039 | 0.33 |
| USDJPY | 0.543*** | -1.402*** | 0.611*** | -2.660*** | 1.417 | 2.015 | 0.33 |
| EURJPY | 1.073*** | -0.901 | 1.680*** | -2.035*** | 2.577 | 2.064 | 0.10 |
| GBPUSD | 0.432*** | -0.185 | 0.314** | -2.110*** | 1.461 | 2.011 | 0.24 |
| EURGBP | 0.704*** | -0.077 | 1.309*** | -2.653*** | 1.320 | 1.912 | 0.08 |
| USDCHF | 0.788*** | -1.194** | 0.779*** | -2.064*** | 1.806 | 1.903 | 0.26 |
| EURCHF | 0.139 | -1.129*** | 0.149 | -0.639* | 0.631 | 1.835 | 0.18 |
| AUDUSD | 1.981*** | -2.076** | 1.498*** | -2.266** | 3.220 | 1.974 | 0.19 |
| NZDUSD | 4.233*** | 7.925* | 5.328*** | -5.154*** | 3.571 | 2.013 | 0.12 |
| USDCAD | 0.703*** | -0.210 | 1.226*** | -4.029*** | 1.617 | 1.967 | 0.17 |
| EURSEK | -0.449 | -3.534*** | 1.060*** | 1.582 | 0.864 | 2.015 | 0.04 |
| EURNOK | 0.536 | 1.105 | 2.503*** | 1.708 | 1.066 | 2.001 | 0.03 |

Note: Regression results between volatilities (as dependent variable obtained from $R_{it} = \sum_{j=1}^{7} \hat{\beta}_{ij} R_{it-j} + \hat{\epsilon}_{it}$) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\sigma_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \sigma_{i,t-j} + \sum_{k=1}^{4} \hat{\gamma}_k OF_{k,i,t} + \hat{\eta}_{i,t}$

[a] The portfolios are constructed on an interval of 2, 2, 4, 2 and 2 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twelve currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on Newey and West (1987).

[c] DW is the *Durbin-Watson* statistic.

a good fit. The results suggest that disaggregate customer order flow impacts on volatility in the foreign exchange market. Furthermore, looking at the results it can be concluded that the Hedge Fund class (H) is the most important class of customer in influencing the volatility. In addition it is positively and significantly affects the volatility in the FX market.

The relationship between volatility and order-flow classified according to trade size is explored in order to investigate the effect of the size of transaction on volatility. The empirical evidence on the role of the size of trade is mixed in stock market. Barclay and Warner (1993) studied the impact of the size of trade on volatility and found that the price change is significantly affected by the medium size trades. Thus they deduced that the informed customers cover up their private information through medium size trades. Jones *et al.* (1994) classified the daily volume into the average trade size and the number of trades and found robust evidence in favour of the number of trades, concluding that the number of trades explains virtually all the variations in volatility. Furthermore, Jones *et al.* (1994) were unable to conclude any positive correlation between volatility and average trade size. While, the size of the trade is classified by Easley and O'Hara (1987), they categorise the trades into large and small transactions and conclude that large trades have a greater ability to move prices than do small trades. In contrast, Barclay and Warner (1993) catalog the trades into small, medium and large sizes. They find that medium trades considerably drive volatility, to a greater extent than small and large trades. Chan and Fong (2000) found the size of the trade has a more profound impact on volatility than the number of trades. In summary, it seems that the impact of the size of the trade on volatility is ambiguous.

To investigate the impact of the trade size on the volatility of foreign exchange rates, the data was transformed according to the trade size in the portfolios.[23] This was done decipher the affect of the large, medium

[23]Each trade is classified according to its transaction size, and there is no common definition for the size of the trades. Although some of the studies, such as Easley *et al.* (1997) on stock market, classified large as greater than 1000 and small as fewer than 1000 shares. Here the customer order-flows are classified into quantiles of 20% resulting in a total of 5 portfolios.

and small transactions. Mainly, because of the fact that the large sales and purchases are said to be the trades that carry the private information. The data have been rearranged and the corresponding volatilities of the large and small trades are obtained from the volatilities model discussed above.

The results of the model discussed in equation 4.6 are presented in Table 4.8, where the column with items *Asset Manager* (AM), *Corporate* (C), *Hedge Fund* (HF) and *Private Customer* (PC) represents the disaggregate order-flow for each class of customers respectively, and the *Aggregate* is the sum of the disaggregate order-flows. Each regression is regressed separately for each currency pair. Only the average of parameters associated with the customer order-flow are reported, at a significance level of 10%, 5% and 1% and the Durbin-Watson statistic and adjusted $R$ square are also reported. Almost all the coefficients in 4.8, for the aggregate and disaggregate data, are statistically significant, and are interpret as billion of US dollars. The large sales are negatively related to the order-flows, whereas, moving towards the large purchases, the sign of the coefficient becomes positive. The negative sign suggests that as the order-flow increases volatility decreases, which may be due to the short sales by the specific kind of customers. The $\bar{R}^2$ value suggests a good model of fit and it can be observed from the results that the values $\bar{R}^2$ are at their peak at both ends, that is, large sales and purchases. In general, the results suggest that the volatility and customer order-flow relationship is robust, and the order-flows contain vital private information. The customer order-flows appear to be the main channel for the transmission of private information in the FX market.

**Table 4.8.:** Estimation of the relationship between the volatilities and the disaggregate customer order-flow in a portfolio-based approach

| | $\gamma^b$ | S.E. | D.W.[c] | $\bar{R}^2$ |
|---|---|---|---|---|
| | Portfolio '1'[a] | | | |
| Asset Manager | -0.459*** | 0.720 | 2.031 | 0.06 |
| Corporate | -0.922*** | 0.572 | 2.056 | 0.04 |
| Hedge Fund | -0.454*** | 0.568 | 2.014 | 0.05 |
| Private Customer | -0.882*** | 0.623 | 1.992 | 0.15 |
| | Portfolio '2'[a] | | | |
| Asset Manager | -0.972*** | 0.534 | 2.042 | 0.16 |
| Corporate | -1.152* | 0.565 | 2.009 | 0.10 |
| Hedge Fund | -0.847*** | 0.597 | 2.029 | 0.06 |
| Private Customer | -1.665*** | 0.427 | 2.095 | 0.11 |
| | Portfolio '3'[a] | | | |
| Asset Manager | -0.466 | 0.337 | 2.023 | 0.17 |
| Corporate | -1.887** | 0.362 | 2.027 | 0.18 |
| Hedge Fund | -0.311 | 0.456 | 2.016 | 0.18 |
| Private Customer | 2.194 | 0.339 | 2.025 | 0.21 |
| | Portfolio '4'[a] | | | |
| Asset Manager | 0.508*** | 0.534 | 2.033 | 0.07 |
| Corporate | 1.842* | 0.820 | 2.036 | 0.13 |
| Hedge Fund | 1.276*** | 0.598 | 2.057 | 0.12 |
| Private Customer | 3.196*** | 0.651 | 2.021 | 0.10 |
| | Portfolio '5'[a] | | | |
| Asset Manager | 0.383*** | 0.596 | 2.018 | 0.16 |
| Corporate | 0.503* | 0.563 | 2.035 | 0.02 |
| Hedge Fund | 0.445*** | 0.572 | 2.079 | 0.06 |
| Private Customer | 1.460*** | 0.594 | 2.012 | 0.12 |

Note: Regression results between volatilities (as dependent variable obtained from $r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}$) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 2, 2, 4, 2 and 2 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twelve currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

The estimates of the above models with various volatility modelling are presented in Table 4.9.

**Table 4.9.:** Estimation of the relationship between the volatilities and the customer order-flow across 12 currencies

| | Realised | | | | Implied | | | | Conditional | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Portfolio '1'[a] | | | | Portfolio '1'[a] | | | | Portfolio '1'[a] | | | |
| | $\gamma^b$ | S.E. | D.W.[c] | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.[c] | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.[c] | $\bar{R}^2$ |
| Asset Manager | -0.257 | 6.358 | 1.993 | 0.63 | -0.887*** | 4.438 | 2.011 | 0.70 | -0.742*** | 6.013 | 2.017 | 0.58 |
| Corporate | 0.017 | 7.013 | 2.010 | 0.56 | -0.697** | 3.862 | 2.003 | 0.69 | -0.360 | 9.326 | 2.019 | 0.43 |
| Hedge Fund | -0.461** | 6.697 | 1.999 | 0.58 | -0.846*** | 4.07 | 2.017 | 0.69 | -0.713*** | 5.729 | 2.020 | 0.57 |
| Private Customer | -1.002** | 7.415 | 1.980 | 0.69 | -0.597 | 4.237 | 1.995 | 0.69 | -0.702 | 5.19 | 1.998 | 0.62 |
| | Portfolio '2'[a] | | | | Portfolio '2'[a] | | | | Portfolio '2'[a] | | | |
| Asset Manager | -2.525*** | 9.7 | 2.024 | 0.57 | -3.382*** | 5.684 | 2.052 | 0.68 | -2.576** | 6.54 | 2.033 | 0.63 |
| Corporate | 0.962 | 6.161 | 1.996 | 0.62 | 0.672 | 4.032 | 1.994 | 0.71 | 0.535 | 5.325 | 1.993 | 0.62 |
| Hedge Fund | -1.132 | 10.461 | 2.017 | 0.58 | -0.737 | 4.502 | 1.990 | 0.66 | -0.579 | 7.018 | 1.995 | 0.52 |
| Private Customer | -3.065* | 7.374 | 1.991 | 0.57 | -2.589 | 4.911 | 2.017 | 0.64 | -2.890* | 7.232 | 2.026 | 0.57 |
| | Portfolio '3'[a] | | | | Portfolio '3'[a] | | | | Portfolio '3'[a] | | | |
| Asset Manager | 1.028 | 4.057 | 1.990 | 0.73 | -2.529** | 2.55 | 1.993 | 0.81 | 0.260 | 4.931 | 2.006 | 0.71 |
| Corporate | -0.900 | 3.547 | 1.996 | 0.81 | -1.443 | 2.345 | 2.005 | 0.83 | 0.311 | 2.609 | 2.005 | 0.82 |
| Hedge Fund | -0.302 | 3.575 | 1.989 | 0.77 | 0.784 | 2.939 | 2.002 | 0.79 | 1.194 | 4.802 | 2.029 | 0.72 |
| Private Customer | 3.643 | 3.444 | 2.000 | 0.78 | 3.233 | 2.321 | 1.997 | 0.83 | 2.015 | 4.016 | 2.005 | 0.75 |
| | Portfolio '4'[a] | | | | Portfolio '4'[a] | | | | Portfolio '4'[a] | | | |
| Asset Manager | 0.726 | 9.419 | 1.995 | 0.58 | 1.278* | 5.162 | 2.020 | 0.63 | 1.817** | 5.925 | 2.022 | 0.58 |
| Corporate | -0.063 | 9.027 | 1.991 | 0.58 | -0.962 | 5.395 | 1.998 | 0.70 | 0.387 | 10.016 | 2.002 | 0.55 |
| Hedge Fund | 1.492* | 7.458 | 1.996 | 0.58 | 2.263*** | 5.181 | 2.007 | 0.68 | 2.910*** | 6.576 | 2.007 | 0.60 |
| Private Customer | 1.536 | 9.249 | 1.981 | 0.56 | 3.854*** | 5.977 | 1.995 | 0.65 | 4.150*** | 7.201 | 1.986 | 0.58 |
| | Portfolio '5'[a] | | | | Portfolio '5'[a] | | | | Portfolio '5'[a] | | | |
| Asset Manager | 0.273 | 8.279 | 1.995 | 0.57 | 0.638*** | 3.457 | 2.009 | 0.70 | 0.568*** | 4.636 | 2.022 | 0.60 |
| Corporate | 0.072 | 8.542 | 2.023 | 0.52 | 1.030 | 4.766 | 2.020 | 0.64 | 0.620 | 5.899 | 2.012 | 0.54 |
| Hedge Fund | 0.383 | 10.105 | 2.007 | 0.52 | 0.064 | 4.261 | 2.005 | 0.71 | 0.220 | 5.458 | 2.008 | 0.62 |
| Private Customer | 1.157*** | 5.607 | 1.995 | 0.62 | 2.083*** | 3.892 | 1.991 | 0.71 | 1.994*** | 5.43 | 2.003 | 0.56 |

Note: Regression results between volatilities (realised, implied and conditional volatility) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 2, 2, 4, 2 and 2 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twelve currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

### 4.3.2. Contemporaneous Relationship between Volatility and Net Aggregate Customer Order-flows

The relationship between volatility and net and gross customer order-flows for aggregate data will now be explored. Following Schwert (1990) and Jones *et al.* (1994), weekly volatilities using equations 4.2 to 4.4 are computed. These volatilities are used as the dependent variable while aggregate customer order-flows plus seven lags of volatilities are used as independent variables in order to control any serial dependence in weekly returns. The model used for the estimation is a modified version of the disaggregate model. Following Schwert (1990) and Jones *et al.* (1994), the following equation (which is a slightly modified version of the disaggregate model) is estimated.

