Short-run Exchange Rate Dynamics in South Africa: A Microstructure Approach

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For my Queen, Patience Sthabile Phiri

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Abstract

This dissertation investigates the short-run variation of the South African Rand versus the US Dollar exchange rate. A market microstructure approach to exchange rate determination is adopted and the central hypothesis is that customer order flow is an important determinant of short-run variation in the exchange rate. Two key objectives are examined. Firstly, the paper looks at the in-sample explanatory power of the order flow as a key determinant of exchange rate variation. Secondly, the practical significance of order flow is evaluated by looking at its out-of-sample forecasting accuracy. The findings from this study suggest that order flow can explain some of the variation in exchange rate; however, a large portion of the exchange rate variation remains unexplained. Further, the out-of-sample performance of the order flow model is found to be inferior to that of the GARCH model for periods up to 6 months and inferior to the naïve Random Walk model at 12 months horizons. The evaluation of a Vector Autoregression model suggests that there are feedback effects from exchange rate returns to order flows. This means that Ordinary Least Squared estimates could be biased and the results thus inaccurate and misleading.

Key words:

Order flow, market microstructure, variations/returns, exchange rates, short-run, forecasting/predictive power, significance

Declaration

This dissertation is my own work and no part of it has been submitted before for an award of a degree in this or any other University. All concepts and ideas from other scholarship/people have attributed accordingly through referencing and citation.

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CHAPTER ONE: INTRODUCTION

Exchange rates are one of the most important prices in international finance. They play a fundamental role within the international financial market and in international trade of goods and services. Thus exchange rates facilitate transactions between different countries across the globe, and provide a necessary link for open economics to operate. A country can either maintain a fixed exchange rate regime or a floating exchange rate regime; and the monetary authorities of a given country usually determine the chosen exchange rate regime. For countries with fixed exchange rate regimes their monetary authorities play an active role in maintaining the chosen rate (commonly known as the peg). However, monetary authorities under a floating exchange rate regime have a very scant role in determining the exchange rate. Under a free-float exchange rate regime the prevailing exchange rate is influenced by the market forces of supply and demand (Caves, 1963).

One of the biggest challenges in international finance, as far as exchange rates are concerned, has been an attempt to economically model the behaviour of floating exchange rates. Most of the proposed models of exchange rate determination have been shown to have a worse empirical performance than the naïve random walk model (RWM) (Meese and Rogoff, 1983 and Frankel, 1984). A significant portion of the observed variations in the exchange rates, especially in the short-run, remains unexplained (Mussa, 1984). Several reasons have been given as to why the initially proposed models of exchange rate determination have failed to explain the observed behaviour of exchange rates. However, recently the most compelling reason given for the poor empirical performance of these models has been dubbed as the lack of microeconomic foundations in these models (Lyons, 1995). Lyons' (1995) pioneering seminal paved way for the emergence of a microstructural theory of exchange rate determination. A microstructure approach to exchange rate determinations emphasises the behaviour of foreign exchange market participants as an important factor in determining variations in the exchange rate. This suggests that the market microstructure of the foreign exchange market is a key element in exchange rate determination. Some theorists (among other, Evans and Lyons, 2002; Osler, 2006) posit that a microstructural models improves upon the RWM and provides promising empirical performance particularly in the short-run.

The present study applies a microstructural model to examine the short-run behaviour of the exchange rate between the South African rand (ZAR) and the United States Dollar ($). This study will evaluate the main hypothesis of the exchange rate microstructure theory; specifically, that order flow is an important explanatory variable for exchange rate determination. The performance of a microstructure model used in this study will be evaluated against the RWM to assess both its explanatory power and forecasting ability. Further, the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and the Vector Autoregressive (VAR) models will also be employed to provide a comprehensive view of the behaviour of the ZAR/$ exchange rate.

1.1 Background to the Study

On the 22nd of July 1944, 45 countries signed the Bretton Woods Agreement of 1944 for monetary and exchange rate management, of which South Africa was a signatory. The Bretton Woods operated on a currency par value system where signatory countries maintained fixed exchange rates which could only be adjusted to address an imbalance of payment in a given country. Under the Bretton Woods system currencies were pegged to the United States dollar and only the International Monetary Fund (IMF) had the authorization to intervene when an imbalance of payment arose (IMF, 2016). The main factors that led to the establishment of the Bretton Woods monetary system were primarily the concerns over exchange rates instability, an attempt to prevent competitive currency devaluations and to promote economic growth through enhanced international trade (Ghizoni, 2013). However, the Bretton Woods system proved un-stainable, mainly due to the United States of America (USA)'s consistent budget deficit, and eventually collapsed and abandoned in 1971.

The collapse of the Bretton Woods monetary system marked the dawn of a whole new conundrum in the international finance arena. Ensuing the collapse of the Bretton Woods system, many countries adopted either a fixed 'managed or dirty float' exchange rate regime as their monetary exchange rate policy. Floating exchange rate regimes were mainly adopted by developed economies (Dreyer, 1978). Under a flexible exchange rate regime an economy's currency is determined within the currency market without any active intervention from monetary authorities. Since the advent of floating exchange rate there has been a significant attempt to understand the market forces that drive variations in these rates from an economic standpoint. Most academic efforts have been channelled towards economic modelling of the behaviour of exchange rates using fundamental macroeconomic variables. However, to date international economists are still baffled by how these exchange rates are determined in the open currency market.

The monetary models of the 1970s (Black, 1973; Dornbusch, 1976; Frenkel, 1976; Mussa, 1976; and Kouri, 1976) provided initial attempts at explaining the behaviour of floating exchange rates. These models generally took the 'asset view' of exchange rates and their main propositions was that the exchange rate behaviour could be determined by the fundamental macroeconomic factors such as inflation, aggregate production, interest rates *inter alia.* These asset view models have come to be understood as the traditional models of exchange rate determination. Initially, the traditional models of exchange rate determination experienced poor empirical performance altogether (Booth and Glassman, 1981; Meese and Rogoff, 1983; Baillie and Selover, 1987; Meese, 1987; and Kearney and MacDonald, 1990).

However, MacDonald and Taylor (1991) re-examined and defended the traditional approach to exchange rate determination by arguing that the previous versions of these models were faulty. After some modifications to the initial version of the monetary model, MacDonald and Taylor (1991) found the model to be empirically plausible in the long-run. Subsequently, the monetary approach gained momentum, with several studies in the early 90s finding evidence that the monetary approach could predict exchange rates in the long-run (Mark, 1995). The empirical validity of these initial findings however was questioned by Kilian (1999). Until recently, the performance of the fundamental macro models of exchange rate determination has enjoyed extensive research attention. Indeed, the fundamental model has enjoyed considerable empirical success in explaining the long-run exchange rate variation (Taylor and Sarno (1998).

The long-run success of the fundamental models of exchange rate determination is, however, not equally shared across all time horizons. In the short-run the fundamental models of exchange rate determination have failed to model the exchange rate behaviour. The poor short-run performance of the fundamental models, combined with the failure to beat the RWM in out-of-sample predictions (Meese and Rogoff, 1983) have been the main shortcomings of the fundamental models. These two shortcomings of the fundamental model have led some pundits to conclude that in short-run there is an '*exchange rate disconnect puzzle'* (Sarno and Taylor, 2002; Evans and Lyons, 2002; and Bachetta and van Wincoop, 2006).

Obsteld and Rogoff (2000) defined the exchange rate disconnect puzzle as the considerably weak relationship between exchange rate and aggregate macroeconomic variables, especially in the short-run. This finding of the exchange rate disconnect puzzle has attracted considerable research into investigating the dynamics of short-run exchange rate behaviour. Compelling theory on fundamental models has attributed the failure of explaining the short-run variations in the exchange rate to their lack of well-specified microeconomic foundations (Lyons, 1995; and Osler, 2006). Indeed, Lyon's (1995) seminal work on microstructural hypotheses in the foreign exchange market became the catalyst into the application of micro-methods in exchange rate determination.

A microstructural approach to exchange rate determination has yielded some promising empirical results at short horizons (Evans and Lyons, 2002a, b; Jalil and Feridum, 2010). Market microstructure literature posits that the behaviour and characteristics of market agents are the major determinants of the short-run variation in the exchange rates, while in fundamental models of exchange rate determination these factors have no apparent role in exchange rate determination (Taylor, 1995 and Osler, 2006). Although evidence from the nascent microstructure literature is convincing, some theorists (Alexius and Sellin, 2012) contend that the microstructure approach has its problems and thus more research into its application is still necessary before this theory is fully adopted. This thus implies that the overall behaviour of exchange rate is still not fully understood and therefore further research is still needed.

1.2 Stylized Facts on Exchange Rates

Although economists have failed to economically model the behaviour of exchange rate, some progress has been made in understanding how exchange rates generally behaviour overtime. There are five stylised facts that have been observed from the behaviour of floating exchange rate pairs in developed markets. Mussa (1984) provides a succinct summary of these exchange rate stylised facts. These are:

i. Exchange rate movements approximately follow a naïve RWM. From a financial economics standpoint this stylised fact implies that the currency market is efficient, and thus it should be impossible to forecast future values of the exchange rate.
ii. There is a strong correlation between the concurrent changes in the spot exchange rate and changes in forward rates for periods up to one year, especially for large changes.
iii. The assumption of Purchasing Power Parity (PPP) does not hold in the short-run, which implies that there is no correspondence between observed short-run variations and PPP.
iv. Variations in exchange rates and current account balances do not have any significant and systematic relationship. This implies that observed exchange rates movement cannot be explained by variations in the current account.
v. There is no apparent correlation between changes in money supply and exchange rates variations, except for countries with higher inflation rates.

The above stylized facts are a double-edged sword in the study of the exchange rates behaviour. The downside to these stylised facts is that they imply that any attempt to economically model the exchange rate behaviour is an impractical adventure. Such a disheartening implication is presumed by the exchange rates variation embodiment of the random walk behaviour. This effectively means that standard economic modelling of the exchange rate behaviour is not sufficient to capture the true behaviour of exchange rates movement (Mussa, 1984). However, the above mentioned stylised facts provide some telling evidence which is useful in improving upon the current models of exchange rate behaviour; and thus should not be a discouragement of the study of exchange rate modelling.

1.3 Historical Overview of South Africa's Exchange Rate System

South Africa was one of the signatories to the Bretton Woods Agreement of 1944. At that time South Africa's currency was the pound, and was fixed to the British pound at a particular rate. South Africa adopted the use of the rand as its main currency in 1961. After the collapse of the Bretton-Woods monetary system in 1971 South Africa experimented with multiple exchange rate policy regimes.

Until the year 2000 the South African monetary policy was actively involved in the determination of foreign currency exchange rate. It is only in the year 2000 that a floating exchange rate regime was fully introduced, where the foreign exchange rate was to be determined by the prevailing market forces of supply and demand. The introduction of a floating exchange rate regime in 2000 was accompanied by a change in South Africa's monetary policy focus from an exchange rate management regime to an inflation targeting policy regime.

By the beginning of 2000 South Africa had vacillated between eight exchange rate regime policies (Aron et al, 2000). The isolation of South Africa from the global community due to its apartheid policy caused significant domestic political and economic instabilities. These political instabilities had a pronounced effect on the foreign exchange market value of the rand and resulted in significant volatility in the demand of the rand. South Africa's exchange rate management system was primarily adopted as a mechanism to stabilize the foreign exchange market of the demand for rand. However, policies of exchange rate management failed at this task and the foreign exchange instabilities persisted (Mtonga, 2011).

The ZAR/$ exchange rate has exhibited significant volatility ensuing the collapse of the Bretton-Woods monetary system. Most importantly, the rand has depreciated significantly against the dollar in the post-Bretton Woods period. Figure 1 shows the evolution of the ZAR/$ nominal exchange rate between 1971 and early 2016. The graph provides some useful insights as it shows how the exchange rates has evolved under different exchange rate regimes adopted by the South African monetary authorities following the collapse of the Bretton Woods system.

Figure 1: ZAR/$ Nominal Exchange Rate (1971-2016)

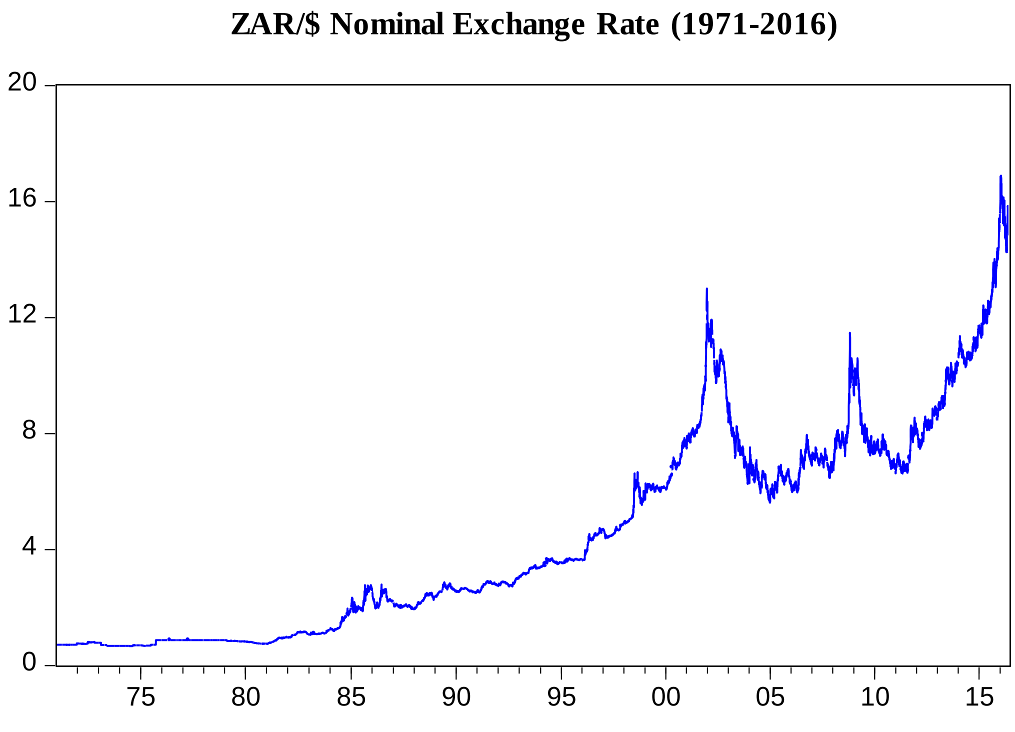

Figure 1 shows the South African Rand (ZAR) to US Dollar ($) exchange rate over time from 1971-2016. The figure indicates that there has generally be an upward trend in the ZAR/$

nominal exchange rate, implying a consistent depreciation of the rand. Pre-1994 depreciations could be conjectured to have been influenced by at least two related factors. Firstly, these depreciations could have been the result of ineffective exchange rate regimes that were adopted during this period. Second, mounting international pressures on the South African apartheid government could have also influenced the overall performance of the rand against other currencies.