$$\sigma_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \sigma_{i,t-j} + \hat{\gamma} \sum_{i=1}^{N_{\text{ccy}}} OF_{i,t} + \hat{\eta}_{i,t}, \tag{4.9}$$

where $\hat{\eta}_{i,t}$ is the error term and where $\hat{\beta}_0$, $\hat{\beta}_j$, for $j = 1, \ldots, 7$ and $\hat{\gamma}$ are coefficients to be estimated. $i$ denotes the foreign currency. $\sum_{i=1}^{N_{\text{ccy}}} OF_{i,t}$ is the aggregate customer order-flow, at time $t$. The model is estimated using ordinary least squares with the Newey and West (1987) estimator in order to adjust the estimates for autocorrelation (as described above). The results are presented in Tables 4.10 and 4.11 for net and gross customer order flows, respectively:

The coefficients are statistically significant but the $\bar{R}^2$ of the models shows that the variations in volatility are not well explained by the aggregate customer order flow. Furthermore, the same aggregate model was estimated with various versions of the volatilities that includes, realised,

**Table 4.10.:** Estimation of the relationship between volatility and aggregate net customer order-flow across 20 currencies

| | Aggregate Net Customer Order Flow | | | | Aggregate Gross Customer Order Flow | | | |
|---|---|---|---|---|---|---|---|---|
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| EURUSD | 0.252*** | 1.975 | 1.985 | 0.04 | -0.009 | 2.090 | 2.005 | -0.01 |
| USDJPY | 0.492*** | 1.974 | 1.989 | 0.06 | -0.024 | 2.126 | 1.998 | -0.01 |
| EURJPY | 0.900*** | 2.787 | 2.028 | 0.03 | -0.071 | 2.908 | 1.996 | -0.01 |
| GBPUSD | 0.279*** | 1.901 | 2.018 | 0.01 | -0.002 | 1.949 | 2.001 | -0.02 |
| EURGBP | 0.581*** | 1.412 | 1.968 | 0.02 | 0.025 | 1.464 | 1.993 | -0.01 |
| USDCHF | 0.316*** | 2.455 | 1.982 | 0.00 | 0.011 | 2.493 | 1.994 | -0.02 |
| EURCHF | -0.176*** | 0.771 | 1.976 | 0.00 | -0.003 | 0.782 | 1.989 | -0.01 |
| AUDUSD | 1.333*** | 3.714 | 1.931 | 0.06 | -0.099** | 3.973 | 1.995 | -0.00 |
| NZDUSD | 3.996*** | 3.736 | 2.007 | 0.08 | -0.531*** | 4.038 | 1.992 | 0.01 |
| USDCAD | 0.712*** | 1.923 | 2.010 | 0.01 | 0.030 | 1.980 | 2.004 | -0.01 |
| EURSEK | -0.148 | 0.909 | 1.995 | -0.01 | 0.174 | 0.905 | 1.997 | -0.01 |
| EURNOK | 1.367*** | 1.079 | 1.999 | 0.02 | 0.112 | 1.115 | 1.996 | -0.01 |
| USDMXN | 0.320 | 2.243 | 1.999 | -0.02 | 0.058 | 2.244 | 2.001 | -0.02 |
| USDSGD | 1.331*** | 0.486 | 1.979 | 0.05 | 0.072 | 0.518 | 1.998 | -0.01 |
| USDHKD | 0.023 | 0.006 | 1.989 | -0.01 | 0.000 | 0.006 | 1.995 | -0.02 |
| USDTRY | 4.875*** | 4.06 | 1.978 | 0.06 | 0.835* | 4.287 | 1.981 | 0.01 |
| EURHUF | 4.759*** | 1.687 | 1.981 | 0.05 | 0.159 | 1.798 | 1.995 | -0.02 |
| EURPLN | 2.580*** | 1.947 | 2.004 | 0.02 | 0.253 | 2.017 | 1.996 | -0.01 |
| EURCZK | 4.091*** | 0.869 | 1.988 | 0.03 | -0.074 | 0.905 | 1.981 | -0.02 |
| EURSKK | 0.490 | 0.309 | 2.007 | -0.01 | 0.969 | 0.308 | 1.982 | -0.01 |

Note: Regression results between volatilities (as dependent variable obtained from $r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}$) and lags of volatilities and contemporaneous aggregate customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\sigma_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \sigma_{i,t-j} + \hat{\gamma} \sum_{i=1}^{N_{\text{ccy}}} OF_{i,t} + \hat{\eta}_{i,t}$

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates use Newey and West (1987).

[c] DW is the *Durbin-Watson* statistic.

implied and conditional volatility. The results with the various volatilities are presented in Tables 4.11 and 4.12 for net and gross customer order flows, respectively. The results of the same model for different measures of volatility are presented in Table 4.13.

**Table 4.11.:** Estimation of the relationship between volatility and gross customer order-flows across 20 currencies

| | Aggregate Net Customer Order Flow | | | | | | | | | | | | Aggregate Gross Customer Order Flow | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Realised | | | | Implied | | | | Conditional | | | | Realised | | | | Implied | | | | Conditional | | | |
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| EURUSD | 0.012 | 1.124 | 1.984 | 0.90 | -0.005 | 0.878 | 1.990 | 0.92 | 0.031 | 0.468 | 2.017 | 0.94 | 0.000 | 1.125 | 1.985 | 0.90 | 0.012** | 0.86 | 2.014 | 0.92 | 0.009** | 0.46 | 2.013 | 0.94 |
| USDJPY | 0.171* | 1.741 | 2.001 | 0.86 | -0.104 | 1.726 | 1.998 | 0.85 | 0.024 | 0.978 | 2.008 | 0.87 | -0.014 | 1.758 | 2.000 | 0.86 | 0.055*** | 1.69 | 1.998 | 0.86 | 0.054*** | 0.936 | 1.991 | 0.87 |
| EURJPY | 0.408* | 2.16 | 1.976 | 0.93 | -0.103 | 2.411 | 2.000 | 0.91 | 0.220 | 3.504 | 2.006 | 0.86 | -0.030 | 2.186 | 1.983 | 0.93 | 0.070 | 2.399 | 1.996 | 0.92 | 0.136** | 3.462 | 2.006 | 0.87 |
| GBPUSD | -0.009 | 1.284 | 1.985 | 0.93 | -0.021 | 0.788 | 2.002 | 0.94 | -0.018 | 0.452 | 1.998 | 0.96 | 0.003 | 1.284 | 1.985 | 0.93 | 0.020* | 0.778 | 2.011 | 0.94 | 0.020* | 0.442 | 1.985 | 0.96 |
| EURGBP | 0.088 | 0.754 | 1.996 | 0.94 | 0.077 | 0.463 | 1.978 | 0.96 | 0.022 | 0.424 | 2.016 | 0.95 | 0.013 | 0.754 | 1.993 | 0.94 | 0.010 | 0.463 | 1.989 | 0.96 | 0.019 | 0.423 | 2.015 | 0.95 |
| USDCHF | -0.016 | 1.321 | 1.998 | 0.88 | -0.184** | 0.999 | 1.999 | 0.87 | -0.067 | 0.834 | 2.005 | 0.88 | -0.002 | 1.322 | 1.999 | 0.88 | 0.045** | 0.993 | 2.012 | 0.87 | 0.041* | 0.821 | 2.006 | 0.88 |
| EURCHF | 0.040 | 0.468 | 1.966 | 0.92 | 0.033 | 0.915 | 1.938 | 0.92 | 0.048 | 1.216 | 1.987 | 0.91 | 0.010 | 0.468 | 1.977 | 0.92 | 0.058** | 0.89 | 1.916 | 0.92 | 0.084*** | 1.162 | 1.963 | 0.92 |
| AUDUSD | 0.237 | 3.663 | 2.003 | 0.94 | -1.047*** | 2.09 | 1.914 | 0.92 | -0.617* | 3.811 | 1.968 | 0.91 | 0.052* | 3.66 | 2.000 | 0.94 | 0.148*** | 2.182 | 1.966 | 0.92 | 0.161*** | 3.755 | 1.992 | 0.92 |
| NZDUSD | 0.114 | 3.666 | 2.001 | 0.90 | -1.455*** | 1.931 | 1.990 | 0.90 | -0.920* | 3.747 | 2.016 | 0.86 | 0.100 | 3.664 | 2.001 | 0.90 | 0.328*** | 1.948 | 1.990 | 0.90 | 0.493** | 3.691 | 2.003 | 0.86 |
| USDCAD | 0.039 | 1.316 | 2.007 | 0.92 | 0.149 | 0.666 | 1.984 | 0.95 | 0.206* | 0.662 | 1.978 | 0.95 | 0.048* | 1.31 | 2.007 | 0.92 | 0.060** | 0.661 | 2.027 | 0.95 | 0.068** | 0.657 | 2.002 | 0.95 |
| EURSEK | 0.056 | 0.587 | 1.998 | 0.96 | -0.125 | 0.581 | 1.994 | 0.95 | 0.167 | 0.319 | 2.003 | 0.97 | 0.094 | 0.586 | 1.994 | 0.96 | 0.221** | 0.574 | 1.990 | 0.95 | 0.179*** | 0.315 | 1.994 | 0.97 |
| EURNOK | -0.535 | 0.766 | 1.993 | 0.93 | 0.147 | 0.689 | 1.986 | 0.92 | -1.714 | 22.943 | 2.004 | 0.44 | -0.025 | 0.772 | 1.995 | 0.93 | 0.152** | 0.685 | 1.980 | 0.92 | 0.006 | 23.005 | 2.005 | 0.44 |
| USDMXN | -0.619 | 2.095 | 2.002 | 0.95 | -0.696 | 8.536 | 1.994 | 0.83 | 0.881 | 2.204 | 1.973 | 0.92 | 0.087 | 2.098 | 1.994 | 0.95 | 0.730** | 8.472 | 1.992 | 0.83 | 0.477** | 2.183 | 1.965 | 0.92 |
| USDSGD | -0.212 | 0.378 | 1.969 | 0.89 | -0.063 | 0.402 | 2.019 | 0.91 | 0.162 | 0.285 | 1.992 | 0.91 | 0.053 | 0.379 | 1.972 | 0.89 | 0.306*** | 0.392 | 2.007 | 0.92 | 0.202** | 0.281 | 2.000 | 0.91 |
| USDHKD | -0.035 | 0.017 | 1.985 | 0.88 | 0.038 | 0.063 | 1.995 | 0.71 | -0.003 | 0.007 | 1.997 | 0.93 | 0.011 | 0.017 | 1.978 | 0.88 | 0.033* | 0.063 | 1.994 | 0.71 | 0.020*** | 0.007 | 1.992 | 0.93 |
| USDTRY | 1.993** | 5.644 | 1.975 | 0.91 | 3.670** | 3.464 | 1.999 | 0.84 | 3.211* | 9.729 | 2.013 | 0.75 | -0.133 | 5.695 | 1.994 | 0.91 | 1.061** | 3.496 | 1.974 | 0.84 | 1.641** | 9.519 | 1.980 | 0.76 |
| EURHUF | 0.619 | 2.797 | 2.000 | 0.90 | 3.089*** | 1.692 | 2.016 | 0.92 | 1.983** | 2.16 | 2.011 | 0.88 | -0.032 | 2.799 | 2.001 | 0.90 | 0.918** | 1.723 | 2.011 | 0.92 | 1.474*** | 2.136 | 1.987 | 0.88 |
| EURPLN | -1.000** | 1.239 | 1.951 | 0.95 | 0.716 | 1.647 | 1.992 | 0.94 | 0.056 | 1.056 | 1.982 | 0.93 | -0.173 | 1.248 | 1.945 | 0.95 | 0.730* | 1.626 | 1.980 | 0.94 | 0.688** | 1.033 | 1.953 | 0.94 |
| EURCZK | -0.177 | 0.869 | 1.967 | 0.93 | 1.674** | 0.692 | 1.998 | 0.94 | 1.395 | 0.814 | 2.001 | 0.91 | 0.644 | 0.865 | 1.965 | 0.93 | 1.338** | 0.684 | 1.996 | 0.94 | 1.594*** | 0.798 | 1.996 | 0.91 |
| EURSKK | 0.550 | 0.726 | 1.998 | 0.87 | 1.121 | 0.145 | 1.990 | 0.97 | 0.575 | 0.312 | 1.995 | 0.94 | -1.762 | 0.721 | 1.991 | 0.87 | 1.145** | 0.144 | 2.007 | 0.97 | 2.378*** | 0.303 | 2.010 | 0.94 |

Note: Regression results between volatilities (realised, implied and conditional volatility) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\sigma_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \sigma_{i,t-j} + \hat{\gamma} \sum_{i=1}^{N_{ccy}} OF_{i,t} + \hat{\eta}_{i,t}$

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

**Table 4.12.:** Estimation of the relationship between the volatilities and the aggregate net customer order-flow across twenty currencies

| | Net Customer Order Flow | | | |
|---|---|---|---|---|
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| Portfolio '1' | -0.346*** | 0.438 | 2.053 | 0.13 |
| Portfolio '2' | -1.120*** | 0.321 | 2.053 | 0.19 |
| Portfolio '3' | -0.231 | 0.307 | 2.002 | 0.09 |
| Portfolio '4' | 1.382*** | 0.275 | 2.015 | 0.14 |
| Portfolio '5' | 0.376*** | 0.421 | 2.029 | 0.17 |
| | Gross Customer Order Flow | | | |
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| Portfolio '1' | 0.751*** | 0.194 | 1.995 | 0.13 |
| Portfolio '2' | 0.333*** | 0.272 | 1.995 | 0.32 |
| Portfolio '3' | 0.185*** | 0.319 | 1.987 | 0.18 |
| Portfolio '4' | 0.080*** | 0.435 | 2.011 | 0.26 |
| Portfolio '5' | 0.024*** | 0.429 | 2.030 | 0.08 |