The ZAR/$ nominal exchange rate remained low and consistent for the most part between 1971 and 1983. This could have been because of the pegging of the ZAR to the pound sterling. A strong upward trend of the exchange rate began in the early 1980s and continued throughout all the period under consideration. Some noticeable peaks in the exchange rate can be seen during the years 2002, 2009-2010 and 2015. The 2009-2010 peaks in the exchange rate are most likely to have been induced by the global financial crisis. At the end of 2015 the ZAR tumbled in reaction to the dismissal of the finance minister by the South African president. The overall depreciation of the ZAR against the US Dollar following the official collapse of the Bretton-Woods system until the end of 2015 is 2110.36%. However, the depreciation of the ZAR 15years prior the inflation targeting regime and 15years post targeting is 221.80% and 81.55%. This suggests that the ZAR depreciated significantly against the dollar in periods pre-float than during the floating era. These results are rather counterintuitive as the general expectation is that the currency will be more volatile under a floating exchange rate regime than in any other exchange rate regime.

1.4 Problem Statement

South Africa's exchange rate has depreciated significantly against the US dollar and other major currencies. Indeed, the depreciation pattern commenced long before the current free floating exchange rate regime. Previously, it could be argued that the political and economic unrest that the country faced under the apartheid rule, and consequently, structures designed to control the foreign exchange market were the major factors affecting the depreciation of the currency. However, with free floating exchange regime in place exchange rate policy design cannot be the culprit. Indeed, the determinants of the exchange rate behaviour are an important query in international finance and world over the variations in exchange rates, especially in the short-run, are still an unresolved puzzle.

Initial attempts to understand factors that determine the pattern of exchange rate proposed macroeconomic based fundamental models such as the flexi-price and sticky price models (Dornbusch, 1976; Frenkel, 1976 & Mussa, 1976). Although these models have enjoyed some empirical success in the long-run, their short-run exchange rate predictions have been reported to have some significant shortcomings in that their predictions inferior to the RWM's predictions (Meese and Rogoff, 1983). This has prompted the development of models amenable to short-run movement of exchange rates. Evans and Lyons' (2002) microstructure model has emerged as one of the compelling models of short-run exchange rate modelling and its empirical performance appears to be convincing. However, the microstructure model has not yet been widely investigated to make conclusive judgement on its effectiveness in determining short-run exchange rate dynamics.

Very few studies have attempted to apply the microstructure methodology to model the behaviour of short-run exchange rate in emerging markets. This study therefore, intends to contribute to the current literature on short-run exchange rate determination by empirically investigating the effectiveness of the microstructure models in explaining the short-run exchange rate fluctuations in South Africa.

1.5 Research Questions and Objectives

The primary objective of this study is to investigate whether a microstructure model of exchange rate determination provides a better explanatory power for short-run exchange rates in South Africa. Particularly, the paper investigates whether order flow is an important explanatory variable of the ZAR/$ exchange rate variation. The study will evaluate the efficacy of the microstructure model by comparing its predictions to those of the RWM.

From the above objectives, the following are the key research questions that are investigated:

- Does a microstructure model provide a better explanation for the observed short-run behaviour of the ZAR/$ exchange rate?
- To what extent is the microstructure predictive outcome better than the RWM both in sample and out-of-sample?
- Is there a simultaneous bias between exchange rates and order?

1.6 Significance of this Study

This study is significant for at least four reasons:

1. The microstructure approach to exchange rate determination models were devised in the US which is a developed economy and thus has different underlying macroeconomic factors to South Africa (which is a developing economy). Therefore, the suitability of this model in the South African environment should be evaluated prior to the model's adoption. Further, the performance of the model will also inform how the model can be adapted into the local environment – if it does not fit the data well.
2. The exchange rates play an important transmission role in many policy evaluation models (Taylor, 2001). Such models include the uncovered interest parity, purchasing power parity to name a few. Generally, these models have been found to be empirically plausible in the long-run. Therefore, breakthrough in understanding exchange rate determination in the short-run might offer some important insights which could be used to inform short-run policy formulation.

3. A rigorous understanding of the short-run exchange rates variation is of paramount importance given the vast impact that the variation of the short-run exchange rate can have on the South African financial market. For instance, in December 2015 when the president of RSA fired the finance minister, the fluctuation in exchange rates led to at least about 15% financial losses for just the banks over the course of 4days (Bonorchis and Kew, 2015). Therefore, it is important to understand what factors affect exchange rate in the short-run as their variability can be pronounced.
4. Although the South African Reserve Bank (SARB) is committed to inflation targeting, its actions indirectly affect the exchange rate as well. Moreover, the monetary policy tools are inherently short-term in nature, therefore, with an understanding of the short-run determinants of exchange rate variation – the SARB can balance its actions in a way that favours the exchange rate movement.

Thus this study hopes to make a theoretical contribution to the currently available body of exchange rate determination literature. Thus, the study shall contribute to the understanding of short-run exchange rate dynamics in South Africa as far as these can be explained by micro-based factors.

1.7 Limitations of the Study

Most market microstructure studies that have attempted to determine whether order flow was an important explanatory variable for exchange rate determination have generally suffered from two challenges. Firstly, the data customer order flow data is not available for public dispensation. This implies that any attempt to investigate exchange rate variations from an order flow point of view is nothing more than an ambitious endeavour. Secondly, researchers that have somehow managed to overcome the first challenge have been met with the challenge of the frequency with which the data is made available. Most of the data on order for has generally been made available at monthly intervals. This means that daily exchange rate variations cannot be readily analysed. The present study is not insulated from the above challenges. The only data on customer trades that could be made available by from the South African Reserve Bank (SARB) is that of net customer foreign exchange turnover. This data is used as the proxy for customer order flow in this study. The main problem with net customer foreign exchange turnover as a proxy for customer order flow is that it is a sum of both purchases and sells of the South African rand, which implies that the data does not accurately capture the buying pressure. In a sense the data does not reflect the essence of order flow. Further, the data can only be made available at monthly horizon, and this affects the estimation of the time series (GARCH) model estimated in this study which is more amenable to higher frequency datasets. Consequently, the conclusions drawn from this study should be taken in conjunction with the above stated limitations.

1.8 Organisation of the Study

This research paper has five chapters. Chapter 1 was presented above, and rest of the paper proceeds as follows: Chapter 2 provides a comprehensive literature review on the evolution of the exchange rate modelling post the Bretton Woods system. Chapter 3 discusses the methodology and data used to conduct the study. The results of the regression model are presented in Chapter 4, and Chapter 5 provides concluding remarks and offers recommendations for future studies in this field.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The determinants of variation in foreign exchange rates have been subject to considerable investigation since the dawn of floating exchange rate regime after the Bretton-Woods system collapse. A floating exchange rate regime allows for the determination of exchange rates through market forces of supply and demand. However, the forces that propel fluctuations in exchange rates remain an empirical puzzle, more so the causes of variations in short horizons. Although considerable research effort has been devoted into understanding factors that cause exchange rate variations reliable empirical results have only been found for long-run exchange rate changes. Most of the proposed models of exchange rate determination have failed to approximate the short-run variations in the exchange rates.

Early exchange rate literature suggested that variations in exchange rates could be understood through models based on macroeconomic fundamentals, such as, inflation, money supply, aggregate production, and interest rates. Subsequently, several exchange rate models were developed using these macro fundamentals as the core determinants of changes in exchange rates. These include, among others, the monetary models, the portfolio balance models, and uncovered interest parity. The most compelling theories of exchange rate determination where those developed from the ‘asset view theory’ of exchange rates. The asset approach to exchange rate determination came about from the observation of the exchange rate behaviour to the behaviour of other assets traded in financial markets such as stocks (Mussa, 1976; 1984). Thus, from the asset view, exchange rates should be determined in a similar fashion as the asset prices. The central hypothesis of the asset market view of exchange rate determination is that the exchange rate plays an equilibrating role in the international market demand for stocks of assets (Frankel, 1979).

The asset market view theory of exchange rate determination hinges on the important assumption that there is perfect capital mobility between countries (Frankel, 1983). This assumption is necessary for the adjustment process of the exchange rates. Specifically, it implies that adjustments in the exchange rate happen in order to restore the equilibrium in the international demand for stocks of assets (Frankel, 1983). Thus, short-run variations in exchange rates will be, by implication, greater than the variation in their macro fundamental variables. The asset market view approach was foundational for the emergence of the key monetary and portfolio balance models of exchange rate determination. These models have been the most dominant in exchange rate empirical studies, especially the monetary models. Although both the monetary models and portfolio balance models share the same underlying principle, their main distinguishing factors is the substitutability of the portfolio assets between domestic and foreign holdings (Frankel, 1983). Monetary models assume perfect substitutability of assets between domestic and foreign holdings, while the portfolio models view domestic and foreign assets as imperfect substitutes (Mussa, 1984).

The initial models from the asset market view of exchange rate determination have come to be considered as the traditional models of exchange rates. Although these models failed at explaining variations in exchange rates (Meese and Rogoff, 1983); they inspired a second generation models of exchange rate determination which fared well empirically. The second generation models of exchange rate determination included those of, among others, MacDonald and Taylor (1991) and Mark (1995). These models had better long-run empirical performance (Meese and Chinn, 1995) however their short-run performance was not any better than the first generation models (Taylor, 1995; & Flood and Taylor, 1996). These empirical failures became the main motivation factor for the need of developing models that are capable of modelling short-run exchange rate variations. The result of this is the microstructure theory pioneered by Evans and Lyons (2002). The following paragraphs will provide a more comprehensive literature on the models of exchange rate determination.

2.2 Traditional Models of Exchange Rate Determination

The monetary and portfolio balance models that were direct derivative of the asset market approach to exchange rate determination qualify to be classified under the traditional models of exchange rate determination. These models generally assumed that investors had rational expectations about the evolution of the exchange rate relevant macroeconomic variables (Mussa, 1984; Black, 2015). While these models emerged from the same underlying theory, the fundamental distinguishing characteristic between these models is their assumption about the substitutability between domestic and foreign assets. Further, the monetary models of exchange rate determination are subdivided into those which assume purchasing power parity at all horizons and those which assume that purchasing power parity only holds in the long-run.

2.2.1 Monetary Models of Exchange Rate Determination

The monetary model of exchange rate determination is the most well-established model of exchange rate determination. The monetary model has received extensive academic attention and its long-run its long-run empirical success at explaining exchange rate variations is well documented.

Dornbusch (1976), Frenkel (1976) and Mussa (1976) were the first theorists to propose the models of exchange rate using the monetary approach. Dornbusch (1976) argued that variations in exchange rate could be understood through a sticky-price monetary model. Three key assumptions underpinned Dornbusch's (1976) sticky-price exchange rate model, namely: (i) perfect capital mobility, (ii) short-run rigidity in the goods market relative to the assert market, and lastly, (iii) consistent expectations across all periods. Short-run inflexibility in the goods market prices is consistent with the notion that the Purchasing Power Parity (PPP) only holds in the long-run, a period after which all markets would have fully adjusted. The sticky-price model therefore allows for short-run exchange rate overshooting due to price short-run price rigidity (Dornbusch, 1976 and Diamandis et al, 1996). The general sticky-price model of exchange rate determination can be presented as follows:

$$s_t = (m - m^*) - \varphi(y - y^*) - \frac{1}{\theta}(i - i^*) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (i)$$

Where, s_t represent the log of nominal exchange rate. Asterisks represent foreign quantities. Y is total output or productivity and I is the interest rate.

Conversely, Frenkel (1976) and Mussa (1976) proposed the monetary model of exchange rate variation under a flexible-price framework. In a flexible-price framework, the goods market prices are assumed to be flexible in the short-run and therefore, the model assumes PPP always holds. Both the sticky-price and flexible-price models share the common assumption of the Uncovered Interest Parity (UIP) (Frankel, 1979).

The monetary approach to exchange rate determination has been subject to extensive empirical investigation. Some (Smith and Wickens, 1986) argue that it is because of the monetary approach's theoretical appeal that it has garnered extensive academic interest. This implies that the relationship between exchange rate and macroeconomic fundamentals is well-grounded. The monetary approach is a substantial initial contribution to the exchange rate literature, and it is perhaps because of its sound theoretical foundations that the model is still alive. Despite its strong theoretical foundations, early studies (Dornbusch, 1980; Boothe and Glassman, 1981; Baillie and Selover, 1987 & Meese, 1987) found discouraging empirical support for the monetary approach. The general price-flexi model of exchange rate determination can be presented by the following equation:

$$s_t = (m - m^*) - \emptyset(\bar{y} - \overline{y^*}) + \gamma(\pi - \pi^*) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (ii)$$

St represents the log of nominal exchange rate, $(m - m^*)$ is the money supply differential between the domestic and foreign economy. $(\bar{y} - \overline{y^*})$ is the average productivity differential between domestic and foreign economy; and $(\pi - \pi^*)$ is the inflation differential between domestic and foreign economy.