Note: Regression results between volatilities (as dependent variable obtained from $r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}$) and lags of volatilities and contemporaneous aggregate customer order-flows, as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \hat{\beta}_j \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 4, 4, 4, 4 and 4 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twenty five currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

**Table 4.13.:** Estimation of the relationship between the volatilities and the aggregate net customer order-flow across twenty currencies

| | Net Customer Order Flow | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Realised | | | | Implied | | | | Conditional | | | |
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| Portfolio '1' | -0.663*** | 5.234 | 2.006 | 0.71 | -0.942*** | 3.709 | 2.027 | 0.74 | -0.714*** | 5.059 | 2.009 | 0.65 |
| Portfolio '2' | -3.028*** | 5.264 | 1.997 | 0.61 | -2.762** | 4.881 | 2.020 | 0.60 | -3.003*** | 4.897 | 1.974 | 0.55 |
| Portfolio '3' | -8.175** | 6.437 | 1.991 | 0.56 | -2.124 | 4.896 | 1.993 | 0.60 | 0.270 | 6.605 | 1.982 | 0.45 |
| Portfolio '4' | 4.206*** | 6.764 | 1.986 | 0.52 | 6.697*** | 4.944 | 1.983 | 0.63 | 7.338*** | 5.425 | 1.993 | 0.55 |
| Portfolio '5' | 0.495* | 5.341 | 2.007 | 0.64 | 0.721*** | 4.397 | 2.028 | 0.70 | 1.047*** | 5.278 | 2.011 | 0.64 |
| | Gross Customer Order Flow | | | | | | | | | | | |
| | Realised | | | | Implied | | | | Conditional | | | |
| | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ | $\gamma^b$ | S.E. | D.W.$^c$ | $\bar{R}^2$ |
| Portfolio '1' | 0.191 | 1.769 | 1.997 | 0.82 | 1.300 | 1.995 | 2.007 | 0.76 | 1.768*** | 1.719 | 1.996 | 0.78 |
| Portfolio '2' | 0.526* | 4.382 | 2.000 | 0.73 | 0.814*** | 3.255 | 2.008 | 0.82 | 0.864*** | 3.468 | 1.999 | 0.77 |
| Portfolio '3' | 0.232** | 3.76 | 2.006 | 0.74 | 0.452*** | 2.769 | 2.008 | 0.71 | 0.389** | 3.788 | 2.020 | 0.67 |
| Portfolio '4' | 0.082*** | 2.467 | 2.029 | 0.88 | 0.125*** | 1.713 | 2.005 | 0.89 | 0.137*** | 1.857 | 2.014 | 0.89 |
| Portfolio '5' | 0.014** | 1.376 | 2.001 | 0.86 | 0.035*** | 1.314 | 2.017 | 0.87 | 0.028*** | 0.91 | 1.992 | 0.87 |

Note: Regression results between volatilities (realised, implied and conditional volatility) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \hat{\beta}_j \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 4, 4, 4, 4 and 4 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twenty currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

### 4.3.3. Asymmetric impact of Customer Order-flow on Subsequent Volatility

This subsection attempts to examine whether the effect of order-flow on subsequent volatility is symmetric. Relevant empirical literature documented the effect of order-flow and subsequent return volatility which is referred as the *leverage effect*.[24] This test basically focuses on examining the negative or positive relation between order-flow and subsequent volatility influenced by the signs of the return, and to understand the contribution of this effect on volatility.

The possible asymmetric effect of trading order-flow on subsequent volatility were tested with the following models, for disaggregate and aggregate respectively:

$$\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_{it} + \hat{\lambda} OF_{it-1} + \hat{\eta}_t,$$

$$\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\lambda} OF_{t-1} + \hat{\eta}_t,$$

where $|\hat{\epsilon}_{it}|$ is the absolute residual obtained from equation 4.2, $OF_{it}$ are the disaggregate order-flow, for the currency $i$, and $OF_t$ are the aggregate order flow at time $t$.

The results of the aggregate and disaggregate asymmetric effect explained in equation 4.7, are presented in Table 4.14 and 4.15, respectively. The varying nature of the signs of the coefficients demonstrate the asym-

[24]See Schwert (1989)

metry in the relationship. Where the signs of the coefficients in Tables 4.14 and 4.15 for $\gamma$ & $\lambda$ are both positive, this suggests the impact of order-flow on the subsequent volatility is positive, meaning liquidity is reduced because of the exogenous opportunities. The positive correlation between the order-flow and subsequent volatility confirms the *liquidity-driven-trade-hypothesis*, that informed investors are investing outside the foreign exchange market due to exogenous investment opportunities. The plausible explanation for the asymmetric effect when positive coefficients are followed by negative and statistically significant indicates that when returns are negative the order-flow will contribute less negatively to subsequent volatility. This can possibly be interpreted as follows: when there is unfavourable news about the underlying foreign exchange asset, customers with better information are restrained from trading by short-selling constraints. Therefore there is less informed trading. This suggests that the subsequent volatility relationship shows a positive contemporaneous relationship and a negative subsequent relation- ship. These results support the *information-driven-trade-hypothesis*, that if the informed investor sells an underlying asset because of some adverse private information, the return will be negative, as this information is already incorporated into the price. Thus, it will followed by a negative return and will result in a lower volatility because the high trade is followed by low trades. Hence, the resulting relationship will be negative. Another conceivable interpretation of the asymmetric effect of the order-flow is the short selling of the underlying setting.

**Table 4.14.:** Asymmetry Estimation of the relationship between the volatilities and the disaggregate customer order-flow across twelve currencies

| | $\gamma^b$ | $\lambda^b$ | S.E. | D.W.[c] | $\bar{R}^2$ |
|---|---|---|---|---|---|
| | Portfolio '1'[a] | | | | |
| Asset Manager | -0.434*** | -0.093 | 0.720 | 2.012 | 0.06 |
| Corporate | -0.921*** | -0.002 | 0.573 | 2.056 | 0.04 |
| Hedge Fund | -0.452*** | -0.005 | 0.569 | 2.012 | 0.05 |
| Private Customer | -0.923*** | 0.147 | 0.623 | 2.013 | 0.15 |
| | Portfolio '2'[a] | | | | |
| Asset Manager | -0.895** | -0.246 | 0.534 | 2.028 | 0.16 |
| Corporate | -1.067 | -0.250 | 0.565 | 2.005 | 0.10 |
| Hedge Fund | -0.855*** | 0.025 | 0.598 | 2.030 | 0.06 |
| Private Customer | -1.611*** | -0.183 | 0.428 | 2.089 | 0.11 |
| | Portfolio '3'[a] | | | | |
| Asset Manager | -0.372 | -0.901** | 0.333 | 2.012 | 0.18 |
| Corporate | -1.871** | -0.094 | 0.362 | 2.026 | 0.18 |
| Hedge Fund | -0.230 | -0.481 | 0.456 | 2.011 | 0.18 |
| Private Customer | 2.193 | 0.746 | 0.340 | 2.018 | 0.21 |
| | Portfolio '4'[a] | | | | |
| Asset Manager | 0.502*** | 0.031 | 0.535 | 2.031 | 0.07 |
| Corporate | 1.201 | 1.940** | 0.814 | 2.037 | 0.14 |
| Hedge Fund | 1.206*** | 0.396 | 0.598 | 2.045 | 0.12 |
| Private Customer | 3.131*** | 0.195 | 0.652 | 2.015 | 0.10 |
| | Portfolio '5'[a] | | | | |
| Asset Manager | 0.399*** | -0.060 | 0.596 | 2.032 | 0.16 |
| Corporate | 0.522* | -0.057 | 0.564 | 2.035 | 0.01 |
| Hedge Fund | 0.411*** | 0.183 | 0.569 | 2.057 | 0.06 |
| Private Customer | 1.479*** | -0.098 | 0.595 | 2.029 | 0.12 |

Note: Regression results between volatilities (as dependent variable obtained from $r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}$) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\lambda} OF_{t-1} + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 2, 2, 4, 2 and 2. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twelve currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

**Table 4.15.:** Asymmetry estimation of the relationship between the volatilities and the aggregate net customer order-flow across twenty currencies

| | Portfolio '1'[a] | | | | |
|---|---|---|---|---|---|
| | $\gamma^b$ | $\lambda^b$ | S.E. | D.W.[c] | $\bar{R}^2$ |
| Portfolio '1' | -0.304*** | -0.100 | 0.437 | 2.023 | 0.13 |
| Portfolio '2' | -0.945*** | -0.426 | 0.320 | 2.016 | 0.19 |
| Portfolio '3' | -0.254 | 0.117 | 0.308 | 2.002 | 0.08 |
| Portfolio '4' | 1.509*** | -0.533 | 0.274 | 2.023 | 0.14 |
| Portfolio '5' | 0.375*** | 0.003 | 0.422 | 2.029 | 0.17 |

Note: Regression results between volatilities (as dependent variable obtained from $r_{i,t} = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j r_{i,t-j} + \hat{\epsilon}_{i,t}$) and lags of volatilities and contemporaneous customer order-flows, aggregate and disaggregate as independent variables in a portfolio based approach. The model estimated is: $\Sigma_t = \hat{\beta}_0 + \sum_{j=1}^{7} \hat{\beta}_j \Sigma_{t-j} + \hat{\gamma} OF_t + \hat{\lambda} OF_{t-1} + \hat{\eta}_t$

[a] The portfolios are constructed on an interval of 4, 4, 4, 4 and 4 observations ascending order-flows. The portfolio 1 & 5 represents the large sales and large purchases respectively, consisting of twenty currencies.

[b] ***, ** ,* represents 10%, 5% and 1% level of significance respectively. Regression estimates are based on the Newey and West (1987) estimation.

[c] DW is the *Durbin-Watson* statistic.

## 4.4. Conclusion

In this chapter, the relationship between volatility and customer order-flow, based on portfolios, with aggregate and disaggregate customer order-flow data is examined. This relationship is found to be robust. Moreover, large sales and purchases are the main channel in the transmission of private information into the foreign exchange markets. This relationship holds for all the foreign exchange rates considered and for the four different measures of volatility. The findings can be summarised in two ways. The first is by analysing the relationship between the order-flow and volatility with aggregate and disaggregate customer data.. Second, the nature of the relationship is tested in the context of symmetric and asymmetric relationships.

Results supports the hypothesis that different classes of customers possess private information which is transmitted to the market by the trading strategies of the better-informed customers. It appears that volatility is significantly affected by customer order-flow and that large trades are the most influential. Further, this relationship asymmetry in the subsequent manner is tested. Although the signs of the coefficients suggests the presence of *liquidity-driven-trade-hypothesis*, a positive subsequent relationship and *information-driven-trade-hypothesis*, a negative subsequent relationship. However, the results are not statistically significant.

# Chapter 5.

# Customer Order Flow, Carry Trade, and Asset Pricing in the Foreign Exchange Market

## 5.1. Introduction

According to the uncovered interest rate parity condition (UIP), assuming investors are risk-neutral, returns from a trading strategy that borrows from a low interest rate currency and invests in a high interest rate currency should be offset by the expected loss from the depreciation of the high interest rate currency. The uncovered interest parity (UIP) is among the most studied and unsolved puzzles within the empirical finance literature. Under UIP, the forward exchange rate should be an unbiased predictor of the future spot rate. However, the prediction of the UIP has been rejected by most studies.[1] The existing literature suggests that when the forward rate indicates a depreciation the higher interest rate currencies systematically appreciate.[2] Hence, the forward rate unbiasedness condition deviates from its underlying fundamentals (UIP). This condition is referred to as the Forward Discount Un-biasedness (FDU) in the international finance literature.

Researchers have proposed a number of explanations for this deviation yet there is no overriding consensus. The systematic bias implies that an investor who borrows from low interest rate currencies and invests in higher rate currencies would be able to make a positive profit from the interest rate differential plus the exchange rate variation. This type of trading strategy is referred to as a *Carry Trade* and is an active research area.

This chapter will examine the reasons for the existence of the Forward Discount Un-biasedness (FDU) and the profitability of carry trades, using

[1]See work on the UIP by Meese and Rogoff (1983), Hansen and Hodrick (1980), Cumby and Obstfeld (1981) and Fama (1984)

[2]See Bilson (1981); Fama (1984); Froot and Frankel (1989); Burnside *et al.* (2007*a*).

a unique weekly UBS data set of currency customer order-flows. The FDU is studied in the context of its importance in the carry trade strategies. In this chapter Fama's (1984) regression estimated that the forward discount was still smaller than 1, the value consistent with uncovered interest rate parity. Furthermore, the FDU and profitability of the carry trade were studied in two segments using a portfolio-based approach: Firstly, using the microstructure approach of Evans and Lyons (2002) was employed. Here it was shown that customers reorganise their portfolios according to the carry trade opportunities arising in the market. Thus customer order flows explain the movements in the realised carry return.

Secondly, an asset-pricing set-up was organised using the GMM approach. It was found that global foreign exchange customer order- flows and volatility innovations significantly explained the cross-section of carry returns. Specifically a highly negative correlation between global order-flows, volatility innovation and carry trade portfolios was revealed. Whereas currencies that fund the carry trade portfolio enable a hedge against the innovation of customer order-flow and volatility.