Dornbusch (1980) investigated the monetary approach using two methods, namely: (i) the PPP condition, and (ii) a macroeconomic fundamentals model of exchange rate. Dornbusch particularly tested for the price-flexi model of exchange rate. He found weak empirical support for the monetary approach from both methods. His findings suggested that there were sustained deviations from PPP and macro fundamental exchange rate determinants could not explain the variation in exchange rates. Dornbusch (1980) argued that the empirical failure of the monetary model was due to missing variables. Dornbusch pointed out that the current account, wealth effects, expectations and relative prices were not accounted for in the basic price-flexi monetary model.

In subsequent studies, modified versions of the monetary model which considered some of the shortcomings identified by Dornbusch (1980) were tested. The in-sample performance of the modified monetary models provided encouraging results. For instance, Hooper and Morton (1982) tested a modified sticky-price model which incorporated both the Current Account (CA) and expectations. The authors reported that the model could explain approximately 80% of the monthly and quarterly variation in trade weighted dollar exchange rate. Moreover, the CA balance and expectation were found to have a pronounced effect of the exchange rates (Hooper and Morton, 1982).

However, the weak out-of-sample performance of the monetary approach led to increasing scepticism about the approach's viability in forecasting exchange rates. For example, Dornbusch (1980) concluded that the weak evidence in favour of the monetary approach suggests that the model is unsatisfactory as an exchange rate determination model. Some (Frankel, 1984) even questioned whether the monetary model was properly specified. Frankel (1984) investigated both the sticky-price and flexible-price models of exchange rate determination. He presented evidence that the sticky-price model had better empirical support relative to the flexible-price model. However, overall the results from both models were discouraging. Moreover, Frankel (1984) pointed out that the money demand functions and long-run real exchange rates were the likely culprits for the breakdown in the monetary model.

In a pioneering seminal work, Meese and Rogoff (1983) interrogated the out-of-sample performance of fundamental and time series models of exchange rate determination. Their findings suggested that these models' performance were similar to those of a random walk (RW) model for one and twelve month horizons. Since the fundamental models could not outperform the RW model, these findings suggest that exchange rate variations are well approximated by the RW. This conclusion was corroborated by earlier studies (Cornell, 1977; Mussa, 1979; and Frenkel, 1981b); which concluded that exchange rates were unpredictable. The finding that exchange rates are well approximated by the RW model is considered a stylised fact. Further, Meese and Rogoff (1983) noted that one reasons for the poor out-of-sample performance of structural models may be due to their unpredictable causal variables. However, the RW model itself is not a good predictor of exchange rate variations (Meese and Rogoff, 1983). This implies that there are other models that can improve upon the RW model, and provide better exchange rate forecasts than the RW model.

2.2.2 Fundamentals Based Models of Exchange Rate Determination

Initial breakthroughs of the fundamentals based models were realized in the early 90s when MacDonald and Taylor (1991) re-examined the monetary approach to exchange rate determination. MacDonald and Taylor (1991) used the multivariate co-integration technique to show that the monetary approach was plausible in the long-run. Subsequently, other studies (Mark, 1995; and Chinn and Meese, 1995) went on to report empirical support for the macro-based fundamental models.

Mark (1995) presented the first empirical evidence to suggest that long-run variations in exchange rates are predictable. He further, employed a nonparametric bootstrapping method to analyse the predictive ability of exchange rate macro fundamentals. His findings showed that exchange rate changes between one and fourth quarters were difficult to predict, however, greater exchange rate predictability was reported at horizons above the fourth quarter. Further, the out-of-sample forecasts from the bootstrap model were found to be superior to the RW model without a drift. Similarly, Chinn and Meese (1995) also showed that exchange rates could be forecasted using macro fundamentals at long horizons.

However, the above findings of long-run exchange rate predictability have been scrutinised by some (see, Killian, 1999). Killian (1999) challenged Mark's (1995) findings of long-run exchange rate predictability. Killian (1999) contended that Mark's methodology was fundamentally problematic, and could potentially induce spurious conclusions. Further, no iota of evidence was found to suggest increased long-run exchange rate variation predictability. On the contrary, Killian (1999) reported less long-run exchange rate predictability, using Mark's method of inference for a larger sample. In addition, Killian also points out that Mark's results are susceptible to misinterpretation and are not an accurate measure of the monetary model's forecasting power. Unfortunately, the forecast results from the modified version of Mark's approach were found not satisfactory either.

Although the fundamental models have been successful at explaining long-run exchange rate variations they have failed considerably at explaining the short-run variation in exchange rate (Taylor, 1995; Flood and Taylor, 1996). Meese and Rogoff (1983a, b) found the RW model to provide better out of sample performance than the fundamental models. Taylor (1995) also yielded to the short-run empirical failure of the macro models and argued that there may be other factors that affect exchange rates in the short-run that are not incorporated into the standard macro fundamental models.

2.2.3 Portfolio Balance Models of Exchange Rate Determination

The portfolio model as it currently applies to floating exchange rate determination was pioneered by Black (1973) and Kouri (1976). Black (1973) developed the portfolio balance model of exchange rate in its partial equilibrium framework. Kouri (1976) extended the model to a general equilibrium framework which allowed for the simultaneous determination of prices and exchange rates. Although these models differ in their specification the central hypothesis of the model remains the same. The general hypothesis of the portfolio model is that exchange rates are determined from the international financial markets (Dooley and Isard, 1981). Thus under a portfolio balance model the exchange rate is viewed as an international market clearing price.

Underlying the portfolio balance model is the notion that investors make their portfolio decisions by choosing to allocate their wealth across three assets, namely, domestic currency and bonds, as well as, foreign bonds (Branson and Henderson, 1984). While bonds are interest bearing instruments, money is not an interest bearing instrument, however, it is held for transactional purposes (Branson and Henderson, 1984). Moreover, domestic, and foreign bonds are deemed imperfect substitutes which imply that an investors' asset allocation between domestic and foreign assets matters and the UIP condition does not hold (Frankel, 1983). From this theory variation in the exchange rate is a result of changes in the balance of payment resulting from changes in investor allocation of their wealth between domestic and foreign assets (Dooley and Isard, 1981). A basic model of portfolio balance can be presented in by the following general framework:

$$s_t = \beta_0 + \beta_1(i - i^*) + b - f \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(iii)$$

Where s_t is the log of exchange rate, $(i - i^*)$ is the interest rate differential between domestic and foreign country, and $b - f$ are the net supplies of domestic and foreign bonds.

The portfolio approach to exchange rate determination has received considerably less academic attention overtime relative to the monetary approach. Black (2015) argues that some of the reasons for this poor academic interest in the portfolio model are due to its computational complexity compared to the monetary models and its detachment of its foundational principles from the modern financial markets. Dooley and Isard (1981) also pointed out to the fact that the inherent assumption in portfolio model that the current account imbalances can only be addressed by issuing a country specific currency denominated debt is inconsistent with how the current international financial market operates. Indeed, states can issue foreign currency denominated debt within the international market.

Although the portfolio balance approach to exchange rate is well-established it has not enjoyed similar academic interest to the monetary model. Its current limelight is intertwined to the microstructure model of exchange rate determination. Several theorists, such as Osler, 2006 and Black, 2015; have shown that the portfolio balance approach to exchange rate determination is the bedrock of the nascent microstructure approach to exchange rate determination. One of the reasons the portfolio balance and microstructure approaches are closely related is that both models have their foundations in microeconomic theory. Branson and Henderson (1984) provide a comprehensive exposition of the microeconomic foundation of the portfolio balance's asset demand from utility optimization functions.

2.2.4 Lessons from the Asset Market Approach Models

The above literature indicates that there are two main shortcomings from the initial models of exchange rate determination. Firstly, the out-of-sample performance of these models is poor compared to that of the RWM (Meese and Rogoff, 1983). Secondly, the models fail dismally at explaining the short-run behaviour of exchange rates. Consequently, these shortcomings of these models have led some pundits (Obsteld and Rogoff, 2000 & Lyons, 2001) to conclude that in short-run there is an exchange rate disconnect puzzle. Obsteld and Rogoff (2000) defined the exchange rate disconnect puzzle as the considerably weak short-run relationship between exchange rate and aggregate macroeconomic variables. The short-run exchange rate puzzle has attracted substantial research interest into the dynamics of exchange rate determination in the short-run. Some (Osler, 2006) have attributed the short-run failure of fundamental models of exchange rate determination to their lack of well-specified micro-foundations.

These empirical failures of the fundamental macro-based models of exchange rate to both approximate the exchange rate at short horizons and to outperform the RW model lead economists to seek alternative models that could address the above quandaries. Lyons' (1995) seminal on microstructural hypothesis in the foreign exchange market was the catalyst into the microstructure approach to exchange rate determination. Following Evans and Lyons' (2002) findings that order flow has a significant explanatory power for exchange rates, the microstructure approach to exchange rate determination has gained momentum as a better alternative to short run exchange rate modelling. Although the microstructure approach is still at its infancy, there is a growing body of compelling evidence that that this approach fits the data better than the fundamental models, and outperforms the RW model at short horizons (Cerrato et al, 2011). Evans and Lyons are currently at the forefront of research on the microstructure approach to exchange rate determination.

2.3 Microstructure Models of Exchange Rate Determination

Exchange rate order flow has been identified as the most important exchange rate determinant from microstructure literature (Evans and Lyons, 2002). Initially, order flow was defined as measure of net buying pressure, which is the "net of buyer initiated and seller initiated orders" (Evans and Lyons, 2002:171). However, recently some researchers have argued that order flow is better looked at as the net value of buyer initiated orders less that of seller initiated orders (Corte et al, 2011).

Most microstructure exchange rate studies consistently find a positive contemporaneous correlation between changes in exchange rates and order flow (Evans and Lyons, 2002; Fans and Lyons, 2003; Corte et al, 2011). Nonetheless, the cause of this observed correlation between order flow and changes in exchange rate has not yet been fully understood (Marsh and O'Rourke, 2005). Marsh and O'Rourke (2005) argue that the contemporaneous correlation between order flow and changes in exchange rate presents a controversy because the nature of this relationship is unclear. Particularly, questions remain as to whether order flow causes changes in exchange rates or vice-versa. Moreover, Marsh and O'Rourke (2005) point out that even if causation ran from order flow to exchange rate, it remains unclear whether this is due to liquidity factors or informational effects of order flow.

So far, three possible explanations for the apparent contemporaneous correlation between order and changes in exchange rates have been offered. These are, (i) that order flow conveys important information about future exchange rates, and therefore, such information should be impounded in the current prices. Given that the information content of order flow has a permanent price effect (Osler, 2006); (ii) Order flows are motivated by liquidity considerations. This stems from the notion that dealers are only willing to hold a certain amount of inventories at any given moment. Therefore, customer orders that causes an inventory imbalance leads to price changes to reflect this imbalance (Stoll, 1978 & Marsh, and O'Rourke, 2005). The above findings suggest that different types of order flow may affect exchange rates in a similar fashion. Lastly, feedback trading has been identified as one of the potential reasons for the correlation between order flow and exchange rates (Marsh and O'Rourke, 2005). This implies that flows are induced by changes in exchange rates.

Some studies have found compelling evidence to rule out feedback and liquidity effects as the possible causes for the contemporaneous correlation between order flow and exchange rates. For instance, Payne (2003) and Killeen et al (2006) find evidence which suggests that there is unidirectional granger causality between order flow and exchange rates were causality strictly runs from order flow to exchange rates. The above findings therefore, rule out feedback trading as the possible reason for the correlation. Further, Marsh and O'Rourke (2005) found that order flows from different customer types affects exchange rates differently. This implies that liquidity effects cannot be the reason behind the correlation between order flow and variations in exchange rates. On the other hand, Corte et al (2011) argue that inter-dealer trading is motivated by inventory and liquidity concerns.

Moreover, some studies (Sager and Taylor, 2008; Cerrato et al, 2011) have also attempted to discover whether lagged order flow values have any correlation with current exchange rates. The results from these studies rule out any correlation between lagged order flow values and current exchange rates. For instance, Cerrato et al (2011) estimated the hybrid model using lagged order flow data and found the coefficient of order flow to be statistically significant for only one out of nine currency pairs (the Euro) For some currency pairs they obtained negative R-squared values which casts serious doubts on the modelling approach. This implies that lagged order flows bear no explanatory power on the current exchange rates. This finding suggests that the positive contemporaneous correlation found between order flow and changes in exchange rates is a stylised fact.

However, the prevailing view in literature is that order flows affect exchange rates because they convey information about exchange rates that the market must impound (Evans and Lyons, 2002; Corte et al, 2011 & Menkhoff et al, 2016). This suggests that order flow plays a transmission role, were information is transmitted from customers to the market via order flow mechanism (Cerrato et al, 2011).

The nature of information contained in order flow has been of interest to researchers for several reasons; one reason being that this knowledge will allow one to understand why order flow is correlated with changes in exchange rates. Evans and Lyons (2002) argue that there are two possible types of information that order flow can convey. They argue that order flow either reflects new information about valuation numerators (for instance, interest rates differentials) or new information about valuation denominators (anything that affects discount rates). The portfolio shift model used by Evans and Lyons (2002) is consistent with the notion that order flow reflects new information about valuation denominators.

Order flow can be distinguished between customer order flow and dealer order flow. Customer order flow arises when there is a customer-dealer trade, and dealer order flows arise due to interdealer trading. Early studies on microstructure approach only focused on the effect of inter-dealer order flow on exchange rate variation due to data constraints (Marsh and O'Rourke, 2005). The empirical results from these early studies are encouraging. For example, Evans and Lyons (2002) and Payne (2003) looked at inter-dealer order flow from direct inter-dealer trading platforms and the brokerage platforms. Both studies found a strong contemporaneous correlation between order flow and variation in exchange rates. The explanatory power of their models was high with over 60% of the variation in exchange rates being explained for some currency pairs.

In addition, Evans and Lyons (2002) investigated the inter-dealer order flow and exchange rate dynamics for two currency pairs (deutsche mark/dollar and yen/dollar) using a portfolio shifts model. Their model is robust because it incorporates both macroeconomic exchange rate determinants and the microstructure order flow determinants. Further, this model accounted for over 60% and 40% of the daily log variation deutsche mark/dollar and yen/dollar exchange rates. To gauge the effect of order flow on the change in exchange rate Evans and Lyons (2002) regressed the change in exchange rate only on the change in interest rate differential. They found the coefficient of determination from this regression to be at most 1% for both currency pairs and the change in interest rate differential was insignificant at the 5% level. Thus, the authors concluded that the explanatory power of their initial regression model was due to order flow.

Bates et al (2003) investigated evolutionary reinforcement learning in the foreign exchange order book and order flow analysis. Although their findings were preliminary in that their data was limited, the data points to the fact that order flow information based trading strategies yield better results than technical indicators based strategies. This suggests that order flow information is instrumental in making informed trading decisions. In this study, non-speculative and retail trades were found to be the most significant determinants of exchange rates variation in one day lagged returns.

Comparing the information content between inter-dealer order flows and customer order flows, early studies found strong informational effect from inter-dealer order flows relative to customer order flow. For instance, Bates et al (2003) found that inter-dealer trading to have a long-term effect on exchange rates, while on the other hand; customer order flows were found to be rapidly mean reverting, only exerting intraday effect on the exchange rate. This suggests that the market construes customer order flows as sentimental; however, inter-dealer flows were shown to carry significant informational flows.

More recently, however, studies are considering customer order flow as a significant explanatory variable for exchange rate variation. Some of the reasons for this change in focus are that data on customer order flows are increasingly becoming available, and more importantly, customer order flows account for most of the foreign exchange trading. According to the Bank of International Settlements (2010) over 60% of foreign exchange turnover is from customer trades.

Cerrato et al (2011) investigated the effect of heterogeneous customer order flow on exchange rates. The authors wanted to see if the microstructure provided better explanation and forecasting for exchange rate variation. Customer order flow was of interest because it stems from the active side of foreign currency trading, which subsequently induces inter-dealer trading. Therefore, customer order flow provides the primary source of all trading in the foreign exchange market and by extension of the variations in the exchange rates due to order flow. This study significantly benefited from the richness of the dataset at their disposal, which covered a period of approximately 7 years. Further, the authors used Lyons' (2002) hybrid model of exchange rate to conduct the analysis. This model has the advantage of incorporating both macro fundamental exchange rate determinants and microstructure order flow.

The estimations from the hybrid model were found to be encouraging. Order flow was significant and correctly signed for seven out of nine currency pairs. However, for macro determinants only the Libor rate differentials were found to be significant and correctly signed for only four currency pairs, while other macro variables either showed significance for only one currency pair or were inconsistently signed (Cerrato et al, 2011). This suggests that macro determinants lack explanatory power.

It is important to point out that the R-squared values reported in Cerrato et al (2011) are markedly small relative the ones reported in Evans and Lyons (2002) which uses a similar model. A small R-squared implies that order flow's explanatory power is low. Other studies (Marsh and O'Rourke, 2005; Evans and Lyons, 2005) also reported similar low R-squared. Conversely, Corte et al (2011) and Bates et al (2003) among others found order to have a high coefficient of determination, explaining in some instances over 60% of changes in exchange rates.

Further, Cerrato et al (2011) considered the extent to which out-of-sample changes in exchange rates can be forecasted using order flow as the main explanatory variable. They found that order flows have considerable forecasting power with respect to exchange rate changes which showed a significant improvement of the RW model. Moreover, the results showed that order flow had lower forecasting errors than the RW model for approximately all currency pairs. However, the statistical differences between the forecasting errors of the two models are not significant (Cerrato et al, 2011). This result suggests that the RW model cannot be ruled out completely.

There is an increasing tendency to disaggregate customer order flow into its various components. This allows the researcher to gauge the impact of different customer types on changes in exchange rates. For instance, Marsh and O'Rourke (2005) analysed the information content of customer order flow to explain the (positive) contemporaneous correlation between order flow and the variation in exchange rates. They found that different components of order flow affected exchange rates differently. Financial traders order flow was found to be positively correlated with, and have a significant impact on changes in exchange rates, while on the other hand, corporate traders order flow was negatively correlated to changes in exchange rate. This conclusion is widely corroborated by other studies (Lyons, 2001; Evans and Lyons, 2004 & Cerrato et al, 2011) reported that financial traders have a more pronounced effect on exchange rates in the short-run. Further, financial traders order flow has been found to convey more informational flows than corporate order flows (Cerrato et al, 2011).

While disaggregating customer order flow data has been instrumental in identifying the impact of each customer type on changes in exchange rate, it also has an added benefit of improving the amount of exchange rate variation that can be explained by order flow and also improves exchange rate forecasts. Cerrato et al, (2011) show that disaggregated customer order flow analysis resulted in significant improvements in the R-squared value relative to the R-squared values from aggregated data. This is a reasonable finding as aggregated data analysis assumes that all customer order flow affects the exchange rate in a similar way.

Similarly, Marsh and O'Rourke (2005) estimated change in exchange rate using aggregate order flow and only found order flow to be significant for two out of six currency pairs at daily horizons and only three of the six currency pairs for weekly horizons. Further, the accompanying R-squared value was close to zero implying that the model fitted the data poorly. Conducting the same regression on disaggregated customer order flow significantly improved the results, suggesting that disaggregated customer order flow has better explanatory power. Forecasts that use disaggregated order flow were also found to have strong forecasting ability than those from aggregate order flows.

Corte et al (2011) investigated disaggregated customer order flow's predictive power for nine major currencies over an eleven-year horizon. Using the carry trade strategies as a yardstick of assessing the predictive power of order flow, Corte et al (2011) found that order flow based trading strategies significantly outperformed carry strategies and had higher Sharpe ratios for both in-sample and out-of-sample forecasts. Further, Corte et al (2011) also found that the benchmark RW strategies have poor in-sample and out-of-sample performance. This suggests that although the RW model has been found to be a better approximation of the changes in exchange rates, it also has deficiencies. This finding is similar to the one obtained by Meese and Rogoff (1983) which showed that the RW model was a poor approximation of changes in exchange rates. On balance, this suggests that the overall understanding of the determination of exchange rate variation is still significantly limited.

Some researchers have also argued that order flow carries some information about the fundamental determinants of exchange rates (Lyons, 2001 & Evans and Lyons, 2004 & 2005). For instance, Evans and Lyons (2005) reported that order flow had considerable forecasting power for both the US and German's fundamentals of GDP growth, inflation, and money growth between one and six months. Furthermore, findings Corte et al (2011) support the notion that order flow is an aggregator of public information about macro fundamental exchange rate determinants.

Specifically, Corte et al (2011) offered a novel contribution to microstructure literature of exchange rate by investigating the determinants of order flow. They investigated the extent to which order flow could be explained by exchange rate relevant public information such as interest, inflation et cetera. They found a strong correlation between order flow and public information strategies, which are to be able to explain between 60% and 75% of the variation in order flow. The cyclical external imbalances strategy was particularly found to have the most significant impact on order flow strategies. Corte et al (2011) concluded that private order flow information content of customer order flow stem from macroeconomic fundamentals. In addition, they argue that the information conveyed by order flow is simply an aggregation of public information. This conclusion is consistent with the notion that order flow has a transmission role.

2.4 Reflections on Exchange Rate Determination

The preceding literature review has highlighted some of the key approaches that have been used to understand the exchange rate variations. The literature showed that most of the methodologies employed in this pursuit still suffer various shortcomings. For instance, the literature highlighted that one of the reasons fundamental models of exchange rate determination have failed to forecast exchange rates at short horizons is due to their lack of well-specified microeconomic foundations. The literature also highlighted that there are still issues with the nascent market microstructure approach to exchange rata determination. Specifically, there appears to be mixed results from microstructure applications and the causality between the order flow variable and exchange rate variation is still disputed. Further, recent studies also report significantly low R-squared than those of initial research into the microstructure approach; which implies that a significant portion of the variation in exchange rates remains unexplained. More importantly though is that most of the studies on the viability of the market microstructure theory as an alternative model of exchange rate determination have mostly been conducted in developed economies. Therefore, the research on microstructure application in developing economies has lagged that of developed economies. This thesis attempts to fill this gap in developing countries by using a microstructure application to investigate the determinants of the ZAR/$ exchange rate. To the author’s understanding this is the first study of this nature to be conducted in South Africa.

CHAPTER THREE: DATA AND METHODOLOGY

3.0 Introduction

This chapter provides a description of the data used to investigate the subject matter of this study as well as the methodologies used. The chapter brings to the fore the major challenge of obtaining the appropriate customer order data for the analysis and how these can be addressed. Furthermore, some of the methodological challenges upon which this research rests are highlighted and ensued by possible ways they can be circumvented. The rest of this chapter proceeds as follows: Section 3.1 presents the data description; Section 3.2 discusses the methodology; and Section 3.3 concludes by discussing forecasting from the models presented in Section 3.2.

3.1 Data description

This research paper uses monthly observations from multiple sources. The period under investigation is between January 2001 and December 2015, which means that there are 180 observations in total. The South African rand (ZAR) and US dollar ($) exchange rate, South African 3month T-Bill and Prime rates were obtained from the South African Reserve Bank (SARB) website. The data on either customer or dealer order flows are not available for public dispensation and thus could not be obtained to conduct research. However, the SARB could give out the data net foreign exchange turnover, which is the gross customer trading volume in each month. The most appropriate data would have been the net volumes of customer trading. Consequently, the net foreign exchange turnover will be used as a proxy for customer order flow. Some draw backs of using the foreign exchange turnover data is that it does not capture the direction of the price pressure – which is the essence of order flow. Thus increases or decreases reflect changes in overall trading activity of which it cannot be deciphered whether it is buy or sell side induced. For the remainder of this paper therefore, the foreign exchange turnover data and order flow are used synonymously. Both the prime and T-bill rate were only available at daily frequencies; therefore, these were converted to monthly frequencies by taking the monthly averages across the sample. Further, the prime rate data was only available from January 2002 – thus we used backward moving averages extrapolation for the first twelve periods to fill out the missing observation. Since there was a drastic decrease in the prime rate from around the end of 2004, we only used the data up to the end of 2004 to construct moving averages to have a good representation of the early rates and thus not downwardly biasing the forecasts. The data on the monthly prime rate and monthly T-bill rate were obtained from the Federal Reserve Bank of St. Louis.

3.2 Methodology

Evans and Lyon's (2002a) hybrid model of exchange rate determination has become standard workhorse model in microstructure empirical work. According to this workhorse model, the exchange rate behaviour can be modelled as a function of both macro and microeconomic factors. This model takes the following functional form:

$$s_t = f(i, m, z) + g(X, I, W) \qquad (1)$$

Thus, the exchange rate return is a function of macroeconomic factors (f), such as, interest rates, money supply; as well as, microeconomic factors (g), factors of order flow, open dealer positions and other micro factors. The fundamental proposition of the Evans and Lyon's model is that order flow has a significant explanatory power for the short-run exchange rate behaviour. Testing for the hypothesis that order is a significant determinant of exchange rate variation at short horizons has been the subject of extensive microstructure literature on exchange rate determination. Most studies on the order flow approach to exchange rate determination have demonstrated that the empirical evidence on order flow is promising (Evans and Lyons, 2002a, b; Danielsson et al, 2002; Love and Payne, 2006 & Jalil and Feridum, 2010).

Consistent with previous literature of microstructure approach to exchange rate determination, the current paper uses Evans and Lyon's (2002a) model to examine the relationship between order flow and exchange rate behaviour in South Africa. Similarly, to many other traditional models of exchange rate behaviour, inherent in Evans and Lyon's hybrid model is the assumption of risk-neutral investors. Consequently, these models do not account for investment risk-premium. Not accounting for differences in the riskiness of different investment landscapes assumes that they are all equally risk and thus investors should be indifferent about where they invest, however, as some theorists have shown (Bekaert and Harvey, 1997 and Estranda, 2000) emerging markets investments are perceived to be riskier than those of developed markets. Therefore, investing in an emerging market should command a risk-premium for the additional risk assumed. Other studies (MacDonald and Taylor, 1992 & de Medeiros, 2004) reported that the omission of some important variables, such as risk-premium, in models of exchange rate determination could be one the reasons why these models have not performed well empirically.

Studies on the effect of order flow on exchange rate behaviour in emerging markets have expanded Evans and Lyon's hybrid model to account for the associated country related risk (de Medeiros, 2004; Duffour et al, 2012; Wu, 2012 & Zhang et al, 2013). For instance, de Medeiros (2004) uses the spread on a Brazilian C-Bond as a proxy for country-risk on Evans and Lyon's hybrid model to analyse the relationship between order flow and the Brazilian real against the US Dollar exchange rate. De Medeiros' findings suggest that the country-risk variable is an important explanatory variable for exchange rate variation. Specifically, De Medeiros found that adding a country-risk premium variable improves the model's coefficient of determination from a mere 6% to 16%. This is consistent with findings from Wu (2013) documented that the country-risk premium is a significant explanatory variable for exchange rate variation in Brazil. In another study, Duffuor (2012) reported similar results for the Ghanaian forex market when the country risk-premium variable was considered.