## 5.2. Economic Theory, Literature Review, & Methodological Issues

### 5.2.1. Economic Theory

Contrary to the theoretical statements of the Forward Discount Unbiasedness (FDU), as outlined above, the Covered Interest Rate Parity (CIP) condition holds that the forward rate of the underlying currency $f_t$ to be delivered at time $t + 1$ should be equal to the spot rate $S_{t+1}$. The examination of the FDU condition via Fama's (1984) regression can be conducted by regressing the change in the spot exchange rate $s_{t+1} - s_t$ on the forward discount, $f_t - s_t$, and in line with the theory parameters of the regression which should be $\alpha = 0$ and $\beta = 1$, the Fama's (1984) regression equation can be written as:

$$s_{t+1} - s_t = \alpha + \beta(f_t - s_t) + \epsilon_t \tag{5.1}$$

Equation 5.1 has been the focus of many studies including Lewis (1995), Engel (1996), Burnside *et al.* (2007*b*) and Bacchetta *et al.* (2009). All these studies demonstrated that the $\beta$ in the above Fama's (1984) regression are $\neq 1$, usually smaller than 1 and sometimes negative. However, other studies, such as Froot and Thaler (1990), supported the results of the above studies, and found that the average $\beta$ coefficients based on 75 estimates was -0.88. In theoretical and policy modelling, UIP is one of the key elements. More recently many central banks have been utilising DSGE models in order to comprehend exactly how a violation in the underlying fundamentals can result in a FDU.[3]

Early research relied on survey data and was based on the analysis of market expectations. Froot and Frankel (1989) investigated the role of forecasting error in explaining the departure of the FDU. They studied the exchange rate forecasts of 1980-1985 for the U.S. dollar against the French franc, the British pound, the Japanese yen and the Deutschmark, obtained

[3]Dynamic stochastic general equilibrium modelling (DSGE) is classified in the applied general equilibrium, that is extensively studies in the contemporary macroeconomics. The characteristic of DSGE modelling it that it attempts to explain the aggregate economic phenomena, on the basis of macroeconomic models derived from the microeconomics. For a detailed discussion on DSGE modelling. (see Balke *et al.*, 2012)

from the AMEX, MMS and *The Economist*.[4] They estimated Fama's (1984) regression by pooling together forecasts from different exchange rates and found that Fama's (1984) $\beta$ were significantly small and negative.

### 5.2.2. Literature Review

Froot and Frankel (1989) findings were studied further by many researchers including Frankel and Chinn (1993); Cavaglia *et al.* (1994); Chinn and Frankel (2002) and Bacchetta *et al.* (2009). These studies added additional currency pairs, longer horizons and various sources for data collection. For instance, Bacchetta *et al.* (2009) examined the forecasts based on 3, 6 and 12 months horizons between August 1986 to July 2005 for seven currency pairs. They found that the Fama's (1984) $\beta$ coefficients for 7 currencies across 3 horizons ranges from -3.62 to -0.76. While researchers like Lewis (1989*a*,*b*) and Evans and Lewis (1995) argued that the systematic forecast error was irrational and that these errors could be caused by the learning and peso problems. Alternatively other researchers argued that the Fama's (1984) $\beta$ could be a delayed response to news development because of ambiguity aversion (Ilut, 2009). Moreover it could be due to the unaccustomed reallocation of the portfolios, as influenced by the rational intention with random walk expectation (Bacchetta and Van Wincoop, 2005), leading to the generation of Fama's (1984) $-\beta$ or the forecast error. Many studies, allowing for forecast error, found violations of the Uncovered Interest Rate Parity condition, and concluded that the deviation indicated a role of risk premia (Jongen *et al.*, 2008).

[4] American Express Company (NYSE: AXP) or AmEx, founded in 1850, is one of the 30 components of the Dow Jones Industrial Average. AMEX specialises in the plastic money business. Approximately 24% of the total dollar volume of credit card transactions in the U.S. is attributed to Amex cards

Consequently it can be deduced that FDU arrises due to the relationship between the risk premia and the UIP condition. Supposedly, if the risk premia is negatively related to the forward discount, then it follows that Fama's (1984) regression has a missing variable bias and the value associated to this variable should be $< 1$. The missing variable/risk premia in Fama's (1984) regression is a key area in empirical finance research. Indeed researchers like Cumby (1988); Hodrick (1989); Bekaert *et al.* (1997) studied the missing variable in Fama's (1984) regression and concluded that an implausible degree of risk aversion is required to obtain a negative $\beta$ coefficient.

The overall results of the above mentioned empirical studies was that Fama's (1984) regression $\beta$ is significantly less than 1 ($\beta < 1$). This deviation of the $\beta$ from its fundamental implies that the carry trade strategy should result in positive profits both from the exchange rate variation and the interest rate differential.[5] Numerous studies on the carry trade strategy found a positive return, in contrast to the underlying fundamental of the FDU which, dictates that the low interest rate currencies tend to depreciate whilst high interest rate currencies appreciate.[6]

Asset pricing is one of various methodologies adopted by researchers to explain the profitably in the carry trade using various global factors. Lustig *et al.* (2011) studied the cross sectional variation in the carry trade returns of several currency portfolios. Advancing this study study, Menkhoff *et al.*'s (2011) constructed global carry trade portfolios using

[5] Trading strategy that borrows in low yield currencies and invests in high yield currencies.

[6] See Galati *et al.* (2007); Burnside *et al.* (2007*a*,*b*, 2011); Brunnermeier *et al.* (2008); Lustig *et al.* (2011)

volatility and liquidity as global factors in a cross-sectional approach.

Academic papers based on asset pricing methodology concluded that currencies with high interest rates are negatively related to global factors, particularly volatility, and result in lower returns during periods of high volatility, or increased uncertainty. Burnside (2011) examined the carry trade and the risk factors defining it. They discovered that the most successful risk factors explaining the trade return are those associated with currency skewness. Breedon (2001) and Lustig *et al.* (2011) suggested that currency skewness is an important risk factor in carry trade returns that is conditional upon the risk reversal.

Recent literature on the microstructure approach, furthermore, has focused on the profitability of carry trade and the FDU. One of the key variables, in microstructure theory, in the study of exchange rate dynamics is the order-flow.[7] Studies such as Evans and Lyons (2002); Berger *et al.* (2008) and Cerrato *et al.* (2011) examined the currency return relationship with order-flow with a microstructure approach and found that order-flows considerably explain the changes in exchange rate returns. The results of Payne (2003); Bjonnes and Rime (2005); Danielsson and Love (2006) and Killeen *et al.* (2006), moreover, came to similar conclusions. More specifically Breedon and Vitale (2010) and Breedon *et al.* (2011) indicated that in a portfolio rebalancing approach order-flows could be a crucial factor in defining the foreign exchange risk premium. Burnside *et al.* (2007*a*) constructed a microstructure framework in which the adverse selection mechanism leads to a forward discount bias. Jylhä and Suominen (2010) studied the carry trade and found a role for illiquidity in explaining the

[7] Signed volume.

FDU.

The motivation behind this study is to use customer order-flow data in order to capture the risk premium in the carry trade returns of foreign exchange market. Therefore, it aims to fill the gap in the existing literature on the origin of the forward discount bias and the portability of the carry trade. Factors influencing the risk premium in the Evans and Lyons's (2002) micro-structure approach and Lustig *et al.*'s (2011) asset pricing approach are investigated.

### 5.2.3. Methodological Issues

#### Foreign Exchange Market and the Risk Factor

According to theories of finance, volatility is negatively related to returns because the investor seeks a risk premium against a positive volatility innovation. [8] The investors risk-return trade-off worsens with a positive volatility innovation. Furthermore, during spells of high unexpected volatility the returns are expected to be low. Hence, those assets that co-vary positively with the innovations in market volatility provide a trading strategy to hedge. Therefore this could result in low returns. This hedging strategy has encouraged researchers in the stock market to explore how exposure of the market risk volatility is priced in cross-sectional returns. Such studies include Ang, Hodrick, Xing and Zhang (2006); Adrian and Rosenberg (2008); Da and Schaumburg (2009). On the basis of the information above volatility is considered to be consistent. Thus, it is intuitive to consider aggregate volatility innovations as a pricing factor. Studies on the aggregate volatility innovations in the stock and

[8] Unexpected high volatility.

foreign exchange markets consider a parsimonious two-factor pricing kernel $m$ with the aggregate volatility innovations and market excess return as two-factors.[9]

$$m_{t+1} = 1 - b_1 rx_{m,t+1} + b_2 \triangle V_{t+1} \tag{5.2}$$

where $rx_{m,t+1}$ is the log market excess return and $\triangle V_{t+1}$ is the innovation of the aggregate volatility. This linear pricing kernel implies an expected return-beta representation for excess returns.

In addition to the 'pricing kernel', use of the covariance of excess returns along with the volatility innovations (in a aggregate market) as a priced source is also related to the literature of coskewness.[10] Coskewness is given by:

$$coskew = \frac{\mathbb{E}[(r_k - \mu_k)(r_m - \mu_m)^2]}{\sigma(r_k)\sigma^2(r_m)} \tag{5.3}$$

where $r_k$, $r_m$ are the return of the portfolio $k$ and the benchmark of the market, respectively; and $\mu$ and $\sigma$ represents mean and standard deviation, respectively.

In the above equation, the covariance decomposition is applied in the numerator. The covariance between excess returns and market volatility also results from this framework, which suggests that the portfolios that exhibit high coskewness provide a hedge against global volatility and so a lower return can be earned.[11] Hence, the coskewness set-up aligns with the stochastic discount factor frame-work. The literature suggests that

[9]Referred to as the stochastic discount factor (SDF) in the literature of finance.
[10]See Harvey and Siddique (1999, 2000); Ang, Chen and Xing (2006)
[11]i.e. Portfolios delivering high returns when market volatility is high.

global volatility innovations play a vital role in the understanding of the cross-section of equity returns.

**Carry Trades**

The currency Carry Trade can be explained by the phenomenon that one can sell low interest rate currencies, *funding currencies*, and invest in the high interest rate currencies *investment currencies.* While the concept of UIP assumes that the gains from investing in high interest rate currencies, *carry gains*, are the interest rate differential and are off-set by the corresponding depreciation of the investment currency. In contrast, empirically, UIP does not hold, and normally the investment currency appreciates instead of depreciating, following a low predictive $R^2$ (see e.g., Fama, 1984). As discussed earlier, the departure of the UIP from its fundamentals is referred as the *forward premium puzzle.* This *forward premium puzzle* is the underlying mechanism that makes the *carry trade* profitable.

The *forward premium puzzle*, which has been studied extensively in empirical economic and finance literature, focuses entirely on the excess returns of the carry trades.[12] Meese and Rogoff's (1983) concluded that the fundamental model of the exchange rate determination was out-performed by the naive random walk model. This is also related to the *forward premium puzzle* that a random walk of the exchange rates allows the investors to gain from the carry trade strategy: The exchange rate differential will not suffer by depreciation because of the random walk. Random walk is the only empirical reason that can be associated with the appreciation of the investment currencies in the UIP hypothesis, and the underlying

[12]See Froot and Thaler (1990); Lewis (1995), and Engel (1996)

exchange rates converge to purchasing power parity in the long run.

More recent studies have tried to explain UIP in various dimensions. Bacchetta and van Wincoop (2007) studied the departure of the UIP in the context of investment decisions and found that the failure may be attributed to the excessive revisions of the portfolios by investors. Lustig and Verdelhan (2007) conducted a cross-sectional study of UIP and found that the high interest rate currencies tend to have high loading on the consumption growth risk. However, Burnside *et al.* (2007*b*) argue that the Lustig and Verdelhan (2007) model is unable to explain the highly significant intercept term that is excess zero-beta rate.

Burnside *et al.* (2007*b*) argue that their model produces a highly significant excess zero-beta rate (i.e., intercept term). Moreover, they assert that the profits of the carry trade are not related to the standard risk factors. However, Jylha and Suominen (2009) argue that those currencies which are loaded at a higher interest-rate and subject to an inflation risk, demonstrate a positive relationship between the returns of carry trade and hedge fund indices.

This study is the first to empirically examine the profitability of the carry trade in terms of customer order-flows, risk, implied and conditional volatility.

## 5.3. Data, Econometric Framework & Results

### 5.3.1. Data and Portfolio Setup

The currency data for the spot and one-week forward exchange rates versus the U.S. dollar (USD) and Euro from $2^{nd}$ November 2001 to $11^{th}$ November 2011 are obtained from the Bloomberg terminal. The analysis in this study is based on the weekly frequency. Although the *realised volatility* proxy is obtained from the daily frequency of the last 30 days of the given week. At first, in line with the existing literature, the spot and forward exchange rates are used in the logarithmic form for the ease of notation and exposition.[13] However, later in the analysis, the level is used, particularly in the cross-sectional asset pricing tests (GMM and CAPM).

The spot and forward exchange rates are denoted in log as $s$ and $f$, respectively. The sample comprises of 20 foreign exchange currencies, which are the EURUSD, USDJPY, EURJPY, GBPUSD, EURGBP, USDCHF, EU- RCHF, AUDUSD, NZDUSD, USDCAD, EURSEK, EURNOK, USD-MXN, USDBRL, USDKRW, USDSGD, USDHKD, USDTRY, EURHUF, EUR- PLN, EURCZK and EURSKK. Five portfolios are formed on the basis of the set-up discussed in the next section, 5.3.2. The data for the spot rate, forward rate, implied and conditional volatilities is collected from Bloomberg.