Given the context of this experiment, and similarly to other studies on emerging markets, it is important to incorporate a country risk-premium variable in the model to capture the non-risk-neutrality characteristic of investors as well as to account for the inherent risk associated with emerging markets. Moreover, foreign exchange markets of emerging economies tend to be inefficient (less liquid) and some have a pronounced black exchange rate market (Duffour et al, 2012). These inefficiencies are motivational for an additional liquidity variable in the exchange rate model for emerging markets (Duffour et al, 2012). However, unlike most emerging economies' forex market, South Africa has a largely active forex market and liquidity factors are not of significant concern. Therefore, the only adaptation to be made to the Evans and Lyon's original model is the addition of a country-risk premium variable. This result in the estimation of the following exchange rate model:

$$\Delta s_t = \beta_0 + \beta_1 \Delta I_t + \beta_2 X_t + \beta_3 \Delta R_t + \varepsilon_t \qquad (2)$$

Where, Δs_t, represents returns on the log first differenced spot exchange rates, ΔI_t, is the change in interest rate differential between domestic and US interest rates and serves as a proxy for exchange rate fundamental macroeconomic variables. X_t is the order flow variable which is defined as the demand pressure on the domestic currency (Evans and Lyons, 2002a). Lastly, ΔR_t and ε_t represents a change in country risk premium differential and a normally distributed error term ($\varepsilon_t \sim N(0, \delta^2)$) respectively.

Fouejieu and Roger (2013) propose that a country risk premium can be measured as the spread between its international cost of borrowing and the risk-free rate. The spread on external borrowing cost has been used as the standard measure of country-risk premium in most finance applications. Some studies which have used this approach to model country risk include De Medeiros (2004) and Wu (2013). This study uses a variant estimate of country-risk premium similar to the one used by Zhang et al (2013). Zhang et al (2013) estimated country-risk premium as the spread between the prime lending rate and the 3-month T-Bill. Therefore, the country-risk premium differential is the difference between the South African and US country-risk premium. This method of country-risk estimation is employed particularly because the data of a South African dollar-bond similar in horizon to the investigation period of this study is not available. However, the data of prime lending rates and T-Bills is immediately available.

Although the above model (2) has enjoyed some extensive empirical success at explaining the behaviour of short-run exchange rate movements, it has equally faced some serious criticism. As the model assumes that causality runs strictly from order flow to changes in exchange rate, some pundits (*inter alia*, Vitale, 2004; Payne and Taylor, 2008 & Zhang et al, 2013) argue that the model fails to account for the possibility of simultaneity bias. Simultaneity bias arises if changes in exchange rate have a concomitant feedback effect on order flow. These feedback effects lead to inaccurate and misleading results, whereby the Ordinary Least Squared (OLS) estimated coefficient of order flow is biased (Vitale, 2004). Other studies have reported overwhelming empirical evidence which suggest a granger-causal relationship running from exchange rate returns to customer order (Payne and Taylor, 2008).

The feedback effects are investigated in this paper using a standard vector autoregressive model (VAR). The standard VAR model suffers the shortcoming of not considering contemporaneous feedback effects, relative to other models of similar fashion such as the structural VAR (SVAR). For instance, Payne (2003) showed that the contemporaneous effect of order flow on exchange rate can be investigated using an SVAR model of the following form:

$$s_t = \sum_{i=1}^{n} \varphi_i s_{t-1} + \sum_{j=0}^{n} \alpha_j X_{t-j} \qquad (3)$$

$$X_t = \sum_{i=1}^{p} \beta_i \, s_{t-i} + \sum_{j=1}^{p} \emptyset_i X_{t-j} \qquad (4)$$

However, a standard VAR model's computational simplicity makes it an attractive model to use. A VAR model also addresses endogeneity problems which are generally prevalent in time series models (Issahaku et al, 2015). The following VAR model will be estimated:

$$s_t = \sum_{i=1}^{n} \varphi_i s_{t-1} + \sum_{j=1}^{n} \alpha_j Y_{t-j} \qquad (5)$$

$$X_t = \sum_{i=1}^{p} \beta_i \, s_{t-i} + \sum_{j=1}^{p} \emptyset_i X_{t-j} \qquad (6)$$

Irrespective of its shortcomings the VAR model (5) and (6) is sufficient to achieve that key concerns of this part of the study. Firstly, it will allow one to investigate the exchange rate feedback effect on order flow. Secondly, it also allows for the assessment of the practical value of order flow as per Sager and Taylor (2008) criterion. Sager and Taylor (2008) propose that if the order flow is of any significance in predicting variations in exchange rates, then its lag values must have a significant explanatory power on current exchange rate returns.

The generic workhorse model of exchange rate order flow has received several criticisms. One of these is that financial time-series data generally suffer from autocorrelation and thus the assumption of homoscedasticity used in the OLS modelling is often violated. Indeed, some theorists (among others, Jalil and Feridum, 2010; Issahaku et al, 2015) have shown that for a longer time series the variance of the exchange rate error term tends to depend on the behaviour of the errors in the previous period – which implies the presence of heteroscedasticity. The above findings provide motivation for the investigation of the exchange rate behaviour using non-linear methods. This task is tackled here. Specifically, the paper investigates ARCH effects in the South African exchange rate data by applying the generalised autoregressive conditional heteroscedasticity (GARCH) model. A GARCH model is generally preferred to an ARCH model because of its parsimony and avoids over-fitting of parameters (Brooks, 2008). The GARCH model is specified as follows:

$$s_t = \beta_0 + \beta_1 I_t + \beta_2 X_t + \beta_3 R_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, \delta_t^2\,) \qquad (7)$$

$$\delta_t^2 = \mu + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \theta_j\, \delta_{t-1}^2 \qquad (8)$$

The above model (7) is the mean equation for the associated GARCH model which is the exchange rate order flow equation observed previously. Equation (8) is a GARCH (q, p) model which relates the current conditional variance to q lags of the squared errors and p lags of its own past values. Instead of using the OLS approach the above equation is estimated using the GARCH methodology. Brooks (2008) argues that a GARCH (1, 1) can sufficiently describe the volatility clustering in the data. This restricting of the analysis to a GARCH (1, 1) results in the estimation of the following GARCH model:

$$\delta_t^2 = \mu + \alpha_1 \varepsilon_{t-1}^2 + \theta_1 \delta_{t-1}^2 \qquad (9)$$

3.3 Forecasting

Sager and Taylor (2008) argue that while a model can provide a good description of the data, its practical significance lies in its out-of-sample forecasting power. Previous studies (Evans and Lyons, 2002a, b; Evans and Lyons, 2005; Killeen et al, 2006; Chinn and Moore, 2011 & Cerrato et al, 2011) on the microstructure approach to exchange rate determination have shown that there is significant contemporaneous relationship between order flow and exchange rate returns. However, numerous other studies indicate that the out-of-sample forecasting power of the order flow models of exchange rate have not been any better than the naïve random walk model (*inter alia*, Payne and Vitale, 2003; Sager and Taylor, 2008 & Chinn and Moore, 2011). If the microstructure model is to be adopted as the official framework of short-run exchange rate determination, its out-of-sample exchange rate predictive power must be better than that of the random walk model. The out-of-sample forecasting power of the microstructure order flow model is thus investigated here. Further, the forecasting power of the GARCH model will also. The forecasting models take the following form for *k-steps* ahead forecasts:

$$\Delta s_{t+k} = \beta_0 + \beta_1 \Delta I_t + \beta_2 X_t + \beta_3 \Delta R_t + \varepsilon_{t+k} \qquad \varepsilon_t \sim N(0, \delta_t^2) \qquad (10)$$

$$\delta_{t+k}^2 = \mu + \alpha_1 \varepsilon_{t-1}^2 + \theta_1 \delta_{t-1}^2 \qquad (11)$$

Models (10 and 11) represent the forecasting models of microstructure order flow and GARCH model respectively. Meese and Rogoff's (1983) random-walk (RW) evaluation criterion has become the standard benchmark with which the exchange rate models' out-of-sample performances are evaluated. The data is divided into two samples and the later set of observations is used as a hold-out sample for out-of-sample forecasting. Like Issahaku et al (2015) the Root Mean Square Error (RMSE) is used as the measure of forecasting accuracy.

A model with better forecasting accuracy is one with the smallest RMSE. The RMSE is specified as follows:

$$RMSE = \sqrt{\frac{1}{F}\sum_{t=1}^{F}\sigma_t} \tag{13}$$

CHAPTER FOUR: REGRESSION OUTPUT AND DISCUSSION

4.0 Introduction

In this chapter the descriptive statistics, as well as, the regression results from both the Ordinary Least Square (OLS) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models are presented. Further, the results of the out-of-sample forecasting accuracy of the aforementioned models against the naïve random walk model are also presented. The chapter is concluded by providing a granger causal relationship between order flow and exchange rate returns using a VAR model and presenting the impulse response functions and variance decomposition of exchange rate returns.

4.1 Preliminary Data Analysis

Table1: Summary Statistics

Summary Statistics				
	DS	DX	DI	DR
Mean	0.35	0.61	-0.75	0.44
Maximum	18.39	40.14	11.80	204.77
Minimum	-10.27	-87.53	-16.59	-252.57
Std. Dev.	3.92	16.56	4.76	53.94
Skewness	1.03	-0.93	-0.47	0.31
Kurtosis	7.05	7.43	4.53	9.47
Jarque-Bera	127.26	142.22	19.86	260.67
Probability	0.00***	0.00***	0.00***	0.00***
Sum	51.09	90.28	-111.63	65.60
Sum Sq. Dev.	2263.79	40325.58	3330.19	427687.20

****; **; * indicate the significance level at 1%, 5% and 10%*

The above table1 depicts the monthly summary statistics for log-differences returns of the spot exchange rate, order flow, interest rate differential and the risk-premium. All the returns are expressed in percentage points and are from 2001 to 2015. The table shows that all the mean returns were positive except for the interest rate differential premium which was about -0.754% for the 15year period under consideration. The standard deviations for the spot rate and interest rate differential returns are relatively lower than those of order flows and risk-premium. The risk-premium has the highest standard deviation of about 53.94% followed by the order flows standard deviation of about 16.56%. Exchange rate and risk-premium returns are positively skewed, while the returns on order flow and interest rate differential are negatively skewed. The Jarque-Bera statistic indicates that all the variables are not normally distributed.

Table 2: Contemporaneous Correlations

Contemporaneous Correlations				
	DI	DR	DS	DX
DI	1	-0.30	0.24	-0.09
DR	-0.30	1	-0.06	-0.10
DS	0.24	-0.06	1	0.04
DX	-0.09	-0.10	0.04	1

Table 2 presents the contemporaneous correlation between the returns on interest rate differential, risk-premium, exchange rates and order flow. Returns on exchange rate and order flow have a positive small correlation of about 3.8%. Interest rate differential and exchange rate returns have a positive correlation of almost 6%. The exchange rate returns are relatively highly correlated to the returns of the risk-premium.

4.2 Regressions Results

4.2.1 Microstructure Model Output

Table 3: OLS Regression Output

Dependent Variable: DS				
Method: Least Squares				
Sample (adjusted): 2001M02 2014M12				
Included observations: 167 after adjustments				
HAC standard errors & covariance				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-4.38	1.30	-3.36	0.00***
DI	0.20	0.07	2.74	0.00***
X	0.00146	0.000434	3.360109	0.00***
R	1.60	0.63	2.55	0.01
R-squared	0.15	Mean dependent var		0.23
Adjusted R-squared	0.14	S.D. dependent var		3.93
S.E. of regression	3.65	Akaike info criterion		5.45
Sum squared resid	2174.90	Schwarz criterion		5.53
Log likelihood	-451.29	Hannan-Quinn criter.		5.48
F-statistic	9.87	Durbin-Watson stat		1.45
Prob(F-statistic)	0.00***	Wald F-statistic		5.26
Prob(Wald F-statistic)	0.00***			

****; **; * indicate the significance level at 1%, 5% and 10%*

Table 3 reports the regression output from the order flow equation (2). The equation was estimated using the Heteroscedasticity and Autocorrelation Consistent (HAC) standard error procedure to correct for both heteroscedasticity and autocorrelation which is usually inherent in time series data. Multiple order flow regressions were conducted the output recorded. Firstly, regressing exchange rate returns on the returns of order flow volumes, interest rate differential, and risk-premium yielded results that were not statistically significant at any reasonable level of significance (above 10%). This was construed as an indication that some of the variables might be affect the exchange rate returns in levels and not return form. This conjecture was investigated further using a step-wise selection method. This is the most significant model (reported in Table 3) and it indicates that both order flow and risk-premium affect exchange rate returns in levels while the interest differential is significant in returns.

All the exchange rate returns explanatory variables are significant at 5% level of significance and the slope coefficients are also correctly signed. Order flow has a slope coefficient of 0.00146 which means that a $1 million increase in net exchange rate turnover is associated with 0.00146% depreciation in the ZAR. Similarly, a one percentage point increase and a 1% increase in the risk-premium and interest rate differential result in approximately 1.6% and 0.2% depreciation in the ZAR. The F-statistic from the regression model is about 9.872 and its associated p-value very close to zero which suggest that the overall regression model is significant. Only 15.376% of the variation in the exchange rate can be explained by the regression model as indicated by the coefficient of determination. Both the R-squared (R^2) and the adjusted R-squared (adj R^2) reported in table 2 are comparable to the ones reported in Sager and Taylor (2008), Chinn and Moore (2011) and Zhang et al, (2013). When the order flow variable was removed from regression, the model's R^2 dropped drastically to about 4.85% which is an indication that this variable is an important explanatory variable for the variations in exchange rates. Further, the risk-premium was found not to be significant when order flow is excluded from the model. Both the order flow and interest rate differential variables are significant regressors on their own, while the risk-premium bears no explanatory power when it's the only explanatory variable in the equation. Since the risk-premium is only significant when the order flow variable is included in the model it suggests that there might be some collinearity between order flow and the risk-premium.

However, the Durbin-Watson (DW) of the above model presents a drawback to the results drawn from the model. The DW is 1.45 which indicates that there is autocorrelation in the model. The issue of autocorrelation is addressed here by including a lag of the depended variable in the regression model. The output of this model is presented in Table 3B. Table 3B shows that including a lag of the dependent variable improves the DW from 1.45 to about 1.87. The DW statistic is still below the desired statistic of 2 but has improved significantly from the initial statistic of 1.45. Both the first and second lags of the dependent variable were included in the model to see if there will be any further improvement in the regression model's DW. The results of this regression are presented in the appendix in table A2. From the table it can be observed that the DW statistic has improved to about 1.94 after the addition of the second lag.

Table 3B: OLS Regression Output

Dependent Variable: DS				
Method: Least Squares				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
HAC standard errors & covariance				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-3.80	1.18	-3.21	0.00
DI	0.16	0.06	2.60	0.01
X	0.001274	0.000395	3.23	0.00
R	1.34	0.54	2.48	0.01
DS(-1)	0.25	0.06	4.20	0.00
R-squared	0.21	Mean dependent var		0.23
Adjusted R-squared	0.19	S.D. dependent var		3.95
S.E. of regression	3.55	Akaike info criterion		5.40
Sum squared resid	2029.70	Schwarz criterion		5.50
Log likelihood	-443.35	Hannan-Quinn criter.		5.44
F-statistic	10.71	Durbin-Watson stat		1.87
Prob(F-statistic)	0.00	Wald F-statistic		9.04
Prob(Wald F-statistic)	0.00			

****; **; * indicate the significance level at 1%, 5% and 10%*

4.2.2 GARCH Model Output

As aforementioned, volatility pooling is one of the financial time series attributes which structural modelling does not account for. However, the homoscedasticity assumption inherent in structural model is often violated in time series observations. A heteroscedasticity test was performed to determine whether there are 'ARCH-effects' in the residuals and thus motivation for the use of a GARCH model. To this end, a linear regression model (2) was estimated and the resulting squared residuals of this model where testing for homoscedasticity using the ARCH test. The default lags (5) were left unchanged, and the results obtained from this test are reported in Table 4 below.

The p-value of the F-statistic is highly significant; therefore, under the null hypothesis that the squared-residual error coefficients are zero, we can reject this hypothesis. Thus we conclude that there is sufficient evidence to suggest the presence of heteroscedasticity. This implies that a GARCH type model is an appropriate model for modelling exchange rate returns.

Table 4: Heteroscedasticity Test: ARCH

F-statistic	466.72	Prob. F(5,169)		0.00***
Obs*R-squared	163.18	Prob. Chi-Square(5)		0.00***
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.14	0.13	-1.05	0.29
RESID^2(-1)	1.23	0.08	16.22	0.00***
RESID^2(-2)	-0.00	0.12	-0.07	0.95
RESID^2(-3)	-0.26	0.13	-1.95	0.05**
RESID^2(-4)	-0.07	0.14	-0.46	0.65
RESID^2(-5)	0.23	0.10	2.41	0.02**
R-squared	0.93	Mean dependent var		3.15
Adjusted R-squared	0.93	S.D. dependent var		5.22
S.E. of regression	1.38	Akaike info criterion		3.51
Sum squared resid	320.37	Schwarz criterion		3.62
Log likelihood	-301.22	Hannan-Quinn criter.		3.56
F-statistic	466.72	Durbin-Watson stat		2.00
Prob(F-statistic)	0.00***			

****; **; * indicate the significance level at 1%, 5% and 10%*

Table 5: Estimates from the GARCH (0, 1) Model				
Dependent Variable: DS				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	-4.41	0.91	-4.85	0.00***
X	0.001468	0.000254	5.77561	0.00***
DI	0.19	0.06	3.24	0.00***
R	1.61	0.48	3.35	0.00***
Variance Equation				
C	2.82	3.42	0.83	0.41
GARCH(-1)	0.79	0.27	2.96	0.00***
R-squared	0.15	Mean dependent var		0.23
Adjusted R-squared	0.14	S.D. dependent var		3.93
S.E. of regression	3.65	Akaike info criterion		5.47
Sum squared resid	21745.00	Schwarz criterion		5.58
Log likelihood	-450.42	Hannan-Quinn criter.		5.51
Durbin-Watson stat	1.45			

****; **; * indicate the significance level at 1%, 5% and 10%*

The estimates from the GARCH model are presented in table 5. Initial estimates from a GARCH (1, 1) model showed that the lagged residual squared coefficient was not significant even at 10% level (see results in the appendix, table G1). When the lagged residual parameter was omitted from the equation the model experienced a marginal increase in the R^2 and all the other variables remained significant. This implies that the exchange rate volatility is better explained by a GARCH (0, 1) model instead. The lagged conditional variance estimate is positive and significant at 1% level of significance. This suggests that higher levels of exchange rate volatility result in the depreciation of the ZAR. All in all, the GARCH model indicants that exchange rate volatility has a significant role in determining exchange rate returns. However, there is no significant difference in the amount of total variation in exchange rate that can be explained by the GARCH model relative to the OLS model. Both models have similar coefficients of determination and adjusted coefficient of determination.

Table 5B: Estimates from the GARCH (0, 1) Model with lags

Dependent Variable: DS				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	-3.55	0.92	-3.86	0.00
DI	0.16	0.06	2.67	0.01
X	0.001249	0.000267	4.67	0.00
R	1.21	0.45	2.68	0.01
DS(-1)	0.25	0.08	3.07	0.00
Variance Equation				
C	3.40	7.23	0.47	0.64
GARCH(-1)	0.72	0.61	1.18	0.24
R-squared	0.21	Mean dependent var		0.36
Adjusted R-squared	0.19	S.D. dependent var		3.89
S.E. of regression	3.51	Akaike info criterion		5.39
Sum squared resid	2125.90	Schwarz criterion		5.52
Log likelihood	-472.88	Hannan-Quinn criter.		5.44
Durbin-Watson stat	1.87			

****; **; * indicate the significance level at 1%, 5% and 10%*

4.3 Comparison of Forecasting Accuracy from the Models

In this sub-section we evaluate the forecasting accuracy from the OLS (OF Model), GARCH and the naïve Random Walk models. The last year in the data was used as a hold-out sample for forecasting purposes. Out-of-sample forecasts are performed for one month, two months, three months, six months, and twelve months forecasting horizons. The resulting forecasting accuracy of the three models is evaluated using the Root Mean Square Error (RMSE) approach. The best forecasting model should have the smallest RMSE. Therefore, if a microstructure models has the best forecasting accuracy, its RMSE is expected to be the smallest compared to that of GARCH and a RW models. The RMSE results from the forecasts are summarized in table 6 for all periods under consideration. The least RMSE for a given period is indicated by a bold font. Table 6 indicates that the GARCH model has the best out-of-sample forecasting accuracy than both the OF and RWM models periods one up to six. For the same period the OF models has the second best forecasting accuracy and its RMSEs are not far from that of the GARCH Model. However, at 12month horizon the naïve RWM yielded the best forecasting accuracy. Overall these results suggest that OF model forecasts no better than both the GARCH and RWM models. The general expectation was that the OF model will have superior forecasting accuracy than these models.

Table 6: Out-Of-Sample Forecasting Accuracy

Period	OF Model	GARCH Model	RWM
1	1.98	**1.93**	2.21
2	1.63	**1.61**	1.81
3	2.37	**2.35**	2.58
6	2.01	**1.98**	2.33
12	3.06	3.03	**2.92**

4.4 VAR Model Output

VAR estimations require all the variables included in the model to be stationary. Therefore, an Augmented Dickey-Fuller (ADF) test was used to test for stationarity in the data. The risk-premium variable was the only one stationary at log-levels which means that the unit-root hypothesis was rejected. Thus this variable was estimated in its level form. The exchange rate and interest rate differential had unit-roots and were thus I (1) stationary. The order flow variable had to be differenced twice for it to be stationary. A multivariate information approach was used to determine the appropriate number of lags the VAR model.

Table 7: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1866.32	NA	71862.68	22.53	22.61	22.56
1	-1687.74	346.41	10134.76	20.58	**20.95***	20.73
2	-1651.44	68.66	7938.92	20.33	21.01	20.60
3	-1617.97	61.70	**6437.53***	**20.12***	21.09	**20.52***
4	-1605.55	22.29	6732.19	20.16	21.44	20.68
5	-1588.15	30.40	6636.38	20.15	21.72	20.79
6	-1573.90	24.21	6803.25	20.17	22.04	20.93
7	-1558.29	25.76	6871.64	20.17	22.35	21.05
8	-1538.83	31.18	6637.25	20.13	22.61	21.13
9	-1523.12	24.42	6720.30	20.13	22.91	21.26
10	-1515.85	10.95	7550.29	20.24	23.31	21.49
11	-1492.66	**33.80***	7020.87	20.15	23.53	21.52
12	-1481.86	15.22	7601.67	20.22	23.89	21.71

The output from the multivariate information criterion is shown in the above table 7. From the table it can be observed that different models of information criterion selected different number of lags, however, most models selected three lags as the appropriate for the VAR model. The most favoured lag selection method in this paper is the Akaike's Information Criterion (AIC) which coincidentally selected the same number of lags with other two models. Thus the chosen number of lags is three, hence a VAR (3) model is estimated. The results of the VAR estimates are presented in Table V2 in the appendix.

From Table V2 it can be observed that the first and third lags of the exchange rate returns have a significant impact on order flows. This suggests that there might be causality running from exchange rate returns to order flows and thus implying the presence of feedback effects. The third lag of exchange rate returns also has a significant impact on the risk-premium. Surprisingly none of the order flow lags have a significant explanatory power on the exchange rate returns. Further the lags of order flows have no explanatory power on any other variables besides its own variable. If order flow was an important explanatory variable its lags would have been expected to have a significant impact on the exchange rate variations

(Sager and Taylor, 2008), however, these results are consistent with an empirical finding which suggests that order flow only has a contemporaneous effect on exchange rates (Marsh and O'Rourke, 2005). The first and second lags of the interest rate differential have a significant effect on the risk-premium. However, the lags of the interest rate differential do not have any significant impact on itself. Finally, the third lag of the risk-premium has significant explanatory power of the exchange rate returns. This suggests that changes in sovereign risk is incorporated slowly into the ZAR/$ exchange rate.

A Granger causality test was run to further investigate the relationship between exchange rate returns and the proposed explanatory variables. The results from the Granger causality test are reported in Table8. The results show that overall there is significant causality for the order flow and risk-premium variables at a 5% level of significance. However, there is no evidence of a lead-lag interaction for the exchange rate returns at any reasonable level of significance. Thus no lags of any explanatory variables have a significant Granger causality effect on the exchange rate returns. Surprisingly, there is a significant causality from the exchange rate returns to order flow even at 1% level of significance. This suggests that there are feedback effects between exchange rate returns and order flows. More importantly this result casts serious doubt on the order variable being a significant explanatory variable for exchange rate returns. The lags of order flow are significant for the interest rate differential returns at the 10% level of significance. Finally, the lags of the interest rate differential returns have a significant causal effect on the risk-premium.

The combined responsiveness of a given dependent variable to unexpected unit shocks to each of the variables are presented in Figure1. Innovations to unexpected exchange rate returns have a negative effect on order flows for the first four and a half periods and their effect becomes temporarily positive in the fifth period but gradually dies out after the sixth period. On the other hand, the effect of innovations in order flow to exchange rate returns oscillates between negative and positive movements. These oscillations gradually die out overtime and by the tenth period these shocks are almost non-existent. The shocks of interest rate differential to innovations in the risk-premium start out negative, however, gradually increase overtime becoming positive in the third period. The effect of the shock does not seem to die out even after the tenth period. Increasing interest rate differential returns have a positive impact on exchange rate returns which gradually dies out overtime and by the ninth period the shock seems to be non-existent.