### 5.3.2. Portfolio Construction

The currencies are allocated to five portfolios at each time period $t$, on the basis of their forward discount $f - s$. Organising the currencies on this

[13]See Fama (1984)

basis is equal to organising them according to the interest rate differential. The portfolios are rebalanced at the end of each week over 11 years. The currencies are organised from low to high interest rates: Portfolio $a$ comprises the currencies with the lowest forward discount (interest rate) and portfolio $e$ contains the high interest rate differential currencies. The weekly excess return of the portfolio $k$ at time $t$ is computed with the help of the following equation:

$$rx_{t+1}^{k} = i_t^k - i_t - \triangle s_{st+1}^{k} \approx f_t^k - s_{t+1}^{k} \tag{5.4}$$

$s$ denotes the log of the spot exchange rate and $f$ is the log of the forward exchange rate. $rx$ is the log of excess return on the exchange rate that is buying a foreign currency in the forward market and then selling it at the spot exchange rate after the time period $t$, where $t$ is one week.

$$rx_{t+1} = f_t - s_{t+1}$$

This log excess return can also be stated in the following manner, i.e., forward discount minus the change in the spot exchange rate.

$$rx_{t+1} = f_t - s_t - \triangle s_{t+1}$$

Theoretically, the forward rate should satisfy the covered interest rate parity condition, i.e., the forward discount is equal to the interest rate differential:

$$i_t^{*} - i_t \approx f_t - s_t$$

Hence, the log of the interest rate differential, less rate of depreciation, is approximately equal to the foreign exchange excess return:

$$rs_{t+1} \approx i_t^* - i_t - \triangle s_{t+1}$$

A carry trade portfolio can be obtained by taking the difference between the returns of portfolio $e$, and $a$, normally referred to as long-short portfolio H/L. This is attained by following the trading strategy by borrowing money from currencies that yield low interest rates, i.e., portfolio $a$, and investing in currencies yielding high interest rates: Portfolio $e$, HMLFX is the notation used in the studies to address underlying issues in the foreign exchange markets.[14] Furthermore, another two portfolios are built, which represent the average of all the currency portfolios, i.e., the average return of a strategy that borrows money in the U.S. (Treasury Bill Rate) and invests in the global market. These portfolios are referred to as the zero-cost portfolio *DOL*.[15]

### 5.3.3. Descriptive Statistics for Portfolios

Descriptive statistics for the portfolios are presented in Table 5.1. The mean, median and standard deviations of the excess returns of the portfolios increase monotonically when moving from portfolio $a$ to $e$. Whereas skewness monotonically decreases along the portfolios from $a$ to $e$ for the sample of all countries, which is in line with the empirical literature (see Lustig *et al.*, 2011). The autocorrelations display some evidence for positive returns for the portfolios HML, $a$ and $b$. Finally, the coskewness was computed using equation 5.3. The coskewness does not reflect any pattern

[14]See Lustig *et al.* (2011)
[15]Lustig *et al.* (2011)

**Table 5.1.:** Descriptive statistics for Portfolios

| | a | b | c | d | e | HML |
|---|---|---|---|---|---|---|
| Mean | -0.41 | -0.15 | 0.00 | 0.14 | 0.40 | 0.81 |
| Median | -0.37 | -0.13 | 0.00 | 0.12 | 0.33 | 0.72 |
| Minimum | -2.18 | -1.03 | -0.32 | -0.15 | 0.06 | 0.24 |
| Maximum | -0.03 | 0.06 | 0.38 | 0.93 | 3.24 | 5.37 |
| Std. Dev. | 0.24 | 0.11 | 0.08 | 0.12 | 0.26 | 0.45 |
| C.V. | 0.57 | 0.78 | 25.50 | 0.90 | 0.67 | 0.55 |
| Skewness | -3.10 | -2.65 | 0.21 | 2.31 | 4.28 | 4.34 |
| Ex. kurtosis | 17.26 | 13.51 | 3.55 | 9.13 | 34.02 | 32.87 |
| Corr (1) | 0.34 | 0.11 | -0.15 | -0.09 | 0.42 | 0.50 |
| CoSkewness | 0.90 | 0.76 | 0.75 | 1.02 | 1.57 | 0.68 |

Note: This table represents the descriptive statistics of the portfolios, DOL is the average across the portfolios and the H/L is the e-a portfolio.

with respect to the mean portfolio excess returns. The average return on holding an equally-weighted zero-cost portfolio of foreign currencies gross returns is about 2% per annum, which suggests U.S. investors earn a positive but low risk premium on holding foreign currency.

Figures 5.1 and 5.2 depict the graphical representation of the carry trade, HML and DOL portfolios. The Credit Crisis of 2008 can be observed in all of the portfolios but is more obvious in $a$ and HML portfolio.

### 5.3.4. Carry Trade Portfolios Return and Autoregression

A simple random walk model is tested; a positive $\beta$ coefficients means *momentum*, past higher returns imply higher future returns, and a negative

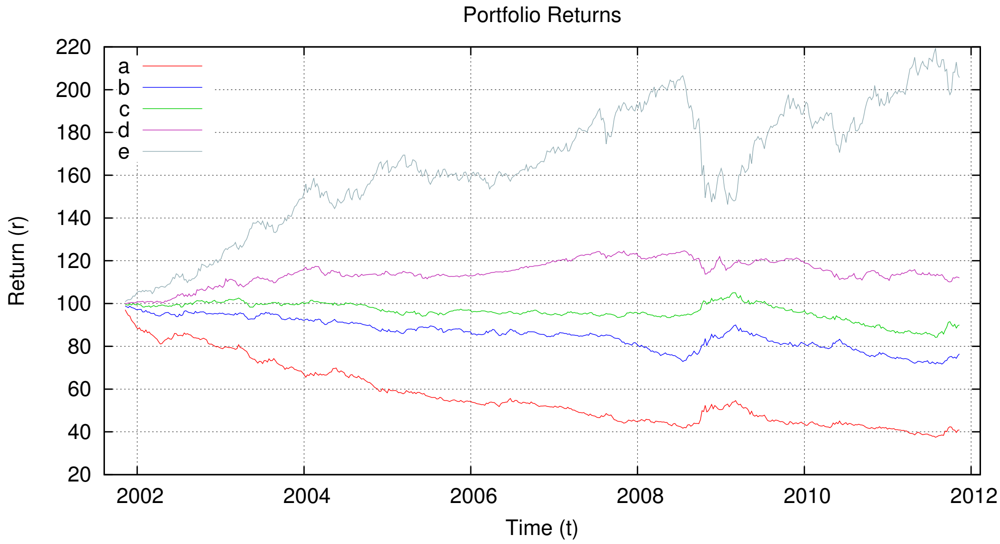


**Figure 5.1.:** Note: This graphs depicts the Carry Trade portfolio returns on the 'y' axis across the time 't' on 'x' axis.

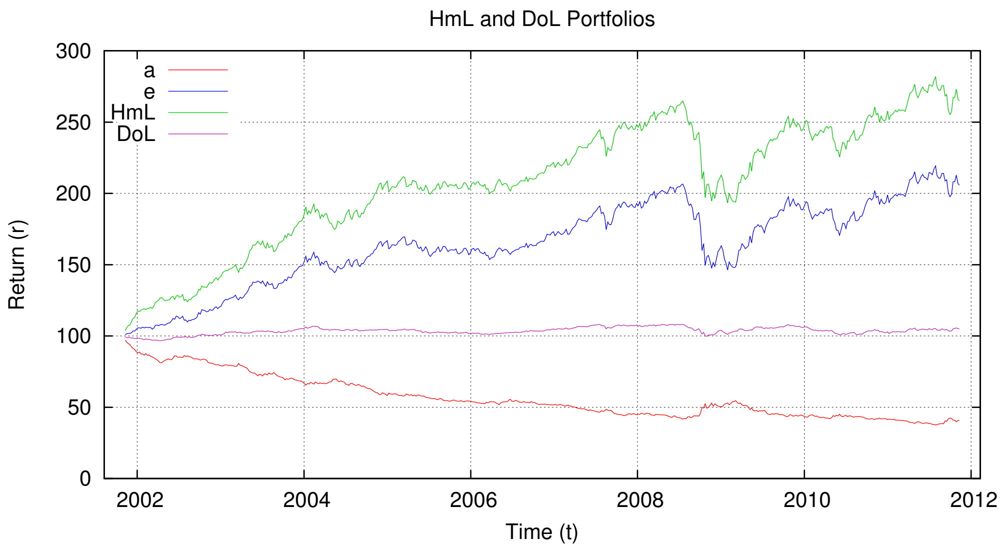


**Figure 5.2.:** Note: This figure depicts the HmL (e-a) & DoL portfolio returns along with the 'a' and 'e' portfolios.

coefficient reflects an *overreaction* or *mean reversion*. The results of the regression of the returns on lagged returns are presented in Table 5.2. The carry trade returns are partially predictable for portfolios $a$ and $e$. A $\beta = 0.40$ means that if returns go up by 100% this year, a rise of 40%

can be expected next year. Thus a trivial amount of *momentum*. All the coefficients are statistically significant. However, the coefficient and $R^2$ of the *Treasury bill* is $\approx 1$. This means the interest rate is highly predictable. If interest rates were high last period, they are extremely likely to be high again this year. Most of the $t$-bill return is known ahead of time.

### 5.3.5. Carry Trade Portfolios and Uncovered Interest Rate Parity

The Uncovered Interest Rate Parity in its simplest version can be presented as:

$$E_t s_{t+1} - s_t = i_t - i_t^*$$

where $s_t$ is the log nominal exchange rate (expressed against the foreign currency). $i_t$ and $i_t^*$ are domestic and foreign one-period nominal interest rates, and $E_t$ is market expectation based on information at time $t$.

The UIP condition states that an expected depreciation in the domestic currency should be offset by an interest rate differential between the domestic and foreign interest rate. Therefore, it may be inferred from the UIP condition that the expected excess return $rx$ should be equal to zero, i.e., there shall be no arbitrage opportunities across currencies. The linearised version of the excess returns form holding the foreign exchange currencies can be expressed as:

$$rx_{t+1} = s_{t+1} - s_t - i_t - i_t^*$$

**Table 5.2.:** Regression results of returns on lagged returns

| | $\beta$ | $S.E.$ | $\bar{R}^2$ | $E(R)$ | $\sigma(E_t(R_{t+1}))$ |
|---|---|---|---|---|---|
| | Portfolio 'a' | | | | |
| Carry Return | 0.349*** | 0.041 | 0.12 | -0.02 | 0.35 |
| Spot Return | 0.350*** | 0.041 | 0.12 | -0.02 | 0.35 |
| | Portfolio 'b' | | | | |
| Carry Return | 0.110** | 0.044 | 0.01 | -0.01 | 0.05 |
| Spot Return | 0.083* | 0.044 | 0.01 | -0.01 | 0.04 |
| | Portfolio 'c' | | | | |
| Carry Return | -0.144*** | 0.043 | 0.02 | 0.00 | 0.05 |
| Spot Return | -0.129*** | 0.043 | 0.01 | 0.00 | 0.04 |
| | Portfolio 'd' | | | | |
| Carry Return | 0.246*** | 0.042 | 0.06 | 0.01 | 0.13 |
| Spot Return | 0.209*** | 0.043 | 0.04 | 0.01 | 0.11 |
| | Portfolio 'e' | | | | |
| Carry Return | 0.429*** | 0.040 | 0.18 | 0.02 | 0.46 |
| Spot Return | 0.436*** | 0.039 | 0.19 | 0.02 | 0.48 |
| | Risk Free 'Treasury Bill' | | | | |
| Risk Free | 0.997*** | 0.004 | 0.99 | 0.02 | 1.65 |

Note: This table represents the regression of returns of lagged returns $rx_t^i = \alpha + \beta rx_{t-1}^i + \epsilon_t$

where $rx$ represents the excess returns at time $t$. If it is assumed that the UIP condition holds then expected excess returns should be $E_t rx_{t+1} = 0$. Comparatively, most studies concluded that non-zero returns are exhibited in the excess returns $rx$. Furthermore, the interest rate differential $i_t - i_t^*$ can systematically predict the excess returns. The estimation of excess returns using the interest rate differential can be seen from the famous Fama (1984) regression that aims to predict excess returns via the interest rate differential. Fama's (1984) regression is:

$$\triangle s_t = \beta_1 + \beta_2(i_t - i_t^*) + \mu_t \tag{5.5}$$

The interest rate differential was replaced with the $f_t - s_t \approx i_t^* - i_t$ and Fama's (1984) regression was estimated. The results are presented in Table 5.3, setting time $t$ to 1 week, 3 and 6 months, 1 and 2 years simultaneously. The coefficients are significant, which indicates the predictability of the excess returns. In sum, the market participants in the foreign exchange market are attracted by the presence of expected excess positive returns. Deviations from UIP, normally referred to as the forward premium puzzle, have received extensive attention among researchers, but there is no consensus offering a single explanation about the deviation from UIP.[16] As discussed earlier, one of the reasons for the deviation is the missing variable, that is the risk premium.