Table 8: VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: DS			
Excluded	Chi-sq	df	Prob.
OF	1.59	3	0.66
DI	1.52	3	0.68
R	2.93	3	0.40
All	6.54	9	0.69
Dependent variable: OF			
Excluded	Chi-sq	df	Prob.
DS	32.29	3	0.00***
DI	0.19	3	0.98
R	0.63	3	0.89
All	35.22	9	**0.00*** **
Dependent variable: DI			
Excluded	Chi-sq	df	Prob.
DS	1.14	3	0.77
OF	7.43	3	**0.06** **
R	0.49	3	0.92
All	9.19	9	0.42
Dependent variable: R			
Excluded	Chi-sq	df	Prob.
DS	4.79	3	0.19
OF	2.74	3	0.43
DI	12.13	3	**0.00*** **
All	18.60	9	**0.03** **

****; **; * indicate the significance level at 1%, 5% and 10%*

Figure 1: Combined Impulse Responses

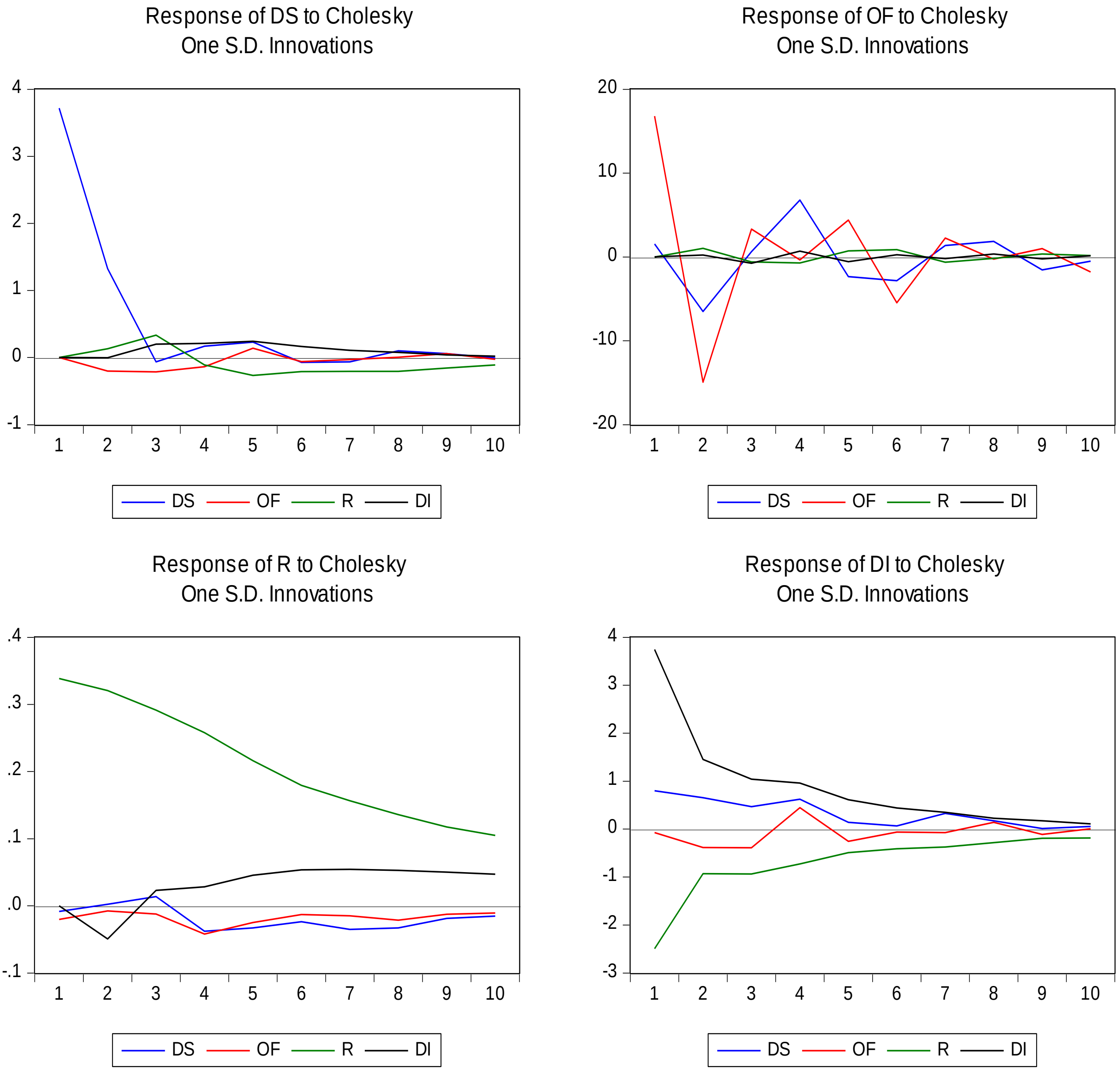

Table 9 displays the variance decomposition of the exchange rate returns for up to ten periods. The table shows that most of the variation (over 95%) in the exchange rate returns is due to its own shocks for the entire period under consideration. For the first period, all the variation in the exchange rate returns is due to its own unexpected innovations. The risk-premium explains most of the variation in exchange rate returns for the third and fourth period. From the fifth to the tenth period most of the variance in the exchange rate returns can be explained by the interest rate differential returns. Surprisingly, innovations in order flow explain the smallest forecast error variance to exchange rate returns. This result suggests either of two things. Firstly, either innovations in order flow have no effect on the variations in exchange rate returns and thus order flow provides no explanatory power for exchange rate returns. Second, it could suggest shocks to order flow have no other explanatory effect on the exchange rate returns beyond their contemporaneous effect. The variance decomposition of the other variables is reported in the appendix in Tables VD 2.

Table 9: Variance Decomposition of Exchange Rate Returns					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	3.72	100.00	0.00	0.00	0.00
2	3.96	99.63	0.26	0.04	0.08
3	3.98	98.39	0.54	0.04	1.03
4	3.99	97.93	0.66	0.39	1.03
5	4.02	97.02	0.77	1.14	1.06
6	4.03	96.57	0.79	1.54	1.10
7	4.04	96.25	0.79	1.78	1.17
8	4.04	95.97	0.79	1.97	1.27
9	4.05	95.80	0.81	2.06	1.33
10	4.05	95.73	0.81	2.09	1.37

Cholesky Ordering: DS OF DI R

CHAPTER 5: SUMMARY, IMPLICATIONS AND CONCLUSION

5.0 Introduction

The determinants of floating exchange rates variation have received considerable academic attention. Since the advent of the floating exchange era many models have been proposed to try and explain the variations in exchange rate, however, most of these models' empirical performance has been poor. This study applied a microstructural approach to investigate the short-run variations in the South African Rand against the US Dollar exchange rate. The findings of the study are summarised in Section 5.1. Section 5.2 examines the implications of these results and Section 5.3 offers the concluding remarks.

5.1 Summary

The main hypothesis of a market microstructure application to exchange rate determination is that customer order flow is a significant explanatory variable for an exchange rate variation. This hypothesis was investigated in this study. Particularly, the study investigated the in-sample performance of the microstructure model, as well as, its out-of-sample forecasting power. The findings reported in this study suggest that an order flow model can explain some of the variation in the exchange rate; however, its explanatory power is very weak – explaining only about 15% of the variation in the exchange rate. The coefficient of determination reported in this study is significantly lower than that reported by some of the early studies on the microstructure approach to exchange rate determination (Evans and Lyons, 2002; Bates et al, 2003; and Corte et al, 2011). A low coefficient of determination reported in this study does not come as a surprise though since other studies have reported similar findings (Marsh and O'Rourke, 2005; and Evans and Lyons, 2005). One of the reasons for differences in findings from the microstructure models is due to differences in data used in the studies.

Moreover, a GARCH (1, 1) model was estimated to investigate whether volatility clustering was a concern. The findings suggest that only past volatility has a significant effect on exchange rate variation. On the other hand, the lagged residuals were found not to have any significant effect on the exchange rate variation. This suggests that the exchange rate variation is best explained by a GARCH (0, 1) model. Nonetheless, the GARCH model did not show any significant improvement in explanatory power from the microstructure model. Its coefficient of determination was slightly lower than that of the microstructure model.

The other central theme of this research was to investigate whether a microstructure model had better out-of-sample forecasting ability compared to the other models. To this end, the out-of-sample performance of the microstructure model was compared to that of the GARCH and Random Walk models. The Root Mean Squared Error was used to determine the type of model with the best forecasting accuracy. The GARCH model had the best forecasting accuracy for periods 1 up to 6, while on the other hand, the Random Walk model performed better at 12-month horizon. The microstructure model performed no better than any of these models at any horizon which was surprising given that other studies have found the microstructure model to improve upon the Random Walk model (Evans and Lyons, 2002; Ceratto et al, 2011; and Fans and Lyons, 2003).

Further, the results from the VAR model indicate that there might be reverse causality from exchange rates to order flow. The lagged values of exchange rate returns had a significant effect on current values of order flow. Moreover, the results from a granger causality test highlight a granger causal relationship between exchange rate and order flow running strictly from exchange rate returns to order flow.

5.2 Implications

5.2.1 Implications for market participant: theoretically the results from a market microstructure analysis can be of great economic benefit to market participants. For instance, if order flow has superior out-of-sample forecasting power relative to other exchange rate models it could improve currency trading strategies that results in great economic benefits. However, as it stands the microstructure model has not yet given conclusive results in terms of the forecasting power of order flow. This implies that the benefit of order flow information to market participants is still indeterminate and thus more research must be done.

5.2.2 Implications for policy makers and regulators: the regulatory framework currently in place is the major hindrance to studies of this nature. Currently, the data on customer order flow is not available for public dispensation and for other endeavours such as academic research. This means that proxy data must be used to conduct research on order flow effect on exchange rate variation. This results in results that are not a true indication of the effect of order flow on exchange rate variation as in most cases the proxy data used is generally not a good proxy. Therefore, the main challenge for policy markers is to find ways of making the order flow data available for research while at the same time maintain customer anonymity. One such way is using pseudo names.

5.3 Conclusion

This paper employed a market microstructural approach to investigate the short-run determinants of the ZAR/$ exchange rate. The paper sought to examine the significance of customer order flow as an explanatory variable for the variation in exchange rates. Monthly observations were used for the analysis for the period between 2001 and 2015.

The findings from this paper provide evidence in favour of order flow as an important variable for exchange rate determination. However, its explanatory power is low. Further, it was found that order flow has a significant effect on exchange rates returns in level form.

However, as Sager and Taylor (2008) indicated, the practical significance of order flow lies in its out-of-sample forecasting power. To this end we evaluated the predictive power of an order flow model relative to the GARCH (0, 1) model and the naïve Random Walk model. Out-of-sample predictions were evaluated for 1 up to 12 months. Evidence from this endeavour suggests that a microstructure model bears no greater out-of-sample predictive power than both the GARCH and random walk model. For the period 1 to 6 the GARCH model yielded the best forecasts, however, at 12 months' horizons the random walk model yielded the best forecast. Surprisingly, for all forecasting periods the microstructure model did not experience any outperformance. This finding, therefore, seems consistent with that of Issahaku et al (2015) who conclude that there is no specific model for forecasting exchange rate but rather the forecasting ability of a model depends on the forecasting context. This might suggest that exchange rate forecasting models are intrinsic to a particular context and thus a model that has shown empirical success in one context might be a wrong model for another context, or might need to be adapted to fit another context.

The paper also investigated the feedback effects between the exchange rate returns and order flow using a VAR approach. The findings suggest that exchange rate returns have a feedback effect on order flow as indicated by the significant lags of exchange rate returns on order flow. The finding of feedback trading casts serious doubt on order flow as a significant explanatory variable for exchange rate returns – it might simply imply that investors are momentum traders. On the other hand, the lags of order flow were found not to have any significant causal effect on the exchange rate returns. This indicates that order flow might only have a transitory effect on exchange rate. Overall, the results from the VAR model could be suggestive of an unclear relationship between order flow and exchange rate returns. Marsh and O'Rourke (2005) also express similar sentiments. Therefore, the main recommendation for future research of this nature would be to investigate further the relationship between order flow and exchange rate returns using a structural vector auto-regression (SVAR) approach which allows for contemporaneous terms.

The findings of this paper should be viewed as preliminary given the limitations of the data used in the study. The data used is that of gross trading volumes by customers and therefore, is not necessarily the best proxy for net customer order flow volumes.

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APPENDIX

Table G1: GARCH (1, 1) Model

		Dependent Variable: DS		
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	-4.41	0.90	-4.94	0.00***
X	0.001466	0.000259	5.66	0.00***
DI	0.19	0.05	3.55	0.00***
R	1.58	0.43	3.71	0.00***
		Variance Equation		
C	3.50	5.59	0.62	0.53
RESID(-1)^2	-0.02	0.04	-0.46	0.65
GARCH(-1)	0.75	0.43	1.73	0.08
R-squared	0.15	Mean dependent var		0.23
Adjusted R-squared	0.14	S.D. dependent var		3.93
S.E. of regression	3.65	Akaike info criterion		5.48
Sum squared resid	2175.09	Schwarz criterion		5.61
Log likelihood	-450.35	Hannan-Quinn criter.		5.53

****; **; * indicate the significance level at 1%, 5% and 10%*

Table V1: VAR (1) Estimates

	DS	OF	DI	R
DS(-1)	0.32	-1.76	0.08	0.00
	-0.07	-0.41	-0.09	-0.01
	[4.28]	[**-4.31**]	[0.86]	[0.78]
OF(-1)	0.01	-0.53	-0.00	0.00
	-0.01	-0.06	-0.01	-0.00
	[0.59]	**[-8.50]**	[-0.25]	[0.25]
DI(-1)	0.024652	0.361982	0.478827	0.000676
	-0.06	-0.31	-0.08	-0.01
	[0.44]	[1.16]	[6.75]	[0.13]
R(-1)	-0.1	1.46	-0.32	0.91
	-0.37	-2.03	-0.46	-0.03
	[-0.27]	[0.72]	[-0.69]	[**26.05**]
C	0.32	-0.32	0.21	0.05
	-0.37	-2.07	-0.47	-0.04
	[0.86]	[-0.16]	[0.45]	[1.49]
R-squared	0.11	0.34	0.27	0.82
Adj. R-squared	0.09	0.33	0.25	0.81
Sum sq. resids	2384.54	72767.95	3774.74	21.46
S.E. equation	3.72	20.57	4.68	0.35
F-statistic	5.23	22.52	15.55	192.51
Log likelihood	-481.31	-783.82	-521.96	-64.44
Akaike AIC	5.49	8.91	5.95	0.78
Schwarz SC	5.584706	9.002977	6.044033	0.87
Mean dependent	0.36	0.17	0.07	0.66
S.D. dependent	3.90	25.10	5.40	0.82

****; **; * indicate the significance level at 1%, 5% and 10%*

Table V2: VAR (3) Estimates				
	DS	**OF**	**DI**	**R**
DS(-1)	0.36	-1.39	0.10	0.01
	-0.10	-0.36	-0.10	-0.01
	[4.57]	**[-3.86]**	[1.04]	[0.72]
DS(-2)	-0.17	-0.63	-0.03	-0.00
	-0.09	-0.40	-0.11	-0.01
	[-1.91]	[-1.56]	[-0.30]	[-0.00]
DS(-3)	0.07	1.26	0.03	-0.01
	-0.08	-0.38	-0.10	-0.01
	[0.85]	**[3.30]**	[0.33]	**[-1.94]**
OF(-1)	-0.01	-0.88	-0.02	0.00
	-0.02	-0.07	-0.02	-0.00
	[-0.76]	[-12.73]	[-1.13]	[0.36]
OF(-2)	-0.02	-0.60	-0.03	0.00
	-0.02	-0.08	-0.02	-0.00
	[-0.94]	**[-7.42]**	[-1.46]	[0.11]
OF(-3)	-0.02	-0.41	0.02	-0.00
	-0.01	-0.07	-0.02	-0.00
	[-1.21]	**[-6.02]**	[0.85]	[-1.19]
DI(-1)	-0.00	0.06	0.39	-0.01
	-0.08	-0.35	-0.10	-0.01
	[-0.01]	[0.184]	**[4.07]**	**[-1.86]**
DI(-2)	0.06	-0.12	0.13	0.02
	-0.08	-0.34	-0.09	-0.01
	[0.80]	[-0.36]	[1.41]	**[3.28]**
DI(-3)	0.02	0.09	0.08	-0.00
	-0.07	-0.32	-0.09	-0.01
	[0.32]	[0.29]	[0.91]	[-0.07]
R(-1)	0.389	3.50	0.11	0.85
	-1.01	-4.58	-1.24	-0.09
	[0.39]	[0.77]	[0.09]	**[9.24]**
R(-2)	0.95	-2.61	-0.82	0.18
	-1.30	-5.88	-1.59	-0.12
	[0.73]	[-0.44]	[-0.51]	[1.53]
R(-3)	-1.50	-0.24	0.52	-0.13
	-0.90	-4.10	-1.11	-0.08
	[-1.65]	[-0.06]	[0.47]	[-1.52]
C	0.39	-0.03	0.06	0.05
	-0.38	-1.75	-0.47	-0.04
	[1.01]	[-0.02]	[0.13]	[1.45]
R-squared	0.16	0.58	0.32	0.84
Adj. R-squared	0.10	0.55	0.27	0.82
Sum sq. resids	2239.61	46062.27	3386.30	18.65

S.E. equation	3.72	16.86	4.57	0.34
F-statistic	2.57	18.89	6.36	68.71
Log likelihood	-471.38	-735.95	-507.55	-52.41
Akaike AIC	5.54	8.56	5.95	0.75
Schwarz SC	5.77	8.79	6.18	0.98
Mean dependent	0.36	0.17	-0.02	0.65
S.D. dependent	3.91	25.20	5.35	0.81

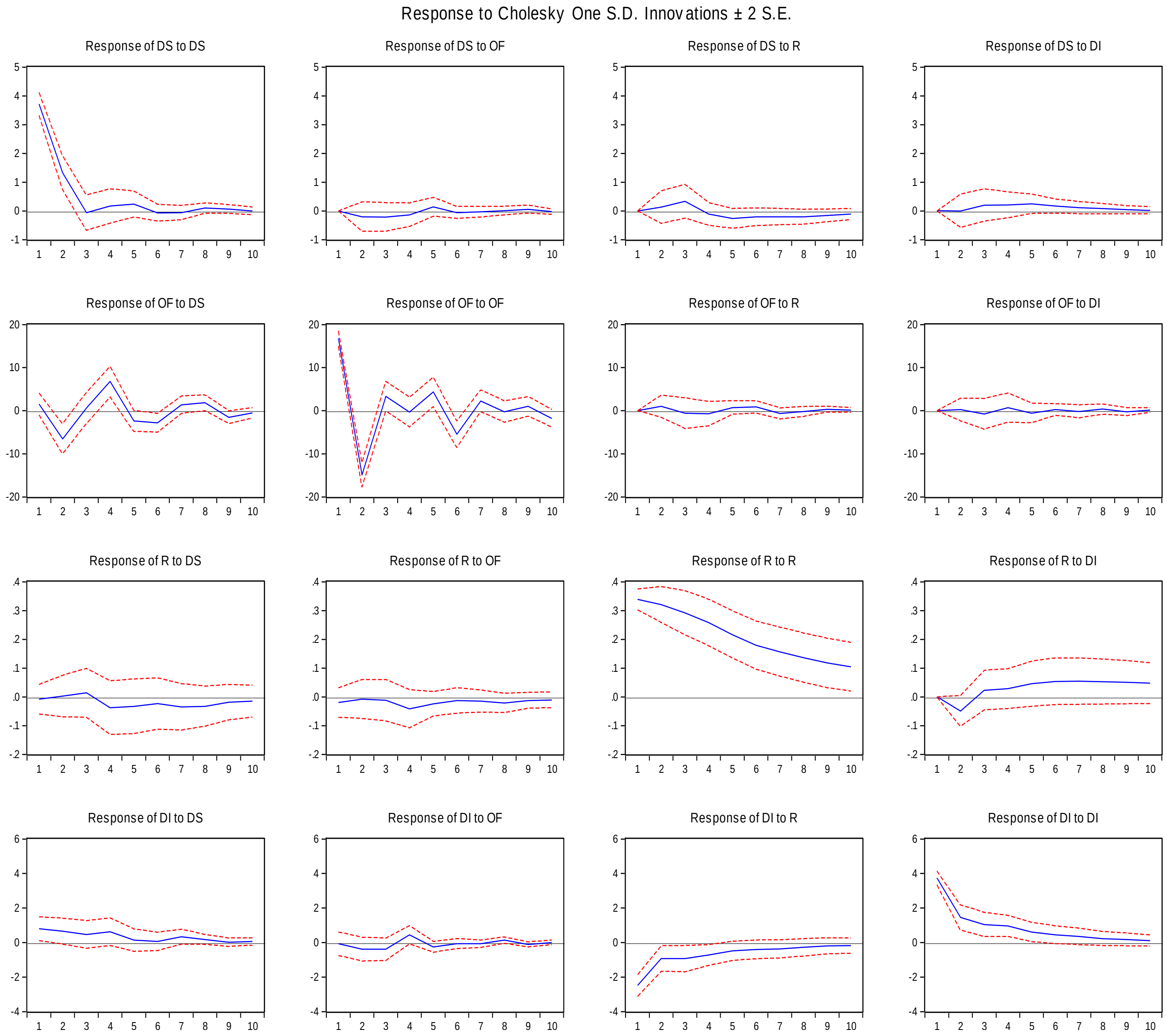
Determinant resid covariance (dof adj.)	6273.14
Determinant resid covariance	4606.73
Log likelihood	-1731.34
Akaike information criterion	20.38
Schwarz criterion	21.32

Table R1: Estimate of a Random Walk Model (RWM)

Dependent Variable: DS				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LAGDS	0.33	0.07	4.42	0.00***
R-squared	0.10	Mean dependent var		0.23
Adjusted R-squared	0.10	S.D. dependent var		3.95
S.E. of regression	3.74	Akaike info criterion		5.48
Sum squared resid	2305.84	Schwarz criterion		5.50
Log likelihood	-453.93	Hannan-Quinn criter.		5.49
Durbin-Watson stat	1.92241			

****; **; * indicate the significance level at 1%, 5% and 10%*

Table IM1: Individual Impulse graphs



Tables VD1: Variance Decompositions

Variance Decomposition of Order Flow					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	16.86	0.85	99.15	0.00	0.00
2	23.47	8.16	91.64	0.02	0.18
3	23.73	8.05	91.59	0.04	0.32
4	24.70	14.97	84.54	0.19	0.31
5	25.21	15.24	84.16	0.30	0.31
6	25.97	15.54	83.77	0.29	0.40
7	26.11	15.65	83.60	0.29	0.46
8	26.18	16.07	83.16	0.31	0.46
9	26.25	16.33	82.88	0.33	0.46
10	26.32	16.28	82.92	0.33	0.46
Variance Decomposition of Interest Rate Returns					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	4.57	3.07	0.02	96.91	0.00
2	4.95	4.37	0.63	95.00	0.00
3	5.18	4.79	1.14	93.91	0.16
4	5.37	5.81	1.75	92.28	0.16
5	5.43	5.74	1.93	92.16	0.18
6	5.47	5.68	1.92	92.20	0.20
7	5.50	5.97	1.91	91.87	0.24
8	5.52	6.03	1.96	91.72	0.28
9	5.53	6.02	2.00	91.69	0.29
10	5.53	6.02	2.00	91.66	0.32
Variance Decomposition of Risk-Premium					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	0.34	0.06	0.35	30.56	69.02
2	0.47	0.04	0.21	37.67	62.09
3	0.55	0.09	0.20	33.72	65.99
4	0.61	0.45	0.64	31.17	67.74
5	0.65	0.65	0.70	29.06	69.59
6	0.68	0.72	0.69	27.46	71.13
7	0.70	0.93	0.69	26.20	72.17
8	0.72	1.10	0.75	25.23	72.92
9	0.73	1.13	0.75	24.54	73.58
10	0.74	1.14	0.76	23.99	74.11

Cholesky Ordering: DS OF DI R

Variance Decomposition of Exchange Rate Returns					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	3.72	95.24	0.97	3.72	0.06
2	3.96	95.24	0.88	3.74	0.13
3	3.98	94.07	1.09	3.94	0.90
4	4.00	93.57	1.18	4.29	0.96
5	4.02	92.55	1.31	4.71	1.43
6	4.03	92.15	1.34	4.83	1.69
7	4.04	91.87	1.34	4.87	1.93
8	4.04	91.57	1.34	4.90	2.18
9	4.05	91.40	1.35	4.91	2.33
10	4.05	91.33	1.36	4.91	2.40
Variance Decomposition of Order Flow					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	16.86	0.00	99.46	0.16	0.38
2	23.47	4.62	94.32	0.09	0.98
3	23.73	4.55	94.18	0.20	1.07
4	24.70	11.13	86.92	0.84	1.11
5	25.21	11.72	86.12	1.05	1.11
6	25.97	11.83	85.90	0.99	1.29
7	26.11	11.90	85.76	0.98	1.37
8	26.18	12.28	85.30	1.05	1.37
9	26.25	12.57	84.97	1.09	1.37
10	26.32	12.52	85.01	1.09	1.38
Variance Decomposition of Interest Rate Differential Returns					
Period	**S.E.**	**DS**	**OF**	**DI**	**R**
1	4.57	0.00	0.00	70.00	3.00
2	4.95	0.55	0.42	69.92	29.11
3	5.18	0.77	0.86	68.62	29.76
4	5.37	1.17	1.65	67.48	29.70
5	5.43	1.15	1.82	67.27	29.76
6	5.47	1.14	1.81	67.11	29.94
7	5.50	1.33	1.79	66.83	30.04
8	5.52	1.36	1.86	66.64	30.14
9	5.53	1.36	1.89	66.57	30.18
10	5.53	1.36	1.89	66.51	30.24

Variance Decomposition of Risk-Premium

Period	S.E.	DS	OF	DI	R
1	0.34	0.00	0.00	0.00	100.00
2	0.47	0.16	0.05	1.00	98.79
3	0.55	0.20	0.06	0.95	98.80
4	0.61	0.46	0.26	0.92	98.36
5	0.65	0.69	0.27	1.18	97.86
6	0.68	0.82	0.25	1.60	97.33
7	0.70	1.11	0.24	1.97	96.68
8	0.72	1.34	0.27	2.31	96.09
9	0.73	1.41	0.27	2.64	95.68
10	0.74	1.46	0.26	2.93	95.35

Cholesky Ordering: R DI OF DS

A2: 2 Lag Microstructure Model Output

Dependent Variable: DS				
Method: Least Squares				
Sample (adjusted): 2001M04 2014M12				
Included observations: 165 after adjustments				
HAC standard errors & covariance				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-3.84	1.18	-3.26	0.00***
DI	0.17	0.06	2.73	0.01***
X	0.001284	0.000394	3.25702	0.00***
R	1.39	0.57	2.45	0.02 **
DS(-1)	0.29	0.07	4.42	0.00***
DS(-2)	-0.14	0.06	-2.37	0.02 **
R-squared	0.23	Mean dependent var		0.23
Adjusted R-squared	0.20	S.D. dependent var		3.96
S.E. of regression	3.53	Akaike info criterion		5.40
Sum squared resid	1984.29	Schwarz criterion		5.51
Log likelihood	-439.31	Hannan-Quinn criter.		5.44
F-statistic	9.38	Durbin-Watson stat		1.94
Prob(F-statistic)	0.00	Wald F-statistic		10.47
Prob(Wald F-statistic)	0.00			

****; **; * indicate the significance level at 1%, 5% and 10%*

A3: 2 Lag Estimates from the GARCH (0, 1) Model

Dependent Variable: DS				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	-3.55	0.93	-3.83	0.00***
DI	0.17	0.06	2.71	0.01 **
X	0.001252	0.000266	4.70	0.00**
R	1.24	0.45	2.80	0.01 **
DS(-1)	0.29	0.09	3.31	0.00***
DS(-2)	-0.12	0.10	-1.25	0.21
Variance Equation				
C	4.22	22.95	0.18	0.85
GARCH(-1)	0.64	1.95	0.33	0.74
R-squared	0.22	Mean dependent var		0.36
Adjusted R-squared	0.20	S.D. dependent var		3.90
S.E. of regression	3.49	Akaike info criterion		5.39
Sum squared resid	2088.45	Schwarz criterion		5.54
Log likelihood	-469.43	Hannan-Quinn criter.		5.45
Durbin-Watson stat	1.93			

****; **; * indicate the significance level at 1%, 5% and 10%*