### 5.3.6. Carry Trade and Aggregate Customer Flow Model

In this section the relationship between carry trade returns, in a portfolio based strategy, and customer order flows is examined; the macro- impact is

[16] See Froot and Thaler (1990) and Engle (1982)

**Table 5.3.:** Fama's (1984) regression results

| | 1 Week | 1 Month | 3 Months | 6 Months | 12 Months | 24 Months |
|---|---|---|---|---|---|---|
| Portfoio 'a' | 0.895*** | 0.919*** | 0.914*** | 0.929*** | 0.916*** | 0.935*** |
| | (0.009) | (0.007) | (0.007) | (0.007) | (0.009) | (0.008) |
| Portfoio 'b' | 0.902*** | 0.937*** | 0.939*** | 0.922*** | 0.918*** | 0.935*** |
| | (0.013) | (0.007) | (0.005) | (0.006) | (0.005) | (0.008) |
| Portfoio 'c' | 0.929*** | 0.946*** | 0.946*** | 0.939*** | 0.975*** | 0.959*** |
| | (0.011) | (0.005) | (0.005) | (0.006) | (0.009) | (0.004) |
| Portfoio 'd' | 0.931*** | 0.967*** | 0.981*** | 0.986*** | 0.986*** | 0.980*** |
| | (0.005) | (0.004) | (0.003) | (0.006) | (0.007) | (0.003) |
| Portfoio 'e' | 0.877*** | 0.923*** | 0.908*** | 0.899*** | 0.945*** | 0.949*** |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.007) | (0.005) |
| HmL | 0.818*** | 0.859*** | 0.850*** | 0.811*** | 0.799*** | 0.841*** |
| | (0.014) | (0.015) | (0.009) | (0.014) | (0.017) | (0.014) |
| DoL | 0.897*** | 0.930*** | 0.930*** | 0.938*** | 0.958*** | 0.956*** |
| | (0.008) | (0.005) | (0.006) | (0.007) | (0.008) | (0.007) |

Note: The results presented in this table are from Fama's (1984) regression model that is $s_t^k - s_t = \beta_1 + \beta_2(f_t^k - s_t) + \mu_t$.

**Table 5.4.:** Estimation of the relationship between contemporaneous order-flow and CT returns

| | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\bar{R}^2$ |
|---|---|---|---|---|
| Portfolio 'a' | -0.018*** | -0.513 | 0.003* | 0.01 |
| | (0.001) | (0.453) | (0.002) | |
| Portfolio 'b' | -0.006*** | 0.954** | 0.002** | 0.01 |
| | (0.000) | (0.408) | (0.001) | |
| Portfolio 'c' | 0.000 | 0.121 | -0.001 | 0.00 |
| | (0.000) | (0.320) | (0.001) | |
| Portfolio 'd' | 0.006*** | -1.905*** | 0.001 | 0.03 |
| | (0.000) | (0.498) | (0.001) | |
| Portfolio 'e' | 0.017*** | -4.569*** | 0.006*** | 0.10 |
| | (0.001) | (0.705) | (0.002) | |
| HmL | 0.035*** | -2.244*** | 0.008*** | 0.06 |
| | (0.001) | (0.600) | (0.002) | |
| DoL | 0.000 | 0.231 | 0.001 | 0.00 |
| | (0.000) | (0.690) | (0.001) | |

The results presented in this table are from Evan and Lyons(2002) regression model that is $\triangle CT_t = \beta_1 + \beta_2 \triangle (i - i^*) + \beta_3 OF_t + \epsilon_t$.

proxies by the interest rate differential. The aggregate customer order-flow is utilised in the following model. The main objective is to determine whether it is order flows that can explain the carry returns or if they are merely a result of customers reacting to the arbitrage opportunities that arise in the market. If the latter is the case then a significant coefficient for the HML portfolio should be expected. The following micro-finance model is that of Evans and Lyons (2002) and is an empirical extension of the work by Cerrato *et al.* (2011). The contemporaneous and lagged models are as follows:

$$\triangle CT_t = \beta_1 + \beta_2 \triangle(i - i^*) + \beta_3 OF_t + \epsilon_t \tag{5.6}$$

$$\triangle CT_t = \beta_1 + \beta_2 \triangle(i - i^*) + \beta_3 OF_{t-1} + \epsilon_t \tag{5.7}$$

The results of the contemporaneous and lagged models are presented in Table 5.4 and 5.5. The customer order-flows significantly explain the large purchase portfolio $e$ and the HML portfolio carry returns. However, in the lagged version the variation in the excess returns of the portfolio $d$ are considerably explained by the order-flows. The contemporaneous model results suggest that customers realise the arbitrage opportunities and rearrange their portfolios according to the available zero cost portfolio set-up opportunities.

### 5.3.7. Consumption-based Asset Pricing Model

Consumption-based pricing models are derived from the linear factor models. These models suggest that the cross-section of average asset returns can be attributed to risk premia associated with their exposure to a small number of risk factors. The consumption-based asset pricing

**Table 5.5.:** Estimation of the relationship between lagged order-flow and CT returns

| | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\bar{R}^2$ |
|---|---|---|---|---|
| Portfolio 'a' | -0.018*** | -0.77* | -0.001 | 0.00 |
| | (0.001) | (0.444) | (0.002) | |
| Portfolio 'b' | -0.006*** | 0.930** | 0.001 | 0.01 |
| | (0.000) | (0.409) | (0.001) | |
| Portfolio 'c' | 0.000 | 0.128 | 0.000 | 0.00 |
| | (0.000) | (0.320) | (0.001) | |
| Portfolio 'd' | 0.006*** | -1.894*** | 0.003*** | 0.04 |
| | (0.000) | (0.495) | (0.001) | |
| Portfolio 'e' | 0.017*** | -4.564*** | 0.000 | 0.07 |
| | (0.001) | (0.721) | (0.002) | |
| HmL | 0.037*** | -2.681*** | -0.002 | 0.03 |
| | (0.001) | (0.603) | (0.002) | |
| DoL | 0.000 | 0.366 | 0.003** | 0.00 |
| | (0.000) | (0.688) | (0.001) | |

The results presented in this table are from Evan and Lyons(2002) regression model that is $\triangle CT_t = \beta_1 + \beta_2 \triangle (i - i^*) + \beta_3 OF_{t-1} + \epsilon_t$.

model suggests that the risk factors are capable of capturing moments in the individual asset returns.[17]

In summary, given the basic consumption-based model an investor's first- order conditions can be computed as:

$$p_t = E_t\left[\beta\frac{u'(c_{t+1})}{u'(c_t)}x_{t+1}\right] \tag{5.8}$$

where $p_t$ is the price of the underlying asset at time $t$ i.e. $p = E(mx)$, $m = \beta\frac{u'(c_{t+1})}{u'(c_t)}$, $c$ represents the consumption of the asset holder and $x$ is the payoff of the asset at time $t$.

The above equation can be estimated using GMM (Generalised Method of Moments). It is assumed that the consumption of customers is proxied by customer order-flows. It can also be explained as the customers rearranging their portfolios based on their expectations about the consumption. Therefore customer orders qualify as a suitable candidates for a proxy of consumption. Furthermore, volatility as a global factor is also utilised. The GMM model is expressed in equation 5.2.

$$m_{t+1} = 1 - b_1 rx_{m,t+1} + b_2\triangle F_{t+1}$$

where $rx$ is the excess return, $F$ is the global factor at time $t$.

### 5.3.8. Cross-Sectional Asset Pricing

In this chapter, $rx^j_{t+1}$ is used to denote the weighted average excess returns on portfolio $j$ at time $t$. Furthermore, the empirical examination is conducted using the excess returns, not log of the excess returns. The

[17]A class of asset pricing theory

intuition behind using excess returns (at level) is to avoid the assumption of having a joint log-normality of the pricing kernel and returns. If it is assumed that no arbitrage opportunities are available in the foreign exchange market, then the excess return should be equal to zero: Hence the zero price return should satisfy the following Euler equation:

$$E_t[M_{t+1} rx^j_{t+1}] = 0$$

where $rx^j_{t+1}$ is the excess return of portfolio $j$ at time $t+1$ i.e., one ahead in the underlying research set-up. $M$ is the stochastic discount factor, and it is assumed that $M$ is linear in the pricing factors:

$$M_{t+1} = 1 - b(\Phi_{t+1} - \mu_\Phi),$$

where $b$ denotes the vector of common factor and the factor mean is denoted by$\mu$. The aforementioned $M$ linear factor model implies a beta pricing model; the beta pricing model suggests that the expected excess returns can be computed by multiplying the betas of each portfolio $\beta^j$ with the factor price $\lambda$. The following equation can be obtained:

$$E[Rx^j] = \lambda\beta^j,$$

where $\lambda = \sum_{\Phi\Phi} b$, $\sum_{\Phi\Phi} = E(\Phi_t - \mu_\Phi)(\Phi_t - \mu_\Phi)'$ represents the variance-covariance matrix of the common risk factors, the regression coefficients of the excess returns $rx^j$ against the factor is denoted by $\beta^j$ for portfolio $j$. There are number of methods in computational finance that suggests the estimation of factor price $\lambda$ and portfolio betas $\beta$. In this chapter two methods for the required parameter estimation are considered: A two-stage OLS estimation following Fama and MacBeth (1973), Henceforth FMB, and a Generalised Method of Moments estimation (GMM) applied to linear factor models, following Hansen (1982). The FMB parameters are computed in a two-stage set-up. In the first stage, a regression model is estimated between the time series of returns against the global factor, and in the second stage, a cross-sectional regression of average return against betas is estimated. In the second stage regression model the constant term is excluded ($\lambda_0 = 0$). The results are presented in the following Tables 5.5, 5.6 and 5.7:

The parameters of equation 5.2 are estimated via the generalised method of moments (GMM) based on Hansen (1982) for implied, conditional and order-flow as global factors. The estimation is based on the pre-specified weighting matrix and the movements' conditions were unrestricted. This is because the question of interest is to access the performance of the model to explain the cross-section of expected currency excess returns textitper se.[18] Tables 5.6, 5.7 and 5.8 present the results of the GMM estimate using implied, conditional volatility and order-flow as global factors in the cross-sectional set-up. The j-statistic reported is measured by the Hansen-Jagannathan method. Standard errors are based on Newey and West (1987) with optimal lag length selection according to Andrews (1993).

The first panel of the tables reports the cross-sectional pricing results. The important coefficient to consider is factor price. A negative price coefficient is obtained for the implied, conditional and order-flow factor. The negative pricing coefficient interprets lower risk premia for portfolios. Portfolios that co-move positively with the factor and order-flow innovations can hedge against volatility innovation. Whereas portfolios

[18]No instrument was used other than constant vector

**Table 5.6.:** Cross-sectional asset pricing results using implied volatility as a global factor

| GMM | DOL | VOL | R2 | J-Statistic |
|---|---|---|---|---|
| b | 0.236 | -0.010 | 0.71 | 0.34 |
| S.E. | (0.155) | (0.007) | | |
| $\lambda$ | 0.236 | -0.014 | | |

Factor Betas

| PF | a | DOL | VOL | R2 |
|---|---|---|---|---|
| a | -1.776*** | 0.806*** | -0.018*** | 0.09 |
| | (0.042) | (0.127) | (0.006) | |
| b | -0.636*** | 0.831*** | -0.007*** | 0.33 |
| | (0.018) | (0.053) | (0.003) | |
| c | -0.011 | 0.803*** | -0.001 | 0.65 |
| | (0.009) | (0.026) | (0.001) | |
| d | 0.602*** | 1.078*** | 0.005** | 0.46 |
| | (0.017) | (0.051) | (0.002) | |
| e | 1.75*** | 1.482*** | 0.021*** | 0.21 |
| | (0.042) | (0.126) | (0.006) | |
| hml | 3.526*** | 0.676*** | 0.039*** | 0.03 |
| | (0.082) | (0.247) | (0.012) | |

Notes: The first panel of the table reports results for all countries from GMM asset pricing procedures. Market prices of risk, the adjusted $R^2$, j-statistics of the factor. $\lambda$ is factor price. Excess returns used as test assets and implied volatility as risk factors. Panel II reports OLS estimates of the factor betas and $R^2$. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). ***, **, * represents the significance level at 1%, 5%, and 10% respectively.

**Table 5.7.:** Cross-sectional asset pricing results using GARCH volatility as a global factor

| GMM | DOL | VOL | R2 | J-Statistic |
|---|---|---|---|---|
| b | -1.299 | 64.741*** | 0.78 | 0.19 |
| S.E. | (1.362) | (5.179) | | |
| $\lambda$ | -0.045 | 0.826 | | |

Factor Betas

| PF | a | DOL | VOL | R2 |
|---|---|---|---|---|
| a | -1.767*** | 0.985*** | -0.063*** | 0.25 |
| | (0.038) | (0.115) | (0.006) | |
| b | -0.635*** | 0.877*** | -0.014*** | 0.36 |
| | (0.017) | (0.052) | (0.003) | |
| c | -0.0130 | 0.792*** | 0.006*** | 0.66 |
| | (0.009) | (0.026) | (0.001) | |
| d | 0.599*** | 1.025*** | 0.019*** | 0.52 |
| | (0.016) | (0.049) | (0.002) | |
| e | 1.744*** | 1.321*** | 0.053*** | 0.30 |
| | (0.039) | (0.119) | (0.006) | |
| hml | 3.511*** | 0.336 | 0.116*** | 0.18 |
| | (0.075) | (0.228) | (0.011) | |

Notes: The first panel of the table reports results for all countries from GMM asset pricing procedures. Market prices of risk, the adjusted $R^2$, j-statistics of the factor. $\lambda$ is factor price. Excess returns used as test assets and GARCH volatility as risk factors. Panel II reports OLS estimates of the factor betas and $R^2$. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). ***, **, * represents the significance level at 1%, 5%, and 10% respectively.

with negative co-variance against the factor demand a risk factor. Panel B of the tables presents the time-series beta estimates of the excess returns against the demeaned DOL and global factor. The estimates of the factors for volatility are small. Yet for the order-flow factor, they are large and significant. The betas tend to be monotonic across the portfolios.

### 5.3.9. Factor-Mimicking Portfolio

In this chapter, a factor-mimicking portfolio of implied volatility innovations was set up, following Breeden *et al.* (1989) and Ang, Hodrick, Xing and Zhang (2006). In factor-mimicking portfolio the implied volatility is taken as dependent variable and estimates the excess returns of the portfolio as independent variable in the following model:

$$\triangle IV = rx_a + rx_b + rx_c + rx_d + rx_e + \epsilon$$

The results of the factor-mimicking portfolio are reported in Table 5.9. Theoretically, estimating a factor-mimicking portfolio has the advantage of allowing the scrutinisation of the factor price of risk in a natural way. The factor-mimicking portfolio assumes the factor as a trading asset. Therefore, the risk price of the underlying portfolio for the given factor should be equal to the mean return of the traded portfolio. Hence, the no-arbitrage condition is satisfied by the factor prices themselves.

The portfolios with negative betas provide a hedge against the volatility innovations. The portfolios ‘a’, ‘d’ and ‘e’ have a negative loading against the volatility innovations and provide a hedging strategy for investors.

**Table 5.8.:** Cross-sectional asset pricing results using customer order-flow as a global factor

| GMM | DOL | VOL | R2 | J-Statistic |
|---|---|---|---|---|
| b | -0.130 | -0.001 | 0.73 | 0.35 |
| S.E. | (0.151) | (0.007) | | |
| $\lambda$ | -0.015 | -0.083 | | |
| | | **Factor Betas** | | |
| PF | a | DOL | VOL | R2 |
| a | -1.800*** | 0.844*** | -0.490 | 0.08 |
| | (0.044) | (0.127) | (0.373) | |
| b | -0.647*** | 0.847*** | -0.223 | 0.33 |
| | (0.019) | (0.053) | (0.156) | |
| c | -0.018** | 0.807*** | -0.175** | 0.64 |
| | (0.009) | (0.026) | (0.077) | |
| d | 0.608*** | 1.068*** | 0.134 | 0.46 |
| | (0.018) | (0.051) | (0.150) | |
| e | 1.785*** | 1.434*** | 0.755** | 0.20 |
| | (0.045) | (0.127) | (0.373) | |
| hml | 3.585*** | 0.590** | 1.245* | 0.01 |
| | (0.087) | (0.248) | (0.728) | |

Notes: The first panel of the table reports results for all countries from GMM asset pricing procedures. Market prices of risk, the adjusted $R^2$, j-statistics of the factor. $\lambda$ is factor price. Excess returns used as test assets and order-flow as global factor. Panel II reports OLS estimates of the factor betas and $R^2$. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). ***, **, * represents the significance level at 1%, 5%, and 10% respectively.

**Table 5.9.:** Estimations of factor mimicking portfolio

| FMMP | $\alpha$ | $rx_a$ | $rx_b$ | $rx_c$ | $rx_d$ | $rx_e$ | $R^2$ |
|---|---|---|---|---|---|---|---|
| IV | -4.778*** | -2.161*** | 1.103 | 7.849*** | -1.259 | 1.578*** | 0.32 |

Notes: The first panel of the table reports results for all countries from GMM asset pricing procedures. Market prices of risk, the adjusted $R^2$, j-statistics of the factor. $\lambda$ is factor price. Excess returns used as test assets and implied volatility and HML as jointly global factor. Panel II reports OLS estimates of the factor betas and $R^2$. The standard errors in brackets are Newey and West (1987) standard errors computed with the optimal number of lags according to Andrews (1991). ***, **, * represents the significance level at 1%, 5%, and 10% respectively.

### 5.3.10. Cross-sectional Asset Pricing Results: Volatility and HML

A joint factor model including the implied volatility and HML portfolio was estimated in line with Lustig *et al.* (2011). The HML was included in the SDF equation 5.2, that is:

$$m_{t+1} = 1 - b_1 rx_{m,t+1} - b_2 HML - b_3 \triangle F_{t+1}$$

The results are presented in Table 5.10. It can be seen from these results that the HML portfolio explains the volatility innovations better when the HML and implied volatility are introduced into a joint SDF. The results are in line with the existing literature. The HML portfolio is very similar to the global volatility factor-mimicking portfolio. The HML portfolio serves as a principal component of the cross-section of carry trade returns, accounting for almost all cross-sectional variations in returns.

In conclusion, when the HML and volatility innovation are jointly estimated in a GMM approach, HML out-performs the volatility innovations in the cross-section of the excess return portfolios.

**Table 5.10.:** Cross-sectional asset pricing results using volatility and HML, as a joint factor

| GMM | DOL | VOL | HML | R2 | J-Statistic |
|---|---|---|---|---|---|
| b | -0.075 | 16.775*** | -0.539*** | 0.42 | 0.19 |
| S.E. | (0.426) | (1.765) | (0.035) | | |
| $\lambda$ | 1.472 | 1.483 | -14.197 | | |

The results presented in this table are from Breeden *et al.*'s (1989) and Ang, Hodrick, Xing and Zhang's (2006) regression model that is $\triangle CT_t = \beta_1 + \beta_2 \triangle(i - i^*) + \beta_3 OF_{t-1} + \epsilon_t$.

## 5.4. Conclusion

A large proportion of finance literature within the context of the foreign exchange market focuses on the FDU puzzle and explaining the profitability of the carry trade. The carry trade refers to the trading strategy which results as a consequence of the forward discount bias: Whereby a discrepancy in the underlying currency with a positive forward premium (high interest rate currency) will appreciate rather than depreciate. This chapter contributes to the literature by analysing the stated issue using novel customer order-flow data provided by the UBS. First, Fama's (1984) regression was estimated and it was found that the forward discount was smaller than 1, the value consistent with uncovered interest rate parity. Furthermore, the forward discount bias and profitability of the carry trade were studied in two segments using a portfolio based approach. First, by using customer order-flow in a microstructure approach, like Evans and Lyons (2002) It was demonstrated that customer order-flows significantly explain the movements in the realised carry return.

Secondly, it was found that the global foreign exchange customer order-flows and volatility innovations are able to significantly explain the cross-section of carry returns in the foreign exchange markets. It was also found that there is a significantly negative correlation between the global order-flow, volatility innovation and carry trade portfolios. Whilst currencies that funds the carry trade portfolio provide a hedge against the innovation of customer order-flow and volatility in the global foreign exchange market.

# Chapter 6.

# Conclusion

Due to its integral role within the fields of economics and finance asset pricing in the foreign exchange market has been the main focus of this thesis. The literature review identified a number of fundamental areas linked to fluctuations in the exchange rate, such as forecasting ability, volatility and profitability of various exchange rate models. Then three empirical questions related to these areas and the overall topic were laid out for analysis.

1 Is the foreign exchange market efficient and can the forecasts of the structural models outperform the naive random-walk model?

2 Can the volatility trend in the foreign exchange market be predicted with the help of microstructure theories using a private data set?

3 Can the carry trade in the foreign exchange market be explained by order-flows and volatility?

Chapter Three examined the first question about the economic significance of the empirical exchange rate models and the economic value of the forecasts. The data set used contained information spanning over three decades, for the following currencies; the UK Pound Sterling (GBP/USD), the Deutschmark/Euro (DEM- EURO/USD), the Japanese Yen (JPY/USD), the Australian Dollar (AUD/USD), and the Canadian Dollar (CAD/USD). The forecasts performance, was assessed according to mean variance, value at risk and performance index finance: These methodologies were used to compare the fundamental exchange rate models with a naive random walk model, selected as a benchmark model. The parameters required for the evaluation methodologies, return and risk, were obtained from the Bayesian linear regression, the Bayesian GARCH, and linear regression. In order to estimate the performance of the forecasts a forecast of a month in advance from each models was used for the in-samples and out-of-samples.

The first section of Chapter 3 explored the relationship between macroeconomic fundamentals and the exchange rate. Parameters were obtained in order to estimate the advanced forecasts. A simple statistical analysis and comparisons analysis revealed that the naive random walk model outperformed the structural exchange-rate models. However, it was shown that investors relied more on the forecasts of the structural models. Whilst the Sharpe Ratio showed that the structural model performed as well as the benchmark model. Furthermore, the *indices of acceptability*, a portfolio performance measuring approach which was recently introduced in the foreign exchange market was looked at. The results from this evaluation concluded that one month ahead forecasts obtained from the monetary model of the exchange rate performed better than the benchmark model.

The second question, concerning the relationship between volatility and the customers trading activity, was answered in Chapter 4. The relationship between volatility and customer order flows was explained in a portfolio-based framework with unique aggregate and disaggregate order flow data. The empirical examination revealed that the relationship was robust Moreover it was revealed that order flow was the main source of transmitting private information into the foreign exchange market. The relationship proved solid across all currencies and dimensions of volatility. No such study has previously been conducted within the context of the foreign exchange market. Thus this is the first set of findings that convincingly explains this relationship in this particular context. The findings can be summarised in two parts; The first explains the relationship between aggregate and disaggregate customer order flow and volatility. While the second part explains the asymmetric impact of volatility in the subsequent period.

Significantly, it was also concluded that volatility in the foreign exchange market is considerably affected by customer order flows. The impact of the size of trade on volatility was also examined, again within a portfolio-based approach. It was found that large sales make more influential trades when affecting volatility in the market. Finally, the *liquidity-driven-trade-hypothesis* and the *information-driven-trade-hypothesis*, representing a positive and a negative subsequent relationship, respectfully, were also looked at. Evidence in support of both hypotheses was found, depending on the time period and the condition of the market at that time.

The third question, as to whether carry trade can be explained by order flows and volatility, was looked at in Chapter 5. The forward discount puzzle is amongst the most researched topics in the empirical finance field. The carry trade is a trading strategy where the investor borrows from a low interest-rate currency and invests in a higher interest-rate currency, zero investment portfolios. A novel data set, provided by the UBS was used, and this was the first time such research was attempted in the context of the foreign exchange market.

In the first section of Chapter 5, Fama's (1984) regression was estimated, in order to establish the existence of the forward discount bias. It was found to be smaller than 1. Furthermore, the forward discount bias and carry trade were studied using theories of microstructure finance and the consumption-based asset-pricing model. The micro-structured approach was in line with the standard model of Evans and Lyons (2002), which attempts to define the relationship between the moment in the carry trade and the customer order flows. The findings in this thesis indicated that the order flow significantly explains the excess returns in the carry trade. Secondly, for the consumption-based asset-pricing model the affects of global innovation customer order flows were considered. It was discovered that both variables greatly explained the cross-section of carry returns. Furthermore, a negative and significant correlation between the global order flow and the volatility innovation using carry trade portfolios was shown. Finally, it was concluded on the basis of the above results that carry profits are the premium paid on the high-risk currencies. In other words they provide a hedge against the innovation of the customer order-flow and volatility in the global foreign exchange market.

## 6.1. The Novelty of Research and Practical Implication

This Ph.D. thesis aims to aide various financial market participants. The first empirical chapter of this thesis, Chapter 3, aims to facilitate the task of portfolio managers in asset management organisations who include foreign exchange in their portfolios as a short-term investment. These portfolio managers can use the new performance measures, known as the *index of acceptability*. It is a novel approach and has never been examined before, specially when the returns are not normally distributed. The *index of acceptability* is less tedious in computation than the other performance evaluation methods. It provides a maximum value at stake in the short-term at any given time, and helps with the optimisation of portfolios. Using this technique, portfolio managers can enhance their portfolio returns as well as the wealth of their investors.

The second empirical chapter analyses the process of automated trading which, accounts for approximately 70% of trading in the foreign exchange market. Therefore, any indicator that defines emerging patterns, or evolution of the economic fundamentals, in the exchange rates is certain to enhance the performance of these trading algorithms in an automated trading system. A user of a trading station using automated trading can write their trading algorithms, then add them into the trading station and both buy and sell the positions based on the algorithm provided. In addition this chapter suggests that if users modelled their trading strategy on the basis of the models provided in Chapter 4 then they would significantly capture the change in the underlying fundamentals via the trading patterns of informed customers.

Lastly, Chapter 5 attempts to assist portfolio managers, particularly in the area of foreign exchange markets, to use carry trade identification strategies to hedge their portfolios against the currencies of high inflation countries. It will also enable them to realise excess returns on high-risk currencies with the minimum level of risk. In addition policymakers can use modelling techniques in order to establish the impact of interest rates and inflation on direct foreign investment in the money market. As far as the author is aware, this is the only study of the foreign exchange market, which explains the carry trade, and the ordering patterns of customers in the foreign exchange market.

# Appendix A.

# Econometric Models

## A.1. Bayesian Regression Model

The Bayesian regression model[1] attempts to explains the variability in one variable $y_i$ (dependent variable) with the help of one or more $x_i$ (independent variable), for individuals $i$ for $i = 1, ...., N$. The linear regression model is presented below:

$$y_i = \beta_1 + \beta_2 x_i + \varepsilon_i \tag{A.1}$$

where $y_i$ is the dependent variable, $x_i$ are the independent (explanatory) variable(s), $\beta_i$ is the intercept and slope term respectively, and $\varepsilon_i$ is an error term.

The error term is the source of randomness about the unexplained variability in the linear relationship between dependent and independent variables. The explanation of the error term requires an assumption; first, the error term is normally distributed with 0 mean and variance $\sigma^2$ $N(0, \sigma^2)$, and $\varepsilon_i, i = 1, ....., n$, are independent of one another, independent

[1]This derivation is from Koop (2008)

and identically distributed (i.i.d.). Hence, the dependent variable $y$ has a normal distribution; second independent variable $x_i$ is independent of error term $\varepsilon_i$, with a probability density function, $P(x_i|\lambda)$, where $\lambda$ is a vector of parameters that does not include $\beta$ and $\sigma^2$.

The likelihood function is defined as the joint probability density function for all the data conditional on the unknown parameters. If $y$ and $x$ are the vectors of observed data for dependent and independent variables, the likelihood function then becomes $p(y, x|\beta, sigma^2, \lambda)$. The second assumption converges the likelihood function into the following equation:

$$p(y, x|\beta, \sigma^2, \lambda) = p(y|x, \beta, \sigma^2)p(x|\lambda) \tag{A.2}$$

The distribution of independent variable $x_i$ is not usually the area of interest; the likelihood function is conditional on $x, p(y|x, \beta, \sigma^2)$. The error term helps the precise form of likelihood function. By using basic rules of probability, the following equations can be obtained:

$$p(y_i|\beta, \sigma^2)$$
$$\mathbb{E}(y_i|\beta, \sigma^2) = \beta x_i$$
$$var(y_i|\beta, \sigma^2) = \sigma^2$$

Using the definition of normal density, the following is obtained

$$p(y|\beta, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left[\frac{(y_i - \beta x_i)^2}{2\sigma^2}\right] \tag{A.3}$$

Finally, since the error term is independent and identically distributed, the dependent variable is also independent and identically distributed and, thus $p(y|\beta, sigma^2 = \prod_i^N p(y_i|\beta,\sigma^2)$ and, therefore, the likelihood function is given by:

$$p(y|\beta,\sigma^2) = \frac{1}{(2\pi)^{\frac{N}{2}}\sigma^N} exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{N}(y_i - \beta x_i)^2\right] \tag{A.4}$$

For the sake of convenience the likelihood function can be written in the following form:

$$\sum_{i=1}^{N}(y_i - \beta x_i)^2 = \nu s^2 + (\beta - \hat{\beta})^2 \sum_{i=1}^{N} x^2 \tag{A.5}$$

where

$$\nu = N - 1$$
$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2}$$
$$s^2 = \frac{\sum(y_i - \hat{\beta}x_i)^2}{\nu}$$

where $\hat{\beta}$, $s^2$ and $\nu$ are the ordinary least squares (OLS) estimators for beta, standard error and degrees of freedom, respectively. Furthermore, for many technical derivations, it is easier to work with the error precision rather than variance. The error precision is defined as: $h = \frac{1}{\sigma^2}$. Using the above results, finally the likelihood function can finally be written as follows:

$$p(y|\beta,h) = \frac{1}{(2\pi)^{\frac{N}{2}}}\left\{h^{\frac{1}{2}}\left[exp(\beta-\hat{\beta})^2\sum_{i=1}^{N}x_i^2\right]\right\}\left\{h^{\frac{\nu}{2}}exp\left[-\frac{h\nu}{2s^{-2}}\right]\right\} \tag{A.6}$$

Priors are a unique and debatable issue of the Bayesian framework. Priors are any information that the researcher has before observing the data; they are subjective and can be of any form. However it is intuitive to select those classes of priors which are analytically tractable and have convenient posterior distribution. If it is assumed that the data have been generated with a particular class of distribution, employing the so-called *natural conjugate* prior guarantees that the posterior will be the same class as prior, and the same function form as likelihood function. Therefore, the interpretation of the prior information is the same as for the likelihood function information.

The Bayesian regression model requires the definition of priors for $\beta$ and $h$ which is denoted by $p)\beta, h)$. The contrast between prior and posterior is that priors are not dependent on data, i.e., $p(\beta, h)$, while, the posterior is dependent on the data $p(\beta, h|y)$. Therefore, it is convenient to write $p(\beta, h) = p(\beta|h)p(h)$ and taking priors in terms of $\beta|h$ and $h$. It can be observed from the likelihood equation A.6 that the natural conjugate prior for the $\beta|h$ will follow a normal distribution, whereas, $h$ follows gamma distribution. The distributions, which are the product of normal and gamma, are called normal-gamma distribution.

$$\beta|h : N(\underline{\beta}, h^{-1}\underline{\mathrm{V}}) \tag{A.7}$$

and

$$h : G(s^{-2}, \nu) \tag{A.8}$$

then the natural conjugate prior for and h is denoted by:

$$\beta, h : NG(\beta, V, s^{-2}, \nu) \tag{A.9}$$

Thereafter, the values of the so-called prior hyper-parameter $\underline{\beta}$, $\underline{\mathrm{V}}$, $\underline{\mathrm{s}}^{-2}$ and $\underline{\nu}$ are selected to reflect prior information.

The posterior density summarises the beliefs, before seeing the data priors and data, held about the unknown parameters. The posterior density summarises all the information, both prior and data based, held about the unknown parameter, $\beta$ and $h$. It is proportional to the likelihood times the prior density. Formally, the posterior of the form is as follows:

$$\beta, h|y : NG(\bar{\beta}, \bar{V}, \bar{s}^{-2}, n\bar{u})$$

where

$$\bar{V} = \frac{1}{\underline{\mathrm{V}}^{-1} + \sum x_i^2}$$

$$\bar{\beta} = \bar{V}(V^{-1}\beta + \hat{\beta}\sum x_i^2)$$

$$\bar{\nu} = \underline{\nu} + N$$

and $\bar{s}^2$ is defined implicitly through

$$\bar{\nu}\bar{s}^2 = \underline{\nu s}^2 + \nu s^2 + \frac{(\hat{\beta} - \underline{\beta})^2}{\underline{V} + \left(\frac{1}{\sum x_i^2}\right)}$$

The following algorithms were used in this chapter for Bayesian Linear Regression:

The interest here is in the estimation of the parameters that are contained in the set $\theta = \{\theta_1, \theta_2\}$, where $\theta_1 = \{\beta_1, \beta_2\}$ and $\theta_2 = \{h\}$ and where $h$ is the error precision: $h = \frac{1}{\sigma^2}$. The normal priors for $\theta_1$ have zero mean and variance one. Prior gamma $\left(\frac{\nu}{2}, \frac{2s^{-2}}{\underline{\nu}}\right)$ is assumed for $\theta_2 = \{h\}$ with mean and degree of freedom $\underline{\nu} = 2$. The following algorithm shows the steps of the Monte Carlo simulation:

1. The Monte Carlo integration used is $\hat{\mathrm{g}}S = \frac{1}{S}\sum_{s=1}^{S} \mathrm{g}\left(\beta^{(s)}\right)$, where S is the number of simulations. $(\beta|y)$. where $y$ is the $\triangle s_t$ from equation (**??**).

2. First, a random draw of $\beta^{(S)}$ is obtained to form the posterior. These random draws are generated by MATLAB random number generator for $t$ distribution.

3. Thereafter the function $\hat{\mathrm{g}}(\beta^{(S)})$ is calculated and the result retained.

4. Steps 2 and 3 are repeated for $S = 10000$

5. Finally, the average of $S$ draws is taken in order to obtain the mean of the posterior distribution of $\beta$.

The empirical standard errors were also computed as follows: Let $\theta^{(S)}$ for $s = 1, ...., S$ be a random sample from $p(\theta|y)$, and define

$$\hat{\mathrm{g}}s = \frac{1}{S}\sum_{S=1}^{S} \mathrm{g}\left(\theta^{(S)}\right)$$

Then $\hat{\mathrm{g}}s$ converges to $E[\hat{\mathrm{g}}(\theta)]$ as S goes to infinity

$$\sqrt{S\{\hat{\mathrm{g}}s - E[\mathrm{g}(\theta)]\}} \to N(0, \sigma_{\mathrm{g}}^2)$$

where $\sigma_{\mathrm{g}}^2 = \ \mathrm{var}[\mathrm{g}(\theta)|y]$. The Monte Carlo integration procedure allows the approximation $\sigma_{\mathrm{g}}$. The term $\frac{\sigma \mathrm{g}}{\sqrt{S}}$ defines the numerical standard error

(NSE).

The number of replications $S$ is set to 10,000.

## A.2. Bayesian GARCH (1,1)

The model for the time varying volatility for one month ahead forecasts of the exchange rates is described in the following equation for return and volatility dynamics:

$$r_t = X_t\gamma + \sigma_{t|t-1}\varepsilon_t \tag{A.10}$$

$$\sigma^2_{t|t-1} = \omega + \alpha\mu^2_{t-1} + \beta\sigma^2_{t-1|t-2} \tag{A.11}$$

where $\mu_{t-1} = r_{t-1}X_t\gamma$, $r_t$ is the observed data on returns of holding a foreign exchange and interest-free instrument for one month. The model's parameters vector is defined by $\theta = (\omega, \alpha, \beta, \nu, \gamma')$ and return observed data is defined by the vector $r = (r_1, ......, r_T)$. The error term $\varepsilon$ is assumed to be distributed with a student's $t$-distribution with $\nu$ degree of freedom, the likelihood function for the models parameters can be written as:

$$L(\theta|r, \mathfrak{J}_0) \propto \prod_{t=1}^{T}\left[(\sigma^2_{t|t-1})^{-1}\left(1+\frac{1}{\nu}\frac{(r_t - X_t\gamma)^2}{\sigma^2_{t|t-1}}\right)^{-\frac{\nu+1}{2}}\right] \tag{A.12}$$

Where $\mathfrak{J}_0$ is the set of information available at $t = 0, \sigma^2_0$ is considered as a known constant, for simplicity. Given the assumption of student's $t$-distribution for the error term, the conditional volatility at time $t$ is given by

$$\frac{\nu}{\nu-2}\sigma_t^2$$

For '$\nu$' greater than 2.

To keep the model simple, it is assumed that the conditional variance parameters have uninformative diffuse prior distributions over their respective ranges.

$$\pi(\omega,\alpha,\beta) \propto 1I_{(\theta_G)} \tag{A.13}$$

where $1I_{(\theta_G)}$ is an indicator function reflecting the constraints on the conditional variance parameters,

$$I_{(\theta_G)} = \begin{cases} 1 & \text{if } \omega < 0, \alpha > 0 \text{ and } \beta > 0 \\ 0 & \text{otherwise} \end{cases} \tag{A.14}$$

Normal priors are selected for regressing parameters,[2] $\gamma$,

$$\pi(\gamma) = N\left(\mu_\gamma, \sum_\gamma\right)$$

Finally, on the basis of above assumptions the posterior distribution of $\theta$ can be written as follows.

$$p(\theta|r,\mathfrak{I}_0) \propto \prod_{t=1}^{T}\left[(\sigma_{t|t-1}^2)^{-1}\left(1+\frac{1}{\nu}\frac{(r_t - X_t\gamma)^2}{\sigma_{t|t-1}^2}\right)\right] exp(-\nu\lambda)exp \tag{A.15}$$

$$\left(-\frac{1}{2}(\gamma-\mu_\gamma)'\sum^{-1}(\gamma-\mu_\gamma)\right) I_{(\theta_G)} \tag{A.16}$$

[2]See: Rachev *et al.* (2008)

The restrictions on $\omega, \alpha$ and $\beta$ are enforced during the sampling procedure by rejecting the draws that violate them.

The following algorithms are used in this chapter for Bayesian GARCH (1,1).

The GARCH algorithm follows Ardia and Hoogerheide (2010) and assumes $\sigma^2_{t|t-1} = \omega + \alpha\mu^2_{t-1} + \beta\sigma^2_{t-1|t-2}$. The conditional volatility is recursive in nature; hence it restricts the use of conjugacy between prior density and the likelihood function. Therefore, the Metropolis-Hastings algorithm is used to draw samples from the posterior distribution. The algorithm is the modified version of the algorithm described by Nakatsuma (1998, 2000). Truncated normal distribution with zero mean and unit variance is selected as prior. Using Bayes' rule, the joint posterior probability distribution is $p(\theta|y) \propto p(y|\theta)p(\theta)$.

The Bayesian GARCH estimations was applied on the returns calculated from the three Monetary Fundamental models and the Random Walk model. These estimations are obtained by the bayesGARCH function of the R language by the CRAN project. The bayesGARCH function is provided by Ardia and Hoogerheide (2010). As an input argument, the prior parameters were provided, as was the length of each MCMC chain, that are $\omega = 0.01$, $\alpha = 0.1$, $\beta = 0.7$, $v = 20$ and the MCMC chain of 10000. The sampler convergence is controlled by the Gelman and Rubin (1992) diagnostic test. The first 10000 draws are discarded from the MCMC draws.

1. First initial values of the prior are drawn for $\theta^0$ from the parameter space of $\theta$

2. For each iteration $j$, draw a (multivariate) realisation, $\theta^*$ from the density conditional on $\theta^{j-1}$, that is the parameter value at the previous step

3. Compute the acceptance probability as $\min\{\frac{p(\theta^*|y)}{p(\theta^{[j-1]}|y)}\frac{q(\theta^{[j-1]}|\theta^*)}{p(\theta^*|\theta^{[j=1]})}, 1\}$. After drawing $U$ from a uniform distribution $U(0,1)$ check if $U \leq$ acceptance probability. If it is, set $\theta^{[j]} = \theta^*$, otherwise, set $\theta^{[j]} = \theta^{[j-1]}$

4. Iterate from step 2 until convergence is obtained

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